TREE SPECIES CLASSIFICATION USING ERS SAR AND MODIS NDVI IMAGES

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ABSTRACT:

A set of ERS SAR and optical MODIS-images were classified to land cover and tree species classes. Different methods for pixel and decision based data fusion were tested. Classifications of featuresets were carried out using Bayes rule for minimum error. The results were not very successful, the classification accuracies of land cover classes varied from 43% to 75%, depending on the used features and classes. The decision based data fusion method, where the a'posteriori probabilities representing the proportions of different land cover classes of low resolution classification are used as a'prior probabilities in high resolution classification looks promising. Using this method, the increase of overall and classwise accuracies can be more than 10 and 25 %-units, respectively.

1. INTRODUCTION

Forest assessment deals with the methods of obtaining information on forest resources: estimation of growing stock, growth and health of the forest. That information is a basis for decisions of the forest industry, the official forest policy and the forest owners. For countries such as Finland, where 30% of exports is based on forestry products and the percentage of the forest area (76%) is the highest in the world, development of inventory methods are a necessity.

The national forest inventory of Finland was the first national inventory in the world to use satellite images (Tomppo 1991). It is based on the use of optical data like Landsat images. Unfortunately weather conditions limit the use of optical data. For example, here in Finland summertime is usually quite cloudy. There are usually only several days in summer when large area of Finland is cloud-free, and during wintertime it is dark also daytime and snow everywhere. These facts have lead to investigate the use of SAR-images in forest inventory.

The previous single frequency / polarization spaceborne SAR-instruments have not been that successful from land cover or forest classification point of view (Herold et.al., 2004, Kurvonen et.al., 2002, Törmä, 1999). This is due to the low information content of individual images and noise which is difficult to remove. Utilization of texture (Kurvonen et.al., 2002, Törmä, 1999), coherence (Gaveau et.al., 2003, Törmä, 1999) or polarization information (Randon et.al., 2001) improve results. The instruments in the new Envisat satellite seem promising due to the multipolarization SAR and low resolution optical instrument MERIS. So, the natural alternative to enhance the information obtained using Envisat SAR is to fuse it with MERIS. Unfortunately, our project has not yet received any Envisat-images, so we have made our early experiments using ERS SAR and MODIS-images.

The aims of this study are

- to evaluate the value of ERS SAR-intensity images in land cover and tree species classification,
- to select the best texture features for classificatiion and their benefits,
- study different factors like the use of temporal data, the effect of the soil of forest stand, the effect of the age of forest stand,
- compare pixelwise and standwise classification, and
- study the possibilities to enhance the classification with low resolution MODIS data.

2. TEST AREA AND DATA

Test area used in this study is situated at Hyytiälä in middle Finland (Lat. 61d50'N, Long: 24d22'E). Hyytiälä has a forestry research station which belong to the Faculty of Forestry and Agronomics at Helsinki University. The area is covered by standwise forest inventory.

2.1 Satellite images

The SAR dataset consists of 8 ERS-2 SAR intensity images taken during 1999. The image resolution is 25 meters, and the raw images have a pixel spacing of 12.5 meters. The characteristics of of ERS-images are illustrated in table 1 (Kramer, 1996). The DEM produced by National Land Survey used in the image processing has a pixel size of 25 meters. The image processing was conducted using Gamma Ltd. Software. It performs topographic correction with a very high positional accuracy (Wegmüller et al. 1998). The images were averaged from 12.5 meter to 25 meter pixel spacing after the image processing.

The optical dataset consists of 176 MODIS-spectrometer images (table 1) taken during 2000. MODIS-spectrometer has 36 channels (Masuoka et.al., 1998) with three different spatial resolution levels. Channels 1 (red: 0.62 – 0.67 µm) and 2 (nir: 0.841 – 0.876 µm) were used due to their relatively high spatial resolution (250 meters) compared to other channels.

