Remote Sensing Aided Spatial Prediction of Forest Stem Volume

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Abstract

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Modern technology such as the Global Positioning System (GPS) and Geographical Information Systems (GIS) provide new opportunities for forest inventory. These technologies allow representation of forest variables using rasters with cell sizes on the order of 25 m. Such rasters can be estimated from remotely sensed data using models of the relationship between the image's digital number and the forest variables. This thesis investigates the possibility of using estimation methods incorporating remotely sensed data as well as spatial similarity of neighbouring field measurements, to improve prediction accuracy compared to using only remotely sensed data.

Two new spatial prediction methods are presented and evaluated: ordinary kriging using information about edges detected in remotely sensed images, and prediction using Markov Chain Monte Carlo (MCMC) simulation of a new Bayesian state-space model. In addition, ordinary kriging, stratified ordinary kriging, ordinary cokriging, collocated ordinary cokriging, simple kriging with varying local means, and spatial regression using the autoregressive response model, are also evaluated. The methods are applied to predict forest stem volume per hectare in boreal forest in northern Sweden (Lat. 64°14'N, Long. 19°40'E) using Landsat TM data and a large field sampled dataset. Prediction accuracy, as well as practical aspects of the methods, is evaluated. In particular, accuracy is compared with Ordinary Least Squares regression (OLS) using remotely sensed data.

Spatial prediction was, with a few exceptions, more accurate than OLS regression. The largest improvement, 49% lower root mean square error (RMSE), was obtained for plot-level predictions by ordinary kriging using information of edges detected in remotely sensed images, although the method is dependent on densely sampled field data. Promising results were also obtained by simple kriging with varying local means. This method performed well (26% lower RMSE than OLS regression for stand-level predictions), is rather straight-forward to apply in practice, and not as dependent on densely sampled field data. The Bayesian state-space model did not provide improved predictions compared to OLS regression. However, Bayesian modelling is promising for application of spatial models of higher complexity than possible with the other methods.

Keywords: spatial dependence, autocorrelation, forest model, Gibbs sampler.

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To Esther

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Appendix

Papers I-IV

The present thesis is based on the following papers, which will be referred to by their Roman numerals:

I. Wallerman, J., Joyce, S., Vencatasawmy, C.P. & Olsson, H. 2002. Prediction of forest stem volume using kriging adapted to detected edges. *Canadian Journal of Forest Research 32*, 509-518.

II. Wallerman, J., Vencatasawmy, C.P. & Olsson, H. 2002. Geostatistical prediction of forest stem volume using Landsat TM data. Accepted for publication in *Photogrammetric Engineering & Remote Sensing*.

III. Wallerman, J., Vencatasawmy, C.P. & Olsson, H. 2002. Prediction of forest stem volume using spatial regression of Landsat TM data. Submitted.

IV. Wallerman, J., Vencatasawmy, C.P. & Bondesson, L. 2003. Spatial simulation of forest using Bayesian state-space models and remotely sensed data. Manuscript.

Introduction

The development of computer technology has provided forest management with many new tools for data capture, data representation, and management planning applications. It is now easy to measure the position of survey plots, forest roads, and stand boundaries in the field within a few meters accuracy using standard Global Positioning System (GPS) equipment. The development in sensor technology has also enabled acquisition of remotely sensed data of the forest at a range of scales. Optical remote sensing data are available from satellite sensors providing images with spatial resolution on the order of 25 m (Landsat TM, Landsat ETM+, SPOT HRVIR) as well as 1 m or less (Ikonos, QuickBird) (Kramer, 2002). This thesis is focused on one possible application of Landsat TM data, as well as other remotely sensed data with similar spatial resolution, using models relating the digital number (DN) recorded by the sensor to forest variables measured on 10 m radius field plots. The analyses are made on stem volume of growing stock per hectare, which is one of the economically most important variables in forest management planning (Walter, 1998). This is a measure in cubic meters per hectare (m^3ha^{-1}) of tree volume including bark but excluding branches and stumps.

Modern technology, including the database and spatial analysis capability of geographic information systems (GIS), provide opportunities to use different representations (*i.e.*, spatial models) of forest data in forest management planning systems. The commonly used model in Sweden is to divide a forest holding (for forest companies in northern Sweden typically sized 5000-50000 ha) into administrative units (in general 0.5-10 ha large polygons) of forest with similar characteristics and collect and represent data by unit means. Such units are here referred to as stands, and the map of stands as a forest stand map. The model represents the forest in each stand as homogeneous with similar properties in each part, and the spatial structure is represented by the map of stand boundaries. This approach enables straight-forward database construction as well as natural units of forest for planning and application of silvicultural treatments. However, this model has limitations. For example, the spatial variation in forest is often gradual, and it is not always easy to identify clear stand boundaries (Lowell, Edwards & Kucera, 1996; De Groeve & Lowell, 2001). Furthermore, the changes in forest can be different for different parts making stand boundaries less meaningful over time, and since data are acquired on a stand basis there will be problems when the stand delineation is changed (Lowell, Edwards & Kucera, 1996). Finally, it is often difficult to outline stands fulfilling the criteria of homogeneity. Several authors describe the forest, at the landscape level, as resembling a mosaic of patches (Lowell, 1994; Lowell, Edwards & Kucera, 1996; Gilbert & Lowell, 1997; Kleinn, 2000). Lowell (1994) suggests that forest should be represented using fuzzy set methods, rather than using conventional thematic maps. Alternatively, the forest may be represented by a raster model where forest variables are modelled by rasters with very high spatial resolution, compared to the size of areas to which silvicultural treatments are applied to. Raster models of the forest have been investigated in a number of studies. For example, Hof & Joyce (1992, 1993) address a forestry planning approach with multiple goals (wildlife and timber production) which is based on more flexible spatial units than fixed stands, including square cell division of forest. Holmgren & Thuresson (1997) and Gunnarsson *et al*. (1998) introduced and investigated a raster model for Swedish forest conditions, using spatial prediction to construct rasters of forest variables, aiming to dynamically define optimal treatment areas. Furthermore, Lu & Eriksson (2000), Lind (2000), and Öhman (2001) address methods to define optimal treatment areas based on such a raster model of the forest.

Data capture, suitable for a raster-based forest model, can be made using objective sampling of field plots including accurately determined positions. These data can be used to produce raster estimates of forest variables by spatial interpolation or by using additional data sources such as remote sensing data. There are several additional benefits from using this kind of method. First, the data are objective and not subject to subjective errors such as surveyor dependent bias. Second, the dataset can be updated by new measurements directed to areas where new information is needed the most. Third, this approach enables estimation of any spatial area, ranging from a single raster cell to forest stands.

Prediction of forest variables using remotely sensed data

The raster-based model for forest management planning is dependent on methods to construct rasters with accurate estimates of forest variables. This may be achieved by predictions based on optical satellite image data similar to the image data provided by Landsat TM. The TM sensor capture data in seven spectral bands including the visible and infrared range of the electromagnetic spectrum, where measurements of each ground resolution cell (approximately the size of a pixel) represent the average spectral response from several trees. In contrast, sensors producing images with spatial resolution on the order of 1 m provide several measurements for each tree. Strahler, Woodcock & Smith (1986) define these two cases as L-resolution and H-resolution data, respectively. Compared to L-resolution data, H-resolution data provide a high level of detail but require conceptually different models describing each tree, since each pixel recording is very dependent on the part of the tree crown from which it is acquired.

Horler & Ahern (1986) studied the forestry information content in Landsat TM data, addressing classification applications, using data from boreal forest in Canada. The Landsat TM bands TM3 (red), TM4 (near-infrared), and TM5 (mid-infrared) were the most useful bands for general forest-cover-type discrimination. Especially the mid-infrared region of the spectrum was identified to be the most sensitive to changes in stem volume, since the spectral response in this range is strongly related to canopy crown closure. Furthermore, the spectral response from the forest decreased with increasing age until 41-60 years after which the rate of change was small. Horler & Ahern (1986), De Wulf *et al.* (1990), and Ardö (1992) indicate shadowing to largely control the forest canopy spectral response.

Using L-resolution data, for example Landsat TM and SPOT data, has proven feasible in forestry applications. Such data may be related to forest variables using inventory measurements made on similar spatial support. Using a model of this relationship, prediction of a forest variable can be made for an entire raster. This approach has been applied using different modelling techniques: ordinary least-squares (OLS) regression (Tomppo, 1988; Hagner, 1990; Ardö, 1992; Trotter, Dymond & Goulding, 1997; Dungan, 1998), artificial neural networks (Foody & Boyd, 1999; Foody, 2000; Tatem *et al*., 2001), the non-parametric Bartlett's grouping method (De Wulf *et al*., 1990; Trotter, Dymond & Goulding, 1997) and *k* Nearest Neighbour estimation (*k*NN) (Kilkki & Päivinen, 1987; Muinonen & Tokola, 1990; Tomppo, 1990; Nilsson, 1997; Holmström, 2001). However, according to Holmgren & Thuresson (1998), the practical value of optical satellite data for forest variable predictions may be too limited for operational forest management planning.

