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Combining optical satellite data and airborne laser scanner data for vegetation classification

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Abstract

The aim of this study was to investigate to which degree the accuracy of vegetation classification could be improved by combining optical satellite data and airborne laser scanner (ALS) data, compared with using satellite data only. A Satellite Pour l'Observation de la Terre (SPOT) 5 scene and Leica ALS 50-II data from 2009, covering a test area in the mid-Sweden (latitude 60° 43' N, longitude 16° 43' E), were used in maximum likelihood and decision tree classifications. Training and validation data were obtained from the interpretation of digital aerial photo stereo models. Combination of SPOT and ALS data gave classification accuracies up to 72%, compared with 56% using only SPOT data. This indicates that integrating features from large area laser scanning may lead to significant improvements in satellite data-based vegetation classifications.

1. Introduction

The combined use of satellite imagery and airborne laser scanner (ALS) data in vegetation mapping is promising, since it makes use of both the spectral information in the optical satellite image and the three-dimensional information in the ALS data.

The EU Habitats Directive has set new and high standards for how protected sites and valuable habitats should be selected and monitored (European Commission 2000, European Commission/DG Environment 2007). In Sweden, with large forest areas, this requires efficient methods for identifying valuable sites over large areas at low costs. The currently available vegetation maps, produced by aerial photo interpretation, cover less than 50% of the land area in Sweden, and there is currently no funding available for producing a national vegetation map with entirely manual methods.

Automated satellite image classification is an established method for producing large area land-cover maps and estimations of forest variables, for example, in the Swedish national version of the European Coordination of Information on the Environment (CORINE) Land Cover database (Hagner and Reese 2007); a statewide land-cover mapping of Wisconsin (Reese et al. 2002); the Land Cover Map of Great Britain (LCMGB) (Fuller et al. 1994); and Moderate Resolution Imaging Spectroradiometer (MODIS) Land Cover (Friedl et al. 2002), just to mention a few. The accuracy obtained for such products based on the two-dimensional optical data like Landsat Thematic Mapper (TM) is, however, limited. ALS data have

proved useful in the mapping of certain vegetation types such as mires (Korpela et al. 2009). Several studies have shown the benefits of combining ALS data with different kinds of imagery, for example, for estimations of forest variables (Hyde et al. 2006, Holmgren et al. 2008, Erdody and Moskal 2010), and for classification and mapping of forests (Hill and Thomson 2005, Dalponte et al. 2008, Ke et al. 2010), rangelands (Bork and Su 2007), urban areas (Haala and Brenner 1999) and coastal and estuarine areas (Chust et al. 2008, Kempeneers et al. 2009). Also imaging radar has been used in combination with optical satellite data, for example, for mapping of deforestation in Brazil (Rignot et al. 1997).

Beginning in 2009, the Swedish National Land Survey (NLS) is collecting laser scanner data for most of the country. Although the main purpose is the production of a new, national Digital Elevation Model (DEM), the nation-wide coverage of laser data might also be a resource for future vegetation mapping.

The objective of our study was to investigate the use of combining ALS data and images from the Satellite Pour l'Observation de la Terre (SPOT) 5 in a vegetation classification. A SPOT scene from late May 2009, covering an area west of Gävle in the mid-Sweden, was used together with the ALS data from the same period. Focus was on mapping forest vegetation and mires according to the classification system of the Swedish national version of CORINE Land Cover database (Engberg 2005).

2. Material and methods

2.1 Study area

The 25 × 50 km² study area is located west of Gävle in mid-Sweden around latitude 60° 43' N, longitude 16° 43' E (figure 1). It is mainly covered by managed hemiboreal forests and mires, here defined as peat-accumulating wetlands with less than 30% canopy cover. These forests are dominated by Scots pine (*Pinus sylvestris*), Norway spruce (*Picea abies*) and birch (*Betula* spp.).

