Classification methodology for land cover mapping of Seyhan Watershed using spectral, spatial and ancillary data.

Berberoğlu, S., Evrendilek, F., and Kılıç, Ş.

suha@cu.edu.tr

1. Introduction

The spectral composition of the radiant flux emanating from Earth's surface provides information about the biological, chemical and physical properties of soil, water and vegetation in terrestrial ecosystems. Airborne and satellite remotely sensed data recorded in optical wavelengths have been used to classify and map vegetative cover (e.g., Running *et al.*, 1995; Townshend, 1992; Dungan *et al.*, 1994) and provide estimates of a wide range of biophysical variables such as Absorbed Photosynthetically Active Radiation (APAR) (Gregoire and Raffy, 1994), canopy cover (Bartlett *et al.*, 1988; Goel, and Reynolds, 1989), LAI (leaf area index) (Curran, *et al.*, 1992; Friedl *et al.*, 1994), biomass (Atkinson and Plummer, 1993;). Remotely sensed data are also being used to estimate canopy chemistry (Zagolski *et al.*, 1996) as a result of our need for the information and our increasing ability to understand and measure canopy spectra (Curran, 1990).

Image classification refers to a variety of methods to identify and characterise objects from imagery. However, the fundamental interactions of radiant energy with the Earth's surface must be understood for remote sensing to be applied efficiently. Current remote sensing techniques enable the successful classification of land cover in temperate regions of the world, however, the Mediterranean environment limits the capability of current remote sensing techniques. In the area traditional classification techniques were failed as a result of (i) similarity of reflectance properties of major land covers which makes spectral separation difficult and (ii) small and spatially variable land cover parcels. These constraints minimised using the synergy of techniques mentioned above. The first problem was tackled by utilising Artificial Neural Networks (ANNs) as a non-statistical approach to spectral discrimination rather than a conventional statistical classifier such as ML. A fundamental difference between these classifiers is statistical approaches depend on assumed model, whereas ANN approach depend only on the data. ANNs are one of several artificial intelligence techniques that have been used for automate image classification as an alternative to conventional statistical approaches.

ANNs in their present form were first published by Rosenblatt (1958) who introduced the concept of the perceptron. His single perceptron was able to classify only linearly separable data and this was an important limitation to its use. Non-linear data separation was achieved in 1980s as a result of increased computing power and the development of algorithms and network topologies. This enabled the use of ANN for the classification of remotely sensed imagery (Key *et al.*, 1989; Benediktsson *et al.*, 1990). Since then, the number of remote sensing studies using ANN have increased dramatically. It has been shown that ANN provided more accurate classification than traditional statistical classifiers (Benediktsson *et al.*, 1990; Wilkinson *et al.*, 1994)

For the second problem, spatial information is critical because spectral information alone often does not recognise adjacent pixels as belonging to the same vegetation class due to spatial variability. This wide range in spatial frequencies can be utilised as a discriminant by land cover classifiers. Land cover classes may be discriminated according to their spatial variability in a remotely sensed imagery where spectral signatures are subtle. Synergy between spatial variability which means texture and spectral brightness has a great potential for image analysis in remote sensing. Spatial variability can be quantified using a texture measure and this then combined with spectral data in a classifier. Measures of texture used were: the variance and statistics derived from the variogram. A key function of geostatistics is variogram which relates variance to spatial separation and provides a concise description of the scale and pattern of spatial variability. The variogram is one means of quantifying the way in which a variable changes spatially. The variogram is defined as half the expected squared difference between paired data values separated by the vector, lag **h**:

$$\gamma(\mathbf{h}) = \frac{1}{2}\mathrm{E}[\{Z(\mathbf{x}) - Z(\mathbf{x}+\mathbf{h})\}^2]$$

The experimental (or sample) variogram is computed for the $p(\mathbf{h})$ paired observations, $z(\mathbf{x}_i)$, $z(\mathbf{x}_i+\mathbf{h})$, i=1, 2,..., $p(\mathbf{h})$:

$$\hat{\gamma}(\mathbf{h}) = \frac{1}{2p(\mathbf{h})}\sum_{i=1}^{p(\mathbf{h})}\{z_v(\mathbf{x}_i) - z_v(\mathbf{x}_i + \mathbf{h})\}^2$$

where, v is the support (the size, geometry and orientation) of the area over which measurements are made. For remotely sensed imagery the lag **h** is measured in units of one side of a pixel.