Prediction accuracy for single raster cells is often low (Curran & Williamson, 1985; De Wulf *et al.*, 1990). Trotter, Dymond & Goulding (1997) used TM data and regression to predict stem volume of mature (stem volume in the range of 190-810 m^3ha^{-1}) *Pinus radiata* plantations in New Zealand, and reported a root mean square error (RMSE) greater than 100 m^3ha^{-1} (with a mean stem volume of 413 m^3ha^{-1}) for cell predictions. Furthermore, the *k*NN method was applied by Holmström & Fransson (2003) to predict forest variables using a combination of SPOT-4 and low-frequency radar data from the airborne CARABAS system. The study by Holmström & Fransson (2003) was made using data from coniferous forest in the south-west of Sweden and reported RMSEs of 64% (of the mean) for plot-level predictions of stem volume using optical data, and 53% using the combination of optical and radar data. The stem volume of the sample plots (10 m radius) was in the range of 0-750 m^3ha^{-1} with a mean value of 171 m^3ha^{-1}. Tokola *et al.* (1996) applied both regression and the *k*NN method on forest in the southern boreal vegetation zone in Finland using data from Landsat TM, SPOT, and the Finnish National Forest Inventory (*i.e.*, relascope sample plots). They reported standard errors, obtained by cross-validation of a large number of plots, of stem volume prediction on the order of 70 to 80 m^3ha^{-1} (>60% of the mean) for plot-level predictions.

Increasing the area to predict, from single plots to forest stands or larger areas, may improve the prediction accuracy. Hagner (1990) predicted forest variables at stand level in boreal forest in northern Sweden, using regression of Landsat TM data and field plot measurements. The reported prediction accuracies, in terms of RMSEs, were 26% (of the mean) for mean stem volume per hectare, 15% for mean diameter, and 21% for mean age. The mean values and stand sizes are not reported. Trotter, Dymond & Goulding (1997) also investigated stand predictions (approximately 40 ha large areas) using TM data, and reported RMSEs of less than 46 m^3ha^{-1}. In a study on coniferous forest in central Sweden, Fransson *et al*. (2001) applied regression of SPOT XS data and field measurements to predict stem volume of stands (5.2 ha mean size and stem volume in the range of 0-305 m^3ha^{-1}) and reported a RMSE of 24% (of the mean 129 m^3ha^{-1}) at best. Holmström & Fransson (2003) also addressed stand level predictions of forest stem volume (in the range of 0-430 m^3ha^{-1} with a mean value of 172 m^3ha^{-1}), using SPOT-4 and CARABAS data, and obtained about 30% RMSE for predictions of stem volume using SPOT-4 data and 22% using both data sources. Optical satellite data have proven useful for county- and nation-wide forest mapping applications (Nilsson, 1997; Reese *et al.*, 2002; Tomppo *et al.*, 2002; Reese *et al.*, 2003).

Spatial prediction of forest variables using remotely sensed data

The accuracy of remote sensing based prediction methods can possibly be increased by incorporating spatially close field measurements of the predicted variable and nearby remote sensing data in each prediction, compared to prediction based on the remote sensing data of the predicted location only. This approach, spatial prediction using remotely sensed data, was addressed by Atkinson, Webster & Curran (1994), Dungan, Peterson & Curran (1994), Curran & Atkinson (1998), and Dungan (1998). There is a large field of statistical spatial models and prediction methods available in the literature, but very few studies are made on prediction of forestry relevant variables using spatial models. This thesis aims to increase the knowledge of remote sensing based spatial prediction of forest variables, through empirical evaluation of methods potentially applicable in operational forestry. In this context, practical application issues and required field sampling efforts are important aspects.

It is meaningful to use spatial prediction only if the predicted variable is spatially dependent. Spatial dependence is said to be present when the value of a variable at one location exerts an influence on the value of the same variable in neighbouring locations (Legendre, 1993; Gilbert & Lowell, 1997). In particular, spatial prediction is only meaningful if the variable is spatially dependent conditional on the spectral features, *i.e.*, the spectral data may describe the spatial structures very well and utilisation of spatially close field measurements will not increase accuracy. Furthermore, Gilbert & Lowell (1997) argued that the presence of spatial dependence does not necessarily imply the possibility of performing accurate spatial prediction.

Spatial variation of forest variables

The spatial structure of a forest is complex. It is the result of geographical variation in soil type, moisture and site index, physical disturbances such as fire and storm felling, as well as competition and pathogens (Czaplewski, Reich & Bechtold, 1994; Kuuluvainen *et al*., 1996; Lowell, Edwards & Kucera, 1996; Gilbert & Lowell, 1997; Bellehumeur & Legendre, 1998; Wells & Getis, 1999; Kleinn, 2000; Stendahl, 2001). Furthermore, silvicultural treatments, such as cleaning, thinning, clear-cutting, and plantation, strongly affect the spatial structure of managed forest (Kuuluvainen *et al*., 1996). In Scandinavia, silvicultural treatments are commonly planned and performed on the basis of a forest stand map, which clearly affects the spatial structure of the forest. Treatments are usually applied to complete stands only and often with the specific aim to reduce the differences within each stand (Kuuluvainen *et al*., 1996). Thus, the stands structure, as well as the history of when and which stands have been selected for treatment, affects the spatial variation of the forest.

The spatial characteristics of forest have been addressed by many authors in the past. Among the first was Matérn (1947, 1960) whose concern was to optimise the field work in National Forest Inventories. Legendre (1993), Bellehumeur & Legendre (1998), and Koenig (1999) pointed out spatial variation and spatial dependence as important aspects of ecological modelling. Clearly, the concept of spatial dependence is only relevant in view of the addressed spatial scale (Hjort & Omre, 1994; Gilbert & Lowell, 1997; Bellehumeur & Legendre, 1998). That is, even though there is no discernable spatial dependence within a small limited area, (*e.g.*, a forest stand), increasing the study area to a landscape probably reveals clear spatial structures. Furthermore, the spatial support of the addressed property is also of crucial importance. Properties of single trees will naturally have different characteristics than an average property of many trees aggregated over an area, such as a field plot.

Within-stand variation

There are many studies made on spatial patterns and dependence of single-tree characteristics, often within a specific stand. These studies mostly analyse ecological implications of single-tree patterns. Leemans (1991) studied the pattern of seedlings, saplings, and canopy trees in Swedish old-growth spruce (*Picea abies*) forest and found that the saplings were not randomly distributed in space, in contrast to seedlings and canopy trees. Similar results were obtained by Wells & Getis (1999) who studied the stand structure within one-hectare large plots of *Pinus torreyana* in California and found that positions of young trees tended to be more aggregated than old within the same stand. Stendahl (2001) analysed data from Swedish forest stands and observed dependence ranges between 10 and 170 m for several properties, such as mean diameter and tree height. Basal area and stem density showed only weak dependence. Several authors described the within-stand spatial structure of natural forest as a mosaic of patches, formed by regeneration within open patches created by disturbances such as storm felling (Hytteborn, Packham & Verwijst, 1987; Leemans, 1991; Kubo, Iwasa & Furumoto, 1996; Moeur, 1997; Kuuluvainen *et al*., 1998; Kuuluvainen, Syrjänen & Kalliola, 1998; Stendahl, 2001). Kuuluvainen *et al*. (1996) addressed differences for managed and primeval boreal spruce forest in southern Finland (two 50 by 50 m forest areas), where the positions of trees in the managed forest showed clear spatial dependence up to 12 m, while no dependence was detected for the pristine forest. The difference seemed to be caused by the understory present in the pristine forest but absent in the managed forest. However, analysing the large trees only showed dependence up to 15 m in the pristine forest. Spatial characteristics have also been incorporated in single-tree growth modelling (Fox, Ades & Bi, 2001).

Large scale variation

Belleheumeur & Legendre (1998) simulated surveys of 10 by 10 m plots using data from a completely measured 50 ha forest in Malaysia and found stem density (for such plot measurements) to be spatially dependent up to 50 m and weakly dependent up to 500 m. Gunnarsson *et al*. (1998) performed a stratified survey of clustered 10 m radius field plots at a 400 ha forest estate in southern Sweden and reported spatial dependence of many variables. For example, stem volume showed ranges of dependency between 80 and 250 m, total age 150 to 250 m, and basal area weighted mean diameter up to 200 m. Natural pine stands in Georgia were investigated by Czaplewski, Reich & Bechtold (1994), who analysed data on distances up to 150 km and detected spatial dependence in basal area growth. This was expected to have been caused by spatial variation of site conditions. Addressing a very large scale with data on distances up to 6000 km, Nekola & White (1999) studied presence and absence of species in North American spruce-fir forest and Appalachian montane spruce-fir forest. They used data from 9 ha large sample plots and forest regions, and found significant spatial dependence (distance decay of similarity).

Spatial models

In this thesis, the applied spatial models are based on the assumption that data are observations of stochastic variables, *Z*, connected to a spatial location, **x**, in the *d*-dimensional Euclidean space $\mathbf{R}^d$. Cressie (1993) defined a general model of such data, here expressed for one-dimensional Z:

$$\{Z(\mathbf{x}) : \mathbf{x} \in D\}, D \subset \mathbf{R}^d \tag{1}$$

Depending on the definition of *D*, this general model can be used to describe data with different spatial characteristics: point pattern data, lattice data, and geostatistical (continuous space) data (see Cressie (1993)). Point process data are characterised by the location **x** being stochastic, *i.e.*, the data are created by "events" occurring at random positions, and no *Z* is specified. *D* is then a point process in $\mathbf{R}^d$ or a subset of $\mathbf{R}^d$. Furthermore, a marked point process is generated if there is a *Z* specified at location $\mathbf{x} \in D$ (Penttinen, Stoyan & Henttonen, 1992; Cressie, 1993; Ver Hoef, Cressie & Glenn-Lewin, 1993). For lattice data, *D* is a fixed (regular or irregular) collection of countable many spatial sites of $\mathbf{R}^d$. Geostatistical data resulting from *D* is a fixed subset of $\mathbf{R}^d$, and $Z(\mathbf{x})$ is a random variable at location $\mathbf{x} \in D$ (Cressie, 1993).

Three approaches to spatial prediction of stem volume using Landsat TM data are investigated: using geostatistical models, spatial regression models defined on an irregular lattice, and Bayesian models defined on a regular lattice.

