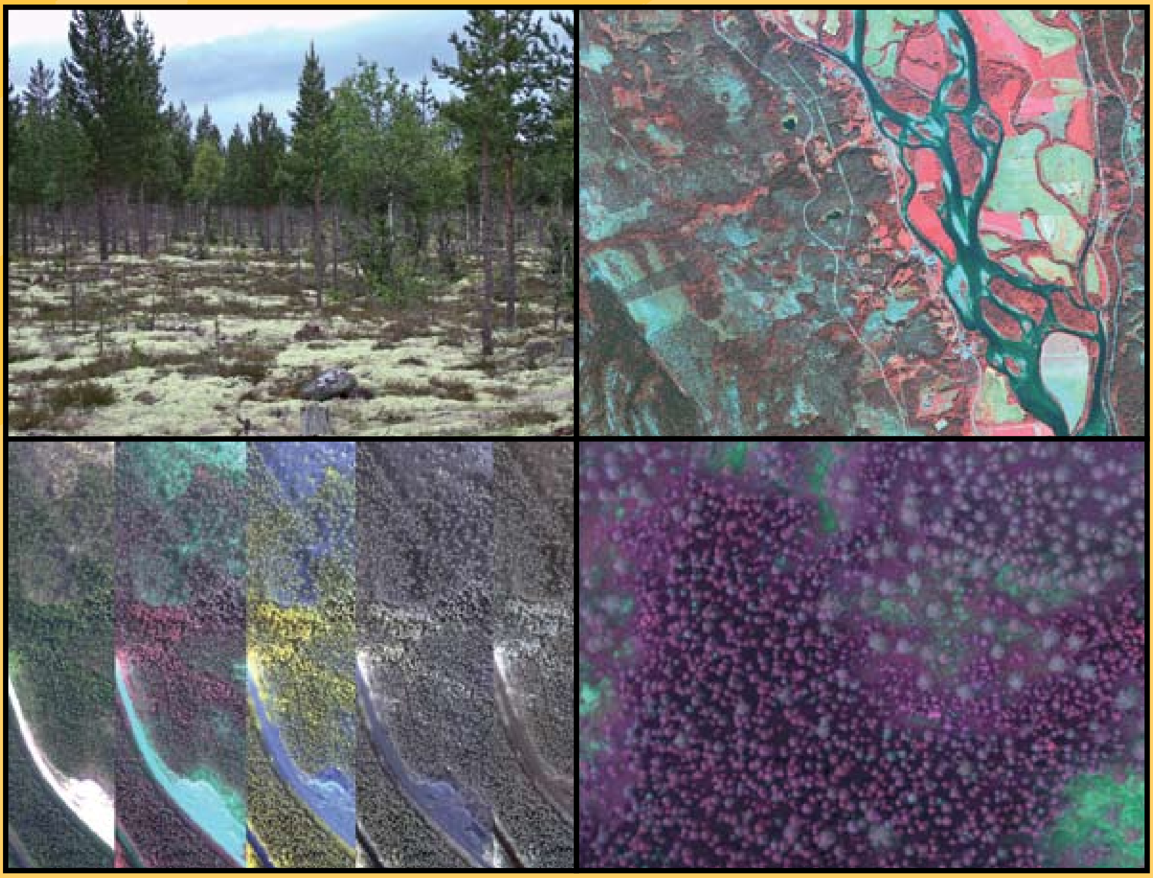
Høgskolen i Hedmark Oppdragsrapport nr. 5 - 2007

Floris Jan Groesz and Leif Kastdalen

Mapping trees and thicket with optical images

Testing the use of high resolution image data for mapping moose winter food resources



Norsk Romsenter
NORWEGIAN SPACE CENTRE

Direktoratet for naturforvaltning

HØGSKOLEN HEDMARK

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Høgskolen i Hedmark

Tittel: Kartlegge trær og busker med optiske bilder. En test på bruk av høyoppløselige bildedata til kartlegging av vinterføde for elg.

Forfattere: Floris Jan Groesz og Leif Kastdalen

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Emneord: Elg – Vinterbeite –Skog -Bildeanalyse - Segmentering - Stor-Elvdal

Sammendrag: Denne undersøkelsen omhandler bruken av HySpex hyperspektrale bildedata og Quickbird satellittdata til klassifikasjon av skog, spesielt skog som er av betydning som beite for elg. Bildedata er hentet fra et mindre område i Stor-Elvdal kommune.

Vi samlet inn feltdata for flere treslag og vegetasjonstyper i studieområdet. Punktene ble nøyaktig kartfestet med GPS og avmerket på detaljert ortofoto (15 cm bakkeoppløsning fotografert med Vexcel UltraCam). Vi klassifiserte en HySpex flystripe (25 cm bakkeoppløsning) og et Quickbird satellittbilde (60 cm bakkeoppløsning). Bildedataene var nøyaktig ortokorrigert. Vi korrigerte ikke for atmosfærisk avvik. For Quickbird dataene beregnet vi en normalisert vegetasjonsindeks (NDVI) og flere teksturbilder ble avledet. For HySpex bildet ble datamengden redusert ved bruk av prinsipal komponentanalyse (PCA) og med minimum støy andel transformasjon (MNF). Begge bilder ble klassifisert med en objektorientert tilnærming med bruk av eCognition software. Etter segmentering benyttet vi nærmeste nabo (NN) som klassifikasjonsmetode. I tillegg utførte vi klassifikasjon basert på support vektor maskin (SVM) og beslutningstre (DT) på det samme datasett som NN klassifikasjonen.

Den gjennomsnittlige klassifikasjonsnøyaktigheten fra analysene på Quickbird dataene var ca 40%. Ved reduksjon av antall klasser til furu, gran, løvtre og annen bakkevegetasjon ble resultatet forbedret til 78%. Det var liten forskjell mellom algoritmene NN, SVM og DT i analysene av Quickbird dataene.

Den gjennomsnittlige klassifikasjonsnøyaktigheten fra analysene på HySpex dataene var ca 63%. Reduksjon til færre klasser forbedret resultatet til 76% for NN klassifikasjonen og til 81% med SVM og DT som klassifikatorer. I klassifikasjonen med HySpex data ble klassene furu, gran, selje godt identifiserte, mens for Quickbird var det kun klassen furu som ble godt (over 70% nøyaktighet) identifisert.

Det var ikke mulig å kartlegge elgbeiteskade med de begrensede feltdata vi hadde tilgjengelig i dette prosjektet. Resultatet av klassifikasjonen er rimelig brukbar for a kartlegge elgbeite. Resultatet kan bli forbedret med et større feltmateriale, ved å benytte hyperspektrale data fra en større del av spekteret, ved å benytte eksisterende kartdata som støtte i klassifikasjonen eller ved å kombinere LIDAR (Light Detection And Ranging) høyde data med de optiske bildedataene. Med disse forbedringer tror vi det er mulig å kartlegge elgbeite nøyaktig, men det trengs mer forskning for å undersøke hvor nøyaktig beiteskader fra elg kan kartlegges.

Vi anbefaler at videre undersøkelser fokuserer på å benytte både LIDAR og optiske flerkanalsbilder i kartlegging av beiteressurser for elg.

Høgskolen i Hedmark

Title: Mapping trees and thicket with optical images. Testing the use of high resolution image data for mapping moose winter food resources.			
Authors: Floris Jan Groesz and Leif Kastdalen			
Number: 5	**Year:** 2007	**Pages:** 36	**ISBN:** 978-82-7671-618-4 **ISSN:** 1501-8571
Financed by: The Norwegian Directorate for Nature Management, Norwegian Space Centre and Hedmark University College			
Keywords: Moose – Winter browsing – Forest - Remote sensing - Segmentation - Stor-Elvdal			

Summary: This study describe the use of HySpex hyperspectral images and QuickBird satellite images for the classification of forest and vegetation in Stor-Elvdal, especially forest and vegetation that are a resource for moose browsing.

Field data was gathered on several tree species and vegetation types in the study area. The sample points were exactly georeferenced with the use of GPS and Vexcel orthophotos. A HySpex flight strip (25 cm resolution) and a QuickBird satellite image (60 cm resolution) of the exact same area were used for the classification. Both images have been orthorectified. No images were atmospherically corrected. For the QuickBird image, the Normalize Difference Vegetation Index and several texture images were calculated. For the HySpex image two data reduction methods were applied: Principal Component Analysis and Minimum Noise Fraction transformation.

