Airborne laser scanning for the identification of boreal forest site types

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Abstract

Boreal forests site types are used to assess the growth potential of the forests and therefore provide important inventory information. A new approach is proposed here for the site quality assessment of mature forests using airborne laser scanner (ALS) data and the k-NN classifier. Both the echo z-value and the intensity value percentiles of different echo types of ALS data were used in the analysis. The data comprised 274 forest stands of varying sizes belonging to five forest site types varying from very fertile to poor forests in the Koli National Park, Finland. The best overall classification accuracy of all the forest site types achieved was 58.0 %, and for a single class 73%. It is concluded that this ALS-based data analysis technique is applicable to the detection of boreal forests site types in large-scale forest inventories.

Keywords: K-NN Classification; Vegetation.

1. Introduction

In Finland forests are classified into fertility site types according to their underground vegetation (Cajander 1926). The current forest site types of Finland have been located and mapped in conventional stand-based forest inventories (Poso 1983). Aerial photographs have also been used to find different forest habitats, but the results have not been accurate or useful enough for large-scale forest inventories (see Uuttera and Hyppänen 1998). However, Airborne Laser Scanning (ALS), which provides spatially accurate 3D information on forests and is already being applied in practical forestry, could potentially replace conventional field inventory methods for determining tree stocking quantities (see Næsset 2004). ALS data are derived from the measured travel times of pulses between a sensor and a target, and since ALS echoes from targets form three-dimensional point clouds (Lim et al. 2003), they provide accurate information on landscapes and forests (see Ritchie et al. 1992; Næsset 1997; Magnussen and Boudewyn 1998; Maltamo et al. 2006).

Multiple ALS echoes with precise x, y and z coordinates can be identified by processing the backscatter energy of a simple pulse. The data yielded by this technology include various echo types (e.g. first, last, intermediate and only echoes), z-values and intensity values, where the z-value is the height of the echo and the intensity value describes the amount of backscattering from it. Height of the above-ground vegetation is usually of greatest interest in forestry applications (see Hyyppä et al. 2001; Lim et al. 2003; Maltamo et al. 2006; Hopkinson et al. 2006). Intensity values have been studied by Brennan and Webster (2006), for example, who found them to be suitable for distinguishing between different surfaces, but it is only very recently that their applicability to the determination of forest characteristics has been investigated (e.g. Hopkinson and Chasmer 2007; Ørka et al. 2007). This is mainly due to difficulties in scaling and normalizing these values or in their interpretation (Ahokas et al. 2006).

The ALS technique has already been applied to the determination of site quality indicators based on the height distribution characteristics of stands containing certain tree species, which is logical since the height characteristics can be obtained accurately from laser data (see Rombouts 2006; Gatziolis 2007). This can, in fact, be seen as a remote sensing-based modification of traditional growth and yield studies in which the classification of sites was based on dominant height-age dependences. The site type classification used in Finnish forest inventories, however, is based on Cajander's (1926) system of fertility classes, which operates on assessable stand characteristics, i.e. ground vegetation characteristics and indicator species, rather than explicitly measurable tree variables.

ALS technology should be capable of distinguishing the forest site types because of differences in crown structures and vertical profiles that differ between different forest site types. We present here an ALS data-based k-nearest neighbour method for doing this employing two alternative uses of data, 1) the use of whole data and leave-one-out cross-validation, and 2) use of separate model and test data, which will be compared in terms of classification accuracy.

2. Method

2. 1. Study area and forest inventory data

The forest area concerned here is located in the Koli National Park (29°50'E, 63°05'N) in eastern Finland, on the borderline between the southern and middle boreal forest vegetation zones after Kalela (1970, in Kalliola 1973). The total area of the Koli National Park is about 3000 hectares. Extensive areas in its northern part have been left unmanaged for decades; whereas forest management operations were carried out in the southern part until the early 1990s. The area is characterized by a highly variable landscape and tree species structure, with altitudes varying between 95–347 metres above sea level (Lyytikäinen 1991). Following the classification of Cajander (1926), the forest site types identified in the Koli National Park were: 1) very rich (e.g., *Oxalis-Maianthemum* type, OMaT), 2) rich (*Oxalis-Myrtillus*, OMT, herb-rich heath forest), 3) medium (*Myrtillus* type, MT, mesic heath forest), 4) rather poor (*Vaccinum* type, VT/EMT, subxeric heath forest) and 5) poor (*Calluna* type, CT/MCClT, xeric heath forest).

