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MIXED-EFFECTS MODELS FOR ESTIMATING STAND VOLUME BY MEANS OF SMALL FOOTPRINT AIRBORNE LASER SCANNER DATA

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ABSTRACT

For this study, hierarchical datasets in that several sample plots are located within a stand were analysed for study sites in the USA and Germany. The German data had an additional hierarchy since the stands are located within four distinct public forests. Fixed-effects models and mixed-effects models with a random intercept on the stand level were fit to each dataset. The coefficients varied significantly also between adjacent study sites. The mixed-effects models significantly improved the estimates and especially reduced the bias which was present for numerous stands in the predictions of the fixed-effects models. The RMSE for the German study site was higher (22.5% to 31.3%) than for the US study site (16.7%).Unlike the American dataset, it was necessary to take the spatial correlation of the data into consideration for the German dataset. A mixed-effects model with random effects on the study site and stand level was fit to the complete German dataset. It provided comparable goodness-of-fit statistics for the local mixed-effects models. The study shows the potential of mixed-effects models in this context. It illustrates that use of mixed models could be a good alternative to the common practise of fitting different models for different groups of data.

1. INTRODUCTION

Over the past decade there has been considerable research in the use of laser scanning for forest measurements. Næsset et al. (2004) and Hyyppä et al. (2004) provide an extensive list of early foundational research in this area in the Scandinavian countries. It was shown that height and density metrics, derived from lidar (light detection and ranging) point clouds can be used as predictor variables in statistical models to estimate forest parameters at the plot level (Magnussen & Boudewyn 1998, Næsset 2004, Andersen et al. 2005, among others). Such models are usually fit using sample plots where both lidar (covariates) and ground-truth information (response) are available. To map the variable of interest, the entire lidar dataset is tessellated into tiles having the same size as a sample plot. Then, the predictor variables are derived and the response is predicted for every tile. Compared to plot-based inventories, estimation errors can be significantly decreased for the area of interest (e.g., a single forest stand), since the number of observations (i.e., the tiles) is usually much higher than the number of sample plots within a stand.

First methods in estimation of timber volume using laser scanning data are described by Nelson et al. (1988) using a profiling lidar system. Nilsson (1996) used data of a small footprint full waveform laser scanner to estimate forest parameters. He deployed the product of intensity and vegetation height as predictor variable to estimate plot volume and was able to explain 78% of the variance. Mean vegetation height and vegetation density (ratio of vegetation hits) were used by Næsset (1997) to estimate stand-wise volumes. A few years later, he presented a two-stage design for a lidar based forest inventory (Næsset 2002) and proved its operational capability (Næsset 2004). He fits separate models for different age- and site quality classes and achieves R^2 between 0.80 and 0.93. Means et al. (2000) reports R^2 between 0.93 and 0.95 for volume estimates in Douglas fir stands in the Cascade Mountains (Oregon, USA). In a study by Packalén and Maltamo (2006) in a Finnish boreal forest, plot volume was assigned to tree species by using the k-MSN method. They report an RMSE of roughly 24% for estimates of total volume. Aardt et al. (2006) segmented homogeneous forest units first and used the lidar vegetation height distribution and the field data for the units to calibrate prediction models. They report R^2 between 0.58 and 0.79 for their study which was located in Virginia (temperate mixed forests).

The predictor variables derived from lidar data are mainly related to the vegetation height and structure (e.g., height- and density metrics, crown cover). The vegetation cover can, under certain circumstances, also be classified into broadleaf and coniferous trees. However, information about the site quality or tree species cannot be derived without additional data. Therefore, predictions for stands with rare site index classes or tree species compositions might deviate from the mean model, resulting in a bias. If the grouping structure (i.e., the stand boundaries) is known, the deviation from the mean model of plot estimates within a stand can be utilized to reduce the bias using mixed-effects models (mixed models). From the statistical point of view, the grouping structure has to be considered since the observations within a group are not independent. In a mixed model, the grouping variable (i.e. the stand-ID) is assumed to be a random sample of a larger population. The effects of the grouping variable are thus a random sample of the population effects and are referred to as random effects.

An in-depth description of mixed models including statistical software is given by Pinheiro and Bates (2002). Another pertinent reference is Vonesh and Chinchilli (1997), where the methods are stressed in more detail. Due to the grouped nature of many ecological related data, mixed models are widely used in forest science and remote sensing. For example, Lappi and Bailey discussed in 1988 already how the variance-covariance structure of tree and stand level measurements can be considered to improve height growth prediction models. Meng et al. (2007) used mixed models for volume and biomass estimation based on Landsat ETM+ images. A method to calibrate lidar data surveyed with different flying heights and scan angles using mixed models is described by Musk and Osborn (2007).