Geostatistical models

The geostatistical framework originates from Matheron (1965), who developed the theory of regionalized variables, *i.e.*, random variables connected to spatial positions. Geostatistical methods have been applied and developed in mining and mineral prospecting industry, soil science (Burgess & Webster, 1980a, b; Yost, Uehara & Fox, 1982a, b), forest inventory (Mandallaz, 2000), ecology (Rossi *et al*., 1992), and GIS applications (Oliver & Webster, 1990). Isaaks & Srivastava (1989), Deutsch & Journel (1992), Cressie (1993), and Goovaerts (1997) give fairly thorough descriptions of geostatistical theory.

A central tool in geostatistical modelling is the semivariogram, a function describing the spatial dependence of the modelled variable. The semivariogram has been used in many remote sensing studies to determine spatial structures (Curran, 1988; Warren, Spies & Bradshaw, 1990; Walter & Brandtberg, 1997; Atkinson & Lewis, 2000). From a model of the variable, including a semivariogram, the geostatistical framework derives optimal (minimised mean-squared prediction error) linear unbiased spatial prediction methods, called kriging predictors. In the simplest form, kriging provides predictions in unobserved points, based on surrounding observations (corresponding to spatial interpolation in deterministic modelling). The geostatistical framework also provides optimal prediction methods utilising additional data sources to possibly increase prediction accuracy, such as the cokriging predictor.

Kriging prediction of forest variables

Kriging has been applied to forest variables with varying success. Using circular plot measurements, Gilbert & Lowell (1997) applied kriging to predict stem volume in a 1500 ha balsam fir (*Abies balsamea*) dominated forest. Prediction based on 5.6 m and 11.3 m radius plots resulted in a prediction RMSE of 54% (of the mean) and 39-46%, respectively. Similar accuracy was obtained by prediction using the sample average only. Applying the dynamic forest management planning concept, Holmgren & Thuresson (1997) used kriging predictions based on 10 m radius plots and digitised aerial photography data to create rasters of stem volume and in-optimality losses for a forest estate (approximately 100 ha) in northern Sweden. The accuracy obtained was regarded acceptable for the addressed planning concept. In a study following the work of Holmgren & Thuresson (1997), Gunnarsson *et al*. (1998) applied stratified kriging prediction of stem volume, total age, annual stem volume increment, and site index, using 10 m radius plots at a 400 ha forest estate in southern Sweden. The kriging prediction showed poor accuracy, especially for prediction of stem volume of hardwoods. Grushecky & Fajvan (1999) obtained kriging predicted maps of canopy cover within a 18 ha hardwood stand in West Virginia but with little correspondence to the true cover. Stendahl (2001) used data from three completely measured stands of coniferous forest in southern Sweden to evaluate accuracy of kriging prediction of diameter and basal area within stands based on different sampling efforts. The data, including accurate position and measurements of each tree, were used to simulate sampling and perform kriging using the sampled data. Systematic samples of diameter and basal area measured on 100 and 200 m^2 plots, with plot spacing varying between 18 and 70 m, were simulated and used in kriging prediction. A similar approach, based on single tree sampling, was used for the variable tree height. The prediction accuracy was generally low, with not more than 30% of the stand variation explained for any variable. King (2000) analysed geostatistical stochastic simulation methods to locate areas of high-value commercial trees in Pennsylvania and found these alternatives superior to kriging.

Cokriging prediction using remotely sensed data

Several studies addressing geostatistical prediction using remote sensing data have been made, although forest applications are few. Dungan, Peterson & Curran (1994) and Dungan (1998) applied regression, cokriging, and a new stochastic simulation method, using synthetic remote sensing datasets to investigate which method to use for different data structures. The main feature of data structure addressed was the direct dependence (correlation coefficient) of the predicted and the explanatory variables. The lowest prediction errors were obtained with cokriging for datasets with a correlation coefficient lower than 0.89. For datasets with a higher correlation coefficient, better results were obtained using regression. Atkinson, Webster & Curran (1994) used airborne multispectral scanner data to predict green leaf area index of barley and biomass of a pasture using cokriging. They concluded that simple regression would have provided useless results and cokriging provided more accurate predictions than kriging.

Spatial regression models

Ordinary Least Square (OLS) regression is commonly applied for raster mapping of forest variables using remote sensing data. Spatial dependence present in the data is usually not identified, and is instead assumed absent. Then, OLS regression does not provide optimal parameter estimation (Upton & Fingleton, 1985; Anselin & Griffith, 1988). Furthermore, the opportunity to incorporate near-by measurements in prediction is not utilised.

In spatial regression, the regression model is extended by incorporating the autocovariance matrix of the lattice structure in the estimation of the model parameters. Spatial regression is a general tool in econometrics (Paelinck & Klaassen, 1979; Ancot, Paelinck & Prins, 1986; Anselin, 1988), but has also been applied in epidemiology to model the spatial distribution of lung cancer (Richardson, Guihenneuc & Lasserre, 1992) and in zoology to model habitat selection (Upton & Fingleton, 1985). These studies aimed to obtain optimal parameter estimates in the presence of spatial dependency. By making different assumptions about the elements of the autocovariance matrix, different variants of spatial regression are obtained. In the simplest form the spatial dependence structure in spatial regression is modelled by spatial weights determining the degree of dependence. For any fixed spatial object, the neighbouring objects are assigned non-zero weights and the other objects are assigned zero weights. The spatial weights are determined prior to estimation of model parameters. This requires a suitable neighbourhood structure on the lattice. For spatial objects in the form of polygons, such as counties, post number regions or other administrative units, it is common to define the weights based on the relative length of common borders between neighbouring polygons (Upton & Fingleton, 1985). Common formulations of the covariance matrix using spatial weights are through the conditional autoregressive (CAR) model and the simultaneous autoregressive (SAR) model (Richardson, Guihenneuc & Lasserre, 1992; Cressie, 1993). Upton & Fingleton (1985) presented the autoregressive response model (AR), which is in essence an approximation of the SAR model. Long (1998) used the AR model as an alternative to OLS regression to analyse wheat yield data using digital aerial imagery, in order to take spatial dependence into consideration. There was a clear difference in parameter significances obtained by the model approaches.

Bayesian models

Adding the spatial dimension to statistical models is not trivial. It may be difficult to define a model which describes the spatial features well without being very complex. In particular, the analytic derivation of efficient parameter estimators is often very difficult. An alternative approach is provided by Bayesian statistics in combination with Markov Chain Monte Carlo (MCMC) stochastic simulation methods (Hjort & Omre, 1994; Gilks, Richardsson & Spiegelhalter, 1996; Gamerman, 1997). The Bayesian statistical approach is based on the assumptions that model parameters are random variables as well as data observations. The distribution of the parameters before data are observed is modelled by the prior distribution. Parameter inference is based on the distribution of the parameters conditional on the observed data: the posterior distribution (Gilks, Richardsson & Spiegelhalter, 1996; Gamerman, 1997). Practical applications of the Bayesian approach have previously been limited to models where the posterior distribution is available analytically from the prior distribution, often in the form of conjugate distributions. The work of Geman & Geman (1984) led to the introduction of MCMC into mainstream statistics via the articles by Gelfand & Smith (1990) and Gelfand *et al*. (1990). The MCMC methods provide alternative inference methods of the posterior distribution using stochastic simulation of cleverly constructed Markov Chains (Gilks, Richardsson & Spiegelhalter, 1996; Gamerman, 1997).

Bayesian and MCMC methods have been used in many forestry and remote sensing relevant applications, often as a method to utilise several conceptually different sources of information. Geman & Geman (1984) and Besag, York & Mollié (1991) used Bayesian methods to restore noisy images, modelling the image as a spatial Markov random field. Ståhl, Carlsson & Bondesson (1994) and Nyström & Ståhl (2001) used Bayesian modelling of parameter distributions, rather than parameter point estimates, to determine the optimal point in time to update the forest stand database using a new survey. Forestry planning was also addressed by Alho & Kangas (1997) and Kangas *et al*. (2000) who used a Bayesian approach for decision support systems in multiple-objective forestry. Green & Strawderman (1992) compared hierarchical and empirical Bayes methods and introduced the MCMC method Gibbs sampler for forestry applications as well as addressed simultaneous estimation of multiple means, a common problem in forestry.

Utilising the Bayesian approach and MCMC methods, Teterukovskiy (2001) presented a method to detect vehicle tracks in remotely sensed images. The method is based on apriori information of the structure of tracks and showed positive results when applied to digitised aerial photographs (1 m pixel size) of Swedish alpine vegetation. Furthermore, in a simulation study, Teterukovskiy (2001) used a MCMC method to reclassify the results from standard non-contextual classification methods (quadratic discriminant analysis and the *k*NN classification), in order to improve classification accuracy using the spatial autocorrelation in the image. The results indicate that the applied approach has the potential to improve classification accuracy.

Vehtari & Lampinen (2000) used Bayesian Multi-Layer Perceptron (MLP) neural networks to locate tree trunks in digital images taken from the ground (from a harvester or similar), for robotic vision applications. Bayesian methods have also been used in ecological spatial modelling applications, such as modelling probability of lichen occurrence on trees by logistic regression with tree properties as covariates (Riiali, Penttinen & Kuusinen, 2001).

Spatial point process models have also been addressed using Bayesian statistics in combination with MCMC methods. Wolpert & Ickstadt (1998) used doubly stochastic Bayesian hierarchical models to account for uncertainty and spatial variation in the underlying intensity measure for point process models, addressing a forest ecology problem. Another example is Heikkinen & Arjas (1999) who used a non-parametric Bayesian approach to model a non-homogeneous Poisson forest affected by concomitant variables, where the information of the latter was limited.

