



## Remotely sensed data controlled forest inventory concept

Adelheid Wallner, Alata Elatawneh, Thomas Schneider, Mengistie Kindu, Britta Ossig & Thomas Knoke

To cite this article: Adelheid Wallner, Alata Elatawneh, Thomas Schneider, Mengistie Kindu, Britta Ossig & Thomas Knoke (2018) Remotely sensed data controlled forest inventory concept, European Journal of Remote Sensing, 51:1, 75-87, DOI: [10.1080/22797254.2017.1403295](https://doi.org/10.1080/22797254.2017.1403295)

To link to this article: <https://doi.org/10.1080/22797254.2017.1403295>



© 2017 The Author(s). Published by Informa UK Limited, trading as Taylor & Francis Group.



Published online: 08 Dec 2017.



Submit your article to this journal [↗](#)



Article views: 567



View Crossmark data [↗](#)

## Remotely sensed data controlled forest inventory concept

Adelheid Wallner, Alata Elatawneh, Thomas Schneider, Mengistie Kindu, Britta Ossig and Thomas Knoke

Institute of Forest Management, TUM School of Life Sciences Weihenstephan, Technical University of Munich (TUM), Freising, Germany

### ABSTRACT

Nowadays, the image of the forest in Germany is changing from monoculture areas to very mixed forests, where individual stands are no longer clearly visible. The objective of this study was to examine the use of remotely sensed data at enterprise level for pre-stratification and sample plot allocation in the planning stage of forest inventories in a very heterogeneous forest. On the basis of RapidEye satellite data and object-based image analysis, a stratified segment-based non-permanent sampling design was developed and evaluated against the results of a permanent systematic sampling design. The relative efficiency (RE) was calculated based on variance estimators for simple random sampling and stratified random sampling for the variable timber volume [ $\text{m}^3/\text{ha}$ ]. By stratification of the sample designs, we achieved an RE of 1.25 for the systematic sampling and 1.34 with the segment-based sampling design. Based on a targeted standard error of 4.6%, the sampling designs were compared with respect to the required sample size. The stratified segment-based sampling design reduced the number of sample plots compared to the systematic sampling design by 28%. Furthermore, it was shown that the possible reduction of sampling plots leads to a cost saving of 21%.

### ARTICLE HISTORY

Received 31 January 2017  
Revised 4 November 2017  
Accepted 6 November 2017

### KEYWORDS

RapidEye data; stratified random sampling; systematic sampling; relative efficiency; segment-based

## Introduction

At present, a change in the forest management concept from monoculture stands to very heterogeneous mixing stands is taking place in Germany (Teuffel et al., 2005). Terrestrial forest inventories are the main suppliers for quantitative and qualitative attributes of the forest structure, including forest types, tree species composition, age class, tree height and other information (Gregoire & Valentine, 2008; Van Laar & Akça, 2007). In Germany, the inventory sampling designs commonly used for the National Forest Inventory (NFI) and for forest enterprises are permanent systematic sampling designs. Forest inventory cycles for the NFI and for the enterprise level are targeted every 10 years (Knoke, 2012). For conducting a permanent systematic sampling inventory, different grid sizes are used. In Bavaria at forest enterprise level, the common grid size is 200 m × 200 m (Neufanger, 2011). The number of sample plots collectable per day depends, *inter alia*, on the spatial connection of the forest area and its topography (Van Laar & Akça, 2007). As a result, data collection across a regular sampling grid is labour-intensive and costs are proportional to the number of sampling plots (Van Laar & Akça, 2007). Additionally, the new forest restructuring will be a challenge for the conventional sampling design to have the targeted precision.

To keep the forest inventory practices efficient, the sampling techniques may rely on ancillary information for stratification, which includes characteristics of the forest or estimates of forest structural information (West, 2015). Stratified sampling can lead to more precise estimates when relatively homogenous and distinctive strata (classes) are delineated compared to simple random or systematic sampling (Saborowski & Cancino, 2007; Särndal, Swensson, & Wretman, 1992). Stratification strives to reduce variance within each stratum, when a significant difference between the strata values exists, and increases the efficiency of inventory sampling designs (Bickford, 1952; Saborowski & Cancino, 2007).

For improving the precision of forest inventories, the implementation of ancillary information from remotely sensed data offers an efficient and inexpensive opportunity (McRoberts & Tomppo, 2007). Recent technological improvements in remote sensing systems deliver data frequently at comparably low costs and wide area coverage (McRoberts & Tomppo, 2007). According to McRoberts, Holden, Nelson, Liknes and Gormanson (2005), this means increased speed, efficiency and precision, as well as higher cost-effectiveness and a more efficient use of time can be achieved for forest inventories.

Approaches of remote sensing-based stratified sampling related to forestry were investigated in the USA as part of the second Northeast Forest Survey,

conducted by Bickford (1952), and were later applied in Finland by Poso (1972). Nowadays, such remote sensing supported stratified sampling designs are used for NFI in different countries (e.g. Switzerland, Finland and USA) (Dahm, 1995; Dees, 2006; Köhl & Sutter, 1991; McRoberts et al., 2005).

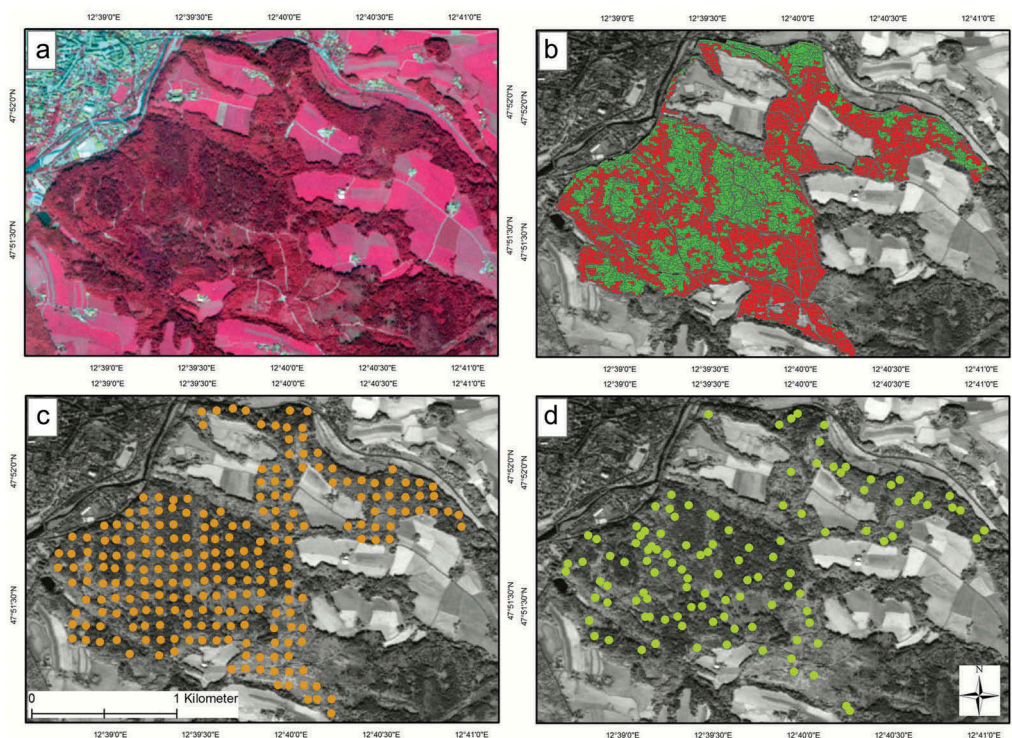
Grafström, Saarela and Ene (2014a) showed the potential of remote sensing information for stratification prior to field sampling. This procedure can be useful in the initial planning stages of field sampling, when the sampling design is established. Two different procedures of pre-stratification by means of ancillary data are possible: on the one hand to reduce the sample size (Grafström, 2013) and/or on the other hand to establish a more efficient sampling design (Nothdurft, Borchers, Niggemeyer, Saborowski & Kändler, 2009). Both possibilities allow for area proportional and spatially distributed sampling supported by the stratification effect (Grafström, 2013; Grafström et al., 2014a; Grafström & Schelin, 2014b). McRoberts and Tomppo (2007) describe examples of locating inventory sample plots in specific strata using pre-stratification to ensure that an efficient (but reduced) sample of plots is selected in the relevant forest area. At the planning stage of enterprise forest surveys, the use of remote sensing-based stratification into forest types (deciduous and coniferous) is currently state of the art and regularly applied, such as in Lower Saxony, Germany (Böckmann, Saborowski, Dahm, Nagel & Spellmann, 1998).

