USING MERIS FOR MOUNTAIN VEGETATION MAPPING AND MONITORING IN SWEDEN

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ABSTRACT

The objective of this study is to apply ENVISAT MERIS data in mapping mountain vegetation in Sweden. The Swedish mountain vegetation is characterized by mosaics of different land cover types; a single MERIS pixel (300 meter IFOV) can consist of several of these different land cover types. "Hard" classifications which produce a single thematic class per pixel often give a low accuracy. While many different unmixing methods are reviewed in the literature, the use of regression trees is reported to be more promising than, for example, Linear Spectral Mixture Analysis. Regression trees handle non-linear data and are non-parametric, and can be well-suited for sub-pixel vegetation fraction estimation. Here, the soft classification methods of regression trees and linear regression are applied using spectral data from a MERIS Level 1B FR image. The image is corrected for atmosphere and illumination, and MTCI and PCA are calculated. Nine-hundred training plots are used for seven major vegetation classes. Preliminary results show that regression trees produce a slightly lower overall RMSE (20.1%) than linear regression (20.6%), although generally slightly higher class-wise biases. Results are promising however, and further improvements will be pursued.

1. INTRODUCTION

The mountain areas of Sweden are an important ecosystem. The Swedish Environmental Protection Agency has as a directive to monitor and protect what they call the "Magnificent Mountain Environment." The mountain vegetation can be affected by different influences, such as large scale defoliation by insects, reindeer grazing, or climate change which may influence vegetation composition. Remote sensing data can be useful in mapping and monitoring the current vegetation as well as dynamic vegetation changes. However, these areas are sometimes difficult to monitor, due to remoteness, cloud cover and often infrequent imaging by fine-resolution satellite images (e.g., SPOT or Landsat) than is needed. ENVISAT MERIS has the advantage of a frequent re-visit time (three days) and capturing large areas within a single date scene. Although MERIS was originally intended as an ocean sensor, its 15 programmable, narrow spectral band widths ranging from 390-1040 nm are also useful in land cover mapping applications [1, 2]

The relatively large pixel size from sources such as MERIS, MODIS, or AVHRR means that a single pixel can contain a mix of several different land cover types. In such cases, "hard" classifications which result in a single land cover class per pixel can result in low accuracy [3], especially when land cover variability is greater than the spatial resolution of the pixel [4]. For this reason, methods to derive more information per pixel as opposed to a single vegetation class label are of interest. "Soft" classification methods which result in continuous values such as class fractions per pixel include variations of Spectral Mixture Analysis (SMA) [5, 6], Artificial Neural Nets (ANN) [7, 8] variations of fuzzy classification [9], linear least squares inversion [10], generalized linear models [11], linear regression [12, 13], and regression trees [14]. For a thorough review of methods for estimating fractional and continuous field mapping, see [8].

In comparing these methods, it has been shown that Linear SMA generally resulted in lower accuracy, most likely due to the limitations imposed by the number of end-member possibilities as well as the assumption of linear mixing properties within the pixel [15]. Methods such as ANN and regression trees have the advantage of being non-parametric and of not assuming a linear relationship between the predicted and dependent variables. Comparisons between the methods have shown that the differences in results between them are essentially marginal [8]. Regression trees have been used widely in recent years to develop products from the MODIS sensor, especially fraction of tree cover [16, 17]. Recent applications have used them to determine fractions of multiple land cover types [15, 18]. In the study [15], regression trees were applied to mapping the fraction of five land cover classes (bare, shrub, grass, conifer and water) in Canada's tundra environment from Landsat data. Using a combined regression and regression tree model, they achieved an average RMSE of 16.43% for fraction mapping. In their case, the high variability of bare soil types was thought to add most to the result error [15, 19]. The authors also expressed an interest specifically in testing MERIS and regression trees for sub-pixel soft classification of land cover types [15].

Regression Trees are part of the Classification and Regression Tree (CART) algorithms as described in [14]. Regression trees are built upon a single "training"

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data set of predictor and dependent variable, where the dependent variable has a continuous value. An advantage of regression trees is that multiple types of input data can be accomodated (both continuous and categorical). For each separate class, a tree is built by starting at the root node and performs all possible splits on each predictor variable. Using goodness-of-split criteria, either Least Squares or Least Absolute Deviation, the optimum node is determined. "Pruning" of the tree using either cross-validation or an independent data set is necessary to prevent over-fitting. After pruning has produced an optimal tree, summary statistics are generated for the terminal nodes. These summary statistics are then applied to the whole data set (satellite image and ancillary data, if used) and a continuous value is estimated for each class. These estimates may require normalizing in order to sum to unity.

