MANAGING FOREST ECOSYSTEMS

Forest Inventory

Methodology and Applications

Edited by
Annika Kangas and Matti Maltamo

Springer

FOREST INVENTORY

Managing Forest Ecosystems

Volume 10

Series Editors:

Klaus von Gadow

Georg-August-University,
Göttingen, Germany

Timo Pukkala

University of Joensuu,
Joensuu, Finland

and

Margarida Tomé

Instituto Superior de Agronomía,
Lisbon, Portugal

Aims & Scope:

Well-managed forests and woodlands are a renewable resource, producing essential raw material with minimum waste and energy use. Rich in habitat and species diversity, forests may contribute to increased ecosystem stability. They can absorb the effects of unwanted deposition and other disturbances and protect neighbouring ecosystems by maintaining stable nutrient and energy cycles and by preventing soil degradation and erosion. They provide much-needed recreation and their continued existence contributes to stabilizing rural communities.

Forests are managed for timber production and species, habitat and process conservation. A subtle shift from *multiple-use management* to *ecosystems management* is being observed and the new ecological perspective of *multi-functional forest management* is based on the principles of ecosystem diversity, stability and elasticity, and the dynamic equilibrium of primary and secondary production.

Making full use of new technology is one of the challenges facing forest management today. Resource information must be obtained with a limited budget. This requires better timing of resource assessment activities and improved use of multiple data sources. Sound ecosystems management, like any other management activity, relies on effective forecasting and operational control.

The aim of the book series ***Managing Forest Ecosystems*** is to present state-of-the-art research results relating to the practice of forest management. Contributions are solicited from prominent authors. Each reference book, monograph or proceedings volume will be focused to deal with a specific context. Typical issues of the series are: resource assessment techniques, evaluating sustainability for even-aged and uneven-aged forests, multi-objective management, predicting forest development, optimizing forest management, biodiversity management and monitoring, risk assessment and economic analysis.

The titles published in this series are listed at the end of this volume.

Forest Inventory

Methodology and Applications

Edited by

Annika Kangas
University of Helsinki, Finland

and

Matti Maltamo
University of Joensuu, Finland

Springer

A C.I.P. Catalogue record for this book is available from the Library of Congress.

ISBN-10 1-4020-4379-1 (HB)
ISBN-13 978-1-4020-4379-6 (HB)
ISBN-10 1-4020-4381-3 (e-book)
ISBN-13 978-1-4020-4381-9 (e-book)

Published by Springer,
P.O. Box 17, 3300 AA Dordrecht, The Netherlands.

www.springer.com

Printed on acid-free paper

Printed in the Netherlands.

TABLE OF CONTENTS

PREFACE

This book has been developed as a forest inventory textbook for students and could also serve as a handbook for practical foresters. We have set out to keep the mathematics in the book at a fairly non-technical level, and therefore, although we deal with many issues that include highly sophisticated methodology, we try to present first and foremost the ideas behind them. For foresters who need more details, references are given to more advanced scientific papers and books in the fields of statistics and biometrics.

Forest inventory books deal mostly with sampling and measurement issues, as found here in section I, but since forest inventories in many countries involve much more than this, we have also included material on forestry applications. Most applications nowadays involve remote sensing technology of some sort, so that section II deals mostly with the use of remote sensing material for this purpose. Section III deals with national inventories carried out in different parts of world, and section IV is an attempt to outline some future possibilities of forest inventory methodologies.

The editors,

Annika Kangas	Professor of Forest Mensuration and Management, Department of Forest Resource Management, University of Helsinki.
Matti Maltamo	Professor of Forest Mensuration, Faculty of Forestry, University of Joensuu.

ACKNOWLEDGEMENTS

In addition to the authors of the chapters, many researchers around the world have helped us by reviewing chapters, suggesting improvements and even checking our calculations. We would like to acknowledge these reviewers for their efforts to improve our work. The errors remaining are nevertheless attributable entirely to the authors.

Burk Thomas	McRoberts Ronald
Czaplewski Raymond	Næsset Erik
Eerikäinen Kalle	Nilsson Mats
Ek Alan	Økland Tonje
Gillis Mark	Olsson Håkan
Gregoire Timothy	Penttinen Antti
Hagner Olle	Rawat Jagdish Kumar
Häme Tuomas	Ringvall Anna
Hobbelstad Kåre	Robinson Andrew
Iles Kim	Salemaa Maija
Kleinn Christopher	Ståhl Göran
Lämås Thomas	Tuomainen Tarja
Lund Gyde	Uuttera Janne
Lundström Anders	Valentine Harry
Magnussen Steen	Varjo Jari
Mandallaz Daniel	Wulder Mike

We would also like to thank Heikki Surakka and Antti Mäkinen, the foresters who calculated many of the examples and drew part of the figures, and Malcolm Hicks for revising the English language in this book. Finally, we would like to thank Foresters Foundation for financial support.

LIST OF CONTRIBUTING AUTHORS

Dr. Jeffrey H. Gove
USDA Forest Service
Northeastern Research Station
P.O. Box 640
Durham, NH 03824
Email: jgove@fs.fed.us

Dr. Juha Heikkinen
Metla Helsinki Research Unit
Unioninkatu 40 A
00170 Helsinki
Email: juha.heikkinen@metla.fi

Dr. Markus Holopainen
Department of Forest Resource Management
P.O. Box 27
00014 University of Helsinki
Email: markus.holopainen@helsinki.fi

M.Sc. Jouni Kalliovirta
Department of Forest Resource Management
P.O. Box 27
00014 University of Helsinki
Email: jouni.kalliovirta@helsinki.fi

Prof. Annika Kangas
Department of Forest Resource Management
P.O. Box 27
00014 University of Helsinki
Email: annika.kangas@helsinki.fi

Dr. Matti Katila
Metla Helsinki Research Unit
Unioninkatu 40 A
00170 Helsinki
Email: matti.katila@metla.fi

Dr. Jyrki Koivuniemi
Metla Research Forest Service,
Vantaa Research Unit
P.O. Box 18
01301 Vantaa
Email: jyrki.koivuniemi@metla.fi

Dr. Kari. T. Korhonen
Metla Joensuu Research Unit
P.O. Box 68
80101 Joensuu
Email: kari.t.korhonen@metla.fi

Dr. Juha Lappi
Metla Suonenjoki Research Unit
Juntintie 154
77600 Suonenjoki
Email: juha.lappi@metla.fi

Prof. Matti Maltamo
University of Joensuu
Faculty of Forestry
P.O. Box 111
80101 Joensuu
Email: matti.maltamo@joensuu.fi

Dr. Lauri Mehtätalo
Metla Joensuu Research Unit
P.O. Box 68
80101 Joensuu
Email: lauri.mehtatalo@metla.fi

Dr. Anssi Pekkarinen
Joint Research Centre
Institute for Environment and Sustainability
Climate Change Unit (T.P. 051)
I – 21020 Ispra (Va)
Email: anssi.pekkarinen@metla.fi

Prof. Simo Poso
Department of Forest Resource Management
P.O. Box 27
00014 University of Helsinki
Email: simo.poso@helsinki.fi

Dr. Charles T. Scott
USDA Forest Service
Northeastern Research Station
11 Campus Boulevard
Suite 200
Newtown Square, PA 19073
Email: ctscott@fs.fed.us

Prof. Timo Tokola
Department of Forest Resource Management
P.O. Box 27
00014 University of Helsinki
Email: timo.tokola@helsinki.fi

Prof. Erkki Tomppo
Metla Helsinki Research Unit
Unioninkatu 40 A
00170 Helsinki
Email erkki.tomppo@metla.fi

M.Sc. Sakari Tuominen
Metla Helsinki Research Unit
Unioninkatu 40 A
00170 Helsinki
Email: sakari.tuominen@metla.fi

PART I
THEORY

CHAPTER 1

INTRODUCTION

ANNIKA KANGAS, JEFFREY H. GOVE AND CHARLES T. SCOTT

University of Helsinki, Finland; USDA Forest Service, Northeastern Research Station, USA

1.1 GENERAL

All decision-making requires information. In forestry, this information is acquired by means of forest inventories, systems for measuring the extent, quantity and condition of forests (Penman et al. 2003). More specifically, the purpose of forest inventories is to estimate means and totals for measures of forest characteristics over a defined area. Such characteristics include the volume of the growing stock, the area of a certain type of forest and nowadays also measures concerned with forest biodiversity, e.g. the volume of dead wood or vegetation (Chapters 8 and 9). This book presents methods and applications for carrying out a forest inventory in different situations.

A forest inventory could in principle be based on a complete census, i.e. on measuring every tree in a given area, but this is usually impossible in forestry because of the large areas involved. Therefore the acquisition of information is typically based on sampling, i.e. only a proportion of the population, a sample, is inspected and inferences regarding the whole population are based on this sample.

There are two main schools of inference in sampling theory, design-based and model-based. In design-based inference, the randomness in the sampling is solely due to the random selection of sampling units (Chapter 2). The population values y_i are regarded as fixed, but unknown. Inference is based on the variation between all possible samples of size n that can be drawn from the population with a given sampling design. The confidence intervals obtained are to be interpreted on the assumption of a hypothetical repetition of samples.

This is not the case in model-based inference (Chapter 3), where the randomness is solely due to the model used for describing the population. In this case, the sampling method does not necessarily have to be random, but the possible correlation between sampling units needs to be accounted for.

A. Kangas and M. Maltamo (eds.), Forest Inventory – Methodology and Applications, 3–11.

Forest inventory is more than sampling, however. Measuring trees and sample plots (Chapter 4) includes many methodological problems that are typical only to this sphere. Forest inventories cover different spatial scales from the stand level to the woodlot level, regional and country level and finally global level. It is evident that these varying scales also require different methodologies. The purposes of inventories may also vary. Stand-level inventories (Chapter 16) can be carried out in order to estimate the number of saplings after regeneration, woodlot-level inventories in order to facilitate harvesting or silvicultural decisions, and regional or country-level inventories in order to enhance policy decisions (Chapters 18-20). Global inventories (Chapter 17) may also serve certain purposes in global-level politics, such as international agreements over actions concerning biodiversity or global warming.

Forest inventories may also be means of estimating the current growing stock, but most often they are carried out at several points of time in order to analyse temporal changes (Chapter 5).

1.2 HISTORICAL BACKGROUND OF SAMPLING THEORY

The use of representative samples was recommended by A. N. Kiaer, a Norwegian statistician, at the end of the 19th century (Bellhouse 1988). Reactions to his recommendation were mainly negative at first, but by 1925 the idea was generally accepted. The idea of samples had been introduced even earlier, but it was Kiaer's campaign that provided the breakthrough for its acceptance (Bellhouse 1988).

In those days the samples were, for most part, purposely selected. The idea of randomization was introduced into survey sampling by A. L. Bowley in 1912 (Bellhouse 1988), but the use of purposive selection remained acceptable for the next decade. Bowley also studied the precision of the estimates obtained, and found purposive sampling to be more efficient than random sampling.

The paper of Neyman (1934) gave the first precise statistical framework for sampling theory. He presented confidence intervals for sample estimates, based on their distribution among all the possible samples of a given size from the given population, so that the estimates for the confidence intervals would apply irrespective of the properties of the original population (except when the sample was very small or the population extremely skewed).

Neyman also provided the reasons why randomization gave a more reasonable solution than purposive selection and outlined the assumptions under which purposive selection would work well, namely when there is a linear relationship between the variable of interest and the available covariates (Bellhouse 1988). Since Neyman's paper random sampling has superseded purposive sampling. Neyman also presented the principles of stratified sampling (1934), although the same ideas had already been put forward by Tschuprow (1923, see Schreuder et al. 1993).

During the next two decades classical sampling theory, or design-based theory as it is called, achieved mathematical and practical acceptance, essentially in the form in which it is used today. The most important developments in design-based theory during those decades were related to sampling with unequal

probabilities (Hansen and Hurwitz 1943), a method by which the precision of the results could, under some conditions, be radically improved. Horwitz and Thompson (1952) provided an unbiased estimator for unequal probability sampling.

The first challenge to the design-based approach was raised by V. P. Godambe in 1955. He showed that no minimum variance unbiased estimator exists among all possible linear unbiased estimators, even for simple random sampling (Rao and Bellhouse 1990). This means that certain estimators for population parameters (such as the sample mean) would not have the minimum variance in all populations. In order to find the best estimator, some assumptions therefore had to be made concerning the population. This aroused interest in an alternative approach to sampling theory, the model-based approach (also called the model-dependent or prediction approach). The foundations of this approach were introduced by Godambe (1955) and later established by Cassel et al. (1977).

1.3 HISTORY OF FOREST INVENTORIES

The main method used in inventories in the 19th century was complete enumeration, but it was soon noted that there was a possibility to reduce costs by using representative samples (Loetsch et al. 1973). Sampling-based methods were used in forestry a century before the mathematical foundations of sampling techniques were described (Doig 1976, Seppälä 1985, Honer and Hegyi 1990, Gregoire 1992, van Hooser et al. 1992, Schreuder et al. 1993, Frayer and Furnival 1999).

In the early days visual estimation was often used, as it was cheap and fast. In North America, for instance, these inventory surveys were carried out at the beginning of the 20th century by "timber lookers", whose years of field experience allowed them to develop the ability to assess timber volumes by eye without the benefit of any measurements. One early common practice was to estimate the volume on an "average tree" within a plot of fixed size and, by knowing the count of stems on the plot, thereby estimate volume on an "average acre", finally expanding to the yield on the tract of land (Graves 1906, p.192). According to Loetch et al. (1973), visual estimation was used until the 1940's in Germany, where learning this method was part of a good training program for a forester in those days. In the Nordic countries, especially in Finland, these visual estimates are still used for acquiring data for management planning at the stand level. In early inventories visual estimates could also be combined with statistical estimates in order to reduce bias (Cajanus 1913, Ilvessalo 1923).

Statistical knowledge was gradually introduced into the forestry literature between 1900 and 1920, primarily in Scandinavia (Loetsch et al. 1973), where the first small-scale forest inventories using systematic strip sampling had been carried out in Sweden in the 1830's by Israel af Ström. An auxiliary purpose in conducting an inventory was that of developing a map showing the distribution of timber, forest types, access and topographic detail. The method of cruising with continuous strips of fixed width covering a known percentage of the land area was most popular into the 1930s because it served both purposes, inventory and mapping.

The most important scientific work in this field in Finland was the inventory carried out in Sahalahti and Kuhmalahti by Werner Cajanus in 1912 (Seppälä 1985). Yrjö Ilvessalo carried out the first four National Forest Inventories between 1921 and 1963 (1927, 1942, 1956, 1962). National inventories in the other Nordic countries started at almost the same time. Since these first inventories were systematic, estimators for the variance in systematic sampling have been intensively developed in these countries (e.g. Lindeberg 1924, 1926, Langsaeter 1926, 1932, Östling 1932, Chapter 10).

However, the systematic use of strips was not the most efficient method. Thus, there began a slow shift from the use of strips to the use of the line-plot system: a systematic sampling design in which relatively small square or, more commonly, circular plots, were taken at set intervals (Robertson 1927). The line-plot method had the advantage of surveying a much smaller percentage of the area for a given accuracy, while still providing a method for mapping.

The next few decades brought a flurry of activity on the application of statistical methods to forest inventory. In the United States, Schumacher and Bull (1932) began the formalization of statistical sampling methods applied to forest inventories, with specific regard to the estimation of sampling errors. Mudgett and Gevorkiantz (1934) also looked at methods for assessing the reliability of area estimates using binomial, Poisson, and Lexian models according to differing assumptions about the random or stratified nature of the populations being sampled. Girard and Gevorkiantz (1939) devoted a large part of their monograph to the calculation of sampling errors, and interestingly, it was evidently Schumacher and Chapman (1942) who published the first known book on sampling in any field.

One of the most important issues in this era was the debate over systematic sampling, because of the heavy reliance on the line-plot and strip methods. Though earlier studies were concerned with this, Hasel (1938) conducted the first thorough study in forestry in regard to timber volume estimation and strongly advocated the randomization principals of R.A. Fisher in the case of heterogeneous populations, while at the same time stating that systematic cruises give closer estimates of the true volume than do random samples. Osborne (1942) conducted a similar study for mapping forest types and arrived at analogous conclusions about the nature of systematic surveys. Finney (1948), using Hasel's data and material from another fully enumerated forest, concluded that the increased precision obtainable from a systematic sample is seldom the sole reason to prefer it over stratified sampling. Finney noted, however, that "this argument would be destroyed" if one could develop a method for assessing the error from a simple, unique systematic sample. Finney's advice on stratification survives to the present, though many surveys continue to employ systematic methods without even the benefit of randomization of the initial sampling location, as suggested by Finney (1947).

Within the same period and subsequently, work on the theory for variance estimation in a systematic survey was greatly advanced by Matérn (1947, 1960, 1986). Since then, in the national forest inventories of Sweden and Finland, systematic cluster sampling design has been used (e.g. Kuusela and Salminen 1969). The ideas of Matérn were employed in assessing the precision of the inventory results (Salminen 1973, Ranneby 1981).

Another very important development in forest inventory was the introduction of sampling with unequal probabilities, namely the work of Bitterlich and Grosenbaugh, and the introduction of the use of an angle gauge to determine whether an individual tree is to be included in the sample. Angle gauge sampling quickly established itself as an efficient method of sampling forests for the characteristic that is of most interest to foresters — timber volume. Angle count sampling was first introduced by Bitterlich in 1947 and 1948, though its conception predated that by almost two decades (Bitterlich 1984, p. 3). Originally, it was envisaged by Bitterlich as a method for determining the basal area density of a forest by means of an angle gauge. The cruiser simply counts those trees whose diameter appears larger than the projected angle. It can be shown through simple geometric relations that each such tree represents a constant basal area per unit land area, and thus a simple count of trees on a 360° sweep of a sample "point" yields an estimate of the basal area in surroundings.

It was Grosenbaugh (1952, 1955, 1958), however, who extended this interpretation to the probabilistic sampling realm, developing a theory for estimating any quantity associated with the sample trees (e.g. volume, biomass, number of individuals) employing probability proportional to size (PPS) sampling methods. Grosenbaugh coined the term "point sampling" because it was in the relation of a randomly chosen point falling within a tree's inclusion area that this probabilistic argument was developed. Shortly afterwards, Palley and Horwitz (1961) gave a rigorous proof that point sampling was unbiased, while providing the statistical derivation of its design-based estimators under conditions of PPS sampling. While point sampling was a major innovation in sampling forests, where it is not feasible to visit every tree, many timber sales require just that.

Lacking in these methods is a generalized framework for estimating the components of forest growth. The continuous forest inventory system (CFI) introduced by Stott (1947) relied on permanent fixed area plots on which all the trees were numbered and remeasured annually. In time, methods like point sampling were also used in place of fixed-area plots, and annual remeasurements have largely given way to periodic 5- or 10-year visits. As the individual trees are numbered, the system allows tracking of each tree's growth and death over time. A second system, introduced to forestry by Bickford (1959) and more formally by Ware and Cunia (1962), optimally combines growth information from permanent plots with volume information from temporary plots. In sampling with partial replacement (SPR), only a portion of the plots that were originally established are remeasured, the rest being replaced with a sample of new plots. CFI can thus be thought of as a special case of SPR where all the plots are remeasured in each time period. SPR was adopted almost immediately by Bickford et al. (1963) in conjunction with double sampling for stratification for the forest survey in the northeastern U.S. and has proved to be an efficient design.

Apart from the work of Matérn (1960), the model-based approach has not been used extensively in forest inventories, although a few exceptions exist, e.g. the works of Mandallaz (1991), Kangas (1993) and Gregoire (1998).

Aerial photographs have also been used in forestry since the early 20th century, mostly for visual interpretation, but also for double sampling (Bickford

1952, see Chapter 14). In recent years information from satellite images has also been used, so that the national forest inventories in Finland and many other countries has become a multi-source inventory (e.g. Tomppo 1992, Bechtold and Patterson 2005, Chapters 11 and 12). Nowadays satellite images are gradually replacing the use of aerial photographs (Czaplewski 1999).

REFERENCES

Bectold, W.A. and Patterson, P.L. 2005. The enhanced Forest Inventory and Analysis Program – national sampling design and estimation procedures. General Technical Report SRS-80. U.S. Department of Agriculture, Forest Sevice, Southern Research Station, Asheville, NC. 85 p.

Bellhouse, D.R. 1988. A Brief History of Random Sampling Methods. In: Handbook of Statistics, 6, Sampling, pp. 1-13. Eds. Krishnaiah, P.R. and Rao, C.R., North Holland.

Bickford, C.A. 1952. The sampling design used in the forest survey of the Northeast. Journal of Forestry 50:290-293.

Bickford, C.A. 1959. A test of continuous inventory for national forest management based upon aerial photographs, double sampling, and remeasured plots. Society of American Foresters Proceedings 1959, Society of American Foresters. p. 143-148.

Bickford, C.A., Mayer, C.E. and K.D. Ware. 1963. An efficient sampling design for forest inventory: The northeastern forest resurvey. Journal of Forestry 61:826-883.

Bitterlich, W. 1947. Die Winkelzählmessung. Allgemeine Forst- und Holzwirtschaftliche Zeitung 58: 94-96.

Bitterlich, W. 1948. Ein neues Messverfahen zur Aufnahame stehender Holzmassen. Österreichs Forst- und Holzwirtschaft 3:89-90.

Bitterlich, W. 1984. The relascope idea: Relative measurements in forestry. Commonwealth Agricultural Bureau, Slough, England. 242 p.

Cajanus, W. 1913. A method for ocular estimation of the growing stock of forests. Tapio 6:77-79.

Cassel, C-M, Särndal, C-E. and Wretman, J.H. 1977. Foundations of Inference in Survey Sampling. John Wiley & Sons, New York. 192 p.

Czaplewski, R.L. 1999. Multistage remote sensing: Toward an annual national inventory. Journal of Forestry 97:44-48.

Doig, I. 1976. When the douglas-firs were counted: the beginning of the forest survey. Journal of Forest History 20:20-27

Finney, D.J. 1947. Volume estimation of standing timber by sampling. Forestry 21:179-203.

Finney, D.J. 1948. Random and systematic sampling in timber surveys. Forestry 22:64-99.

Frayer, W.E. and Furnival, G.M. 1999. Forest survey sampling designs. A history. Journal of Forestry 97:4-10.

Girard, J.W. and Gevorkiantz, S.R. 1939. Timber cruising. USDA Forest Service, Forest Survey Report. 160 p.

Godambe, V.P. 1955. A Unified theory of sampling from finite populations. Journal of the Royal Statistical Society series B, 17:269-278.

Graves, H.S. 1906. Forest Mensuration. John Wiley and Sons, NY. 458 p.

Gregoire, T. 1992. Roots of Forest inventory in North America. A paper presented at the A1 Inventory Working Group session at the SAF National Convention held at Richmond, VA 25.-28.10.1992.

Gregoire, T. 1998. Design-based and model-based inference in survey sampling: appreciating the difference. Canadian Journal of Forest Research 28:1429-1447.

Grosenbaugh, L.R. 1952. Plotless timber estimates—new, fast, easy. Journal of Forestry 50:32-37.

Grosenbaugh, L.R. 1955. Better diagnosis and prescription in southern forest management. Southern Forest Experiment Station Occasional Paper 145, 27 p.

Grosenbaugh, L.R. 1958. Point-sampling and line-sampling: Probability theory, geometric implications, synthesis. Southern Forest Experiment Station Occasional Paper 160, 34 p.

Hasel, A.A. 1938. Sampling error in timber surveys. Journal of Agricultural Research 57:713-736.

Hansen, M.H. and Hurwitz, W.N. 1943. On the theory of sampling from finite populations. Annals of Mathematical Statistics, 14:333-362.

Honer, T.G. and Hegyi, F. 1990. Forest inventory – Growth and yield in Canada: Past, present and future. The Forestry Chronicle 66:112-117.

Horvitz, D.G. and Thompson, D.J. 1952. A generalization of sampling without replacement from a finite universe. Journal of American Statistical Association 47:663-685.

Ilvessalo, Y. 1923. Research into the condition of private forests in the middle part of government district Häme Acta Forestalia Fennica 26.

Ilvessalo, Y. 1927. Suomen metsät. Tulokset vuosina 1921-1924 suoritetusta valtakunnan metsien arvioinnista. Communicationes Instituti Fororestalis Fenniae 11.

Ilvessalo, Y. 1942. Suomen metsävarat ja metsien tila. II valtakunnan metsien arviointi. Communicationes Instituti Fororestalis Fenniae 30.

Ilvessalo, Y. 1956. Suomen metsät vuosista 1921-24 vuosiin 1951-53. Kolmeen valtakunnan metsien inventointiin perustuva tutkimus. Communicationes Instituti Fororestalis Fenniae 47.

Ilvessalo, Y. 1962. IV Valtakunnan metsien inventointi. 1. Maan eteläpuoliskon vesistöryhmät. Communicationes Instituti Fororestalis Fenniae 56.

Kangas, A. 1993. Estimating the parameters of systematic cluster sampling by model based inference. Scandinavian Journal of Forest Research 8:571-582.

Kuusela, K. and Salminen, S. 1969. The 5th national forest inventory of Finland. General design, instructions for field work and data processing. Communicationes Instituti Fororestalis Fenniae 69.

Langsaeter, A. 1926. Om beregning av middelfeilen ved regelmessige linjetaksering. Meddel. fra det norske Skogforsøksvesen 2(7):5-47. (In Norwegian).

Langsaeter, A. 1932. Nøiaktigheten ved linjetaksering av skog, I. Meddel. fra det norske Skogforsøksvesen 4:431-563.

Lindeberg, J.W. 1924. Über die Berechnung des Mittelfehlers des Resultates einer Linientaxierung. Acta Forestalia Fennica 25. 22 p.

Lindeberg, J.W. 1926. Zür Theorie der Linientaxierung. Acta Forestalia Fennica 31.6:1-9.

Loetsch, F., Zöhrer, F. and Haller, K. 1973. Forest Inventory. Vol I-II 436+ 469 p. BLV Verlagsgesellschaft.

Mandallaz, D. 1991. A Unified Approach to Sampling Theory for Forest Inventory Based on Infinite Population and Superpopulation Models. Chair of Forest Inventory and Planning, Swiss Federal Institute of Technology (ETH), Zurich. 242 p.

Matérn, B. 1947. Metoder att uppskatta noggrannheten vid linje- och provytetaxering. Meddelanden från Statens Skogsforskningsinstitut. Band 36(1). 138 p.

Matérn, B. 1960. Spatial Variation. Stochastic models and their application to some problems in forest surveys and other sampling investigations. Meddelanden från Statens Skogsforskningsinstitut. Band 49(5). 144 p.

Matérn, B. 1986. Spatial variation, Lecture Notes in Statistics 36, Springer-Verlag, NY. 151 p.

Mudgett, B.D. and Gevorkiantz, S.R. 1934. Reliability in forest surveys. Journal of the American Statistical Association 29:257-281.

Neyman, J. 1934. On the two different aspects of the representative method: the method of stratified sampling and the method of purposive sampling. Journal of the Royal Statistical Society 97:558-606.

Osborne, J.G. 1942. Sampling errors of systematic and random surveys of cover-type areas. Journal of the American Statistical Association 37:256-264.

Östling, J. 1932. Erforderlig taxeringsprocent vid linjetaxering av skog. Sveriges Skogsvårdsföreningens Tidskrift 30.

Palley, M.N. and L.G., Horwitz. 1961. Properties of some random and systematic point sampling estimators. Forest Science 7:52-65.

Penman, J., Gytarsky, M., Hiraishi, T., Krug, T., Kruger, D., Pipatti, R., Buendia, L., Miwa, K., Ngara, T., Tanabe, K. and Wagner, F. (Eds.) 2003. Good practice guidance for land use, land-use change and forestry. Intergovernmental Panel on Climate Change: IPCC National Greenhouse Gas Inventories Programme. Kanagawa Japan: Institute for Global Environmental Strategies (IGES) for the IPCC. http://www.ipcc-nggip.iges.or.jp/public/gpglulucf/gpglulucf_contents.htm

Ranneby, B. 1981. Medelfelsformler till skattningar baserade på material från den 5:de riksskogstaxeringen. Sveriges lantbruksuniversitet, Institutionen för biometri och skogsindelning. Rapport 21. Umeå, 19 p.

Rao, J.N.K. and Bellhouse, D.R. 1990. History and Development of the Theoretical Foundations of Survey Based Estimation and Analysis. Survey Methodology 16:3-29.

Robertson, W.M. 1927. The line-plot system, its use and application. Journal of Forestry 25:157-163.

Salminen, S. 1973. Tulosten luotettavuus ja karttatulostus valtakunnan metsien V inventoinnissa. Summary: Reliability of the results from the fifth national forest inventory and a presentation of an output-mapping technique. Communicationes Instituti Forestalis Fenniae 78(6). 64 p.

Schreuder, H.T., Gregoire, T.G. and Wood, G.B. 1993. Sampling Methods for Multiresource Forest Inventory. John Wiley & Sons. New York. 446 p.

Schumacher, F.X. and Bull, H. 1932. Determination of the errors of estimate of a forest survey with special reference to the bottom-land hardwood forest region. Journal of Agricultural Research 45:741-756.

Schumacher, F.X. and Chapman, R.A. 1942. Sampling methods in forestry and range management. Duke University, School of Forestry Bulletin 7. 222 p.

Seppälä, R. 1985. Forest Inventories and the Development of Sampling Methods. Silva Fennica 3: 218-219.

Stott, C.B. 1947. Permanent growth and mortality plots in half the time. Journal of Forestry 45:669-673.

Tomppo, E. 1992. Multi-source national forest inventory of Finland. Proceedings of Ilvessalo Symposium on National Forest Inventories organized by IUFRO S4.02. Metsäntutkimuslaitoksen tiedonantoja 444. pp. 52-60.

Tschuprow, A.A. 1923. On the mathematical expectation of the moments of frequency distributions in the case of correlated observations. Metron 2:461-493.

Van Hooser, D.D., Cost, N.D. and Lund, H.G. 1992. The history of forest survey program in the United States. pp. 19-27. In: Preto, G and Koch, B. (Eds.) Forest resource inventory and monitoring and remote sensing technology. Proceedings of the IUFRO Centennial Meeting in Berlin 31.8.-4.9.1992. Japan Society of Forest Planning Press, Tokyo University of Agriculture and Technology 3-5-8 Saiwaicho, Fuchu, Tokyo, 183 Japan.

Ware, K.D. and Cunia, T. 1962. Continuous forest inventory with partial replacement of samples. Forest Science Monograph 3, 40 p.

CHAPTER 2

DESIGN-BASED SAMPLING AND INFERENCE

ANNIKA KANGAS

University of Helsinki, Finland

2.1 BASIS FOR PROBABILITY SAMPLING

The target of sampling is usually a finite population of N elements called sampling units. A sample s is a subset of this population with size n. A sample can be any subset of the population, but usually a random sample is used.

For sampling to fulfil the requirements of random sampling, it is enough that 1) a set S_n of all samples s of size n that it is possible to obtain can be defined; 2) each sample has a known probability $p(s)$ of being selected; 3) the probabilities are non-zero and the sum of these probabilities is one $\sum_{s \in S} p(s) = 1$, and 4) the sample s is selected according to the probabilities $p(s)$. The units are selected independently, i.e. selection of any one unit does not affect the selection of others. No other requirements are needed. The probabilities $p(s)$ then define the sampling design (Särndal et al. 1992, p. 8). Lund and Thomas (1989) provide a good overview of various sampling designs used in forest and stand inventories. It is worth noting, however, that systematic sampling does not fulfil the above requirements of independent selection, and this will affect inferences based on this sampling design (section 2.4.).

Another important probability measure is the inclusion probability π_i. This measures the probability of each sampling unit i entering the sample s. The inclusion probability and selection probability are connected (see section 2.2). When these probabilities are known, the sample statistics of interest can be calculated. The most general estimators that apply to all kinds of sampling design are those based on

A. Kangas and M. Maltamo (eds.), Forest Inventory – Methodology and Applications, 13–38.

arbitrary inclusion probabilities. An estimate $\hat{T}$ for total value T of some interesting variable y in the population can be calculated with the Horwitz-Thompson estimator as

$$\hat{T} = \sum_{i=1}^{n} \frac{y_i}{\pi_i}, \tag{2.1}$$

where π_i is the inclusion probability of unit i. The variance estimator for the Horwitz-Thompson estimator is

$$\mathrm{var}(\hat{T}_{HT}) = \frac{1}{2} \sum_{i=1}^{n} \sum_{\substack{j=1 \\ j \neq i}}^{n} \frac{\pi_i \pi_j - \pi_{ij}}{\pi_{ij}} \left(\frac{y_i}{\pi_i} - \frac{y_j}{\pi_j} \right)^2, \tag{2.2}$$

where π_{ij} is the probability of units i and j both being included in the sample at the same time, provided all the inclusion probabilities are above zero. All the estimators developed for different sampling designs can be derived from these general formulae.

Although the variance of the values of y in the population affects the estimates, the variance of an estimator in design-based inference is not statistically dependent on the distribution of y (Gregoire 1998). The expected value of an estimator and the variance of the estimators are based on the variation in the estimates (i.e. values of the estimators) between all the possible samples s in the set S_n. Since all the randomness comes from the selection of the sampling units, not from the population itself, the values of y in the population are treated as fixed but unknown (for a different situation, see Chapter 3). This also means that design-based inference is independent of the potential spatial correlation between the sampling units (Gregoire 1998). It is enough that the units are not correlated in terms of their selection.

One estimator of the mean value of y in the population is the sample mean, the expected value of which can be calculated as

$$E(\hat{\bar{y}}_s) = \sum_{S_n} \hat{\bar{y}}_s p(s). \tag{2.3}$$

This is the weighted mean of all possible sample means, weighted with the probability $p(s)$ of selecting each sample s. An estimator is design-unbiased, i.e. unbiased under a certain sampling design, if and only if its expected value coincides with the true population value. The bias of an estimator for the mean value is then defined as (see Schreuder et al. 1993 p. 21)

$$B(\hat{\bar{y}}_s) = E(\hat{\bar{y}}_s) - \bar{Y}, \tag{2.4}$$

where $\overline{Y}$ is the true population mean. The variance of the estimator is

$$V(\hat{\bar{y}}_s) = E\left\{\hat{\bar{y}}_s - E(\hat{\bar{y}}_s)\right\}^2 = \sum_{S_n}\left(\hat{\bar{y}}_s - E(\hat{\bar{y}}_s)\right)^2 p(s) \tag{2.5}$$

and the mean square error (MSE) of the estimator is

$$MSE(\hat{\bar{y}}_s) = E\left(\hat{\bar{y}}_s - \overline{Y}\right)^2 = \sum_{S_n}\left(\hat{\bar{y}}_s - \overline{Y}\right)^2 p(s) = V(\hat{\bar{y}}_s) + \left\{B(\hat{\bar{y}}_s)\right\}^2. \tag{2.6}$$

More generally, the expected value, bias and variance can be defined in the same way for any estimator $\hat{Y}_s$ based on observed values y_i from sample s (Särndal et al. 1992 p. 40).

In typical sampling situations the population is easy to define and finite, whereas in forest inventories the population may be infinite and is often difficult to define. In many cases the population to be inventoried is assumed to be that of sample plots, i.e. the sampling unit is a sample plot (Shiver and Borders 1996 p. 59). This is justified by the fact that the interest lies in the forest characteristics per unit area, such as volume per hectare and so on. Consequently, the size of the population is often assumed to be the number of similar-sized sample plots that will fit into the area, i.e. the total area divided by the plot area. This definition is the easiest to operate with.

Such a definition is not adequate on all occasions, however. For instance, when circular sample plots are used it is not possible to divide the area into mutually exclusive plots that cover the whole of it. In point (or plotless) sampling with a relascope or angle gauge, the size of the sample plot is zero, so that the number of potential sampling units per unit area in infinite, as is the size of the population. When the aim is to estimate the forest area, the population is defined based on plots or points.

In addition to stand-level characteristics, tree-level characteristics such as the mean diameter or number of stems may be of interest, so that the most natural population would be the population of trees. On some occasions the trees may also be the primary sampling units, e.g. with sampling proportional to size in a stand, for example for relascope sampling. If the sampling units are trees, the size of the population is practically never known. One definition that would be adequate in many situations is that the population consists of trees but the sampling unit is a plot.

2.2 SIMPLE RANDOM SAMPLING

Simple random sampling, SRS, can be done either with or without replacement. Sampling with replacement means that each unit can be selected several times. This method is not very important in practice, but it is of theoretical importance as many formulae for this design are very simple. The probability *p(s)* of selecting a given

sample s of size n out of the population of size N is $p(s) = 1/N^n$ (Särndal et al. 1992 p. 50), as there are N^n samples of size n that can be drawn from the population. In this case, the inclusion probability can be calculated as one minus the probability of not drawing a certain unit i, i.e. $\pi_i = 1-(1-1/N)^n$, and the probability of selecting two units i and j is $\pi_{ij} = 1-2(1-1/N)^n + (1-2/N)^n$ (Särndal et al. 1992 p. 50).

In sampling without replacement, on the other hand, each unit can be selected only once and the selection and inclusion probabilities are not quite as easy to calculate as in the earlier case. The number of possible samples is nevertheless $\frac{N!}{(N-n)!n!}$ and the probability of each of these being selected is its inverse

$$p(s) = \frac{(N-n)!\,n!}{N!}. \tag{2.7}$$

The inclusion probability for any unit i is $\pi_i = n/N$ and the probability of selecting two units i and j is $\pi_{ij} = \left(n(n-1)/N(N-1)\right)$ (Särndal et al. 1992 p. 66).

The estimators for the mean and its variance can then be derived from these probabilities with (2.1) and (2.2). Although the Horwitz-Thompson estimator is for the total value, the estimators for the total value $\hat{T}$ and mean $\hat{\bar{y}}$ are related according to

$$\hat{T} = N\hat{\bar{y}} \tag{2.8}$$

and their variances according to

$$\mathrm{var}(\hat{T}) = N^2\,\mathrm{var}(\hat{\bar{y}}), \tag{2.9}$$

assuming in both cases that the population size N is known.

One estimator for the population mean in SRS is the sample mean

$$\hat{\bar{y}} = \frac{1}{n}\sum_{i=1}^{n} y_i, \tag{2.10}$$

where y_i is the value of the variable of interest for unit i. For sampling without replacement, an estimator for its variance is

$$\mathrm{var}(\hat{\bar{y}}) = \left(1 - \frac{n}{N}\right)\frac{s_y^2}{n}, \tag{2.11}$$

while that for sampling with replacement is

$$\text{var}(\hat{\bar{y}}) = \frac{s_y^2}{n}, \tag{2.12}$$

where s_y^2 is the sample variance of y. The true variance of the sample means could be calculated if the population variance S_y^2 were known, but usually it is not. Therefore, estimators of the sampling variances are given in this chapter and not formulae for the true sampling variances. The formula for sampling with replacement (eq. 2.12) can also be used if the population is assumed to be infinite or very large.

The standard error of the mean is

$$s_e = \sqrt{\text{var}(\hat{\bar{y}})}\ . \tag{2.13}$$

This describes how much the sample means from different samples vary around the true mean. In the case of design-based sampling, the standard error can be interpreted as implying that the sample mean deviates less than $\pm 1.96 s_e$ from the true mean in 95 samples out of 100 selected. This is based on the assumption that the distribution of sample means is normal. The statements concerning the accuracy of sampling are correspondingly based on the assumption of repeated sampling.

The proportion of a certain class i can be estimated from

$$\hat{p}_i = \frac{n_i}{n}, \tag{2.14}$$

where n_i is the number of sampling units belonging to class i. Its variance is estimated as

$$\text{var}(\hat{p}_i) = \left(1 - \frac{n}{N}\right) \frac{\hat{p}_i(1 - \hat{p}_i)}{n-1}\ . \tag{2.15}$$

2.3 DETERMINING THE SAMPLE SIZE

The number of units to be selected is obviously limited by the budget. However, the minimum amount of units that should be selected depends on the requirements on the accuracy of the estimator. The sample size n can be calculated from the probability that the deviation of the sample mean from the true mean μ is less than a given d with probability $1-\alpha$, $P(|\bar{y} - \mu| \leq d) = 1 - \alpha$.

If it is assumed that the sample means follow a normal distribution, an equation (for sampling without replacement)

$$d = z_{\alpha/2}\sqrt{\frac{N - n}{N}}\frac{S}{\sqrt{n}} \tag{2.16}$$

can be obtained from the probability statement, where $z_{\alpha/2}$ is the critical value for the normal distribution, i.e. the value above which a normally distributed value is located with a probability *α/2*. Then, *n* is

$$n = \left(\frac{z_{\alpha/2}}{d}\right)^2 \left(\frac{N - n}{N}\right) S^2 . \tag{2.17}$$

In practice, the sample size is first solved for an infinite population (to avoid *n* on both sides of the equation):

$$n_0 = \left(\frac{z_{\alpha/2}}{d}\right)^2 S^2 \tag{2.18}$$

and then, based on this, for finite populations as

$$n = \frac{n_0}{\left(1 + \frac{n_0}{N}\right)} . \tag{2.19}$$

The equation requires knowledge of the population variance S^2, which is typically unknown. It can be estimated, however, from previous surveys or a pilot study. If the estimate for the variance is calculated from a sample, Student's t-distribution is used instead of the normal distribution and a corresponding critical value, $t_{\alpha/2}$, is used.

In the case of proportions, an upper bound for the sample size is obtained by assuming p_i to be 0.5, which gives the maximum variance.

2.4 SYSTEMATIC SAMPLING

In systematic sampling, every k^{th} unit is typically selected into the sample. This means that there has to be a predefined order among the sampling units. It also means that the number of possible samples is only *k*. The predefined order is typically easy in a forest inventory, as the plots are always perfectly ordered with respect to their coordinates. In forest inventory, the number of possible samples may be infinite, if point sampling is applied. If the plots have fixed size, and they are not allowed to overlap, the size of the plot defines the number of possible samples. Furthermore, when the first unit is selected, the selection of the other sampling units follows automatically. Thus the units are not independently selected, and no design-based estimators exist for the standard errors of systematic sampling.

In theory, standard errors can be calculated for systematic sampling from

the variance between all the k samples. It can be proved that the standard error depends on the inner correlation ω:

$$\omega = 1 - \frac{n\sigma_w^2}{(n-1)\sigma^2} = \frac{\sigma_b^2 - \sigma^2/n}{(n-1)\sigma^2/n}, \tag{2.20}$$

where

$$\sigma_w^2 = \frac{\sum_{i=1}^{n}\sum_{j=1}^{k}(y_{ij} - \bar{y}_j)^2}{nk} \text{ and } \sigma_b^2 = \frac{\sum_{j=1}^{k}(\bar{y}_j - \bar{y})^2}{k}.$$

Since $\sigma^2 = \sigma_w^2 + \sigma_b^2$, the variance of the mean is

$$var(\hat{\bar{y}}) = \frac{\sigma^2}{n}[1 + (n-1)\omega] = \sigma_b^2. \tag{2.21}$$

Therefore, the larger the within-sample variance σ_w^2 is compared with the total variance σ^2, the smaller the standard error of systematic sampling. A heterogeneous sample represents the population better. On the other hand, the smaller the between-sample variation σ_b^2 is, the smaller the standard error. If ω is negative, systematic sampling is more efficient than SRS. Unfortunately, (2.21) cannot be used as an estimator for variance if only one sample is measured; it only can be used for theoretical analysis.

In many cases SRS estimators are also used in systematic sampling. This is reasonable if the order of the units is completely random, but if there is a trend in the population, the SRS standard error overestimates the standard error of systematic sampling. On the other hand, if there is periodical variation in the population, systematic sampling may be highly inefficient (Särndal et al. 1992 p. 82).

Apart from using SRS estimators, the standard error of a systematic sample can be calculated 1) by taking several small samples and determining the variation between them (Chapter 10), 2) by using approximate formulae (Chapter 10), or 3) by using formulae from stratified sampling (section 2.5). The sample is then divided into several strata along the trend.

In a forest inventory, there may be a trend within any one forest stand if the site index increases from one side to the other, for example. There is also a large-scale trend in a north-south direction in Finland due to changes in climate conditions. Periodical variation within a stand might be due to the ditch network, and large-scale periodic variation could be due to hills etc.

Example 2.1 Heikki Surakka

In an inventory of a 100-hectare forested area in Southern Finland the sample plots were laid out on a square grid where both the line interval and the plot interval was 100 metres. Altogether 102 circular and point sample plots were measured. If the average diameter at breast height was less than 8 cm, the trees were measured on a circular sample plot of radius 2.52 metres (area 20 m^2). Otherwise point sampling was used with a basal area factor of 2, and if there were also understorey trees, they were measured on a circular plot of size 20 m^2 as well. An estimate for stem volume per hectare was calculated for each sample plot.

SRS estimators can always be used for population means and totals, and in this example, an SRS estimator was also used for the sampling variance. The mean stem volume per hectare was

$$\hat{\bar{y}} = \frac{1}{n}\sum_{i=1}^{n} y_i = \frac{1}{102}\sum_{i=1}^{102} y_i = 193 m^3/ha \,,$$

where y_i is the stem volume per hectare of plot i. In order to calculate the standard error of the mean, we first have to determine the population and sample sizes (N and n). In general, if we had only circular plots or fixed-area plots of any other shape, then n could be simply determined as the number of sample plots and N as [total area] divided by [sample plot size], i.e. the number of sample plots located and shaped so that whole area is covered with no overlapping. As the size of a point sample plot is variable, it is impossible to determine N and n accurately, but we can estimate an approximate sampling ratio $f=n/N$:

$$f = \frac{\sum_{i=1}^{n} a_i}{A} = \frac{\sum_{i=1}^{102} a_i}{100.0} = 0.0200 \,,$$

where a_i is the area of the circle from which the basal area median tree is counted as belonging to plot i and A is the total area. We can then calculate the sample variance, which is an estimator of the population variance:

$$s_y{}^2 = \frac{1}{n-1}\left(\sum_{i=1}^{n} y_i{}^2 - \frac{\left(\sum_{i=1}^{n} y_i\right)^2}{n}\right) = \frac{1}{101}\left(\sum_{i=1}^{102} y_i{}^2 - \frac{\left(\sum_{i=1}^{102} y_i\right)^2}{102}\right) = 12601\left(m^3/ha\right)^2 .$$

The standard error of the mean stem volume per hectare is

$$s_{\hat{\bar{y}}} = \sqrt{\left(1 - \frac{n}{N}\right)\frac{s_y{}^2}{n}} = \sqrt{(1 - 0.0200)\frac{12601}{102}} = \sqrt{121.07} = 11.0 m^3 / ha \, .$$

In this case, the sampling ratio is so small that the finite population correction factor *1 - n/N* can be ignored.

The estimate for the total stem volume is

$$\hat{T} = A\hat{\bar{y}} = 100.0 \cdot 193.25 = 19325 m^3$$

and its standard error

$$s_{\hat{T}} = \sqrt{\mathrm{var}\left(\hat{T}\right)} = \sqrt{A^2 \, \mathrm{var}\left(\hat{\bar{y}}\right)} = \sqrt{100{,}0^2 \cdot 121.07} = \sqrt{1210700} = 1100 m^3 \, .$$

The confidence interval for the true population mean is

$$\left(\hat{\bar{y}} - z_{(\alpha/2)} s_e ; \hat{\bar{y}} + z_{(\alpha/2)} s_e\right),$$

where $z_{(\alpha/2)}$ is a value from the normal distribution with a confidence level α. Thus the 95% confidence interval for the true mean stem volume per hectare would be

$$(193.25 - 1.96 \cdot 11.00; 193.25 + 1.96 \cdot 11.00) = \left(172 m^3 / ha; 215 m^3 / ha\right).$$

Example 2.2

The proportion of the population that is of a certain character is often a matter of interest, for example the proportion of a given tree species or a given site type. Let us assume that we now want to know the proportion of mineral sites in this 100-hectare inventory area. A decision has to be made for every sample plot regarding its soil class, i.e. it is either a mineral site, spruce swamp or pine bog. The estimate for the proportion of mineral sites is

$$\hat{p}_{ms} = \frac{n_{ms}}{n} = \frac{81}{102} = 0.79 \, ,$$

where n_{ms} is the number of mineral site sample plots and n is the total number of plots. Thus mineral sites make up 79% of the inventory area and mires 21%.

The standard error is estimated as follows:

$$s_{\hat{p}_{ms}} = \sqrt{\left(1-\frac{n}{N}\right)\frac{\hat{p}_{ms}\left(1-\hat{p}_{ms}\right)}{n-1}} = \sqrt{\left(1-0.0200\right)\frac{0.79412\cdot\left(1-0.79412\right)}{102-1}}$$

$$= \sqrt{0.0015864} = 0.040$$

Table 2.1 Plot data for the inventory area.

Plot ID	Soil class[a]	Volume m^3/ha	Basal area m^2/ha	Plot area[b] m^2	Stratum[c]	Plot ID	Soil class	Volume m^3/ha	Basal area m^2/ha	Plot area m^2	Stratum
1	1	155	26	71	2	52	1	236	34	90	2
2	1	242	32	118	2	53	1	217	34	83	2
3	1	108	18	65	2	54	3	157	16	310	3
4	2	269	26	335	2	55	3	135	22	75	2
5	1	114	18	74	2	56	3	284	32	235	3
6	1	93	16	64	2	57	1	33	2	20	1
7	1	201	32	88	2	58	1	74	10	126	3
8	1	80	12	115	1	59	2	430	40	317	3
9	1	66	14	37	1	60	1	340	30	361	3
10	1	363	34	316	3	61	1	315	28	359	3
11	1	171	22	163	2	62	3	93	18	42	2
12	1	217	26	135	2	63	3	23	4	93	2
13	1	36	13	20	1	64	1	45	5	20	1
14	1	176	24	118	2	65	1	360	42	159	3
15	1	278	32	178	3	66	1	181	18	209	3
16	1	210	22	267	3	67	1	330	30	467	3
17	1	20	3	20	1	68	2	224	34	84	2
18	1	347	32	405	3	69	2	209	30	106	3
19	1	260	32	177	3	70	1	371	38	208	3
20	1	164	14	406	3	71	1	248	34	107	2
21	1	149	26	62	2	72	1	247	38	80	2
22	2	25	6	20	1	73	1	445	38	385	3
23	1	407	44	212	3	74	1	130	20	85	2
24	2	330	32	280	3	75	1	223	22	256	3
25	2	368	36	286	3	76	1	408	38	448	3
26	1	114	14	173	3	77	1	241	24	289	3
27	1	221	18	491	3	78	1	89	16	60	1
28	1	310	26	406	3	79	1	278	30	219	3
29	1	85	19	20	1	80	1	355	30	445	3
30	1	344	34	276	3	81	3	66	8	240	3
31	3	288	32	213	2	82	1	247	26	230	3
32	1	141	20	154	3	83	1	136	22	67	2
33	1	224	24	235	3	84	1	166	22	147	2
34	1	297	28	278	3	85	1	151	24	75	2
35	1	212	22	271	3	86	1	164	22	118	2
36	3	227	26	184	2	87	1	119	28	26	2
37	2	208	18	491	3	88	1	169	24	105	2
38	1	263	30	224	3	89	1	0	0	20	1
39	1	0	0	20	1	90	2	164	22	104	2
40	1	242	24	240	3	91	1	112	20	59	2
41	1	392	34	357	3	92	1	63	6	388	1
42	1	255	24	342	3	93	1	109	10	489	2
43	2	196	22	199	3	94	3	36	8	31	1
44	1	130	20	86	3	95	1	140	22	80	2
45	1	0	0	20	1	96	1	215	22	299	2
46	1	339	32	275	3	97	1	64	6	427	1
47	1	386	36	304	3	98	1	59	12	40	1
48	2	224	22	332	3	99	1	103	16	83	2
49	2	255	30	177	3	100	1	130	14	256	2
50	1	124	18	123	3	101	1	37	4	296	1
51	1	195	20	272	3	102	1	18	2	491	1

[a]Soil class: 1=Mineral site
2=Spruce swamp
3=Pine bog

[b]Plot area: In the case of point sample plot it is the area of the circle from which the basal area median tree is counted as belonging to plot, otherwise 20 m^2.

[c]Stratum: 1=Open areas, seedling stands and stands of seed trees
2=Middle aged stands
3=Mature stands

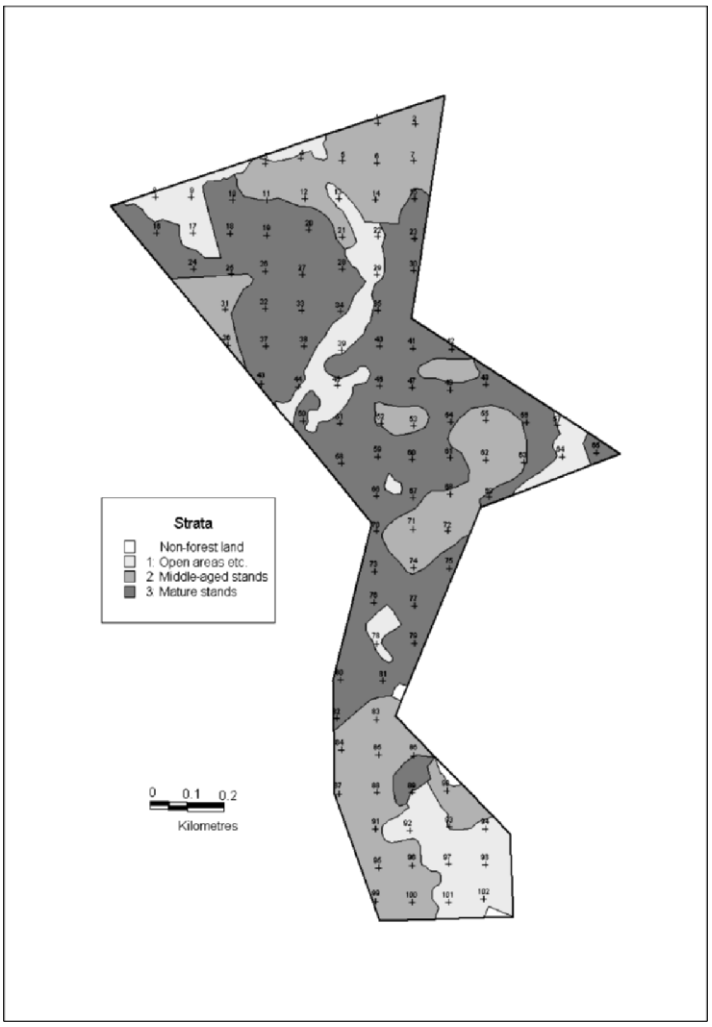


Figure 2.1 The inventory area, strata and sample plot locations.

2.5 STRATIFIED SAMPLING

In stratified sampling there exists certain auxiliary information according to which the population can be divided to homogeneous groups or strata. Stratified sampling is in most cases more efficient than SRS, meaning that the standard errors are smaller. Each stratum can be interpreted as a small sub-population, for which the estimates are calculated using suitable estimators. Typically, selections within strata are performed using SRS, but systematic sampling, for instance, can also be used. The population values are then obtained as weighted averages of the sub-population values as

$$\hat{\bar{y}}_{STR} = \sum_{h=1}^{L} W_h \hat{\bar{y}}_h , \tag{2.22}$$

with an estimator of variance

$$\text{var}(\hat{\bar{y}}_{STR}) = \sum_{h=1}^{L} W_h^2 \text{var}(\hat{\bar{y}}_h) = \sum_{h=1}^{L} W_h^2 \frac{s_h^2}{n_h} - \sum_{h=1}^{L} W_h \frac{s_h^2}{N} , \tag{2.23}$$

where L is the number of strata, W_h is the proportion of stratum h and s_h^2 is the sample variance within stratum h :

$$s_h^2 = \sum_{i=1}^{n_h} \frac{(y_{hi} - \bar{y}_h)^2}{n_h - 1} . \tag{2.24}$$

Stratified sampling generally becomes more efficient with increasing homogeneity within the strata, as the weighted averages of small variances are obviously smaller than those of large variances, although the allocation of sampling units to strata also has an effect on the variance.

The allocation of sampling units to strata h can take place in several ways, being either constant, proportional, Neyman (optimal) or optimal with respect to costs. Constant allocation means that, a constant number of units is selected from each stratum. In proportional allocation, the proportion of selected units $f = n_h/N_h$ is similar in each stratum h, while in Neyman allocation the number of units selected depends on both the size of the stratum and the variation within it. This method is more efficient than the former ones if the variation varies among strata, meaning that it gives the smallest standard error for a given n. The sample size in each stratum is then

$$n_h = n \frac{W_h S_h}{\sum_{h=1}^{L} W_h S_h} . \tag{2.25}$$

If the measurement costs vary between the strata, this can be accounted for by choosing

$$n_h = n \frac{W_h S_h / \sqrt{c_h}}{\sum_{h=1}^{L} W_h S_h / \sqrt{c_h}} \tag{2.26}$$

where c_h is the measurement cost in stratum h. This allocation gives the smallest standard error for a given budget.

The stratification can also be performed after the sample has been selected (=post-stratification). In this case it cannot be used for allocating the sample optimally, but the estimators of stratified sampling can be used. This could be useful if post-stratification is less costly than stratification before sampling for some reason. In the case of known stratum sizes and proportional allocation, post-stratification is almost as efficient as "normal" stratification (Särndal et al. 1992 p. 265). If the stratum sizes are not known, this will introduce additional error (see Chapter 14).

Example 2.3 Heikki Surakka

The same 100-hectare area was then post-stratified with the help of aerial photographs. Three strata were defined:

Stratum	*A*	*n*
Open areas, seedling stands and stands with seed trees	18.0	18
Middle-aged stands	33.3	35
Mature stands	48.7	49

The mean stem volumes per hectare for each stratum are

$$\hat{\bar{y}}_1 = \frac{1}{n_1}\sum_{i=1}^{n_1} y_i = \frac{1}{18}\sum_{i=1}^{18} y_i = 42 m^3/ha$$

$$\hat{\bar{y}}_2 = 167 m^3/ha \text{ and}$$

$$\hat{\bar{y}}_3 = 268 m^3/ha$$

and the standard errors of the mean stem volumes per hectare are

$$s_{\hat{\bar{y}}_1} = \sqrt{\left(1-\frac{n_1}{N_1}\right)\frac{s_{y_1}{}^2}{n_1}} = \sqrt{(1-0.01147)\frac{827.35}{18}} = \sqrt{45.437} = 6.7 m^3/ha$$

$$s_{\hat{\bar{y}}_2} = 10.0 m^3/ha \text{ and}$$

$$s_{\hat{\bar{y}}_3} = 13.3 m^3/ha\ .$$

Total stem volumes for each stratum are

$$\hat{T}_1 = A_1 \hat{\bar{y}}_1 = 18.0 \cdot 41.976 = 756 m^3$$

$$\hat{T}_2 = 5557 m^3 \text{ and}$$

$$\hat{T}_3 = 13033 m^3$$

and the standard errors of the total stem volumes are

$$s_{\hat{T}_1} = \sqrt{\text{var}\left(\hat{T}_1\right)} = \sqrt{A_1{}^2\ \text{var}\left(\hat{\bar{y}}_1\right)} = \sqrt{18.0^2 \cdot 45.437} = \sqrt{14722} = 121 m^3$$

$$s_{\hat{T}_2} = 334 m^3 \text{ and}$$

$$s_{\hat{T}_3} = 649 m^3\ .$$

The mean stem volume per hectare for the whole area is

$$\hat{\bar{y}}_{str} = \sum_{h=1}^{3} W_h \hat{\bar{y}}_h = 0.180 \cdot 41.976 + 0.333 \cdot 166.84 + 0.486 \cdot 267.67 = 193 m^3/ha$$

and its standard error

$$s_{\hat{\bar{y}}_{str}} = \sqrt{\sum_{h=1}^{3} W_h{}^2\ \text{var}\left(\hat{\bar{y}}_h\right)} = \sqrt{0.180^2 \cdot 45.437 + 0.333^2 \cdot 100.27 + 0.487^2 \cdot 177.72}$$
$$= \sqrt{54.734} = 7.4 m^3/ha.$$

The total stem volume for the whole area is

$$\hat{T}_{str} = \sum_{h=1}^{3} \hat{T}_h = 755.6 + 5557.1 + 13033.4 = 19346 m^3$$

and its standard error

$$s_{\hat{T}_{str}} = \sqrt{\sum_{h=1}^{3} \mathrm{var}\left(\hat{T}_h\right)} = \sqrt{14722 + 111246 + 421372} = \sqrt{547340} = 740 m^3.$$

Example 2.4

In this example we will demonstrate how to determine the sample size. The question is derived from the previous examples. How many sample plots would be needed in normal systematic sampling to have the same standard error of the mean stem volume per hectare as in stratified sampling?

First we determine the allowable deviation of the sample mean from the population mean. The standard error of the mean stem volume per hectare in stratified sampling was 7.4 m^3/ha. If we use a 95% confidence level, the confidence interval and the allowable deviation will be $\pm 1.96 \cdot 7.4$ m^3/ha.

To determine the sample size, the population variance should be known. As it is not known, it has to be estimated from the sample.

The sample size needed for an infinite population is

$$n_0 = \left(\frac{t_{\alpha/2}}{d}\right)^2 s_y{}^2 = \left(\frac{1.960}{1.960 \cdot 7.3983}\right)^2 \cdot 12601 = 230\,,$$

but for finite populations, the size of the population should be known. We can estimate this by dividing the total area by the average plot area:

$$\hat{N} = \frac{A}{\bar{a}} = \frac{100.0}{0.01961} = 5098\,.$$

The sample size for a finite population is now

$$n = \frac{n_0}{\left(1 + \frac{n_0}{N}\right)} = \frac{230.22}{\left(1 + \frac{230.22}{5098.3}\right)} = 220\,.$$

2.6 CLUSTER SAMPLING

Cluster sampling is used when the population can be divided to separate groups. In forest inventory these are typically groups of sample plots located near each other or groups of trees located near each other. (Each sample plot could also be interpreted as a cluster of trees if the mean values for trees were of interest.) In cluster sampling the clusters are the basic sampling units. In one-stage cluster sampling, all the units within a selected cluster are measured, while in multi-stage cluster sampling another sample is selected from within the cluster. The sampling units at different stages vary.

Cluster sampling is not usually as efficient as the other selection methods given a fixed size of sample n. This is because the sampling units in one cluster may be correlated, i.e. the new information resulting from measuring a new unit is less than it would be if the units were independent. The usefulness of cluster sampling is based on cost efficiency: it is usually possible to measure more units with the same budget when they are located in clusters. In a forest inventory a cluster design will reduce walking distances in the forest. It is also typical for the clusters to be laid out in a systematic fashion, the groups of plots forming a line or a rectangular of a certain size, and for this reason the definition of a cluster is also somewhat more complicated in forestry than for clusters formed by families, classes or schools as in the social sciences.

The estimator for the population mean is the mean of the cluster means:

$$\hat{\bar{y}}_{CLU} = \sum_{\alpha=1}^{a} \frac{\hat{\bar{y}}_{\alpha}}{a}, \tag{2.27}$$

where a is the number of clusters selected and $\hat{\bar{y}}_{\alpha}$ is the mean in cluster α. If the clusters are of different sizes, this formula might be biased. The bias occurs if the variable of interest is dependent on the cluster size, e.g. if it has larger values in larger clusters. The mean estimator should then be calculated as a weighted mean of the clusters. If y is independent of cluster size, the results are unbiased, although equal size is assumed (Cochran 1977). The variance estimator of the mean is

$$\text{var}(\hat{\bar{y}}_{CLU}) = \left(1 - \frac{a}{A}\right) \sum_{\alpha=1}^{a} \frac{(\hat{\bar{y}}_{\alpha} - \hat{\bar{y}}_{CLU})^2}{a(a-1)}, \tag{2.28}$$

where A is the total number of clusters. The efficiency of cluster sampling increases as the variation between cluster means decreases, i.e. the more homogeneous the clusters are. This, on the other hand, depends on the inner heterogeneity of the clusters: the larger the amount of the population variation that is within-cluster variation, the better. The principle is similar to that of systematic sampling presented in section (2.4). This can be expressed using the intra-cluster correlation ω

$$\varpi = \frac{\sigma_b^2 - \sigma_w^2/(B-1)}{\sigma^2}, \tag{2.29}$$

where B is the size of a cluster. The variance in cluster sampling can then be presented as (Cochran 1977, Tokola and Shrestra 1999)

$$\text{var}(\hat{\bar{y}}_{CLU}) = \left(1 - \frac{a}{A}\right)\frac{S^2}{aB}\left[1 + (B-1)\varpi\right]. \tag{2.30}$$

Thus the smaller the intra-cluster correlation is, the smaller the variance.

In two-stage cluster sampling, the variance of the mean is larger, because the second-stage sample also contains sampling error. The variance is

$$v(\hat{\bar{y}}_{CLU}) = \left(1 - \frac{a}{A}\right)\frac{s_b^2}{a} + \left(1 - \frac{b}{B}\right)\frac{a}{A}\frac{s_w^2}{ab}, \tag{2.31}$$

where

$$s_b^2 = \frac{1}{a-1}\sum_{\alpha=1}^{a}(\hat{\bar{y}}_\alpha - \hat{\bar{y}}_{CLU})^2 \text{ and}$$

$$s_w^2 = \frac{1}{a(b-1)}\sum_{\alpha=1}^{a}\sum_{\beta=1}^{b}(y_{\alpha\beta} - \hat{\bar{y}}_\alpha)^2,$$

and where B is the population size within a cluster and b is the corresponding sample size.

2.7 RATIO AND REGRESSION ESTIMATORS

In a stratified inventory information on some auxiliary variables is used both to plan the sampling design (e.g. allocation) and for estimation, or only for estimation (post-stratification). Stratification is not the only way to use auxiliary information, however, as it can be used at the design stage, e.g. in sampling proportional to size (section 2.8). It can also be used at the estimation stage in ratio or regression estimators, so that the standard error of the estimators can be reduced using information on a variable x which is known for each sampling unit in the population. The estimation is based on the relationship between the variables x and y. In ratio estimation, a model that goes through the origin is applied. If this model does not apply, regression estimator is more suitable. The ratio estimator for the mean is

$$\hat{\bar{y}}_{rat} = \frac{\bar{y}}{\bar{x}} \bar{X} = r\bar{X} \,, \tag{2.32}$$

where $\bar{X}$ is the mean of a variable x in the population and $\bar{x}$ in the sample . Ratio estimators are usually biased, and thus the root mean square error (RMSE) should be used instead of the standard error. The relative bias nevertheless decreases as a function of sample size, so that in large samples (at least more than 30 units) the accuracy of the mean estimator can be approximated as (Cochran 1977 p. 155)

$$\text{var}(\hat{\bar{y}}_{rat}) \cong \left(1 - \frac{n}{N}\right) \sum_{i=1}^{n} \frac{(y_i - rx_i)^2}{n(n-1)} \,. \tag{2.33}$$

The ratio estimator is more efficient the larger the correlation between x and y relative to the ratio of the coefficients of variation. It is worthwhile using the ratio estimator if

$$corr(x, y) > \frac{1}{2} \frac{CV(x)}{CV(y)} \,. \tag{2.34}$$

The (simple linear) regression estimator for the mean value is

$$\hat{\bar{y}}_{reg} = \bar{y} + \hat{\beta}(\bar{X} - \bar{x}) \,, \tag{2.35}$$

where $\hat{\beta}$ is the OLS coefficient of x for the model, which predicts the population mean of y based on the sample means. In a sampling context, the constant of the model is not usually presented, but the formula for the constant, $\hat{\alpha} = \bar{y} + \hat{\beta}\bar{x}$, is embedded in the equation. The model is more efficient the larger the correlation between x and y. The variance of the regression estimator can be estimated as

$$\text{var}(\hat{\bar{y}}_{reg}) = \left(1 - \frac{n}{N}\right) \sum_{i=1}^{n} \frac{\left[(y_i - \bar{y}) - \hat{\beta}(x_i - \bar{x})\right]^2}{n(n-2)} \,. \tag{2.36}$$

Example 2.5 Heikki Surakka

There were also data for the same 100-hectare area that contained only basal area measurements. These had been collected from a very dense grid with a basal area factor of 1. The sample covered the area so well that the estimates (mean and total basal areas) can be regarded as true, as if every tree included in the area had been measured. We will next use the basal area as an auxiliary variable and determine the

mean stem volume per hectare by ratio estimation. There is a very high correlation between stem volume and basal area, and the relationship is almost linear and goes through origin.

First we calculate the ratio between the estimates:

$$r = \frac{\bar{y}}{\bar{x}} = \frac{193.25}{22.373} = 8.6376m \ .$$

As the true mean basal area was slightly smaller than the estimate for the mean basal area, the ratio estimate for mean stem volume per hectare is smaller than that obtained without ratio estimation:

$$\hat{\bar{y}}_{rat} = r\bar{X} = 8.6376 \cdot 22.254 = 192 m^3 / ha$$

Its variance estimate is

$$\begin{aligned} \text{var}\left(\hat{\bar{y}}_{rat}\right) &= \left(1 - \frac{n}{N}\right) \sum_{i=1}^{n} \frac{\left(y_i - rx_i\right)^2}{n(n-1)} = (1 - 0.0200) \sum_{i=1}^{102} \frac{\left(y_i - 8.6376 \cdot x_i\right)^2}{102 \cdot (102-1)} \\ &= 23.280 \left(m^3 / ha\right)^2 \end{aligned}$$

and the standard error estimate

$$s_{\hat{\bar{y}}_{rat}} = \sqrt{23.280} = 4.8 m^3 / ha \ .$$

The ratio estimate for total stem volume is

$$\hat{T}_{rat} = rT_x = 8.6376 \cdot 22.254 \cdot 100.0 = 19197 m^3$$

and its standard error is

$$\begin{aligned} s_{\hat{T}_{rat}} &= \sqrt{\left(1 - \frac{n}{N}\right) T_x{}^2 \frac{1}{\bar{X}} \sum_{i=1}^{n} \frac{\left(y_i - rx_i\right)^2}{n(n-1)}} \\ &= \sqrt{(1 - 0.0200) \cdot \frac{(22.254 \cdot 100.0)^2}{22.254} \sum_{i=1}^{102} \frac{\left(y_i - 8.6376 \cdot x_i\right)^2}{102 \cdot 101}} = \sqrt{232802} = 482 m^3 \end{aligned}$$

2.8 SAMPLING WITH PROBABILITY PROPORTIONAL TO SIZE

The basic properties of sampling with arbitrary probabilities (2.1) can also be utilized in sampling with probability proportional to size (PPS), such as sampling with a relascope. It is then assumed that unit *i* is selected with the probability kx_i, where *k* is a constant and *x* is a covariate (diameter of a tree in relascope sampling). PPS sampling is more efficient the larger the correlation between *x* and *y*. For perfect correlation the variance in the estimator would be zero (Schreuder et al. 1993 p. 46). PPS sampling might even be less efficient than SRS, however, if the correlation were negative. This could be the case when multiple variables of interest are considered simultaneously, for example, when correlation with one variable (say volume) might give efficient estimates but the estimates for other variables (say health and quality) might not be so good.

In practice, PPS sampling can be performed by ordering the units, calculating the sum of their sizes (say $\sum x_i$), and calculating $\sum x_i / n$. The probability of a unit *i* being selected is then $x_i \big/ \sum x_i$ and a cumulative probability can be calculated for the ordered units. A random number *r* is then picked and each unit with a cumulative probability equal to (or just above) *r, r+1, r+2,...r+n-1* is selected for the sample. Every unit of size greater than $\sum x_i / n$ is then selected with certainty.

2.9 NON-LINEAR ESTIMATORS

The simple variance estimators presented in the above sections are not applicable to non-linear estimators. A typical example of a non-linear estimator is a ratio of two estimators, $\hat{Y}_1 / \hat{Y}_2$. Although the mean value in the whole sample is a linear estimator, the mean in any sub-population is a ratio estimator, because the number of sample units in the sub-population, n_s, is a random variable having a variance that needs to be accounted for.

In such situations, the non-linear estimator needs to be linearized in order to be able to derive an (approximate) formula for the variance estimator. The ratio estimator $g(\hat{\mathbf{Y}}) = \hat{Y}_1 \big/ \hat{Y}_2$ (where $\hat{\mathbf{Y}}$ is the vector of estimators) can be linearized using Taylor series expansion. The variance can then be estimated as

$$\text{var}(g(\hat{\mathbf{Y}})) = \text{var}\left(\sum_{j=1}^{2} \frac{\partial g(\hat{\mathbf{Y}})}{\partial y_j} (\hat{Y}_j - Y_j) \right), \qquad (2.37)$$

giving

$$\mathrm{var}(g(\hat{\mathbf{Y}})) = \frac{1}{\hat{Y}_2^2}\left(\mathrm{var}(\hat{Y}_1) + \left(\frac{\hat{Y}_1}{\hat{Y}_2}\right)^2 \mathrm{var}(\hat{Y}_2) - 2\frac{\hat{Y}_1}{\hat{Y}_2}\mathrm{cov}(\hat{Y}_1, \hat{Y}_2) \right). \qquad (2.38)$$

The Taylor series approach applies in the general case. In most simple cases, however, separate linearization is not required, since the estimators already presented for the variance of a ratio estimator can be used directly (and can be derived using 2.37, for instance: compare 2.38 with 2.41). An example of a non-linear estimator is the case where whole stands (or compartments) are sampling units. Then, as the stands are of different sizes, the sampled area is not known before sampling but is also a random variable. The proportion of the area fulfilling a certain condition may be estimated as

$$\hat{R} = \sum_{i=1}^{n} A_i z_i \Big/ \sum_{i=1}^{n} A_i , \qquad (2.39)$$

where z_i is an indicator variable with the value 1 if the condition is fulfilled and zero otherwise, and A_i is the area of the stand i. The standard error of this estimator can then be approximated as (Cochran 1977)

$$S_{\hat{R}} = \sqrt{\frac{1}{\mu_x^2}\frac{S_u^2}{n}\left(\frac{N-n}{N}\right)} , \qquad (2.40)$$

where

$$S_u^2 = \frac{\sum_{i=1}^{n} A_i^2 z_i^2 + \hat{R}^2 \sum_{i=1}^{n} A_i^2 - 2\hat{R}\sum_{i=1}^{n} A_i^2 z_i}{n-1} \qquad (2.41)$$

and $\mu_x = \frac{A_T}{N}$ is the mean area of the sampling units. Assuming that the mean area is estimated with the sample mean, this formula can be simplified to (Heikkinen, personal information)

$$S_{\hat{R}} = \sqrt{\frac{n}{\left(\sum_{i=1}^{n} A_i\right)^2} \frac{(1-\hat{R})^2 \sum_{z=1} A_i^2 + \hat{R}^2 \sum_{z=0} A_i^2}{n-1} \frac{N-n}{N}} . \qquad (2.42)$$

This means that it is enough to separate the areas of stands fulfilling the condition and those not fulfilling it.

2.10 RESAMPLING

In many cases the capacity of modern computers can be utilized to estimate the sampling variances. There are several methods that work in quite a similar fashion, e.g. jackknife and bootstrap methods. These work as follows:

1) Draw K replicate samples of size n from the original sample (of size n) with replacement.
2) For each replicate, calculate the estimator of interest (e.g. mean or ratio).
3) Estimate the variance of this estimator from the variance between the estimates from replicate samples.

The replicate samples have to be drawn using the original design, i.e. with SRS for simple random sampling, by strata for stratified sampling etc., which means that these simple resampling estimators are not useful for systematic sampling. They nevertheless make variance estimation easy for complex sampling designs and for non-linear estimators.

In Bootstrap method, at least about 100, preferably more than 500 replicates are drawn. The estimator is then

$$\text{var}(\hat{\theta}_{BOOT}) = \frac{\sum_{k=1}^{K}(\hat{\theta}_k - \hat{\theta}_{BOOT})^2}{K - 1}, \tag{2.43}$$

where

$$\hat{\theta}_{BOOT} = \frac{\sum_{k=1}^{K}\hat{\theta}_k}{K} \tag{2.44}$$

is the mean of the estimates from replicate samples.

For systematic sampling, parametric bootsrap may be an option. In parametric bootstrap, the distribution F of the sampling units is estimated based on the sample data. The distribution could be, for example, normal distribution. The bootstrap samples are then sampled from the estimated distribution. After that, the parametric bootstrap proceeds similarly as the simple bootstrap.

In the jackknife method, jackknife samples $x_{(i)}$ are taken, defined as samples with the i^{th} observation left out, e.g. $x_{(i)} = (x_1, x_2, \ldots, x_{i-1}, x_{i+1}, \ldots, x_n)$. $\hat{\theta}_{(i)}$ is then the i^{th} jackknife replication of the estimator $\hat{\theta}$. From these jackknife replications, pseudo-values are calculated as

$$\theta_i^{(p)} = n\hat{\theta} - (n-1)\hat{\theta}_i . \tag{2.45}$$

The jackknife variance can then be estimated as

$$\text{var}(\hat{\theta}_{JACK}) = \frac{\sum_{i=1}^{n} (\hat{\theta}_i^{(p)} - \hat{\bar{\theta}})^2}{n(n-1)}, \tag{2.46}$$

where

$$\hat{\bar{\theta}} = \frac{\sum_{i=1}^{n} \theta_i^{(p)}}{n}$$

is the mean of the replicate pseudo-values. The original sample estimator could also be used instead (e.g. Pahkinen and Lehtonen 1989). The same variance estimator could also be written without using pseudo-values as (Efron and Tibshirani 1998)

$$\text{var}(\hat{\theta}_{JACK}) = \frac{n-1}{n} \sum_{i=1}^{n} (\hat{\theta}_i - \hat{\bar{\theta}}_i)^2 . \tag{2.47}$$

In this formula the differences between the jackknife resamples are assumed to be small relative to the variation between the pseudo-values, and therefore the value is inflated by *(n-1)/n* (Efron and Tibshirani 1998).

2.11 SELECTING THE SAMPLING METHOD

Optimal data acquisition can be considered from several points of view. Traditionally, it has been understood as the sampling design giving minimum variance for certain estimates, e.g. mean volume, with a given budget. The inventory costs can be assumed to include fixed costs that are similar for each sampling design, costs per cluster (in a cluster design), costs per plot, and costs per sample tree. The total costs can then be expressed as a function of the number of clusters (m) and plots (n) measured, e.g.

$$C = C_f + C_m m + C_n n . \tag{2.48}$$

If the costs differ between sub-populations, this should also be accounted for in the cost function.

The variance can also be expressed as a function of the number of plots and clusters, even though this is non-linear. If there are several variables of interest, either one variable is chosen or the variances of all of them are combined in some way, e.g. using a weighted sum. Burkhart et al. (1978) suggested that the largest variance or the variance of the most important variable should be used to determine the sample size, while Scott and Köhl (1993) used the accuracy relative to the

desired level of accuracy and averaged across all the variables. The problems can then be presented as a single (non-linear) optimization problem:

$$\begin{aligned} &Minimize\ \ S = \frac{1}{K}\sum_{k=1}^{K}\frac{s_k(m,n)}{S_k} \\ &Subject\ to \\ &C_t = C(m,n) \end{aligned}, \tag{2.49}$$

where K is the number of variables of interest, S is the desired level of accuracy and s is the actual level of accuracy as a function of number of clusters and plots, C_t is the given cost level and C is the actual cost as a function of number of clusters and plots. There may also be more restrictions. A non-linear optimization problem can be fairly difficult to solve, however, and linear optimization is not applicable (Scott and Köhl 1993).

Expressing the variance of the estimator as a function of the number of plots requires information on the population variance S^2. This is typically obtained from a previous study or from a small preliminary sample. In some cases it is possible to anticipate the population variance mathematically, assuming the locations of trees in the area to follow a known random process such as a Poisson process (Mandallaz and Ye 1999).

Another approach is to minimize the cost function at a given precision level. Constraints can then be given separately for all the variables of interest, e.g. the maximum variance level as

$$s_k < S_k\ . \tag{2.50}$$

It is also possible to minimize the utility function, which is the weighted sum of the inventory costs and MSE (Päivinen 1987). The problem then becomes a non-constrained optimization, which is easier to solve. The problem of weighting the costs and accuracy remains, however.

In some cases it is not necessary to compare methods in an optimization problem of the kind presented above, as the cost-effectiveness of the designs can be compared using the relative efficiency of the alternatives (provided they reflect the same costs). The efficiency of alternative A relative to B can be defined as the variance of alternative A divided by the variance of alternative B (Scott and Köhl 1993, Pahkinen and Lehtonen 1989):

$$DEFF = V(\hat{\bar{y}})_A / V(\hat{\bar{y}})_B\ . \tag{2.51}$$

For a cluster sampling design, for example, the *DEFF* coefficient, assuming a constant number of clusters and constant cluster size, can be derived from formula (2.27) as $DEFF = \left[1 + (B-1)\varpi\right]$, where ω is the intra-cluster correlation. In the case of cluster sampling the latter can be defined as (Cochran 1977)

$$\varpi = \frac{\sigma_b^2 - \sigma^2}{(B-1)\sigma^2}, \tag{2.52}$$

where σ_b^2 is the between-cluster variance, σ^2 is the total variance, and B is the size of the cluster. This enables different cluster shapes such as an L-shaped or square tract, or different plot distances within a cluster, to be compared (Tokola and Shrestra 1999). Similar problems can also be solved using a model forest, e.g. based on a satellite image, in which different designs can be compared (Päivinen 1987).

Another point of view is to optimize the intervals between subsequent forest inventories so that the information is always fresh enough for decision making at minimum cost. In such cases, the database can be updated in terms of forest growth by means of growth and yield models. Silvicultural measures can be ascertained from the forest owner or from aerial images, for instance (Anttila 2002, Hyvönen and Korhonen 2003).

It is evident, however, that the traditional approach based on the mean square errors of the estimates does not necessarily produce any information regarding the usefulness of the measured information for decision-making purposes. This aspect has been studied using cost-plus-loss analysis, in which the expected losses due to non-optimal decisions caused by inaccurate data are added to the total costs of the forest inventory (Hamilton 1978, Burkhart et al. 1978). Ståhl et al. (1994), for example, analysed whether it is more profitable to make accurate inventories at long intervals or moderately accurate inventories at shorter intervals.

The hardest part of cost-plus-loss analysis is to define the expected losses. Holmström et al. (2003), when studying the usefulness of different inventory methods for decision-making, defined the average loss in terms of the net present value (NPV) in the next 5-10 years, where the optimal NPV was taken to be the maximum value without any restrictions. This analysis suggested that extensive field sampling methods were worthwhile in the case of mature stands where the optimal treatment was to be expected in the near future. This kind of approach is a simplification of the true situation, however, as all decisions can be revised. The errors may therefore be non-symmetric in the sense that cuttings proposed for too early a stage can be postponed (provided the necessity can be observed in the field), but those proposed for too late a period cannot be transferred to an earlier occasion.

REFERENCES

Burkhart, H.E., Stuck, R,D., Leuschner, W.A. and Reynolds, M.A. 1978. Allocating inventory resources for multiple-use planning. Canadian Journal of Forest Research 8:100-110.

Cochran, W.G. 1977. Sampling techniques. 3rd edition. Wiley, New York.

Efron, B. and Tibshirani, R.J. 1998. An introduction to the Bootstrap. Monographs on Statistics and Applied Probability 57. Chapman & Hall / CRC. 436 p.

Gregoire, T. 1998. Design-based and model-based inference in survey sampling: appreciating the difference. Canadian Journal of Forest Research 28:1429-1447.

Hamilton, D.A. 1978. Specifying precision in natural resource inventories. In: Integrated inventories of renewable resources: proceedings of the workshop. USDA Forest Service, General technical report RM-55:276-281.

Holmström, H., Kallur, H. and Ståhl, G. 2003. Cost-plus-loss analyses of forest inventory strategies based on kNN-assigned reference sample plot data. Silva Fennica 37:381-398.

Loetsch, F., Zöhrer, F. and Haller, K. 1973. Forest Inventory. Vol I-II 436+ 469 p. BLV Verlagsgesellschaft.

Lund, H.G. and Thomas, C.E. 1989. A primer on stand and forest inventory designs. Gen. Tech. Rep. WO-54. Washington, DC; USDA Forest Service. 96 p. http://www.fs.fed.us/rm/ftcol/publications/outofprint/wo_54.pdf

Mandallaz, D. and Ye, R. 1999. Forest inventory with optimal two-phase, two-stage sampling schemes based on the anticipated variance. Canadian Journal of Forest Research 29:1691-1708.

Pahkinen, E. and Lehtonen, R. 1989. Otanta-asetelmat ja tilastollinen analyysi. Gaudeamus. 286 p.

Päivinen, R. 1987. Metsän inventoinnin suunnittelumalli. Summary: A planning model for forest inventory. University of Joensuu, Publications in Sciences N:o 11. 179 p.

Särndal, C-E., Swensson, B. and Wretman, J. 1992. Model assisted survey sampling. Springer-Verlag. 694 p.

Schreuder, H.T., Gregoire, T.G. and Wood, G.B. 1993. Sampling Methods for Multiresource Forest Inventory. John Wiley & Sons. New York. 446 p.

Scott, C.T. and Köhl, M. 1993. A method for comparing sampling design alternatives for extensive inventories. Mitteilungen der Eidgenössischen Forschunganstallt für Wald, Schnee und Landschaft. Band 68, Heft 1.

Shiver, B.D. and Borders, B.E. 1996. Sampling techniques for forest resources inventory. John Wiley & Sons. 356 p.

Ståhl, G. 1994. Optimizing the utility of forest inventory activities. Swedish University of Agricultural Sciences, Department of Biometry and Forest Management. Report 27.

Ståhl, G., Carlson, D. and Bondesson, L. 1994. A method to determine optimal stand data acquisition policies. Forest Science 40:630-649.

Tokola, T. and Shrestra, S.M. 1999. Comparison of cluster-sampling techniques for forest inventory in southern Nepal. Forest Ecology and Management 116:219-231.

CHAPTER 3

MODEL-BASED INFERENCE

ANNIKA KANGAS

University of Helsinki, Finland

3.1 FOUNDATIONS OF MODEL-BASED INFERENCE

Any survey can be separated into three stages, design stage, estimation stage and inference stage. The design stage means selecting the design by which the data is gathered, the estimation stage selecting and using the estimators for the parameters of interest, i.e. population means and totals, and the inference stage analyses concerning the accuracy of these estimators, i.e. the calculation of standard errors and confidence intervals.

Models can be used at several stages in sample surveys. They can be used in the design stage, for instance, to select the most efficient sampling design, or in the estimation stage as ratio or regression estimators, or in the inference stage by using autocorrelation models to estimate the variance in systematic sampling (Cochran 1946, Bellhouse 1988). Hansen et al. (1983) used the term model-based to describe strategies that utilize models in the design stage, estimation stage or both and the term model-dependent for strategies which used models in the inference stage. Schreuder et al. (1993) nevertheless use the term model-based to refer specifically to the use of models for inference, and the same approach is adopted here.

The principal difference between the model-based and classical approaches lies in the source of randomness they utilize (Särndal 1978). In classical, design-based sampling theory the source of randomness is the probability introduced by the sampling design to the various subsets of the population. Inference rests on the stochastic structure introduced by the sample selection. Even when models are used, the validity of inference is ensured by the sampling design and not by the validity of the model. In fact, models that incorporate auxiliary information can be used regardless of whether they are valid or not (Mandallaz 1991).

A. Kangas and M. Maltamo (eds.), Forest Inventory – Methodology and Applications, 39–52.

In the model-based approach the observed values y_i are assumed to be random, not fixed as in the design-based case. They are considered to be the realized outcome of random variables Y_i having a joint distribution ξ. The so-called superpopulation ξ is modelled to reflect the available background information about the population (Cassel et al. 1977). The concept of superpopulation dates back at least to the paper of Cochran (1946) on systematic sampling.

In the model-based (or model-dependent) approach the inference rests entirely upon the validity of the model describing the real world (Mandallaz 1991). All the randomness in this inference is due to the population, not to the sampling method as in the design-based approach. Where the latter requires independent selection of units, the model-based approach considers the independence of the sampling units themselves, and thus (potential) spatial correlations between the sampling units need to be taken into account. On the other hand, the method by which the sample is selected is not considered important. If the model is valid, randomization is not needed and the sample may be selected in a purposive manner. Even in the case of purposive sampling, however, the sample must not be selected purposively with respect to values of y_i (Gregoire 1998). In any case, random selection (or objective selection, as in systematic sampling) is usually used to ensure the validity of inference even though the approach is model-based, as the inferences will then be robust with respect to possible model misspecification.

In the model-based approach it is possible to make a distinction between inference concerning 1) the (finite) population values themselves and 2) the superpopulation that has generated the finite population (Särndal et al. 1992 p. 514). If we assume that a simple model describing the superpopulation ξ is

$$y_i = \mu + e_i \,, \tag{3.1}$$

where y_i is the value of variable y at point i belonging to the area of interest, its expected value (with respect to the model) will be $E_\zeta(y_i)=\mu$, and the variance of errors $V_\zeta(e_i)=\sigma^2$, units i and j are independent $Cov_\zeta(e_i,e_j)=0$ and e_i's can be assumed to be normally distributed. As the finite population of N units is also assumed to be a sample from this superpopulation, its mean $\overline{Y}$ is also a random variable. This means that the superpopulation parameter μ does not generally coincide with the population parameter $\overline{Y}$. It can be said that model-based inference gives a prediction of the population parameter.

It is therefore necessary to decide whether interest is focused on inference concerning the finite population parameters (descriptive or enumerative inference) or concerning the superpopulation parameters (analytic inference) (Schreuder et al. 1993 p. 204, see also section 10.6). In the case of descriptive information, the variance of interest would be the prediction variance, $\mathrm{var}(\mu - \overline{Y})$, rather than the variance in the superpopulation model parameter $\mathrm{var}(\mu)$ (Mandallaz 1991 p. 125).

In the design-based case an estimator is considered design-unbiased if its expected value in the set of all possible samples coincides with the population value. In the model-based case, the respective feature is model-unbiasedness. An estimator

μ, for instance, is regarded as a model-unbiased estimator for the population parameter if the expected value of the difference between the estimator $\hat{\mu}$ and the population parameter $\overline{Y}$ is zero with respect to the model ζ, given a sample s $E_\zeta(\hat{\mu} - \overline{Y}|s) = 0$ (Särndal et al. 1992 p. 534). In the general case, as the super-population is infinite, the expected value for the estimator $\hat{Y}$ of population parameter Y is the integral over the superpopulation model ζ.

$$E_\zeta(\hat{Y}) = \int \hat{Y} d\xi \,, \tag{3.2}$$

and the model-based variance is

$$V_\zeta(\hat{Y}) = \int \left\{\hat{Y} - E(\hat{Y})\right\}^2 d\xi \,. \tag{3.3}$$

The model-based variance can be used in the design stage in order to obtain a sample that minimizes this variance, and, given the sample s, (3.3) could be used to select the minimum variance estimator (e.g. Särndal et al. 1992 p. 516).

In cases where random sampling is used, the estimators can be required to be both design and model-unbiased. The expected values and variances can then be calculated both under the design and the model, as $E_\zeta E_p(\hat{Y})$ and $E_\zeta E_p(\hat{Y} - E(\hat{Y}))^2$. Variances of this kind, called anticipated variances (Särndal et al. 1992 p. 516), can be useful for optimizing the sample design.

3.2 MODELS

In the general case, the model used for model-based inference can be a general linear model (see Searle 1971, Graybill 1976, Lappi 1993 or any textbook on general linear models)

$$\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon} \,, \tag{3.4}$$

where $\mathbf{y}$ is an n-vector of the observed dependent variables, $\mathbf{X}$ is an $n \times p$ matrix of independent variables, $\boldsymbol{\varepsilon}$ is an $n \times 1$ vector of errors and $\boldsymbol{\beta}$ is a $p \times 1$ vector of model parameters. It is assumed that $E(\boldsymbol{\varepsilon}) = \mathbf{0}$ and the variance-covariance matrix of errors is $\text{var}(\boldsymbol{\varepsilon}) = \sigma^2\mathbf{I}$, where $\mathbf{I}$ is an $n \times n$ identity matrix. This means that the errors are mutually independent ($\text{cov}(\varepsilon_i, \varepsilon_j) = 0, \forall\ i \neq j$) and homoscedastic ($\text{var}(\varepsilon_i) = \sigma^2\ \forall\ i$).

The parameters can then be solved by the ordinary least squares method with

$$\hat{\boldsymbol{\beta}} = (\mathbf{X'X})^{-1}\mathbf{X'y} \,, \tag{3.5}$$

producing

$$\text{var}(\hat{\boldsymbol{\beta}}) = \hat{\sigma}^2(\mathbf{X'X})^{-1} \tag{3.6}$$

and $\text{var}(\hat{y}_i) = \text{var}(\varepsilon_i) = \sigma^2$ .The estimator for the residual variance is

$$\hat{\sigma}^2 = \frac{(\mathbf{y} - \mathbf{X}\hat{\boldsymbol{\beta}})'(\mathbf{y} - \mathbf{X}\hat{\boldsymbol{\beta}})}{n - p}. \tag{3.7}$$

In an even more general case, $\text{var}(\boldsymbol{\varepsilon}) = \sigma^2\mathbf{V}$, where $\mathbf{V}$ is an $n \times n$ matrix and the diagonal includes the possible weights of the observations (leading to WLS, i.e. Weighted Least Squares) and the off-diagonal cells the correlations among the errors (leading to GLS, i.e. Generalized Least Squares). The parameters can then be estimated from

$$\hat{\boldsymbol{\beta}} = (\mathbf{X'V^{-1}X})^{-1}\mathbf{X'V^{-1}y}\ , \tag{3.8}$$

and the estimator for their variance is

$$\text{var}(\hat{\boldsymbol{\beta}}) = \hat{\sigma}^2(\mathbf{X'V^{-1}X})^{-1}\ . \tag{3.9}$$

With these general models, the estimator for the population mean is

$$\hat{\mu} = \hat{\boldsymbol{\beta}}\overline{\mathbf{X}}\ , \tag{3.10}$$

where $\overline{\mathbf{X}}$ is the mean matrix of *x*-variables in the population. Its (analytic) variance is

$$var(\hat{\mu}) = \overline{\mathbf{X}}'\text{var}(\hat{\boldsymbol{\beta}})\overline{\mathbf{X}} = \sigma^2\overline{\mathbf{X}}'(\mathbf{X'V^{-1}X})^{-1}\overline{\mathbf{X}}\ . \tag{3.11}$$

When the prediction variance for new observations (i.e. those not belonging to the sample) are calculated, an additional error term needs to be accounted for. The prediction error for one observation y_0 is then

$$var(y_0 - \hat{y}_0) = \sigma^2\mathbf{x_0}'(\mathbf{X'V^{-1}X})^{-1}\mathbf{x_0} + \sigma^2 \tag{3.12}$$

and that for the mean of *m* new uncorrelated observations with the same values of regressors $\mathbf{x_0}$ is

$$var(\overline{y} - \hat{\overline{y}}) = \sigma^2\mathbf{x_0}'(\mathbf{X'V^{-1}X})^{-1}\mathbf{x_0} + \sigma^2/m\ . \tag{3.13}$$

In a model-based framework, therefore, formula (3.11) describes the

uncertainty concerning the superpopulation parameter and formula (3.13) that concerning the prediction variance of the mean. Assuming the simplest model (3.1), with only an intercept term but no independent variables, the estimator (3.10) simplifies to a sample mean of y and the variance estimator for the superpopulation parameter to the SRS sampling variance for an infinite population,

$$\text{var}(\hat{\mu}) = \hat{\sigma}^2(\mathbf{1'I}^{-1}\mathbf{1})^{-1} = \frac{\hat{\sigma}^2}{n}, \tag{3.14}$$

where **1** is an n-vector of ones, n is the number of sampling units and $\hat{\sigma}^2$ the normal variance calculated from the sample. The estimator for prediction variance of the population parameter, $\text{var}(\hat{\mu} - \overline{Y})$, in a finite population of N units (of which (N-n) are new and n are known) is (see Gregoire 1998 p. 1436)

$$\text{var}(\hat{\mu} - \overline{Y}) = \hat{\sigma}^2\left(\frac{1}{n} - \frac{1}{N}\right). \tag{3.15}$$

Thus the prediction error of the population mean is slightly different from the variance of the superpopulation parameter in a finite population, although the difference is small if N is large. It also means that even if the sample size were N, i.e. the whole population were measured, the estimate of the superpopulation parameter would still be uncertain while the variance of the population parameter approaches zero when n approaches N.

An important special case is the model through the origin

$$y_i = \beta X_i + \varepsilon_i \tag{3.16}$$

with a variance proportional to the value of x_i, $\text{var}(y_i) = \sigma^2 x_i$. The estimator for $\hat{\beta}$ is then

$$\hat{\beta} = \sum_{i \in S} y_i \Big/ \sum_{i \in S} x_1 \tag{3.17}$$

and the estimator for its variance is

$$\text{var}(\hat{\beta}) = \left(1 \Big/ \sum_{i \in S} x_i\right)^2 \sum_{i \in S} \hat{\sigma}^2 x_i = \frac{\hat{\sigma}^2}{\sum_{i \in S} x_i}, \tag{3.18}$$

where, according to the WLS formula,

$$\hat{\sigma}^2 = \frac{1}{n-1}\sum_{i\in S}(y_i - \hat{\beta}x_i)^2 / x_i \,. \tag{3.19}$$

The optimal sampling strategy with this model would be to select the units with the largest values of x for the sample, i.e. to maximize the value of $\sum_{i\in S} x_i$ (Royall 1970). An analytic inference for $\text{var}(\hat{\mu})$ can be calculated with (3.11), and the estimator for descriptive inference in a finite population is (Gregoire 1998)

$$\text{var}(\hat{\mu} - \overline{Y}) = \frac{\hat{\sigma}^2}{N^2} T_x \left(\sum_{i\in R} x_i \Big/ \sum_{j\in S} x_j \right), \tag{3.20}$$

where S denotes a sample and R those units that belong to the population P but not to the sample S.

Example 3.1

Assume a population of 125 trees where the diameter d and volume v of each tree are known. A (non-random) sample of 32 trees from this population are measured. The population parameters are presented in Table 3.1 and the sample trees in Table 3.2.

Table 3.1 Population parameters.

	Total	Mean	Standard deviation
Volume v	9477.036 dm^3	75.82 dm^3	48.10 dm^3
Diameter d	1485 cm	11.88 cm	3.55 cm

The task is to estimate the mean volume of the trees in the population. The sample mean is 93.30, and the estimate of standard deviation in the sample is 41.02. It is assumed that the population is generated with model (3.1) and that the observations are mutually independent. Based on these assumptions, the estimated standard deviations are 7.25 for the superpopulation parameter with formula (3.14) and 6.255 for the population mean with formula (3.15). In this small population the difference between analytic and descriptive inference is clear.

Table 3.2 Sample trees.

d cm	v dm^3	d cm	v dm^3
9.2	38.32	13	80.08
9.7	42.23	13.1	84.91
10.9	50.30	13.3	81.29
11.1	57.32	13.4	86.90
11.3	57.59	13.7	90.11
11.6	62.54	13.9	95.43
11.8	70.06	13.9	95.43
12	68.89	14.8	116.39
12	67.88	14.9	108.63
12.2	65.96	15.3	120.97
12.4	70.26	16	129.39
12.5	73.57	16.7	148.50
12.6	70.30	16.8	144.35
12.8	84.57	18.2	174.58
12.9	78.87	18.4	174.82
13	81.27	20	214.02

For an example accounting for spatial autocorrelation, see Chapter 10.

