

Dissertationes Forestales 118

Methods in general model localization

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Academic dissertation

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ABSTRACT

The aim of this study was to evaluate and test methods which could improve local estimates of a general model fitted to a large area. In the first three studies, the intention was to divide the study area into sub-areas that were as homogeneous as possible according to the residuals of the general model, and in the fourth study, the localization was based on the local neighborhood.

According to spatial autocorrelation (SA), points closer together in space are more likely to be similar than those that are farther apart. Local indicators of SA (LISAs) test the similarity of data clusters. A LISA was calculated for every observation in the dataset, and together with the spatial position and residual of the global model, the data were segmented using two different methods: classification and regression trees (CART) and the multiresolution segmentation algorithm (MS) of the eCognition software. The general model was then re-fitted (localized) to the formed sub-areas.

In kriging, the SA is modeled with a variogram, and the spatial correlation is a function of the distance (and direction) between the observation and the point of calculation. A general trend is corrected with the residual information of the neighborhood, whose size is controlled by the number of the nearest neighbors. Nearness is measured as Euclidian distance.

With all methods, the root mean square errors (RMSEs) were lower, but with the methods that segmented the study area, the deviance in single localized RMSEs was wide. Therefore, an element capable of controlling the division or localization should be included in the segmentation-localization process. Kriging, on the other hand, provided stable estimates when the number of neighbors was sufficient (over 30), thus offering the best potential for further studies. Even CART could be combined with kriging or non-parametric methods, such as most similar neighbors (MSN).

Keywords: CART (classification and regression tree), Getis statistics, kriging, LISA (local indicator of spatial association), recursive partitioning, regression modeling, segmentation, spatial autocorrelation

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Klaukkala, May 2011

Minna Rätty

LIST OF ORIGINAL ARTICLES

This dissertation consists of a summary and the four following articles, which are referred to by roman numerals I-IV. Articles I-IV are reprints of previously published articles, reprinted here with the permission of the publisher.

- I** Rätty, M. and Kangas, A. 2007. Localizing general models based on local indices of spatial association. *European Journal of Forest Research* 2/2007: 279-289.
doi: 10.1007/s10342-006-0147-1
- II** Rätty, M. and Kangas, A. 2008. Localizing global models with classification and regression trees (CART). *Scandinavian Journal of Forest Research* 5/ 23: 419-430.
doi: 10.1080/02827580802378826
- III** Rätty, M. and Kangas, A. 2010. Segmentation of Model Localization Sub-areas by Getis Statistics. *Silva Fennica* 44(2): 303-317.
<http://www.metla.fi/silvafennica/full/sf44/sf442303.pdf>
- IV** Rätty, M., Heikkinen, J. and Kangas, A. 2011. Kriging with External Drift in Model Localization. *Mathematical and Computational Forestry & Natural-Resource Sciences (MCFNS)* 3: 1-14. <http://mcfns.com/index.php/Journal/article/view/MCFNS.3-1>

Ms Minna Rätty was the corresponding author in all four (I-IV) articles. Rätty participated in all stages of all articles and wrote the first manuscript versions.

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INTRODUCTION

Forest modeling

The forest inventory of a large area, such as the National Forest Inventory of Finland (NFI, NFI...2010) and similar inventories in other countries, are based on a sample of the growing stock (Shiver and Borders 1996, Johnson 2000). In Finland, the tenth inventory round was already completed in 2008 (NFI10... 2010). The measured information includes different types of variables describing, for example, the locations of sample plots, individual trees, whole stands, and growing sites, as well as information about the health of the forest. The total values for the entire population under investigation are estimated based on the sample measured. The results of the inventory serve various purposes, including governmental legislation, forest owner support, and wood supply planning for the forest industry. In Finland, the results are published in MetINFO (MetINFO... 2010), Metsätieteen aikakauskirja (<http://www.metla.fi/aikakauskirja/>, available in Finnish only) and the Finnish Statistical Yearbook of Forestry (Statistical Yearbook... 2010).

Forest inventory data usually include two different kinds of measured trees: tally trees, for which only some basic measurements such as diameter at breast height (DBH) and tree species have been recorded, and sample trees, which are measured more thoroughly. The data may include, for example, height and upper stem diameters in addition to basic measurements. Any missing, unmeasured variables for the tally trees are estimated with the help of the sample trees. This generalization has many alternatives, however. The easiest and therefore most attractive alternative is to use a study area-wide, “global” or “general” regression model, but the problem with such a model is that although it may be unbiased in general, predictions for local areas may in fact be biased. Removing this spatial (local) bias would render estimates of a global model more accurate. The process by which local bias is removed is known as localization.

Several alternatives to implementing localization are also available, provided that sample trees are available in the localization. First, a global model fitted to the whole sample data in the inventory could be adjusted in different ways: a trend can be added which removes the differences between different regions (e.g. Korhonen 1992, 1993), correction coefficients/equations could be attached to the global model, or totally different models could be used in different regions. Second, the spatial correlation between neighboring observations, which is distance dependent, could be used in the localization. This method is called kriging (e.g. Webster and Oliver 2007). Mixed-model methods could be considered a special case in which the correlation is constant for a stand and zero elsewhere (Lappi and Malinen 1994, Kangas and Korhonen 1995, Mehtätalo 2005). Third, the k-nearest neighbors (k-nn) could also be employed in the localization (Korhonen and Kangas 1997, Sironen et al. 2008). In k-nn, the similarity is measured as a distance in feature space, and the values of the most similar neighbors serve to predict the missing value (Moer and Stage 1995).

The aim of this study was to develop and evaluate methods for localizing a large-area model. In this thesis, local estimates were approached according to the first and second alternatives indicated above. In all four studies, the global model automatically included the trend function, and some experiments were conducted using both correction coefficient and

regional re-fitting. This thesis could be divided into two parts. In the first part, different methods were tested in order to determine the proper segmentation for the whole study area, which would distinguish local biased areas and, with a re-fitting (localizing) of the global model, reduce residual errors in local estimates. We used information about the similarities of the neighboring observations to divide the study area. In the second part, the localization was based purely on the spatial correlation and neighbors, thus requiring no segmentation of the area.

Spatial autocorrelation and spatial indicators

Spatial association, spatial indicators and variograms

Tobler (1970) introduced “the first law of geography: everything is related to everything else, but near things are more related than distant things”, which was the first definition of spatial autocorrelation, also known as spatial association (SA). Simply put, points closer together in space are more likely to have similar characteristics than those that are farther apart. This association has served estimation and interpolation purposes in spatial applications. Well-known methods which rely on this property include, for example, inverse distance weighting (IDW) (Shepard 1968), trend surfaces (Miller 1956), splines (Schoenberg 1946a, 1946b), and kriging (Matheron 1963), just to name a few.

The SA statistics measure the degree of dependency among observations in a geographic space. These measures include, among others, spatial indicators which can be categorized into global and local according to the extent of their use. If the indicator is applied to the entire dataset at once, it is considered global, and if it is applied only for a fraction of the data at a time, it is considered local. Most of the indicators feature both global and local versions (Anselin 1995, Boots 2002). Global indicators of spatial association signal whether clusters of similar values exist in the area, but cannot identify the number or location of clusters within the study area. Their use in practice is therefore limited (e.g. Cliff and Ord 1981).

SA between observations can also be defined as a continuous function. In kriging, SA is modeled with a variogram. In a variogram, the correlation depends on the Euclidian distance and direction between the neighboring observations and calculation point (Cressie 1991). The empirical sample variogram is estimated based on the empirical data, or more precisely, the residuals of the global model, and the combination of both the global model as a general trend and the sample variogram as a SA forms the kriging. Kriging enables one to predict values for points lacking measurement of the dependent variable within the study area.

Local indicators of spatial association

Local indicators of spatial association (LISA) have two common requirements: 1) every LISA should indicate the clusterization around the pivot, which is the centre point of the calculation, and 2) the sum of all LISAs calculated over the study area should be proportional to the corresponding global indicator (Anselin 1995). In a study area, every observation in turn serves as a pivot (i.e. a LISA is calculated for every observation in the dataset, and the sum of all these LISAs must be proportional to the global indicator, which has been calculated with exactly the same parameters (e.g. neighborhood and weighting)).