In a mixed model, the variance is split into “within” and “between” group variance. The coefficients and standard errors for predictor variables that vary less within than between the groups are therefore more accurate than in a model without the grouping information. Another advantage of a mixed model, compared to a fixed-effects model with the grouping level as a dummy variable, is that predictions can also be made for individuals with grouping levels not present in the dataset used to fit the model (e.g., in this case those stands without sample plots). In a forest inventory context, a mixed model provides an additional advantage. A model can be fit to a large dataset (e.g., to a well inventoried public forest) and subsequently be calibrated with few sample plots for a new forest area (e.g., a small private forest).

If $\boldsymbol{y}$ is the vector of the dependent variables, $\boldsymbol{X}$ is the design matrix of the fixed effects $\boldsymbol{\beta}$ and $\boldsymbol{Z}$ is the design matrix of the random effects $\boldsymbol{b}$, the general form of a mixed-effects model is written

$$\begin{aligned} \boldsymbol{y} &= \boldsymbol{X\beta} + \boldsymbol{Zb} + \boldsymbol{\epsilon}, \\ \boldsymbol{b} \sim \mathrm{N}(0, \boldsymbol{D}), &\quad \boldsymbol{\epsilon} \sim \mathrm{N}(0, \boldsymbol{R}), \end{aligned} \tag{1}$$

with the blocked diagonal matrices $\boldsymbol{D}$ and $\boldsymbol{R}$ that represent the covariance structure of the random effects and the error terms respectively. The coefficients, the random effects and the covariance structures $\boldsymbol{D}$ and $\boldsymbol{R}$ are estimated using the restricted maximum likelihood method (REML).

The objective of this study was to find out if information about the stand-level grouping of sample plots can be used to improve predictions of a regression model. Furthermore, we wanted to know how the model coefficients vary between the study sites and if it is reasonable to fit one hierarchical model for all (German) study sites. Another interest of ours was to see if it is necessary to consider the spatial correlation of the observations since this was neglected in studies regarding lidar-based forest inventories so far.

2. MATERIAL AND METHODS

2.1 American dataset

The study site in the USA is part of Capitol State Forest and is managed by the Washington State Department of Natural Resources. In the remainder of the text "US" will be used to refer to this study site. The terrain is moderate with elevations varying from 300 to 425 m. The forest is composed primarily of Douglas-fir (*Pseudotsuga menziesii,* 81%) and western hemlock (*Tsuga heterophylla,* 13%). Additional species present include western red cedar (*Thuja plicata,* 2%) and few deciduous hardwoods such as red alder (*Alnus rubra,* 3%) and maple (*Acer spp.*, <1%). The height of dominant trees in the study area was approximately 50 m. The mean volume measured at the sample plots was 558 m^3/ha.

A total of 98 fixed area field inventory plots were established over a range of stand conditions in 1999. Plot sizes ranged from 0.02 to 0.2 ha. Measurements acquired at each plot included species and diameter at breast height (DBH) for all trees greater than 14.2 cm in diameter. In addition, height was measured on a representative selection of trees using a hand-held laser rangefinder. The heights of the remaining trees within a plot were estimated using forest stand height curves and the DBH. Inventory plot locations were surveyed with a Topcon ITS-1 total station and are accurate to within 1 m.

The Saab TopEye lidar system mounted on a helicopter was used to map approximately 5.25 km^2 of the study area in the spring of 1999 (before foliation) with an average density of 5 points per m^2.

2.2 German datasets

Between the years 2000 and 2004 the complete state of Baden-Württemberg was covered with a lidar survey (approx. 0.5 returns m^{-1}) to derive a digital terrain model. We selected four public forests in which forest inventories were carried out in the same time, or 1 year after the lidar survey as study sites. The inventories in the study sites followed the standard procedure of the Baden-Württemberg forest service and comprises of sample plots positioned on the intersections of a 100 x 200 m sample grid. The study sites Triberg State Forest (TB), Waldkirch City Forest (WKC), Waldkirch State Forest (WKS) and Forbach State Forest (FB) are located in the Black

Forest area and are characterized by elevations between 400 - 1000 m and high slopes up to 35°. The forest is managed using a group selection system, where the regeneration phase may take several decades (clearcuts are forbidden in Germany). A total of 33 different tree species can be found in these forests. Most common species include Norway spruce (*Picea abies,* 57%), silver fir (*Abies alba,* 19%) and beech (*Fagus sylvatica,* 14%).

