Comparison of stand volume predictions based on airborne laser scanning data versus aerial stereo images

(With 5 Figures and 5 Tables)

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(Received December 2015)

KEY WORDS – SCHLAGWÖRTER

Stand volume prediction; spatial prediction; k-nearest neighbour; random forest; regional inventory; airborne laser scanning; aerial stereo images.

Schätzung des Bestandesvorrats; räumliche Vorhersage; k-Nächste-Nachbarn; Random Forest; regionale Inventur; luftgestütztes Laserscanning; Stereo-Luftbilder.

1. INTRODUCTION

Practicing sustainable forest management requires information on both the status of and change in stand parameters. Such information is available on a large spatial scale from regional forest inventories (RFI). The major purpose of RFI is the estimation of parameters at the administrative district level. Yet most dendrometrical variables, such as timber volume per hectare, are also required at the forest stand level. In most cases only a few sample plots, sometimes even none, are situated in each forest stand. This makes provision of relevant stand-level information almost impossible as long as the estimations are solely based on RFI data.

Remote sensing can be used to bridge the gap between the coarse spatial resolution of information obtained from the usually wide-meshed RFI sampling grid and the need for precise data for each of the relatively small forest stands. Recent studies have presented various methods to increase the precision of spatial predictions by combining forest inventory and remote sensing data. Approaches for predicting target variables for small areas can be classified into parametric (NÆSSET, 1997; MEANS et al., 2000; NÆSSET, 2004; HOLLAUS et al., 2007) and non-parametric regression methods, such as the frequently-applied most similar neighbor (MSN) method from MOEUR and STAGE (1995) using canonical correlations between the target and the auxiliary variables (ANTTILA, 2002; MALINEN, 2003; NOTHDURFT et al., 2009). In the three latter studies the MSN method was extended to *k*-MSN, which included more than one neighbor for the prediction of the target variable. BREIMAN (2001) presented another nonparametric approach, the random forest (RF) approach an enhanced regression and classification tree technique. In some recent comparative studies, RF proved to be superior to other imputation techniques (HUDAK et al., 2008; ESKELSON et al., 2009; LATIFI et al., 2010). According to CROOKSTON and FINLEY (2008), RF can also be used to determine nearest neighbors (LATIFI et al., 2010). STRAUB et al. (2010) showed that a parametric approach and the *k*-nearest neighbor (*k*-NN) method resulted in approximately the same prediction error. However, in general, there is no single method which outperforms all others in all possible applications.

Nowadays, the potential of aerial stereo images (ASI) and airborne laser scanning (ALS) data for the estimation of dendrometrical variables has been examined in several studies (e.g. JÄRNSTEDT et al., 2012; NURMINEN et al., 2013; STRAUB et al., 2013, RAHLF et al., 2014). These studies indicate that while the accuracy of predictions of forest attributes with ASI can be similar to that with ALS; predictions based on ALS always have a smaller root-mean-square error (RMSE). Yet ALS data are not readily available everywhere due to their high cost. Currently, ASI data are about a half to a third of the cost of ALS data (WHITE et al., 2013). Moreover, ASI data provide additional information that cannot be acquired from ALS data such as color or even a normalized difference vegetation index if a near infra red band is available. In the state of Hessen, Germany, ASI data are readily available as they are used in double sampling for stratification as a standard inventory design. In this approach the aerial images are used in the first phase to stratify sample plots into age classes and dominant tree species groups (SABOROWSKI et al., 2010). Such classification is not easily achieved with ALS (WHITE et al., 2013). However, ALS data enable the calculation of both surface and terrain heights from the same data source, whereas ASI data merely allow the crown surface to be modeled by means of digital photogrammetry using image matching techniques (NUSKE and NIESCHULZE, 2004). Thus, for the ASI data, an additional terrain model is required in order to derive vegetation heights. Such a terrain model may be available from land surveying offices or a previous ALS flight campaign. As some of the laser pulses pass through the upper canopy layer, ALS may even provide additional height information on sub-canopy layers and hence on stand structure. Furthermore with ASI, it is often difficult to derive photogrammetric heights in deep shadows (LILLESAND et al., 2004).

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The target variables in this study are the total timber volume and the timber volume of European beech (*Fagus sylvatica* L.) trees with a DBH over 60 cm (common target diameter in Hessen, Germany). In many inventories European beech trees with a DBH ≥ 60 cm, were estimated separately to achieve higher precision in this class in view of the high value of the timber.

The main objectives of the study were to compare i) the suitability of auxiliary variables derived from ASI and ALS to predict the timber volume per hectare for each forest stand in the study area (total timber volume and timber volume of beech trees with DBH ≥ 60 cm), and ii) the precision of the nonparametric prediction methods *k*-MSN and RF. As part of the first aim we also investigated whether a systematic spatial shift had occurred and whether the auxiliary variables can be aggregated to speed up the calculations.

2. MATERIAL

2.1 Study area

The study area is located in Krofdorfer Forest, in Hessen, Germany. The elevation ranges from 200 m to about 400 m. The forested area is stocked mainly with European beech (*Table 1*). European beech forests are the natural forest ecosystems in large regions in central Europe. Current silviculture programs in Germany pay more attention to close-to-nature objectives than in the past. This is the reason why forests that are mainly stocked with European beech become increasingly important. Regional inventory data from the first quarter of 2010 is available for the entire forest. ASI data are available for 1625 ha and ALS data for 1178 ha. The 1060 ha over which these datasets overlap define the study area. ALS and ASI data were obtained in 2009.

2.2 Remote sensing data

The digital ASI data were recorded by a large-format matrix camera (Z/I imaging, serial number: DMC01-122) on 29 July 2009. The spatial resolution of the ASI is 20 cm and the overlap of the images is 70% in longitudinal and 40% in latitudinal direction. The four channels red, green, blue, and near infrared (NIR) were recorded with a radiometric resolution of 12 bit. A Global Navigation Satellite System and Inertial Measurement Unit (GNSS/IMU) system recorded the position of the image center and the rotation angles continuously during the flight.

Every location of the study area was covered by at least two, but mostly three, overlapping images (ASI) so that a digital surface model (DSM) could be derived via stereoscopic analysis. Photogrammetric heights were measured automatically using the image matching routine, based on the normalized cross-correlation algorithm, in the add-on module eATE (enhanced Automatic Terrain Extraction) for the commercial photogrammetry software LPS (Intergraph 2014). To calculate aboveground vegetation heights to a high resolution using the ASI-DSM, a digital terrain model (DTM) with a spatial resolution of 5 m x 5 m obtained from the Hessian land surveying office (Hessische Verwaltung für Bodenmanagement und Geoinformation) was used. The DTM was available for the entire state and was generated using a combination of ASI and ALS data (hvbg 2014).

From the ALS data, a DSM and a DTM were derived. The ALS flight campaign (flying height: 300 m) took place between 9th and 10th July 2009. The scanning frequency was 240 kHz with an aperture angle of 16°, using the TopEye MK3 scanner system. Laser scanning systems usually emit short, intense pulses, and the time

Tab. 1

Description of forests within the study area based on RFI data. The stem volume of the tree was calculated using an existing routine implemented in the BWINPro forest growth simulator based on stand height curves and tree volume functions (Nagel, 1999).

Beschreibung der Wälder innerhalb des Untersuchungsgebietes mit Hilfe einer regionalen Inventur. Das Derbholz der Bäume wurde mit einer Funktion des Waldwachstumssimulators BWINPro mittels Bestandeshöhenkurven und Volumenfunktionen berechnet (Nagel, 1999).