The objective of the work presented here is to investigate the use of MERIS full resolution data in mapping fractions of basic mountain vegetation classes using soft classification methods. The two methods which are tested and compared are regression trees and linear regression.

2. MATERIALS AND METHODS

2.1 Materials

One MERIS Level 1B full-resolution (300m) image acquired July 31st, 2005 was used. The image had two large cloud areas in the north and south and a jet contrail in the middle. The MERIS wavelengths followed the standard spectral band widths. Bands 11 and 15 have been excluded from this analysis, due to their sensitivity to oxygen absorption and water vapor, respectively.

As training and evaluation data, a land cover classification developed from an Image 2000 Landsat ETM+ image acquired July 29, 2000 was used. The land cover classification was created using unsupervised classification and labeled using field and photo-interpreted data from the National Inventory of Landcapes in Sweden (NILS). The classification accuracy for 19 classes was 74%.

Additional data included a 50-m DEM and a 1:100 000 scale land-cover map from the National Land Survey, and a polygon-based aerial photo-interpretation.

2.2 Study area

The study area was the cloud free portion of the MERIS image which measured 400 km in the north-south direction and 150 km east-west. It covered the mountain areas of the provinces of Västerbotten and northern Jämtland (between 62° and 65° N latitude). The elevation in the Swedish mountains in the study area ranges from approximately 250 to 1500 m.a.s.l.

2.3 Methods

The aim of the paper is to test the application of regression trees and linear regression for deriving a soft classification of mountain vegetation classes using MERIS data. The MERIS data have been pre-processed to correct for atmospheric and illumination effects, registered to the Swedish coordinate system, the MERIS Terrestrial Chlorophyll Index (MTCI) was calculated, and principal components analysis (PCA) was used to transform the 13 spectral bands in order to derive uncorrelated band information for use in the classification.

An atmospheric correction using BEAM software's Simple Method for Atmospheric Correction (SMAC) [20] was applied using the recorded horizontal visibility for that day (75 km) and the parameters as measured by MERIS. Geometric registration to the Swedish coordinate system was first attempted using the supplied tie-points, however due to the high topographic variation, the result produced misregistration between the MERIS and Landsat data that were not acceptable. Instead, control points were chosen visually to do a co-registration between geo-corrected Landsat images and the raw MERIS image. Small lakes, approximately one MERIS pixel in size, were often used as control points since they were plentiful in the mountain environment, readily seen in the MERIS images, and easily matched to Landsat images. Any apparent clouds and cloud shadows in the subset were masked from the image using manual delineation.

Due to the large topographic variation, an illumination correction was performed using the c-correction [21] and a 50-m DEM. Cosine of the incidence angle, which is used in the correction, was derived at 50 m resolution and resampled using cubic-convolution to the MERIS pixel size. Slope and aspect were similarly derived from the 50 m DEM.

MTCI was calculated according to [22] with the expectation that it might help differentiate between the cover types. PCA was used to reduce the dimensionality of the MERIS data since correlation between the MERIS bands is high [2]. In our case, PC1, PC2 and PC3 respectively explained 75%, 23% and 1% of the variation in the data (98% total), with PC1 representing the near-infrared MERIS bands, and PC2, the visible bands. Before band transformation by PCA, non-mountain vegetation was masked from the image using the 1:100 000 scale Swedish "Road Map."

Two soft classification methods were tested: regression trees and linear regression. These methods require separate input training data sets for each class to be estimated. Having both heterogeneous mixes and homogenous training areas is advantageous. In this light, 100 homogenous training sets were collected from a photo-interpretation from the NILS inventory which is distributed as a nation-wide systematic random sample. In addition, 800 heterogeneous plots were randomly sampled over the study area; the fractions of vegetation classes from a Landsat-based mountain vegetation classification were extracted for the corresponding area of the MERIS pixel. Corresponding spectral values from PC1, PC2 and MTCI were extracted, as well as the elevation and slope from the resampled DEM.

Seven land cover classes were defined: bare rock, grass heath, other heath (dry and mesic), meadow, wetland, mountain birch, and water. Spectral responses are given in Fig. 1. Examining the spectral signatures from "pure," and hypothetically unmixed pixels of these types show that they are well-separated using the 13 MERIS bands and the PCA-MTCI combination. Discriminant analysis results in 89% and 92% total correctly classified, respectively. Of the 13 band MERIS dataset, the best accuracy was achieved with the minimum band of bands 3, 5, 7, 9, 10, and 14.