Besag, York & Mollié (1991) addressed Bayesian spatial statistics and showed the framework of Bayesian image restoration to be useful for a broad class of spatial models. The work demonstrated applications in archaeology (irregular point measurements), epidemiology (measurements of administrative zones), and in medical images (ordinary raster images). Besag *et al.* (1995) presented the class of pair-wise prior distribution functions and examples of applications to spatial statistics. This class of models was expected to be useful in modelling spatial dependence using the prior distribution.

Objectives

The main objective of this thesis is to empirically evaluate the accuracy improvement by including spatial data in remote sensing based prediction. Also addressed are the practical applicability and influence of field sampling intensity on the studied methods. Accuracy evaluation is based on prediction of stem volume per hectare at a 5917 ha test site of boreal forest using a large sample of objectively measured field plots and multispectral optical data from the Landsat 5 TM satellite sensor.

The specific objectives of the studies described in papers I-IV are listed below.

I. To introduce and evaluate a new search strategy for data, based on edge detection in remote sensing data, to improve accuracy of ordinary kriging prediction. The method is designed to adapt to the presence of sharp edges in the forest. The new method is compared with ordinary kriging and stratified ordinary kriging, using stratification of remote sensing data.

II. To evaluate geostatistical methods suitable for utilising with remotely sensed data. Two cokriging methods and simple kriging with varying local means are compared with OLS regression predictions. Effects of sampling intensity are also addressed.

III. To evaluate the spatial autoregressive response model for spatial prediction. The effects of neighbourhood size and spatial weights definition as well as sampling intensity are addressed.

IV. To introduce a Bayesian state-space model for spatial simulation of forest variables using Gibbs sampler simulation. The model is applied to spatial prediction of stem volume and the prediction accuracy is investigated.

The studies were carried out within the framework of a project aiming to develop methods for dynamic forest management planning systems, *i.e.*, systems not based on a traditional stand delineation of the forest.

Material

Field data

The analyses made in the papers I-IV are based on data from the Brattåker forest estate (Lat. 64°14'N, Long. 19°40'E) outside the town of Vindeln in the north of Sweden. The 5917 ha large estate consists of boreal forest and is owned and managed by the forest company Holmen Skog AB. The forest is fairly homogeneous and rather intensively managed. The elevation varies between 160 and 400 m above sea level. Two objectively performed field data collections on the estate were used: a stratified survey of 2604 sample plots, and a field survey of 51 stands selected from the company's stand database.

The 2604 circular plots (10 m radius) were surveyed in 1996 using systematic and stratified sampling (Figure 1) (Wallerman, 1998). Stratification was made using Landsat TM data and aimed to allocate a higher sampling intensity to older (more economically valuable) forest than to young and regenerating forest. The strata were defined by a combination of segmentation and unsupervised classification of a precision corrected Landsat TM scene (path 194, row 014) with an image acquisition date of June 13, 1995. First, the area was segmented into spectrally homogeneous areas of size 0.5-5 ha using directed-tree clustering followed by region growing (Hagner, 1990). Then, independent of the segmentation, the image was classified into 25 classes by pixel-wise unsupervised clustering. These 25 classes were subjectively merged into 5 major forest types. Finally, the sampling strata were defined by the segmentation where each segment was assigned the majority class of the pixels within it. The general forest characteristics of the sampling strata are presented in Table 1. A majority of the plots (2101 plots) was laid out in a systematic grid design with stratum-unique grid spacing. In addition, 503 plots were used to assess the spatial dependency at distances shorter than the systematic grid spacing. One such additional plot was allocated close to each 6th systematic grid plot in stratum 1, to each 7th in stratum 2, to each 2nd in strata 3 and 4, and to all plots in stratum 5. The allocation was random in eight directions and at 25 m, 50 m or 75 m distances from the selected regular grid plot. Sampling was made using the sampling and estimation routines of the Forest Management Planning Package (Jonsson, Jacobsson & Kallur, 1993). In particular, each tree within a plot was callipered and several additional variables were measured on a sub-sample of trees in order to estimate stem volumes accurately. Each plot centre was positioned using the mean coordinates of real-time differentially corrected GPS measurements. On average, 36 measurements were used for each plot position. Some of the plots were not used due to obvious errors in the position or loss of part of the survey data.

Fifty-one evaluation stands (0.5-22 ha) were surveyed in the year 2000. The selection of stands was random and stratified on the stem volume per hectare according to the forest company's stand database in order to provide a set of stands ranging from low to high stem volume. Each stand was surveyed using systematic sampling with on average nine field plots of 10 m radius, and the sampling routines previously described (Jonsson, Jacobsson & Kallur, 1993). Only the estimated stand means, corrected for four years of growth to reflect the forest state in 1996, were used from this survey. The estimated stem volume of the surveyed stands ranged from 13 m^3ha^{-1} to 294 m^3ha^{-1} with an average of 160 m^3ha^{-1}. The average standard error of the estimated stand stem volumes was 11% of the mean.

The sample plot survey data were used as prediction data as well as to evaluate plot-level prediction accuracy. This was made by dividing the complete plot survey dataset (dataset C) in two parts: the prediction dataset (dataset P) and the evaluation dataset (dataset E). The 2101 systematically spaced sample plots were assigned to dataset P, and the 503 extra plots were assigned to dataset E. This approach was used since the errors of spatial prediction methods are expected to decrease the closer a predicted location is to a measured location. Then, a feasible sampling design is a regular grid of plots, possibly denser in areas with high variation, and is a design most likely to be applied in practice. The focus of this thesis is to evaluate the accuracy of methods applied on such a regular dataset, leaving the extra plots an evaluation dataset. The data from the stand survey were used to evaluate stand-level prediction accuracy.

Remote sensing data

The analyses were based on a multispectral optical Landsat 5 TM satellite scene (path 193, row 015) with an image acquisition date of August 11, 1996. The TM sensor provides 8-bit data from measurements of the electromagnetic spectrum in seven spectral bands, from the visible spectrum; TM1: 0.45-0.52 μm (blue), TM2: 0.52-0.60 μm (green), TM3: 0.63-0.69 μm (red), to the infrared (IR) spectrum; TM4: 0.76-0.90 μm (near IR), TM5: 1.55-1.75 μm (mid IR), TM7: 2.08-2.35 μm (mid IR), and TM6: 10.4-12.5 μm (thermal IR) (Lillesand & Kiefer, 2000). The scene was geometrically precision-corrected to the Swedish National Grid (RT90) and re-sampled to 25 m pixels by the Swedish company SSC Satellitbild. The geometric processing of the image is based on orbital modelling together with a library of ground control points of Sweden, and typically results in a geometrical accuracy of one-half of a pixel. The scene is cloud-free over the study area and contains no shadows cast by topographic effects. Radiometric and atmospheric corrections were not applied since the area of interest is fairly small, contained no visible variations in atmospheric conditions, and since the methods applied do not require absolute reflectance measurements. Image data for each surveyed plot were extracted using cubic convolution sampling.

Descriptive statistics

The surveyed plot dataset is influenced by the stratification, which assigned more samples to older forest. Table 2 and Figure 2 show statistics and histograms for the complete dataset (dataset C) and a reduced dataset (dataset R, 1155 plots). Dataset R was constructed from dataset C, to reduce the effects of the preferential sampling introduced by the stratification. This was made by randomly thinning strata one to three to the spatial sampling intensity used in stratum four. It was not regarded useful to thin the data to the lowest sampling intensity (stratum five), to obtain equal sampling intensity in all parts, since stratum five was very sparsely sampled. The relationship between the stem volume data and Landsat TM bands TM4 and TM5 is not linear (Figure 3). Applying a logarithmic transformation, *ln*(*volume*+1), to the stem volume data results in a near-linear relationship to the image data (Table 3, Figure 3).

Figures 4 and 5 show exploratory spatial descriptions of dataset C. Figure 4 shows estimated covariance of plot measured stem volume observations separated by distances from 0 to about 2000 m, for datasets C and R. The ranges, *i.e.*, the distance at which the covariance has declined to approximately zero, are similar for the datasets but the variances (the covariance at distance 0 m) are not. Figure 5 shows visualisations of the spatial distribution of stem volume in the study area. The images in Figure 5 are constructed by spatial smoothing of dataset C, using moving-window averages and inverse distance weighting interpolation (Isaacs & Srivastava, 1989).