		Total	European beech	European beech (DBH ≥ 60 cm)
	number of trees	1746	1099	70
DBH [cm]	mean	32.65	30.91	66.04
	standard deviation	16.65	17.61	4.77
age [years]	mean	84.43	81.5	149.74
	standard deviation	49.67	48.23	14.31
	number of heights	448	276	50
height [m]	mean	25.07	25	37.34
	standard deviation	8.98	9.48	3.56
number of observations		193	174	52
stem volume [m^3 ha^{-1}]	mean	320.09	225.4	170.67
	standard deviation	159.25	148.78	100.15
	min	0	2.3	88.34
	max	825.78	776.55	517.3

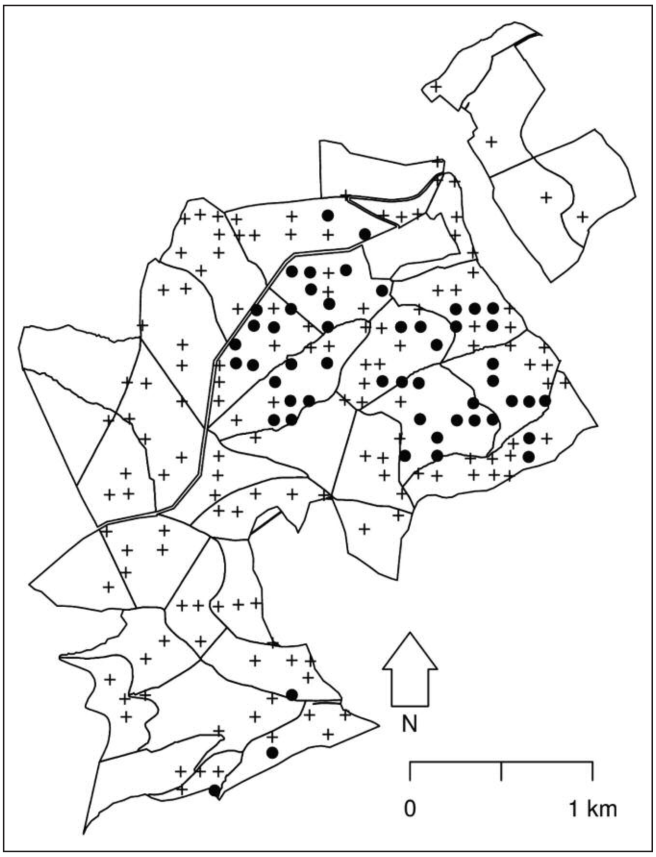

Fig. 1
Spatial distribution of RFI-plots.
Dots indicate plots with European beech with DBH ≥ 60 cm.
Räumliche Verteilung der RFI-Plots.
Punkte markieren Plots mit dicken Buchen (BHD ≥ 60 cm).

interval measured between the emission of a pulse and the detection of the reflected signal is used to calculate the distance between the laser system on the airplane and the object. Knowing the position of the laser system, the height of the objects above mean sea level can be derived. The data were classified into a ground and top surface using proprietary algorithms by the vendor; the algorithm is not available to us.

In this study the digital surface models, and hence the digital vegetation models, were represented by point clouds. The spatial distribution of the ALS and the image-based points (vectors with north, east, and height values) was, thus, irregular. The average density of ALS data classified as topmost surface was 60 points per m^2, and 24 points per m^2 for the DSM derived from ASI. The point density of the ALS data set was quite high (relative to other studies (e.g. HOLLAUS et al., 2007, HUDAK et al., 2008), because it was originally acquired to analyze leaf area index (FLECK et al., 2011). The average density of ALS points classified as terrain was 6 points per m^2. For some small areas, height measurements were not available. Photogrammetric measurements became less reliable or even impossible in regions with low contrast, such as in deep shadows or in areas with highly recurrent structures. Therefore, the resulting point cloud from image matching may contain areas with sparse points or even small gaps (usually much smaller than 1 m^2). However, most forest stands within the study area could be represented by a high point density.

2.3 Field Measurement

The RFI is carried out approximately every ten years. It was conducted as double sampling for stratification, with a 100 m x 100 m grid in the first phase. This 100 m x 100 m grid is constant over time. The permanent plots were located using a differential global positioning system, and marked for repeated inventories. At each phase-one grid point, a plot of 13 m radius was surveyed. One of eight strata was assigned to each of these phase-one sample plots by the visual interpretation of aerial images. The strata were defined by age class ([0-40], [41-80], [81-120], [121-∞] in years) and dominant tree species (deciduous or coniferous). In the second phase, a predefined proportion of first-phase sample plots was selected from each stratum (*Figure 1*), and two concentric circles of 13 m (DBH ≥ 30 cm) and 6 m (7 cm ≤ DBH < 30 cm) radius were surveyed on the ground (HESSEN-FORST, 2012). Second-phase plots of higher age classes had a higher probability of selection, leading to a higher representation of European beech trees with DBH ≥ 60 cm (*Table 1*) in the sample. In total, 193 phase-two plots were established within the study area and a total of 1746 trees were surveyed, including 63% European beech, 16% common oak, 7% Norway spruce and 14% other tree species. The average stem density on the RFI plots was 1678 stems per ha. The DBH was measured for each selected tree, but height measurements were only recorded for one tree per species, layer, and plot. In the upper canopy layer, a dominant tree was chosen for height measurement, whereas in each of the lower canopy layers, an average tree was chosen (HESSEN-FORST, 2012).

3. METHODS

3.1 Auxiliary variables

The auxiliary variables were calculated for 25 m x 25 m subareas in which the study area were subdivided.

The vegetation heights based on both remote sensing data sources (ASI and ALS) were used separately but similarly. To capture the variation within the 25 m x 25 m subareas, we discretized the heights into a raster of 5 m x 5 m pixels. Pixels without any vegetation height measurements were removed from the data set. Beyond vegetation heights, both remote sensing data sources also contained additional information. The ALS data provided extra information on the calibrated intensity, and the ASI data included spectral information. The spectral information was used to calculate the normalized difference vegetation index (NDVI)

$$NDVI = \frac{NIR - \mathrm{red}}{NIR + \mathrm{red}} \tag{1}$$

according to LILLESAND et al. (2004). The NDVI was assigned to all image vegetation heights from ASI data.

For each of the 25 m x 25 m subareas different auxiliary variables in a different resolution are available: Vegetation heights original points and 5 m square raster values, NDVI, intensity of the reflected laser pulse and

Tab. 2

Sets of auxiliary variables used for spatial prediction of timber volume (number of variables).

Satz von Hilfsvariablen, die für die räumliche Vorhersage des Vorrats verwendet worden sind (Anzahl der Variablen).

Name	Data source	Auxiliary variables
ALS.1 (13)	ALS	height metrics (points)
ALS.int (8)		lidar intensity
ALS.2 (21)		height metrics (points), roughness index
ALS.2.int (29)		height metrics (points), roughness index, lidar intensity
ALS.3 (21)		height metrics (raster), roughness index
ALS.4 (34)		height metrics (points), roughness index, height metrics (raster)
ALS.4.int (42)		height metrics (points), roughness index, height metrics (raster), lidar intensity
ASI.1 (13)	ASI	height metrics (points)
ASI.NDVI (8)		NDVI
ASI.2 (21)		height metrics (points), roughness index
ASI.2.NDVI (29)		height metrics (points), roughness index , NDVI
ASI.3 (21)		height metrics (raster), roughness index

roughness parameter (variance of the vegetation heights). The 5 m square raster was employed to identify if the auxiliary variables can be aggregated previously to speed up the calculations. For each of the subareas simple descriptive statistics were calculated for each variable: Arithmetic mean, percentiles (0.05, 0.25, 0.5, 0.75, 0.95), skewness, kurtosis. Together with these descriptive statistics, for the vegetation heights (points and raster) the proportion of height measurements in the five height classes ([0, 2], [2, 5], [20, 25], [25, 30], [30, ∞]) were used as predictor variables. One height class [5, 20] had been omitted because it is a linear combination of the other height class proportions. We found that alternative classifications such as different class widths and total number of classes as well as alternative percentiles did not change the results notably. Preliminary tests using alternative classifications varying in the number and the widths of the classes (e. g. [0, 1], [1, 2], … , [28, 29], [30, ∞]) showed differences of less than 2% with respect to the RMSE in the resulting target variables.