A LISA can be expressed as a weighted sum of observations in a defined neighborhood (I Eq. 3). The weight can be either binary, proportional to the Euclidian distance between the pivot and the neighboring observation, or it can be based on some property of the observation (Reed and Burkhard 1985). The neighborhood can be limited by the number or the distance or both. The definition of the neighborhood depends on the dataset. For an irregular point dataset point, the distance limitation avoids the large neighborhoods in the gaps and edges of the study area, but ensure that all points have neighbors within the selected range is important.

Four well-known local indicators include Moran's I_i (I Eq. 5, Anselin 1995), Geary's c_i (I Eq. 6, Anselin 1995), G_i and G_i^* (I Eq. 7-8, Getis and Ord 1992) (Eq. 1-4):

$$I_i = \frac{x_i - \bar{x}}{s^2} \sum_j w_{ij} (x_j - \bar{x})^2, \quad j \neq i \quad (1)$$

$$c_i = \frac{1}{s^2} \sum_j w_{ij} (x_i - x_j)^2, \quad j \neq i \quad (2)$$

$$G_i = \frac{\sum_j w_{ij} x_j}{\sum_j x_j}, \quad j \neq i \quad (3)$$

$$G_i^* = \frac{\sum_j w_{ij} x_j}{\sum_j x_j} \quad (4)$$

where i is a pivot, j is an observation, x is the variable of interest, \bar{x} is the mean of x in the study data, s is the standard deviation of x in the whole dataset (no weighting), and w_{ij} is the weight given to the j :th observation.

The interpretation of Moran's I_i follows Pearson's correlation coefficient: positive means clusterization of similar values, negative means a cluster of opposite-signed values around the pivot, and zero means there is no cluster and the neighborhood is heterogenic or the mean of a cluster is near zero. For Geary's c_i , the interpretation follows variance/variogram: all indicator values below one indicate a cluster of similar values, and those above one indicate a cluster of dissimilar values. For G_i and G_i^* , which also are known as Getis statistics, the interpretation is simple: all values differing in either direction from the mean of the whole dataset indicate a cluster. Depending on the sign of the indicator value, there is a cluster of either positive or negative observations. The only difference in the indicators is that in G_i^* , the pivot i belongs to the neighborhood also.

Since the interpretations of LISAs differ from each other, standardizing them helps to interpret results. In standardization, indicators are introduced on the same scale, which is the Z distribution with a mean of zero and a standard deviation of one, $N(0,1)$, by subtracting from the indicator the mean of all indicators and dividing the subtraction by the standard deviation of the indicators in the dataset (I Eq. 9) (Eq. 5):

$$Z[\Gamma_i] = \frac{\Gamma_i - E[\Gamma_i]}{\sqrt{\text{Var}[\Gamma_i]}} \quad (5)$$

where Γ_i is a LISA, $E[\]$ the expected value, and $\text{Var}[\]$ the variance.

Objectives of the thesis

The main goal is to obtain more accurate local estimates for the form height of a tree by localizing the global model of the form height of a tree fitted over the entire study area. The form height is measured as the ratio of the volume of a tree to its diameter at breast height (DBH) (i.e. the height of a pole whose diameter equals the DBH). Though the global model may be generally unbiased and trendless on a global level, local biases could be found and removed.

The first task was to determine whether LISA could distinguish areas of low/high residuals from the study area (I). If so, the LISA calculated from the residuals of the global model could serve as an indicator in segmentation. The latter three papers examine the following three methods in order to obtain local estimates for the form height model: classification and regression trees (CART) (II), multiresolution segmentation (MS) in eCognition Professional 4.0 software (III), and kriging with external drift (KED) (IV).

The target in the first three articles was to divide the study area into sub-areas that were as homogeneous as possible in terms of the residual of the form height of the tree. The localization is a two-phase process in which the localization of sub-areas is first delineated, and then the model is re-fitted to the sub-areas. In the last method (KED), the localization is not limited to a certain sub-area and no indicators are used. Instead, the neighborhood of the localization point serves to adjust the estimate. The global model is localized using the given inventory data without external data sources. Success was measured as a change in the residual error. The shared target of all papers was to improve accuracy of the local estimates.

Finally, the formed sub-areas in II and III were grouped according to the classification introduced in III (Table 3). In this extended summary, these results were further elaborated in order to determine whether the value of a LISA in a sub-areas could be used directly to divide the sub-areas into those requiring localization and those requiring no localization, or even those where a level-correction equal to the local bias is sufficient.

MATERIALS

Field data

The data came from the ninth National Forest Inventory of Finland (NFI9) (no repeated measures data) covering the southern part of Finland. The data included all sample trees measured on both private and state forest land and in managed and unmanaged forests from 11 administrative forestry centers in 12 regions (Fig. 1). The study area belonged to the boreal zone, and the forests were mixed, with Scots pine (*Pinus sylvestris* L.), Norway spruce (*Picea abies* L.) and Silver Birch (*Betula pendula* L.) as the dominant species.

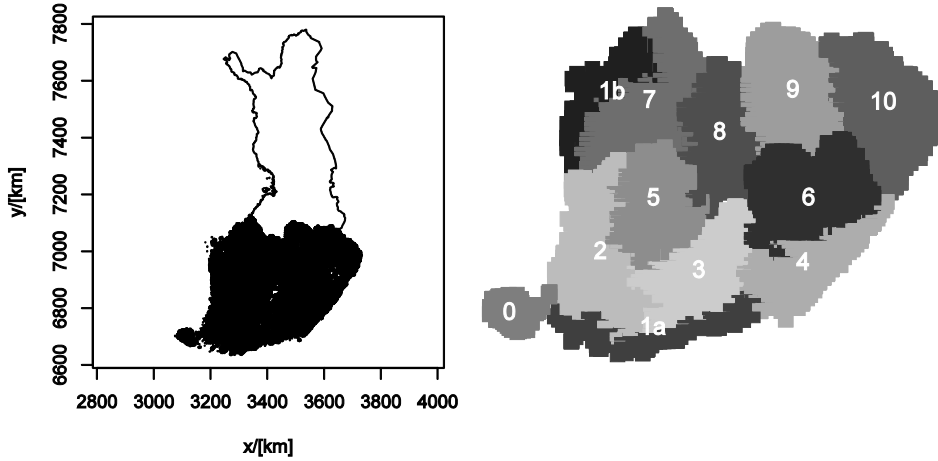


Figure 1. The study area and the forestry centers.

The NFI9 used systematic cluster sampling, where plots were arranged in clusters and trees were measured from these angle gauge plots (also known as variable radius or unequal probability sample plots) using a basal area factor (BAF) of 2 m²/ha. Trees belonging to the plot were selected with an angle gauge, and every seventh tallied tree was measured as a sample tree. Of all the trees measured, we selected the healthy Scots pines whose heights and diameters were measured at breast height (DBH) (i.e. sample trees). In the inventory, every seventh tree selected was a sample tree. With these limitations, the dataset consisted of 19 175 trees (I Table 1). The DBH of an average tree was 20.6 cm, the volume 331 l, the height 15 m and the form height 7 m.

The sampling design in the inventory varied according to the study area (NFI9... 2010). The sample plots were arranged into clusters, and the shape of the clusters, the number of plots in the clusters, the plot-to-plot distances, and the cluster-to-cluster distances differed depending on the forestry centre (IV Table 2). Some descriptions about the real distances between trees can be found in Table 3 (IV), which lists by forestry center the distances to the 40, 60 and 100 closest neighbors. The sample trees selected in the dataset were from 14 782 plots in 3 536 clusters.