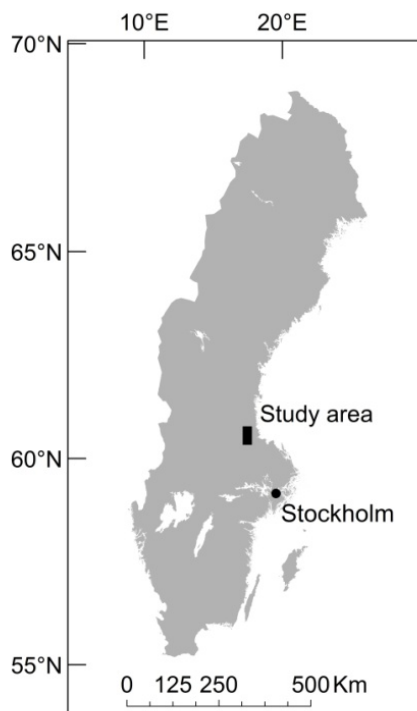


Figure 1. Map of the study area.

2.2 Remote-sensing data

The optical satellite data used in this study was a SPOT 5 HRG XS scene from 31 May 2009. The pixel size was 10 m × 10 m for the green, red and near-infrared bands and 20 m × 20 m for the shortwave infrared band. The image has been geometrically precision corrected to the grid system Swedish Reference Frame 1999 (SWEREF 99), with an error of less than 0.5 pixels. Within the framework of the national DEM production, NLS performed a laser scanning of the study area during 29–31 May 2009 using a Leica ALS 50-II scanner carried by a fixed-wing aircraft. The flying altitude was approximately 2300 m, the average point density 1.6 m⁻² and the maximum scanning angle ±20°.

2.3 Vegetation reference data

Ground-truth data were collected through the interpretation of colour-infrared aerial photos. The photos were acquired by NLS at 4800 m above the average ground level in 2008 and 2009 using a Z/I Digital Mapping Camera (DMC) and interpreted in a digital photogrammetric work station. While a basic sample of images was randomly distributed in the study area, a set of additional images were selected from areas where the less frequent deciduous and mixed forest classes are more common in order to represent all classes. Class proportions in the ground-truth data set are therefore not entirely representative for the region. Within the stereo images, 1548 circular sample plots with 10 m radius were distributed in a grid with 500 m spacing and a randomly selected starting point. The following data were registered per plot: mean tree height, tree species composition (percentage of canopy cover), diffuse canopy cover (percentage) and vegetation class. Canopy cover is defined as the area of the ground covered by a vertical projection of the canopy (Jennings et al. 1999). Diffuse canopy cover means the total vertical projection of the tree crowns on the ground, including any gaps within the crowns (Allard et al. 2003). The classification scheme has seven classes based on the refined Swedish national version of the European CORINE Land Cover database (Engberg 2005). Unlike in CORINE, no minimum mapping unit was used in this study. Class definitions are given in table 1. Due to few training areas, the classes coniferous, deciduous and mixed forest on mire, that is forest meeting the criteria of 30% canopy cover and 5 m tree height but growing on mire, were excluded from the classification and are not shown in table 1. Plots where the dominating class covered less than 70% were excluded from the reference data set. Large spectral outliers were examined closer by visual interpretation of the satellite image and aerial photos and excluded if the presence of roads, water, large gaps between trees and so on could explain the spectral anomalies. After exclusion of outliers, the data set consists of 780 plots. From each class, two-thirds of the plots were randomly selected as training areas and the remaining third was used for validation.

2.4 Processing of remote-sensing data

Laser returns were classified as ground or vegetation returns using a progressive Triangulated Irregular Network (TIN) densification method (Axelsson 1999, 2000), implemented in the TerraScan software (Terrasolid Ltd., Helsinki, Finland) (Soininen 2004). A DEM was estimated by linear TIN interpolation with the laser returns classified as ground hits. First step, ground elevation was calculated in 0.5 m raster cells as

the mean elevation of ground hits within each cell. Second, empty cells were assigned elevation values by TIN interpolation of the filled cells. The height value

(dz) of a laser return was computed as the difference between the z-value of the laser return and the z-value of the DEM.

Table 1. Class definitions.

