FUZZY CLASSIFICATION OF MEDITERRANEAN TYPE FOREST USING ENVISAT MERIS DATA

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ABSTRACT

The aim of this study was to classify Envisat MERIS and Landsat ETM satellite sensor imagery using fuzzy classification techniques such as, linear mixture modelling and artificial neural networks. The images were classified successfully using these two techniques. The fuzzy results were more accurate then hard classification. Landsat ETM imagery was classified using maximum likelihood classifier and the output was resampled to 300 m to produce test data. Land cover classes comprised agriculture, bare ground, Tukish pine (*Pinus brutia*), Crimean pine (*Pinus nigra*), Lebanese cedar (*Cedrus libani*), Taurus fir (*Abies sp.*), Juniper (*Juniperus sp.*) and water. The classification accuracy was poor as there was insufficient number of training pixels available for these classes. As a result of this, overall accuracy was considered to evaluate the potential of these techniques. Overall results of soft classification from linear mixture modeling and artificial neural network and hard classification were 80%, 78% and 57% respectively. It can be concluded that soft classifiers particularly ANN for classifying Mediterranean type forest cover has a great potential. Additionally, there is no significant difference between soft classification outputs for certain land cover classes from linear mixture modeling and artificial neural networks, however artificial neural networks tackled pixels with high degree of mixing more accurately than LMM.

1. INTRODUCTION

In the field of nature conservation in particular, analysis of landscape pattern is becoming more important as areas of natural and semi-natural habitat are fragmented into smaller patches, with important consequences for their flora and fauna (Bastin 1997). Remotely sensed data is an ideal source for mapping land cover and land uses at a variety of spatial and temporal scales (Roughgarden *et al*. 1991, Foody 1995, 1996a).

Noting is completely clear in nature. Defining the "what is in a pixel?" numerically, very important for understanding the earth surface in remote sensing science. Increased spatial information may be valuable in a variety of situations. The forthcoming range of satellite spectrometers (e.g. MODIS, MERIS) provided detailed attribute information at relatively coarse spatial resolutions (e.g. 250m, 500m, 1km) (Aplin and Atkinson 2001).

Most of forests are destroyed by human pressure such as agriculture, fire and industrial activities. However; numbers of detrimental impacts such as, erosion and flood risks are reduced by forest areas. Detecting the proportional distribution of forest areas is very important for applicable risk management.

Mediterranean forest is mostly includes mixed type of tree species. Traditional hard per-pixel classification of remotely sensed images is limited by mixed pixels (Cracknell 1998). Soft classification overcomes this limitation by predicting the proportional membership of each pixel to each class. Mapping is generally achieved through the application of a conventional statistical classification, which allocates each image pixel to a land cover class. Such approaches are inappropriate for mixed pixels, which contain two or more land cover classes, and fuzzy classification approach is required (Foody 1996b).

In this study, two soft classification methods were compared to classify forest area using Envisat MERIS and Landsat ETM data in the Eastern Mediterranean Region of Turkey.

Linear mixture modelling (LMM) and Artificial neural network (ANN) methods are used with two different classification approaches: First one is detailed classification approach, which includes all coniferous trees (Lebanese cedar, Turkish pine tree, Crimean pine tree, Taurus fir tree juniper tree) and other land covers. Second approach considers only essential land covers types including water, agriculture, forest and bare ground.

2. METHODS

The accuracy of both fuzzy techniques was compared on the bases of classification accuracy. There are four essential steps in this study:

i) Reference data collection to train and test the classification.

ii) Creating test data using Landsat ETM imagery.

iii) Detailed and general classifications of Envisat MERIS data using LMM, ANN classification techniques.

iv) Testing and comparing LMM and ANN results.

i) Detecting the land use/cover with satellite sensor imagery relies on the quality of training and testing data. Land cover attributes were collected from reference plots in the study area. Additionally, forest maps were utilized for accuracy assessment and classification of Landsat ETM data.

ii) Multispectral Landsat ETM images with a spatial resolution of 30 m were used to derive reference land cover data. Eight land cover types; Turkish pine (*Pinus brutia*), Crimean pine (*Pinus nigra*), Taurus fir (*Abies cilicica*), juniper tree (*Juniperus excelsa*), bare ground, agricultural areas and water were classified using maximum likelihood classifier. 12.047 training

pixels were derived for classification of Landsat ETM image. The resulted image was used for accuracy assessment of soft classifications.

iii) Envisat MERIS data was classified using LMM and ANN techniques. Pure pixels were extracted from training data to apply LMM techniques. Same data set was used for both classifications to ensure comparability of the results. The hard classification of MERIS data was also implemented using ANN. Detailed and general hard and soft classifications were compared.

iv) ANN hard classification result was tested with 500 random selected points. LMM and ANN soft classifications were compared with rescaled Landsat ETM results. All soft classification results were compared on the basis of correlation coefficients.