Both images were classified by an object oriented approach with use of the software eCognition. After a segmentation procedure, a Nearest Neighbour (NN) classification method was applied. In addition to the Nearest Neighbour classification, Support Vector Machines (SVM) and a Decision Tree (DT) classification was performed on the same classes and sample data.

The overall classification accuracy of the QuickBird classification was about 40%. Regrouping the classing into 'pine, 'spruce', 'deciduous', and 'other groundcover' improved the result up to 78%. There was little difference between the results of the NN, the SVM, and the DT classifiers for the Quickbird images. The overall classification accuracy of the HySpex classification was about 63%. Regrouping the classes improved the result to 76% (for the NN classifier) to 81% (for the SVM and DT classifiers). The HySpex classification discriminated the classes 'pine' good, 'spruce', and 'willow' reasonably well, while the QuickBird classification only discriminated the class 'pine' reasonably well (over 70% accuracy).

We were not able to map the browsing pressure with the limited field data we had available in this study. We did not used methods to identified single tree crowns, but we believe tree crown identification could improve the result for moderate browsed trees. For hard browsed pine trees the biomass of needles are very low and the trees will therefore be difficult to indentify from above, even on images with ground resolution down to 15 cm.

The classification results can be reasonably useful for the mapping of moose browsing resources. The results could be improved by taking more and more accurate field samples, by using extended hyperspectral image

data, by adding existing maps as support for the classification, or by using LIDAR (Light Detection And Ranging) height data.

More research is needed to investigate whether it is possible to map moose browsing pressure, and we suggest using a combination of LIDAR and optical images for mapping the browsing resources available for moose.

Foreword

This project describes a work in the use of optical sensor for forest classification in Stor-Elvdal municipality. The project was initiated as a test to investigate the capacity of optical sensors available today as a source to capture information of forest damage from moose browsing and the biomass of winter food for moose.

The project is financed by the Norwegian Directorate for Nature Management and the Norwegian Space Centre through the SatNat program. An addition financial support is given from Hedmark University College through their moose projects.

The satellite and hyperspectral data is owned by Hedmark University College. The field work was done by Tore Horten and Rosemarie Popp. Stor-Elvdal grunneierlag let us use data from their moose browsing survey, however within this project we were not able to use them as ground truth in the classification.

Evenstad, June 2007

Floris Groesz	Leif Kastdalen	Torstein Storaas
Hedmark University College	Project manager SatNat	Hedmark University College

Innhold

1 Study area

The study area is located in the municipality of Stor-Elvdal, in the province of Hedmark. The valley Østerdalen with the river Glomma is the main landscape feature in the area (Figure 1).

The vegetation belong to the Boreal zone, the hills surrounding the valley are dominated by Norway spruce (*Picea abies*) and Scots pine (*Pinus sylvestris*), and interspersed with a few deciduous species such as birch (*Betula* spp.) and aspen (*Populus tremula*). Along Glomma and adjacent rivers different species of willow (*Salix spp.*) are common. The climate is continental with low temperatures and snow rich winters. Altitude varies from 250 m in south to 1000 m above sea level in the north-west. Forestry is important in the local economy. Moose migrate down to the valley when the snow starts to accumulate in the hills, so in winter time the moose population aggregates in the lower elevations. The young pine forests at lower elevations are heavily browsed.

2 Material and methods

2.1 Field data

The field data was collected by visiting sites in the field, describing several parameters and determining the coordinates with GPS. The accuracy of the GPS location varied from several meters to about 10 meters. Therefore the exact location was also marked on orthophoto made from Vexcel Ultra Cam images at 15 cm resolution. The descriptions were divided in the three types

- Single trees (identifiable on the Vexcel orthophoto)
- Bushes or groups of small trees
- Other Ground cover.

The following parameters were determined for each point.

Waypoint nr	From GPS
Date	
UTM X	
UTM Y	
Precision	Precision of the coordinates (estimated by the GPS)
Species	Tree species
Tree height (m)	
Crown height (m)	Height above ground were the crown starts
Stem dhh (cm)	Stem diameter at 1,5 meter height (if possible to measure)
Stem d 10cm (cm)	Stem diameter at 10 cm height if it is not possible to measure it at 1.5 meter.
Crown dia1 (m)	Crown diameter (in case the crown is not circular than this is the largest length of the crown cross section
Crown dia2 (m)	Crown diameter orthogonal to the 1st crown diameter in case the crown is not circular
Browsing degree 1-4	Browsing degree measured from 1, no browsing to 4 heavily browsed.
Crown form (vertical): R,E,S,P	R = Round E = Ellipse S = Cone P = Pear
Crown dens %	Crown density in vertical direction.
Ground coverage %	Dominating ground cover types and their % of coverage
Comments	

Extra samples of agricultural fields were taken without fieldwork and based on visual interpretation of the Vexcel orthophoto.

2.2 Images

The following images were available for the area:
- QuickBird satellite image
- HySpex hyperspectral image
- Vexcel Ultra Cam digital aerial photos

The first two were used for classification, while the Vexcel images have only been used to improve spatial accuracy of the field data (the GPS data).

2.2.1 QuickBird

The QuickBird satellite was launched in 2001 and is operated by Digital Globe. From an orbit of 450 km QuickBird takes images with a swath width of 16.5 km in four multispectral channels and one panchromatic (Table 1).

Table 1. *QuickBird image characteristics.*

Band	Spectral range (nm)	Pixel size on the ground (m)
Blue	450 to 520	2.4
Green	520 to 600	2.4
Red	630 to 690	2.4
Near-IR	760 to 900	2.4
Panchromatic	445 to 900	0.6

2.2.2 HySpex

The HySpex sensor is an airborne sensor produced and operated by the company Norsk Elektro Optikk (NEO) HySpex is a so called pushbroom scanner, which means that the image is scanned line by line. In the VNIR mode, HySpex acquires radiance in 160 bands, ranging from 400 nm to 1000 nm, each with a bandwidth of 3.7 nm. See Table 2 for more characteristics or visit (www.neo.no/HySpex/) The HySpex sensor is also capable to record in the SWIR (Short Wave InfraRed) mode, but this mode was not available for this area. The SWIR mode ranges from 1000 nm to 1700 nm. The pixel size of the used image was 0.25 meter.

Figure 1. *Overview of the* QuickBird image.

Table 2. *HySpex sensor characteristics VNIR module*

Module	VNIR-1600
Detector	Si CCD 1600*1200
Spectral range	0.4-1µm
Spatial pixels	1600
FOV across track	17□
Pixel FOV across track/ along track	~0.185mrad/ 0.37mrad
Spectral sampling	3.7nm
# spectral bands	160
Digitization	12bit
Frame rate to HD	120fps

2.3 Image preparation and pre-processing

The Quickbird image has been orthorectified using a digital elevation model (DEM) derived from the N50 contour curves. Root Mean Squared (RMS) error for the rectified Quickbird image was 2 meters. No atmospheric correction or terrain normalization was applied.

The Quickbird image has been pansharpened with the sharpening model in the PCI Geomatics software, which combines the panchromatic (0.6 meter) image and the multispectral (2.4 meter) image into a multispectral image with a 0.6 meter pixel size. The results are in this report referred to as a Pansharpened Merge (PSM).

Images of the following textures were derived from the panchromatic image: homogeneity, contrast, angular second moment, with a window size of 5x5 pixels. More information on the used algorithms can be found in the PCI Geomatica User Manual and in Haralick 1973. A normalized difference vegetation index (NDVI) was calculated in the following way using the PSM image as input: ([Near Infrared Band] – [Red Band]) / ([Near Infrared Band] + [Red Band]).

The HySpex images were georectified by NEO with the use of a digital elevation model derived from elevation data in the national N5 map series. The image values were converted to radiance. The NDVI values was calculated and used to mask the areas with no vegetation. Band number 100 (766 nm) and 73 (667 nm) were used for the calculation. All pixels with an NDVI lower than 0.3 were masked. With 160 different channels it was necessary to do some data reduction before the analyses.

2.3.1 Data reduction

We used two alternatives for data reduction. Principle Component Analysis (PCA) and Minimum Noise Fraction Linear Transformation (MNF).

Principal Components Analysis is a procedure for transforming a set of correlated variables (image bands) into a new set of uncorrelated variables. This transformation is a rotation of the original axes to new orientations that are orthogonal to each other and therefore there is no correlation between variables. The result of PCA is the same number of output bands as the number of input bands. The output bands however, are ordered by the amount of variance in the band. This means that the first PCA bands contain most information, while the last PCA bands contain almost no information. Figure 2 illustrates this by showing the first 8 components of the originally 160 band HySpex image.