Table 2. *Descriptive statistics of sample plot data*

Variable	Dataset	Unit	Min	Max	Mean	Median	s
Stem volume	C	m^3ha^{-1}	0	479	130	127	97.4
Stem volume	R	m^3ha^{-1}	0	479	100	81	95.8
Transformed stem volume	C	$ln(m^3ha^{-1})$	0	6.17	4.25	4.85	1.54
Transformed stem volume	R	$ln(m^3ha^{-1})$	0	6.17	3.69	4.41	1.77
Transformed stem volume	P	$ln(m^3ha^{-1})$	0	6.17	4.31	4.87	1.50
Transformed stem volume	E	$ln(m^3ha^{-1})$	0	6.06	3.98	4.71	1.70
TM4	C	DN	25.8	84.6	48.1	46.1	9.78
TM4	P	DN	25.8	80.7	47.9	45.9	9.51
TM4	E	DN	27.4	84.6	48.9	46.6	10.8
TM5	C	DN	17.5	92.9	39.9	35.6	13.7
TM5	P	DN	18.4	92.9	39.2	35.0	13.2
TM5	E	DN	17.5	90.3	42.5	38.0	15.1

Table 3. *Correlation coefficients of plot measured stem volume data and Landsat TM4 and TM5 data, based on the complete dataset (dataset C)*

	Stem volume	Transformed stem volume	TM4	TM5
Stem volume	1	0.82	-0.52	-0.62
Transformed stem volume		1	-0.56	-0.79
TM4			1	0.61
TM5				1

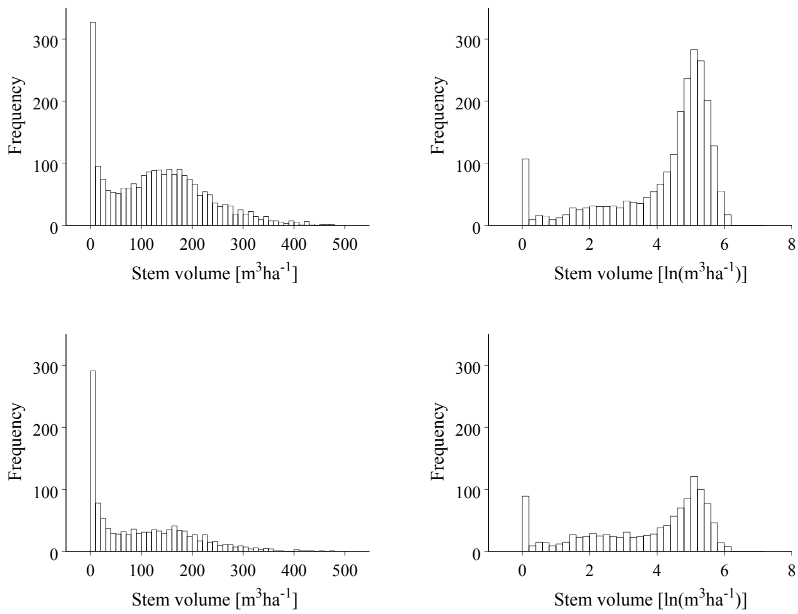


Figure 2. Histograms of plot measured stem volume data. Top: complete dataset (dataset C, *n*=2604), bottom: reduced (de-stratified, *n*=1155) dataset (dataset R). Left: stem volume, right: logarithmically transformed stem volume.

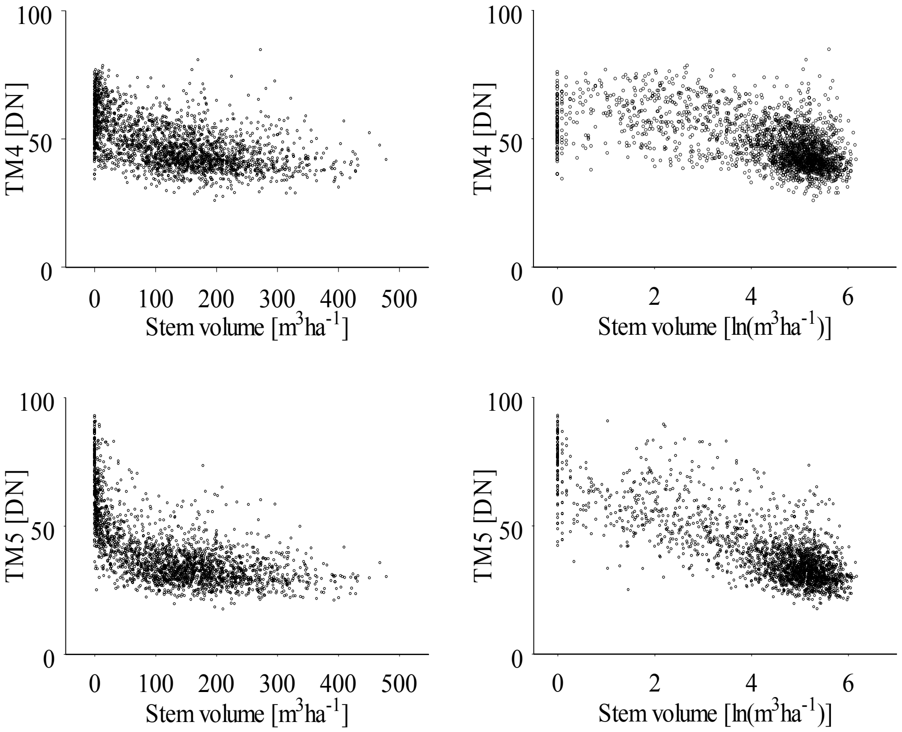


Figure 3. Scatterplots of Landsat TM data, extracted using cubic convolution, to plot measured stem volume data (left) and logarithmically transformed plot measured stem volume data (right). The scatterplots are based on the complete dataset (dataset C).

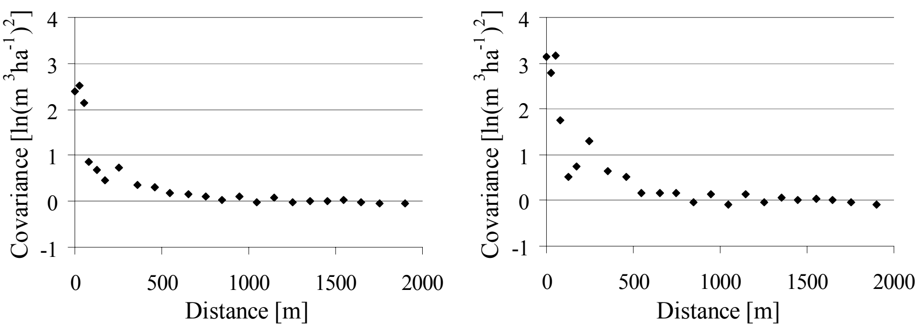


Figure 4. Spatial covariance of the logarithmically transformed plot measured stem volume data. Left: covariance based on the complete dataset (dataset C), right: covariance of the thinned (de-stratified) dataset (dataset R).

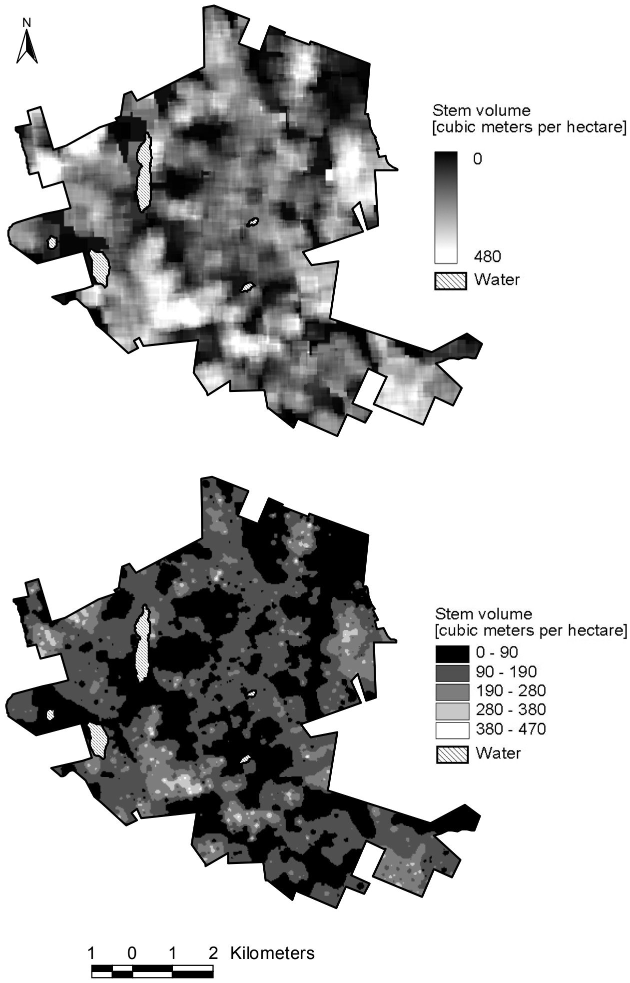


Figure 5. Visualisations of the spatial structure of the plot measured stem volume data (dataset C). Top: image created by moving-window average using 225 by 225 m window size. Bottom: image created by inverse distance weighting using the ten closest plots and power of two.

Methods

Geostatistical models (Papers I and II)

In papers I and II, the variable stem volume is modelled as a random function Z(**x**), where **x** is a position in the two-dimensional Euclidean space $\mathbf{R}^2$:

$$Z(\mathbf{x}) = m(\mathbf{x}) + \varepsilon(\mathbf{x}), \mathbf{x} \in \mathbf{R}^2 \qquad (2)$$

In Equation 2, $m(\mathbf{x})$ is a deterministic mean structure and $\varepsilon(\mathbf{x})$ is a spatially dependent random deviation, assumed second-order stationary with isotropic semivariogram $\gamma(h)$:

$$\gamma(h) = \tfrac{1}{2}Var[Z(\mathbf{x}_i) - Z(\mathbf{x}_j)],\ h = |\ \mathbf{x}_i - \mathbf{x}_j\ | \qquad (3)$$

From Equations 2 and 3, the geostatistical framework derives kriging predictors, which are methods to predict Z in an unobserved location, $\mathbf{x}_0$. Kriging predictors are optimally weighted linear combinations of the available observations, such as the ordinary kriging predictor (Cressie, 1993):

$$\hat{Z}(\mathbf{x}_0) = \sum_{i=1}^{n} \lambda_i Z(\mathbf{x}_i) \qquad (4)$$

The weights λ_i are derived to minimise the mean-squared prediction error (optimal prediction) and provide unbiased prediction. Depending on the model, such as the structure of $m(\mathbf{x})$, many different kriging predictors are available. For example, the ordinary kriging predictor (Equation 4) is based on assuming $m(\mathbf{x})$ to be unknown and constant in space ($m(\mathbf{x})=m$), or constant at least within a limited neighbourhood of the predicted point. In contrast, the simple kriging predictor assumes $m(\mathbf{x})$ to be known. Simple kriging possibly provides a way to enhance prediction accuracy by incorporation of additional data. This can be done by estimation of $m(\mathbf{x})$ using the additional data sources, such as optical remote sensing data, and use of SK to predict the spatially dependent residual.

