Mapping Forest Parameters Using Decision Trees and Multitemporal Landsat ETM+ Data

Dagrun Vikhamar[1] and Gunnar Fjone[2]

[1]Gjøvik University College, P.O. Box 191, 2802 Gjøvik, Norway.
dagrunv@geo.uio.no. Phone: +47-2285-59272
Now at: Department of Geosciences, University of Oslo, Norway.

[2]Fjone, 3854 Nissedal, Norway.
gunnar.fjone@forest.no. Phone: +47-9069-6816

Abstract – Forest parameters are mapped using decision trees and Landsat ETM+ data. Reference data consist of forest stand registrations. The mapped parameters are tree species, age groups, wood volume per hectare and productivity classes. Accuracy assessment is carried out using national forest inventory data. The study area for the project is Østfold County in South Norway.

Keywords-component; forest mapping; Landsat; decision tree; optical, multitemporal.

I. INTRODUCTION

Forests cover approximately 37% of the area in Norway. Since long, forests are an important resource for timber production. The diversity of wildlife and plants depends on the coverage and the composition of the forest. Consequently, information about the forest is of interest for botanists, zoologists, nature conservationists as well as for private and public forestry.

The aim of this work is to map forest parameters for large regions using multitemporal Landsat ETM+ images and ancillary data. Furthermore, a second aim is to explore the suitability of using available databases from private and public forestry. A full description of the analysis can be found in [1].

II. DECISION TREE ANALYSIS

The classification scheme is based on decision tree methods, since these techniques can handle large and heterogeneous datasets. Østfold, a county in Southern Norway, is chosen as test area. The dataset consists of three Landsat ETM+ images acquired within a two years period (spring 2001, summer 2001, autumn 1999), terrain parameters derived from a digital elevation model, map of vegetation zones and a heat index map.

Decision tree methods strongly depend on large amounts of reference data representing the classes and their spectral variability. Therefore, all available digital maps of forest stands within the test area were used to build and test the decision trees (Figure 1a). Reference data for non-forested areas were derived from a data base called 3Q (Figure 1b). This data base includes information about the farming landscape (crop fields, pastures and impervious areas).

The mapped forest parameters are tree species, age groups, wood volume per hectare and productivity classes. An accuracy assessment was carried out using data from the national forest inventory. Mapped forest parameters were compared to the values registered at sample locations of 250-1000 m^2. The accuracy was tested both by using the pixel center value and the eight nearest neighboring pixels. Success is counted if one of the eight neighbors, or the center pixel, was attributed to the estimated class. The motivation for the two tests is to account for uncertainties related to geometric coregistration of the data sets and transition zones between classes. Of the two tests, using exclusively the pixel center value is the strictest test.

Software used for the decision tree analysis was See5 [2].

III. RESULTS

Resulting maps and producer's accuracy for control points are presented in the following sections.

A. Tree species

Four classes were mapped: 1) Spruce; 2) Pine; 3) Deciduous forest; and 4) Mixed forests. Classes were determined based on registered wood volume per hectare per tree species. A threshold of 95% was used to distinguish the classes. As an example, forest stands having more than 95% of spruce would be classified as spruce. This means that other tree species may constitute up to 5%.

Based on the reference data, a decision tree was built by including pruning and boosting functions. The resulting map is presented in Figure 2a. An error matrix showing the producer's accuracy based on registrations from the national forest inventory is shown in Table I.

When neighboring pixels are included in the accuracy test, both pine and mixed forest perform well. The accuracy is lower for spruce forest, while deciduous forest has only one correctly classified control point. For both classes there were too few control points. Additionally, the reference data (forest stands) used to build the decision tree were poor for deciduous forests.