The Minimum noise fraction (MNF) transformation is a method for producing component images that are ordered in terms of image quality. This method seeks to concentrate image noise present in the input channels into as few output components as possible. In contrast, the principal components (PCA) transformation seeks to concentrate image variance into as few output components as possible. Only when the noise in the set of input channels is uncorrelated and has equal variance across all of the bands will the PCA transform produce component images that are ordered in terms of image quality (source: PCI Geomatica User Manual), (Green et al, 1988). Figure 3 shows the first 8 components of MNF.

The PCA was performed only on the image after doing the NDVI masking, while the MNF was performed both on the image with and without the NDVI mask. The reason to mask non vegetated areas is to focus on the vegetation areas. A large part of the variance in an image can be caused by spectral difference between vegetation and non vegetation. These differences could then be dominant in the first components of the transformed image. If none vegetated areas are masked out then differences between vegetation types could dominate the first components of the transformed image.

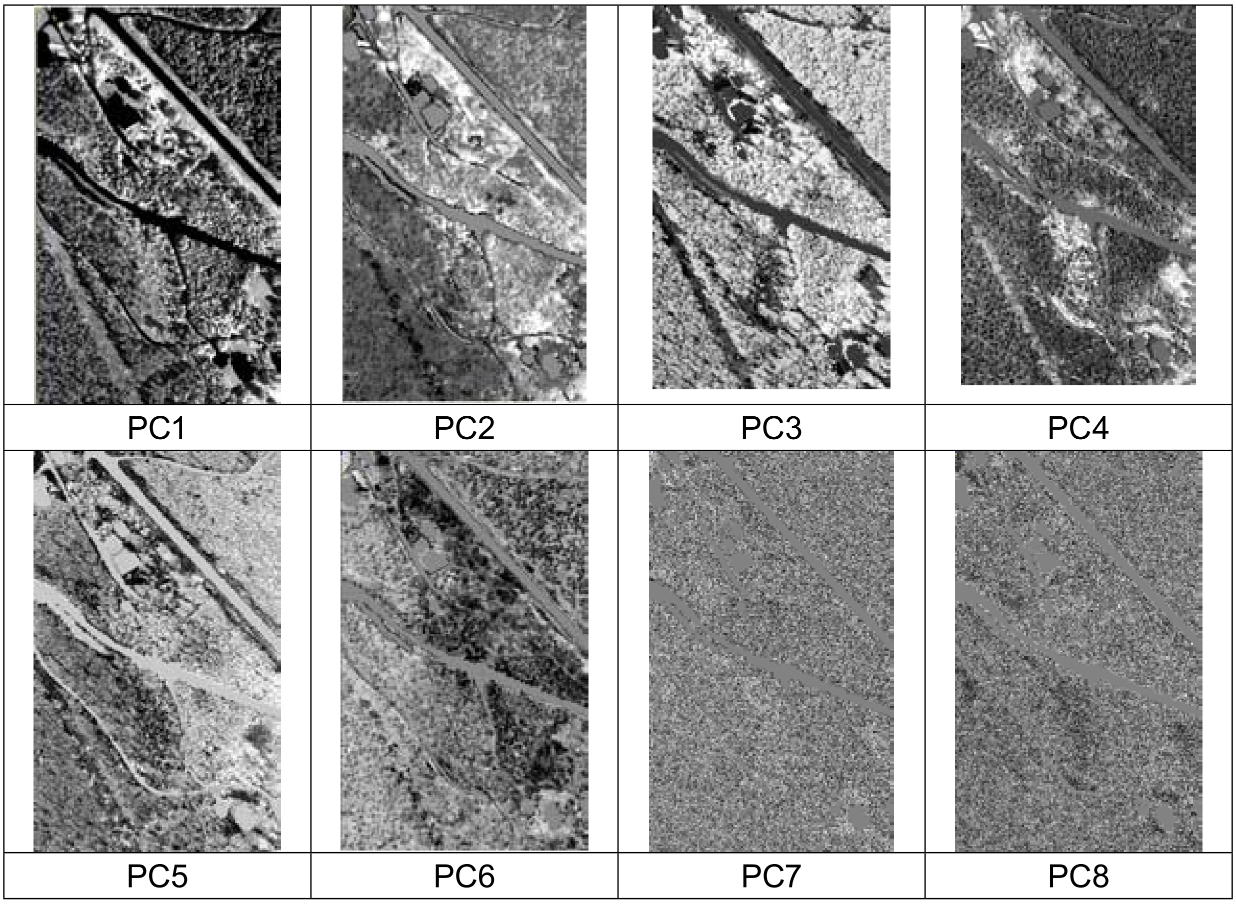

Figure 2. *Principle Components of HySpex image. PC1 (top left) is the first component. In total 8 components are displayed. The information in each component decreases from the 1st to the 8th component.*

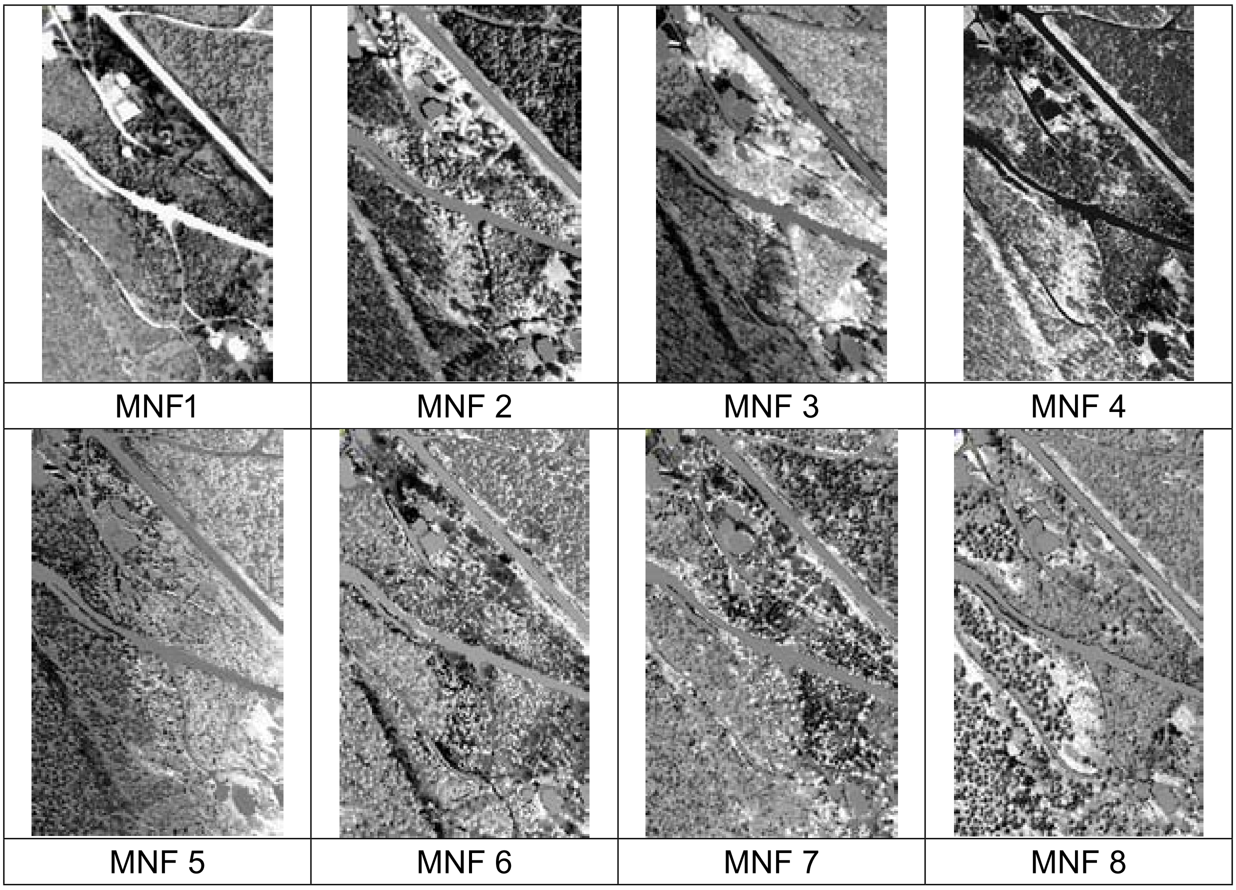

Figure 3. *MNF components of HySpex image. MNF1 (top left) is the first component. In total 8 components are displayed. The information in each component decreases from the 1st to the 8th component.*

Figure 4 and Figure 5 show how rapidly the variance decrease as the number of the component increases. Variance in the image contains both information and noise. The components of the PCA have a generally higher variance than the MNF components. This is probably caused by the fact that the MNF transformation removed a large part of the noise in the image. It can be concluded that there is relatively a very low amount of information in the components 10 and higher.