The objective of this study was to investigate an innovative sampling design, for a highly structured test site forest in order to either achieve a higher inventory precision or allow a smaller sample size for a required precision and therefore reduced cost. Hence, the research question focused on whether a segment-based design is able to achieve a result consistent with the conventional permanent systematic sampling design. The innovative sampling design used the method of object-based segmentation and pre-classification of RapidEye data. We assume that the segmentation based on spectral features and a subsequent classification resulted in strata that retained the condition of homogeneity for the forest canopy features and should represent in reality tree patches, which are smaller than forest stands.

## Materials and methods

### Test site

The study was conducted in the municipal forest owned by the city of Traunstein, located in south-eastern Bavaria, Germany. Geographical coordinates of the test site are 47°52' N and at 12°39' E (Figure 1 (a)). The region of interest covers a broad range of the pre-alpine landscape, particularly areas with steep slopes. Elevations range from 600 to 700 m above sea level. The soils are of glacial sediments,



**Figure 1.** (a) RapidEye data from 7 September 2009 displayed as a colour-infrared (CIR) composite with the following bands: NIR (red), red (green) and green (blue); (b) Second-level classification result with segment boundaries of the test site into coniferous-dominated (green) and deciduous-dominated (red) forest classes; (c) Systematic distribution of 2008 forest inventory sample plots (orange points); (d) Stratified random distribution of 2010 inventory sample plots (green points).

originally left by receding glaciers at the culmination of previous ice ages. The climatic conditions are characterized by a mean annual precipitation of 1600 mm and a mean annual temperature of 7.3°C (Moshhammer & Pretzsch, 2010). The forest covers an area of ~232 ha, and the dominant tree species are Norway spruce (*Picea abies* (L.) H. Karsten) (49%), European beech (*Fagus sylvatica* L.) (21%) and White fir (*Abies alba* Mill.) (15%). The stand-type structures range from even-aged spruce monoculture stands to uneven-aged mixed stands, depending on management history and soil conditions (Moshhammer & Pretzsch, 2010).

### Data preparation

#### Data set

For the presented work level, 3A products provided by RapidEye Science Archive (RESA) at the German Aerospace Centre (DLR) were used as subsets to the test site (shown in Figure 1(a)). For further quality control, the radiometric, sensor and geometric corrected RapidEye image was checked for geometric correctness using ENVI® 4.3 (ENVI, 2009). For the mono-temporal analysis, we had two reasons to use an image acquired on 7 September 2009. First, only one year had passed since the last field inventory in the area. Second, Elatawneh, Rappl, Rehus, Schneider and Knoke (2013) found that September represented in Bavaria the best period of the year to use image classification for distinguishing between coniferous and deciduous tree species.

#### Stratification

RapidEye data were analysed with the object-oriented image processing approach offered by the eCognition® Developer 9 software package (eCognition Developer 9.0 2004). A hierarchical two-level classification based on the membership function was developed. At the first level, we differentiated forest versus non-forest, and at the second level, the forest types coniferous and deciduous dominated. The segmentation was performed with the multi-resolution algorithm (Baatz & Schäpe, 2000) considering the spectral information supplemented

by the Normalized Differenced Vegetation Index (NDVI) (Rouse, Haas, Schell, Deering, & Harlan, 1974) and the simple ratio of the blue/green bands (Kindu, Schneider, Teketay, & Knoke, 2013; Schneider et al., 2013). The different homogeneity settings for scale, shape and compactness were defined empirically by trial and error. The result was an image divided into segments with respect to the spectral values and indices (Pekkarinen & Tuominen, 2003).

Based on the first segmentation level, we performed an initial stratification into urban, water and forest via knowledge-based classification employing eCognition® and the implemented membership function concept. Urban and water segments were classified based on the values for the NDVI. Forest area was classified based on the values derived from the standard deviation of the near-infrared (NIR).

At the second segmentation level, we classified the forest class into coniferous- and deciduous-dominated forest. Special attention was given to the segment size and the spectrally homogenous demarcation of the forest types (deciduous, resp. coniferous dominated). The weights for the bands and indices were set according to our a priori knowledge of the forest class. For classification, the digital values of the NIR and NDVI were used. Thresholds for the spectral values and for the applied membership functions are given in Table 1 and the classification result is shown in Figure 1(b). The second-level segments of our test site had a size range between 100 m<sup>2</sup> and 6100 m<sup>2</sup>, with an average size of 1300 m<sup>2</sup>.

After completing the second segmentation level, the accuracy was assessed using colour-infrared (CIR) aerial images from 2009 provided by the Bavarian State Office for Digitizing, Broadband and Survey (LDBV) with a spatial resolution of 0.2 m. The images were also set to the extent of the test site and overlaid with a grid of 50 m by 50 m. The 435 grid points were buffered to the size of a sample plot (500 m<sup>2</sup>). The images were visually interpreted based on the same definition as Straub, Stepper, Seitz and Waser (2013) (coniferous stratum if percentage of coniferous >50% and deciduous stratum if percentage of coniferous ≤50%) to produce the verification data. The accuracy assessment

**Table 1.** Parameters used in each of the two different segmentation levels and for the classification in level 2 applied to the RapidEye data using eCognition® software.

Process	Strata	Level	Scale	Shape	Compactness	Bands	Weight
Segmentation	Forest/non-forest	1	60	0.2	0.3	Red edge	5
						Blue/green, green	3
Segmentation	Forest types	2	50	0.2	0.6	Red, NIR and NDVI	1
						NDVI, NIR	5
						Green, blue/green, Red edge, blue	3
Classification	Coniferous dominated	Classification (membership function)				Red	1
						NIR	35.6–62.5%

NIR: near-infrared; NDVI: Normalized Differenced Vegetation Index

was conducted by creating an error matrix that included the overall accuracy, producer and user accuracy. Furthermore, a Kappa analysis (Congalton, 1991) and the total disagreement, separated into components of quantity and allocation (Pontius & Millones, 2011), were performed.

### Segment-based sample plot allocation

As a precondition for the segment-based sampling design, a sample size reduced by 50% of the conventional sampling design was set (representing 114 inventory plots). The sample plot position was defined by the automatically calculated centre of gravity (COG) of the selected segments and represented a class characterized by a total area inventory based on spectral features. This is considered a novel application of COG, as it is usually used in neighbourhood distance calculation in digital image processing (Batz et al., 2004; Rutzinger, Höfle, Pfeifer, Geist, & Stötter, 2006), for noise identification in grey-level images (Van Assen, Egmont-Petersen, & Reiber, 2002) or as an offset for position accuracy using laser data (Morsdorf, Meier, Allgöwer, & Nilesch, 2003).

The classification result and the COG points were exported from eCognition® as shape files for further analysis in a geographic information system (GIS). Furthermore, we assumed that all segments assigned to a class carry the class properties. This allows for introducing an area threshold (larger than 500 m<sup>2</sup>) for sample plot segment candidates, assuring that the sample plot allocated via the COG is completely within the segment. Additionally, to realize an equal distribution of the inventory plots and to avoid clustered sampling, the test site was manually divided into four sub-areas. The area-proportional allocation of the experimental sample design with the predefined sample size of 114 sample plots was calculated based on the equation described in Cochran (1977). The defined areas of sample plots serve to link the spectral properties with forest canopy features, in our case the timber volume. For data collection, the locations of the sample plots in the forest were reached via differential global navigation satellite systems.