Regression model for the form height of a single tree

The variable, form height and model selected for the study were used in two previous studies (Korhonen 1993, Kangas and Korhonen 1995) (I Eq. 12). The shape of a tree significantly impacts the estimates predicted with the model, and any local variation in it could lead to biases in volume and other variables whose estimation is based on the form height (Eq. 6):

$$\frac{v}{d^2} = \beta_0 + \beta_1 d + \beta_2 d^2 + \beta_3 \ln(BA) + \alpha_1 XC + \alpha_2 XC^2 + \alpha_3 XC \cdot YC + \alpha_4 YC + \alpha_5 YC^2 + \alpha_6 RDIST + \varepsilon \quad (6)$$

where the β and α are regression coefficients; v is the volume; DBH is the diameter of the tree at breast height; BA is the total basal area; and XC , YC , and $RDIST$ are variables related to the spatial position calculated as (Eq. 7-9):

$$XC = \frac{X - 60}{1000} \quad (7)$$

$$YC = \frac{Y - 6620}{1000} \quad (8)$$

$$\begin{cases} RDIST = \frac{1}{DIST + 0.05}, & DIST \leq 20 \\ RDIST = 0, & DIST > 20 \end{cases} \quad (9)$$

where X and Y are the geographical co-ordinates. X is the distance from the Greenwich meridian, and Y is the distance from the Equator in kilometers. $DIST$ is the Euclidian distance from the coastline. All variables are expressed in kilometers. To be precise, the dependent variable was proportional only to the form height, since the volume (v) and the diameter of the tree at breast height (DBH) were in different units, and the dependent variable rather than the square of DBH should have been divided by the basal area of the tree. Despite these differences, the variable is called form height (fh) later in this doctoral thesis.

The form height regression model can be divided into two parts. The first part consisted of the tree variables (DBH and the square of DBH) and stand variable (total basal area of the plot including all tree species, BA). The latter part was the spatial trend, which included spatial co-ordinates XC and YC , and the distance from the coastline, $RDIST$, which was added to the model to remove the global trend in the residuals of the first part (I Fig. 3). The $RDIST$ variable models the effect of the sea (e.g. wind load) on the tree stems in the coastal regions of Finland. The coastal regions are the result of land rising from the sea, so the ecological conditions on growing sites are exceptional (Karlsson 1997, 2000).

METHODS

Localization – process description

Localization can be illustrated as a four phase process: fitting the original model, calculating the spatial association, segmentation/kriging, and localization or results/evaluation (Fig. 2). The starting point is fitting the global model (i.e. the regression model) (Eq. 6) to the entire inventory data. The residuals of the global model are transferred to the next phase, where they are used either in calculating the local index (LISA) or in kriging to estimate an empirical sample variogram. In the third phase, the study area is segmented or kriged with the help of the variables calculated in the second phase. The resulting segments are called sub-areas. In the final phase, the actual results are obtained either after re-fitting the regression model to the segments or by cross-validating the kriging

and then comparing the residuals and prediction errors to the initial situation (phase I). The re-fitting process is also known as localization.

All the above-mentioned methods are introduced in following sub-chapters. Although the introduction already briefly defined LISAs (Eq. 1-4), they are reviewed here, and selections related to them, introduced. In addition to the LISAs, variograms modeling the spatial correlation in the data are also reviewed, and the methods in the third phase, explained. Finally, the measures used to evaluate the segmentations and to compare the methods are introduced, and the last sub-chapter of this section presents the methods used to group the segments.

Raw data (Phase I)

At the starting point are the fitted global model (Eq. 6) and the residuals for every observation in the dataset (Fig. 2). The studies then follow two different study lines: one where the LISAs are utilized in the localization, and another where kriging is applied.

Calculation of spatial association (Phase II)

LISA – weighting and selection

The variable (x in Eq. 1-4) for which the LISAs are calculated is the residual of the global regression model, ε (Eq. 6). The residual of a regression model is the difference between the true measured value, fh , and the model estimated value, $\hat{f}h$ (I Eq. 13):

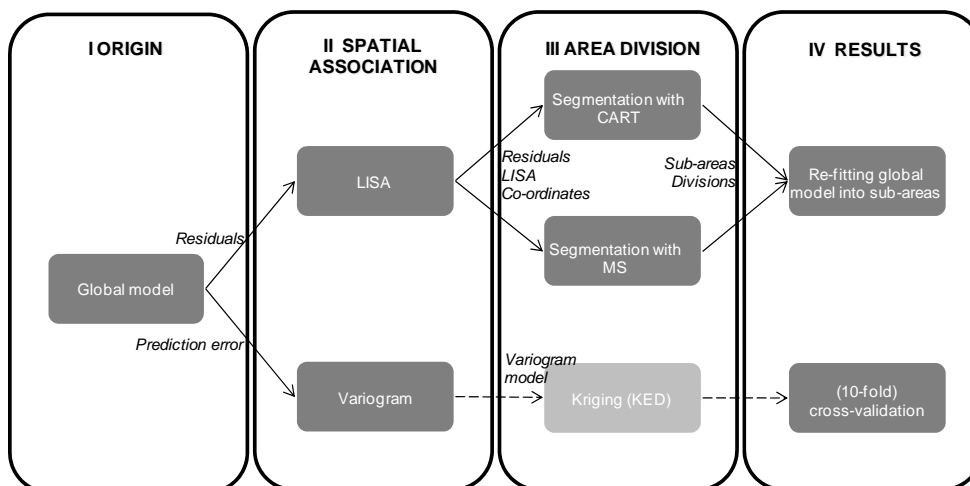


Figure 2. The actual phases of the localization process with three different methods: CART (classification and regression trees), MS (multiresolution segmentation), and KED (kriging with external drift).

$$\varepsilon = fh_i - \hat{f}h_i \quad (10)$$

In all LISAs (Eq. 1-4), the weighting is binary. If the observation belongs to the neighborhood, it is assigned a unit weight. Otherwise, the weight is zero (Eq. 11):

$$\begin{cases} w_{ij} = 1, & r_{ij} \leq 20 \\ w_{ij} = 0, & r_{ij} > 20 \end{cases} \quad (11)$$

where r_{ij} is the Euclidian distance in kilometers between pivot i and observation j . All LISAs were assumed to follow normal distribution (more in discussion) and were normalized according to Eq. 5. The LISAs and their suitability for use as an indicator in the segmentation were tested in article I. The evaluation is based on the visual contemplation of the LISAs over map, in addition to the changes in RMSE (introduced later). A LISA should enhance division of the study area into homogeneous sub-regions of reasonable size (large enough to permit re-fitting of the regression model).

Variograms

In kriging, the global trend is “adjusted” with the residual information (Eq. 10) from the points predicted with the same model in the neighborhood of the calculation point. This method can take into account both the distance and the direction between points. The spatial autocorrelation between neighboring observations \mathbf{s}_1 and \mathbf{s}_2 is modeled using a variogram (IV Eq. 4, e.g. Isaaks and Srivastava 1989, Cressie 1991, Webster and Oliver 2007):

$$2\gamma(\mathbf{s}_1 - \mathbf{s}_2) = \text{var}(\varepsilon(\mathbf{s}_1) - \varepsilon(\mathbf{s}_2)), \quad (12)$$

where \mathbf{s}_1 and \mathbf{s}_2 are the positions, 2γ is the variogram and ε is the residual of the global model (Eq. 6). Typically, the variogram features three main characteristics: a nugget effect, a sill and a range. The nugget effect is the height of the jump of the semivariogram at the discontinuity at the origin, the sill is the limit of the variogram tending to infinite lag distance, and the range is the distance at which the difference of the variogram from the sill becomes negligible. In addition, a partial sill is sometimes used, which is the sill minus the nugget effect.

The process is considered intrinsically stationary if the expected value of the difference in residuals (ε) remains constant (inside the brackets in Eq. 12) at all distances h . In addition, if the variogram is not direction dependent, the process is isotropic, and Eq. 12 can be estimated using a sample variogram. In the sample variogram for all possible data pairs in the data, the difference and the distance between them is calculated, and lastly, the point pairs are classified into distance classes (Eq. 13):

$$2\hat{\gamma}(h) = \frac{1}{|N(h)|} \sum_{N(h)} (\varepsilon(\mathbf{s}_i) - \varepsilon(\mathbf{s}_j))^2 \quad (13)$$

where h is a distance class and $|N(h)|$ is the number of observations belonging to this distance class, to a lag. The width of the lag is the only parameter that the modeler can change. The averaging of the sample variogram can be controlled by changing the width. With narrow lags, the number of observations falling in a lag is low, and a single deviating observation can significantly impact the class average. On the other hand, with wide lags, the averaging conceals the actual trends. To these data, the width of a lag was set to 200 m, or little less than the plot-to-plot distance in clusters, which depended on the region at 250-300 m (NFI9... 2010, IV Table 1). Therefore, the first lag in the sample variogram shows the correlation within the same plot, where the target tree is located.