Data	ERS (microwave)	MODIS (optical)
Wavelenght	5.7 cm (C-band, 5.3 GHz)	1: 0.62 – 0.67 µm 2: 0.841 – 0.876 µm
Number of images and acquisition times	8: 31.3., 16.4., 5.5., 9.6., 14.7., 8.10., 27.10. and 12.11.1999	176: 1.4. – 30.9.2000
Spatial res. (m)	25 – 30	250

Table 1: Overview of the acquired satellite images.

2.2 Ground truth

The area of Hyytiälä research station is covered by standwise forest inventory made during 1995 - 2001. Data collection is based on visual interpretation of aerial photographs and field measurements. Inventory contains almost 4000 stands, but these are not all applicable in this study. Stands are rather small; the average, median and maximum sizes are 2.1, 1.2 and 428.6 hectares, respectively.

2.3 Classification systems

In order to study the information properties of the satellite images, different kind of classification systems were created using standwise forest inventory. Training and test sets for classification were selected using random sampling. The desired number of samples per class was 1000 but it is smaller for some small classes. The border pixels between stands were removed before sampling.

Training data for MODIS-classification was acquired by estimating the proportions of land cover classes for each MODIS-pixel. This approach was chosen because the size of MODIS-pixel is 6.25 ha and the average size of stands is 2.1 ha.

2.3.1 Land cover / use classification: This classification was used to determine the suitability of the used satellite images to discriminate general land cover types. There were 2223 stands in this classification and their average, median, minimum and maximum sizes were 2.6, 1.6, 0.07 and 428.6, respectively. The classes in this classification are, including statistics as number of stands, average size (ha), number of pixels, number of pixels in training set and number of pixels in test set:

1. Water: 23, 7.1, 2133, 556, 518
2. Pine dominated forest: 1382, 2.5, 45367, 1347, 1361
3. Spruce dominated forest: 558, 2.1, 15314, 1065, 1114
4. Deciduous tree dominated forest: 88, 1.8, 2304, 573, 531
5. Agricultural land: 1, 77.9, 1197, 317, 276
6. Open bog: 36, 14.3, 2031, 520, 498
7. Open land: 135, 2.5, 4723, 1024, 1022

2.3.2 Tree species vs. development class: This classification was used to determine the suitability of the used satellite images to discriminate tree species according to the amount of trees. In other words, is it better to use these images to separate tree species or the amount of trees. There were 1652 stands and their average, median, minimum and maximum sizes were 2.6, 1.8, 0.14 and 63.0, respectively. The classes in this classification are:

1. Pine, sapling: 275, 2.6, 9015, 1021, 996
2. Pine, young stand: 443, 2.7, 15515, 1075, 1130
3. Pine, middle aged stand: 290, 3.4, 11856, 1079, 1073
4. Pine, regeneration maturity: 112, 2.1, 3073, 973, 865
5. Spruce, sapling: 97, 2.5, 3037, 959, 854
6. Spruce, young stand: 63, 1.9, 1748, 566, 492
7. Spruce, middle aged stand: 162, 2.3, 4823, 1050, 1049
8. Spruce, regereration maturity: 133, 2.3, 4201, 955, 952
9. Deciduous, sapling: 27, 2.2, 898, 245, 203
10. Deciduous, young stand: 35, 1.9, 965, 261, 215
11. Deciduous, middle aged stand: 15, 1.6, 288, 113, 120

2.3.3 Tree species vs. soil type: This classification was used to determine the suitability of the used satellite images to discriminate tree species according to soil type. In other words, does the soil type have some effect to the tree species classification. There were 1718 stands and their average, median, minimum and maximum sizes were 2.6, 1.7, 0.07 and 63.0, respectively. The classes in this classification are:

1. Pine on mineral soil: 970, 2.8, 33693, 986, 1023
2. Pine on hardwood swamp : 27, 1.4, 813, 226, 182
3. Pine swamp: 199, 2.6, 6971, 1011, 1044
4. Spruce on mineral soil: 337, 2.3, 10012, 1026, 1017
5. Spruce on hardwood swamp: 112, 2.2, 3801, 1100, 1037
6. Deciduous on mineral soil: 47, 2.1, 1317, 344, 310
7. Deciduous tree on hardwood swamp: 26, 1.6, 728, 251, 197