### Inventory field data

The conventional forest inventory (systematic sampling) was performed in 2008 by the Chair of Forest Growth and Yield Science at the Technical University of Munich (TUM). Measurements were taken on 228 inventory sample plots of the permanent regular sampling grid of 100 m × 100 m (illustrated in Figure 1(c)). The second inventory was carried out in 2010 by the Institute of Forest Management of the TUM. According to the

targeted 50% reduction goal, 114 plots based on the innovative sampling design as described in the section segment-based sample plot allocation (Figure 1(d)) were defined.

Both sampling surveys were conducted according to the Bavarian State forest inventory guideline (Neufanger, 2011), which is based on three concentric circles. This method involves three nested circles: a small circular plot with 31 m<sup>2</sup> (3.15 m radius), a medium circular plot with 125 m<sup>2</sup> (6.31 m radius) and a large circular plot with 500 m<sup>2</sup> (12.62 m radius). First, all trees with a diameter at breast height (the diameter of a tree is measured at 1.3 m above ground) smaller than 10 cm and located in the smallest (31 m<sup>2</sup>) circular plot were recorded. Second, all trees with a DBH between 10 cm and 30 cm within the medium circular plot were recorded, and finally, all trees within the largest circle (500 m<sup>2</sup>) with a DBH greater than 30 cm were measured and recorded (Neufanger, 2011). The main variables recorded at the inventory plots are DBH, tree species, tree height, age class and position with respect to the sample point. The measured tree height and DBH were used to generate height-diameter models for each inventory plot, based on the equation by Petterson (1955) and adjusted for Bavaria. This model was used for each inventory plot to receive height information for trees without *in situ* recorded height measurements. Height information, DBH and the tree species-specific form factor (Van Laar & Akça, 2007) were combined in allometric models and used to estimate the volume of a single tree. Based on the allometric models, the timber volume (in cubic meters per hectare) at plot level was calculated.

The variable timber volume of the two inventory databases (2008 and 2010) was used to compare the different sampling designs (segment-based sampling design and systematic sampling design). The data sets used had a two-year difference and appeared appropriate for comparison of the sampling designs because the harvested amount of timber volume was mostly equal to the annual increment (Moshhammer & Pretzsch, 2010). We used two approaches to check if this assumption was true. First, to rule out differences in the data sets, the statistical similarity of variances was evaluated by an *F*-test with a predefined significance threshold of  $p = 0.05$ . Assuming harvest and increment occurred uniformly across the study area, we thus expected the same variance of standing timber volumes from both inventory methods. Second, we applied a Chi-square test to check the similarity of the distribution of timber volumes between the two data sets. To achieve this, the empirical distribution in 2010 was compared with the expected distribution.

## Sampling methods

### Simple random sampling estimators

For evaluating structural forest information (e.g. volume in timber inventories), simple random sampling (SRS) estimators are usually applied to a systematic sampling approach (Dees, 2006; Kangas & Maltamo, 2006; Köhl, Magnussen, & Marchetti, 2006; Shiver & Borders, 1996). For example, Shiver and Borders (1996) showed that variance estimators developed for SRS can also be applied to systematic sampling as valid, but conservative estimates of the population variance. However, criticism by Cochran (1977) and Köhl et al. (2006) pointed out that using SRS estimators with systematic sampling could lead to an overestimate, on average, of the actual error. We accepted this potential disadvantage and assumed that the systematic sampling represents a random distribution over the population of this very heterogeneous forest because the starting point of the sampling grid was random. The SRS estimators were also used for the segment-based sampling because the distribution of the population was random. Furthermore, the estimators used in our study should be simple, easy to calculate, valid with respect to accuracy and transferable to practice.

According to McRoberts, Nelson and Wendt (2002), the estimated variance of the mean is used to calculate the relative efficiency (RE) for comparing the stratification effect of two different sampling methods whereby  $n$  needs to be constant. The standard error of the sample mean  $s_{\bar{y}}$  is a measure of precision and is used to compare the precision obtained by SRS with other estimators (Cochran, 1977). The estimated variance of the mean and the standard deviation are all calculated without using a finite population correction (fpc) factor because less than 5% of the population has been sampled (Cochran, 1977; Shiver & Borders, 1996; Dees, 2006).

### Stratified sampling

Stratified sampling (*Str*) was introduced to facilitate a more efficient sampling scheme in heterogeneous areas (Knoke, 2012; Shiver & Borders, 1996). Using this method, the population of the study site was divided (stratified) into spectrally homogeneous sub-populations (Cochran, 1977; Kangas & Maltamo, 2006; Dees, 2006), which we refer to here as strata (deciduous- and coniferous-dominated forest). The stratum weights,  $W_h$  were defined as the proportion of each stratum size in relation to the total population area ( $W_h = \frac{N_h}{N}$ ), where  $N_h$  is the size of stratum  $h$ , and  $N$  is the population size ( $N = \sum_{h=1}^L N_h$ ) (Table 4). The estimated variance of the stratified population mean,  $s_{\bar{y}_{str}}^2$ , and the relative standard error of the stratified population mean,  $rs_{\bar{y}_{str}}$ , were calculated based on the formulas provided by Cochran (1977).

However, if post-stratification violates the assumption of an area-proportional allocation of sample plots, it is necessary to apply a correction term. Thus, for the analysis of the effects of post-stratifying the data obtained in 2008, an appropriate correction was made according to Cochran (1977), which had the effect of increasing the calculated variance (by only 0.4%). The relative standard error of the stratified population was estimated by the ratio of the estimated standard error and the estimated mean of the stratified population. It is an index of relative precision of the estimate (Köhl et al., 2006).

### Variance analysis of different sampling designs

The RE was used to quantify the efficiency of the different designs in combination with stratified sampling (McRoberts et al., 2002). To compute this ratio, it is first necessary to calculate the estimated variance of the population mean of each data set whereby  $n$  is constant. In this case, we compared the estimated variance of the estimated population mean of SRS ( $s_{\bar{y}}^2$ ) as a “benchmark” design, with the estimated variance of the estimated population mean of Str ( $s_{\bar{y}_{str}}^2$ ) as a candidate design. We defined RE according to McRoberts et al. (2002) as:

$$RE = \frac{s_{\bar{y}}^2}{s_{\bar{y}_{str}}^2}, \quad (1)$$

where  $RE > 1.0$  indicates a precision gain, when the variance of the estimated population mean of the candidate design is less than the variance of the overall estimated mean of the benchmark design.

### Determining sample size

The ideal sample sizes for a desired precision were calculated for systematic sampling and segment-based sampling, with and without stratification. The strata obtained by the 2010 survey were used for carrying out a post-stratification for the systematic sampling design. The formulas for determining the ideal sample sizes both dependent on and independent of the stratification are described below. The calculation of an ideal sample size for a desired precision was used to compare the efficiency of different sample designs. The equation for the ideal sample size  $n$  of SRS for a desired precision ( $s_{\bar{y},desired}^2$ ) can be calculated as follows from Cochran (1977):

$$s_{\bar{y},desired}^2 \geq \frac{s_y^2}{n} \quad (2)$$

$$n \geq \left( \frac{s_y}{s_{\bar{y},desired}} \right)^2 \quad (3)$$

For a desired precision ( $s_{\bar{y},desired}^2$ ), the ideal sample size  $n$  for Str with an area-proportional sample plot

allocation can be calculated according to Cochran (1977) with the equation:

$$s_{\bar{y},\text{desired}}^2 \geq \frac{1}{n} * \sum_{h=1}^L W_h * s_h^2 \quad (4)$$

$$n \geq \frac{\sum_{h=1}^L W_h * s_h^2}{s_{\bar{y},\text{desired}}^2} \quad (5)$$

### Cost comparison between pure terrestrial and RapidEye data supported forest inventory

Finally, a cost comparison between a systematic sampling inventory and segment-based sampling inventory using RapidEye data was carried out for a desired standard error of 4.6%. The value was derived from the systematic sampling design used as a reference (228 sample plots). The analysis considered the costs involved in each of the following working steps: GIS analysis, terrestrial inventory sampling, purchasing remotely sensed data, data preparation and analysis. The cost of recording one terrestrial inventory plot was estimated to be around €50 (Walter & Kessler, 2009). The RapidEye data acquired from the archive and used in this analysis cost approximately €1 per square kilometre (Apollo Mapping, 2014) with a minimum order size of 500 km<sup>2</sup>. The costs for data preparation and data analysis were calculated based on actual working hours. Based on the average gross hourly wage, as set out in the public serve payment scheme in 2015, an experienced worker (with at least three years working experience) with the appropriate skills to carry out such analysis costs €38 per hour. For the preparation and analysis of the RapidEye data by applying the method described in this study, it was estimated that eight working hours were needed. For the subsequent GIS analysis, including the location of the inventory sample plots and the extraction of their geographic coordinate, approximately two working hours were calculated.