A variogram model is fitted to a resultant empirical sample variogram. Exponential, Gaussian, circular, Bessel, and spherical models were tested (Bailey and Gatrell 1995). Since the models have their limitations in form and bending to the point cloud, it is possible to split the model into two different parts where the first part models the short-range nugget effect and the second part, the actual trend. These kinds of models are known as nested variogram models. Although the parts could be of different model types, here the models were always the same for both the short-range and long-range parts. The variogram models for the actual kriging and evaluation were selected based on visual inspection. Since the fitted variogram models formed two groups (Fig. 3, IV Table 5), one of each was selected, namely spherical and Bessel variogram models.

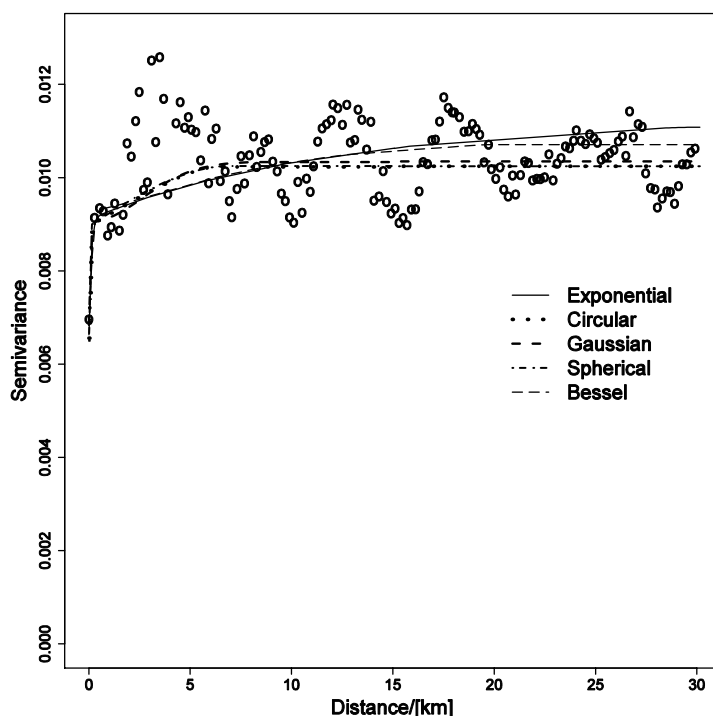


Figure 3. Sample variogram (points) and fitted variogram models (lines).

Segmentation or division of large area/population (Phase III)

Classification and regression trees (CART)

This method is known as either CART or recursive partitioning. The version developed by Breiman et al. (1984) has been followed, and since the dependent (the form height) is a continuous variable, the type of CART is the regression tree. The basic idea in CART is to divide the whole population (data) into smaller units which are homogeneous with respect to the dependent variable, but has served various purposes, such as variable selection and the prediction of the absence or presence of some tree properties (e.g. cavity, defoliation) (Fan et al. 2003a, b, Candau and Fleming 2005) or the crown class of trees (Nigh and Love 2004). Negron (1997) and Dobbertin and Binging (1998) replaced logistic regression models with CART in the estimation of tree mortality.

The algorithm identifies the most profitable variable from the independent variables (in regression model Eq. 6), thus minimizing deviance in the dependence, which is either the residual (Eq. 10) or LISA. The profitability of the division is measured as a decrease in the coefficient of determination, R^2 . The variable for which the decrease is the largest is selected, and the population is divided with respect to its certain value. The divided parts of the population are then studied separately, and the dividing process continues. The process can be illustrated as a “tree” where each division in a node forms two branches, and the results of all the splits are in the end nodes, or “leaves”. If the result of division is purely spatial (i.e. all divisions in the tree are based on the co-ordinate variables of model Eq. 6), the leaves of the regression tree form sub-areas of the study area.

Without any limitations, the partitioning process would result in a regression tree with single observations in its leaves. This process would lead to the over-explanation of problems, or over-fitting, where the system finds single noisy events instead of actual trends in the data, but this would be inappropriate. The sizes of the regression trees or the number of observations in the leaves have therefore been limited in four different ways, both directly and indirectly: 1) the minimum number of observations in a leaf has been set to 50, and 2) the minimum number of observations needed in a node for a split has been set to 100. Besides, 3) the value of the complexity parameter (cp), which denotes the minimum required change in the coefficient of the determination (R^2) in a division, was set to $cp = 0.001$, and 4) the regression trees already created could be pruned to match a larger cp than was used in the creation of the original regression tree. The pruning cuts the least profitable branches from a regression tree according to the change in R^2 to correspond to the set value of cp.

MVPART (multivariate partitioning) is the version of CART in which two dependent variables, the residuals and the LISA, could concurrently exist in the regression tree (Therneau and Atkinson 1997). The algorithm is very similar to the CART with two exceptions: the size of the regression tree (the number of end nodes) could be set directly, but the sizes of the end nodes (the number of observations) could not be controlled. Both these properties could also have been implemented in the CART.

Multiresolution segmentation (MS)

An alternative to the previous CART method is to use image segmentation to divide the study area. eCognition Pro 4.0 software (Definiens Imaging, later versions Definiens Pro) can segment any kind of rasters passed to it (eCognition... 2009). The residuals (Eq. 10) and

LISAs constitute a point dataset and can be converted to images in which the pixels correspond to the value of the indicators. These images can be analyzed using the algorithms of the software. The software uses general object-oriented image analysis in which the initial segmentation is based on primary features, such as the digital value of pixels (Benz et al. 2004).

In segmentation, merging pixels form the objects (sub-areas). This process employs a bottom-up region-merging technique. The merging is controlled by a heterogeneity parameter of which the threshold value is given through the scale parameter (Benz et al. 2004). The heterogeneity parameter combines the color and shape variables. Color information is carried in the pixels as a digital value, and the shape is a compromise between the smoothness of the borderline and the compactness of the delineated sub-area. Therefore, the final segmentation is the result of an optimization process which combines both the variables and their preferences. The larger the value of the scale parameter, the larger the sub-areas in the segmentation (i.e. the increase in the scale parameter value allows more heterogeneity in the sub-areas).

If the similarity information from the neighboring observations is provided to the program as a raster image, would the resulting segmentations improve the estimates of the global model when the model is localized for these segmented sub-areas? The residuals and LISAs were converted to rasters with IDW (Longley et al. 2005), and the raster images were passed to the eCognition software. The multiresolution segmentation algorithm in the eCognition software, and the initial segmentation procedure in particular, was employed to divide the area into sub-areas. The settings in the segmentation were made to favor the information in the pixels at the expense of the shape variables, since one intention is to utilize the digital value as fully as possible. This means that the parameters of the initial segmentation remained at their default values.

With the two variables, residuals and LISA, four combinations served as raster layers: 1) residuals of the global model, 2) LISA, 3) residuals and LISA, and 4) residuals weighted by the inverse of the layer variances and LISA. Several segmentations were made for each of these four layers by changing the value of the scale parameter. Each of the segmentations featured more than one segment (i.e. sub-areas into which the regression model could be re-fitted).