Forest characteristics were recorded within sample plots consisting of four concentric circle plots (i.e. they have the same centre) with radii of 2 m, 3 m, 6 m and 12 m. Trees with a diameter at breast height (DBH) greater than 7 cm, 10 cm, 15 cm and 30 cm, respectively, were recorded within the four circle plots. This design raises the efficiency of the inventory since it reflects that most of the forest volume is stored in large trees. The heights of the two tallest trees per species were measured in each plot using a Vertex angle measurement instrument. The heights of the remaining trees within a plot were estimated using forest stand height curves and the DBH. Single tree volumes were calculated using DBH and height as parameters for taper and volume functions of the Baden-Württemberg state forest service (Kublin, 2003).

The response variable, plot volume per ha, was calculated as

$$V_i = \sum_{j=1}^{n_i} v_{ij} \cdot w_{ij} \qquad (2)$$

where V_i is the volume per ha on the ith sample plot, n_i is the number of trees, v_{ij} is the volume of the jth tree and w_{ij} is a weighting factor accounting for the different inclusion probabilities according to the four plot radii for different diameter classes. An overview of the study site characteristics can be found in Table 1.

Plots intersecting stand or forest borders were excluded from the data since only those trees are measured that belong to the stand containing the plot center. A total of 2445 inventory plots, were used as terrestrial reference data for the remotely sensed data. Stand borders were digitized from orthophotos as a part of the inventory and adjusted to meet operational purposes during the field work. Additional information describing the stands that could be used as covariates was not available for this study.

Table 1: Study site characteristics.

Study site	Statistic	Top height (m)	Volume (m³/ha)	Mean lidar veg. height (m)	Canopy cover lidar (%)	Coniferous proportion lidar (%)	Avg. # of plots within a stand	Number of observations
TB	Min.	5.20	9.1	1.25	2.23	1.37	3.32	625
	Mean	25.71	416.2	18.19	93.72	75.69		
	Max.	41.25	1193.0	33.80	100.00	100.00		
WKC	Min.	7.03	10.9	4.34	14.29	0.00	2.44	511
	Mean	27.50	440.7	21.25	96.95	55.20		
	Max.	45.35	1089.0	36.96	100.00	100.00		
WKS	Min.	6.30	19.9	4.76	37.95	0.00	2.42	278
	Mean	26.83	422.4	20.99	98.25	54.29		
	Max.	51.00	990.8	37.65	100.00	100.00		
FB	Min.	5.10	7.0	1.07	2.90	0.00	3.14	1031
	Mean	25.70	355.5	16.88	87.98	73.16		
	Max.	44.53	1265.0	32.98	100.00	100.00		

2.3 Computation of predictor variables

A digital terrain model (DTM) and a digital surface model (DSM) was computed for both test sites using the software *TreesVis* (Weinacker et al., 2004) for the German and Fusion 2.0 (McGaughey et al., 2004) for the American study site. An evaluation of the American DTM, presented in Reutebuch et al. (2003), found an average lidar elevation error of 22 cm. For the German study site, a DSM was derived from the first (DSM_F) and the last return (DSM_L) vegetation returns. Canopy height models (CHM, CHM_F, CHM_L) were computed by subtracting the DTM from the associated DSM. The lidar vegetation height was determined by calculating the difference between the elevation of the lidar vegetation data (raw data) and the corresponding DTM raster bin elevation.

Circular subsets of the same radius as the corresponding sample plot (12 m for the German and 5 to 16 m for the American study site) were created from the first return lidar raw data. The quartiles and the mean of the lidar vegetation heights were calculated for each subset to characterize the vegetation height distribution. Vegetation density metrics were derived by dividing the range between the highest and lowest measurement into 10 classes and determining the proportion of measurements within each class. *Fusion 2.0* was used for the raw data manipulation.

Since broadleaf trees in leaf-off condition had only a few vegetation returns in the last return data, they do not show up in the CHM_L. Therefore, a classification of the pixels into those belonging either to coniferous or broadleaf trees was possible by subtracting the CHM_L from the CHM_F. The result was normalized with the CHM_F. By comparison with orthophotos, a threshold of 0.3 was found to separate coniferous and broadleaf pixels well (equation 3). It should be noted that Larches (*Larix spp.*) are a potential problem for this classification approach, since they are deciduous conifers. However, few larches were present in the study area so we felt the classification approach was applicable.