The sets of auxiliary variables employed have been provided in *Table 2*. Variable sets ALS.1-ALS.4.int relate to airborne laser scanning data, and ASI.1-ASI.4.NDVI to aerial stereoscopic image data. "Height metrics (raster)" and "height metrics (points)", "NDVI", "intensity", and "roughness index" all represent the statistics of the respective parameters defined in this section above. Variable sets ALS.4.int and ASI.4.NDVI contain the complete set of available auxiliary variables for the respective data source.

Since the points of the DSM and DTM were not measured at the same locations, the vegetation heights were calculated by local interpolation of the DTM heights for both data sets. Therefore a two-dimensional linear regression model

$$\widehat{height_{(DTM)}} = \beta_0 + \beta_1 \cdot east + \beta_2 \cdot north \qquad (2)$$

was fitted separately to the DTM height measurements of each single 25 m x 25 m subarea. *East* and *north* indicate the coordinates of DTM points. The size of the subareas was approximately equal to the area of RFI plots. As mentioned above, the image-based vegetation heights were calculated by employing the 5 m x 5 m DTM raster, which was interpreted as a point cloud, whereas the ALS-based vegetation heights were derived by obtaining the difference between the heights of the points classified as topmost surface and as terrain. The DTM height at any DSM point location was again estimated by a local regression model for the corresponding subarea.

3.2 Derivation of the predictor variables

Since only a few tree heights were available on each plot, we calculated the timber volume of all trees using an existing routine in the BWINPro forest growth simulator based on stand height curves and tree volume functions (NAGEL, 1999). The total stem volume per hectare of all living trees on plot i (V_i) was estimated by

$$V_i = \sum_{j=1}^{m_i} \frac{10000}{\pi r_{ij}^2} v_{ij} \qquad (3)$$

with m_i the number of trees on plot i, r_{ij} the radius (m) of the concentric circle in which tree (i,j) was measured, and v_{ij} the timber volume of the respective tree.

3.3 Prediction methods

k-MSN regression

Local smoothing approaches can be considered as solutions provided for locally-defined regression problems. The k-nearest neighbor (k-NN) prediction of the target variable $y = f(x)$ was calculated using the following equation:

$$\hat{f}(x) = ave_{i \in N(x)}\, y_i \qquad (4)$$

where $N(x)$ is the index set of the k-NNs related to the p-dimensional vector of auxiliary variables x in the feature space and the target variable y. With this approach, the dendrometrical variables were predicted for a target area from the mean value of variables from "similar" plots, where similarity between a target subarea and the reference subarea comprising an inventory plot was measured by means of the auxiliary variables and a distance function.

In this study we used the distance function from MOEUR and STAGE (1995):

$$d_i=\sqrt{(x_i-x)^T\Gamma\Lambda^2\Gamma^T(x_i-x)} \quad (5)$$

In this equation Γ represents the canonical coefficients and Λ^2 the squared canonical correlations. It takes into account correlations among the auxiliary variables as well as their explanatory power by canonical correlation analysis.

Random forest

Regression trees are commonly used to select relevant auxiliary variables from a high-dimensional variable set. However, a single regression tree often is not sufficiently robust for predictions. Therefore, BREIMAN (2001) introduced the RF technique, in which a sequence of regression trees is built via bootstrapping. Each tree is fitted to a subsample of the complete data set. In addition, the optimum splitting variable is chosen from only a subset of the auxiliary variables randomly chosen at each node. The collection of all regression trees is then used in the prediction phase. The resampling approach avoids overfitting and provides robust results, because questions of interaction among the variables are handled automatically (VENABLES and RIPLEY, 2007). The R-package randomForest (LIAW and WIENER, 2002; R CORETEAM, 2013) was used for all calculations and additionally provides information on variable importance as defined by BREIMAN (2001). The importance is estimated by out-of-bag estimates – after each tree construction the value of a variable is randomly permuted and the corresponding tree is then fitted again. The output is the percent increase in misclassification rate as compared to the case with all variables intact (BREIMAN, 2001).

Prediction of the target variable at stand level

For each of the 25 m x 25 m subareas, the total volume and the volume of larger European beech trees were predicted using RF and *k*-MSN approaches. Then, at the

Tab. 3

Results of cross validation of 14 different sets of auxiliary variables (cf. *Table 2*) predicting the total timber volume per hectare. The best performing *k*, in case of the *k*-MSN is reported here. Absolute RMSE and bias are shown in m^3 ha^{-1} additionally the relative RMSE is reported (relative to the arithmetic mean). RF(13) and RF(5) denote that random forest has been applied with the 13 and 5 best auxiliary variables.

Ergebnisse der Kreuzvalidierung von 14 verschiedenen Sätzen von Hilfsvariablen (vergl. *Tabelle 2*) für die Vorhersage des Gesamtvorrates je Hektar. Für die Vorhersagen mittels *k*-Nächste-Nachbarn wird das *k*, das zu dem geringsten RMSE (Wurzel der mittleren quadratischen Abweichung) führt, wiedergegeben. Der Absolute RMSE und der systematische Fehler werden in m^3 ha^{-1} dargestellt. Zusätzlich wird der relative RMSE (relativ zum arithmetischen Mittelwert) gezeigt. RF(13) und RF(5) bezeichnen Random Forests mit den 13 und 5 wichtigsten Hilfsvariablen.

Name	Method	k	RMSE	Rel. RMSE	Bias
ALS.1	*k*-MSN	18	117.17	0.37	2.05
ALS.int	*k*-MSN	43	140.91	0.44	17.1
ALS.2	*k*-MSN	10	109.72	0.34	-3.22
ALS.2.int	*k*-MSN	17	110.99	0.35	-0.46
ALS.3	*k*-MSN	34	111.32	0.35	2.05
ALS.4	*k*-MSN	21	113.86	0.36	-0.32
ALS.4.int	*k*-MSN	20	116.43	0.36	-1.19
ALS.4.int	RF		104.67	0.33	1.56
ASI.1	*k*-MSN	15	113.05	0.35	0.32
ASI.NDVI	*k*-MSN	128	160.06	0.5	4.9
ASI.2	*k*-MSN	26	115.83	0.36	5.88
ASI.2.NDVI	*k*-MSN	23	122.24	0.38	1.59
ASI.3	*k*-MSN	27	117.71	0.37	1.69
ASI.4	*k*-MSN	21	122.22	0.38	3.75
ASI.4.NDVI	*k*-MSN	22	129.33	0.4	2.08
ASI.4.NDVI	RF		112.89	0.35	-1.23
ASI.4.NDVI	RF(13)		114.52	0.36	1.18
ASI.4.NDVI	RF(5)		117.26	0.36	1.05

Tab. 4

Results of cross validation of 14 different sets of auxiliary variables (cf. *Table 2*) predicting the timber volume of European beech (DBH ≥ 60 cm) per ha. The best performing *k*, in case of the *k*-MSN is reported here. Absolute RMSE and bias are shown in m^3 ha^{-1} additionally the relative RMSE is reported (relative to the arithmetic mean). RF(11) and RF(3) denote that random forest has been applied with the 11 and 3 best auxiliary variables.

Ergebnisse der Kreuzvalidierung von 14 verschiedenen Sätzen von Hilfsvariablen (vergl. *Tabelle 2*) für die Vorhersage des Holzvorrat von dicken Buchen (BHD ≥ 60 cm) je Hektar. Für die Vorhersagen mittels *k*-Nächste-Nachbarn wird das *k*, das zu dem geringsten RMSE (Wurzel der mittleren quadratischen Abweichung) führt, wiedergegeben. Der Absolute RMSE und der systematische Fehler werden in m^3 ha^{-1} dargestellt. Zusätzlich wird der relative RMSE (relativ zum arithmetischen Mittelwert) gezeigt. RF(11) und RF(3) bezeichnen Random Forests mit den 11 und 3 wichtigsten Hilfsvariablen.