The classification scheme opens for flexible use of the reference data. Wood volume per hectare is registered as a continuous variable per tree species. Therefore, the class threshold for tree species can easily be adjusted. Consequently, the resulting map will vary for different class thresholds. In the presented experiment a threshold of 95%

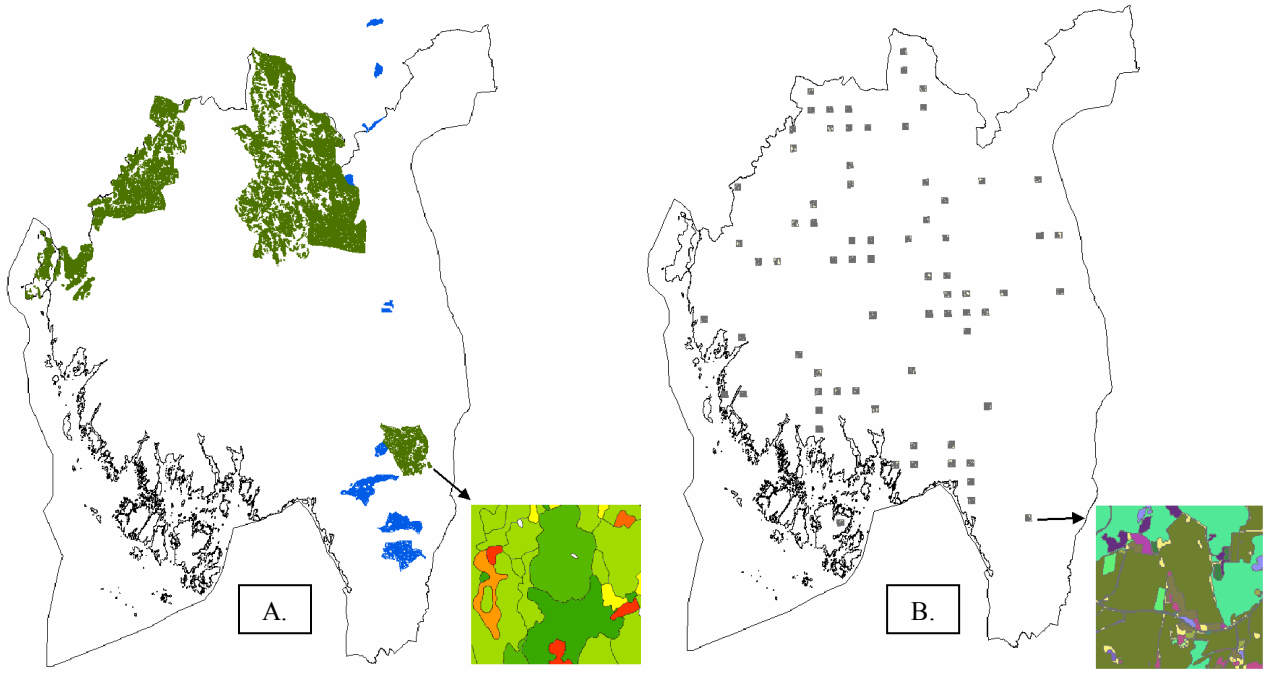


Figure 1. Reference data used to build decision trees: A. Forest stand maps; and B. Non-forested areas represented by a farmer landscape data base (3Q). Forest stand maps consist of uniform forested areas where parameters are registered: e.g. cutting class, tree species, wood volume and productivity class. 3Q data include information about crop fields, pastures and also impervious areas.

was used in order to identify areas with homogenous stands of single tree species.

B. Age groups

The stage of forest development was mapped using cutting classes, which are registered in the forest reference data. Three age groups were mapped: 1) Clear cuts and regenerated forests; 2) Young forests; and 3) Old forest. As previously described, maps of forest stands were used as reference data to train the decision tree algorithm. Control points from the national forest inventory were used for accuracy assessment. Results are shown in Figure 2b and Table II.

Best results are obtained for old forest. Poor results are obtained for clear cuts and regenerated forests. The poor results can be explained by quick changes of vegetation within clear cuts due to clogging and replanting. There is a time shift of up to six years between the Landsat images and the forest stand registrations. Still, clear cuts should be easier to identify using other classical methods, e.g. unsupervised clustering. Only decision tree techniques were tested in this study.

C. Wood volume per hectare (forest density)

The parameter total wood volume per hectare was used as an indicator for forest density. The wood volume represents the volume of stems of the trees. The stem volume is not necessarily correlated to the crown coverage, which is the actual observation of the satellite sensor. Unfortunately, crown coverage was not registered in the forest stand data bases. Three classes were distinguished: 1) Low density (1-10 m^3/ha); 2) Medium density (10-25 m^3/ha); and 3) High density (more than 25 m^3/ha). As previously described, maps of forest stands were used as reference data to train the decision tree algorithm. Control points from the national forest inventory were used for accuracy assessment. Results are shown in Figure 2c and Table III.