Depending on the canopy height models, the ith pixel p_i is assigned the value 1 if it is considered as covering a coniferous tree and the value 0 otherwise:

$$p_i \begin{cases} 1 & (\mathrm{CHM}_{\mathrm{F},i} - \mathrm{CHM}_{\mathrm{L},i})/\mathrm{CHM}_{\mathrm{F},i} \leq 0.3 \\ 0 & (\mathrm{CHM}_{\mathrm{F},i} - \mathrm{CHM}_{\mathrm{L},i})/\mathrm{CHM}_{\mathrm{F},i} > 0.3 \end{cases} \tag{3}$$

A visual analysis of the classification result revealed that pixels on the boundaries of coniferous forest are systematically misclassified as coming from deciduous trees, since the last return data here are already reflected from the ground. This also shows up in the comparison of the coniferous proportion estimated from lidar with the percentage of coniferous volume measured at a plot (Figure 1): The correlation between the two decreases considerable, if plots with low canopy cover are considered.

The variable canopy cover (*CC*) is the proportion of pixels within a sample plot where the CHM_F is larger than two meters, to the total amount of pixels within a sample plot.

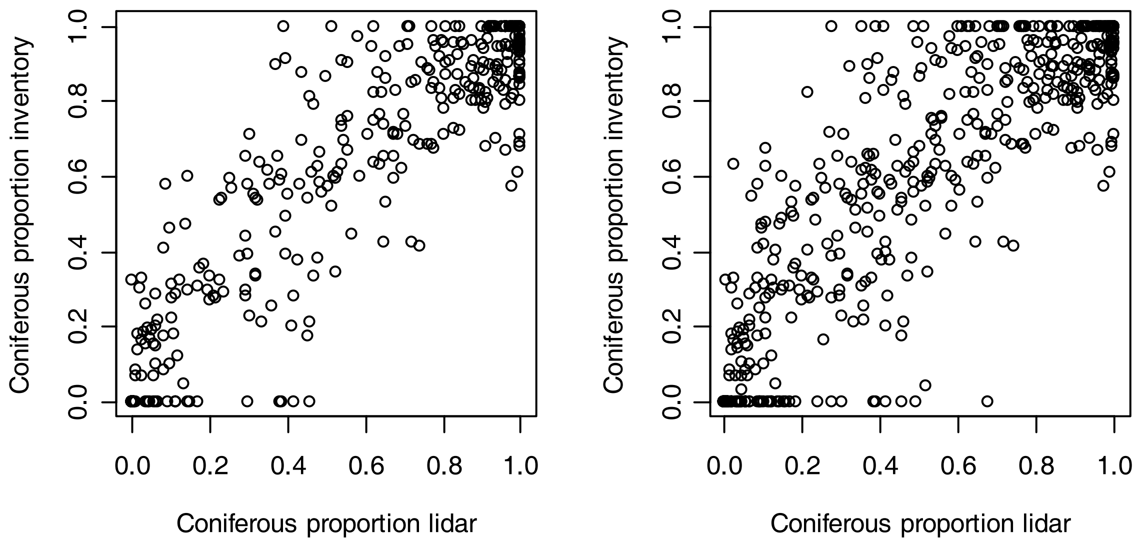

Figure 1: Comparison of coniferous proportion (by volume) measured in the inventory and the proportion of coniferous canopy cover derived from lidar data for sample plots with a closed canopy (left-hand graphic) and for all sample plots of the study site WKC (right-hand graphic).

2.4 Modeling

We started modeling with the largest German dataset (FB). After analyzing scatter plots and correlations between the response and the candidate covariates, the mean vegetation height measured by lidar data (*mean.l*) was found to be the most influential predictor variable. A model containing this predictor variable was significantly improved by including canopy cover (*CC*) and coniferous proportion (*CP*) and their interaction term with *mean.l*. To represent heteroscedasticity, we included a variance function based on a power of δ of the fitted values (equation 4). This local model was re-parameterized for every German study site. Since the covariates were significant in each study site, we call it the basic local model. Probably due to the classification errors and the small amounts of deciduous trees, the coefficient of the covariate *CP* was not significant for the US study site. It was therefore not included into the models of the US study site.