2.1 Test data

Landsat ETM data was classified using maximum likelihood classifier. Eight major land cover types were detected in the study area. Classified image was recoded to extract land cover classes separately. Classified data was scaled to 300m spatial resolution which is equal to full spatial resolution of one MERIS pixel. Thus, each MERIS pixel represented 100 Landsat ETM pixels.

2.2 Linear Mixture Modelling

LMM is based on the assumption that class mixing is performed in a linear manner and, thus, adopts a least squares procedure to estimate the class proportions within each pixel. The idea is that a continuous scene can be modeled as the sum of the radiometric interactions between individual cover types weighted by their relative proportions (Graetz 1990). The form of the mixture model is:

$$DN_i = \sum_{c=1}^{n} f_{ic} DN_{ic} + \varepsilon_i \qquad \sum_{c=1}^{n} f_{ic} = 1 \qquad (1)$$

Where DN_i is the spectral value of a pixel in waveband i, f_{ic} is the pure pixel function of c to calculate for each band, C is the land use class, ϵ is the waveband, n is the band count, DN_{ic} is the spectral contribution of cover type c and $\_i$ is the term.

LMM depends on assumptions about the physical conditions on the ground. In a complex and non-random landscape, the linear mixture model is a reasonable approximation to extract information about land cover proportions from mixed pixel signatures (Drake 1990).

2.3 Artificial Neural Network

The ANN is one of several artificial intelligence techniques that have been used for automated image classification as an alternative to conventional statistical approaches. There are numbers of ANN models within the literature for pattern recognition such as Kohonen self – organizing maps, single layer perception and multi layer perceptron (MLP). One of the most popular learning schemes for multi-layer perceptron is the back propagation (BP) learning algorithm. A typical BP network contains one input layer, one output layer and one or more hidden layers (figure 1).
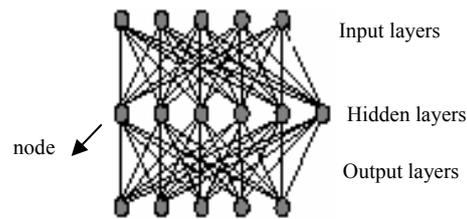

Figure 1. Multi – layer perceptron model

Input values can be spectral bands or additional information such as digital elevation model. The final processing layer called output layer and in this case is land cover classes. Layers between input and output layers are termed hidden layers. The number of hidden layers and units are defined by user. Learning rate, learning momentum and training cycle are necessary variables while designing network. The learning rate determines what portion of calculated weight change will be used for weight adjustment (Jacobs, 1988). The momentum term may prevent oscillations in the system and may help the system escape local minima of the error function in the training process (Hertz *at al.,* 1991).

Network weights are adjusted to minimize an error based on a measure of the difference between the desired and actual feed-forward network output. This process is repeated iteratively until the total error in the system decreases to a pre-specified level or when a pre-specified number of iterations are reached. This threshold must be determined experimentally and controls the generalization capability and total training time.

3. STUDY AREA AND DATA

The study area is located on the Taurus Mountain chain in the Eastern Mediterranean region of Turkey (Figure 2). The study area is approximately 180 X 65 km and comprises pure and mixed conifer forests. Dominant tree species are Crimean pine *(Pinus nigra),* Lebanese cedar *(Cedrus libani)*, Taurus fir *(Abies cilicica)*, Turkish pine *(Pinus brutia)*, and juniper *(Juniperus excelsa)* (Davis 1965). The prevailing climate is Mediterranean characterized by mild and rainy winters and hot and dry summers. The total annual rainfall is approximately 800 mm. The mean annual temperature between 1990 and 2002 was 19 ºC, with mean minimum and maximum temperatures of 8 ºC in January and 30 ºC in July, respectively (TSMS 2005). Dominant soils of the forest stands are classified as Lithic Xerorthent of Entisol and developed on fluvial and lacustrine materials during the Oligocene Epoch (Soil Survey Staff 1998).