## Results

### Accuracy assessment of the RapidEye classification

The forest-type classification showed an overall accuracy of 84% with the KHAT statistic of 0.78. The

KHAT result shows a substantial level of agreement for the classified forest. The classification approach resulted in a total disagreement of 17%. The quantity disagreement with 7% accounts for more than a quarter of the total disagreement, whereby two quarters of the total disagreement accounts for allocation disagreement. For both the coniferous- and deciduous-dominated forest classes, the producer's accuracy was greater than 80%. The user's accuracy for coniferous-dominated forest was 79%, while that for deciduous-dominated forest was 87% (Table 2). Consequently, the error matrix revealed that some deciduous-dominated forest objects were mistakenly identified as coniferous-dominated and vice versa.

### Post-stratification combined with systematic sampling

As a first step, a quantitative comparison of the variance estimator SRS of 2008 data (SRS<sub>2008</sub>) to stratified sampling of 2008 data (Str<sub>2008</sub>) was conducted. Both estimators were tested using the total of 228 inventory sample plots (Table 3). For the post-stratification, the same strata as those received from the remote sensing-based classification were used. The relative standard error of the Str<sub>2008</sub> estimator was 4.2% compared with 4.6% for the SRS<sub>2008</sub> estimator. Furthermore, the RE was calculated with 1.25

**Table 3.** Results of the methods of SRS<sub>2008</sub> and Str<sub>2008</sub> based on timber volume [m<sup>3</sup>/ha] for the inventory data of 2008.

	Inventory 2008 (n = 228)	
	SRS <sub>2008</sub>	Str <sub>2008</sub>
$\bar{y}_{\text{grid}}$	325.4 m <sup>3</sup> /ha	$\bar{y}_{\text{str.grid}}$ 321.2 m <sup>3</sup> /ha
$s_{y_{\text{grid}}}$	226.1 m <sup>3</sup> /ha	$s_{y_{\text{str.grid}}}$ 201.9 m <sup>3</sup> /ha
$s_{y_{\text{grid}}}\%$	69.5%	$s_{y_{\text{str.grid}}}\%$ 62.9%
$s_{y_{\text{grid}}}^2$	224.3 (m <sup>3</sup> /ha) <sup>2</sup>	$s_{y_{\text{str.grid}}}^2$ 179.1 (m <sup>3</sup> /ha) <sup>2</sup>
$s_{y_{\text{grid}}}$	15.0 m <sup>3</sup> /ha	$s_{y_{\text{str.grid}}}$ 13.4 m <sup>3</sup> /ha
$rs_{y_{\text{grid}}}$	4.6%	$rs_{y_{\text{str.grid}}}$ 4.2%
	RE	1.25

Note: SRS = simple random sampling; n = number of sample plots;  $\bar{y}$  = sample mean;  $s_y$  = standard deviation;  $s_y\%$  = coefficient of variation;  $s_{\bar{y}}^2$  = estimated variance of the sample mean;  $s_{\bar{y}}$  = estimated standard error of the sample mean;  $rs_{\bar{y}}$  = relative standard error of the estimate of the sample mean; Str = stratified sampling;  $\bar{y}_{\text{str}}$  = mean of the stratified population;  $s_{y_{\text{str}}}$  = standard deviation of the stratified population;  $s_{y_{\text{str}}}\%$  = coefficient of variation of the stratified population;  $s_{y_{\text{str}}}^2$  = estimated variance of the stratified population mean;  $s_{y_{\text{str}}}$  = estimated standard error of the stratified population mean;  $rs_{y_{\text{str}}}$  = relative standard error of the stratified population mean; RE = relative efficiency.

**Table 2.** The error matrix showed the accuracy assessment between areas classified as coniferous- and deciduous-dominated forest using RapidEye data classification and those identified in the CIR-image interpretation.

RapidEye classification	Reference data			Total	UA
	Coniferous-dominated forest	Deciduous-dominated forest			
Coniferous-dominated forest	145	38		183	0.79
Deciduous-dominated forest	33	219		252	0.87
Total	178	257		435	
PA	0.81	0.85			
KHAT	0.78	Overall accuracy			0.84

UA: user's accuracy; PA: producer's accuracy.

The result of a kappa analysis is the KHAT statistic, which is another measure of accuracy for the classification result (Cohen, 1960).

and supports the improvement by post-stratification. The coefficient of variation and the estimated variance of the stratified population mean underpinned the above results.

**Pre-stratification combined with segment-based sample plot allocation**

The evaluation of the standard error for the 2010 data illustrated that the technique of pre-stratification combined with segment-based plot allocation was effective. The estimated standard error for stratified sampling of 2010 data (Str<sub>2010</sub>) (5.5%) was lower than for SRS of 2010 data (SRS<sub>2010</sub>) (6.4%, Table 5). Also, the reduced coefficient of variation was in line with the improvement in precision described above. A more detailed analysis showed that the coniferous-dominated stratum was characterized by a lower coefficient of variation (46.2%) compared to a value of 75.4% for the deciduous-dominated stratum (Table 4). These results confirmed that the stratification worked well for the coniferous-dominated stratum but not as well for the deciduous-dominated stratum. Additionally, the estimated means of the coniferous- and deciduous-dominated strata showed high differences. The coniferous-dominated stratum had, with 47,118 (m<sup>3</sup>/ha)<sup>2</sup>, a higher estimated variance than the deciduous-dominated stratum, with an estimated variance of 31,750 (m<sup>3</sup>/ha)<sup>2</sup>. In Table 4, the proportion of area to strata size and the results of the descriptive statistics are listed. A quantitative comparison between the estimators of SRS<sub>2010</sub> and Str<sub>2010</sub> was conducted to evaluate the effect of the stratification. The calculated RE for the stratification approach was 1.34 and therefore greater than 1 (Table 5). As a result, an increase in precision of 0.9 percentage points (14%) was achieved for Str<sub>2010</sub> compared to SRS<sub>2010</sub>.

**Comparing the sampling designs**

In the two previous sections, the focus was on the stratification effect caused by remotely sensed data. In the following section, the different sampling designs were analysed regarding efficiency. Descriptive statistical values of the 2008 systematic sampling design and the 2010 segment-based sampling design showed high overall similarity for the timber volume [m<sup>3</sup>/ha] (Table 6). Furthermore, the resulting tree species compositions of both inventory methods were

**Table 5.** Results of the methods of SRS<sub>2010</sub> and Str<sub>2010</sub> based on timber volume [m<sup>3</sup>/ha] for the inventory data of 2010.