Data from an additional source (a secondary variable), available at every prediction location and dependent on the predicted variable (the primary variable), can also be used in cokriging prediction. Regarding the secondary variable as a random function, $Y(\mathbf{x})$, the ordinary cokriging predictor is formed by extending the ordinary kriging predictor to incorporate secondary data (Cressie, 1993):

$$\hat{Z}(\mathbf{x}_0) = \sum_{i=1}^{n} \lambda_i^Z Z(\mathbf{x}_i) + \sum_{j=1}^{m} \lambda_j^Y Y(\mathbf{x}_j) \qquad (5)$$

The weights λ^Z_i and λ^Y_j are determined similarly to the kriging weights using the semivariogram of $Z(\mathbf{x})$, $\gamma_Z(h)$, and the semivariogram of $Y(\mathbf{x})$, $\gamma_Y(h)$, as well as a model of the spatial cross-dependence structure, the cross-semivariogram $\gamma_{ZY}(h)$ (Cressie, 1993):

$$\gamma_{ZY}(h) = \tfrac{1}{2}Var[Z(\mathbf{x}) - Y(\mathbf{x}+\mathbf{h})]. \qquad (6)$$

Spatial regression models (Paper III)

Spatial regression may provide a means to incorporate spatial structures in regression. The spatial regression model addressed here is the autoregressive response model (AR) (Upton & Fingleton, 1985; Kelejian & Prucha, 1997). This model is essentially an approximation of the simultaneous autoregressive model (SAR) (Richardson, Guihenneuc & Lasserre, 1992; Cressie 1993).

Let **Z** be the (n×1) vector of n forest variable observations Z_i, **X** the (n×k) design matrix with 1's in the first column and the corresponding values of the (k-1) independent variables in the other columns, **b** the (k×1) vector of unknown model parameters, **e** the (n×1) vector of unobserved random errors, and **I** the (n×n) unit matrix. Then, the AR model is (Upton & Fingleton, 1985)

$$\mathbf{Z} = \rho\mathbf{WZ} + \mathbf{Xb} + \mathbf{e},\ \mathbf{e} \sim \mathrm{N}(0, \sigma^2\mathbf{I}), \tag{7}$$

where spatial dependence is modelled by the term $\rho\mathbf{WZ}$, where ρ is an unknown spatial correlation parameter and **W** is a (n×n) spatial weight matrix defining the pre-determined neighbourhood of each observation i. For observation i, each neighbouring observation, j, is assigned a non-zero weight in position (i, j) of **W**, for $i \neq j$. Thus, the aim is to arrive at independent residuals. A drawback is the pre-requisite of a known spatial weight matrix, which must be properly defined for each application. A predictor of an unobserved Y_{n+1} is proposed:

$$\hat{Y}_{n+1} = \hat{\rho}\sum_{i=1}^{n} w_{(n+1),i}Y_i + \hat{\beta}_0 + \hat{\beta}_1 X_{(n+1),1} + \hat{\beta}_2 X_{(n+1),2} + ... + \hat{\beta}_{k-1} X_{(n+1),(k-1)} \tag{8}$$

The predictor is based on the estimated model parameters $\hat{\rho}$ and $\hat{\beta}$, the k-1 independent variables X and weights $w_{(n+1),i}$ corresponding to the location n+1.

Bayesian state-space models (Paper IV)

The Bayesian approach is based on the assumption that parameters, $\boldsymbol{\theta}$, as well as the data, $\mathbf{x}$, are generated by stochastic processes. The joint distribution, $f(\boldsymbol{\theta}, \mathbf{x})$, is the distribution over all random quantities (Gilks, Richardsson & Spiegelhalter, 1996) and comprises two parts: a prior distribution $\pi(\boldsymbol{\theta})$ and a likelihood $f(\mathbf{x} \mid \boldsymbol{\theta})$. The prior distribution describes the uncertainty of the parameters before data are observed, and the likelihood describes the sampling distribution of the data. Inference on the parameters is made using the distribution of parameters conditional on the observed data, the posterior distribution $f(\boldsymbol{\theta} \mid \mathbf{x})$. Specifying the prior and the likelihood (Gilks, Richardsson & Spiegelhalter, 1996)

$$f(\boldsymbol{\theta}, \mathbf{x}) = f(\mathbf{x} \mid \boldsymbol{\theta})\, \pi(\boldsymbol{\theta}), \tag{9}$$

the posterior is available using Bayes theorem,

$$f(\boldsymbol{\theta} \mid \mathbf{x}) = \frac{\pi(\boldsymbol{\theta}) f(\mathbf{x} \mid \boldsymbol{\theta})}{\int \pi(\boldsymbol{\theta}) f(\mathbf{x} \mid \boldsymbol{\theta}) d\boldsymbol{\theta}} \tag{10}$$

The presented model has, due to the spatial setting, high dimension (one parameter per raster cell) and it is very difficult to analyse the posterior distribution analytically. Instead, parameter inference is made using a MCMC stochastic simulation method, the Gibbs sampler. The Gibbs sampler is based on iterative simulation of a Markov Chain constructed such that the posterior distribution appears as the stationary distribution of the chain. Often it is sufficient to be able to draw random samples from the full conditional distributions (*i.e.*, the distribution of each parameter conditional on the remaining parameters and the data) to apply MCMC inference. Furthermore, it is often sufficient to know the shape of the full conditional distribution function. Parameter inference is made using ergodic sample statistics of a large number of simulations from the chain.

Results

Summary of Paper I

This paper presents a new method to perform ordinary kriging predictions using information derived by edge detection in remotely sensed imagery. The new method is designed to adapt to the complex spatial variation of forest, especially managed forest. Managed forests are expected to show a mix of gradual transitions, caused by gradual variation in site conditions, and sharp edges, caused by logging operations (Lowell, Edwards & Kucera, 1996; Gunnarsson *et al.*, 1998). Although complete stand polygons are homogeneously thinned or clear cut, the varying evolution within stands may eventually cause a stand to have boundaries with less pronounced, or indistinguishable, parts as well as distinct parts. Then, it is not expected to be efficient to represent the sharp spatial transitions with closed polygons, but rather with open-ended lines – edges. If the edges are known, ordinary kriging prediction may be improved by using only sample plots located on the same side of any known edge as the predicted point. This paper explores the possibility of improving the accuracy of ordinary kriging prediction of stem volume using Landsat TM data to detect the presence of sharp transitions. Two different approaches are utilised. First, edge detection of TM data is used to estimate the presence and strength of edges. These edges are used in each kriging prediction to select only sample plots located on the same side of any edge as the predicted location. Second, the TM data are used to define homogeneous strata and each stratum is predicted separately. These approaches, stratified ordinary kriging and ordinary kriging with edges, were applied to predict stem volume and the results were compared with ordinary kriging without any additional information.

The new method performed better than ordinary kriging and stratified ordinary kriging. Using the detected edges resulted in 41% prediction RMSE (in per cent of the mean stem volume) of cells, stratified ordinary kriging in 45%, and ordinary kriging in 58%.

Summary of Paper II

The geostatistical framework provides possibilities to incorporate remote sensing data in the model of stem volume, $Z(\mathbf{x})$. Two different approaches are evaluated, using remote sensing data to model the mean structure, $m(\mathbf{x})$, or treating the remote sensing data as a random function, $Y(\mathbf{x})$, dependent on $Z(\mathbf{x})$ (a secondary variable). Prediction based on the former approach was made using simple kriging with varying local means (SK) (Goovaerts, 1997). Ordinary cokriging (CK) and colocated ordinary cokriging (CCK) were used for prediction based on the latter approach. The accuracy of stem volume prediction obtained was compared with accuracy obtained by OLS regression and ordinary kriging (OK) prediction. Furthermore, the effects of sampling intensity for the dataset used in prediction were addressed. This was made by applying the methods on the complete dataset as well as on two reduced datasets. SK and OLS were applied using data from TM4 and TM5, an approach expected to extract most of the information present in the remote sensing data. CK and CCK were only applied using TM5 data due to the complex co-regionalisation model required for utilisation of more than one secondary variable. To enable comparison, SK and OLS were applied using TM5 only, as well as using the combination of TM4 and TM5.

The SK and CK predictors showed, in most cases, higher accuracy than OLS regression and OK predictions of stem volume. CCK predictions were not successful. Accuracy in terms of RMSE at stand level was 36% (of the mean) for SK using TM5 as well as when applied using TM4 and TM5, 37% for CK using TM5, 48% for OLS regression using TM5 and 46% when applied using TM4 and TM5, and 40% for OK, when applied on the full dataset. Reducing the dataset to 50% and 25% of the number of sampled plots resulted in approximately no difference in performance ranking for the methods. The SK method showed similar, or higher, stand level prediction accuracy compared to CK. Thus, SK is expected to be a useful method to utilise several additional data sources, since SK is easier to apply than CK and provides equal accuracy. OK performed surprisingly well for plot-level prediction, 58%, when applied on the full dataset, to be compared with spatial prediction methods using image data: 71% for SK using TM5 and 67% when applied using TM4 and TM5. Due to the spatial structure of the expected error from spatial prediction, most attention should be directed to the ranking of accuracy obtained from stand level predictions.