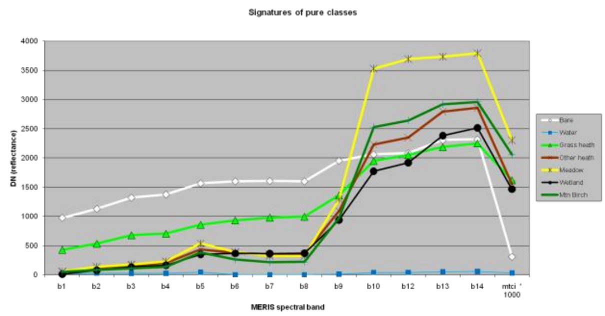

Figure 1. Spectral signatures of the seven cover types over all MERIS bands and MTCI. Meadow (yellow), mountain birch (dk green), other heath (brown), bare rock (white), grass heath (lt green), wetland (black circles), and water (black squares along bottom), are shown.

The 800 heterogeneous training data samples had on average three different cover types of greater than 10% fraction. Tab. 1 gives a summary of the heterogeneous data samples which is also an indication of the land cover composition.

Table 1. A summary of the 800 heterogeneous training samples.

Class	**No. samples where class is present**	**Mean cover %**
Water	131	29.7%
Bare rock	207	11.3%
Grass heath	178	13.9%
Other heath	404	54.6%
Meadow	337	19.5%
Wetland	327	22.8%
Mtn. Birch	345	37.2%

Regression trees were implemented using ENVI software's Rule Generator-Numeric Modeler extension. The algorithm is based on GUIDE [23]. A regression tree based on the input training data is created for each class, as is a resulting image file with pixel-wise predicted fractions for that cover type. Similar training data input was required for linear regression; however, just the spectral data were used (PC1, PC2, and MTCI). The regressions were implemented in Minitab. A regression equation was determined for each individual class using the significant input variables for that class.

In both methods, when combining the resulting fraction images for all classes, the sum of fractions for a single pixel is greater than 1. Therefore the fractions are summed and new fractions are calculated proportionally so that they sum to one.

3. RESULTS

With the regression tree method, trees were built for each class. The significant bands used in splitting nodes in the trees are given in parentheses for each class: water (pc1); bare rock (pc2, elevation); grass heath (pc2, elevation); other heath (pc1, pc2, MTCI); meadow (pc1, MTCI, slope); wetland (pc2, slope); and mountain birch (pc1, pc2, MTCI, and elevation). An example of one of the larger regression trees created during this work is shown in Fig. 2.

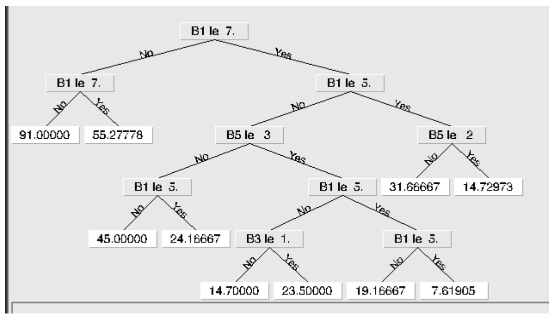

Figure 2. Regression tree created for Meadow. B1 is PC1, B3 is MTCI, and B5 is slope. R^2 was 41.5%.

Linear regression equations were calculated for each vegetation class and the corresponding R^2 values are provided in Tab. 2.

Table 2. The significant bands ($p < 0.005$) and corresponding R^2 values for each class' linear regression equation.

Class	Signif. bands	R^2
Water	pc1	81.9%
Bare rock	pc1, pc2	48.7%
Grass heath	pc1, pc2	31.6%
Other heath	pc1, pc2, MTCI	24.2%
Meadow	pc1, MTCI	38.5%
Wetland	pc1, pc2, MTCI	10.1%
Mtn. Birch	pc1, pc2	48.2%

A separate set of evaluation data consisted of 100 randomly selected plots within the study area. RMSE and bias was calculated for each individual class and as a total for both regression tree and linear regression results. The results are given in Tab. 3.

Table 3. RMSE and bias (in %) from accuracy assessment with 100 samples for both regression tree and linear regression. The lower RMSE is in bold.

	Regression Tree		Linear Regression	
Class	RMSE	Bias	RMSE	Bias
Water	**15.1**	4.4	19.6	3.1
Bare rock	**13.6**	3.6	14.3	1.3
Grass heath	**21.1**	3.7	21.5	4.5
Other heath	**26.4**	6.7	28.0	-2.2
Meadow	17.9	-4.2	**17.4**	-0.9
Wetland	23.8	-13.0	**20.3**	-7.4
Mtn. Birch	**19.6**	-1.2	20.6	1.4
Total	**20.1**	--	20.6	--

When the resulting files from regression tree and linear regression are "hardened" (i.e., where the dominant class fraction determines the class label), regression trees have a higher percent correct in all classes compared to regression. The overall number correctly classified in this case with regression trees was 65% as compared to 61% from linear regression. An example of a three-band combination for a smaller area is given in Fig. 3. The visual result from regression appears to be "smoother" with graduated changes between pixels whereas the regression tree result has more discrete units of classes.