Kriging with the external drift (KED) in the local neighborhood

Instead of dividing the study area, the localization could be continuous so that for every point in the dataset, the neighborhood is defined and used to localize the function. The basic model, which the variable under consideration (\mathbf{Z}) is assumed to follow, in universal kriging (UK) is:

$$\mathbf{Z} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\delta} , \quad (14)$$

where the \mathbf{X} matrix contains the covariates of the model (Eq. 6), $\boldsymbol{\beta}$ is the parameter vector, and $\boldsymbol{\delta}$ is the residuals of a zero-mean intrinsically stationary random process with a variogram (2γ). Then the predictor of \mathbf{Z} for point \mathbf{s}_B is \mathbf{Z}^* (Eq. 15):

$$\mathbf{Z}^*(\mathbf{s}_B) = \mathbf{c}'\hat{\boldsymbol{\Sigma}}^{-1}\mathbf{Z} + (\mathbf{x} - \mathbf{X}'\hat{\boldsymbol{\Sigma}}^{-1}\mathbf{c})'\hat{\boldsymbol{\beta}}_{EGLS} , \quad (15)$$

where \mathbf{c} is a vector of the correlations between the prediction point and the surrounding observations, $\hat{\Sigma}$ is an estimated variance-covariance matrix where the defined variogram model for observations estimates all elements, the covariates for point \mathbf{s}_B are in the \mathbf{x} vector, and the estimated generalized least-squares estimator for $\boldsymbol{\beta}$ in Eq. 15 is (Eq. 16):

$$\hat{\boldsymbol{\beta}}_{EGLS} = \left(\mathbf{X}'\hat{\Sigma}^{-1}\mathbf{X} \right)^{-1} \mathbf{X}'\hat{\Sigma}^{-1}\mathbf{Z} \quad (16)$$

Kriging with external drift (KED) (Hengl et al. 2003) or kriging with distinction or residual kriging (Schabenberger and Gotway 2005) is near universal kriging (UK), but in KED, the global mean or the global trend (Eq. 14) includes at least one variable unrelated to the spatial position. In this case, both the diameter and the basal area are indeed such variables.

The neighborhood of an observation could cover the entire study area or could be limited by the number of or distance to neighbors or by any combination of these two criteria. If the data pattern is irregular, the limitation by the number of neighbors is more secure, since it precludes situations in which an observation has no or only a few neighbors. The calculation capacity is also a practical limitation, since the process includes inverting large matrices. Given the above-mentioned limitations, the evaluation was carried out with 10-fold cross-validation or leave-one-out cross-validation for the model, where the dataset is either randomly divided into 10 equal-sized folds or only the one observation, for which the prediction is made, is extracted (Pebesma and Wesseling 1998, Pebesma 2004). The model is estimated for a fold with the rest of the dataset, and as a result, generates an estimation/prediction error for every observation in the dataset.

Measures for evaluation (Phase IV)

All four articles (I-IV) include some common measures for comparing and evaluating the results after either re-fitting the regression model (i.e. localization) or cross-validating the KED (Eq. 17-21):

- 1) The sum of the residuals (Eq. 10) over a region is an estimate of the bias (II Eq. 6):

$$\text{bias} = \frac{\sum_{i=1}^n \varepsilon_i}{n} \quad (17)$$

- 2) The root mean square error (RMSE) combines the bias and the standard deviation (SD) in the residuals (I Eq. 11):

$$\text{RMSE} = \sqrt{\text{bias}^2 + SD^2} \quad (18)$$

- 3) The aggregate estimate of the standard error is the weighted sum of the regional mean squared errors, or MSEs (II Eq. 10):

$$se_{aggr} = \sqrt{\frac{\sum_{i=1}^m n_i^2 MSE_i}{\left(\sum_{i=1}^m n_i^2\right)}}, \quad (19)$$

where MSE is the square of RMSE, m is the total number of sub-areas, and n is the number of observations within the sub-area i (Eq. 18).

4) The relative change in RMSE in the localization of sub-area i when the RMSE of the localized model is compared to the global model RMSE for the entire study area (i.e. $RMSE_{glo} = 0.1027 \text{ dm}^3 \text{ cm}^{-2}$) (II Eq. 8):

$$\Delta RMSE_i = \frac{RMSE_{i,loc} - RMSE_{glo}}{RMSE_{glo}} \cdot 100\% = \frac{RMSE_{i,loc} - 0.1027}{0.1027} \cdot 100\% \quad (20)$$

5) The relative change in RMSE in the localization of sub-area i when the RMSE of the localized model is compared to the global model RMSE in the same sub-area before localization, $RMSE_{i,glo}$ (II Eq. 9):

$$\Delta RMSE_{i,loc} = \frac{RMSE_{i,loc} - RMSE_{i,glo}}{RMSE_{i,glo}} \cdot 100\% \quad (21)$$

The individual residuals as such do not reveal the entire situation in the localization, and are therefore combined as either regional RMSE or study area-wide in aggregate standard error (Eqs. 19-21, above). The regression model localized (re-fitted) regionally by forestry center (Fig. 1) serves as a reference.

Classification of the sub-areas

By definition, the LISA that differs from zero indicates that the pivot or its surroundings or both (depending on the indicator, the pivot either does or does not belong to the neighborhood of the pivot, Eqs. 1-4) also differ from zero (Getis and Ord 1992), which indicates a bias in the residuals of the global model, since the LISAs were calculated from the residuals. This bias could be removed by localizing (re-fitting) the model or by simply adding a level correction constant which equalizes the local bias to the global model. Here I tested whether the sub-areas could be classified into groups according to the LISA in the sub-area and whether localization of the global model (re-fitting) could be replaced with a level correction equalizing the local bias. These calculations are a new contribution to evaluation of the results from articles II and III.

The assumption was that the benefits of localization are the greatest in the sub-areas where the mean of LISA differs significantly from zero. This improvement was measured by the absolute value of the localized $RMSE_{i,loc}$. For this comparison, the classification introduced in article III (Table 3) was also applied to CART. The sub-areas were classified into three different classes: positive, negative, and neutral. If both the mean of the $LISA + 1\sigma$ (standard deviation) and the mean of the $LISA - 1\sigma$ in the sub-area were positive, the sub-area was classified as positive. If both were negative, the sub-area was

classified as negative. If the sub-area fit neither of the previous classes, it was classified as neutral. This classification was also applied with a standard deviation value of 1.5σ .

The possibility of replacing the re-fitting with the level correction was also tested for every sub-area. In practice, this involved a comparison between the resulting $RMSE_{i,bias}$, in which the local bias was removed from the $RMSE_{i,glo}$ value in that sub-area i in question and the actual localized $RMSE_{i,loc}$ (the RMSE of the re-fitted model). This is the easiest way to remove the local bias, so this kind of level correction would be an attractive alternative to localization.

RESULTS

Selection of the LISA

Comparison of the different LISAs (Moran's I_i , Geary's c_i , G_i and G_i^*) revealed that the first two indicators could show only a couple of small-sized areas in which the standardized indicator value differed significantly from zero (I Fig. 4a, b). On the contrary, both Getis statistics could reveal a cluster of both negative and positive values as well as neutral areas (I Fig. 4c, d).

From the two Getis statistics, which were equally suitable for the task, G_i^* was selected for future study, because this index also included the pivot in the neighborhood, thus revealing at the same time the uniformity of the pivot in its neighborhood (Getis and Ord 1996). The first localization trial based on G_i^* actually lowered the RMSEs in all sub-areas selected (I Fig. 5, Table 5).

Comparison of segmentations: CART, MS and KED with the division of the study area into the traditional forestry centers

Single sub-areas

At a global level, the original regression model of form height had an RMSE of $0.1027 \text{ dm}^3 \text{ cm}^{-2}$. When the study area was segmented for localization purposes, the resultant segmentations included various numbers of sub-areas (II Table II, III Table 2). The traditional forestry centers divide the southern part of the country into 12 regions, a division that was adapted to the results of kriging also, though the kriging was applied to the entire study area (IV Table 7). In kriging, the SA between observations ranged from 5.2 km (Bessel) to 6.8 km (spherical variogram model) (IV Table 4). The Bessel model approaches its sill asymptotically, so the range reported is only about one-fourth of an effective range (Webster and Oliver 2007), whereas the range reported for the spherical model is equal to the effective range. Since the proportion of the nugget effect of the sill is larger than that of the partial sill, the observation beyond the effective range may also bear a weight (e.g. Webster and Oliver 2007, p. 168).