	Inventory 2010 (n = 114)	
	SRS <sub>2010</sub>	Str <sub>2010</sub>
$\bar{y}_{segment}$	330.7 m <sup>3</sup> /ha	$\bar{y}_{str,segment}$ 331.1 m <sup>3</sup> /ha
$s_y$ segment	225.5 m <sup>3</sup> /ha	$s_{y,segment}$ 194.9 m <sup>3</sup> /ha
$s_y$ segment %	68.2%	$s_{y,segment}$ % 58.9%
$s_{\bar{y}}^2$ segment	446.2 (m <sup>3</sup> /ha) <sup>2</sup>	$s_{\bar{y},segment}^2$ 333.1 (m <sup>3</sup> /ha) <sup>2</sup>
$s_{\bar{y}}^2$ segment	21.1 m <sup>3</sup> /ha	$s_{\bar{y},segment}^2$ 18.3 m <sup>3</sup> /ha
$rs_{\bar{y}}^2$ segment	6.4 %	$rs_{\bar{y},segment}^2$ 5.5 %
	RE	1.34

Note: SRS = simple random sampling; n = number of sample plots;  $\bar{y}$  = sample mean;  $s_y$  = standard deviation;  $s_y$ % = coefficient of variation;  $s_{\bar{y}}^2$  = estimated variance of the sample mean;  $s_{\bar{y}}$  = estimated standard error of the sample mean;  $rs_{\bar{y}}^2$  = relative standard error of the estimate of the sample mean; Str = stratified sampling;  $\bar{y}_{str}$  = mean of the stratified population;  $s_{y, str}$  = standard deviation of the stratified population;  $s_y$ % = coefficient of variation of the stratified population;  $s_{\bar{y}, str}^2$  = estimated variance of the stratified population mean;  $s_{\bar{y}, str}$  = estimated standard error of the stratified population mean;  $rs_{\bar{y}, str}^2$  = relative standard error of the stratified population mean;  $RE$  = relative efficiency

**Table 6.** Descriptive statistical values are listed in the forest variable timber volume [m<sup>3</sup>/ha] from the inventory data of 2008 and 2010.

	Inventory data 2008 (systematic sampling)	Inventory data 2010 (segment-based sampling)
Sample size	228	114
Plot type	concentric circles	concentric circles
Plot size [m <sup>2</sup> ]	500	500
Min. [m <sup>3</sup> /ha]	0	0
Max. [m <sup>3</sup> /ha]	968.5	1055.5
Mean [m <sup>3</sup> /ha]	325.4	330.7
$s_y$ [m <sup>3</sup> /ha]	226.1	225.5
$s_y^2$ [m <sup>3</sup> /ha] <sup>2</sup>	51129	50862

Note:  $s_y$  = sample standard deviation,  $s_y^2$  = sample variance

comparable (Table 7). In the study, an F-test was used in order to show that both sample sets were selected from the same total population, in spite of a two-year time difference between sampling. The results ( $F(113.227) = 1.02$ ;  $p > 0.05$ ;  $n = 342$ ) showed that the systematic sampling design produced no significant difference in the variance (Table 3) compared to the segment-based sampling design (Table 5). Consequently, there is no indication that the two-year difference had a negative influence on the sampling data sets. A Chi-square test was conducted to evaluate the effect of segment-based sampling on the whole distribution of the standing timber volumes. Using the 2008 distribution as the expected distribution, the segment-based sampling

**Table 4.** Overview of the stratified 2010 inventory data shown is sample mean, variance and coefficient of variation from the coniferous- and deciduous-dominated strata based on timber volume.

	Area [ha]	$W_h$	n	Inventory 2010		
				$\bar{y}_h$ [m <sup>3</sup> /ha]	$s_h^2$ [(m <sup>3</sup> /ha) <sup>2</sup> ]	$s_y$ % [%]
Coniferous dom.	94	0.41	46	470	47,118	46.2
Deciduous dom.	138	0.59	68	236	31,750	75.4

$W_h$ : stratum weights; n: number of sample plots;  $\bar{y}_h$ : sample mean;  $s_h^2$ : estimated variance;  $s_y$ % coefficient of variation of the stratified population.



**Table 7.** Tree species composition based on timber volume [ $\text{m}^3/\text{ha}$ ] calculated from forest inventory sample plots of 2008 (228 sample plots) and 2010 (114 sample plots).

Survey	Inventory 2008 (systematic sampling) (%)	Inventory 2010 (segment-based sampling) (%)
Tree species composition		
Norway spruce ( <i>Picea abies</i> (L.) H. Karsten)	49	46
White fir ( <i>Abies alba</i> Mill.)	15	14
Other coniferous	3	2
European beech ( <i>Fagus sylvatica</i> L.)	21	22
European ash ( <i>Fraxinus excelsior</i> L.)	5	7
Sycamore maple ( <i>Acer pseudoplatanus</i> L.)	4	6
Other deciduous	3	3

design was compared to the systematic sampling design. The result showed that there is no significant difference between the expected frequencies using the percentage distribution from 2008 and the actually observed frequencies (2010) ( $p$ -value of 0.45, Figure 2). Consequently, in our case, sampling in spectrally homogenous segments with two-year difference showed no influence on the sample distribution. Finally, the stratification showed an RE of 1.34 obtained with the segment-based sampling, which was greater than the RE of 1.25 with systematic sampling. This indicates an improved stratification effect by means of the segment-based sampling design compared to the systematic sampling design.

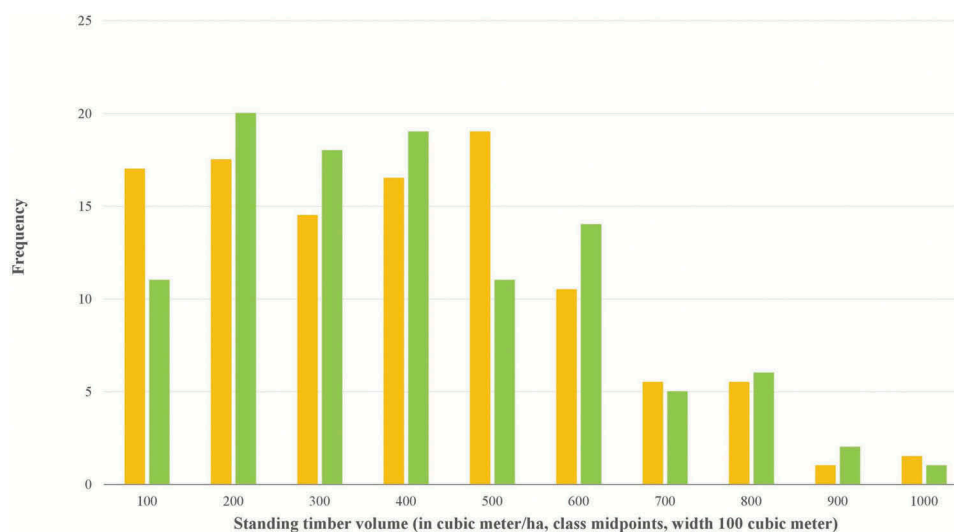
### Sample size and precision of sampling designs

The two sampling designs (systematic sampling and segment-based sampling) were evaluated for a desired standard error of 4.6% derived from the systematic sampling 2008 with 228 sample plots. The systematic sampling was analysed with the estimator for SRS and Str. The ideal sample size was computed by applying the SRS estimator to the data of 2008 (Equation (3)) and the application of the Str estimator to the data of 2008 and 2010 (Equation (5)). A lower number of sample plots