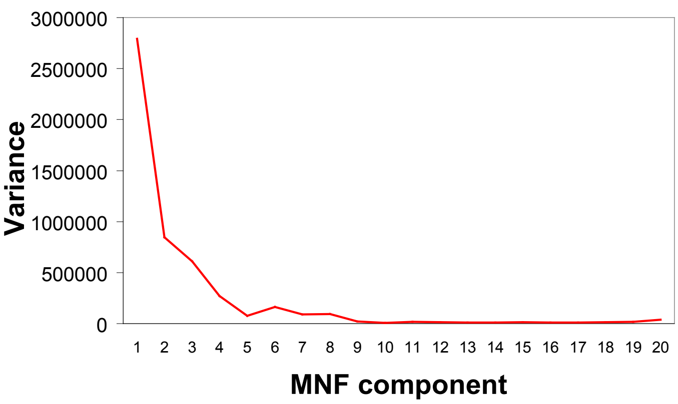

Figure 4. *MNF components of HySpex image and their variance.*

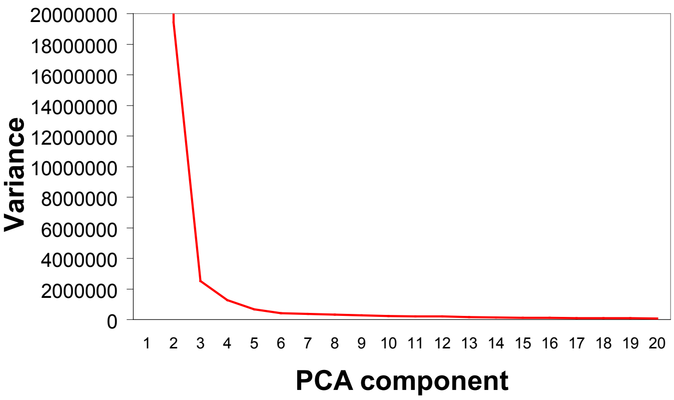

Figure 5. *PCA components of HySpex image and their variance.*

The first 12 components of each data reduction method were used further in the classification. The other components did presumably not contain useful information. (This has not been tested).

2.4 Image classification

The software eCognition can be used for object-oriented image classification. Contrary to pixel based image classification, where each pixel in an image is analysed and classified separately, object-oriented classification works with image objects. To be able to do this, the image has to be divided into groups of pixels, together forming an object or a so called segment. This step is called segmentation. eCognition makes uses of a multiresolution segmentation process, where several image layers are divided simultaneously into homogeneous groups of pixels. Each segment receives characteristics derived from the image, for example the mean value of a band for the segment, information on the shape and position of the segment, information on the neighbouring segments of the segment, or on segments of a higher or lower scale.

For the Quickbird image all layers were imported into eCognition. The image was segmented on one level using the PSM bands Blue, Green, Red, and Near Infrared. The following parameters were used: Scale 15, Shape factor 0.1, Compactness 0.9. Shadow areas were masked. For the HySpex image we used the layers of the MNF and PCA with NDVI mask. In addition we used the layers of the MNF without NDVI masked.

For the HySpex images three eCognition projects were created: one for MNF_NDVI, one for PCA_NDVI, and one for MNF. The image was segmented on all the components of MNF. The following parameters were used: Scale 15, Shape factor 0.1, Compactness 0.9.

2.5 Field samples

An ESRI shapefile with sample locations was also imported into the eCognition projects. A part of the field samples were not recognizable on the QuickBird image, especially small trees (of about 1.5 meter high). They were visible on the Vexcel orthophoto, but not on the QuickBird and the HySpex images. These samples had to be rejected.

Table 3. *Number of samples for each class. Classes in bold have over 10 samples.*

Class name		Number of sample areas Quickbird	HySpex	Grouped class name
Alder	(Alnus glutinosa)	**11**	9	Deciduous
Birch	(Betula pendula /pubescens)	**69**	**39**	Deciduous
Larch	(Larix deciduas)	1	0	Deciduous
Aspen	(Populus tremula)	**25**	7	Deciduous
Beech	(Fagus sylvatica)	2	0	Deciduous
Pine	(Pinus Sylvestris)	**51**	**45**	Pine
Rowan	(Sorbus Aucuparia)	**20**	9	Deciduous
Spruce	(Picea Abies)	**81**	**64**	Spruce
Willow	(Salix caprea)	**35**	**15**	Deciduous
Lichen		4	3	Other groundcover
Moss		1	5	Other groundcover
Fireweed		7	1	Other groundcover
Blueberry		0	2	Other groundcover
Raspberry		7	2	Other groundcover
Grass		**11**	2	Other groundcover
Rock		1	3	Other groundcover
bare soil		1	0	Other groundcover
Agriculture		**85**	0	Other groundcover
Total		**412**	**206**	

Due to the rejection of samples we got very few training data in several classes (Table 3). The minimum number of samples needed is dependent of the classification algorithm used and the number of features (variables). It is difficult to specify an exact number of samples needed. As an estimate, classes with less than 10 samples are critical to use in this case.

2.6 Classifiers

In eCognition you can only use the k-Nearest Neighbour classification with k = 1 (1NN). The NN classifier is not building a model for doing the classification. Instead it calculates a distance metrics and classify according to the closes training samples measured with the used metric. With k=1 only the closest sample is used. Sometimes it is better to look at a group of samples and classify according to the most dominant. That is done when the classifier use k>1.

The classifiers use a simple principle: first, each class needs to be defined by a certain amount of representative samples. Each sample is an image object and has features (variables extracted from image data or other GIS data). An example of a feature is the “mean value of the red channel” of an object, or the “standard deviation of the green channel” of an object.

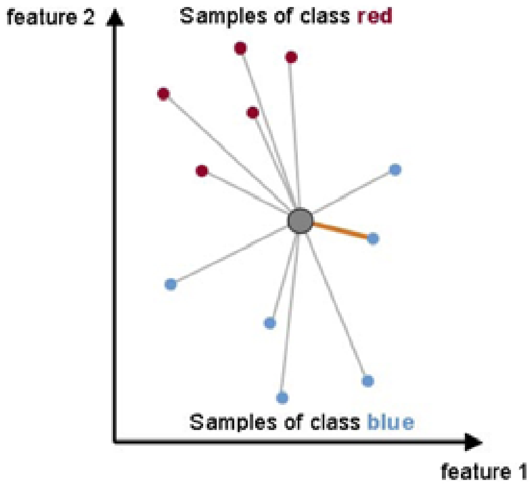

Figure 6. *The principle of a 1-Nearest Neighbour classifier (source: eCognition User Guide).*

Nearest Neighbour

The 1-NN classifier searches for each 'unknown' image object, the closest sample object in feature space and labels the image object with that class.

Figure ***1*** shows this principle for one unknown image object, two classes and two features. The image object is assigned to the class 'blue' because a 'blue' sample is closest to it in the two-dimensional feature space.

The 1-NN classifiers make their predictions based on local information, while other algorithm (decision tree and Support Vector Machine) try to find a global model that fits the entire input space. Because the classification is made locally a 1-NN classifier is very susceptible to noise. On the other hand, if the samples give a good representation of the classes the algorithms work well with few samples.

Decision Trees

In addition to the Nearest Neighbour classification done in eCognition we tested two other algorithms. For doing that we had to export the sample data with all features to a table, and use other software in the analysis. All samples that were created by eCognition were exported, including the same features that were used for the NN classification. Thereby we have the exact same dataset as in the NN classification. The accuracy for the different algorithms was tested by n-fold cross validation.

One of the other algorithms we tested was the TreeBoost (Friedman 1999). This algorithm is optimized for improving accuracy based on decision tree classification. TreeBoost generate a number of decision tree models. The residual from the first tree are fed into the next tree with an attempt to reduce the error in the first tree. The final predicted value is formed by adding the weighted contribution of each tree. A full TreeBoost series can consist of hundreds of trees.