Example 3.2

In this example estimates for the mean volume and its standard error are calculated using the model-based formulae (3.10) and (3.17)-(3.20). First, the estimate for parameter β is calculated with (3.17):

$$\hat{\beta} = \frac{\overline{y}}{\overline{x}} = \frac{93.30}{13.54} = 6.889$$

The estimate for the population mean is then

$$\hat{\mu} = \hat{\beta}\overline{X} = 6.889 \cdot 11.88 = 81.841 dm^3 .$$

The residual variance is estimated with

$$\hat{\sigma}^2 = \sum_{i=1}^{n} \frac{(y_i - \beta x_i)^2}{(n-1)} = \sum_{i=1}^{102} \frac{(y_i - 6.889 \cdot x_i)^2}{(32-1)} = 37.467 \left(dm^3\right)^2 ,$$

the descriptive variance with

$$\text{var}(\hat{\mu} - \overline{Y}) = \frac{\hat{\sigma}^2}{N^2} T_x \left(\sum_{i \in R} x_i \Big/ \sum_{j \in S} x_j \right) =$$

$$\frac{37.467}{125^2} \cdot 1485 \left(1051.6 \Big/ 432.4 \right) = 8.64 (dm^3)^2$$

and the standard error estimate as

$$s_{\hat{\mu}} = \sqrt{8.64} = 2.939\, dm^3 .$$

The ratio estimate for the total stem volume is

$$\hat{T}_y = \hat{\beta} T_x = 6.889 \cdot 1485 = 10230.16\, dm^3$$

and its standard error

$$\text{var}(\hat{T}_y - T_y) = \hat{\sigma}^2 T_x \left(\sum_{i \in R} x_i \Big/ \sum_{j \in S} x_j \right) =$$

$$37.467 \cdot 1485 \left(1051.6 \Big/ 432.4 \right) = 135000.6 (dm^3)^2 .$$

Using analytic inference, the corresponding variances would be

$$var(\hat{\mu}) = \overline{\mathbf{X}}' \text{var}(\hat{\boldsymbol{\beta}}) \overline{\mathbf{X}} = 11.88^2 \cdot 0.086449 = 12.2 (dm^3)^2 \quad \text{and}$$

$$var(\hat{T}_y) = N^2 \overline{\mathbf{X}}' \text{var}(\hat{\boldsymbol{\beta}}) \overline{\mathbf{X}} = 125^2 \cdot 11.88^2 \cdot 0.086449 = 190638.9 (dm^3)^2 ,$$

both again somewhat larger than that of the descriptive inference.

3.3 APPLICATIONS OF MODEL-BASED METHODS TO FOREST INVENTORY

Some examples of model-based inference can also be found in the forestry literature. Design-based and model-based inferences have been compared in papers by Schreuder and Wood (1986) and Gregoire (1998), for instance.

A simple example of a forestry application is the paper of Pekkonen (1983), who used a polynomial volume model

$$y_i = \beta_1 x_1 + ... + \beta_k x_i^k + e_i , \tag{3.21}$$

where x_i is the diameter of tree i, as a superpopulation model for estimating the total timber volume in a given stand. The parameters of the volume model were estimated from a sample, and the total timber volume was then estimated by

$$\hat{T} = \sum_{i \in s} y_i + \sum_{i \notin s} \hat{y}_i , \tag{3.22}$$

where the first term on the right-hand side is the total volume of sample trees and the second term the total volume of the other trees, estimated using the superpopulation model. Other examples of the use of model-based methods for timber estimation include the papers of Schreuder (1984), Schreuder and Thomas (1985).

The efficiency of sampling can often be greatly increased by using auxiliary information. In a forest inventory this may mean information obtained from previous studies, from satellite images or from GIS, for instance. These sources provide information which can be used for stratification of the population in the design-based approach. In a model-based framework, information from GIS was used by Mandallaz (1991, 1993). The model-based approach enabled several classifying variables and interactions to be used without complex analysis.

Auxiliary information can also be used for small-area estimation (Chapter 7). When estimates are desired for subdivisions of a population, design-based estimators often have unacceptably large sampling errors. In such a case it is preferable to use at least partially model-based estimators. Small area estimators have been studied by Särndal (1984) and Särndal and Hidiroglou (1989), for example, and in a forestry context by Green et al. (1987), Mandallaz (1991, 1993), Kangas (1996) and Lappi (2001).

In Scandinavian national forest inventories, models have been used to develop the sampling design and to develop error estimators for systematic strip sampling and systematic cluster sampling (Chapter 10). These estimators are still based on a design approach, however. Purely model-based estimators of the mean volume and its standard error were presented by Kangas (1993, 1994). The variation in volume in the area was divided into two components, the trend and the (correlated) random errors. Spatial autocorrelation was taken into account by estimating the covariance between the sample plots as a function of distance. The trend component was described with a second-order surface

$$\begin{aligned} y_i = {} & \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \beta_3 x_{3i} + \beta_4 x_{1i} x_{2i} + \beta_5 x_{1i} x_{3i} + \beta_6 x_{2i} x_{3i} + \\ & \beta_7 x_{1i}^2 + \beta_8 x_{2i}^2 + \beta_9 x_{3i}^2 + \varepsilon_i . \end{aligned} \tag{3.23}$$

where y_i is the volume (m^3/ha) at point i and x_{1i} and x_{2i} are the coordinates of point i

and x_{3i} is its altitude. Thus it is assumed that the mean volume varies in the region with respect to location.

The most important application of model-based inference may nevertheless be the possibility of choosing the optimal sampling strategy. This can be based on the anticipated variance (section 3.1) in a sample under the assumed model. Optimal sampling strategies have been discussed by by Schreuder and Quyang (1992), Mandallaz (2002), Mandallaz and Lanz (2001) and Mandallaz and Ye (2000), for instance.

Another example of a situation where model-based methods may possibly be useful is the incorporation of information from previous surveys. Such information can be used in a continuous forest inventory system, for example (van Deusen 1989). It is also possible to update sample data using growth models and to combine this information with new sample survey data (Dixon and Howitt 1979). Data from previous surveys can similarly be used to determine the sampling scheme (Schreuder and Thomas 1985). The modelling approach can be extended directly to the analysis of non-sample errors (Little 1982).

3.4 MODEL-BASED VERSUS DESIGN-BASED INFERENCE

Since model-based methods were first presented, purposive sampling has again been discussed, and it has been shown to be not only possible but even desirable in certain situations. This strategy has been criticized, however, because it may lead to severe bias if the model assumptions are not correct. In this case statements about the sampling error may also be misleading.

Following that criticism, much of the work of modellers has been devoted to constructing robust model-based strategies. The search for a robust strategy often leads to the recommendation that the sampling design should be probabilistic (Godambe 1982) or that the sample should be balanced (Royall 1992). A balanced sample means that the sample moments of the covariates are equal to those in the population. If the model does not include all the relevant covariates, however, the selected sample may not be balanced with respect to these covariates and the results may thus be biased. A probabilistic design will, on average, provide an approximately balanced sample for regressors that have been overlooked as well.

In contrast to model-based inference, design-based inference is usually considered to be robust. According to Brewer and Särndal (1983), probability sampling is robust by definition: since the inference does not depend on a model, there is no need to discuss what happens in the case of model breakdown. Hansen et al. (1983) expressed the view that the design-based approach is robust because a minimum number of assumptions are made about the population, and personal bias in sample selection and model selection is eliminated.

In the model-based approach some model deviations can be controlled by choosing an appropriate sampling design, but there can never be complete robustness. The framework for inference is completely different in these two approaches, however. Often modellers and randomisers will make identical inferences from identical samples, e.g. in simple random sampling. If in the further

analysis of a population it is agreed that stratification should have been used, a modeller will say that the model was mis-specified and the inference was thus biased. In this same situation a randomiser may say that all that has happened is that there has been a loss of efficiency. Thus the results are interpreted differently, and the modeller's bias is transformed into the randomiser's sampling variance (Smith and Njenga 1992).

Brewer and Särndal (1983) described six approaches to sampling, which are progressively less dependent on model assumptions.

> 1. The Model-Based Bayesian Approach. Inference is based on an assumed model and on the specified prior distributions of its parameters. The estimators are developed and the sample is selected in order to minimize Bayesian risk.
>
> 2. The Model-Based Non-Bayesian Approach. Inference is based on an assumed model without using prior distributions for its parameters. The estimators are developed so as to be minimum variance unbiased estimators and sampling is conducted in order to minimize the variance of the estimator under the model.
>
> 3. The Robust Model-Based Non-Bayesian Approach. This approach differs from the previous approach in that the sample is selected in order to achieve a balance. The estimators are also developed so as to be unbiased under a closely related alternative model.
>
> 4. Probability Sampling with Modelling. Inference may be either design-based or model-based with this approach. The design is chosen to minimize the model expectation of the design-based MSE.
>
> 5. Classical Probability Sampling. Selection is probabilistic and inference is design-based.
>
> 6. Inference Without Exchangeability. In this approach an attempt is made to make inferences without assumptions about exchangeability.

In the first two strategies the sample is purposively selected, so that these approaches may lead to erroneous inference if the model is not an accurate description of the population. If, on the other hand, the model is correct, these approaches are reliable and cost-effective (Schreuder et al. 1993). In the third approach, random selection is not required, but it may be used because simple random sampling produces a balanced sample on average. According to Brewer and Särndal (1983), the most reasonable choices are approaches 3, 4 and 5, but they prefer approach 4. The last approach has yielded some theorems on the non-existence of optimal estimators, but is of little practical value.

Proponents of model-based inference argue that after a sample has been drawn, the soundness of the inference depends on the sample itself and not on the

process used to obtain it. In the design-based approach the sampling variance is averaged over all possible samples of realized values, and the resulting sampling variance does not describe how the sample performs but only how samples of the same size perform on average. With the model-based method, inference from the sample may be sound even when the sample is atypical.

The model-based approach is sometimes judged to be radically different from the traditional approach, and perhaps even controversial. A philosophical consensus among the different approaches to sampling theory is not likely, but from a pragmatic point of view the differences are not so great and the different approaches will lead to similar conclusions, at least in large samples. Actually, the model-based approach confirms many classical results.

REFERENCES

Bellhouse, D.R. 1988. Systematic Sampling. In: Handbook of Statistics, 6, Sampling, pp. 125-145. Eds. Krishnaiah, P.R. and Rao, C.R., North Holland.

Brewer, K.R.W. and Särndal, C-E. 1983. Six approaches to enumerative survey sampling. In: Incomplete Data in Sample Surveys, Vol 3. Eds. Madow, W.G., Olkin, E and Rubin, D.B.. Academic Press, NY. pp. 363-405.

Cassel, C-M, Särndal C-E. and Wretman, J.H. 1977. Foundations of Inference in Survey Sampling. John Wiley & Sons, New York. 192 p.

Cochran, W.G. 1946. Relative accuracy of systematic and random samples for a certain class of populations. Annals of Mathematical Statistics, 17:164-177.

Dixon, B. and Howitt, R. 1979. Continuous forest inventory using a linear filter. Forest Science 25: 675-698.

Graybill, F.A. 1976. Theory and applications of the linear model. Duxbury Press, N. Scituate M. 704 p.

Green, E.J., Thomas, C.E. and Strawderman, W.E. 1987. Stein-Rule Estimation of Timber Removals by County. Forest Science 33:1054-1061.

Godambe, V.P. 1982. Estimation in Survey Sampling: Robustness and Optimality. Journal of American Statistical Association 77:393-406. (With discussion).

Gregoire, T. 1998. Design-based and model-based inference in survey sampling: appreciating the difference. Canadian Journal of Forest Research 28:1429-1447.

Hansen, M.H., Madow, W.G. and Tepping, B.J. 1983. An Evaluation of Model-Dependent and Probability-Sampling Inferences in Sample Surveys. Journal of American Statistical Association 78: 776-793.

Kangas, A. 1993. Estimating the Parameters of Systematic Cluster Sampling by Model Based Inference. Scandinavian Journal of Forest Research 8:571-582.

Kangas, A. 1994. Classical and model based estimators for forest inventory. Silva Fennica 28:3-14.

Kangas, A. 1996. Small area estimates using model based methods. Canadian Journal of Forest Research 26:758-766.

Lappi, J. 1993. Metsäbiometrian menetelmiä. Silva Carelica 24. 182 p.

Lappi, J. 2001. Forest Inventory of Small Areas Combining the Calibration Estimator and a Spatial Model. Canadian Journal of Forest Research 31: 1551-1560.

Little, R.J.A. 1982. Models for nonresponse in Sample Surveys. Journal of American Statistical Association 77:237-250.

Mandallaz, D. 1991. A Unified Approach to Sampling Theory for Forest Inventory Based on Infinite Population and Superpopulation Models. Chair of Forest Inventory and Planning, Swiss Federal Institute of Technology (ETH), Zurich. 242 p.

Mandallaz, D. 1993. Geostatistical Methods for Double Sampling Schemes: Application to Combined Forest Inventories. Chair of Forest Inventory and Planning, Swiss Federal Institute of Technology (ETH), Zurich. 133 p.

Mandallaz, D. 2002. Optimal sampling schemes based on the anticipated variance with lack of fit. Canadian Journal of Forest Research 32:2136-2243.

Mandallaz, D. and Lanz, A. 2001. Forest inventory: further results based on the anticipated variance. Canadian Journal of Forest Research 31:1845-1853.

Mandallaz, D. and Ye, R. 2000. Forest inventory with optimal two-phase two-stage sampling schemes based on the anticipated variance. Canadian Journal of Forest Research 29:1691-1709.

Pekkonen, T. 1983. Leimikon puuston ennustaminen regressioennustinta käyttäen. Metsäntutkimus-laitoksen tiedonantoja 86.

Royall, R.M. 1970. On finite population sampling theory under certain linear regression models. Biometrika 57:377-387.

Royall, R.M. 1992. Robustness and Optimal Design Under Prediction Models for Finite Populations. Survey Methodology 18:179-185.

Särndal, C-E. 1978. Design-based and Model-based Inference in Survey Sampling. Scandinavian Journal of Statistics 5:27-52.

Särndal, C-E. 1984. Design-Consistent versus Model-Dependent Estimation for Small Domains. Journal of American Statistical Association 79:624-631.

Särndal, C-E. and Hidiroglou, M.A. 1989. Small Domain Estimation: A Conditional Analysis. Journal of American Statistical Association 84:266-275.

Särndal, C-E., Swensson, B. and Wretman, J. 1992. Model assisted survey sampling. Springer-Verlag. 694 p.

Schreuder, H.T. 1984. Poisson sampling and some alternatives in timber sales sampling. Forest Ecology and Management 8:149-160.

Schreuder, H.T., Gregoire, T.G. and Wood, G.B. 1993. Sampling Methods for Multiresource Forest Inventory. John Wiley & Sons. New York. 446 p.

Schreuder, H.T. and Quyang, Z. 1992. Optimal sampling strategies for weighted linear regression estimation. Canadian Journal of Forest Research 22:239-247.

Schreuder, H.T. and Thomas, C.E. 1985. Efficient sampling techniques for timber sale surveys and inventory updates. Forest Science 37:1497-1525. With discussion.

Schreuder, H.T. and Wood, G.B. 1986. The choice between design dependent and model-dependent sampling. Canadian Journal of Forest Research 16:260-265.

Searle, S.R. 1971. Linear models. John Wiley & Sons, New York. 532 p.

Smith, T.M.F. and Njenga, E. 1992. Robust Model-Based methods for Analytic Surveys. Survey Methodology 18:187-208.

Van Deusen, P. 1989. Multiple-occasion partial replacement sampling for growth components. Forest Science 35:388-400.

CHAPTER 4

MENSURATIONAL ASPECTS

ANNIKA KANGAS

University of Helsinki, Finland

4.1. SAMPLE PLOTS

4.1.1 Plot size

In forest inventory problems, the size of the plots to be measured needs also to be decided in addition to selection of the number of plots. The larger the plots are, the more time-consuming and expensive it is to measure them, and obviously the number of sample plots that can be measured with a given budget is larger when the plots are small. On the other hand, the variation among plots in the population, S_y^2, diminishes as the plot size increases (Shiver and Borders 1995 p. 60).

Clusters of smaller sub-plots (or combined plots) have been used on many occasions instead of single plots, typically in large-area surveys such as national inventories (see Chapter 11). A cluster plot typically consists of small circular plots (or point-sampling plots, section 4.2) that form a geometrical figure such as a triangle or rectangle. There are two benefits entailed in the use of clusters (Loetsch et al. Vol II p. 345). First, the location and layout of a cluster of several small plots is faster and more accurate than the measuring of large single plots. In addition, the coefficient of variation is smaller than for single plots of the same total area.

The optimal plot size thus depends on both the measurement costs and the observed variation. This question has been studied by Nyyssönen (1966) and Nyyssönen et al. (1971), for instance. Gambill et al. (1985) presented a method for determining plot size that minimizes the total cruising time (i.e. costs) and provides a specified level of precision, while Scott et al. (1983) discussed a method for determining the optimal spacing of sub-plots in clusters and Scott (1993) one for determining the optimal cluster design.

It can be shown that the spatial pattern of forests has an effect on the optimal plot size. If the trees are located according to a Poisson distribution, the ratio

A. Kangas and M. Maltamo (eds.), Forest Inventory – Methodology and Applications, 53–63.

of the variance to the population mean, σ^2/μ, for number of stems will assume the value 1, whereas it will be larger than 1 for a clustered population and smaller than 1 for a systematic population. The more clustered the population is, the larger the plot size should be in order to obtain a certain coefficient of variation in the number of trees per plot. Also, the smaller the plot, the faster the coefficient of variation $(CV = \sigma/\mu)$ increases with the variance/mean ratio (Fig. 4.1), although the latter ratio also depends on the sample plot size: i.e. σ^2/μ tends to increase as plot size increases (Loetsch et al. 1973 Vol II p. 332).

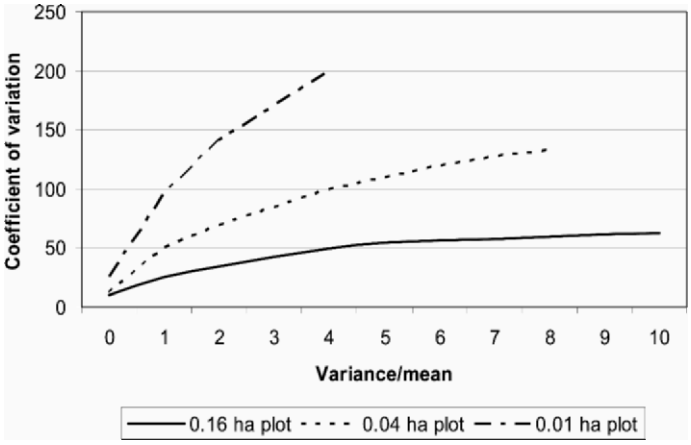


Figure 4.1 Illustration of the effect of spatial pattern (variance/mean ratio) and plot size on the coefficient of variation (modified from Loetsch et al. 1973).

The size of plot also determines the inclusion area for each tree. When circular plots of radius *r* are used, the inclusion area is a circle also of radius *r* centred on the tree. In other words, a certain tree will be tallied if the sample plot is located in its inclusion area. Thus the inclusion probability of a tree is its inclusion area divided by the total forest area (Schreuder et al. 1993 p. 114). The inclusion probabilities for rectangular plots are calculated in the same way, but now the inclusion area of a certain tree is a rectangle centred on it, having the same area and same orientation as the original sample plots (Ducey et al. 2004). These inclusion probabilities are needed for calculating edge corrections (section 4.4).

4.1.2 Plot shape

The usual plot shapes used in forest inventories are rectangular, square and circular. Rectangular plots are established by first defining one side and two corners, after which right angles are traced at these corners and the other two corners are located (Schreuder et al. 1993). The distance between the last two corners, and also the two

diagonals if possible, should be measured in order to check the measurements, as a rectangular plot is fairly vulnerable to errors in determination of the right angles. If the angles at the first two corners are 5 degrees too wide, this will cause the plot area to be 8.3% too large (Loetsch et al. 1973 p. 317, Schreuder et al. 1993). A square plot can also be established working from the centre, by measuring the distance $a/\sqrt{2}$ to the corner along each diagonal. This approach is much less vulnerable to errors.

Another form of plot is a strip, i.e. a long, narrow rectangle. In strip sampling the measurer usually walks along the central line of the strip and checks its width now and then, e.g. with a pole (Loetsch et al. 1973 p. 318). It is also possible to walk along one side of the strip. Strips are not very commonly used nowadays, except for sampling rare populations (Chapter 8). This is due to the fact that the line-plot type of inventory includes far less measurements but is just as efficient (section 1.3).

The trees in plantation forests are often planted in rows and columns which are not exactly parallel, so that it may be difficult to establish a plot of exactly the specified size. It is therefore usually advisable to establish a plot with corners mid-way between the rows (Schreuder et al. 1993 p. 295), otherwise the plot estimates may be biased due to inaccuracies in the areas. Since plantations usually show periodic variation, systematic sampling may also be highly inefficient. If the plot centres always fall between two rows, for instance, the nearest rows will always be either just inside or just outside a plot (Shiver et Borders 1995 p. 60).

Circular plots are easy to establish when the radius is not very large, and they are also not very vulnerable to errors in plot area. The length of the perimeter will increase as the radius increases, however, and so will the number of trees on the edge of the plot. Thus circular plots with a large radius are not very efficient (Schreuder et al. 1993, Loetsch et al. 1973). In many cases combined circular plots can be established, i.e. plots that consist of several concentric circles, the smaller circles being used for smaller trees and the larger circles for larger trees.

It is assumed with all plot types that the terrain will be level and the plot will lie entirely within the stand. If these assumptions are not fulfilled, a slope correction or edge correction will be needed (section 4.4).

4.2 POINT SAMPLING

Point sampling (also known as angle-gauge sampling, Bitterlich sampling, plotless sampling or variable radius plot [VRP] sampling) is a sampling method that is unique in forest inventories. The principles were first introduced by Walter Bitterlich (1947, see also Bitterlich 1984). In point sampling the trees do not have an equal probability of being included in the sample, but instead the probability is proportional to the tree size, or more exactly to the basal area of the tree (PPS sampling). This was first noted by Grosenbaugh (1952).

Trees with a basal area exceeding a certain viewing angle α are selected for

the sample (Fig. 4.2). The radius r at which the basal area of the tree just exceeds the critical angle defines the plot area for a tree of this size, and each tree is measured in a circular plot having an area proportional to its basal area, giving (Loetch et al. 1973 Vol II p. 348)

$$\frac{\frac{\pi}{4}d_i^2}{\pi r_i^2} = \frac{\frac{\pi}{4}d_j^2}{\pi r_j^2}, \tag{4.1}$$

where d_i (d_j) is diameter of tree i (j) and r_i (r_j) is the limiting radius for that diameter.

In angle-gauge sampling, the inclusion probabilities for each tree can be calculated as the inclusion area divided by the total area, as with circular plots. In this case, however, the inclusion area around each tree depends on its diameter, i.e. large trees have larger inclusion areas than small trees. The radius of this inclusion area is the limiting radius for trees of that size.

Each tree in a stand represents the same basal area, namely BAF m^2/ha, where BAF is the basal area factor. The estimator for any variable of interest is (see section 2.8 and Chapter 8)

$$\hat{Y} = \sum_{j=1}^{m}\sum_{i=1}^{N_k}\frac{y_i}{\pi_i}, \tag{4.2}$$

where the inclusion probability $\pi_i = g_{ji}/BAF$, and g_{ji} is the basal area of tree i at sampling point j, m is the number of sampling points, N_j is the number of trees at point j and BAF is the basal area factor of the angle gauge used. Typically, either 1 (m^2/ha) or 2 factors are used in Finland. If the variable of interest y_i is the basal area g_i, it is enough to count the trees filling the angle, so that the method provides a quick means of measuring the basal area. For other variables, such as the number of trees, the diameters of the trees also need to be measured.

Angle-gauge sampling can also be used in many other applications. In vertical point sampling, for example, the trees are selected in proportion to their squared height, i.e. the trees filling a vertical angle gauge are selected. This approach of estimating the mean squared tree height was proposed by Hirata (1955).

Angle-gauge sampling requires certain assumptions to be fulfilled (Grosenbaugh 1958, Schreuder et al. 1993). These are fairly similar to the ones that apply to plot sampling, namely that

1. The trees are vertical and their cross-sections are circular.
2. The terrain is level (or else a slope correction is made).
3. The sample trees are visible from the point location (or from another point at same distance, or else their diameter and distance can otherwise be checked), and

4. The area from which the trees can be selected lies entirely within the stand (or else an edge correction is made)

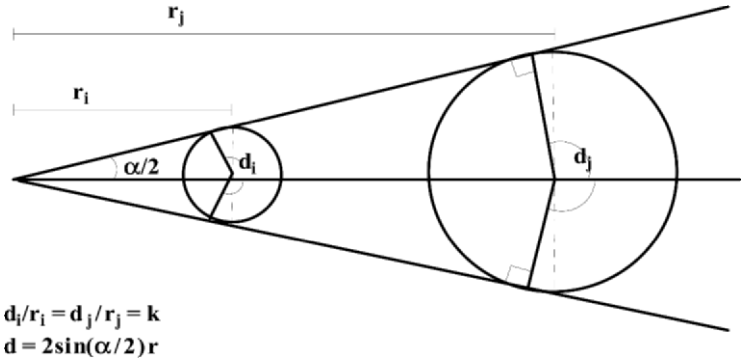


Figure 4.2 The principle of a relascope: k is a relascope constant, $k = 2\sin(\alpha/2)$, *α is the viewing angle and the basal area factor* $BAF = 10^4 \sin^2(\alpha/2)$ *(Loetsch et al. 1973 p.349).*

It has been seen in many studies (e.g. Laasasenaho and Päivinen 1986) that larger basal area factors give systematically larger basal areas. This is most probably due to the fact that a small basal area factor allows large trees to be included in the point sample from long distances. This means that not all the trees are necessarily visible, or that there is a possible inclusion area beyond the stand edge. It is obvious that many measurers will ignore edge corrections in practical work (section 4.4), or fail to check whether trees that are further away should be counted. Consequently, it is advisable to use factors giving about 6-10 trees per sample point on average, to avoid factors that would cause trees to be included from long distances.

4.3 COMPARISON OF FIXED-SIZED PLOTS AND POINTS

If fixed area sampling and variable radius sampling are compared in such a way that one plot is compared with one point, the result usually is that plot sampling is more efficient. This is because plots usually include more tallied trees than points. If measurement costs are accounted for, point sampling can be more efficient.

Matérn (1972), who compared the two sampling methods in a theoretical framework, concluded that with a given number of measured trees, the point sampling method is more efficient for determining the basal area or the volume of the stand. This result has been confirmed in other studies (Schreuder et al. 1987, Scott 1990). Although the number of stems is more efficiently measured with plots of a fixed size, Schreuder et al. (1987) found that the number of stems by diameter classes could also be measured more efficiently using variable-radius plots. It has also been stated that change (i.e. mortality, ingrowth) (Scott 1990) is more efficiently measured with fixed-radius plots. In any case, point sampling estimates

for growth are often more complex (Chapter 5). In general, it can be concluded that variables associated with large diameter classes or correlated with current basal area are better estimated with point samples and variables associated with small diameter classes are more efficiently measured with fixed-area plots.

4.4 PLOTS LOCATED ON AN EDGE OR SLOPE

4.4.1 Edge corrections

In many cases a sample plot may happen to be located in a void in a stand, such as on a road, in a lake or beneath a power line. In these cases the surveyor may be tempted to move it to a wooded spot. If the stand area includes voids, plots located on those spots will, however, be needed in order to calculate the mean volume accurately (Shiver and Borders 1995). Only if power lines etc. are excluded from the stand area should one not place plots there. Correspondingly, if the distance between the plots should be 200 metres the distance across a power line, for instance, should not be counted in this (Shiver and Borders 1995).

A special approach is needed when plots are located near a stand edge. For example, if a circular plot is located so that the distance from its centre to the stand edge is less than its radius r, the total area of the plot inside the stand will be less than the nominal area, so that, if no corrections are made, fewer trees will be measured than should be and the approach will result in a biased volume, i.e. an underestimate (Schreuder et al. 1993). The basic reason for the bias, however, is that the varying inclusion probabilities of the trees are not accounted for. If a tree is so near to the stand edge that its inclusion area is partly outside the border, its inclusion probability will be smaller than it should be (see Gregoire 1982).

The problem has been known for a long time, and the first attempts to correct the bias were presented by Finney and Palca (1948). Their method is itself biased, however. One solution that is often attempted is to move the plot away from the stand edge to the inside of the forest (the "Move-to-r" approach). Circular plots located nearer to the edge than their radius r, for instance, are moved to a point at a distance r from the stand boundary. This means, however, that the trees within a distance r from the edge have a smaller inclusion probability than those further inside the stand. Furthermore, the inclusion probability of the trees in the zone to which the plots are moved increases. This will lead to biased estimates if the border zone is different from the interior forest (Schreuder et al. 1993 p. 299). If trees grow better near the boundary than inside the forest, for instance, the stand volume may be underestimated.

Another approach is to measure a sample plot on the edge so that only the portion inside the stand is actually measured. This means that the true area of the plot inside the stand needs to be defined, which may be a complex matter when using circular plots, for example. The area of each plot also has to be accounted for when calculating the mean volume of the stand, i.e. by attaching more weight to plots with a smaller area (see Beers 1966). This method also produces biased estimates (Schreuder et al. 1993), but correct estimates can be achieved if each tree

in the plot is weighted separately according to the inverse of its inclusion area, (Beers 1966, Iles 2003 p. 627).

There are also other valid procedures for measuring plots at a stand edge. The most popular one is the "mirage method", as presented by Schmid-Haas (1969, see also Beers 1977, Schmid-Haas 1982, Gregoire 1982). When the radius *r* of a circular plot is larger than the distance *x* from the edge, a mirroring sample plot is located at a similar distance *x* from the edge on the other side and only the trees inside the original stand are measured on this mirroring plot (Fig. 4.3). This method exploits the concentric approach. With mirage method the folding of the plot works correctly, so that the inclusion area of each and every tree need not to be considered separately, and still the method provides unbiased estimates (Gregoire et al. 1982).

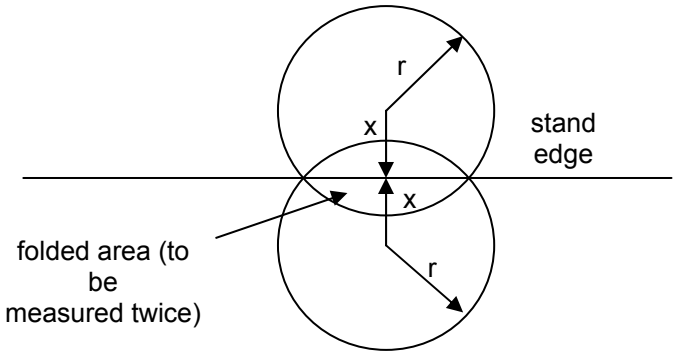


Figure 4.3 Illustration of the mirage method.

The good point about the mirage method is that it is also directly suited for point sampling. It is not without problems, however. It requires the assumption to be made that the border is almost linear (e.g. Iles 2003). Corners may encounter problems in the case of two crossing borders, for instance, where some trees need to be counted once, some twice and some three or four times (Fig. 4.4.). Erroneous use can also produce biased estimates: if the plot is not circular, the mirage plot may contain trees that were not in the original sample (e.g. Ducey et al. 2001). This possibility needs to be accounted for. In some cases it may also be difficult to define the mirage plot, as it may border onto a lake, a cliff or even the lawn of a house.

A new and very promising method for edge correction is the "walkthrough method" (Ducey et al. 2004). This is based on the inclusion areas for single trees. It requires measurement of the distance between the tree and the centre of the plot, after which a similar distance is measured on the other side of the tree (i.e. it is

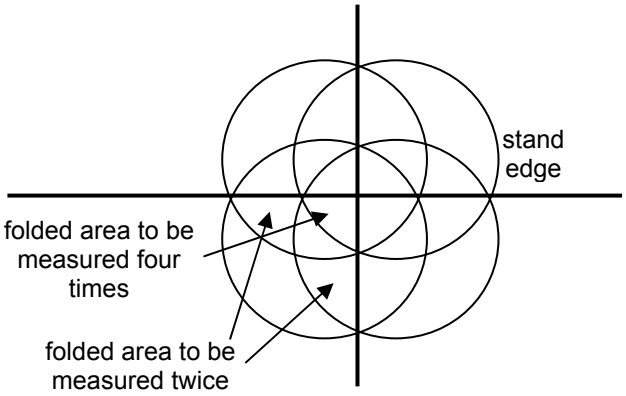


Figure 4.4 Illustration of the mirage method in a corner.

assumed that the measurer walks through the tree in a constant direction for the same distance). If the point achieved in this way lies within the area, the tree is measured once, otherwise (i.e. the point is reached over the boundary) it is measured twice (Fig. 4.5). This method is simple to apply in the field and does not require linear borders. There are still problems involved, however. There may be cases in narrow areas where both a sample point that lies within the inclusion area of the tree and its walkthrough point are outside the area (Iles 2003). In such a case these areas are neither counted in the original sample nor compensated for by the walkthrough method.

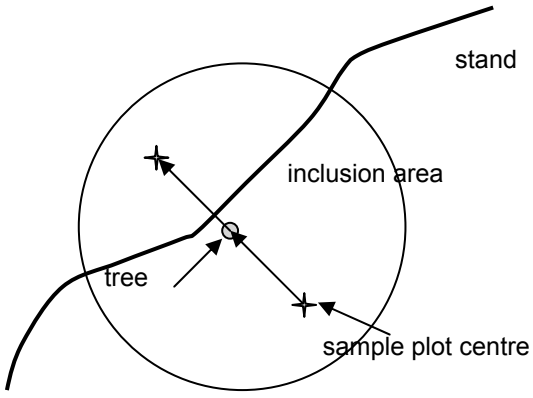


Figure 4.5 Illustration of the walkthrough method. The tree in the figure is counted twice, as the walkthrough point lies outside the boundary.

There are also many other methods for tackling this problem. Those interested could consider including sample points that lie outside the areas

(Masuyama 1954), or the related "toss-back" method of Iles (2001, 2003) and Flewelling and Iles (2004). Other unbiased approaches are to use the enlarged tree circle method (Barrett 1964, Schreuder et al. 1993), Grosenbaugh's method (1958) or the tree concentric method (Gregoire and Scott 1990).

Edge correction problems also need to be accounted for when using clusters of sub-plots (Scott and Bechtold 1995, Hahn et al. 1995), although the edge effect becomes smaller the larger is the area to be surveyed.

4.4.2 Slope corrections

If plots are located on a slope and the distance is measured along the slope, the plot as projected to the horizontal will actually be an ellipse with too small an area. This will obviously cause bias in the estimates if it is not accounted for. The slope can be accounted for exactly if the distance of each tree from the centre of the plot is measured horizontally. This also applies to point sampling. Measuring the exact horizontal distances may be tedious, however, if there are many such plots, and difficult if the slope is steep.

Another possibility is to enlarge the radius of the circular plot by multiplying it by $\sqrt{1/\cos\beta}$, where β is the maximum slope angle (Bryan 1956). The plot as projected to the horizontal will then be a circle with the correct area. In the case of a rectangular plot, the sides perpendicular to slope will remain unaffected but the sides parallel to slope need to be extended by $1/\cos\beta$ (Loetsch et al. 1973 Vol II p. 324). If the plot is not oriented parallel or perpendicular to the gradient of the slope, the corrections will obviously be more complicated.

A correction for the slope can be made in point sampling by dividing the estimate for the basal area by the cosine of the maximum angle of the slope at the sampling point (Schreuder et al. 1993 p. 119). The problem with this method, however, is the varying sampling intensity on different slopes (Del Hodge 1965). Furthermore, the correction only applies to total basal area, since it means varying the basal area factor for individual trees (Loetsch et al. 1973 Vol II p. 354).

Del Hodge (1965) presented a method in which the angle gauge was adjusted for the maximum slope so that the inclusion areas of the trees were correct. Another possibility is to adjust the angle gauge separately for each tree (Bruce 1955). This can be done fairly conveniently with a prism. There also exist instruments that make such corrections automatically, e.g. the Spiegel relascope (Shiver and Borders 1995 p. 91). This last method is the only one in which the inclusion areas for the trees are circular.

All in all, it is fairly easy to make a slope or edge correction. The most problematic cases are ones where both types of correction are needed (Ducey et al. 2001). When the inclusion areas are ellipses, for instance, the mirage plot may contain trees even if the original plot does not, i.e. the mirrored area does not entirely overlap with the original plot.

REFERENCES

Barrett, J.P. 1964. Correction for edge-effect bias in point-sampling. Forest Science 10:52-55.

Beers, T.W. 1966. The direct correction for boundary-line slopover in horizontal point sampling. Purdue Univ. Agric. Exp. Sta. Lafayette, IN Res. Bull. 786. 56 p.

Beers, T.W. 1977. Practical correction of a boundary overlap. Southern Journal of Applied Forestry 1:16-18.

Bitterlich, W. 1947. Die WinkelZählmessung. Allg. Forst. Holzwirtsch. Ztg. 58:94-96.

Bitterlich, W. 1984. The Relascope Idea. Commonwealth Agricultural Bureau. Farnham Royal. 242 p.

Bruce, D. 1955. A new way to look at trees. Journal of Forestry 53:163-167.

Bryan, M.B. 1956. A simplified method of correcting for slope on circular sample plots. Journal of Forestry 54:442-445.

Del Hodge, J. 1965. Variable plot cruising. A short-cut slope correction method. Journal of Forestry 63:176-180.

Ducey, M., Gove, J.H. and Valentine, H.T. 2004. A walkthrough solution to the boundary overlap problem. Forest Science 50:427-435.

Ducey, M., Gove, J.H., Ståhl, G. and Ringvall, A. 2001. Clarification of the mirage method for boundary correction, with possible bias in plot and point sampling. Forest Science 47:242-245.

Finney, D.J. and Palca, H. 1948. The elimination of bias due to edge-effects in forest sampling. Forestry 23:31-47.

Flewelling, J. and Iles, K. 2004. Area-independent sampling for total basal area. Forest Science 50: 512-517.

Gambill, C.W., Wiant, H.V. Jr. and Yandle, D.O. 1985. Optimum plot size and BAF. Forest Science 31:587-1078.

Gregoire, T. 1982. The unbiasedness of the mirage correction procedure for boundary overlap. Forest Science 28:504-508.

Gregoire, T. and Scott, T. 1990. Sampling at the stand boundary: A comparison of the statistical performance among eight methods. In: Proc. XIX World Forestry Congress IUFRO. Montreal, Canada. Aug. 5-11, 1990. Publ. No. FWS-3-90, Virginia Polytechnic Inst. and Univ., Blacksburg, pp. 78-85.

Grosenbaugh, L.R. 1952. Plotless timber estimates – New, fast, easy. Journal of Forestry 50:32-37.

Grosenbaugh, L.R. 1958. Point-sampling and line-sampling: probability theory, geometric implications, synthesis. U.S. For. Serv. South. For. Exp. Stn. Occas. Pap. No. 160.

Hahn, J.T., MacLean, C.D., Arner, S.L. and Bechtold, W. 1995. Procedures to handle inventory cluster plots that straddle two or more conditions. Forest Science Monograph 31:12-25.

Hirata, T. 1955. Height estimation through Bitterlich's method vertical angle-count sampling (In Japanese) Jap. J. For. 37:479-480.

Iles, K. 2001. Edge effect in forest sampling, Part II. Inventory and cruising newsletter 53:1-3. John Bell & Associates, Corvallis, OR.

Iles, K. 2003. A sampler of inventory topics. Kim Iles & Associates Ltd., Nanaimo, Canada, 869 p.

Laasasenaho, J. and Päivinen, R. 1986. On the checking of inventory by compartments. Folia Forestalia 664. 19 p. (In Finnish with English summary).

Loetsch, F., Zöhrer, F. and Haller, K. 1973. Forest Inventory. Vol I-II 436+ 469 p. BLV Verlagsgesellschaft.

Masuyama, M. 1954. On the error in crop cutting experiment due to the bias on the border of the grid. Sankhya 14:181-186.

Matérn, B. 1972. The precision of basal area estimates. Forest Science 18:123-125.

Nyyssönen, A. 1966. On the efficiency of some methods of forest survey. Proc 6th World For. Congr. Madrid, p. 2473-2475.

Nyyssönen, A., Roiko-Jokela, P. and Kilkki, P. 1971. Studies on improvement of the efficiency of systematic sampling in forest inventory. Acta Forestalia Fennica 116. 26 p.

Schmid-Haas, P. 1969. Stichprobenam Waldrand. Mitt. Schwiz. Anst. Forstl. Versuhswes. 45:234-303.

Schmid-Haas, P. 1982. Sampling at the forest edge. p. 263-276. In: Statistics in theory and practice: Essays in honor of Bertil Matérn. Ranneby, B. (Ed.). Swedish University of Agricultural Sciences, Umeå, Sweden.

Schreuder, H.T., Banyard, S.G. and Brink, G.E. 1987. A comparison of three sampling methods in estimating stand parameters for a tropical forest. Forest Ecology and Management 21:119-128.

Schreuder, H.T., Gregoire, T.G. and Wood, G.B. 1993. Sampling Methods for Multiresource Forest Inventory. John Wiley & Sons. New York. 446 p.

Scott, C. T. 1990. An overview of fixed versus variable radius plots for successive inventories. In: Proc. IUFRO Symp. "State-of-the-art Methodology of Forest Inventory", Syracuse, N.Y. Aug. 1989. USDA For. Serv. Gen. Tech. Rep. PNW-GTR-263. pp. 97-104.

Scott, T., Ek, A.R. and Zeisler, T.R. 1983. Optimal spacing of plots comprising clusters in extensive forest inventories. Pp. 707-710. In: Renewable resource inventories for monitoring changes and trends. Soc. A,. For. Publ. SAF 83-14.

Scott, T. 1993. Optimal design of a plot cluster for monitoring. Pp. 233-242 In: The optimal design of forest experiments and forest surveys. Rennols, K. and Gertner, G. (eds.). London UK., Univ. of Greenwich, Sch. of. Math., Stat. and Computing.

Scott, T. and Bechtold, W.A. 1995. Techniques and computations for mapping plot clusters that straddle stand boundaries. Forest Science Monograph 31:46-61.

Shiver, B.D. and Borders, B.E. 1996. Sampling techniques for forest resources inventory. John Wiley & sons. 356 p.

CHAPTER 5

CHANGE MONITORING WITH PERMANENT SAMPLE PLOTS

SIMO POSO

University of Helsinki, Finland

5.1 CONCEPTS AND NOTATIONS

There is nothing else permanent in nature but change. Everything is moving, as the Greek philosopher Herakleitos stated some 2500 years ago. In even-age forestry, forest stands develop from open areas and young plantations to mature stages, and in all situations individual trees either grow annually, are felled or face a natural death through the struggle for existence, storms or other sources of damage. Changes in forest growing stock can be measured and to some extent attributed to human activities and changes in general growth factors: temperature, moisture, nutrients and light conditions. The estimation of such changes has become an increasingly important objective in forest inventories and in other contexts. Duncan and Kalton (1987), in their comparison of alternative survey designs in relation to various inventory objectives, found that remeasurement of permanent sample units is the best and often the only way to estimate components of change over time and aggregate data for individuals over time.

When forest inventories and monitoring surveys are based on the use of permanent sample plots the definition of the necessary terms should be connected with the performing of periodic measurements. Discussions of the respective terminology and methodology have been presented by many authors, e.g., Chapman and Meyer (1949), Beers (1962), Ware and Cunia (1962), Nyyssönen (1967), Cunia and Chevrou (1969), Newton et al. (1974), Martin (1982), van Deusen (1989), Päivinen and Yli-Kojola (1989), Gregoire (1993) and Eriksson (1995). We will concern ourselves here only with changes in tree and growing stock dimensions and quantities. Changes in stand variables such as site indices or environmental properties are not included.

The sampling unit can be a plot of either fixed or variable size, the most common fixed-sized plots being circular ones and the most common variable-sized plots concentric circular plots or Bitterlich relascope plots (or units of horizontal

A. Kangas and M. Maltamo (eds.), Forest Inventory – Methodology and Applications, 65–84.

point sampling). Concentric circular plots are ones in which trees belonging to the class of "small trees" are included or tallied on the basis of a shorter radius than "large trees". The number of classes can also be greater than this.

Regardless of the type and size of the plot, the plot-based measurements are transformed or expanded for an area of standard size (A_{std}), e.g. 10,000 m^2 or one hectare, using the expansion factor

$$e_i = \frac{A_{std}}{a_i}, \tag{5.1}$$

where a_i is the plot size corresponding to the size of the tree i.

Example 5.1

A_{std} = 10,000 m2 (one hectare)
dbh = 23.6 cm
The basal area factor is 1 (one tree on the plot corresponds to 1 m^2/ha or the maximum plot radius for the tree is 50·dbh).
The maximum radius for tree i to be included in the plot =11.8 m
Then

$$a_i = 3.1416 \cdot (11.8\ m)^2 = 437.43\ m^2,$$

and

The tree expansion factor 22.86 means that one tree tallied on the plot

$$e_i = \frac{10000\ m^2}{437.43\ m^2} = 22.86$$

corresponds to 22.86 trees/ha.

The tree expansion factor e_i is constant for every tree and measuring time in the case of fixed-sized plots, but with variable-sized plots it may vary depending on the size of the tree. If relascope plots are used, for example, the tree expansion factor at the time of the later measurements will be smaller than it was at the beginning, on the assumption that the trees will have grown.

The equation for estimating plot values Y_{jdt} for plot j, domain d and time t is calculated by multiplying the tree values by the per-standard-area expansion

factor for each tree and summing over all the trees belonging to the given domain and plot:

$$Y_{jdt} = \sum_i Y_{jit} \delta_{jid} \tag{5.2}$$

where $Y_{jit} = e_{jit} y_{jit}$ (tree value expanded to standard area, e.g. hectare, y_{jit} is the value for the variable of interest in the case of tree i at time t on plot j) and

$$\delta_{jid} = \begin{cases} 1, \textit{if tree i belongs to domain d} \\ 0, \textit{otherwise} \end{cases}.$$

The tree domains define the sets of trees which are of interest in the data analysis, and can be defined by tree species, threshold diameter, site class, age class or administrative unit, for example.

It is highly recommended that every tree on a permanent sample plot should be identified by mapping, e.g., by polar coordinates (bearing and distance from the plot centre to each tree), in order to facilitate the relocation of particular trees, and the necessary measurements of the desired tree and forest variables should be made with care. For good comparison, similar rules should be followed every time. It would be also good for successive height measurements on a tree to be made from the same compass bearing, as trees rarely grow exactly vertically and the accuracy of the change will be emphasized more markedly than the accuracy of the height measurement itself. The date of each measurement should be recorded to an accuracy of one day.

Assume that a set of living trees (n_1) on a certain plot have been measured at time 1. The same plot will be measured after a certain interval (at time 2) hopefully following the same tree sampling and measuring rules as on the first occasion, resulting in the same or possibly somewhat different set of living trees (n_2). The plot measurements can be repeated as many times as is thought desirable. The time axis, the points from the initial measurement, t_1, until the last measurement, t_k, and the notations employed here are illustrated in Figure 5.1.

The number of trees at the beginning and end of the measuring period may differ because of cutting, mortality, tree ingrowth and changes in plot size. Equally, the number of trees at the beginning of next measuring period may be smaller than the number of the trees at the beginning or at end of the previous one because mortality and cutting will not be included in further calculations, e.g., n_2 is smaller than $n_1 \cup n_2$. The union of trees during a measuring period, e.g., $n_1 \cup n_2$, is classified here according to life and sample status as follows:

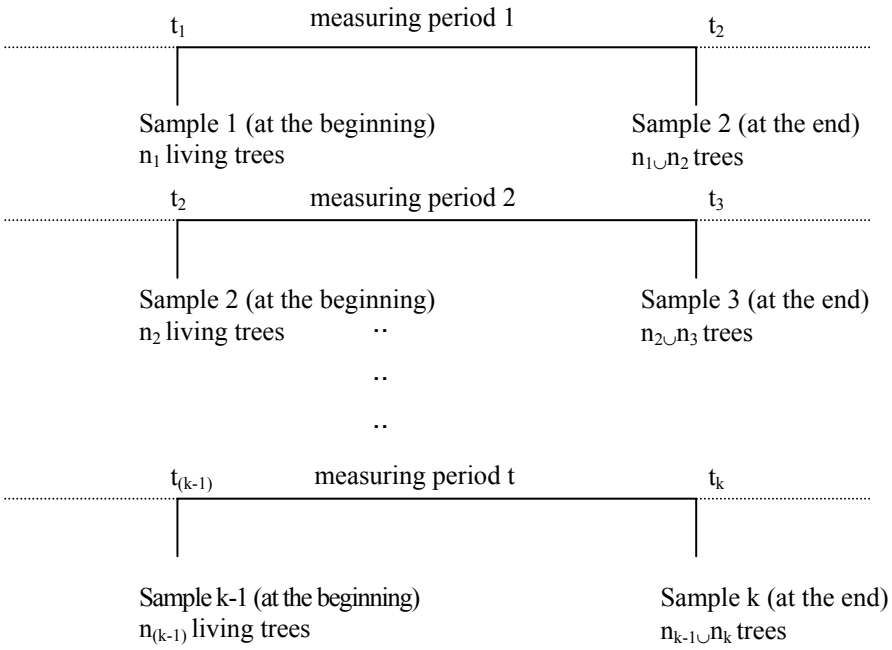


Figure 5.1 Terms related to periodic measurements made on permanent sample plots.

Classification according to life status:

1. Living tree: the tree is alive both at the beginning and at the end of the measuring period
2. Mortality tree: the tree died naturally during the measuring period
3. Cut tree: the tree was cut during the measuring period

Classification according to sample status:

a. Original tree: the tree is in the sample at the beginning of the measuring period.
b. Ingrowth tree: the tree did not fulfil the requirements for the population (usually meaning that it did not meet the minimum diameter requirement) at the beginning of the measuring period but did so by the end , so that it is included in the sample for the end of the period.
c. Ongrowth tree: the tree fulfilled the minimum diameter requirements for the population both at the beginning and at the end of the measuring period, was not big enough to be included in the sample at the beginning, but it was grown to the required size during the measuring period. (This status is relevant only for variable-size plots).

5.2 CHOICE OF SAMPLE PLOT TYPE AND TREE MEASUREMENT

Fixed-sized plots are simple to measure and estimate, and their efficiency relative to variable-sized plots becomes higher when change monitoring is emphasized over state monitoring and the accuracy of local estimates is emphasized relative to population estimates. According to Poso and Waite (1995), circular plots of fixed size are very much more efficient for estimating basal area increment than for estimating basal area. Concentric plots entail the same calculation problems as relascope plots, related mainly to ongrowth trees.

Complete tree data, either measured or estimated, are required both at the beginning and at the end of the measuring period for calculating the volumes possessing certain desired categories. Assuming that calculation of the volume of an individual tree is based on information about its species, height and diameter at breast height, the following data are required:

1. Time of measurement at the beginning of the measuring period, t_1
2. Time of measurement at the end of the measuring period, t_2
3. Tree number or other identification for location, e.g., coordinates
4. Tree species
5. d_1, dbh at the beginning of the measuring period
6. d_2, dbh at the end of the measuring period
7. h_1, height at the beginning of the measuring period
8. h_2, height at the end of the measuring period
9. Life status (1, 2, 3)
10. Sample status (a, b, c)
11. Time of cutting in the case of cutting
12. Time of death in the case of mortality

Complete tree data means that the above 12 data items should be available for calculating the results for the plot. If not all of the values for the variables of interest have been measured, estimates obtained by means of models will be needed. The following tree variables commonly fall into the class of lacking data:

d_2 and h_2 of cut and mortality trees
d_1 and h_1 of ingrowth trees
d_1 and h_1 of ongrowth trees
h_1 and/or h_2 of original trees (sampling decision, not observational inability)
time of cutting in the case of cut trees
time of death in the case of mortality trees

Change estimation is based on the difference between two successively measured quantities, e.g., $V_k - V_{(k-1)}$. Both quantities are subject to measurement errors, which can badly affect the quality of the estimation. If the standard deviation in measuring is denoted as s_y and no systematic measurement errors exist, the standard deviation of the difference is $\sqrt{2}s_y$. Systematic measuring errors are particularly harmful if they act in different directions in successive measurements. On the other hand, their

effects will be minimal if they are equal in size and direction (the errors cancel each other when calculating the difference). There are good reasons to emphasize the need for more accurate measurements on permanent than on temporary sample plots.

The most important variable in measurements performed on a sample plot is usually diameter at breast height. In order to minimize the standard deviation and the effect of systematic errors, measurement of circumference is preferable over direct measurement of the diameter with callipers.

All feasible variables should be included in the measurements and stored as data, within the limits of economic possibility. Eriksson (1995) suggests that trees which do not yet belong to the sample but will probably do so by the next occasion, i.e., ingrowth and ongrowth trees, could be included in the measurements in order to improve the accuracy of later estimates.

5.3 ESTIMATING COMPONENTS OF GROWTH AT THE PLOT LEVEL

Equation (5.2) is applicable when calculating volumes and volume increments for plot j, but it does not define the set of trees which should be included in the calculation. There are two main alternatives: to use the trees measured at the beginning of the measuring period (Sample 1, n_1 trees) or to use the trees measured at the end of the measuring period (Sample 2, $n_1 \cup n_2$ trees). The third alternative would be to use both sets of trees and to pool the outcome for the final estimate. Accordingly, Equation (5.2) may be concretized for alternative samples as follows:

$$Y_{jdt} = \sum_{i=1}^{n_1} Y_{jit}\delta_{jid} \quad \text{(based on Sample 1)} \tag{5.3}$$

or

$$Y_{jdt} = \sum_{i=1}^{n_1 \cup n_2} Y_{jit}\delta_{jid} \quad \text{(based on sample 2).} \tag{5.4}$$

The set of trees represented by the union $n_1 \cup n_2$ is by definition always equal to or larger than n_1 because the former still contains cut and mortality trees , and also ingrowth trees and, in the case of variable-sized plots, ongrowth trees as well. The union $n_1 \cup n_2$ can be written as the number of trees at the beginning of the measuring period + the number of ongrowth and ingrowth trees.

Volume and volume increment are usually assigned great importance in forest inventories and change monitoring. The next examples are built up on these variables. The volumes of different tree domains at the beginning and end of the measuring period and their changes during the period are elementary to the analyses, while the estimation of other variables, e.g. basal area and basal area increment, monetary value and value increment, or mean height and mean height increment could follow roughly the same scheme.

Assume that Y_{jdi} in Equations 5.2, 5.3 and 5.4 refers to volume and Y_{jdt} =

V_{jdt} . Then the components of the volumes at the beginning (V_{jd1}) and end (V_{jd2}) of the measuring period can be calculated. Calculation of the periodic volume increment for living original and ongrowth trees can be based on Sample 2, for example, in accordance with Equation (5.5).

$$\{(V_{jd2} - V_{jd1}) = \sum_{i=1}^{n_1 \cup n_2} (V_{ji2} - V_{ji1})\delta_{jid} \mid \mathrm{d} = \text{living original or ongrowth tree}\} \qquad (5.5)$$

The expected output of Equation 5.5 is equal to that based on Sample 1:

$$\{\sum_{i=1}^{n_1} (V_{ji2} - V_{ji1})\delta_{jid} \mid d = \text{living original tree}\}$$

Recommendations for dealing with the various components needed for calculating the gross periodic volume increment on sample plot j, in domain d, and during a given measuring period are compiled in Table 5.1.

Table 5.1 Recommendations for estimating the periodic increment in volume (m^3/ha between t_1 and t_2) for a permanent sample plot.

Component of periodic gross volume increment	Trees and expansion factors in Sample 1	Trees and expansion factors in Sample 2	Basis for final estimate
- living, original trees	(V_2-V_1)*	V_2-V_1	Sample 2
- living, ingrowth trees	not reasonable	V_2	Sample 2
- living, ongrowth trees	not reasonable	V_2-V_1	Sample 2
- mortality, original trees	(V_2-V_1)*	(V_2-V_1)**	Sample 1
- mortality, ingrowth trees	not reasonable	V_2	Sample 2
- mortality, ongrowth trees	not reasonable	V_2-V_1	(-)***
- cut, original trees	(V_2-V_1)*	not reasonable	Sample 1
- cut, ingrowth trees	not reasonable	V_2	Sample 2 or models
- cut, ongrowth trees	not reasonable	V_2-V_1	(-)***
Gross periodic volume increment ****			Sum of the above values

* The expected increment is equal to the sum of the increments based on Sample 2 for the union of original and ongrowth trees of respective life status.
** Estimation may not be reasonable if the mortality trees have undergone transformation through bark shrinkage or breaking at the top, for example.
*** This component is already included in Sample 1 and is relevant only in the case of Sample 2.
**** The recommendations for estimating volume increments for various tree

classes (components) are also valid for subsets of n_1 or $n_1 \cup n_2$ among the trees, e.g., for tree species. The term "gross periodic volume increment" may not be applicable in this case.

Estimation of volume and volume increment by components is useful for forest management purposes. The gross volume increment covers all trees in all tree classes and indicates the quality of the site class. The net volume increment equals the gross volume increment minus the volume of mortality trees, and the ratio of net volume increment to gross volume increment indicates the efficiency of forestry. The net change of volume is the difference in the volumes of living trees at times 2 and 1.

As seen in Table 5.1, volumes (V_1) and (V_2) and volume increments for the union of living original and ongrowth trees can be calculated on the basis of both Sample 1 and Sample 2. Large differences suggest that there must have been a large number of "border trees" in the sample plot which were dropped out on one occasion and included on another. In this case pooling of the outputs from Samples 2 and 1 might be feasible for monitoring the trend in volume at the plot level.

The above estimator of gross periodic volume increment (the "sum of above values" in Table 5.1), where the whole volume of ingrowth trees is regarded as increment, may not always be what is wanted. The volume increment of ingrowth trees can also be estimated as the difference $V_2–V_1$ (common when temporary plots are used) or $V_2–V_{t'}$, where t' refers to the time within the measuring period when the tree reached the threshold size (Eriksson 1995).

The calendar length of measuring period should be transformed into the number of growth seasons, as the use of this as the divisor when calculating average annual increments will improve the quality of the estimate. The same is true when applying growth models. Waite et al. (1996) started and ended the growth season on May 20 and August 15 respectively for coniferous trees and June 1 and July 31 for deciduous trees under the conditions prevailing in Central Finland and used curvilinear regression when estimating the progress of the growth season.

Cut trees are usually cut before the end of the measuring period and mortality trees have died within this time. For these tree classes the length of the measuring period is regarded as the number of growth seasons for which the trees really grew after they were measured at the beginning of the measuring period. If the exact date of cutting or mortality is not known it can be assumed to be the middle of the measuring period. This is common practice in Forest Inventory and Analysis in the U.S.A. (Scott 2004).

There are problems in measuring ingrowth and ongrowth volumes and increments for cut trees, and problems may also arise for mortality trees, as the whole trunk, or at least the top of the tree or the bark may have fallen down. These problems suggest that estimation of the ingrowth and ongrowth of mortality and cut trees should be based on models.

5.4 MONITORING VOLUME AND VOLUME INCREMENT OVER TWO OR MORE MEASURING PERIODS AT THE PLOT LEVEL

The building of time series to describe the development of individual stand variables for each permanent sample plot is fairly simple when plots of fixed size are used, but the procedure is more complex in the case of variable-sized plots and results in many alternative outputs, as illustrated for volume and volume increment, in m^3/ha, in Figure 5.2.

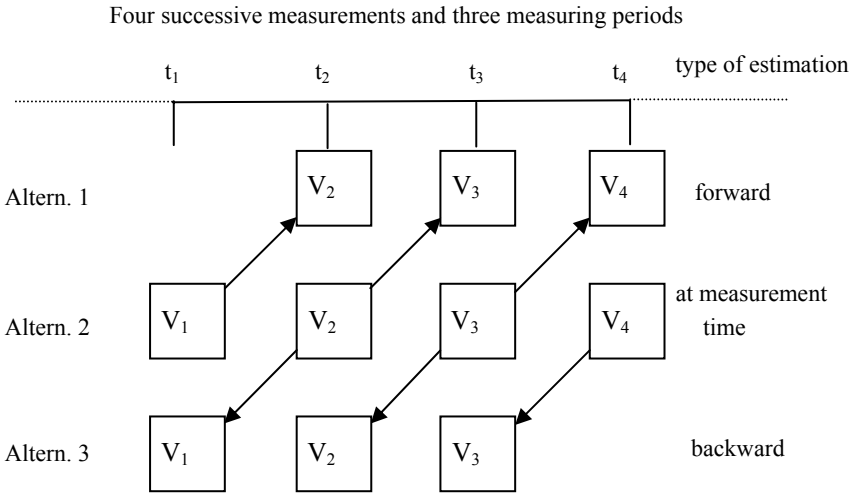


Figure 5.2 Illustration of alternative means of estimating volume and volume increment.

Alternative 2 in Figure 5.2 corresponds to traditional volume estimation, where the time of measurement and estimation coincide, while Alternative 1 corresponds to forward calculations made on the basis of Sample *i-1* (cf. Column 2 in Table 5.1) and Alternative 3 to backward calculations made on the basis of Sample *i+1* (cf. Column 3 in Table 5.1). The procedure results in two or three volume estimates for each occasion or time of measurement. The lines with arrows refer to samples with the same set of trees, which makes them comparable for the purposes of increment estimation.

The expected estimates for the two or three alternative volume estimates for each time of measurement are equal if it is assumed that the volumes do not include ingrowth trees. Correspondingly, the two alternative volume increment estimates can be expected to be equal without the effect of ingrowth trees. The relevant questions are which of the alternatives would be the best (most accurate) and whether it would be reasonable to employ a pooling technique so that all the alternatives would affect the final estimates. No papers dealing with pooling in this connection are available and nor is it possible to make any recommendation here.

The common equation for monitoring volume and checking the compatibility and additivity of the estimates over one or more measuring periods is

$$V_2\text{-}V_1 = S_2\text{-}S_1\text{+}I\text{-}M\text{-}C, \quad (5.6)$$

where V is the volume of living trees at time 2 or 1, S is the volume of the survivor trees, i.e. living original trees at the end or beginning of the measuring period, I is the volume of ingrowth trees at the end of the measuring period, M is the volume of mortality trees at the time of death, and C is the volume of cut trees at the time of cutting.

Equation 5.6 can be used to check the compatibility of component estimates. Handling ingrowth and ongrowth trees correctly is the key to compatible estimators (Roesch et al. 1991). Another approach would be to estimate any component that is lacking. The volume of cut trees, for example, can be estimated as $C = S_2\text{-}S_1\text{+}I - M + V_1 - V_2$.

Example 5.2

Some simple examples can be taken to demonstrate the calculation of the volume and volume increment, m^3/ha, of a tree on a simple circular plot or a more complex relascope plot.

a) Assume a simple circular sample plot of radius 10 m and one tree on it with dbh 25.5 cm and volume 0.554 m^3 at the beginning of the measuring period. This leads to a tree expansion factor of 10000 $m^2/(\pi(10\ m)^2)$ = 31.831 trees/ha represented, or 31.831·0.554 = 17.634 m^3/ha. Assume further that the dbh and volume of the tree have increased to 26.5 cm and 0.609 m^3 respectively during the measuring period. The tree expansion factor remains constant. The volume at the end of period will then be 31.831·0.609 = 19.385 m^3/ha and the volume increment 19.385-17.634 =1.750 m^3/ha. The plot volumes and volume increments are estimated by summing the hectare-based values calculated for individual trees on the plot.
b) Assume the above tree had been measured on a relascope plot with a basal area factor (BAF) of 1, i.e. each tree corresponds to 1 m^2/ha of basal area. The tree expansion factors at the beginning and end of the measuring period will then be:

   - at the beginning: 10000 $cm^2/(\pi$ /4 $(25.5\ cm)^2$) = 19.581, and
   - at the end: 10000 $cm^2/(\pi$ /4 $(26.5\ cm)^2$) = 18.131.

   The volume of the tree at the beginning and end of the period will be accordingly:

   - at the beginning: 19.581·0.554 = 10.854 m^3/ha, and
   - at the end: 18.131·0.609 = 11.042 m^3/ha.

   The volume increment for the relascope tree can be calculated either forwards, backwards or, if possible, both ways (cf. Fig. 5.2). Calculation both ways is possible and reasonable if the tree has been measured both at the beginning and

at the end of the measuring period.

forwards: $19.581/\text{ha}\,(0.609\,\text{m}^3 - 0.554\,\text{m}^3) = 1.071\,\text{m}^3/\text{ha}$
backwards: $18.131/\text{ha}\,(0.609\,\text{m}^3 - 0.554\,\text{m}^3) = 0.997\,\text{m}^3/\text{ha}$

The forward and backward estimates differ because the plot sizes differ, the earlier one corresponding to dbh 25.5 cm and the latter to 26.5 cm.

For a very simple illustration, assume that 10 trees similar to the tree considered above were included in a forward calculation and 12 trees in a backward calculation (two of the trees were ongrowth trees). The increment estimates at the plot level would be

forwards: $10 \cdot 1.071$ m3/ha = 10.710 m3/ha,
and
backwards $12 \cdot 0.997$ m3/ha = 11.960 m3/ha

Both estimates can be regarded as unbiased because no ingrowth trees were included. This means that the final increment estimate on the plot level can be based on pooling. If ingrowth trees exist, they add volume and volume increment only in backwards estimation. If pooling is not applied the choice of backwards estimation (use of Sample 2) is recommended whenever possible, because Sample 2 usually corresponds to a larger plot area than Sample 1 and is more informative (cf. Nyyssönen and Kilkki 1965). For cut trees, and probably also for mortality trees, the use of Sample 2 is not reasonable, so that Sample 1 and forwards calculation is the only choice for volume and volume increment calculations involving these tree classes.

Mortality trees can be handled as living trees provided that they can also be measured at the end of the measuring period.

Example 5.3

A situation in which trees have been sampled by relascope with basal area factor (BAF) of 1 (each tree corresponds to 1 m^2/ha in basal area) is illustrated in Table 5.2. The existence of one tree in each of nine sample/life-status classes would hardly be likely in reality but is reasonable for illustration purposes.

Table 5.2 Example of data needed for volume and volume increment calculations. The heights and breast height diameters which cannot be measured but must be estimated on the basis of other trees or general models are in parentheses.

Tree no.	Sample status	Life status	d, mm	h, dm	Time of measurement yyyymmdd
1	original	living	255	243	19980923
			265	249	20030826
2	ingrowth	living	(47)	(45)	19980923
			51	48	20030826
3	ongrowth	living	(175)	(172)	19980923
			182	178	20030215
4	original	mortality	204	181	19980923
			212	187	20030215*
5	ingrowth	mortality	(48)	(35)	19980923
			52	37	20030215*
6	ongrowth	mortality	(103)	(92)	19980923
			110	99	20030215*
7	original	cut	267	245	19980923
			(277)	(251)	20030215*
8	ingrowth	cut	(49)	(42)	19980923
			(52)	(45)	20030215*
9	ongrowth	cut	(50)	(40)	19980923
			(53)	(42)	20030215*

* estimated or registered time of mortality or cut.

Assume that the data on the nine trees are from a variable-sized or relascope plot on which one tree corresponds to one m^2/ha and that a dbh of at least 50 mm is required for a tree to be included in the population. As the dbh and height have been measured or estimated for each tree, the volume model $y = f(species, dbh, h)$ can be used to estimate the volume of each tree. We then arrive at the following tables:

Table 5.3 A Volumes at the beginning of the measuring period, based on Sample 1 ($V_1(2)$, volume at measuring time, see Fig 5.2) and Sample 2 ($V_1(3)$, volume calculated backwards, see Fig 5.2).

Tree no.	Sample status/ life status	Volume at the beginning of the measuring period			
		volume of tree, dm^3	Tree expansion factor	$V_1(2)$ m^3/ha	$V_1(3)$* m^3/ha
1	Original living	554.3	19.581	10.854	10.050
2	Ingrowth living	5.6	576.387	(3.228)	2.741
3	Ongrowth living	204.6	41.575	(8.506)	7.865
4	Original mortality	287.3	30.595	8.790	8.139
5	Ingrowth mortality	3.3	552.621	(1.824)	1.554
6	Ongrowth mortality	42.2	120.015	(5.065)	4.441
7	Original cut	611.4	17.860	10.920	(10.146)
8	Ingrowth cut	5.8	530.296	(3.076)	(2.731)
9	Ongrowth cut	5.7	509.296	(2.903)	(2.584)

*The tree expansion factor is as given in Table 5.3 B, e.g., 10.050 = 18.131·0.5543

(Figures in parentheses are based on estimated rather than measured dbh and height values)

Table 5.3 B Volumes at the end of the measuring period, based on Sample 1 ($V_2(1)$) and Sample 2 ($V_2(2)$).

Tree no.	Sample status/ life status	Volume at the end of the measuring period			
		v, dm^3	expansion factor	$V_2(1)$ m^3/ha	$V_2(2)$ m^3/ha
1	Original living	609	18.131	11.925	11.042
2	Ingrowth living	6.8	489.52	(3.919)	3.329
3	Ongrowth living	227.3	38.439	(9.450)	8.737
4	Original mortality	318.1	28.330	9.732	9.012
5	Ingrowth mortality	3.9	470.87	(2.155)	1.836
6	Ongrowth mortality	51	105.23	(6.121)	5.367
7	Original cut	667.6	16.594	11.924	(11.078)
8	Ingrowth cut	6.8	470.87	(3.606)	(3.202)
9	Ongrowth cut	6.8	453.27	(3.463)	(3.082)

(Figures in parentheses are based on estimated rather than measured dbh and height values)

Table 5.3 C Volume increment during the measuring period (five growing seasons). For forward and backward calculations, see Fig. 5.2.

Tree no.	Sample status/ life status	Volume increment (see Tables 5.3 A and 5.3 B)	
		Forward calculation $V_2(1) - V_1(2)$	Backward calculation $V_2(2) - V_1(3)$
1	Original living	1.071	0.992
2	Ingrowth living	(0.692)	0.587
3	Ongrowth living	(0.944)	0.873
4	Original mortality	0.942	0.873
5	Ingrowth mortality	(0.332)	0.283
6	Ongrowth mortality	(1.056)	0.926
7	Original cut	1.004	(0.933)
8	Ingrowth cut	(0.530)	(0.471)
9	Ongrowth cut	(0.560)	(0.499)

(Figures in parentheses are based on estimated rather than measured dbh and height values)

The calculations based on Sample 2 (backward calculation) give lower values for both volume and volume increment than do those based on Sample 1 (forward calculation). This is because the tree expansion factors of Sample 2 are expected to be smaller due to tree growth. In the case of tree number 1, the ratio of the tree expansion factors is 19.581/18.131 = 1.080. This corresponds to the ratio of plot sizes; the Sample 2 plot is 1.080 times the size of the Sample 1 plot. The expected number of ongrowth trees corresponding to tree 1 is 0.080. This leads us to conclude that the expected volume based on Sample 1 with original trees will be equal to the expected volume based on Sample 2 with original and ongrowth trees.

Table 5.4 Example of output based on Tables 5.3 A, 5.3 B, and 5.3 C.

	V_1	V_2	V_2-V_1	Remarks
Original living tree	10.050	11.042	0.992	Based on Sample 2*
Ingrowth living tree	0	3.329	3.329	Based on Sample 2
Ongrowth living tree	7.865	8.737	0.872	Based on Sample 2
Original mortality tree	8.139	9.012	0.873	Based on Sample 2*
Ingrowth mortality tree	0	1.836	1.836	Based on Sample 2
Ongrowth mortality tree	4.441	5.367	0.926	Based on Sample 2
Original cut tree	10.920	11.924	1.004	Based on Sample 1
Ingrowth cut tree	0	3.202	3.202	Based on Sample 2
Ongrowth cut tree	2.584**	3.082**	0.498**	Based on Sample 2

* Volumes and volume increments for original living and mortality trees can also be

calculated on the basis of Sample 1, whereupon the expected result would be equal to the sum of original and ongrowth trees based on Sample 2.
** This component is meaningless if calculations are based on Sample 1.

Examples of calculations based on the above tables:

Volume of living trees at the beginning of the measuring period:
V_1(living) = 10.050 + 7.865 + 8.139 + 4.441 + 10.920 = 41.415 m^3/ha.

Volume of living trees at the end of the measuring period:
V_2(living) = 11.042 + 3.329 + 8.737= 23.108 m^3/ha.

Volume of mortality trees:
V_2(mortality) = 9.012 + 1.836 +5.367= 16.215 m^3/ha.

Volume of cut trees:

V_2(cut) = 11.924 + 3.202 = 15.126 m^3/ha.

Gross periodic volume increment:
I(gross) = 0.992 + 3.329 + 0.872 + 0.873+1.836+0.926 + 1.004 + 3.202
= 13.034 m^3/ha.

Net periodic volume increment:
I(net) = 0.992 + 3.329 + 0.872 + 1.004 + 3.202 = 9.399 m^3/ha.

Net change of volume:
E(V_2(living) – V_1(living)) = E (I(gross) – V(Mortality) – V(Cut))
V_2(living) – V_1(living) = 23.108 – 41.415 = –18.307 m^3/ha
I(gross) – V(Mortality) – V(Cut) = 13.034. – 16.215 – 15.126 = –18.307 m^3/ha.

5.5 ESTIMATING POPULATION PARAMETERS

The focus in forest inventories has shifted from assessing current values and net change to understanding the dynamics of the components of net change. This means that sampling with permanent plots will gain more ground. The two alternative sampling designs developed especially for using permanent sample plots are "Continuous Forest Inventory" (CFI) or "Complete Remeasurement Sampling" as introduced by Stott (1947) and Sampling with Partial Replacement (SPR). These designs can be combined with other methods such as stratification and double sampling for stratification (Scott and Köhl 1994).

In CFI, all plots established at the beginning of the first measuring period (occasion 1) are remeasured on all subsequent occasions. Forest surveys are typically conducted on a 5-20-year cycle, with faster growing areas on a shorter

cycle (Scott 1998). Two common methods of selecting samples are random drawing (simple random sampling), and use of a grid (systematic sampling). A systematic sample is well distributed across the population and is preferable to simple random sampling. Simple random sampling estimators can be employed, however, although the variance estimator tends to lead to slight overestimation (Reber and Ek 1983).

Complete remeasurement sampling (CFI, Continuous Forest Inventory) is not efficient for estimating current variables and infrequent phenomena, e.g. fungal infections, on the basis of cumulative samples. Complete remeasurement sampling reflects changes in plot values only, and changes in population during the measuring period brought about by additions to or subtractions from the forest area would require changes in the sample. Some old plots would have to be abandoned and some new plots established in order to keep the sample representative.

Measurement of a permanent sample plot is more expensive than measurement of a temporary plot, due to the cost of documenting both plot and tree locations and relocating the plots and trees following disturbances. This can easily lead to the idea of a design in which both types of plot are used in combination. When introducing their design known as Sampling with Partial Replacement (SPR) for forest inventory purposes, Ware and Cunia (1962) presented efficient unbiased, estimators for the current values of variable and for net change in those variables. Bickford et al. (1963) then improved the variance estimators for the components and the sample-based variance estimates for the whole calculation and also extended the two-occasion case to double sampling for stratification. Further studies to develop SPR were carried out by Cunia and Chevrou (1969, extension to three or more occasions), Newton et al. (1974, an efficient estimator for net change), Scott (1981, net change estimators), Schreuder et al. (1987, bootstrapping and jackknifing methods for estimating sample-based variances) and van Deusen (1989, a generalized least squares application).

SPR in its typical form is based on both permanent and temporary sample plots. The following example involving an estimator for the population total with two measurement occasions follows the notation introduced by Schreuder et al. (1993). The population total is estimated on the first occasion based on all the sample plots measured at that time, and on the second occasion by combining two independent estimates: the total estimated from the new units measured only on the second occasion and a regression estimate in which the coefficients are obtained from those plots measured on both occasions and the estimated total for the variable of interest is based on all first-occasion units.

Let n plots be drawn from N plots in the population on each of two occasions. Let m plots be common between the two samples and u be the number not shared. Thus $u = n - m$.

Let $\hat{Y}_{im}$, $\hat{Y}_{iu}$ and $\hat{Y}_{in}$ be the estimates of Y_i, the population total on the i^{th} occasion (i=1,2) based on the common plots (m), the plots not held in common (u) and all the sample plots of a particular occasion (n), respectively. In addition, let $\hat{\beta}$ be the regression coefficient estimator based on the m common plots, let σ_1^2 and σ_2^2, respectively, be the variances of y at times 1 and 2, let σ_{12} be the covariance of

y at times 1 and 2, and let ρ be the correlation between observations at times 1 and 2. An unbiased estimator of Y_2 based on the u new plots at time 2 would then be

$$\hat{Y}_{2u} = N\sum_{i=1}^{u} y_{2i}/u \ , \tag{5.7}$$

with the variance

$$V(\hat{Y}_{2u}) = N^2\sigma_2^{\ 2}/u$$

and the variance estimator $v(\hat{Y}_{2u}) = s_2^{\ 2}(1)/u$, where $s_2^{\ 2}(1)$ is the within-sample variance of the u plots on which the y_{2i} were measured. A regression-based estimator of Y_2 using the m common plots at times 1 and 2 is

$$\hat{Y}_{2mr} = \hat{Y}_{2m} + \hat{\beta}(\hat{Y}_{1n} - \hat{Y}_{1m}) \tag{5.8}$$

with variance

$$V(\hat{Y}_{2mr}) = N^2\frac{\sigma_2^{\ 2}}{m}(1-\frac{u}{n}\rho^2)\,. \tag{5.9}$$

The combined estimator of Y_2 is the weighted mean, the weights usually being the reciprocals of the sample variances, that is

$$\hat{Y}_2 = (\hat{w}_1\hat{Y}_{2u} + \hat{w}_2\hat{Y}_{2mr})/(\hat{w}_1 + \hat{w}_2)\ , \tag{5.10}$$

where $\hat{w}_1 = 1/v(\hat{Y}_{2u}), \hat{w}_2 = 1/v(\hat{Y}_{2mr})$. More complete equations including SPR with more than two measurement occasions can be found in the literature cited.

The proportion of permanent plots depends on the objectives of the inventory and the correlation between successive measurements. According to Schreuder et al. (1993), the optimum ratio is

$$\left(\frac{m}{n}\right)_{opt} = \frac{\sqrt{1-\rho^2}}{1+\sqrt{1-\rho^2}} \quad . \tag{5.11}$$

5.6 CONCLUDING REMARKS

Permanent fixed-area and concentric circular plots are preferable to relascope plots when change monitoring is emphasized. Ingrowth is a highly variable process that causes variation, especially in volume increment, regardless of the type of sample plot used. Concentric circular plots are variable-sized plots, as are relascope plots, and both of them deal with ongrowth trees. The size and type of plot may vary for different inventory and monitoring purposes, e.g. a larger plot size would be feasible for rarely occurring phenomena than for tree volume estimation.

The essential and costly aspect of the use of permanent sample plots is the acquisition and maintenance of tree data which fulfil the requirements of accuracy and completeness. Not all the data needed can be measured, and some, e.g. data on cut trees, must be based on estimation by means of models.

The values for quantitative variables of interests on a given plot, e.g. tree volume and basal area, can be calculated on the basis of either Sample 1 (n_1 trees), or Sample 2 ($n_1 \cup n_2$ trees), or both, or else estimated by means of models. It is not always clear which is best. When the plot data are to be compared and aggregated over time it may be feasible to use pooling in order to reduce the "random" effect of ingrowth and ongrowth trees. The volume of original living trees based on Sample 1, for example, is expected to coincide with the sum of the volumes of original and ongrowth trees based on Sample 2 (Figure 5.1). If there are major differences, they probably originate from trees which are close to the threshold value, either inside or outside the sample plot. The monitoring and profiling of plot variables over time may be useful for planning silvicultural treatments. The gross volume increment, for example, gives an idea of the productivity of the site, and the net volume increment in relation to the gross volume increment an idea of the degree of utilization. The increment rates of different tree species and diameter classes can be compared in order to optimize thinning practices.

One problem related to the use of permanent sample plots, especially ones of variable size, is the compatibility or additivity, e.g. the time-additivity of the change components. This did not become relevant in the examples quoted in this chapter. The definitions were in accordance with those given by Eriksson (1995) and proved to be free of this problem. Other references to this issue are made by van Deusen et al. (1986) and Roesch et al. (1991), for example.

The main emphasis in the above was on the determination and monitoring of volume and volume increment. The analysis and change monitoring of other stand variables, such as mean diameter, mean height or biodiversity indicators, would require additional examination.

Continuous Forest Inventory, with or without stratification, is efficient for estimating net change and components of change for a population, while Sampling with Partial Replacement is more efficient for estimating current values. The disadvantages of this design, however, are that the estimators easily become complex and the calculations are sensitive to errors. Regressions must be fitted for every variable and the regression estimators do not always behave well and must be monitored carefully, especially since disturbed (harvested) plots can significantly

alter the results (Scott 1998). Finally, tables produced using SPR have the property that cells do not sum up at the margins (Scott and Köhl 1994).

Permanent sample plots are the only means of estimating all the components of change. They also provide data for fitting to models for growth projection purposes. Permanent sample plots together with information about human activities and natural conditions give us a powerful means for understanding and developing forestry, and the results of numerical analyses are generally much more convincing and useful than more or less professional opinions.

REFERENCES

Beers, T. W. 1962. Components of Forest Growth. Journal of Forestry 60:245-248.

Bickford, C.A. 1959. A test of continuous inventory for national forest management based upon aerial photographs, double sampling and remeasured plots. Proceedings of Society of American Foresters. San Francisco, California, pp. 143-148.

Chapman, H.H. and Meyer W.H. 1949. Forest Mensuration. McGraw-Hill Book Company. New York. 522 p.

Cunia, T. and Chevrou, R.B. 1969. Sampling with partial replacement on three or more occasions. Forest Science 15:204-224.

Duncan, G.J. and Kalton, G. 1987. Issues of design and analysis of surveys across time. International Statistical Review 55:97-117.

Eriksson, M. 1995. Compatible and Time-Additive Change Component Estimators for Horizontal-Point-Sampled Data. Forest Science, Vol. 41:796-822.

Gregoire, T.G. Estimation of forest growth from successive surveys. Forest Ecology and Management 56:267-278.

Martin, G.L. 1982. A Method for Estimating Ingrowth on Permanent Horizontal Sample Points. Forest Science 28:110-114.

Newton, C.M., Cunia, T. and Bickford, C.A. 1974. Multivariate estimators for sampling with partial replacement on two occasions. Forest Science 20:106-116.

Nyyssönen, A. 1967. Remeasured sample plots in forest inventory. Meddelelser fra det Norske Skogförsöksvesen. 84 (XXII):191-220.

Nyyssönen, A. and Kilkki, P. 1965. Sampling a stand in forest survey. Acta. Forestalia Fennica 97.

Päivinen, R. and Yli-Kojola, H. 1989. Permanent sample plots in large-area forest inventory. Silva Fennica 23:243-252.

Poso, S. and Waite, M-L. 1995. Calculation and Comparison of Different Permanent Sample Plot Types. Silva Fennica 28:159-169.

Reber, C.A. and Ek, A.R. 1983. Variance estimation from systematic samples in Minnesota timber stands. Canadian Journal of Forest Research 13:1255-1257.

Roesch, F.A., Green, E.J. and Scott, C.T. 1991. Compatible Basal Area and Number of Trees Estimators

from Remeasured Horizontal Point Samples. Forest Science 37:136-145.

Schreuder, H.T., Li, H.G. and Scott, C.T. 1987. Jackknife and bootstrap estimation for sampling with partial replacement. Forest Science 33:676-689.

Schreuder, H.T., Gregoire, T. G. and Wood, G. B. 1993. Sampling Methods for Multisource Forest Inventory. John Wiley Sons, New York. 446 p.

Scott, C.T. 1981. Simplified estimators for sampling with partial replacement on multiple occasions. Univ. Minn. Coll. For., Dep. For. Resour. Staff Pap. Ser. 23. 48 p.

Scott, C.T. 1998. Sampling methods for estimating change in forest resources. Ecological Applications 8:228-233.

Scott, C.T. 2004. Written communication.

Scott, C.T. and Köhl, M. 1994. Sampling with Partial Replacement and Stratification. Forest Science 40:30-46.

Stott, C.B. 1947. Permanent growth and mortality plots in half the time. Journal of Forestry 45:669-673.

Van Deusen, P.C., Dell, T.R. and Thomas, C.E. 1986. Volume growth estimation from permanent horizontal points. Forest Science 33:583-590.

Van Deusen, P.C. 1989. Multiple-occasion partial replacement sampling for growth components. Forest Science 35:388-400.

Waite,M-L., Riihijärvi, I. and Poso. S. 1996. The PSP System. Software for Calculating and Analyzing Permanent Tree and Sample Plot Data. University of Helsinki, Department of Forest Resource Management Publications 12. 82 p.

Ware, K.D. and Cunia, T. 1962. Continuous forest inventory with partial replacement of samples. Forest Science Monogr 3. 40 p.

CHAPTER 6

GENERALIZING SAMPLE TREE INFORMATION

JUHA LAPPI, LAURI MEHTÄTALO AND KARI T. KORHONEN
Finnish Forest Research Institute

Some characteristics, e.g. tree height, may be rather expensive to measure, so that we may not want to measure them for all trees in an inventory but just for a subset, called here *sample trees*. We will then want to generalize the sample tree information to cover the *tally trees,* for which basic measurements, usually diameter at breast height and tree species, are available. In addition, we are often interested in many characteristics of trees which are too expensive to measure even on sample trees, e.g. stem volume or tree biomass. If these variables can be predicted using sample tree variables, we may then want to generalize the sample tree information to obtain predictions for the tally trees as well.

The first section of this chapter describes briefly different approaches to modelling sample tree variables using tally tree variables (called tally tree regression), while the second shows how auxiliary data can be utilized if the inventory data is too limited for performing tally tree regressions. The difference between real sample tree variables (e.g. tree height) and predicted sample tree variables (e.g. tree volume and biomass) will be ignored in the first two subsections, but in the third subsection we will take a closer look at the consequences of the three-level model structure created by observed tally tree variables, observed sample tree variables and predicted sample tree variables.

6.1 ESTIMATION OF TALLY TREE REGRESSION

Let y denote the sample tree variables (e,g, height, predicted volume or predicted biomass) and let $\mathbf{x}$ denote tally tree measurements (e.g. dbh). The tally tree regression model is

A. Kangas and M. Maltamo (eds.), Forest Inventory – Methodology and Applications, 85–106.

$$y_i = E\left(y|\mathbf{x}_i\right) + e_i = f\left(\mathbf{x}_i|\boldsymbol{\beta}\right) + e_i ,$$

where y_i, $\mathbf{x}_i$ and e_i are the sample tree variable, the vector of tally tree variables and the residual, respectively, for sample tree i and $\boldsymbol{\beta}$ is a vector of parameters. The assumptions regarding the form of $f\left(\mathbf{x}_i|\boldsymbol{\beta}\right)$ and the properties of e_i depend on the modelling situation, see Weisberg (1985) and Davidian and Giltinan (1995) for a general formulation of a regression model.

In forestry applications, a transformation of y is often modelled instead of y itself, in order to solve the problem of heteroscedastic residuals. In many cases, it also makes the model linear with respect to some transformations of $\mathbf{x}$. Techniques for fitting non-linear models and estimating variance functions have developed rapidly in recent years, and these are now commonly available in modern statistical software packages (e.g. Pinheiro and Bates 2000). Modelling of the dependence of predicted sample tree volume on tree diameter using non-linear regression and a variance function is demonstrated in Example 6.1.

Forest inventory data are usually collected from several plots with several sample trees per plot. Hierarchical datasets of this kind can naturally be modelled through a mixed modelling approach. A mixed model for variable y in the case of tree i on plot k is defined as

$$y_{ki} = E\left(y|\mathbf{x}_{ki,}\mathbf{b}_k\right) + e_{ki} = f\left(\mathbf{x}_{ki}|\boldsymbol{\beta},\mathbf{b}_k\right) + e_{ki} ,$$

where y_{ki}, $\mathbf{x}_{ki}$ and e_{ki} are the sample tree variable, the tally tree variable vector and the residual, respectively, for sample tree i on plot k; $\boldsymbol{\beta}$ is the vector of fixed parameters and $\mathbf{b}_k$ the vector of random parameters on plot k. Thus the random parameters vary from plot to plot. The expectations for these parameters are usually assumed to be 0 and their variances are estimated at the model fitting stage. The realized values of the random parameters can be predicted for each plot in the dataset. When using the model for prediction purposes, one can use either expectations or predictions for the random parameters, the former approach giving population-level predictions and the latter plot-level predictions. In addition to the plots, stands, clusters or measurement occasions may create additional levels of grouping in the data. For a formal presentation of the approach, readers are referred to Lappi (1993), Davidian and Giltinan (1995), Pinheiro and Bates (2000) and McCulloch and Searle (2001). Forestry applications of linear mixed models have been reported by Lappi (1991), Gregoire et al. (1995) and Mehtätalo (2004), for example, and non-linear models by Gregoire and Schabenberger (1996) and Fang et al. (2001). Both a non-linear and a linear mixed-effects modelling approach to the dataset of Example 6.1 are illustrated in Example 6.2.

An important point to note, as discussed by Diggle et al. (2002), for instance, is that in an inventory we are estimating a cross-sectional regression function (population average) for y. The resulting function is not generally a logical

one for describing how y in a single tree is related to the development of $\mathbf{x}$ over time (subject-specific curve). For instance, in cross-sectional data $H(D)$ often decreases with respect to D when D is large, even though the height of each single tree grows as D grows. This results from the fact that in inventory data trees with a large D are usually open-growing ones that have been allocating resources to diameter growth rather than height growth. Thus the growth allometry of individual trees does not provide theoretical reasons for any specific functional form for $E(y|\mathbf{x})$.

There are also approaches that do not require definition of the functional form of $E(y|\mathbf{x})$. One approach is to compute class means for y in various classes of $\mathbf{x}$. The y values for tally trees can then be obtained either by using class means directly or by interpolating them. The bias in the estimated $E(y|\mathbf{x})$ is small in these methods, but the estimation variances can be large because the large number of parameters (class means) has to be estimated. This approach does not make proper use of the smoothness of $E(y|\mathbf{x})$. There are many methods nowadays for estimating flexible regression functions without any theoretical parametric models, e.g. regression splines, kernel smoothing, local regression and smoothing splines (see Hastie et al. 2001). Smoothing splines may provide a good general basis for future large-scale inventories.

The approaches presented above may be problematic if there is more than one variable that should be generalized. In such a case, regression models are required for each variable and it is difficult to ensure that the estimates for a single tally trees are logical and harmonized. One solution for avoiding such problems is non-parametric nearest neighbour (k-nn) estimation. The principle is simple. For each tally tree we search for the sample trees that are most similar to it and calculate the (weighted) mean of y for these trees. Similarity is measured with respect to tally tree variables $\mathbf{x}$. For example, the estimate of stem volume (or saw log volume) for a tally tree is the (weighted) mean value of stem volumes (or saw log volume) of its nearest neighbours. This technique was employed by Korhonen and Kangas (1997) to generalize sample tree information for tally trees.

Example 6.1 Estimation of tally tree regression using weighted non-linear least squares

This example uses non-linear regression to fit a volume model to sample tree data. Note that the volume modelled is not the actual volume but a prediction based on diameter and height (see section 6.3). The dataset consists of 385 Scots pine trees measured on 16 plots, being a subset of the INKA data originally collected for growth and yield studies (Gustavsen 1998). All these trees were measured for diameter and height, but just 61 trees were selected as sample trees for this example (Table 6.1), the remaining 324 trees being left as tally trees.

The volume of tree i in the sample tree data seemed to follow a non-linear model

$$y_i = \exp(a + b \ln x_i) + e_i ,$$

where a and b are model parameters, x_i is the diameter of tree i, $i=1,...,N$, and N is the total number of trees in the data. Since, as seen in Figure 6.1a, the variance of the volume clearly increased as a function of diameter, it was assumed that

$$\mathrm{var}(e_i) = \sigma^2 x_i^{2\delta} .$$

Using this assumption, the model was fitted using weighted non-linear least squares. The initial guesses for the estimates, obtained from a linearized ordinary least squares regression, were a = -2.373 and b = 2.632, and the final parameter estimates obtained were

a = -2.365, b = 2.631, σ^2 = 0.01025^2 and δ = 2.677.

The variance function seemed to homogenize the variance well (Figure 6.1b), and the resulting model (see Figure 6.3) was used to predict the volumes of tally trees, giving a RMSE for the predictions of 19.04 dm^3.

Table 6.1 The sample tree data of Examples 6.1-6.3. Volume is a prediction based on diameter and height (Laasasenaho 1982). Plot 51 was not included in the modelling data.

plot	Diameter,	Height,	Volume,	plot	Diameter,	Height,	Volume,
1	5	4.9	6.17	10	14.9	14	122.60
1	8.3	7.7	23.31	11	10.3	8.4	38.33
1	9.7	9	35.99	11	12.2	10.9	66.48
2	5.2	5.6	7.28	11	5.7	7.3	10.58
2	6.3	5.8	10.93	11	7.7	9.8	24.41
2	7.6	7.2	18.58	11	7.6	8.5	21.16
2	10.1	9.1	39.34	11	10.2	10.4	44.83
2	8.1	7.2	21.09	11	9.2	10.3	36.24
3	15.2	11.6	108.14	12	12.7	13	83.84
3	10.7	9.3	44.90	12	11.6	13	70.10
3	8	7.2	20.58	12	25.7	18.6	458.78
4	12	13.1	75.47	12	12.2	13.3	79.02
4	12.7	12.1	78.74	12	13.4	13.6	96.97
4	15.1	13.4	121.07	12	19.5	17.5	253.89
5	18.7	19.6	259.58	12	22.1	19.7	361.11
5	22.2	18.9	350.64	12	18.4	18	232.59
6	3.3	3.1	2.19	13	9.1	7.8	28.27

6	5	3.9	5.45	13	10.3	8.1	37.23
6	3.7	3.8	2.95	13	5.7	5.3	8.43
6	3.1	3.1	1.93	13	9.1	7.7	27.99
6	4	3.3	3.27	13	12.1	8.7	54.22
6	4.5	3.6	4.27	14	6.7	6.2	12.94
7	13.1	10.3	72.92	14	7	5.6	13.16
7	13.5	10	75.47	14	4.9	5.6	6.46
7	15.1	10.3	96.45	15	5.4	8.2	10.41
7	9.5	7.8	30.79	15	6.5	8.2	15.06
8	21.7	14.1	257.33	16	4.8	6.5	6.89
8	10.4	9.2	42.06	16	7.4	7	17.25
8	17	13.8	156.79	16	5	5.3	6.49
8	6	7.4	11.85				
8	14.9	11.4	102.43	51	3.9	4	3.36
9	21.5	16.9	297.46	51	8.1	5.6	17.60

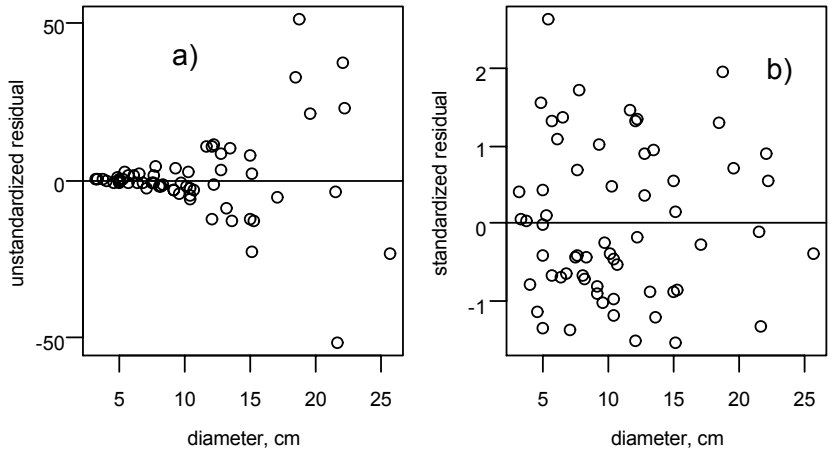


Figure 6.1 Unstandardized (a) and standardized (b) residuals of the weighted non-linear least squares fit. The standardized residuals were obtained by dividing the unstandardized residuals by the square root of the estimated variance function.

Example 6.2 Estimating plot-specific tally tree regression using a mixed model.

It can be clearly seen from Figure 6.2, in which the observed volumes for trees on the same sample plot are connected by dashed lines, that the residuals of the volume model are correlated for a single plot. Thus we assume a non-linear mixed model

$$y_{ki} = \exp(\alpha + a_k + b \ln x_{ki}) + e_{ki},$$

where y_{ki}, x_{ki} and e_{ki} are the volume, diameter and residual of tree i on plot k. Now $i = 1,\ldots,N_k$, where N_k is the total number of trees on plot k. The same model as in example 6.1 was assumed for the residual variance, the only difference being that parameter a was now defined as $\alpha + a_k$, i.e. it was assumed to be specific for each plot with the variance var(a_k) and expectation α. Fitting the model by means of restricted maximum likelihood gave the following parameter estimates:

$$\alpha = -2.001,\ b = 2.473,\ \mathrm{var}(a_k) = 0.1316^2,\ \sigma^2 = 0.006995^2 \text{ and } \delta = 2.548.$$

Predictions of a_k (McCulloch and Searle 2001, p. 247-262; Pinheiro and Bates 2000, p. 71) were calculated for each plot to obtain plot-specific volume models. The population curve and plot-specific curves for each plot are shown in Figure 6.2. Using the plot-specific curves, the RMSE of the volume prediction was 13.67dm^3, which shows a considerable reduction as compared with the model without random effects. This can be interpreted in two ways. From a statistical point of view, random effects can either be said to be part of the error term or can be considered to be random parameters. In the first interpretation, the original errors in the model with random effects are decomposed into two components, plot-level errors and tree-level errors, while in the second, the decrease in RMSE is obtained by adding a large number of additional parameters to the model.

In some cases it is desirable to use linear mixed models rather than non-linear ones. To demonstrate the difference between the two, the model

$$\ln y_{ki} = \alpha + a_k + b \ln x_{ki} + e_{ki}$$

was fitted to the data. Note that the first two terms of the model are obtained by taking a logarithm of the non-linear model without the error term. The difference between the non-linear and linearized models lies in the assumptions regarding the error term (see McCulloch and Searle 2001, p. 78). Fitting of the linearized model to the data gave the parameter estimates

$$\alpha = -2.002,\ b = 2.472,\ \mathrm{var}(a_k) = 0.1341^2 \text{ and } \mathrm{var}(e_{ki}) = 0.06067^2.$$

The estimates for the fixed parameters are almost equal to those of the non-linear model, the differences between the random parameters resulting from different assumptions concerning the error variance.

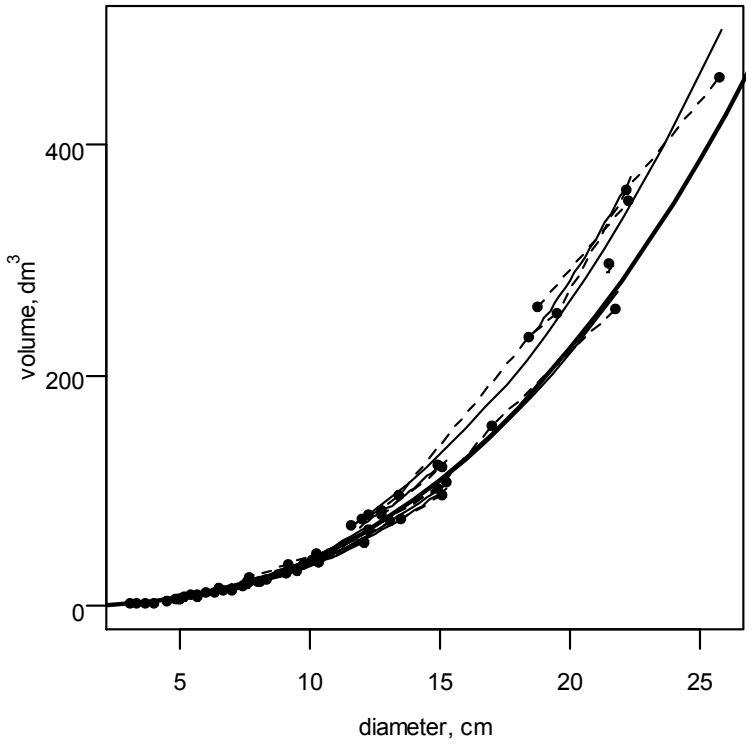


Figure 6.2 Observed volumes plotted against diameter. Observations from the same plot are connected by dashed lines. The thick solid line shows the population curve and the thin solid lines the plot-specific curves. Note that each plot-specific curve is plotted within the range of sample tree diameters of the plot and most of the 16 plot-specific curves are for diameters less than 15 cm.