Best results are obtained for low forest density (low wood volume per ha). The statistics are uncertain for some classes, e.g. high density, due to few control points.

D. Productivity class

Productivity class is a classification system for the fertility of the soil. It describes the potential height of trees at the age of 40 years. Productivity class is usually measured from soil samples.

The project carried out an experiment to test the possibility to map productivity class using Landsat images. Three classes were mapped: 1) Low productivity (0-11 meter); 2) Medium productivity (12-19 meter); 3) High productivity (over 20 meter). Reference data and control data remained the same as in the previous experiments. Results are shown in Figure 2d and Table IV.

Best results are obtained for low and medium productivity classes. Despite that satellite observations do not provide a direct measure of the productivity, we believe that satellite measurements are a good proxy. This is probably related to the vigorousness of the vegetation. Additionally, the results show interesting similarities to the wood volume map. The topic should be studied in future.

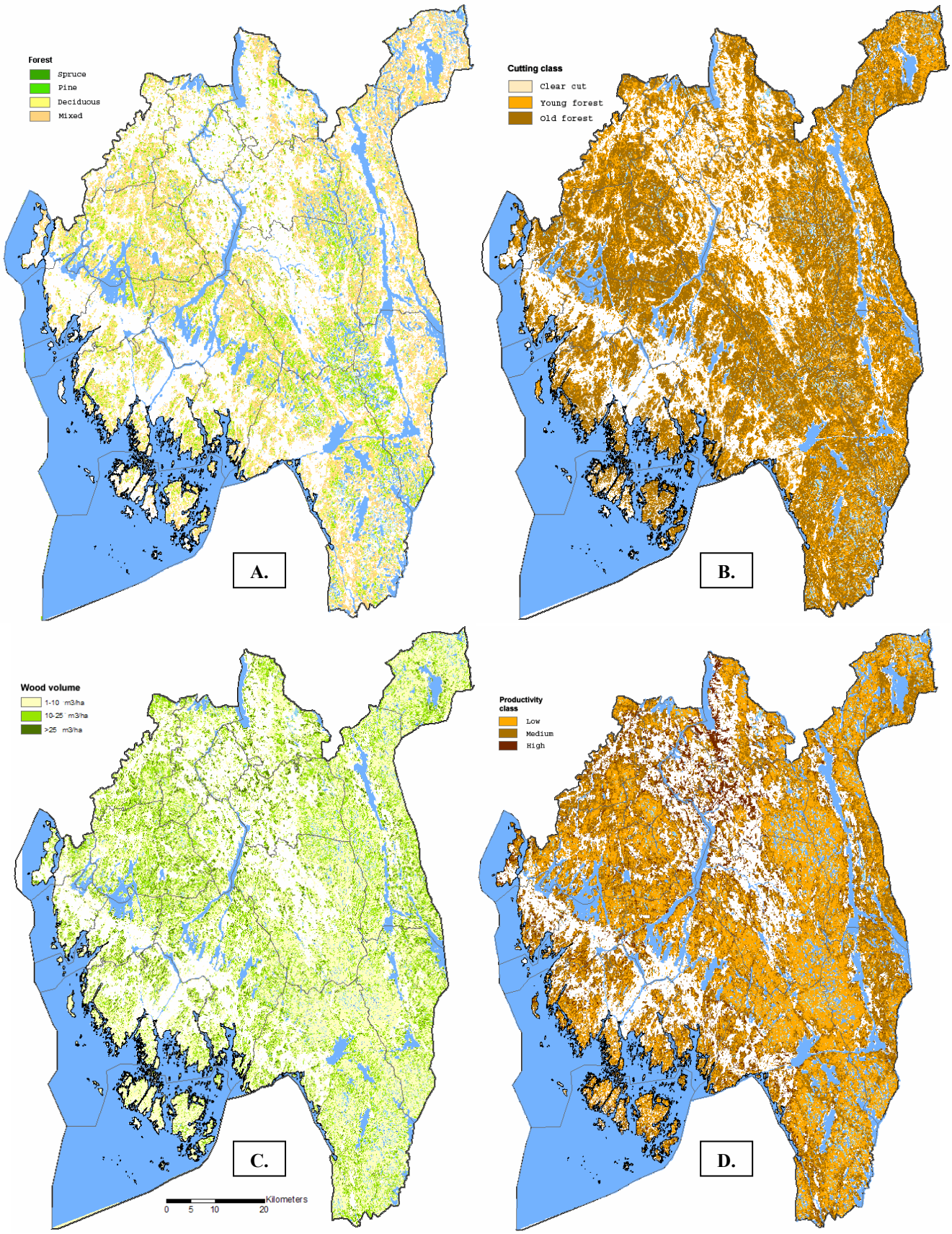


Figure 2. Resulting maps from decision tree analysis: A. Tree species; B. Age groups; C. Wood volume per hectar and D. Productivity class. White represents non-forested areas.

TABLE I. CONTROL POINT ACCURACY FOR TREE SPECIES

Class	Center Pixel (%)	8 Neighboring Pixels (%)
Spruce[a]	17	56
Pine	42	86
Deciduous[a]	0	4
Mixed forest	51	92
Total	44 (n=745)	85 (n=745)

a. Less than 100 control points

TABLE II. CONTROL POINT ACCURACY FOR AGE GROUPS

Class	Center Pixel (%)	8 Neighboring Pixels (%)
Clear cuts[a]	6	25
Young forests	54	90
Old forest	73	98
Total	63 (n=731)	93 (n=731)

a. Less than 100 control points

TABLE III. CONTROL POINT ACCURACY FOR WOOD VOLUME PER HECTAR (FOREST DENSITY)

Class	Center Pixel (%)	8 Neighboring Pixels (%)
Low density	76	99
Medium density	37	84
High density[a]	21	61
Total	57 (n=745)	89 (n=745)

a. Less than 100 control points

TABLE IV. CONTROL POINT ACCURACY FOR PRODUCTIVITY CLASS

Class	Center Pixel (%)	8 Neighboring Pixels (%)
Low productivity	76	94
Medium prod.	37	93
High prod.	24	69
Total	58 (n=735)	90 (n=735)

IV. SUMMARY