Multispectral Landsat ETM imagery representing different types of forest cover recorded in August 2003 were used as testing data. An Envisat MERIS image of August 2003 was selected as it was relatively free of haze and cloud. Envisat MERIS is one of the payloads on the European Space Agency's Envisat and is radiometrically the most accurate imaging spectrometer in space (Dash and Curan 2004). It has 15 programmable (2.5–20 nm wide) wavebands in the 390–1040 nm region and a spatial resolution of 300 m. Because of its fine spectral and moderate spatial resolutions, and three-day repeat cycle, Envisat MERIS is a potentially valuable sensor for the measurement and monitoring of terrestrial environments at regional to global scales (Verstraete *et al.* 1999). Training data includes 1:25,000 scale Government Forestry Department and topographic maps and ground data collected from the field.
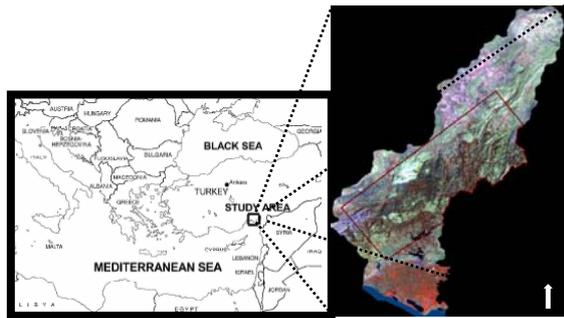
Figure 2. The location of the study area

Land covers	Producer's accuracy	User's accuracy	Kappa accuracy
Bare	% 97	% 99	% 98
Turkish pine	% 96	% 99	% 98
Crimean	% 94	% 80	% 74
Lebanese	% 99	% 74	% 84
Juniper	% 77	% 74	% 73
Taurus fir	% 80	% 61	% 60
Agriculture	% 100	% 98	% 98
Water	% 100	% 100	% 100
Overall	**% 93**	**% 86**	**% 90**

Table1. Accuracies of Landsat ETM classification

4. RESULTS

The dominant tree species are Turkish pine and Crimean pine in the study area (figure 3). ANN and LMM classified dominant tree species successfully. However, Juniper, Taurus fir and Lebanese cedar were classified with poor accuracy using both fuzzy techniques.

4.1 Accuracy Assessment

Landsat ETM image was classified using ML classifier. Six ETM wavebands, digital elevation model (DEM) and aspect data derived from DEM were used to inform classifier for more accurate classification (figure 3). The classification was reasonably accurate to use as a reference data. In this study overall accuracy of reference data (kappa statistics) was 90%. The accuracy figure was derived using 500 randomly selected ground control points (table 1).
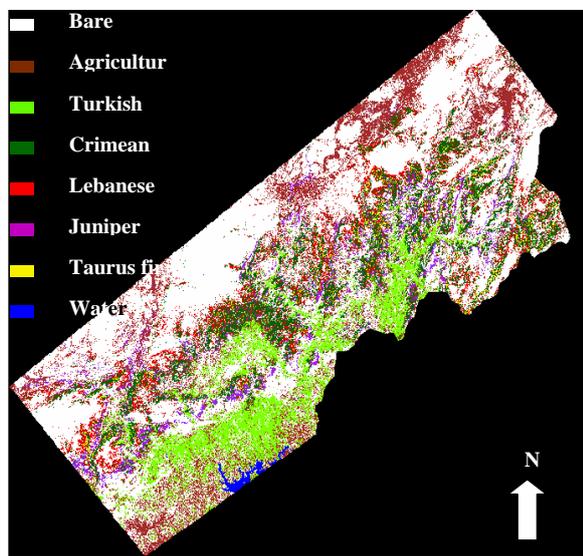

Figure 3. Classified Landsat ETM image using ML classifier (6 band + DEM + Aspect).

4.2 Linear Mixture Modelling (LMM)

Training data was derived from Government Forest Maps and reference plots for LMM. Pure pixels were extracted from the data set consisting of 286 pixels and tested with randomly selected pixels. A limited number of pixels were used to train the model because the LMM technique requires spectral endmembers.

4.3 Artificial Neural Networks (ANN)

Size of training set, network architecture, learning rate, learning momentum and number of training cycles are essential variables in ANN applications. Classification accuracy depends on these variables. The settings of these variables in this analysis were as follows: i) Size of training set; 286 pixels were selected as a training set. ii) Network architecture; the number of input units was 16 (MERIS wavebands and DEM). The number of hidden layers has a secondary effect. The dominant factor is the number of units within the hidden layers. Ideally, the first hidden layer of a network should contain two to three times the number of input layer units (Lippmann 1987, Paola and Schowengerdt 1997). In this study, the network architecture consisted of a single hidden layer with 33 nodes. iii) Learning rate; its value ranges between 0.1 and 0.9. The smaller the learning rate, the smaller the changes in the weights of the network at each cycle. The optimum value of the learning rate depends on the characteristics of the error surface. The network was trained with a learning rate of 0.1 as this resulted in the most accurate classification. However, this rate requires more training cycles than a larger learning rate. iv) Learning momentum; momentum is added to the learning rate to incorporate the previous changes in weight with the current direction of movement in the weight space. It is an additional correction to the learning rate to adjust the weights and ranges between 0.1 and 0.9. The network was trained with a back-propagation learning algorithm and a learning momentum value of 0.5. v) Number of training cycles; the network was trained until the root mean square (rms) error reduced to a constant value which is considered acceptable. This is one of the most important issues for ANN as it is easy to over-train, which may reduce the generalization capability of the network. The network was trained with 8643 cycles, this provided the most accurate network.