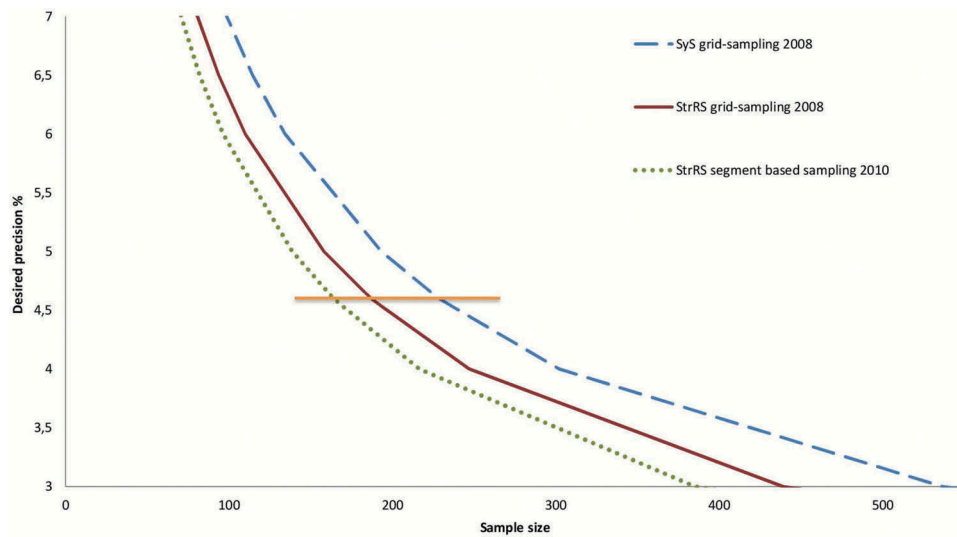
were necessary to obtain a given precision with the  $\text{Str}_{2008}$  and  $\text{Str}_{2010}$  estimator (shown in Figure 3 as the solid and dotted lines) than with the  $\text{SRS}_{2008}$  estimator (shown as the dashed line). One hundred and eighty-seven sample plots (a reduction by 18%) were necessary to achieve the desired precision level by using the systematic sampling design with the  $\text{Str}_{2008}$  estimator. The segment-based sampling design combined with the  $\text{Str}_{2010}$  estimator showed an ideal sample size of 164 sample plots reflecting a 28% reduction. This approach revealed a lower sample size by 23 sample plots compared to the  $\text{Str}_{2008}$  estimator and 64 sample plots less than the  $\text{SRS}_{2008}$  estimator.

### Comparison of cost to sample size and precision

The costs for systematic sampling and segment-based sampling of stratified remotely sensed data were calculated on the same level of precision (4.6%) as the above calculated ideal sample size. Table 8 shows that the inventory costs for segment-based sampling with stratified RapidEye data were 21% lower compared to systematic sampling. The cost calculation revealed a cost difference of approximately €2400 between the two sampling methods.



**Figure 2.** The expected frequency distribution of 2008 is shown in orange and the segment-based sampling frequency distribution (2010) in green.



**Figure 3.** Required sample sizes (x-axis) for certain desired precisions (y-axis, standard error %) for the stratified sampling (Str) and simple random sampling (SRS) estimators are shown for the 2008 and 2010 inventory data. The dashed line represents the SRS estimator for 2008 data, and the applied Str estimator are illustrated as the solid line for 2008 data and as the dotted line for 2010 data. The horizontal solid line represents the desired precision level of 4.6%.

**Table 8.** Cost comparison of the systematic sampling design and stratified segment-based sampling design of RapidEye data calculated for ideal sample size and desired standard error of 4.6%.

Categories	Systematic sampling design	Stratified segment-based sampling design
Remotely sensed data		€500 (archive data)
Data preparation and analysis		€302
GIS analysis	€75	€75
Terrestrial inventory sampling	€11,400	€8200
	(228 sample plots × €50)	(164 sample plots × €50)
Overall costs	€11,475	€9077

## Discussion

### Usability of high-resolution remotely sensed data in the planning phase

As shown in this study, ancillary data based on remote sensing information offer great potential to support forest inventories. Compared to other optical remote sensing systems, RapidEye has the big advantage of combining high spatial and temporal resolution, as it can bypass the problem of cloud coverage (Dees, 2007; Elatawneh, Wallner, Manakos, Schneider, & Knoke, 2014). This made the system quite suitable at enterprise level for forest inventory and monitoring applications in European forests. The classification result of the RapidEye data confirmed the possibility to classify spectrally homogeneous segments of a heterogeneous forest into the forest classes deciduous dominated and coniferous dominated. The overall accuracy of the classification was 84%, and a KHAT value of 0.78 was achieved. Schneider et al. (2013) reported an overall accuracy between 66% and 70% in a study using RapidEye data for deciduous, coniferous and mixed forest classification for a test site in Freising (Germany). Stoffels et al. (2015) demonstrated an accuracy of

91% for forest-type classification (coniferous and deciduous strata) for a spatially adaptive classification approach combining RapidEye and SPOT4 and 5 data, based on a spatial resolution of the map product 10 m × 10 m. The studies of Fehlert (1984), Kenneweg, Förster and Runkel (1991) and Wallner, Elatawneh, Schneider and Knoke (2015) confirm that a pixel size of 5 m spatial resolution does not allow for the detection of single trees, but can achieve acceptable accuracies in the detection of forest types. The total disagreement of 17% with a quantity disagreement of 7% underlines the statements of the mentioned studies.

The segmentation approach described was conducted on the one hand for an object-based image classification of the test site and on the other hand to derive spectrally homogeneous segments for inventory plot allocation. Using the segment-based stratified allocation design, we intended to allocate sample plots in spectrally homogeneous segments that represent all parts of the forest, including forest edges and especially the different development stages of the forest. Therefore, the segment size was the most crucial part because a large minimum segment size results in high

within-segment variation (Nilsson et al., 2003) and a small minimum segment size in a low within-segment variation (Pekkarinen & Tuominen, 2003). This effect means that, within large segments, different forest types could potentially exist, whereas small segments could represent homogenous forest types. The result of the field study confirmed that larger segments (coniferous-dominated forest) had a higher statistical variance ( $47,118 \text{ (m}^3/\text{ha)}^2$ ) compared to smaller segments (deciduous-dominated forest) with lower statistical variance ( $31,750 \text{ (m}^3/\text{ha)}^2$ ).

### Applicability for forest inventories

The pre-stratified segment-based plot allocation method using RapidEye data indicated improved results compared to systematic sampling. For the purpose of comparing the cost efficiency of the sampling designs, an ideal sample size was calculated for the segment-based sampling design of 2010 to obtain a relative standard error of 4.6%. Using the SRS<sub>2008</sub> estimator, 228 sample plots were necessary, while for the Str<sub>2010</sub> estimator, only 164 sample plots were needed to reach the same level of precision. The results revealed a reduction potential in sample size of more than 28% as applied in practice and therefore also a reduction in costs. Similar results have been shown by Nothdurft et al. (2009) in his study for a fixed sample size in an anonymised private forest enterprise in southern Germany. The approach of double sampling for stratification based on orthophotos and stand age was used to estimate timber volume of larger spruce and fir trees as well as larger hardwood trees. A cost reduction for coniferous trees of 19% and for hardwood trees of 59% could be achieved compared to unstratified SRS. Whether the reduction of the standard error from 5.5% to 4.6% by increasing the sample plot number from 114 to 164 is worth the economic costs from the economic point of view is a decision of the forest management.

Our results further indicate that stratified sampling might be more efficient than systematic sampling if the variability between strata is high (Särndal et al., 1992). Calculating the RE as a measure for the stratification effect showed that, for the 2008 and 2010 data sets, the efficiency of the timber volume estimation was increased. The RE ranged between 1.25 and 1.34. McRoberts et al. (2002) classified a test area into four strata and obtained RE values for the total volume ranging from 1.25 to 1.75 using data from Landsat TM imagery and ancillary data. These values are quite similar to those found in our study, even when working with data of much lower spatial resolution.

However, the stratification of the test site was conducted solely for two strata which already resulted

in an improvement in precision. Cochran (1977) described that stratification into more than six strata provides marginal benefit for precision. The stratification was not further refined because ancillary height information would be necessary for an improved classification result with respect to the highly structured forest of the test site. Nevertheless, our experimental approach still needs to be tested in further studies with more than two strata.

Our experimental sampling design was based on an area-proportional design. As recommended by Grafström (2013), the samples need to be well distributed in geographical space, which we achieved by dividing the test site into four sub-areas. The small variation of the mean timber volume of the 2010 inventory compared to the 2008 data proved that the design was successful. Nevertheless, the received high within-strata variance of coniferous-dominated stratum and the high coefficient of variation for deciduous-dominated stratum indicated that there is still leeway for improvement.