If y_k is the response for the kth sample plot, $\beta_0 ... \beta_5$ are the coefficients, ϵ_k is an independent error term with a variance model depending on a power of δ of the fitted values, and n is the number of sample plots, the basic model can be written as

$$\begin{aligned} y_k = {} & \beta_0 + \beta_1 mean.l_k + \beta_2 CC_k + \beta_3 CP_k + \\ & \beta_4 CC_k \cdot mean.l_k + \beta_5 CP_k \cdot mean.l_k + \epsilon_k \\ & k = 1, ..., n \qquad \epsilon_k \sim N(0, \sigma^2 \hat{y}_k^{2\delta}). \end{aligned} \tag{4}$$

Four extended models were compared with the basic model: i) local mixed-effects models with a random intercept on the stand level; ii) local mixed-effects models including an exponential spatial correlation structure (equation 5); iii) a global mixed-effects model with random effects for the coefficients on the study site level and a random intercept on the stand level; and, iv) a global mixed-effects model including an exponential spatial correlation structure (equation 6). The American data were not included in the global models since the parameters of the lidar survey were too different. Therefore, one might argue that the American study site comes from a different population than the German study sites.

In a future application phase, predictions for stands without any sample plots will be conducted. Therefore, fixed-effects models including the grouping information of the sample plots as a dummy variable were not fit.

Models (ii) can generally be expressed as

$$\begin{gathered} y_{jk} = \beta_0 + b_{0,j} + \beta_1 x_{1,jk} + ... + \beta_m x_{m,jk} + \epsilon_{jk} \\ k = 1, ..., n_j, \qquad j = 1, ..., l, \qquad b_{0,j} \sim N(0, \sigma_1^2), \qquad \epsilon_j \sim N(0, R_j), \end{gathered} \tag{5}$$

where y_{jk} is the response variable for the *k*th sample plot in the *j*th stand, $x_{1,jk}..x_{m,jk}$ are the *m* fixed effects, $\beta_0..\beta_m$ are the coefficients thereof, n_j is the number of sample plots within a stand and *l* is the number of stands. The stand random effects $b_{0,j}$ are assumed to be independent for different *j* and the within-group errors, ϵ_{jk} are assumed to be independent for different *j* and to be independent of the random effects. One assumption in standard regression models is that the observations are independent. A spatial correlation in the data results in a biased estimation of the error variance (usually an underestimation) and hence yield overly positive significant tests for the coefficients. Therefore, we model the spatial correlation structure between sample plot k, k' in stand j by an exponential function of the Euclidian distance s ($s = ||p_{jk}, p_{jk'}||$) between the two plot positions $p_{jk}, p_{jk'}$, i.e., $\mathrm{cor}(\epsilon_{jk}, \epsilon_{jk'}) = \exp(-s/\rho)$. The corresponding semivariogram is $1 - \exp(-s/\rho)$ which is generally used in geostatistics to describe spatial dependency structures. In terms of the semivariogram, ρ is a range parameter and the practical range where the semivariogram reaches 95% of the sill is 3ρ. We further assumed that the error variance is heteroscedastic with the variance of ϵ_{jk} increasing with a power of the expectation value of the response, i.e. $\mathrm{var}(\epsilon_{jk}) = \sigma^2 \hat{y}_{jk}^{2\delta}$. With these assumptions, the error covariance matrix $R_j(n_j \times n_j)$ entries are $\sigma^2 \hat{y}_{jk}^{2\delta},\ k = 1, ..., n_j$ in the diagonal and $\mathrm{cov}(\epsilon_{jk}, \epsilon_{jk'}) = \exp(-s/\rho)\ \sigma \hat{y}_{jk}^{\delta}\ \sigma \hat{y}_{jk'}^{\delta}$ in the off-diagonal elements.

The general form of the global models is

$$\begin{gathered} y_{ijk} = \beta_0 + b_{0,i} + b_{0,ij} + (\beta_1 + b_{1,i}) x_{1,ijk} + ... + (\beta_m + b_{m,i}) x_{m,ijk} + \epsilon_{ijk} \\ i = 1, ..., o, \qquad b_i \sim N(0, D), \end{gathered} \tag{6}$$

where *i* is the study site index, *o* is the number of study sites and *D* is the $m \times m$ variance-covariance matrix of the random effects on the study site level. The variance and correlation functions associated with the models (ii) include the additional index *i*.