Class	Canopy cover (%)	Tree height (m)	Species composition (%)		No. of sample plots, training	No. of sample plots, evaluation
			Coniferous	Deciduous		
Clear cut†	0-100	<2	0-100	0-100	87	43
Young	0-100	2-5	0-100	0-100	23	12
Coniferous 5-15 m	≥30	>5, ≤15	≥70	<30	94	47
Coniferous >15 m	≥30	>15	≥70	<30	185	93
Deciduous	≥30	>5	<30	≥70	81	41
Mixed	≥30	>5	30-70	30-70	23	11
Mire‡	≤30	any	0-100	0-100	27	13

Notes: †The plot should show traces of felling, e.g. stumps, machine tracks and debris. ‡ Peat-accumulating wetland. This ground type is not allowed for any other class.

Laser data were extracted in 10 m × 10 m grid cells coinciding with the SPOT pixels. A height threshold of 10% of the maximum laser height in each cell and ≥ 1.0 m was applied in order to separate canopy returns from returns of ground, stones and low vegetation. Several features were extracted from the laser data within each raster cell, based on the dz distribution of laser returns above the height threshold: 10th percentile (P_{10}), 20th percentile (P_{20}), ..., 90th percentile (P_{90}), 95th percentile (P_{95}) and 100th percentile (P_{100}). A vegetation ratio (V) was calculated as the ratio between the number of laser returns above the height threshold and the total number of returns.

2.5 Classification and accuracy assessment

Classification was done with the ENVI software version 4.7 (ITT Visual Information Solutions, Boulder, CO, USA), using the maximum likelihood method. Image data for the training and validation plots were extracted from the SPOT image and the ALS rasters with nearest-neighbour sampling. A first classification was done with the four SPOT bands, and different combinations of height percentiles and/or vegetation ratio from the ALS data were tested as additional bands. Classification with only ALS data was tested in order to better understand the influence of these data on the result. A decision tree classification was also tested. In the first step, a threshold on V was used to split the pixels into two groups: (1) clear-cuts and mires (low V) and (2) other classes. The threshold $V = 0.31$ was selected as the value giving the largest number of correctly classified

plots in the training data. Second, a maximum likelihood classification with the SPOT bands as predictors was made on each group separately. Pixels classified as coniferous forest were then classified as 5–15 m or >15 m using the threshold obtained from linear regression between P_{90} and aerial photo-interpreted tree height.

3. Results

Classification using only the four SPOT bands gave an overall accuracy of 55.8%. The error matrix (table 2) shows that many clear-cuts were classified as young forest, and that the two coniferous classes were often mixed up.

When looking at the entire reference data set, Pearson correlation coefficient between V and aerial photo-interpreted canopy cover was 84.3%. The correlation between height percentiles and mean tree height ranged from 59.5% to 71.9% for P_{10} to P_{50} and decreased slightly for higher percentiles. For the two coniferous classes, the highest correlation, 93.2%, was found for P_{90} . Using P_{50} and V as additional bands in the classification resulted in an overall accuracy of 70.0%. Without V the accuracy was 65.8%. The improvement is mainly due to less confusion between clear-cuts and young forest and between the two coniferous classes. Table 3 shows the error matrix.

When using ALS data alone, P_{50} and P_{90} gave good results for coniferous forest and mire, but the overall accuracy was only 50.4% and the result was particularly bad for deciduous forest and clear-cuts. Adding V improved the result for these two classes, but the overall accuracy remained low, 58.5%.

The highest overall accuracy, 71.9%, was obtained with the decision tree. The majority-filtered classification image is similar to the one from the best maximum likelihood classification (figure 2(d)), but slightly more heterogeneous and possibly with some more confusion between young forest and coniferous forest 5–15 m. Kappa analysis of the error matrices for classification with only SPOT data and for the decision tree classification (SPOT and ALS data) indicates that

the latter method is significantly better at a confidence level higher than 99%.

Overall classification accuracies for different band combinations are shown in table 4, together with producer's accuracies for each class. Classification images for a part of the study area are shown in figure 2 together with the SPOT 5 image and the P_{50} raster. After validation of the result, post-processing of the classified images was made with a 5×5 pixels majority filter.

Table 2. Error matrix for maximum likelihood classification using only SPOT data.