Support Vector Machine

The other algorithm we tested was the support vector machine (SVM). This is a broader range of algorithms and was originated from research in statistical theory (Vapnik 1995, 1998). SVM have shown to work well with high-dimensional data and avoids the dimensionality problem, often a serious limitation for many other methods.

We will not explain the method behind SVM here. It is complex and well explained in several books (Tan et. al. 2005, Abe 2005). Shortly the SVM look for a hyperplane that can linearly separate the data in an optimal way. For using the algorithm with a high number of features the data are transformed to higher dimensional space by using a kernel function. We used the SVM software from the LIBSVM project (Chang and Lin 2005), and selected a Radial Basis Function as the kernel function.

2.6.1 Feature selection

Several combinations of features were tested for both types of image data using the feature selection options in eCognition. The method built into eCognition for testing the successfulness of a classification is to calculate the separability of the samples in the defined feature space. If the separability is low it means that the samples of the different classes are very close (or alike) in feature space. The assignment of 'unknown' image objects to these classes will then be quite arbitrary. If the separability is high it means that the classes are well defined and easy to differentiate.

A tool called 'Feature Space Optimization' in eCognition calculates the optimum set of features to use based on a group of classes and their samples. The tool proposes a number of samples and reports a 'separation distance'. The tool is designed for uncorrelated features. The features used are all derived from image data and image bands are strongly correlated. This mean that the result of Feature Space Optimization' in eCognition will not necessarily be the optimum feature set to use.

Therefore several proposed feature sets from the Quickbird image were tested by means of a 5-fold cross validation (Table 4). The set of samples was divided in five parts. 4/5 was used as training sample for the classification and the 5th for validation. This process was repeated five times.

The following feature sets from the HySpex image were tested:

- The first 12 components of the MNF with a NDVI mask
- The first 12 components of the MNF without a NDVI mask
- The first 12 components of the PCA.

The used combinations of these features are listed in the Table 9, Table 11 and Table 13 together with the classification results. The classification result was derived by a 3-fold cross validation, since the number of samples was fewer for the HySpex classification than the QuickBird.

For the TreeBoost and the SVM a n-fold cross validation can be calculated automatically as a part of the analysis.

***Table 4**. Features that were tested for the QuickBird classification.*

Feature name	Explanation
mean PAN	Mean value of the panchromatic band (0,6 m pixel size)
mean MS-BLUE	Mean value of the blue band (2,4 m pixel size)
mean MS-GREEN	Mean value of the green band (2,4 m pixel size)
mean MS-RED	Mean value of the red band (2,4 m pixel size)
mean MS-NIR	Mean value of the near infrared band (2,4 m pixel size)
mean PSM-NDVI	Mean value of the NDVI calculation based on the PSM image
mean PSM-BLUE	Mean value of the PSM blue band (0,6 m pixel size)
mean PSM-GREEN	Mean value of the PSM green band (0,6 m pixel size)
mean PSM-RED	Mean value of the PSM red band (0,6 m pixel size)
mean PSM-NIR	Mean value of the PSM near infrared band (0,6 m pixel size)
mean PAN-HOM	Mean value of homogeneity texture filter based on the panchromatic band
mean PAN-CON	Mean value of contrast texture filter based on the panchromatic band
mean PAN-ASM	Mean value of angular second moment texture filter based on the panchromatic band
studded PAN	Standard deviation of the panchromatic band (0,6 m pixel size)
stddev MS-BLUE	Standard deviation of the blue band (2,4 m pixel size)
stddev MS-GREEN	Standard deviation of the green band (2,4 m pixel size)
stddev MS-RED	Standard deviation of the red band (2,4 m pixel size)
stddev MS-NIR	Standard deviation of the near infrared band (2,4 m pixel size)
stddev PSM-NDVI	Standard deviation of the NDVI calculation based on the PSM image
ratio MS-BLUE	Value of MS-BLUE divided by the total of MS-BLUE, MS-GREEN, MS-RED, MS-NIR
ratio MS-GREEN	Value of MS-GREEN divided by the total of MS-BLUE, MS-GREEN, MS-RED, MS-NIR
ratio MS-RED	Value of MS-RED divided by the total of MS-BLUE, MS-GREEN, MS-RED, MS-NIR
ratio MS-NIR	Value of MS-NIR divided by the total of MS-BLUE, MS-GREEN, MS-RED, MS-NIR
ND RED-BLUE	Normalized difference of MS-RED and MS-BLUE
ND GREEN-BLUE	Normalized difference of MS-GREEN and MS-BLUE

3 Results

The moose browsing occurs from about 0,5 meter to 3 meters above the ground and mainly on the species pine, rowan, aspen and willow. The browsing damage can be easy to notice from the ground (see Figure 7), but more difficult to detect from above. We were clearly not able to separate out the browsing levels on the images, even when the pixel resolution was down to 25 cm as the HySpex data. With the limited number of sample data we had available we find it unnecessary to do analysis of browsing pressure. The data could not differentiate the pressure with any good confidence.

We got some data on moose browsing damage from a survey Stor-Elvdal grunneierlag conducted in 2006. The accuracy of the GPS points from this browsing survey was not good enough to relate this field data to the exact same area in the images, and we lack a digital forest plan with data of sufficient quality. We did not go further in analysing this data.

Instead we focused on the use of images for the classification of tree species, and other ground components.

Figure 7. *Moose browsing in Stor-Elvdal.*

3.1 QuickBird images

3.1.1 Nearest Neighbour classification

Table 5 presents five different feature sets, their content, and their separation distance. Many more feature sets were tested, but only the most interesting sets are shown. Feature set 1 (FS1) consists of the mean values of all four multispectral bands and of the mean value of the panchromatic band, a 5 dimensional feature space. This resulted in a separation distance of 0.085. For an explanation of all features see Table 4.

Table 5. *Feature sets and separation distance for the QuickBird Nearest Neighbour classification.*

Feature Set name	**FS1**	**FS5**	**FS13**	**FS14**	**F15**
Separation distance	**0.085**	**0.135**	**0.548**	**0.684**	**0.928**
Number of features	**5**	**6**	**6**	**6**	**11**
mean PAN	1	1	1		
mean MS-BLUE	1	1			
mean MS-GREEN	1	1			
mean MS-RED	1	1			
mean MS-NIR	1	1		1	1
mean PSM-NDVI			1	1	
mean PSM-BLUE					
mean PSM-GREEN					
mean PSM-RED					
mean PSM-NIR					
mean PAN-HOM		1		1	1
mean PAN-CON				1	1
mean PAN-ASM					1
stddev PAN			1		1
stddev MS-BLUE					
stddev MS-GREEN					1
stddev MS-RED					
stddev MS-NIR					1
stddev PSM-NDVI			1		
ratio MS-BLUE					
ratio MS-GREEN					
ratio MS-RED					1
ratio MS-NIR					1
ND RED-BLUE			1	1	1
ND GREEN-BLUE			1	1	1

Table 6. *Cross validation results for the QuickBird Nearest Neighbour classification.*

5-fold cross validation		FS1	FS5	FS13	FS14	F15
Grouped Overall Accuracy	**Average**	**0.65**	**0.68**	**0.75**	**0.69**	**0.69**
Grouped Kappa	**Average**	**0.50**	**0.56**	**0.64**	**0.56**	**0.57**
grouped Overall Accuracy	T1234-V5	0.60	0.64	0.72	0.66	0.62
grouped KAPPA	T1234-V5	0.43	0.49	0.58	0.51	0.46
grouped Overall Accuracy	T1235-V4	0.63	0.76	0.79	0.72	0.72
grouped KAPPA	T1235-V4	0.46	0.66	0.70	0.59	0.61
grouped Overall Accuracy	T1245-V3	0.69	0.68	0.78	0.74	0.88
grouped KAPPA	T1245-V3	0.58	0.58	0.70	0.64	0.84
grouped Overall Accuracy	T1345-V2	0.74	0.75	0.82	0.73	0.62
1grouped KAPPA	T1345-V2	0.61	0.64	0.74	0.58	0.45
grouped Overall Accuracy	T2345-V1	0.57	0.58	0.61	0.61	0.62
grouped KAPPA	T2345-V1	0.42	0.45	0.46	0.48	0.49
Overall Accuracy	**Average**	**0.40**	**0.38**	**0.40**	**0.40**	**0.41**
KAPPA	**Average**	**0.31**	**0.29**	**0.31**	**0.30**	**0.32**
Overall Accuracy	T1234-V5	0.40	0.40	0.40	0.42	0.34
KAPPA	T1234-V5	0.31	0.30	0.32	0.34	0.26
Overall Accuracy	T1235-V4	0.29	0.31	0.35	0.35	0.41
KAPPA	T1235-V4	0.22	0.23	0.27	0.25	0.31
Overall Accuracy	T1245-V3	0.49	0.44	0.47	0.46	0.56
KAPPA	T1245-V3	0.39	0.34	0.37	0.35	0.48
Overall Accuracy	T1345-V2	0.37	0.35	0.37	0.32	0.28
KAPPA	T1345-V2	0.29	0.26	0.29	0.24	0.20
Overall Accuracy	T2345-V1	0.46	0.42	0.41	0.43	0.47
KAPPA	T2345-V1	0.36	0.32	0.29	0.33	0.37