Upcoming, free-of-charge remote sensing systems (e.g. Sentinel-2) with similar sensor technology create the opportunity to repeat the introduced inventory design with even lower costs. For forest management, a repetition of sampling after a couple of years is important to collect information on tree increment and mortality. Using a pre-stratified design for monitoring can be problematic because stratum boundaries can change, and sampling efficiency will thus be degraded over time. The magnitude of this effect depends upon how dynamic the stratum boundaries are. Appropriate, potentially complicated reallocation of sample plots to adjust for changing strata boundaries could be required if there is an increased change on landscape level. For stratified inventories, the method of partial replacement was already successfully applied in former studies (Bickford, Mayer, & Ware, 1963; Saborowski, Marx, Nagel, & Böckmann, 2010). In general, this method combines the advantages of permanent and temporary sample plots (Van Laar & Akça, 2007). Partial replacement is widely used to resample a certain amount of sample plots, whereby the remaining numbers of sample plots are sampled on different occasions. The method was also applied to avoid special treatment at inventory plots by forester recognition. Even though the experimental sample design did not need a higher effort compared to the systematic sampling approach, but it should still be tested in further studies.

### Conclusions

Three major conclusions can be drawn from this study. First, the stratification based on RapidEye data with a 5 m spatial resolution helped to substantially increase the precision of the forest inventory estimates. Second, stratified segment-based plot

allocation proved to be more efficient than stratified systematic sampling. We determined an RE of 1.25 for the stratified systematic sampling and 1.34 for the stratified segment-based sampling. Third, the results indicated that cost-efficiency could be increased while maintaining the same level of precision of 4.6% due to the reduced sample size. Specifically, positioning the sample plots in spectrally homogenous segments reduced the ideal sample size by 28% compared to the conventional applied systematic sampling inventory. Our results showed the potential of using remotely sensed data for forest stratification to aid terrestrial inventory methods. The method could benefit from the advantages of RapidEye satellite systems, including the high spatial resolution, which made it applicable for highly structured forests, as well as the high temporal resolution, which offered the opportunity to acquire cloud-free data, and the modest costs for data acquisition. Completing terrestrial inventories without the stratified segment-based sampling is labour-intensive and expensive. Nevertheless, as shown in the Discussion section, the segment-based sampling design had some limitations because the segment size was variable, which needs to be further investigated. From an operational point of view, the methodology showed some potential for practical application, especially to support forest inventories of highly structured forests.

### Acknowledgements

Adelheid Wallner is the lead author. She performed the analysis and wrote the manuscript. The sampling design was developed by Alata Elatawneh, Thomas Schneider and Adelheid Wallner. The field work and some first analysis were done by Britta Rau. Remotely sensed data processing was done by Alata Elatawneh and Adelheid Wallner. The framework of the manuscript and detailed edits were the work of Adelheid Wallner, Thomas Schneider and Mengistie Kindu. Thomas Knoke provided research coordination, statistical support and outstanding contributions to the paper.

The authors are grateful to RESA of the DLR for the provision of RapidEye data and especially for their excellent support. The authors also thank the Chair for Forest Growth and Yield, TUM, the site manager of the test site forest, Mr. Fischer, and the Bavarian State Institute of Forestry for providing the reference data. The authors would also like to thank Laura Carlson and Elizabeth Gosling for language editing, Stephan Haug and Hannes Petermeier for statistical support, Arne Nothdurft for valuable advice on sampling designs and the anonymous reviewers.

### Funding

This work was supported by the Federal Ministry of Economics and Technology [number 50EE0919]; RapidEye Science Archive (RESA) of the German Aerospace Centre (DLR) [317]; we are grateful to

“Deutsche Forschungsgemeinschaft” (DFG) for financial support of the study [KN 586/11-1]

### References

- Apollo Mapping (2014). RapidEye pricing. Web site (online 23 November 2014). Retrieved from (<https://apollomapping.com/imagery/medium-resolution-satel-lite-imagery/rapideye>)
- Baatz, M., & Schäpe, A. (2000). Multiresolution segmentation: An optimization approach for high quality multi-scale image segmentation. *Journal of Photogrammetry and Remote Sensing*, 58, 12–23.
- Bickford, C.A. (1952). The sampling design used in the forest survey of the northeast. *Journal of Forestry*, 50, 290–293.
- Bickford, C.A., Mayer, C.E., & Ware, K.D. (1963). An efficient sampling design for forest inventory: The north-eastern forest resurvey. *Journal of Forestry*, 61, 826–833.
- Böckmann, T., Saborowski, J., Dahm, S., Nagel, J., & Spellmann, H. (1998). Die weiterentwicklung der betrieb-sinventur in niedersachsen. *Forst Und Holz*, 53(8), 219–226.
- Cochran, W. (1977). *Sampling techniques*. New York: John Wiley & Sons. INC, (pp. 428).
- Congalton, R.G. (1991). A review of assessing the accuracy of classifications of remotely sensed data. *Remote Sensing of Environment*, 37, 35–46. doi:10.1016/0034-4257(91)90048-B
- Dahm, S. (1995). Bundeswaldinventur - auswertungsmodelle und Vorschläge zur Effektivitätssteigerung. *Mitteilungen Der Bundesforschungsanstalt Für Forst-Und Holzwirtschaft*, 180, 144.
- Dees, M. (2006). Kombination von Fernerkundung und Stichprobeninventur bei betrieblichen und nationalen Waldinventuren. *Schriftenreihe Freiburger Forstliche Forschung*, 37, 194.
- eCognition Developer (9.0) (2004). User Guide [Computer software]. Munich: Trimble Germany GmbH.
- Elatawneh, A., Rappl, A., Rehush, N., Schneider, T., & Knoke, T. (2013). Forest tree species identification using phenological stages and RapidEye data: A case study in the forest of Freising. In E. Borg (Eds.), *From the basics to the service* (pp. 21–38). *Proceedings of the 5th RESA-Workshop*. Berlin, Neustrelitz: Gito Verlag.
- Elatawneh, A., Wallner, A., Manakos, I., Schneider, T., & Knoke, T. (2014). Forest cover database updates using multi-seasonal RapidEye data – Storm event assessment in the Bavarian forest national park. *Forests*, 5, 1284–1303. doi:10.3390/f5061284
- ENVI (2009). ENVI Zoom User’s Guide [Computer Software]. Web site (online 20 January 2016). Retrieved from [http://www.harrisgeospatial.com/portals/0/pdfs/envi/ENVI\\_Zoom\\_User\\_Guide.pdf](http://www.harrisgeospatial.com/portals/0/pdfs/envi/ENVI_Zoom_User_Guide.pdf)
- Fehlert, G.P. (1984). *Kalibrierung von MSS-satellitenbilddaten zur auswertung zeitlicher reflexionsänderungen an fichtenbeständen*. DLR-Forschungsbericht (Report No. DFVLR FB84-44). DLR (Germany).
- Grafström, A. (2013). Why well spread probability samples are balanced. *Open Journal of Statistics*, 03, 36–41. doi:10.4236/ojs.2013.31005
- Grafström, A., Saarela, S., & Ene, L.T. (2014a). Efficient sampling strategies for forest inventories by spreading the sample in auxiliary space. *Canadian Journal of Forest Research*, 44, 1156–1164. doi:10.1139/cjfr-2014-0202