6.2. GENERALIZING SAMPLE TREE INFORMATION IN A SMALL SUBPOPULATION

We may need to estimate $E(y|\mathbf{x})$ in a small population or subpopulation where not many sample trees have been measured. The subpopulations may be stands or small administrative areas, for instance. If we are using sample tree information collected only from the target subpopulation, the estimation errors in $\hat{E}(y|\mathbf{x})$ may be large. We may thus try to use some prior information to obtain a smaller MSE for $\hat{E}(y|\mathbf{x})$, even though the estimate for $\hat{E}(y|\mathbf{x})$ may be biased for the given subpopulation. Two such methods will be shortly discussed in the following, mixed estimation and mixed models.

6.2.1 Mixed estimation

Mixed estimation can be applied if there are two datasets available: a dataset sampled from the current target population and an auxiliary dataset from a population which we anticipate to be quite similar to the target population. The two are then combined, with less weight attached to the observations in the auxiliary dataset than to those in the target population. Korhonen (1993) used mixed estimation to calibrate the data of the 8th Finnish National Forest Inventory using data from the previous inventory.

More specifically: let $\mathbf{y}_1$ and $\mathbf{y}_2$ be the vectors of the dependent variables for the sample as obtained from the target population and from the auxiliary population, respectively. Using the example above, these could be the values of the sample tree volume equation $V(D,H)$, possibly divided by a function $s(D)$ used to stabilize the error variance. Let us assume a linear model $\mathbf{y}_1 = \mathbf{X}_1\mathbf{b} + \mathbf{e}$ and let $\mathbf{X}_1$ and $\mathbf{X}_2$ be the model matrices from the two samples, respectively. In mixed estimation $\mathbf{b}$ is estimated by $\hat{\mathbf{b}} = \left(\mathbf{X}_1'\mathbf{X}_1 + \lambda\mathbf{X}_2'\mathbf{X}_2\right)^{-1}\left(\mathbf{X}_1'\mathbf{y}_1 + \lambda\mathbf{X}_2'\mathbf{y}_2\right)$ instead of the ordinary least squares estimate $\left(\mathbf{X}_1'\mathbf{X}_1\right)^{-1}\mathbf{X}_1'\mathbf{y}_1$. Thus a weighted least squares regression is applied in which the weights on the observations of the target population are 1 and those on the observations of the auxiliary population are λ. If the two populations do not deviate much, the resulting estimate will have a smaller MSE even if it is biased. For more information on mixed estimation, see Theil and Goldberger (1961) and Toutenburg (1982). Use of the mixed estimation approach with the non-linear volume model of Example 6.1 is illustrated in Example 6.3.

Ridge regression is another biased estimation method that can provide parameter estimates having a smaller MSE error than OLS, especially in small datasets. In this method the parameter estimates are shrunken towards zero. Both mixed estimation and ridge regression are formally similar to the prediction of random parameters using mixed models. Mixed models have a more natural theoretical basis, however.

6.2.2 Applying mixed models

If we are making an inventory in several subpopulations or classes which can be considered a priori to be similar, we can employ techniques which 'borrow strength' from other subpopulations. The classes can be sample plots or stands, for instance. The fitting of a mixed model was discussed in section 6.1. We now show how an estimated mixed model can be employed to predict tally tree regressions for small subpopulations outside the estimation data.

Mixed model prediction is based on linear prediction theory, which we will first explain briefly. Assume that we have a vector of random variables, **h**, which can be divided into two parts

$$\mathbf{h} = \begin{bmatrix} \mathbf{h}_1 \\ \mathbf{h}_2 \end{bmatrix},$$

where $\mathbf{h}_1$ and $\mathbf{h}_2$ are random vectors of length 1 or more. It is assumed that $E(\mathbf{h}_1)=\boldsymbol{\mu}_1$, $E(\mathbf{h}_2)=\boldsymbol{\mu}_2$, $\text{var}(\mathbf{h}_1)=\mathbf{V}_1$, $\text{var}(\mathbf{h}_2)=\mathbf{V}_2$, and $\text{cov}(\mathbf{h}_1,\mathbf{h}_2\text{'})=\mathbf{V}_{12}$. Using the notation of McCulloch and Searle (2001, p. 247), this can be written as

$$\begin{bmatrix} \mathbf{h}_1 \\ \mathbf{h}_2 \end{bmatrix} \sim \left(\begin{bmatrix} \boldsymbol{\mu}_1 \\ \boldsymbol{\mu}_2 \end{bmatrix}, \begin{bmatrix} \mathbf{V}_1 & \mathbf{V}_{12} \\ \mathbf{V}_{12}\text{'} & \mathbf{V}_2 \end{bmatrix} \right). \tag{6.1}$$

Assume that we have observed the random vector $\mathbf{h}_2$ and want to predict vector $\mathbf{h}_1$. The Best Linear Predictor of $\mathbf{h}_1$ is

$$BLP(\mathbf{h}_1) = \hat{\mathbf{h}}_1 = \boldsymbol{\mu}_1 + \mathbf{V}_{12}\mathbf{V}_2^{-1}(\mathbf{x}_2 - \boldsymbol{\mu}_2), \tag{6.2}$$

with a prediction variance of

$$\text{var}(\hat{\mathbf{h}}_1 - \mathbf{h}_1) = \mathbf{V}_1 - \mathbf{V}_{12}\mathbf{V}_2^{-1}\mathbf{V}_{12}\text{'} \tag{6.3}$$

(McCulloch and Searle 2001, p. 250). Thus, if the expectations and variance-covariance matrices of two random vectors are known and either one of them is observed, the other one can be predicted, and the variance of the prediction error can be calculated using Equation (6.3). If $\mathbf{h}$ follows the multinormal distribution, BLP will also be the Best Predictor. If the matrices $\mathbf{V}_1$, $\mathbf{V}_2$ and $\mathbf{V}_{12}$ and the vector $\boldsymbol{\mu}_2$ are replaced in the calculations by their estimates, the resulting predictor is the Estimated Best Linear Unbiased Predictor (EBLUP). Henderson mixed model equations lead to equivalent equations that do not require the inverse of $\mathbf{V}_2$ and are thus more convenient when the number of sample trees in the subpopulation is large (see Searle et al. 1991, Lappi 1991).

Assume that the sample tree variables in subpopulation k are written in vector $\mathbf{y}_k$, and assume that they follow a mixed model

$$\mathbf{y}_k = \mathbf{f}(\mathbf{x}_k, \beta) + \mathbf{Z}\mathbf{b}_k + \mathbf{e}_k, \tag{6.4}$$

where $\mathbf{f}(\mathbf{x}_k, \beta)$ is the fixed part of the model, giving $E(\mathbf{y}|\mathbf{x}_k)$, $\mathbf{b}_k$ includes the random parameters for subpopulation k, $\mathbf{Z}$ is the design matrix corresponding to the random coefficients and $\mathbf{e}_{ki}$ is the vector of residuals. The design matrix has a row for each sample tree, which includes those observed predictors which have a random coefficient. Linearity in the random part is required for simplicity. For prediction of the random parameters of non-linear mixed models, see Pinheiro and Bates (2000) and Fang et al. (2001).

Let us note var(**b**)=**D** and var(**e**)=**R.** Estimates for these matrices are available from the estimation stage of the model. If the errors are homogeneous and uncorrelated, **R**=σ2**I**. Let us define $\mathbf{h}_1=\mathbf{b}_k$, $\mathbf{h}_2=\mathbf{y}_k$ in equation (6.1). Using model (6.4) we obtain $\mathbf{V}_1=\mathbf{D}$, $\mathbf{V}_2=\mathbf{ZDZ'}+\mathbf{R}$ and $\mathbf{V}_{12}=\mathbf{DZ'}$. Now we can use equation (6.2) to predict the random parameters in subpopulation k, denoted by $\hat{\mathbf{b}}_k$, and equation (6.3) to calculate its prediction error, $\mathrm{var}\left(\hat{\mathbf{b}}_k-\mathbf{b}_k\right)$.

According to model (6.4), the prediction regarding tree i in subpopulation k is

$$\hat{y}_{ki}=E\left(y\left|\mathbf{x}_{ki},\mathbf{y}_k\right.\right)=f\left(\mathbf{x}_{ki},\beta\right)+\mathbf{z}\hat{\mathbf{b}}_k\ .$$

The variance in the predictions is needed for calculating their confidence intervals, for example, and for correcting for bias if y_{ki} is not on an arithmetic scale. Ignoring the estimation error in the fixed parameters, the prediction variance is

$$\mathrm{var}\left(\hat{y}_{ki}-y_{ki}\right)=\mathbf{z}\,\mathrm{var}\left(\hat{\mathbf{b}}_k-\mathbf{b}_k\right)\mathbf{z'}+\mathrm{var}\left(e_{ki}\right),$$

where **z** is the row of **Z** that corresponds to the observation $\mathbf{x}_{ki}$.

The above approach can be used when the sample tree variables in the modelling data coincide with those in the target population data. Using the volume example, predicted sample tree volumes based on diameter and height can be used if the volumes in the modelling data are based on same volume model. This is not the case, however, if the volumes in the modelling data are true volumes based on stem analysis and the sample tree volumes are predictions based on diameter and height. A multivariate approach for predicting sample tree volumes using measured sample tree heights, developed by Lappi (1991), is presented in Example 6.4.

Example 6.3 Generalizing sample tree information to a small subpopulation

Assume that we want to generalize the volumes for tally trees on a plot that is not included in the modelling data of the previous examples. Assume that two sample trees were measured on the plot (plot 51 in Table 1). This example demonstrates the use of both mixed estimation and mixed model prediction for generalizing sample tree information.

Mixed estimation

In order to homogenize the residual errors, the model of Example 6.1 was transformed to

$$\frac{y_i}{s(x_i)} = \frac{1}{s(x_i)}\exp(a + b\ln x_i) + e_i ,$$

where, based on the variance function of Example 6.1, $s(x_i) = x_i^{2.68}$.

The dataset used in the previous examples was taken here as the auxiliary dataset for mixed estimation. Since the auxiliary data include 61 trees and the plot data only 2, uniform weighting of all the observations in the combined dataset would have given too much weight to the auxiliary data. Defining the weights as $\lambda=1$ in the plot data and $\lambda=2/61=0.0328$ in the auxiliary data gives half of the weight to the plot data and half to the auxiliary data. Fitting of the model to the combined data using weighted least squares gave the parameter estimates

$$a = -2.400 \text{ and } b = 2.631.$$

The resulting curve is shown by the dashed line in Figure 6.3. One can see that it is more accurate than the population curve of Example 6.1, but clearly gives excessively large volumes for the sample trees. The RMSE of the prediction was 12.51 dm^3 and the bias (predicted-observed) 8.80 dm^3.

Another approach to mixed estimation would have been to generate an artificial auxiliary dataset using an existing volume model (Pekkonen 1982). In this case, for example, one could have used the model of Example 6.1 to generate artificial trees with diameters varying systematically within the diameter range of the tally trees. The mixed estimation model would then have been fitted to the dataset consisting of the observed sample trees and the artificial sample trees and the weighting of the auxiliary data could have been controlled by the number of artificial trees.

Mixed model prediction

In this example the random parameters of the linearized volume model of Example 6.2 were predicted for the plot using the two measured sample trees of plot 51 (Table 6.1). Since the only random parameter in our example is the constant term, the average of the residuals includes all the information that is needed for predicting the random effect and equations (6.1 and 6.2) can be simplified. Let us first calculate the average of the observed logarithmic volumes as $\bar{y}_k = \frac{1.21+2.87}{2} = 2.04$. The average of the expected logarithmic volumes is obtained using fixed parameters of the model: $\mu = \frac{1.36+3.17}{2} = 2.27$. Equation (6.1) now takes the form

$$\begin{bmatrix} a_k \\ \bar{y}_k \end{bmatrix} \sim \left(\begin{bmatrix} 0 \\ \mu \end{bmatrix}, \begin{bmatrix} \operatorname{var}(a_k) & \operatorname{var}(a_k) \\ \operatorname{var}(a_k) & \operatorname{var}(a_k) + \operatorname{var}(e_{ki})/n_k \end{bmatrix} \right),$$

where $n=2$, $\operatorname{var}(a_k) = 0.134^2$ and $\operatorname{var}(e_{ki}) = 0.0607^2$. The Best Linear Unbiased Predictor of a_k is calculated to be

$$\hat{a}_k = \frac{n_k \operatorname{var}(a_k)}{\operatorname{var}(e_{ki}) + n_k \operatorname{var}(a_k)} (\bar{y}_k' - \mu) = \frac{2 \cdot 0.134^2}{0.0607^2 + 2 \cdot 0.134^2} (2.04 - 2.27) = -0.206 .$$

Thus, according to the model (see example 6.2), the expected logarithmic volume on the plot is

$$E(\ln y_{ki} \mid \bar{y}_k) = -2.002 - 0.206 + 2.47 \ln x_{ki} = -2.208 + 2.47 \ln x_{ki} .$$

Before applying the exponential transformation to obtain the volumes on an arithmetic scale, half of the error variance needs to be added to the logarithmic prediction. The error variance consists of the residual error $\operatorname{var}(e_{ki}) = 0.0607^2$ and the prediction error of the plot effect,

$$\operatorname{var}(\hat{a}_k - a_k) = \operatorname{var}(a_k) - \frac{n_k \left[\operatorname{var}(a_k) \right]^2}{\operatorname{var}(e_{ki}) + n_k \operatorname{var}(a_k)} = 0.134^2 - \frac{2 \cdot 0.134^4}{0.0607^2 + 2 \cdot 0.134^2}$$
$$= 0.00167.$$

Thus, the volume expectation is

$$E(y_{ki} \mid \bar{y}_k) = \exp\left[-2.208 + \frac{0.00167 + 0.00368}{2} + 2.47 \ln x_{ki} \right]$$
$$= \exp(-2.202 + 2.47 \ln x_{ki}),$$

which is shown with a solid line in Figure 6.3. The predictions are more accurate than in the mixed estimation approach (RMSE 4.43), but they are still slightly biased for plot 51, the observed bias being 3.01 dm^3.

Both the mixed estimation and mixed model prediction approaches lead to a plot-specific volume model that is obtained from the population curve by shrinking it towards the observed volumes of the sample trees. In mixed estimation the degree of shrinkage depends on the *ad hoc* weights assigned to the auxiliary data, while in the mixed model approach it is defined by the estimated within-plot and between-plot variances in the mixed model.

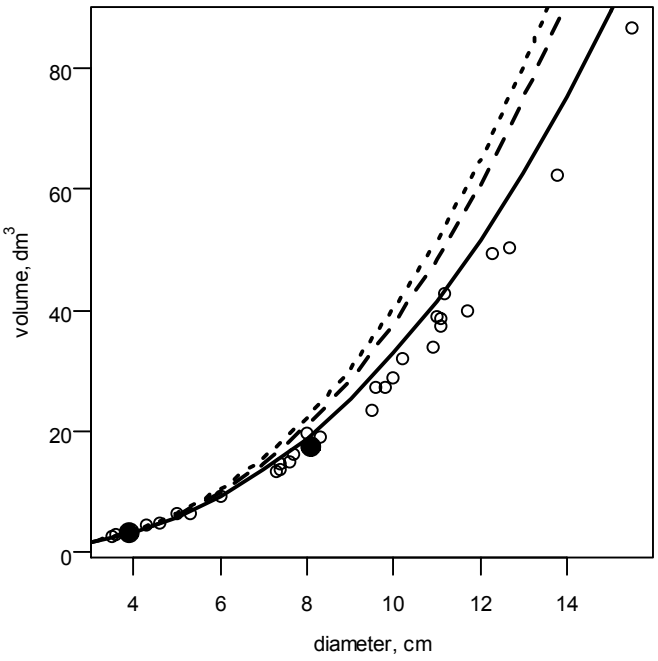


Figure 6.3 The dataset and fitted curves of Examples 6.1 and 6.3. The black circles show the true volumes of the two sample trees and the open circles those of the tally trees. The dotted line shows the expected curve of Example 6.1, the dashed line the curve obtained with mixed estimation and the solid line that obtained with mixed model prediction.

Example 6.4 The multivariate case

Lappi (1991) constructed the following multivariate model for the logarithmic height and logarithmic volume of tree i in stand k from stem analysis data (Laasasenaho 1982):

$$\ln H_{ki} = 3.410 - 18.58\frac{1}{D_{ki}} + a_{0k} - a_{1k}\frac{1}{D_{ki}} + e_{ki} \text{ and}$$

$$\ln V_{ki} = 2.704 - 48.93\frac{1}{D_{ki}} + 1.387\ln D_{ki} + c_{0k} - c_{1k}\frac{1}{D_{ki}} + u_{ki},$$

where D_{ki} is DBH + 7 cm, parameters a_{0k}, a_{1k}, c_{0k} and c_{1k} are stand-specific random parameters and e_{ki} and u_{ki} are residuals with estimated variances of $\text{var}(e_{ki}) = 0.01113$, $\text{var}(u_{ki}) = 0.01540$ and covariance $\text{cov}(e_{ki}, u_{ki}) = 0.01040$. Let us write the random

parameters as vectors $\mathbf{a}_k = (a_{0k} \quad a_{1k})$' $\mathbf{c}_k = (c_{0k} \quad c_{1k})$' and define $\mathbf{b}_k = (\mathbf{a}_k$' $\mathbf{c}_k$')'. The estimated dispersion matrix of $\mathbf{b}_k$ is (Lappi 1991)

$$\operatorname{var}(\mathbf{b}_k) = \mathbf{D} = \left[\begin{array}{cc|cc} 0.04739 & -0.3887 & 0.05082 & -0.4772 \\ -0.3887 & 20.64 & -0.6036 & 24.88 \\ \hline 0.05082 & -0.6036 & 0.05988 & -0.7876 \\ -0.4772 & 24.88 & -0.7876 & 31.11 \end{array}\right]$$

$$= \left[\begin{array}{c|c} \mathbf{D}_1 & \mathbf{D}_{12}\text{'} \\ \hline \mathbf{D}_{12} & \mathbf{D}_2 \end{array}\right] = [\mathbf{C} \quad \mathbf{H}].$$

The last two parts define a partition of matrix **D** that is needed in the following calculations. The measured height of a sample tree will be used below to predict the random parameters of the volume function. Assume that two sample trees of diameters 20 and 30 cm and heights 20 and 26 m have been measured. The measured heights follow the model

$$\mathbf{y}_k = \boldsymbol{\mu} + \mathbf{Z}\mathbf{a}_k + \mathbf{e}_k ,$$

where vector $\mathbf{y}_k$ includes the measured logarithmic heights, $\mathbf{y}_k = \begin{bmatrix} \ln 20 \\ \ln 26 \end{bmatrix} = \begin{bmatrix} 3.00 \\ 3.26 \end{bmatrix}$, and $\boldsymbol{\mu}$ their expectations, which are obtained using the first two terms of the height model as $\boldsymbol{\mu} = \begin{bmatrix} 2.72 \\ 2.91 \end{bmatrix}$. Matrix **Z** is the design matrix of the random part, i.e., $\mathbf{Z} = \begin{bmatrix} 1 & 1/(20+7) \\ 1 & 1/(30+7) \end{bmatrix}$, and $\mathbf{a}_k$ and $\mathbf{e}_k$ are unknown vectors of random parameters and random residuals with variances $\operatorname{var}(\mathbf{a}_k) = \mathbf{D}_1$ and $\operatorname{var}(\mathbf{e}_k) = \mathbf{R} = 0.01113 \cdot \mathbf{I}$. Using the height and volume models, equation (6.1) can be written as

$$\begin{bmatrix} \mathbf{b}_k \\ \mathbf{y}_k \end{bmatrix} \sim \left(\begin{bmatrix} \mathbf{0} \\ \boldsymbol{\mu} \end{bmatrix}, \begin{bmatrix} \mathbf{D} & \mathbf{C}\mathbf{Z}\text{'} \\ \mathbf{Z}\mathbf{C}\text{'} & \mathbf{Z}\mathbf{D}_1\mathbf{Z}\text{'} + \mathbf{R} \end{bmatrix} \right)$$

and the BLUP of $\mathbf{b}_k$ is (Equation 6.2)

$$\hat{\mathbf{b}}_k = \mathbf{CZ'}\left(\mathbf{ZD}_1\mathbf{Z'}+\mathbf{R}\right)^{-1}\left(\mathbf{y}_k-\boldsymbol{\mu}\right)=\begin{pmatrix}0.244\\0.985\\0.230\\1.131\end{pmatrix},$$

i.e. the predicted random parameters are $a_{0k}=0.244$, $a_{1k}=0.985$, $c_{0k}=0.230$ and $c_{1k}=1.131$. The predicted logarithmic heights and volumes are obtained by writing these estimates into the height and volume models.

In order to arrive at unbiased predictions of volumes and heights, half of the prediction variance was added to the predicted logarithmic heights and volumes before applying the exponential transformation. The prediction variance of random parameters was first calculated to be

$$\begin{aligned}\operatorname{var}\left(\hat{\mathbf{b}}_k-\mathbf{b}_k\right) &= \mathbf{D}-\mathbf{ZC'}\left(\mathbf{ZD}_1'\mathbf{Z}+\mathbf{R}\right)^{-1}\mathbf{CZ'}\\ &= \begin{pmatrix} 0.0212 & -0.536 & 0.0266 & -0.648\\ -0.536 & 17.6 & -0.716 & 21.3\\ 0.0266 & -0.716 & 0.0372 & -0.918\\ -0.648 & 21.3 & -0.918 & 26.8\end{pmatrix}.\end{aligned}$$

Ignoring the estimation errors in the fixed parameters, the prediction variances of the predicted logarithmic heights were then obtained from the diagonal of

$$\operatorname{var}\left(\hat{\mathbf{y}}_k\,*-\mathbf{y}_k\,*\right)=\mathbf{Z}*\operatorname{var}\left(\hat{\mathbf{a}}_k-\mathbf{a}_k\right)\mathbf{Z}*'+0.01113\mathbf{I},$$

where $\mathbf{y}_k$* denotes the heights of the tally trees, **Z*** the design matrix of tally trees and $\operatorname{var}\left(\hat{\mathbf{a}}_k-\mathbf{a}_k\right)$ includes the first two rows and columns of $\operatorname{var}\left(\hat{\mathbf{b}}_k-\mathbf{b}_k\right)$ (see the definition of $\mathbf{b}_k$). The height and volume models corrected for population level and local bias are shown in Figure 6.4.

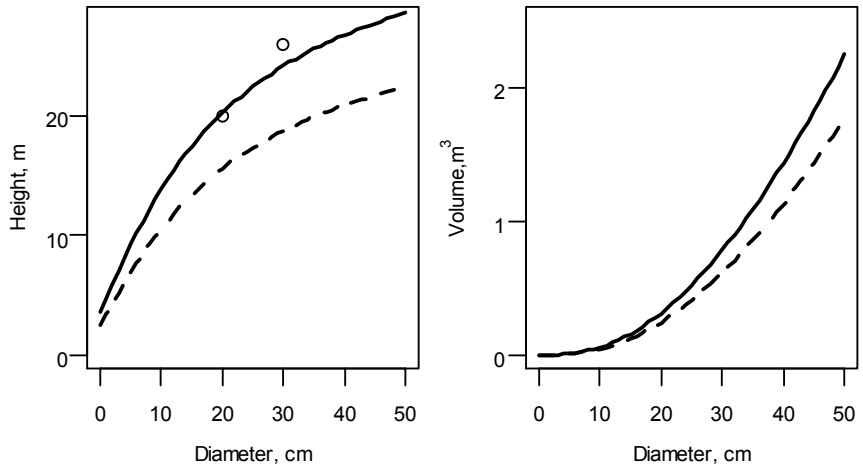


Figure 6.4 Predicted height and volume models when random parameters are 0 (dashed lines) and are predicted using the two observed heights shown in the plot on the left.

6.3 A CLOSER LOOK AT THE THREE-LEVEL MODEL STRUCTURE

Let y denote a variable for which we do not have any measurements in the inventory data (e.g. stem volume), let $\mathbf{x}$ denote tally tree measurements (e.g. dbh), and let $\mathbf{z}$ denote sample tree variables for which we have some measurements (e.g. tree height). The statistical analysis is straightforward if we assume that both $\mathbf{x}$ and $\mathbf{z}$ are random vectors. We then assume that we know the conditional expectation $E\left(y|\mathbf{x},\mathbf{z}\right)$ (called here the sample tree regression) and the conditional variance $\mathrm{var}\left(y|\mathbf{x},\mathbf{z}\right)$, which have been estimated from previous research data. The sample tree regression can be applied using sample tree measurements (note that $\mathrm{var}\left(y|\mathbf{x},\mathbf{z}\right)=\mathrm{var}\left(y-E\left(y|\mathbf{x},\mathbf{z}\right)|\mathbf{x},\mathbf{z}\right)$). We would like to estimate the tally tree regression $E\left(y|\mathbf{x}\right)$ and its residual variance $\mathrm{var}\left(y|\mathbf{x}\right)$ using a random tree sample from the target population.

The conditional expectation $E\left(y|\mathbf{x}\right)$ can be presented as (see Rao 1973, p. 97)

$$E\left(y|\mathbf{x}\right)=E_{\mathbf{z}|\mathbf{x}}E\left(y|\mathbf{x},\mathbf{z}\right) \tag{6.5}$$

where $E_{\mathbf{z}|\mathbf{x}}$ denotes the expectation over the distribution of $\mathbf{z}$ for a given value of $\mathbf{x}$.

There are two approaches for estimating the tally tree regression $E(y|\mathbf{x})$ using (6.5). First, if we have a random sample from the population, the tally tree regression $E(y|\mathbf{x})$ can be estimated using the sample tree regression function $E(y|\mathbf{x},\mathbf{z})$ as the dependent variable which is regressed on $\mathbf{x}$, as in Examples 6.1 and 6.2. The multivariate approach presented in Example 6.4 can also be shown to be equivalent to this approach.

A second possibility is to estimate the conditional distribution of **z** for a given value of **x** and then compute the expected value for $E(y|\mathbf{x},\mathbf{z})$ with respect to this conditional distribution. If $E(y|\mathbf{x},\mathbf{z})$ is not linear with respect to **z**, a numerical integration or approximation method is needed to compute the expected value.

The prediction variance of *y* can be expressed as (see Rao 1973):

$$\operatorname{var}(y|\mathbf{x}) = E_{\mathbf{z}|\mathbf{x}} \operatorname{var}(y|\mathbf{x},\mathbf{z}) + \operatorname{var}_{\mathbf{z}|\mathbf{x}} E(y|\mathbf{x},\mathbf{z}). \tag{6.6}$$

When $E(y|\mathbf{x})$ is estimated by regressing observed values of $E(y|\mathbf{x},\mathbf{z})$ on $\mathbf{x}$, the estimator $\hat{E}(y|\mathbf{x})$ also entails some estimation error. When *y* is predicted for tally trees using $\hat{E}(y|\mathbf{x})$, i.e. $\hat{y} = \hat{E}(y|\mathbf{x})$, the expected squared error consists of both the estimation error of the regression model ($\hat{E}(y|\mathbf{x}) - E(y|\mathbf{x})$) and the residual variance $\operatorname{var}(y|\mathbf{x})$ of the true model $E(y|\mathbf{x})$. Thus, for a given $\hat{E}(y|\mathbf{x})$:

$$E\left((\hat{y}-y)^2|\mathbf{x}\right) = \left(\hat{E}(y|\mathbf{x}) - E(y|\mathbf{x})\right)^2 + \operatorname{var}(y|\mathbf{x}). \tag{6.7}$$

The estimation error $\hat{E}(y|\mathbf{x}) - E(y|\mathbf{x})$ consists of both the random error of the estimation procedure and possible model mis-specification error, i.e. a bias. If the bias component can be assumed to be small, the expected squared error over repeated estimations of $\hat{E}(y|\mathbf{x})$ will be

$$E\left((\hat{y}-y)^2|\mathbf{x}\right) = \operatorname{var}\left(\hat{E}(y|\mathbf{x})\right) + E_{\mathbf{z}|\mathbf{x}} \operatorname{var}(y|\mathbf{x},\mathbf{z}) + \operatorname{var}_{\mathbf{z}|\mathbf{x}} E(y|\mathbf{x},\mathbf{z}). \tag{6.8}$$

The first component of (6.8) results from the estimation errors in the model and the last two components are the residual errors of sample tree regression and tally tree regression, respectively**.**

As an example, let us assume that dbh, denoted as *D,* is the tally tree measurement, and dbh and height, denoted as *H*, are sample tree measurements, and we want to predict the volumes of the tally trees, denoted as *V*. The known sample tree volume equation is denoted by $V(D,H)$ and the unknown tally tree volume equation by $V(D)$, that is $V(D,H)=E(V|D,H)$, and $V(D)=E(V|D)$. The relation between *V* and *D* is dependent on the history of the stands, so that we cannot assume that there exists a universal relationship $V(D)$ which is constant from inventory to inventory. Using (6.5), we obtain

$$V(D)=E_{H|D}V(D,H).$$

Adopting the first approach, the volume of the tally trees can be predicted by constructing a regression function for $V(D,H)$ with respect to *D*. Taking the estimation error of $V(D)$ into account as well, the expected squared error is (Equation 6.8):

$$E\left(\hat{V}(D)-V\right)^2=\text{var}\left(\hat{V}(D)-V(D)\right)+E_{H|D}\,\text{var}\left(V|D,H\right)+\text{var}_{H|D}\,E\left(V|D,H\right).$$

(6.9)

The conditional variances may be easier to understand if they are presented in an equivalent form showing that they are variances of residual errors:

$$\text{var}\left(V|D,H\right)=\text{var}\left(V-V(D,H)\right) \quad \text{and}$$

$$\text{var}_{H|D}\,E\left(V|D,H\right)=\text{var}\left(V(D,H)-V(D)\right)$$

The last two terms in (6.9) are now the residual variance of the sample tree volume equation (estimated from true volumes in original research data) and the variance of the sample tree volume function around its expected value, i.e. the residual variance of the tally tree volume equation. Referring to Example 6.1, the first term is the estimation variance of the model, the second term is the residual variance of the volume equation of Laasasenaho (1982) and the third term is the residual variance of the estimated model.

Adopting the second approach, we first estimate the conditional distribution of *H* for a given *D* and then compute the expected value of $V(D,H)$ with respect to this distribution. The most important property of the conditional distribution of *H* for a given *D* is the expected value $H(D)$, i.e. the height/dbh curve. If the distribution

of H for a given D is approximated by its expected value, i.e. the whole probability mass is shifted to the expected value, we obtain the common simple approach in which $V\left(D,H\left(D\right)\right)$ is used to predict tally tree volumes (Clutter et al. 1983, West 2004). This is justified if $V\left(D,H\right)$ is linear with respect to H, that is $V\left(D,H\right)=g\left(D\right)H$ for a known function of g. In this case $E\left(V\left(D,H\right)\middle|D\right)=g\left(D\right)H\left(D\right)$ (see Rao 1973, p. 97). But because the volume is slightly non-linear with respect to height for a given dbh, the use of $V\left(D,H\left(D\right)\right)$ entails a certain bias. If the error variance is to be computed using only the error variance of $V\left(D,H\right)$, the third term in (6.9) will be ignored. For an error analysis of this approach, see Gregoire and Williams (1992).

If the error variance of the height equation $H\left(D\right)$ is also estimated, a simple approximation for the distribution of H for a given D is a two-point distribution which places half of the probability mass on the expected value plus standard deviation and half on the expected value minus the sd. Using this two point distribution, we arrive at the approximations:

$$E\left(V\right)\approx 0.5\left(E\left(V\middle|D=d,H=\mu-\sigma\right)+E\left(V\middle|D=d,H=\mu+\sigma\right)\right) \qquad (6.10)$$

$$\begin{aligned}\operatorname{var}\left(V\right)\approx{}& 0.5\left(\operatorname{var}\left(V\middle|D=d,H=\mu-\sigma\right)+\operatorname{var}\left(V\middle|D=d,H=\mu+\sigma\right)\right)+\\ & 0.5\left(\left(E\left(V\middle|D=d,H=\mu-\sigma\right)-E\left(V\right)\right)^2+\left(E\left(V\middle|D=d,H=\mu+\sigma\right)-E\left(V\right)\right)^2\right),\end{aligned} \qquad (6.11)$$

where d is the diameter of the tally tree, μ its expected height and σ the standard deviation of the height prediction (Example 6.5).

The above equations can be applied to individual trees if the trees in the inventory data are assumed to be independent. The assumption of a model with plot-level random effects, for example, implies that the trees on the same plot are correlated, and the conditional expectations must be computed by taking into account the tally tree and sample tree variables for all the trees on the same plot.

Example 6.5 Use of the distribution of H|D to estimate tally tree volumes.

Recalling the calibrated height model of Example 6.4, let us now assume that we are predicting the volumes of tally trees of diameters 10, 20 and 30 cm. The design matrix of the last equation of Example (6.4) is

$$\mathbf{Z}^* = \begin{pmatrix} 1 & 1/(10+7) \\ 1 & 1/(20+7) \\ 1 & 1/(30+7) \end{pmatrix}$$

and the variance-covariance matrix of the prediction error becomes

$$\mathrm{var}\left(\ln \hat{\mathbf{h}}_k - \ln \mathbf{h}_k\right) = \begin{pmatrix} 0.130 & 0.00820 & 0.00319 \\ 0.00820 & 0.117 & 0.00449 \\ 0.00319 & 0.00449 & 0.116 \end{pmatrix}.$$

The expectations for the logarithmic heights of the tally trees are shown in the second column of Table 6.2 and the standard deviation of their prediction errors, obtained from the diagonal of $\mathrm{var}\left(\ln \hat{\mathbf{h}}_k - \ln \mathbf{h}_k\right)$, in the third column. The volumes of the tally trees were first calculated by the traditional approach, using the expected height (H_1) to predict the volumes (V_1) and applying bias correction in the prediction of the heights (Table 6.3). Ignoring the height prediction error, the standard error in prediction (sd(V_1)) was calculated to be $\mathrm{sd}\left(V \middle| D, H\right) \approx 0.075 E\left(V \middle| D, H\right)$ (Laasasenaho 1982). In the second approach, two predicted heights were calculated for each tally tree: one obtained by subtracting the standard deviation of the prediction from (H_2) and the other by adding it to (H_3), the prediction of the expected log height before exponential transformation to calculate the volumes of the tally trees (V_2 and V_3). The final volume estimates, V_4, were obtained as averages of V_2 and V_3 (Equation 6.10). The prediction variance (sd(V_4), Equation 9.11), takes into account both the height prediction error and the volume function prediction error .

There are only slight differences in the point estimates of volume, but considerable differences in the prediction errors. The merits of the second approach over the first are that a realistic estimate of the prediction variance is obtained and that bias correction based on Taylor series approximation and normality of the errors in the prediction of log height is not needed.

Table 6.2 Predicted heights and volumes of the three tally trees and their prediction errors.

D	ln$H$	sd(ln$H$)	H_1	H_2	H_3
10	2.619	0.1739	13.93	11.53	16.33
20	3.002	0.1266	20.30	17.69	22.92
30	3.179	0.1274	24.21	21.14	27.27

Table 6.3 Predicted volumes of the three tally trees and their prediction errors.

D	V_1	V_2	V_3	V_4	sd(V_1)	sd(V_4)
10	55.56	47.09	64.06	55.57	4.167	9.475
20	305.7	269.3	342.2	305.8	22.93	43.13
30	788.9	695.3	882.9	788.9	59.17	111.0

REFERENCES

Clutter, J.L., Fortson, J.C., Pienaar, L.V., Brister, G.H., Bailey, R.L. 193. Timber management. A quantitative approach. Wiley, New York. 333 p.

Davidian, M. and Giltinan, D.M. 1995. Nonlinear models for repeated measurement data. Monographs on statistics and applied probability 62. Chapman & Hall/CRC, London. 359 p.

Diggle, P.J., P. Heagerty, K.-Y. Liang, and S.L. Zeber. 2002. Analysis of longitudinal data. Second edition. Oxford University Press. 379 pp.

Fang, Z, Bailey, R.L. and Shiver, B.D. 2001. A multivariate simultaneous prediction system for stand growth and yield with fixed and random effects. Forest Science 47: 550-562.

Gregoire, T.G. and Williams, M. 1992. Identifying and evaluating the components of non-measurement error in the application of standard volume equations. The Statistician 41: 509-518.

Gregoire, T.G. and Schabenberger, O. 1996. A non-linear mixed-effects model to predict cumulative bole volume of standing trees. Journal of Applied Statistics 23: 257-271.

Gregoire, T.G., Schabenberger, O. and Barrett, J.P. 1995. Linear modeling of irregularly spaced, unbalanced, longitudinal data from permanent-plot measurements. Canadian Journal of Forest Reserach 25: 137-156.

Gustavsen H.G. 1998. Volymtillväxten och övre höjdens utveckling i talldominerande bestånd i Finland – en utvärdering av några modellers validitet i nuvarande skogar. The Finnish Forest Research Institute. Research Notes 707.

Hastie, T, Tibshirani R. and Friedman, J. 2001. The elements of statistical learning: Data Mining, Inference and prediction. Springer, New York. 533pp.

Kangas, A. 1997. On the prediction bias and variance in long-term growth projections. Forest Ecology and Managagement 96: 207-216.

Korhonen, K.T. and Kangas, A. 1997. Application of nearest-neighbour regression for generalizing sample tree information. Scandinavian Journal of Forest Research 12: 97-101.

Korhonen, K.T. 1993. Mixed estimation in calibration of volume functions of Scots pine. Silva Fennica 27: 269-276.

Laasasenaho, J. 1982. Taper curve and volume functions for pine, spruce and birch. Communicationes Instituti Forestalis Fenniae 108.

Lappi, J. 1991. Calibration of height and volume equations with random parameters. Forest Science 37: 781-801

Lappi, J. 1991. Calibration of height and volume equations with random parameters. Forest Science 37: 781-801.

Lappi, J. 1993. Metsäbiometrian menetelmiä. Silva Carelica 24. University of Joensuu, 182 p.

McCulloch, C. E. and Searle, S. R. 2001. Generalized, linear, and mixed models. John Wiley & Sons. 325 p.

Mehtätalo, L. 2004. A longitudinal height-diameter model for Norway spruce in Finland. Canadian Journal of Forest Research 34: 131-140.

Pekkonen, T. Leimikon puuston tilavuuden arviointi regressioennustinta käyttäen. [Regression estimators in predicting the volume of a stand marked for cutting. In Finnish]. Finnish Forest Research Institute. Research Notes 86.

Pinheiro, J.C. and Bates, D.M. 2000. Mixed-Effects Models in S and S-PLUS. Springer, New York. 528 p.

Rao, C.R. 1973. Linear statistical inference and its applications. Wiley, New York. 625 pp.

Searle, S.R., Casella, G. and McCulloch, C.E. 1991. Variance components. Wiley, New York. 501 p.

Theil, H. and Goldberger, A.S. 1961. On pure and mixed statistical estimation in economics. International Economical Review 2:65-78

Toutenburg, H. 1982. Prior information in linear models. Wiley. Chischester. 215 pp.

West, P.W. 2004. Tree and forest measurement. Springer, Berlin. 167 p.

CHAPTER 7

USE OF ADDITIONAL INFORMATION

JUHA LAPPI AND ANNIKA KANGAS

Finnish Forest Research Institute, University of Helsinki, Finland

7.1 CALIBRATION ESTIMATION

If there are not enough sample plots to give sufficiently good inventory results using only forest measurements, we may try to make use of auxiliary variables correlated with forest variables. The most obvious way is to use ratio or regression estimators (Section 2.7). The calibration estimator of Deville and Särndal (1992) is an extension of the regression estimator for obtaining population totals using auxiliary information. Both regression and calibration estimators can be employed if there are auxiliary variables for inventory sample plots known for which the population totals are also known, e.g. variables obtained from remote sensing or from GIS systems. The appeal of calibration estimators for forest inventories comes from the fact that they lead to estimators which are weighted sums of the sample plot variables, where the weight can be interpreted as the area of forest in the population that is similar to the sample plot.

The basic features of the calibration estimator of Deville and Särndal (1992) in terms of estimating means can be described as follows. Consider a finite population U consisting of N units. Let j denote a general unit, thus $U = \{1, \ldots, j, \ldots, N\}$. In a forest inventory the population is a region where units are pixels or potential sample plots. The units in a forest inventory will be referred to here as 'pixels', and it will be assumed that an inventory sample plot gives values to the forest variables for an associated pixel. Each unit j is associated with a variable y_j and a vector of auxiliary variables $\mathbf{x}_j$. The population mean of $\mathbf{x}$, $\overline{\mathbf{X}} = N^{-1}\sum_U \mathbf{x}_j$ is assumed to be known. The y variables in a forest inventory are forest variables and the x variables can be spectral variables from remote sensing or geographical or climatic variables obtained from GIS databases.

A. Kangas and M. Maltamo (eds.), Forest Inventory – Methodology and Applications, 107–117.

Assume that a probability sample S is drawn, and y_j and $\mathbf{x}_j$ are observed for each j in S, the objective being to estimate the mean of y, $\overline{Y} = N^{-1}\sum_U y_j$. Let π_j be the inclusion probability and d_j the basic sampling design weight $d_j = (N\pi_j)^{-1}$, which can be used to compute the unbiased Horvitz-Thompson estimator

$$\hat{\overline{Y}}_d = \sum_s d_j y_j \,. \tag{7.1}$$

A calibration estimator

$$\hat{\overline{Y}} = \sum_s w_j y_j \tag{7.2}$$

is obtained by minimizing the sum of distances, $\sum_s G(w_j, d_j)$, between the prior weights d_j and posterior weights w_j for a positive distance function G, taking account of the calibration equation

$$\sum_s w_j \mathbf{x}_j = \overline{\mathbf{X}} \,. \tag{7.3}$$

If the distance between d_j and w_j is defined as

$$G_1(w_j, d_j) = (w_j - d_j)^2 / d_j \,, \tag{7.4}$$

the calibration estimator will be the same as the regression estimator

$$\hat{\overline{Y}}_r = \sum_s w_j y_j = \hat{\overline{Y}}_d + \left(\overline{\mathbf{X}} - \hat{\overline{\mathbf{X}}}_d\right)' \hat{\mathbf{b}} \,, \tag{7.5}$$

where $\hat{\overline{\mathbf{X}}}_d$ and $\hat{\mathbf{b}}$ (a weighted regression coefficient vector) are

$$\hat{\overline{\mathbf{X}}}_d = \sum_s d_j \mathbf{x}_j \quad \text{and} \tag{7.6}$$

$$\hat{\mathbf{b}} = \left(\sum_s d_j \mathbf{x}_j \mathbf{x}_j'\right)^{-1} \sum_s d_j \mathbf{x}_j y_j \,. \tag{7.7}$$

If the model contains an intercept, the corresponding variable x will be one for all observations, and the calibration equation (7.3) will then guarantee that the weights w_j add up to one. This means that when estimating totals, the

weights Nw_j will add up to the known total number of pixels in the population. Thus Nw_j can be interpreted as the total area, in pixel units, for plots of forest similar to plot j. The standard least squares theory implies that the regression estimator (7.5) can be expressed in the form

$$\hat{\bar{Y}}_r = \sum_s w_j y_j = \overline{\mathbf{X}}' \hat{\mathbf{b}} . \tag{7.8}$$

It is assumed that the intercept is always among the parameters.

Estimator (7.7) is defined if the moment matrix $\sum_s d_j \mathbf{x}_j \mathbf{x}_j'$ is non-singular. Some of the weights w_j in (7.2) implied by Eqs. (7.6)-(7.8) may be negative. Non-negative weights are guaranteed if the distance function is infinite for negative w_j. Deville and Särndal (1992) presented four distance functions producing positive weights.

Minimization of the sum $\sum_s G(w_j, d_j)$ so that (7.3) is satisfied is a non-linear constrained minimization problem. Using Lagrange multipliers, the problem can be reformulated as a non-linear system of equations which can be solved iteratively using Newton's method (for details, see Deville and Särndal 1992). If the initial values of the Lagrange multipliers are set to zero, the first step will produce w_j's of the regression estimator (7.5).

Since the calibration estimator is asymptotically equivalent to the regression estimator, Deville and Särndal (1992) suggest that the variance of the calibration estimator should be computed in the same way as the variance of the regression estimator using regression residuals. There is no design-unbiased estimator of the variance in systematic sampling (Schreuder et al. 1993).

The emphasis on area interpretation for the weights has the same argument behind it as was used by Moeur and Stage (1995) for the most similar neighbour method (MSN), where unknown plot variables are taken from a plot which is as similar as possible with respect to the known plot variables. In both methods each sample plot represents a percentage of the total area, and all the forest variables are logically related to each other. The difference is that in the calibration estimator we obtain an estimate of the area of the sample plot for the whole population whereas in the MSN method each pixel is associated with a sample plot. Since there is no straightforward way of showing that the MSN method produces optimal results in any way at the population level, it may be safer to use the calibration estimator for computing population-level estimates for forest variables. The problem with the calibration estimator is that it does not provide a map. If a map is needed, then the weights provided by the calibration estimator need to be distributed over pixels using separate after-processing.

Lappi (2001) proposed a 'small-area' modification of the calibration estimator which can be used when several subpopulation totals are required simultaneously. He used satellite data as auxiliary information for computing

inventory results for counties. Sample plots in the surrounding inclusion zone are also used for a given subpopulation so that the prior weight decreases as distance increases. The error variance is computed using a spatial variogram model. Block kriging (Cressie 1986) provides an optimal estimator for subpopulation totals under such a model, but kriging can produce negative weights for sample plots, and the weights are different for each *y* variable. Thus it is not possible to give areal interpretations to sample plot weights in kriging.

7.2 SMALL AREA ESTIMATES

Small area estimation is needed when estimates are required for subdivisions or domains of the population. Although the estimates for the whole population may be quite reliable, only a few sample units may fall into a given domain *i*, whereupon the classical design-based estimators may have unacceptably large errors. Accurate estimates for all small areas usually require overall sample sizes that are much too large to be within normal budget constraints (Särndal and Hidiroglou 1989). Thus, in order to improve the estimates of the domains, information from nearby areas can be used.

Small area estimators are typically at least partially model-based (Schreuder et al. 1993) and are referred to as synthetic or global estimators when information for the whole area is used instead of just the information from the domain i of interest (Särndal and Hidiroglou 1989). Estimators based only on information for the domain of interest are referred to as local estimators.

The classical local estimator for a domain *i* is

$$\hat{\bar{y}}_i = \sum_{j \in s_i} \frac{y_j}{n_i}, \tag{7.9}$$

where s_i denotes the sample drawn from domain *i* and n_i is the sample size in *i*. This estimator is unreliable for small sample sizes, however. The simplest possible model that can be used for small area estimation is

$$y_j = \mu + \varepsilon_j \quad for \quad j = 1,...,N . \tag{7.10}$$

Under model (7.10) the global estimator of the mean for domain *i* is thus

$$\hat{\bar{y}}_{iSYN} = \sum_{j \in s} \frac{y_j}{n}, \tag{7.11}$$

where *s* denotes the sample taken from the whole area and *n* is the total sample size. In fact, this is the sample mean for the whole population. The simplest global estimate is thus the overall sample mean for all domains *i*. As $n > n_i$, the estimates obtained with (7.11) will have a lower variance than the local estimates (7.9), but they will be badly biased unless the domain mean is the same as the population

mean, $\overline{Y}_i = \overline{Y}$, in all domains. With this model, the synthetic estimator (7.11) would differ from the domain mean even if all the units in domain *i* were measured, i.e. $n_i = N_i$.

A compromise between these two estimators is to combine the estimators (7.9) and (7.11). Under model (7.10), the best linear unbiased estimator for the domain mean $\overline{Y}_i$ is (Schreuder et al. 1993, p. 318)

$$\hat{\bar{y}}_{iCOM} = \frac{n_i}{N_i}\bar{y}_i + \left(1 - \frac{n_i}{N_i}\right)\bar{y} \tag{7.12}$$

If all the units in domain *i* were measured, the domain mean would have the weight 1 in this case and population mean 0, giving the correct estimate.

If additional information is available, it is possible to use a model (Ericksen 1973,1974, Mandallaz 1991, see sections 3.2, and 2.7)

$$y_j = \mathbf{x}_j\boldsymbol{\beta} + \varepsilon_j \quad for \quad j = 1,\ldots, \tag{7.13}$$

where $\mathbf{x_j}$ is a ($p+1$) vector of independent variables at point (plot) *j*. The coefficients $\boldsymbol{\beta}$ are estimated for the whole population and global estimates for domain *i* are obtained by

$$\hat{\bar{y}}_{iREG} = \overline{\mathbf{X}}_i\hat{\boldsymbol{\beta}}, \tag{7.14}$$

where $\overline{\mathbf{X}}_i$ contains the true average values for the independent variables of domain *i*. The estimator of its variance (assuming infinite population or analytic inference) is

$$Var(\hat{\bar{y}}_{iREG}) = \hat{\sigma}^2\overline{\mathbf{X}}_i(\mathbf{X'X})^{-1}\overline{\mathbf{X}}_i, \tag{7.15}$$

where $\mathbf{X}$ is the $n \times (p+1)$ matrix containing values for the independent variables for each sample point and $\hat{\sigma}^2$ is the estimator for the model residual variance (Eq. 3.7). If only the intercept of model (7.13) is significant, this model reduces to (7.10). The estimator (7.14) is almost the same as the estimator (3.10) presented in section 3.2. The only difference is that in (7.14) the model coefficients are estimated for the whole population whereas $\overline{\mathbf{X}}_i$ is for domain *i*.

Synthetic methods of estimation assume that small areas have characteristics similar to those of the larger areas of which they are part (Gonzales 1973). If this assumption is unjustified, the synthetic estimators will be biased. If the bias component does not tend towards zero as the sample size increases, the estimator is design-biased (Särndal 1984). On the other hand, if an estimator is biased under the assumed model it can be said to be model-biased. A biased

estimator may still be useful if its MSE is smaller than that of an unbiased estimator and if the presence of bias is acceptable.

This bias in synthetic estimators can be reduced by combining an unbiased estimator with a design-biased but low variance estimator, for example, so that the weight of the unbiased estimator increases as the sample size in the small domain increases. Such attempts have included the use of shrinkage or empirical Bayes estimators (Green et al. 1987, see also Hulting and Harville 1991).

It is also possible to correct the estimates obtained with global models by using residuals observed in domain *i* (Särndal 1984, Särndal and Hidiroglou 1989). Mandallaz (1991) proposed a global estimator

$$\hat{\bar{y}}_{iSUR} = \bar{\mathbf{X}}_i\hat{\boldsymbol{\beta}} + (\bar{y}_i - \bar{\mathbf{x}}_i\hat{\boldsymbol{\beta}}), \tag{7.16}$$

where $\bar{\mathbf{x}}_i$ is the vector of sample means and $\bar{\mathbf{X}}_i$ is the vector of true means in a small area *i*. In (7.16) the synthetic model-based estimator (7.14) is corrected for the bias by means of the residuals observed in the small area *i*.

The estimator of its variance is (Mandallaz 1991)

$$Var(\hat{\bar{y}}_{iSUR}) = \frac{1}{n_i(n_i - 1)}\sum_{j\in s_i}(r_{ji} - \bar{r}_i)^2, \tag{7.17}$$

where r_{ji} is the observed residual in domain *i* and plot *j*.

An alternative model for domain estimation would be

$$y_{ij} = \mathbf{x}_{ij}\boldsymbol{\beta} + c_i + \varepsilon_{ij} \quad for \quad j = 1,... \; and \; \; i = 1,...,k, \tag{7.18}$$

where $c_i \sim N(0,\sigma_w^2)$ is a random domain effect, $\varepsilon_{ij} \sim N(0,\sigma_e^2)$ is a random plot effect and *c* and ε are mutually independent (Battese et al. 1988). The difference relative to model (7.13) is that the residual error term in (7.18) is divided into two components. The domain effect describes the difference of domain *i* from the population mean, which makes it useful for estimating the domain mean. The global estimator for the domain mean is then (Prasad and Rao 1990)

$$\hat{\bar{y}}_{iMIX} = \bar{\mathbf{X}}_i\hat{\boldsymbol{\beta}} + \hat{c}_i, \tag{7.19}$$

where the domain effect $\hat{c}_i$ can be estimated by

$$\hat{c}_i = \frac{\sigma_w^2}{\sigma_w^2 + \frac{\sigma_e^2}{n_i}}(\bar{y}_i - \bar{\mathbf{x}}_i\hat{\boldsymbol{\beta}}) = \gamma_i(\bar{y}_i - \bar{\mathbf{x}}_i\hat{\boldsymbol{\beta}}) \tag{7.20}$$

and γ_i is the (constant) correlation within domain *i*, calculated from the variances in the domain and plot effects and the number of plots.

The estimator of $\hat{c}_i$ (7.20) is biased for a given c_i, but unbiased over the distribution of domains (Lappi 1993). Thus the estimator (7.19) is also model-biased for a given domain but unbiased over the distribution of domains. The larger the within-domain correlation, and the larger the difference $(\bar{y}_i - \bar{\mathbf{x}}_i\hat{\boldsymbol{\beta}})$, the larger the predicted $\hat{c}_i$ in (7.19) is. As the variance σ_e^2 approaches infinity, the correlation approaches one and estimator (7.19) approaches estimator (7.16). This means that the global estimator of the mean (7.19) is corrected by means of the observed residuals, as in (7.16), but the amount of this correction depends on the correlation within the domains. The mean square error of (7.19) can be calculated using the theory of linear models, details of which can be found in Prasad and Rao (1990).

If only the intercept of the fixed part of model (7.18) is significant, the estimator (7.19) reduces to a linear combination of the estimate for the total area mean and the observed mean in domain *i*:

$$\hat{\bar{y}}_{iMIX} = \left(1 - \frac{\sigma_w^2}{\sigma_w^2 + \frac{\sigma_e^2}{n}}\right)\hat{\mu} + \left(\frac{\sigma_w^2}{\sigma_w^2 + \frac{\sigma_e^2}{n}}\right)\bar{y}_i \qquad (7.21)$$

This estimator is quite similar to simple James-Stein estimators or the combined estimator (7.13) (Schreuder et al. 1993). Treating the domain effect as random provides a means of combining the domain mean efficiently with the estimator of the population mean.

Geostatistical methods provide interesting possibilities in small area estimation in a forestry context, since in most cases the auxiliary information includes coordinate locations. With these methods it is possible to take the autocorrelations present in the data explicitly into account, instead of just constant within-domain correlation as in the mixed model. In kriging methods, the autocorrelation between the sample plots is usually assumed to depend purely on the distance between the sample plots and to decrease with increasing distance. In a mixed model, however, this correlation is approximated by means of an average correlation over a predefined area. Thus the mixed model approach can be considered a special case of kriging. The kriging method has been presented by Journel and Huijbregts (1978), Burgess and Webster (1980a, 1980b), Ripley (1981) and Cressie (1986), for example, and for small area estimation by Mandallaz (1993) (see also Chapter 10). Examples of small area estimation in forestry are provided by Green et al. (1987), Mandallaz (1991), Kangas (1996) and Lappi (2001), for example.

Example 7.1

The example is based on simulated data. Assume a 1000 hectare area with five distinct regions of interest. The volume of each region is surveyed. There is a satellite image available, and the near-infrared (NIR) channel is used as auxiliary information.

The true data were obtained assuming that the NIR was a normally distributed variable with mean 0.2482 and standard deviation 0.0364. A dataset of 1000 observations for the regions was generated, and the true volumes were obtained from a model

$$V_i = 322.7473 - 714.951\,\mathrm{NIR}_i + \varepsilon_i,$$

where the standard deviation of ε_i was 38.66 m^3/ha. The true mean values for NIR and volume in each area, calculated from these data, are presented in Table 7.1.

Table 7.1 True values for volume and NIR.

District	size, ha	NIR	Volume m^3/ha	STD
1	94	0.22893	155.5	43.82
2	69	0.25104	140.7	40.43
3	123	0.26008	139.2	42.34
4	537	0.28201	120.4	45.40
5	177	0.31497	92.5	44.35
sum/mean	1000	0.27802	122.5	47.84

A sample of 50 plots was taken from the area at random. The values of NIR and volume for each sample plot are presented in Table 7.2.

Table 7.2 The sample.

District	NIR	VOL	District	NIR	VOL
1	0.176512	212.6	4	0.264825	182.3
1	0.212170	154.4	4	0.322347	70.3
1	0.234031	170.8	4	0.313223	130.6
1	0.196743	139.9	4	0.326355	95.3
1	0.261204	159.6	4	0.264030	116.0
1	0.235359	123.9	4	0.308574	93.6
1	0.191436	222.9	4	0.313137	12.8
2	0.244882	133.2	4	0.240222	142.5
2	0.281133	70.8	4	0.281222	75.0
2	0.252457	2.6	4	0.281231	127.1
2	0.268814	119.0	4	0.330613	132.3
2	0.268588	136.6	4	0.313529	114.9
3	0.237107	169.6	4	0.261752	114.9
3	0.253262	115.8	4	0.270598	115.1
3	0.242354	141.9	4	0.327834	57.7
3	0.268941	98.7	5	0.265201	141.3
3	0.301190	163.5	5	0.319447	81.6
3	0.273860	35.5	5	0.321587	120.4
4	0.291545	116.2	5	0.272238	115.9
4	0.259637	98.5	5	0.277245	142.2
4	0.277605	110.7	5	0.309464	82.6
4	0.239459	182.7	5	0.309751	89.2
4	0.339731	56.0	5	0.275660	67.6
4	0.226967	148.9	5	0.366935	28.3
4	0.229883	202.5	5	0.326796	44.8

A linear regression model, having the characteristics presented in Table 7.3, was estimated from the sample data.

Table 7.3 Model statistics.

Regression Statistics	
R^2	0.428969
Adjusted R^2	0.417073
Standard Error	37.28421
Observations	50

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	50125.37	50125.37	36.0585	2.46E-07
Residual	48	66725.41	1390.113		
Total	49	116850.8			

	Coefficients	*Std Error*	*t Stat*	*p-value*
Intercept	330.9492	36.24291	9.13142	<0.000
NIR	−784.192	130.5926	−6.00487	<0.000

Estimates for the small area obtained with various formulae are presented in Table 7.4.

Table 7.4 Estimates for the small area.

District	n	NIR	$\hat{\bar{y}}_i$ (7.9)	$s_e(\hat{\bar{y}}_i)$ (2.12)	$\hat{\bar{y}}_{iSYN}$ (7.11)	$\hat{\bar{y}}_{iREG}$ (7.14)	$\hat{\bar{y}}_{iSUR}$ (7.16)	$s_e(\hat{\bar{y}}_{iSUR})$ (7.17)
1	7	0.22893	169.2	13.79	115.6	151.4	158.5	11.387
2	5	0.25104	92.5	25.35	115.6	134.1	102.0	31.773
3	6	0.26008	120.8	20.36	115.6	127.0	123.0	20.389
4	22	0.28201	113.5	9.45	115.6	109.8	116.3	6.946
5	10	0.31497	91.4	12.21	115.6	84.0	83.1	8.346
total	50	0.27802	115.6	6.91	115.6	112.9	112.9	5.216

REFERENCES

Battese G.E., Harter, R.M. and Fuller, W.A. 1988. An Error-Components Model for Prediction of County Crop Areas Using Survey and Satellite Data. Journal of American Statistical Association 83:28-36.

Burgess, T.M. and Webster, R. 1980. Optimal Interpolation and Isarithmic Mapping of Soil Properties. I The Semi-variogram and Punctual Kriging. Journal of Soil Science 31:315-331.

Burgess, T.M. 1980. Optimal Interpolation and Isarithmic Mapping of Soil Properties. II Block Kriging. Journal of Soil Science 31:333-341.

Cressie, N. 1986. Kriging Nonstationary Data. Journal of American Statistical Association 81:625-634.

Deville, J.C. and Särndal, C.E. 1992. Calibration estimators in survey sampling. Journal of the American Statistical Association 87: 376-382.

Ericksen, E.P. 1973. A method for combining sample survey data and symptomatic indicators to obtain estimates for local areas. Demography 10:137-160.

Ericksen, E.P. 1974. A regression method for estimating population changes of local areas. Journal of American Statistical Association 69:867-875.

Gonzales, M.E. 1973. Use and Evaluation of Synthetic Estimates. Proceeding of Social Statistics Section, American Statistical Association. 73:7-15.

Green, E.J., Thomas, C.E. and Strawderman, W.E. 1987. Stein-Rule Estimation of Timber Removals by County. Forest Science 33:1054-1061.

Hulting, F.L. and Harville, D.A. 1991. Some Bayesian and Non-Bayesian Procedures for the Analysis of Comparative Experiments and for Small-Area Estimation: Computational Aspects, Frequentist Properties, and Relationships. Journal of American Statistical Association 86:557-568.

Journel, A.G. and Huijbregts, C.J. 1978. Mining Geostatistics. London, Academic Press.

Kangas, A. 1996. Small area estimates using model based methods. Canadian Journal of Forest Research 26:758-766.

Lappi, J. 1993. Metsäbiometrian menetelmiä. Silva Carelica 24. 182 p.

Lappi, J. 2001. Forest Inventory of Small Areas Combining the Calibration Estimator and a Spatial Model. Canadian Journal of Forest Research 31:1551-1560.

Mandallaz, D. 1991. A Unified Approach to Sampling Theory for Forest Inventory Based on Infinite Population and Superpopulation Models. Chair of Forest Inventory and Planning, Swiss Federal Institute of Technology (ETH), Zurich. 242 p.

Mandallaz, D. 1993. Geostatistical Methods for Double Sampling Schemes: Application to Combined Forest Inventories. Chair of Forest Inventory and Planning, Swiss Federal Institute of Technology (ETH), Zurich. 133 p.

Moeur, M. and Stage, A.R. 1995. Most Similar Neighbor: An Improved Sampling Inference Procedure for Natural Resource Planning. Forest Science 41:337-359.

Prasad, N.G.N. and Rao, J.N.K. 1990. The Estimation of the Mean Square Error of Small Area Estimators. Journal of American Statistical Association 85:163-171.

Ripley, B.D. 1981. Spatial Statistics. John Wiley and Sons. New York. 252 p.

Särndal, C-E. 1984. Design-Consistent versus Model-Dependent Estimation for Small Domains. Journal of American Statistical Association 79:624-631.

Särndal, C-E. and Hidiroglou M.A. 1989. Small Domain Estimation: A Conditional Analysis. Journal of American Statistical Association 84:266-275.

Schreuder, H.T., Gregoire, T.G. and Wood, G.B. 1993. Sampling Methods for Multiresource Forest Inventory. John Wiley and Sons. New York. 446 p.

CHAPTER 8

SAMPLING RARE POPULATIONS

ANNIKA KANGAS

University of Helsinki, Finland

8.1 METHODS FOR SAMPLING RARE POPULATIONS

8.1.1 Principles

Rare populations, such as downed trees or single valuable living trees, are often important with respect to biodiversity, for example. The problem is that such populations are difficult to cope with in a normal forest inventory. In the sample plot inventory method designed for surveying the mean volume of living trees, the area of a sample plot is typically very small relative to the total area. In such a case, only a few observations from rare populations (or perhaps none at all) will be obtained. The standard errors may therefore be very large. For these reasons, specific methods have been developed for sampling rare populations. A typical case is that of estimating the volume of downed woody debris in area level (see Ringvall 2000, Ståhl et al. 2001). A few recently developed methods are included in this chapter, but there are numerous others for those interested, see Bebber et al. (2003) and Williams and Gove (2003), for example.

The estimating of wildlife populations constitutes a field of application which is in many respects different from tree surveys. Animals can move and hide, and the sampling process itself may cause them to move. Thus a true sampling frame may not exist and the probability of any one animal being sampled has in many cases been calculated after the sample has been drawn (Schreuder et al. 1993). Hence the probability of errors is also greater in animal surveys. The primary parameters of interest in wildlife surveys are usually population size or density, birth and mortality rates and immigration and emigration rates.

A. Kangas and M. Maltamo (eds.), Forest Inventory – Methodology and Applications, 119–139.

8.1.2 Strip sampling

Strip sampling is often used for rare population inventories. Since this method typically covers a large area compared with plot sampling, it means a lot of work when applied to living trees. Since the autocorrelation between two subsequently located parts of the strip is high, this method is also inefficient for use with living trees. Observations on rare populations are typically located so far apart, however, that autocorrelation is not a problem. The workload in strip inventory is not prohibitive when rare populations are involved.

Strip sampling can be regarded as a sample plot inventory in which the plots are very large. Computationally, the easiest case is when the area is divided into N non-overlapping strips and n strips are selected from these by simple random sampling. The strips may also be selected using a certain spacing, however, in which case they may be (at least partially) overlapping. In sampling downed trees, the case may be either that 1) whole logs are measured if the butt is located on the strip, or that 2) only the parts of the logs that are located on the strip are measured. The former assumption is used in this chapter. Sometimes the same formulae may apply to both cases. For volume estimation, for instance, both definitions can be employed in the same formulae. For estimating the number of downed logs, however, the first case is more straightforward.

One problem with this approach is that the strips are usually of different lengths and areas, so that their mean is an inefficient estimator for population mean (Shiver and Borders 1996). This problem can be overcome by using the strip area as an auxiliary variable x. The estimator for the total volume (or other variable of interest) will then be (see Stehman and Salzer 2000)

$$\hat{T}_R = \hat{R}A_T = \frac{\sum_{i=1}^{n} V_i}{\sum_{i=1}^{n} A_i} A_T , \tag{8.1}$$

where V_i is the total volume of strip i , A_i is the area of strip i and A_T is the total area.

If the mean volume per hectare is of interest, it is enough to estimate the ratio $\hat{R} = \sum_{i=1}^{n} V_i \Big/ \sum_{i=1}^{n} A_i$. The estimator of variance for the estimator (8.1) is obtained with (Cochran 1977)

$$Var(\hat{R}) = \frac{1}{\mu_x^2} \frac{\hat{s}_u^2}{n} \left(\frac{N-n}{N} \right), \tag{8.2}$$

where

$$\hat{s}_u^2 = \frac{\sum_{i=1}^{n} V_i^2 + \hat{R}^2 \sum_{i=1}^{n} A_i^2 - 2\hat{R} \sum_{i=1}^{n} A_i V_i}{n-1} \quad \text{and}$$

$\mu_x = \frac{A_T}{N}$ is the mean area of strips, N is the total number of strips in the area and n is the number of sampled strips.

The variance estimator for total volume is obtained by multiplying the variance of the ratio (8.2) by A_T^2. The true mean area of the strips is often unknown and can be replaced with the mean area in the sample (Thompson 1992, p. 62).

8.1.3 Line intersect sampling

Line intersect sampling (LIS) was first presented by Canfield (1941) and was developed in the 1960s to sample the amount of slash and fuel wood remaining after logging and for estimating road lengths, for example (Warren and Olsen 1964, Matérn 1964, van Wagner 1968). Nowadays, it is often used for estimating the number of downed trees in biodiversity contexts.

Assume a line located in an area in a direction θ. This method implies that all the objects intersected by the line are included in the sample. The probability of a tree being selected is dependent on the length of the sampling line L and the effective length of the tree l', i.e. its (maximum) length perpendicular to the sampling line. If the tree is assumed to be a line (i.e. it has no width) this can be calculated directly from its angle γ with the sampling line, $l' = l \sin(\gamma)$.

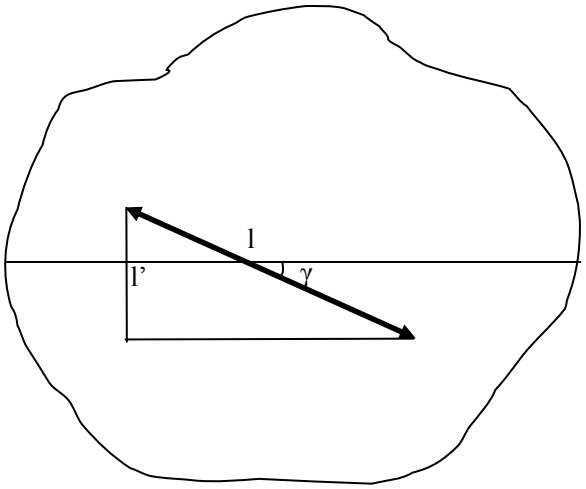


Figure 8.1 Scheme of line intersect sampling.

The total value of a variable of interest, y, per area A, according to the Horwitz-

Thompson estimator (see sections 2.1 and 2.8), is then (Kaiser 1983 p. 969)

$$\hat{T} = \frac{1}{L}\sum_{i=1}^{n}\frac{y_i}{l'(\theta)}, \tag{8.3}$$

where the effective length is given as a function of the sampling line angle θ. If the tree is not horizontal but tilted at an angle δ_i, the effective length will also depend on $cos(\delta_i)$. If the angles are measured, there is no need to make any assumptions concerning their distribution. This is quite tedious, however. If it is assumed that the sampling line angle θ varies uniformly between 0 and π, the expected value of the effective length of tree i is $E(l_i'(\theta)) = 2l_i/\pi$ (Kaiser 1983). From these results an estimator for the total value of y per square metre can be obtained with (De Vries 1973)

$$\hat{T} = \frac{\pi}{2L}\sum_{i=1}^{m}\frac{y_i}{l_i}, \tag{8.4}$$

where L is the the total length of the lines (m), l_i is the lengtht of the tree i (m), y_i is the variable of interest for unit i (e.g. volume, weight, length) and m is the number of units observed.

If the volume of the trees is defined using Huber's formula as

$$v_i = \pi\left(\frac{d_i}{2}\right)^2 l_i, \tag{8.5}$$

where d_i is the (intersectional) diameter of tree i (cm), the equation (8.4) can be transformed to (De Vries 1973 p. 8)

$$\hat{T} = \frac{\pi^2}{8L}\sum_{i=1}^{m} d_i^2 . \tag{8.6}$$

This formula gives the volume directly in cubic metres per hectare. If the interest lies in estimating the length of downed trees, a count of the trees intercepting the line is sufficient, since the length is then reduced from (8.4). If the interest lies in the volume, is will suffice to measure the diameters of the trees. If other characteristics such as the number of downed trees per hectare are desired, the lengths of the trees need to be measured as well.

The diameter of an intercepting tree can be measured either in the middle of the log, at both ends (using Smalian's volume formula) or at the point where the tree intersects with the line. The main issue is to obtain an unbiased estimate of the mean diameter of the trees. The sampling line chooses one diameter from each tree, and the mean of these gives an unbiased estimate for the mean in the population (Van

Wagner and Wilson 1976). Therefore all these methods given fairly similar results, at least in large samples.

The variance of the LIS estimator can be calculated from the variation between the lines (De Vries 1974 p. 133):

$$Var(\hat{T}) = \frac{\sum_{j=1}^{n} L_j(\hat{T}_j - \hat{T})^2}{(n-1)\sum_{j=1}^{n} L_j}, \tag{8.7}$$

where n is the number of lines, $\hat{T}_j$ is the total volume per hectare estimated from line j, $\hat{T}$ is the total volume per hectare in the area and L_j = length of line j.

The formulae presented above assume that the lines are measured in random directions, or that the trees have fallen in random directions. If these assumptions are not correct, the formulae may give inefficient estimates. In many cases, however, the downed trees may tend to fall in a certain direction, with exactly the same orientation in the extreme case. Bell et al. (1996) noted in a simulation study that one single sampling line gave large errors for certain mean angles. This probably holds true for several parallel lines, but lines in the shape of a square or L gave practically as good estimates with all mean angles.

There is no need as such to make any assumptions concerning the orientation of fallen trees in random sampling, however, as the inference is based on the design and the population of fallen trees is assumed to be fixed. If the sampling lines are located systematically, the situation is similar to ordinary systematic sampling: the inferences are based on the assumption of random orientation of the trees if formulae for random sampling are to be used.

Example 8.1

Antti Mäkinen

The inventory was carried out over an area of about 150 hectares at Tytinmäki, employing 6 east-west lines located at 100 metre intervals. The lines were directed from. The diameters of all downed trees intersecting the lines were measured at the intersection point (Table 8.1) and the volume per hectare for each line was calculated with $\hat{T}_i = \frac{\pi^2}{8L_i}\sum_{j=1}^{m_i} d_j^2$. The results for each line i are presented in the Table 8.2.

Table 8.1 Measured data.

Tree	Line	d	Tree	Line	d	Tree	Line	d	Tree	Line	d
1	1	4.6	53	2	28.7	115	3	5.8	167	5	9.1
2	1	17.8	54	2	11.1	116	3	13.7	168	5	5.7
3	1	5	55	2	8.9	117	3	14.8	169	5	11
4	1	8	56	2	6.1	118	3	5.9	170	5	7.2
5	1	5.5	57	2	8.8	119	4	26.9	171	5	9.6
6	1	9	58	2	10.4	120	4	12.4	172	5	28.4
7	1	19.3	59	2	5.5	121	4	9	173	5	7.7
8	1	7.6	60	2	16.9	122	4	11.5	174	5	14.9
9	1	10.8	61	2	15.8	123	4	5.7	175	5	7.4
10	1	7.9	62	2	14.7	124	4	8	176	5	12.2
11	1	21	63	2	6.1	125	4	9.3	177	5	8.1
12	1	8.2	64	2	6.2	126	4	12.4	178	5	10.1
13	1	13.5	65	2	13.6	127	4	7.5	179	5	13.8
14	1	16.5	66	2	5.8	128	4	8.9	180	5	7.7
15	1	10	67	2	7.8	129	4	10.3	181	5	11.5
16	1	7	68	2	5.7	130	4	7	182	5	15.9
17	1	5.5	69	3	7.4	131	4	9.5	183	5	5.2
18	1	31	70	3	5.8	132	4	16.1	184	5	7
19	1	24.7	74	3	5.8	133	4	6.2	185	5	25.1
20	1	7.5	75	3	5.5	134	4	8.7	186	5	12.5
21	1	8.4	77	3	6.1	135	4	16	187	5	24.6
22	1	13.5	80	3	7.7	136	4	11.8	188	5	13.2
23	1	16.5	81	3	5.4	137	4	31.5	189	5	8.1
24	1	9	83	3	7.4	138	4	9.2	190	5	15.8
25	1	12	84	3	5.2	139	4	6.9	191	5	5.3
26	1	8.5	87	3	7.3	140	4	22.6	192	5	5.9
27	1	5.4	89	3	11.3	141	4	12.2	193	6	6.4
28	1	5.6	90	3	6.8	142	4	8.2	194	6	10.7
29	1	5.8	91	3	10.4	143	4	17.7	195	6	13.3
30	1	18	92	3	29.3	144	4	5	196	6	5.2
31	1	9	93	3	5.1	145	4	8.6	197	6	28.5
32	2	9	94	3	9.9	146	4	13.8	198	6	12.5
33	2	22.4	95	3	25.7	147	4	29.2	199	6	15.8
34	2	11.8	96	3	17.9	148	4	7.5	200	6	14.8
35	2	7.4	97	3	18.9	149	4	12.5	201	6	5.4
36	2	7	98	3	9.7	150	4	16	202	6	9.9
37	2	13.4	99	3	6.7	151	4	12	203	6	5
38	2	12	100	3	7.5	152	4	10.9	204	6	14.6
39	2	33.4	101	3	14.7	153	4	14.1	205	6	7
40	2	14.5	102	3	13.6	154	4	11.2	206	6	19.8
41	2	7.2	103	3	7.3	155	4	6	207	6	7.3
42	2	6.5	104	3	5.9	156	4	5.8	208	6	12.4
43	2	18.3	105	3	14	157	4	5.4	209	6	11.6
44	2	26.2	106	3	11.3	158	4	6	210	6	23.2
45	2	11.2	107	3	5.4	159	4	9.7	211	6	16.8
46	2	7.8	108	3	11.2	160	4	6.3	212	6	6.7
47	2	11.4	109	3	5.8	161	4	14.6	213	6	14.9
48	2	27.7	110	3	7.7	162	5	6.9	214	6	8.5
49	2	10.8	111	3	13.7	163	5	5.2			
50	2	6.2	112	3	9.8	164	5	11.5			
51	2	8.5	113	3	11.2	165	5	9			
52	2	24.3	114	3	28.6	166	5	8.2			

Table 8.2 The line results.

i	$D_i = \sum_{j=1}^{m_i} d_j^2$	L_i	$\hat{T}_i = \frac{\pi^2}{8L_i} D_i$	$L_i(\hat{T}_i - \hat{T})^2$
1	5238.35	1900	3.401345	3003.639
2	7909.99	1700	5.740329	1988.981
3	5973.66	1800	4.094282	573.3578
4	7420.71	1300	7.042257	7385.942
5	4849.16	1400	4.273151	208.0733
6	4104.17	1300	3.894859	758.4263

The volume per hectare is then the (weighted) mean of T_i or

$$\hat{T} = \frac{\pi^2}{8L}\sum_{i=1}^{6} D_i = \frac{\pi^2}{8 \cdot 9400} \cdot 35496.04 = 4.659$$

and the estimated standard deviation is

$$S_e(\hat{T}) = \sqrt{\frac{\sum_{i=1}^{6} L_i (T_i - T)^2}{(6-1)9400}} = \sqrt{\frac{13918.42}{(6-1)9400}} = 0.544 .$$

8.1.4 Adaptive cluster sampling

Adaptive cluster designs have been discussed at least since the work of Wald in 1947. In an adaptive design the probability of selecting a new unit depends on the value of the variable of interest y in the previous unit. This kind of design is necessarily sequential (Thompson 1990, Thompson and Seber 1996). Adaptive designs have been regarded as useful in cases where some rare characteristic is clustered in the population. For instance, it could be assumed that given one individual of a rare species, other individuals are also likely to exist nearby. Thus concentrating the sample in the neighbourhood of the one known individual is likely to produce others. The neighbourhood may be defined using spatial proximity, or other proximity measures.

The basic design for adaptive cluster sampling includes an initial sample of size n_1, selected using simple random sampling. The selection could be made either with or without replacement (see Chapter 2), but a design without replacement is assumed in this chapter. The mean for this sample is an unbiased estimator of the population mean.

It is assumed that for each sampling unit i there is a neighbourhood A_i, which also includes the unit i itself. If the initial sample is based on a grid of square units, (Figure 8.2), the neighbourhood can be defined, for instance, in terms of

adjacent squares to the left, right, top and bottom of unit *i*. The neighbourhood does not depend on the values of *y* in the units. The neighbourhood is also symmetric, i.e. if *i* is a neighbour to *j*, then *j* is also a neighbour to *i*.

The selection of additional units from the neighbourhood depends on the condition *C*, which can, for example, be defined so that it is satisfied by every value of *y* larger than or equal to a predefined value *c*. If a sample unit *i* satisfies the condition *C*, all the units in its neighbourhood will be included in the sample. If any of those units satisfies the condition, then its will also be included, and so on.

All the units selected as a result of first selecting unit *i* for the initial sample belong to the same cluster, and all the units in one cluster that satisfy condition *C* belong to a same network. Consequently, selecting any of the units in the network results in selecting all the other units as well. The units in the cluster that do not satisfy the condition, i.e., do not belong to the network, are called edge units. Selection of an edge unit does not result in the selection of any other units. These edge units are regarded as networks of size one.

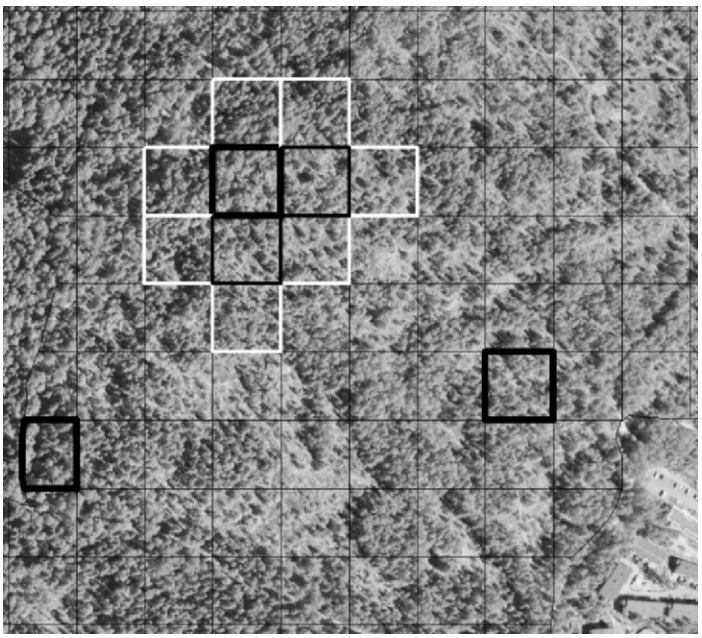


Figure 8.2 Adjusted cluster sampling based on squares. The first-order sample squares are delimited with thick black lines and the additional units with thinner lines. The additional units satisfying condition C are delimited with black lines and those not satisfying the condition with white lines.

Thus each unit will be included in the sample if a) any unit of the network it belongs to is selected, or b) any unit of the network of which unit i is an edge unit is selected (Thompson 1990). Assume m_i to be the number of units in the network to which unit i belongs and a_i to be the number of units in networks of which unit i is an edge unit. Then a_i will be zero if unit i belongs to a network and m_i will be one if unit i is an edge unit. The probability p_i of selecting unit i in any one of n_1 draws will then be

$$p_i = \frac{m_i + a_i}{N} \tag{8.8}$$

and the probability of unit i being included in all the draws will be (Thompson 1990)

$$\alpha_i = 1 - \binom{N - m_i - a_i}{n_1} \Big/ \binom{N}{n_1}. \tag{8.9}$$

In this kind of sample, the classical sample mean is a biased estimator. In principle, a Horwitz-Thompson estimator (see Chapter 2.1) could be used with the inclusion probabilities, but some of the a_i:s, i.e., sizes of networks for which a_i is an edge unit, may be unknown. Therefore the estimator is modified so that only the initial sample of n_1 units and the units belonging to the networks (and satisfying the condition) are used. The modified Horwitz-Thompson estimator is then calculated using the inclusion probabilities for those units, to yield

$$\alpha_i^* = 1 - \binom{N - m_i}{n_1} \Big/ \binom{N}{n_1}. \tag{8.10}$$

If an indicator variable J_i is defined as having the value 0 if the unit i does not satisfy the condition or does not belong to the initial sample and the value 1 otherwise, an unbiased estimator for the mean is obtained using (Thompson 1990)

$$\hat{\bar{y}}_{HT*} = \frac{1}{N} \sum_{i=1}^{v} \frac{y_i J_i}{\alpha_i^*}, \tag{8.11}$$

where v is the number of distinct units in the sample.

To obtain a variance estimator for this, the notation is changed to include distinct networks k instead of units i. The sum of the values of y in network k is denoted as $y_{k.}$. The inclusion probability α_i^* is the same for all units in network k and is denoted with π_k. The probability of one unit belonging to networks j and k is defined as

$$\pi_{jk} = 1 - \frac{\binom{N-m_j}{n_1} + \binom{N-m_k}{n_1} + \binom{N-m_j-m_k}{n_1}}{\binom{N}{n_1}}, \quad (8.12)$$

and an unbiased estimator for the variance of $\hat{\bar{y}}_{HT*}$ would be

$$\mathrm{var}(\hat{\bar{y}}_{HT*}) = \frac{1}{N^2}\sum_{k=1}^{\kappa}\sum_{j=1}^{\kappa} y_k . y_j . (\pi_{kj} - \pi_k \pi_j)/(\pi_k \pi_j \pi_{kj}), \quad (8.13)$$

where κ is the number of distinct networks. Estimates for the mean and its variance can also be calculated with a modified Hansen-Hurwitz type estimator (Thompson 1990).

Adaptive schemes have been used in forestry by Roech (1993, 1994) and Acharya et al. (2000), for instance. Roech (1993) used a probability proportional to size (i.e. point sampling-type estimator) instead of simple random sampling in the initial sample. This type of sampling is potentially very efficient, but may be inconvenient in the field as the final sample size cannot be determined beforehand.

8.1.5 Transect and point relascope sampling

In transect relascope sampling (TRS), logs on the forest floor are viewed using a wide-angle relascope. All trees of a length great enough to fill the angle-gauge at any point on the survey line are included in the sample (Ståhl 1998). In point relascope sampling (PRS), on the other hand, trees are included in the sample only if they fill the angle-gauge when viewed from certain sampling points (Gove et al. 1999).

Estimation in transect relascope sampling (Fig 8.2) is based on the Horvitz-Thompson estimator. The estimator for the total value T of any variable of interest is obtained as (Ståhl 1998)

$$\hat{T} = D\sum \frac{y_i}{l_i(1/\sin v + \cot v \cos w_i)}, \quad (8.14)$$

where D is the distance between the lines (= A/L , i.e. the total area divided by the length of the line), v is the angle of the relascope , l_i = the length of tree i and w_i the angle between tree i and the line.

The probability of a log being included in the sample is calculated as the width h of its inclusion area perpendicular to the survey line divided by the distance D between the lines (Figure 8.3).

However, if it can be assumed that the direction of the transects is random, or that the logs have fallen in random directions, the angle w does not have to be

measured. Then the formula can be simplified (as in the LIS case) to

$$\hat{T} = D\sum \frac{y_i}{l_i(1/\sin v + 2/\pi \cot v)}. \quad (8.15)$$

If the variable of interest is the total length of the fallen trees, the formula can be further simplified, as y_i and l_i cancel each other out. Assuming that the true area A is known, that n transects of fixed length L are laid out in random directions, and that y_{ki} is the volume of log i on transect k and l is its length, the estimator for the total volume can be presented as (Ringvall et al. 2001)

$$\hat{T} = \frac{A}{nL}\left(\frac{1}{\sin v} + \frac{2}{\pi}\cot v\right)^{-1} \sum_{k=1}^{n}\sum_{i=1}^{m_k} \frac{y_{ki}}{l_{ki}}. \quad (8.16)$$

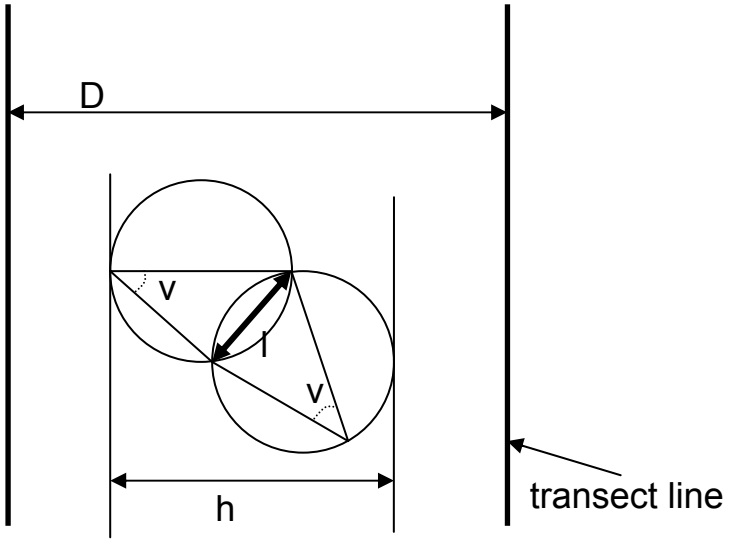


Figure 8.3 The scheme for transect relascope sampling. The tree is represented by the thick arrow. It can be seen with the angle v from any point in the two circles. The measurer cruises the transect line and measures the tree if the transect goes through either of these circles (i.e. the transect goes between the thin lines which define the width of the inclusion area h). The tree in the figure is not included in the sample, since the transect line does not intercept h.

As in angle-count sampling, the first term (excluding area A) can be interpreted here as a relascope factor λ, while l_{ki}/λ is the inclusion probability of the trees. This differs from normal angle-count sampling, however, in that the angles v are much larger. The estimator is comparable to LIS, but it is possible to draw more sample trees with the same sampling line length L. The estimator of variance can be calculated as for LIS, namely by calculating the variation between the transects.

In the case of point relascope sampling, an estimate for a variable y interest for the entire tract, based on a single sampling point k, is estimated as follows (Gove et al. 1999, 2002):

$$\hat{T}_k = A\left(\frac{\pi - v + \sin v \cos v}{2\sin^2 v}\right)\sum_{k=1}^{m_k}\frac{y_{ki}}{l_{ki}^2} = A\lambda\sum_{k=1}^{m_k}\frac{y_{ki}}{l_{ki}^2}, \tag{8.17}$$

where A is the tract area, λ is the relascope factor, which is dependent on the relascope angle v, m_k is the number of observations made from point k and l_{ki} is the length of log i as observed at point k.

As the sampling probability in point relascope sampling is proportional to the squared length of downed trees (length in transect relascope sampling), an estimate for the squared length of downed trees can be obtained simply by counting the trees filling the angle-gauge.

If the points are selected at random, the estimate for the tract total will be the average of the point estimates, and the variance can be obtained from the variation between the points, as in SRS (Gove et al. 2002):

$$\mathrm{var}(\hat{T}) = \frac{1}{n(n-1)}\sum_{k=1}^{n}\left(\hat{T}_k - \hat{T}\right)^2. \tag{8.18}$$

The transect and point relascope sampling methods require slope corrections (section 4.4) as well as normal plot-based methods (Ståhl et al. 2002).

8.1.6 Guided transect sampling

Variables such as downed tree volume might be very difficult to see from remote sensing material, but it is often possible to observe other variables that are correlated with them and in this way to distinguish those parts of the area that are of greatest interest. In guided transect sampling, remote sensing material is used as auxiliary information in order to increase the probability of a transect passing through an area of interest.

Guided transect sampling is a two-stage sampling method. In the first stage, strips of large width are systematically located in the area to be sampled and divided into a grid of cells (Figure 8.4). The objects to be sampled are then selected from among the grid cells in the strips to form a route or strip within them (Figure 8.5). The idea is to select the grid cells forming the route with probabilities proportional to covariate values. The selected route is measured on strip survey principles, for example.

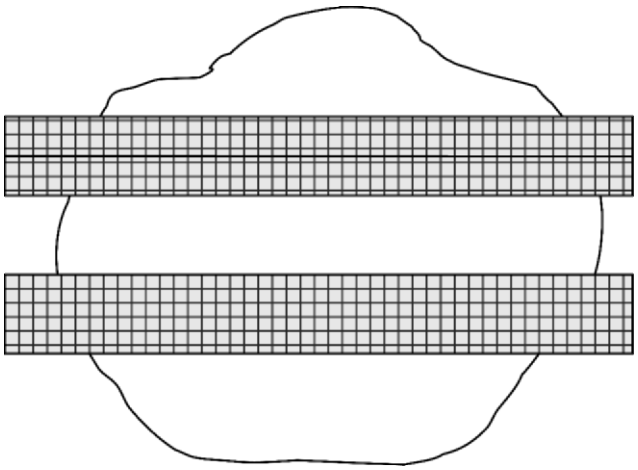
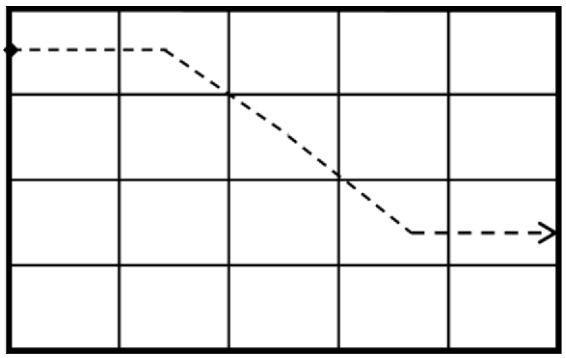


Figure 8.4 Two transects selected from an area.



Figuer 8.5 A route within one transect. .

The route, i.e. the grid cells to be measured, can be selected in several ways, e.g. by allowing only transitions from one cell to a neighbouring cell in an onward grid cell column (Figure 8.4), or else transitions to any cell in an onward column (within the first-phase strip). Furthermore, a probability can be calculated for each transition, so that the route is formed step by step. Another possibility is to calculate the probability for the whole route at one time. In this case, a large number of possible routes are first generated without considering the covariate data and the final route is selected from among these, based on PPS sampling using the sum of the covariate values of the grid cells through which the route passes (scaled to the sum of that for all routes) as the probability value (Ståhl et al. 2000); viz,

$$q = \frac{Q_i}{\sum_{k=1}^{K} Q_k}, \tag{8.19}$$

where

$$Q_k = \sum_{j=1}^{m_k} x_{kj},$$

given that x_{ki} is the covariate value for route k at cell j, m_k is the number of cells on route k, and the covariate value is the pixel value for a satellite channel or numerical aerial photo channel, for example.

Selection is based on arbitrary probabilities, and the results of the inventory are calculated using the Horwitz-Thompson estimator. The estimate for the total value is (Ståhl et al. 2000)

$$\hat{T}_i = \sum_{j=1}^{m_i} \frac{y_{ij}}{\pi_{ij}}, \tag{8.20}$$

where y_{ij} is the variable of interest in strip i and grid cell j and π_{ij} is the inclusion probability of grid cell j in strip i

In the case presented here, the inclusion probability can be calculated as the sum of the covariate values for all the routes including cell j divided by the sum of all covariate values:

$$\pi_{ij} = \frac{\sum_{s \in S} Q_s}{\sum_{l \in L} Q_l}. \tag{8.21}$$

The variance of this estimator could in principle be calculated using the Horwitz-Thompson variance estimator (2.2), but unfortunately not all the joint inclusion probabilities π_{ij} are larger than zero, as is required (i.e. only one cell is selected from each column). The variance could nevertheless be estimated from the variation between the first-stage strips.

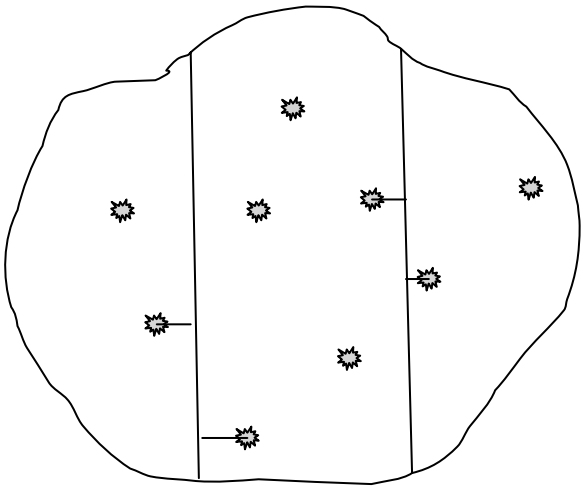


Figure 8.6 The scheme for line transect sampling.

8.2 WILDLIFE POPULATIONS

8.2.1 Line transect sampling

Line transect sampling (LTS), which has been used for estimating the density of wildlife populations (see Buckland et al. 1993), is based on (randomly located) lines on which the objects of interest (e.g. game animals) are observed. The objects themselves are assumed to be randomly distributed in the area (Burnham et al. 1980 p. 14). It is assumed that the probability of observing object i depends on the distance from the line, i.e., the longer the distance the smaller the probability of observation. There are four assumptions on the reliability of the estimates depends (Burnham et al. 1980 p. 14):

1. The probability directly on the line is one, i.e. objects on the line are never missed.
2. The objects do not move before or after being sighted, i.e. each animal is counted, and is counted only once.
3. Distances and angles are measured exactly, and
4. Sightings do not depend on each other but are independent events.

The distance is measured as a perpendicular (or right-angle) distance from the line (Figure 8.6). If it cannot be measured directly, it can be calculated from the sighting distance and the sighting angle (the angle between the transect and the line of sight) .

Given the function $g(x)$ describing the probability of observation as a function of distance x, an unbiased estimate of the density D is obtained as (e.g. Burnham et al. 1980)

$$\hat{D} = \frac{n}{2L\hat{a}}, \tag{8.22}$$

where

$$\hat{a} = \int_0^w g(x)dx, \tag{8.23}$$

w is the maximum distance at which observations are made, and $\hat{a}$ can be interpreted as half of the effective strip width.

This formula can be rewritten in the form (Schreuder et al. 1993, p. 329)

$$\hat{D} = \frac{n\hat{f}(0)}{2L}, \tag{8.24}$$

where n is the number of observations along the line, *f(0)* is the detectability curve, i.e. the probability of detection evaluated at distance 0, assuming $f(x) = g(x)/a$, i.e. *f(x)* is similar to *g(x)* except that it is scaled to integrate to one, and L is the length of the line.

The function g can be estimated using the exponential probability distribution, for example, as

$$g(x) = e^{-\lambda x}. \tag{8.25}$$

Although estimating the detectability curve is not easy, once achieved, it can be used to determine the density, as (Gates et al. 1968 p. 138)

$$\hat{D} = \frac{n}{2L\widehat{C}}, \tag{8.26}$$

where

$$\widehat{C} = \frac{\sum_{i=1}^{n} x_i}{n-1}.$$

In this and all other formulae based on (8.22), $\hat{a}$ can be interpreted in the manner of a mean sighting distance. The variance of this estimator can be calculated from the variability between the independent lines. The overall density is (Schreuder et al. 1993 p. 329)

$$\hat{D}_{LTS} = \frac{\sum_{i=1}^{R} l_i \hat{D}_i}{L}, \tag{8.27}$$

where l_i is the length of transect i, R is the number of transects and L is the total length of the transects. The variance is then

$$S^2_{D_{LTS}} = \frac{\sum_{i=1}^{R} l_i (\hat{D}_i - \hat{D}_{LTS})^2}{L(R-1)}. \tag{8.28}$$

8.2.2 Capture-recapture methods

There are many variations on capture-recapture methods for estimating the sizes of animal populations (Krebs 1998). The simplest one was developed for closed populations (i.e. it is assumed that no immigration or emigration takes place). In this approach a sample of n_1 individuals is first captured, marked and released. Then, at a later time (after the animals have been re-distributed over the area), a new sample of n_2 animals is captured and the number m of marked animals among them is calculated.

The traditional estimator for the capture-recapture scheme is the Petersen estimate, or Lincoln index (Seber 1982, 1986, Shiver and Borders 1996, p. 329)

$$\hat{N} = \frac{n_1 n_2}{m}, \tag{8.29}$$

where n_1 and n_2 are the animals sampled on the first and second occasions, respectively, and m is the number of marked animals among those captured on the second occasion. This estimate is biased, however, and another, less biased, formulation has been proposed (Pollock et al. 1990, p. 10):

$$\hat{N} = \frac{(n_1+1)(n_2+1)}{(m+1)} - 1. \tag{8.30}$$

This modified version was originally given by Chapman (1951). The first model is based on the assumption of a binomial distribution, or sampling with replacement, and the latter on a hypergeometric distribution, or sampling without replacement (Seber 1986, p. 274). Even this estimate may be highly erroneous with values of m under 10, however. The variance of this estimator can be approximated as (Seber 1982)

$$Var(\hat{N}) = \frac{(n_1+1)(n_2+1)(n_1-m)(n_2-m)}{(m+1)^2(m+2)}. \tag{8.31}$$

Many other, more complex capture-recapture methods for open populations and multiple captures have been based on this same idea (e.g. Seber 1982, 1986, Otis et al. 1978, Pollock et al. 1990).