Figure 4 shows the results of LMM and ANN techniques. Additionally, detailed and general accuracy results were given in table 2 and 3. Reference and predicted data correlation plots are shown in figure 5.
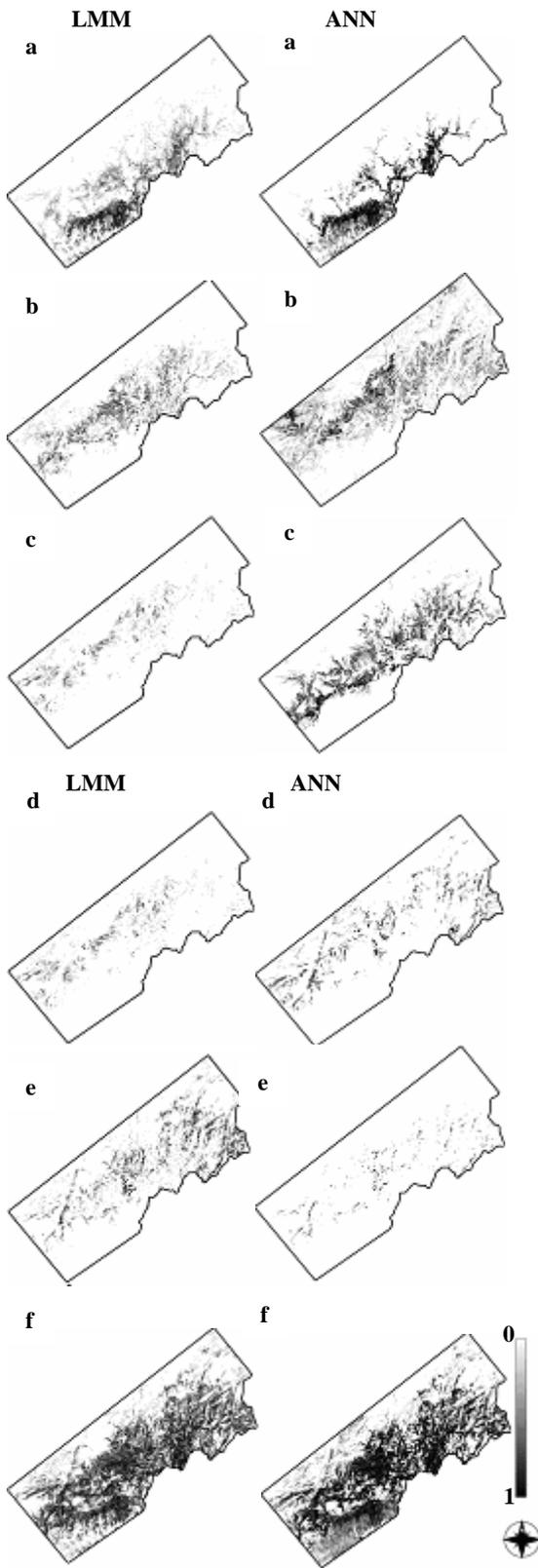
Figure 4. Sorf classification results (a: Turkish pine, b: Crimean pine, c: Juniper, d: Lebanese cedar, e: Taurus fir and f: General soft classification of forest).
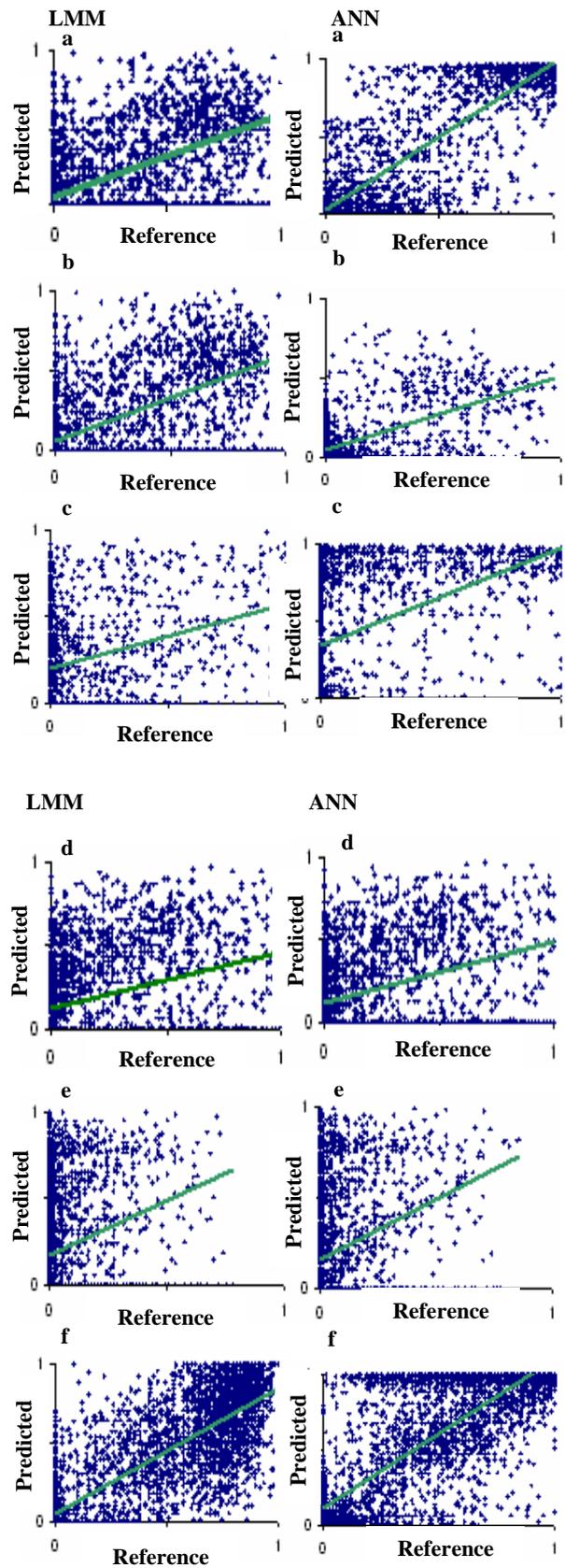
Figure 5. Correlations with testing data. (a: Turkish pine, b: Crimean pine, c: Juniper, d: Lebanese cedar, e: Taurus fir and f: General soft classification).