Name	Method	k	RMSE	Rel. RMSE	Bias
ALS.1	*k*-MSN	18	70.42	0.41	-3.28
ALS.int	*k*-MSN	43	86.88	0.51	0.57
ALS.2	*k*-MSN	10	72.42	0.42	-1.83
ALS.2.int	*k*-MSN	17	73.44	0.43	-4.85
ALS.3	*k*-MSN	34	73.42	0.43	-8.28
ALS.4	*k*-MSN	21	75.29	0.44	-7.34
ALS.4.int	*k*-MSN	20	76.41	0.45	-7.58
ALS.4.int	RF		73.75	0.43	1.94
ASI.1	*k*-MSN	15	69.34	0.41	-4.75
ASI.NDVI	*k*-MSN	128	89.53	0.52	-7.37
ASI.2	*k*-MSN	26	74.02	0.43	-9.68
ASI.2.NDVI	*k*-MSN	23	75.37	0.44	-10.65
ASI.3	*k*-MSN	27	72.25	0.42	-6.83
ASI.4	*k*-MSN	21	75.17	0.44	-6.40
ASI.4.NDVI	*k*-MSN	22	76.87	0.45	-7.38
ASI.4.NDVI	RF		69.10	0.41	2.33
ASI.4.NDVI	RF(11)		70.17	0.41	-0.39
ASI.4.NDVI	RF(3)		69.42	0.41	0.40

Tab. 5

Means of plotwise differences of absolute prediction errors (alternative-hypothesis) are tested one-sided against the null-hypothesis of zero mean differences (α = 0.05) using a t-test (B) if the data are normally distributed or otherwise a Wilcoxon signed rank test (A). The normal distribution was tested using a Shapiro-Wilk test (α = 0.05).

Durchschnittliche plotweise Abweichung der absoluten Vorhersagefehler. Es wird einseitig gegen die Null-Hypothese getestet, dass die mittleren Abweichungen Null sind (H1: mittlere Abweichung > 0; α = 0.05). Wenn die Daten normalverteilt sind, wird ein t-Test (B), sonst ein Wilcoxon Rangsummen Test (A) verwendet. Die Normalverteilungsannahme wird mit dem Shapiro-Wilk Test (α = 0.05) getestet.

	Target variable	Variable set 1	Method 1	Variable set 2	Method 2	Test	p-value	Abs. Mean differences
a	larger beech volume	ASI.1	*k*-MSN	ALS.1	*k*-MSN	A	0.48	1.08
	larger beech volume	ASI.2	*k*-MSN	ALS.2	*k*-MSN	A	0.36	1.6
	larger beech volume	ASI.3	*k*-MSN	ALS.3	*k*-MSN	A	0.01	1.93
	larger beech volume	ASI.4	*k*-MSN	ALS.4	*k*-MSN	A	0.06	0.12
	total volume	ASI.1	*k*-MSN	ALS.1	*k*-MSN	A	0.30	4.12
	total volume	ASI.2	*k*-MSN	ALS.2	*k*-MSN	A	0.22	6.11
	total volume	ASI.3	*k*-MSN	ALS.3	*k*-MSN	A	0.47	6.39
	total volume	ASI.4	*k*-MSN	ALS.4	*k*-MSN	A	0.04	12.9
b	larger beech volume	ASI.2	*k*-MSN	ASI.2.NDVI	*k*-MSN	A	0.29	1.35
	larger beech volume	ASI.4	*k*-MSN	ASI.4.NDVI	*k*-MSN	A	0.29	1.7
	total volume	ASI.2	*k*-MSN	ASI.2.NDVI	*k*-MSN	A	0.24	6.41
	total volume	ASI.4	*k*-MSN	ASI.4.NDVI	*k*-MSN	A	0.23	7.11
	larger beech volume	ALS.2	*k*-MSN	ALS.2.int	*k*-MSN	A	0.21	1.02
	larger beech volume	ALS.4	*k*-MSN	ALS.4.int	*k*-MSN	A	0.32	1.12
	total volume	ALS.2	*k*-MSN	ALS.2.int	*k*-MSN	A	0.09	1.27
	total volume	ALS.4	*k*-MSN	ALS.4.int	*k*-MSN	A	0.04	2.57
c	larger beech volume	ALS.4	*k*-MSN	ALS.2	*k*-MSN	A	0.11	2.87
	total volume	ALS.4	*k*-MSN	ALS.2	*k*-MSN	A	0.18	4.14
	larger beech volume	ASI.4	*k*-MSN	ASI.2	*k*-MSN	A	0.00	1.15
	total volume	ASI.4	*k*-MSN	ASI.2	*k*-MSN	A	0.27	6.39
	larger beech volume	ALS.3	*k*-MSN	ALS.2	*k*-MSN	A	0.01	1
	total volume	ALS.3	*k*-MSN	ALS.2	*k*-MSN	A	0.37	1.6
	larger beech volume	ASI.3	*k*-MSN	ASI.2	*k*-MSN	A	0.14	1.77
	total volume	ASI.3	*k*-MSN	ASI.2	*k*-MSN	A	0.33	1.88
d	larger beech volume	ASI.4.NDVI	RF	ASI.4.NDVI	RF(11)	A	0.36	1.07
	larger beech volume	ASI.4.NDVI	RF	ASI.4.NDVI	RF(3)	A	0.10	0.32
	total volume	ASI.4.NDVI	RF	ASI.4.NDVI	RF(13)	A	0.22	1.63
	total volume	ASI.4.NDVI	RF	ASI.4.NDVI	RF(5)	B	0.04	4.37

forest stand level, the target variables were predicted by calculating the averages over the subareas in the stand.

3.4 Validation methods

Comparison of prediction methods and auxiliary variables

The spatial prediction methods (*k*-MSN and RF) were compared using two different groups of auxiliary variable sets derived from the ASI and ALS data which were completed by NDVI and intensity respectively. Precision and accuracy were evaluated for the different prediction approaches and the two data sources with RMSE and bias in comprehensive leave-one-out cross validations.

Position errors

A systematic spatial shift between the remote sensing data and the terrestrial sample plots can be a peculiar source of prediction error. To examine where systematic position errors may have affected prediction precision, the RFI sampling grid was sequentially shifted in x and y direction in 5 m steps. After each shift, a cross validation was carried out.

Testing differences of prediction errors

We tested the significance of the observed differences between prediction errors of two groups (auxiliary variable sets and prediction methods). Prediction errors are the absolute diviations between the observed and predicted values for each plot. Means of plotwise differences of absolute prediction errors are tested one-sided against the null-hypothesis of zero mean differences ($\alpha = 0.05$) using the t-test if the data are normally distributed or otherwise the Wilcoxon signed rank test. We checked whether the data follow a normal distribution (null-hypothesis) using the Shapiro-Wilk test ($\alpha = 0.05$).

4. RESULTS

4.1 Effects of the different data sources using identical prediction methods

Results of the *k*-MSN and RF are shown in *Table 3* and *4*. ALS data and ASI differed only slightly in terms of there precision and accuracy. For total timber volume, a comparison of the corresponding variable sets revealed that, with the exception of ALS.1 and ASI.1, the precision of the estimate with ASI data was only marginally lower than that with ALS data. For the ALS.1 and ASI.1 data, the RMSE was even smaller for the ASI data than the ALS data. For the prediction of the volume of large European beech trees (DBH ≥ 60 cm), no auxiliary variable set was clearly more precise than another, in four of the 8 data sets (*Table 4*) the ASI data led to more precise results.