Generally, the results show that the accuracy is higher on area level than on pixel level. On pixel level (center pixel) none of the classes reach 90% accuracy. If neighboring pixels are included 46% of the classes get better than 90% accuracy: Mixed forest, young and old forest, low density, low and medium productivity.

Several factors affect the classification accuracy. Geometric positioning of single satellite images is approximately 0.5 pixels. The geometric errors may be larger outside the control points. Accurate coregistration of images and ancillary data sets are crucial for per-pixel classification methods. Wood volume registration errors in the forest stand data may in average reach up to 24% [3]. The classification will never be better than the reference data used to train the algorithm. Accuracy was tested using an independent data set from the national forest inventory, where each control area constituted only 1/3 of the size of a Landsat pixel. Consequently, if the forest variables vary significantly around a control area, the overlaying Landsat pixel may be mapped to another class.

Maps showing forest parameters presented in this paper are of special interest for several applications: regional statistics and wildlife monitoring. The maps show a probability of occurrence for a certain class at a certain location. Such maps may be used to map potential habitat areas for specific animals. This requires knowledge about habitat-vegetation associations for the actual animal. As an example, the number of moose in Norway has largely increased during the last 50 years. Larger food supply is the result of an altered forestry, which increased the areas of clear cuts and young forests. Maps showing tree species, age groups and clear cuts will help predicting the food supply, and thereby the number of moose.

The presented classification scheme has considerable potential for further development towards an operational system. It is based on techniques that reduce the use of expert knowledge by using routines which can be implemented to run automatically. This requires availability of digital forest stand data of a uniform format.

Future work may concentrate on improving the classification by using other reference data. More work should be carried out on testing the robustness of the classification results by testing different decision trees and input data.

V. ACKNOWLEDGEMENT

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