One can also decide before the second occasion to continue until a fixed number m of marked animals are captured. In such a case the estimation is indirect, and the estimator (without replacement) is (Shiver and Borders 1996, p. 333)

$$\hat{N} = \frac{(n_1 + 1)n_2}{m} - 1 , \tag{8.32}$$

with the (approximate) variance estimator

$$Var(\hat{N}) = \frac{(n_1 - m + 1)(\hat{N} + 1)(\hat{N} - n_1)}{m(n_1 + 2)} . \tag{8.33}$$

Besides the requirement for a closed population, the basic assumptions behind the capture-recapture model are (Otis et al. 1978, Pollock et al. 1990, Schreuder et al. 1993)

1. All animals have a similar probability of capture.
2. The marked individuals are randomly distributed among the population after the initial capture.
3. The marks do not get lost or overlooked.
4. Marking does not affect the probability of recapture.

The first of these assumptions is likely to be violated, as the probability of capturing males, for instance, may be greater than that of capturing females. Likewise the fourth one may be violated, as the animals captured on the first occasion may be more wary the next time, so that the probability decreases, or in some cases they may become "trap happy", i.e. the probability of capture may increase.

8.2.3 The wildlife triangle scheme

Wildlife populations in Finland are monitored using a triangle census programme that began in the late 1980's (Lindén et al. 1996). The base unit is a permanent route of length 12 km that forms an equilateral triangle (each side is 4 km). These wildlife triangles are traced out by local hunteing clubs and censused twice a year by volunteers. Tetraonids (capercaillie *Tetrao urogallus*, black grouse *Tetrao tetrix* L, hazel grouse *Bonasia bonasia* L. and willow grouse *Lagopus lagopus* L.) are censused in a belt of width 60 m by a chain of three people in mid-August, the total census area covered by one triangle thus being 0.72 km^2. The whole monitoring programme, comprising some 1500 triangles at present, is coordinated by the Finnish Game and Fisheries Research Institute (Lindén et al. 1996). The triangles are not randomly located, however.

In the wildlife triangle scheme all birds are assumed to be detected in the

above-mentioned 60m belt. Thus the method is essentially a strip census, a special case of line transect sampling with a probability of 1 for detecting birds over the whole strip. The density can then be estimated simply by

$$D = \frac{n}{A} = \frac{n}{2l\mu}, \tag{8.34}$$

where A is the area of the strip, l is its length and 2μ is its total width (Högmander 1995).

In winter counts, when animal tracks in the snow are counted, the situation is more complicated. The counting is done either after a snowfall or by checking the triangle twice and either marking or covering the tracks on the first occasion, so that the counting proper is done the next morning (Lindén et al. 1996). All tracks intercepting the triangle are counted. Counts of this kind are used for calculating the relative densities of 34 mammal species, including mountain and brown hares, red and flying squirrels, red and arctic foxes, pine marten and so on. These relative densities could also be transformed to absolute densities, but such calculations are not usually made.

REFERENCES

Acharya, B., Bhattarai, G., de Gier, A. and Stein, A. 2000. Systematic adaptive cluster sampling for the assessment of rare tree species in Nepal. Forest Ecology and Management 137:65-73.

Bebber, D.P. and Thomas, S.C. 2003. Prism sweeps for coarse woody debris. Canadian Journal of Forest Research 33:1737-1743.

Bell, G., Kerr, A., McNickle, D. and Woollons, R. 1996. Accuracy of the line intersect method of post-logging sampling under orientation bias. Forest Ecology and Management 84:23-28.

Buckland, S.T., Anderson, D.R., Burnham, K.P. and Laake, J.L. 1993. Distance sampling. Chapman & Hall.

Burnham, K.P., Anderson, D.K. and Lake, J.K. 1980. Estimating of density from line transect sampling of biological populations. Wildlife Monographs 72. The Wildlife Society. Washington DC. 202 p.

Canfield, R.H. 1941. Application of the line interception method in sampling range vegetation. Journal of Forestry 39:388-394.

Chapman, D.G. 1951. Some properties of the hypergeometric distribution with applications to zoological censuses. Univ. Calif. Publ. Stat. 1:131-160.

Cochran, W.G. 1977. Sampling techniques. 3rd edition. Wiley, New York.

Ducey, M.J., Jordan, G.J. and Valentine, H.T. 2002. A practical modification of horizontal line sampling for snag and cavity tree inventory. Canadian Journal of Forest Research 32:1217-1224.

Gates, C.E., Marshall, W.H. and Olson, D.P. 1968. Line transect method of estimating grouse population densities. Biometrics 24:135-145.

Gove, J.H., Ringvall, A., Ståhl, G. and Ducey, M.J. 1999. Point relascope sampling of downed coarse woody debris. Canadian Journal of Forest Research 29:1718-1726.

Gove, J.H., Ducey, M.J. and Valentine, H.T. 2002. Multistage point relascope and randomized branch sampling for downed coarse woody debris estimation. Forest Ecology and Management 155: 153-162.

de Vries, P-G. 1973. A general theory on line intersect sampling with application to logging residue inventory. Mededelingen Landbouwhogeschool Wageningen. Nederland. 73-11. 23 p.

de Vries, P.G. 1974. Multi-stage line intersect sampling. Forest Science 20:129-133.

Högmander, H. 1995. Methods of spatial statistics in monitoring of wildlife populations. Jyväskylä. Studies in computer science, economics and statistics 25. 98 p.

Kaiser, L. 1983. Unbiased estimation in line-intercept sampling. Biometrics 39:965-976.

Krebs, C.J. 1998. Ecological Methodology. 2nd edition. Addison-Wesley Educational Publishers, Inc.

Lindén, H., Helle, E., Helle, P. and Wikman, M. 1996b. Wildlife triangle scheme in Finland: methods and aims for monitoring wildlife populations. Finnish Game Research 49:4-11.

Otis, D.L., Burnham, K.P., White, C.G. and Anderson, D.R. 1978. Statistical inference from capture data on closed animal populations. Wildlife Monographs No. 62.

Pollock, K.H., Nichols, J.D., Brownie, C. and Hines, J.E. 1990. Statistical inference for capture-recapture experiments. Wildlife Monographs. The Wildlife Society, Washington DC. 97 p.

Ringvall, A. 2000 Assessment of sparse populations in forest Inventory. Development and evaluation of probability sampling methods. SLU Silvestria 151.

Ringvall, A., Ståhl, G., Teichmann, V., Gove, J.H. and Ducey, M.J. 2002. Two-phase approaches to point and transect relascope sampling of downed logs. Canadian Journal of Forest Research 31:971-977.

Roech, F.A. Jr. 1993. Adaptive cluster sampling for forest inventories. Forest Science 39:655-669.

Roech, F.A. Jr. 1994. Incorporating estimates of rare clustered events into forest inventories. Journal of Forestry 92:31-34.

Schreuder, H.T., Gregoire, T.G. and Wood, G.B. 1993. Sampling Methods for Multiresource Forest Inventory. John Wiley and Sons. New York. 446 p.

Seber, G.A.F. 1982. The estimation of animal abundance and related parameters. New York, Macmillan.

Seber, G.A.F. 1986. A review of estimating animal abundance. Biometrics 42:267-292.

Shiver, B.D. and Borders, B.E. 1996. Sampling techniques for forest resources inventory. 356 s.

Stehman, S.V. and Salzer, D.W. 2000. Estimating density from surveys employing unequal-area belt transects. Wetlands 20:512-519.

Ståhl, G. 1998. Transect relascope sampling – a method for the quantification of coarse woody debris. Forest Science 44:58-63

Ståhl, G., Ringvall, A. and Lämås T. 2000. Guided transect sampling for assessing sparse populations. Forest Science 46:108-115.

Ståhl, G., Ringvall, A. and Fridman, J. 2001. Assessment of coarse woody debris – a methodological overview. Ecological Bulletins 49:57-70.

Ståhl, G., Ringvall, A., Gove, J.H. and Ducey, M.J. 2002. Correction for slope in point and transect relascope sampling of downed coarse woody debris. Forest Science 48:85-92.

Thompson, S. K. 1990. Adaptive cluster sampling. Journal of American Statistical Association 85: 1050-1059.

Thompson, S.K. 1992. Sampling. John Wiley, New York.

Thompson, S.K. and Seber, G.A.F. 1996. Adaptive sampling. John Wiley & Sons. New York.

van Wagner, C.E. 1968. The line intersect method in forest fuel sampling. Forest Science 14:20-26.

van Wagner, C.E. and Wilson, A.L. 1976. Diameter measurement in the line intersect method. Forest Science 22:230-232.

Warren, W.G. and Olsen, P.F. 1964. A line intersect technique for assessing logging waste. Forest Science 10:267-276.

Williams, M.S. and Gove, J.H. 2003. Perpendicular distance sampling: an alternative method for sampling downed coarse woody debris. Canadian Journal of Forest Research 33:1564-1579.

CHAPTER 9

INVENTORIES OF VEGETATION, WILD BERRIES AND MUSHROOMS

MATTI MALTAMO

University of Joensuu, Finland

9.1 BASIC PRINCIPLES

Analysis of the vegetation cover is an important part of plant ecology, and the monitoring of temporal changes in the abundance of different plant species is important in relation to the biodiversity aspects, for example. In addition, floristic mapping produces information on species ranges and the abundance of rare plant species. The abundance and occurrence of understorey plant species has also been used as an indicator of site fertility. Assessment of the vegetation forms a part of some national forest inventories, as on the permanent sample plots of the National Forest Inventory (NFI) in Finland.

The aims of specific inventories of wild berries and mushrooms differ from those of other vegetation inventories, however, as interest may be focused on only the part of the population, those berries that are important for picking. Important aspects are then the prediction of annual yields and the time of ripening and the analysis of regional variability in yields.

9.2 VEGETATION INVENTORIES

9.2.1 Approaches to the description of vegetation

Vegetation science examines the relationship between the occurrence or abundance of plant species and environmental factors (Lawesson 2000). Different concepts can help us to understand variations and changes in vegetation patterns. The nature of vegetation stands can be seen as continuous or discontinuous, leading to two contrasting views (Whittaker 1962): 1) the continuum concept, in which variations in vegetation in response to environmental factors are continuous, and 2) the

A. Kangas and M. Maltamo (eds.), Forest Inventory – Methodology and Applications, 141–153.

community-unit theory, in which the occurrence of vegetation is expected to follow natural groups of species. There are more or less discontinuities between vegetation stands, and these form integrated plant communities (c.f. Austin and Smith 1989).

Certain countries have long traditions in vegetation surveys, and there are many different approaches and theories for the description of vegetation. According to Økland (1990), vegetation classifications usually include three phases: 1) the analytic phase, in which homogenous stands are selected, one or more sample plots are defined in each stand and the vegetation of these plots is analysed, 2) the synthetic phase, in which the results are tabulated according to the similarities and differences in species composition between the plots, and 3) the syntaxonomic phase, in which the plots are arranged into plant communities according to the tradition followed.

The Central European tradition of classifying vegetation into plant communities follows the Braun-Blanquet system, whereas in the Nordic countries attention is paid most to the quantitative differences in species abundances. Other approaches include the Anglo-American school, which uses a classification of vegetation types according to the dominance by one or more species (Whittaker 1978). In Russia, Sukachew (1928) recognised ecological series of plant units somewhat similar to those used in Finland (Whittaker 1978).

The basic ideas of the Braun-Blanquet approach are the following (Braun-Blanquet 1932, Kent and Coker 1992):

1. The floristic composition of plant communities is used to classify types of vegetation. In the field, sample plots (relevés) are located subjectively in homogeneous vegetation stands, and a minimum area for each is determined by studying the number of plant species, first within a small area and then increasing the plot area until the number no longer increases.

2. Species abundance is estimated using a simple class scale which links shoot frequency with coverage. The classes are the following: one or a few individuals, occasional and less than 5% of total plot area , abundant and with very low cover or less abundant but with higher cover (in any case less than 5%), very abundant and less than 5% cover, 5-12.5%, 12.5-25%, 25-50%, 50-75% and 75-100% of cover (Økland 1990).

3. Diagnostic species whose ecological properties are the most effective indicators of the vegetation stands are used to organize the data into a hierarchy of plant communities. The fundamental unit of this classification is the plant association, which has a characteristic species combination.

Statistical methods play only a minor role in the Braun-Blanquet approach. More information about this method can be found in the textbooks of Whittaker (1978), Økland (1990) and Kent and Coker (1992), for example.

The Nordic approach also includes similar basic phases of classification to those of the Braun-Blanquet approach, but the main emphasis is on quantitative differences in species abundance (Salemaa et al. 1999). The abundance of a plant

species is usually estimated using coverage or frequencies. Coverage estimates are classified to form scales (see 9.2.2). Vegetation data are usually collected from a large number of small sample plots, and a fixed sampling design has been employed more recently.

Gradient based approaches to vegetation monitoring are emphasised in the Nordic countries. The term ecological gradient can be defined as a gradual change in any ecological factor (Økland 1990), i.e. it is assumed that biotic and abiotic conditions vary along continuous gradients to form a complex gradient. In such a case vegetation and site classifications can be made simultaneously and lead to a non-hierarchical, multidimensional classification of sample plots along gradient axes (Økland 1990).

The site-type approach has been used in Finland for the classification of forest site types. The Finnish botanist A.K. Cajander developed a system in which the species of the ground and field layers are used as indicators of site properties (Cajander 1909, 1913). Site types are characterized by dominant, constant, differential and characteristic species, and a range of these types including all successional stages and parallel types is used in each region. A corresponding approach has also been adopted to the characterization of Finnish mires (Ruuhijärvi 1960).

9.2.2 Recording of abundance

The abundance of a species is recorded using either qualitative or quantitative characteristics (Økland 1990). A typical qualitative measure is presence/absence (Økland 1990, see also Ståhl 2002), while quantitative indicators include cover estimation, frequency in sub-plots and point frequency. Plant biomass has also been used as a measure of abundance, but since this requires harvesting of the plants, it cannot usually be employed on a large scale or on permanent plots (Salemaa et al. 1999).

In the case of cover estimation, the percentage plant cover or various cover and cover-abundance scales can be used. These values are usually assessed visually in the field. It is also possible to use automatic image analysis methods, e.g. digitized photographs, for vegetation analysis, but their usefulness is dependent on the vertical structure of the vegetation (Vanha-Majamaa et al. 2000). It is also worth noting that detection is related to the size of the plant(s) and the resolution of the images.

Cover estimates are usually subjective, vary between observers and include considerable sampling error (Lawesson 2000). A historical example of a cover scale used in the Nordic countries is Norrlin's abundance-density scale, which is based on shoot densities measured in 10 grades (Pakarinen 1984). The values 1-7 are related to the average distances between plant specimens, the whereas the highest values (8-10) are defined by the mixture of other species (Pakarinen 1984). A corresponding classification is Hult's five-grade scale and its later modifications.

The first application of direct coverage estimation was the use of decimal cover classes 1-10 (0.1, 0.2, …, 1.0) by Kujala (1936). Nowadays, direct percentage

cover is the main method used to assess the abundance of plant species in Finland, although some rounding off of percentages higher than 5% may take place. A scale of 0.1, 0.2, 0.5, 0.7, 1, 2, 5, 7, 10, 15, 20, 25 , 30, 40, …, 90, 93, 95, 97, 98, 99 and 100% is used in the NFI, for example (Tonteri 1990). Cover classes are also used to speed up fieldwork.

The description of abundance in terms of frequency requires recording of the occurrence of the plant species in subplots. Correspondingly, in the case of point frequency a regular or random arrangement of pins is placed on a sample plot and the touch frequency of each species is calculated to provide a measure of abundance (Økland 1990). Methods which include the measurement of frequencies are more time-consuming than ones based on cover estimation.

9.2.3 Sampling methods for vegetation analysis

Vegetation studies are usually carried out by means of sampling. According to Økland (1990), there are three main steps in the sampling of vegetation:

1. Placement of sample units
2. Determination of plot size and shape
3. Determination of the number of sample plots.

Selective (subjective) sampling is a widely used method in conjunction with the Braun-Blanquet approach. The statistical properties of this method are poor, however, and statistical tests of species abundance or areal estimates are not always valid (Økland 1990). The representation of rare species and vegetation types can be guaranteed, however, since these aspects can be emphasized when selecting the plots. The time required for plot selection is also minimal.

Random sampling meets the statistical prerequisites and is therefore a good choice for the estimation of species abundance and the definition of site types. The extremes on the gradient, e.g. rare species and vegetation types, may not be found, however, and redundant information will be collected. The sample may also be statistically clustered and the designation of plots is time-consuming (Økland 1990). Therefore modifications of basic random sampling are often recommended (Jongman et al. 1987). The use of different methods of stratified (restricted) random sampling at least means that the selection of plots in the field is more effective.

Systematic sampling is also widely used in vegetation studies (Jongman et al. 1987). Sampling can be done on two-dimensional or one-dimensional grids, the latter being called transects (Økland 1990). These transects can be open or closed depending on whether all the plots defined are chosen for the sample or not. In an open transect some plots may be rejected, but in a closed transect all the plots are measured. Systematic sampling can produce accurate coverage of a given area. An example of systematic sample design including open transects and different levels of subplot is presented in Figure 9.1.(Økland and Eilertsen 1993).

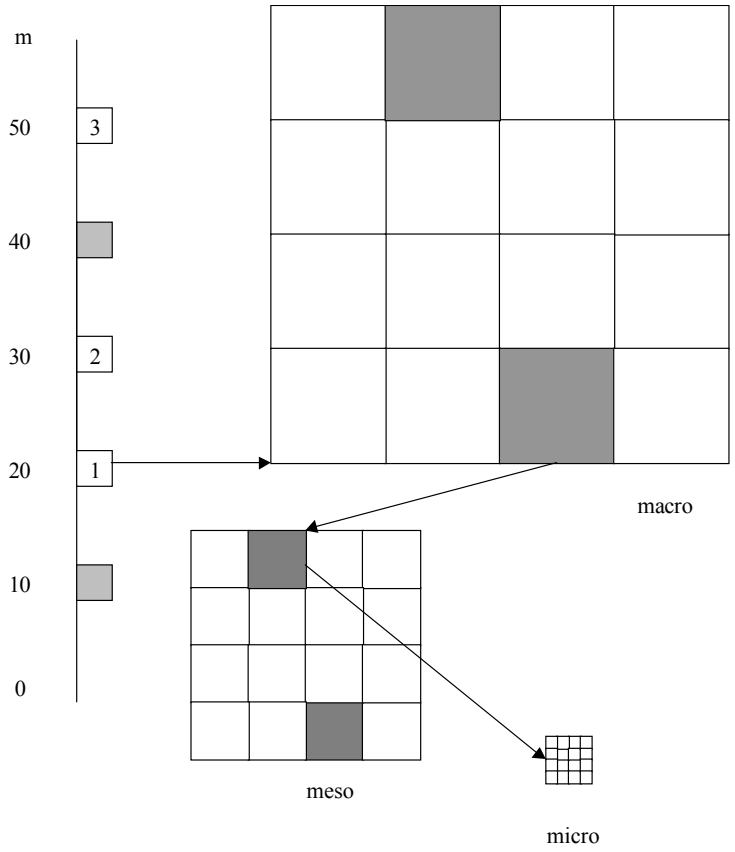


Figure 9.1 A sampling design for analysing boreal forest vegetation, according to Økland and Eilertsen (1993). The location of open transects is given on the left. Putative macro-level sample plots are delimited every tenth metre along the transect and are accepted or rejected according to given criteria. These macro plots, each 16 m^2, are then divided into 16 subplots of 1 m^2 each and two are chosen at random as meso-level plots and further divided into 16 subplots, each of size 0.0625 m^2, two of which (in corresponding locations to the meso plots) are taken as micro plots and again divided into 16 subplots. Finally, the presence/absence of each species is recorded in each subplot at the meso and micro-levels.

The sample units in vegetation surveys have traditionally been square in shape, although other alternatives such as circular or rectangular plots have been used. Measurement of a square plot is easy and it can also be easily divided into subplots. The benefit of a rectangular plot lies in the ability to describe homogeneous vegetation in a clustered plant distribution, whereas a circle has only a minor edge effect compared with other shapes (Lawesson 2000).

The optimal size of plot depends on the homogeneity of the plant

communities and the representativeness of the plots (Økland 1990). The homogeneity of plant species can be defined as the existence of an equal number of individuals in all parts of the area. Correspondingly, the species in a plant community should be homogeneously distributed. Finally, ecological homogeneity can be defined by specifying a range of variation along each complex gradient that should not be exceeded within in an individual plot (for more details, see Økland 1990).

The requirement of homogeneous sample plots inevitably leads to a small size, since variation on the most important gradients should be greater between plots than within them. Small-scale changes in the vegetation may not be detected on large plots, whereas these will more probably have a species composition which reliably reflects the environmental conditions. This is referred to as the representativeness of plots (Økland 1990).

Since there is no exact way to determine the optimal plot size it has to be decided separately in each case (see Jalonen et al. 1998, Salemaa et al. 1999). Some Finnish examples of the sizes (and number) of plots in one forest stand include ten to forty plots of 0.25 m^2 (Kujala 1936), 20 quadrats of 1 m^2 in an area of 30 x 40 m (Jalas 1962), three quadrats of either 2 or 4 m^2 Hinneri (1972) and 5-15 sample plots of size 0.25 m^2 on mires (Heikurainen 1953). Considerably larger plots of size 100 m^2 have also been used for cover estimation, however (Kujala 1964), having originally been established by the NFI for tree measurement purposes.

The number of plots required is dependent on the following aspects (Økland 1990): the expected variation in ecological conditions and vegetation in the area, the method used for defining the sample plots, plot size, the desired representation of gradients and vegetation types and the time available for the fieldwork. The sample should also ensure further data analysis and yield data that can lead to an understanding of the ecological demands of individual species.

Various aspects of sampling design in vegetation surveys have been emphasized, e.g. in the textbook of Lawesson (2000), where traditions and current aspects are considered separately for each of the Nordic country. Other reviews are those presented by Knapp (1984), Pakarinen (1984), Kenkel (1989), Økland (1990), Kent and Coker (1992) and Elzinga et al. (2001).

9.3 EXAMPLES OF VEGETATION SURVEYS

Floristic mapping has long traditions in Finland. The earliest flora was published in 1673, by Til-Landz (see Lawesson 2000), and large-scale mapping of plant species has been undertaken by Hulten (1950), by Jalas and Suominen for the 'Atlas Florae Europaea' (1967) and by Lahti et al. (1995) for a series of digital maps depicting the distribution of 1604 vascular species in Finland.

The project "Atlas of the Vascular Plants of Finland (Kurtto and Lahti 1985) divided Finland into 10x10 km quadrats which each included 100 quadrats of 1x1 km. The aim was to examine the distribution of vascular plants using as many of the smaller quadrats as possible. Nowadays 2 401 small quadrats located in 249 larger quadrats are being investigated, which means that 6.5% of the country's land

area is being examined intensively

Information on forest site types has been collected as a part of the Finnish NFI since 1921, when the first inventory was started (Ilvessalo 1927), and the third inventory, in 1951-53, assessed the vegetation on 12 000 circular plots of size 100 m^2 situated on survey lines running from south-west to north-east. Kujala (1964) published frequency maps for 189 plants included in the floristic data for this 3rd National Forest Inventory. During the 8th inventory, in 1985-1986, 3 000 permanent plots were established (Reinikainen et al. 1998), located systematically within Finland, and these were re-examined in 1995. The radius of the original plot of trees was 10 m, and the vegetation was examined on four sub-plots of size size 2 m^2 located systematically along the diameter of the plot in a south-north direction. Percentage cover was used as a quantitative measure for vegetation assessment.

Although special attention has been paid to the statistical representativeness of the NFI vegetation data (see Reinikainen et al. 1998), the sampling design has not been optimal for vegetation surveys, since it was a compromise between the inventories of the tree stock and the plants. The results of the national inventories concerning changes in the frequencies and abundances of forest and mire plants were published in the textbook by Reinikainen et al. (2001). Mäkipää and Heikkinen (2003) studied large-scale changes in the abundance of terricolous bryophytes and macrolichens in Finland, and Tonteri (1990) and Korpela (2005), for instance, have analysed the NFI vegetation data.

Pan-European monitoring of forest vegetation was launched in the EU/ICP Forest Level II Programme (Manual on methods… 1998). The Level II network in Finland consists of 31 sample areas: 27 on mineral soil sites and 4 on peatlands. As a pilot study, alternative methods for the long-term monitoring of forest vegetation were tested on 9 Finnish Level II plots in 1998 (Salemaa et al. 1999), comparing the Nordic percentage cover method and the Braun-Blanquet method. The sampling design is presented in Figure 9.2. Percentage cover was used on the small quadrats (0.25, 1 and 2 m^2) and the Braun-Blanquet scale on the larger plots (25 and 900 m^2). The results showed that there are considerable differences in the mean coverages obtained by these approaches. The average number of species increased with quadrat size ($0.25 < 1 < 2 < 25 < 900$ m^2), although in most cases it did not increase essentially after 16 quadrats (size 1 m^2 or 2 m^2) (Salemaa et al. 1999).

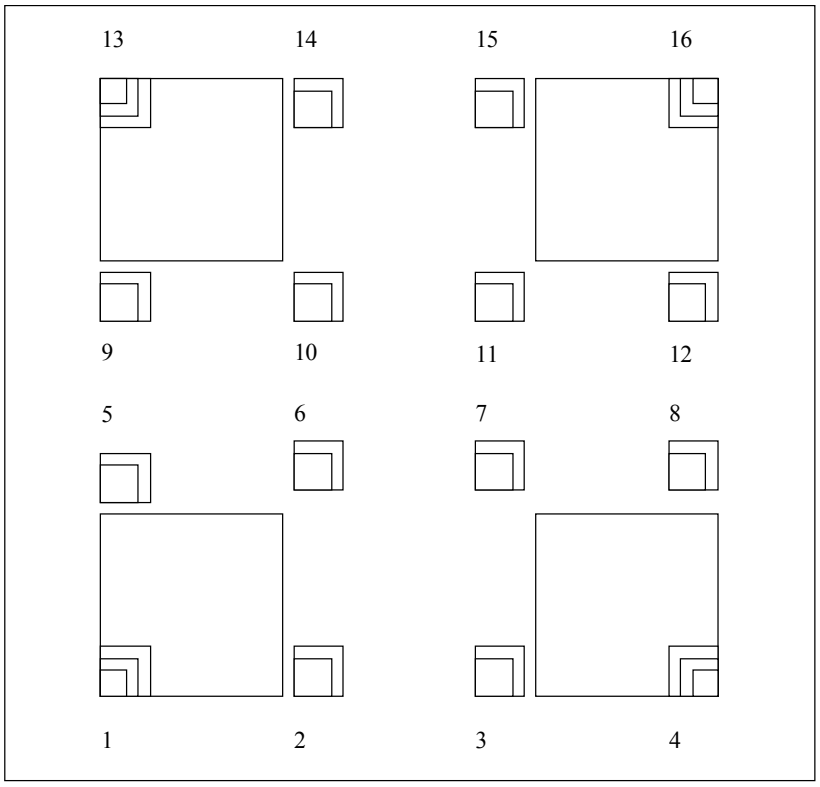


Figure 9.2 The sampling design used in a pilot study for the Finnish Eu/ICP Level II programme (Salemaa et al. 1999). For quadrat sizes, see text. In the final design a total of 16 quadrats sized 2 m^2 were marked out systematically. The occurrence of a species is also recorded outside the quadrats for areas of 400 m^2 (common sample area).

9.4 INVENTORIES OF MUSHROOMS AND WILD BERRIES

In general, berry species and macrofungi can be surveyed in the same way as vascular plants (see previous chapter). If the object of interest is non-wood forest products, however, i.e. edible wild berries and mushrooms picked for household use or trade, the methodology and aims may differ from those of a basic vegetation inventory. The regional economic importance of some species, e.g. the mushroom *Boletus edulis* in Northern Karelia, Finland, may be very high. Inventories of mushrooms and wild berries have been conducted in the Nordic countries, Russia and Poland, for instance (Eriksson et al. 1979, Kalinowski 1999, Kukuev 1999, Salo 1999), most of the studies being concerned with one municipality (Jaakkola

1983, Raatikainen and Raatikainen 1983), although national surveys have also been carried out in Sweden and Finland (Eriksson et al. 1979, Salo 1999).

The main aim of inventories of non-wood forest products is to study the yields of these and their ripening. Thus the abundance of berry plant species as such is not of great importance, as it is also for them to produce berries. In addition, there are very marked annual and regional variations in yields due to site conditions, pests and climate (Solantie 1983). It is also possible that unripe berries and very small mushrooms may be picked by people or eaten by animals before they are counted. Therefore, inventories and forecasting systems for these products must include permanent plots which are checked several times during the growing season. There also exist both empirical and expert models for the prediction of yields (Ihalainen et al. 2002, 2003).

The date of flowering and the numbers of unripe and ripe berries are recorded during the growing season (Salo 1999), and in some cases the biomass is also estimated (Laakso et al. 1990). Correspondingly, the numbers of edible mushrooms, identified by species, are usually recorded.

The sizes and numbers of sample plots have varied in different inventories of wild berries and mushrooms. In the case of cowberries (Vaccinium vitis-idaea), the size of the plot has been as small as 0.25 m^2 (also 4 and 10 m^2), whereas cloudberries (Rubus chamaemorus) have been examined on plots of size 1- 20 000 m^2 (Raatikainen and Pöntinen 1983). Saastamoinen (1982) proposed the use of circular 1 m^2 sample plots which could be measured quickly using a rake, while according to Veijalainen (1982) plot size has varied between 8-1 500 m^2 in the case of mushrooms, the optimum size being about 100 m^2.

The sampling design used in inventories of wild berries and mushrooms has also varied. Jaakkola (1983) used a systematic line inventory in which the sample quadrats were located in clusters, while in Sweden the NFI sampling design was used to define circular plots arranged in clusters, inside which wild berries were assessed on circular sub-plots (Eriksson et al. 1979). Correspondingly, in the sampling design of the 7th NFI was used eastern Finland to establish permanent plots for the monitoring of wild berries and mushrooms (Salo 1993; Figure 9.3). Three plots were located in each original NFI cluster. The location of sample plots may also be random if the area to be examined is small, e.g. one stand.

The current national system for forecasting wild berry and mushrooms yields in Finland is based on 2 200 permanent plots in 440 forest compartments (Salo 1999). Each stand possesses 5 experimental plots of 1 m^2 located subjectively in the most productive part of the stand. This network was established in 1997 and is monitored three times a year. The fieldwork is carried out by researchers at the Finnish Forest Research Institute, staff from schools of agriculture and forestry, qualified natural product advisers and members of the 4H organisation (Salo 1999). The drawback with the system is the subjective placement of plots, which means that the statistical properties of the results are questionable, and may also lead to excessively optimistic yield forecasts.

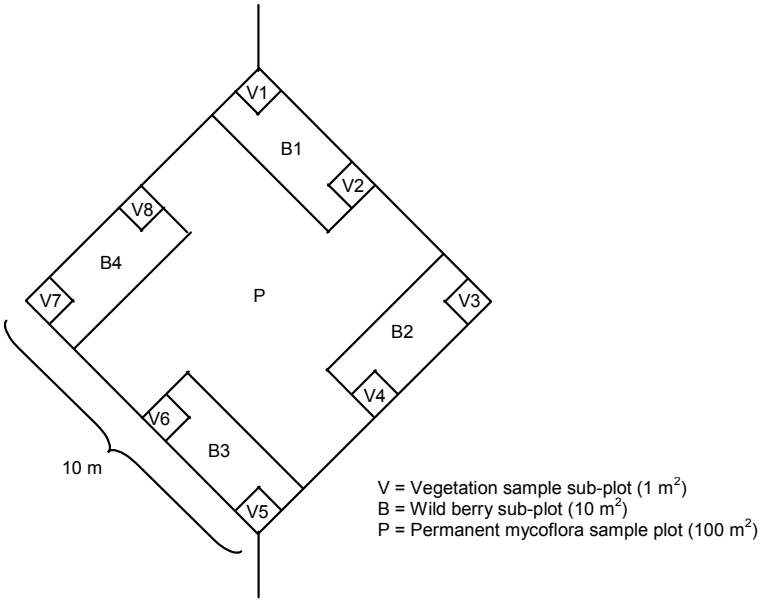


Figure 9.3 Layout of an NFI-based permanent plot (100 m^2) and location of the wild berry sub-plots, which formed one berry sample plot (40 m^2) (Salo 1993). The permanent plot also included vegetation sampling sub-plots.

REFERENCES

Austin , M.P. and Smith, T.M. 1989. A new model for the continuum concept. Vegetatio 83: 35-47.

Braun-Blanquet, J. 1932. Plant sociology: the study of plant communities (English translation). McGraw-Hill, New York. 438 p.

Cajander, A.K. 1909. Über Waldtypen. Fennia 28(2): 1-175.

Cajander, A.K. 1913. Studien über die Moore Finnlands. Acta Forestalia Fennica 2: 1-208.

Elzinga, C.L., Salzer, D.W., Willoughby, J.W. and Gibbs, J.P. 2001. Monitoring plant and animal populations. Blackwell Science, Inc. 360 p.

Eriksson, L. Ingelög, T. and Kardell, L. 1979. Blåbär, lingon, hallon. Förekomst och bärproduktion i Sverige 1974-1977. Report 16, Section of Environmental Forestry, The Swedish University of Agricultural Sciences. pp. 1-124.

Heikurainen, L. 1953. Die kieferbewachsenen eutrophen Moose Nordfinnlands. Annales Botanici Societatis Zoologicæ Botanicæ Fennicæ ´Vanamo´ 26(2): 1-189.

Hinneri, S. 1972. An ecological monograph on eutrophic deciduous woods in the SW archipelago of Finland. Annales Universitates Turkuensis A II 50: 1-131.

Hultén, E. 1950. Atlas över växternas utbredning i Norden. Generalstabens litografiska anstalts förlag. Stokjholm. 512 p.

Ihalainen, M., Alho, J., Kolehmainen, O. and Pukkala, T. 2002. Expert models for bilberry and cowberry yields in Finnish forests. Forest Ecology and Management 157: 15-22.

Ihalainen, M., Salo, K. and Pukkala, T. 2003. Empirical prediction models for Vaccinium myrtillus and V. vitis-idaea berry yields in North Karelia, Finland. Silva Fennica 37(1): 95-108.

Ilvessalo, Y. 1927. Suomen metsät. Tulokset vuosina 1921-24 suoritetuista valtakunnan metsien arvioimisesta. Summary: The forests of Suomi (Finland). Results of the general survey of the forests of the country carried out during the years 1921-24. Communicationes Instituti Forestalis Fenniae 11: 1-616.

Jaakkola, I. 1983. Rovaniemen maalaiskunnan marjasatoinventointi. Metsäntutkimuslaitoksen tiedonantoja 105: 137-143.

Jalas, J. 1962. On the use of similarity studies in forest vegetation studies. Luonnon Tutkija 66: 3-13.

Jalas, J. and Suominen, J. 1967. Mapping the distribution of European vascular plants. Memoranda Societatis pro Fauna et Flora Fennica 43: 69-72.

Jalonen, J., Vanha-Majamaa, I. and Tonteri T. 1998. Optimal sample and plot size for inventory of field and ground layer vegetation in a mature Myrtillus type boreal spruce forest. Annales Botanici Fennici 35: 191-196.

Jongman, R.H., ter Braak, C.J.F. and van Tongeren, O.F.R. 1987. Data analysis in community and landscape ecology. Pudoc Wageningen. 295 p.

Kalinowski, M. 1999. Inventory of understorey vegetation resources in Poland. In: Niskanen, A. and Demidova (eds.) Research approaches to support non-wood forest products sector development. EFI Proceedings 29. pp. 46-48.

Kenkel, N.C., Juhász-Nagy, P. and Podani, J. 1989. On sampling procedures in population and community ecology. Vegetatio 83: 195-207.

Kent, M. and Coker, P. 1992. Vegetation description and analysis. A practical approach. John Wiley & Sons. Chichester. 363 p.

Knapp, R. (ed.) 184. Sampling methods and taxon analysis in vegetation science. Handbook of Vegetation Science 4. Hague. 370 p.

Korpela, L. 2004. The importance of forested mire margin plant communities for the diversity of managed boreal forests in Finland. Metsäntutkimuslaitoksen tiedonantoja 935. 60 p. + appendices I - IV.

Kujala, V. 1936. Über die Vegetationsgrenze von Mittel- und Nord-Finnland. Communicationes Instituti Forestalis Fenniae 22(4): 5-95.

Kujala, V. 1964. Metsä- ja suokasvilajien levinneisyys- ja yleisyyssuhteista Suomessa. Communicationes Instituti Forestalis Fenniae 59(1): 1-137.

Kukuev, Y. 1999. Non-wood forest products in Northwest Russia. In: Niskanen, A. and Demidova (eds.) Research approaches to support non-wood forest products sector development. EFI Proceedings 29. pp. 53-61.

Kurtto, A, Lahti, T. 1985. Suomen kasviatlasprojekti alkaa kesällä1985. Lutukka 1: 4-5.

Laakso, S., Lehtinen, P. and Raatikainen, M. 1990. Kuusen ja männyn vaikutus mustikan esiintymiseen, kukintaan ja marjasatoon. Memoranda Societatis pro Fauna et Flora Fennica 66: 47-53.

Lahti, T., Lampinen, R. and Kurtto, A. 1995. Suomen putkilokasvien levinneisyyskartasto. Versio 2.0 (1604 karttaa tietokannassa). Helsingin yliopisto, Luonnontieteellinen keskusmuseo, Kasvimuseo, Helsinki. 23 p.

Lawesson, J., E. (ed.) 2000. A concept for vegetation studies and monitoring in the Nordic countries. Temanord 2000: 517. 125 p.

Mäkipää, R. and Heikkinen, J. 2003. Large-scale changes in abundance of terricolous bryophytes and macrolichens in Finland. Journal of Vegetation Science 14: 497-508.

Manual on methods and criteria for harmonized sampling, assessment, monitoring and analysis of the effects of air pollution on forests. 1998, 4th edition. Part VIII, Assessment of ground vegetation. UNECE Programme Coordination Centre, Hamburg. 12 p.

Økland, R.H. 1990. Vegetation ecology: theory, methods and applications with reference to Fennoscandia. Sommerfeltia Supplement 1: 1-123.

Økland, R.H. and Eilertsen, O. 1993. Vegetation-environment relationships of boreal coniferous forests in the Solhomfjell area, Gjerstad, S Norway. Sommerfeltia 16: 1-254.

Pakarinen, P. 1984. Cover estimation and sampling of boreal vegetation in northern Europe. In Knapp, R. (ed.) Sampling methods and taxon analysis in vegetation science. Handbook of Vegetation Science 4. Hague. pp. 34-44.

Raatikainen, M. and Pöntinen, M. 1983. Puolukkasadon ennustamisesta. In: Salo, K. and Sepponen, P. (eds.) Luonnonmarja- ja sienitutkimuksen seminaari, osa 1. Joensuu 6.-7.10.1982. pp. 104-115.

Raatikainen, M. and Raatikainen, T. 1983. Mustikan sato, poiminta ja markkinointi Pihtiputaalla. Summary: The berry yield, picking and marketing of Vaccinium myrtillus in the commune of Pihtipudas, northern central Finland. Silva Fennica 17(2): 113-123.

Reinikainen, A., Mikkola, K., Vanha-Majamaa, I., Nousiainen, H. and Tamminen M. 1998. Metsä- ja suokasvillisuuden seuranta VMI:n yhteydessä. In: Annila, E. (ed.) Monimuotoinen metsä: Metsäluonnon monimuotoisuuden tutkimusohjelman väliraportti. Metsäntutkimuslaitoksen tiedonantoja 705. pp. 20-73.

Reinikainen, A., Mäkipää, R., Vanha-Majamaa, I. and Hotanen, J.-P. 2001. Kasvit muuttuvassa metsäluonnossa. Kustannusosakeyhtiö Tammi. Helsinki. 384 p.

Ruuhijärvi, R. 1960. Über die regionale Einteilung der nordfinnischen Moore. Annales Botanici Societatis Zoologicæ Botanicæ Fennicæ ´Vanamo´ 31(1): 1-360.

Saastamoinen, O. 1982. Pikamenetelmä metsämarjasatojen inventointiin. In: Salo, K. (ed.) Metsämarja- ja sienisatotutkimuksen menetelmäongelmia. Metsäntutkimuslaitoksen tiedonantoja 37. pp. 31-33.

Salemaa, M., Monni, S., Royo Peris, F. and Uhlig, C. 1999. Sampling strategy for the assessments of temporal changes in ground vegetation in boreal forests. In. Raitio, H. and Kilponen, T. (eds.). Forest condition monitoring in Finland, National report 1998. Metsäntutkimuslaitoksen tiedonantoja 743. pp. 117-127.

Salo, K. 1993. The composition and structure of macrofungi communities in boreal upland type forests and peatlands in North Karelia. Karstenia 33: 61-99.

Salo, K. 1999. Principles and design of a prognosis system for an annual forecast of non-wood forest products. In: Niskanen, A. and Demidova (eds.) Research approaches to support non-wood forest products sector development. EFI Proceedings 29. pp. 35-44.

Solantie, R. 1983. Suomen luonnonmarjat, ilmasto ja sää. In: Salo, K. and Sepponen, P. (eds.) Luonnonmarja- ja sienitutkimuksen seminaari, osa 1. Joensuu 6.-7.10.1982. pp. 38-49.

Sukachew, V.N. 1932. Principles of classification of the spruce communities of European Russia. Journal of Ecology 49: 1-29.

Ståhl, G. 2002. Presence/absence sampling in vegetation surveys. In: Heikkinen, J., Korhonen, K.T., Siitonen, M., Strandström, M. and Tomppo, E. (eds.) Nordic trends in forest inventory, management and modelling. Proceedings of SNS meeting in Solvalla, Finland. April 17-19, 2001. Metsäntutkimuslaitoksen tiedonantoja 860. pp. 125-127.

Tonteri, T. 1990. Inter-observer variation in forest vegetation assessments. Silva Fennica 24: 189-196.

Vanha-Majamaa, I., Salemaa, M., Tuominen, S. and Mikkola, K. 2000. Digitized photographs in vegetation analysis - a comparison of cover estimates. Applied Vegetation Science 3: 89-94.

Veijalainen, H. 1982. Metsämarja- ja sienisatojen mittauksessa käytetyistä koealoista. In: Salo, K. (ed.) Metsämarja- ja sienisatotutkimuksen menetelmäongelmia. Metsäntutkimuslaitoksen tiedonantoja 37. pp. 20-25.

Whittaker, R.H. 1962. Classification of natural communities. The Botanical Review 28: 1-239.

Whittaker, R.H. 1978. Classification of plant communities. Dr W. Junk Publishers, The Hague, Netherlands. 408 p.

CHAPTER 10

ASSESSMENT OF UNCERTAINTY IN SPATIALLY SYSTEMATIC SAMPLING

JUHA HEIKKINEN

Finnish Forest Research Institute, Finland

10.1 INTRODUCTION

What is the best way to distribute sample plots over an inventory area? In the absence of any specific prior knowledge about the area, simple random sampling (SRS, section 2.2) is often recommended because of its objectivity and readily available design-based assessment of uncertainty. SRS can easily locate some sample plots very close together, however, and leave large gaps elsewhere. Intuitively, a more representative sample would be obtained by spreading the plots evenly over the inventory area (Figure 10.1).

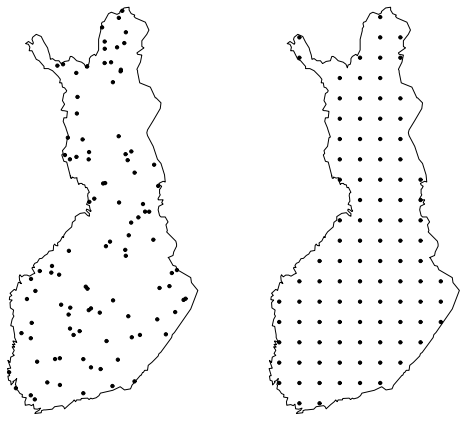


Figure 10.1 101 locations selected by simple random sampling (left) and by spatially systematic sampling (right).

A. Kangas and M. Maltamo (eds.), Forest Inventory – Methodology and Applications, 155–176.

Spatially systematic sampling is indeed commonly used in forest inventories both because it has been considered more efficient than SRS and because the fieldwork is simpler to implement. It is usually superior in efficiency if the target population is *spatially autocorrelated*, that is, if nearby values for the forest variables inventoried tend to be more similar than distant ones (for a more detailed discussion, see, for example, sections 8.9 and 8.13 of Cochran 1977). Systematic sampling can also be dangerous if the target variable varies periodically and the wavelength coincides with the sampling interval, but this can be regarded as a rare and unfortunate coincidence (see Milne 1959, Matérn 1960, Dunn and Harrison 1993).

A major problem in systematic sampling is the difficulty of assessing the sampling error. As we read in section 2.4, design-unbiased variance estimation is impossible (see also section 8.11 of Cochran 1977). The first attempts to deal with this problem were apparently made in the context of Scandinavian forest inventories in the 1920's and 1930's, and more general interest in systematic sampling arose in the 1940's (Osborne 1942, Cochran 1946, Matérn 1947, Yates 1948, Quenouille 1949). Although activity in this field of research seems to be growing again (see Dunn and Harrison 1993, Sherman 1996, Aubry and Debouzie 2000, D'Orazio 2003, Flores et al. 2003), it seems that the methods proposed by Matérn (1960) are still the most generally useful for forest inventory purposes.

The main aim of this chapter is to describe Matérn's variance estimators, which are based on local spatial differencing. The early development of such estimators is briefly described in section 10.3, and section 10.4 explains how Matérn's estimators are applied to the national forest inventory in Finland. Note that sampling error is regarded here as a means of assessing the uncertainty in inventory results on the basis of observed data. When different sampling designs are compared in the planning stage of an inventory, the sampling error needs to be assessed on different grounds, e.g. on the basis of statistical models describing typical forests (see Cochran 1946, Matérn 1960).

But a model-based approach is also needed for analysing the properties of variance estimators when systematic sampling is applied to autocorrelated populations. In particular, model-based analysis shows that Matérn's estimators are safe in the sense that they generally overestimate the sampling error. This is discussed in section 10.5, which also describes a class of statistical models appropriate for spatially autocorrelated populations and tries to shed some new light on the issue of descriptive versus analytic inference (section 3.1).

The model-based approach can be taken even further by deriving the inventory results and their variance estimators directly from the assumed statistical model. Kriging is a well-known technique for doing this with spatial models. Section 10.5 contains a brief discussion of its potential in an inventory context (see also sections 3.3 and 7.2).

Although this chapter concentrates on sampling error, this is by no means the only source of uncertainty in the results of an inventory. The effects of other kinds of error are briefly discussed in section 10.6.

Computational details are generally omitted in the examples provided in this chapter, but the computer code for reproducing the examples and the link to the freely available software applied in them (R Development Core Team 2004, Ribeiro and Diggle 2004) are given on the web page

http://www.metla.fi/pp/JuHe/pub/InventoryBook

10.2 NOTATION, DEFINITIONS AND ASSUMPTIONS

This chapter deals mainly with the problem of estimating the mean value of a forest variable y over an inventory region U, formally a bounded set in $\boldsymbol{R}^2$. It is assumed that the true value $y(u)$ of y can in principle be defined (although it is not actually observed) at each point $u \in U$. The unknown mean value to be estimated is then

$$\overline{Y}(U) = \int_U y(u)\, du / |U|,$$

where $|U|$ is the area of U. In other words, it is assumed that the target population is an infinite collection of point locations.

The observed values y_i on n sample plots, $i = 1,2,\ldots,n$, are considered to be pointwise observations $y_i = y(u_i)$ located at the centre points u_i of the plots. In reality the observations may be averages, such as estimates of the total volume of the trees on the plot divided by the plot area. But if the plots are small relative to the distance between them, they can be considered points for all practical purposes. This will avoid some unnecessary complications (see the end of section 2.1).

For simplicity, equal probability sampling is assumed, that is, the probability density for inclusion in the sample is assumed to be the same for all points of U. This requirement is naturally satisfied by simple random sampling and by *spatially systematic plot sampling*, where a regular network of sample plot centres is randomly positioned over U.

It is assumed throughout this chapter, except in sections 10.4 and 10.5.4, that $\overline{Y}(U)$ is estimated by the sample mean

$$\overline{y} = \frac{1}{n}\sum_{i=1}^{n} y_i .$$

Equal probability sampling guarantees that $\overline{y}$ is a design-unbiased estimator of $\overline{Y}(U)$.

Example 10.1 and most of section 10.3 deal with *line surveys*. In that case, y_i is the observed mean value of y over the i'th survey line (or survey strip; see the discussion of points versus plots above). To keep the formulae as simple as possible, it is assumed that all lines are of equal length, although this is rarely the case in practice. In particular, the un-weighted mean $\overline{y}$ is design-unbiased only under this assumption; in the general case, y_i should be weighted by the length of line i.

Small-area estimation is one of the important inventory problems that are not treated in this chapter. The target could be $\overline{Y}(W)$, for example, for a sub-region $W \subset U$. Rather than estimating $\overline{Y}(W)$ using the sample mean over plots within W, it may be desirable to utilise information from sample plots outside W as well through synthetic estimators of some kind (see section 7.2 and Chapter 12). Methods discussed in section 10.5.4 might then be useful.

10.3 VARIANCE ESTIMATORS BASED ON LOCAL DIFFERENCES

10.3.1 Restrictions of SRS-estimator

The design-based variance of systematic sampling (equation 2.5) measures the variability of $\overline{y}$ in hypothetical replications of the inventory obtained with repeated random shifts of the whole network of sample plots. Such replications would lead to different estimates $\overline{y}_k$, $k = 1, 2,...,K$, whose empirical variance

$$v_K(\overline{y}) = \sum_{k=1}^{K} (\overline{y}_k - \overline{Y}(U))^2 / K \tag{10.1}$$

measures the uncertainty in $\overline{y}$ due to sampling. The *design-based variance*, $\mathrm{V}(\overline{y}) = \mathrm{E}(\overline{y} - \overline{Y}(U))^2$, can be regarded as the limit of $v_K(\overline{y})$ when the number of replications, K, tends to infinity.

The square root $\mathrm{S}(\overline{y}) = \sqrt{\mathrm{V}(\overline{y})}$ is the *design-based standard error* of $\overline{y}$. The numerical results of the examples are presented in terms of standard errors, as these are easier to interpret: the width of the 95% confidence interval for $\overline{Y}(U)$ is approximately $4\,\mathrm{S}(\overline{y})$ (section 2.2). Theoretical results and formulae, on the other hand, are simpler in terms of variances. For simple random sampling,

$$s^2(\overline{y}) = \frac{1}{n(n-1)} \sum_{i=1}^{n} (y_i - \overline{y})^2 \tag{10.2}$$

is a design-unbiased estimator of $\mathrm{V}(\overline{y})$ (section 2.2). If spatial autocorrelation in y can be ignored, that is, if model (3.1) is assumed, then model-based arguments lead to an essentially identical estimator (3.14) whatever the sampling design. The main object of interest in this chapter, however, are cases with substantial spatial autocorrelation, where spatially systematic sampling is usually more efficient than SRS, and, accordingly, $s^2(\overline{y})$ should overestimate $\mathrm{V}(\overline{y})$, because its value is typically larger for systematic samples than for random samples of the same size.

Example 10.1

Ilvessalo (1923) reports the results of a line survey in two Finnish municipalities, Sahalahti and Kuhmalahti, conducted in 1912 as a pilot study for the first national forest inventory in Finland (Ilvessalo 1927). Figure 10.2 (left) shows the observed proportions of forest land on the 16 survey lines of the Ilvesvuori sub-region (about 3,000 hectares). The clear trend is due to the concentration of agricultural areas in the north-eastern part of the region; the lines run in an approximately E-W direction with their numbering starting from the south.

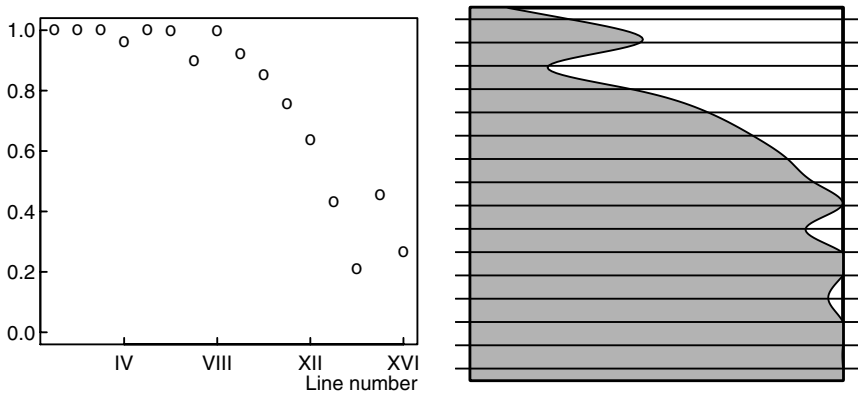


Figure 10.2 Left: Proportion of forest land on 16 survey lines in the Ilvesvuori region in the 1912 inventory of forests in Sahalahti and Kuhmalahti (Ilvessalo 1923, table 1 and figure 23). Right: An imaginary inventory region in which the shaded part is forest and the unshaded part is non-forest. The proportions of forest in the 'survey lines' displayed are equal to those on the left.

For the sake of an example, let us create an artificial rectangular study region from which the observed proportions could have been sampled (Figure 10.2, right). Computing (10.1) from $K=100$ repeated random shifts of the network of 16 equidistant lines gives an approximation $\mathrm{S}(\bar{y}) \approx \sqrt{v_K(\bar{y})} = 0.017$ to the true standard error. In contrast, the standard error estimated from the observed proportions by (10.2) is $s(\bar{y}) = 0.071$.

Real inventory regions are usually more fragmented than the one in Figure 10.2 (right), which reduces the overestimation of variance. Nevertheless, any degree of spatial continuity invalidates the assumptions behind (10.2). In order to quantify the gain in efficiency obtained by using systematic sampling instead of SRS, alternative variance estimators are required.

10.3.2 Development of estimators based on local differences

It had already been realised in the first large-scale Scandinavian inventories that the overestimation of sampling error resulting from applying (10.2) to systematic samples can be substantial, and alternatives were actively studied in the early 20th century (see Ilvessalo 1923, Lindeberg 1924, Langsaeter 1926, Östling 1932, Lindeberg 1926, Langsaeter 1932). This led to remarkable pioneering work in the development of line survey methodology and systematic sampling. Forest inventory problems also served as a powerful motive for the development of the general methodology of spatial statistics (Matérn 1960).

One way to reduce the overestimation is to model spatial trends explicitly by means of a deterministic function $\mu(u)$, $u \in U$. The variance could then be estimated on the basis of the observed residuals $y_i - \hat{\mu}(u_i)$ (Figure 10.3, middle), which would replace the differences from the overall mean $\bar{y}$ in (10.2) (Figure 10.3, left).

Trend modelling is highly subjective, of course. The first four national inventories of Finland (see Ilvessalo 1927), which were conducted as line surveys, employed a more objective variance estimator suggested by Lindeberg (1924). Instead of differences from the overall mean or from the trend model, this was based on differences between observations from successive lines (Figure 10.3, right). If all the lines are of the same length, then Lindeberg's formula is

$$\hat{\mathrm{V}}(\bar{y}) = \frac{1}{n(n-1)} \sum_{i=2}^{n} \frac{(y_i - y_{i-1})^2}{2}. \qquad (10.4)$$

Under quite general assumptions, (10.4) still leads to overestimation, which can be reduced by using higher-order differences (Langsaeter 1926, Lindeberg 1926). An interesting detail to note is that the use of differencing as a device for obtaining stationarity and thereby valid estimations by ergodicity arguments has later become a standard tool in time series analysis (Box and Jenkins 1976).

Example 10.2

Figure 23 of Ilvessalo (1923) shows a trend model fitted by eye to the data shown in Figure 10.2 (left). A rather accurate reproduction (Figure 10.3, middle) was obtained using the piecewise polynomial

$$\hat{\mu}(u) = \begin{cases} 100, & \text{for } u \in [1,4.5), \\ ax^4 + bx + c, & \text{for } u \in [4.5,11), \text{ and} \\ dx + e, & \text{for } u \in [11,16], \end{cases} \tag{10.3}$$

where the integer values of u correspond to the line numbers in Figure 10.3 and parameters *a, b, c, d* and *e* were chosen so that $\hat{\mu}(u)$ is continuous and equal to the observed proportions for lines 10, 11 and 12 (X-XII). Use of the differences $y_i - \hat{\mu}(u_i)$ gives an estimate of 0.02 for the standard error. This is much closer to the 'truth' than was the SRS-based estimate $s(\bar{y})$ (see Example 10.1).

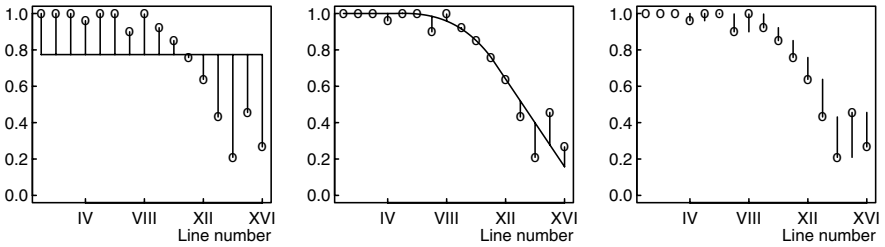


Figure 10.3 Differences of the observations in Figure 10.2 (left) from their overall mean (left), from the trend model (10.3) (middle), and from the observation of the previous line (right).

Example 10.3

For the Ilvesvuori data set (Examples 10.1 and 10.2), the use of first differences already yields a substantial improvement over $s(\bar{y})$: as (10.4) gives the standard error estimate $\sqrt{\hat{\mathrm{V}}(\bar{y})} = 0.023$.

Simple differencing works in the context of line surveys because the lines form an ordered sequence. But when the sampling units are essentially points on a plane, as in plot surveys, there is no natural order as required by (10.4). One way of

generalising (10.4) to a rectangular grid of sampling units (Figure 10.1, right) is to replace the terms $(y_i - y_{i-1})^2 / 2$ with

$$T_g = (y_{g,i1} - y_{g,i2} - y_{g,i3} + y_{g,i4})^2 / 4 \tag{10.5}$$

computed from observations on rectangular groups g of four adjacent sampling locations

$$\begin{matrix} u_{g,i3} & u_{g,i4} \\ u_{g,i1} & u_{g,i2} \end{matrix}$$

The form of T_g can be motivated by regarding $(y_{g,i1} + y_{g,i4})/2$ and $(y_{g,i2} + y_{g,i3})/2$ as two local linear predictors for the value of y at the centre of the group. T_g is then the squared difference of these two predictors, measuring the uncertainty about the unobserved values of y.

Variance estimators based on local spatial differences, as in (10.5), were introduced into forest inventories by Matérn (1947), although he refers to an even earlier use in agricultural field trials (Kristensen 1933). The following section gives more details on their use in the context of ratio estimation.

10.4 VARIANCE ESTIMATION IN THE NATIONAL FOREST INVENTORY IN FINLAND

In the Finnish national forest inventory, described in more detail in Chapter 11, clusters i of sample plots form a systematic rectangular grid (like that in Figure 10.1, right, but denser) covering the inventory region. The targets of the inventory include proportional and absolute areas, mean values for forest variables in various strata and total values over the region. Ratio estimators (section 2.7) of the general form

$$\hat{M} = \frac{\sum_i y_i}{\sum_i x_i} \tag{10.6}$$

can be employed for all these tasks. When estimating the mean tree volume on forest land, for example, x_i is the number of sample plots in cluster i that are located in forest land and y_i is the sum of the mean volumes on those plots.

The general reason why ratio estimation is needed is that the number of sample plots representing the target population (e.g. forest land) varies between clusters. In other words, the effective sample size is random. Ratio estimation is also useful when the population mean is known for an auxiliary variable that is correlated with the target variable (see sections 2.7 and 11.3.1).

The assessment of sampling error is based on the variability in *cluster-level residuals*

$$z_i = y_i - \hat{M}x_i. \tag{10.7}$$

To see why plot-level variability would give a false picture of the true sampling error, let us compare cluster sampling with spatially systematic sampling, where individual plots are located as evenly as possible. Plot-level variability is expected to be larger in the latter case than in simple random sampling if positive spatial autocorrelation is present. As discussed previously, this leads to $s^2(\bar{y})$ overestimating the design-based variance. In contrast, when plots in one cluster are forced to be near each other, the plot-level observations can be expected to vary less than in simple random samples. Therefore there is a severe risk of *underestimating* the sampling error if it is assessed on the basis of plot-level variability (see also section 2.6).

On the other hand, as discussed in section 10.3.1, application of (10.2) to the cluster level would usually lead to overestimation, which can be reduced by employing (10.5). The design-based variance of the ratio estimator $\hat{M}$ can be approximated by (Cochran 1977, section 6.3)

$$\mathrm{V}(\hat{M}) \approx \frac{\mathrm{V}(\sum_i y_i - Mx_i)}{(\sum_i x_i)^2},$$

and if each cluster i belongs to four groups g, then the variance on the right hand side can be estimated by $\sum_g T_g$, where $T_g = (z_{g,i1} - z_{g,i2} - z_{g,i3} + z_{g,i4})^2 / 4$ as in (10.5). This leads to

$$\hat{\mathrm{V}}(\hat{M}) = \frac{\sum_g T_g}{(\sum_i x_i)^2}. \tag{10.8}$$

A great practical advantage of estimator (10.8) is that its computation is an entirely routine task; in particular, no statistical modelling is involved. One practical issue that needs to be handled concerns the region boundaries, but this is easily taken care of, as demonstrated by Matérn (1960, section 6.7): If cluster i in group g is outside the inventory region U, then the corresponding z_i is taken to be 0.

A rectangular grid of individual sample plots is of course a special case of the cluster design considered here, with cluster size 1. If the estimator is the sample mean of plot-level measurements y_i ($x_i = 1$ for all plots), $\hat{M} = \bar{y}$, then an obvious idea would be to compute the T_g's from y_i's rather than from the z_i's of (10.7). This

leads to the same result as working with the residuals, provided that y_i is set to y for plots outside U. For example, if $u_{g,i1}$, $u_{g,i2}$ and $u_{g,i3}$ are inside U and $u_{g,i4}$ outside, then

$$T_g = (z_{g,i1} - z_{g,i2} - z_{g,i3})^2 / 4 = (y_{g,i1} - \hat{M}x_{g,i1} - y_{g,i2} + \hat{M}x_{g,i2} - y_{g,i3} + \hat{M}x_{g,i3})^2 / 4$$
$$= (y_{g,i1} - y_{g,i2} - y_{g,i3} + \bar{y})^2 / 4.$$

Example 10.4

For the data shown in Table 2.1 and Figure 2.1, (10.8) gave standard errors of 8.8 m^3/ha for stem volume (Example 2.1) and 0.032 for the proportion of mineral soils (Example 2.2). Both are substantially smaller than the SRS-based estimates reported in Examples 2.1 and 2.2.

As for the other examples, the computational details can be found on the web page

http://www.metla.fi/pp/JuHe/pub/InventoryBook

As indicated by Examples 10.1-10.4, local differencing can lead to much more accurate estimators of sampling errors than (10.2) if there is pronounced spatial autocorrelation. A model-based approach is required, however, in order to derive any general properties for estimators of this kind.

10.5 MODEL-BASED APPROACHES

The statistical analysis of uncertainty in inventory results is in general based on considering the estimate $\bar{y}$ to be a realised outcome of a random variable. In the design-based approach described in Chapter 2 (see also section 10.3.1), the randomness in $\bar{y}$ is considered to be solely due to random selection of the sampling locations u_i, while the response surface $y(u)$, $u \in U$, is treated as a fixed but

unknown parameter to be estimated. In many cases, in particular when sampling locations are selected independently of each other, this approach leads to an easily applicable analysis of uncertainty without the need to make any assumptions about the target population (section 3.4). For systematic sampling, however, design-based assessment of uncertainty is impossible due to the lack of repeated random selections. Furthermore, the potentially greater efficiency of systematic sampling relative to simple random sampling relies on the assumption of spatial autocorrelation in y.

The effect of autocorrelation can only be incorporated into the analysis if the values $y(u)$ are modelled as (realisations of) random variables rather than fixed parameters. Only then can one even talk properly about the correlation between $y(u)$ and $y(u')$ for two locations $u, u' \in U$. Such *model-based analysis* could proceed by first formulating a statistical model (*superpopulation*; section 3.1) that attempts to capture the essential features of the response surface $y(u)$, $u \in U$, and then estimating the unspecified parameters of this model from the inventory data. This model could be used to predict the surface over unobserved locations, leading to a predictive distribution of $\overline{Y}(U)$ (subsection 10.5.4).

The main aim in this section, however, is to see what model-based analysis can reveal about the properties of variance estimators (subsection 10.5.2). These properties depend on the model adopted, of course. Subsection 10.5.1 describes a general class of models for spatially autocorrelated populations, where useful results can be derived from quite general assumptions. The issue of descriptive versus analytic inference (section 3.1) is revisited in subsection 10.5.3.

10.5.1 Modelling spatial variation

A commonly applied spatial model, a generalisation of (3.1), is

$$y(u) = \mu(u) + z(u), \tag{10.9}$$

where μ is a deterministic mean value surface and z is a zero-mean (usually Gaussian) spatial process of correlated residuals (Cressie 1993) with a common variance $\mathrm{V}(z(u)) = \sigma^2$, $u \in U$ and a stationary covariance function

$$\mathrm{Cov}(z(u), z(u')) = C(u'-u) = \sigma^2 \rho(u'-u),$$

which implies that the correlation between $z(u)$ and $z(u')$ depends on the relative location of u' with respect to u. The general purpose of decomposition (10.9) is to capture the large-scale variation, or trends, in μ and the small-scale spatial correlation in z. The distinction between 'large scale' and 'small scale' is vague, of course, and therefore the decomposition is definitely non-unique and is usually highly dependent on the modeller's judgement; "one man's trend is another man's correlation."

Example 10.5

To see why (10.9) might be a useful model, let us look at some 'forests' that can be simulated according to a rather simple special case of it, namely that with a constant mean value $\mu(u) = \mu_0$, $u \in U$ and an isotropic Gaussian correlation function

$$\rho(h;\phi) = \exp(-(|h|/\phi)^2), \tag{10.10}$$

where $|h|$ is the length of the vector h, i.e. the distance between the points of interest. In order to obtain a clearer view of the essential features, a one-dimensional region $U = [0, 1]$ was used in the simulation. We may imagine, for example, that U represents one line transect across an inventory area and $y(u)$ represents the mean volume around a point at distance u along the transect.

Figure 10.4 (left) shows 9 'forests' simulated with $\mu_0 = 100$, $\sigma = 25$ and $\phi = 0.3$. The variability in each realisation is similar, due to the same correlation function, but the mean volumes deviate greatly from 100, since the correlation is relatively strong. Reducing the value of ϕ leads to more rapidly variable 'forests' (Figure 10.4, middle), while changing the type of correlation function leads to different local smoothness properties (Figure 10.4, right).

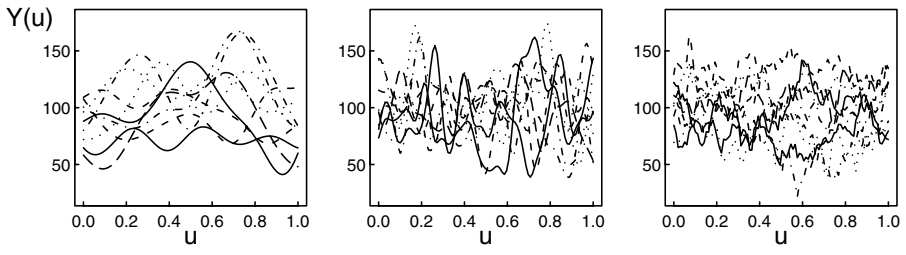


Figure 10.4 Nine realisations of three stationary processes on [0,1] with a common mean $\mu_0 = 100$ and a common standard deviation $\sigma = 25$ but different correlation functions. Left and middle: Gaussian correlation function (10.10) with $\phi = 0.3$ (left) and $\phi = 0.05$ (middle). Right: Exponential correlation function $\rho(h;\phi) = \exp(-|h|/\phi)$, $\phi = 0.3$.

There are other ways of modelling fluctuations of this kind, of course, such as splines, kernel functions or local polynomials (Cleveland et al. 1992, Green and Silverman 1994, Wand and Jones 1995, Fan and Gijbels 1996, Loader 1999, Wood 2003), but the modelling of small-scale features as spatial correlations has become the standard in spatial statistics (Cressie 1993). One of its advantages is that great variations involving different kinds and scales of spatial features can be included in model families with only a few parameters and that these parameters can usually be quite easily estimated from the data at hand. Another advantage is the availability of useful theoretical results, like that of the next subsection.

10.5.2 Model-based variance and its estimation

If *y(u)* is considered a random variable, then the population mean $\overline{Y}(U)$ will be random, too, and so will the design-based variance $\mathrm{V}(\overline{y})$. An appropriate model-based measure of uncertainty is then the expected value of $\mathrm{V}(\overline{y})$,

$$\mathrm{E}(\overline{y} - \overline{Y}(U))^2, \tag{10.11}$$

where the expectation applies both over the distribution of random surfaces y and over any randomisation involved in sampling (Cochran 1946).

For simple random sampling, $s^2(\overline{y})$, as defined by (10.2), is an approximately unbiased estimator of (10.11) whatever the correlation structure in the superpopulation. For systematic sampling, on the other hand, $s^2(\overline{y})$ overestimates (10.11) if y is positively autocorrelated, unless a strong periodicity occurs with a wavelength equal to the sampling interval (Ripley 1981, section 3.2).

A remarkable result provided by Matérn (1947, 1960) is that the average of any set of quadratic forms

$$T_g = (\sum_{i=1}^{m} a_i y_{g,i})^2 \tag{10.12}$$

satisfying the restrictions

$$\sum_{i=1}^{m} a_i = 0 \text{ and } \sum_{i=1}^{m} a_i^2 = 1 \tag{10.13}$$

is a positively biased estimator of (model-based) variance per sample point (n times 10.11) under very weak model assumptions. The essential requirement is that y is (a realisation of) a spatial process (like 10.9) in which the correlation function $\rho(h)$ decreases monotonically with increasing inter-point distance $|h|$.

The terms in the sum of (10.4) and the T_g's defined by (10.5) are examples of quadratic forms (10.12). Note that the division of the difference by 2 in (10.4) and by 4 in (10.5) is needed to meet the conditions (10.13). This ensures that an unbiased variance estimator is obtained when there is no spatial autocorrelation.

In summary, although the estimators of sections 10.3 and 10.4 generally give smaller values than (10.2), they can still be usually regarded as safe overestimates.

Example 10.6

18 sets of 'inventory data' were simulated by selecting one simple random sample and one systematic sample, both of size 30, from each simulated 'forest' of Figure 10.4 (left). The resulting simple random samples are shown in Figure 10.5 and the systematic samples in Figure 10.6.

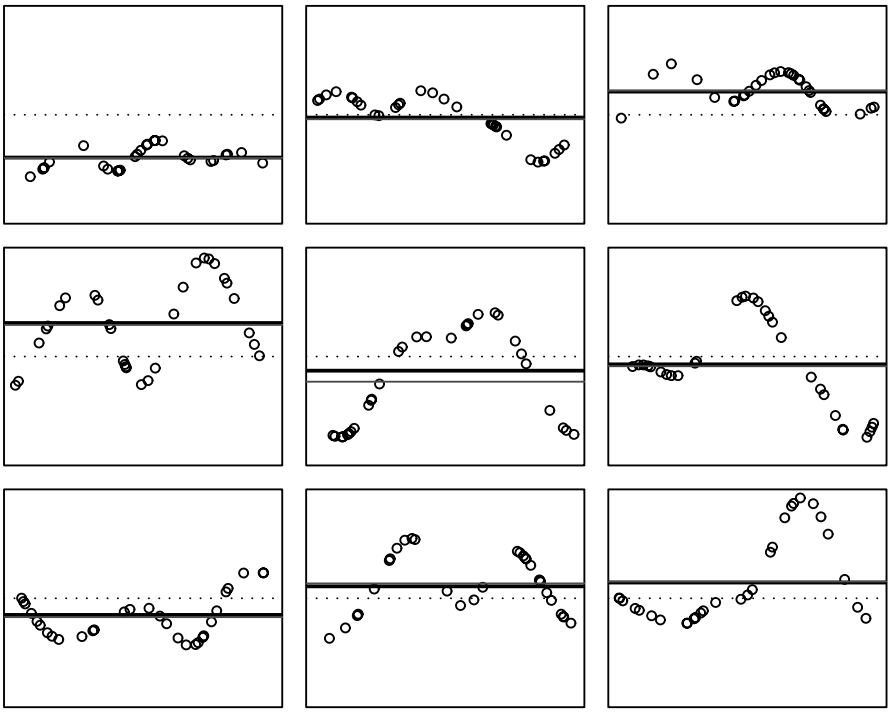


Figure 10.5 Simple random samples of size 30 from the nine simulated populations of Figure 10.4 (left). The superpopulation mean $\mu_0 = 100$ is shown as dotted horizontal lines, the population means as thick horizontal lines and the sample means as thin solid lines (often indistinguishable from the population means).

The differences $\bar{y} - \bar{Y}(U)$ are seen more clearly in Figure 10.7, where it is evident that systematic sampling does a better job in estimating $\bar{Y}(U)$. For example, the simple random sample taken from the fifth forest (the one in the centre of the layout) underestimates $\bar{Y}(U)$ badly (by comparison with the systematic sample from the same forest), mainly due to the cluster of locations we happened to sample at the left-hand end of the forest.

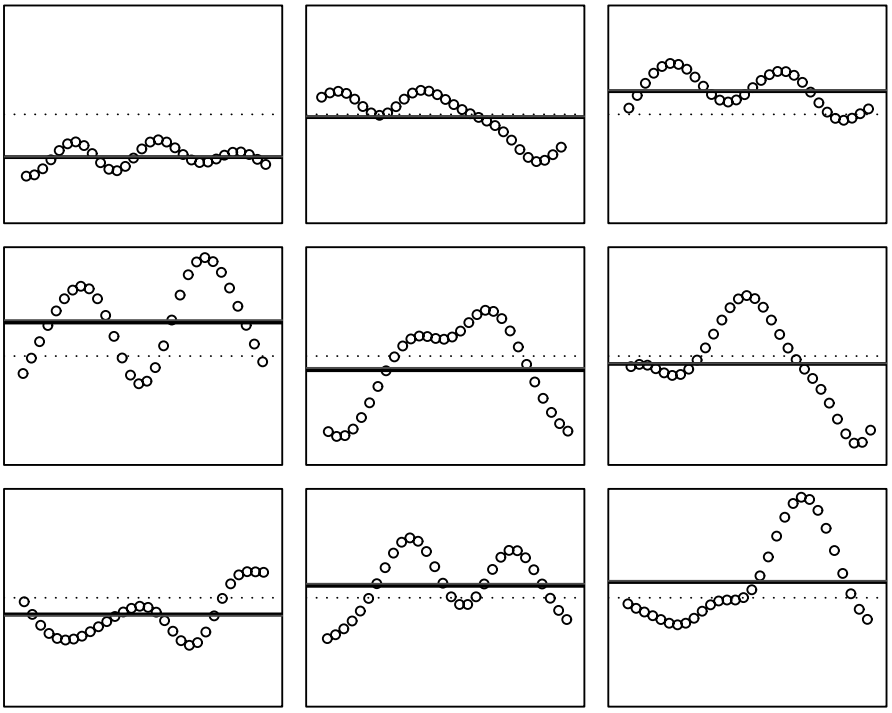


Figure 10.6 Systematic samples of size 30 from the nine simulated populations of Figure 10.4 (left). The population means are shown as thick horizontal lines. The sample means cannot be distinguished from the population means on the scale used here.

Since we have repeated samples in this example, the true sampling error variance (10.11) in the simulated model can be estimated consistently by

$$\frac{1}{9}\sum_{k=1}^{9}(\bar{y}_k - \bar{Y}_k(U))^2, \tag{10.14}$$

where $\bar{Y}_k(U)$ is the population mean for the k'th simulated forest, and $\bar{y}_k$ is the mean in the sample selected from that forest. The square roots of (10.14), approximating the true standard errors associated with the two sampling designs, are 2.6 for the simple random samples and 1.0 for the systematic samples.

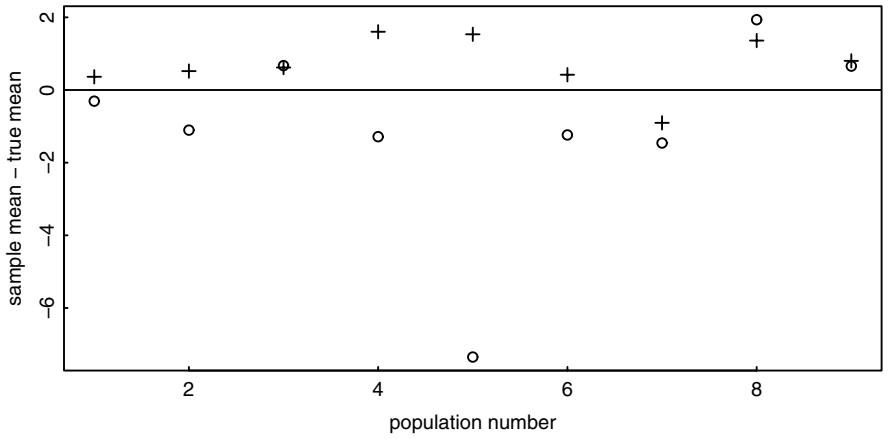


Figure 10.7 Differences between the sample means and the corresponding population means in the samples of Figures 10.5 (o's; SRS) and 10.6 (+'s; systematic).

The standard error estimates computed by (10.2), on the other hand, vary between 1.2 and 5.9 (but are quite similar in both kinds of sample, as indicated in Figure 10.8). Thus, again, $s(\bar{y})$ clearly overestimates the sampling error associated with systematic sampling, but appears to be appropriate (as it should be) for simple random sampling.

The standard error estimates obtained from the systematic samples by (10.4) vary between 0.5 and 1.4. That is, the differencing method indeed gives a much better assessment of the precision when estimating $\bar{Y}(U)$ from systematic samples.

Yet another way to illustrate the performance of $s(\bar{y})$ is by means of 95% confidence intervals computed from the simulated samples using (10.2) (boxes in Figure 10.8). The true population means $\bar{Y}(U)$ are always within the intervals, but in the systematic samples they tend to be quite close to the centre of the interval (sampling error overestimated), whereas in the random samples they seem to vary more randomly within the interval, as they should if the sampling error were correctly estimated.

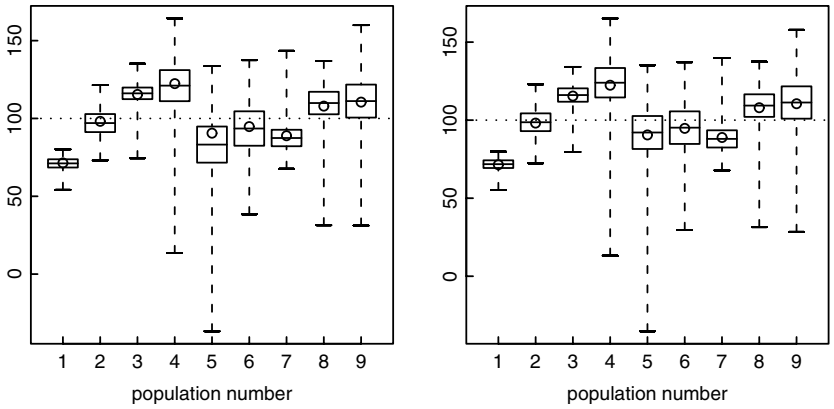


Figure 10.8 Population means (circles) and 95% confidence intervals (boxes) around the sample means (horizontal lines within the box) computed using (10.2) for the samples of Figures 10.5 (left; SRS) and 10.6 (right; systematic). The 'whiskers' show confidence intervals for the superpopulation mean (Example 10.7) based on the maximum likelihood estimator of (10.15). The dotted horizontal line is at the true superpopulation mean of 100.

10.5.3 Descriptive versus analytic inference

Note that (10.11) is an appropriate measure of uncertainty when $\bar{y}$ is considered an estimator of the population mean $\overline{Y}(U)$. But $\bar{y}$ could also be used to estimate the superpopulation mean μ_0 for model (10.9), with $\mu(u) = \mu_0$, $u \in U$. In that case, (10.11) should be replaced by

$$E(\bar{y} - \mu_0)^2 , \tag{10.15}$$

which may be substantially different if $\overline{Y}(U)$ is highly variable in the model adopted (Example 10.7).

But how do we decide whether we are doing descriptive inference (on population values) or analytic inference (on superpopulation parameters)? One possible interpretation of a superpopulation is: "(an infinite set of) forests considered to be similar to our *U*". Thus, if we wish to study the relationship between two forest variables, for example, and to generalise the results based on data from one specific region (our *U*) to all similar forests, then we are trying to estimate superpopulation parameters. If the variables of interest are spatially autocorrelated, then the observations from one region will be mutually positively correlated realisations from

the superpopulation whatever the sampling design. In that case, $s^2(\bar{y})$ would *underestimate* (10.15) for all sampling designs (see Cressie 1993, p. 14 and Example 10.7 below). In general, spatial autocorrelation should be taken into account in the case of analytic inference even with simple random sampling. This can be done through the generalised least squares approach, for example (section 3.2), or with models allowing for the autocorrelation where likelihood-based inference is concerned.

In an inventory, however, we are usually interested in the particular region *U* from which the data were collected, and hence in the particular population which was actually sampled. The superpopulation was only introduced in order to take spatial autocorrelation into account. An inventory is therefore by definition a case of descriptive inference.

Example 10.7

In Example 10.6 the population means $\overline{Y}(U)$ varied much more around the superpopulation mean μ_0 than the sample means differed from the corresponding population means. As a result, the SRS confidence intervals (boxes) of Figure 10.8 contained the true value 100 of μ_0 only in 5 cases (2 random and 3 systematic). That is, $s(\bar{y})$ clearly underestimates the error of $\bar{y}$, when $\bar{y}$ is considered an estimator of μ_0. This happens both for simple random and systematic samples.

The 'whiskers' in Figure 10.8 show the 'appropriate' confidence intervals for μ_0, obtained using maximum likelihood estimates of (10.15), based on the model that was actually used to simulate the data (see caption to Figure 10.4). Population number 1 is obviously quite an extreme realisation of the model, but the confidence intervals computed from samples of both kinds taken from all the other populations do contain the true value of μ_0.

10.5.4 Kriging in inventories

When assessing the precision of inventory estimates on the basis of an already given data set (as opposed to designing its collection, for example), it could well be argued that the average (10.11) over all the samples we *might have* collected using the design in question is not the most appropriate measure (see end of section 3.4). A purely model-based measure of uncertainty is the *conditional* mean-squared prediction error

$$E\{(\bar{y} - \overline{Y}(U))^2 \mid y_1, \ldots y_n\}\,, \tag{10.16}$$

conditioned by sample plot locations that were actually realised from the design and by the values observed at those locations. Note that, completely opposite to (10.1), the observed $\bar{y}$ is treated as fixed in (10.16), the randomness being in the unobserved values $y(u)$, $u \notin \{u_1, \ldots, u_n\}$.

Kriging (see Chiles and Delfiner 1999, Webster and Oliver 2001, Wackernagel 2003; also section 7.2) is one approach for replacing $\bar{y}$ with an optimal predictor (under an assumed and/or estimated superpopulation model), which minimises (10.16). An estimate of the minimised prediction error will be an automatic by-product.

If the configuration of sample plot locations is not regular, then the unweighted mean $\bar{y}$ may not be the most efficient predictor of $\bar{Y}(U)$. In particular, isolated sample plots should usually receive more weight than those in clusters, as they contain more 'new' information. In kriging the correlation model estimated from the data is used to derive the optimal weighting (see end of section 3.3).

The kriging variance (10.16) for Gaussian superpopulations following model (10.9) depends on the covariance function and on the number and locations of the sample plots, but not on the observed values y_i. It will therefore be different for different realisations of a simple random sampling design, but almost equal in all realisations of a systematic sampling design. Furthermore, for a systematic sample, all plots except those near the boundaries of U will have a similar configuration of neighbouring plots and essentially equal $\int_U Cov(Z(u), Z(u'))\,du'$, which means that they will receive similar weights and $\bar{y}$ will be practically optimal. This may be one reason for Matérn (1960) not suggesting kriging-type estimators (Cressie 1990). If the proportion of plots near the boundary of U is high, however, kriging might be useful for deriving appropriate weightings for those plots.

If systematic cluster sampling is applied and only a part of the sample plots lie within the target population, say in forest land, then there will be different numbers of relevant plots in different clusters (section 10.4). The above discussion may then suggest that plots in clusters where there are fewer forest land plots should receive more weight (Kangas 1993). On the other hand, the reason for the smaller number of relevant plots in a cluster is that there is less forest land there, so that in order to derive appropriate kriging weights a forest land map would be needed.

As discussed in section 7.2, kriging is a worthwhile alternative for small-area estimation. References to some kriging applications in forestry can be found in Nieschulze (2003) and Wallerman (2003). The general tendency in the production of official statistics, including forest inventory results, is nevertheless to rely on design-based assessments of uncertainty (see de Gruijter and ter Braak 1990). Although model-based estimators are often more efficient, design-based ones are usually more robust (section 3.4). For example, kriging variance is highly sensitive to model specification, in particular to the estimated short-range correlations, on which there may not be very much information in the data (Kangas 1993), so that the uncertainty may just as well be underestimated as overestimated.

10.6 OTHER SOURCES OF UNCERTAINTY

There are, of course, many other components of uncertainty in inventory results in addition to sampling error, although it should be noted that the variance estimators considered in this chapter automatically include the effect of random (symmetric)

measurement errors, as such errors increase the variability in y_i (see Cochran 1977, section 13.10).

The effect of systematic measurement errors is not included, however, and these should be assessed separately (Cochran 1977, sections 13.9-13.16), as should model errors. For example, if y is the tree volume, then y_i will usually be predicted by a model using measurements of certain covariates (see section 11.3.2). Residual variation, which is not captured in the systematic part of the model, will be missing from the point predictions, and consequently the variation in the predicted y_i's will be smaller than it would be if they were measured directly. As a result, the variance estimators considered in this chapter underestimate the total error if the model errors are substantial. Cunia (1965, 1987) explains how to deal with this. Furthermore, even random measurement errors in the covariates can lead to biased predictions of y if a non-linear model is used (Kangas 1996).

ACKNOWLEDGEMENTS

The constructive comments of Annika Kangas, Ron McRoberts and Antti Penttinen on an earlier version have greatly helped to improve this chapter. I am also grateful to Malcolm Hicks for revising the language.

REFERENCES

Aubry, P. and Debouzie, D. 2000. Geostatistical estimation variance for the spatial mean in two-dimensional systematic sampling. Ecology 81:543-553.

Box, G. E. and Jenkins, G. M. 1976. Time Series Analysis: Forecasting and Control. Holden Day, San Francisco.

Chiles, J.-P. and Delfiner, P. 1999. Geostatistics. Wiley, New York.

Cleveland, W. S., Grosse, E. and Shyu, W. M. 1992. Local regression models. In S. J. M. Chambers and T. J. Hastie (eds.), Statistical models in S. Chapman and Hall, New York. pp. 309-376.

Cochran, W. G. 1946. Relative accuracy of systematic and stratified random samples for a certain class of populations. Annals of Mathematical Statistics 17:164-177.

Cochran, W. G. 1977. Sampling techniques. Wiley, New York, 3rd edition.

Cressie, N. A. C. 1990. The origins of kriging. Mathematical Geology 22:239-252.

Cressie, N. A. C. 1993. Statistics for Spatial Data. Wiley, New York, revised edition.

Cunia, T. 1965. Some theory on reliability of volume estimates in a forest inventory sample. Forest Science 11:115-128.

Cunia, T. 1987. On the error of continuous forest inventory estimates. Canadian Journal of Forest Research 17:436-441.

de Gruijter, J. J. and ter Braak, C. J. F. 1990. Model-free estimation from spatial samples: A reappraisal of classical sampling theory. Mathematical Geology 22:407-415.

D'Orazio, M. 2003. Estimating the variance of the sample mean in two-dimensional systematic sampling. Journal of Agricultural, Biological, and Environmental Statistics 8:280-295.

Dunn, R. and Harrison, A. R. 1993. Two-dimensional systematic sampling of land use. Applied Statistics 42:585-601.

Fan, J. and Gijbels, I. 1996. Local polynomial modeling and its applications. Chapman and Hall, London.

Flores, L. A., Martínez, L. I. and Ferrer, C. M. 2003. Systematic sample design for the estimation of spatial means. Environmetrics 14:45-61.

Green, P. J. and Silverman, B. W. 1994. Nonparametric regression and generalized linear models. A roughness penalty approach. Chapman and Hall, London.

Ilvessalo, Y. 1923. Untersuchungen über den Zustand der Privatwälder in den mittleren Teilen des Läns Tavastehus. Die Wälder der Gemeinden Sahalahti und Kuhmalahti. Acta Forestalia Fennica 26: 1-137. (In Finnish with German summary).

Ilvessalo, Y. 1927. The forests of Suomi (Finland). Results of the general survey of the forests of the country carried out during the years 1921-1924. Communicationes Instituti Forestalis Fenniae 11, 613 p. (In Finnish with English summary).

Kangas, A. 1993. Estimating the parameters of systematic cluster sampling by model based inference. Scandinavian Journal of Forest Research 8:571-582.

Kangas, A. 1996. On the bias and variance of tree volume predictions. Scandinavian Journal of Forest Research 11:281-190.

Kristensen, R. K. 1933. Bestemmelse af middelfejlen ved hjælp af differensdannelser. Tidsskrift for Planteavl 39:349.

Langsaeter, A. 1926. Om beregning av middelfeilen ved regelmessige linjetaksering. Meddelelser fra det norske Skogforsøksvesen 2.7:5-47.

Langsaeter, A. 1932. Nøiaktigheten ved linjetaksering av skog, I. Meddelelser fra det norske Skogforsøksvesen 4:431-563.

Lindeberg, J. W. 1924. Über die Berechnung des Mittelfehlers des Resultates einer Linientaxierung. Acta Forestalis Fennica 25.

Lindeberg, J. W. 1926. Zür Theorie der Linientaxierung. Acta Forestalis Fennica 31.6:1-9.

Loader, C. 1999. Local regression and likelihood. Springer-Verlag, New York.

Matérn, B. 1947. Methods of estimating the accuracy of line and sample plot surveys. Meddelanden från Statens Skogsforskningsinstitut 36.1. (In Swedish with English summary).

Matérn, B. 1960. Spatial variation. Meddelanden från Statens Skogsforskningsinstitut 49.5, 144 p. Also appeared as number 36 of Lecture Notes in Statistics. Springer-Verlag, New York, 1986.

Milne, A. 1959. The centric systematic area-sample treated as a random sample. Biometrics 15: 270-297.

Nieschulze, J. 2003. Regionalization of variables of sample based forest inventories at the district level. Ph.D. thesis, Faculty of Forest Sciences and Forest Ecology, Georg-August-University Göttingen. http://webdoc.sub.gwdg.de/diss/2003/nieschulze

Osborne, J. G. 1942. Sampling errors of systematic and random surveys of cover-type areas. Journal of the American Statistical Association 37:256-264.

Quenouille, M. H. 1949. Problems in plane sampling. Annals of Mathematical Statistics 20:355-375.

R Development Core Team. 2004. R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. http://www.R-project.org

Ribeiro Jr, P. J. and Diggle, P. J. 2004. geoR: geoR - functions for geostatistical data analysis. R package version 1.4-9. http://www.est.ufpr.br/geoR

Ripley, B. D. 1981. Spatial statistics. Wiley, New York.

Sherman, M. 1996. Variance estimation for statistics computed from spatial lattice data. Journal of the Royal Statistical Society, Series B 58:509-523.

Wackernagel, H. 2003. Multivariate geostatistics. Springer-Verlag, Berlin, 3rd edition.

Wand, M. P. and Jones, M. C. 1995. Kernel smoothing. Chapman and Hall, London.

Wallerman, J. 2003. Remote sensing aided spatial prediction of forest stem volume. Acta Universitatis Agriculturae Sueciae Silvestria 271, 41 p.

Webster, R. and Oliver, M. A. 2001. Geostatistics for environmental scientists. Wiley.

Wood, S. N. 2003. Thin plate regression splines. Journal of the Royal Statistical Society, Series B 65:95-114.

Yates, F. 1948. Systematic sampling. Philosophical Transactions of the Royal Society of London, Series A 241:345-377.

Östling, J. 1932. Erforderlig taxeringsprocent vid linjetaxering av skog. Sveriges Skogsvårdsföreningens Tidskrift 30.

PART II
APPLICATIONS

CHAPTER 11

THE FINNISH NATIONAL FOREST INVENTORY

ERKKI TOMPPO

Finnish Forest Research Institute, Finland

11.1 INTRODUCTION

The National Forest Inventory has been producing large-area forest resource information on Finland since the beginning of the 1920s. The ninth inventory rotation was conducted in 1996-2003 and the tenth began in 2004.

The information generated by the Finnish National Forest Inventories (NFI) has traditionally been made use of in large-area forest management planning, e.g. in the planning of cutting, silviculture and forest improvement regimes at the regional and national levels, in decisions concerning forest industry investments and as a basis for forest income taxation. It has also provided forest resource information for national and international statistics such as the United Nations/FAO Forest Resource Assessment procedure and the Ministerial Conference on the Protection of Forests in Europe (MCPFE). It currently also produces information on forest health status and damage, biodiversity and carbon pools and changes in these for the Land Use Land Use Change (LULUCF) reports of the United Nations Framework Convention on Climate Change (UNFCCC). The NFI covers all forests and the information has been used by all ownership groups for justifying and calibrating their own results. It serves as a central information source and tool for use in forestry, the forest industry and forest environment decisions and policy making.

The sampling design and plot and stand-level measurements have been changed in the course of time to respond to contemporary requirements and to optimize the use of the available resources.

The sampling system in the First National Inventory was line-wise survey sampling, introduced by Professor Yrjö Ilvessalo (Ilvessalo 1927). The line interval was 16 kilometres in most parts of the country, but for error estimation purposes, an interval of 13 kilometres was used in one province and 10 kilometres in the Åland

A. Kangas and M. Maltamo (eds.), Forest Inventory – Methodology and Applications, 179–194.

Islands. Plot measurements were carried out in line strips of width 10 metres. The plot length was 50 metres and the interval between plots 2 km. Similar sampling systems with different sampling intensities were employed in the following three inventories up to 1963.

Detached tracts have been employed instead of continuous lines since the fifth inventory (1964-1970) (Kuusela and Salminen 1969). This design is statistically more effective and was also favoured by social developments and the improved road network. At the same time, the inventory became a continuous operation and proceeded by regions from south to north. The fixed-sized sample plots were also changed to Bitterlich plots (angle gauge plots, or PPS sampling, the size being determined by the basal area of a tree at breast height). A new feature in the 5th, 6th and 7th inventories was the use of aerial photographs in Northern Finland (Poso 1972, Poso and Kujala 1971). Two-phase stratified sampling (stratification based on aerial photographs) was employed in the 5th and 6th inventories and photo interpretation plots in the 7th inventory (Mattila 1985).

The ground sampling intensity has been adapted to the variability in forests, taking into account the necessary budget constraints. The sampling intensity in Northern Finland has thus been lower than that in Southern Finland.

About one fifth of the sample plots have been made permanent since the 8th inventory in Northern Finland (1992-1994), and the establishment of such plots was completed for the entire country in the 9th inventory. The aim is to be able to obtain information of a kind that cannot be derived from temporary plots, e.g. the amount and structure of the drain, detailed changes in land use and other changes taking place, and also to reduce the standard error of some estimates.

The length of each cycle, comprising one complete inventory, has been dependent on the funds granted in the national budget, the smallest areal unit for which results are required and the statistical precision of the estimates that is considered desirable. The first four inventory rotations took about three years each, while the next five took 6 to 9 years each. The rotation will be shortened to 5 years from the 10th inventory, which started in 2004.

The main administrative unit for forestry in Finland is the Forestry Centre district, commonly comprising 0.8 - 5.0 million ha of forest land. The mainland is divided into 13 such districts, with the Åland Islands forming an additional one. The standard error in the estimated growing stock volume for these districts is between 2.7 and 1.9 per cent, and that for the entire country 0.6 per cent (Tomppo et al. 1997, 1998, 2001).

Forest statistics for small areas have been computed since 1990 using satellite images and digital map data, e.g. land use data, elevation data and soil data, in addition to field measurements. The role of this multi-source technique is to be able to produce geographically localized information for areas smaller than is possible using field data only, e.g. for individual municipalities, which in Southern Finland typically have an area of some 10 000 ha. The image analysis methods have been chosen in such a way that estimates for all the variables considered in the inventory can be computed for each pixel. The entire country has been processed two and a half times by the method (up to the end of 2004).

The method is described in Chapter 12, and related methods for removing errors caused by errors in the digital input maps in Chapter 13. This chapter describes the field sampling system used in the 9th National Forest Inventory and the relevant calculation methods.

11.2 FIELD SAMPLING SYSTEM USED IN NFI9

The sampling unit used in the ninth inventory rotation, in the years 1996-2003, was a cluster, also referred to as a tract. The sampling design was adapted to the variability in the forests, the distances between two tracts varying from 6 km x 6 km in the southernmost part of the country to 10 km x 10 km in Lapland. The NFI9 sampling designs in the southernmost part of the country, Central Finland and Northern Finland are shown in Figure 1 (Figure 1a, 1b and 1c). The distances between clusters were 10 km x 10 km in the municipality of Kuusamo and in the southern part of Lapland and 7 km x 7 km elsewhere in Northern Finland.