Table 1. Descriptive statistics for stand areas in hectares by forest site type in the whole data.

	Whole data 336.7 ha (N=274)						
Forest site type	N	%	Min	Max	Sum	Mean	S.D.
Herb-rich (1)	61	22	0.03	5.8	44.36	0.73	0.91
OMT (2)	60	22	0.13	12.13	89.04	1.48	2.12
MT (3)	60	22	0.16	7.77	82.95	1.38	1.37
VT (4)	60	22	0.12	6.46	77.7	1.29	1.14
CT (5)	33	12	0.04	7.02	42.92	1.3	1.58

N is the number of stands; % is the proportion of site types; Min is the minimum, Max is the maximum, Mean is the average area of the forest site types in hectares and S.D. the standard deviation. Herb-rich denotes very rich (1), OMT rich (2), MT medium (3), VT rather poor (4) and CT poor (5) forest site types (Cajander 1926).

The data were randomly assigned into the modelling data and test data, both of which included stands from the northern and southern parts of the National Park. In terms of development classes, the stands used in the analyses were either advanced thinning or mature stands, as these closed boreal forest stands represented advanced successional stages with an advanced ground vegetation and were therefore ideal for site type classification by the method of Cajander (1926). The data comprised 274 forest stands covering an area of 337 ha. The modelling data consisted of 184 forest stands and comprised an area of 241 ha, while the test data consisted of 90 forest stands and covered a total area of 96 ha. The data is presented by forest site types in Table 1.

2.2. Airborne laser scanner data

The scanning was performed on 13th July, 2005, using an Optech ALTM 3100 laser scanner. Two Global Positioning System (GPS) ground stations were used and a total of nine transects were flown at an altitude of 900 metres and a flight speed of 75 m/s. The area covered was approximately 2200 hectares. The laser pulse repetition rate was 100 KHz and the scanning frequency of a swath was 70 Hz, at an angle of ± 11 degrees. The pulse density of the data was $3.9/m^2$, but because of nominal side overlap (35%) and variation in the terrain the actual ground hits varied from approximately $3.2/m^2$ to $7.8/m^2$. The data echoes collected included EUREF-FIN coordinates (*x*, *y* and *z*), flight line numbers, intensity values and echo types in four classes: 1 = only echo, 2 = first echo, 3 = intermediate echo and 4 = last echo. The DTM was produced by the Finnish Geodetic Institute from the last and only echo data using a pixel size of one metre, employing the TerraScan software, which uses the method proposed by Axelsson (2000). In order to analyse the ALS data, the first step was to convert the orthometric heights to an above-ground scale by subtracting the DTM from the corresponding ALS heights (Hyyppä et al., 2005). The laser hits are presented by forest site types in Table 2.

Table 2. Numbers of laser echoes/m^2 by forest site types and proportions (%) of the different types of echoes including the z value and intensity value in the whole data. The letters f, o, l and i indicate the first, only, last and intermediate echoes, respectively, whereas fo is the sum of first and only echoes.

Forest site type	all	fo	f/fo, %	o/fo %	l/fo %	i/fo %	all/fo %
Herb-rich (1)	7.3	5.0	37.3	62.7	38.0	6.2	144.2
OMT (2)	7.0	5.0	35.7	64.3	36.3	5.6	141.9
MT (3)	6.8	4.8	34.9	65.1	35.7	5.1	140.8
VT (4)	6.4	4.7	32.1	67.9	32.8	4.0	136.8
CT (5)	6.2	5.0	22.5	77.5	22.9	1.7	124.6

2.3. *k-NN* classification

Classification of forest site types was obtained by using the non-parametric k-NN classifier. Consequently, nearest neighbour methods have been widely used for estimating continuous forest variables (e.g. by Moeur and Stage 1995; Holmström et al. 2001; Maltamo et al. 2006), although they have not been extensively studied in connection with estimating discrete forest variables.