The variogram within a moving window has been used to quantify texture in remotely sensed imagery by several researchers (Miranda *et al.*, 1996; Carr, 1996). Miranda *et al.* (1992) found that variograms could be used to distinguish effectively between different land cover classes and increase the accuracy of classifications. Carr (1996) used the semivariance and spectral information separately and in combination in a supervised classification with several different algorithms. Carr (1996), like other authors, observed that classification accuracy was greater when the semivariance was used in combination with spectral information than when the latter was used alone. Another approach has been to use the square root of the difference between paired observations rather than the semivariance (half the squared difference) for discriminating land cover classes (Lark, 1996).

Image texture provided horizontal variation within the image and vertical variation has been characterised by DEM which is also valuable information as the land cover classes strictly associated with altitude. Synergy of the techniques mentioned above enabled more accurate classifications than those obtained using standard techniques alone. The accuracy figures were derived using 1000 randomly selected ground control points. Therefore, this study focused on the techniques that were likely to help solve existing problems associated with land cover mapping in the region.

2.Data Processing

The land use of the area is intensive and is dominated by agricultural, urban and tourist activities. Diverse environmental structures such as, geology, soil, climate, hydrology and vegetation interact strongly with these land use activities. These interactions have shaped the environment which is typical of this part of the Mediterranean region. The major land cover classes are agriculture, bare ground, grassland, pinus brutia, pinus nigra, cedrus libani, Abies sp., water, wetland, settlement, snow, bulrush, sand.

The study benefits from a large and detailed land cover database derived from four data sources: Landsat ETM image dated 5 May 2003, topographic maps, State Hydraulic Works (DSI) land cover records and ground data from field surveys.

3.Geometric rectification

The image was geometrically corrected and geocoded to the Universal Transverse Mercator (UTM) coordinate system by using 1:25,000 scale topographic maps. 15 regularly distributed ground control points (GCPs) were selected from the image. It was then spatially resampled to a spatial resolution of 30 m. Resampling was done by using a nearest neighbour algorithm. The transformation had a root mean square (RMS) error 0.7 indicating that the image was accurate to within one pixel.

4.Supervised classification

Image classification was carried out using ML and ANN algorithm with supervised training (Figure 1). The classifier was provided with the spectral reflectance properties of each class in the form of the mean reflectance for each spectral waveband and the associated covariance matrix. This data was

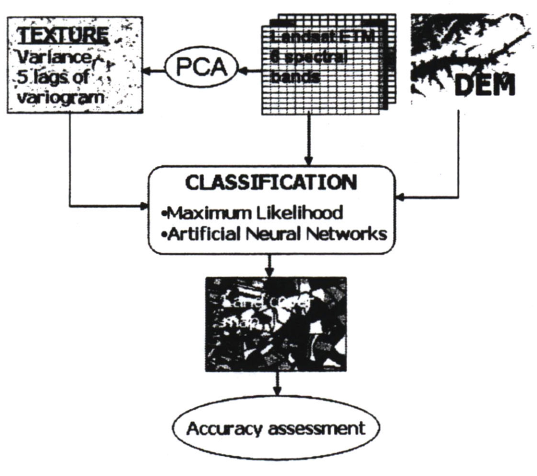

Figure 1. Flow diagram of the study.

generated from a selection of sample training pixels for each class provided from ground data.

All texture measures were extracted from the first principal component of the six wavebands and these were used to create 'texture waveband(s)'. Then, per-pixel ML and ANN classifications were applied. Evaluation of the utility of these two classifiers and associated texture measures was based on classification accuracy.

Variogram coefficients used as texture measures included (i) an approximation of variogram range, (ii) the semi-variance at various lags and (iii) variance. The variogram range was computed using two approximations; (i) the method of Ramstein & Raffy (1989) and (ii) the roots of the first derivative of a third-order polynomial fitted to the variogram. Both approximations were unstable in the first approach and this was because the semi-variance at large lags was computed from too few data and in the second approach this was because the small number of pixels in each window restricted the number of lags for which semi-variance could be computed. In many instances, very large ranges were estimated if the variograms did not reach a limit. Therefore, range was not employed in the analysis. The texture measures derived from the average values of semi-variance at lags of 1, 2, 3, 4 and 5 pixels over a moving window.

Table 1. The standard set of user defined variables.