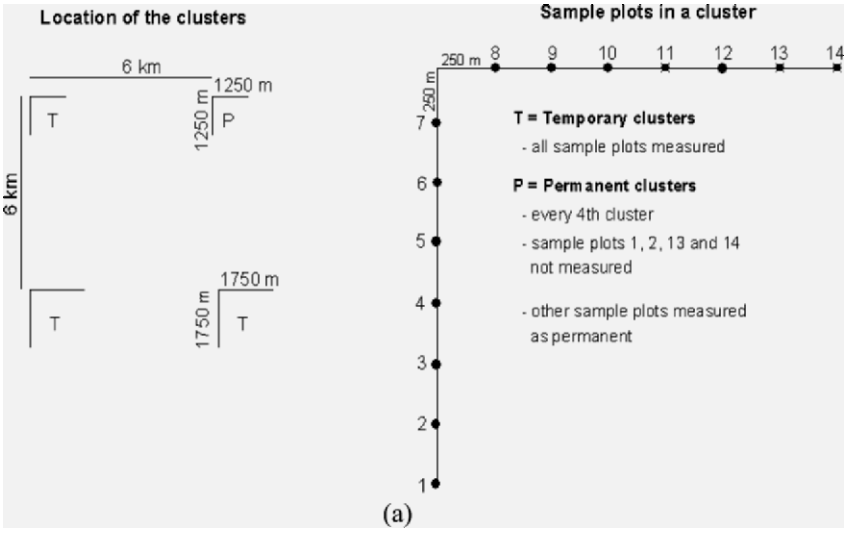
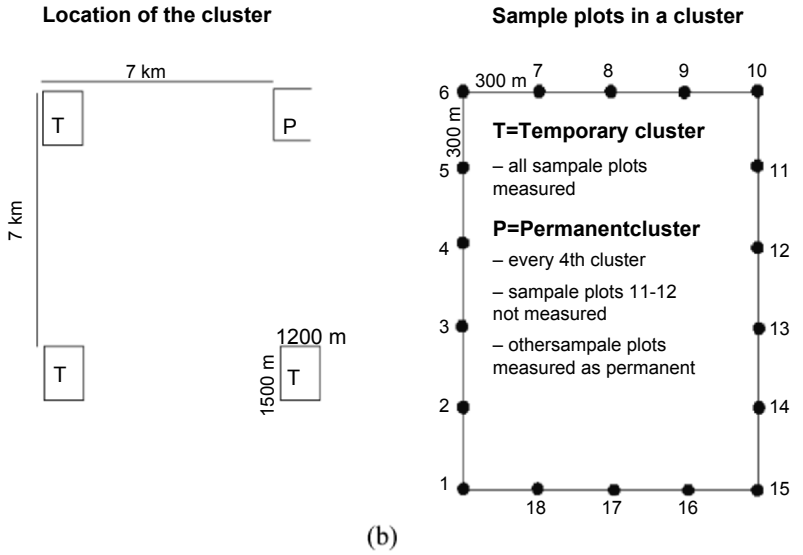
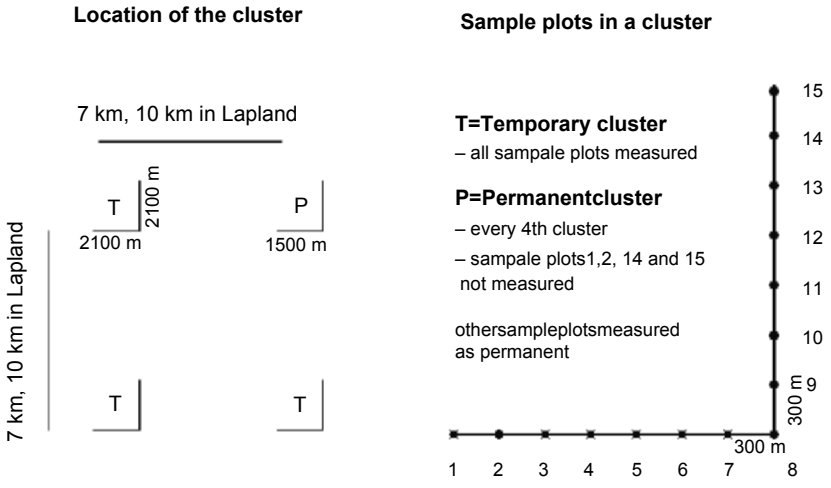


Figure 1. Field sampling designs used for the ninth National Forest Inventory in the southernmost part of Finland (a), in Central Finland (b) and in Northern Finland (c), except for the three northernmost municipalities, where two-phase stratified sampling was employed.


Location of the cluster
7 km
T
P
7 km
T
1200 m
1500 m
T
Sample plots in a cluster
300 m
7
8
9
10
6
300 m
T=Temporary cluster
– all sampale plots measured
5
11
P=Permanentcluster
– every 4th cluster
4
12
– sampale plots 11-12 not measured
3
13
– othersampale plots measured as permanent
2
14
1
15
18
17
16

(b)


Location of the cluster
7 km, 10 km in Lapland
T
2100 m
2100 m
P
1500 m
7 km, 10 km in Lapland
T
T
Sample plots in a cluster
T=Temporary cluster
– all sampale plots measured
P=Permanentcluster
– every 4th cluster
– sampale plots1,2, 14 and 15 not measured
othersampleplotsmeasured as permanent
15
14
13
12
11
10
300 m
9
300 m
1
2
3
4
5
6
7
8

(c)

Satellite image-based digital volume maps and sampling simulations were employed to evaluate different sampling designs. For each design tested, 1000 samples were chosen and standard deviations for the mean volume computed (Henttonen 1991) and assumed to represent the standard error in mean volume. Another quite important aspect was that a sampling unit (cluster) should represent one day's work on average. It was found that the 'optimum' design depended on the distribution of forest land and the heterogeneity of the forests, for instance, and therefore varied from south to north and from east to west. The sampling intensity was fitted to the spatial variation in forests throughout the whole country, being lower in the north than in the south.

The two-phase stratified sampling applied to the area of the three northernmost municipalities was based on three variables: 1) the per cent of waste land (e.g. open bogs and very poor mineral sites like open rocks), 2) the volume of growing stock and 3) on predicted cumulative day-time temperature. The two first variables were predictions of multi-source forest inventory in a form of thematic maps.

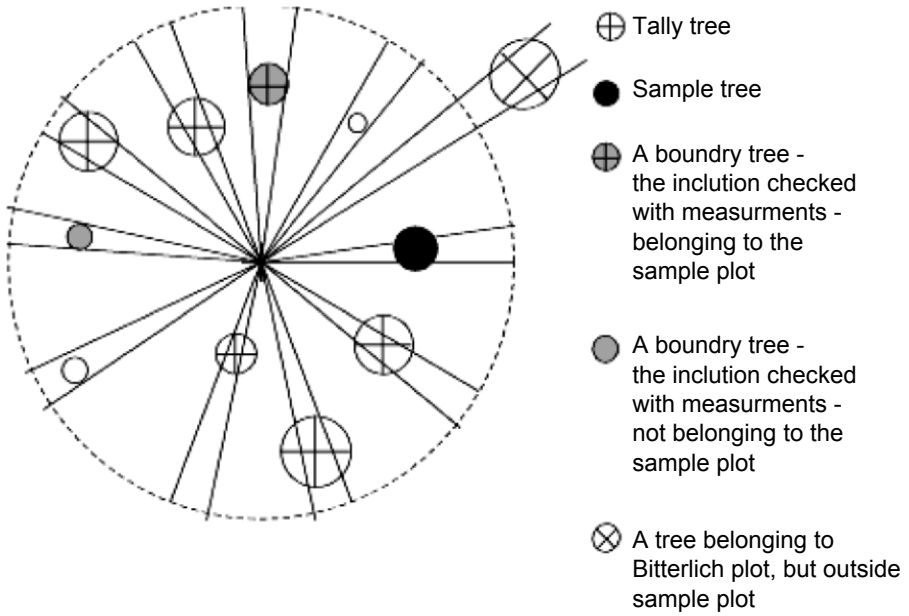


Figure 2. A sample plot as used in NFI9. The maximum radius for trees to be counted was 12.52 m in Southern Finland (q=2) and 12.45 m in Northern Finland (q=1.5). Every 7th tree is measured as a sample tree. The trees are counted by crews, starting at the beginning of the field season.

The sample plot was a Bitterlich plot (angle-gauge plot) and the tally trees were selected with a relascope, the basal area factor (BAF) being 2 in Southern Finland and 1.5 in Northern Finland. The maximum radius was 12.52 m and 12.45 m, respectively (corresponding to breast height diameters of 34.5 cm and 30.5 cm, respectively). Where a relascope could not be used for judging inclusion reliably, this was checked by measuring the distance and diameter of the tree at a height of 1.3 m. Reducing the radius of a sample plot detracted very little from the reliability of the estimates, but it did ease the amount of fieldwork noticeably in some cases, as the number of divided sample plots (i.e. sample plots belonging to two or more stands or strata) decreased. The use of maximum distance may also have reduced errors caused by possible unobserved trees, usually located a long distance from the plot centre and behind other trees. Every 7^{th} tally tree was measured as a sample tree, see Figure 2.

In the Finnish NFI schema forestry land is divided into productive forest land, poorly productive forest land, unproductive forest land (also called waste land) and forestry roads (for definitions, see Kuusela and Salminen 1969). Note that the national definitions of both forest land and poorly productive forest land deviate from the definitions of forest land and other wooded land of the FAO (2001), although the FAO definitions are currently applied in parallel with the national definitions in the Finnish NFI. The main tree species in the Finnish forests are Scots pine (*Pinus sylvestris* L.), Norway spruce (*Picea abies* (L.) Karst.), birch (*Betula* spp.), aspen (*Populus tremula* L.) and alder (*Alnus* spp.). Some hardwood species such as oak (*Quercus robur*) are common locally in the extreme south of the country.

The number of field plots on land in the 9th Finnish National Forest Inventory was 81 249 in the entire country, of which 67 264 were on forestry land, 62 266 on forest land and poorly productive forest land, and 57 457 on forest land alone. Note that the land area and water area by municipalities are assumed to be known and the figures are based on the statistics of Land Survey Finland (Finlands ... 2003). The field plots were geolocated with a GPS system, and trees were measured on those plots which contained forest land and/or poorly productive forest land.

11.3 ESTIMATION BASED ON FIELD DATA

The NFI results can be divided into area, volume and increment estimates. The NFI plots cover the entire land area of the country and its waterways, so that the inventory produces area estimates not only for forestry land strata but for all land use classes. Forest land and forestry land are divided into sub-categories on the basis of site, ownership, silviculture and cutting regimes, treatments needed and growing stock, e.g. tree species composition, age and mean diameter of trees.

11.3.1 Area estimation

Area estimation is based on the total land area and inland water areas which are known or assumed to be error-free, and on the number of centre points of the plots. In brief, the area estimate of a land stratum is the number of plot centres in the stratum divided by the total number of plot centres and multiplied by the known land area. Due to the fact that the number of plot centres on land is a random variable (depending on the design), the area estimators are ratio estimators (Cochran 1977)

$$a_s = \frac{\sum_{i=1}^{n} y_i}{\sum_{i=1}^{n} x_i} A = \frac{\bar{y}}{\bar{x}} A \,, \qquad (11.1)$$

where a_s is the area estimate of the stratum s, A the land area on the basis of the official statistics of the Finnish Land Survey (Finlands ... 2003), y_i is 1, when the centre point of the plot belongs to the stratum in question and 0 otherwise, x_i is 1 when the centre point is on land and 0 otherwise, and n is the number of centre points on land (see Tomppo et al. 1997, 1998, 2001). Examples of land strata are forest land, spruce-dominated forest land and forest land thinned during the last ten years.

11.3.2 Volume estimation

Volume in the Finnish NFI means tree stem volume over bark (that is with bark), from above the stump to the top of the tree, excluding branches. All trees of height at least 1.3 m (i.e., breast height diameter > 0 cm) are included in the volume estimate. The volume estimators are ratio estimators in a similar manner to the area estimators (Eq. 11.1). Briefly, to obtain the mean volume for a given stratum, the mean volumes of all trees belonging to that stratum are summed and divided by the number of field plot centre points in the stratum. The mean volume of a tree means here the volume per hectare represented by the tree (see formulas 11.3a and 11.3b). The indicator variable y_i in the nominator of (11.1) is replaced with the mean volume represented by a tree, or the mean volume of timber assortment class of interest represented by the tree, on field plot i when computing mean volume or total volume estimates. For total volumes, the mean volumes have to be multiplied by the area estimate for the stratum in question.

The mean volumes (m^3/ha) and total volumes (m^3) are estimated as follows:

1. Volumes and volumes by timber assortment classes are predicted for sample trees (every 7th tally tree) using volume functions and taper curve models

(Laasasenaho 1982) and sample tree measurements (see Kuusela and Salminen 1969, Tomppo et al. 1997, 1998).
2. The volumes of tally trees are predicted by strata using the volume predictions for the sample trees and measured and observed tally tree, stand and site variables.
3. Mean volumes are tabulated by computation strata.
4. Area estimates are calculated for the volume strata.
5. Total volumes are tabulated by computation strata.

11.3.2.1 Predicting sample tree volumes and volumes by timber assortment classes

The volumes of the sample trees are predicted using the volume functions of Laasasenaho (1976, 1982), the parameters of the functions having been estimated for the following tree species or tree speices: pine, spruce, birch, aspen, alder, and Siberian larch, (*Larix siberica*, Ledeb.). Models for pine or birch are used for other conifereous and broad-leaved tree species respectively. The explanatory variables of the models are (measured) diameter at breast height $d_{1.3}$, (measured) upper diameter d_6 (for trees of height at least 81 dm) and (measured) height h. The model is thus of the form:

$$\text{current volume over bark } v_{ob,0} = f(\text{tree species}, d_{1.3}, d_{6.0}, h).$$

Separate unpublished models of small trees are employed for trees shorter than a certain tree species-specific threshold, i.e. pine 4.5 m, spruce 3.5 m, birch 6.5 m, aspen 5.0 m and alder 4.0 m.

The volumes of timber assortment classes can also be predicted for sample trees using the taper curve models of Laasasenaho (1982). The explanatory variables are $d_{1.3}$, d_6 (for trees of height at least 81 dm), height h and lengths of the stem parts of different timber assortment classes.Account is also taken of the minimum length requirements, quality requirements and relative unit prices of the timber assortments. A tree stem is assumed to be cut into timber assortments in such a way as to maximize its value. The relative unit price classes are: saw timber (class I) 3, saw timber (class II) 2.5, saw timber (class III) 2 and pulp wood 1.

11.3.2.2 Predicting volumes for tally trees

When using Bitterlich sampling (angle-gauge plots), each tree represents the same basal area per hectare. It is thus convenient to work with quantities called form heights rather than single tree volumes when computing mean volumes or total volumes. Form height is defined as

$$fh = \frac{v}{g}, \tag{11.2}$$

where v is the volume of a tree stem (or the volume of a timber assortment in a tree) and $g = \pi d_{1.3}^2 / 4$ is the intersectional area of the tree at breast height.

Form heights are predicted for tally trees by the non-parametric k nearest neighbour (k-NN) estimation method. For each tally tree whose volumes are to be predicted, the k nearest sample trees are sought, the distance metric applied being Euclidean distance in the Cartesian product space of tree-level variables, tree species, $d_{1.3}$, and tree quality class, and stand-level variables, region code, cumulative day time temperature, site fertility class and stand establishment type. The weighted average of form heights (11.2) for the k nearest sample trees is then used as a predictor for the form height of the tally tree. The weight is the squared diameter of the sample tree. A similar method is employed when predicting the form height of a timber assortment. Only the variables $d_{1.3}$ and tree species group (coniferous vs. non-coniferous) are employed for trees with $d_{1.3}$ < 2 cm, due to the small number of sample trees of a small diameter.

In the case of small strata, e.g. exceptionally thick trees on poor sites, the distances from the nearest neighbours may be high, that is, similar sample trees are rare or do not exist in the current inventory for the region. A priori form height prediction is used as additional information when predicting volumes for these trees, the a priori information being the predicted volume as a function of $d_{1.3}$ and tree species group. The prediction models employed have been estimated using sample trees from neighbouring regions and/or sample trees from the previous inventory.

In total, 18 prediction models are estimated for each region (6 tree species or species groups multiplied by three form height models, corresponding to total volume, saw timber volume and waste wood volume). Sample trees from the previous inventory are not used in estimating form height models for timber assortments, due to changes in the timber quality requirements between inventories. The final form height prediction is a weighted average of the k-NN prediction and a priori prediction (Tomppo et al. 1998).

11.3.3.3 Computing volumes for computation units

The mean volume (m^3/ha) represented by a tree identified using angle-gauge sampling is

$$u = q f h. \tag{11.3a}$$

The maximum distance from the plot centre assigned to tally trees is 12.52 m in Southern Finland, where q = 2, and 12.45 m in Northern Finland, where q = 1.5. Trees thicker than 34.5 or 30.5 cm, respectively, are counted in a fixed-radius plot of area $a = \pi R^2$, where R is the maximum distance. The mean volume represented by this type of tree is

$$u = \frac{g}{a} fh, \tag{11.3b}$$

where g is the basal area of the tree, $g = \pi d_{1.3}^2 / 4$.

The mean volume (m^3/ha) of a stratum is estimated using the formula

$$v_s = \frac{\sum_{i=1}^{n} \sum_{k=1}^{n_i} u_{i,k}}{\sum_{i=1}^{n} x_i}, \tag{11.4}$$

where v_S is the estimate for the mean volume of a stratum S, n is the number of centre points of plots on land in the region, $u_{i,k}$ is the mean volume represented by tree k in stratum S on plot i, n_i is the number of trees in stratum S on plot i and x_i is 1 if the centre of plot i belongs to stratum S and 0 otherwise.

The total volume estimate is

$$V_S = v_S a_S \tag{11.5}$$

where a_S is the estimate for the area of the stratum.

Note that the method takes into account plots shared between two or more calculation strata, so that trees belonging to the stratum in question in parts of a plot that do not include the centre are also included in the sum in formula (11.4). It is assumed in volume estimation that the plot parts are distributed purely randomly between any two arbitrary strata s_1 and s_2. That is, for plots whose centre points belong to s_2 , the expected area of the plot parts belonging to s_1 is the same as the area of the plot parts belonging to s_2 whose centre points belong to s_1.

11.4 INCREMENT ESTIMATION

Volume increment in the Finnish NFI means the increase in tree stem volume over bark, from above the stump to the top of the tree. The annual volume increment is calculated as an average over five years, based only on full growing seasons, assuming that tree growth has finished by August 1. Thus the increments in the five years preceding the inventory year are used for trees measured before August 1, and those in the inventory year and the four preceding years for trees measured on or after August 1.

The phases in calculating the volume increment of a stratum are:

1. prediction of the annual increments in sample trees
2. calculation of the average increments for sample trees by diameter classes (at 1 cm intervals) and by strata, e.g. land use classes, site fertility classes and tree species groups

3. calculation of the total increment for survivor trees in each stratum by diameter classes, by multiplying the average increment for trees in each diameter class by the number of tally trees in that class and summing the increments over the diameter classes
4. calculation of the final increment adding the drain increment to that for the survivor trees.

The need for the last phase is explained below. The sample tree variables employed in the volume increment calculation, in addition to those required in the volume calculation, are: bark thickness, diameter increment in five (full growth) years at a height of 1.3 m (above ground) and height increment. The height increment is measured only for coniferous trees, while that for broad-leaved trees is predicted by means of models (Kujala 1980).

The change in bark thickness must be taken into account in volume calculations, and this is done by introducing the ratio 'volume over bark divided by the basal area under bark (at a height of 1.3 m)'. It is assumed that the change in this ratio is parallel to the average change calculated from a large set of sample trees (Kujala 1980).

To present the calculation of volume increments more formally, the following variables and notations are introduced (cf. Kujala 1980).

d = diameter of tree at height 1.3 m in the inventory year
d_6 = diameter of tree at height 6 m in the inventory year
b = double bark thickness
h = height of tree in the inventory year
i_d = diameter increment
i_h = height increment
h_{-5} = height of tree 5 years before the inventory year
$g_{ub,0}$ = basal area of tree under bark in the inventory year ($= \pi(d-b)^2/4$)
$g_{ub,-5}$ = basal area of tree under bark 5 years before the inventory year ($= \pi(d-i_d-b)^2/4$)
$v_{ob,0}$ = volume of tree over bark in the inventory year
$v_{ob,-5}$ = volume of tree over bark 5 years before the inventory year
i_v = annual volume increment
$r_0 = v_{ob,0} / g_{ub,0}$, current volume over bark divided by current basal area under bark
$r_{-5} = v_{ob,-5}/g_{ub,-5}$, volume over bark 5 years ago divided by basal area under bark 5 years ago
$\hat{r}_0$ = predicted ratio of current volume over bark to current basal area under bark'
$\hat{r}_{-5}$ = predicted ratio of volume over bark 5 years ago to basal area under bark 5 years ago

The predicted ratios $\hat{r}$ are calculated using models for r based on NFI6 data for Southern Finland by tree species covering over 40 000 sample trees. The only explanatory variable is tree height, h. The ratio r may be regarded as a form height

when using the basal area under bark. For a discussion of the reliability of this approach, see Kujala (1980).

1. Predicting the annual increment in a sample tree

1a. For a sample tree, take the current volume over bark as presented in 11.3.2.1. i.e.

$$v_{ob,0} = f(\text{tree species},\ d_{1.3}, d_{6.0}, h)\ . \qquad (11.6).$$

1b. Calculate the ratio

$$r_0 = v_{ob,0} / g_{ub,0}. \qquad (11.7)$$

1c. Calculate the predicted ratios $\hat{r}_0$ and $\hat{r}_{-5}$ using the estimated models.

1d. Define

$$r_{-5} = r_0 - (\hat{r}_0 - \hat{r}_{-5})\ . \qquad (11.8)$$

1e. Define

$$v_{ob,-5} = r_{-5} \times g_{ub,-5}\ . \qquad (11.9)$$

1f. Define

$$i_v = (v_{ob,0} - v_{ob,-5}) / 5 \qquad (11.10)$$

It is assumed that for each individual tree, the derivative of the ratio r, dr/dh, is same as that for the ratio predicted by the model. The bark of trees growing on poor sites is usually thicker than that of trees growing on fertile sites, which will increase the value of r. On the other hand, the form height of trees on poor sites is usually lower than that of trees on fertile sites. These facts cancel each other out to some extent, making the change in r as a function of h almost a tree species-specific constant.

Example 11.1 (Kujala 1980).

For pine, $\hat{r} = 0.39h + 2/(h-1.3) + 0.77\sqrt{h-1.3}$ (omitting a constant 0.39).

Let us take a pine tree with $d = 16$ cm, $d_6 = 11$ cm, $h = 12$ m, $b = 15$ mm, $i_d = 20$ mm and $i_h = 1.9$ m. Then $g_{ub,0} = 0.01651$ m^2, $g_{ub,-5} = 0.01227$ m^2 and $h_{-5} = 10.1$ m. From the taper curve models, $v = 0.1207$ m^3. Hence, $r = 7.309$. From the pine model for $\hat{r}$, $\hat{r}_0 = 7.386$, and $\hat{r}_{-5} = 6.450$. By formula (11.8) $r_{-5} = 6.373$, and thus by formula (11.9) $v_{ob,-5} = 6.373 \times 0.01227$ m^3 = 0.0782 m^3. Thus $i_v = 0.0085$ m^3.

---

2. Calculation of average increments in sample trees by diameter classes

The increment strata are composed in such a way that it can be assumed that the expected volume increase by diameter class is the same for each tree in a stratum. Thus the land use class (forest land, poorly productive forest land), main site class (mineral soil, spruce mire, pine mire), site fertility class and cumulative daytime temperature are all stratification factors in addition to tree species. The increment in tally trees of a diameter class *d* is the average increment in the sample trees multiplied by the number of tally trees, i.e.

$$i_{v,s,d} = n_{t,S,d} \times \bar{i}_{v,s,d} , \tag{11.11}$$

where $n_{t,S,d}$ is the number of tally trees in stratum S and diameter class d and $\bar{i}_{v,s,d}$ the average increment in sample trees in stratum S and diameter class d.

3. Total increment in survivor trees

The total increment is summed over the diameter classes and calculation strata:

$$i_v = \sum_s \sum_d i_{v,s,d} . \tag{11.12}$$

4. Total increment and increment in the drain

Only increments in trees that have survived until the inventory time can be measured. To calculate the total increment over the five-year calculation period, the increments in the trees that have either been cut or have died naturally during the calculation period have to be added to the increment for the survivor trees. If a tree was cut two years before the inventory time, for instance, the increment in the first three years of the period has to be taken into account.

The total drain consists of the following components

1) cutting removals reported by forest industry companies,
2) non-commercial roundwood removals, e.g. contract sawing and fuel wood used in dwellings,
3) estimates of harvesting losses, including those arising from silvicultural measures, based on a special study by the Finnish Forest Research Institute,
4) volume of unrecovered natural losses (currently 2.5 mill. m^3).

It is assumed that the percentage increment in trees that have subsequently been cut or have died is on average 70% of that in survivor trees. The fact that drain

statistics are compiled by calendar years whereas inventory measurements in a region are carried out during the growing season, often partly before August 1 and partly on or after that date in the same region, has to be taken into account when calculating the increment represented by the drain, which is done by dividing the inventory region into two sub-regions on an area basis. The tree species strata for drain statistics are pine, spruce and broad-leaved trees. The increment for a tree species is

$$0.7\frac{i_v}{v}\sum_j p_{y_j} q_{y_j} \ , \tag{11.13}$$

where i_v is the increment in the survivor trees of that species (tree species group), v is the volume of the survivor trees of that species (tree species group), p_{y_j}, j=1,2 is the proportion of that land area measured before August 1 in the inventory year (j = 1) or from August 1 onwards (j=2), q_{y_j}, j=1,2 is a function of the annual drain volumes $v_{dr,t}$ as follows:

$$q_{y1} = (v_{dr,t-5} + 3\ v_{dr,t-4} + 5\ v_{dr,t-3} + 7\ v_{dr,t-2} + 9\ v_{dr,t-1} + 5\ v_{dr,t})/2, \tag{11.14}$$

$$q_{y_2} = (v_{dr,t-4} + 3\ v_{dr,t-3} + 5\ v_{dr,t-2} + 7\ v_{dr,t-1} + 4\ v_{dr,t})/2,$$

$5_{vdr,t-k}$, $k = 0,...5$, is the volume of the drain in year t-k and t is the inventory year (Salminen 1993).

The total increment is the sum of the increment in survivor trees and the increment in the drain (Kuusela and Salminen 1969).

11.5 CONCLUSIONS

The methods employed for calculating the results of the Finnish 9th National Forest Inventory, together with the field measurements and a brief account of the sampling design, have been described in this chapter . The sampling design was decided upon and modified on the basis of experiences and information gathered from the previous inventories. Sampling simulation studies were conducted in all the inventory regions to optimize the design, given acceptable maximum standard errors in the mean volume and total volume of growing stock and estimated measurement costs.

The estimation methods had also gained their current form during previous inventories and through experiences accumulating since the 1920s.

Some basic facts affecting the estimation methods are that NFI9 was based on temporary plots (permanent plots were established in the course of that survey, or in NFI8 in the case of Northern Finland), the land area is assumed to be known and the tally tree plot is an angle-gauge plot (Bitterlich plot). Both the area and volume estimators are ratio estimators. Area estimation is based on the number of centre points of plots.

In volume estimation all the trees belonging to the stratum in question are counted, including trees on parts of a plot that do not include the centre point. All trees are assigned to calculation strata in the field measurements. The sum of tree level volumes per hectare is divided by the area estimate for the stratum concerned. The area estimates are also based on the number of centre points in the volume calculations. This method avoids time-consuming-measurements of the areas of parts of plots in the field and produces statistically unbiased estimates if the boundaries between the calculation strata intersect the field plots purely at random. That is, for the, the area of the parts of plots whose centre points belong to s_2 that belong to s_1 is the same as the area of parts of plots with centre points belonging to s_1 that themselves belong to s_2.

Measurement of the areas of parts of angle-gauge plots would be very difficult or impossible in practice. Note that this method for handling divided plots is also applicable to the case of fixed-radius field plots.

Increment estimation is based on increment borings and height increment measurements performed on sample trees (height increment models in the case of broad-leaved trees). In principle, this method corresponds to the use of permanent plots for increment estimation but produces estimates with a lower standard error than the method which uses volume differences on permanent plots, due to the fact that errors in diameter measurements are usually greater than errors in the measurement of diameter increment cores. NFI also produces information about growth variation (Henttonen 2000), but the increment estimates given in normal publications are presented without growth variation corrections.

NFI10 began in 2004 and is proceeding in a different way from NFI9, with one fifth of the plots in the entire country being measured each year. Thus country-level estimates can be updated annually and regional-level estimates within 2-3 years of the start of the survey. A new estimation method is under development which takes into account the fact that both temporary and permanent plots are used (roughly one fifth of the plots are permanent).

Method used for estimating the standard errors in the area and volume calculations is based on the ideas presented by Matérn (1960) and is described and discussed in detail in the article by Heikkinen in this book, Chapter 10.

REFERENCES

Cochran, W. G. 1977. Sampling techniques. 3rd ed. New York, Wiley.

FAO. 2001. Global Forest Resource Assessment 2000. FAO Forestry Paper 140. Rome 2001. ISBN 92-5-104642-5.

Finland's land area by municipalities on January 1, 2003. 2003. Land Survey Finland. Internet address: www.nls.fi/kartta/julkaisu/alat2003.html.

Henttonen, H. 1991. VMI8:n Pohjois-Suomen otanta-asetelmien vertailu satelliittikuvatulkinnan avulla. Manuscript. Finnish Forest Research Institute.

Henttonen, H. 2000. Growth variation. In: Mälkönen, E. (ed.). Forest condition in a changing environment - the Finnish case. Forestry Sciences, Vol. 65. Kluwer Academic Publishers. p. 25-32.

Ilvessalo, Y. 1927. The forests of Suomi Finland. Results of the general survey of the forests of the country carried out during the years 1921-1924. (In Finnish with English summary). Communicationes ex Instituto Quaestionum Forestalium Finlandie 11.

Kujala, M. 1980. Runkopuun kuorellisen tilavuuskasvun laskentamenetelmä. Summary: A calculation method for measuring the volume growth over bark of stemwood. Folia Forestalia 441:1-8.

Kuusela, K. and Salminen, S. (1969). The 5th National Forest Inventory in Finland. General design, instructions for field work and data processing. Commununicationes Instituti Forestalis Fenniae, 69.4, 1-72.

Laasasenaho, J. 1976. Männyn, kuusen ja koivun kuutioimisyhtälöt. Lisensiaattityö. Helsingin yliopisto. Metsänarvioimistieteen laitos. 89 p. + appendices.

Laasasenaho, J. 1982. Taper curve and volume functions for pine, spruce and birch. Seloste: Männyn, kuusen ja koivun runkokäyrä- ja tilavuusyhtälöt. Communicationes Instituti Forestalis Fenniae 108:1-74.

Matérn, B. 1960. Spatial variation. Meddelanden från statens skogsforskningsinstitut, 49:1-144. Also appeared as Lecture Notes in Statistics 36. Springer-Verlag. 1986.

Mattila, E. 1985. The combined use of systematic field and photo samples in a large-scale forest inventory in North Finland. Seloste: Systemaattisen ilmakuva- ja maastonäytteen yhteiskäyttö laajan metsäalueen inventoinnissa Pohjois-Suomessa. Communicationes Instituti Forestalis Fenniae 131:1-97.

Poso, S., 1972. A method of combining photo and field samples in forest inventory. Commununicationes Instituti Forestalis Fenniae, 76(1).

Poso, S. and Kujala, M. 1971. Ryhmitetty ilmakuva- ja maasto-otanta Inarin, Utsjoen ja Enontekiön metsien inventoinnissa. Summary: A two-phase forest inventory method based on photo and field sampling as applied in Northernmost Lapland. Folia Forestalia 132. 1-40.

Salminen, S. 1993. Eteläisimmän Suomen metsävarat 1986–1988. Folia Forestalia 825. 111 s.

Tomppo, E., Varjo, J., Korhonen, K., Ahola, A., Ihalainen, A., Heikkinen, J., Hirvelä, H., Mikkelä, H., Mikkola, E., Salminen, S. and Tuomainen, T. 1997. Country report for Finland. In: Study on European Forestry Information and Communication Systems. Reports on forestry inventory and survey systems. Vol. 1. European Commission, p. 145-226.

Tomppo, E., Henttonen, H., Korhonen, K.T., Aarnio, A., Ahola, A., Heikkinen, J., Ihalainen, A., Mikkelä, H., Tonteri, T. and Tuomainen, T. 1998. Etelä-Pohjanmaan metsäkeskuksen alueen metsävarat ja niiden kehitys 1968-97. Julkaisussa: Etelä-Pohjanmaa. Metsävarat 1968-97, hakkuumahdollisuudet 1997-2026. Metsätieteen aikakauskirja - Folia Forestalia 2B/1998: 293-374 (in Finnish).

Tomppo, E., Henttonen, H. and Tuomainen, T. 2001. Valtakunnan metsien 8. inventoinnin menetelmä ja tulokset metsäkeskuksittain Pohjois-Suomessa 1992-94 sekä tulokset Etelä-Suomessa 1986-92 ja koko maassa 1986-94. Metsätieteen aikakauskirja 1B/2001: 99-248 (in Finnish).

CHAPTER 12

THE FINNISH MULTI-SOURCE NATIONAL FOREST INVENTORY – SMALL AREA ESTIMATION AND MAP PRODUCTION

ERKKI TOMPPO

Finnish Forest Research Institute, Finland

12. 1 INTRODUCTION

12.1.1 Background

The first forest resource assessments were total cover inventories based either on visual assessments or, in small areas, on counting all trees with a given minimum size., The development of statistically designed sampling-based forest inventories began at the end of 19th century and the beginning of the 20th. The purpose was to get accurate country level and sub-country level forest resource information. Nevertheless, some countries still base their national forest assessments on stand-level (or compartment-level) inventories with visual assessment, possibly assisted by remote sensing data. One problem, in addition to possible biases in visual estimation, is the lack of methods to asses the errors of the estimates for large areas on statistical basis.

Forest decision-making and data utilisation often require information on smaller units than it is possible to reach with sparse field measurements only, and the meeting of this requirement by a field sampling-based method alone would require a many times greater sampling density and thus very much higher measurement costs. Field measurements are one of the most expensive components of sampling-based forest inventories, often the most expensive one of all.

The spatial variation in forests is often such that field measurements in a certain area can also be made use of in neighbouring areas by employing a relevant extrapolating, or 'information borrowing' technique.

This need, that of obtaining forest resource information for smaller areas than would be possible with field data only without increasing the costs of the

A. Kangas and M. Maltamo (eds.), Forest Inventory – Methodology and Applications, 195–224.

inventory significantly, was a driving force behind starting the development of the multi-source forest inventory method (MS-NFI) in connection with the Finnish national forest inventory (NFI). Furthermore, new natural resource satellite images provided new possibilities for increasing the efficiency of the inventories at relatively small additional costs.

One basic requirement placed on the method was that it should be able to provide information applicable to forestry decision-making. Thus methods that are often employed in satellite image-aided approaches, which produce only maps of forest types or land use classes, were not considered satisfactory. Methods were sought for that would be able to provide area and volume estimates, possibly broken down into sub-classes, e.g., by tree species, timber assortments and stand-age classes. In the optimal case, the method had to be able to provide all the same estimates for small areas as the field data-based method provides at national and regional levels. Note that the number of variables measured in the field is usually high, typically ranging from 100 to 400, and that estimates of additional variables are calculated from these measured ones.

One possible approach had been the use of separate or simultaneous regression models, or logistic regression models, for the variables of interest (Trotter et al. 1997, McRoberts 2005, Tomppo 1987, 1992), but one disadvantage was that models had to be derived separately for the variables or groups of variables to be predicted, so that the dependence relations in the predictions did not correspond to the original dependence relations between the field variables. Furthermore, this approach was somewhat laborious for practical applications because models had to be derived separately for each set of satellite images.

These were the reasons for selecting the k-NN approach, which had been used for several decades in image analysis and pattern recognition (see Fix and Hodges 1951). A somewhat similar method, a grouping method, had been used earlier in Northern Finland with aerial photographs and visual interpretation to reduce errors in the estimates (Poso, 1972), and was suggested by Kilkki and Päivinen (1986) for use with satellite images. A further advantage of this method was that it simultaneously produces thematic maps about forest resources .

It soon became obvious that any digital map which could separate forestry land from other land use classes with moderate accuracy could reduce the errors. Note that the maps do not need to be perfect in accuracy, as some of the effects of map errors on the estimates can be removed and handled in a statistically sound way (Katila et al. 2000, Katila and Tomppo 2002, see also Chapter 13 in this book).

The input data for the Finnish multi-source inventory are thus NFI field data, satellite images and digital map data of different types, e.g., basic map data, soil data for stratifying between mineral soil, spruce mires, pine mires and open bogs, and a digital elevation model.

The k-NN estimation method is non-parametric and thus avoids the need for explicit models, but it does presume that the total variation in all the forest variables is well represented by the field sample plots. This method in which the entire field data vector is predicted simultaneously (one vector or the weighted mean

of *k* vectors will serve as the predictor for an un-known field data vector), also preserves the covariance structure of the field variables better than do methods which predict each variable separately (for each element of the vector).

The pixel-level predictions of the variables can be arranged in the form of thematic maps , in which the covariance of the variables is close to that of field variables, which are more applicable for forestry, ecological and environmental purposes than maps in which the predictions have been made separately (Pakkala et al. 2002).

Pixel-level errors are typically high with the k-NN method, but this is also the case with other methods when space-borne satellite images with a spatial resolution of 20 - 30 m are used. The use of *k* field plots instead of one reduces errors caused by random variation in the image data. Several studies are available about the effect of the value of *k* on errors (Franco-Lopez et al., 2001, Katila and Tomppo, 2001, Tokola et al., 1996). High value of k usually decreases RMSE but also shifts the predictions towards the mean. Pre-processing of images and noise reduction also reduce errors and improve the quality of the estimates, particularly at the pixel level. Examples of other error sources are within-stand variation in forest parameters, dislocation of the field plots compared with the image coordinates and numerous other factors affecting pixel-level prediction errors (see the error source discussion in the Conclusion chapter of this article). A method for reducing the second of these problems is presented by Halme and Tomppo (2001).

The k-NN method has also been used or tested in forest inventories outside of Finland, its popularity being based on the simplicity of the basic method and on the facts that there is no need to estimate any model parameters, and particularly that the final calculation of the estimates returns to a result close to that reached with field data only. Franco-Lopez et al. (2001) tested the method both for estimation and map production with data from Forest Inventory and Analysis (FIA) programme of the US Department of Agriculture Forest Service. The outcome was that for map production a small value ok *k* keeps the variation of forest variables in the predictions better that higher values while for statistics, higher value of *k* gives samller RMSE. McRoberts et al. (2002) introduced an interesting stratified estimation method based on the k-NN technique for reducing the errors in forest area estimates in the FIA programme. Haapanen et al. (2004) also tested k-NN method for forest area estimation with US FIA data and noticed that both band weighting and the value of *k* depends very much on the case, image, image conditions and field data.

The performance of the k-NN method with different sets of remote sensing data, including simulated data, used for error estimation, and with the Swedish national inventory was studied in the doctoral thesis of Nilsson (1997). The operative k-NN-based Swedish system is described in Reese et al. (2003). The goal of the system is to produce forest maps both for forestry and ecological purposes.

The main goal in developing the corresonding Norwegian system was to be able to produce forest resource estimates at the municipality level, as in the Finnish MS-NFI (Gjertsen et al. 1999, Gjertsen and Eriksen, 2004).

The possibilities for applying k-NN predictions to harvest planning on radiata pine plantations in New Zealand were studied in Tomppo et al. (1999), who showed that the pixel-level errors were high but could be reduced by using stand age and years since the last thinning as ancillary information. These variables are known for planted forests, and therefore the method showed some promise.

The reduction of errors in small-area estimation with multi-temporal images by the k-NN technique was studied in Nordrhein-Westfalen, Germany (Diemer et al. 2000). The entire inventory concept, from planning of the field sampling design to calculation of the estimates both with field data only for large areas and with a k-NN based multi-source technique for small areas is presented by Tomppo et al. (2001) for an application in Heilongjiang province, North-East China.

12.1.2 Progress in the Finnish multi-source inventory

Development of the Finnish MS-NFI began in 1989, and the first operative results were calculated in 1990 (Tomppo, 1990, 1991, 1996). The method has been modified continuously since then and new features added (Katila et al. 2000, Katila and Tomppo 2001 and 2002). The core of the current method is presented in Tomppo and Halme (2004).

Any digital land use map or land cover data can be used to improve the accuracy of the predictions (Tomppo, 1991, 1996). Methods for removing the effects of possible map errors from the predictions are presented by Katila et al. (2000) and Katila and Tomppo (2002) (see also Chapter 13).

Application of the k-NN estimation method presumes the selection of 'estimation parameters' for each satellite image and for the other data employed along with the image (Katila and Tomppo 2001). Operative application of the method has also shown that the predictions, particularly those of volumes by tree species, may be biased if the area of interest is large and covers several vegetation zones with different tree species compositions (Figure 12.3, Section 12.4.3). One reason for this bias is that mapping from the field data vector space to the image data vector space is not necessarily an injection when the area in question is large. (A function $f: A \rightarrow B$, is injective or one-one, or is an injection, if and only if for all a, b in A, $f(a) = f(b) \Rightarrow a = b$, that is no two different inputs give the same output.). Varying imaging conditions within the area of a satellite image can also alter the covariance structure between the field data and the image data. The biases will be reduced if the set of potential nearest neighbours can somehow be restricted.

In the first operative applications of the Finnish multi-source inventory (MS-FNFI), a sub-set of field plots was selected for potential nearest neighbours in the image space for each pixel, usually field plots within a certain geographical distance from the pixel in question. The goal was to find a sub-area in which a certain spectral vector would correspond to a unique field data vector and vice versa. Methods and criteria for selecting a (pixel-dependent) geographical area from which the nearest field plots (in the spectral space) for each pixel can be selected, i.e. the maximum horizontal and vertical search distances, are studied in Katila and Tomppo

(2001). A regular-shaped search region, e.g. a circle or rectangle, has previously been employed, but vegetation zone boundaries are more complex, and the shape and size of the area selected will typically vary with the location of the pixel on the image (ground element, Figure 12.3, Section 12.4.3).

Tomppo and Halme (2004) presented another method for guiding the selection of field plots that has been in an operative use since early in the year 2000. This employs additional variables in the distance metric, i.e. additional elements in the distance metric vector, to guide the selection of nearest neighbours. The elements are variables describing large-area variations in forest characteristics, e.g., mean volumes by tree species, and are map-form predictions of those variables. A relevant, practical variation scale for these variables and their predictions would range between 40 km and 60 km. Variation on this scale can be computed from field data only, e.g. from field data acquired in the current or preceding inventory of the area.

The method also employs band transformations in addition to the original image bands, since it is assumed that band ratios will improve the identification of tree species, although all the information from the satellite images is already in the original bands. An optimization method based on a genetic algorithm was developed to find the weight vector, a method that considerably reduces the errors both at the pixel level and in areas of different sizes. The method is called the ik-NN method (improved k-NN method) in Tomppo and Halme (2004).

One of the open problems related to the k-NN method is the lack of an analytical method for estimating the standard error of any estimate for an area of an arbitrary size. This problem has been solved in the non-parametric local Bayesian regression method utilising Markov Chain Monte Carlo (MCMC) estimation proposed by Taskinen and Heikkinen (2005). A Bayesian method with a state-space model has also been employed by Wallerman et al. (2003). The current progress with model-based approach has shown some promise also for error estimation for k-NN method (Kim and Tomppo, 2005, McRoberts et al., 2005).

12.2. INPUT DATA SETS FOR THE BASIC AND IMPROVED k-NN METHODS

12.2.1 Processing of field data for multi-source calculations

The core idea in employing multi-source data is to estimate new area weights for field sample plots. Furthermore, digital thematic maps can be created, in principle for any arbitrary variable in the NFI. Examples of map themes would be spatial distributions of site fertility, mean age and diameter of stand, volumes by tree species and timber assortments and volume increment in the growing stock by tree species.

The basic computation unit in image processing is a picture element, a pixel. The pixel size employed with Landsat TM images, for example, is 25 m x 25 m. Therefore it is more convenient to work with volumes per unit area than with volumes of tallied trees. Volumes per hectare are estimated for each sample plot by

tree species and by timber assortment classes based on the tally tree volumes.
The estimation of volumes and volumes of timber assortments for tally trees from field measurements is described in Chapter 11 of this book. The tree level volumes are transformed to volumes per hectare in the MS-NFI using the basal area factor and the maximum radius of the plot. Otherwise, the field variables used are similar to those in the NFI calculations performed using field data only. As the calculations based on field measurements do not involve increment estimates for tally trees, increment estimates are not usually produced using the multi-source method.

12.2.2 Satellite images

Images from the Landsat 5 TM or Landsat 7 ETM+ sensors are the most suitable for operative applications, by virtue of the fairly large coverage area of each image combined with moderate spatial and spectral resolution. These images are given priority when choosing satellite images to cover an area. If these images are not available, e.g. due to clouds, either Spot 2 -4 XS HRV images or IRS-1 C LISS images have been used so far.

The land area of Finland is 30.4473 million hectares, and the total area together with lakes and rivers is 33.8145 million hectares. This was covered by means of 36 Landsat 5 TM images and 2 Spot 2 XS HRV images in NFI8 and its updating in Southern Finland (field data from 1990-1994), and by 40 Landsat 5 TM or Landsat 7 ETM+ images and 4 IRS-1 C LISS images in NFI9 (1996-2003).

Areas corresponding to the cloud-free parts of satellite images are used in operative applications. Forests under clouds and in cloud shadows are assumed to be similar on the average to those on the cloud-free part of the same areal unit (e.g. municipality).

All images are rectified to the national coordinate system, and point-type objects (e.g. small islands) are identified on both the satellite images and the base maps and a regression model fitted to their image coordinates and map coordinates. Second-order polynomial regression models are usually employed for this purpose:

$$\begin{aligned} u &= a_l + b_l x + c_l y + d_l x^2 + e_l y^2 + f_l xy + \varepsilon_u \\ v &= a_c + b_c x + c_c y + d_c x^2 + e_c y^2 + f_c xy + \varepsilon_v \end{aligned} \tag{12.1}$$

where u and v are the image coordinates, x and y the map coordinates and ε_u and ε_v the random errors. A typical number of control points would be around 50.

An image element, i.e. a pixel, can be assigned to each ground element with the resulting model. The nearest neighbour method has been applied to a re-sampling of the images to a pixel size of 25 m × 25 m, which is somewhat smaller than the Landsat TM and ETM+ pixel size and slightly larger than the Spot 2 -4 XS HRV pixel size. This size was selected for practical reasons, as narrower objects (e.g. roads) can be distinguished than at the original resolution of Landsat 5 TM, for

instance. The absolute values of the residuals in the model, i.e., $\hat{\varepsilon}_u$ and $\hat{\varepsilon}_v$, typically range from 0.3 pixels to 0.6 pixels.

12.2.3 Digital map data

Digital map data are used to reduce the errors in the estimates. The errors in both the area and total volume estimates can be reduced significantly by the multi-source method if the distinguishing of forestry land from non-forestry land can be supported by digital map information in addition to satellite images. The effect of possible map errors on the estimates can be reduced by two alternative statistical methods (Katila et al. 2000, Katila and Tomppo 2002). The first is a calibration method using a confusion matrix derived from the land use class distributions on the basis of field plot data and map data, and the second employs stratification of the field plots on the basis of map data (see Chapter 13 in this book). The map information is used to separate forestry land from other land use classes, such as arable land, built-up areas, roads, urban areas and single houses. In addition, a map is used to stratify the forestry land area and corresponding field plots into a mineral soil stratum and a peatland soil stratum (spruce mires, pine mires, open bogs and fens).

The digital map data purchased from the National Land Survey of Finland represent one basic data source in the operative MS-NFI. This database, called "Topo", is the most accurate digital map covering most of the country (Topographic, ..., 1998), the map data for the remaining area being taken from several data sources, mainly provided by the National Survey of Finland (Katila and Tomppo, 2001).

A digital elevation model is used in two ways, for stratification on the basis of elevation data and for correcting the spectral values by reference to the angle between solar illumination and the terrain normal. The latter method is described in detail by Tomppo (1992). Stratification in this context means the maximum vertical distance for possible nearest neighbours to a pixel (see formula (12.2)). The selection of parameters for stratification and spectral correction has been studied by Katila and Tomppo (2001). The basic computation unit in the multi-source inventory is the municipality. The number of these in the entire country is about 500 and their land areas range from around 1000 hectares to some hundreds of thousands of hectares. Digital municipality boundaries are used to delineate the units (Tomppo, 1996).

12.2.4 Large-area forest resource data

The basic k-NN method was employed in NFI8 and the improved ik-NN method was introduced during NFI9. The latter employs a coarse scale variation in the key forest variables to guide the selection of field plots, from which the data are transferred to the pixel to be analysed. The variation is presented in the form of large-scale digital forest variable maps (Figure 12.3, Section 12.4.3), derived either from the current inventory data or from the data of the preceding inventory.

The data produced by the 9th Finnish NFI9 (1996-2003) for Southern Finland were already available when the method was introduced. The inventory progressed by regions, and new large-area maps were created for the MS-NFI calculation whenever the field data for one region were available. The number of field plots on land in the entire country in the NFI9 was 81 249, including 67 264 on forestry land, on 62 266 forest land and poorly productive forest land, and 57 457 on forest land alone. All the plots on forest land and poorly productive forest land were used for the final large-area maps.

The variables were selected in such a way that their values indicate the areas in which the covariance structure between field variables and image variables would be approximately constant. It is assumed that the mapping from field data to image data, conditional for large-scale forest variables, is a bijection. A function, *f:* $A \rightarrow B$, is bijective, or a bijection, or a one-to-one correspondence, if it is both injective (no two values map to the same value) and surjective (for every element of *B* there is some element of *A* which maps to it), that is there is exactly one element of *A* which maps to each element of *B*. Tree species composition or vegetation zones may reflect areas of these types in Finnish forests. Volumes by tree species on forest land and poorly productive forest land were therefore selected as variables. These variables also describe the average variation in the key inventory variables to be estimated in k-NN analysis. The maps were created as follows. The averages of the plot-level mean tree stem volumes (m^3/ha) were computed by field plot clusters, and a map of Finland with a pixel size of 1 km × 1 km was 'filled' with these cluster-level averages using a nearest neighbour method, i.e. the values were taken from the nearest cluster (in geographical space). The map was filtered three times using a moving average with window sizes of 20 km × 20 km, 11 km × 11 km, and 25 km × 25 km (Figure 12.3, Section 12.4.3).

12.3 BASIC k-NN ESTIMATION

As given in section 12.2.4, basic non-parametric k-NN estimation was employed for the MS-NFI calculations during NFI8 and at the beginning of NFI9. The basic principles of the k-NN method should first be described. We recall that each field plot has a certain area representativeness, a plot weight, sometimes called a plot expansion factor when forest inventory estimates are calculated from pure field data. This plot weight can be the total land area divided by the number of field plots on land if either systematic or systematic cluster sampling is employed (Kuusela and Salminen 1969, Tomppo 2005, Chapter 11). In the MS-NFI, new plot weights (not equal for each plot) are calculated for each plot on an areal unit, e.g. municipality, basis (Tomppo 1996). The weights are calculated for each field plot $i \in F$, where F is the set of field plots on forestry land. These plot weights are sums of satellite image pixel weights over the forestry land mask pixels.

The pixel weights are in turn calculated by a non-parametric k-NN estimation method that utilises the distance metric *d*, defined in the feature space of the satellite image data (Tomppo 1991, 1996). The *k* nearest field plot pixels (in terms of *d*), i.e. pixels that cover the centre of a field plot $i \in F$, are sought for each

pixel p under the forestry land mask of the cloud-free satellite image area. A maximum distance is usually set in both a horizontal and a vertical direction in order to avoid selecting the nearest plots (spectrally similar plots) from a region in which the response of the image variables to the field variables is not equal to that of the pixel under consideration. This is necessary due to the fact that the mapping from field data to spectral data is not a bijection in a large area. One reason for this is that the covariance structure between the field variables and image variables may vary from one vegetation zone and one image sub-area to another. Stratification on the basis of soil information is also employed for the same reason (Katila and Tomppo 2001). The feasible set of nearest neighbours for pixel p is thus

$$\{p_i \mid d^{(x,y)}_{p,p_i} \le d^{(x,y)}_{\max}, d^{z}_{p,p_i} \le d^{z}_{\max}, R(p_i) = R(p)\}, \tag{12.2}$$

where $d^{(x,y)}_{p,p_i}$ is the geographical horizontal distance from pixel p to pixel pi, d^{z} the vertical distance, $d^{(x,y)}_{\max}$ and $d^{z}_{\max}$ their maximum permitted values, and R(p) the indicator function of mineral soil/peatland soil (Tomppo 1990, 1991, 1996, Katila and Tomppo 2001).

Denote the nearest feasible field plots by $i_1(p),...,i_k(p)$. The weight $w_{i,p}$ of field plot i on pixel p is defined as

$$\begin{aligned} w_{i,p} = & \quad \frac{1}{d^{t}_{p_i,p}} \Bigg/ \sum_{j \in \{i_1(p),\ldots,i_k(p)\}} \frac{1}{d^{t}_{p_j,p}}, \text{ if and only if } i \in \{i_1(p),\ldots,i_k(p)\} \\ = & \quad 0 \text{ otherwise.} \end{aligned} \tag{12.3}$$

The power t is a real number, usually $t \in (0,2]$. The distance metric d in the operative MS-NFI was earlier

$$d^{2}_{p_j,p} = \sum_{l=1}^{n_c} (f_{l,p_j} - f_{l,p})^2, \tag{12.4}$$

where

$$f_{l,p_j} = f^{0}{}_{l,p_j} / \cos^{r}(\alpha) \tag{12.5}$$

is the normalised intensity value of the spectral band (or feature) l. The normalising is done on the basis of the slope and aspect variation, taking $f^{0}_{l,pj}$ as the original intensity of the spectral band l, α the angle between the terrain normal and the solar illumination, r the applied power due to non-Lambertian surface and n_c the number of spectral features (Tomppo, 1996). Only original spectral bands with equal weights (=1) were employed in the old operative k-NN approach.

In practice, k-NN estimation means transferring field data vectors from k field plots to each pixel, the field plots being pixel-specific. The k vectors are weighted in inverse proportion to the distance from the pixel in question with the given distance metric. The basic principle of the k-NN method with k = 2 is demonstrated in Figure 12.1.

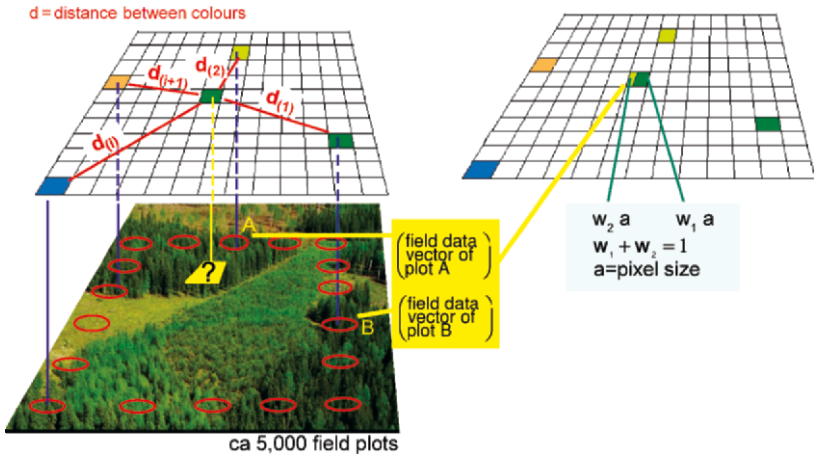


Figure 12.1 A simplified demonstration of the k-NN method with k = 2.

To estimate forest parameters for areal units, the field plot weights on the pixels, $w_{i,p}$ are summed for the areal units (e.g. municipalities) in an image analysis process extending over the pixels belonging to each unit. The weight of plot i in areal unit u is denoted by

$$c_{i,u} = \sum_{p \in u} w_{i,p} . \tag{12.6}$$

Reduced weight sums $c^r_{i,u}$ are obtained from the formula (12.7) if clouds or their shadows cover part of the areal unit u. The real weight sum for plot i is estimated by means of the formula

$$c_{i,u} = c^r_{i,u} \frac{\hat{A}_{s,u}}{\hat{A}^r_{s,u}} , \tag{12.7}$$

where $\hat{A}_{s,u}$ is the estimated area of forestry land in unit u, and $\hat{A}^r_{s,u}$ the estimated area of forestry land in unit u not covered by the cloud mask.

The areas can be taken from digital maps or estimated by means of field plots. It is thus assumed that the forestry land covered by clouds areal unit u is on average similar to the rest of the forestry land in that unit with respect to the forest variables (cf. Tomppo and Halme 2004).

The weights (12.6) and (12.7) are calculated separately for the mineral soil stratum and peatland stratum within the forestry land, and also for other land use classes such as arable land, built-up land, roads and water bodies if a stratification-based map correction method is employed (Katila and Tomppo 2002, Chapter 13). Alternatively, a statistical calibration and confusion matrix can be used to reduce the effect of map errors on the estimates (Katila et al. 2000, Chapter 13 in this book).

After the final field plot weights on the areal units have been calculated, ratio estimation is employed to obtain the estimates (e.g., Cochran 1977). In this sense the estimation procedure is similar to that using field plot data only. Volume estimates, for example, for areal unit u and reference unit s are calculated in the following way. Mean volumes are estimated by the formula

$$v = \frac{\sum_{i \in I_s} c_{i,u} v_{i,t}}{\sum_{i \in I_s} c_{i,u}}, \tag{12.8}$$

where $v_{i,t}$ is the estimated volume per hectare of timber assortment (log product) t on plot i and I_s the set of field plots belonging to stratum s. The corresponding total volumes are obtained by replacing the denominator in formula (12.8) with 1.

The forest variable estimators for areal unit u thus utilise information from outside unit u. The k-NN estimator is therefore a kind of synthetic estimator (Gonzales, 1973).

Mean and total volume increments could be estimated in a similar manner, but increments are not predicted for tally trees in the NFI, but instead can be understood as constant within increment calculation strata, i.e. in relation to tree species, diameter class and site factor class over increment calculation regions. These regions are usually so large that the within-region variation in growth factors is high, so that predictions based on such constants do not correspond to the real variation between MS-NFI areal units (municipalities).

Some examples of estimates obtained with MS-NFI are given in Table 12.1. These are from the 8th inventory, with field data and satellite images for 1992, and concern the Kainuu Forestry Centre District (Tomppo et al. 1998). The estimates are: distribution of forestry land into sub-classes (Table 12.1a), and mean and total volume of growing stock on forest land and on poorly productive forest land (PPF land, sometimes called scrub land) (Table 12.1b).

Table 12.1a Distribution of forestry land into sub-classes.

	Forest land		PPF land		Waste land		Forestry land, Total	
	ha	%	ha	%	ha	%	ha	%
Hyrynsalmi	113370	83.7	14435	10.7	7689	5.7	135494	100.0
Kajaani	92850	88.8	7798	7.5	3971	3.8	104619	100.0
Kuhmo	388155	83.7	49706	10.7	25737	5.6	463598	100.0
Paltamo	73713	89.0	6429	7.8	2708	3.3	82850	100.0
Puolanko	191331	80.7	30259	12.8	15389	6.5	236980	100.0
Ristijärvi	69148	87.7	6613	8.4	3120	4.0	78881	100.0
Sotkamo	222928	90.0	16846	6.8	7985	3.2	247759	100.0
Suomussalmi	389616	77.0	65185	12.9	50876	10.1	505677	100.0
Vaala	88493	75.6	18862	16.1	9661	8.3	117016	100.0
Vuolijoki	52272	82.3	8344	13.1	2921	4.6	63536	100.0
Total, MS-NFI	1681876	82.6	224477	11.0	130057	6.4	2036410	100.0
Total, NFI	1659701		222675		142749		2025124	
Standard error of NFI	13895		8969		7863		8582	

For the purposes of the MS-NFI, forestry land (FRYL) consists of forest land (FL), poorly productive forest land (PPFL) and waste land (WL). In the national classification, forestry roads and depots together with some other minor areas connected with forestry are included in the forestry land. Note that totals for the entire forestry centre district are given in two ways in Table 12.1a) and Table 12.1b), based on the one hand on the MS-NFI and on the other hand on the field inventory only (NFI). The standard errors for the forestry centre totals in Tables 12.1a and 12.1b are based on NFI. The error estimation method is presented in Chapter 10 in this book (Heikkinen); see also Matérn (1960). In addition to the tables present above, the following other tables were given in MS-NFI8 for all the municipalities in Finland: areas of mineral soil and peatland soils on FL, SRCL and WL separately, tree species dominance on FL and SRCL separately, areas of age classes on FL, mean volumes (m^3/ha) by age classes on FL, areas of development classes on FL; mean volumes (m^3/ha) by development classes on FL, mean and total volumes by tree species, timber assortment classes on FL and on FL and SCRL combined and some relative distributions for the area and volume estimates.

Table 12.1b Mean and total volume of growing stock on forest land and on poorly productive forest land .

	Forest land			Poorly productive forest land		
	ha	m^3/ha	1000 m^3	ha	m^3/ha	1000 m^3
Hyrynsalmi	113370	67.4	7638	14435	12.0	173
Kajaani	92850	68.8	6386	7798	11.1	87
Kuhmo	388155	74.9	29083	49706	11.4	567
Paltamo	73713	83.2	6133	6429	12.8	82
Puolanko	191331	69.7	13341	30259	13.2	399
Ristijärvi	69148	68.7	4748	6613	11.1	73
Sotkamo	222928	75.7	16870	16846	11.5	194
Suomussalmi	389616	66.1	25747	65185	10.4	678
Vaala	88493	64.0	5661	18862	13.3	251
Vuolijoki	52272	74.6	3900	8344	10.2	85
Total, MS-NFI	1681876	71.1	119507	224477	11.5	2589
Total, NFI	1659701	70.8	117000	222675	12.6	2800
Standard error of NFI	13895	1.4	2494	8969	0.7	198

Predictions of certain (optional) forest variables are written in the form of a digital map during the procedure, e.g. the land use classes outside forestry land are transferred to mapform predictions directly from the digital map file. Within the forestry land, the variables are predicted from the weighted averages of the *k* nearest neighbours (see Tomppo, 1991, 1996).

A pixel-level prediction $\hat{m}_p$ of variable *M* for pixel *p* is defined as

$$\hat{m}_p = \sum_{i \in F} w_{i,p}\, m_i \,, \tag{12.9}$$

where m_i is the value of the variable *M* on plot *i*.

The mode or median value is used instead of the weighted average for categorial variables, i.e. land use class, site fertility class, stand age, mean diameter of stand, mean height of stand, and volumes by tree species (pine, spruce, birch, other broad-leaved trees) and by timber assortment class. The total number of maps is thus over 20. An example of an output map from MS-NFI8 is shown in Figure 12.2.

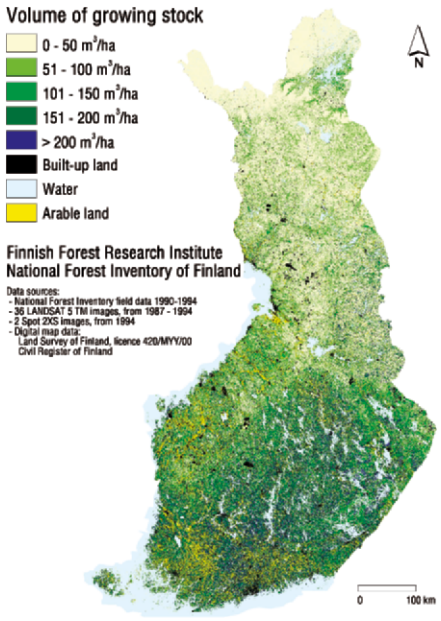


Figure 12.2 Map depicting the volume of growing stock, produced in the Finnish multi-source national forest inventory. Note that the classification is done for the visual image. The unit in the original digital data is 1 m^3/ha.

12.4 THE IMPROVED k-NN (ik-NN) METHOD

As stated earlier, one of the main problems in practical applications of the k-NN method is how to select the sub-area and sub-set of the field plots from which the potential nearest neighbours are sought for each pixel. Another problem is the selection of the spectral features of the distance metric (12.4) in order to achieve as small errors as possible.

These problems were studied by Tomppo and Halme (2004), who introduced a method called ik-NN, the improved k-NN method. A summary of the method is presented here. The overall aim of the improved method is to minimize the errors attached to predictions based on the multi-source inventory, both at the pixel level and particularly at higher areal levels (from several tens of thousands of hectares up to several millions of hectares).

Two modifications of the k-NN estimation method were introduced:

1) the use of supplementary ancillary variables in addition to spectral data for selecting neighbours,
2) the use of 'optimal' weights for both the image features and the ancillary information. A vector consisting of these elements is called a vector of explanatory

variable weights and denoted by ω. A method was developed for using ancillary data and finding the optimal explanatory variable weights.

As for the first modification, the complexity of the problem was reduced by selecting a few core variables and studying their estimates. Volumes by tree species were selected as the variables, since tests with age class distributions, and also earlier experiments, had shown that the errors in the predictions for other variables are reduced when those attached to volumes by tree species are minimized (Tomppo et al. 1998).

The optimization was carried out solely at the pixel level. It was hoped, and later checked, that larger area errors would decrease once the weights were optimized. This was considered to be the ultimate check of the success of the procedure.

A weighted sum of pixel level biases and RMSE's of the predictions was selected as the objective function. The weights are called fitness function weights and denoted by γ (12.10). The variables employed were: 1) total volume, 2) volume of pine, 3) volume of spruce, 4) volume of birch and 5) volume of other broad-leaved tree species. These 10 variables have also been used in operative applications of the method. The fitness (objective) function to be minimized with respect to ω is:

$$f(\omega, \gamma, \hat{\delta}, \hat{\bar{e}}) = \sum_{j=1}^{n_e} \gamma_j \hat{\sigma}_j(\omega) + \sum_{j=1}^{n_e} \gamma_{j+n_e} \hat{\bar{e}}_j(\omega), \qquad (12.10)$$

where $\boldsymbol{\gamma} > 0$ are user-defined coefficients for the pixel level standard errors $\hat{\sigma}_j$ and biases $\hat{\bar{e}}_j$ in forest variable j (applied in a genetic algorithm) and $\boldsymbol{\omega}$ is the weight vector to be estimated (formula 12.11). the feasible set of weight vectors is denoted by $\boldsymbol{W}$.

The pixel-level biases and errors in the multi-source inventory (k-NN) estimates are

$$\hat{\sigma}_m = \sqrt{\frac{\sum_{i \in F} (\hat{m}_i - m_i)^2}{n_F}}$$

and the bias

$$\hat{\bar{e}} = \frac{\sum_{i \in F} (\hat{m}_i - m_i)}{n_F},$$

where m_i is the observed value of the variable to be estimated (e.g. total volume), $\hat{m}_i$ its estimate on plot i and n_F the number of field plots.

The fitness function weights, bias weights and RMSE weights were experimentally given values and then fixed. This weighted sum was the criterion in the search for good weight vectors for image features and ancillary information.

Since determination of the large-area predictions for the forest variables, even for one weight vector, is an extremely computer-intensive task, the pixel-level objective function (formula 12.10) has to be taken as a proxy for the real objective. This is a major source of imprecision in the process, alongside the choice of variables and fitness function weights and the non-optimality of the optimization result.

Note that the explanatory variable weights (ω) are sought in such a way as to optimize the prediction of the selected variables, in this case volumes. Note also that the Landsat pixel measures information from an area that is larger than the size of a field plot (Halme and Tomppo 2001). This discrepancy is interpreted as a measurement error: a large one in the case of satellite images. It was decided to seek the weight vector using only field plots sufficiently far from the nearest stand boundary or land use class boundary to reduce this error. In practice a minimum distance of 20 metres was used. This decision was also motivated by the fact that another source of error is the location of the field plots with respect to the satellite image pixels. It is important to note that the final large-area and municipality group-level estimates and error validation are calculated in operative applications using all the NFI field plots and weights obtained from optimization with plots located at least 20 metres from the nearest stand boundary.

The predictions and their standard errors calculated from field data only are employed to validate all the multi-source predictions in areas ranging from several hundreds of thousand hectares to several million hectares. This is due to the fact that multi-source error estimation for areas larger than a pixel (field plot) is complicated and no solution has yet been found. Satisfactory predictions for groups of municipalities (at the level of several hundreds of thousands of hectares) and at the pixel level are assumed to be satisfactory at the levels of a few thousand and some tens of thousands of hectares as well. However, also note the recent model-based development in error estimation for areas of arbitrary size, mentioned earlier (Kim and Tomppo, 2005, McRoberts et al. 2005).

A new distance metric proposed by Tomppo and Halme (2004) introduced two types of new element into the distance vector: 1) transformations of spectral bands, and 2) coarse-scale predictions of some key forest variables (formula 12.11), also called ancillary variables. All possible ratios of spectral bands were used, as it was hoped that band ratios could distinguish between tree species, e.g. pine and spruce, better than the original bands. The use of large area forest variables as additional elements directed the selection of nearest neighbours to forests that were similar to the target pixel (cf. Figures 12.3, 12.4, 12.5 and 12.6). All the elements were finally weighted. The distance metric, also applied to the operative MS-NFI, was thus

$$d^2_{p_j,p} = \sum_{l=1}^{n_f} \omega_{l,f}{}^2 (f_{l,p_j} - f_{l,p})^2 + \sum_{l=1}^{n_g} \omega_{l,g}{}^2 (g_{l,p_j} - g_{l,p})^2 \ , \qquad (12.11)$$

where $f_{l,p}$ is the l^{th} image variable, $g_{l,p}$ the large-area prediction for the l^{th} forest variable, n_f the number of image variables (or features), n_g the number of coarse-scale forest variables and $\boldsymbol{\omega}_f$ and $\boldsymbol{\omega}_g$ the weight vectors for the image features and coarse-scale forest variables, respectively. A pixel size of 1 km × 1 km is used in the coarse-scale forest variable predictions $g_{l,p}$. (Note the different pixel sizes for large-area forest variables and satellite image data.)

The values for the elements of the weight vector to be estimated are derived from an optimization employing a genetic algorithm, as given below. The first phase of ik-NN is to run the optimization algorithm, possibly by strata in the applications, e.g. for the mineral soil stratum and mire and bog stratum separately. The procedure then returns to the basic k-NN estimation.

12.4.1 Simplified sketch of the genetic algorithm

A genetic-type algorithm was selected due to the complexity of the optimization problem and because the optimization problem may have several local optima. The method noticeably reduces errors both at the pixel level and over areas of some thousand square kilometres or larger.

Genetic algorithms that imitate the behaviour of genes are currently used to solve difficult optimization problems such as combinatorial problems, but they are also popular for modelling economic and ecological phenomena and machine learning (see Mitchell 1996). Genetic algorithms often produce good results with problems that are hard to solve, but they also require a considerable amount of adjustment to fit the algorithm to the problem.

The following outline of the algorithm serves two purposes: it illustrates the principles of a genetic algorithm in general, and the version presented is similar to the genetic algorithm application discussed in this paper. For more information on genetic algorithm schemes, see Mitchell (1996, also Tomppo and Halme 2004).

The elements and operators of genetic algorithms originate from biology. The candidate solution vector is called a chromosome and a group of chromosomes is called a population. One population is a generation. The operators are: selection of chromosomes (the criterion being their fitness), the crossover of chromosomes producing new offspring and the random mutation of new offspring.

The account below does not include all the features of the algorithm employed in this paper. A more detailed version is presented by Tomppo and Halme (2004). In a genetic algorithm, the value of the objective function for a trial solution is called the fitness value of the solution.

The key parameters of the algorithm are:

n_{gen} = number of generations

n_{pop} = number of weight vectors in one population and number of vectors in the medipopulation (these need not be the same)

p_u = probability used in uniform crossover
p_c = probability of accepting an inferior solution created by mutation
p_m = mutation probability
p_{rm} = radical mutation probability
p_{t1} = probability 1 in selection
p_{t2} = probability 2 in selection

The definitions of the parameters are given in the following simplified sketch, borrowed from Tomppo and Halme (2004).

1. Initialisation
Generate the initial population with n_{pop} random weight vectors. Calculate their fitness values (12.10). Set the generation count to 1.

2. Selection
In this step a medipopulation (an intermediate group of weight vectors between two populations) is formed. Choose two weight vectors in the population (e.g. randomly or successively at some point) the fitness values of which are to be compared. The one with the better fitness value is chosen as a member of the medipopulation with the probability p_{t1}, and the one with the poorer fitness value is chosen as a member with the probability $1\text{-}p_{t1}\text{-}\ p_{t2}$. They are both members with the probability p_{t2}. Repeat until the medipopulation consists of n_{pop} vectors. Note that several copies of vectors may occur.

3. Crossover
In this step a new population is formed. A uniform crossover is carried out with two successive vectors of the medipopulation ***a*** and ***b*** (parent vectors) to produce two offspring ***c*** and ***d***. This will mean that, with probability p_u, the *kth* element (k = 1, …, n) of ***c*** (***d***) will come from ***a*** (***b***) and $(1\text{-}\ p_u)$ from ***b*** (***a***); Pick the vector having the best fitness in the set consisting of both offspring and parents to be a member of the next population. Repeat until the population consists of n_{pop} vectors. Increase the generation count by 1. Stop when the count is equal to n_{gen}.

4. Mutation
In this step the weight vectors in the new population may undergo mutation.
Each element in each vector of the population has a mutation probability p_m. Two kinds of mutation can occur: radical (probability p_{rm}) (the element is subtracted from 1) or non-radical (the element is changed by +-20 per cent). The mutant vector replaces the original vector as a member of the population if its fitness is better than that of the original vector. If its fitness poorer, it replaces the original vector as a member of the next population with a probability p_c and whereas the original vector has the probability $1\text{-}\ p_c$ of remaining a member of the population. Go to 2.

An element changes by +-20 per cent if non-radical mutation takes place. This percentage was observed to perform well.

12.4.2 Application of the algorithm

Practical solutions obtained when applying the genetic algorithm are described in this section. The optimization problem to be solved is the distance metric that gives the lowest value for a linear combination of the RMSEs and biases. An 'optimal' weight vector for the elements of the distance metric has to be sought.
Let the vector $\gamma > 0$ (formula 12.10). The objective function can therefore be denoted by $f(\boldsymbol{\omega}, \hat{\boldsymbol{\sigma}}, \hat{\bar{e}})$. The objective as a function of $\boldsymbol{\omega}$ is not continuous.

After numerous experimental runs to develop the method, upper bounds were introduced for the elements of the weight vector. This was because the objective seemed to be unexpectedly flat, providing a huge number of "equally good or almost equally good" solutions. No meaningful losses in the optimal values for the objective function were observed due to these bounds (Tomppo and Halme 2004, see Tables 12.2 and 12.3). Thus the set of feasible weight vectors W fulfils the condition

$$W = \left\{ \omega \in R_n^+,\ 0 \le \omega_k \le uppe_k,\ k = 1,...,n,\ \sum_{k=1}^{n} \omega_k = 1 \right\},$$

where $uppe_j$ = upper bound for variable j
n_g = number of large-area forest variable estimates employed
n_f = number of spectral image variables employed
$n = n_g + n_f$ = sum of the number of spectral image and ancillary variables.

The variables employed in the fitness function (formula 12.10) were 1) mean volume (m^3/ha) of all tree species on the field plot, 2) mean volume of pine, 3) mean volume of spruce, 4) mean volume of birch (two species) and 5) mean volume of other broad-leafed tree species. The values of the vector $\boldsymbol{\gamma}$ (formula 12.10) were sought at the beginning and finally fixed at $\boldsymbol{\gamma}$=(0.3, 0.6, 0.6, 0.2, 0.1, 0.5, 1, 1, 0.2, 0.1). The first five elements are the coefficients of the estimates of the standard errors $\hat{\sigma}_j$ and the rest those of the estimates of the biases $\hat{\bar{e}}_j$, cf. formula (12.10). In the fitness function, the biases were given weights larger than the standard errors and the biases for pine and spruce were given especially large weights. The aim was to reduce the biases of the corresponding estimates both at the pixel level and for large areas because of problems in distinguishing between pine and spruce volumes in some areas.

The parameter values that worked successfully were:
n_{pop} = 50
n_{gen} = 30 - 80
p_u = 0.75
p_m = 0.05

$p_{rm} = 0.35$
$p_c = 0.5$
$p_{t1} = 0.95$
$p_{t2} = 0.03$.

These values seem to work well for all multi-source data sets and have also been employed in the operative MS-NFI since implementation of the method.

12.4.3 Reductions of the bias and standard error of the estimates at the pixel level and regional level

To demonstrate the performance of the ik-NN method and to show the difference between the errors of the estimates obtained with the ik-NN and k-NN methods, some results are shown for an area in Eastern Finland. These results are part of the operative MS-NFI and were obtained when ik-NN method was being developed.

The area covers the major parts of the Eastern Savo and Northern Karelia Forestry Centre Districts, whose total land area is 3.222 million hectares and forestry land area 2.861 million hectares. The NFI9 was conducted in this area in 1999 and 2000. The total number of field plots was 11 415. Some results for a sub-area of 2.22 million hectares with 1.97 million hectares of forestry land (not covered by clouds or cloud shadows on the satellite image used) are shown here. The remaining area was arable land and built-up areas. The area was covered by two Landsat 7 ETM+ images, 186-16 and 186-17 obtained on June 10, 2000 (Figure 12.3).

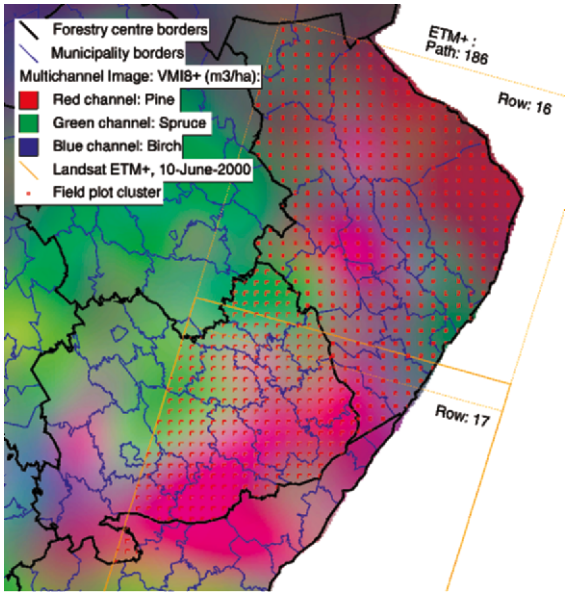


Figure 12.3 Large-scale variation in mean volumes of the main tree species, with boundaries of municipalities and forestry centre districts, field plot clusters and Landsat ETM + image boundaries.

The first phase in applying the ik-NN method is to calculate the weights (ω) (formula 12.11). This is done using only field plots that are far enough away from the nearest stand boundary or land use class boundary (20 metres). The goal is to try to avoid the effect of mixed pixels on the weights. It should be recalled that all the field plots with their calculated weights are used in the estimation phase. The main objective in introducing the ik-NN method was to reduce the bias attached to the predictions both at the pixel level and, particularly, over larger areas, with the ultimate goal of improving the estimation of pine and spruce volumes. Examples of pixel-level (field plot-level) biases for predictions of volumes by tree species for the k-NN estimates (k-NN), k-NN predictions using large-area variables (k-NN la) and ik-NN methods using leave-one-out cross-validation and field data-based volume predictions $\hat{V}_F$ as a reference are shown in Table 12.2 (Efron and Tibshirani 1993).

Table 12.2 Examples of biases attached to k-NN predictions, k-NN predictions with large-area variables (k-NN, la) and ik-NN predictions at the pixel level (field plot level) on the mineral soil stratum, leave-one-out cross-validation, using field data-based volume predictions $\hat{V}_F$ as a reference. 1953 field plots, k=5, upper bounds employed.

	$\hat{V}_F$	Bias	Stand err. of bias	Bias a)	Stand. err. of bias	Bias b)	Stand. err. of bias	Reduction
		k-NN	k-NN	k-NN, la	k-NN, la	ik-NN	ik-NN	a) / b)
Volume	*m³/ha*	*m³/ha*	*m³/ha*	*m³/ha*	*m³/ha*	*m³/ha*	*m³/ha*	%
Pine	63.750	2.430	1.648	2.230	1.570	-0.002	1.539	99.925
Spruce	38.883	-3.167	1.304	-4.725	1.293	-0.005	1.260	99.891
Birch	15.903	-0.961	0.684	-1.571	0.696	-0.199	0.701	87.346
O. br. l.	3.874	-0.382	0.376	-0.430	0.383	-0.133	0.389	69.057
Total	122.303	-2.021	1.827	-4.432	1.764	-0.259	1.800	94.152

A total of 1953 field plots located at least 20 *m* from the nearest stand boundary were employed. Spruce volume was significantly underestimated. The addition of large-area variables to k-NN did not alone reduce the biases, but a reduction was noticeable with ik-NN, although all the predictions were somewhat lower for birch and other broad-leaved tree species than for pine and spruce (Columns a/b in Tables 12.2 and 12.3 indicate the relative decrease in the absolute value for the bias.) This is a consequence of the selection of the weights fixed in the fitness function rather than of the capability of remote sensing data for distinguishing broad-leaved tree species, for instance. The biases are much less than one standard error for all of the variables.

An example of the bias reductions achieved for the peatland soil stratum is shown in Table 12.3. Here 638 field plots located at least 20 *m* from the nearest stand boundary were employed. The relative bias reductions for pine and spruce

volumes are about as high as for the mineral soil stratum, that for birch a little less and that for other broad-leaved tree species much less, although the original absolute biases for broad-leaved trees were small. The biases divided by the predictions were nevertheless high due to the low value of the predictions. All the pixel-level biases for volume predictions were satisfactory.

Table 12.3 Biases in k-NN predictions, k-NN predictions with large-area variables (k-NN, la) and ik-NN predictions at the pixel level (field plot level) on the peatland soil stratum using leave-one-out cross-validation and field data-based volume predictions V_F in the comparison, with 638 field plots, k = 5, tolerance = 5 × correlation coefficient with ik-NN.

	$\widehat{V}_F$	Bias	Stand err. of bias	Bias a)	Stand. err. of bias	Bias b)	Stand. err. of bias	Reduction
		k-NN	k-NN	k-NN, la	k-NN, la	ik-NN	ik-NN	a) / b)
Volume	*m³/ha*	*m³/ha*	*m³/ha*	*m³/ha*	*m³/ha*	*m³/ha*	*m³/ha*	*%*
Pine	50.101	1.735	1.888	1.610	1.813	0.012	1.924	99.255
Spruce	10.498	-1.482	1.268	-2.694	1.214	-0.019	1.738	99.295
Birch	7.633	-0.454	0.760	-1.092	0.762	-0.303	1.151	72.253
O. br. l.	0.305	-0.029	0.128	-0.069	0.125	-0.062	0.757	10.145
Total	68.525	-0.231	2.058	-2.241	1.975	-0.367	0.123	83.623

This method also controls for regional-level errors in addition to pixel-level errors and biases. The predictions are validated at the level of groups of municipalities as follows. The area in question is divided into sub-areas with forest and other wooded land areas, ranging typically between 150 000 ha and 300 000 ha. The objective in the division is to create sub-areas that are as homogeneous as possible with respect to mean volumes by tree species, with their forest and other wooded land area being at least 150 000 ha (Figure 12.4). The evaluation is carefully designed to identify possible confusions in mean volume predictions by tree species. This is possible if the within-group variation is as small as possible and the between-groups sub-area variation is as high as possible. The field data-based estimates of areas and volumes by tree species and their standard errors are calculated for these areas. All the field plots on forestry land (excluding forestry road plots) were employed both in the field data-based estimation and in the multi-source estimation.

Examples of the predictions for mean volumes by tree species (m^3/ha) are given for two municipality groups in Table 12.4. The table also gives standard errors for the field data-based predictions. The table enables multi-source predictions to be compared with the field data estimates and assessed in terms of the field databased standard errors.

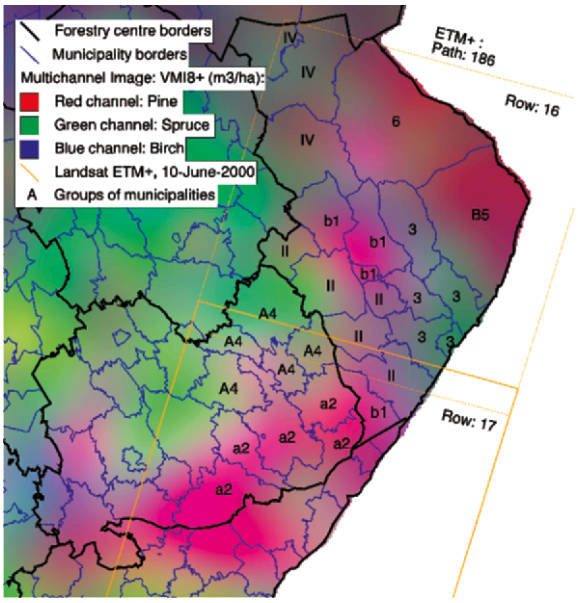


Figure 12.4 Areal units used for the compilation of Table 12.4, together with municipalities and forestry centre boundaries, displayed on large-scale volume maps.

The distinction between pine and spruce is often not good enough (Table 12.4). In both areas the mean volume of pine was originally over-estimated and that of spruce under-estimated. The mean volumes of pine in these areas are lower than in the neighbouring areas and also lower than the averages for the entire area in question.

The ik-NN method gave lower deviations from the field data-based predictions, and thus more accurate predictions, in both sub-areas. The predictions for the mean volumes of birch and other broad-leaved trees obtained using the ik-NN method were also nearer to the field data-based predictions than for the k-NN method; or at least they did not deviate any more than the latter. (Note that more weight is often given to pine and spruce volumes in formula (12.10) than to birch or other broad-leaved tree volumes.)

Table 12.4 Estimates of the volume of growing stock (m^3/ha) on forest and other wooded land (a) and its standard error (a_{er}) by tree species based on field data and on the k-NN method (b), ik-NN method (c) and ik-NN method when the resulting large-area weights have been multiplied by 10 (d), for two municipality groups. The estimated area of forest land and other wooded land is 241 200 ha for group 3 and 234 700 ha for group A4 (Figure 12.4). The multi-source estimates are compared with the field data-based estimates.

Group 3	a	a_{er}	b	b-a	c	c-a	d	d-a
Pine	48.6	2.9	53.8	5.2	47.5	-1.1	49.7	1.1
Spruce	38.5	2.5	35.6	-2.9	41.9	3.4	40.3	1.8
Birch	15.7	1.2	15.7	-0.0	15.8	0.1	15.9	0.2
Other br. 1.	4.3	0.6	3.7	-0.6	3.6	-0.7	3.1	-1.2
Total	107.2	3.3	108.8	1.6	109.0	1.8	108.9	1.7

Group A4	a	a_{er}	b	b-a	c	c-a	d	d-a
Pine	47.9	3.2	56.3	8.4	49.1	1.2	51.0	3.1
Spruce	53.7	2.8	49.6	-4.1	56.9	3.2	55.8	2.1
Birch	18.1	1.2	18.5	0.4	17.5	-0.6	18.0	-0.1
Other br. 1.	8.1	0.9	5.4	-2.7	6.0	-2.1	5.7	-2.4
Total	127.9	4.2	129.7	1.8	129.4	1.5	130.6	2.7

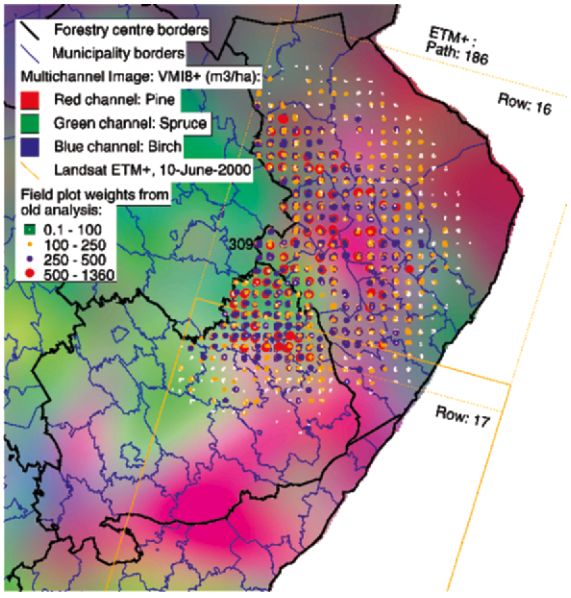


Figure 12.5 Distribution of weights for an individual municipality (east of 309) with the old k-NN method: large-area information is not used, only the original bands with even weights are employed.

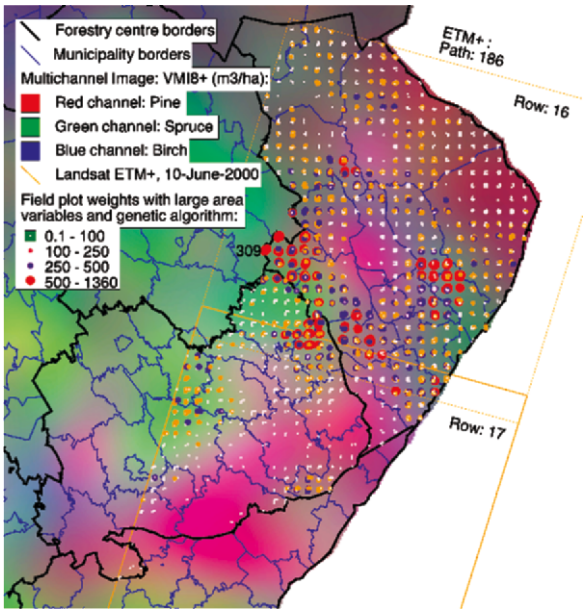


Figure 12.6 Distribution of weights for an individual municipality (east of 309) with the ik-NN method: large-area information, the original bands and band ratios with optimised weights are employed.

Use of information on large-area variations in forest variables in conjunction with the ik-NN method noticeably reduces the problem of distinguishing pine dominant stands from spruce dominant ones, for instance, or of estimating the volumes by tree species. The effect on the weights of the field plots, i.e. on the quantities $c_{i,u}$ in formula (12.7), is demonstrated in Figures 12.5 and 12.6. The weights are given for the northernmost municipality in sub-area II (east of the number 309). The weights were more evenly spread over the entire area covered by field plots with the k-NN method than with ik-NN. On the other hand, the field plots in forests with a tree species composition similar to that of municipality 309 obtained higher weights with ik-NN than with k-NN. Note that field plots in only two forestry centre districts were employed.

12.5 CONCLUSIONS

The Finnish National Forest Inventory has been using a satellite image-aided multi-source method since 1990 in order to obtain results for smaller areas than is possible using field data only. The entire country has been covered twice by this method. The method is under continuous refinement. During the ninth inventory (1996-2003), the method was enhanced by introducing certain new features: 1) the use of large-area

forest variables for directing the selection of nearest neighbours, 2) the use of an optimization method based on a genetic algorithm to weight both large-area forest variables and satellite image variables, and 3) two optional methods were developed to remove the effect of map errors on the estimates. The new ik-NN method performs noticeably better than the original k-NN method. The use of information on large-area forest variables considerably reduces the problem of distinguishing stands with different tree species, or tree species composition, and reduces the errors entailed in the estimates of volumes by tree species. This has been a serious problem in areas where large-area tree species dominance changes, e.g. where spruce-dominated forests change into pine-dominated ones or vice versa, a common occurrence in the Boreal region. Note that any relevant data, such as soil data or vegetation zone data, can be employed as ancillary data. The method, which is already in operative use in the Finnish multi-source forest inventory, reduces the biases and standard errors both at the pixel level and in larger areas. Comparisons with the k-NN method have been made with numerous Landsat TM and ETM+ images, and the method seems to perform well and to give in practice predictions with smaller errors than the old k-NN method did. Validation has been carried out, as is always the case in operative applications, at the pixel level and at the level of municipality groups, for which predictions and standard errors can be computed by means of field data only.

Two methods for reducing the errors in predictions caused by possible errors in the digital base maps are in use in the operative MS-NFI, a calibration method (Katila et al. 2000) and a stratification method (Katila and Tomppo 2002, Chapter 13). The new ik-NN method is applicable with both map correction methods. When using the stratification method, field plots outside the area of forestry land can be employed and separate weights can be calculated for different strata, as is done within forestry land for the mineral soil stratum and peatland soil stratum.

The pixel-level and stand-level errors of the estimates are rather high with current satellite images, for several reasons. The error sources in pixel-level predictions of forest variables have been listed in many papers (e.g. Katila 2004, and Tomppo et al. 1998). Examples are 1) possible errors in field data measurements and the models used to estimate tree and plot variables, 2) errors in the geographical location of field plots and their corresponding pixels, 3) field measurements apply to areas which do not correspond to the area of a satellite image pixel, 4) it is very seldom that all the factors affecting the spectral response of a satellite image are measured in the field, sometimes not all trees and seldom the ground vegetation, 5) the radiometric resolution of the sensors is inadequate (the sensors are not able the recognize all the variation in the target area, i.e. two targets in the field may give the same spectral response), 6) scattering of radiance in the atmosphere, 7) within-image variation in imaging conditions (different parts of an image are subject to different solar illumination and atmospheric conditions), 8) the variation in the field plots may not cover all the variation in the field, and 9) possible timing differences between the field data and image data. Furthermore, 10) soil moisture variation in the target area may affect the spectral properties, so that two areas with the same growing stock

may have different spectral properties, or two areas with different growing stock may have same spectral properties.

There are several methods for assessing pixel-level errors. Leave-one-out cross-validation has been employed in many cases, and Kim and Tomppo (2005) applied variogram modelling to the spectral space. The finding of a generally applicable error estimation method for areas larger than a pixel is a challenging task. Since the error in the predictor of a variable depends on the true value of the variable, errors are spatially correlated, and spatial dependences in the image itself make the error structure even more complex. Lappi (2001) presented a different, calibration-type approach to multi-source estimation, together with a variogram-based variance estimator, and some other interesting variogram approaches are currently under development (McRoberts et al. 2005).

Practical applications of the multi-source inventory technique are also currently facing other problems. One of the most serious ones related to optical area images in certain regions of the globe is the availability of images obtained under cloud-free conditions. The most applicable satellite sensor, Landsat 7 ETM+, has suffered from a scan line corrector failure since 2003. Several correction methods have been introduced, but the quality of the product is not the same as before (see USGS 2005). One advantage of the k-NN method is that it is applicable to all image material. The precision of the estimates depends on the spectral, spatial and radiometric resolution of the sensor, however, and some image material may presume the use of other image material as an intermediate step between the field data and the final image data (Tomppo et al. 2002). Furthermore, the precision of the estimate will depend on how the k-NN method is applied, as seen above. A lot of research work has been carried out to analyse the errors and improve the precision of the estimates, and the process is still going on.

REFERENCES

Cochran, W. G. 1977. Sampling techniques. 3rd ed. New York: Wiley.

Diemer, C., Lucaschewski, I., Spelsberg, G., Tomppo, E., and Pekkarinen, A. 2000. Integration of terrestrial forest sample plot data, map information and satellite data. An operational multisource-inventory concept. In: Ranchin, T. and Wald, L. (Eds.), Proceedings of the Third Conference "Fusion of Earth Data: Merging Point Measurements, Raster Maps and Remotely Sensed Images" January 26-28, 2000. Sophia Antipolis, France. SEE/URISCA, Nice. pp. 143-150.

Efron, B. and Tibshirani, R. 1993. An Introduction to the Bootstrap. Chapman & Hall, New York.

Fix, E. and Hodges, J.L. 1951. Discriminatory analysis - nonparametric discrimination: consistency properties. Report no. 4, US Air Force School of Aviation Medicine, Random Field. Texas.

Franco-Lopez, H., Ek, A. R. and Bauer, M. E. 2001. Estimation and mapping of forest stand density, volume, and cover type using the k-nearest neighbors method. Remote Sensing of Environment 77: 251-274.

Gjertsen, A.K., Tomppo, E. and Tomter, S. 1999. National forest inventory in Norway: Using sample plots, digital maps, and satellite images. In: IEEE 1999 International Geoscience and Remote Sensing Symposium, Hamburg, Germany. pp. 729-731.

Gjertsen, A. K. and R. Eriksen 2004. Test av MSFI-metoden: Nøyaktighetstest på datasett fra Østfold og Hobøl. Ås, Norsk institutt for jord- og skogkartlegging NIJOS: 52. (In Norweigian).

Gonzales, M. E. 1973. Use and evaluation of synthetic estimators. In: Proceedings of the Social Statistics Section. American Statistical Association, Washington. pp. 33-36.

Haapanen, R., Ek, A. R., Bauer, M. E. and Finley, A. O. 2004. Delineation of Forest/nonforest land use classes using nearest neighbor methods. Remote Sensing of Environment 89: 265-271.

Halme, M. and Tomppo, E. 2001. Improving the accuracy of multisource forest inventory estimates by reducing plot location error - a multicriteria approach. Remote Sensing of Environment 78: 321-327.

Katila, M. 2004. Controlling the estimation errors in the Finnish multisource National Forest Inventory (Doctoral dissertation). The Finnish Forest Research Institute, Research Papers 910. 36 p. + 4 publications.

Katila, M., Heikkinen, J. and Tomppo, E. 2000. Calibration of small-area estimates for map errors in multisource forest inventory. Canadian Journal of Forest Research 30: 1329-1339.

Katila, M. and Tomppo, E. 2001. Selecting estimation parameters for the Finnish multisource National Forest Inventory. Remote Sensing of Environment, 76: 16-32.

Katila, M. and Tomppo, E. 2002. Stratification by ancillary data in multisource forest inventories employing k-nearest-neighbour estimation. Canadian Journal of Forest Research 32(9): 1548-1561.

Kilkki, P. and Päivinen, R. 1987. Reference sample plots to combine field measurements and satellite data in forest inventory. University of Helsinki, Department of Forest mensuration and management. Research Notes 19: 209-215.

Kim, H-J. and Tomppo, E. 2005. Model-based prediction error uncertainty estimation for k-nn method. Revision submitted to Remote Sensing of Environment.

Kuusela, K. and Salminen, S. 1969. The 5th National Forest Inventory in Finland. General design, instructions for field work and data processing. Commununicationes Instituti Forestalis Fenniae 69.4: 1-72.

Lappi, J. 2001. Forest inventory of small areas combining the calibration estimator and a spatial model. Canadian Journal of Forest Research 31: 1551-1560.

Matérn, B. 1960. Spatial variation. Meddelanden från statens skogsforskningsinstitut, 49(5): 1-144. Also appeared as Lecture Notes in Statistics 36. Springer-Verlag. 1986.

McRoberts, R. E: 2005. Using inventory data, satellite data, and logistic regression model to estimate forest area and the precision of the estimates. Manuscript submitted to Remote Sensing of Environment.

McRoberts, R. E., Nelson, M. D. and Wendt, D. G. 2002. Stratified estimation of forest area using satellite imagery, inventory data, and the k-Nearest Neighbors technique. Remote Sensing of Environment 82: 457-468.

McRoberts, R. E., Tomppo, E. O., Finley, A. O. and Heikkinen, J. 2005. Variance estimators for nearest neighbors technique. USDA Forest Service, St. Paul, Minnesota. Finnish Forest Research Institute. Manuscript.

Mitchell, M. 1996. An Introduction to Genetic Algorithms, The MIT Press. USA. ISBN 0-262-13316-4.

Nilsson, M. 1997. Estimation of forest variables using satellite image data and airborne lidar. Ph.D. thesis, Swedish University of Agricultural Sciences, Department of Forest Resource Management and Geomatics. Acta Universitatis Agriculturae Sueciae. Silvestria, 17.

Pakkala, T., Hanski, I. and Tomppo, E. 2002. Spatial ecology of the three-toed woodpecker in managed forest landscapes. In: Korpilahti, E., and Kuuluvainen, T. (eds.). Disturbance dynamics in boreal forests: Defining the ecological basis of restoration and management of biodiversity. Silva Fennica 36(1): 279-288.

Poso, S., 1972. A method of combining photo and field samples in forest inventory. Commununicationes Instituti Forestalis Fenniae 76(1).

Reese, H., Nilsson, M., Granqvist Pahlén, T., Hagner, O. Joyce, S., Tingelöf, U., Egberth, M. and Olsson, H. 2003. Countrywide estimates of forest variables using satellite data and field data from the National Forest Inventory. Ambio 32. pp. 542-548.

Taskinen, I. and Heikkinen, J. 2005. A nonparametric Bayesian method for assessing uncertainty in thematic maps of forest variables. Revision submitted to Journal of Agricultural, Biological, and Environmental Statistics.

Tokola T., Pitkänen J., Partinen S. and Muinonen E. 1996. Point accuracy of a non-parametric method in estimation of forest characteristics with different satellite materials. International Journal of Remote Sensing 17: 2333-2351.

Tomppo, E. 1987. Stand delineation and estimation of stand variates by means of satellite images. In: Remote Sensing-Aided Forest Inventory. University of Helsinki, Department of Forest Mensuration and Management, Research Notes No. 19: 60-76.

Tomppo, E. 1990. Designing a Satellite Image-Aided National Forest Survey in Finland. In: The Usability of Remote Sensing For Forest Inventory and Planning, Proceedings from SNS/IUFRO workshop in Umeå 26 - 28 February 1990. Swedish University of Agricultural Sciences, Remote Sensing Laboratory, Report 4. 43-47. Umeå, Sweden. ISBN 91-576-4208-7.