3. INTERPETATION METHODS

In order to extract relevant information and produce as good classification as possible, there is need to fuse these two different kinds of satellite data sets. Data fusion can be performed on different levels (Pohl and van Genderen, 1998):

- Pixel based fusion: This means that the measurements or measured physical parameters have been fused. In other words, the feature vector is combined directly from different datasources.
- Feature based fusion: This means that features have been extracted from different data sources using e.g. image segmentation. In this case the features can be e.g. size, shape and average intensity level of areas. These features form feature vectors describing the extracted objects.
- Decision based fusion: This means that the objects have been identified from individual data sources and then these interpretation results are combined using e.g. rules to reinforce common interpretation.

Data fusion in this study is mostly based on pixel based fusion, but also one kind of decision based fusion is tested. Pixel based fusion is performed by constructing different featuresets.

There is a large amount of data, so different methods for feature extraction and selection are needed. Feature selection means that the best set of images is chosen from all images using some criteria like the separability of classes. Feature extraction means that new images are computed from the original ones containing as much relevant information as possible. The classification of featuresets using different classification systems was carried out using Bayes rule. Different classification methods were tested with MODIS NDVI-mosaics and in the end these were classified using Maximum Likelihood classifier.

3.1 Feature selection

3.1.1 Bhattacharyya-decision theoretic distance: Class separability was measured using the Bhattacharyya distance. It is a probabilistic distance between two classes. Classes are supposed to be normally distributed, so classes are defined by their mean vectors and covariance matrices (Devivjer et.al, 1982). Then Bhattacharyya distance was transformed so that the range of distance would be between 0 and 2, the latter meaning perfect separability.

3.1.2 Branch-and-bound algorithm: Branch-and-Bound feature selection algorithm was used to select the best subset of images from all images according to the separability of classes. The selection criteria was the average interclass divergence. The divergence is a measure of separability between two classes, computed using class means and covariances. It is assumed that the classes are normally distributed (Devivjer et.al., 1982).

3.2 Feature extraction

3.2.1 Weekly NDVI-mosaics from MODIS: In order to decrease the amount of MODIS-data it was decided to compute weekly NDVI-mosaics. Normalized Difference Vegetation Indices were computed using red and near-infrared channels as (NIR–RED)/(NIR+RED). Then these NDVI-images were grouped according to their acquisition week. Finally, the weekly mosaic was constructed by selecting the maximum NDVI-value of individual images as mosaic value in order to get rid of clouds.

3.2.2 Texture features from ERS-images: Texture can be defined as a variation of the pixel intensities in image subregion. The assumption is that the intensity variation of different land-use classes are different and by characterizing texture by using some measure we can help class discrimination. Texture features describing the spatial variation of image grey levels were computed from original intensity images (12.5 m pixel size) using Haralick's co-occurence matrix (Haralick et.al., 1973). A co-occurrence matrix is a two-dimensional histogram of grey levels for a pair of image pixels which are separated by a fixed spatial relationship. Following texture measures were computed from co-occurrence matrix: Angular Second Moment, Contrast, Correlation, Dissimilarity, Entropy, Homogeneity, Mean and Standard Deviation.

3.2.3 Principal component analysis: Principal component transformation is a linear transformation which rotates the coordinate axis of the feature space according to the covariance of data (Richards, 1993). The result of the transformation is a new set of images, where in principle, the first images correspond to the information needed in classification and the latter images correspond to the random components like speckle. It should be noted that the image variance is used as a measure of image information and it can depend on the scaling of images.