The smallest RMSE for the total volume prediction, was obtained for an ALS data set with RF (*Table 3*) and

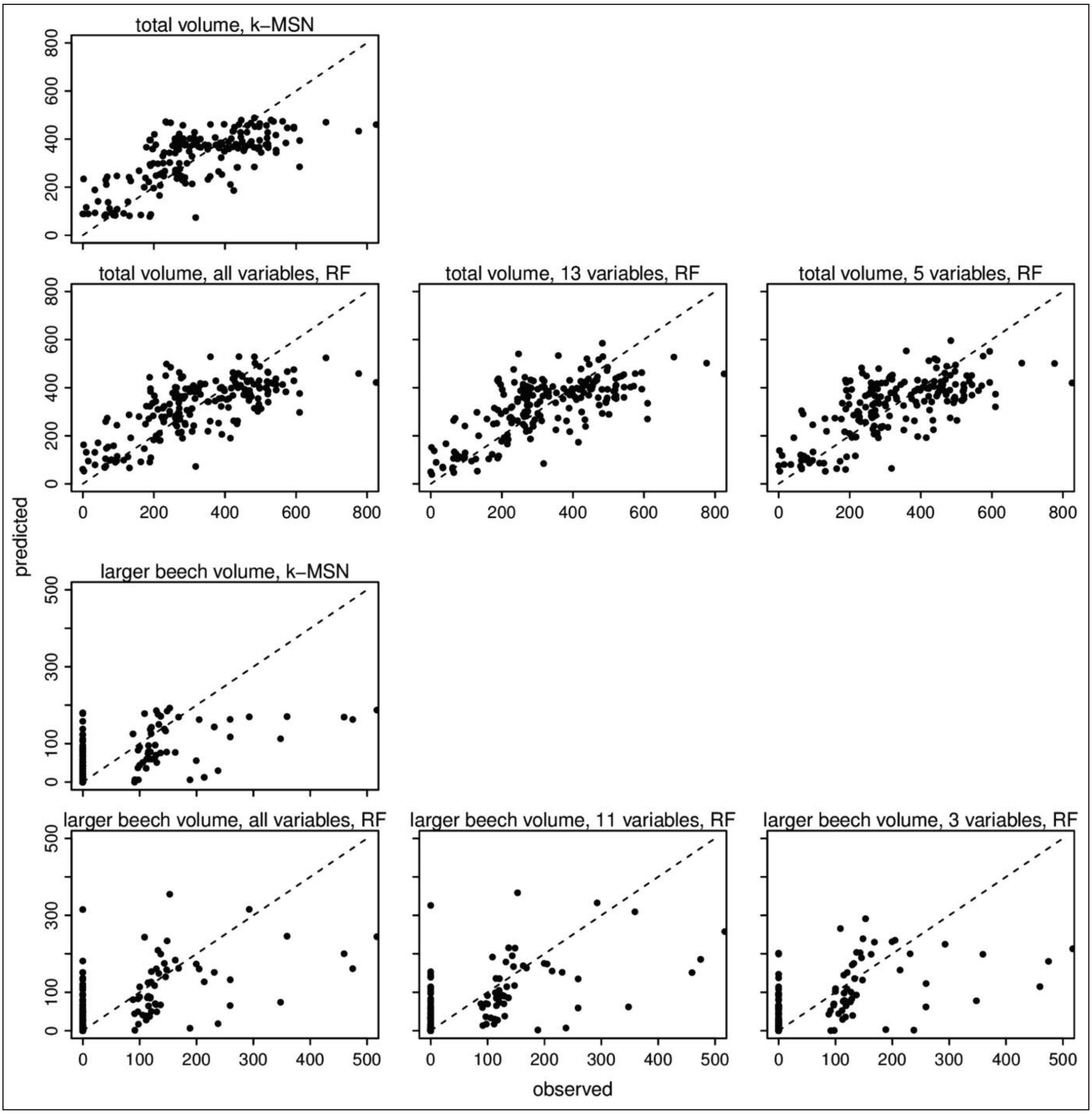

Fig. 2

Scatterplot of observed and predicted timber volume in m^3 ha^{-1}, using variable set ASI.4.NDVI for *k*-MSN and 3 different ASI variable sets for RF.

Streudiagramm von beobachteten und vorhergesagten Holzvorräten in m^3 ha^{-1}. Es wird das Hilfsvariablenset ASI.4.NDVI für die *k*-Nächste-Nachbarn-Methode und 3 verschiedene Hilfsvariablengruppen für Random Forest verwendet.

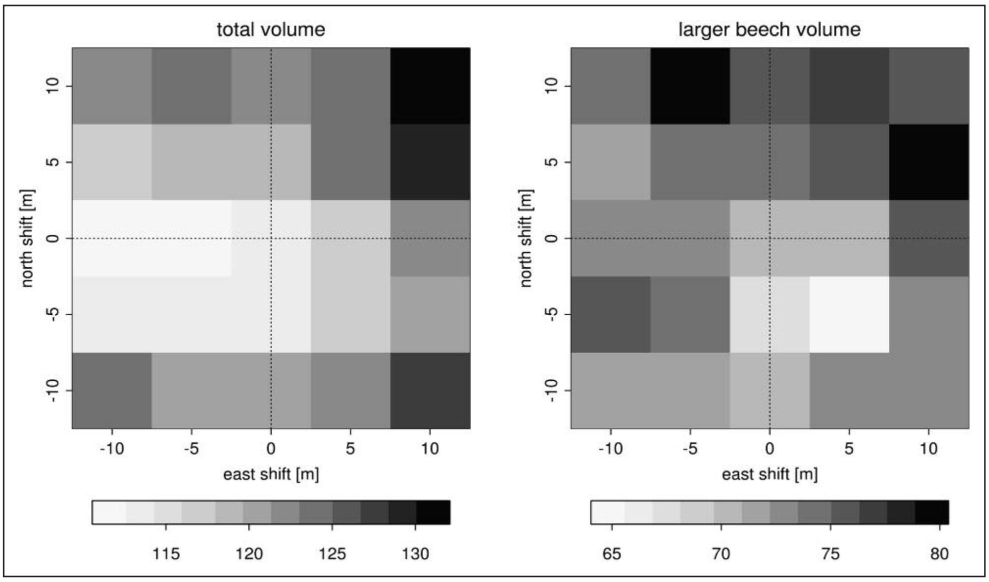

Fig. 3

RMSEs ($m^3\ ha^{-1}$) resulting from relocations of the RFI sampling grid and RF predictions with variable set ASI.4.NDVI.

RMSEs (Wurzel der mittleren quadratischen Abweichung, $m^3\ ha^{-1}$) verursacht durch eine Verschiebung des RFI-Rasters und darauf basierende Random Forest Vorhersagen mit dem Hilfsvariablensatz ASI.4.NDVI.