Tomppo, E. 1991. Satellite Image Based National Forest Inventory of Finland. International Archives of Photogrammetry and Remote Sensing 28 (7-1): 419-424.

Tomppo, E. 1992. Satellite image aided forest site fertility estimation for forest income taxation. Acta Forestalia Fennica 229. 70 p.

Tomppo, E. 1996. Multi-source National Forest Inventory of Finland. In: R. Vanclay, J. Vanclay, and S. Miina (Eds.), New Thrusts in Forest Inventory. Proceedings of the Subject Group S4.02-00 'Forest Resource Inventory and Monitoring' and Subject Group S4.12-00 'Remote Sensing Technology'. vol. 1. IUFRO XX World Congress 6-12 Aug. 1995, (pp. 27-41) Tampere, Finland. EFI Proceedings, 7. European Forest Institute. Joensuu. Finland.

Tomppo, E., Katila, M., Moilanen, J., Mäkelä, H. and Peräsaari, J. 1998. Kunnittaiset metsävaratiedot 1990-94. Metsätieteen aikakauskirja - Folia Forestalia 4B/1998: 619-839 (in Finnish).

Tomppo E., Goulding C. and Katila M. 1999. Adapting Finnish multi-source forest inventory techniques to the New Zealand preharvest inventory. Scandinavian Journal of Forest Research 14: 182-192.

Tomppo, E., Korhonen, K.T., Heikkinen, J. and Yli-Kojola, H. 2001. Multisource inventory of the forests of the Hebei Forestry Bureau, Heilongjiang, China. Silva Fennica 35: 309-328.

Tomppo, E., Nilsson, M., Rosengren, M., Aalto, P. and Kennedy, P. 2002. Simultaneous use of Landsat-TM and IRS-1C WiFS data in estimating large area tree stem volume and aboveground biomass. Remote Sensing of Environment 82:156-171.

Tomppo, E. and Halme, M. 2004. Using coarse scale forest variables as ancillary information and weighting of variables in k-nn estimation: a genetic algorithm approach. Remote Sensing of Environment 92: 1-20.

Topographic Database of Finland. 1998. The National Land Survey of Finland. Helsinki. Finland. http://www.nls.fi/kartta/maps/topodb.html.

Trotter, C.M., Daymond, J.R. and Goulding, C.J. 1997. Estimation of timber volume in a coniferous plantation forest using Landsat TM. International Journal of Remote Sensing 18: 2209-2223.

USGS, 2005. LANDSAT PROJECT. http://landsat7.usgs.gov/slc_enhancements/

Wallerman, J., Vencatasawmy, C.P. and Bondesson, L. 2003. Spatial simulation of forest using Bayesian state-space models and remotely sensed data. In: Wallerman, J. 2003. Remote sensing aided spatial prediction of forest stem volume. Acta Universitatis Agriculturae Sueciae, Silvestria 271.

CHAPTER 13

CORRECTING MAP ERRORS IN FOREST INVENTORY ESTIMATES FOR SMALL AREAS

MATTI KATILA

Finnish Forest Research Institute, Finland

13.1 INTRODUCTION

Digital maps and satellite images are the most commonly available sources of auxiliary data for use in forest inventories. These sources have been used in traditional sampling-based inventories to delineate the inventory area (Chapter 11) or as a part of the sampling design (Chapter 2), and in multisource forest inventories they are used to obtain estimates for smaller areas than when employing pure field data only (Chapter 12). Topographic maps are useful for separating forestry land from water and other land use classes, but the maps are seldom up to date, there are locational errors and land use classes on the map that do not correspond to those in the field plot data. Errors also arise during the post-processing of map data, e.g. while rasterizing small or narrow map themes to coarse-resolution raster images (Katila et al. 2000).

It can be seen from the confusion matrix between the Finnish national forest inventory (NFI) field plots and numerical map data (Table 13.1) that the proportion of forestry land based on the map data is overestimated (row sum n_h per column sum n_l), with field plots truly belonging to forestry land (first column) distributed over all the map-based land use classes. The bias in the land use class or other areal cover type estimates obtained from remote sensing or map data can be corrected by means of the error probabilities contained in the confusion matrix (Czaplewski and Catts 1992, Walsh and Burk 1993), the field sample employed being based on a statistical sampling design (Card 1982). Two common statistical calibration estimators (Brown 1982) have been used in remote sensing

A. Kangas and M. Maltamo (eds.), Forest Inventory – Methodology and Applications, 225–233.

applications: classical calibration (Hay 1988), introduced by Grassia and Sundberg (1982), and inverse calibration (Card 1982), introduced by Tenenbein (1972).

Table 13.1 Distribution of land use classes among field plots by map strata in an area in Western Finland.

	land use class l									
	Forestry land		Arable		Built-up etc.		Water		Total	
stratum h	%	$n_{h,l}$	%	$n_{h,l}$	%	$n_{h,l}$	%	$n_{h,l}$	%	n_h
Forestry land	93.6	4709	2.0	103	3.9	194	0.5	25	100.0	5031
Arable	3.0	37	95.6	1198	1.4	18	0	0	100.0	1253
Built-up land and roads	21.7	81	14.2	53	63.8	238	0.3	1	100.0	373
Water	0.5	5	0.4	4	0.4	4	98.8	1025	100.0	1038
Total % / n_l	62.8	4832	17.7	1358	5.9	454	13.7	1051	100.0	7695

In the following examples a calibration method is used to reduce map errors in the Finnish multi-source national forest inventory (MS-NFI) small-area estimates (Katila et al. 2000). The method is based on inverse calibration which is is extended to the field plot weights obtained by k-nearest neighbour estimation (chapter 12.3).

13.2 LAND USE CLASS AREAS

The NFI estimates for large areas, or regions, in Finland are based on field data only, whereas the municipality-level (small-area) estimates are determined by the MS-NFI method, using satellite images and digital map data (chapter 12.3). The area of forestry land in the MS-NFI is delineated based on the numerical map data, and in some cases from satellite image data (Tomppo 1991).

Calibration of map errors in the NFI estimates is based on the confusion matrix between the NFI land use classes of the field sample plots and the corresponding classes obtained from map data for a large region. In the example, the field plots and the inventory area were stratified into four main land use classes (Table 13.1) and the proportion of land use class l within each map stratum h was first estimated in terms of the plot count ratio

$$\hat{P}_{h,l} = \frac{n_{h,l}}{n_h} \tag{13.1}$$

calculated over the entire region. The calibrated estimate for land use class *l* is

$$A_l^* = \sum_h \hat{P}_{h,l} A_h \,, \tag{13.2}$$

where A_h is the area of map stratum *h*.

A_l^* is the unbiased post-stratification estimator for the region. If we can expect the map errors to be evenly distributed over the whole region, the proportions estimated for the large region can be used to calibrate the land use class estimates for small areas, too. This leads to synthetic estimation (chapter 7.2), where it is assumed that the small areas have the same characteristics as the large area to which they belong (Gonzales 1973). Ratios computed by municipalities are too variable, and for this reason a need arises for specific small-area estimation. The calibrated area estimator is then obtained by summing the corresponding proportions of the municipality-level stratum areas:

$$A_{U,l}^* = \sum_h \hat{P}_{h,l} A_{U,h}, \tag{13.3}$$

where $A_{U,h}$ is the area of stratum *h* in a particular municipality U. The properties of the synthetic municipality-level estimators (eq. 13.3) depend greatly on the homogeneity of the map strata with respect to their land use class distributions: if the true proportions $P_{U_h,l}$ were constant for all municipalities within a region, then the estimators would be unbiased. Calibration by reference to the confusion matrix in Table 13.1. reduces the forestry land area estimates for the municipalities in the given area in Western Finland (Fig. 13.1).

Example 13.1

Area of forestry land in the defined area in Western Finland according to map data: 7973 km^2

Calibrated area of forestry land:
0.936 ·7973 + 0.03·2383 + 0.217 · 632 + 0.005 · 1815 = 7680 km^2

Area of forestry land in the municipality of Jalasjärvi according to map data: 38 127 ha

Calibrated area of forestry land in the municipality:
0.936 · 38127 + 0.03 ·10666 + 0.217 · 1601 + 0.005 · 441 = 36356 ha

---

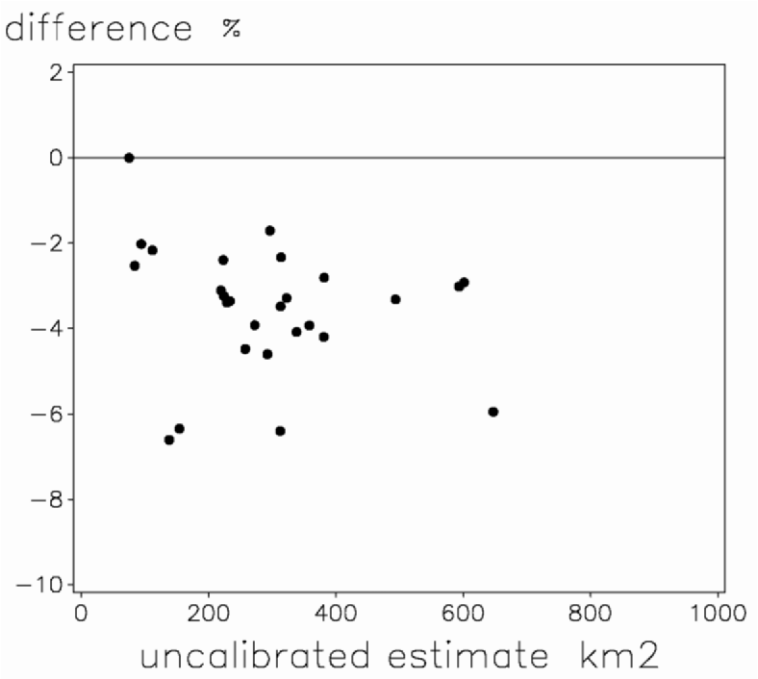


Figure 13.1 Percent difference between calibrated and uncalibrated MS-NFI estimates for the area of forestry land (km^2) in each municipality in the given area in Western Finland plotted against the uncalibrated estimates.

13.3 CALIBRATED PLOT WEIGHTS

Map errors, or more precisely, errors in the estimates of the areas of forestry land, affect the MS-NFI estimators for municipalities. The forest parameter estimates are weighted sums of field plot data, i.e. field plot weights $w_{i,p}$ for pixel p defined by *k*-NN estimation and their sums $c_{i,U}$ over the computation unit (municipality) *U*. The sum of field plot weights over a computation unit is equal to the area of forestry land based on map data (chapter 12.3). Calibration of these weights for the map errors is not a straightforward matter in an MS-NFI context, essentially because non-forestry land field plots are not employed in the MS-NFI estimation procedures and because the map strata do not correspond exactly to the NFI land use classes. A heuristically derived method for calibrating the field plot weights was proposed by Katila et al. (2000), in which the sum of the calibrated weights for computation unit U is equal to the calibrated forestry land area estimator $A^*_{U,FRYL}$.

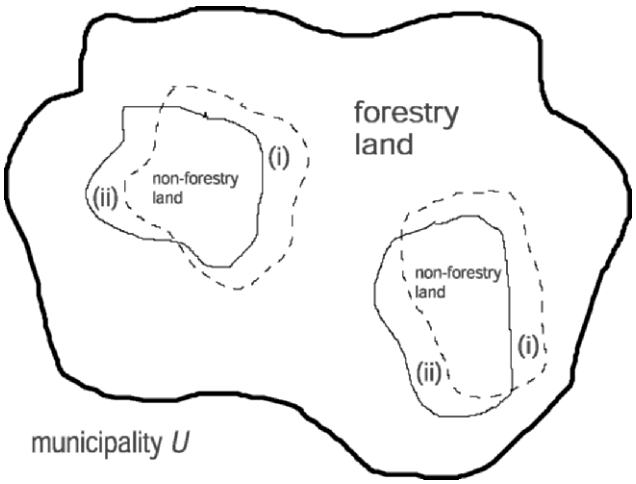


Figure 13.2 Two types of map error in small-area estimates.

We must deal with two types of error attributable to map errors (Fig. 13.2). First, the contribution of pixels which are falsely classified as forestry land on the basis of the map data must be eliminated (type (i) error, Fig. 13.2). The contribution of each non-forestry land use class l is estimated from the proportion given by the confusion matrix and area of the forestry land (FRYL) stratum

$$\hat{P}_{FRYL,l} A_{U,FRYL} = \hat{P}_{FRYL,l} \sum_i c_{i,U} \,. \tag{13.4}$$

Since there is no direct way of estimating the field plot weights $w_{i,p}$ reliably for the forestry land stratum pixels p that actually belong to land use class l, this is based on the assumption that they are on average similar to the pixels in the map strata which best represent land use class l, e.g. the arable land map stratum and the NFI arable land use class. The union of the map strata which represent land use class l is denoted by $\mathbf{h}(l)$. The pixel weights $w_{i,p}$ of the field plots are determined for all pixels p within these strata in the same manner (k-NN) as for those within the forestry land stratum in the ordinary MS-NFI (chapter 12.3). The average weight of a field plot on pixels whose actual land use class is l is then estimated by

$$\overline{w}_{i,U_{\mathbf{h}(l)}} = \frac{c_{i,U_{h(l)}}}{\sum_i c_{i,U_{h(l)}}}. \tag{13.5}$$

To account for map errors in the other direction (type (ii) error, Fig. 13.2), that is, for pixels in the non-forestry land strata which actually belong to forestry land, it is assumed that in each computation unit they are on average similar to the pixels in

the forestry land stratum of that unit. This leads us to scale the downward-calibrated weights up by the area correction factor

$$A^*_{U,FRYL} \Big/ A^*_{U_{FRYL},FRYL} = \frac{\sum_h (\hat{P}_{h,FRYL} \sum_i c_{i,U_{h(l)}})}{\hat{P}_{FRYL,FRYL} \sum_i c_{i,U}}, \tag{13.6}$$

where the nominator is the calibrated small-area estimate for FRYL and the denominator the calibrated FRYL area for the FRYL stratum alone. As a result, the calibrated weights are

$$c^*_{i,U} = \frac{A^*_{U,FRYL}}{A^*_{U_{FRYL},FRYL}} \left(c_{i,U} - \sum_{l \neq FRYL} \hat{P}_{FRYL,l} A_{U,FRYL} \overline{w}_{i,U_{h(l)}} \right). \tag{13.7}$$

It should be noted that although these weights add up to $A^*_{U,FRYL}$, the positivity of the individual weights is not guaranteed.

The calibration typically increases the mean volume estimates and reduces the forestry land area estimates for small areas if forestry land is overestimated by the map data (Fig. 13.3, Example 13.2).

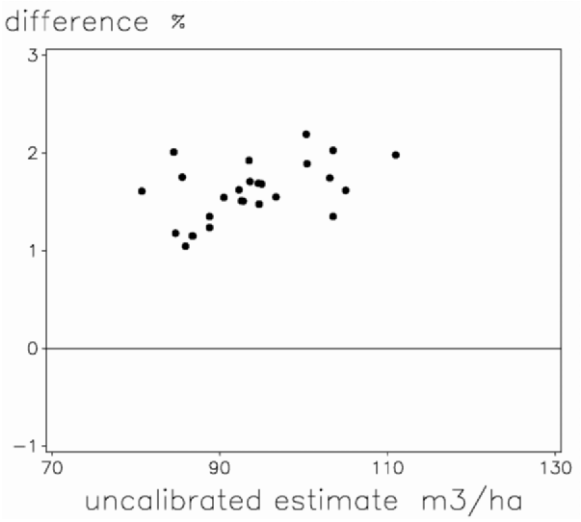


Figure 13.3 Percent differences between calibrated and uncalibrated MS-NFI estimates for each municipality plotted against the uncalibrated estimates, mean volume (m^3/ha), Western Finland.

Example 13.2 Calibrating the plot weights.

The following will serve as a simplified confusion matrix (c.f. Table 13.1) between field plot land use classes (forestry land and non-forestry land) and land use classes based on map data:

	***NFI land use class* l**		
Stratum *h*	Forestry land %	Non-forestry land %	Total %
Forestry land	93.6	6.4	100
Non-forestry land	4.6	95.4	100

Data derived from 10 field plots were used to estimate the forestry parameters for computation unit *U* : area of FRYL, 74.30 ha; area of non-FRYL, 8.95 ha.

For type (i) error (eq. 13.4), area of non-FRYL to be removed from FRYL: $\hat{P}_{FRYL,l} A_{U,FRYL}$ = 0.064·74.30 ha = 4.76 ha.

For type (ii) error, (eq. 13.6),
$A^*_{U,FRYL} / A^*_{U_{FRYL},FRYL}$ = (0.936·74.30 ha + 0.046·8.95 ha)/(0.936·74.30 ha) = 1.006.

	Plot weight on FRYL $c_{i,U}$	Plot weight on non-FRYL $c_{i,U_{h(l)}}$	Field plot volume v_i	Proportion of field plot to non-FRYL area $\overline{w}_{i,U_{h(l)}}$	Weight to be removed (eq. 13.4 and 13.5) $\hat{P}_{FRYL,l} A_{U,FRYL} \overline{w}_{i,U_{h(l)}}$	Calibrated weights on FRYL (eq. 13.7) $c^*_{i,U}$
Plot no.	ha	ha	m3/ha		ha	ha
1	4.03	1.30	105	0.146	0.693	3.36
2	9.27	2.29	0	0.256	1.216	8.10
3	6.87	0.24	74	0.027	0.129	6.78
4	1.65	0.17	32	0.019	0.091	1.57
5	21.57	0.39	48	0.043	0.206	21.49
6	2.67	0.21	66	0.024	0.112	2.57
7	4.20	0.19	217	0.022	0.103	4.13
8	12.63	0.38	17	0.042	0.201	12.51
9	3.11	2.80	0	0.313	1.487	1.64
10	8.29	0.97	0	0.109	0.517	7.82
Sum	74.30	8.95	-	1	4.76	69.96

Original mean volume estimate: $\sum_i c_{i,U} v_i \Big/ \sum_i c_{i,U}$ = 44.7 m3/ha

Calibrated mean volume estimate: $\sum_i c^*_{i,U} v_i \Big/ \sum_i c^*_{i,U}$ = 45.9 m3/ha

The small-area estimates obtained from the Finnish MS-NFI can be validated against the pure field inventory estimates and their standard errors for sub-regions (groups of municipalities). In the area concerned here, calibration of the MS-NFI estimates did not cause reveal any systematic errors in the forestry land area and volume estimates relative to the pure field data estimates (Fig. 13.4). The corrections in most groups of municipalities bring the estimates closer to those of the field inventory.

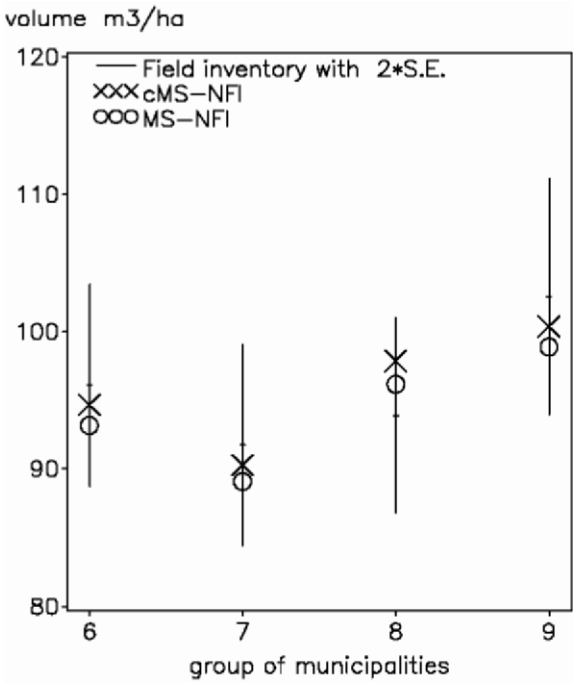


Figure. 13.4 Groups of municipalities: pure field data estimates ± double standard error, MS-NFI estimates and calibrated (cMS-NFI) estimates, mean volume (m^3/ha), Western Finland.

Despite the rather simple idea of the calibration, it is quite laborious when implemented in the MS-NFI, as the calculation is more complicated than in the original MS-NFI and some field plots are given negative weights. Another method, called stratified MS-NFI, has been presented for reducing the effect of inaccurate map data on forest resource estimates (Katila and Tomppo 2002), in which k-NN estimation is applied by strata. All the field plots within each map stratum, irrespective of their land use class in the field measurements, are used simultaneously for estimating the areas of the land use classes and forest variables within the particular stratum. Both of these methods have been employed in the operative MS-NFI in Finland (chapter 12).

REFERENCES

Brown P.J. 1982. Multivariate calibration. Journal of Royal Statistical Society Series B 44: 287-321.

Card D.H. 1982. Using known map category marginal frequencies to improve estimates of thematic map accuracy. Photogrammetric Engineering and Remote Sensing 48: 431-439.

Czaplewski R.L. and Catts G.P. 1992. Calibration of remotely sensed proportion or area estimates for misclassification error. Remote Sensing of Environment 39: 29-43.

Gonzalez M.E. 1973. Use and evaluation of synthetic estimators. In Proceedings of the Social Statistics Section. American Statistical Association, Washington. pp. 33-36.

Grassia, A. and Sundberg, R. 1982. Statistical Precision in the Calibration and Use of Sorting Machines and other Classifiers. Technometrics 24(2): 117-121.

Hay, A. M. 1988. The derivation of global estimates from a confusion matrix. International Journal of Remote Sensing 9:1395-1398.

Katila M. Heikkinen J. and Tomppo E. 2000. Calibration of small-area estimates for map errors in multisource forest inventory. Canadian Journal of Forest Research 30: 1329-1339.

Katila M. and Tomppo E. 2002. Stratification by ancillary data in multisource forest inventories employing k-nearest neighbour estimation. Canadian Journal of Forest Research 32: 1548-1561.

Tenenbein A. 1972. A double sampling scheme for estimating from misclassified multinomial data with applications to sampling inspection. Technometrics 14: 187-202.

Tomppo E. 1991. Satellite image-based national forest inventory of Finland. International Archives of Photogrammetry and Remote Sensing 28: 419-424. Proceedings of the Symposium on Global and Environmental Monitoring, Techniques and Impacts, 17-21 Sept. 1990, Victoria, British Columbia, Canada.

Walsh, T.A. and T.E. Burk. 1993. Calibration of satellite classifications of land area. Remote Sensing of Environment 46(3):281-290

CHAPTER 14

MULTIPHASE SAMPLING

SAKARI TUOMINEN, MARKUS HOLOPAINEN AND SIMO POSO

Finnish Forest Research Institute, University of Helsinki, Finland

14.1 INTRODUCTION

Forest inventories are often required to cover large areas, so that the measuring of every tree in the field for the necessary data acquisition would be unrealistic. Sometimes, simple systematic field sampling may be a good method for data collection, but even so the walking distances from one sampling unit to another may become long, increasing the inventory costs. Multiphase sampling may offer a possibility for keeping inventory costs moderate. This requires the availability of suitable auxiliary (ancillary) data, which should fulfil the following two requirements:

a) the auxiliary data for a sample unit should be distinctly correlated with the field data for the same unit, and

b) the unit costs of the auxiliary data should be markedly less than that of field data.

Potentially useful sources of auxiliary data are remote sensing imagery (aerial photographs, satellite and radar imagery), maps and estimates from old forest inventories, for example.

It is also desirable that the auxiliary data should cover the whole inventory area homogeneously, i.e. the level of correlation between the field and auxiliary data should not vary much within the inventory area.

The units employed in multiphase sampling are the same at all levels. Thus Schreuder et al. (1993) give the definition "A sampling design where the same size of sampling unit is used at each phase (level) of sampling, but fewer units are selected at each succeeding phase." In the practice, however, "same size" must be interpreted somewhat loosely. If the sampling unit is a circular plot in the field, for example, the corresponding unit on the aerial photograph or satellite image may be a pixel or combination of pixels, with the idea that the correlation between the data from the various phases should be as close as possible. Alternatively, old inventory

A. Kangas and M. Maltamo (eds.), Forest Inventory – Methodology and Applications, 235–252.

data on a forest stand can be used as auxiliary data for the first phase units located in the area of the stand.

Two-phase sampling comprises essentially two techniques (Cochran 1977): double sampling for stratification and double sampling for regression. Both techniques have been used in forest inventories for several decades. The basic idea in both cases is to improve the estimation efficiency for population parameters, while the methods proved to be quite inflexible for estimating local parameters. A special application called a grouping method was developed to cope with this problem and to answer the question of how to use aerial photographs in forest inventories (Poso and Kujala 1971, Poso 1972). Later, when first-phase data became widely available in digital format, research work was carried out to develop two-phase sampling to meet inventory needs on both the whole population and the local level and to utilise the potentials of satellite imagery (Poso et al. 1984). The associated software was created by Waite (1993) and Wang et al. (1997). In addition, the k-nearest neighbour (k-nn) method was developed especially for meeting the needs for local data (Kilkki and Päivinen 1987, Muinonen and Tokola 1990, Tomppo 1993).

All types and sizes of sampling units are possible when applying multiphase sampling. Very small units probably produce low correlations between the phases and very large units become expensive to measure in the field and would often fall into the area of more than one forest stand. The problem of sample unit selection will not be discussed further in this chapter.

Classical sampling theory usually requires random location for the sampling units. That is very rarely achieved in reality, however. The first-phase sample should cover the inventory area as evenly as possible to make sure that every part is represented. Regardless of the type of multiphase application, the first-phase sample can be drawn assuming a square grid which is laid over the inventory area so that each square defines the location of a sample unit. Maps with co-ordinate lines provide a good tool for this, because each first-phase unit can be identified individually by its co-ordinate values.

Under the present assumptions, all applications of multiphase sampling require field data, i.e. data which fulfil the requirement that all variables of interest should be measured with the desired accuracy. Great importance should be laid on how the sample units are selected for field measurements, as stratification of the first-phase units into homogeneous strata on the basis of the first-phase data would make it possible to allocate the field units more efficiently.

14.2 DOUBLE SAMPLING FOR STRATIFICATION WHEN ESTIMATING POPULATION PARAMETERS

The idea of double sampling, or two-phase sampling, was introduced by Neyman (1938) and was first applied to a forest inventory in the USA (Bickford 1952, 1953, 1961, Bickford et al. 1963). The statistical basis of the method is explained by Cochran (1963, 1977).

For estimating population parameters such as mean volume and the

proportion of forest in an area, double sampling (two-phase sampling) for stratification, as described by Cochran (1977), may turn out to be the best choice. With local data gaining in importance, other double sampling applications will probably become more attractive, too (cf. Section 14.4.).

Stratification of the first-phase units to form strata that are as homogeneous as possible in relation to the variables of interest is central to the successful application of this method. One or more of the alternative stratification procedures listed below can be employed:

a. Stratification of the inventory area before drawing the first-phase sample (e.g. into administrative units, forested and non-forested land or mineral soil and peatland from maps, resulting in area stratification)
b. Stratification of the first-phase units before the drawing the second-phase (field) sample (i.e. pre-stratification). This makes it possible to draw the field sample in the optimal way.
c. Stratification of the first-phase units after drawing the field sample (i.e. post-stratification). This means that stratification is used only for applying the two-phase sampling estimators.
d. Stratification of the first-phase units for optimising estimation of the variable of particular interest (separate stratification for each variable of interest).

The difference between the concepts of stratum and area class should be understood. Distribution of the total inventory area into area classes (e.g. forested and non-forested areas, clear-felled areas and other areas) may be the main objective of the inventory and stratification the tool employed to attain this objective efficiently. In some cases, the aim of the stratification is to produce strata that coincide with the area classes (straightforward interpretation of area classes). The fieldwork can then be directed towards checking the compatibility and finding models to change the stratum areas into class areas.

The number of auxiliary data sources, and especially the auxiliary data variables (features), may become very high. Satellite imagery with six channels, for example, produces six auxiliary data values and two satellite images (e.g. in change monitoring) would produce 12 values for each first-phase unit. Adding other auxiliary data sources would further increase this number. One problem is how to weight the various auxiliary data sources and which procedures to use for successful stratification. One way to deal with the problem is to transform the original auxiliary data to principal components (Singh and Harrison 1985) and to utilize the latter instead of the original variables for stratification purposes. Where the variables in many auxiliary data sources are highly intercorrelated (e.g. the channel values in satellite imagery), principal component values do not correlate with each other.

The efficiency of stratification with double sampling is closely linked to concept of variance within strata versus total variance. The smaller the ratio of within-strata to total variance, the more efficient will be a forest inventory based on double sampling.

Double sampling, like other multiphase applications, can be divided into 8 steps (some recommendations are included):

1. Delineation of the inventory area (Figure 14.1.a).
   Determination of the inventory area using the official map co-ordinate system is preferable.
2. Generation of the first-phase sample for the inventory area (Figure 14.1.b).
   The first-phase sample is usually created automatically by the computer and the first-phase data are usually in digital format. The size of the first-phase sample depends on the objective of the inventory, but the number of units is usually high.
3. Acquisition of auxiliary data for the first -phase sample units.
   The best auxiliary data are closely correlated with the forest variables of interest, and their acquisition cost is low. Data produced by visual interpretation of aerial photographs and data from old management inventories are usually fairly well correlated with the actual forest characteristics, but they are often more expensive than auxiliary data based on digital or digitised remote sensing material.
4. Stratification of the first-phase sample units (Figure 14.1.c).
   Stratification before drawing the field sample is recommended, i.e. all the relevant first-phase data are acquired for the first-phase sample units and the units are then stratified into as homogeneous strata as possible with respect to the forest variables of interest (see also Chapter 2).
5. Determining the number of second-phase sample units, i.e. field plots, and allocating these to the strata.
   The number of second-phase sample units is usually decisive for the accuracy of population parameters in inventories (cf. Eq. 14.12). All inventory results, such as distributions of forest parameters, are based on the characteristics of the second-phase sample units, and if a characteristic is not represented among these units it will not be present in the inventory results either. The number of second-phase units is a compromise between the desired level of accuracy and the available monetary and professional resources.
6. Drawing the field plots. (Figure 14.1.d)
   After the number of second-phase sample units has been determined, a decision has to be made on how the units are to be allocated to the various strata. The basic alternatives are proportional and optimal allocation (see also Chapter 2).

   a) Proportional allocation is recommendable if the field variables in each stratum are regarded as equally important for the inventory and the within-stratum variances and the unit cost of the second-phase sample units do not vary too much from one stratum to another. In a multipurpose forest inventory it is often difficult to evaluate the importance of each forest variable, and consequently proportional allocation is preferable. Complete proportionality cannot be attained when only integers are acceptable as values for m_h. A well-performed proportional allocation produces a field

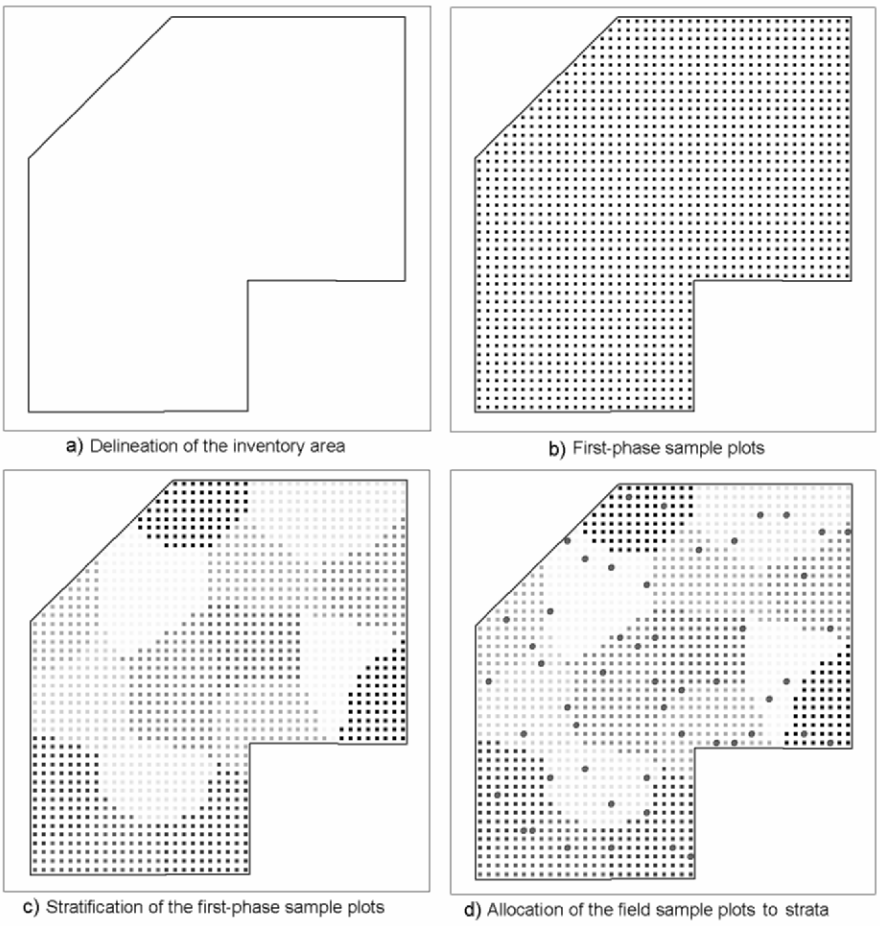


Figure 14.1 The two-phase sampling procedure.

plot sample, on the basis of which statistical means and variances can be calculated directly by simple arithmetic procedures. The formula for allocating the total number of field plots, m, to strata when proportional allocation is employed is

$$m_h = w_h m, \tag{14.1}$$

where m_h is the number of second-phase units in stratum h (closest integer) and w_h is the proportion the total area represented by stratum h, i.e. $w_h = {n_h}/{n}$, number of first-phase units in stratum h divided by total number of first-phase units.

b) Optimal allocation implies that those strata which are regarded as most important, i.e. those that have the highest variances or the lowest unit costs, should be assigned more second-phase sample units than would be suggested by proportional allocation. This requires the person operating the method to have a priori knowledge of the properties of the strata. If unit costs c_h and the standard deviations s_h vary between strata, then optimum allocation as obtained with

$$m_h = m \frac{\frac{w_h s_h}{\sqrt{c_h}}}{\sum \frac{w_h s_h}{\sqrt{c_h}}} \tag{14.2}$$

may be recommendable.

7. Measurement of the field plots.

As field data (i.e. ground truth data) are considered accurate, great effort should be expended on the location and measurement of each plot. Mistakes in location reduce the correlation between the auxiliary and field data and hence detract from the accuracy of the inventory. The weight of one field plot is usually fairly large, corresponding to the area it represents, i.e. its weight is a_h/m_h, where a_h refers to the inventory area belonging to stratum h.

8. Estimation of population parameters and their accuracy.

The best and most consistent estimates for the total population are those based on single tree measurements in the field. Each tree in the sample should be weighted with the inverse value of its sampling probability. For local estimation, stand characteristics, e.g. the distribution of the plot area by site classes or volume, m^3/ha, should be calculated for every field sample plot separately.

A field sample plot should usually be measured in the format which fulfils the GIS requirements: i.e. the location of each plot should be determined using the official geocoordinate system and each tree on the plot should be mapped in terms of polar co-ordinates, for example.

The estimators for quantitative variables, e.g. mean volume, and sampling error variance are (see also Chapter 2)

$$\bar{y} = \sum_{h=1}^{l} w_h \bar{y}_h \tag{14.3}$$

and

$$s_{\bar{y}}^2 \approx \sum_{h=1}^{l} \frac{w_h^2 s_h^2}{m_h} . \quad (14.4)$$

A more precise estimator for the variance (cf. Schreuder et al. 1993) would be

$$s_{\bar{y}}^2 = \sum_{h=1}^{l} \frac{w_h^2 s_h^2}{m_h} - \frac{1}{N} \sum_{h=1}^{l} w_h s_h^2 + \frac{g_1}{n} \sum_{h=1}^{l} w_h (\bar{y}_h - \bar{y})^2 , \quad (14.5)$$

where w_h is the proportion of first-phase units in stratum h, m_h is the number of field plots in stratum h, l is the number of strata and N is the size of the population. N should be taken here as the total inventory area divided by the area of one sample unit, and $g_1=(N-n)/N-1)$.

The last term in the variance of the mean estimator refers to the fact that the first-phase sample does not entirely represent the population. The formula is correct if the first-phase sample is drawn at random, but the sample probably represents the population better if a square grid model has been employed for defining the first-phase sample, and consequently variance estimators that assume random sampling lead to overestimation.

Categorial variables such as site index and development stage related to rotation are also usually of great interest in forest inventories. Note P_j = proportion of variable $j = N_j/N$. The corresponding estimator is:

$$p_j = \sum w_h p_{jh} , \quad (14.6)$$

where $p_{jh} = m_{hj}/m_h$, and the estimator for the variance v_{pj} is

$$v_{pj} \approx \sum_{h=1}^{l} \frac{w_h^2 p_j (1 - p_j)}{m_h - 1} + \frac{1}{n} \sum_{h=1}^{l} w_h (p_{jh} - p_j)^2 . \quad (14.7)$$

A key measure of the usefulness or efficiency of the stratification is the ratio between the average variance within the stratum and the total variance, i.e.,

$$s_{y_h}^2 (average) / s_y^2 (total) . \quad (14.8)$$

The within-stratum variance may vary substantially from one stratum to another. The average variance is a weighted value, i.e.

$$s_{y_h}^2 (average) = \sum_{h=1}^{l} w_h s_{y_h}^2 . \quad (14.9)$$

The smaller the ratio (14.8.) the more efficient is the stratification.

There are numerous types of auxiliary data, and there may not be any general rule for technical stratification procedures.

14.3 DOUBLE SAMPLING FOR REGRESSION

Assume a linear regression, $y=a+bx$ (y refers to second-phase data, field measured data, a to a constant for the regression line, b to the coefficient of regression, and x to the first-phase data). If the first and second-phase sample units are drawn by probabilistic design, the mean can be estimated as (Cochran 1977)

$$\bar{y}_{lr} \approx \bar{y}_m + b(\bar{X}_n - \bar{X}_m), \tag{14.10}$$

where $\bar{y}_m$ is the mean based on the second-phase sample units, b is the regression coefficient, $\bar{X}_n$ is the mean of the first-phase data for n sample units and $\bar{X}_m$ the mean of the first-phase data for m sample units.

The variance of the mean can be estimated as (Cochran 1977)

$$v_{\bar{y}} \approx s_y{}^2 \left(\frac{(1-r^2)}{m} + \frac{r^2}{n} \right), \tag{14.11}$$

where r is the coefficient of correlation between x and y.

If the unit cost of the first-phase sample is significantly high, as in the case of ocular photo interpretation, and the population parameters are of greatest interest, then the optimum ratio of first to second-phase sampling units, n/m, is roughly (Cochran 1977)

$$n/m = \sqrt{f \frac{r^2}{1-r^2}} \text{ or } \sqrt{f \frac{\text{variance between strata}}{\text{variance within strata}}}, \tag{14.12}$$

where f is the unit cost ratio, second-phase unit/first-phase unit, and r is the correlation coefficient.

The number of second-phase units depends on the targeted costs of the sampling procedure and the accuracy requirement. If C_T is the money allocated to sampling, c_1 the unit cost of the first-phase sample and c_2 the unit cost of the second-phase sample, then

$$m = C_T / (c_2 + (n/m)c_1). \tag{14.13}$$

If the regression model $y_i = f(x_i) + e_i$ has been solved for m field and first-phase plots, then the estimate for any of the first-phase sample units is obtained by

$$\hat{y}_j = f(x_j), \tag{14.14}$$

where *j* refers to any of the first-phase plots.

The residuals e_i, i.e. the differences between the estimated and the true or measured values, can be calculated only for plots measured in the field. The Mean Square Error (MSE)

$$MSE = \frac{\sum_{i=1}^{m} e_i^2}{m - p - 1}, \tag{14.15}$$

where *m* is the number of field plots and *p+1* is the number of explanatory variables, including the intercept term (see also Chapter 6).

MSE values can be used to estimate the variance and standard error of the mean

$$v_{\ddot{y}} \approx \frac{MSE}{m}, \text{ and } s_{\ddot{y}} \approx \sqrt{\frac{MSE}{m}}. \tag{14.16}$$

14.4 FOREST INVENTORY APPLICATIONS OF TWO-PHASE SAMPLING

For forest management purposes, a forest inventory is required to produce results in the form of forest statistics and thematic maps (map-format estimates). The interest in local parameters (forest characteristics for relatively small geographical areas such as sample plots, forest stands or compartments) is likely to lead to a fairly dense grid of first-phase sample units and a special estimation procedure. A scheme for a multi-source forest inventory application utilizing several data sources and two-phase sampling for estimating local (stand) forest characteristics is presented in Figure 14.2.

14.4.1 The grouping method – two-phase sampling for stratification with one second-phase unit per stratum

The "Grouping Method" is a modification of the original concept of double sampling for stratification as described by Poso and Kujala (1971) and Poso (1972) in order to meet the multi-purpose and flexibility characteristics required by national forest inventories in Finland.

The method allows unbiased estimation of means and distributions in a forest population employing the same estimators as presented for double sampling. In addition, estimates can be obtained for any sub-population of the first-phase sampling units, on account of the fact that one second-phase sample unit per stratum is drawn and measured in the field. Inventory results, i.e. stand variables, are calculated individually for each second-phase sample unit and then transferred as such to each first-phase sample unit belonging to the same stratum. Consequently,

all first-phase sample units are supplied with formally complete inventory data, and inventory results can be calculated for any desired set of sample units.

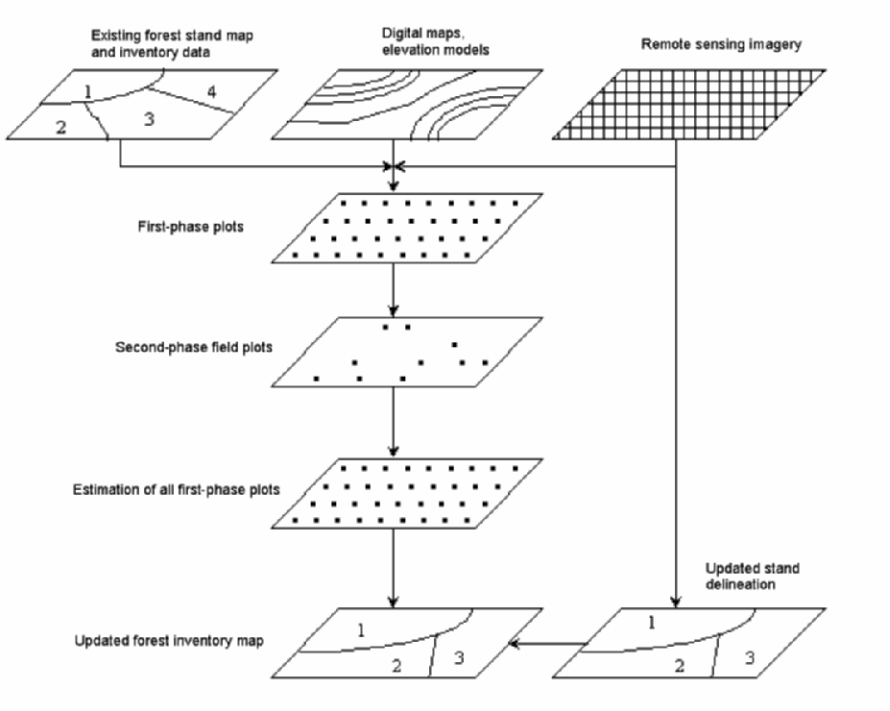


Figure 14.2 An example of the two-phase sampling procedure for estimating stand-level forest characteristics.

Since only one second-phase sample unit is drawn per stratum, the within-stratum variances cannot be estimated without specific arrangements. For this purpose the strata can be combined together into larger groups on the assumption that the variances in the strata belonging to a particular group are equal. The variances are then estimated by studying the distributions of values in the field plots belonging to the group. After the within strata variances have been estimated, the estimators produced by double sampling for stratification are applicable.

The method was applied to national forest inventories in Northern Finland in association with aerial photograph interpretation in 1970-1980. Earlier, stratification of the first-phase sample units had been used for drawing the field sample, together with restricted random drawing to concentrate the fieldwork in specific areas. In the case of extensive forest areas, this procedure made it possible to minimize travel costs and markedly improve the efficiency of the inventory. In later applications (Mattila 1985) the field plots were sampled in clusters

independently of the first-phase data and stratification was carried out after measuring the field plots. The sizes of the strata varied greatly in this application, however, which had a detrimental effect on the accuracy of the inventory (Poso and Kujala, 1978).

14.4.2 Stratification with mean vector estimation

This method resembles the grouping method in imputing the per stratum estimates for each first-phase sample unit, but the estimates are usually based on more than one second-phase sample unit. Estimation of local parameters is based on estimates generalised for each first-phase sample unit. The estimation of population parameters should in general be based on single-tree field measurements with weights inversely proportional to sampling probability. This can be regarded as an application of two-phase sampling for stratification.

Generalising of the stratum data on the basis of more than one field plot per stratum leads to a disadvantageous averaging problem, in that the proportions of very high and low values in the distributions of forest attributes become underestimated. This may be illustrated by a simple example.

Example 14.1

The data consist of field plots belonging to two strata, say Stratum 1 and Stratum 85. Only site index, main tree species and volume, m^3/ha, are included in this illustration. It is assumed that three plots are measured in the field for both strata. The average values show the strata estimates, which are to be imputed to the first-phase plots in the relevant strata. The average values for site index, tree species and volume are the median, mode and arithmetic mean, respectively.

Table 14.1 Mean vector consisting of different types of forest variables.

	Stratum 1			Stratum 85		
Plot	Site	Tree sp.	Vol.	Site	Tree sp.	Vol.
1.	1	1	0	2	2	185.4
2.	1	1	8.5	2	2	450.1
3.	3	3	6.5	1	1	305.5
Aver.	2	1	5.0	2	2	313.7

All of the first-phase sample units belonging to Stratum 1 will be assigned the values 2 for site index, 1 for tree species and 5.0 for volume. The corresponding values for the first-phase plots belonging to Stratum 85 are 2, 2 and 313.7.

The estimates for categorial variables can be calculated as modes (nominal scale variables) or medians (ordinal scale variables) of the field observations within the stratum. For binary-type variables, where a certain attribute is either present or not, probabilities based on the presence of the attribute among the field plots can be applied.

The more sample plots per stratum are measured in the field, the more accurate are the estimates, but the optimum number of field plots per stratum is difficult to estimate. The average number in most applications ranges from 5 to 10. If the desired total number of field plots (second-phase units) has been determined, the desired number of field plots per stratum can be reached by regulating the number of strata. It is also often advisable to use geographical distances in the stratification in addition to the auxiliary data. In other words, the basis for stratification of the first-phase units should include the auxiliary (first-phase) data and information about geographical location. The objective is to avoid placing sample plots that are geographically very distant from each other in the same stratum.

More detailed estimates would be obtained if the calculations could be based on single tree measurements instead of mean vectors for the field plots; weighting the characteristics of each tree by the inverse of their sampling probability in the stratum. The procedure is the same as was described in connection with double sampling (14.2). Aggregation of the detailed stratum data at the level of the whole population would be unbiased and free of the averaging effect.

14.4.3 K nearest neighbour method with mean vector estimation

Another estimation method that can be employed in connection with two-phase sampling is the k-nearest neighbour (k-nn) method. This is based on the fact that each first and second-phase sample unit has an exact location in the n-dimensional feature space defined by the first-phase (auxiliary) data. Each auxiliary data variable forms one dimension in the feature space. Estimation of a first-phase unit is then based on the k (usually 3-10) field plots that are nearest to the first-phase plot in the feature space. The k field plots may be given different weights depending on their distances away from the unit in the feature space.

K-nn estimation was introduced by Kilkki and Päivinen (1987) as a reference sample plot method in which k is 1, and it has later been extensively used in connection with the Finnish national forest inventories (Tomppo 1993, see Chapter 12). K-nn estimation is based on a heuristic model and the estimation is not design-based. It is not possible to control the weight of an individual field plot (at the population level) in the estimation procedure. Thus, k-nn may produce biased results if aggregated for an entire population.

The estimates for numerical (ratio-scale) forest variables can be calculated as average values of the variables of the nearest neighbours. Equations for unweighted (eq. 14.17) and inverse distance-weighted (eq. 14.18) k-nn estimates are shown.

$$\hat{y} = \sum_{i=1}^{k} y_i / k \tag{14.17}$$

and

$$\hat{y} = \sum_{i=1}^{k} w_i y_i \,, \tag{14.18}$$

where $\hat{y}$ is the estimate for variable y , y_i is the measured value of variable y in i^{th} nearest neighbour plot, and k is the number of nearest neighbours,

$$w_i = \frac{1}{d_i^{\,z}} / \sum \frac{1}{d_i^{\,z}} \,, \tag{14.19}$$

is the weight for plot i, where typically $z \geq 1$ and

$$d_i = \sqrt{\sum_{j=1}^{p} (x_{obsj} - x_{estj})^2} \tag{14.20}$$

is the Euclidean distance from the i^{th} nearest neighbour, $x_{obs,est}$ is the auxiliary data value for the observed and estimated plots and p is the number of auxiliary data variables (in the feature space). When $d = 0$, some positive non-zero value close to 0 is given to d.

For ordinal scale (categorial) forest variables (such as forest site) the medians of the nearest neighbours can be employed for estimation purposes, while for nominal scale variables (e.g. dominant tree species) the modes of the nearest neighbours are appropriate (refer to Table 14.1) For binary-type attributes, the k-nn estimates can be calculated as probabilities (eq. 14.24):

$$P = \frac{\sum_{i=1}^{k} y_i}{k} \tag{14.21}$$

where P is the probability of the presence of variable y and y_i = measured value of variable y in the i^{th} nearest neighbour plot (0 or 1).

In general, when a large number of field plots are available for k-nn estimation, an increase in the number of nearest neighbours (value of k) will improve the accuracy of the estimates (Tokola et al. 1996). On the other hand, k-nn estimation is affected by a similar averaging problem to that explained in 14.4.2, except when k = 1. The higher the value of k, the more averaging occurs in the estimates. Thus, the optimal value of k is a trade-off between the accuracy of the estimates and proportion of the original variation (among the field plots) retained in the estimates.

14.5 MULTI-PHASE SAMPLING WITH MORE THAN TWO PHASES

The use of more than two phases has been discussed in some research papers (e.g., LaBau and Winterberger 1989, Päivinen 1994), and estimators for a population with more than two phases of sampling have been presented by Jeyaratnam et al. (1984). The phases could consist of data from satellite images (first phase), aerial photographs (second phase) and field measurement (third phase), for example. The Alaska Integrated Resource Inventory System (AIRIS) even tested a four-phase inventory design involving satellite imagery as the first phase, high altitude aerial photography as the second phase, low altitude colour photography as the third phase and field sampling as the fourth phase (LaBau and Winterberger 1989). The results were disappointing, however, as the correlations between the dependent variables of interest and their covariates were not satisfactory (Schreuder et al. 1993).

Another possibility for handling several data sources is to apply two-phase sampling separately with alternative sources: satellite imagery + field data, or aerial photographs + field data. Final estimates can then be calculated by a weighted procedure in which the weights are inversely propotional to the estimated error variances for the data sources (Poso et al. 1999). It has been shown that the use of more than one auxiliary data source together with field data improves the estimation accuracy (Poso et al. 1999).

14.6 ESTIMATION TESTING

As distinct from ground truth values, estimated forest variables are generally not perfectly accurate. Thus estimates should always carry a measure of their accuracy. The accuracy of estimates can be tested on sample plots (i.e. field plots) for which both estimated and measured values are known. Distinct estimation and test sets have been used for this purpose in some cases, but more often a procedure called leave-one-out cross validation is applied, where each field plot is estimated independently of its ground truth value and the estimated and ground truth values are then compared.

For numerical variables, estimates of bias and RMSE can be used as measures of estimation accuracy.

$$Bias = \frac{\sum_{i=1}^{n}(\hat{y}_i - y_i)}{n} \tag{14.22}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(\hat{y}_i - y_i)^2}{n}} \tag{14.23}$$

$$RMSE\% = 100 * \frac{RMSE}{\bar{y}}, \tag{14.24}$$

where y_i is the measured value of variable y on plot i and $\hat{y}_i$ is the estimated value of variable y on plot i, $\overline{y}_i$ is the mean of the observed values, and n is the number of plots.

Estimates of categorial variables can be tested using error matrices (or confusion matrices). An example of an error matrix in Table 14.2. involves 100 sample plots and an estimated variable possessing five categories (a, b, c, d and e) each represented on 20 measured plots.

The error matrix answers the following questions:

1. On what proportion of the sample plots is the variable correctly estimated?
2. What proportion of each class is correctly estimated?
3. Is the proportion of a certain class over or under-estimated?
4. Are the estimation errors randomly distributed?

Table 14.2 Example of an error matrix.

	Estimated					
Measured	A	b	C	D	E	Total
A	12	5	3	0	0	20
B	2	15	3	0	0	20
C	1	3	13	3	0	20
D	0	0	9	9	2	20
E	0	0	2	5	13	20
Total	15	23	30	17	15	100

Class	Omission	Commission	Correct	Kappa
A	0.400	0.150	0.600	0.093
B	0.250	0.400	0.750	0.109
C	0.350	0.850	0.650	0.074
D	0.550	0.400	0.450	0.058
E	0.350	0.100	0.650	0.103
Total	0.380	0.380	0.620	0.525

The error of omission refers to observations belonging to a certain category and erroneously classified in another category, whereas the error of commission refers to observations erroneously classified in a certain category while belonging to another. Thus their totals are equal. The proportion of observations that are classified into the correct category is a generally used measure of estimation accuracy in the case of a categorial variable, although in some situations this proportion can be high even though the estimation has not been successful, as in the case where a very high proportion of the observed values belong to a single category. It is then recommendable to use the kappa value (κ) as a statistical measure, as this indicates the success of the classification relative to a random assignment of the observations to categories. A general definition of kappa is that given in equation 14.24, and a more specific examination is presented by Campbell (1987).

$$\kappa = \frac{p_0 - p_e}{1 - p_e}, \tag{14.25}$$

where p_0 is the proportion of correct estimates and p_e the proportion of correct estimates in a random classification.

The following interpretations have been suggested for kappa (Landis and Koch, 1977):

<0.00	Poor
0.00 - 0.20	Slight
0.21 - 0.40	Fair
0.41 - 0.60	Moderate
0.61 - 0.80	Substantial
0.81 - 1.00	Almost Perfect

14.7 CONCLUDING REMARKS

The density of the first-phase sample is primarily dependent upon the need and purpose of the inventory data. For local information, e.g. forest compartments or stands used in forest management planning, a density corresponding to a distance of some 20 – 50 m is reasonable, but for large-area inventories the density requirement could be lower. If both population and local parameters are of great interest, however, and the marginal cost of increasing the number of first-phase sample units is low, then it is reasonable to select a high-density first-phase sample.

The objective in a forest inventory application may be to obtain estimates for the total inventory area or map-form estimates for individual first-phase sample units in the inventory area. In the case of forest variables for an entire inventory area it is important that the estimates should be unbiased, while in the case of variables for individual first-phase sample units, the accuracy at this level is of the greatest importance and the extent of the bias is not so important. As local estimates are often biased (e.g. due to averaging) it is not advisable to derive the estimates for an entire inventory area as sums of first-phase unit estimates. Instead, they should be calculated directly on the basis of the original field plot data, weighting each field plot by the area it represents.

REFERENCES

Bickford, C.A. 1952. The Sampling Design used in the Forest Survey of the Northeast. Journal of Forestry 50.4: 290-293. Washington D. C.

Bickford, C.A., 1953. Increasing the efficiency of airphoto Forest Surveys by better Definition of Classes. Northeastern Forest Experiment Station. Station Paper No. 58: 1-9. Upper Darby.

Bickford, C.A. 1961. Stratification for Timber Cruising. Journal of Forestry 59.10: 761-763. Washington D. C.

Bickford, C.A., Mayer, C. G. and Ware, K. D. 1963. An efficient Sampling Design for Forest Inventory: the Northeastern Forest Resurvey. Journal of Forestry 61.11: 826-833. Washington D.C.

Campbell, J.B. 1987. Introduction to remote sensing. The Guilford Press, New York. 551 p.

Cochran, W.G. 1963. Sampling Techniques. John Wiley & Sons, Inc. New York–London-Sydney.

Cochran, W.G. 1977. Sampling Techniques. John Wiley & Sons. 2nd edition.

Häme, T. 1988. Interpretation of forest changes from satellite scanner imagery. University of Helsinki, Department of Forest Mensuration and Management. Research Notes, 21:119-133.

Jaakkola, S. 1987. Satellite remote sensing for forest inventory. An overview of the SNS-project in forestry remote sensing. University of Helsinki, Department of Forest Mensuration and Management, Research Notes 19. 21 p.

Jeyaratnam, S., Bowden, D.C., Graybill, F.A. and Frayer, W.E. 1984. Estimation in multiphase designs for stratification. Forest Science 30: 2, pp. 484-491.

LaBau, V.J. and Winterberger, K. C. 1989. Use of four-phase sampling design in Alaska multisource vegetation inventories. University of Helsinki, Dept. of Mensuration and Management. Res.Notes No. 21: 89-102.

Landis R.J. and Koch G. G. 1977. The measurement of observer agreement for categorical data. Biometrics 33:159-174.

Mery, G. and Bahamondez, C. 1995. A remote sensing-based forest inventory in the natural forest of Malleco, Chile. University of Helsinki, Department of Forest Resource Management, Publication 8.

Muinonen, E. and Tokola T. 1990. An application of remote sensing for communal forest inventory. In: Proceedings from SNS/IUFRO workshop in Umeå 26-28 Feb. 1990 (pp. 35-42). Remote Sensing Laboratory , Swedish University of Agricultural Sciences, Umeå (Report 4).

Neyman, J. 1938. Contribution to the Theory of Sampling Human Populations. Jour. Amer. Stat. Assoc., 33: 101-116.

Päivinen, R. (ed). 1994. IUFRO International Guidelines for Forest Monitoring. IUFRO World Series Vol. 5. University of Joensuu, Faculty of Forestry.

Peng, S. 1987. On the combination of multitemporal satellite and field data for forest inventories. Acta Forestalia Fennica 200. The Society of Forestry in Finland. Helsinki. 95 p.

Poso, S. 1972. A method of combining photo and field samples in forest inventory. Communicationes Instituti Forestalis Fenniae. Dissertation. IFBN 951-40-0012-0.

Poso, S., Häme, T. and Paananen, R. 1984. A method of estimating the stand characteristics of a forest compartment using satellite imagery. Silva Fennica, 18:261-292.

Poso, S., Karlsson, M., Pekkonen, T. and Härmä, P. 1990. A system for combining data from remote sensing, maps, and field measurements for forest planning purposes. University of Helsinki, Department of Forest Mensuration and Management, Research Notes 23. 40 p. ISBN 951-45-5524-4.

Poso, S. and Kujala, M. 1971. Ryhmitetty ilmakuva- ja maasto-otanta Inarin, Utsjoen ja Enontekiön metsien inventoinnissa. Summary: A two-phase forest inventory based on photo and field plot sampling as applied in northernmost Lapland. Folia Forestalia 132: 40 p.

Poso, S. and Kujala, M. 1978. A method for national forest inventory in northern Finland. Communicationes Instituti Forestalis Fenniaea 93(1). 54 p.

Poso, S., Paananen, R. and Similä, M. 1987. Forest inventory by compartments using satellite imagery. Silva Fennica, 21:69-94.

Poso, S., Wang, G. and Tuominen, S. 1999. Weighted Alternative Estimates when Using Multi-Source Auxiliary Data for Forest Inventory. Silva Fennica, 33(1):41-50.

Schreuder, H.T., Gregoire, T.G. and Wood, G.B. 1993. Sampling methods for multi-resource forest inventory. John Wiley & Sons. New York 446 p.

Shiver, B.D. and Borders, B.E. 1996. Sampling techniques for forest resource inventory. John Wiley & Sons, Inc. New York. 356 p.

Tokola, T., Pitkänen, J., Partinen S. and Muinonen, E. 1996. Point accuracy of a non-parametric method in estimation of forest characteristics with different satellite materials. International Journal of Remote Sensing, Vol. 17, No. 12, 2333-2351.

Tomppo, E. 1993. Multi-source national forest inventory of Finland. Proceedings of Ilvessalo Symposium. The Finnish Forest Research Institute, Research Paper 444: 52-60.

Waite, M.L. 1993. Documentation of the SMI/92 forest management planning system. Department of Forest Resource Management, University of Helsinki.

Wang, G.,Waite, M-L. and Poso, S. 1997. SMI User's Guide for Forest Inventory and Monitoring. 336 p. ISBN 951-45-7841-4.

CHAPTER 15

SEGMENTATION

ANSSI PEKKARINEN AND MARKUS HOLOPAINEN

Joint Research Centre, Italy, University of Helsinki, Finland

15.1 INTRODUCTION

The spatial resolution of the RS material available in digital format has continuously improved since Landsat 1, and several satellite imaging systems currently provide data that has a spatial resolution that is better than 5 metres. Furthermore, the availability of aerial imagery has significantly increased thanks to new image compression algorithms and the development of web-based services (METRIA 2003, ILMARI 2003). In addition to aerial photography, very high spatial resolution (VHR) data are available from airborne imaging spectrometers (e.g. AISA, CASI) and active sensors such as airborne laser scanners (Toposys, ALTM and ILRIS-3D) and airborne radars (e.g. CARABAS and GEOSAR). These sources provide interesting data for forest inventory applications, but also place new requirements on image analysis methods.

A typical traditional remote sensing aided forest inventory application is based on pixel-level image analysis, either unsupervised or supervised. In unsupervised applications the pixels are classified into spectrally homogeneous groups which are assigned forest characteristics based on a priori knowledge or information gathered for the classes in the field. In supervised approaches the analysis is usually based on existing field information. If the information has been gathered using relatively small field plots, the signature file that serves as an interpretation key in the image analysis is compiled by assigning the spectral information to the field plots using the particular image pixel on which the plot is located. Both of these approaches, unsupervised and supervised, are reasonable if the pixels are large enough to cover an area that can be considered "forest". If the pixels are significantly smaller, however, and the object to be analysed consists of several image pixels, a pixel-by-pixel analysis is not applicable and a contextual approach is required in which the image is divided into spatial entities, i.e. regions,

A. Kangas and M. Maltamo (eds.), Forest Inventory – Methodology and Applications, 253–269.

that can be used as basic units instead of pixels (Blaschke and Strobl 2001). These regions can be determined with the help of image segmentation.

15.2 IMAGE SEGMENTATION

15.2.1 General

Image segmentation is the division of an image into spatially continuous, disjoint and homogeneous regions. More formally, following the notation presented by Pal and Pal (1993), if a digital image is presented as

$$F_{PxQ} = [f(x,y)]_{PxQ},$$

where PxQ is the size of the image (columns x rows) and $f(x,y) \in G_L = \{0,1,...,L-1\}$ is the set of possible grey-level values G_L, image segmentation is partitioning of the image F into a set of homogeneous regions S_i in such a manner that

$$\bigcup_{i=1}^{n} S_i = F \text{ with } S_i \bigcap S_j = \varnothing,\ i \neq j.$$

The homogeneity of the regions is controlled with a homogeneity criterion, denoted by $P(S_i)$. The criterion has to be true for all unique regions and false for adjacent regions. It thus ensures that every region is distinct from the others. More formally: $P(S_i \bigcup S_j)$ has to be false when S_i is adjacent to S_j. $P(S_i)$ can be determined in any convenient manner, e.g. it can be set in such a way that a segment may include only pixels that carry the same grey-level value. In real-world applications, however, the criterion is usually much more complicated and may consist of a set of spectral and geometrical rules.

15.2.2 Image segmentation techniques

Image segmentation techniques can be classified in many ways depending on the level of detail included. Examples of different classifications can be found in segmentation reviews (Fu and Mui 1981b, Haralick and Shapiro 1985a, Pal and Pal 1993b) but from the viewpoint of forest inventory applications a simple classification into pixel, edge and region-based methods is sufficient.

Pixel-based image segmentation methods include image thresholding, clustering in the feature space and other methods that rely on pixel-level information and employ it in the global feature space. *Image thresholding* is a pixel-based technique in which an image is turned into a binary one in such a way that the objects of interest are separated from the background. Selection of the appropriate threshold value is usually based on a priori known properties of the object and

background. *Image clustering* can be seen as a multi-dimensional extension of thresholding (Fu and Mui 1981a). As both image thresholding and clustering methods produce results that may have several spatially discontinuous units that carry the same label, the result does not fulfil the definition of segmentation until the spatially continuous regions have been identified and re-labelled. This can be done using connected a component labelling (CCL) algorithm, also known as clumping (Jain et al. 1995).

Edge-based image segmentation methods differ significantly from pixel-based ones. The first phase in all edge-based segmentation algorithms is of course detection of the edges. An edge point (pixel) in an image can be defined as: "... a point in an image with coordinates [i, j] at the location of a significant intensity change in the image." (Jain et al. 1995).

Given this definition, it is obvious that, in order to decide whether a pixel is an edge pixel or not, one needs to analyse it and its neighbourhood. Edge detection generally consists of a) filtering, b) enhancement and c) detection (Jain et al. 1995). The filtering step is needed because most of the edge enhancement methods are relatively sensitive to image noise and therefore perform better when using a smoothed input. The edge enhancement phase is usually carried out with specific edge operators that emphasize pixels having significantly different values from their neighbours. Most of these operators, such as those known as "Roberts", "Sobel" and "Prewitt", are based on discrete approximation of the gradient, which in the case of images is a two-dimensional equivalent of the first derivative (Jain et al. 1995). They usually produce adequate results for most applications, even though they typically result in relatively thick edges. If a more precise location of the edges is needed, this can be found using second derivative operators such as Laplacian and Second Directional Derivative (Jain et al. 1995).

The remaining step in edge detection after image filtering and edge enhancement is the recognition of edge points (pixels) among the edge candidates. This is usually done by means of thresholding. In the simplest case, all pixels having an edge magnitude above a given threshold T are considered to be edge pixels. In many real-world cases that deal with noisy images, however, it may be very difficult to find a threshold with which the probability of detecting false edges remains low while all the relevant edges are found. Therefore it may often be necessary to use conditional threshold values that take contextual information into account. After edge detection all the edge pixels that have been detected are linked and meaningful boundaries are composed.

Region-based image segmentation techniques differ from pixel and edge-based methods in the way they deal with spatial relationships. Region-based techniques can all be seen as region growing techniques (Zucker 1976) or further divided into region growing, merging and splitting techniques and their combinations. The latter classification is used here.

There are several approaches to region growing. The algorithm may require a set of seed pixels or regions with which the process is started, or it may simply start with the initial image and process it pixel-by-pixel. If seeding is required, the seed pixels or areas may be shown interactively on the screen or selected automatically. If seeding is not required, the processing usually begins from the top

left corner of the image and proceeds from left to right and from top to bottom. Regardless of the processing details, region growing techniques usually join neighbouring pixels into one region if their spectral properties are similar enough, determined in terms of a homogeneity criterion, for example, or a combination of homogeneity, size and some other characteristics (Zucker 1976). Following the definition of segmentation, the region growing process is terminated after every pixel has been assigned to a segment.

In region merging and splitting techniques the image is divided into sub-regions and these are merged or split according to their properties. In region merging, the basic idea is to start with initial regions, i.e. single pixels or areas determined using any initial segmentation technique, and to merge similar adjacent ones. Region splitting methods operate in the opposite fashion, i.e. the input usually consists of large segments that are divided into smaller sub-segments by reference to simple geometric rules. After that, the homogeneity of the sub-segments is assessed and if they are not homogeneous enough they are further divided and the process is continued. The basis for the splitting or merging may be spectral similarity between the segments or the magnitude and length of their common edge, for example (Zucker 1976).

15.2.3 Segmentation software

It may be difficult to select the appropriate image segmentation approach and algorithm for a specific task on the basis of the algorithm description, as the approaches typically have certain advantages and disadvantages that cannot be recognized prior to testing of the algorithms with actual imagery. In addition, several algorithms may result in similar segmentation outputs. In practice, the decision is usually made between the algorithms that are commercially available, which are unfortunately few in number. Practically the first commercially available segmentation software packages that were designed for the analysis of remote sensing data were released in 2000 (Schieve et al. 2001), since when interest in their development has increased, so that segmentation tools are currently available for many leading image processing software packages such as Erdas Imagine and ENVI. One software package that deserves explicit mention in a forestry context is eCognition, the multivariate segmentation procedure in which is based on a region merging technique that starts with regions of size one pixel. The region merging algorithm is iterative and merges adjacent regions on the basis of their spectral and spatial properties. The main parameters controlling the algorithm are scale and homogeneity criteria. The “scale” parameter, which makes use of information on the homogeneity of the segments, restricts the permitted heterogeneity of the resulting segments and can thus be used to control their size, while the homogeneity criteria can be controlled by weighting the “colour” and “shape” parameters. “Colour” refers to the spectral properties of the segments and “shape” to their geometric properties. Furthermore, the shape parameter is a combination of the segments “smoothness” and “compactness”, which can be weighted by the user (Baatz et al. 2002). The eCognition software was recently strengthened with a new tool designed for

automated tree crown delineation (Definiens 2003).

15.3 SEGMENTATION IN FOREST INVENTORIES

The idea of using image segmentation as a tool for analysing earth observation imagery is not new, of course. In their segmentation review, Haralick and Shapiro (1985) cite EO image segmentation studies that were conducted as early as the mid-1970's. The actual need for image segmentation tools was only recognized later, however, soon after the launch of the Landsat 4 (1982) and SPOT 1 (1986) satellites, which introduced new sensors that provided images with considerably improved spatial resolution. In addition to the early pioneers of satellite image segmentation, many other scientists in the RS community were convinced that these sensors had begun a new, contextual era in the analysis of satellite images.

Although the need for contextual image analysis methods was recognized, few segmentation aided forestry applications of EO were proposed. Many of them were presented in Scandinavia and developed on the basis of ideas of Narendra and Goldberg (1980). Tomppo (1987) tested a method for the estimation of several attributes relevant to stand delineation, namely total volume, mean diameter at breast height, mean age and proportions of spine, spruce and deciduous trees by volume. Similar methods have been applied to land cover classification (Parmes and Kuittinen 1988), the segmentation of Landsat and SPOT imagery (Parmes 1992) and the spatial generalisation of pixel-level change detection (Häme 1991) and forest site fertility classification results (Tomppo 1992).

Approaches based on alternative segmentation algorithms have also been presented. Hagner (1990) introduced *"t-ratio segmentation"* and used it for the automatic delineation of stands. The author described the method as *"a type of region growing algorithm",* but it can be also classified as a region merging method. The same segmentation method has later been used for change detection (Olsson 1994). A segmentation method aimed at the delineation of stands for the construction of forest canopy reflectance models has also been presented (Woodcock and Harward 1992) and later employed for the generalisation of change detection results (Woodcock and Macomber 2001).

In general, segmentation methods produced promising results in stand delineation, the estimation of forest parameters and the post-processing of the results of pixel-based analysis. It has been concluded, for example, that stand delineation *"seems to work quite well"*, that *"it is possible to develop a stand-wise forest inventory method based on the satellite images"* (Tomppo 1987) and that segmentation-based stand delineation with SPOT imagery followed by manual editing gives comparable results to those achieved with visual interpretation of aerial images (Hagner 1990). In addition, the precision of stand-level estimates of volume and mean diameter was found to be comparable to the results of a subjective field inventory (Hagner 1990).

In spite of the relatively good results, the number of segment-based forestry applications remained low. There are two probable reasons for this. First, it was

soon observed that improved spatial resolution in satellite imagery did not necessarily require contextual image analysis methods, for despite the preliminary doubts, pixel-level analysis worked reasonably well with these images. Secondly, there was a lack of commercial image segmentation software.

The need for segmentation was perceived again in the 1990's, when the increasing availability of digitized aerial photographs and the slowly but surely approaching launches of new-generation satellites re-stimulated discussions concerning contextual image analysis. Following that, interest in object-oriented image analysis has steadily increased and the pixel-based approach has been more seriously criticized (Blaschke and Strobl 2001). This criticism is understandable in contexts such as the classification of buildings, landscape patches, agricultural fields and forest stands, when it is a question of considering the spatial relation between a pixel and the object of interest.

The fact that image segmentation provides a reasonable way of determining contextual VHR image analysis units has recently been recognized and image segmentation has been tested in numerous applications such as the delineation of habitats for biodiversity assessment (Holopainen 1998), the delineation of individual tree crowns from aerial and other high spatial resolution imagery (Pitkänen 2001, Gougeon 1995, Burnett 2003), change detection (Pekkarinen and Sarvi 2002, Saksa et al. 2003), the estimation of forest characteristics from AISA imagery, adjustment of the radiometry of aerial photographs (Tuominen and Pekkarinen 2004) and the stratification of forest areas (Pekkarinen and Tuominen 2003). Even commercial services that are based on segmentation technology and aim at stand-level inventories are already available (FACT 2004). In addition to optical imagery, image segmentation has increasingly been used for analysing airborne laser scanning (ALS) in applications such as the delineation of trees for change detection and growth estimation (Yu et al. 2003) and the extraction of forest inventory parameters (Diedershagen et al. 2003).

15.4 SEGMENTATION EXAMPLES

15.4.1 General

This section provides examples of the results of various segmentation methods and aims at illustrating the general properties of each method, but first let us briefly discuss the main factors that have an effect on the selection of an appropriate segmentation approach.

The applicability of different segmentation methods to a particular problem depends, of course, on the task to be carried out and the spatial, spectral and radiometric properties of the imagery employed. Thus segmentation that aims at the delineation of stands from medium-resolution multi-spectral satellite imagery may require a completely different approach from segmentation of individual tree crowns from aerial photographs. If the spatial resolution of the image material is coarse in relation to the object of interest all the segmentation approaches are generally likely to produce reasonable results, but in the opposite case region-based methods often produce better segmentation results. In addition to spatial resolution, the spectral and radiometric resolution of the imagery must also be considered when choosing the

segmentation approach, but these factors can be usually taken into account by adjusting the segmentation parameters and selecting appropriate image channels as the input to the segmentation process. Some types of imagery nevertheless have special properties that have to be taken into account when choosing the segmentation approach. Probably the most commonly used information source of this kind is aerial photography.

The spectral properties of the objects present on aerial photographs depend on their location in the spatial domain. This situation is typical of all imagery acquired using wide-angle instruments at low altitudes and is caused by the sun-sensor-object geometry, topography, film properties and camera optics etc. The magnitude of the phenomenon depends greatly on the properties of the object, e.g. the vegetation and forest types (Holopainen and Wang 1998a, 1998b, Holopainen and Jauhiainen 1999). Attempts have been made to solve this problem by employing a priori information on the objects to be imaged (Holopainen and Wang 1998b) or pre-stratification of other remote sensing imagery (Holopainen and Jauhiainen 1999, Tuominen and Pekkarinen 2004), but it can still be concluded that because of the complex radiometry, it is advisable to base the segmentation of aerial imagery on methods that operate locally, i.e. on edge and region-based approaches.

The best segmentation is often achieved with a combination of several techniques. Our experiences show, for example, that it is usually advisable to conduct the segmentation of VHR imagery in two phases: first a large number of spectrally homogeneous initial segments are derived, and then the initial segments are merged by region-based techniques to form applicable processing units. This is just a general observation, however, and in practice the best combination of appropriate segmentation tools for a specific task can often be found only by trial and error.

15.4.2 Example material

The following examples illustrate different segmentation techniques. The examples were derived using a spectrally generalized AISA image of an area in Southern Finland. The original 30 channels of the AISA image were generalized to four spectral channels that correspond to those of the new-generation very high resolution satellite imagery. The examples employ only the green channel of the generalized imagery (Figure 15.1). Details of the original image and the generalization process are given by Pekkarinen (2002).

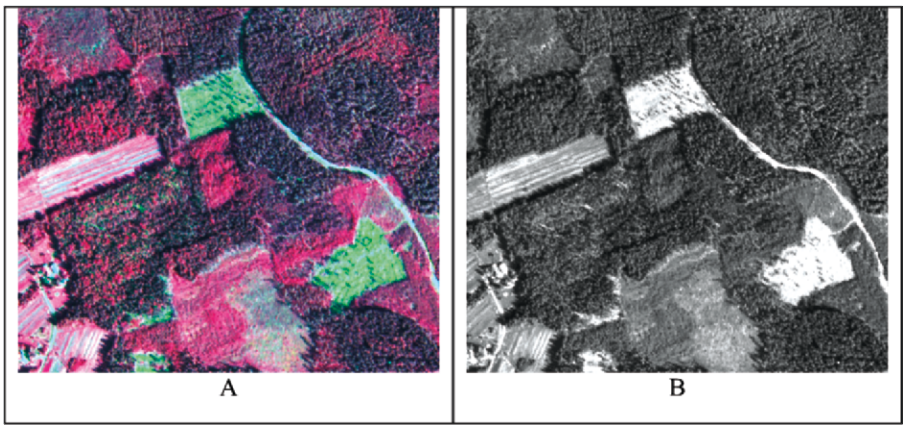


Figure 15.1 A subset of a spectrally generalized AISA image. Green, red and NIR channels (A) and green channel (B) © METLA 2004.

15.4.3 Example 1: Pixel-based segmentation

In our first example we derive a pixel-based segmentation using the green channel and image thresholding. The shape of the histogram of the green channel, shown in Figure 15.2, is typical of images of forested areas that do not include water bodies.

The image was binarized into classes 0 (white) and 1 (black) using a threshold set to 15. After that all the segments were composed by assigning each spatially continuous region a unique label. The outcome of the binarization and the resulting segment borders are shown in Figure 15.3.

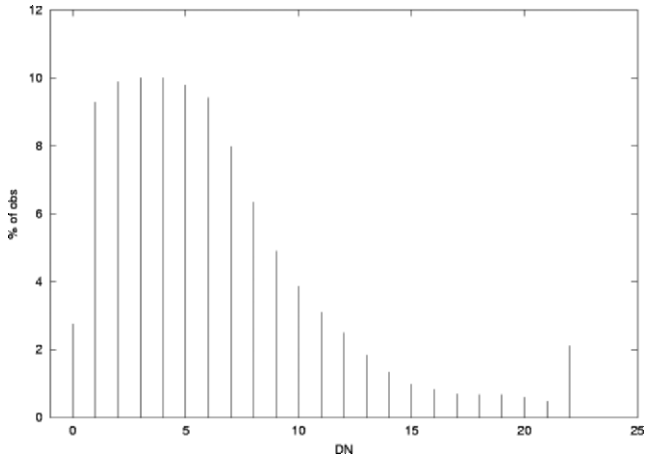


Figure 15.2 Histogram of the green channel of the spectrally generalized AISA image.

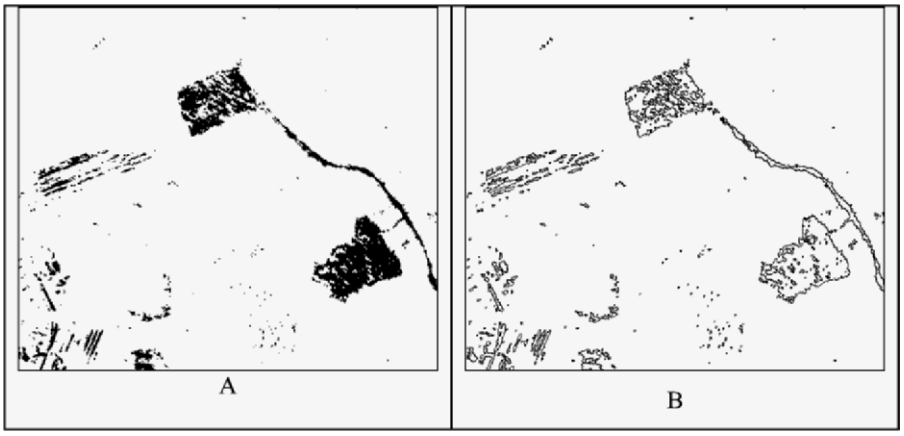


Figure 15.3 Binarized green channel (T = 15) of the spectrally generalized AISA image(A) and the resulting segment borders (B).

Thresholding is a simple technique with quite limited applications to forestry and pixel-level segmentation is more often accomplished by means of clustering which can be seen as multi-dimensional extension of thresholding. In the following example we cluster the AISA image using the well known *k*-means algorithm and 10 spectral classes. The clustering output is presented in Figure 15.4a and an example of the resulting segments in Figure 15.4b. Note that, following the definition of segmentation (section 15.2.1), all the pixels in a certain segment must be spatially connected. Neither the threshold nor the clustering output will meet this criterion until the spatially continuous areas have been assigned unique labels.

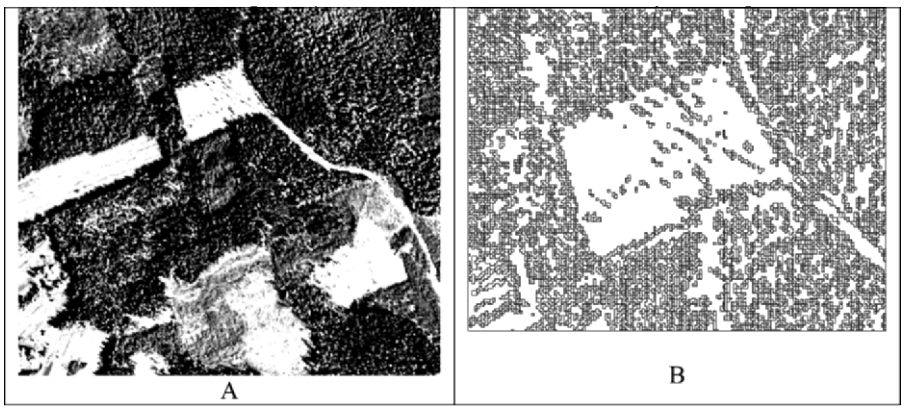


Figure 15.4 Clustered green channel of the spectrally generalized AISA image and an example of the resulting segment borders.

Pixel-based algorithms are problematic as far as the segmentation of VHR imagery is concerned, as high local variation typically results in a large number of tiny segments that are often not applicable to a forest inventory. The labelling of the spatially continuous components in our clustering example, for instance, resulted in almost 50 000 segments of an average size of approximately 4 pixels.

15.4.4 Example 2: Edge detection

Our second example illustrates various edge operators and their edge detection results. Edges, i.e. significant local changes in image intensities, are often detected by means of first and second derivatives, because they can be observed as peaks in the first and zero crossings in the second (Figure 15.5). The two-dimensional equivalents of these are the gradient and the Laplacian, respectively.

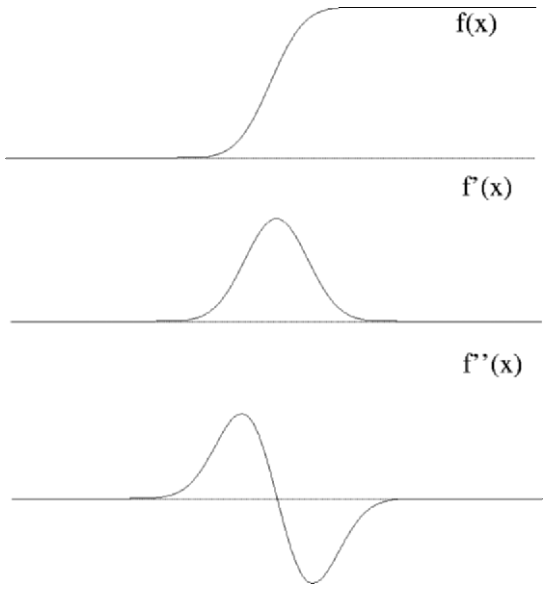


Figure 15.5 Function f(x), describing a ramp edge, and its first (f'(x)) and second (f''(x)) derivatives.

In practice, the gradient and the Laplacian are usually approximated by convolving the original image with the appropriate kernel masks, i.e. relatively small weight matrices that are placed on the pixel being processed, so that the convoluted value is computed as the weighted sum of the corresponding pixels. The local average for a 3 x 3 pixel window, for example, can be computed using a 3 x 3 cell convolution kernel in which all the cells have a weight 1/9. Our examples employ two edge operators: Sobel and Laplacian. The gradient is determined by means of approximations of the partial derivatives s_x and s_y using the convolution masks

shown in Figure 15.7 and the Laplacian is approximated using the left-hand mask presented in Figure 15.8, for example.

-1	0	1
-2	0	2
-1	0	1

1	2	1
0	0	0
-1	-2	-1

Figure 15.6 Sobel convolution masks for partial derivatives in the directions x (left) and y (right).

0	1	0
1	-4	1
0	1	0

1	4	1
4	-20	4
1	4	1

Figure 15.7 Laplacian convolution masks.

In our Sobel experiment the magnitude of the gradient was determined using the square root of the sum of the squared partial derivatives s_x and s_y. Finally, the actual edges were detected using the gradient magnitude image and a threshold set to 170. The results of these operations are presented in Figure 15.8.

Gradient-based edge detection typically produces thick edges in cases where the intensity changes rapidly, e.g. at step-like edges), while the Laplacian, which detects edges that cause zero-crossing in the second derivative, produces a locationally more accurate edge detection result but is sensitive to image noise and therefore often produces a large number of false edges. In our example (Figure 15.9) the vast majority of the pixels present zero crossings and are therefore regarded as edges.

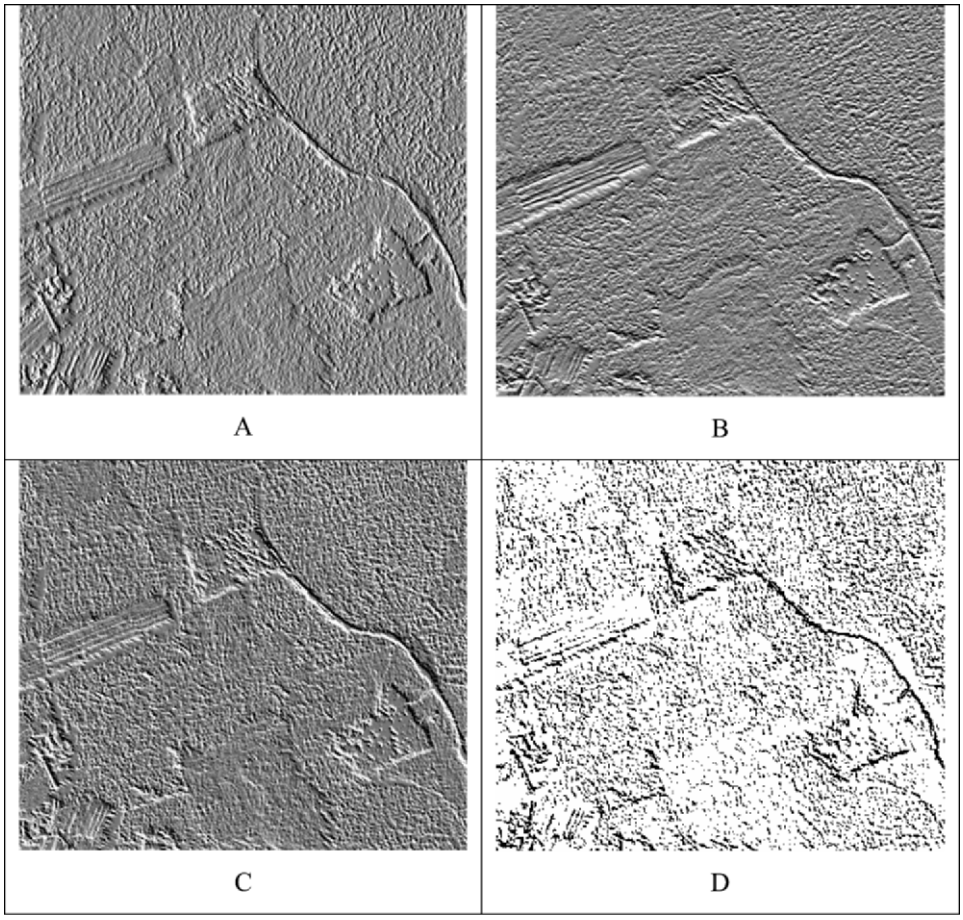


Figure 15.8 Sobel operator-based edge enhancement and detection results. Partial derivatives in the directions x (A) and y (B), gradient magnitude (C) and edge pixels detected (D). The light pixels in A, B and C represent high values and the black pixels in D represent the resulting edges.

Standard edge detection algorithms are obviously very sensitive to the high local variation present in VHR images and produce a considerable number of false edges. It should be noted, however, that our examples do not give a realistic impression of the performance of edge-based methods. Much better results can be achieved if the imagery is smoothed prior to edge enhancement and detection.

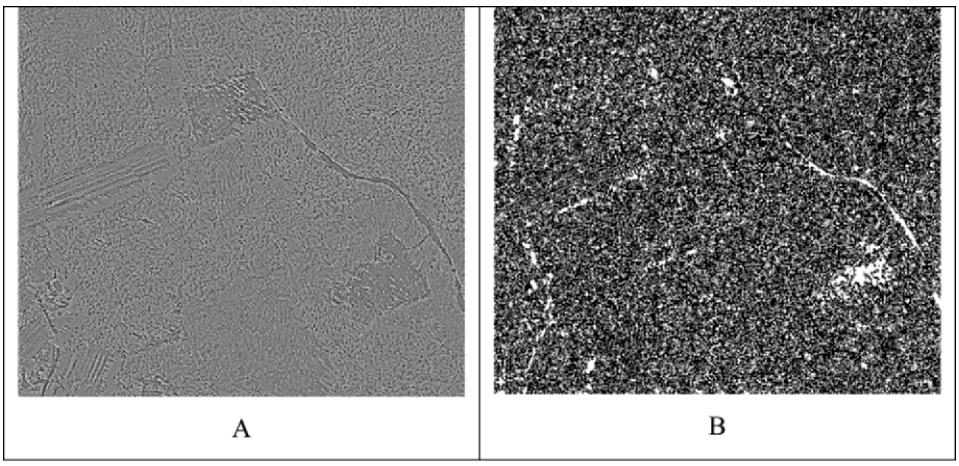


Figure 15.9 Laplacian of the green channel of the spectrally generalized AISA image (A) and the zero crossings, represented as black pixels (B).

15.4.5 Example 3: Region segmentation

The following figures illustrate the results of two region segmentations derived using a similar input but different region merging rules. The first example (Figure 15.11 A) is based on an iterative region merging approach that takes each original pixel as an initial region and proceeds by merging regions that are spectrally similar. The similarity of adjacent regions was measured by means of the absolute difference in their mean values. The similarity threshold was set at 30 digital numbers, i.e. adjacent regions are merged if the difference between their spectral averages is less than 30 DNs. The second example uses the same input, but the region merging was controlled using a minimum region size threshold of 500 pixels. In other words, all the regions that were smaller than the given threshold were merged with their spectrally nearest adjacent region and the merging process was iterated until all the regions were larger that 500 pixels in size.

The second region-based segmentation example illustrates the results of a two-phase segmentation process in which the initial segments were derived using the method originally described by Narendra and Goldberg (1980) and implemented by Pekkarinen (2002). The initial segmentation was used as the input to a region merging algorithm controlled by the same minimum segment size threshold as in the example above (500 pixels).

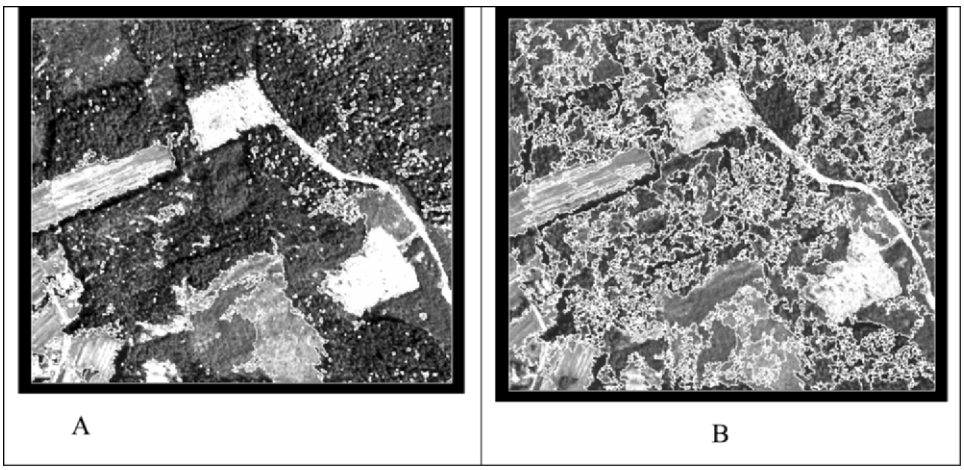


Figure 15.10. Region merging results of A) an algorithm controlled by a spectral similarity threshold, and B) an algorithm controlled by a minimum region size threshold.

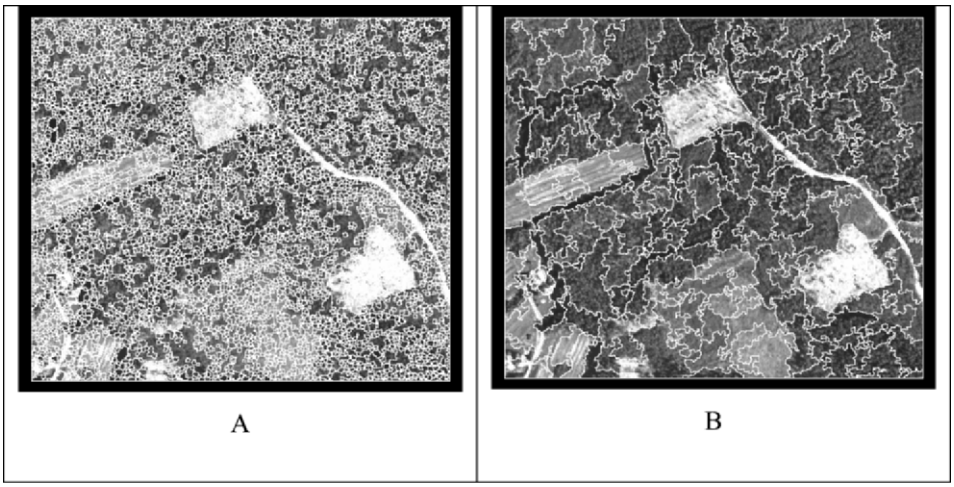


Figure 15.11. Segments derived using the two-phase method described in Pekkarinen (2002): initial segments (A) and a region derived using a minimum segment size of 500 pixels (B).

REFERENCES

Baatz, M., Benz, U., Dehghani, S., Heynen, M., Höltje, A., Hofmann, P., Lingenfelder, I., Mimler, M., Sohlbach, M., Weber, M. and Willhauck, G. 2002. eCognition - User Guide 3. Series eCognition - User Guide 3 2004p.

Blaschke, T. and Strobl, J. 2001. What's wrong with pixels? Some recent developments interfacing remote sensing and GIS. GeoBIT/GIS 6: 12-17.

Canny, J. 1986. Computational approach to edge detection. IEEE Transactions on pattern analysis and machine intelligence PAMI-8(6): 679-898.

Definiens 2003. www.definiens-imaging.com

Diedershagen, O., Koch, B., Weinacker, H. and Schutt, C. (eds.). 2003. Combining Lidar- and GIS data for the extraction of forest inventory parameters. ScandLaser Scientific Workshop on Airborne Laser Scanning of Forests. Umeå, Sweden. Swedish University of Agricultural Sciences, Department of Forest Resource Management and Geomatics 112. 273 p.

FACT 2004. www.falconinformatics.com

Fournier, R.A., Edwards, G. and Eldridge, N.R. 1995. A catalogue of potential spatial descriminators for high spatial resolution digital images of individual crowns. Canadian Journal of Remote Sensing, 21:285-298.

Fu, K.S. and Mui, J.K. 1981. A survey of Image Segmentation. Pattern Recognition 13(1): 3-16.

Hagner, O. 1990. Computer aided forest stand delineation and inventory based on satellite remote sensing. In: Proceedings from SNS/IUFRO workshop in Umeå 26-28 February 1990: The usability of remote sensing for forest inventory and planning. Swedish University of Agricultural Sciences. Remote sensing laboratory. Umeå. p.

Häme, T. 1991. Spectral interpretation of changes in forest using satellite scanner images. Acta Forestalia Fennica 222: 111.

Haralick, R.M. and Shapiro, L.G. 1985 Survey: Image Segmentation Techniques. Computer Vision, Graphics, and Image Processing 29(1): 100-132.

Holm, M., Lohi, A., Rantasuo, M., Väätäinen, S., Höyhtyä, T. Puumalainen, J., Sarkeala, J. and Sedano, F. 1999. Creation of large mosaics of airborne digital camera imagery. Proceedings of the 4th Airborne Remote Sensing Conference and Exhibition, Ottawa, Canada, 21-24 June 1999, Vol II, pp. 520-526.

Holopainen, M. 1998. Forest Habitat mapping by means of digitized aerial photographs and multispectral airborne measurements. University of Helsinki, Department of Forest Resource, publications 18: 1-49.

Holopainen, M. and Jauhiainen, S. 1999. Detection of peatland vegetation types using digitized aerial photographs. Canadian Journal of Remote Sensing, 25:475-485.

Holopainen, M. and Wang, G. 1998a. The calibration of digitized aerial photographs for forest stratification. International Journal of Remote Sensing, 19:677-696.

Holopainen, M. and Wang, G. 1998b. Accuracy of digitized aerial photographs for assessing forest habitats at plot level. Scandinavian Journal of Forest Research, 13:499-508.

ILMARI 2003. www.ilmari.fi

Jain, R., Kasturi, R. and Schunck, B.G. 1995. Machine vision. McGraw-Hill International Editions.

King, D., 1995, Airborne multispectral digital camera and video sensors: a critical review of system designs and applications. Canadian Journal of Remote Sensing, 21, 245-273.

Leckie, G.D., Beaubien, J., Gibson, J.R., O'Neill, N.T., Piekutowski, T. and Joyce, S.P. 1995. Data processing and analysis for mifucam: a trial of MEIS imagery for forest inventory mapping. Canadian Journal of Remote Sensing, 21:337-356.

METRIA 2004. www.metria.fi.

Mikkola, J. and Pellikka, P. 2002. Normalization of bi-directional effects in aerial CIR photographs to improve classification accuracy of boreal and subarctic vegetation for pollen-landscape calibration. International Journal of Remote Sensing, 23:4719-4742.

Narendra, P.M. and Goldberg, M. 1980. Image segmentation with directed trees. IEEE

Transactions on Pattern Analysis and Machine Intelligence PAMI-2: 185-191.

Olsson, H. 1994. Monitoring of Local Reflectance Changes in Boreal Forests using Satellite Data. Department of Biometry and Forest Management. Series Monitoring of Local Reflectance Changes in Boreal Forests using Satellite Data. Swedish University of Agricultural Sciences, Umeå. 39 p.

Pal, N.R. and Pal, S.K. 1993a. A review on image segmentation techniques. Pattern recognition 26(9): 1277-1294.

Parmes, E. and Kuittinen, R. 1988. Image segmentation in unsupervised and supervised land cover classification from satellite images. International Archives of Photogrammetry and Remote Sensing, Vol. 27, Part B10. Proceedings of the 16th International Congress of ISPRS, Kyoto 1988. pp. III-237 - III-243.

Parmes, E. 1992. Segmentation of SPOT and Landsat satellite imagery. The Photogrammetric Journal of Finland 13(1): 52-58.

Pekkarinen, A. 2002. Image segment-based spectral features in the estimation of timber volume. Remote Sensing of Environment 82: 349-359.

Pekkarinen, A. and Sarvi, V. (eds.). 2002. Detection of clearcuttings with help of high-altitude panchromatic aerial photographs and image segmentation. Operational Tools in Forestry using Remote Sensing Techniques. ForestSAT Symposium. Edinburgh, Scotland, August 5th-9th 2002p.

Pekkarinen, A. and Tuominen, S. (eds.). 2003. Stratification of a forest area for multisource forest inventory by means of aerial photographs and image segmentation. Advances in Forest Inventory for Sustainable Forest Management and Biodiversity Monitoring. Dordrecht, Netherlands. Kluwer Academic Publishers. Forestry sciences 76. 111-123 p.