3.3 Computed featuresets

Pixel based data fusion was performed by constructing different featuresets for classification. The selected dimension of feature space was six. These featuresets were:

1. The six best median filtered ERS-intensity images chosen from all ERS-intensity images using Branch-and-Bound algorithm. The size of filtering window was 3x3 pixels. The chosen images were taken 31.3., 16.4., 5.5., 9.6., 14.7., 8.10.1999.
2. The principal component analysis was performed to all median filtered ERS-intensity images. The six first principal component images were chosen.
3. The three first PCA-images were computed from median filtered intensity images. Texture images were computed using features Mean and Angular Second Moment for all unfiltered intensity images (12.5 m pixel size), averaging them to 25 m pixel size, normalizing features to zero mean and unit variance and performing the principal component analysis. Three first principal component images were chosen.
4. The three first PCA-images were computed from median filtered intensity images. The two first PCA-images were computed from texture features as previously. MODIS NDVI-mosaic (week 31) was selected as the sixth feature.
5. The two first PCA-images were computed from median filtered intensity images. The two first PCA-images were computed from texture features. The principal component analysis was also performed for all MODIS NDVI-mosaics and the two first principal component images were chosen.
6. The two first PCA-images were computed from median filtered intensity images. The two first PCA-images were computed from texture features. Two features were computed from the a'posteriori probabilities of Maximum Likelihood classification of MODIS NDVI-images. The first MODIS NDVI-feature was the a'posteriori probability of forest classes. The second feature was the sum of a'posteriori probabilities of classes agricultural land and open land.

3.4 Classification algorithms

3.4.1 Bayes rule: Classifications of featuresets were performed using Bayes rule for minimum error with k-nearest neighbor density function estimation method (Devivjer et.al., 1982). Number of nearest neighbors, k, varied from 1 to 15. A'priori probabilities for classes were equal or a'posteriori probabilities of MODIS NDVI-classification were used as a'priori probabilities. This is one way to perform decision based fusion; use the result of low-level interpretation as input to a higher level interpretation (Schneider et.al., 2003). Classification errors were estimated using resubstitution and holdout methods, meaning that the ground truth data was divided to training and test sets. In resubstitution method the same set is used as training and test set (optimistically biased method) and in holdout method data is divided to training and test sets (pessimistically biased) (Devivjer et.al., 1982).

3.4.2 Classification of MODIS-images: The aim of the classification of MODIS NDVI-mosaics was to produce the proportions of different land cover classes for each MODIS pixel. The classifications were made using Spectral Angle Mapper (Kruse et.al., 1993), Spectral Unmixing (Kruse et.al., 1997), fuzzy Maximum Likelihood (Wang, 1990) and traditional Maximum Likelihood (Lillesand and Kiefer, 1994) classifiers.

3.5 Error measures

The success of classification was measured using error matrix in the case of featuresets and computing bias, RMSE and correlation in the case of MODIS NDVI-classification.

3.5.1 Error matrix and measures: One of the most common means to examine the classification result is to form classification error matrix which compares the relationship between reference data and classification result on class-by-class basis. The columns of error matrix correspond to the reference data, showing into which classes the reference pixels have been classified. The rows of error matrix correspond to classes in the classification result. Several accuracy measures like Overall accuracy, Producer's accuracies of individual classes, User's accuracies of individual classes and Kappa coefficient were computed from error matrix (Lillesand and Kiefer, 1994).

3.5.2 Error measures for MODIS-classification: The result of the classification MODIS NDVI-mosaic was the proportions of the land cover classes within MODIS-pixels. In this case the accuracy of classification was evaluated by computing bias, root-mean-square-error and correlation between training data and estimated proportions.

4. RESULTS

4.1 Feature selection for ERS SAR-images

4.1.1 Individual ERS-images: Figure 1 represents the average separabilities of land cover classes as function of average transformed Bhattacharyya-distance. The best separabilities have been acquired using images taken 5.5.1999, 16.4.1999 and 8.10.1999, but even in these cases the average separability is rather low. The corresponding weather conditions have been full snow cover with raining wet snow, 50% snow cover with raining wet snow quite heavily, and it has been raining (Pulliainen, 2004). So, it seems that the best conditions in order to separate these land cover classes are wet snow or ground. The worst separabilities have been acquired using images 14.7.1999 (no rain) and 27.10.1999 (some rain). Class water is the most separable class, the worst are agricultural field and open land. Median filtering of the intensity images increases the separability. The separabilities are higher with 25m pixel size than 12.5m pixel size.