VARIABLES	VALUE
Input layer	6-8 units
1.hidden layer	(3x input layer)
Error	0.001
Output layer	30 (amalgamated to 14)
Learning rate	0.01
Learning momentum	0.01
Number of cycles	2000-3000
Learning function	Back propagation
Update function	Topological order
Initialisation	Randomise Weight
Transfer function	Sigmoidal function

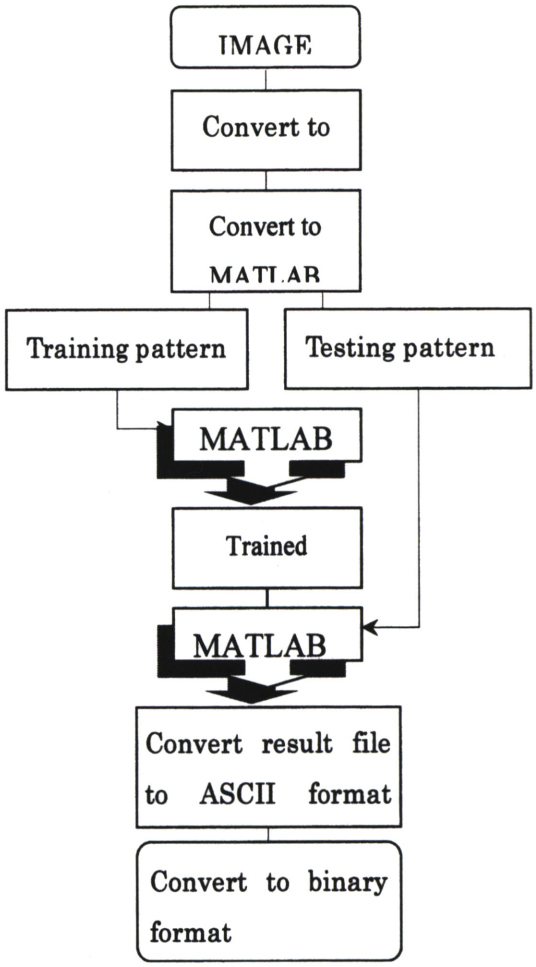

Figure 2. Summary of supervised classification with MATLAB.

5.Accuracy Assessment

Accuracy was expressed by the error matrix, which represents the degree of agreement between the classified land cover and observed land cover. Accuracy results were derived using 1000 random points for the classified images using per-pixel classification.

6.Results

The Landsat ETM image of the study area comprised approximately 120 km by 190 km, of agriculture, bare ground, grassland, pinus brutia, pinus nigra, cedrus libani, abies sp., water, wetland, settlement, snow, bulrush, sand. A supervised ML classification technique was applied using Erdas Imagine software for comparison with the ANN classification (Figure 3).

To indicate the variation on the image, variograms have been calculated for each land cover classes.