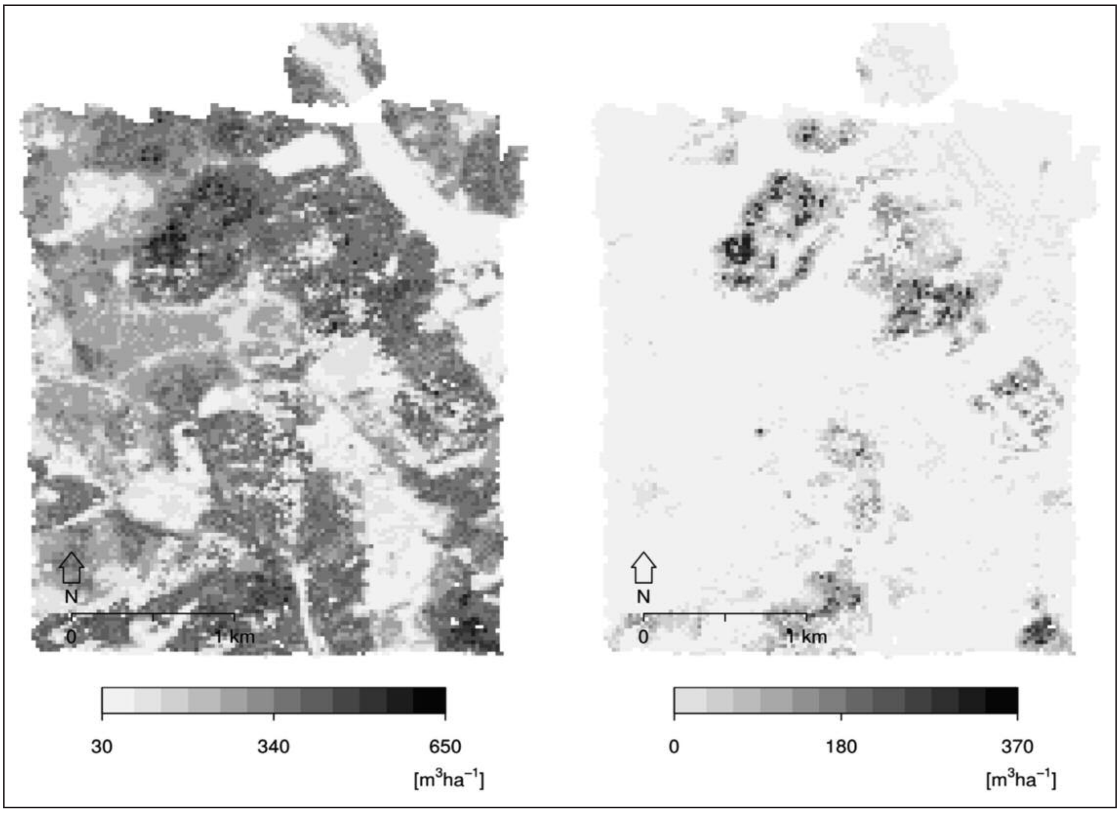

Fig. 4

Predicted timber volume ($m^3\ ha^{-1}$) based on RF using the 13 most important auxiliary variables from variable set ASI.4.NDVI for total volume (left) and using the complete auxiliary variable set for beech volume of trees with DBH ≥ 60 cm (right). Spatial resolution: 25 m x 25 m.

Mittels Random Forest vorhergesagter Holzvorrat ($m^3\ ha^{-1}$). Für den Gesamtvorrat (links) werden die 13 wichtigsten Hilfsvariablen des Hilfvariablensatzes ASI.4.NDVI verwendet und für den Vorrat der dicken Buchen (BHD ≥ 60 cm, rechts) werden alle Hilfsvariablen verwendet. Die räumliche Auflösung beträgt 25 x 25 m.

for the prediction of the volume of larger European beech trees, for an ASI data set (ASI.4.NDVI with RF, *Table 4*).

Using the additional information of intensity and NDVI as well as the vegetation height led to a decrease in precision in all cases of ALS and ASI data for both target variables (compare ALS.2 and ALS.2.int, ASI.2 and ASI.2.NDVI, ALS.4 and ALS.4.int, ASI.4 and ASI.4.NDVI, cf. *Table 3* and *4*). The differences were mostly not significant (*Table 5b*).

By using spatially discretized raster height information in addition to pointwise height measurement, RMSE increased from 109.72 $m^3 ha^{-1}$ to 113.86 $m^3 ha^{-1}$ (ALS.2 and ALS.4, total volume) for ALS variables and from 115.83 $m^3 ha^{-1}$ to 122.22 $m^3 ha^{-1}$ (ASI.2 and ASI.4, total volume). This trend was similar for both response variables. Using only raster data (ALS.3 and ASI.3), precision was lower still (compare ALS.3 and ALS.2, ASI.3 and ASI.2). The raster data provided the additional benefit of reduced computing time. The difference in precision was not significant for most results (*Table 5c*).

4.2 Effects of prediction methods using identical data sources

The RF approach was only carried out with the complete variable sets ALS.4.int and ASI.4.NDVI. Within the latter, also for two groups of the most important ASI variables. These two groups were determined by ranking the auxiliary variables according to their variable importance. Two steep drops were observed after the inclusion of the 5th and 13th ranked variable in the prediction of total timber volume and after the inclusion of the 3rd and 11th ranked variable for the timber volume of large European beech trees. These drops were used as cut-off points. By reducing the number of auxiliary variables used in the predictions to the most important ones, we assumed no notable increase in prediction error would result. For all 8 RF variants reported in *Table 3*, *4*, and *Figure 2*, a random forest of 500 regression trees was created. Larger numbers of regression trees did not essentially change the precision of the predictions. Using the set of 13 and 11 most important auxiliary variables, respectively, instead of the complete variable set, led only to a slight, mostly insignificant decrease in precision of total volume predictions (cf. *Table 5d*)

The cross validation (*Table 3* and *4*) revealed that the precision of RF with ALS variables ($RMSE_{total\ volume}$ = 104.67, $RMSE_{larger\ beech}$ = 73.73) was similar to RF with ASI variables ($RMSE_{total\ volume}$ = 112.89, $RMSE_{larger\ beech}$ = 69.10) and the precision of RF was similar to that of *k*-MSN for both target variables (ALS: $RMSE_{total\ volume}$ = 116.43, $RMSE_{larger\ beech}$ = 76.41; ASI: $RMSE_{total\ volume}$ =

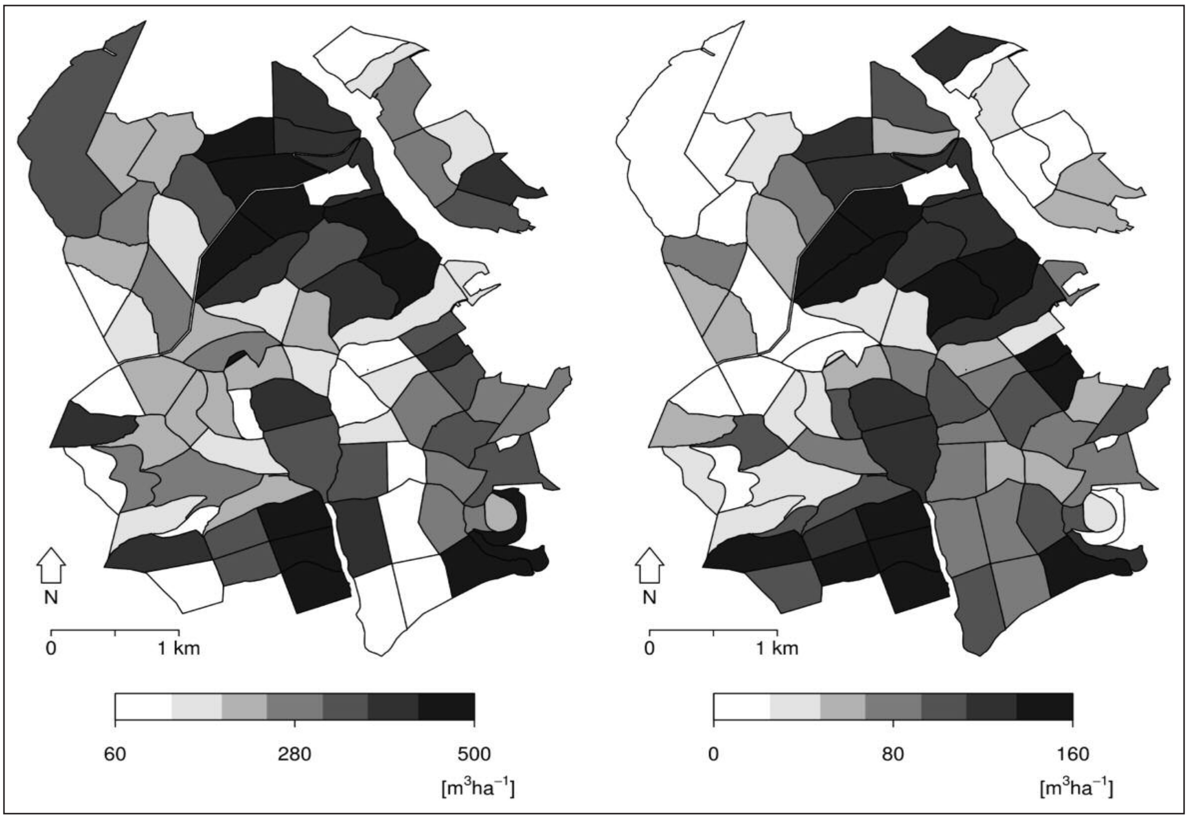

Fig. 5

Predicted timber volume ($m^3 ha^{-1}$) for 86 forest stands based on RF using 13 most important auxiliary variables from variable set ASI.4.NDVI for total volume (left) and using the complete auxiliary variable set for beech volume (DBH ≥ 60 cm, right).