We applied two different ways to use our data. The whole data was divided into reference (modelling) and target (test) data; method described below is the same in both approaches, i.e. whole data approach and model/test data approach. Then a suitable distance metric is chosen to find the nearest neighbour(s). After that the distances between the target units and the reference units are calculated and nearest neighbour(s) are assigned to the target units. Finally estimates for the target units are calculated based on the attributes of the chosen neighbours. At least three issues need to be considered when using the k-NN method: 1) a suitable distance metric, 2) the number of neighbours to be used, and 3) the weighting of the neighbours (LeMay and Temesgen 2005).

A Minkowski distance of order one between the distributions was taken as the distance metric. In the case of discrete distributions it can be defined with the equation (Eqn 1):

$$D_{pq} = \sum_{i=1}^{n} |p_i - q_i| \quad , \qquad (1)$$

where D_{pq} is the distance between the laser echo distributions to be compared, p_i is the proportion of observations of target units in class i, q_i is the proportion of observations of reference units in class *i*, and *n* is the number of classes in the distributions. The value of D_{pq} ranges between 0 (the distributions compared are the same) and 2 (the distributions compared have no observations in the same classes). The chosen distance metric is based on the absolute differences between the laser echo distributions of the target and reference stands and is suitable in situations in which the predictor variables are distributions with unknown characteristics (in this case laser echo height and intensity distributions) and it is assumed that the form of the distribution contains most of the information on the variables of interest (in this case forest site type classes). The distance value can be used in weighting the neighbours by subtracting it from the maximum value, which is 2. When using more than one predictor (i.e. distributions of laser echoes of different types), the distances are calculated separately for the various distributions and then summed using subsequently determined optimal weights.

The classification rule needed for applying the k-NN based classifier was adjusted for the case of several neighbours (*n*) as follows:

1. $n = 1$: the value of the predicted variable is the value of the nearest neighbour
2. $n > 1$: the weights of the neighbours are summed by class and the estimated class for the target unit is the one with the highest sum of weights.

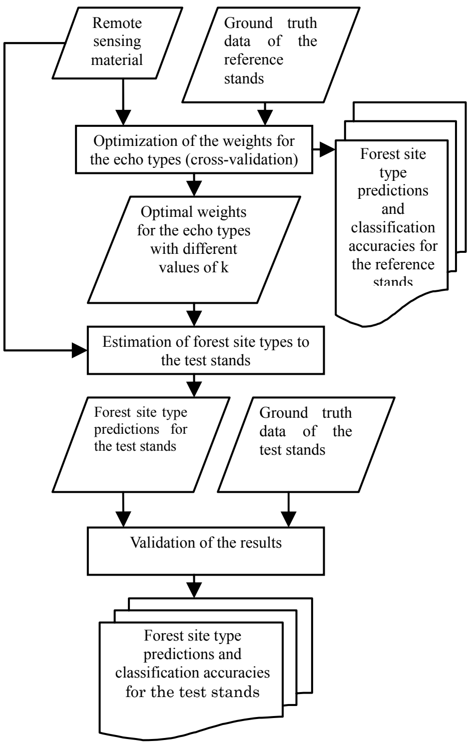

Figure 1: The k-NN estimation procedure.

For the k-NN classification procedure the laser echo heights were classified into 10 cm classes, with the negative echo heights assigned to a class 0 (note that some ALS hits always occur below the DTM level). This classification provided enough observations for all the approximately 300 classes. The laser echo intensities were thereafter classified with a class width that resulted in a corresponding number of classes. The optimal weights for the different types of echoes were searched for by optimizing the overall classification accuracy. The optimization algorithm weighted the combinations systematically so that every echo type was given a weight from 0 to 1 at intervals of 0.1. In addition, all the combinations of weights, which summed to 1, were examined. The optimization was performed on the whole data and modelling data only and used a leave-one-out cross-validation technique in which the target unit was left out of the reference data. The test stands were classified using the optimal weights found from modelling data and the nearest neighbours were searched for only from the modelling (reference) data. In the case of several neighbours ($n > 1$), the procedure provides not only class estimates but also an idea of the closeness of the target unit to the other classes. However, it should be remembered that the forest site type classes may express the fertility levels on an ordinal scale, but the tree cover of those types should be handled as they are in a nominal scale. The k-NN estimation procedure applied for in the case of using separate modelling and test data is presented in the form of a flowchart in Figure 1.