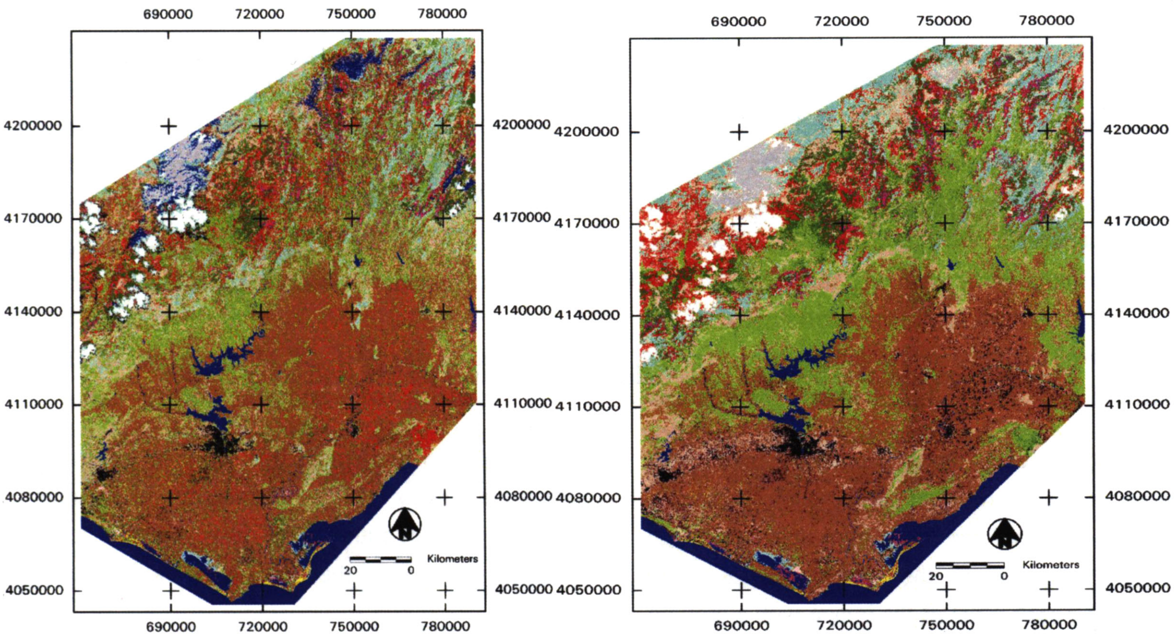

Figure 3. Maximum likelihood classification (a) and incorporating DEM (b).

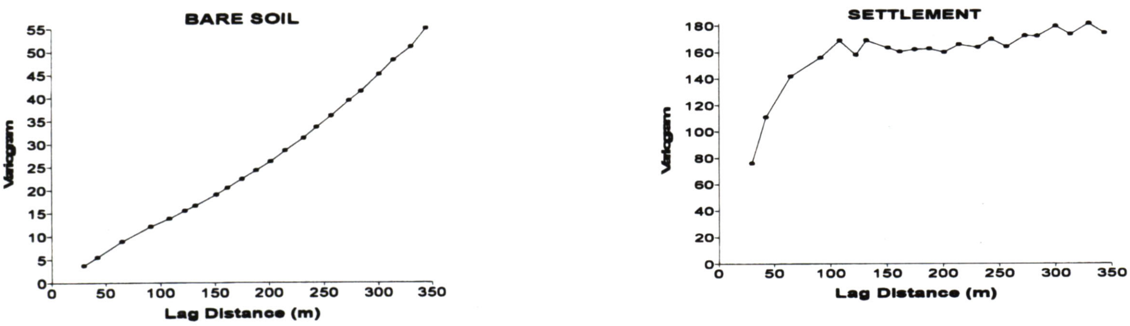

Figure 4. Variograms from Landsat ETM imagery

Sample size of variograms small because of small land cover parcels. One extreme value has dramatic effect on the variogram. However, variogram provided useful textural information for the land cover classes. The texture measures derived from the average values of semi-variance at lags of 1, 2, 3, 4 and 5 pixels over a moving window. These texture measures provided additional information to the classifiers where the spectral discrimination of major land cover classes is subtle such as, settlement and bare soil (Figure 4).

The size of this window should be related to the size of objects in the scene. For example, when classifying a large continuous area of Brazilian rain forest Miranda and Carr calculated variogram textural measures over large windows (e.g., 22 by 22 pixels for training) (Miranda *et al.*,1998). However, Miranda *et al.* (1996) suggested that smaller window sizes were preferable for the calculation of variogram texture where land covers were smaller in area and large windows would increase the risk of contamination by class mixing. For this reason in this study a window size of 11 by 11 was used. It is possible to calculate semi-variance at a lag of 1 pixel by using smaller window sizes such as 3 by 3, however computing semi-variance at a lag of 1 pixel over a larger window provides more robust measures over a wider range of lags. For each pixel, average values of semi-variance for lags of 1 to5 pixels were computed and used in the classification along with spectral data. There is a strong linear correlation between semi-variance at a lag of 5 pixels and variance and pixels diverting from this

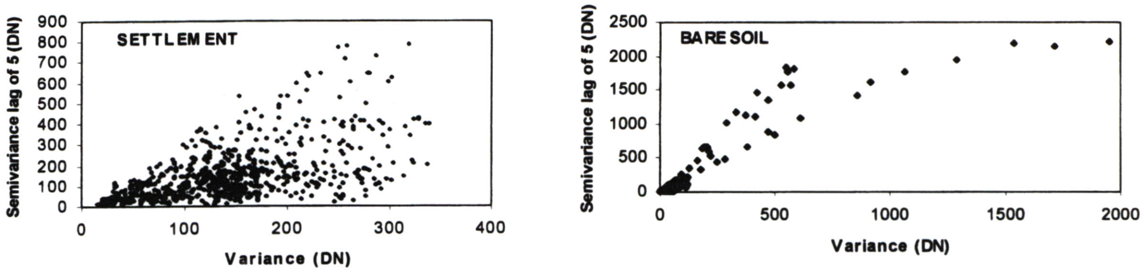

Figure 5. Relationship between semi-variance and variance for two land cover classes

linear trend tended to be edge pixels or pixels with extreme values as a result of class mixing (Figure 5).