In Table 6 the corresponding results of the cross validation can be seen. The table is divided in two parts: the lower part shows overall accuracies and kappa index for all feature sets, five times for each 5-fold cross validation, and one average. The top part shows overall accuracies for **grouped** classes. These classes are deciduous (all deciduous tree species), pine, spruce, and other ground cover (all other vegetated and non-vegetated groundcover). The classes were grouped because it was expected that different deciduous tree species would be hard to separate in a QuickBird image.

FS1 has an overall accuracy for all classes of 0.40 and a kappa index of 0.31. The accuracy and kappa for the grouped classes are 0.65 and 0.50. Kappa index is the coefficient of agreement, ranging from 0 (no agreement) to 1 (full agreement).

When we compare the separation distance of each feature set from Table 5 with the overall accuracies, we see that an increase in separation distance does not result in the same increase in overall accuracy / kappa index. eCognition user manual reports (Definiens, 2000-2004) that Feature Space optimization does not function optimal with strongly correlated features. This makes very hard to choose the optimum feature set for a classification.

While there is almost no difference in performance of different feature sets in overall accuracy, there is difference in grouped overall accuracy. FS13 yields the best results for the grouped overall accuracy.

***Table 7** Confusion matrix of the QuickBird classification expressed in percentage. Only selected classes are shown.*

Classification \ Reference	Alder	Birch	Aspen	Pine	Rowan	Spruce	Willow
Alder	**0**	3	12	2	10	7	6
Birch	27	**36**	40	6	35	21	34
Aspen	9	10	**20**	0	5	0	14
Pine	9	6	4	**73**	0	15	0
Rowan	9	4	8	2	**5**	0	9
Spruce	27	23	8	18	10	**43**	11
Willow	9	16	8	0	30	11	**17**
Sum	100	100	100	100	100	100	100

Table 7 shows the confusion matrix of the QuickBird classification of selected classes. The marked cells (bold) show the percentage of reference cells of each class that were correctly classified. For example, 36 % of the 'birch' samples were correctly classified. Only the class 'pine' scores above 70% correct. There is large confusion between deciduous species and between spruce and deciduous species.

One reason for the low accuracies is the fact that the field samples contained a large variation. Samples for the class 'spruce' could vary from 2 meter high young trees with low crown density to 25 meter mature spruces with dense crowns. There were too few field samples available to divide the classes further into age classes or to put samples of young trees aside. Mature trees in production forest are easier to discriminate than young trees or combinations of young and mature trees in a natural environment.

3.1.2 Support Vector Machine and TreeBoost classification

SVM and TreeBoost classification were tested in order to compare these classifiers with the NN classifier from eCognition. For this comparison we tested only Feature Set 1 and 13 with a classification to four classes. Table 8 shows the accuracy results for the SVM and TreeBoost classification with the same sample data as the NN classification.

***Table 8.** Cross validation results for the QuickBird Support Vector Machine and TreeBoost classification. For comparison the results of eCognition NN classification are repeated.*

	SVM		TreeBoost		eCognition NN	
5 fold cross validation	**FS1**	**FS13**	**FS1**	**FS13**	**FS1**	**FS13**
Grouped Overall Accuracy	0.76	0.78	0.75	0.77	0.65	0.75

The results of SVM and TreeBoost are only slightly better than the results of the eCognition NN classification. While the eCognition NN classification result improves remarkably by choosing another Feature Set, there is almost no difference between the feature sets in case of SVM and TreeBoost classification.

3.2 HySpex images

3.2.1 Nearest Neighbour classification

Table 9 shows the different feature sets for the MNF_**NDVI** classification. This is the MNF where the non-vegetated areas were masked out. The separation distance increases with an increase in the number of features. Since the features (or components) are uncorrelated, the feature space optimization tool of eCognition will function well. In order to save time and effort, only 4 feature sets were tested with cross validation. These are listed in Table 10. Both overall accuracy and grouped overall accuracy increase with an increase of used features.

Table 9. *Feature sets and separation distance for the HySpex MNF_NDVI classification.*

Feature Set name	FS1	FS2	FS3	FS4	FS5	FS6	FS7	FS8	FS9	FS10	FS11	FS12
Separation distance	**0.017**	**0.191**	**0.387**	**0.603**	**0.833**	**1.032**	**1.24**	**1.34**	**1.376**	**1.422**	**1.455**	**1.474**
Number of features	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
NDVI mask MNFLT B1 m												1
NDVI mask MNFLT B2 m							1	1	1	1	1	1
NDVI mask MNFLT B3 m						1		1	1	1	1	1
NDVI mask MNFLT B4 m					1		1	1	1	1	1	1
NDVI mask MNFLT B5 m		1	1	1	1	1	1	1	1	1	1	1
NDVI mask MNFLT B6 m										1	1	1
NDVI mask MNFLT B7 m			1	1	1	1	1	1	1	1	1	1
NDVI mask MNFLT B8 m				1	1	1	1	1	1	1	1	1
NDVI mask MNFLT B9 m	1	1	1	1	1	1	1	1	1	1	1	1
NDVI mask MNFLT B10 m										1	1	1
NDVI mask MNFLT B11 m									1		1	1
NDVI mask MNFLT B12 m						1	1	1	1	1	1	1

Table 10. *Cross validation results for the HySpex MNF_NDVI classification.*

3-fold cross validation		FS3	FS6	FS9	FS12
grouped Overall Accuracy	**Average**	**0,64**	**0,73**	**0,75**	**0,76**
grouped Kappa	**Average**	**0,48**	**0,60**	**0,64**	**0,65**
grouped Overall Accuracy	T12-V3	0,68	0,78	0,82	0,80
grouped Kappa	T12-V3	0,53	0,68	0,72	0,70
grouped Overall Accuracy	T13-V2	0,56	0,64	0,65	0,64
grouped Kappa	T13-V2	0,37	0,47	0,49	0,48
grouped Overall Accuracy	T23-V1	0,68	0,76	0,80	0,83
grouped Kappa	T23-V1	0,55	0,66	0,71	0,76
Overall Accuracy	**Average**	**0,56**	**0,62**	**0,62**	**0,63**
Kappa	**Average**	**0,45**	**0,52**	**0,52**	**0,54**
Overall Accuracy	T12-V3	0,60	0,70	0,64	0,64
Kappa	T12-V3	0,49	0,61	0,54	0,54
Overall Accuracy	T13-V2	0,41	0,45	0,52	0,52
Kappa	T13-V2	0,29	0,35	0,42	0,42
Overall Accuracy	T23-V1	0,66	0,71	0,69	0,73
Kappa	T23-V1	0,56	0,61	0,60	0,64

Table 11 and Table 12 show the different feature sets and cross validation results for the HySpex_**MNF** classification. This is the MNF classification without any vegetation masking. Overall accuracy and kappa are lower than in the MNF_NDVI classification and so is the separation distance. Increasing the amount of features used in the classification does not increase the accuracy in this classification.