- Grafström, A., & Schelin, L. (2014b). How to select representative samples. *Scandinavian Journal of Statistics*, 41, 277–290. doi:10.1111/sjos.12016
- Gregoire, T.G., & Valentine, H.T. (2008). *Sampling strategies for natural resources and the environment. Applied environmental statistics*. Boca Raton: Chapman & Hall/CRC.
- Kangas, A., & Maltamo, M. (2006). *Forest inventory: Methodology and applications* (pp. 362). Berlin: Springer Kluwer.
- Kenneweg, H., Förster, B., & Runkel, M. (1991). *Diagnose und Erfassung von Waldschäden auf der Basis von Spektralsignaturen: Untersuchung und Kartierung von Waldschäden mit Methoden der Fernerkundung* (Report part B). (Germany).
- Kindu, M., Schneider, T., Teketay, D., & Knoke, T. (2013). Land use/land cover change analysis using object-based classification approach in Munessa-Shashemene landscape of the Ethiopian highlands. *Remote Sensing*, 5, 2411–2435. doi:10.3390/rs5052411
- Knoke, T. (2012). *Forstbetriebsplanung*. Stuttgart: Ulmer.
- Köhl, M., Magnussen, S., & Marchetti, M. (2006). *Sampling methods, remote sensing and GIS multiresource forest inventory. Tropical forestry* (pp. 373). Berlin: London: Springer.
- Köhl, M., & Sutter, R. (1991). Verwendung von Luftbildern zur Holz-Vorratsschätzung im Schweizer Landesforstinventar (LFI). *Zeitschrift Für Photogrammetrie Und Fernerkundung*, 59, 165–176.
- McRoberts, R.E., Nelson, M.D., & Wendt, D.G. (2002). Stratified estimation of forest area using satellite imagery, inventory data, and the k-nearest neighbors technique. *Remote Sensing of Environment*, 82, 457–468. doi:10.1016/S0034-4257(02)00064-0
- McRoberts, R.E., Holden, G.R., Nelson, M.D., Liknes, G.C., & Gormanson, D.D. (2005). Using satellite imagery as ancillary data for increasing the precision of estimates for the forest inventory and analysis program of the USDA forest service. *Canadian Journal of Forest Research*, 35, 2968–2980. doi:10.1139/X05-222
- McRoberts, R.E., & Tomppo, E. (2007). Remote sensing support for national forest inventories. *Remote Sensing of Environment*, 110, 412–419. doi:10.1016/j.rse.2006.09.034
- Morsdorf, E., Meier, E., Allgöwer, B., & Nilesch, D. (2003). Clustering in airborne laser scanning raw data for segmentation of single trees: 3-D reconstruction from airborne laser scanner and InSAR data. In H.-G. Maas, G. Vosselman, & A. Streilein (Eds.), *Proceedings of the "ISPRS" XXXIV-3/W13*. Dresden. Web site (online 5 January 2015). Retrieved from <http://www.isprs.org/proceedings/XXXIV/3-W13/>
- Moshhammer, R., & Pretzsch, H. (2010). *Forstwirtschaftsplan 2010: Forstbetrieb Stadtwald Traunstein*. Freising: Chair of Forest Growth and Yield Science at the TUM.
- Neufanger, M. (2011). *Richtlinien für die mittel- und langfristige forstbetriebsplanung in den bayerischen staatsforsten. Forstlenkungsrichtlinien - FER 2011*. Regensburg: Bayerische Staatsforsten.
- Nilsson, M., Folving, S., Kennedy, P., Puumalainen, J., Chirici, G., Corona, P., Tomppo, E. (2003). Combining remote sensing and field data for deriving unbiased estimates of forest parameters over large regions. In P. Corona, M. Köhl, & M. Marchetti (Eds.), *Advances in forest inventory for sustainable forest management and biodiversity monitoring* (pp. 19–32). Dordrecht, Boston, London: Kluwer Academic Publishers.
- Nothdurft, A., Borchers, J., Niggemeyer, N., Saborowski, J., & Kändler, G. (2009). A repeated forest inventory based on double sampling for stratification. *Allgemeine Forst- und Jagdzeitung*, 180(7–8), 133–140.
- Pekkarinen, A., & Tuominen, S. (2003). Stratification of a forest area for multisource forest inventory by means of aerial photographs and image segmentation. In P. Corona, M. Köhl, & M. Marchetti (Eds.), *The advances in forest inventory for sustainable forest management and biodiversity monitoring* (pp. 111–123). Dordrecht, Boston, London: Kluwer Academic Publishers.
- Pettersson, H. (1955). *Die Massenproduktion des Nadelwaldes. Mitteilungen Der Forstlichen Forschungsanstalt Schwedens*, 45, 1–189.
- Pontius, R.G.J., & Millones, M. (2011). Death to Kappa: Birth of quantity disagreement and allocation disagreement for accuracy assessment. *International Journal of Remote Sensing*, 32, 4407–4429. doi:10.1080/01431161.2011.552923
- Poso, S. (1972). A method for combining photo and field samples in forest inventory. *Communications Instituti Forestalis Fenniae*, 76, 1–133.
- Rouse, J.W., Haas, R.H., Schell, J.A., Deering, D.W., & Harlan, J.C. (1974). *Monitoring the vernal advancement and retrogradation (greenwave effect) of natural vegetation*. (Report NASA/OSFC, Type III Final), Remote Sensing Centre, Texas A&M University, College Station, TX, (USA). (online 5 November 2013) Retrieved from <http://ntrs.nasa.gov/archive/nasa/casi.ntrs.nasa.gov/19750020419.pdf>
- Rutzinger, M., Höfle, B., Pfeifer, N., Geist, T., & Stötter, J. (2006). Object-based analysis of airborne laser scanning data for natural hazard purposes using open source components. *International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences*, 36(4/C42).
- Saborowski, J., & Cancino, J. (2007). About the benefits of poststratification in forest inventories. *Journal of Forest Science*, 53, 139–148.
- Saborowski, J., Marx, A., Nagel, J., & Böckmann, T. (2010). Double sampling for stratification in periodic inventories – Infinite population approach. *Forest Ecology and Management*, 260, 1886–1895. doi:10.1016/j.foreco.2010.08.035
- Särndal, C., Swensson, B., & Wretman, J.H. (1992). *Model assisted survey sampling. Springer series in statistics*. New York: Springer.
- Schneider, T., Elatawneh, A., Rahlf, J., Kindu, M., Rapp, A., Thiele, A., Hinz, S. (2013). Parameter determination by RapidEye and TerraSAR-X Data: A step toward a remote sensing based inventory, monitoring and fast reaction system on forest enterprise level. In J.M. Krisp, L. Meng, R. Pail, & U. Stilla (Eds.), *Earth Observation of Global Changes (EOGC)* (pp. 81–107). Berlin, Heidelberg: Springer.
- Shiver, B., & Borders, B. (1996). *Sampling techniques for forest resource inventory*. New York, Chichester, Brisbane, Toronto, Singapore: John Wiley & Sons, INC.
- Stoffels, J., Hill, J., Sachtleber, T., Mader, S., Buddenbaum, H., Stern, O., Ontrup, G. (2015). Satellite-based derivation of high-resolution forest information layers for operational forest management. *Forests*, 6, 1982–2013. doi:10.3390/f6061982
- Straub, C., Stepper, C., Seitz, R., & Waser, L.T. (2013). Potential of UltraCamX stereo images for estimating timber volume and basal area at the plot level in mixed European forests. *Canadian Journal of Forest Research*, 43, 731–741. doi:10.1139/cjfr-2013-0125

- Teuffel, K.F., Baumgarten, M., Hanewinkel, M., Sauter, U.H., Wilpert, K., Konold, W., & Spiecker, H. (2005). *Waldumbau: Für eine zukunftsorientierte Waldwirtschaft Ergebnisse aus dem Südschwarzwald*. Berlin: Springer.
- Van Assen, H.C., Egmont-Petersen, M., & Reiber, J. (2002). Accurate object localization in gray level images using the center of gravity measure: Accuracy versus precision. *Image Processing, IEEE Transaction, 11*, 1379–1384. doi:10.1109/TIP.2002.806250
- Van Laar, A., & Akça, A. (2007). *Forest Mensuration*. Dordrecht, Netherland: Springer.
- Wallner, A., Elatawneh, A., Schneider, T., & Knoke, T. (2015). Estimation of forest structural information using RapidEye satellite data. *Forestry, 88*, 96–107. doi:10.1093/forestry/cpu032
- Walter, S., & Kessler, J. (2009). Zahlenwald. *Das Magazin Der Bayerischen Staatsforsten, 6*(Web site),1–26. (Online 2 May 2014). Retrieved from [http://www.baysf.de/fileadmin/user\\_upload/07-publikationen/Magazin\\_06\\_Zahlenwald.pdf](http://www.baysf.de/fileadmin/user_upload/07-publikationen/Magazin_06_Zahlenwald.pdf)
- West, P.W. (2015). *Tree and forest measurement*. Cham, Heidelberg, New York, Dordrecht, London: Springer.