Pellikka, P. 1998. Development of correction chain for multispectral airborne video data for natural resource assessment. Fennia,176:1, Geographical Society of Finland, pp. 1-10.

Pitkänen, J. 2001. Individual tree detection in digital aerial images by combining locally adaptive binarization and local maxima methods. Canadian Journal of Forest Research 31: 832-844.

Saksa, T., Uuttera, J., Kolström, T., Lehikoinen, M., Pekkarinen, A. and Sarvi, V. 2003. Clear Cut

Detection in Boreal Forest Aided by remote Sensing. Scandinavian Journal of Forest Research 18(6): 537-546.

Schieve, J., Tufte, L. and Ehlers, M. 2001. Potential and problems of multi-scale segmentation methods in remote sensing. GeoBIT/GIS 6: 34-39.

Strahler, A.H., Woodcock, C.E. and Smith, J.A. 1986. On the nature of models in remote sensing. Remote Sensing of Environment 20: 121-139.

Tomppo, E. (ed.). 1987. Stand delineation and estimation of stand variates by means of satellite images. Remote Sensing-Aided Forest Inventory. University of Helsinki, Department of Forest Mensuration and Management Research Notes 19. 60-76 p.

Tomppo, E. 1992. Satellite image aided forest site fertility estimation for forest income taxation. Acta Forestalia Fennica 229: 1-70.

Tuominen, S. and Pekkarinen, A. 2004. Local radiometric correction of digital aerial photographs for multi source forest inventory. Remote Sensing of Environment 89: 72-82.

Woodcock, C. and Harward, V.J. 1992. Nested-hierarchical scene models and image segmentation. Interational Journal of Remote Sensing 13: 3167-3187.

Woodcock, C. and Macomber, S. 2001. Monitoring large areas for forest change using Landsat: Generalization across space, time and Landsat sensors. Remote Sensing of Environment 78: 194-203.

Yu, X.W., Hyyppä, J., Rönnholm, P., Kaartinen, H., Maltamo, M. and Hyyppä, H. (eds.). 2003. Detection of harvested trees and estimation of forest growth using laser scanning. ScandLaser Scientific Workshop on Airborne Laser Scanning of Forests. Umeå, Sweden. Swedish University of Agricultural Sciences, Department of Forest Resource Management and Geomatics112. 273 p.

Zucker, S., W. 1976. Region Growing: Childhood and Adolescence. Computer Graphics and Image Processing 5: 382-399.

CHAPTER 16

INVENTORY BY COMPARTMENTS

JYRKI KOIVUNIEMI AND KARI T. KORHONEN

Finnish Forest Research Institute, Finland

16.1 BASIC CONCEPTS AND BACKGROUND

Inventory by compartments is the method typically used for acquiring data for traditional forest management planning purposes. It is based on the concept of the forest stand, which is traditionally defined as a geographically contiguous parcel of land whose site type and growing stock is homogenous (e.g. Lihtonen 1959 p. 9, Ilvessalo 1965 p. 159, Davis and Johnson 1987 p. 29, Poso 1994 p. 95). In this context, compartment can almost be considered a synonym for forest stand, but a compartment must be also a suitable cutting unit or treatment unit for silvicultural measures and need not necessarily be as homogenous as a forest stand.

Detailed forest management plans cannot be produced without compartment-wise estimates of site characteristics and growing stock and without silvicultural treatment proposals for each compartment. The latter must be made within the field inventory, because otherwise the planner has no way of ensuring that in the optimum solution to the forest management planning problem every compartment will be treated silviculturally in a feasible manner. Models describing forests and forestry in forest management planning packages (e.g. MELA, Siitonen et. al. 1996) are merely simplifications of reality.

Sampling theory could be used to estimate the sample size needed to attain a certain required level of accuracy in estimates of growing stock, but if the compartments are small the sample sizes become so large that the inventories will be too expensive. In Nordic countries and in Central Europe, where compartments are rather small, a solution to the problem has been found in terms of a subjective method called "inventory by compartments", which is partially based on visual assessment of the growing stock.

Inventory by compartments will be illustrated in this chapter by describing a Finnish application. The area of forestry land in Finland is about 26 million ha, of which 60% is owned by private persons. All the forests owned by the state or by

A. Kangas and M. Maltamo (eds.), Forest Inventory – Methodology and Applications, 271–278.

forest companies have been inventoried. Almost all the privately-owned forests have been inventoried at least once by forestry centres, and at the moment the databases of the forestry centres cover about 11 million ha of forest. The average area of a compartment in southern Finland is about 1.5 - 2 ha. Compartments under 0.5 ha are not used unless the area is environmentally valuable.

16.2 HISTORY OF THE INVENTORY METHOD IN FINLAND

Inventory by compartments is the oldest method for conducting inventories of forest areas. The basic ideas were developed in Central Europe long before the days of mathematical sampling theory (Loetsch and Haller 1973 pp. 7-9). Management planning by stands began in the state-owned forests of Finland in 1907 (Lihtonen 1959 p. 289). Inventory by stands in the early 20th century differed markedly from inventory by compartments as it is performed today, mostly on account of the availability of base maps and the existence of two inventions: aerial photography and the relascope. If no base maps were available for a particular area in earlier times, a land survey had to be included in the inventory. In Finland, aerial photographs were first used for making forestry maps in 1946. Delineation of the compartment borders is much easier with aerial photographs than with base maps and field measurements. The relascope was invented in Austria in 1947 (Loetsch and Haller 1973 p. 8). Before this, the volume of growing stock had to be assessed on the basis of visual estimates of stand density and a few tree height measurements (Ilvessalo 1965). The relascope solved the problem of measuring stand density, and following its invention just a few sample plots have needed to be measured at subjectively selected locations in each compartment. These sample plot measurements can then be subjectively weighted to calculate the mean basal area (m^2/ha), mean diameter, mean height and mean age of the growing stock in a compartment. Volumes of growing stock by tree species can be taken from stand volume tables based on estimated basal areas and mean heights (Nyyssönen 1954).

16.3 INVENTORY BY COMPARTMENTS TODAY

16.3.1 The inventory method

Forest companies in their own forests and the Forest and Park Service in the state-owned forests have now replaced traditional inventory by compartments with a continuous updating approach, so that large inventory projects carried out at regular intervals are no longer needed. Instead, the forest resource database is updated immediately after cutting or the implementation of a silvicultural measure in a compartment and the increment in the growing stock is updated by means of growth models.

The forestry centres still continue the tradition of inventories by compartments at 10 – 15 year intervals in private forests, but again the old inventory data are updated by mean of growth models before the new inventory. The first step in the inventory is delineation of the compartment borders using digital aerial

photographs, base maps and the old inventory data. The old inventory data are also used in the field inventory, being valuable for assessing site characteristics, for example. In the field work, a surveyor visits every compartment, checks the compartment borders, measures 2-8 sample plots at subjectively selected locations in each compartment (Figure 16.1) and makes proposals for silvicultural treatment over the next 10-year planning period. The sample plots are relascope plots (relascope factor usually 1 or 2) in thinning and mature stands, and circular plots (usually of radius 4 m) in seedling stands.

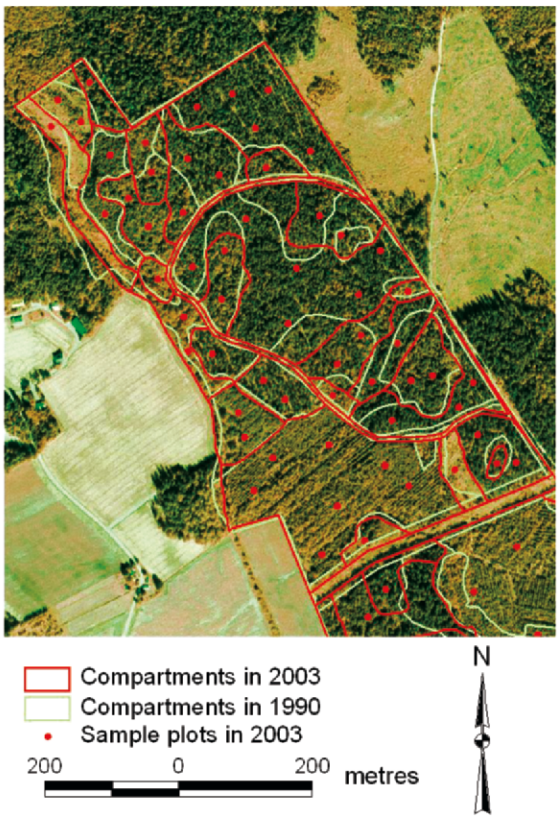


Figure 16.1 Compartments identified in the inventory by compartments in 1990 and 2003, and sample plots measured in the 2003 inventory in a forest located near Riihimäki in southern Finland that is managed by Finnish Forest Research Institute. (Aerial photograph 2001, © FM-Kartta Oy).

The relascope plots are used for estimating the basal area (G, m^2/ha), mean diameter (D, cm), mean height (H, m) and mean age (T) of the growing stock, all recorded by tree species and tree storey. Mean diameter is the diameter of the basal area median tree. Mean heights and mean ages are usually measured only for one or

two representative median trees in the whole compartment and not for every sample plot. For young stands, the number of stems (N, stems/ha) is measured instead of the basal area on fixed-radius plots. Even though several sample plots may be measured in order to estimate the mean characteristics, only one mean value for each tree species and tree storey is recorded for each variable in a compartment. Mean values are calculated using field computers. The original plot-level values are not stored in the compartment database.

16.3.2 Estimation methods

The estimation of stem volume, volumes by timber assortments and growth consists of the following stages.

1. Prediction of diameter distribution.
2. Selection of representative trees (model trees) from the theoretical diameter distribution.
3. Prediction of volumes and increment for the model trees.
4. Summation of compartment-level results.

Prediction of diameter distribution

The diameter distribution in thinning stands or mature stands is usually estimated by means of regression models predicting the parameters of the Weibull distribution (see Mykkänen 1986 and Kilkki et al. 1989). (Weibull distribution models actually predict the basal area distribution, but the term diameter distribution is used here for simplicity.) Other methods for estimating diameter distributions in addition to those based on parametric density functions have been developed recently (for distribution-free methods, see Kangas and Maltamo 2000a and 2000b, and for non-parametric methods based on a database of known diameter distributions, see Haara et al. 1997). Tree height distributions are employed in seedling stands instead of diameter distributions.

Selection of representative trees from the theoretical diameter distribution

Usually 10 representative trees (model trees) are selected systematically at fixed distances from the predicted diameter (or height) distribution and the number of stems represented by each is derived from the cumulative basal area distribution and the basal area of the model tree itself, so that the sum of the basal areas of model trees is equal to the measured basal area for the tree species and storey.

Prediction of volumes and increment for the model trees

The total height of each selected model tree is estimated by mean of general height models calibrated by reference to the measured height of the basal area median tree. Stem volume is predicted by means of general volume functions, using diameter and height as regressors. Volumes by timber assortments are estimated with tables as a

function of tree diameter and height. Volume increment is predicted using tree-level diameter and height increment models.

Estimation of compartment-level results

The number of stems represented by each model tree is derived as described above, and the compartment-level results are obtained simply by summing the estimated tree-level values multiplied by the representative factor.

16.4 ACCURACY OF THE INVENTORY BY COMPARTMENTS METHOD AND SOURCES OF ERROR

Inventory by compartments is still the most efficient inventory method for acquiring data for the purposes of detailed forest management planning. Another reason for its popularity is that the unit of assessment is intended to be the same as the smallest unit of forest management. The delineation of compartment borders and the making of proposals for cuttings and other silvicultural measures can also be regarded as the preliminary stages of forest management planning. Despite its popularity, however, the inventory method has also been criticized. It is considered expensive, the inventory results are not always accurate enough, and their accuracy cannot be estimated on the basis of measurements made in the inventory.

Main reason for the problems is that even a visually highly homogeneous compartment can show considerable variation in sample plot basal areas, and thus also in volumes, if sample plot sizes are kept at practical level (Figure 16.2). In inventory by compartments surveyors seldom measure sample plots in locations where the characteristics of the growing stock reach or come close to local maximum values, or if they do so, then they also balance out these local maxima with local minima. This procedure reduces random variation in the compartment-level characteristics of the growing stock as compared with probabilistic sampling, but the compartment-level results will be biased if the surveyor's impression of the average amount of growing stock along the route that he walks differs from the real situation. The largest compartment-level errors, however, arise from the fact that surveyors do not visit every part of the compartment. Unless a surveyor walks through the compartment in parallel to the trend in a given characteristic of the growing stock, quite large errors are very likely to occur.

Several studies have been published on the reliability of inventory by compartments. The sources of error mentioned include:

- random and systematic measurement errors (e.g. in observing basal areas and locating compartment boundaries)
- "sampling errors" when locating the relascope plots (quotation marks needed to indicate that this is not true sampling error, because the locations are selected subjectively
- model errors in estimating diameter distributions, tree heights, stem volumes etc.

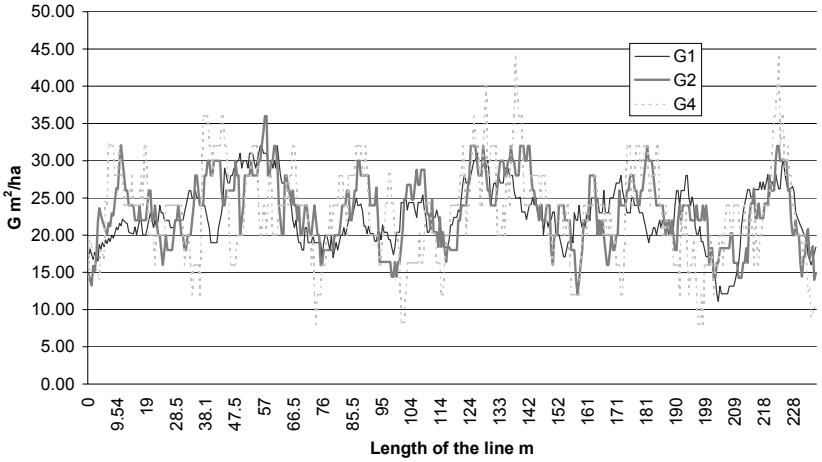


Figure 16.2 Basal areas of relascope plots located on a straight line through a homogeneous spruce stand in southern Finland (Koivuniemi 2003), calculated with relascope factors 1, 2, and 4 (G1, G2 and G4, respectively). The mean diameter and mean height of the growing stock were 23 cm and 17 m.

According to these publications, the magnitude of the measurement and "sampling" errors (RMSE, root mean square error) for the mean volume estimate is approximately 25% (Table 16.1). The errors depend on the surveyor, however, and RMSE's may vary from less than 15% to more than 40%. In addition, systematic errors occur, these being up to 20% at the surveyor level (Haara and Korhonen 2004). Experienced surveyors are usually able to collect data with higher precision than unexperienced ones, whereas it has been shown that training does not improve the quality of the data produced by experienced surveyors (Ståhl 1992).

The accuracy of the results over the whole area inventoried can be estimated and systematic errors in compartment-level estimates can be reduced if the traditional inventory by compartments method is supplemented with an inventory based on probability sampling (Lindgren and Jonsson 1978, Laasasenaho and Päivinen 1986 and Jonsson et al. 1993). Estimation of the accuracy of the inventory results for the whole area is based on stratification and a two-stage sampling procedure in which the area is stratified into homogeneous groups of compartments and stage 1 consists of the sampling of compartments from the strata and stage 2 of systematic sampling of circular or relascope plots within each selected compartment. The accuracy of the inventory results can also be calculated for each stratum.

Table 16.1. Biases (b) and standard deviations (s) of errors in the estimation of growing stock characteristics made in inventories by compartments, according to Finnish studies (Haara and Korhonen 2004). Relative values in percentages are shown in parentheses. The characteristics studied were D_{gM} = diameter of the basal area median tree, G = basal area, H_{gM} = height of the basal area median tree, and V = mean volume.

Characteristic of growing stock	Statis-tic	Study Poso (1983)	Laasasenaho and Päivinen (1986)	Pigg (1994)	Haara and Korhonen (2004)
D_{gM} (cm)	b		-1.0	-0.8	0.4
			(-4)	(-4.8)	(2.4)
	s		2.2	2.5	2.3
			(10)	(14.1)	(12.6)
G (m^2/ha)	b		-0.1	0.2	0.5
			(-1)	(1.2)	(2.7)
	s		3.3	2.8	3.9
			(16)	(18.5)	(19.6)
H_{gM} (m)	b		-0.6	-0.2	-0.01
			(-3)	(-2)	(-0.05)
	s		2.1	1.7	2.4
			(11)	(14.1)	(15.7)
V (m^3/ha)	b				2.4
					(1.6)
	s	36-66	32-37		37.5
		(29-38)	(17-24)		(24.8)

The compartment-level estimates can be calibrated using regression techniques. In the simplest such technique, the compartment-level estimates achieved by an objective inventory method are predicted as a function of the estimates achieved by the traditional inventory by compartments method.

REFERENCES

Davis, L. S. and Johnson, K. N. 1987. Forest management. 3rd edition. McGraw-Hill Book Company. 790 p.

Haara, A., Maltamo, M. and Tokola, T. 1997. The k-nearest-neighbour method for estimating basal-area diameter distribution. Scandinavian Journal of Forest Research 12: 200-208.

Haara, A. and Korhonen K. T. 2004. Kuvioittaisen arvioinnin luotettavuus. Metsätieteen aikakauskirja 4/2004:489-508. (In Finnish).

Ilvessalo, Y. 1965. Metsänarvioiminen. WSOY. 400 p. (In Finnish).

Jonsson, B. and Lindgren, O. 1978. En metod för uppskattning av ett skogsinnehav och för kalibrering avokulärskattade värden. Summary: A method for estimating properties of a forest and for calibration of ocular estimates. Sweriges Skogsvårdförbunds Tidskrift 76:493-505.

Jonsson, B. Jacobsson, J. and Kallur, H. 1993. The Forest Management Planning Package. Theory and application. Studia Forestalia Suecica. 189. 56 p.

Kangas, A. and Maltamo, M. 2000a. Percentile based basal area diameter distribution models for Scots pine, Norway spruce and birch species. Silva Fennica 34(4): 371-380.

Kangas, A. and Maltamo, M. 2000b. Performance of percentile based diameter distribution prediction and Weibull method in independent data sets. Silva Fennica 34(4): 381-398.

Kilkki, P., Maltamo, M., Mykkänen, R. and Päivinen, R. 1989. Use of the Weibull function in estimating the basal area dbh-distribution. Silva Fennica 23(4): 311-318.

Koivuniemi, J. 2003. Metsiköihin ja paikannettuihin koealoihin perustuvan kuvioittaisen arvioinnin tarkkuus. Summary: The accuracy of the compartmentwise forest inventory based on stands and located sample plots. Doctoral thesis. Publications of the Department of Forest Resource Management 36. University of Helsinki. 160 p.

Laasasenaho, J. and Päivinen, R. 1986. Kuvioittaisen arvioinnin tarkistamisesta. Summary: On the checking of inventory by compartments. Folia Forestalia 664. 19 p.

Lihtonen, V. 1959. Metsätalouden suunnittelu ja järjestely. WSOY. 355 p. (In Finnish).

Loetsch, F. and Haller, K. E. 1973. Forest inventory. Volume 1. BLV Verlagsgesellschaft. 436 p.

Mykkänen, R. 1986. Weibull-funktion käyttö puuston läpimittajakauman estimoinnissa. Master's thesis. University of Joensuu, Faculty of Forestry. 80 p. (In Finnish).

Nyyssönen, A. 1954. Metsikön kuutiomäärän arvioiminen relaskoopin avulla. Summary: Estimation of stand volume by means of the relascope. Communicationes Instituti Forestalis Fenniae 44(6): 31.

Pigg, J. 1994. Keskiläpimitan ja puutavaralajijakauman sekä muiden puustotunnusten tarkkuus Metsähallituksen kuvioittaisessa arvioinnissa. Master's thesis. University of Helsinki. Department of Forest Resource Management. 92 p. (In Finnish).

Poso, S. 1983. Kuvioittaisen arvioimismenetelmän perusteita. Summary: Basic features of forest inventory by compartments. Silva Fennica (17)4: 313-349.

Poso, S. 1994. Metsätalouden suunnittelun perusteet. Publications of the Department of Forest Resource Management 5. University of Helsinki. 155 p. (In Finnish).

Siitonen, M., Härkönen, K., Hirvelä, H., Jämsä, J., Kilpeläinen, H., Salminen, O. and Teuri, M. 1996. MELA Handbook, 1996 Edition. The Finnish Forest Research Institute Research Papers. 622. 452 p.

Ståhl, G. 1992. En studie av kvalitet i skogliga avdelningsdata som insamlats med subjektiva inventerigsmetoder. Summary A study on the quality of compartmentwise forest data acquired by subjective inventory methods. Swedish University of Agricultural Sciences. Department of Biometry and Forest Management. Rapport 24. 128 p.

CHAPTER 17

ASSESSING THE WORLD'S FORESTS

ANNIKA KANGAS

University of Helsinki, Finland

17.1 GLOBAL ISSUES

17.1.1 Issues of interest

The Food and Agricultural Organization (FAO) of the United Nations has a long history of global forest resource assessments (FRA). The FRA programme has two major components (FFRI2003):

1. Global assessment and reporting
2. Support for national forest assessments

The global assessment component has two objectives: to compile, analyse and report forest information covering all countries, and to maintain mechanisms and arrangements for global reporting. The support component also has two major objectives: to support countries in developing, packaging and using forest information and to establish an international framework for reporting on forest resources.

R. Zon, in collaboration with the United Stated Forest Service, prepared the first report on global forest resources in 1910 (Zon 1910), and this was updated in 1923 (Zon and Sparhawk 1923). The first world forest inventory was carried out by the FAO in 1947-1948, and it subsequently conducted such inventories every fifth year from 1953 to 1963. In these first assessments the FAO used a questionnaire to obtain the information from the individual countries (Holmgren and Persson 2002), but this approach could not be used later as the capacity for forest inventories had decreased in many countries. Thus expert judgments, in which all possible information from different sources was collected and an expert tried to infer the state of the country's forests from this, were also used in the 1970s and 1980s (Holmgren and Persson 2002). The assessments made in the 1970's were essentially regional, but a global synthesis of them was prepared as well (Persson 1974).

In the latest two assessments, the assessments of forests in the tropical

A. Kangas and M. Maltamo (eds.), Forest Inventory – Methodology and Applications, 279–291.

region are based on remote sensing, but those in the temperate and boreal zones on questionnaires. A panel of experts (FFRI 1996) made recommendations with respect to the major issues of data acquisition and the compilation of information for FRA 2000 at the Kotka III meeting, and work for the new assessment, FRA 2005, discussed at the Kotka IV meeting (FFRI 2003), is currently going on.

Forest areas and area changes have been a major issue in the assessment of global forest resources. The forest area has been seen as a simple indicator of the status of the world's forests, and therefore as an important means of monitoring changes. Changes in forest area may be due to land use changes, such as afforestation, deforestation and expansion of the natural forests, or internal changes within a forest class, such as reforestation, regeneration of natural forests, forest degradation and improvement.

Forest area can also be a problematic concept, however, as an indicator of the health of the ecosystem. The environmental, social or economic values of forests may not necessarily be related to their absolute extent, for instance. Thus the forests that are of the greatest environmental importance may be scattered and involve a small area, and their economic value may be related more to species distribution and volume than to forest area, while social values may be interrelated with other local interests such as agriculture.

The shortage of forest resources has always been a concern, and balancing of the supply with the needs requires information. Wood is needed for construction, for pulp and paper, for fuel and energy and for carbon sequestration, among other things, so that wood volume and biomass have been among the most important parameters in assessments of global forest resources. The issues considered in the Forest Resources Assessment 2000 (FRA 2000) were much wider than those of earlier assessments, however, the topics of interest being:

forest area and its changes,
wood volume and woody biomass,
forest plantations,
trees outside the forests (TOF),
biological diversity,
forest management,
forests in protected areas,
fires,
wood supplies and
non-wood forest products.

Ideally, a global forest assessment should address all the benefits of forests and the full range of potential beneficiaries, from local users to the global population (Holmgren and Persson 2002). This chapter will briefly review the most important results, namely forest area, volume and biodiversity considerations, although the main attention will be focused on methodological issues.

17.1.2 Forest area

Up to the more recent assessments, the definition of forest was 20% canopy cover in the temperate and boreal zones and 10% cover in the tropical zone. In FRA 2000, however, 10% cover was used for all countries, and while a canopy cover between 5% and 10% was classified as an "other wooded area", a category which in earlier inventories had required a 10%-20% canopy cover. This change required much work in order to compare the results with earlier assessments, the discrepancies being largest in Russia and Australia, where extensive areas of forests with a canopy cover between 10%-20% exist.

Even a specific canopy cover threshold is not a straightforward definition of forest, however, for the definition used in FRA 2000 also involved a land use classification. When another land use, e.g. agriculture, predominates in an area, it cannot be defined as a forest. Thus oil palms and rubber trees are included in forests, but fruit orchards and agroforestry areas are not. Similarly national parks are included but urban parks are not (FRA 2000).

According to FRA 2000, the global forest area is 3 869 million hectares and accounts for 30% of the land area. The net change has been a decrease of 9.4 million hectares per year, implying 14.6 million hectares of deforestation of natural forests and an increase of 5.2 million hectares in the area of forest plantations.

17.1.3 Wood volume and woody biomass

The wood volume was defined in global assessments as the stem volume of all living trees more than 10 cm in diameter at breast height (or above buttresses if these are higher) over bark, measured from the stump to the top of the bole (volume over bark, VOB). The above-ground biomass was defined as that of the woody parts of trees (stem, bark, branches, twigs), alive or dead, shrubs and bushes, excluding stumps and roots, foliage, flowers and seeds.

Suitable data were available for most developed countries, while estimates for the developing countries had to be based on local inventories in many cases, inventories that only covered certain aspects such as commercial forests, or inventories limited to a few species. Biomass studies in these countries were even less common.

Another problem was that the national results were seldom compatible with the FAO definitions. The volume could be defined to include trees above 5 cm or 50 cm at breast height, for example. The largest minimum diameters were often used in humid regions such as Indonesia, and the smallest in dry regions of Africa. The volumes of the missing dbh classes were estimated with regression equations between dbh class and volume, or with volume expansion factors (VEF) when regression could not be used.

The volume data were converted to biomass with the formula (FRA 2000)

$$\mathrm{TFB} = \mathrm{VOB} \cdot \mathrm{WD} \cdot \mathrm{BEF}, \tag{17.1}$$

where TFB is the total forest biomass (t/ha), VOB is volume over bark (m^3/ha), WD

is volume-weighted average wood density (t/m^3) and BEF is the biomass extension factor, i.e. the ratio of whole tree oven-dry biomass to the oven-dry biomass of the inventoried stem volume.

The estimated global volume of forests in 2000 was 386 billion cubic metres and the above-ground woody biomass was 422 billion tonnes. The wood volume increased by 2 percent between FRA 1990 and FRA 2000, and at the same time the woody biomass decreased by 1.5%.

There are considerable numbers of trees, however, that are not located in forests but grow in gardens and parks, in cities, on farms, in fruit orchards or beside roads. These, too, may be important both environmentally and economically. They may provide shade, shelter and food, they may improve the landscape and they may protect the soil. No global assessment of the volume or biomass of such TOF trees has ever been made, although many studies exist for specific areas. In many areas TOF may be more important than forests, e.g. in Kerala, India, where as much as 93% of the wood production was estimated to be from trees growing outside the actual forests.

17.1.4 Biodiversity and conservation

Biodiversity is a complicated issue, and for that reason only certain specific aspects can be monitored. The variables considered must be simple, uniform and easily understood, and they should represent major values in forest biodiversity. Such variables are typically based on indicators or indirect (surrogate) measures. The FAO Expert Consultation on Global Forest Assessment 2000 (FFRI 1996) recommended the following variables:

naturalness (natural forests, semi-natural forests and plantations)
protection status (IUCN categories, Table 17.1)
fragmentation
better information on forests in specific ecological zones.

There are obstacles even to the assessment of such simple-looking variables as these, however. World maps indicating diversity at the ecosystem or species level, for instance, typically have a resolution of 10 kilometres or more, and national-level summaries are even less detailed. Therefore, part of the meaning of diversity may be lost when the data are averaged over large areas (FRA 2000).

As data on biodiversity are scarce, two separate studies were carried out in the assessment: a review of the literature in each country on the number of species occurring in forests and a consideration of the spatial attributes of forests.

The literature review was carried out in order to estimate the importance of forests as habitats. Typically, fairly good information was available on all species, but only limited information on those occurring in forests. The data concerning trees are limited, for example, due to the problems of defining this group, and no data at all were available on reptiles, birds and mammals occurring in forests. The value of

assessments based on the number of endangered species is therefore seriously limited (FRA 2000).

The spatial analysis could be carried out fairly easily. Three aspects of fragmentation were considered, namely area effects, edge and gradient effects and isolation effects. Area effects are based on the assumption that small patches support fewer species and are more vulnerable than larger patches, edge effects imply that the interface with non-forest ecosystems has negative effects on environmental variables, and isolation effects means that the gene flow between one population and others of the same species will be reduced. This approach was found to be technically feasible, but the problem remains that its relevance to biodiversity has not been determined (FRA 2000).

The area under protection was determined in two ways, through questionnaires sent to national and regional land management agencies and by overlaying global protected area maps on global forest cover maps. Since the global protected area map in some cases included only a reference point and not the actual shape of the area, a circular area had to be used. The result is that the map is not accurate for any given protected area but is mainly a cross-tabulation of the two maps (FRA 2000).

Table 17.1 Categories of protected areas according to IUCN (McNeely and Miller 1984).

Category	Definition
I - Strict nature reserve / wilderness area	Protected area managed mainly for science or wilderness protection
II - National park	Protected area managed mainly for ecosystem protection and recreation
III - Natural monument	Protected area managed mainly for conservation of specific natural features
IV – Habitat / species management area	Protected area managed mainly for conservation through management intervention
V – Protected landscape / seascape	Protected area managed mainly for landscape / seascape conservation and recreation
VI – Managed resource protection area	Protected area managed for the sustainable use of natural ecosystems

The total extent of forests in protected areas was estimated to be 479 million hectares, or 12.4% of the total forest area (Tables 17.2 and 17.3). In Europe the proportion is only 5.0%, which is partly explained by the fact that Siberia has no officially protected areas. There were considerable discrepancies in the comparisons between the answers to the country questionnaires and the global maps, especially since some countries had reported that the whole country was a protected area, since a general law to this effect existed, whereas others reported only strictly protected areas.

Table 17.2 Forests in protected areas, based on the global protected area map (FRA 2000).

Region	Forest area in 2000 (million hectares)	Forest in protected areas	Proportion (%)
Africa	650	76	11.7
Asia	548	50	9.1
Oceania	198	23	11.7
Europe	1039	51	5.0
North and Central America	549	111	20.2
South America	886	168	19.0
Total	3869	479	12.4

Table 17.3 Forests in protected areas by ecological domain, based on the global protected area map (FRA 2000).

Ecological domain	Forest area 2000 (million hectares)	Forest in protected areas	Proportion (%)
Tropical	1997	304	15.2
Subtropical	370	42	11.3
Temperate	507	83	16.3
Boreal	995	49	5.0
Total	3869	479	12.4

17.2 METHODOLOGY

17.2.1 Global forest resources assessment

The formal requests sent to country representatives in 1996 and 1998 in order to compile the latest national-level statistics included specific guidelines aimed at obtaining data that would be well structured and compatible with the terms and definitions of FRA 2000. For those countries that had no suitable inventory data, assessments were compiled from partial inventories and/or subjective estimates (FRA 2000). Also, validation of the results was required from all countries (Holmgren and Persson 2002). This work could not have been done without the collaboration of forestry professionals in each country. The assessment represents 212 countries, of which 160 participated in workshops or worked with FAO staff in their countries (FRA 2000).

The forest assessment information collected is subject to many sources of uncertainty. The information is very variable with respect to terms and definitions, for example, to the extent that over 650 definitions of forest were noted in 110 independent surveys representing 132 developing countries (FRA 2000). A massive effort was made to harmonize the results (FAO 2002), but there is still no means of

assessing the accuracy of such adjustments. Another aspect is that it may be in the interest of the countries to exaggerate or hide some issues. A country may want to give exaggerated deforestation figures, for example, in order to gain international assistance for their forestry sector, while another may exaggerate the area of protected forests, and so on (Holmgren and Persson 2002).

Another source of uncertainty is the fact that in many countries the national inventory is not based on sampling but on management plan inventories (Holmgren and Persson 2002). Only a few countries could derive statistical confidence intervals even for the forest area or area change data (FRA 2000), and in some cases there may not be a long enough time series available for estimating the changes. Of the 137 developing countries, for example, only 22 have repeated inventories, 54 relied on a single inventory, 33 had only data from a partial inventory and 28 had had no inventory at all (Holmgren and Persson 2002, FRA 2000).

17.2.2 Temperate and boreal forest assessment

Assessment in the temperate and boreal regions, i.e. in the 55 industrialized countries, was entrusted to a team of government-nominated specialists formed in Geneva by UN/ECE and FAO and was carried out using questionnaires. The representatives of each country received a number of tables to be filled in according to FAO definitions (FAO 2002). Thus they were obliged to adjust their national definitions. They were also asked to give the likely range for their assessments. The representatives were aided in this by meetings and personal communications.

The main issues affecting the reliability of the data were 1) the differences in definitions (definition error) and 2) non-response. The possible effects of these are analysed in the main report (TBFRA 2000). Differences in the reference period may also have caused some errors, as the oldest data for TBFRA 2000 were from 1986 (Germany) and most recent data from 1998 (Iceland). It should also be noted that the forest area of the four largest countries, Canada, the USA, Russia and Australia, accounts for about 85% of the world's total forest area, so that possible errors in their figures will have had a major effect on the results.

Five out of the 55 countries did not answer the questionnaire at all: two countries from the former Yugoslavia together with Kyrgyzstan, Turkmenistan and Uzbekistan, but they comprise only 2.2% of total land area and 0.6% of forest area involved. Non-response was more severe in the case of certain attributes, however. Every country was able to give its total forest area and the area of other wooded lands, but it was difficult in many countries to give an assessment of annual removals, especially on other wooded lands.

The effects of definition errors were considered with respect to two variables, namely the definition of forest and the definition of the volume of a single tree. The definitions accepted, 10% crown cover and the possibility of achieving a height of 5 m, are the "lowest common denominators" for all the countries. The definitions of crown cover varied from 0% to 30% in 19 western Europe countries, those of minimum area from 0 ha to 0.5 ha, those of minimum production from 0 m^3/ha to 4 m^3/ha and those of minimum width a forest patch from 0 m to 40 m. The definition of forest used in Ireland (20%, 0.5 ha, 4 m^3/ha and 40 m) would give the

lowest forest area and that used in of Luxemburg (0%, 0 ha, 0 m^3/ha and 0 m) the largest (TBFRA 2000).

The volume of a single tree depends on three issues: 1) the minimum dbh threshold, 2) the starting point for stem volume (ground or stump) and 3) the minimum top diameter. The definitions for the first varied from 0 in Finland to 12 in Switzerland, and those for the third from 0 in Finland to 7.5 in Spain. The FRA definition was 0 cm minimum dbh, stump height and 0 cm minimum top height (the same as in Finland and Sweden), and therefore the top volumes, stump volumes and volumes of small trees had to be analysed separately in many countries. Adjustments were made by means of models, special investigations or expert judgments. The forest area was analysed in Finland, for instance, with a model applying parameters from the Finnish NFI, and in Switzerland from a survey using aerial photographs (TBFRA 2000).

17.2.3 Pan-tropical remote sensing survey

Since the greatest deficiencies were in the tropical data, a separate tropical survey based on remote sensing was carried out. The objectives were (FRA 2000):

1) to monitor tropical forest cover and its changes over the past 20 years at the regional and pan-tropical levels
2) to analyse trends in forest cover change in the intervals 1980-1990 and 1990-2000
3) to study the dynamics of changes in forest cover
4) to identify the causal mechanisms behind deforestation, and
5) to complement existing country-specific information by providing spatially and temporally consistent data on the state of the forests and changes in this.

The survey was designed on a two-stage stratified sampling basis, in which the areas were divided into regions and sub-regions and the sub-regions further into a maximum of three strata corresponding to their forest cover and expected deforestation rates (FRA 2000, Czaplewski 2002). Those strata with higher expected deforestation rates were sampled proportionally more intensively (Czaplewski 2002).

The population was defined as consisting of 1203 LANDSAT frames, representing all the frames in which the forest cover was more than 10% and the land area more than a million hectares (FRA 2000). Based on the country data, 87% of the tropical forests belonged to a sampling frame. Of these frames, 117 were selected for the sample, representing 10% of the area. This small percentage has been criticized (e.g. Tucker and Townshend 2000) and may indeed not be large enough for inference on a national scale, but it is large enough on a continental or global scale, which was the intention (Czaplewski 2002).

There were three LANDSAT images used for each unit in the sample, and those were taken that came as near as possible to the reference years 1980, 1990 and 2000. All the images were interpreted visually from hard copies. They were processed in three bands as standard false-colour infrared prints to a scale of 1:250 000 (FRA 2000). The older images had been interpreted previously for an earlier assessment, but where new data such as vegetation maps were available, they were re-interpreted. All the images were interpreted at the same time, not independently.

The classification, carried out using a 2·2 km^2 grid, was into ten classes, of which nine were visible (Table 17.4). Analyses of forest cover were then performed on this classification using three definitions of forest. In the strictest one (f1) only the closed forests were included, in f2 both the closed and open categories were used, together with some of the fragmented forests, a definition that comes closest to the country reports, and in the last definition (f3) the long fallow class was also included, as well as a higher proportion of the fragmented forests. The result of the analysis is a matrix of changes between classes from one image to another (FAO 1999a) that enabled calculating forest change rates according to the different definitions. The aggregated results were calculated by treating each image as a cluster, and by calculating the results with ratio estimators, as the land area in each image is a random variable (FRA 2000).

Table 17.4 Classification used in the pan-tropical image analysis (FRA 2000).

Land cover categories	Land cover classes	Description
Natural forest		
Continuous forest cover	Closed canopy	Canopy cover > 40%
	Open canopy	Canopy cover 10-40%
	Long fallow	Forest affected by shifting cultivation
Fragmented forest	Fragmented forest	Mosaic of forest/non-forest
Non-forest		
Other wooded land	Shrubs	
	Short fallow	Agricultural areas with short fallow periods
Non-woody areas	Other land cover	Includes urban and agricultural areas, areas with less than 10% woody vegetation cover
	Water	
Human-made woody vegetation	Plantations	Forest and agricultural plantations
Non-visible	Non-interpreted	Clouds, burnt woodland, shadow

Since the average dates of the images were 1977, 1989 and 1998, the observed deforestation rates had to be adjusted to obtain estimates of trends between the target years. This was done by two methods (FRA 2000): a constant method, in which it was assumed that the changes in land cover were constant and unchanging during the period and could be calculated using one reference date, and a linear method in which the changes were assumed to occur gradually requiring the use of both the available change rates. Both methods inevitably introduce errors into the analysis, but there is no general methodology to account for this uncertainty.

The results of the survey were fairly well correlated with the country data obtained by means of the questionnaires, although the satellite-based survey gave lower rates of deforestation than the country data, especially in Africa, where the difference was statistically significant. The major cause of deforestation in Africa was the establishment of small-scale agriculture, while in Asia and Latin-America it was the establishment of large-scale agriculture.

17.2.4 Global mapping

One result of the FRA 2000 project was a global map of the forests, as had already been proposed at the Kotka III meeting (Lund and Blue 1997). This map is based on AVHRR data, with a pixel sizeof 1 kilometre (FAO 2001). Such data are suitable, because the resolution is coarse enough and there is enough material, on account of the daily imaging schedule (FAO 2001). The daily data cycle also means that the AVHRR data could be formed into 10-day composites. This was done by the EROS Data Center (EDS). The data initially consisted of five calibrated AVHRR bands, and a NDVI (normalized difference of vegetation index) band. For global mapping purposes, the 10-day composites were used to form a monthly composite and the number of bands was reduced to two (red and infrared), together with the NDVI band:

$$NDVI = \frac{NIR - R}{NIR + R}, \tag{17.2}$$

where NIR is the near-infrared value and R is that of the red channel. The areas on the global map are classified into five classes (Table 17.5). The most problematic parts for mapping are to obtain cloud-free data for all the areas and to piece together a large number of images. In spite of the efforts made, some Pacific islands could not be mapped because of deficiencies in the data. The last three classes could be fairly directly derived from the U.S. Geological Survey (USGS) EDC database (FAO 2001), but the closed and open/fragmented classes could not be directly inferred from the USGS seasonal forest cover type classes.

A new methodology was therefore developed for this latter task, based on spectral mixture analysis (SMA), which means that the pixels are assumed to consist of fractions of surface components. As the resolution of the AVHRR data is coarse, this is obviously the case. Mixture analysis aims at estimating the number of surface components, or end members, within the target pixels. The endmembers can be, for

instance, green vegetation, soil and rocks and shadow (see Smith et al. 1990, Roberts et al. 1993 for details). In mixture analysis, also other data with better resolution, such as LANSAT TM data are required.

As the variation on a global scale is paramount, and a sufficiently large TM dataset would be difficult to obtain, geographical stratification was used. Moreover, the analysis was performed separately for pixels with low, medium and high infrared reflectance. Pixels with low infrared reflectance contain burned areas, new forests and water, for instance. These pixels were classified on the basis of their NDVI values, as NDVI is considered to be insensitive to illumination variation (Holben et al. 1986). The pixels with high infrared reflectance contained forest land, agricultural land and non-vegetated land and were classified using mixture analysis with three end members, while those with mid-range infrared reflectance contained coniferous and mixed forests, fragmented forests, open woodlands, shrubland and grassland and were classified using linear scaling with red band reflectance, as forest cover density is closely correlated with red band reflectance (Yang and Prince 1997). Thus stratification was performed in order to improve the classification (for further details, see FAO 1999b, 2001).

Table 17.5 Classification used in the global mapping (FRA 2000).

FRA 2000 class	FAO definition
Closed forest	Canopy cover of trees more than 40% and height over 5 metres
Open or fragmented forest	Canopy cover of trees between 10% and 40% and height over 5 metres
Other wooded land	Canopy cover of trees between 5% and 10% and height over 5 metres, or shrub or bush cover of over 10% and height less than 5 metres
Other land cover	All other land, including urban and agricultural land, grassland and barren land
Water	Inland water

Validation of the global map with the available material showed its accuracy in this analysis to be about 80% for all the forest classes (FRA 2000). The closed forests could be mapped most accurately and the other wooded lands the least accurately (Table 17.6).

In addition to the global maps of forests, a map of ecological zones was also produced. This was based on the existing national and regional potential vegetation maps, climate data and satellite imagery (FRA 2000). The third type was a map of protected areas, the input for which was collected directly from the countries.

Table 17.6 Validation results for the global map (FAO 2001).

	Global validation dataset						
FAO legend	1	2	3	4	Row total	User's	Standard error
1	65	2	3	8	78	83.33	0.42
2	13	9	3	17	42	21.43	0.64
3	1	2	6	10	19	31.58	1.10
4	3	8	2	160	173	92.49	0.20
Column total	82	21	14	195	312		
Producer's	79.27	42.86	42.86	82.05			
Standard error	0.45	1.10	1.37	0.28			

17.2.5 Forest information database

All the data gathered in the process were placed in the FORIS (Forestry Information System) database, a Web-based system with its main user interface at the FAO Forestry Department web site http://www.fao.org/.

The data are organized by country, subject, species, publication and organizational entity, and the information can be presented in all the FAO's official languages, namely Arabic, Chinese, English, French and Spanish.

REFERENCES

Czaplewski R. 2002. On sampling for estimating global tropical deforestation. FAO Working paper 60.

FAO 1999a. Remote sensing and forest monitoring in FRA 2000 and beyond. Working paper 8.

FAO 1999b. FRA 2000. Global forest cover map. Working paper 19.

FAO 2001. FRA 2000. Global forest cover mapping. Final report. Working paper 50.

FAO 2002. Second expert meeting on harmonizing forest-related definitions for use by various stakeholders. Rome, Italy. Food and Agriculture Organization of the United Nations.

Forest resources of Europe, CIS, North America, Australia, Japan and new Zealand. Main report. UN-ECE/FAO Contribution to the Global Forest Assessment 2000. Geneva Timber and Forest Study Papers, No. 17. (TBFRA 2000)

Global Forest Resources Assessment 2000 Main Report. FAO Forestry Paper 140, FAO, Rome, 2001, 479 p. (FRA 2000)

Holmgren, P. and Persson, R. 2002. Evolution and prospects of global forest assessments. Unasylva No. 210.

Holben, B., Kimes, D. and Fraser, R.S. 1986. Directional reflectance response in red and near–IR bands for three cover types and varying atmospheric conditions. Remote Sensing of Environment 19: 213-236.

Lund, H.G. and Blue, R. 1997. Report on the workshop on remote sensing support for the global resource assessment (FRA 2000 – remote sensing). In: Nyyssönen, A. and Ahti, A. (eds.). Proceedings of FAO Expert Consultation on Global Forest Resources Assessment 2000. Kotka, Finland, 10-14 June 1996. The Finnish Forest Research Institute, Research Papers 620.

McNeely J.A. and Miller 1984. National parks, conservation and development: the role of protected areas in sustaining society. Proceedings of the World Congress on National Parks held on 11-12 October 1982 in Bali, Indonesia. Smithsonian Institution Press, Washington, DC.

Persson, R. 1974. World Forest Resources – review of the world's forests in the early 1970s. Research Note 17. Royal College of Forestry, Stockholm, Sweden.

Proceedings of FAO Expert Consultation on Global Forest Resources Assessment 2000 in Cooperation with ECE and UNEP with the Support of the Government of Finland (Kotka III). Kotka, Finland, 10-14 June 1996. Nyyssönen, A. and Ahti, A. (Eds.) The Finnish Forest Research Institute, Research Papers 620. (FFRI 1996)

Proceedings of FAO Expert Consultation on Global Forest Resources Assessments – Linking National and International Efforts (Kotka IV). Kotka, Finland, 1-5 July 2002. Luhtala, A. and Varjo, J. (Eds.) The Finnish Forest Research Institute, Research Papers 889. (FFRI 2003)

Roberts, D.A., Smith, M.O. and Adams, J.B. 1993. Green vegetation, nonphotosynthetic vegetation and soils in AVIRIS data. Remote Sensing of Environment 44:255-269.

Smith, M.O., Ustin, S.L., Adams, J.B. and Gillespie, A.R. 1990. Vegetation in deserts: I. A regional measure of abundance from multispectral images. Remote Sensing of Environment 31:1-26.

Tucker, C.J. and Townshend, J.R.G. 2000. Strategies for monitoring tropical deforestation using satellite data. Int. J. Remote Sensing 21. 1461-1472.

Yang, J. and Prince, S.D. 1997. A theoretical assessment of the relation between woody canopy cover and red reflectance. Remote Sensing of Environment 59:428-439.

Zon, R. 1910. The forest resources of the world. United States Department of Agriculture. Forest Service Bulletin No. 83. Washington DC, USA, Government printing Office. 91 p.

Zon, R. and Sparhawk, W.N. 1923. Forest Resources of the World. New York, NY: McGraw-Hill Book Co.

PART III
CASES

CHAPTER 18

EUROPE

TIMO TOKOLA

University of Helsinki, Finland

18.1 SWEDEN

18.1.1 Swedish National Forest Inventory

The main purpose of the NFI, which has been taking place since 1923, is to describe the state of forest resources in Sweden, e.g. growth and cuttings, and to trace changes in these. The NFI is a part of the Official Statistics of Sweden (Swedish National Inventory of Forests 2004), however, and thus has numerous fields of application, being, among other things, a powerful resource for environmental monitoring. As a basis for the statistical design of the survey, a geostatistical analysis has been used to determine the variation within areas, the importance of the size of the sample plot, the time required and the economic practicability of the available resources. The analysis has resulted in a division of the country into 5 regions, the designing of survey tracts, a weighting between permanent and temporary survey tracts and a standard size of sample plot (Matern 1960, Matern, 1981, Ranneby, 1981a, Ranneby, 1981b, Hägglund 1985, von Segebaden 1992). Variograms have been used to describe variations in land use, forest volume and topography (Matern 1960, Ranneby, 1981b), and these spatial functions have been used to define an effective layout for the survey tracts.

The Swedish NFI is based on the systematic sampling of tracts, so that the current design, including both permanent tracts (established in 1983) and temporary ones, covers the whole country every year. The tracts consist of circular plots (Fig 18.2) within which samples of the trees, ground vegetation, etc, are selected and used for estimating the total volume of all trees, the total area of land covered by a certain vegetation type, and so on.

A. Kangas and M. Maltamo (eds.), Forest Inventory – Methodology and Applications, 295–308.

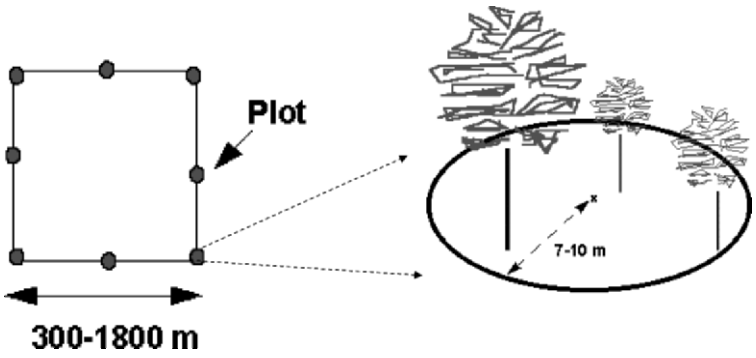


Figure 18.1. The cluster and plot layout used in the Swedish National Forest Inventory (SNFI Web page).

The tracts are square or rectangular in shape and vary in size between different parts of Sweden. They are systematically distributed over the whole country, but lie closer together in the south than in the north (Fig. 18.3). Temporary tracts are surveyed only once, whereas permanent tracts are re-surveyed regularly (Swedish National Inventory of Forests 2004).

Plot size (m)	Trees calipered (cm)
1	<4
3.5	4-9.9
7-10	>10
20	Large trees

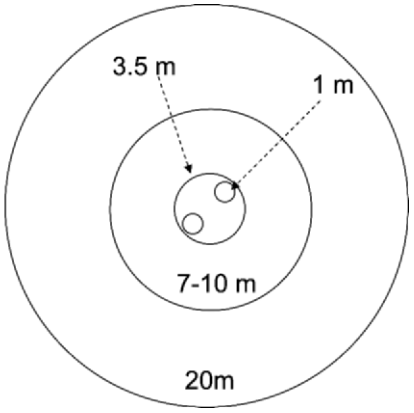


Figure 18.2. Plot layout used in the Swedish National Forest Inventory.

Particular sets of attributes are assessed in different parts of a plot (Figure 18.2):

• Tree and shrub layer. All trees higher than breast height (1.3 m above ground) are calipered (diameter measured), the ages of the sample trees are counted from

annual rings in a core obtained from the stem at breast height, and the cores are sent to a laboratory for further measurements.

• Ground vegetation. The type of ground vegetation is roughly assessed according to 16 field layer and 6 ground layer categories which form the basis of the site index classification. A total of 267 species and groups of species are assessed and coverage is recorded for 71 of these on small subplots.

• Site conditions. Soil moisture and surface water flow on the plot are assessed, and also its inclination and typographic position. A site index is determined to estimate its site quality class. In addition, the effects of forestry and other human activities are assessed.

• Position in the landscape. The position of the plot is determined, with regard partly to administrative boundaries and partly to its location in relation to landscape elements such as roads, fields and lakes. North and east coordinates are also recorded, together with altitude. Since 1996 the positions of all plots have been defined using GPS.

One to three subsamples from each of the circular sampling areas are collected from the O-horizon with a soil corer. Equal numbers of subsamples are collected from each soil horizon, after which all the subsamples for a particular horizon are pooled. The vegetation layers are thoroughly surveyed, giving extensive information on the vegetation in each area. After collection, the soil samples are stored at room temperature in cotton bags for a maximum of one week before transportation to the laboratory, where they are dried to constant weight in a chamber.

The Swedish NFI presents its results in a variety of ways, ranging from the supplying of individual figures over the telephone to extensive analyses that includes year-round work. Some standard tables including mean values for the last 5 years are presented in an annual publication called *Skogsdata*. The results from 1983 up to the present are the easiest to handle and the fastest to present, but many results from as far back as 1923 can be shown and compared. As the Swedish NFI is carried out on the basis of systematic sampling, the precision of its figures can be estimated (see Chuan-Zong and Ranneby 1992) using specific approximations. The density of the tracts/plots can be adjusted by using information for a 5-year period in order to give high precision for estimates at a county level, whereas more extensive estimations for smaller units such as municipalities or catchment areas require modified methods of field sampling (a denser sampling network) and/or remote sensing techniques (Swedish National Inventory of Forests 2004). Annual results are presented on the Internet (http://www-nfi.slu.se/).

The Forest Soil Inventory is a detailed inventory of the soils on the permanent plots based on sampling of the humus layer and mineral soil to a depth to one metre and assessment of a number of attributes, including soil type, mineral texture, type of humus, degree of humification and thickness of the humus layer. Samples are also taken from the various soil horizons for later analysis of pH, nitrogen and carbon levels, degree of base saturation, heavy metal content, etc.

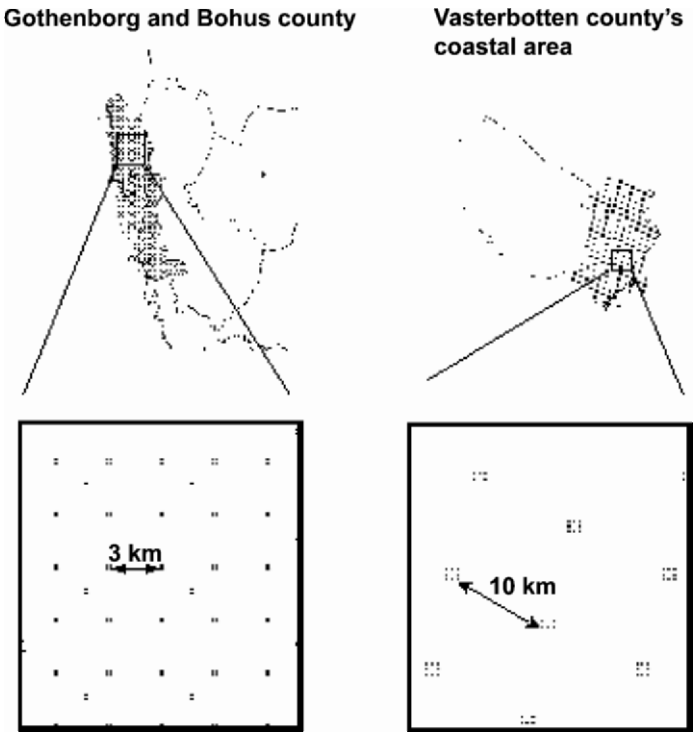


Figure 18.3 The distance between clusters varies in different parts of Sweden.

18.1.2 Inventory for forest management planning

One especially striking feature of Sweden as compared with other timber-producing countries around the world is that private companies are the largest single category of forest owners, accounting for 44% of the country's forests, while approximately 32% are family-owned. The average size of a private forest holding is about 50 hectares. These holdings are the dominant category in the southern part of the country, accounting for 80% of the forest land. The state owns 17% of the productive forest land and other public owners account for 7%.

Sampling procedures have been used in forest inventories and intensively implemented for stand surveys for a long time in Scandinavia by comparison with other European countries. Ocular assessment of stands is employed in Sweden, but as this method is liable to subjective bias, the resulting estimates are supplemented with inventories based on PPS sampling or systematically distributed circular plots and calibrated accordingly. Wood procurement mapping is applied only on a limited

scale, the most important reason being the large forest properties owned by the paper companies and the lower level of market competition (relative to Finland).

18.2 GERMANY

Around 30% of Germany is covered with forests, of which a good third consist of deciduous trees. Over half of the approx. 11.1 million ha of forests in Germany are owned by the federal states or municipalities and 44% are privately owned (Bundeswaldinventur 2002). Forestry in general is organized at the level of the federal states, and most forest management projects are implemented by the states' forest administrations. Although the federal states are the large forest owners, the federation as such owns only about 4% of the total forest area. All the forest areas in the country are considered "close to natural" and are managed, i.e. there is not a single untouched or virgin forest left, as a result of a long period of historical development. Forest damage, mainly from air pollution and storms, is an important issue (Akça 1994).

The maintaining of the various ecological and socio-economic forest functions requires differentiated forest inventory methods to support the management, sustainment and conservation goals. Forest inventories can be categorized according to the size of the inventory area and the significance of the inventory for forest enterprise policy and economic management of the forests (Table 18.1).

Table 18.1 An overview of inventory methods employed at various management levels.

Inventory Level	Inventory Method	Goals and target variables
National	National Forest Inventory	Forest Area and Volume Increment Survey
	National Forest Damage Inventory	Inventory of Forest Damage
	National Soil Condition Survey	Evaluation of Soil Condition
Regional	Forest Framework Planning	Inventory of forest attributes relevant to regional land use planning
	Forest Functions Mapping	Recording of forest functions
	Forest Biotope Mapping	Biotopes within forests
Forest Enterprise	Site Type Mapping	Recording of natural site conditions
	Forest Management	Providing an internal aid to information, control and planning

One essential source of recorded data for forest inventories is fieldwork. Forest maps are mostly derived from the German basic map (scale 1:5 000) or topographical maps (scale 1:25 000). The use of remote sensing methods is limited

to aerial photographs or orthophoto consulted for update purposes, the mapping of forestry data, the definition of forest stands in the context of forest management planning and as an orientation aid in inventories at the level of forest enterprises and regional planning. Satellite images are rarely used as yet in forestry practice. Cartographic presentation of the recorded results and/or the defined management measures is normal practice in every forest inventory procedure (Akça 1994).

At the federal level, the results of the National Forest Inventory, National Forest Damage Inventory and the National Soil Condition Survey particularly serve forest policy purposes. The results of the regional management procedure are for the most part presented in the form of maps, while rge results of forest framework planning are presented on two forms of map: a map of forest functions, which shows the forest functions aspired to (currently planned and legally binding forest functions), and a measures map, which defines the foreseen changes and the measures required to attain the goals. Various thematic maps are made for the individual forest enterprises within the framework of forest management and site type mapping. These illustrate the current conditions, planned improvement measures or the desired future situation and are drawn up for given forest units or areas under common cultivation, and therefore specifically take ownership into account (Akça 1994).

18.2.1 National Forest Inventory: Natural forests

Inventories are made over the entire territory of Germany in order to record the size and distribution of the forested areas and timber reserves (National Forest Inventory), the degree of forest damage (National Forest Damage Inventory) and the prevailing soil conditions (National Soil Condition Survey). The first national forest inventory took place in 1986 -1990, and the main fieldwork for the second was carried out in 2001-2002 and the results published in 2004 (Polley 2001, Bundeswaldinventur 2002).

The collection of data for the second national forest inventory was based on permanent field sample plots chosen from among approximately 44 000 square cluster plots of size 150 x 150 m with a systematic layout on either a 4 km × 4 km or 2 km × 2 km grid, depending on the state concerned (Figure 18.4). About 400 000 sample trees were measured in the second inventory and about 150 variables were recorded for the sample plots (Survey instructions for Federal Forest Inventory II, 2000).

Each corner of a cluster plot located in a forest forms the centre of an angle-count sampling sub-plot with a basal area factor of 4. This sub-plot type is used to define the sample trees, which are described in more detail to form the basis for a wide variety of evaluations. The following trees are included:

- those falling into the angle-count sample (basal area factor 4) that are
- either alive or have died recently (fine branchwood maintained in full) and
- belong to the same stand as that in which the centre point of the sample lies and
- have a diameter at breast height of at least 7 cm.

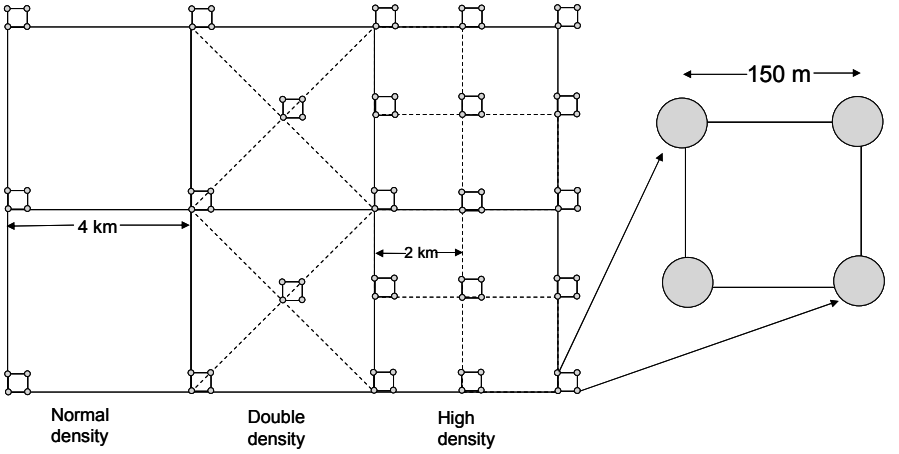


Figure 18.4 Cluster layout for the second NFI in Germany. Each cluster contains 4 plots.

In addition, angle-count sampling with basal area factor of 1 or 2 is carried out, in which the trees are counted as a basis for describing the forest structure by species and storey., Stand boundaries are not taken into consideration, but the angle-count sampling is subjected to regular reflexion at the forest edges.

In addition, use is made of specific sample sub-plots or circles within the cluster plots (Figure 18.5):

1. Each plot corner located in forest is taken as the centre of a sample circle with a radius of 1.75 m in which all trees over 50 cm high and under 7 cm in diameter at breast height are surveyed.

2. A circle of radius 1.00 m is located 5 m away from the corner of the plot, generally to the north, for the recording of all trees of height 20 cm to 50 cm.

3. The occurrence of deadwood is determined in a circle of radius 5 m around the plot corner.

4. Trees up to 4 m in height, the shrub layer and the ground vegetation are surveyed in a circle of radius 10 m around each plot corner.

5. Site characteristics and forest edges are recorded in a circle of radius 25 m around each plot corner located in forest.

If a sample circle of radius 1.75 m or 5 m is crossed by a stand boundary, the course of this boundary is surveyed and only the part cut off by it in which the cluster plot corner is located is considered for inventory purposes.

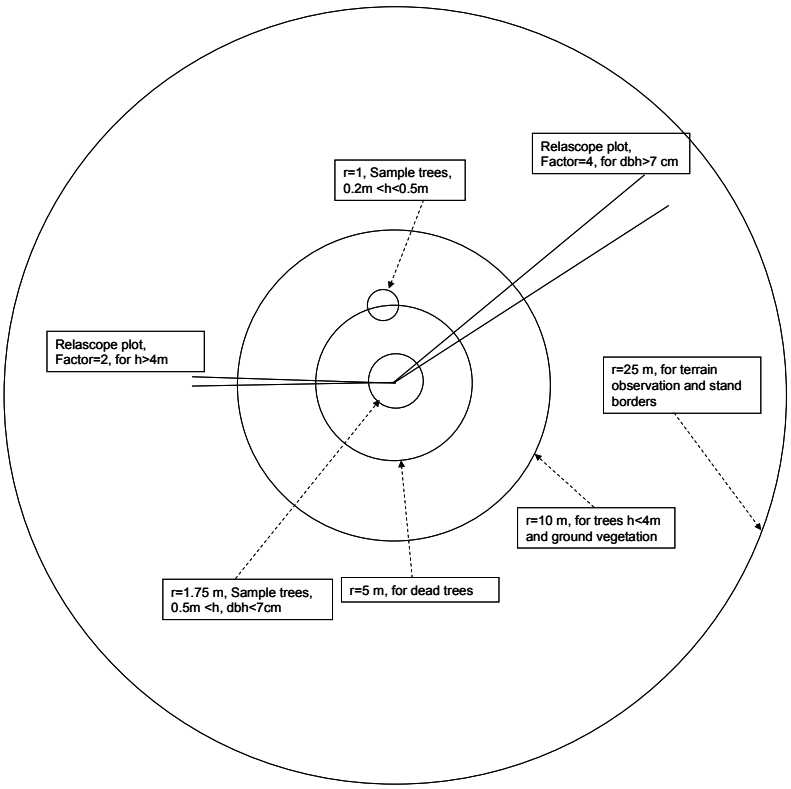


Figure 18.5 Plot layout for the NFI in Germany.

Forest edges are surveyed within a radius of 25 m of all plot corners located in forest. In addition, stand boundaries which are not forest edges must be included in the survey,

1. if they intersect the boundary circle of a sample tree defined by angle-count sampling with basal area factor of 4. These are all stand boundaries within a radius of 25 times the breast-height diameter around the trees defined in angle-count sampling. Stand boundaries which are further than 25 m from the plot corner are not surveyed, however.
2. if they divide a sample circle of radius 1.75 m or 5 m, provided that some sample elements (trees of height at least 50 cm and diameter at breast height up to 6.9 cm, or deadwood) are available in the circle (Polley 2001).

The stand boundaries surveyed during the Federal Forest Inventory need to be checked. The surveying of these and of forest edges is simplest if the horizontal

distance and azimuth are determined for two points on the boundary line. If the stand boundary does not run in a straight line, a further point must be surveyed at the knickpoint. The survey points on the stand boundary should be at least 10 m apart (Polley 2001).

18.2.2 Regional inventories

Regional administration and planning is organized by the Bundersländer (i.e. forest administration is located in the national Ministry of Finance). Various forms of map material produced by contractors are used for environmental decision-making.

Forest framework planning, forest functions mapping and forest biotope mapping are employed as forest policy management aids at the regional level. **Forest framework planning** sets the goals for proper forest sustainment, forest development and forest management and defines the measures to be taken, **forest functions mapping** describes the various functions of the individual forest areas, including a forest's special recreation value or particular importance for climatic conditions, and **forest biotope mapping** records and localates biotopes within the forests. All three management aids and their respective inventory methods serve the essential purpose of sustaining and improving the various functions of the forests beyond the enterprise level and regardless of ownership for the benefit of the population and the balance of nature. Their results should be taken into account by all internal and external decision-makers dealing with forest questions (Akça 1994).

18.2.3 Forest management planning: compartment level inventory

Forest management plans are produced for landowners, and there are a large number of consultants bidding for contracts to prepare such plans for the largest landowners. The most important objective in a forest inventory is to obtain information for the internal operational management of forest enterprises. Two supplementary inventories are employed at this level (Akça 1994).

Site type mapping describes existing site conditions and potential natural forest stands within the properties of the forest enterprises and forms the basis of silvicultural planning in a forest enterprise. Apart from defining natural forest stands, it offers proposals and possibilities for assisting in the choice of tree species and forest stands. The results of this inventory and mapping method are of long-term importance due to the relative continuity of site conditions (Akça 1994).

Forest management inventories contribute to obtaining information for the management of individual forest enterprises. Forest management may be viewed as a combination of the instrumental aids of inventory, control and planning. In this manner, by recording and analysing internal and external natural economic and organizational site conditions, proposals can be made for the silvicultural management of forest enterprises which conform to the goals laid down for this (Akça 1994).

It is of particular importance that regional and internal inventory methods

should complement one another. Internal management planning should be in accord with the goals set at a regional level. National inventories provide fundamental information for formulating regional and internal guidelines based on the political and legislative decisions derived from them (Akça 1994).

The recording of conditions within forest management basically comprises three sectors:

1. Surveying of forested areas and forest development
2. Surveying of forest stands (timber reserves, timber increment, management conditions)
3. Surveying of the landscape (cultivational, environmental and ecological) importance of forested areas (conservational and recreational functions).

The purpose of surveying forest stands is to record the locations and sizes of the areas owned by given forest enterprises. Forest stand (compartment or sub-compartment) definition mapping is above all an aid to planning and control, providing a real distribution system. Moreover, a forest stand map should serve as an aid to orientation, forest surveying, the transport, logging and processing of timber, to creation of order in an area and forest protection. Within the forest enterprise itself, the areas are subdivided once again, according to their use being seen either as wood production areas (forested areas) or non-wood production areas (e.g. forest roads or timber depots). The forest stands (compartments and sub-compartments) form the base for recording timber volumes and improvement conditions, thereby permitting investigations into current production potential and future development possibilities. The third sector of an internal "natural inventory" is the recording of forested areas of landscape importance (cultivational, environmental and ecological). Counted among these are the conservational and recreational functions of the forests, which are of relevance to the silvicultural and economic management of the areas.

The data are either digitized on location by means of mobile data input systems or else digitized centrally. In this wayu the forest management data can be stored and evaluated centrally for each state. Analogue mapping is performed at the Forest Management and Planning Institutes and is very seldom carried out digitally. The integration of digitally stored and administrative data with their respective spatial relations in the form of geographical information systems is in the development phase in various federal states (Akça 1994).

18.3 OTHER EUROPEAN AREAS

Planning procedures are continuously being adapted to current needs and conditions, so that there are many different procedures in use within Europe today. The fact that federal systems usually leave forest planning to the authorities of each state or canton and the existence of different regulations for public and private forests have led to a situation in which there are no uniform regulations for forest planning within Central Europe and consequently no uniform sampling procedures. Data on stands and enterprises are mainly collated through a combination of total tallies, ocular assessments for taxation purposes and sample surveys. In some East European countries the situation is different, as recent reforms of the property laws and planned economy have provided a basis for uniform regulations. Remarks on current

domain and stand inventory practices in certain selected countries are provided below (Köhl 1992).

In **Norway**, the sixth NFI began in 1986 and results were presented for the year 1990. The results of seventh inventory were available for year 1996. The sampling design applied in NFI is systematic sampling and single-stage cluster sampling. Field data collection for the sixth inventory employed clusters of plots forlaid out in a grid pattern over the whole country with 3 km spacing. The basic shape of each cluster was a half square (L-shape), and the plots were located 300 m apart within each cluster. The southernmost plot was established as a permanent plot, while the others were temporary ones. Although the 3 km grid was fixed, the number of plots and the distance between them within a cluster sometimes differed between counties. If the percentage of forest land or the total area of the county was small, the number of plots was increased. This led to clusters of up to 12 sample plots (Tomter, 1992). Permanent sample plots are circular, fixed area plots of 250 m^2. Temporary sample plots are concentric fixed area plots of 100 m^2 and 250 m^2 for trees larger than 5 cm and 20 cm, respectively. (EC 1997)

Forest management plans in Norway are prepared by private institutions, principally forest-owner organisations, as a service for their own members and other interested parties. The planning process is as follows:

1. Aerial photographs are taken of the area for which a plan is to be prepared.
2. The aerial photographs are compared with a map of the area and the forest stands are identified and classified.
3. Records are prepared with the aid of the map while out in the forest. All the stands are systematically examined, and various measurable factors are recorded, such as average tree height and diameter, number of trees, yield class and age, and data associated with multiple land-use considerations (edge zones beside water, marshland, rivers and roads, and also large deciduous trees and hollow trees, the amount of dead wood, vegetation types etc.).
4. The data are processed and the findings are presented in the completed forest management plan.

In **Austria**, sampling design applied in the Austrian Forest Inventory (AFI) is a systematic cluster sampling. The field work of first inventory was carried out 1961-70. Since 1981 four permanent sample plots, located in the corner of the square, have formed the tract with a side-length of 200m. Distance between tracts is 3.89 km. Data are collected from circular concentric plots with areas of fixed area 300 m for stand data, bitterlich plots for trees with diameter larger than 10.5 cm and fixed circular plots of 21 m^2 for trees between 5-10.5 cm. (EC 1997) Forest holdings are either surveyed by means of ocular assessment of individual stands or sampling procedures. Standing timber reserves are estimated on the basis of yield tables for stands between 20 and 60 years of age and by point sampling for those between 60 and 80 years. Stands over 80 years old are assessed on fixed-area plots or by means of total tallies. The sampling units are systematically distributed, one or two plots per hectare, or sometimes one per two hectares, being surveyed, depending on the stand conditions. Stand features, site characteristics and data for individual trees are recorded, and this information can then be extrapolated to larger units such as whole forest holdings, stand units or large stands. The current practice thus employs a

mixture of ocular assessments and sample surveys (Köhl 1992).

In **France,** the first cycle of National Forest Survey (IFN) started in 1960 and lasted nearly 20 years. The second inventory ended 1994. The IFN service is part of Department of Agriculture and field data is mainly collected by local departments. The sampling is a 3 step double sampling for stratification:

1) Aerial photographs are interpretated to stratify categories defined by land cover type, localisation and ownership. Systematic photo-plots (25 m radius circle) are distributed on photographs and plots are assigned to strata.
2) Photo interpretation is checked in the field and modifications to interpretation is carried out.
3) Field plots are chosen randomly among plots in the various strata. Field plots are temporary plots and consist of three concentric circle plots. Trees are measured on plot with different radius (6m, 9m and 15 m). Regeneration is assessed on nine plots of 2.26 m radius.

The sampling fraction may vary from one department to another. Data are stored in a national forest survey database. (EC 1997).

The national forest inventory in the **United Kingdom** employs the yield and production sections of the Forest Management Tables for all stands except final felling crops. A diversity of methods are used for collating data on privately-owned forests, volume being estimated on the basis of yield tables, while standing volume is extrapolated from visual assessment, the measurement of felled trees or, in exceptional cases, point sampling. (Köhl 1992).

National forest inventories are undertaken by the Forestry Commission. The first assessment was done 1924 and has been repeated on average every 15 years. The sampling frame covers all of Great Britain. Randomly selected square 1 km temporary field plots are assessed using aerial photography then two 250 m by 250 m are sampled at random from within the 1 km square. The yield models are empirical and based upon periodic measurements from 1500 permanent and 1000 temporary sample plots. (EC 1997).

Switzerland has been described as the land of control and selection forestry. Continuous forest inventory techniques have been combined with control to furnish an inventory system that has been implemented in many Swiss cantons. Control sampling is based on permanent plots, while standing reserves are calculated from tariffs. Increment is determined through the comparison of data on standing reserves in successive inventories. Control sampling can justifiably be regarded as a procedure combining the classic methods of forest planning with the possibilities offered by sample surveys. Because of its practicalities and its many interesting possibilities for solving particular problems, the procedure has been widely adopted even outside Switzerland. A review of current methods shows that stand surveys for forest management planning are usually based not on sampling but on ocular assessments. Sample surveys are as a rule reserved for district-level inventories. One of the main arguments against the use of sample procedures for stand inventories is that most forest stands in Europe are relatively small and the sampling intensity must be very high to produce acceptably precise results.

Since the observation of what came to be known as “a new type of forest damage” (forest decline) in the forests of Central Europe in the early 1980’s, forest

health monitoring has been introduced at the national and local levels. The variables of interest in such inventories are ocular assessments of crown transparency and discoloration (Köhl 1992).

The goal of the National Forest Inventory (NFI) is to record the current state and recent development of the Swiss forests in a representative and reproducible manner using various data sources. To this end, the second inventory (1993–1995) employed a combination of methods. A double sampling design made use of aerial photos on a 0.5×0.5 km grid in the first phase to estimate strata sizes, to identify forest plots and stocks outside the forest and to provide reference points for the field survey and field sample plots on a 1.4×1.4 km grid in the second phase to record a number of variables connected with individual trees and stands, young growth and damage by game, together with features of the surrounding areas. The plot layout was a concentric circle of 200 and 500 m^2 with thresholds at diameters of 12 and 36 cm. Diameter at 7 metres and height were recorded for a sub-sample of the first-stage trees, following a scheme with inclusion probabilities proportional to the expected error of the volume estimates. The work and costs involved in the different steps of the terrestrial survey were recorded and evaluated, and ongoing training of the survey teams and control surveys were employed to ensure high-quality data. Further information was obtained by interviewing representatives of the local forest services, from external data sources, from models describing the site conditions and from specially designed studies of forest transportation systems and the effects of game browsing on tree growth. The data were stored in a relational database and evaluated using statistical software developed specifically for this purpose. Static models were used to evaluate the following complex forest characteristics: the volume of standing and cut timber, tree growth, the work and cost involved in timber felling and extraction, the sustainability of forest regeneration, the protection provided by forests against avalanches and rockfalls, the recreational value of the forests, and the biotope values of the stands and forest edges. Furthermore, a dynamic model was developed which yielded prognoses for the future development of each individual tree in particular management scenarios (Köhl 1992).

REFERENCES

Akça, A. 1994. Forest Inventory Systems in the Federal Republic of Germany. In: Kennedy, P.J. , Päivinen, R. and Roihuvuori, L. 1994. Proceedings of International Workshop of "Designing a system of Nomenclature for European Forest Mapping", European Forest Institute, Joensuu, Finland, 13th-15th June 1994. Report EUR 16113 EN. p. 207-214.

Bundeswaldinventur 2002. http://www.bundeswaldinventur.de/

Chuan-Zong L, Ranneby B, 1992. The precision of the Estimated Forest Data from the National Forest Survey 1983–1987, 54, Department of Forest Survey, Swedish University of Agricultural Sciences.

EC 1997. Study on European Forestry Information and Communication system. Volumes 1 and 2. Office for Official Publications for the European Communities. 1328 p. Luxembourg, Belgium.

FIA 2004. Forest Inventory and Analysis, Phase 2 and Phase 3: Ground, Measurements FIA Fact Sheet Series. 2 pp.

Hägglund B, 1985. En ny svensk riksskogstaxering. – Inst. f. Skogstaxering, SLU, Umeå. Rapport Nr 37.

Köhl, M. 1992. Stand inventory techniques in Europe. In: Proceedings of the Stand Inventory Technologies: An International Multiple Resource Conference, World Forestry Center, Sept. 13-17, 1992. American Society for Photogrammetry and Remote Sensing.

Matern, B. (1960) Spatial variation. Medd. Statens Skogsf. Inst. 49(5). Also appeared as number 36 of Lecture Notes in Statistics. Springer-Verlag, New York, 1986.

Matern, B. 1981, Funderingar om provträd I riksskogstaxeringen. Inst. f. Skogstaxering, SLU, Umeå. NUTAX-Rapport Nr 8.

Polley, H, ed. 2001. Survey instructions for Federal Forest Inventory II, (2001-2002) 2nd corrected and revised reprint, May 2001. Bundesministerium für Verbraucherschutz, Ernährung und Landwirtschaft (BMVEL), Bonn, Germany. 109 pp.

Ranneby, B. 1981a. Provytestorlekens betydelse vid skogsinventeringar. Inst. f. Skogstaxering, SLU, Umeå. NUTAX-Rapport Nr 4.

Ranneby, 1981b, Den topograpfiska variationen inom olika områden. En redovisning av skattade korrelationfunktioner. Inst. f. Skogstaxering, SLU, Umeå. NUTAX-Rapport Nr 5.

The Swedish National Inventory of FORESTS, 2004. 4 pp. Brochure, See, http://www-nfi.slu.se/

Tomter, S.M. 1992. The National Forest Inventory of Norway. Proceedings of Ilvessalo Symposium on National Forest Inventories, Finland 17-21. August 1992. The Finnish Forest Research Institute. Research Papers 444. 279 p.

von Segebaden 1992. The Swedish National Forest Inventory – a Review of Aims and Methods. Proceedings of Ilvessalo Symposium on National Forest Inventories, Finland 17-21. August 1992. The Finnish Forest Research Institute. Research Papers 444. 279 p.

CHAPTER 19

ASIA

TIMO TOKOLA

University of Helsinki, Finland

19.1 INDIA

Established in 1965 as the Pre-Investment Survey of Forest Resources and reorganized 1981, the Forest Survey of India (FSI) is entrusted with the responsibility of surveying forest resources over the entire country. It has its central organization in Dehradun and zonal offices in Bangalore (southern), Kolkata (eastern), Nagpur (central) and Shimla (northern).

The primary mandate of the FSI is:

- to prepare a State of Forest Report biennially, providing an up-to-date assessment of the forest cover and monitoring changes in this,
- to undertake a Forest Inventory, an Assessment of Trees Outside Forest and an Assessment of Wood Consumption,
- to prepare thematic maps to a scale of 1:50 000 using aerial photographs,
- to function as a nodal agency for the collection, compilation, storage and dissemination of spatial data on forest resources,
- to conduct training of forestry personnel in the application of technologies related to resource surveying, remote sensing, GIS, etc.
- to strengthen its own research and development infrastructure and to conduct research into applied forest survey techniques,
- to support State/UT Forest departments for forest resources surveying, mapping and inventory purposes, and
- to undertake special studies/consultancies related to forestry and to create customised training courses for SFD's and other organisations on a project basis.

A. Kangas and M. Maltamo (eds.), Forest Inventory – Methodology and Applications, 309–324.

Its current activities include:

- a Forest Cover Assessment
- a Forest Field Inventory
- Forest Inventory Data Processing and Analysis
- an assessment of Trees Outside Forests (TOF)
- an assessment of the Consumption and Utilisation of Wood and NWFP in the Household Sector
- Training and Extension

These current activities also include special studies and consultancy work, such as support for the State Forest Departments in connection with their forest inventories and GIS capacity building. The current field inventory data also allow the assessment of non-wood forest products (NWFPs), the carbon stock contained in the forest biomass and forest soil and biodiversity indices.

IRS 1C / 1D LISS images are used for forest cover mapping. The whole of India can be covered with 342 LISS images, with a rate of overlap between adjacent scenes of about 20%. The FSI acquires the system-corrected images from National Remote Sensing Agency (NRSA). The most suitable image acquisition date in India is after the rainy season, i.e. from October to January, which is also the best time for the observation of deciduous forests. Tests have also been made with the use of IRS PAN imagery together with LISS data, in order to improve the present forest cover mapping and the estimation of the numbers of trees outside the forest area.

19.1.1 Forest cover mapping

Biannual forest cover mapping has been one of the major activities of the FSI central office. Earlier, Landsat MSS and TM data were used as the primary sources, but Indian Remote Sensing satellite images have been adopted since the fifth mapping exercise. The methodology has been developed from the level of visual interpretation to complete digital processing lasting the course of the latest inventories (1999-2001). All the new maps in the 2001 forest cover mapping were produced by digital methods.

For digital interpretation, satellite data is procured in digital form from the National Remote Sensing Agency in Hyderabad and basic radiometric and stretch corrections are applied to remove radiometric defects and improve the visual impact of the False Colour Composite. Geometric rectification of the data is carried out by reference to scanned topographic maps. No digital elevation model is available.

The forest cover is described in terms of the following classes:

1. Dense forest (forest cover/canopy density > 40%)
2. Open forest (forest/canopy density 10-40%)
3. Mangrove (special areas)
4. Scrub (poor growth and forest cover/canopy density < 10%)
5. Non-forest

The data classification procedure is the following:

1. The forest areas in the scene are classified digitally. Topographic maps,

vegetation maps from the previous mapping cycle and field control for unclear locations are used in this classification.
2. The forest cover is classified in terms of density using NDVI transformation. The threshold values for the density classes are determined for the NDVI image and these areas are used directly as forest cover estimates. Shadow areas in the scenes are treated separately.
3. Mangroves are interpreted separately due to their special reflectance, texture and location characteristics.
4. The classified scenes are mosaicked and reports by state and district are extracted using boundary layers.

Topographic maps to scales of 1:1 million and 1:250 000 were used earlier as primary reference data, but nowadays 1:50 000 topographic maps are used for digital image processing. The entire country is covered by 363 map sheets on a scale of 1:250 000 or 5200 sheets on a scale of 1:50 000.

19.1.2 Forest inventory

National Forest Inventory has been one of the major activities of the FSI and the Pre-Investment Survey of Forest Resources. The old inventory system was based on two-stage random sampling with post-stratification. Prior to 1982, stratification was based on aerial photographs, which were used to derive thematic maps, but from that year onwards each topographic map (1:50 000) has been divided into a grid of 36 elements covering 2 ½' × 2 ½' of latitude and longitude, with two sample points marked in each grid square at random. The inventory data are collected from a square plot of 0.1 ha laid out on the ground at each of these sample points. The FSI covered an area of about 680 000 km^2 and produced 130 inventory reports between 1965-1995.

Between 1996 and 2001 the inventory activities of FSI were concentrated on the assessment of "trees outside the forest", and traditional forest inventory work was suspended. Since 80% of the country's forest area had been inventoried by 1995-1996, it was felt at that juncture that it was important to assess trees outside the forest, as these had traditionally not been inventoried at all and little quantitative information existed on them. TOF also provide support for the rural economy and for food security.

The policy changed in 2001-2002, and work began on establishing a new methodology for integrated forest resource assessment. The FSI proposed that it should supplement the usual field inventory with measurements of several other parameters in order to obtain a comprehensive assessment of forest resources inside and outside forest areas at the national level. Additional data will now be collected during the field inventory stage to assess regeneration status, biodiversity indices and soil carbon in forest areas. Along with the assessment of trees outside forests in rural and urban areas, assessments of the utilisation of wood and non-

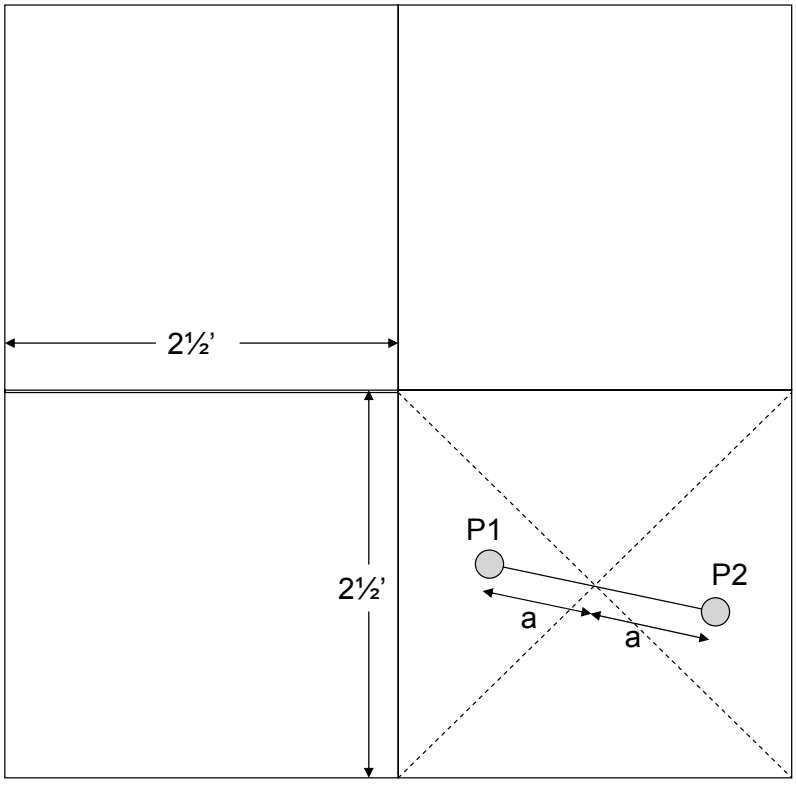


Figure 19.1 The sampling design for forest inventories (1965-1995) was systematic, with a grid size of 2.5' × 2.5' of latitude and longitude. Each grid cell contained 2 sample plots, each of 0.1 ha in size (31.62 × 31.62 m). The location of the first plot inside the grid cell is selected at random and the second is linked to it, being located at the same distance from the cell centre in the opposite direction.

wood forest products will be carried out through a household survey. Field data will be collected from sample plots based on stratification of the country into physiographic zones, each covering several states, and the drawing of a sample of 5% districts every year for a detailed inventory. Measurement of the field sample plots in selected districts will be entrusted to the zone offices in Bangalore, Kolkata, Nagpur and Shimla). The plots will be allocated by reference to the topographic map sheets (1:50 000), each map being divided into a grid of 144 elements representing 1 ¼' × 1 ¼' of latitude and longitude, and two cells of 2 ½' × 2 ½' selected at random from these, after which every second cell was systematically selected to form a sample sub-grid. One sample point will be marked at the centre of each of these cells. Thus two sample points are allocated to the centres of the cells of a small grid within one cell of the large grid. The plots include main plots of size 0.1 ha, four small "soil, forest floor and carbon" plots in the corners and four plant biodiversity

plots (3m × 3m and 1m × 1m) located about 50 m away on the diagonals of the main plot. This new design has been tested in pilot inventories in Bangalore, and time studies were carried out as well

The field data are currently collected using nine forms, the content of which can be described as follows:

1) Plot approach form, containing information on team composition, time required to reach the plot and timing of the measurements,
2) Plot description form, containing plot-level descriptions of general soil, crop and bamboo characteristics. The data are collected from 0.1 ha plots (31.62 m x 31.62 m).
3) Plot enumeration form, on which the species and diameters of all trees are listed,
4) Sample tree form, on which additional measurements made on the sample trees are recorded (dominance, dbh, height, crown width),
5) Bamboo enumeration by clumps form, on which the quantities of bamboo are enumerated by quality and diameter classes and by species,
6) Bamboo enumeration form for non-clumping culms, on which the quantities of bamboo are enumerated by quality and diameter classes and by species,
7) Bamboo weight form, which contains more detailed data on the sample bamboo stands by species (diameter, length, utilizable length, weight)
8) Herbs, shrubs and regeneration form, which contains data on the herb plots (1 m × 1m) and shrub and regeneration plots (3 m × 3 m). Species and collar diameter are recorded.
9) Soil and Forest Floor Carbon form, which contains data on gravel/soil and the weight by volume of the forest floor.

Some basic GPS models have been procured and will be used for navigation to the field sample plots. The FSI has around 40 field teams engaged on the field inventory work at present, each led by an FSI official, the rest of the team being hired on a contractual basis. The work would require the formation of around 75 teams, however. The field season is about 8-10 months, depending on the rains. About 2000 forest plots and their associated vegetation survey plots are currently measured each year. The data are also checked on a regular basis after collection, especially if the figures appear to be illogical. The data are stored mainly at Dehradun, where the volume characteristics etc. are also calculated on the basis of local models developed by the FSI, state departments and the FRI.

19.1.3 Trees outside the forest (TOF) and the household survey

TOF and household surveys are performed in parallel, and it was these that constituted the main activity of the inventory unit between 1991 and 2001. The methodology used at that time was based on conventional means of assessing TOF. Altogether 180 districts (out of the total of 593) were covered by the traditional method. Trees in about 2000 villages were enumerated, and related household surveys were carried out. More recently, a new sampling methodology has been tested in pilot areas, where outlines for the sample size and the shape and size of the plots were determined. Studies for stratification of the tree cover in rural areas into block, linear and scattered shapes have been carried out separately. Plot sizes may differ between strata. A new comprehensive assessment of tree resources outside the forest area will follow the procedure listed here:

1. Stratification of the country's geographical area into physiographic zones,
2. Selection of 10% of the districts every two years,
3. Delineation of the forest area and non-forest area in each district,
4. Use of remote sensing techniques for stratification of the forest and non-forest areas,
5. Generation of separate estimates for rural and urban non-forest areas,
6. Use of LISS III and PAN data,
7. Geometric correction,
8. Digital interpretation of satellite image data,
9. Overlaying of digitised forest boundaries on the classified imagery wherever available – to provide the TOF area,
10. Use of the fused LISS III and PAN data to give the TOF stratification,
11. Further division of the rural areas into three strata, block, linear and scattered, using the remote sensing images,
12. Use of sampling units as the sampling frame in the national urban statistics, and
13. Selection of the optimum number of sampling units in each district for the survey.

Household and wood consumption assessment is a separate exercise. A demand exists for data of this type, even though these surveys are very time-consuming. The following procedure will be used in the household surveys:

1. Household surveys will be conducted in rural and urban areas in selected districts.
2. Working Plans or utilization practices will be sought for local NWFPs, to provide the basis for preparing a schedule for NWFP utilization and consumption. The tradition of NWFP utilization and its timing can vary between areas.

3. The blocks of the national urban survey framework will be used in urban areas.
4. A list of households will be prepared.
5. Different classes of household will be indicated on this list.
6. 12 households will be selected within three pre-defined strata after a random start.
7. Ten villages adjacent to the peripheral plots of forest will be selected systematically in each rural area.
8. Ten villages will be selected at random from among the remaining ones.
9. Households will be selected as in the case of the urban areas.
10. The data will be recorded according to a prepared schedule.
11. In addition to consumption data, the report will also include sources of NWFPs
    a. From the market
    b. From the forests
    c. From collections

19.1.4 Forest management planning

The planning and management of forests forms an integral part of environmental planning. GIS technology is being put to use by several State Forest Departments (SFD) in order to prepare management plans within their administrative domains. The key areas in which GIS technology is being employed are (1) demarcation of environmentally degraded areas, including potential ones, and (2) developing models for locating centres of viable economic activity in order to ease pressure on the environment. Some SFDs are very advanced in this respect but others need further assistance and training. The FSI has provided expertise and training for several State Forest Departments in the use of Remote Sensing and GIS for the preparation of working plans.

A project for the assessment of TOF approved by the Forest Department, for example, involves estimation of the growing stock and the numbers of trees by species and diameter class located outside forests. Remote sensing techniques will be used to stratify the area concerned into three geometrical formations, i.e. linear, scattered and block plantations, after which field data will be collected and analysed. The project is expected to be completed within 18 months. The PAN data from IRS satellites 1C and 1D to be used in this project will be provided by the Forest Department itself.

19.2 INDONESIA

Indonesia's tropical forests are among the richest in the world. Some 75% of the country is covered by natural forests (about 143 million hectares), half of it "production forest". The coverage of natural forest is decreasing very rapidly, however, due to poor concession management, illegal logging, forest fires and land use conversion (e.g. to agriculture).

The government owns all the land in Indonesia and grants concessions to companies, local people manage the land in many areas as if it were their own, and thus the forestry companies are obliged to co-operate with them. Processed wood products generate up to 18% of the national income from exports. An urgent need exists for data on the actual extent of the forests, their biophysical characteristics, the process of deforestation and land cover change, and data are also needed for the verification of sustainable forest management and the surveillance of forest reserves. The Indonesian government has been working on an inventory of forests since 1989, using a combination of aerial photography and ground checks. The acquisition of useful information has often been prevented by cloud, fog and rain, however.

The Indonesian forests can be divided into natural forests and tree plantations, the latter covering 9.9 million ha, (3.5 million ha rubber, 1.5 million ha teak, and 3.9 million ha other broadleaved trees, including 1.1 million ha of industrial pulpwood plantations). Through the Ministry of Forestry, the Indonesian government and the Association of Forest Concession Holders are working together to develop systems for managing the Indonesian tropical rain forests. These bodies have the authority to define accepted systems and regulations governing forestry mapping and inventories of forest estates.

Information on Indonesian forestry is collected at three levels:

1. National level, based on maps on a scale of 1:2,500,000 covering the whole of Indonesia.
2. Provincial level, based on maps to a scale of 1:250,000.
3. Concession holder level, based on larger-scale maps, typically 1:25,000., The system provides information for each concession on forest cover types and contours, a digital elevation model, a five-year logging plan, a yearly logging plan, timber volumes, commercial species, replanting, etc.

19.2.1 The National Forest Inventory

The National Forest Inventory Project conducted by the government of Indonesia since 1989 (Revilla and Liang 1989, Sutter 1990a) has involved the use of remote sensing technologies coupled with a Digital Image Analysis System (DIAS) and a Geographic Information System (GIS) integrated with a Field Data Processing System (FDPS). This represents the first extensive inventory of forest resources (trees, rattan, bamboo, nipa and sagu) in Indonesia and, in view of the relatively high access cost involved, it was designed to collect as much field sample data as possible. The field data include details collected from permanent sample plots (PSP)

and temporary sample plots (TSP) which are to be used for forest status and change assessment at the national and province levels, respectively. Landsat MSS and TM images were used in combination with field data to produce the map presentations, however.

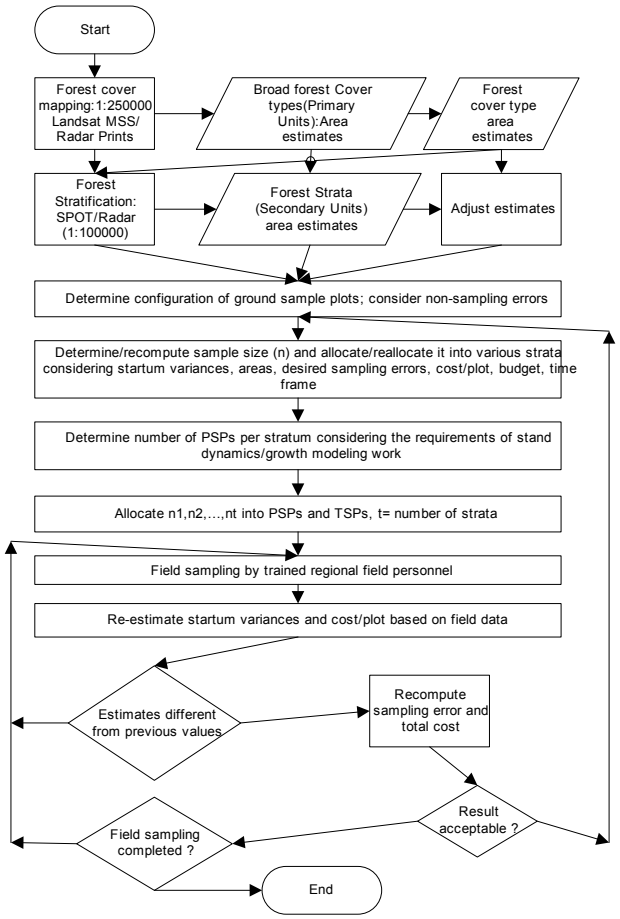


Figure 19.2 The NFI Sampling Design Process in Indonesia (3-stage sampling) (Revilla and Liang 1989, Sutter 1990a).

The plot clusters (Figure 19.3), distributed systematically with a random start, are arranged in a 20 × 20 km grid cell. All legal forest lands, as indicated on the Forest Land Use Planning Maps, are covered regardless of vegetation type. This includes all production forests, plantation forests and forests at higher altitudes, and protection and conservation forests at altitudes greater than 1,000 metres. There are about 3,300 plot clusters distributed throughout the country, except for the island of Java.

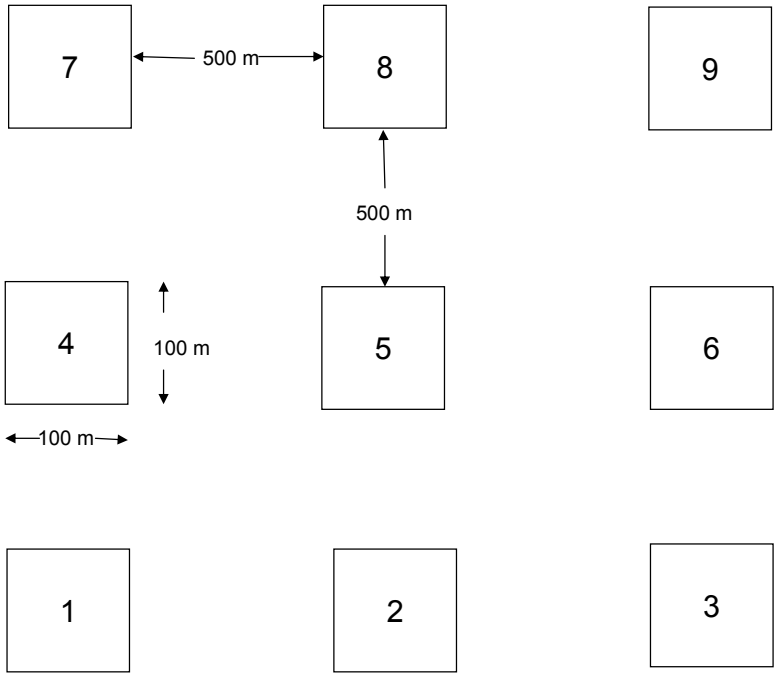


Figure 19.3 Plot cluster layout used in the Indonesian NFI. Each TSP contains 9 tracts and each PSP is a 1 ha plot (Revilla and Liang 1989, Sutter 1990a, Sutter 1990b).