Both 5 lags of the variogram and additional variance values over the entire images were measured for each pixel of the image with a moving 11x11 window on the first principal component band. These texture measures were used in the same way as a band within ML (Figure 6).

The ANN classifier utilised more accurately spectral, spatial and DEM information than ML classifier did (Figure7). The accuracy results with user's and producer's accuracies and kappa statistics are given in table 2.

7. Discussins and conclusions

One of the principle findings was that the ANN classifier utilised texture more effectively than ML. The ANN was at its most useful where the spectral properties of the land cover classes was complex and overlapped in feature space.

For the classification of land cover the variogram measure of spatial variability with DEM provided a more accurate classification than did spectral data alone.

The clouds had two effects on the image. Firstly, they reduced the reflectance, especially along the cloud shadow edge. Secondly, clouds increased the reflectance around the area of cloud shadow. Change in ground reflectance as a result of clouds led to misclassification. For example, grassland on the edge of cloud shadow has been variously classified as a forest.

ACKNOWLEDGEMENTS

The authors would like to thank DAAD (Deutscher Akademischer Austausch Dienst e.V.) for financial support (A/04/17633) of Dr.Süha Berberoğlu to implement this work in Institute for Photogrammetry (IFP), University of Stuttgart, Germany. The authors are also grateful to IFP members of staff for their assistance and hospitality.

REFERENCES

Atkinson, P.M. and Plummer, S.E., 1993. The influence of the percentage cover and biomass of clover on the reflectance of mixed pasture. International Journal of Remote Sensing; 14: 1439-1444.

Bartlett, D.S., Hardisky, M.A., Johnson, R.W., Gross, M.F., Klemas, V. and Hartman, J.M., 1988. Continental scale variability in vegetation reflectance and its relationship to canopy morphology. International Journal of Remote Sensing; 9: 1223-1241

Benediktsson, J.A. and Sveinsson, J.R., 1997. Feature extraction for multisource data classification with artificial neural networks. International Journal of Remote Sensing; 18:727-740.

Carr, J. R., 1996. Spectral and textural classification of single and multiple band digital images. Computers and Geosciences; 22: 849–865.

Curran, P.J., 1990. Remote sensing of canopy chemistry. Remote Sensing and Global Change. Remote Sensing Society, Nottingham, pp. 41-48.

Curran, P.J., Dungan, J.L. and Gholz, H.L., 1992. Seasonal LAI in slash pine estimated with Landsat TM. Remote Sensing of Environment; 39: 3-13.

Deutsch, C. and Journel, A. G., 1992. GSLIB: Geostatistical Software Library and User's Guide. Oxford University Press, New York.

Deutsch, C. and Journel, A. G., 1992. GSLIB:

Geostatistical Software Library and User's Guide. Oxford University Press, New York.

Dungan, J.L., Peterson, D.L and Curran, P.J., 1994. Alternative approaches for mapping vegetation quantities using ground data image data. Environmental Information Management and Analysis. Edited by W. K. Michener, J.W.Brunt and S.G. Stafford. Taylor & Francis, London, pp.237-261.

Foody, G. M. and Arora, M. K., 1997. An evaluation of some factors affecting the accuracy of classification by an artificial neural network. International Journal of Remote Sensing; 18: 799–810.

Friedl, M.A., Michaelsen, I., Davis, F.W., Walker, H. and Schimel, D.S., 1994. estimating grassland biomass and leaf-area index using ground and satellite data International Journal of Remote Sensing; 15: 1401-1420.

Goel, N.S. and Reynolds, N.E., 1989. Bidirectional canopy reflectance and its relationship to vegetation characteristics. International Journal of Remote Sensing; 10: 107-132.

Gregoire, C. and Raffy, M., 1994. Spatialized APAR for heterogeneous pixels. International Journal of Remote Sensing; 15: 2393-2401

Key, J., Maslanik, J.A. and Schweiger, A.J., 1989. Classification of merged AVHRR and SMMR Arctic data with neural networks. Photogrammetric Engineering and Remote Sensing; 55:1331-1338.

Lark, R. M.,1996. Geostatistical description of texture on an aerial photograph for discriminating classes of land cover. International Journal Remote Sensing; 17: 2115–2133.

Miranda, F. P., MacDonald, J. A. and Carr, J. R., 1992. Application of the semivariogram textural classifier (STC) for vegetation discrimination using SIR-B data of Borneo. International Journal of Remote Sensing; 13: 2349–2354.