The coefficients were estimated by restricted maximum likelihood (REML) using the functions *gls* and *lme* included in the *nlme* library (Pinheiro and Bates, 2002) within the *R* environment (R Development Core Team, 2007).

3. RESULTS AND DISCUSSION

Local mixed effects models with a random intercept on the stand level (models (i)) were significantly better than the basic models on all study sites. The volume RMSE range between 93.0 m³/ha (16.7% of the mean observed value) on the US study site, 102.6 m³/ha (24.3%) on the WKS study site and 133.6 m³/ha (32.1%) on the TB study site. Compared with the basic models, the RMSE improved about 2% to 4%. In general, it can be observed that, compared to the basic model, the median residual per stand was closer to zero. The reduced bias on the stand level was achieved becasue sample plots within a stand tend to differ at a similar rate from the basic model. The effect of the mixed-models on the residuals is depicted for selected stands of the study site WKS in Figure 4 (upper row). In the box-and-whisker-plots of Figure 4 the residuals coming from the different models are plotted against the stand-ID[1]. The selected stands had to contain more than two sample plots with a mean absolute residual of at least 100 m³/ha in the basic model prediction. The model parameters are given in Table 2.

Reasons for bias in some stands, besides rare tree species and site indices, might be uncommon taper shapes, varying density of small trees in the understory (i.e. two layers of trees, which probably does not change *mean.l* explicitly) or other incidents that change the canopy structure but are not reflected in the selected covariates and are not common in the study site. The reliability of the influence of the random effect increases with increasing numbers of sample plots and homogeneity within a stand.

The spatial distribution of the sample plots is not optimal for determining the spatial correlation between the observations since the smallest distance between sample plots is 100 m. Nonetheless, the inclusion of a spatial correlation structure improved the statistical models for the German study sites significantly (models (ii)). Also, semivariograms revealed that, at least the next neighbors were correlated (Figure 2).

For the American study site no evidence of spatial correlation was found which could be a result of the high homogeneity of this site.

To get a better estimate for the spatial correlation structure of the data, it would be good to have some areas with a higher sample plot density in future studies. Then, also small scale spatial variation (nugget effect) could be estimated (Diggle and Ribeiro 2007).

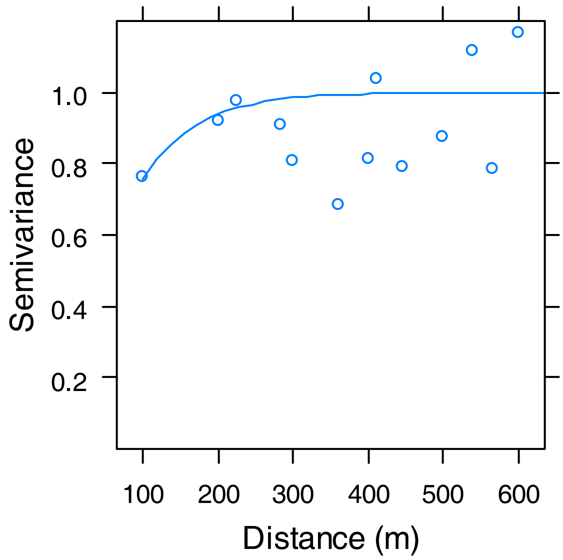

Figure 2: Empirical semivariance (points) and estimated correlation structure (line) of the Pearson residuals of model (ii) for study site Forbach.

[1] The stand-ID is a catenation of the forest-, district- and department-ID and the stand specific age.

Table 2: Model parameters.

	Global mixed-effects model, German study site[1]		Local mixed-effects model, US study site	
Covariate	Estimate	p-value	Estimate	p-value
Intercept	251.08	0.14	-93.35	0.74
Mean.l	-14.81	0.20	3.27	0.68
CC	-242.46	0.23	52.28	0.88
CP	-78.46	0.07		
Mean.l CC	31.66	0.02	21.63	0.03
Mean.l CP	11.33	<0.01		
δ	0.42		0.42	
ρ	67.7			
Stand level deviation	22.78		116.59	
Residual deviation	10.01		7.03	

Allowing for the spatial correlation in the data, resulted in a smaller influence of the random effects on the stand level (Figure 4, right-hand graphics). This occurred because plots within a stand were close together and part of the variance was explained by the spatial correlation.