Table 11. *Feature sets and separation distance for the HySpex MNF classification.*

Name	FS21	FS22	FS23	FS24	FS25	FS26	FS27	FS28	FS29	FS30	FS31	FS32
Separation distance	**0.032**	**0.191**	**0.441**	**0.634**	**0.841**	**1.006**	**1.08**	**1.159**	**1.196**	**1.236**	**1.283**	**1.291**
Number of features	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
MNFLT B1				1	1	1	1	1	1	1	1	1
MNFLT B2			1							1	1	1
MNFLT B3						1	1		1		1	1
MNFLT B4					1	1	1	1	1	1	1	1
MNFLT B5		1		1	1	1	1	1	1	1	1	1
MNFLT B6								1	1	1	1	1
MNFLT B7			1	1	1	1	1	1	1	1	1	1
MNFLT B8								1	1	1	1	1
MNFLT B9		1	1	1	1	1	1	1	1	1	1	1
MNFLT B10										1	1	1
MNFLT B11												1
MNFLT B12	1						1	1	1	1	1	1

Table 12. *Cross validation results for the HySpex MNF classification.*

3 fold cross validation		FS23	FS26	F29	F32
grouped Overall Accuracy	**Average**	**0.73**	**0.72**	**0.69**	**0.72**
grouped KIA	**Average**	**0.60**	**0.60**	**0.55**	**0.59**
grouped Overall Accuracy	T12-V3	0.78	0.78	0.74	0.78
grouped KIA	T12-V3	0.66	0.673	0.619	0.67
grouped Overall Accuracy	T13-V2	0.667	0.583	0.563	0.594
grouped KIA	T13-V2	0.522	0.406	0.371	0.417
grouped Overall Accuracy	T23-V1	0.729	0.797	0.763	0.78
grouped KIA	T23-V1	0.61	0.71	0.653	0.682
Overall Accuracy	**Average**	**0.57**	**0.61**	**0.58**	**0.60**
KIA	**Average**	**0.45**	**0.51**	**0.47**	**0.50**
Overall Accuracy	T12-V3	0.6	0.68	0.62	0.66
KIA	T12-V3	0.481	0.587	0.51	0.559
Overall Accuracy	T13-V2	0.458	0.448	0.427	0.458
KIA	T13-V2	0.351	0.333	0.308	0.352
Overall Accuracy	T23-V1	0.644	0.695	0.695	0.695
KIA	T23-V1	0.522	0.605	0.588	0.595

Table 13 and Table 14 show the different feature sets and cross validation results for the HySpex_**PCA** classification. In this case, only the feature set FS49 (consisting of 9 features) has been cross validated. Overall accuracy, kappa, grouped overall accuracy and grouped kappa are lower than in the MNF and in the MNF_NDVI classification.

Table 13. *Feature sets and separation distance for the HySpex PCA classification.*

Name	FS41	FS42	FS43	FS44	FS45	FS46	FS47	FS48	FS49	FS50	FS51	FS52
Separation distance	0.036	0.19	0.365	0.595	0.752	0.872	0.95	0.997	1.03	0.997	0.932	0.892
Number of features	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
NDVI mask PCLT B1		1	1	1	1	1	1	1	1	1	1	1
NDVI mask PCLT B2									1	1	1	1
NDVI mask PCLT B3					1	1	1	1	1	1	1	1
NDVI mask PCLT B4										1	1	1
NDVI mask PCLT B5			1	1	1	1	1	1	1	1	1	1
NDVI mask PCLT B6											1	1
NDVI mask PCLT B7								1	1	1	1	1
NDVI mask PCLT B8							1	1	1	1	1	1
NDVI mask PCLT B9	1	1	1	1	1	1	1	1	1	1	1	1
NDVI mask PCLT B10						1	1	1	1	1	1	1
NDVI mask PCLT B11												1
NDVI mask PCLT B12				1	1	1	1	1	1	1	1	1

Table 14. *Cross validation results for the HySpex PCA classification.*

3 fold cross validation		FS49
grouped Overall Accuracy	**Average**	**0.69**
grouped KIA	**Average**	**0.55**
grouped Overall Accuracy	T12-V3	0.72
grouped KIA	T12-V3	0.572
grouped Overall Accuracy	T13-V2	0.646
grouped KIA	T13-V2	0.497
grouped Overall Accuracy	T23-V1	0.695
grouped KIA	T23-V1	0.571
Overall Accuracy	**Average**	**0.51**
KIA	**Average**	**0.38**
Overall Accuracy	T12-V3	0.5
KIA	T12-V3	0.364
Overall Accuracy	T13-V2	0.458
KIA	T13-V2	0.346
Overall Accuracy	T23-V1	0.559
KIA	T23-V1	0.436

The marked cells in Table 15 show the percentage of reference cells of each class that were correctly classified in the HySpex NDVI classification. 86% of the 'pine' samples were correctly classified. The classes 'pine', 'spruce' and 'willow' can be detected quite well. There is a large confusion between the deciduous tree species.

Table 15. *Confusion matrix of the HySpex MNF_NDVI classification. Only selected classes are shown.*

Classification \ reference	Alder	Birch	Aspen	Pine	Rowan	Spruce	Willow
Alder	**11**	10	0	0	11	5	0
Birch	44	**56**	29	5	11	11	0
Aspen	0	3	**43**	0	11	0	0
Pine	22	0	0	**86**	0	5	0
Rowan	22	0	29	0	**11**	3	20
Spruce	0	23	0	7	22	**72**	7
Willow	0	3	0	0	33	3	**73**
Sum	100	100	100	100	100	100	100

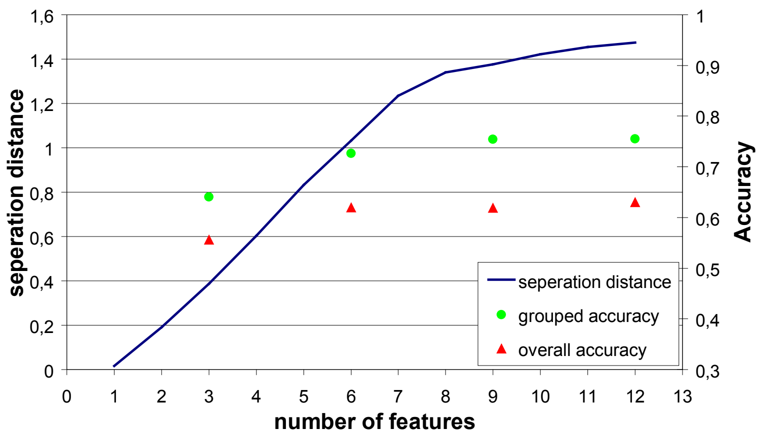

Figure 8. *Separation distance and accuracy for HySpex MNF classification.*

The Euclidian separation distance for the HySpex_**MNF** classification is plotted as a blue line in Figure 8. This separation measure is reported in eCognition as a helpful tool for feature reduction. The figure shows first a steady increase with an increasing number of features. From 8 features and up the curve flattens. The accuracies, displayed as green and red markers, show the same trend and reach a top of about 0.76.

3.2.2 Support Vector Machine and TreeBoost classification

Table 16 shows the accuracy results for the SVM and TreeBoost classification, using the same sample data as for the eCognition NN classification. Only Feature Set 3 and 12 were tested for the four grouped classes.

Table 16. *Cross validation results for the HySpex MNF_NDVI Support Vector Machine and TreeBoost classification. For comparison the results of eCognition NN classification are repeated.*

	SVM		**TreeBoost**		**eCognition NN**	
3 fold cross validation	**FS3**	**FS12**	**FS3**	**FS12**	**FS3**	**FS12**
Grouped Overall Accuracy	0,63	0,81	0,64	0,81	0,64	0,76

The accuracies from SVM and TreeBoost are both 5% higher than the results from eCognition NN classification for feature set 12. SVM and TreeBoost have equal accuracies. Both eCognition NN, SVM and TreeBoost show an increase in accuracy when more features are used. This is illustrated by the difference between FS3 (3 features) and FS12 (12 features).

4 Discussion, conclusion and recommendations

4.1 Discussion

It is not very practical to use optical aerial or satellite sensors to measure browsing damage, since these sensors measure from above. Browsing can take place at the lower, reachable parts of the crowns of mature trees, or at the whole crowns of young trees. In the case of mature trees, the damaged part of the crown is easily obscured by the unaffected part of the crown above it. This makes the browsing damage invisible from above, no matter how detailed the sensor can make an image. In case of young trees, browsing damage eliminates almost all green biomass of the tree. This leaves only the stem and branches, which are almost invisible from above. To make it worse the young trees are difficult to separate from ground vegetation.

Optical images from above do not seem an obvious choice for detecting moose browsing damage at the level of single trees. At the level of forest stands they could be useful in case of browsing damage at young trees. If an existing forest map is available, giving information on soil productivity, planted (or natural re-growth) tree species, and the tree age, then images could be used to detect differences of vegetation quantity. For example, if to forest stands have equal soil productivity, tree species and age, and one stand has less re-growth, then this difference could be caused by moose browsing. Other causes like deceases or slightly different environments could also be the cause.