3. Results

The classification results were calculated with one, three and five nearest neighbours, and optimal weights were determined for the accuracy of classification of the stands into all forest site types. All the neighbourhood combinations were computed for the stands in the whole data as well as to the test data and both z and intensity values were used with different weights (Table 3) to optimize the classification results. The z-values have the highest weights with one neighbour, whereas the weight of the intensity increases with three and five neighbours.

Table 3: Weights of variable distributions used in the k-NN method with 1, 3 and 5 neighbours in two approaches: 1) whole data (N=274) 2) test data (N=90)

Classification	Z-values (*z*)						Intensity values (*i*)					
method	sum *z*	F	l	i	fo	lo	sum *i*	f	l	i	fo	lo
1NN – 1)	0.8		0.2		0.1	0.5	0.2	0.1				0.1
1NN – 2)	0.9	0.1	0.2		0.3	0.3	0.1					0.1
3NN – 1)	0.4	0.1	0.1			0.2	0.6	0.1	0.1		0.4	
3NN – 2)	0.2		0.2				0.8	0.1	0.1	0.4	0.2	
5NN – 1)	0.5		0.2		0.1	0.2	0.5	0.3		0.1	0.1	
5NN – 2)	0.4	0.1				0.3	0.6	0.2	0.2	0.1		0.1

f denotes the first pulse, l the last pulse, i the intermediate pulse, fo the first and only pulses together and lo the last and only pulses together.

A forest classification percentage matrix for all of the five forest types is presented in Table 4, where the diagonal shows the correct classifications. The best overall classification result (58.0%) was achieved with the whole data with 5 nearest neighbour and the best single class classification (poor, CT 72.7%) with 1 nearest neighbour. In the case of the whole data, the decreased numbers of neighbours (1 or 3) altered the classification of some stands and decreased the overall classification accuracy (Table 4). The success rates obtained for the classification of herb-rich forests, for example, were 52.5% and 62.3% with one and five neighbours, respectively. The classification done by the test data gave only slightly worse overall classification percentages than with the whole data. In addition, some single class classifications were even better when using the test dataset.

With one nearest neighbour the classification percentage was highest (34.4%) in class 3 (medium, MT) and decreased to classes 1 (17.8%) (very rich, OMaT) and 5 (11.1%) (poor, CT). With five nearest neighbours the classification percentage varied more evenly over the five classes (Table 4).

Table 4: Classification success rates (%) matrix obtained by the k-NN method with 1, 3 and 5 nearest neighbours for all forest site types in two approaches: 1) whole data (N=274) 2) test data (N=90)

1NN – 1) 56.6 %

	1*	2	3	4	5
1*	52	23	18	2	5
2	15	45	32	8	0
3	7	15	63	13	2
4	2	3	23	57	15
5	0	0	3	24	73
	17	19	30	20	14

3NN – 1) 56.9 %

	1	2	3	4	5
1	59	21	15	2	3
2	18	47	27	8	0
3	10	18	60	10	2
4	0	8	17	65	10
5	0	0	6	42	52
	19	21	27	24	9

5NN – 1) 58.0 %

	1	2	3	4	5
1	62	20	13	0	5
2	20	43	28	8	0
3	10	20	58	10	2
4	0	8	12	68	12
5	0	0	0	42	58
	20	20	24	24	11

1NN – 2) 55.6 %

	1	2	3	4	5
1	60	20	20	0	0
2	10	50	40	0	0
3	10	15	60	15	0
4	0	5	35	45	15
5	0	0	0	30	70
	18	20	34	17	11

3NN – 2) 55.6 %

	1	2	3	4	5
1	60	10	30	0	0
2	25	45	20	5	5
3	15	15	65	5	0
4	10	10	20	50	10
5	0	0	0	40	60
	24	18	30	18	10

5NN – 2) 54.4 %

	1	2	3	4	5
1	65	25	10	0	0
2	20	40	35	5	0
3	5	30	55	10	0
4	10	15	15	50	10
5	0	0	0	30	70
	22	24	26	18	10

*1 denotes very rich herb-rich forests (e.g. OMaT), 2 rich (OMT), 3 medium (MT), 4 rather poor (VT) and 5 poor (e.g. CT), including all poor forest sites (Cajander 1926).