When all single results from articles II-IV were brought together in a table, it was evident that the mean values for all four different methods were near each other (Table 1). In particular the RMSEs for the division of the forestry centers and kriging were similar. The segmentations with multiresolution segmentation (MS) yielded the most extreme

RMSEs (both the highest and the lowest RMSEs), whereas the mean RMSEs for CART were higher than for MS, but lower than for the first two methods (kriging and division of the forestry centers).

Overall results

An aggregate estimate of the standard error sums up the RMSEs of the single sub-areas in the segmentations, which renders the segmentations comparable as a whole (Eq. 19). The above-mentioned RMSE of the global model serves as a reference. These results for different methods appear in following tables of the individual articles: Table VII (II) for CART, Table 7 (III) for segmentation with eCognition, and Table 7 (IV) for KED, with all collected here in Table 2. The aggregate estimate of the standard error for the forestry centers was $0.1016 \text{ dm}^3 \text{ cm}^{-2}$ (II Table VIII).

For both of the area segmentation methods, CART and multiresolution segmentation, the level of the global model's standard error was exceeded only once in both methods. The averages for the errors in the division methods lay near $0.1 \text{ dm}^3 \text{ cm}^{-2}$, which was considerably lower than the RMSE for the global model or forestry centre division. This was also the level which the KED approached when the number of neighbors increased.

When the localized RMSEs of single sub-areas in segmentations were compared to the RMSE of the global model ($0.1027 \text{ dm}^3 \text{ cm}^{-2}$), the localized RMSE was smaller than the global one in 60% (range 40-100%) of cases (Table 3). When the localized RMSEs were compared to the global model RMSE in the same sub-area before localization, the percentage was 75% (range 58-100%). When the number of sub-areas decreased in the segmentation, the localized RMSE was more likely to be smaller than the original one in the sub-area.

The classification of sub-areas

Before classifying the CART-based sub-areas, two regression trees were rejected from calculation, Trees 2 and 3 (II Table II), because they were not spatial in nature. Those trees used non-spatial dividers, namely diameter at breast height and basal area. Also, sub-areas with fewer than 30 observations were excluded from future studies because for normality, assumptions regarding the re-fitting (localization) of a regression model recommended a minimum of 30 objects. This limitation will affect only those segmentations that used eCognition software (Compare Table 3 to Table 2 in III).

Given the above-mentioned limitations, classification of the sub-areas into three classes according to the mean G_i^* value and its deviance from zero yielded the distribution shown in Fig. 4. The numbers of positive and negative sub-areas were almost exactly the same, and the number of neutral sub-areas was 14% smaller than the others. All together there were eight more negative sub-areas than positive ones. The resulting classification at the segmentation level was also distributed quite evenly (Table 3). In 14 of all the segmentations, the majority of sub-areas was classified as positive; in 16 segmentations, the majority comprised negative sub-areas, and in 8, neutral. The latter could mean either that all the sub-areas were neutral or the numbers of negative or positive sub-areas were equal.

Table 1. The RMSEs ($\text{dm}^3 \text{cm}^{-2}$) for different segmentation methods: administrative forestry centers (FC), classification and regression trees (CART), segmentation with the multiresolution procedure in eCognition (MS), and kriging with external drift (KED).

<i>Segmentation</i>	<i>RMSE</i>				
	<i>Min</i>	<i>1Q</i>	<i>Mean</i>	<i>3Q</i>	<i>Max</i>
FC	0.0817	0.0981	0.0999	0.1045	0.1159
CART	0.0655	0.0910	0.1004	0.1083	0.1514
MS	0.0057	0.0855	0.0977	0.1096	0.2563
KED	0.0806	0.0959	0.0988	0.1052	0.1156

Table 2. The aggregate estimates of the standard error ($\text{dm}^3 \text{cm}^{-2}$) (SD) for different methods: multiresolution segmentation (MS), classification and regression trees (CART), and kriging (KED) for both Spherical (Sph) and Bessel (Bes) variogram models.

<i>MS</i>			<i>CART</i>		<i>KED</i>	<i>Sph</i>	<i>Bes</i>
<i>Name</i>	<i>Areas</i>	<i>SD</i>	<i>Areas</i>	<i>SD</i>	<i>Neighbors</i>	<i>SD</i>	<i>SD</i>
G*130	4	0.1010			20	0.3136	15.95
Weight56	5	0.1018			30	0.1122	0.1126
G*103	6	0.1006			40	0.1058	0.1061
Weight36	9	0.0998	11	0.1012	50	0.1032	0.1034
Res47	10	0.1025	12	0.1001	60	0.1016	0.1011
Res35	15	0.1023	15	0.1017	70	0.1002	0.1007
Res;G*60	16	0.0981	16	0.0999	80	0.0996	0.1000
G*87	17	0.0983			90	0.0993	0.0996
Res27	22	0.1029	20	0.1003	100	0.0987	0.0987
Res;G*48	23	0.1019	23	0.0994			
Weight27	24	0.0997	24	0.1008			
G*65	25	0.0994					
G*50	35	0.0986					
Res20	39	0.0988	38	0.1007			
Res;G*35	43	0.1018	44	0.1003			
Weight20	54	0.1004	50	0.0994			
G*38	62	0.0991					
Res14	73	0.0967					
Res;G*26	78	0.0997					
G*29	84	0.0986					
Weight14	89	0.0988					
G*22	120	0.1016	121	0.1028			
Res;G*18	120	0.1016	127	0.1026			
Res10	140	0.1002					
Weight10	150	0.1004					
G*17	177	0.0983					
Res;G*13	192	0.1025					
G*13	265	0.0998					
Res;G*10	291	0.1014					
G*10	366	0.1009					

Table 3. The sub-areas in the segmentations with eCognition and CART, the classification of single sub-areas (SUM), and the percentages of sub-areas where the RMSE of the localized model is either lower than that of the global model (Global) or lower than that of the global model RMSE in the same sub-area (Global in sub-area). The sub-areas are classified according to the mean of G_i^* in positive (+1), negative (-1) and neutral (0) ones and, if there are more positive than negative sub-areas, the sum is positive, and vice versa.

	Sub- areas	SUM	Global [%]	Global in sub-area [%]
G*10	248	13	67	79
G*13	211	3	60	75
G*17	161	-8	67	75
G*22	113	-7	58	66
G*29	80	-3	58	63
G*38	58	-3	59	66
G*50	34	-4	59	65
G*65	25	-2	68	76
G*87	17	0	59	71
G*103	6	-3	83	100
G*130	4	-2	100	100
Weight10	133	7	62	65
Weight14	84	2	63	70
Weight20	51	4	59	80
Weight27	23	0	57	91
Weight36	9	0	44	89
Weight56	5	0	40	100
Res10	130	-8	55	63
Res14	72	-2	60	76
Res20	39	-3	64	82
Res27	22	-2	77	91
Res35	15	-1	67	93
Res47	10	0	60	90
Res;G*10	224	6	65	67
Res;G*13	172	-4	60	59
Res;G*18	112	2	51	58
Res;G*26	73	-3	60	66
Res;G*35	41	0	59	68
Res;G*48	23	3	57	70
Res;G*60	16	1	63	63
Tree1	11	2	45	82
Tree4	127	1	57	68
T4P1	38	1	61	76
T4P2	15	1	73	80
Tree5	50	2	60	74
T5P1	24	-1	67	79
T5P2	20	0	60	75
T5P3	12	0	67	75

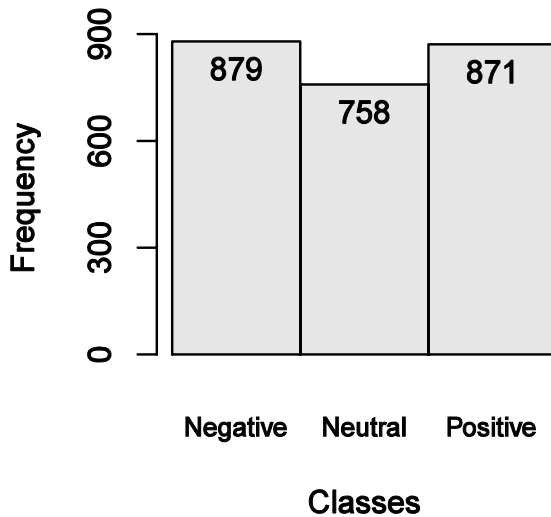


Figure 4. The classification of sub-areas in CART and multiresolution segmentations into three classes according to the mean of G_i^* .