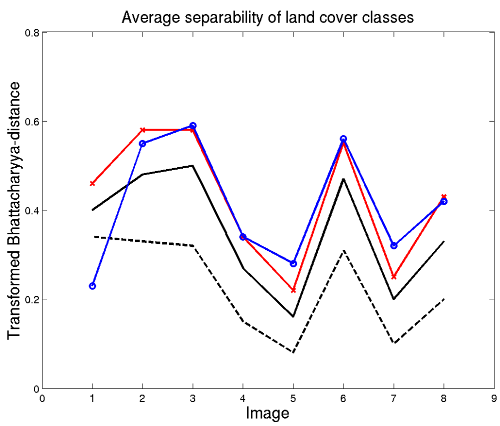

Figure 1. The average separabilities of land cover classes as function of average transformed Bhattacharyya-distance, dashed line means that separabilities have been computed from original ERS-intensity images, solid median filtered intensity images, solid line with "x" texture feature Mean and solid line with "o" texture feature Angular second moment.

In the case of tree species vs. development class, the separabilities between classes are very low. The best image is taken 14.7.1999 in dry and warm conditions. In the case of tree species vs. soil type, the separabilities between classes are very low. The best image is taken 31.3.1999, in full wet snow cover and rainy (water) conditions.

4.1.2 Texture features: The separabilities of texture images varied a lot depending on the used texture feature. The best ones were Angular Second Moment and Mean, their average separabilities as function of image are represented in figure 1. The behaviour of the average separability is very similar than in the case of intensity images. In the case of texture feature Angular Second Moment, the most separable land cover class is water, the worst are pine forest and open land. In the case of texture feature Mean, the most separable land cover class is water, the worst pine, deciduous forest and open land.

As the classification system is tree species vs. development class, the separabilities are rather low. The most separable classes are middle aged pine in image taken 8.10.1999 and spruce sapling in image taken 31.3.1999. As the classification system is tree species vs. soil type, the separabilities are low. The most separable classes are pine and spruce on mineral soil.

4.1.3 Best SAR-images: The best subsets of ERS-images were selected using Branch-and-Bound algorithm with average interclass divergence as selection criteria. The four most important images were taken 5.5., 16.4., 8.10. and 9.6.1999, in the case of intensity images and land cover classes. Two of these images have been taken in wet snow conditions, one in rainy and on in rather dry conditions.

The most important texture features varied a lot depending on the classification system. The three most important features for land cover classification were Mean, Entropy and Standard deviation, and the worst was Homogeneity. The three most important features for tree species vs. development class classification were Homogeneity, Contrast and Dissimilarity, and the worst was Angular Second Moment. The three most important features for tree species vs. soil type classification were Angular Second Moment, Mean and Correlation, and the the worst was Dissimilarity.

4.2 Classification of MODIS-images

Fuzzy means were calculated using weekly NDVI maximum images and training data for every class. The idea was that the fuzzy means could be used as training data in a supervised classification. Figure 2 represents these means for land cover classes. The beginning of the growing season can be seen during weeks 16-18 from the beginning of the year. Lower values during the weeks 23 and 27 are probably due to bad weather.

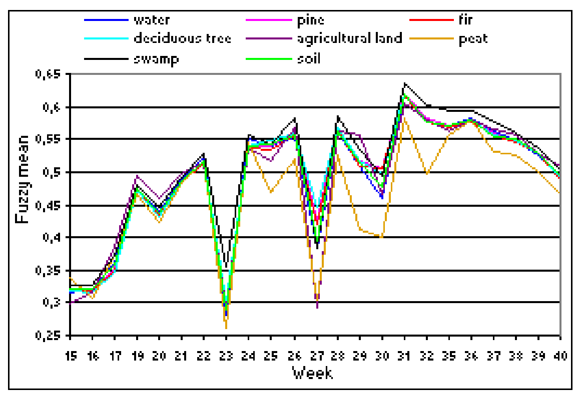

Figure 2. The fuzzy means of different land cover classes computed from MODIS NDVI-mosaics.