4. Discussion

The aim of this work was to employ ALS data in an automated search for different forest site types using the k-NN method to classify forest stands. The method yielded promising results for separating forest site types. We used two data approaches and found that the difference between the analyses based on the whole data approach and the modelling and test data approach were negligible. With the whole data k-NN provided slightly better results in classification with more neighbours, whereas if we used separate modelling and test data the best results were achieved with only one neighbour. However, there is no major difference depending on which approach is used; the larger data provides with more options to choose the “right” site type.

One interesting result was that more fertile site types appeared to have higher proportion of first, last and intermediate laser echoes as well as the total amount of echoes. In addition, higher proportions of only echoes were observed in stands belonging to the poor forest site types (Table 2).

The forests of the southern part of the National Park were subject to forest management practices until the mid-1990's and the proportion of forests at early stages in their development was higher there than in the northern part. In addition, the variation in altitude was smaller. It was not possible, however, to make any division between the northern and southern parts of the area when distributing the stands into the modelling and test data, because the number of forest stands applicable to the analysis was somewhat limited. It is therefore not completely certain how the ALS data-based automated search for forest site types would perform on an independent test dataset. However, the whole data approach did not separate different data sets and provided only results how the method works if there were larger reference data available. We used leave one out method, and in this case every stand had 273 possibilities to the nearest neighbours. We found that with larger reference data and appropriate delineation of the forest stand the results would be improved.

The method is based on vertical changes in echo clouds in different forest site types. One explanation for the significance of vertical indicator characteristics may be that the proportion of deciduous trees, which differ from spruce in the shape of their crowns, for instance, is often higher in more fertile forests. It was also observed that the intensity value correlated positively with the number of deciduous trees. One explanation for this could be that the laser pulse is in the near-infrared part of the spectrum and therefore reflects more strongly from deciduous canopies.

One advantageous property of the k-NN estimator is its ability to utilise a high number of explanatory variables, so that it uses data efficiently. In most of the cases when classification failed the resulting class was, however, in the "nearby" classes with a most similar tree species structure and silvilcultural recommendations corresponding to the correct forest type class. This result is worthwhile because it shows that ALS data and the k-NN non-parametric classifier are suitable for forest site type classification in general. Mistakes in the determination of forest site type classes are also possible in a forest inventory by stands, especially in borderline cases. In general, nearest neighbour methods are sensitive to the reference data, and biased estimates are often obtained for a forest stand with counterparts that are missing from the reference data. More emphasis should therefore be placed on the process of choosing the reference data.

The k-NN method was applicable to the selection of mature forests site types, and the results show that the success rates were moderate, varying from 54 to 58%. In many cases the characteristics used in the forest site type classification were so diverse that at this point it was not possible to say whether the subjective stand-wise inventory technique or the objective ALS data-based method provides more reliable results. One issue to be also considered is the variation within forest stands. It would be possible in future work to divide the stands into more homogeneous "micro-stands" or grids, and apply them as the basic units for forest site type classification. An overall forest site type map could then be produced by combining adjacent grids or micro-stands. In addition, digital aerial images and digital terrain models could give valuable additional information for classification purposes. Moreover, our method based on the vertical distribution of vegetation and can therefore be used in other vegetation zones where the ALS is applicable (e.g., no echoes originate from the ground in dense rain forests). However, further studies are needed to ensure the applicability of the method to different local conditions.

Acknowledgements

This research was conducted in the Faculty of Forestry, University of Joensuu, and the Joensuu Research Unit of the Finnish Forest Research Institute. It was partly funded by the Maj & Tor Nessling foundation and Finnish Ministry of the Environment through the project "A monitoring system based on modern remote sensing imagery for natural forests and restored forests in conservation areas" (decision no. YM89/5512/2004). This conference expenses was mainly funded by Metsämiestensäätiö. We are grateful to these institutions for resources and funding.

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