The overall accuracy of the classification of all classes (9 classes listed in Table 3) is generally low. Only the classes pine, spruce and willow perform reasonably well.

Using the HySpex image increases the classification results compared to using the QuickBird image, keeping the classification algorithms the same. Overall accuracy increases from 40% to 63%. Where the QuickBird image could only separate the class pine well, the HySpex image separates spruce and willow in addition to pine. It is remarkable that the classification result of the grouped classes (Pine, spruce, deciduous, other groundcover) does not increase so much when HySpex is used instead of QuickBird.

The accuracies of the classification are not very high. A part of the reason for this is the fact that the number of sample areas is not high, and the fact that the samples of the classes have a large variation. This could be improved by taking more samples in general, by further dividing classes into subclasses (age or size), and by taking more homogeneous samples for these subclasses. But still then there would be confusion between several classes. Young spruce, for example, is very alike mature deciduous tree species on images. And grass and small bushes are difficult to separate from mature deciduous tree species.

The classification results in our study are comparable to those of (Kamagata et al. 2006). He used three different methods to classify vegetation in an IKONOS image. Object-base, pixel-based and ISODATA classification method were compared. The vegetation classes were Evergreen broad-leaved forest, Deciduous broadleaved forest, Secondary Grassland, Wetland vegetation, Conifer plantations, and Bamboo groves. Object-based classification resulted in an overall accuracy of 64% and a kappa index of 0.55. Pixel-based classification scored 60% and 0.49, while ISODATA gave the lowest results, 54% and 0.39.

There is no large difference in classification result between the different algorithms. Nearest Neighbour, Support Vector machines, and TreeBoost all perform almost equally on the QuickBird image. On the HySpex image SVM and TreeBoost perform about 5% better than Nearest Neighbour. The HySpex image contains much more information than the QuickBird image. Apparently, SVM and TreeBoost are better to make use of this higher information content.

No ancillary data has been used in our study. Using Digital terrain models or for example soil productivity maps could increase classification results. (Förster and Kleinschmit, 2006) compared results of a QuickBird classification in the Bavarian forest with and without the use of ancillary information. Ancillary information consisted of Digital Terrain Models (DTM), soil maps and silvicultural maps. An object oriented image classification method was performed with the software eCognition. The tree species Beech, Spruce, Black Alder, Larch and Sycamore were used as classes. Overall accuracy of 75 to 77 % was reached with the use of ancillary information and 64 to 70 % without the use of ancillary information.

The use of other sensors could also improve results. We used a hyperspectral sensor with bands from 400 to 1000 nm. The short wave infrared part of the spectrum (from 1000 to 2500 nm) also contains valuable information for vegetation studies. (Clark et al. 2005) used the HYDICE hyperspectral scanner in combination with field spectra for the classification of tropical tree species. HYDICE has 210 bands ranging from 400 nm to 2500 nm. This sensor data was also used to simulate an IKONOS image. Both pixel based classification and Individual Tree Crown delineation (ITC) was used. The highest accuracy was reached at crown level with 30 optimally selected bands. Overall accuracy was 92 %. The IKONOS simulated data gave an overall accuracy at crown level of 59 % (Linear Discriminant Analysis), 50 % with Maximum Likelihood Classification (MLC), and 20 % with Spectral Angle Mapper (SAM).

Individual Tree Crown delineation (Leckie et al. 2005) could be another method to improve classification results. This approach delineates individual trees from aerial or satellite images and classifies the tree species. ITC functions best on not to dense forest, which means no overlapping crowns. Of course the tree crowns should be large and dense enough to be detected, but this is mainly dependant on the image characteristics. Trees with height less than 3 meters might be hard to detect.

Furthermore, LIDAR (Light Detection And Ranging) data and optical images form a powerful combination (Leckie et al. 2003). Optical images are best for classifying tree / vegetation species and vegetation health, while LIDAR is best for measuring heights and densities. These two sensor types complement each other and could improve a part of the classification errors encountered in our study: the confusion of ground vegetation, bushes, and deciduous tree crowns, and the confusion of young spruce trees and deciduous trees. Incorporating height classes from LIDAR data would eliminate these problems.

It is likely that the use of LIDAR in combination with optical data can increase the classification results by 10 to 20%. As an estimate, the use of ancillary data could increase the classification results by about 10%, of course depending on the quality of the ancillary data. It cannot be expected that these improvements will be evenly divided over all classes: some classes might show large improvements in classification accuracy, while others will not show any improvement.

4.2 Conclusions

The following conclusions can be drawn with respect to the QuickBird image classification:

- Overall accuracy of all classes using NN classification reached 40%, the kappa index 0.31
- Overall accuracy of grouped classes ('pine', 'spruce', 'deciduous', 'other groundcover') using NN classification reached 75%, the kappa index 0,64
- QuickBird could discriminate the class 'pine' reasonably well in this study area.
- Support Vector Machines did not improve the classification much when using the same samples and features as the NN classification (78%). Neither did the TreeBoost classification (77%).

- The following conclusions can be drawn with respect to the HySpex image classification:
- Overall accuracy of all classes using NN classification reached 63%, the kappa index 0.54
- Overall accuracy of grouped classes ('pine', 'spruce', 'deciduous', 'other groundcover') using NN classification reached 76%, the kappa index 0.65
- HySpex (400nm -1000nm) can discriminate the classes 'pine' good, 'spruce', and 'willow' reasonably well.
- Minimum Noise Fraction transformation with the use of NDVI masking yields higher classification accuracy than MNF without NDVI masking.
- Minimum Noise Fraction transformation with the use of NDVI masking yields higher classification accuracy than Principal Component Analysis.
- Both Support Vector Machines and TreeBoost classification improved the accuracy by 5 % using the same 12 features as the NN classifier.

The main conclusion concerning the use of eCognition:

- The parameter 'separation distance' of the feature space optimization tool in eCognition is not useful to find the optimal feature set for a Nearest Neighbour classification when the features are correlated. By optimal is meant: the feature set resulting in the highest classification accuracy. Feature space optimization is useful when features are non correlated; this is the case with PCA and MNF.

General conclusions:
Optical images alone (aerial nor satellite) are not suitable to map moose browsing pressure.

It is difficult to say whether the classification results of maximal 70 to 80 % are high enough to be valuable for the mapping of moose browsing resources. It's is however certain that the accuracies of some important classes are too low to be of value.

The end result of a classification is determined by the input image, the classification method, and the classes / samples. Several classification methods on two different types of images reached comparable results. Although some methods perform slightly better there is no large difference. The HySpex image yields slightly better results than the QuickBird image, but again there was no major improvement. ***Therefore, the highest potential for improvement lies in choosing samples with a higher quality and combine the optical data with LIDAR data.*** There are three main factors determining the quality of samples. The first is complexity of the classes and the landscape. The second is the amount of samples that are taken. The third is the amount of errors made in collecting the samples. In forest classification the use of LIDAR is increasing, so for future mapping this type of data will be more available.

The grouping of the samples into four classes decreased the complexity and increased the accuracy of the classification. However, the results of some classes (for example spruce) were still lower than expected. The amount of samples taken was too low for a good training and validation of the classifiers. The low accuracy of some classes indicates that the samples contained a high amount of errors.

4.3 Recommendations

There are several options to improve the results of the vegetation classification in this area.

- The most important is probably to add other sensor data like LIDAR (Light Detection And Ranging) data. Measuring height of the vegetation, LIDAR gives information that is complementary to passive optical images and therefore very useful for a classification.
- A second option is to add more image data. In addition to the VNIR mode used in this study, the HySpex sensor could be used in the SWIR mode (which ranges from 1000 nm to 1700 nm). This could improve the classification significantly. Such options do not exist in case of the QuickBird sensor.
- A third option is to make use of existing information like height models, geomorphologic maps, existing forest maps, and other maps as support in a classification.
- A fourth option is to collect more and more accurate samples of all class that will be mapped.

If these recommendations are followed, we believe it is possible to map moose browsing resources with high accuracy. More research is needed to investigate whether it is possible to map moose browsing pressure.

5 Abbreviations and Acronyms

DT	Decision Tree
GPS	Global Positioning System
LIDAR	Light Detection And Ranging
MNF	Minimum Noise Fraction
NDVI	Normalized Difference Vegetation Index
NN	Nearest Neighbour
NEO	Norsk Elektro Optikk
PCA	Principal Component Analysis
PSM	Pan Sharpened Merge
RMS	Root Mean Squared
SVM	Support Vector Machine

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