Classification data	Validation data							User's accuracy (%)
	Clear-cut	Young	Coniferous 5-15 m	Coniferous >15 m	Deciduous	Mixed	Mire	
Clear cut	24	1	0	0	0	0	2	88.9
Young	13	8	4	1	2	1	1	26.7
Coniferous 5-15 m	1	0	14	20	3	0	0	36.8
Coniferous >15 m	1	0	23	53	1	3	0	65.4
Deciduous	0	3	1	5	29	0	0	76.3
Mixed	0	0	5	13	6	7	0	22.6
Mire	4	0	0	1	0	0	10	66.7
Producer's accuracy (%)	55.8	66.7	29.8	57.0	70.7	63.6	76.9	Overall accuracy 55.8

Table 3. Error matrix for maximum likelihood classification using SPOT data, P_{50} and V.

Classification data	Validation data							User's accuracy (%)
	Clear-cut	Young	Coniferous 5-15 m	Coniferous >15 m	Deciduous	Mixed	Mire	
Clear cut	33	0	0	1	0	0	4	86.8
Young	3	12	4	1	3	0	0	52.2
Coniferous 5-15 m	0	0	31	5	4	3	0	72.1
Coniferous >15 m	1	0	7	67	3	3	0	82.7
Deciduous	0	0	1	3	27	2	0	81.8
Mixed	0	0	4	16	4	3	0	11.1
Mire	6	0	0	0	0	0	9	60.0
Producer's accuracy (%)	76.7	100	66.0	72.0	65.9	27.3	69.2	Overall accuracy 70.0

4. Discussion

The objective of this study was to investigate to which degree a vegetation classification using optical satellite images could be improved by integrating ALS data. The combined use of these two data sources increased the classification accuracy by 16% compared with those using only satellite data. The highest overall accuracy was obtained when using P_{90} and V together with SPOT data in a decision tree. ALS data helped distinguish between height classes with similar spectral signatures, while optical satellite data were important for species discrimination.

P_{50} and P_{90} alone did not work well for separating clear-cuts, but the result improved from 11.6% to 41.9% when adding V . If one single tree, or part of a tree, is present in a clear-cut pixel, the height percentiles will be strongly affected by that tree since most of the lower vegetation will fall below the height threshold and will not count as vegetation hits. The height percentiles may therefore have values similar to those in higher forest classes. The vegetation ratio will still be low, which explains the improvement in accuracy when this variable was used in the classification.