Detailed Classifications	LMM	ANN Soft	ANN Hard
Bare Ground	78%	72%	60%
Agriculture	60%	58%	12%
Water	99%	98%	85%
Turkish Pine	85%	89%	56%
Crimean Pine	60%	63%	30%
Lebanese Cedar	35%	40%	8%
Taurus Fir	26%	31%	0%
Juniper	34%	44%	7%
Overall	**60%**	**62%**	**33%**

Table 2. Detailed Classification results (correlation coefficients for LMM and ANN soft results; kappa statistic for ANN hard result).

General Classifications	LMM	ANN (Soft)	ANN (Hard)
Bare ground	79%	72%	70%
Agriculture	59%	55%	18%
Forest	84%	83%	45%
Water	99%	100%	85%
Overall	**80%**	**78%**	**57%**

Table 3. General Classification results (correlation coefficients for LMM and ANN soft results; kappa statistic for ANN hard result).

5. DISCUSSION AND CONCLUSIONS

This study demonstrated the suitability of Envisat MERIS imagery for mapping conifer forest using fuzzy techniques in the Mediterranean region. The two techniques were assessed for this purpose with the limited training data. The comparison was based on prediction accuracy. The test data was derived from Landsat ETM image.

The main findings of this study were:

- Envisat MERIS data hold a great potential in general classifications despite of limited training pixel and single date Envisat MERIS image. The outputs of general classification were reasonably accurate. The accuracy of the results is likely to be increased by including multi-temporal Envisat MERIS images.

- Fuzzy classification of conifer forest was achieved using LMM and ANN with a reasonable accuracy of 84% and 83% respectively.

- This study showed that soft classification results were more accurate than hard classifications. Turkish pine (pinus brutia) and Crimean pine (pinus nigra) accuracies in ANN and LMM applications were acceptable when used the detailed classification

approach. ANN tackled pixels with high degree of mixing more accurately than LMM. The main reason for the poor accuracy of LMM was that utilization of limited range of training data.

- Additionally, calcareous soil has a large effect on the reflectance from a sparse Mediterranean forest. High reflectance from soil causes a soil albedo effect; hence the signal reflected from the soil background can potentially overwhelm the relatively small component reflected from vegetation. As a result of this, LMM largely suffered from predicting the proportion of tree classes within the pixels.

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