The aim of the classification of MODIS NDVI-mosaics was to produce the proportions of different land cover classes for each MODIS pixel. First, the fuzzy means were used as training data for Spectral Angle Mapper and Spectral Unmixing classifications. Unfortunately the results were quite poor. Fuzzy supervised classification was also carried out. After calculating the fuzzy means and fuzzy covariance matrix, the membership values for each class were computed. Results of this method were slightly better than previous ones.

Due to poor results of previous algorithms, the Bayesian Maximum Likelihood classification was carried out. Training data pixels whose proportion of the main class was more than 50 % formed the training set of that class. These pixels were decided to represent absolute and single classes. The a'posteriori probabilities produced by BML were used to represent the proportions of different land cover classes within each MODIS-pixel.

The a'posteriori probabilities were compared to training proportions of different classes and measures like bias, RMSE and correlation computed. The best classes were Agricultural land (bias –15.7, RMSE 40.2, correlation 0.61), Open bog (-2.8, 17.4, 0.55) and Water (-3.3, 27.1, 0.43). The worst classes were forest classes, then the correlations were very low (0.20-0.04).

4.3 Classification of featuresets

The classification errors of land cover classes are represented in figure 3. For each featureset, classifications were performed with varying k for both training and test sets. The a'priori probabilities of classes were equal. The final overall accuracy was estimated as the mean overall accuracy of the training and test sets with highest test set overall accuracy. Overall accuracies of different featuresets are rather low, the feature extraction using principal component analysis and texture increase the accuracy only a little. The use of MODIS-features increases the overall accuracy more, from 43% to about 50%.

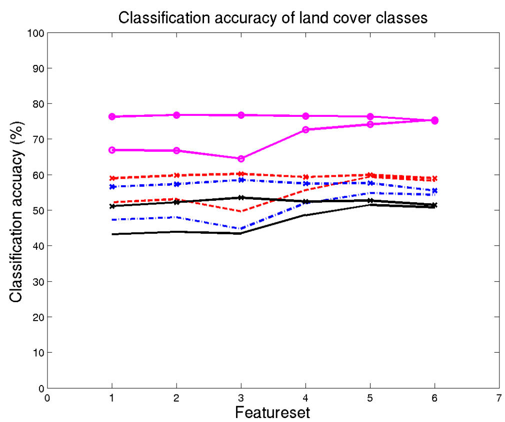

Figure 3. Solid line represents the overall accuracy of land cover classes, dashed line the mean of producer's accuracies and dash-dot line the mean of user's accuracies of classes. Lines with "x" perpresent the cases when the a'prior probabilities have been estimated from MODIS images. Lines with "o" represent the cases when classes have been merged to four.

The best class is water, its classwise accuracies are about 90% and the variation between featuresets is quite low. The classwise accuracies of forest classes are low, varying from 20% to 45%. Forest classes are mainly mixed with each other but also to agricultural land with featuresets 1-3. The class agricultural land is classified reasonably well with featuresets 4-6, then the classwise accuracies are more than 80%. Agricultural land benefits from the use of MODIS-features. Classwise accuracies are lower with featuresets 1-3, producer's accuracies are less than 30% and user's accuracies about 80%. This means that if image pixel is classified as agricultural land, then it quite likely that it is agricultural land in the field. Agricultural land is mainly mixed with open land and pine dominated forest. The accuracies of class open bog are moderate with featuresets 1 and 2, between 60-70%. The use of texture and MODIS-classification decrease the classwise accuracies. Open bog is mainly mixed with pine and spruce dominated forest. The class open land is classified rather badly, classwise accuracies are aroung 40%. It is mainly mixed with forest classes and agricultural land. The mixing of different classes happen a quite similar way with different featuresets.

The overall accuracies of tree species vs. development class classification varied from 20% (featuresets 1 and 2) to 30% (featureset 5). When the classes are merged to three tree species classes, then the overall accuracies vary from 38% to 45%. When the classes are merged to four development classes, the overall accuracies vary from 49% to 57%. This means that the features are a bit more sensitive to the size of the trees than species.