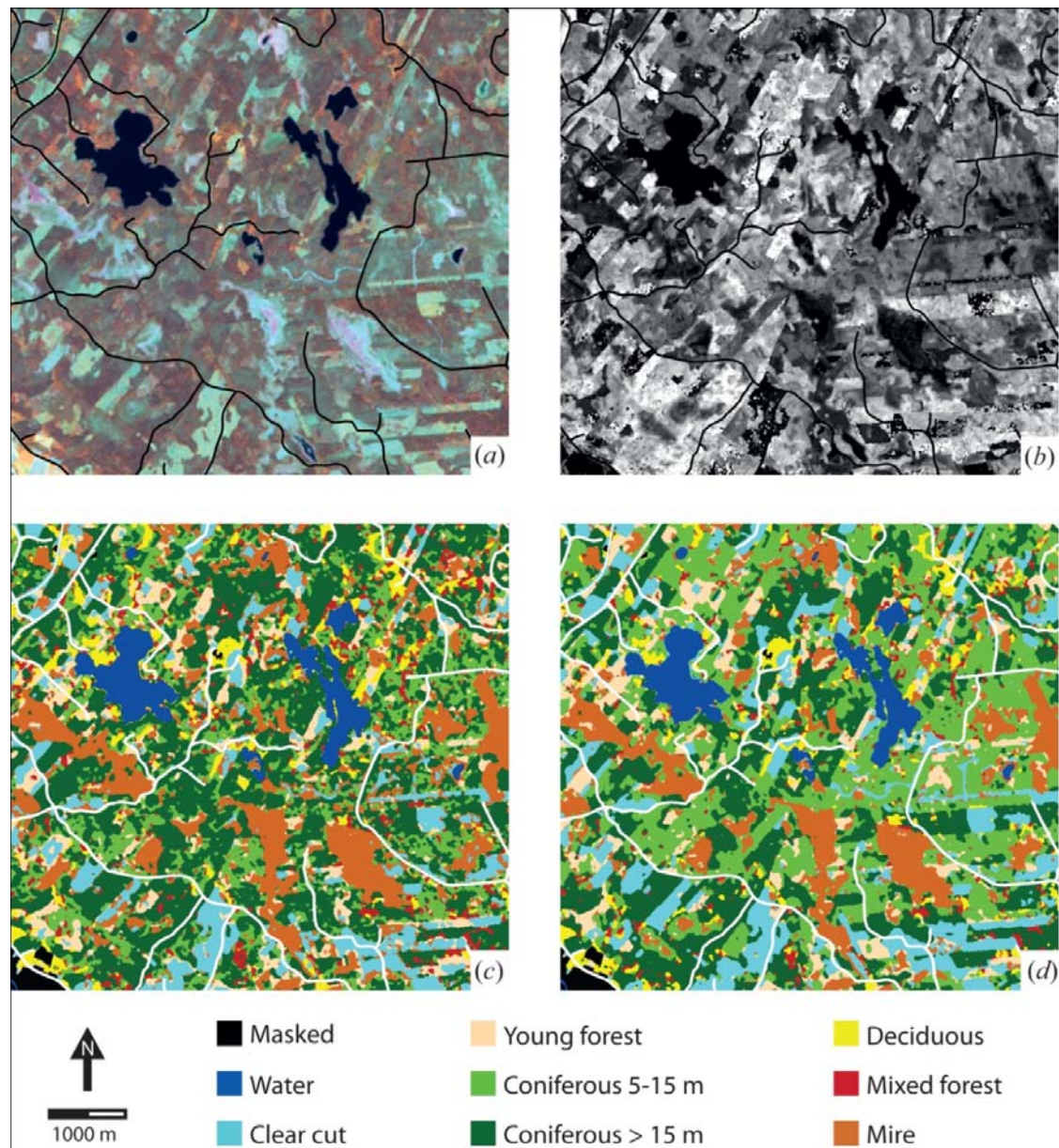


Figure 2. A 6.6×6.2 km part of the study area. (a) The SPOT image, (b) the P_{50} raster, (c) classification using SPOT data and (d) classification using SPOT data together with P_{50} and V . Water and roads are from the Swedish National Land Survey's

topographic map and road map. Urban and agricultural areas from the topographic map are masked out. A 5×5 pixels majority filter has been applied to the classified images.

The low accuracy when using only SPOT data is partly due to confusion between the two height classes of coniferous forest. There is little spectral difference between these classes, and the height information from ALS data is necessary in order to separate them from each other. Clear-cuts that are old enough to have some vegetation are spectrally close to young forest, which might explain the confusion between these two classes. In addition, it is difficult to accurately measure the height of small trees in aerial photo stereo models. This may cause errors in the reference data set and might be one reason for the relatively low classification accuracies. These errors, however, have no

implications on the overall conclusion that using features from large area laser scanning would lead to significant improvements in satellite data-based land-cover classifications.

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Table 4. Over-all accuracy and classwise producer's accuracies (%) for different band combinations.

Bands*	Clear cut	Young	Coniferous 5-15 m	Coniferous >15 m	Deciduous	Mixed	Mire	Over-all
S1-S4	55.8	66.7	29.8	57.0	70.7	63.6	76.9	55.8
S1-S4, P_{50}	58.1	83.3	61.7	72.0	63.4	36.4	76.9	65.8
S1-S4, V	69.8	75.0	36.2	52.7	68.3	36.4	76.9	56.5
S1-S4, P_{50} , V	76.7	100	66.0	72.0	65.9	27.3	69.2	70.0
P_{50} , P_{90}	11.6	16.7	74.5	80.6	2.44	18.2	84.6	50.4
P_{50} , P_{90} , V	41.9	83.3	63.8	77.4	17.1	36.4	84.6	58.5
decision tree†	67.4	66.7	68.1	77.4	70.7	63.6	76.9	71.9

* S1-S4 are the four SPOT bands, P_{50} and P_{90} are the 50th and 90th height percentiles, and V is the vegetation ratio. † The decision tree uses V , P_{90} and the four SPOT bands as predictors.

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