19.2.2 Concession renewal mapping

The Indonesian Association of Forest Concession Holders has set up a company (PT MAPINDO PARAMA) to monitor forest exploitation and conversion, whether to agriculture, settlement, or replanting. The company monitors a total of 85 million hectares, and its concessions, which are awarded for 20 years, are divided into 35 lots. A concession entitles the holder to exploit one lot per year. Most of the timber companies are forced to use this company's products.

Any company seeking renewal of its concession must demonstrate compliance with the logging regulations during the previous concession period. As it is designed to fulfil a range of needs, the forest resource information system developed by MAPINDO manages data from several sources, including:

1. Aerial photographs to a scale of 1:20,000, used to assess forest cover types and commercial timber volumes. The survey takes five years to complete and will be repeated every five years. Aerial photos are also used to compile contour and vegetation maps to a scale of 1:25,000, and are combined with field survey data to classify forests on the basis of type,

crown density, stand height and crown diameter.

2. Synthetic aperture radar (SAR) imagery. A pilot study using airborne SAR supplemented with GPS position data was undertaken in the mountainous parts of Kalimantan. Oblique SAR is capable of acquiring images with a resolution of 6 metres irrespective of cloud cover. This one-year study will result in topographic contour and thematic maps covering much of central and eastern Kalimantan.
3. Satellite imagery is being used for the annual monitoring of forest exploitation. The images are used to produce a general classification by forest type and to identify the areas to be left as primary forest or to be exploited as forest estates.

19.2.3 Forest management planning: compartment-level inventories of natural forests

The silvicultural system known as Indonesian Selective Cutting and Planting comprises logging practices with a diameter limit and forest regeneration. This was initially referred to in 1972 as Indonesian Selective Cutting (TPTI). It is a series of planned forest management activities which include logging, regeneration and tending of the forest stands in order to ensure the sustainability of timber or other forest production. To achieve the expected target, the following series of activities and schedules have been established for each harvesting area:

Stage of TPTI Activities	Time of Implementation (year) (Et = time of harvesting operation)
Organization of working area	Et – 3
Stand inventory before logging	Et – 2
Opening up of forest area	Et- 1
Logging	Et
Liberation	Et+ 1
Inventory of residual stand	Et+ 1
Procurement of planting stock	Et + 2.
Enrichment planting	Et + 2
First-stage tending	Et + 3
Advanced tending	
a. Liberation	Et + 4
b. Thinning	Et + 9
	Et+ 14
	Et+ 19
Forest protection and research	Continually

The annual logging units have traditionally been 1 km × 1 km blocks, and the present regulations recommend natural borders for the delineation of these units. Timber companies are keen to find locations with a high volume of valuable trees, and thus they usually use aerial photos to locate the forests with the highest

potential. The dense crown cover makes the interpretation of single trees difficult, however, and it is also difficult to identify species from a bird's eye view. (The identification of trees is even difficult from the ground.).

According to the TPTI rules, a stand inventory (Pre-felling inventory, cruising) has to be carried out one year before harvesting, in order to determine the volume of trees over 50 cm in diameter to be harvested. For this purpose the logging unit is tallied in detail, tree by tree, and individual trees are located within the square area (all trees over 50 cm). These tree location maps must be submitted with the application for a logging license.

An inventory of the residual stand (after-felling inventory) has to be made in all forest areas two years after logging, to check the condition of the forest stand at that stage. This differs from the pre-felling inventory in that all trees over 20 cm in diameter are measured and regeneration is estimated by sampling. Tree location maps are produced to control the logging intensity.

19.2.4 Forest management planning: compartment-level inventories of plantation forests

The most important plantation organization is Perum Perhutani, the state-owned forestry company, which has 1.36 million hectares of plantations, mostly of teak (within a total of 3 million hectares of forest). The management method, called Clear Cutting with Artificial Regeneration (THPB), has been practised in Java since 1880. The tree species most frequently planted up to now consist of indigenous or exotic species, the most common exotic species are *Acacia mangium, Acacia crassicarpa, Acacia auriculiformis, Gmelina arborea and Eucalyptus urophylla.*

Figure 19.4 A typical sample of a young Acacia mangium plantation.

The THPB silvicultural system can be used for establishing a plantation

forest either for land rehabilitation or for the industrial production of fast growing species (HTI). An example of its implementation is the conversion of natural forest into plantation forest, e.g. the conversion of non-teak forest in Java into pine forest, agathis forest etc. Other examples are the establishment of mangrove forests, the establishment of plantation forests along the coast and the reforestation of alang-alang (Imperata cylindrica) fields outside Java. In practice, the THPB method is very close to Scandinavian stand-bsed forest management system.

Since the value of the plantation forests is an object of interest for the financing institutions (banks), supporting agencies (Indonesian government bodies) and timber/paper companies, inventory methods are developing rapidly in this sector and the companies are constantly open to innovations.

Private forest estates have started to use orthophotographs and EnsoMosaic products (Figure 19.4) in their forest plantation information systems. The resulting images are used to plan fieldwork and to control the quality of wood resources. Mostly paper prints are used to digitize the delineation of stands, which are classified according to planting year and species. Tree attribute information is collected from subjectively located field sample plots by means of specific tallysheet, relascope and height estimation tools. Companies store the inventory data mostly in GIS data layers.

19.3 CHINA

China conducted 4 national forest resource inventories in the period 1973-1993. The results achieved in the Fourth National Forest Resource Inventory (1989-1993) revealed that the land area used for forestry purposes is 262.89 million ha, with a forest area totalling 133.7 million ha and a forest cover of 13.92%, an increase of 8.03 million ha compared with the results of the Third National Forest Resource Inventory (1984-1988). Likewise, the plantation area had increased by 2.78 million ha, from the previous figure of 31.01 million ha to 33.79 million ha, representing an average annual increment of 650,000 ha.

The huge flood problems experienced in China in summer 1998 caused the government to impose a total logging ban in order to preserve the natural drainage basins. Since that time local foresters in the natural forest sector have been mainly responsible for forest planning and design, the planting trees and research, while plantation forestry has started to grow in southern China as foreign investors (e.g. all the most important paper manufacturers) have entered the country.

Aerial photography was introduced in 1954. It was first used to delineate the boundaries of stands and working units such as compartments and sub-compartments, and then to deduce forest types, tree species, site indices, stand volumes and other stand variables. Angle count sampling was introduced in 1957 to improve on the ocular estimation technique, and stratified sampling was first tried in 1963. Since then, the forest inventory technique has progressively moved over from ocular estimation to statistical sampling. Meanwhile, research and experimentation has been focused on inventory methods that would be suitable for different areas, conditions and management levels, such as two-stage and multistage sampling

inventories, double sampling with regression, and regression based surveys with visual estimation and field mensuration, etc. Most of these methods have already been put into practice.

In order to monitor the dynamic changes taking place in national forest resources, a CFI (continuous forest inventory) system has been set up in all the provinces with permanent sampling plots. There are 250,000 permanent sampling plots in the whole country. 15 provinces have been remeasured since 1986, and satisfactory results have been achieved.

Remote sensing data have been used for forest mapping and monitoring in China for more than 40 years. Foresters used only aerial photographs for inventory purposes between 1950 and 1970, but use has also been made of satellite remote sensing data since 1980, although mostly in development projects rather than everyday operations.

19.3.1 National Forest Inventory: natural forests

The area of China is covered by a permanent field sample plot network which is planned to be measured in 5-year periods. The sample plots are in general 20×30 m^2 in size and located in 2 km $\times$ 4 km grid cells. There are a total of about 230 000 sample plots over the whole country. Altogether 35 variables are measured on each plot, and the data are stored in a Dbase database. The NFI results are calculated using field samples for administrative units.

19.3.2 Forest management planning: compartment-level inventories

A province in the Chinese forest management planning system includes several forestry bureaus. each divided into several forest farms (e.g. one sample forestry bureau includes 12 forest farms). Each forest farm comprises several compartments as its administration units, and these compartments are then divided into sub-compartments according to their silvicultural condition. In terms of Finnish forestry, the Chinese forest compartments correspond primarily to forest farms and the sub-compartments to forest stands, but the management areas or treatment units are usually more extensive in China.

Data from the stand inventories are recorded in a forest register, which includes stand information such as area, species, age, volume, growth and degree of stocking by sub-compartments. The forest registers are then summed to apply to larger management units. The accuracy of this compilation method depends on the stand inventory techniques employed, e.g. aerial photography, visual estimation, sampling techniques and yield tables. The number of sample points ranges between 3 and 14 depending on the size of the sub-compartments. The compilation method has now beeen taken into use and supplemented with stratification based on aerial photographs or satellite images.

19.4 OTHER ASIAN AREAS

Industrial plantation forest inventories are very similar in all the Asian countries

(and actually world-wide), since the rotation time is short and investment relatively high (so that intensive inventories are acceptable). Thus aerial photographs are commonly used in conjunction with field sampling .

Remote sensing is also particularly useful for extensive or distant areas of forest where access is difficult, and these techniques, including aerial photography, are arousing much interest in connection with the tropical forests of south Asia in particular. Aerial photographs provide us with certain strata, such as forest types, density classes and height classes, and it is possible in some cases to identify certain tree species and to assess the volume of their growing stock. Most countries began to use aerial photographs as a means of stratifying forest lands when carrying out a national forest inventory after the Second World War, and then as the tool for forest planning and management.

The following paragraphs briefly describe the use of remote sensing data in selected Asian countries:

Japan

There are a great number of pure plantations, totalling 10 million ha, so that stratification techniques are very useful for reducing internal variance smaller and applying various models for the assessment of actual forests (Minowa 1992).

Taiwan

The national forest inventory employs aerial photography in its primary sampling. Approximately 134,000 photo points were selected over the entire island, after which field locations were selected at an density of one per 900 hectares, which resulted in 4,132 locations (2,491 in forests) for the entire island (Minowa 1992).

Korea

The fourth national forest inventory was conducted between 1986 and 1990 (the first one in 1962-1964). To reduce the number of field plots, cost and time, a stratified double sampling technique was adopted with the combined use of aerial photographs and ground surveys.

Forest lands were classified into several types using B&W aerial photographs on a scale of 1: 15000. The number of sampling plots was determined statistically in order to be able to estimate the total growing stock with a relative precision of 5% at the 95% confidence level (Minowa 1992).

Philippines

The national forest inventory employs a two-stage sampling approach using small scale aerial photographs (1:60,000) and Landsat false colour composites (FCC) as the area frame and relascope samples as the ground truth information. A two-stage design was introduced in 1983 that concentrated the field sampling in selected forest strata. In order to keep the standard error below 3%, a total of 2,000 field clusters are required. These clusters are allocated to the regions and provinces in proportion to their forest cover (Minowa 1992).

Malaysia

Inventory methods in Malaysia have traditionally been very similar to those in Indonesia, and the Malysian natural forest management system is very similar to the Indonesian TPTI system (Minowa 1992).

Thailand

Remote sensing has been used by the Royal Forest Department as a useful technique for national forest inventory purposes. Landsat images in particular can reduce the time and personnel needed for assessing the existing forest area over the entire country, as a survey can be completed in only one year as compared with ten years when conventional aerial photographs are used (Minowa 1992).

Aerial photography was first applied to forestry in 1955, for the delineation of various forest types and the compilation of forest maps. The Thailand National Remote Sensing Programme was established in 1972. At present, aerial photographs and Landsat images are being used to compile maps of forest types, forest land use, vegetation cover and existing forests. Landsat images cannot be used for the classification of all forest types, however, and consequently both aerial photographs and Landsat data are used in the national forest inventory.

Interpretationa made in the office by trained staff are verified by means of ground surveys.

REFERENCES

FIA 2004. Forest Inventory and Analysis, Phase 2 and Phase 3: Ground, Measurements . FIA Fact Sheet Series. 2 pp.

Forest Survey of India, 1996. Inventory of Forest Resources of India. Forest Survey of India, Ministry of Environment and Forest, Dehra Dun, India, 268 pp.

Forest Survey of India, 2001. Information Brochure, Forest Survey of India, Ministry of Environment and Forest, Dehra Dun, India, 4 pp

Forest Survey of India, 2002. State of Forest Report 2001. Forest Survey of India, Ministry of Environment and Forest, Dehra Dun, India, 130 pp.

Minowa, M. 1992. Stand Inventory Techniques in Asia. In: Proceedings of the Stand Inventory Technologies: An International Multiple Resource Conference, World Forestry Center, Sept. 13-17, 1992. American Society for Photogrammetry and Remote Sensing.

Revilla, J.A.V. and Liang, D. H. 1989. The national forest inventory of Indonesia. UTF/INS/066/NFI Field Document 3. FAO, Jakarta, Indonesia. 35pp.

Sutter, H. 1990a. Feasibility study on the sampling design for the national forest inventory of Indonesia. UTF/INS/066/NFI Field Document 5. FAO, Jakarta, Indonesia. 99pp.

Sutter, H. 1990b. Field instructions for the national forest inventory of Indonesia. UTF/INS/066/NFI Field Document 6. FAO, Jakarta, Indonesia. 41pp.

Zulfilkhar, Ir.1992. Sampling design of temporary and permanent sample plot for the national forest inventory of Indonesia. In: Proceedings of the Stand Inventory Technologies: An International Multiple Resource Conference, World Forestry Center, Sept. 13-17, 1992. American Society for Photogrammetry and Remote Sensing.

CHAPTER 20

NORTH AMERICA

TIMO TOKOLA

University of Helsinki, Finland

20.1 CANADA

Canada is steward of about 10% of the world's forests and 30% of the world's boreal forests. Around 34% of the country's total area of 909 million hectares is classified as forest land, and 293 million hectares of these forests are potentially available for commercial forestry at the present time In terms of forest type, 66% of Canada's forests contain softwood, 12% hardwood and 22% are mixed forests. The forest land is mainly owned by public instances (the provincial governments 77% and federal government 16%), and only 7% is in private ownership. Provincial forest lands may or may not be assigned to industry for timber harvesting under a wide variety of agreements (State of Canada's Forests 2003-2004).

Each Canadian province and territory has its own legislation, regulations, standards and programmes through which it allocates harvesting rights and management responsibilities for the forests within its jurisdiction. In addition, many provinces and territories have legislation that requires public participation in forest management planning and allocation processes.

Each province has made major investments in forest management inventories in terms of organisation, technology and data. The federal government, primarily through Natural Resources Canada, participated directly in the earlier development of these inventories, but the present federal role is restricted to research and development, the inventories on federally administered land and the compilation of national forestry statistics. There are many mechanisms providing for provincial cooperation for inventory purposes, the most visible of which is the Canadian Forest Inventory Committee (CFIC), which is a forum for inventory specialists from all jurisdictions to meet, exchange information and tackle problems of mutual concern. Procedures for aggregating the many provincial inventories into one national

A. Kangas and M. Maltamo (eds.), Forest Inventory – Methodology and Applications, 325–340.

inventory have been developed through the CFIC's collective cooperation, the working details being negotiated separately with each province.

20.1.1 Provincial-level management inventories

A typical forest management inventory in Canada is based on maps to a scale of about 1:20 000 made from stereo aerial photographs. Volume estimates are generally added to each stand (forest type polygon) based on regional volume relationships calculated for temporary sample plots. Because of the large areas involved and their remoteness, only a small proportion of the stands can be visited at the time of performing the inventory.

The inventory process usually takes place in a province over something like a 10 or 15-year cycle, and a new inventory will progressively replace the old one. The inventories are designed for periodic planning at the management unit level and must provide reasonable general information on every stand. Management inventories can also serve as a basis for subsequent local and more specialised operational surveys.

Although management inventories are designed to give the best current information that the available funds will allow and local forestry staff have a good working knowledge of the inventory's accuracy and peculiarities, estimates of their precision or of changes are not usually available or expected in the balance of user priorities. The regions of greater activity tend to receive the most frequent and intensive inventory attention and lower interest areas may be covered by less intensive reconnaissance inventories.

As specifications and standards tend to improve with each cycle, a new inventory cannot generally be compared with an old one in order to estimate changes. Permanent sample plots (PSPs) are not usually a direct component of Canadian inventories, although products of PSP studies such as growth and yield relationships may be integrated into inventories.

New inventory methods such as spatially referenced data and image handling technology or the modelling of stand development are increasingly allowing the maintenance and updating of existing inventories until new ones can be produced. Inventory priorities and funding have primarily been fuelled by timber interests, and Canadian forest management and inventory specialists are currently striving to sort out society's new expectations regarding the state-owned forest resources and to develop inventory techniques to handle these expectations. Above all, they would like to obtain the extra funds necessary to upgrade this massive investment in information that starts to become outdated at the moment of publication.

It is recognized that better basic descriptions of forest vegetation, sites and the activities taking place would all improve the ability of the inventory data to serve different needs, and would also allow for better tracking and modelling, in order both to update inventories and to project them forward in time for use as planning scenarios.

Example of a provincial inventory: the Vegetation Resources Inventory of British Columbia

The Vegetation Resources Inventory (VRI) is a process for assessing the quantity and quality of timber and other vegetation resources in British Columbia, providing an account of these that is of known accuracy and is more complete than past forest inventories. The VRI has broader in scope than past inventories, and more reliable, because it use statistically accurate procedures and detailed ground sampling to augment estimates deduced from air photographs.
The Vegetation Resources Inventory use:
1. interpretations of air photographs
2. ground sample measurements
3. statistical analysis and adjustment of the initial estimates

The Ministry is responsible for coordinating and auditing the completed vegetation resources inventories, which is conducted by private industry and other stakeholders according to approved standards and procedures. Specialized contractors is hired to conduct the ground sampling.

20.1.2 National forest inventories, national aggregation

Canada's National Forest Inventory is aggregated from various sources, mostly provincial management inventories based on forest type maps made from air photographs. The national inventory takes advantage of an infrastructure of source inventories that are basically similar, and procedures have been developed to combine inventories with different specifications and to overcome gaps in the data. Inventories in this form are now entering their third five-year cycle, in which modern computer technology is being used to handle georeferenced data (Lowe 1991, 1994).

There has been considerable investment in map-based inventories across most of the forested regions of Canada since the 1950s, and there are many similarities in the methods used despite the temporal differences and those occurring between and within jurisdictions. There has been a convergence of basic inventory characteristics through cooperative liaison and the application of similar techniques to similar problems. The forest inventory organisations were some of the earliest operational users of computers for handling large stand lists and associated bodies of information (Lowe 1991, 1994).

Up to and including the 1976 national inventory, the practice was to collect and publish provincial-level summaries for each jurisdiction. Standardisation in certain key topics was encouraged, especially through the conditions placed upon federal contributions to provincial inventories and through federal inventories of more remote areas. Inventory specialists from the various jurisdictions met several times in the 1970s as part of a wider, federally coordinated effort to rationalise and standardise the country's conversion to metric units, and they found the meetings so beneficial that they continued in the form of the Canadian Forest Inventory

Committee. From the national perspective, this has encouraged voluntary compatibility and a converging evolution of inventory methods (Lowe 1991, 1994).

Using geographic information system (GIS) technology and capitalising on the circumstances described above, the 1981 national inventory collected, standardised and aggregated data from various source inventories on a map sheet basis, using each map sheet as one of the 43 000 'cells' in the national inventory. The target cell size was 10 km by 10 km, and this proved to be a very suitable level of resolution on national scales of about 1:20 million (Lowe 1991, 1994).

The national inventory is not a sample but a complete census of stands, providing a level of detail that can be used for creating regional or national statistics, thematic maps and national spatial studies. It is not suitable for intensive local examination, nor has it been approved for such.

The 1986 and 1991 inventories improved progressively in content, quality and process, but their principles were the same. The basic production steps for the 1991 inventory were:

1. Exploration and documentation of the conversion of datasets between the provincial inventories and the national inventory in such matters as terms and classes. Recoding from the province-specific data was required in order to extract data according to national standards.
2. Quality check and aggregation. The data were checked rigorously and aggregated from the stand level to the cell level.
3. Missing values. Since not all source inventories can supply data for every attribute in all situations, many of 'holes' had to be filled by calculation on the basis of local knowledge.
4. Auxiliary information. Some other categories of regional information that are not part of the source inventories are combined with the national inventory to calculate new attributes.

One weakness of Canada's aggregated inventory is that the data are the best available in the source inventories at the time of collection. Thus the average age of the data collected for the 1986 inventory was 10 years and it was not practicable to update the national inventory by calculation. It should be noted, however, that the provincial forest management inventories from which the national inventory is aggregated every five years are improving rapidly in their incorporation of changes to keep them more up-to-date (Lowe 1991, 1994).

Inventories based on re-measurement plots can monitor changes extremely well. This has been perhaps the weakest aspect of Canada's national inventory, that the provincial inventories are not primarily designed to estimate change. The new NFI has been designed to meet such monitoring needs, however, for in the new national forest inventory programme design launched in 1997 all potential sample locations are indicated on a national 4 x 4 km network, with a preferred sampling intensity represented by a 20 x 20 km grid of sampling points nested within the national 4 x 4 km grid. Even so, Canada depends on input from

its provinces, which are encouraged to use the grid, but are not required to do so if they are using a statistically valid design and can provide the necessary core data.

20.1.3 Industrial forest management inventories

The two inventory methods used by industry across Canada, and their objectives, are:

1. Management Inventory
The objective is to provide general forest statistics over a large area so that a management plan and allowable cut can be determined. The information required includes the volume of mature timber by species, the area of immature timber, growth rate and information on access routes.

2. Operational Inventory
The objective is to provide specific forest statistics over a small area so that logging plans can be prepared. The information required includes forest type maps, the volume of mature timber by species and diameter class and topographical data.

Most companies use similar inventory methods for both management and operational inventories, with the operational inventory representing an intensification of the management inventory in order to obtain more detailed information and to improve the accuracy over a reduced area.
Methods for **management inventories** vary, but basically employ the following four broad inventory methods (Caesar 1975):

Method 1: Pre-Stratification

1. Type maps are prepared by interpreting photographs prior to the fieldwork.
2. Temporary field plots are measured in all the important strata for determining volume.
3. Stand and stock tables are prepared for all forest types from the plot data.

This method is used almost universally by industry in the Western Provinces, in Quebec and to some extent in the Maritimes, and provides the most detailed results. An accurate forest type map is produced based on photo interpretation and can be checked by ground examination. Plot measurements combined with reliable volume tables and reduction factors for waste and defects provide detailed stand information for each type. Volumes are based on actual measurements. Reliance on human judgment and the use of averages are eliminated almost entirely. As a result of the increased fieldwork, more information is obtained regarding stand conditions, access routes and other values such as soil, water and wild-life.

Method 2: No Stratification

1. The forest classification is derived from the interpretation of photo points located in accordance with a mechanical grid. The proportion of photo

points falling within one forest type is used to calculate the area of that type.
2. Timber volume is calculated from areal volume tables using stand descriptions derived from the interpretations of the photo points.
3. Maps are prepared using existing compartment maps and photo point measurements.

Forest type maps are prepared using existing management plans, and only the attributes are updated. It is assumed that no change take place in the stand borders. Volumes are projected from average tables, and the accuracy of the results is entirely dependent on the ability of the interpreter to classify the stands consistently. As there are no field measurements for volume, it is not possible to produce reliable stand data such as volume by species or diameter class.

Method 3: Post-Stratification

1. Temporary field plots are established in the principal types to determine the forest classification.
2. Type maps are prepared from photographs after the fieldwork.
3. Timber volume is derived from normal yield tables using stand descriptions derived from the photographs.

This method has been developed by the province of Ontario and has been adopted by industry at the government's request. Forest type maps are prepared based on photo interpretation combined with limited field examinations. Volumes are predicted indirectly on the basis of photo classification using basal area, age, species and site. None of these variables can be measured on the photographs. Thus, for all stands not examined on the ground, the accuracy of results is entirely dependent on the interpreter's judgment, and his ability to classify stands consistently. As a result of there being no field measurements of volume, it is not possible to produce reliable stand data such as volume by species and diameter class.

Method 4 C.F.I. (Continuous Forest Inventory)

1. No stratification.
2. Permanent field plots are established and used to determine timber volume and growth.
3. Maps can be prepared using existing compartment maps by calibrating thematic information using new information.

Overall volume data and growth data are provided, but maps are rarely derived. Once the plots have been established, and the computer program set up, re-measurement and updating of total volume can be done fairly economically.

There are a number of variations within the four general methods just described that can be introduced concerning measurement techniques and the intensity of the work. The methods differ in their costs and the results that they produce. When deciding which method to use, the forester must determine the

amount of detail that is required and must then devise a means of obtaining it given the available funds. The selection of the method for a forest management inventory is an important decision, since once the method has been introduced it is costly to change it at a later date. Pre-stratification and post-stratification can cost the same, although pre-stratification is normally considered the most expensive alternative. Optimum allocation of samples in pre-stratification may even so cost less than a post-stratification case in which a random sample is distributed over the same area. If post-stratification is based on existing field sample plot material, however, significant savings can be achieved. The establishment and measurement of permanent plots is normally quite costly, although it provides the best alternative for monitoring purposes.

Some considerations that influence the selection of a method for forest management inventories are put forward in the following (Caesar 1975).

1. Type of forest management practised
If sustained yield management is being practised it is necessary to know the timber volume by forest types, area by age classes and site index so that the annual allowable cut can be determined and a cutting budget can be prepared for a full rotation. Thus a detailed inventory with forest type maps is required. If the area is being managed to provide a fixed volume per year over a short term, then it is sufficient to know the total volume, approximate species distribution and volume per acre.

2. Timber supply
If timber is plentiful, general information concerning total volume is adequate and the accuracy of the results is not critical, but if timber is scarce and it is necessary to compete for supplies, then detailed stand information is required and accurate results are essential.

3. Timber value
If all the timber is pulpwood, the species composition and diameter distribution are not of great importance, as it is usually sufficient to know the approximate species composition and volume per acre. If the timber includes sawlogs, veneer logs and pulpwood, however, it becomes important to know the volume by species and volume by diameter class, so that the volumes suitable for the various conversion processes can be determined. This requires a detailed inventory.

4. Forest variation
If the forest has suffered little disturbance and the stands are homogeneous, a forest inventory can be carried out with less intensive work than for a disturbed forest with heterogeneous stands.

5. Forest access
The availability of access routes and the ease with which field crews can be moved through the area will greatly influence the cost of the fieldwork. Thus there will be a tendency in inaccessible areas to adopt methods that are heavily dependent on air photographs.

6. Available data
If suitable aerial photographs and base maps are available from outside sources, this will reduce costs and may influence the inventory methods used.

7. Government regulations
Provinces lay down regulations intended to establish minimum standards for forest inventories carried out by industry.

8. Form of tenure
The type of timber holding will affect the method and intensity of a management inventory. If the land is held in fee simple, then the company will normally be preparing long-range management plans and a detailed inventory will be required. If the lands are held under a short-term occupation agreement, a detailed inventory will not be required and it will usually be adequate to determine the location and approximate volume of the timber so that a logging programme can be developed.

9. Other values
Where a forest inventory is to include other values such as soil, water, wildlife or recreation, more comprehensive procedures are necessary than if only timber volume is to be assessed.

20.2 THE UNITED STATES OF AMERICA

The United States had 747 million acres of forest land in 1997, amounting to 33% of the country's total land area. Reserved forest land has doubled since 1953 and now stands at 7% of all forest land. This reserved area includes state and federal parks and wilderness areas but not conservation easements, i.e. areas protected by non-governmental organizations, nor most urban and community parks and reserves. Timber land is fairly evenly distributed among the three major regions of the United States, but other forest land, such as slow-growing spruce forests in the interior of Alaska or pinyon-juniper forests in the interior west, dominate many western landscapes and comprise more than one-fourth of all U.S. forest land.

The U.S. forests are predominantly natural stands of native species, with planted forests most common in the east and south. After intensive logging in the late 19th century and early 20th century, 55% of the forests on the nation's timber land were less than 50 years old and 6% more than 175 years old. While most timber products harvested from U.S. forests have been increasing in quantity since 1976, the greatest gains have been in fibre for pulp and composite products. Much of this increase has been in hardwoods, as new technologies improve the utilization of these species.

Large companies provide a market for many types of logs, wood fibre and chips. Private woodland owners may choose to harvest their own timber and sell the cut product (e.g. veneer and sawlogs, pulpwood, posts, poles, etc.) or sell the trees as

they stand and allow the buyer to cut and remove them. The latter method is referred to as stumpage sales. Non-industrial private woodland owners own approximately 40% of Minnesota's commercial forest land, for example, and over 40% of the timber harvested in the state is derived from these lands. Many of these landowners receive a significant income from their woodlands each year.

Many large forest industries provide forest management and marketing assistance to private woodland owners. In addition, there are consulting foresters who provide a wide range of fee-paying land management services, including timber harvesting and marketing assistance. The fees for such harvesting and marketing assistance are usually a percentage of the gross receipts from the sale. These consultants can also act as agents for landowners during timber sales. The range of services provided by these private sector foresters usually exceeds those provided by public foresters.

20.2.1 The National Forest Inventory

The Forest Inventory and Analysis (FIA), the nation's forest census, which commenced in 1930, reports on the status of the forest area and trends in this and on its location, the species, size and health of the trees, total tree growth, mortality and removals by harvesting wood production and utilization rates in terms of the various products and forest land ownership. The enhanced FIA programme includes information relating to tree crown condition, soils, ozone indicator plants, complete vegetative diversity and coarse woody debris. The programme is managed by the research and development organization within the USDA Forest Service in cooperation with state and private forestry and the national forest system. The FIA has been in operation under various names (Forest Survey, Renewable Resources Evaluation, and now Forest Inventory and Analysis) for some 70 years, and its programme, covering forests on all forest lands within the US, is implemented in cooperation with a variety of partners, including state forestry agencies and private landowners, who grant access to their lands for data collection purposes.

The FIA provides objective and scientifically credible information on key forest ecosystem processes: how much forest there is, what it looks like, whether the forest area is increasing or decreasing, how quickly trees are growing, dying and being harvested, and how the forest ecosystem is changing over time with respect to soil and other vegetative community attributes. The FIA is the only programme that provides consistent, credible and periodic data for all forest lands (public and private) within the United States.

The FIA has three levels of internal management: an executive level involving senior executives from the Forest Service and state forestry agencies, who provide broad policy guidance, a management level consisting of field programme managers from the Forest Service and states responsible for implementing the programme on a day-to-day basis, and a technical level consisting of groups of technical specialists drawn from the Forest Service and states who develop, document and review the procedures. The work is coordinated from five regional

field offices across the country, with each region maintaining its own internal set of regional customers and partners who collaborate over implementation of the programme.

The FIA consists of a nationally consistent core programme which can be enhanced at the regional, state or local level to address special interests. The national core consists of three phases:

1. Phase one (P1) is a remote sensing-based classification of the land into forest and non-forest, during which spatial measurements of fragmentation, urbanization and distance variables etc. are made. This phase has historically been done using aerial photography, but is now changing to a system based on satellite imagery.

2. Phase 2 (P2) consists of a set of field sample locations distributed across the landscape with approximately one location (FIA plot) every 6,000 acres. Field crews visit these locations to collect a variety of forest ecosystem data. Non-forest locations are also visited as necessary to quantify the rates of land use change.

3. Phase 3 (P3) involves a subset of the phase two plots (approximately 1 every 96,000 acres), which are visited during the growing season in order to collect an extended suite of ecological data covering a full vegetation inventory, tree and crown condition, soil data, lichen diversity, coarse woody debris and ozone damage.

Under the annual approach, data are collected on a subset of the plots in all states every year. This is a departure from the historical FIA approach of sampling states sequentially in a cycle. Ultimately, the goal is to sample 20% of all field plots in every state every year.

Maps, aerial photographs/imagery and global positioning system (GPS) units are made use of to install the ground plots properly. The information on a photo is used to establish a starting point (SP), an easily recognizable feature that can be seen on the photo and/or found using land use patterns. The crew then navigates to the plot centre (PC) either by means of this information or using a GPS instrument. Once the crew has traversed along the azimuth and distance to the PC from the SP, they will examine the photo, verify that they are actually at the PC and record the GPS readings. All this information will be useful in helping future FIA field crews to re-locate the plot. Any additional information that future crews need in collecting the data is also included in the general plot notes. The FIA gathers quantitative and qualitative measurements for all forested field plots that describe

- Tree diameter, length, damage, amount of rotten or missing wood and tree quality.
- Tree regeneration.
- Site quality information.
- Stocking.

- General land use.
- General stand characteristics such as forest type, stand age and disturbance.
- Changes in land use and general stand characteristics.
- Estimates of growth mortality and removals.

The current measurements made on the Phase 3 subset of plots may be grouped into the following categories:

- Crown conditions – generally good crown conditions are signs of vigorous trees and poor crown conditions are symptoms of trees under stress.
- Soil condition – soil erosion and compaction are measured and soil samples are collected for the analysis of physical and chemical properties, including estimates of site fertility.
- Lichen communities – lichen species richness and abundance are measured on the plot. The presence or absence of certain lichen species may be indicative of air quality, climate changes and ecosystem biodiversity.
- Vegetation diversity and structure – the composition, abundance and spatial arrangement of the vegetation (species and growth forms) in the forest are measured to determine such aspects as vegetative diversity, presence and abundance of exotic and introduced plant species, fuel loading, wildlife habitat suitability and carbon cycling.
- Down woody debris – measurements of the amount of coarse and fine wood on the ground can provide an estimate of carbon storage, soil erosion potential, fire fuel loading and, combined with the vegetation structure data, wildlife habitats.

A FIA plot consists of a cluster of four circular subplots spaced out in a fixed pattern. The plot is designed to provide a sampling location for all P2 and P3 measurements. Subplots are never reconfigured or moved, but a plot may straddle more than one ‘condition class’, such as two forest types or a forest and a meadow. A condition class is a specific combination of environmental attributes such as land use, forest type, stand age and other attributes which collectively describe a homogeneous area. Every plot exists in at least one condition class and may include more than one. If multiple condition classes occur on a plot, each is described separately. Forested condition classes are further subdivided into the following groups (listed in order of priority): reserved status, owner group, forest type, stand size class, regeneration status and tree density. If any of these attributes changes within a plot, an additional condition class must be defined and described. The rest of the variables within the condition class-level data are used to describe the condition class in more detail, but changes in these auxiliary variables are not used to define an additional class.

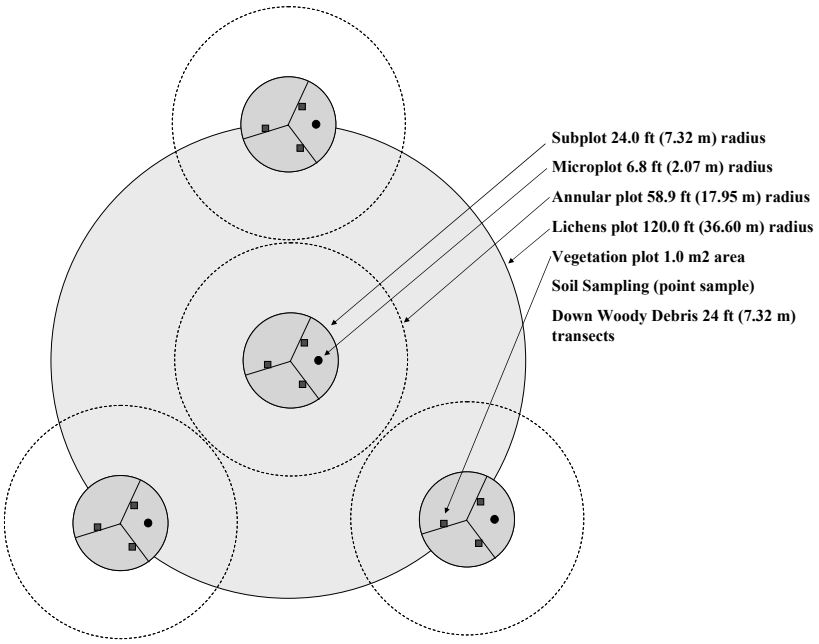


Figure 20.1 Phase 2 (P2)/Phase 3 (P3) Plot Design in the USA's NFI

An overview of the FIA is provided in the following list:

- Primary measurement protocols designed for field plots
- 0.40-ha primary sampling unit (2×2-pixel area)
    - trees measured on 0.06 ha (less than one 30-m Landsat pixel in area)
- 5×5-km grid over the entire conterminous territory of the USA
    - 360,000 field plots in the USA, of which
    - 120,500 are forested
- Each field plot re-measured every
    - 9-12 years in the eastern USA (cost $1,800-$2,600 per forested field plot)
    - 20 years in the western USA (cost $3,700-$7,600 per forested field plot)
    - An average 2-person field crew can survey 1 forested field plot per day
    - 300 permanent staff, plus a small army of seasonal "plot-getters"
- Stratification to improve precision (statistical efficiency)
- Use currently made of aerial photos from the National Aerial Photography Program (NAPP)
    - 1×1-km grid
    - over 9,000,000 photo-plots in the conterminous USA
    - nominal 0.4-ha photo-plot
    - repeated every NAPP cycle

- Replacing NAPP with Landsat 7
    - better mesh, with a shift to annual re-measurement of field plots
    - provides maps, and not just a "dot grid" of photo-plots
    - may be less expensive
- Forest/Non-forest Landsat classification adequate for statistical stratification
    - Forest and tree measurements mostly equal 0 in thenon-forest stratum, which is the largest single gain in efficiency
    - High classification accuracy needed to achieve practically significant gains in efficiency
- Classification of detailed forest types valuable
    - Detail needed for regional analyses and modelling
    - At least 80-90% accuracy needed for significant statistical efficiency
- New land cover classifications probably needed every 5 years, or else updates every 5 years through change detection

20.2.2 Industrial forest management planning: stand-level inventory

The private forestry companies have mostly forest maps produced by means of ground data collection and photo-interpretation. One example is Sierra Pacific Industries' forest mapping in Northern California, where the forests are classified according to following scheme: Forest Type (based on species composition – true fir forest, Douglas fir forest, mixed conifer forest, ponderosa pine/Douglas fir forest, ponderosa pine forest, knobcone pine forest), size class (based on tree diameter – 0-6 inches, 6-12 inches, 12-24 inches and > 24 inches) and crown closure (0-20%, 20-40%, 40-70%, >70%).

Fifteen years ago most large companies maintained an adequate staff and computer system to collect, process and analyse their inventory information. Contractors were not general protocol for these companies as they were with smaller organizations and independents. Since this time, however, staffs have been trimmed to the point where an outside labour force is mandatory, and the industry is currently going through further evaluations and changes concerning software and hardware configurations. Software maintenance and design is becoming more dependent on central sources and outside consultants, and large companies are now sharing much of the same software and common data configured for their specific needs. This continuing and growing external element is now leading to further outside expertise in inventory design, initialization, maintenance and analysis.

20.2.3 Cruising, scaling and volume estimation

Cruising is the process of measuring forest stands to determine characteristics such as average tree size, volume and quality. The primary purpose is to obtain a volume estimate for appraisal and for the preparation of timber sales.

Scaling is the determination of the gross and net volume of logs. The primary purpose is to determine the volume by product or species that will be charged at a predetermined rate, also known as "scaling for payment". Conventional scaling entails measuring log diameters and lengths and applying an approved set of rules to make deductions for defects. This process is intended to determine the gross and net volumes of a given number (generally log truck loads) of logs. Another method that is being used more frequently is weight scaling, especially for low-value material involving a single species/product, or where all the products being weighed are more or less of the same value.

20.3 MEXICO

Mexico has carried out three activities that can be identified as "national forest inventories", although technically they are not complete forest inventories, as they do not include all of the parameters and procedures that are typically part of one. Of these, only the first, the *Inventario Forestal (1964-1980),* was based on the use of aerial imagery supported by extensive field sampling to establish the location, extent, wood volume and commercial value of forest stands. The *Inventario Forestal* therefore comes closest to being a complete forest inventory.

The second and third "inventories" were essentially updates of land use/land cover (LU/LC) maps using remote sensing imagery and were not in fact complete inventories. The second was based on an analysis of low-resolution Advanced Very High Resolution Radiometer (AVHRR) imagery and was published on a scale of 1:1,000,000 as part of the *Gran Visión* report from the *Secretaría de Agricultura* (SARH). The purpose of this inventory was to produce a quick estimate of the extent of forest lands to support Mexico's information needs at the national level, most of which were related to international treaties.

Mexico's most recent (and third) national inventory was completed in 1994. Called the *Inventario Nacional Forestal Periódico (1992-1994)*, it was a LU/LC map based on visual interpretation of Landsat Thematic Mapper (TM) imagery and field measurements on about 20,000 plots obtained through systematic sampling and intended for the determination of vegetation type. It produced cartographically to a scale of 1:250,000 for the purpose of providing information on the location, extent and timber volume on forest lands to support the country's operational needs. In fact this forest inventory only produced location and extent data for three fourths of the country and yielded no data on timber volumes.

Mexico has now embarked on a new national inventory,, the *Inventario Nacional Forestal* (INF), which defines "forest" as any area covered by naturally occurring trees, scrub, or arid zone vegetation. The *Instituto Nacional de Investigaciones Forestales* (INIFAP) carries out the inventory under the supervision of the *Comisión Nacional Forestal* (CONAFOR) and with funding from CONAFOR's parent agency, the *Secretaría de Medio Ambiente y Recursos Naturales* (SEMARNAT). CONAFOR provides detailed guidelines for the collection of inventory field data, which will provide wood volume estimates that

can be used to "characterize" some of the INEGI LU/LC classes in terms of carbon content. Since the early 1980s the INF has been the only government-approved source of wood volume data in Mexico.

SEMARNAT is responsible for the design and supervision of the national forest inventory, which follows closely the design of the USDA Forest Service FIA and the Canadian Forest Service inventories. Thus the new survey will generate data for Mexico that are comparable to those for the rest of North America. Implementation of the forest inventory survey is underway, with modest progress being made in the basins of the rivers Lerma-Santiago in Central Mexico and Pánuco in the state of Veracruz. Limited progress is also being made in parts of the states of Hidalgo and Jalisco.

By overlaying a sampling grid on Land use/land cover maps produced by the *Instituto Nacional de Estadística Geografía e Informática* (INEGI), the INF can produce sample wood volume data for all areas mapped as "forest" on the INEGI's Series III maps. The grid spacing is 5 km × 5 km for tropical and temperate forest, 10 km × 10 km for scrub land and 20 km × 20 km for arid zones. The INEGI maps are restricted to "forest" classes, i.e areas where INF field data have been collected. That is, the INF sampling grid "selects" points that fall into "forest" classes and excludes points that fall into other classes such as agriculture, urban areas and water bodies.

Although the primary focus of the INF is on estimating the commercial potential of forest lands, the survey also collects data and information on scrub land and arid zone vegetation.

REFERENCES

Anon. 1999. Plot-based National Forest Inventory Design for Canada: An interagency partnership project. NFI design version 2.0 March 31, 1999. 62 p. http://www. pfc.forestry.ca/monitoring/inventory/ canfi/docs/design2_e.pdf

ARD and Grupo Darum 2002. *Mexico - Critical Analysis of the Current Deforestation Rate Estimates*. Report submitted to the United States Agency for International Development. 32 p, http://www.dec.org/pdf_docs/PNACP628.pdf

Bonnor, GM, 1982: Canada's forest inventory 1981. Dep. Environ., Can. For. Serv. For. Statistics and Systems Br.

Caesar, R.P.F. 1975. Canadian Industrial Forest Inventory Methods State of Art. In: Proceedings of the workshop – Canadian Forest Inventory Methods, June 1975. University of Toronto Press:35-42.

Dirección del Inventario Nacional Forestal. 2002. Manual Para Realizar los Trabajos de Campo del Inventario Nacional Forestal y de Suelos 2000-2006. Mexico City: Subsecretaría de Gestión para la Protección Ambiental, Dirección General de Federalización y Descentralización de Servicios Forestales y de Suelo. 63 p.

FIA 2004. Forest Inventory and Analysis, Phase 2 and Phase 3: Ground, Measurements
FIA Fact Sheet Series. 2 pp.

Forestry Canada, 1988: Canada's forest inventory 1986. Can. Govt. Publishing Centre.

Gray, S.L. and Nietmann, K., 1989: Canada's forest inventory 1986: technical supplement. For. Can., Petawawa Natl. For. Inst., Inf. Rep. PI-X-86.

Gray, S.L. and Power, K. 1997. Canada's forest inventory 1991: the 1994 version - technical supplement. 1997. Information Report BC-X-363. 73 p. Victoria, BC ; Natural Resources Canada, Canadian Forest Service, Pacific Forestry Centre, http://warehouse.pfc.forestry.ca/pfc/4944.pdf

Haddon B., ed. 1988: Forest inventory terms in Canada, 3rd edition. Can. Govt. Publishing Centre.

Lowe J.J. 1991: Canada's forest inventory: the sustainable commercial timber base and its growth rate. Proc. nat. conf. Canada's Timber Resources, For. Can., Petawawa Natl. For. Inst., Inf. Rep. P1-X-101.

Lowe J.J. 1994. National Forest Inventory by Aggregation of Existing Inventories. Proceedings of Ilvessalo Symposium on National Forest Inventories. Finland 17-21 August, 1992. IUFRO S4.02. The Finnish Forest Research Institute. Research Papers 444. pp.

Lowe, J.J. Power, K. Marsan, M. 1996. Canada's forest inventory 1991: summary by Terrestrial Ecozones and Ecoregions. Information Report BC-X-346E. Victoria, BC: Natural Resources Canada, Canadian Forest Service.

Lund, H. Gyde, Thomas, Charles E. 1989. A primer on stand and forest inventory designs. Gen. Tech. Rep. WO-54. Washington, DC: U.S. Department of Agriculture; Forest Service. 96 p. (PDF: 4.1 MB) http://www.fs.fed.us/rm/ftcol/publications/outofprint/wo_54.pdf.

Pentony, Mark F. 1992. How to Contract for Small and Large Inventories. Stand Inventory Technologies Symposium: An International Multiple Resource Conference, World Forestry Center, Sept. 13-17, 1992. Bethesda, MD: American Society for Photogrammetry and Remote Sensing.

SARH 1994a. Inventario Nacional Forestal de Gran Visión. Mexico 1991-1992. Reporte Principal. Mexico City: Secretaría de Agricultura y Recursos Hidráulicos, Subscretaría Forestal. 53 p.

SARH 1994b. Inventario Nacional Forestal Periódico. Mexico City: Secretaría de Agricultura y Recursos Hidráulicos, Subscretaría Forestal. UNAM. 2000. Inventario Forestal Nacional 2000-2001. Informe Final a SEMARNAP. Universidad Nacional Autónoma de Mexico. Instituto de Geografía. 266 p.

State of Canada's Forests 2003-2004. Electronically available in http://www.nrcan.gc.ca/cfs-scf/national/what-quoi/sof

PART IV

FUTURE

CHAPTER 21

MODERN DATA ACQUISITION FOR FOREST INVENTORIES

MARKUS HOLOPAINEN AND JOUNI KALLIOVIRTA

University of Helsinki, Finland

21.1 INTRODUCTION

Detailed, timely information on forests is required for traditional forest management, forest certification and the assessment of forest biodiversity, and this increased demand for information, combined with the desire to reduce costs, has created a need to increase the efficiency of forest data acquisition. Technologies for acquiring spatial forest resource data have developed rapidly in recent years. Fieldwork has been enhanced by global satellite positioning systems, automatic measuring devices, field computers and wireless data transfer, and modern remote sensing is now able to provide cost-efficient spatial digital data that are more accurate than ever before. This chapter scrutinizes the possible ways in which these new technologies could be used in forest inventories.

21.2 REMOTE SENSING

21.2.1 Digital aerial photos

Aerial photos have traditionally been the most common source of remote sensing imagery for use in forest inventories. As a result of technological advances, the interpretation of aerial photographs has evolved from analogue imagery and devices to digital applications. An analogue aerial photo can be digitized by scanning, or else the photos can be taken directly with digital cameras. Digital aerial photos can be rectified to the desired coordinate system, and the effects of terrain elevation can be considered with a digital elevation model. The result of such a rectification, an orthophoto, is spatially almost as accurate as an ordinary map, and the image is highly scalable. Digital orthophotos are currently used mostly as background images

A. Kangas and M. Maltamo (eds.), Forest Inventory – Methodology and Applications, 343–362.

in forestry mapping and geographic information system (GIS) applications, e.g. for on-screen visual interpretation. The next, considerably more demanding step will be to utilize the imagery in fully automatic computerized interpretation.

21.2.2 Spectrometer imagery

A spectrometer is a device capable of imaging extremely narrow bands over a broad range of wavelengths. In other words, the device's spectral resolution is high. The visible light and near-infrared wavelength ranges can be imaged by up to 300 bands, and measurements can be taken either on the ground or from aircraft. The advantages of spectrometer imaging over other remote sensing techniques are (i) the abundance of wavelength bands, and (ii) the ability to select certain narrow wavelength bands. A function of all imaged wavelength bands, or a spectral fingerprint, can also be used to improve accuracy in the interpretation phase. Furthermore, basic information on the spectral properties of the objects deduced is acquired which can be utilized in the interpretation of other remote sensing imagery.

21.2.3 High-resolution satellite imagery

Langley (1975) was one of the first to test imagery from space for forest inventory purposes, since when the technology has vastly improved. The most notable advance in modern satellite remote sensing has been the marked improvement in spatial resolution. The first commercial satellite having a spatial ground resolution < 1 m, IKONOS, was launched in 1999. This had a ground resolution in the panchromatic mode of 0.8 m (nadir point), and the ground resolutions of the 4 bands ranging from 0.45 μm to 0.9 μm in the multiband mode were 3.2 m. A single IKONOS image covered an area of 11 km x 11 km. The American QuickBird 2 satellite, launched in 2001, had a ground resolution of 0.61 m in the panchromatic mode and 2.44 m in the multiband mode. Modern high-resolution satellite imagery provides a highly attractive alternative to digital aerial photography and can be used in mapping applications, for example, which to date have been carried out in Finland exclusively with aerial photos. In forestry, high-resolution satellite imagery could in principle be used for forest planning purposes, but the high cost of these images has hindered such development up to now.

21.2.4 Microwave radars

Radar imaging is an active remote sensing technology in which radiation emitted by the device itself is measured. The device emits recurrent microwave pulses of a certain frequency and the receiver in turn measures the radiation reflected from different ground objects. The main advantage of radar imagery is its high temporal resolution, as images can be acquired at practically any time, while optical satellite imagery may be hard to come by in Finland due to the often cloudy conditions.

Radar imagery is thus an interesting alternative for forest mapping, given that its accuracy is sufficient for acquiring detailed plot and compartment information.

Microwave satellite images have so far not been able to supply sufficiently detailed information, but they have proved suitable for large-area forest mapping where optical satellite imagery has not been available. Future radar sensors will also be able to produce highly detailed forest imagery. Several sensors having spatial resolutions of 1-3 m are currently being planned, e.g. the TerraSAR sensor, which will have a ground resolution of 1 m, complete polarmetry (polarization = direction of oscillation), stereo imaging and interferometry imaging (phase difference of two separate radar signals). It is planned that TerraSAR images should be available within 5 years. Due to the appropriate resolution and number of imaging channels (several frequencies, polarizations, imaging angles, imaging times), satellite radar imagery will also soon be able to provide valuable detailed information for forestry purposes.

21.2.5 Profile imaging

Profile imaging is aimed at producing height profiles of objects by imaging the area of interest in parallel flight paths. Since the flight altitude is only 100-200 m, a single flight path covers a relatively narrow strip of terrain, but a 3-dimensional (3D) profile of the imaged area can be obtained by combining several flight-path images. One example of a profiling sensor is profiling microwave radar. It has been shown by Hyyppä (1993) that profiling microwave radar is capable of measuring the mean and dominant height of the growing stock in a stand, the basal area, stem volume, crown height, development class and soil type. The main problem has arisen from the low ground width of the images, so that the resulting flight path density in operative use has been so high that imaging costs have soared astronomically.

21.2.6 Laser scanning

Laser scanning provides more promising remote sensing material than profile imaging. This technique makes it possible to reach even the single-tree level in forest imaging. A laser scanner emits an infrared laser pulse, and each image row consists of a 3D point cloud representing near-adjacent ground elements. The x, y and z coordinates are derived for each measurement, and both 3D terrain and crown models can be derived by analysing the measurements, so that the difference between these models provides a height model for the growing stock. The main advantage of this technology compared with optical remote sensing is that the physical dimensions of the imaged objects can be measured directly (Hyyppä and Inkinen 1999).

21.3 USE OF MODERN REMOTE SENSING IN FOREST INVENTORIES

21.3.1 Accuracy of remote sensing in forest inventories

When considering remote sensing in forest inventories one must weigh its costs and benefits, i.e. the reductions in fieldwork costs, against the costs stemming from the acquisition, preprocessing and interpretation of the remote sensing imagery. If remote sensing is regarded as beneficial, the next step is to consider the type of remote sensing to be employed. Should the imagery be acquired by satellite or by aircraft, and what is the most suitable spatial, spectral, radiometric and temporal resolution of the imagery, or should active remote sensing be used? These issues depend on the size of the inventory area, the purpose of the inventory (mapping, monitoring), the desired level of accuracy (region, compartment, tree) and the imaging costs. In other words, if the purpose of the inventory is, say, to locate highly stocked areas for wood-purchasing purposes, highly detailed information may not necessarily be required. In this case the use of moderate-cost mid-resolution imagery (e.g. Landsat) may be recommended. On the other hand, if the purpose is to assess intra-compartment variation or single-tree characteristics, airborne optical imagery or laser scanning may be the best choice.

Promising results in generalizing field inventory results to large forest areas have been achieved using remote sensing (e.g. Tokola 1990, Tomppo 1990, Tokola and Heikkilä 1997, Katila and Tomppo 2001, Hyvönen 2002, Katila 2004), but apart from visual interpretation of aerial photos, remote sensing has rarely been used for forest planning in connection with compartment-based inventories in Finland, for two main reasons. Firstly, delineation of the compartment boundaries is a highly subjective matter and thus difficult to accomplish automatically by means of computerized methods, and secondly, computerized interpretation methods have so far not been sufficiently accurate.

Recent results (e.g. Holopainen 1998, Hyyppä and Inkinen 1999, Pitkänen 2001, Tuominen and Poso 2001, Pekkarinen 2002, 2004, Anttila 2002a, b, Anttila and Lehikoinen 2002, Hyvönen 2002, Uuttera et al. 2002) suggest that the most suitable type of remote sensing imagery for forest-planning purposes in Finland is currently digital aerial photos and that for large-area inventories passive satellite imagery. The main advantages of mid-resolution satellite imagery over aerial photos are its markedly lower acquisition cost per areal unit and its higher spectral resolution. High-resolution satellite imagery (e.g. IKONOS) is very much comparable to aerial photos, but the main advantages of the latter lie in their slightly better spatial resolution, lower imaging costs and above all the long tradition of using them in forest planning. Visual photo interpretation has been carried out for decades and inventory staff can therefore be conveniently trained to use and interpret digital aerial photos.

If only the accuracy of remote sensing is considered, the most promising fields of development are those related to the direct measurement of object characteristics. Laser scanning and individual tree measurements using digital aerial photogrammetry are examples of these technologies. Applications of airborne laser

scanning in forestry include the determination of terrain elevations (Kraus and Pfeifer 1998), estimation of mean the height and volume of stands (Næsset 1997a, 1997b), estimation of the height and volume of individual trees (Hyyppä and Inkinen 1999, Brandtberg 1999), tree species classification (Brandtberg et al. 2003, Holmgren and Persson 2004) and measurement of forest growth and detection of harvested trees (Yu et al. 2004). The accuracies of laser-scanning estimates at the tree, plot and stand levels are very similar or even better than those achieved in traditional field inventories (Holmgren 2003, Næsset 2004). The first research to compare laser-derived forest inventory estimates with estimates obtained by other remote sensing methods at a single test site was carried out by Hyyppä and Hyyppä (1999), who discovered that laser-derived attributes were more accurate than those obtained with other remote-sensing inventory methods. The results also showed that laser scanning is the only remote sensing method that meets the requirements for accuracy in operative stand-based forest inventories.

The heights of individual trees can be measured to a maximum accuracy of 50 cm using laser scanning or digital photogrammetry (Hyyppä and Hyyppä 1999, Korpela 2004), and basal area and stem volume at the stand level can be obtained with a standard error of about 10% if the relationship between the height and diameter of the tree can be resolved appropriately. Use of a distribution function can be of help in assessing the amount of wood in the second and third storeys (Maltamo et al. 2004). Tree species can be deduced with about 80-90% accuracy for individual trees (Persson et al. 2002, Holmgren and Persson 2004), and laser surveying provides a digital elevation model (DEM) with an accuracy between 20 cm and 40 cm in hilly, forested areas (Hyyppä et al. 2000, Ahokas et al. 2003). The accuracies of 2D and 3D measurements made on digital aerial photographs and laser scans compared with a traditional compartment-based inventory are shown in Table 21.1.

Table 21.1 Accuracies (RMSE%) of different forest inventory methods (Uuttera et al. 2002 (a), Korpela 2004 (b), Næsset 2004 (c), dgM = mean diameter, hgM = mean height, n/ha = stem number, age = mean age).

	3D and laser scanning			Compartment-based inventory			2D photographs		
	A	B	c	a	b	c	a	b	c
d_{gM} (cm)	15	15	15	15	15	18	20	20	23
h_{gM} (m)	4	4	4	15	15	18	20	20	23
n/ha	20	20	20	20	20	23	65	65	70
age (a)	20	20	30	25	28	25	20	20	30

21.3.2 Stand-, plot- and tree-level measurements on digital aerial photographs

A basic problem inherent in compartment-based inventories is how to measure intra-compartment variance. In traditional inventories information on mean and total values is derived and used for different tree strata, but no information exists on how this stratum information is distributed among the compartments. This problem can be solved, however, by combining positioned field sample plot data with modern remote sensing data. The objects to be interpreted may be smaller and more concretely defined than actual planning compartments, such as fixed-sized plots, automatically defined image segments, or even single trees.

There are at least two ways of assessing intra-compartmental variance by remote sensing. The first of these uses analyses of image tone and texture features at the segment or plot level. In this case the objects to be analysed are either automatically derived image segments or systematically distributed fixed-sized plots (see Holopainen 1998, Pekkarinen 2004, Tuominen and Pekkarinen 2005). This approach requires successful correction of radiometric distortions in the high-resolution imagery.

The imaging geometry at the time of exposure and the vegetation structure will greatly affect the illumination and cause bidirectional reflectance effects (Kimes et al. 1980, Kimes 1984, Li and Strahler 1986, Kleman 1987, Leckie 1987, King 1991, Abuelgasim and Strahler 1994, Fournier et al. 1995), which can be observed in the form of variations in brightness, especially in airborne images, where objects in the direction of the incoming solar radiation expose their shady sides to the sensor and those in the opposite direction expose their illuminated sides. As a result, the same forest or vegetation type will have totally different reflectance values and texture features depending on its position in the photograph (Figure 21.1). Empirical corrections for bidirectional reflectance have been applied successfully to aerial photographs (e.g. by Holopainen and Wang 1998a, 1998b, Tuominen and Pekkarinen 2004), video images (e.g. by King 1991, Franklin et al. 1995, Pellikka 1998) and multispectral scanner data (e.g. by Leckie 1987, Leckie et al. 1995).

In addition to segment or plot-level estimations, tree-level analyses can be performed, in which tree crown models are derived using either digital photogrammetry or laser scanning. Tree heights can also be derived during the crown identification phase, and other tree characteristics are derived using various tree models. This approach requires successful tree crown identification, especially in 2-storey and multistorey stands, and appropriate tree models.

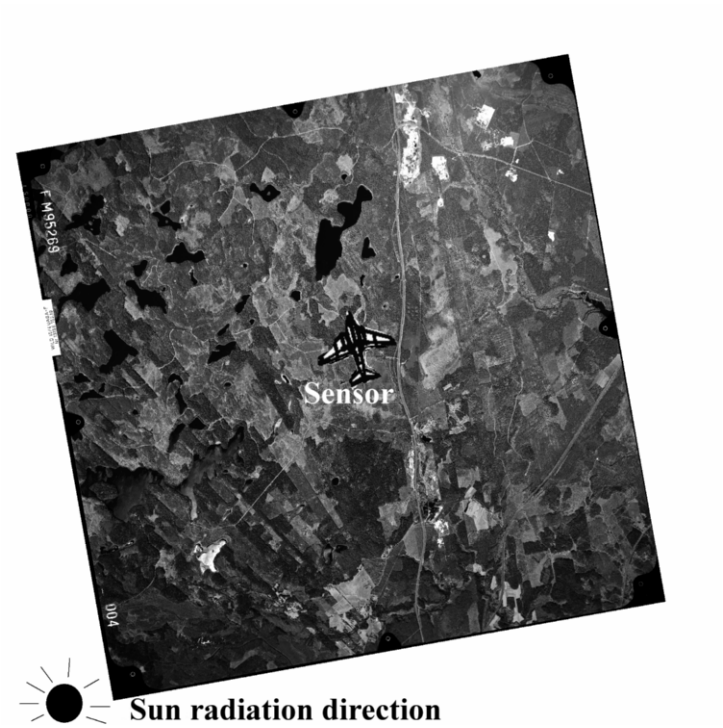


Figure 21.1 The impact of bidirectional reflectance and atmospheric backscattering is seen in the form of intensified brightness in the opposite part of the image from the incoming irradiance. Hyytiälä, Finland, June 24 1995, 2:30 pm solar time, red band of the 1:30 000 photograph (Holopainen and Wang 1998a).

There are several 2D approaches for interpreting tree crowns in single digital aerial photographs. A crown model can be derived and corresponding crowns can be sought for in the image. Problems nevertheless arise from the fact that crown images vary greatly depending on the illumination of the crowns and their location in the image. Another alternative is to analyse the image statistically to identify pixel sets having high grey tones and to assume that they depict actual tree crowns. This approach is in turn highly dependent on the imaging scale used and the conditions encountered. The image can also be divided statistically into segments representing crowns and non-crowns. Furthermore, the borders between illuminated crowns and intermediate areas can be sought. Finally, combinations of these approaches can be used (Holopainen et al. 2000, Anttila and Lehikoinen 2002). These techniques have mainly been used with single images (Figure 21.2).

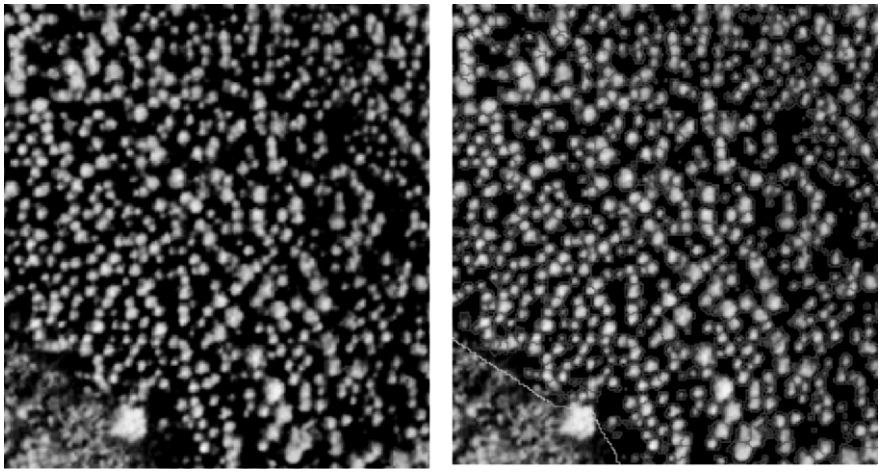


Figure 21.2 Interpreting tree crowns in a single digital aerial photograph by the 2D method. Image copyright Arbonaut Ltd.

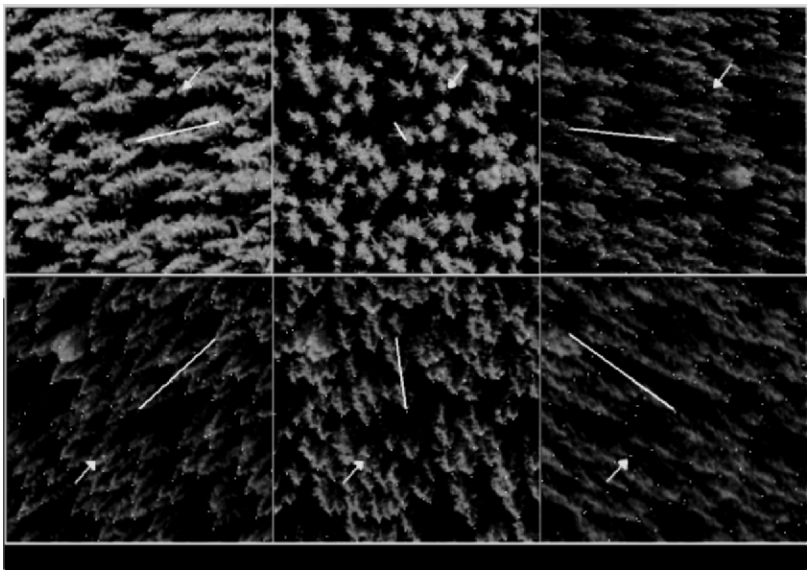


Figure 21.3 3D measurements of tree tops. Colour infrared aerial photographs to a scale of 1:6000. Ca. 20-m high specimens of Norway spruce. Pixel size 14 µm. Front, Front-Side, Back-side, Back, Back-Side and Front-Side illuminated views. Manually measured (multiple image matching using six images) tree top positions (white dots). 18.1 m "trunk" rom apex (200.8 m a.s.l.) to DTM superimposed (white lines). A 5 m long sun-ray projected at Z =200.8 m a.s.l. (yellow arrows) (Korpela 2004). Image copyright FM-Kartta International Ltd.

Korpela (2004) presented a new forest inventory method in which multiple digitized aerial photographs are used for manual and semiautomatic 3D positioning of treetops, species classification and measurements of tree height and crown width (Figure 21.3). Tree height and volume can be measured with the same accuracy as by laser scanning, and tree species can be determined with about 80-90% correctness (Korpela 2004). It is possible to achieve better accuracies using 3D digital photogrammetry than with an inventory method based on 2D measurements of digital aerial photographs (Uuttera et al. 2002, Korpela 2004).

When operating on the segment or plot level the imagery to be analysed may consist of rather small-scale (1:20 000 – 1:30 000) digital aerial photos or even high-resolution satellite images. Tree-level analyses in turn require stereo pairs (2 or more) of large-scale digital aerial photos (at least 1:16 000) or laser scanner images. The costs of a reliable tree-level analysis are therefore considerably higher than those of a segment or plot analysis. Independent of the approach used, successful analyses require accurately measured and located ground-truth data. The accuracy of the analysis can also be improved by the use of advance information such as previous compartment-based inventory results. The tree-level approach is further dependent on models depicting the relationships between tree characteristics. Finally, theoretical models taking into account trees that are invisible in the remote sensing imagery are also required.

21.3.3 Stand-, plot- and tree-level measurements using laser scanning

Extraction of forest variables using laser scanner data can be divided into two categories: inventories performed at the stand or plot level, and individual tree-based inventories. From a methodological point of view, methods can be divided into statistical and image processing-based retrieval methods (Hyyppä et al. 2004).

In the statistical methods, features and predictors are assessed from the laser derived surface models and point clouds used for forest parameter estimation, typically by means of regression analysis. Percentiles in the distribution of canopy heights have been used as predictors in regression models for estimating mean tree height, basal area and volume (Lefsky et al. 1999, Magnussen et al. 1999, Means et al. 2000, Næsset 1997a, 1997b, Næsset and Okland 2002, Næsset 2002). Næsset (2002) estimated several forest attributes using a two-stage procedure applied to field data. His canopy height metrics included quantiles corresponding to the 0,10,…90 percentiles of the first pulse laser canopy heights and corresponding statistics, whereas canopy density corresponded to the proportions of both first and last pulse laser hits above the 0,10,…90 quantiles for the total number of pulses.

Physical features such as crowns, individual trees, group of trees, or whole stands can be delineated using image processing techniques on laser scanner data (Hyyppä et al. 2004), and tree locations can be found by detecting local image maxima. In laser scanning a local maximum is detected using the canopy height model, after which the edge of the crown can be found using the processed canopy height model. This approach can provide tree counts, tree species, crown area, canopy closure, gap analysis and volume and biomass estimates (Gougeon and Leckie 2003).

Hyyppä and Inkinen (1999) were the first to demonstrate a tree-based forest inventory using a laser scanner in which maxima in the canopy height model were used for finding trees and segmentation for edge detection. In this way 40 to 50% of the trees in coniferous forests could be correctly segmented. Persson et al. (2002) improved the crown delineation and were able to link 71% of the tree heights with reference trees. Other attempts to use a tree-based approach have been reported by Brandtberg et al. (2003) Leckie et al. (2003), and Popescu et al. (2003), for instance. Methods for obtaining tree-based measurements using laser scanner data are still under development, however, and empirical studies on the quality of the approaches are needed.

21.3.4 Integration of laser scanning and aerial imagery

The acquisition of laser scanning and digital aerial photographs could be integrated in the future. Laser data provide accurate tree height information, which is missing from single aerial photographs, whereas digital aerial photos provide more details of the spatial geometry and more colour information that can bee used for classifying tree species and health. Both provide information on crown shape and size. The first attempts at integrating laser scanner data with aerial imagery have been reported by St-Onge (1999), Leckie et al. (2003) and Persson et al. (2004). Further studies are nevertheless required on methods for integrating laser scanner data with aerial imagery for forest inventory purposes.

Due to the low imaging altitudes and complicated preprocessing and interpretation procedures, the costs of laser scanning are currently quite high. The availability of laser data is improving significantly year by year, however, and the costs are steadily decreasing due to the acceptance of new systems with higher sampling densities and higher flight altitudes. The present costs of laser surveying are highly dependent on the size and shape of the test site. The most economic use of laser scanning in forestry is to apply it to strip-base sampling, since long strips are economic to fly. Laser scanning samples could be used in a compartment-based forest inventory if a cheaper remote sensing material (e.g. digital aerial photographs) were available for generalizing them to an entire forested area (Holopainen and Hyyppä 2003).

21.4 IMPROVING THE QUALITY OF GROUND-TRUTH DATA IN REMOTE SENSING ANALYSIS

21.4.1 Development of field measuring devices

One of the major factors affecting the accuracy of numerical image interpretation regarding stand-level analyses is the accuracy of the ground-truth data used. The standard error in stand data derived from compartment-based forest planning inventories, commonly used as ground-truth data, is as high as 26 – 36% (Poso 1983) or 15 – 24% (Laasasenaho and Päivinen 1986), which is naturally also

reflected in the interpretation accuracy. Ground-truth errors may in fact be even larger than the actual interpretation errors. It is therefore of the utmost importance to improve the accuracy of ground-truth data.

Modern measuring equipment provides a reliable means for improving the efficiency and accuracy of field measurements. Modern field measurements are carried out with the aid of field computers and satellite-positioning systems, with which measured forest data can be transferred directly to databases accompanied by accurate positioning data. Devices for improving the efficiency and accuracy of stock measurements have also been developed thanks to rapid technological progress, but although various electronic dendrometers, callipers and height-measuring devices have already been tested, the efficiency of forest data collection has not improved significantly. Devices equipped with laser technology, for example, have been tested in the United States (Carr 1992, 1996, Williams et al. 1999), but these have been shown by Skovsgaard et al. (1998) and Parker and Matney (1999) to be inefficient and too expensive. In general, the usability of measuring devices with new technology has been quite poor. To be efficient, a device should enable the measurement of at least the basic tree characteristics. Some new field measurement devices equipped with laser technology have developed recently, and the exploitation of digital photographs seems to be becoming more realistic.

21.4.1.1 Terrestrial lasers

Laser scanners have opened up a new dimension in the field of surveying with their data capturing properties. Laser scanning is increasingly being used in various applications and it is also a promising method for forest inventories. Several companies are now marketing laser scanners for terrestrial applications, e.g. Leica, Optech, Riegl and Zöller + Fröhlich. According to Fröhlich and Mettenleiter (2004), terrestrial laser scanners can be categorized by the principle used in their distance measurement system. Both the range and the resulting accuracy of the system correlate with the distance measurement principle (i.e. pulse, phase or triangulation). The most popular measuring system at the moment is pulsed time of flight, which allows measurements of distances up to several hundreds of metres. Another common technique for medium ranges is the phase measurement principle, whereas the optical triangulation technique allows measurements only up to distances of few metres. For forestry applications (e.g. to create a three-dimensional model of a forest stand) a laser scanner using the pulse or phase principle and equipped with GPS seems to be appropriate.

A raw scanned data set contains a huge number of points, and the recognition of trees in point clouds is essential for estimating forest characteristics. According to Aschoff and Spiecker (2004), tree detection has to run quickly and almost automatically for terrestrial laser scanners to be useful in a forest inventory context, and they present a semi-automatic algorithm for detecting trees that contains several steps: 1. The scanned data is filtered to eliminate outliers in the point cloud. 2. A digital terrain model (DTM) is generated, on the basis of which horizontal

layers at a constant distance above the terrain are generated. 3. Objects that are not of interest in the layers, such as bushes and tree crowns, are filtered out. 4. A validation check on the resulting trees is performed by linear regression. The processing time is an essential consideration for using the method in a standard forest inventory application, and some work still has to be done on the filtering methods and data collection to make the algorithm quick enough for practical forestry use (Aschoff and Spiecker 2004).

Some forestry tests using laser scanners operating on a phase principle have already been carried out. Thies and Spiecker (2004), for example, have tested the IMAGER 5003 laser measuring system produced by Zoller + Fröhlich in order to evaluate its measuring accuracy for detecting tree stems under typical forest conditions following the method presented by Aschoff and Spiecker (2004), i.e. deriving diameters at breast height (DBH), tree heights and coordinates for tree positions. The accuracy of tree position determination was almost as good as with a conventional tachymeter, and diameters were also measured with good accuracy, but tree heights were overestimated quite considerably, so that the method still needs to be improved. A possible source of error in any case of automatically derived DBH could be the DTM, because of ground vegetation and rocks on the ground. Thies and Spiecker (2004) emphasize that no terrestrial laser scanning system is yet ready for practical forestry use. Although terrestrial laser scanning offers advantages such as the opportunity to determine the quality of the timber contained in standing trees and less dependency on the observer, careful attention should be paid to economic aspects when considering its adoption.

21.4.1.2 Laser relascope

Development of a laser relascope, in practice a combination of a dendrometer and a relascope (Kalliovirta et al. 2005), was initiated in 1998. The device is based on laser measurements of angles and distances, and enables tree heights and tree diameters at arbitrary heights to be measured at plot centres without actually physically touching the trees. All the measurements can be positioned accurately using GPS (Laasasenaho et al. 2002, Koivuniemi 2004).

The third laser relascope prototype includes a laser rangefinder, a variable-width slot with a fixed-length arm, an electronic compass, an electronic inclinometer, a data collection/processing unit and a GPS receiver (Figure 21.4). Data from sensitive elements are saved in the data collection/processing unit, which also contains a data collection program that can perform some calculations. A serial port is included in the device for charging the batteries and transferring data to a PC, and a data collection program for transfer from a PC to the laser relascope. A rechargeable battery and back-up battery are used as power sources. This newest prototype weighs about 2 kg and can be folded to make carrying easier. The length of the device is 92 cm when in use for measurement purposes and 51 cm when folded for carrying.

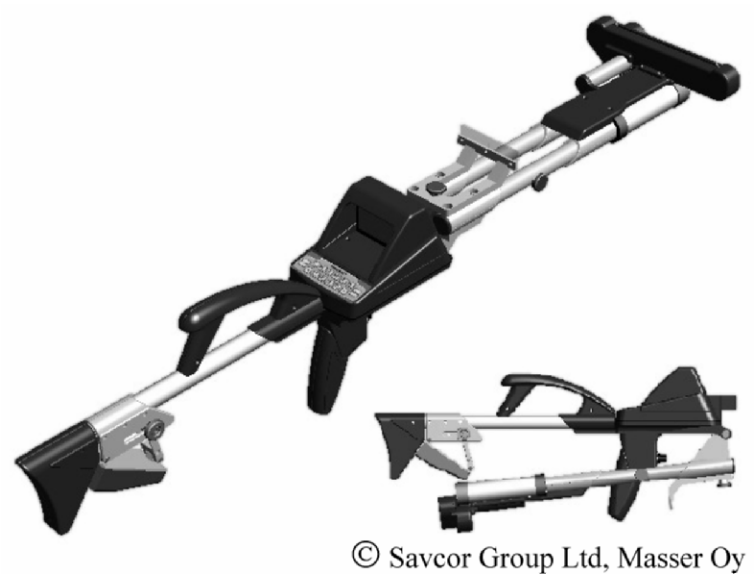


Figure 21.4 The third laser relascope prototype, opened out for measuring and folded for carrying.

The basic principles behind relascope measurements (Bitterlich 1949) are used to measure tree diameters. When the relascope slot sides are positioned exactly at the sides of the trees, the relationship between the diameter of the tree and the viewing distance is the same as the relationship of the slot width to the arm's length. The distance from the eye of the measurer to the tree is measured with a laser rangefinder. In addition, the distance between the eye of the observer and the slot of the relascope, i.e. the length of the fixed relascope arm, is known. Therefore, when the width of the slot is known, the diameter of a tree can be calculated by triangulation (Räty 2001). The width of the movable slot is adjusted using a tiny electric motor run by the measurer with a toggle switch. To measure stem diameters, the sides of the slot must be adjusted to the sides of the tree (Figure 21.5). To ensure that the distance between the eye of the measurer and the slot of the relascope is always the same, a support is provided for the observer's cheek. A transparent sight plate is placed in front of the processing unit, and for appropriate measurements the upper edge of this sight plate must be in line with the slot. The vertical aiming line in the centre of the sight plate must be directed at the centre of the stem, and the laser is similarly directed at the centre of the stem.

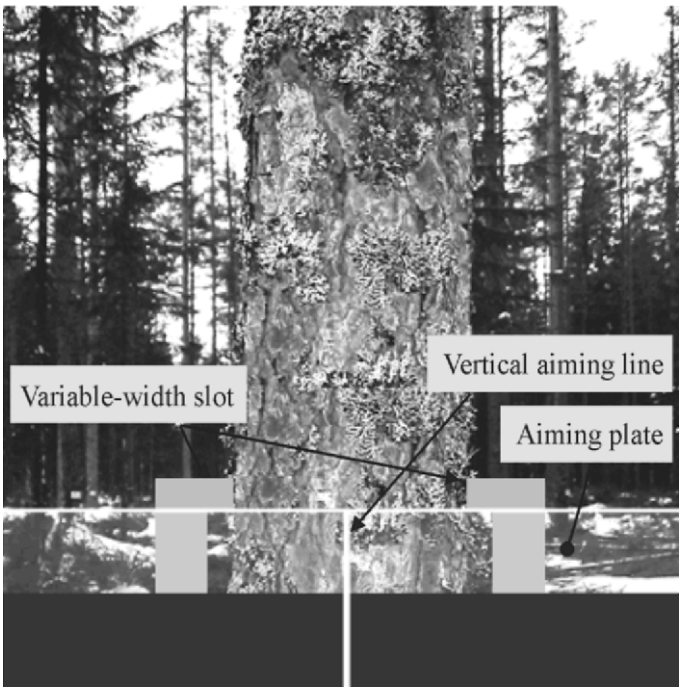


Figure 21.5 Aiming with the laser relascope.

According to Kalliovirta et al. (2005), the laser relascope gives almost unbiased diameter measurements (overestimation 1.3 mm) at measuring distances of 1.4–15.0 m, the standard error in their tests being 8.2 mm. In height measurements, the device produced unbiased results with the standard error of 4.9 dm, but the volumes calculated for the plots were overestimated by 2.2 m^3/ha (1.4%) on average. The standard error was 4.5 m^3/ha, i.e. 2.8% of the mean volume. The measuring of a sample point took an average of 15.5 min and the measuring of a single tree 85 s. Although the device was too slow for practical inventory work on a compartment basis, it is suitable for collecting accurate ground-truth data for remote sensing analysis.

21.4.1.3 Digital cameras

Tree stem measurements based on digital images represent an interesting attempt to increase the accuracy of the measurements and reduce the dependency on the observer. The cost of such an imaging system is also quite low. Juujärvi et al. (1998) studied a digital camera-based method for estimating the stem diameters of growing trees for forest inventory purposes that employed a single camera, a laser rangefinder and a calibration stick. Tree diameter estimation is a challenging 3D machine vision task, the problem being that of transforming the 2D image

information to a three-dimensional model of the tree stem. Because of the texture richness of the trees and the diverse light conditions, the results were not accurate enough when the image information alone was used, but combination of the image data with a theoretical stem curve model provided realistic results (Juujärvi et al. 1998). A combination of automated photo interpretation with laser relascope measurements could offer an interesting solution to this problem in the future.

21.4.2 Field data acquisition using logging machines

Another new, interesting ground-truth data source is stock data recorded on logging machines. Modern logging machines are commonly equipped with GIS software and GPS devices, enabling data on each harvested tree to be positioned to an accuracy of a couple of metres (Rasinmäki and Melkas 2005). By combining harvested stock data with GPS positioning data, valuable ground-truth data on harvests and changes in forest resources can be obtained efficiently (Laasasenaho et al. 2002). Rasinmäki and Melkas (2005) introduced a method that can be used to estimate the tree composition and volume of arbitrary subdivisions of a harvested stand. The average RMSE of the volume estimates varied from 4% for 0.4 ha subregions to 29% for 0.03 ha subregions. The stand subdivision method affected the accuracy of volume estimation only in the smallest subregions. Compared with the use of harvester data as such, i.e. without tree location simulation, the improvement in total and species-specific volume estimates varied from 5% to 35%.

The development of a stem database for aggregating stem data after collecting has been initiated by Metsäteho (Räsänen 1999). The database is compiled while harvesting stands with modern harvesters, which collect and save accurate stem data in a standardized form that is easy to import into the database. According to Räsänen (1999), one of the uses of the stem database could be as ground-truth data based on reference stands. Stem databases are now being compiled extensively by Finnish forest enterprises. A suitable approach for using reference stands in a stem database is the non-parametric k-Most Similar Neighbour (k-MSN) method (Malinen et al. 2001), which is based on distance-weighted nearest-neighbour estimation in which the k most closely identical stands, found by using variables describing the site and tree stock, are used to estimate the characteristics of the target stand. .

REFERENCES

Abuelgasim, A.A. and Strahler, A.H. 1994. Modeling bidirectional radiance measurements collected by the advanced solid-state array spectroradiometer (ASAS) over Oregon transect conifer forests. Remote Sensing of Environment, 47:261-275.

Ahokas, E. Kaartinen, H., Hyyppä, J. 2003. A quality assessment of airborne laser scanner data. In proceedings of Workshop '3-D reconstruction from airborne laserscanner and InSAR data'. Dresden, Germany, 8-10 October 2003.

Anttila, P. 2002a. Updating stand level inventory data applying growth models and visual interpretation of aerial photographs. Silva Fennica 36:549-560.

Anttila, P. 2002b. Non-parametric estimation of stand volume using spectral and spatial features of aerial photographs and old inventory data. Canadian Journal of Forest Research 32:1849-1857.

Anttila, P. and Lehikoinen, M. 2002. Kuvioittaisten puustotunnusten estimointi ilmakuvilta puoliautomaattisella latvusten segmentoinnilla. Metsätieteen aikakauskirja 3/2002: 381-389. (In Finnish.)

Aschoff, T. and Spiecker, H. 2004. Algorithms for the automatic detection of trees in laser scanner data. In Proceedings of the ISPRS working group VIII/2. Laser –Scanners for Forest and Landscape Assessment. Freiburg, Germany, October, 3-6 2004.

Bitterlich, W. 1949. Das Relaskop. The Relascope (in German). Allgemeine Forst- und Holzwirtschaftliche Zeitung, 60.Jhg., Folge 5/6 März 1949.

Brandtberg, T. 1999. Automatic individual tree-based analysis of high spatial resolution remotely sensed data. PhD thesis, Acta Universitatis Agriculturae Sueciae, Silvestria, 118, Swedish University of Agricultural Sciences, Uppsala, Sweden, 47 p.

Brandtberg, T., Warner, T., Landenberger, R. and McGraw, J. 2003. Detection and analysis of individual leaf-off tree crowns in small footprint, high sampling density lidar data from the eastern deciduous forest in North America. Remote Sensing of Environment 85:290-303.

Carr, B. 1992. Using laser technology for forestry and engineering applications. The Compiler 10:5-16.

Carr, B. 1996. Using the Criterion 400 and Impulse 200 laser instruments to accurately measure trees. The Compiler 14:6-12.

Fournier, R.A., Edwards, G. and Eldridge, N.R. 1995. A catalogue of potential spatial discriminators for high spatial resolution digital images of individual crowns. Canadian Journal of Remote Sensing 21:285-298.

Franklin, S.E., Waring, R.H., McCreight, R.W., Cohen, W.B. and Fiorella, M. 1995. Aerial and satellite sensor detection and classification of western spruce budworm defoliation in a subalpine forest. Canadian Journal of Remote Sensing 21:299-308.

Fröhlich, C. and Mettenleiter, M. 2004. Terrestrial laser scanning – new perspectives in 3D surveying. In Proceedings of the ISPRS working group VIII/2. Laser –Scanners for Forest and Landscape Assessment. Freiburg, Germany, October, 3-6 2004.

Gougeon, F. and Leckie, D. 2003. Forest information extraction from high spatial resolution images using an individual tree crown approach. Information report BC-X-396. Natural Resources Canada, Canadian Forest Service, Pacific Forestry Center, 26 p.

Holmgren, J. 2003. Estimation of forest variables using airborne laser scanning. PhD Thesis. Acta Universitatis Agriculturae Sueciae, Silvestria 278. Swedish University of Agricultural Sciences, Umeå, Sweden.

Holmgren, J and Persson, Å. 2004. Identifying species of individual trees using airborne laser scanning. Remote Sensing of Environment 90:415-423.

Holopainen, M. 1998. Forest habitat mapping by means of digitized aerial photographs and multispectral airborne measurements. University of Helsinki, Department of Forest Resource Management, Publications 18. Doctoral thesis.

Holopainen, M. and Hyyppä, J., 2003, Possibilities with laser scanning in practical forestry. Proceedings from the ScandLaser Conference, Umeå, pp. 264-273.

Holopainen, M., Lukkarinen, E. and Hyyppä J. 2000. Metsän kartoitus lentokoneesta. Helsingin yliopiston metsävarojen käytön laitoksen julkaisuja 26. (In Finnish.)

Holopainen, M. and Wang, G. 1998a. The calibration of digitized aerial photographs for forest stratification. International Journal of Remote Sensing 19:677-696.

Holopainen, M. and Wang, G. 1998b. Accuracy of digitized aerial photographs for assessing forest habitats at plot level. Scandinavian Journal of Forest Research 13:499-508.

Hyvönen, P. 2002. Kuvioittaisten puustotunnusten ja toimenpide-ehdotusten estimointi k-lähimmän naapurin menetelmällä Landsat TM –satelliittikuvan, vanhan inventointitiedon ja kuviotason tukiaineiston avulla. Metsätieteen aikakauskirja 3/2002: 363-379.

Hyyppä, J. 1993. Development and feasibility of airborne ranging radar for forest assessment. Helsinki University of Technology, Laboratory of Space Technology, 112 pp. ISBN 951-22-1888-7.

Hyyppä, J., Hyyppä, H., Litkey, P., Yu, X., Haggrén, H., Rönnholm, P., Pyysalo, U. Pitkänen, J. and Maltamo, M., 2004, Algorithms and methods of airborne laser scanning for forest measurements. Proceedings of the NatScan conference, October 3-6, 2004, Freiburg, Germany.

Hyyppä, H. and Hyyppä, J., 1999, Comparing the accuracy of laser scanner with other optical remote sensing data sources for stand attribute retrieval. The Photogrammetric Journal of Finland 16:5-15.

Hyyppä, J. and Inkinen, M. 1999. Detecting and estimating attributes for single trees using laser scanner. The Photogrammetric Journal of Finland 16:27-42.

Hyyppä, J., Pyysalo, U., Hyyppä, H., Samberg, A. 2000. Elevation accuracy of laser scanning-derived digital terrain and target models in forest environment. In proceedings of 20th EARSeL Symposium and Workshops, Dresden, Germany, 14-17 June, 2000.

Juujärvi, J., Heikkonen, J., Brandt, S. and Lampinen, J. 1998. Digital image based tree measurement for forest inventory. SPIE Conference on Intelligent Robots and Computer Vision XVII: Algorithms, Techniques, and Active Vision 3522:114-123.

Kalliovirta, J., Laasasenaho, J. and Kangas, A. 2005. Evaluation of the Laser-relascope. Forest Ecology and Management 204:181-194.

Katila, M. and Tomppo, E. 2001. Selecting estimation parameters for the Finnish multisource National Forest Inventory. Remote Sensing of Environment 76:16-32.

Katila, M. 2004. Controlling the estimation errors in the Finnish multisource National Forest Inventory. Doctoral thesis. Finnish Forest Research Institute, Research Papers 910, 2004.

Kimes, D.S. 1984. Modeling the directional reflectance from complete homogeneous vegetation canopies with various leaf orientation distributions. Journal of the Optical Society of America 1:725-737.

Kimes, D.S., Smith, J.A. and Ranson, K.J. 1980. Vegetation reflectance measurements as a function of solar zenith angle. Photogrammetric Engineering and Remote Sensing 46:1563-1573.

King, D. 1991. Determination and reduction of cover-type brightness variations with view angle in airborne multispectral videography. Photogrammetric Engineering and Remote Sensing 57: 1571-1577.

Kleman, J. 1987. Directional reflectance factor distributions for two forest canopies. Remote Sensing of Environment 23:83-96.

Koivuniemi, J. 2004. The accuracy of the compartmentwise forest inventory based on stands and located

sample plots (In Finnish). University of Helsinki, Department of Forest Resource Management, Publications 36. 160 p.

Korpela, I. 2004. Individual tree measurements by means of digital aerial photogrammetry. PhD-thesis. Silva Fennica. Monographs 3. 93 p.

Kraus, K. and Pfeifer, N. 1998. Determination of terrain models in wooded areas with airborne laser scanner data. ISPRS Journal of Photogrammetry and Remote Sensing 53, pp. 193-203.

Laasasenaho, J., Koivuniemi, J., Melkas, T. and Räty, M. 2002. Puuston mittaus etäisyyden- ja kulmanmittauslaitteella. Metsätieteen aikakauskirja 3/2002: 523-530.

Laasasenaho, J. and Päivinen, R. 1986. Kuviottaisen arvioinnin tarkastamisesta. Summary: On the checking of inventory by compartments. Folia Forestalia 664. 19 p.

Langley, P.G. 1975. Multistage variable probability sampling. PhD Dissertation, Berkeley, CA, University of California, 101 p. Dissertation thesis 75-22538.

Leckie, G.D. 1987. Factors affecting defoliation assessment using airborne multispectral scanner data. Photogrammetric Engineering and Remote Sensing 53:1665-1674.

Leckie, G.D., Beaubien, J., Gibson, J.R., O'Neill, N.T., Piekutowski, T. and Joyce, S.P. 1995. Data processing and analysis for mifucam: a trial of MEIS imagery for forest inventory mapping. Canadian Journal of Remote Sensing 21:337-356.

Leckie, D., Gougeon, F., Hill, D., Quinn, R., Armstrong, L. and Sheenan, R. 2003. Combined high-density lidar and multispectral imagery for individual tree crown analysis. Canadian Journal of Remote Sensing 29:633-649.

Lefsky, M., Cohen, W., Acker, S., Parker, G., Spies, T., Harding, D. 1999. Lidar remote sensing of the canopy structure and biophysical properties of Douglas-fir western hemlock forests. Remote Sensing of Environment 70:339-361.

Li, X. and Strahler, A.H. 1986. Geometric-optical bidirectional reflectance modeling of a conifer forest canopy. IEEE Transactions on Geoscience and Remote Sensing, 30:276-292.

Magnussen, S., Eggermont, P. LaRiccia, V.N. 1999. Recovering tree heights from airborne laser scanner data. Forest Science 45:407-422.

Malinen, J. Maltamo, M. and Harstela, P. 2001. Application of most similar neighbour inference for estimating marked stand characteristics using harvest and inventory generated stem databases. International Journal of Forest Engineering 12:33-41.

Maltamo, M., Eerikäinen, K., Pitkänen J., Hyyppä, J. and Vehmas, M. 2004. Estimation of timber volume and stem density based on scanning laser altimetry and expected tree size distribution functions. Remote Sensing of Environment 90:319-330.

Means, J., Acker, S., Harding, D., Blair, J., Lefsky, M., Cohen, W., Harmon, M., McKee, A. 1999. Use of large-footprint scanning airborne lidar to estimate forest stand characteristics in the western cascades of Oregon. Remote Sensing of Environment 67:298-308.

Næsset, E., 1997a, Determination of mean tree height of forest stands using airborne laser scanner data. ISPRS Journal of Photogrammetry and Remote Sensing, 52, pp. 49-56.

Næsset, E., 1997b, Estimating timber volume of forest stands using airborne laser scanner data. Remote

Sensing of Environment 61:246-253.

Næsset, E. 2002. Predicting forest stand characteristics with airborne scanning laser using practical two-stage procedure and field data. Remote Sensing of Environment 80:88-99.

Næsset, E. 2004, Practical large-scale forest stand inventory using a small-footprint airborne scanning laser. Scandinavian Journal of Forest Research 19:164-179.

Næsset, E. and Økland, T. 2002. Estimating tree height and tree crown properties using airborne scanning laser in a boreal nature reserve. Remote Sensing of Environment 79:105-115.

Parker, R.C. and Matney, T. G. 1999. Comparison of optical dendrometers for prediction of standing tree volume. Southern Journal of Applied Forestry 23:100-107.

Pekkarinen, A. 2002. A method for the segmentation of very high spatial resolution images of forested landscapes. International Journal of Remote Sensing 23:2817-2836.

Pekkarinen, A. 2004. Image segmentation in multi-source forest inventory. Doctoral thesis. Finnish Forest Research Institute, Research Papers 926.

Pellikka, P. 1998. Development of correction chain for multispectral airborne video camera data for natural resource assessment. FENNIA, 176:1-110. Geographical Society of Finland. Helsinki.

Persson, Å., Holmgren, J. and Söderman, U. 2002. Detecting and measuring individual trees using an airborne laser scanner. Photogrammetric Engineering and Remote Sensing 68:925-932.

Persson, Å., Holmgren, J., Söderman, U. and Olsson, H. 2004. Tree species classification of individual trees in Sweden by combining high resolution laser data with high resolution near infrared digital images. Proceedings of the Natscan Conference, pp.204-207.

Pitkänen, J. 2001. Individual tree detection in digital aerial images by combining locally adaptive binarization and local maxima methods. Canadian Journal of Forest Research 31:832-844.

Popescu, S., Wynne, R. and Nelson R. 2003. Measuring individual tree crown diameter with lidar and assessing its influence on estimating forest volume and biomass. Canadian Journal of Remote Sensing 29:564-577.

Poso, S. 1983. Kuvioittaisen arviointimenetelmän perusteita. Summary: basic features of forest inventory by compartments. Silva Fennica 17:313-349.

Räsänen, T. 1999. Runkopankki puunhankinnan ohjuksen apuvälineenä. Metsätieteen aikakauskirja 4/1999: 727-729.

Rasinmäki, J. and Melkas, T. 2005. A method for estimating tree composition and volume using harvester data. Scandinavian Journal of Forest Research 20:85-95.

Räty, M. 2001. Laserrelaskoopin virheanalyysi. Error analysis of the Laser-relascope (in Finnish, with English abstract). Master's thesis in forest mensuration. University of Helsinki.

Skovgaard, J.P., Johannsen, V.K. and Vanclay, J.K. 1998. Accuracy and precision of two dendrometers. Forestry 71:131-139

St-Onge, B . 1999. Estimating individual tree heights of the boreal forest using airborne laser altimetry and digital videography. International Archives of Photogrammetry and Remote Sensing, Vol 32, part 3-W14, pp. 179-184.

Thies, M. and Spiecker, H. 2004. Evaluation and future prospects of terrestrial laser scanning for

standardized forest inventory. In Proceedings of the ISPRS working group VIII/2. Laser –Scanners for Forest and Landscape Assessment. Freiburg, Germany, October, 3-6 2004.

Tokola, T. 1990. Satelliittikuvan ja VMI-koealatiedon käyttö metsätalousalueen puuston inventoinnissa. Joensuun yliopisto, metsätieteellinen tiedekunta. Lisensiaattitutkimus. 53 p.

Tokola, T. and Heikkilä, J. 1997. Improving satellite based forest inventory by using a priori site quality information. Silva Fennica 31:67-78.

Tomppo, E. 1990. Satellite image based National Forest Inventory of Finland. Photogrammetric Journal of Finland 12:115-120.

Tuominen, S. and Poso, S. 2001. Improving multi-source forest inventory by weighting auxiliary data sources. Silva Fennica 35:203-214.

Tuominen, S. and Pekkarinen, A. 2004. Local radiometric correction of digital aerial photographs for multi-source forest inventory. Remote Sensing of Environment 89:72-82.

Tuominen, S. and Pekkarinen, A. 2005. Performance of different spectral and textural aerial photograph features in multi-source forest inventory. Remote sensing of Environment 94:256-268.

Uuttera, J., Hiltunen, J., Rissanen, P., Anttila, P. and Hyvönen, P., 2002, Uudet kuvioittaisen arvioinnin menetelmät – Arvio soveltuvuudesta yksityismaiden metsäsuunnitteluun. Metsätieteen aikakauskirja, 3, 523-531. (In Finnish)

Williams, M., Cormier, K., Briggs, R. and Martinez, D. 1999. Evaluation of the Barr and Stroud FP15 and Criterion 400 laser dendrometers for measuring upper stem diameters and heights. Forest Science 45:53-61.

Yu, X.W., Hyyppä, J., Rönnholm, P., Kaartinen, H., Maltamo, M and Hyyppä, H. 2004. Automatic detection of harvested trees and determination of forest growth using airborne laser scanning. Remote Sensing of Environment 90:451-462.

Managing Forest Ecosystems

1. K. von Gadow, T. Pukkala and M. Tomé (eds.): *Sustainable Forest Management.* 2000 ISBN 0-7923-6356-6
2. K. von Gadow (ed.): *Risk Analysis in Forest Management.* 2001 ISBN 0-7923-6900-9
3. D.L. Schmoldt, J. Kangas, G.A. Mendoza and M. Pesonen (eds.): *The Analytic Hierarchy Process in Natural Resource and Environmental Decision Making*. 2001 ISBN 0-7923-7076-7
4. K. von Gadow, J. Nagel and J. Saborowski (eds.): *Continuous Cover Forestry*. Assessment, Analysis, Scenarios. 2002 ISBN 1-4020-0659-4
5. H. Sverdrup and I. Stjernquist (eds.): *Developing Principles and Models for Sustainable Forestry in Sweden*. 2002 ISBN 1-4020-0999-2
6. T. Paukkala (ed.): *Multi-objective Forest Planning*. 2002 ISBN 1-4020-1097-4
7. G.J. Arthaud and T.M. Barrett (eds.): *Systems Analysis in Forest Resources*. Proceedings of the Eighth Symposium, held September 20-27, 2000, Snowmass Village, Colorado, USA. 2003 ISBN 1-4020-1256-X
8. R.A. Monserud, R.W. Haynes and A.C. Johnson (eds.): *Compatible Forest Management*. 2003 ISBN 1-4020-1536-4
9. C.G. Williams (ed.): *Landscapes, Genomics and Transgenic Conifers*. 2006 ISBN 1-4020-3868-2
10. A. Kangas and M. Maltamo (eds.): *Forest Inventory*. Methodology and Applications. 2006 ISBN 1-4020-4379-1