Mittels Random Forest vorhergesagter Vorrat ($m^3 ha^{-1}$) für 86 Bestände. Für den Gesamtvorrat (links) werden die 13 wichtigsten Hilfsvariablen des Hilfvariablensatzes ASI.4.NDVI verwendet und für den Vorrat der dicken Buchen (BHD ≥ 60 cm, rechts) werden alle Hilfsvariablen verwendet.

129.33, $RMSE_{larger\ beech}$ = 76.87). Generally, the RF was found to be approximately unbiased.

Since the RF has stochastic components, the RMSE and bias of predictions varied among repeated RFs. This variation was negligible, from a practical point of view. However, the auxiliary variables that best explained the target variables differed among the repeated RFs. This was found to be affected by the correlations among some auxiliary variables. In all cases no one auxiliary variable was clearly dominant. Yet, for all repeated RFs, auxiliary variables with height-related predictors dominated in the set of most important variables identified.

k-MSN and RF tend to underestimate total volume and volume of larger European beech on plots with a very high total volume per hectare and overestimate on plots with a low timber volume. Particularly for plots with zero measurements, all methods predicted a non-zero volume, usually below 100 $m^3\ ha^{-1}$. This particular error was lower for RF than with *k*-MSN (*Figure 2*). This "bias towards the mean" was often observed in NN-methods and can be explained by the fact that the nearest neighbors of units at the extremes resulted in more moderate values.

4.3 Possible effect of the position error

The effects of systematic position errors on prediction precision were examined using RF and the variable set ASI.4.NDVI. The different RMSE values resulting from virtual relocations of the sampling grid are shown in *Figure 3*. A minimum RMSE was obtained if the RFI sampling grid was shifted by (5 m, –5 m) for large European beech tree volume and by (–5 m, 0 m) for total volume. However, the relative change in RMSE was negligible in comparison with the total RMSE using the original sampling grid without relocation.

4.4 Map of volume predictions for the entire study area

For each subarea, both target variables were predicted (*Figure 4*) using the RF approach. For predictions of the total volume, 13 auxiliary variables were used whereas the complete set of auxiliary variables was used to predict the volume of large European beech trees (DBH ≥ 60 cm). *Figure 5* shows predictions of both target variables for the subareas in each of the 86 forest stands.

5. DISCUSSION

5.1 Effects of the different data sources

The major finding of our study was that spatial predictions based on ALS data are mostly but not always more precise than those based on ASI data. However, the differences in this study are small and usually insignificant in terms of the plotwise differences in prediction errors. This is consistent with results of previous studies (JÄRNSTEDT et al., 2012; NURMINEN et al., 2013; STRAUB et al., 2013). The precise height measurements and the more detailed characterization of the vertical stand structure with ALS do not necessarily lead to more precise spatial predictions. Using only the discretized raster information leads to similar accuracy compared to using the point based metrics, with a very high resolution. A high covariate resolution is therefore not important to achieve a high accuracy. The high spatial autocorrelation of the target as well as the auxiliary variables may have an effect here.

The average total volume of the RFI-plots was 320 $m^3\ ha^{-1}$, the relative RMSE for the best performing ALS model was 33% and for the best performing ASI model was 35% or about 105 $m^3\ ha^{-1}$ respectively 113 $m^3\ ha^{-1}$ (cf. *Table 3*). This is also in accordance with results of preceding studies (JÄRNSTEDT et al., 2012; NURMINEN et al., 2013; STRAUB et al., 2013; BREIDENBACH et al., 2010). The RMSE of the simple sample mean is given by the standard deviation in volume per hectare and, in our study, it was 159 $m^3\ ha^{-1}$. Compared to this simple predictor, our RF-approach achieved a 30% increase in precision. For the timber volume of large European beech trees (DBH ≥ 60 cm), the RMSE was about 70 $m^3\ ha^{-1}$ compared to the standard deviation 100 $m^3\ ha^{-1}$ (cf. *Table 1*). In the studies by Järnstedt et al. (2012) and NURMINEN et al. (2013), still smaller RMSEs were attained. This could be explained by the relatively homogenous forests at their study sites and the smaller total timber stock. A comparison of the relative RMSEs obtained in our study to those of JÄRNSTEDT et al. (2012) shows that the results are similar. STRAUB et al. (2013) studied highly structured forests and obtained results comparable with ours. These earlier studies showed a general, yet still small increase in precision with ALS data over ASI data, this is in general consistent with the results of our study.

Remote sensing approaches generally still miss viable solutions to automatically detect single trees in Central European conditions and thus rely on vague proxies to estimate the number of trees per hectare. Estimation of volumes for certain species is even harder due to the unsolved problem of reliable species recognition from remote sensing data in closed stands. Thus, our prediction error is comparable to studies based on remote sensing but still high in comparison to terrestrial inventories, especially in case of larger beech trees. Further we believe that an increase of spatial and spectral resolution and advances in image processing will lead to better auxiliary variables such as number of trees, average crown sizes and species group.

While the remote sensing data were collected in July 2009, the terrestrial survey was carried out few months later in the first quarter of 2010. This might be another source of prediction error. But in this case, no trees were harvested in the interim and the error possible occurred because of tree growth can be assumed very small if one considers the rather long production periods of forests compared to the short delay of the terrestrial survey. Moreover, the main objective of this study was to compare the suitability of auxiliary variables derived from ASI and ALS data. The time between the acquisition of the ASI and the ALS data was less than one month, what can only have negligible effects on the differences of prediction errors arising from the two data sets.

5.2 Effects of prediction methods

Our study shows that the precision of RF and k-MSN is similar irrespective of the remote sensing data source. We also tested regression based approaches that showed higher errors in terms of RMSE. However, one can not conclude by this, that regression based approaches are in generally less precise. We could not find a clear interaction between the two nonparametric prediction methods and the source of remote sensing data. Moreover, we found that neither the NDVI of ASI nor the intensity of ALS provided relevant additional information for spatial prediction of timber volume per hectare, although the spectral information of ASI enables the visual interpretation of tree species (WHITE et al., 2013). The NDVI did not seem to improve the volume predictions in our case. The suitability of other spectral variables, in combination with height metrics, should be tested in further studies for other areas and target variables. STRAUB et al. (2013) stratified their subareas by the dominant tree species group (deciduous and coniferous) using a logistic regression model fitted to extra training data, what resulted in slightly smaller RMSEs. However, extra training data, especially for large European beech trees, is not readily available as yet.

Lower RMSE values for timber volume predictions of large European beech trees result from a relatively large number of plots with correctly predicted timber volume of zero (cf. *Figure 2*). If one considers only plots containing large European beech trees and predictions larger than zero, the RMSE would become approximately as high as for the total volume. Whereas larger relative RMSE values for timber predictions of large beech trees results from the fact that the threshold has also to be identified by remote sensing data. When predicting variables for areas which do not belong to the target population (for example beech trees, DBH = 55 cm), the resulting error is extremely high, as the observed stem volume is 0 $m^3\ ha^{-1}$.