If the localization into the sub-areas was replaced with a level correction in which the local bias in the sub-area was subtracted from the global model $RMSE_{i,glo}$ in the same sub-area, the corrected RMSEs ($RMSE_{i,bias}$, Table 4) were smaller than the original global model RMSEs ($RMSE_{i,glo}$, Table 5). The changes were greatest in the group of negative sub-areas, and smallest in the neutral class. The mean RMSE was 3.2% lower than the original in the negative class, whereas in the positive class, it was only 1.9% lower. On the other hand, with respect to the actual localized RMSEs ($RMSE_{i,loc}$), the level-corrected RMSEs were 3.0-1.1% higher (Table 6). But then, the greatest differences were in the extremes of the localized RMSEs. The minimum RMSEs were considerably lower for localized models than for the level correction (18-34%), whereas the maximums in the negative and positive sub-areas were higher for localized models than for level-adjusted ones (12-31%). The change in neutral class with level correction was and should have been zero, since the sub-areas in the neutral class by definition have no bias if G_i^* is zero. But in the case of the heterogenic sub-area with a near-zero mean ($G_i^* = 0$), localization could lower the RMSEs (as it did) by 2%. Otherwise, the difference between these two localization methods is minor: 1% for positive and 3% for negative classes.

Then the sub-areas were re-classified so that 1.5σ was subtracted from and added to the mean of G_i^* or, in other words, the neutral class was widened. The mean G_i^* in the negative and positive classes differed from zero with greater probability ($p = 0.033$). This new classification lowers the mean of the neutral and positive classes (Table 7). The negative class remained about the same, whereas for the positive class with increased minimum RMSEs and decreased maximum RMSEs (i.e. decreased range of RMSEs), the effect of classification on the neutral class was opposite: the range actually increased.

Table 4. RMSEs ($\text{dm}^3 \text{cm}^{-2}$) when a constant level correction that equals the local bias in the sub-areas is applied to every sub-area, $\text{RMSE}_{i,\text{bias}}$, classified according to the mean G_i^* and its deviation in the sub-area.

<i>Class</i>	<i>Min</i>	<i>1Q</i>	<i>RMSE</i>		
			<i>Mean</i>	<i>3Q</i>	<i>Max</i>
Negative	0.0635	0.0888	0.0980	0.1065	0.1419
Neutral	0.0628	0.0936	0.1028	0.1111	0.1670
Positive	0.0687	0.0910	0.1026	0.1142	0.1724

Table 5. RMSEs ($\text{dm}^3 \text{cm}^{-2}$) before localization, global RMSEs in sub-areas, $\text{RMSE}_{i,\text{glo}}$, classified according to the mean G_i^* and its deviation in the sub-area.

<i>Class</i>	<i>Min</i>	<i>1Q</i>	<i>RMSE</i>		
			<i>Mean</i>	<i>3Q</i>	<i>Max</i>
Negative	0.0733	0.0915	0.1012	0.1096	0.1463
Neutral	0.0633	0.0937	0.1032	0.1115	0.1671
Positive	0.0699	0.0926	0.1046	0.1161	0.1733

Table 6. The localized RMSEs ($\text{dm}^3 \text{cm}^{-2}$) when the sub-areas are classified into three classes according to the mean G_i^* and one length of the standard deviation, $\text{RMSE}_{i,\text{loc}}$.

<i>Class</i>	<i>Min</i>	<i>1Q</i>	<i>RMSE</i>		
			<i>Mean</i>	<i>3Q</i>	<i>Max</i>
Negative	0.0537	0.0856	0.0951	0.1036	0.1619
Neutral	0.0536	0.0914	0.1009	0.1105	0.1414
Positive	0.0513	0.0897	0.1015	0.1131	0.2504

Table 7. The RMSEs ($\text{dm}^3 \text{cm}^{-2}$) for localized models when the classification of sub-areas is based on mean $G_i^* \pm 1.5\sigma$ (standard deviation of G_i^*).

<i>Class</i>	<i>Min</i>	<i>1Q</i>	<i>RMSE</i>		
			<i>Mean</i>	<i>3Q</i>	<i>Max</i>
Negative	0.0561	0.0860	0.0953	0.1032	0.1619
Neutral	0.0513	0.0884	0.0998	0.1105	0.2504
Positive	0.0611	0.0917	0.1006	0.1114	0.1411

DISCUSSION

If the measurement data from an inventory of a large area could be generalized to the population with a single global (= population-wide) model, it would be easy to implement. Unfortunately, the resulting estimates could be locally biased (spatial bias). A method

which could indicate the biased sub-regions, delineate them, and remove the bias would improve the estimation considerably. In this thesis, local indicators of spatial association (LISA) served as the indicator, and the segmentation of the study area was tested with two different methods: recursive partitioning (CART) and multiresolution segmentation (MS). Both methods used spatial location together with LISA and residual information calculated from the global model to determine the homogeneous localization sub-areas. An alternative to these methods is to localize every single observation with its neighborhood with no intention to divide the study area (KED). The results were compared to the traditional forestry centre division of the study area (Fig. 1). To determine the reference, the global model was localized to 11 administrative units in 12 regions.

The spatial indicators were developed to identify “hot” and “cold” spots (i.e. small-scale phenomena which differ significantly from their surroundings) (e.g. Getis and Ord 1996). The original idea in LISAs has been to test whether the local indicator differed statistically significantly from zero. Several articles (e.g. Anselin 1995, Ord and Getis 1995, Boots and Tiefelsdorf 2000) have questioned the actual normality of the standardized indicators (Eq. 5). In these studies, neither normality nor statistical significance are important. Only sub-areas that were as homogeneous as possible were wanted, and LISA was the measure used. Here LISAs were calculated from the residuals of the global model, so any deviation from zero could indicate local bias.

Some have suggested that the LISAs, especially the Getis statistics G_i and G_i^* , are suitable for image segmentation (Wulder and Boots 1998). The intention is to delineate sub-areas with enough observations for the re-fitting of the regression model. For some of the studies, the limit for minimum observations in a sub-area was set to as few as 10 observations (III), but in study II, the limit was set to 50, and in the kriging analysis, the number was from 20 to 100. This summary employed a limit of 30. Compared to the size of the dataset (19 175 trees), the sub-areas may have been small in area, even with these minimum limits, but in studies II (Fig. 4) and III (Table 2), the largest sub-areas covered almost $\frac{3}{4}$ of the data.

Another issue was the dependence between neighboring LISAs. Since every LISA was calculated from a 20-km circular neighborhood, the neighboring LISAs were correlated if their neighborhoods overlapped. This posed no problem because LISAs are not used as such, but only as indicators to show the areas of low and high values of the residuals. On the other hand, the LISA is treated here as a point datum, bound to a single point when it actually represents the area, or neighborhood, from which it was calculated. Each point had equal-sized (distance-limited) neighborhoods as well as its own LISA to which the decision can be based. A LISA calculated for a certain model (residuals of a model) can represent only the features of that particular model. Therefore, any segmentation based on a LISA is invalid for another model. So, if the system has more than one model, they all have their own segmentations.

Looking at the RMSEs for single sub-areas, the lowest range from 6% to 80% (Table 1), and the first quartile ranges from 83% to 96% of the global model RMSE ($0.1027 \text{ dm}^3 \text{ cm}^{-2}$), but the dispersion in localized RMSEs was wide. Kriging seems to be close to the forestry centre division results (Table 1), but this result is somewhat misleading. The kriging estimates could have been improved if the number of the neighbors were increased. But in study IV, the increase stopped when the RMSEs and aggregate standard errors were smaller than the references, which were the RMSE of the global model and the standard error of the forestry centre division. Therefore, kriging could have performance better than presented in article IV.