Compared to the local mixed-effects models, the reduction in bias per stand was smaller in the predictions of the global model (Figure 4, lower row). However, it was still advantageous to fit a global model because the coefficients for a new study site could now be derived by calibration of the model. The time difference between inventory and lidar survey was also used as predictor variable for the global model but did not have a significant influence on the models. We assumed that the variance was too high to depict the growth of one year.

The influence of canopy cover (*CC*) and coniferous percentage (*CP*) was similar on all study sites: An increase of these variables resulted in higher volume estimates. A larger volume estimate with increased *CP* seems plausible since the stem wood proportion is significantly larger for conifers given the same tree height. The observed influence of *CC* was also expected, since an open or fractal forest structure is expected to have a smaller volume estimate than a closed forest.

Given these results, it would be plausible to also include a triple-interaction term between *mean.l*, *CC* and *CP*. However, due to the high correlation between the covariates (>0.95), we decided against this approach. Somewhat unexpectedly, the absolute value of the coefficients for *CC* and *CP* differed considerable between the study sites (Figure 3). It is peculiar that the prediction for 100% *CC* and *CP* were similar for all study sites. The deviance in the coefficients of *CC* and *CP* might be a result of the lack of sample plots with very low *CC* or *CP* on some study sites. For example, there were only a few sample plots with low coniferous proportions in the study site Triberg (TB). The same was true for canopy cover in the study site Waldkirch State Forest (WKS, see Table 1). This could also be the reason why the global model for these study sites tended to predict values that are closer to the mean model.

[1] The variance-covariance matrix for random effects on the study site level is omitted due to the limited space.

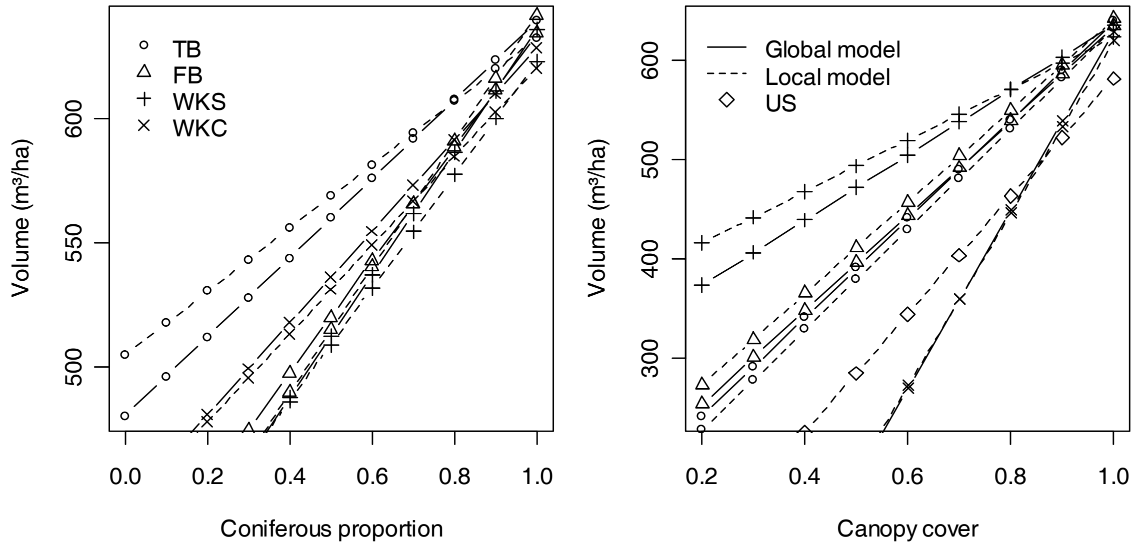

Figure 3: Predictions of the global model including spatial correlation and local mixed-effects models including spatial correlation for the study sites Triberg (TB), Forbach (FB), Waldkirch State Forest (WKS) Waldkirch City Forest (WKC) and Capitol Forest (US) with mean.l fixed at 25 m and the other not varying covariable fixed at 100%.