Using k-MSN or, more general, k-NN methods, the final prediction is calculated as the mean of the k-nearest neighbor units. Although MCROBERTS (2012) pointed out that the effect of weighting might be small, we believe it is still recognizable. Therefore, we additionally tested a local polynomial regression method, in which a variable number of NN were weighted by distance through the application of kernel functions. Our first tests did not lead to notable reductions in RMSE. However, we intend to undertake further tests with local polynomial regression and different parameterizations.

More flexible methods could also be applied for the interpolation of the DTM, e.g. a geostatistical approach in which the DTM heights are averaged with weights depending on their distance to a DSM point (CRESSIE, 1993). Likewise a nonparametric smoothing approach based on two-dimensional splines (FAHRMEIR et al., 2007) could be appropriate. The latter two approaches were tested. However, the two-dimensional linear regression proved to be sufficiently precise and flexible to derive local DTM values within small subareas and was very fast.

5.3 Effect of the position error

We also investigated if the prediction error can be partially explained by a spatial shift between the remote sensing data and the terrestrial sample plots. There are slight increases in precision when shifting the terrestrial sample plots appropriately, however the optimum shift directions differ between the two target variables. The rather high spatial autocorrelation of the target as well as the auxiliary variables might lead to a low effect of shifting the RFI-plots.

6. CONCLUSIONS

Our study has shown that the precision of RF and k-MSN is similar irrespective of the remote sensing data source. The auxiliary variables that explained the target variables in the best differed among the repeated RFs, probably because of the high correlation among the auxiliary variables. The height-related predictors were identified as the most important variables when using variable importance evaluation. Spatial predictions based on ALS data are only slightly more precise than those based on ASI. The advantage of ALS data over ASI data vanishes, when predicting volume of larger beech trees. This can be explained by the fact, that there is a strong connection between the upper canopy layer and the large beech tree volume. In that case the best performing variable set, which would be chosen in practical applications, is even based on ASI data. The need of an additional terrain model if using ASI data should be taken into account in this context. Since most of the differences of ASI and ALS prediction errors are not significant, one can only conclude that the data sources lead to generally comparable results. Acquisition of ALS data is considerably more expensive than of ASI data, which are often already available from other monitoring projects. Thus one would commonly prefer ASI data for periodically predicting timber volume at stand level.

7. ABSTRACT

Practical forest management requires information on dendrometrical forest parameters in a high spatial resolution, particularly interesting is the timber volume. Nearest neighbor techniques and the random forest approach were employed in this study to predict timber volume per hectare (total stem volume and stem volume of large beech trees, DBH ≥ 60 cm) at forest stand level. The predictions were based on sample plot data from a regional forest inventory and selected sets of auxiliary variables derived from two different remote sensing data sources – airborne laser scanning (ALS) data and aerial stereo images (ASI) – to quantify and compare prediction precision. Existing studies conclude that ALS data provide more precise height information, but also that acquisition of ALS data is more expensive than of ASI data, which are often already available from other monitoring projects. Currently the cost of ASI data is about a half to a third of ALS data. To make spatial predictions we compared two frequently used methods for imputation: random forest and k-most similar neighbors. For both methods, the prediction precisions (RMSE) were similar. Most promising was the fact that the two differ-

ent sources of auxiliary variables resulted in predictions of almost the same precision. The similarity between ASI and ALS predictions suggest that ASI may serve as a lower-cost alternative to ALS data for estimating many forest stand-level variables.

8. ZUSAMMENFASSUNG

Titel des Beitrages: *Vergleich der Vorhersage des Bestandsvorrats mittels luftgestützter Laserscanning-daten und Stereo-Luftbildern.*

In der Forstpraxis werden dendrometische Informationen in einer hohen räumlichen Auflösung benötigt. Von besonderem Interesse ist der Holzvorrat. In diese Studie werden Nächste-Nachbarn-Methoden und der Random Forest Ansatz verwendet, um den Vorrat je Hektar (Gesamtvorrat, Vorrat dicker Buchen, BHD ≥ 60 cm) auf Bestandesebene zu schätzen. Die Vorhersagen erfolgen auf Grundlage von Stichprobenflächen einer regionalen Forstinventur und verschiedenen Gruppen von Hilfsvariablen. Die Hilfsvariablen stammen aus zwei verschiedenen Fernerkundungsdatensätzen: luftgestütztes Laserscanning und Stereo-Luftbilder. Ein Ziel der Studie ist die Vorhersagegenauigkeit in Abhängigkeit von der Fernerkundungsdatenquelle zu quantifizieren. Bisherige Studien kommen zum Schluss, dass luftgestütztes Laserscanning zu genaueren Vorhersagen führt, aber auch, dass Laserscanning Daten teurer sind als Stereo-Luftbilder. Derzeit kosten Stereo-Luftbilder etwa die Hälfte bis ein Drittel von luftgestützten Laserscanning Daten. Die räumlichen Vorhersagen wurden mit zwei häufig genutzten Methoden, der k-Nächste Nachbarn-Methode und dem Random Forest Ansatz, durchgeführt. Die Vorhersagegenauigkeit der Methoden war vergleichbar. Besonders vielversprechend ist, dass die Vorhersagen mit unterschiedlichen Fernerkundungsdaten fast die gleiche Präzision aufwiesen. Die Ähnlichkeit der Vorhersagen lässt den Schluss zu, dass Stereo-Luftbilder eine günstigere Alternative zu luftgestütztem Laserscanning für die Vorhersagen von Bestandesparametern sind.

9. RÉSUMÉ

Titre de l'article: *Comparaison des prévisions de volumes de peuplements au moyen de données par levé scanner laser aéroporté et au moyen de photos aériennes en stéréoscopie.*

Dans la pratique, la gestion forestière nécessite l'utilisation d'informations dendrométriques avec une définition spatiale élevée. Il est particulièrement intéressant de connaître le volume de bois. Dans la présente étude, la méthode des plus proches voisins et la méthode des forêts aléatoires sont utilisées pour estimer le volume par hectare à l'échelle du peuplement (volume total, volume des gros bois de diamètre ≥ 60 cm). Les prévisions s'appuient sur la base de surfaces d'échantillonnage d'un inventaire forestier régional et de différents groupes de variables. Les variables émanent de deux choix différents de données par photos satellites: levé scanner laser aéroporté et des photos aériennes en stéréoscopie. Un but de cette étude est de quantifier l'exactitude des prévisions en lien avec les sources de données de photos satellites. Les études réalisées jusqu'ici arrivent à cette conclusion que le levé laser aéroporté apporte les prévisions les plus exactes mais aussi que les données de laser aéroporté sont plus onéreuses que les photos aériennes en stéréoscopie. Actuellement le coût des photos aériennes en stéréoscopie s'élève à la moitié voire le tiers du coût des levés par laser aéroporté. Les prédictions spatiales ont été réalisées au moyen de deux des méthodes les plus fréquemment utilisées, la méthode des k plus proches voisins et la méthode des forêts aléatoires. L'exactitude de la précision des méthodes est comparable. De façon particulièrement prometteuse, on remarque que les prédictions avec différentes données satellites présentent presque la même précision. Les similitudes de prédictions conduisent à la conclusion que les photos aériennes en stéréoscopie sont une meilleure alternative au levé scanner aéroporté pour les prédictions des paramètres de peuplements.

10. ACKNOWLEDGMENTS

The authors would like to express their gratitude to the Center for Forest Survey and Conservation (FENA) of "Hessen-Forst", the state forest enterprise in Hesse, and to the Forest Planning Department of "Niedersächsische Landesforsten", the state forest enterprise in Lower Saxony, for financing this study. We also would like to thank FENA for providing the aerial images and RFI data as well as STEFAN FLECK for providing the ALS data. Moreover, we would like to thank FALKO ENGEL for fruitful discussion and support. Furthermore we would like to thank HELEN DESMOND for language editing.

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