4. DISCUSSION

The results from the accuracy assessment show that regression trees resulted in a slightly lower RMSE (20.1%) than with linear regression (20.6%), both overall and on a per class basis. The regression trees may have performed slightly better due to the inclusion of the ancillary data from the elevation model. However, linear regression shows lower per class bias.

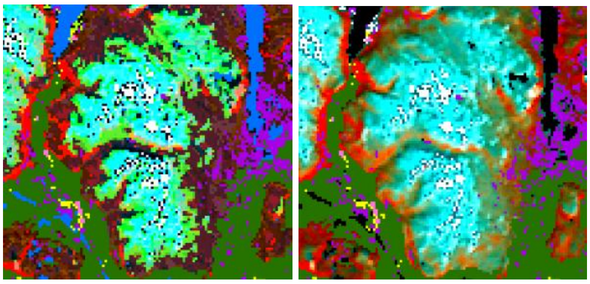

Figure 3. The result in a three-band file with meadow, grass heath and bare rock in RGB (higher relative values are brighter). The regression tree result is on the left and linear regression on right. In the center of the picture is the highest mountain in the study area, where we expect to see high percentages of these cover types.

The trends for class accuracy are similar between the two methods. The class "other heath" has the highest RMSE, perhaps due to the fact that this class typically had the widest range of values in the training data (Tab. 1). As seen by the low R^2 value from the linear regression (Tab. 2), and by noting that the residuals were not distributed normally, it is likely that the combination of the two types of heath (dry and mesic) are too different to combine together into one type. Likewise with wetland, where a low R^2 value from linear regression and non-normally distributed residuals show the effect of combining three different wetland classes into one. It is also important to note that a 1:100 000 scale wetland mask was used to help in the Landsat classification and therefore, where wetland is present, it may be somewhat over-classified in the Landsat classification, and therefore in the input data. The negative bias for wetland may be a result of this. Within-class variability can affect the result negatively and should be minimized [24].

Vegetation types that typically had lower fractions represented within a pixel, such as grass heath (see Tab. 1), had larger errors in quantifying the higher fractions. This leads to the idea that a better representation of the class variability may be needed for a better result. Non-major classes which would not be well-represented in the training data should perhaps not be included in this classification. Large errors from minor classes can affect the overall accuracy of the other classes. Other studies [8, 12] show that the result from linear regression is influenced by the *a priori* information of the training sets.

The class of water was not well-predicted considering its unique signature, and was perhaps under-represented in the training data. The narrow and low range of water's DN in the visible and N-IR bands may also explain why it is not being distinguished in mixed pixels. Similar problems with water occurred in other studies [8, 15].

In regression trees, use of the MTCI band was found beneficial in three classes, specifically other heath, meadow, and mountain birch. These classes have a signature with a steep slope at the red-edge region.

The regression tree worked better than a previously created hard classification for this area, where dominant classes tended to be over-classified and resulted in a 58% overall accuracy [25]. In comparison to others' results when classifying multiple land cover types from regression trees (e.g., [15] with 16.43% overall RMSE from regression trees), the accuracies were quite comparable. This study has used seven classes, including a wetland class which is often a highly variable class that is difficult to classify. This study has not looked into the effect of "distant and proximate" training data because the study area was relatively similar. However, if working with the entire mountain chain, this issue would be relevant and should be taken into consideration.

The results of the regression tree and linear regression were promising. Further investigation into the regression tree will be done, as this study was a preliminary test. Additional ancillary data can be investigated and incorporated into the training data. Improving the quality and supplementing the input training data may give a better result, although previous studies show the methods should be robust to training data errors [13]. Stratification of the study area may be beneficial. In addition, using a combination of classification methods, such as regression trees for mixed pixels and another method for the more extreme fractions (i.e., absent and pure), should be tried in producing an end product.

5. CONCLUSIONS

The objective of this study was to investigate the use of MERIS full resolution data in mapping fractions of basic mountain vegetation classes using soft classification methods. The two methods which were tested and compared were regression trees and linear regression. The seven classes of bare rock, grass heath, other heath, meadow, wetland, mountain birch and water were classified. Regression trees resulted in slightly lower overall RMSE (20.1%) than linear regression (20.6%), although per-class bias was slightly higher for regression trees. These results are preliminary, and further investigation into variations in the regression tree method as well as improved input data, appears to offer a promising technique for fraction mapping of mixed pixels for mountain vegetation.

6. ACKNOWLEDGEMENTS

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