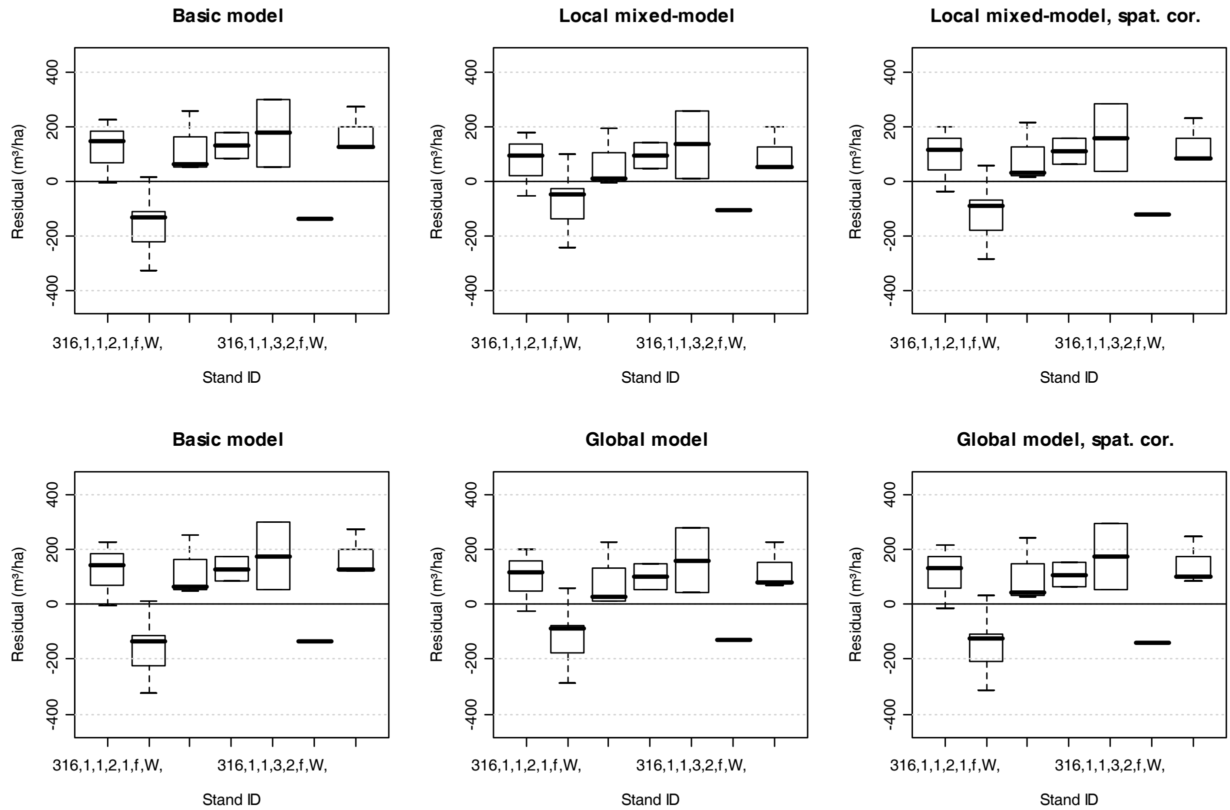

Figure 4: Residuals of different models for selected stands of Waldkirch State Forest (the basic model is displayed twice for easier comparison).

The observed errors for the US study site (16.7%) was comparable to those reported by Næsset (2002), but somewhat higher than those reported by Means et al. (2000) (73 m³ ha^{-1}). As a result of the considerably higher heterogeneity due to the wider range of tree species and stand types, the errors for the German study site were much higher. Aardt et al. (2006), whose study site was probably more similar to the German site, reported smaller absolute RMSE (40-68 m³ ha^{-1}) than we observed for the German site. However, the range of stand volumes in their data was significantly smaller than in this study.

4. CONCLUSIONS

Parametric regressions can result in biased predictions for forest stands. We showed that the bias can be reduced, considering the grouping of sample plots within stands. The grouping structure was modelled using mixed-effects models including a random effect on the stand level. The model coefficients for adjacent study sites were surprisingly different. Nonetheless, a global model with random effects for the coefficients on the study site level was well able to describe the data. This global model could be calibrated to a new study site using fewer sample plots than would be necessary to fit a completely new model. The results of this study also indicate that other researchers who stratified their data and used different models for each stratum (e.g., Næsset 2002) could potentially enhance their models with random effects on the level of these strata. However, this of course has to be verified in the particular case. An additional benefit would be that the amount of data for modelling is then larger.

Future work will strive to better understand the causes for differing coefficients at the study sites and the bias observed at the stand level. The stands, represented as polygons, on the German site were delineated based on operational considerations. Hence, small groups of trees were included with adjacent but different (in terms of species composition and age) stands to avoid creating small stands. We speculate that stand delineations that result in more homogeneous conditions within each stand will lead to lower within-stand variance and larger between-stand variance which could further improve the models.

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