Summary of Paper III

The autoregressive response model (AR) (Upton & Fingleton, 1985) may provide a useful spatial prediction approach. It is an intuitive approach, being essentially an extension of OLS regression to incorporate spatial properties. The AR model is expected to provide a straight-forward way to incorporate several remote sensing data sources. The AR model was applied, using one as well as several bands of Landsat TM as explanatory data, using a weight matrix defined from spatial dependency in residuals from OLS regression. The influences of neighbourhood definition (size and weighting model) as well as sampling intensity are addressed. The AR method showed up to 8% increase in prediction accuracy (RMSE) of stem volume at plot and stand level compared to OLS regression. The model fit showed deficiencies, since the residuals were not independent. Compared to OLS regression, the AR residuals showed on average 53% (29-100%) lower spatial dependency (measured by the Moran's *I* index (Upton & Fingleton, 1985; Cressie, 1993)) compared to OLS regression residuals. Clearly, this may be caused by inoptimal specification of the spatial weight matrix.

Summary of Paper IV

A regular lattice is a natural space definition for raster prediction methods. In combination with Bayesian models, it may be possible to define flexible spatial models of forest and remote sensing data. In particular, spatial dependence can be modelled using spatial weighting of neighbouring cells. Here, the aim is to assess the forest stem volume in each lattice cell using field measurements of a subset of cells and remote sensing data for each cell. Thus, the model is defined with the unknown cell values as the parameter vector. The spatial properties were modelled using the conditional autoregressive (CAR) model as prior distribution, and remote sensing data and field measurement data were incorporated through the posterior distribution. Predictions from this high dimensional model were made using ergodic averages of a large number of Gibbs sampler simulations.

Applied on the data, each simulation showed mean and variance as well as spatial covariance as expected from field measurement data. Furthermore, the spatial structure was clearly influenced by the spectral data. On the other hand, the accuracy obtained, 76% RMSE (in per cent of the mean) for plot predictions and 60% RMSE for stand predictions, was not an improvement compared to OLS regression.

Comparison of results

The spatial methods addressed in the four papers were applied and empirically evaluated using the same dataset, with some minor exceptions. Figures 6 and 7 present the most important results from the studies.

Highest plot level accuracy was obtained by OK using no image data and by OK using information of edges detected in TM imagery (Figure 6). Compared to OLS regression, OK predictions showed at the most 28% lower RMSE, while OK using edge information was even more accurate, with 49% lower RMSE than OLS regression. The results from stand level predictions show a different accuracy ranking of the methods. Simple kriging with varying local means (SK) performed the best. The RMSE of predictions made by SK using TM5 was 26% lower than the RMSE obtained by OLS regression on TM5 (Figure 7). Using TM4 together with TM5 reduced the difference to 21%.

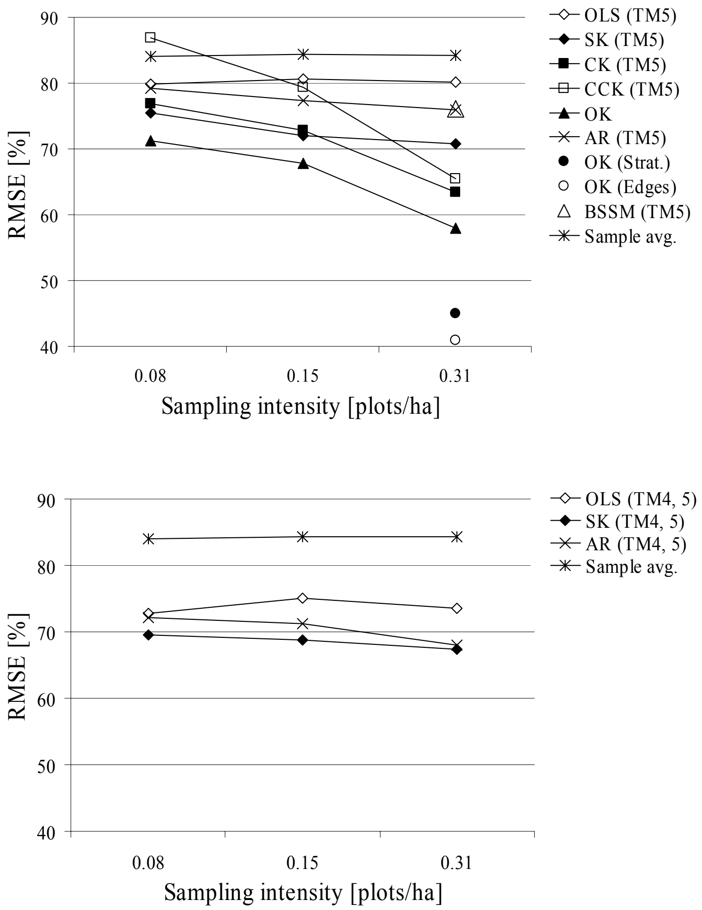
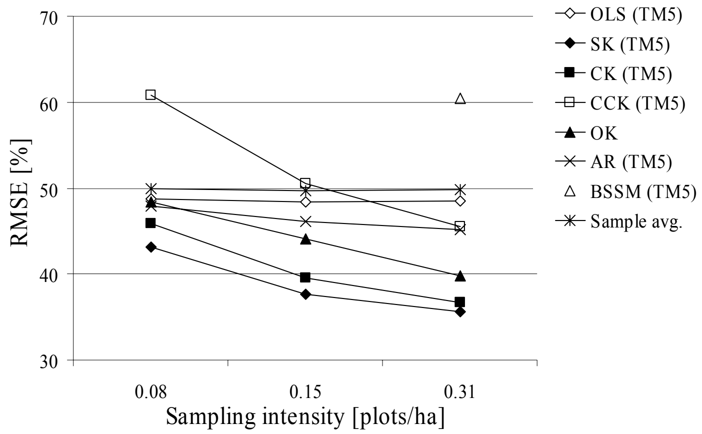


Figure 6. Accuracy of plot level predictions of stem volume, in relation to the sampling intensity of the dataset used for prediction. OLS=OLS regression, SK=simple kriging with varying local means, CK=ordinary cokriging, CCK=colocated ordinary cokriging, OK=ordinary kriging, AR=autoregressive response model using exponential weight function and 600 m neighbourhood size, OK(Strat.)=stratified ordinary kriging, OK(Edges)=ordinary kriging using detected edges, BSSM=Bayesian state-space model, and Sample avg.=prediction using the sample average. Additional data sources utilised, such as Landsat TM bands, are stated in parentheses.



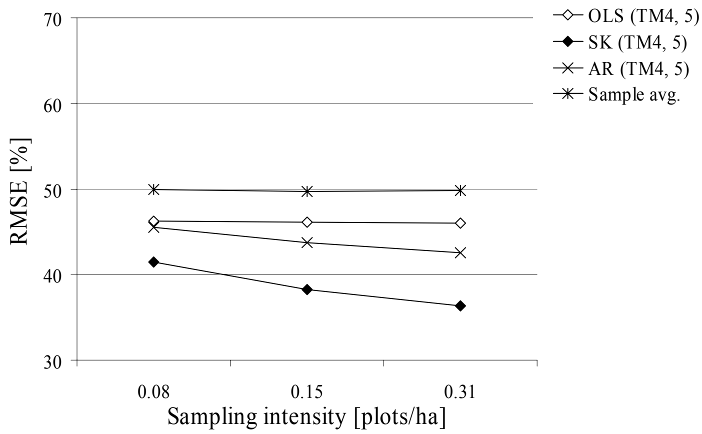


Figure 7. Accuracy of stand level predictions of stem volume, in relation to the sampling intensity of the dataset used for prediction. OLS=OLS regression, SK=simple kriging with varying local means, CK=ordinary cokriging, CCK=colocated ordinary cokriging, OK=ordinary kriging, AR=autoregressive response model using exponential weight function and 600 m neighbourhood size, BSSM=Bayesian state-space model, and Sample avg.=prediction using the sample average. The Landsat TM bands utilised are stated in parentheses.

The stratification of the dataset increases the influences of the older forest on the results. This sampling design was chosen in order to be representative for an applied case of forest management planning, and the results should be interpreted with this in mind. The stratification probably reduced the benefits from using remotely sensed data, since older forest corresponds to the optical spectrum where optical remote sensing data contributes less about forest stem volume. Furthermore, the prediction biases reported are determined by the difference in means of the prediction and evaluation datasets (datasets P and E, respectively). This is due to the method used to correct logarithmic bias (Holm, 1977).

Discussion

Incorporation of spatial information in remote sensing based predictions improved the accuracy compared to OLS regression for most methods, when applied to stem volume. The new OK method using information of detected edges performed well, although the method is dependent on a dense field sampling of data. A dense sampling is required because there should not be any area isolated from all field data by the edges detected. With some exceptions, there were no large differences in prediction accuracy between the different remote sensing based spatial prediction approaches applied. The methods differ mainly in the ease of practical application and modelling flexibility. Utilising Landsat TM data in the predictions directly, *i.e.*, using the methods ordinary cokriging (CK), collocated ordinary cokriging (CCK), simple kriging with varying local means (SK), using the autoregressive response model (AR), and the Bayesian state-space model (BSSM), was not as successful as ordinary kriging (OK) using information about detected edges. An important result is that the SK approach performed at least as well as the more complex method CK. Applying CK requires construction of a co-regionalisation model from the data, which may be a difficult task especially if several secondary variables are used. The ranking of the geostatistical methods corresponds fairly well to those reported by Dungan (1998). That is, OLS regression was inferior to kriging methods, given the same spatially dependent data, for the degree of correlation present. Even more straight-forward to apply than SK is the AR method, an approach which may be seen as a spatial extension of OLS regression. The AR approach did provide more accurate (8% less RMSE) predictions than OLS regression, indicating the potential of the method. Further investigations are necessary, though, regarding how to define the spatial weights from data, and which statistical properties the applied predictor has. The Bayesian method applied in this thesis showed the potential of the flexible framework provided by Bayesian models and Markov Chain Monte Carlo (MCMC) simulation to address highly complex spatial models. The model provided realistic simulations of stem volume although the predictions were not an improvement over OLS regression. Clearly, the model can be improved further by incorporation of parameters in the simulation and possibly also by utilising the pair-wise prior models described by Besag *et al.* (1995).