The overall accuracies of tree species vs. soil type classification varied from 30% (featuresets 1 and 2) to 38% (featureset 5). When the classes are merged to three tree species classes, the overall accuracies vary from 51% to 57%. When the classes are merged to three soil type classes, the overall accuracies vary from 47% to 53%. This means that the features are a bit more sensitive to the tree species than soil type.

4.3.1 A'priori probabilities from MODIS: The use of the a'posteriori probabilities of MODIS NDVI-classification as a'priori probabilities of Bayes classification increases the overall accuracies of featuresets 1-3 from about 43% to more than 50% (figure 3). The increase is smaller for featuresets 4-6, which already use information from MODIS in one way or another. The increase of overall accuracy is about 1-3 %-units. The increase of classwise accuracies are very small for class water, otherwise the increase can be even 25 %-units with the featuresets 1-3. Increase is much smaller for featuresets 4-6. When the mixing of classes is studied, it can be seen that forest classes are more mixed between each other than using equal a'priori probabilities.

In the cases of tree species vs. development class or soil type the a'prior probabilities of classes were acquired from the a'posteriori probabilities of classes pine, spruce and deciduous tree of MODIS-classification. These did not increase the overall accuracies much, only 1-3 %-units depending on the featuresets or classes.

4.3.2 Merging of classes: The merging of classes to four classes (water, forest, agricultural and open land, and open bog) increases the overall accuracies to about 65%-75%, depending on the featureset (figure 3). The accuracies are lower with featere sets 1-3 when equal a'priori probabilities are used, but increase as MODIS-features are used. When a'priori probabilities have been acquired from MODIS-classification, the overall accuracies do not vary much between different featuresets, they are always around 75%.

4.3.3 Comparison of pixelwise and standwise classification: Tree species classes of land cover classification system were used to compare pixelwise and standwise classification. Data for standwise classification was acquired by computing the stand means of the featuresets. Stand means were divided to training and test sets and classified using Bayes rule for minimum error. Figure 4 illustrates the overall accuracies as well as the mean of user's and producer's accuracies as the function of featuresets. In general, standwise classificaton increases the overall classification accuracy, the gain is 10%-units or more. But the drawback is that as the classwise accuracies of pine increase, those accuracies for deciduous tree decrease. This is most likely due to that the pine stands are larger than deciduous tree stands, so mean values are more reliable for pine and the amount of stands for deciduous tree is rather small, especially compared to pine.

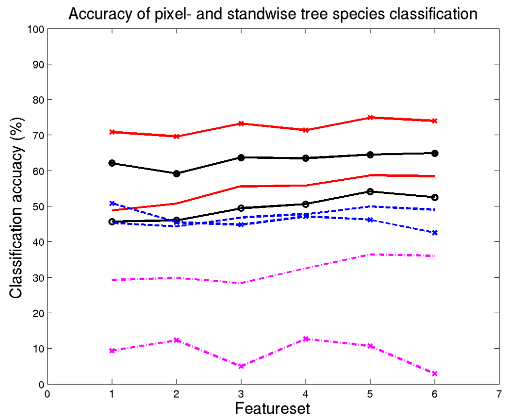

Figure 4. The classification accuracies of pixelwise and standwise tree species classifications. The solid line with "o" represents the overall accuracies, solid line the mean of user's and producer's accuracies of pine, dashed spruce and dashdot deciduous trees. The accuracies of standwise classifications have been represented with "x".

5. CONCLUSIONS

These results illustrate that it is difficult to make accurate land cover classification using one frequency, one polarization microwave information even if there are some temporal resolution or low resolution optical data available. More information about the target would be needed, like interferometric coherence, or more than one frequency or polarization. The feature extraction increased classification accuracy a bit but not much. The standwise classification increases accuracy due to feature averaging.

The decision based data fusion using a'posteriori probabilities of low resolution classification as a'priori probabilities of high resolution classification shows promise, but needs some development. The increase of overall and classwise accuracies in this study were more than 10 and 25 %-units, respectively. One alternative could be to compute lower resolution images from ERS-images and form them to hierachical series. Interpretation would begin from lowest level and higher level could use lower-level interpretation as input.

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