Because LISA was used, G_i^* yielded either high positive or negative values if the calculation point and its surrounding differed from zero in either the positive or negative direction; G_i^* yielded zero if the surrounding was either near zero or heterogeneous. The relationship between the value of G_i^* and the localized RMSE in the segmentations of studies II and III were analyzed. The classification was adopted from the article III (Table 3) with some changes. Only the sub-areas with at least 30 observations were used in the calculations, because only then was the amount of data sufficient to re-fit the regression model. When the sub-areas formed with CART and MS were classified according to the above-mentioned method, the localization lowered the RMSEs by 2% (neutral class), 3% (positive class), and 6% (negative class) (Tables 5 and 6). With level-correction, the change was 0%, 2%, and 3%, respectively (Tables 4 and 5).

For the classification in study III, the mean of G_i^* in a sub-area had to differ from zero by one standard deviation in order to belong to a class other than neutral. One standard deviation corresponds to 0.841 of cumulative probability in normal distribution, whereas one and a half standard deviation corresponds to 0.933 of the cumulative probability function. Widening the confidence interval should emphasize the impact of localization in the sub-areas belonging to the negative and positive classes. The negative class remained about the same, and the major changes occurred in the neutral class, which became more heterogeneous (i.e. the range of localized RMSEs increased after changes in classification) (Table 7). Of course, some changes in the extreme RMSE values of the positive class did occur; the minimum increased and the maximum decreased. After all, the classification method applied here did not yield the result expected. The expectation was that the negative and positive classes would produce lower mean RMSEs and narrower ranges for RMSEs than would the neutral class. This expectation did occur for the negative class, but not for the positive one. No correlation was found between the LISA and the result of localization despite the differences between the classes.

The two first methods mentioned above aimed to divide the study area into sub-areas that were as homogeneous as possible. The sub-areas did not need to be pre-determined; rather, the method needed to be flexible in forming the sub-areas. Such segmentation needed to be valid only for the data in use, along with the variables and model of interest. Localization is two-phase process in which the localization sub-areas are first delineated, and then the model is re-fitted to the sub-area. As previously reviewed, even though the local RMSEs and study area-wide standard errors could be reduced by using with all three of the methods, the RMSEs did increase in localization for some of the sub-areas in the segmentation or regions in the study area, and the RMSEs did exceed the level of the original global model. No correlation between the size of the sub-area and the localized RMSE could be found, as both extremes seemed more probable for the small sub-areas than for the larger sub-areas. Some kind of control should therefore be added to the method, which could separate those sub-areas in which the localization pays off from those which should remain as they were after applying the global model. For control purposes, the classification of the sub-areas was attempted according to the values of G_i^* in the sub-area, but failed to solve the problem.

Although the basic properties and limitations of the LISAs have been discussed in the beginning of the section, the methods employed have their limitations. The CART/MVPART selects the most profitable split among all variables one at a time, but cannot optimize the whole process. So, all splits are final and cannot be changed later in the process, which could be evident for the result, because sometimes an earlier optimal split could become unprofitable after subsequent divisions. Smyth et al. (2006a, b) have

implemented “factor scores” and principal component scores in the MVPART to reduce the effect of noise in the data on the clusterization.

KED suffers from the sparse point pattern the trees create. The strongest correlation between neighbors is lost since the minimum plot-to-plot distances have been increased in the latest NFI rounds from the seventh inventory (compare to Figs. 4 and 5 in Tomppo et al. 2001 and Fig. 2 in IV). The strongest correlation is between neighbors on the same plot with the pivot; the problem is that usually there are only zero to two neighbors. The point pattern could be made denser by introducing other tree species into the model. Numerous alternatives remain which could improve the local estimates. Interestingly, the study of Miller and Franklin (2002) combines kriging via a local spatial variable, which they call a kriged value, to CART, and some studies combine CART and other features of the stand or tree, even satellite imagery (Moisen and Frescino 2002, Franklin 2003, McKenney and Pedlar 2003). So, KED could help CART or vice versa. One natural option to kriging is geographically weighted regression (GWR) (Brunsdon et al. 1996). In GWR, the model coefficients are estimated using weighted least-squares regression such that the weight is a diagonal matrix, and a single element of the weight matrix is a function of the distance between the pivot and the observation. Studies have shown GWR to yield accurate (local) predictions (Zhang and Shi 2004, Zhang and Gove 2005).

In summary, all the methods utilizing LISA, namely CART and MS, and dividing the study area into smaller sub-areas were promising. The aggregate standard errors were lower than the RMSE of the global model, but compared to the division of the study area into forestry centers, the benefits of the segmentations were not obvious. The final “control element”, which could turn these methods into a tool, together with the re-fitting of the global model, was not attained. There is no guarantee that a delineated sub-area is worth localizing with either of the methods. The only relationships found between any property of the sub-area and the localized RMSE went contrary to the hypothesis (III Table 5a-b, Table 6-7) and proved useless for the evaluation of sub-areas. This surely merits further study. The localization pays off if the result always reaches at least the level attained with the forestry centers method. If the diagnostic, which could serve for pre-selection of the suitable sub-areas (where the localization pays off) and the flexibility in the delineation could be combined, the method would prove powerful. CART offers better opportunities for such a tailoring. A method of mixed estimation (Korhonen 1993) where, in addition to the present inventory data, information from other datasets, such as from previous inventories or neighboring areas, could also be utilized in localization, thus improving and stabilizing the estimates. Still, almost any spatial segmentation of the sub-areas with LISA yielded standard errors lower than the RMSE of the global model and, if the level of the division into forestry centers serves as a reference, nearly all segmentations were either near or below it (II Table V, III Table 7).

So, roughly speaking, segmentation of the study area is worthwhile, because it lowers the RMSEs, but cannot guarantee on a sub-area level that localization will decrease the RMSE of that particular sub-area or the creation of some kind of system to ensure this. Such a system could simply separate those sub-areas where localization is used from those where no localization at all is applied. Such a system could be designed for the segmentation of large areas with large datasets, where the sub-areas are of reasonable size and there are sufficient data for localization. One possibility to evaluate segmentation is to carry out a statistical F test, which evaluates whether the segmentation is worthwhile. Such a test compares the global model and a model that includes classification into sub-areas.

Because KED requires no segmentation, the results were compared to a forestry-centre level, which are quite large compared to the regions extracted in the two previous studies (II, III). However, the results show that increasing the number of neighbors (i.e. increasing the size of the neighborhood) lowers the prediction errors in the estimates, but no optimum size of the neighborhood was determined. The predictions it provides are the most stable, and standard errors are lower than with the reference. Future research could focus on the study of spatial correlation in hierarchical data, which was modeled here with a nested variogram model. CART has the potential to be more efficient than the traditional forestry centre division of the study area, but without the further study suggested earlier in this section, the result may vary unpredictably.

CONCLUSIONS

All the three methods used proved to lower RMSEs and aggregate standard errors. In the segmentations of classification and regression trees (CART) and multiresolution segmentation (MS) for some sub-areas, changes in localization were positive (i.e. the RMSEs decreased), but on the other hand, leaving some sub-areas without localization would have yielded more accurate results because localization increased the RMSEs considerably. The lack of explanation for this variation in previous studies warranted a new approach. A relationship between G_i^* , the decision variable in the delineation of the sub-areas, and the result of the localization, the local RMSE, was identified by classifying the sub-areas into negative, neutral and positive according to the mean G_i^* values. The negative class did perform little more accurately, but the differences were minor. This leads to the conclusion that the final segments are more or less compromises between the decision variables: residuals, G_i^* , spatial position and method-based restrictions, which in MS are shape related, and in CART, node size related. The residuals and G_i^* may impact the segmentation of the sub-areas less than the others together. On the other hand, both methods (MS and CART) lowered the RMSEs by more than a level correction, which equaled the regional bias. In kriging (KED), localization was not restricted to a certain sub-area, but the results were examined at the regional level. Spatial autocorrelation was found between observations, but since the point pattern was sparse, the effect of local adjustment from the neighbors should be enforced in other ways. One option could be to make the point pattern denser by introducing other tree species into the model.

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