The OK method produced more accurate plot predictions than methods utilising image information (Figure 6), but SK and CK were more accurate than OK for stand predictions. It is not intuitive to obtain higher accuracy using OK compared to a method incorporating more information (*i.e.*, image data). Since the differences in performance of all methods are small, this result may be due to random variation. Errors in image rectification and measurements of plot positions may also result in reduced accuracy at the plot level. That is, predictions are based on image data acquired from a slightly different location than the predicted plot. Such errors affect plot level accuracy but cancel out when predicting a stand. It may also be a result of the method used for plot level accuracy evaluation. Accuracy was evaluated on plots often close to one of the regularly spaced plots used as prediction data. The influence of the data plot is then high, and image data may not provide very much additional information. Furthermore, the semivariogram and the cross-semivariogram models were estimated using image data extracted by cubic convolution, a method which may provide data not closely reflecting the spatial variance of the image data. In this case, prediction will be made by slightly in-optimal weights and the consequences may be high at predictions close to data plots where the difference in weights is large. With these considerations in mind, the stand prediction results are expected to provide the most reliable performance ranking of the methods.

Prediction based on remote sensing data only, using the OLS regression approach, showed poor accuracy, and only limited improvement from prediction by the sample average. Hagner (1990) performed stand level predictions of stem volume, in an area close to the study area in this thesis, and reported a RMSE of 26% (of the mean) of stand stem volume predictions made by OLS regression using Landsat TM and 24% using subjective field methods. The accuracy obtained here is lower, at the most 36-41% depending on the sampling intensity. On the other hand, this thesis addresses the possibility of enhancing remote sensing based predictions using spatial as well as spectral data. Thus, the methods were applied to enable comparison between spatial methods and OLS regression using similar data, *i.e.*, the field surveyed plots and TM4 and TM5. Furthermore, the methods were also applied using TM5 only to enable basic application of CK and CCK without the inherent problems of estimating complex co-regionalisation models for several secondary variables. There may be an opportunity to enhance the accuracy by more complete utilisation of the remote sensing data, using enhanced models and possibly principal component analysis. On the other hand, the most information of stem volume is expected to be present in TM4 and TM5.

Today, data capture for forest management planning is commonly made by stereo aerial photography interpretation (Åge, 1985) to preliminary delineate stands and estimate stand level variables. Each stand is then visited in the field, to correct preliminary boundaries and estimates. The accuracy of this method was investigated by Ståhl (1992) who reported a standard error of about 12% for stand estimates of stem volume. Furthermore, Ståhl (1992) reported 20% standard error from subjective field estimation, without support of any measurements. Thus, using TM data, the methodology applied in this thesis did not produce as accurate estimations as required in forest management planning. However, the methodology is general and applicable to other sources of remotely sensed data than Landsat TM, sources possibly providing higher forest information content. Furthermore, the results of the present thesis show that, using spatial prediction methods, it is possible to account for low information content of the remotely sensed data by increasing the field sampling intensity.

Analyses were made on the forest variable stem volume per hectare only. This variable shows a very complex spatial structure influenced by management activities. In particular, the spatial structure is influenced by sharp edges and forest stand structures. In light of the spatial scale addressed (approximately 5000-50000 ha), stem volume in managed forests is expected to be similar within each stand, but often clearly dissimilar between different stands. Thus, spatial prediction of this particular variable may be most successful in natural forests without manmade stand structures. On the other hand, the methods applied here are expected to use, to some degree, the information of the forest spatial structure present in the image data, including sharp edges. The method presented in Paper I was designed specifically to adapt to sharp edges and proved successful. The other methods used local spectral data and thus may be expected to adapt to the spatial structure implied by the image, including sharp edges. The tendency to do so is clearly connected to the direct dependency between the predicted variable and the image data, which is a dependency that is not very strong for TM data and stem volume. The results obtained here suggest, using intensively field sampled data, the TM image data were more useful as description of the spatial structure of the forest than as explanatory data in pixel level prediction models of stem volume.

The dataset utilised is unique in several ways. The estate is intensively sampled and the dataset provides a large amount of objectively field measured data. The forest is managed by a forest company and it is expected to be less heterogeneous than privately owned forest. For example, there are only small amounts of deciduous forest at the estate. The spatial prediction approach is expected to be most useful in homogeneous forest and may not perform as well in, for example, privately owned Swedish forests. Furthermore, the terrain at the test site is fairly hilly for Swedish conditions and may cause poor results in remote sensing based estimates where slope effects are not considered. Zuba (2002) analysed these effects on the TM scene and field dataset used here, in the scope of improving classification and OLS regression predictions of stem volume. The result showed improvements from application of the most common terrain normalisation methods. An important characteristic of the dataset is also the stratified sampling design, which allocated more sample plots to the older forest. That is, to forest with fairly closed canopy where TM data contains the least information about stem volume.

Conclusions

Incorporation of spatial information was useful for increasing accuracy of Landsat TM based remote sensing predictions of stem volume, although the benefits were clearly dependent on the field sampling intensity. In particular, spatial prediction provided means to increase the accuracy by increasing the field sampling intensity, which the OLS regression method did not.

The new ordinary kriging method incorporating information about edges detected in the Landsat TM image provided an efficient way to utilise the remote sensing data in spatial prediction, especially with densely sampled field data. More generally, simple kriging with varying local means (Goovaerts, 1997) is proposed as a suitable method for forestry applied spatial prediction. Utilisation of highly complex spatial models is also possible, using Bayesian models.

Future research

There are other promising remote sensing technologies which may provide data of more use for forestry applications than Landsat TM, such as the high-resolution satellite sensors Ikonos and QuickBird, and airborne laser and low-frequency radar systems. The future technology development and implementation in forestry is also expected to provide intensively sampled field data with accurately determined positions, for example harvester data and data collected using hand-held computers with integrated GIS and GPS resources. With these considerations in mind, spatial prediction methods should provide a beneficial framework for many applications, including implementation of a raster forest model. Furthermore, spatial prediction will possibly be useful in operational applications of a raster forest model to provide predictions of forest variables other than stem volume. In particular, the range of spatial prediction approaches applied here may provide solutions for most cases, from the straight-forward utilisation of a single spectral band in cokriging or several bands in simple kriging with varying local means, to prediction of forest variables requiring complex models merging conceptually different data sources in Bayesian models.

Spatial models applied using remote sensing data are expected to provide new opportunities for optimal sampling design in forestry applications. Image data may provide information about forest spatial structure and enable optimal spatial allocation of field sampling efforts. For example, image data of a forest stand describe the heterogeneity of the stand and should aid in optimal allocation of field sample plots or provide optimal weighting of already surveyed plots. Furthermore, using image data in spatial models can be an efficient way to provide real-time sampling support to forest surveyors in the field, using accurate GPS positioning. Then, sampling efforts can be directed, given the samples made, to areas where new samples benefit the most. This task can possibly be efficiently addressed using Bayesian methods, since the distribution (uncertainty remaining, given the observed data) of all random quantities are available directly through the model. Furthermore, Bayesian modelling in combination with Gibbs sampling may provide a tool to evaluate sampling strategies by simulation, using a large number of simulated realisations of forest variables. Simulations of the forest variable can be made conditional to suitable remotely sensed image data in order to provide realistic spatial structure of the simulations. MCMC methods may also provide multivariate simulations, where the dependence structure in the data is preserved, yet easily provide a large number of simulations to enable thorough evaluation of the analysed sampling method.

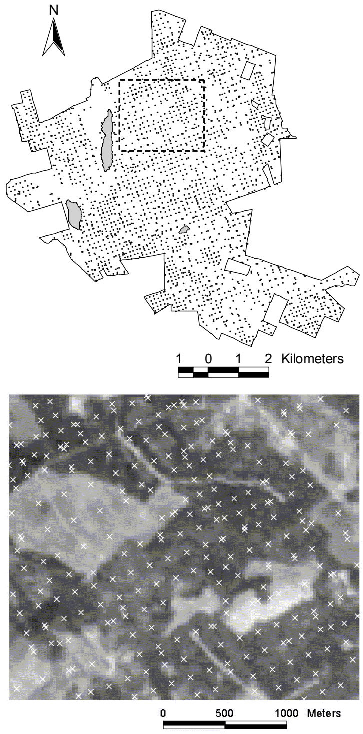


Figure 1. Overview of the Brattåker test site (top) and a more detailed portion showing Landsat TM (bottom). The centre of each field plot is marked by a dot (top) or a white cross (bottom), lakes are shaded in grey and the area corresponding to the detailed portion is marked by a dashed box in the overview. Landsat TM image produced by Satellus/Metria.

Table 1. *Strata characteristics, descriptive statistics of sample plots within each stratum at the Brattåker estate*

Stratum No.	General forest type	Area [ha]	No. of plots	Mean age [yrs]	Mean density [stems/ha]	Proportion [%] Pine, Spruce, Broadleaf
1	Sparse forest	1391	880	87	967	43, 49, 8
2	Dense forest	2029	964	64	1124	44, 38, 18
3	Pine heath	524	328	96	769	79, 18, 3
4	Young forest	1627	386	22	1619	42, 32, 26
5	Regenerating / clear-cut forest	346	46	8	1523	60, 34, 6

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