Miranda, F.P., Fonseca, L.E.E., Carr, J.R. and Taranik, J.V., 1996. Analysis of JERS-1 (Fuyo-1) SAR data for vegetation discrimination in northwestern Brazil using the semivariograms textural classifier (STC). International Journal of Remote Sensing; 17: 3523-3529.

Miranda, F.P., Fonseca, L.E.N. and Carr, J.R., 1998. Semivariogram textural classification of JERS-1 (fuyo-1) SAR data obtained over a flooded area of the Amazon rainforest. International Journal of Remote Sensing; 19: 549-550.

Ramstein, G. and Raffy, M., 1989. Analysis of the structure of radiometric remotely-sensed images. International Journal of Remote Sensing; 10: 1049–1073.

Rosenblatt, F., 1958. The perceptron: a probabilistic model for information storage and organisation in the brain. Psychological Review; 65: 386-408.

Running, S.W., Loveland, T.R., Pierce, L.L., Nemani, R.R. and Hunt, E.R., 1995. A remote sensing based vegetation classification logic for global land cover analysis. Remote Sensing of Environment; 51: 39-48.

Townshend, J.R.G. and Justice, C.O., 1995. Spatial variability of images monitoring changes in the normalized difference vegetation index. International Journal of Remote Sensing; 16: 2187-2195.

Wilkinson, G.G., Fierens, F. and Kanellopoulos, I., 1994. Integration of neural and statistical approaches in spatial data classification. Geographical Systems; 2:1-20.

Zagolski, F., Pinel, V., Romier, J., Alcayde, D., Fontanari, J., Etchegorry, J.P.G., Giordano, G., Marty, G., Mougin, E. and Joffre, R., 1996. Forest canopy chemistry with high spectral resolution remote sensing. International Journal of Remote Sensing; 17: 1107-1128.

Table 2. The classification accuracy of using Maximum Likelihood and Artificial Neural Networks incorporating texture (variance and var ogram lags of 5 pixels), DEM and spectral bands (non-thermal 6 Landsat ETM bands).

	ML 6 bands			ML 6 bands + DEM			ML 6 bands + DEM +			ANN 6 bands + DEM +		
LAND COVERS	PA (%)	UA (%)	Kappa	PA (%)	UA (%)	Kappa	PA (%)	UA (%)	Kappa	PA (%)	UA (%)	Kappa
Agriculture	79.22	67.03	0.5716	58.44	88.24	0.8471	57.14	91.67	0.8917	85.71	90.41	0.8754
Bare ground	43.48	41.67	0.3735	73.91	56.67	0.5346	65.22	55.56	0.5227	60.87	73.68	0.7174
Grassland	35.71	57.69	0.5161	54.76	57.50	0.5139	47.62	62.50	0.5711	73.81	83.78	0.8145
Pinus brutia	46.81	70.97	0.6621	57.45	77.14	0.7340	57.45	71.05	0.6631	76.60	80.00	0.7672
Pinus nigra	35.48	73.33	0.7061	45.16	53.85	0.4912	41.94	50.00	0.4488	93.55	54.72	0.5008
Cedrus libani	57.14	18.18	0.1643	71.43	35.71	0.3434	85.71	22.22	0.2056	14.29	50.00	0.4893
Abies sp.	60.00	17.65	0.1640	59.00	15.79	0.1431	60.00	15.79	0.1451	59.00	18.20	0.1520
Water	95.35	83.67	0.8126	53.49	100.00	1.0000	53.49	100.00	1.0000	90.70	97.50	0.9713
Wetland	33.33	25.00	0.2432	100.00	15.79	0.1503	100.00	16.67	0.1591	66.67	100.00	1.0000
Settlement	75.00	56.25	0.5462	83.33	41.67	0.3949	75.00	45.00	0.4295	75.00	75.00	0.7407
Snow	68.42	100.00	1.0000	94.74	94.74	0.9442	100.00	95.00	0.9470	84.21	94.12	0.9376
Bulrush	100.00	100.00	1.0000	100.00	52.94	0.5164	100.00	50.00	0.4862	100.00	56.25	0.5504
Sand	93.33	87.50	0.8691	93.33	82.35	0.8152	100.00	83.33	0.8255	100.00	83.33	0.8255
Overall accuracy		64.07			63.17			61.68			79.94	

PA: Producer's Accuracy
UA: User's Accuracy

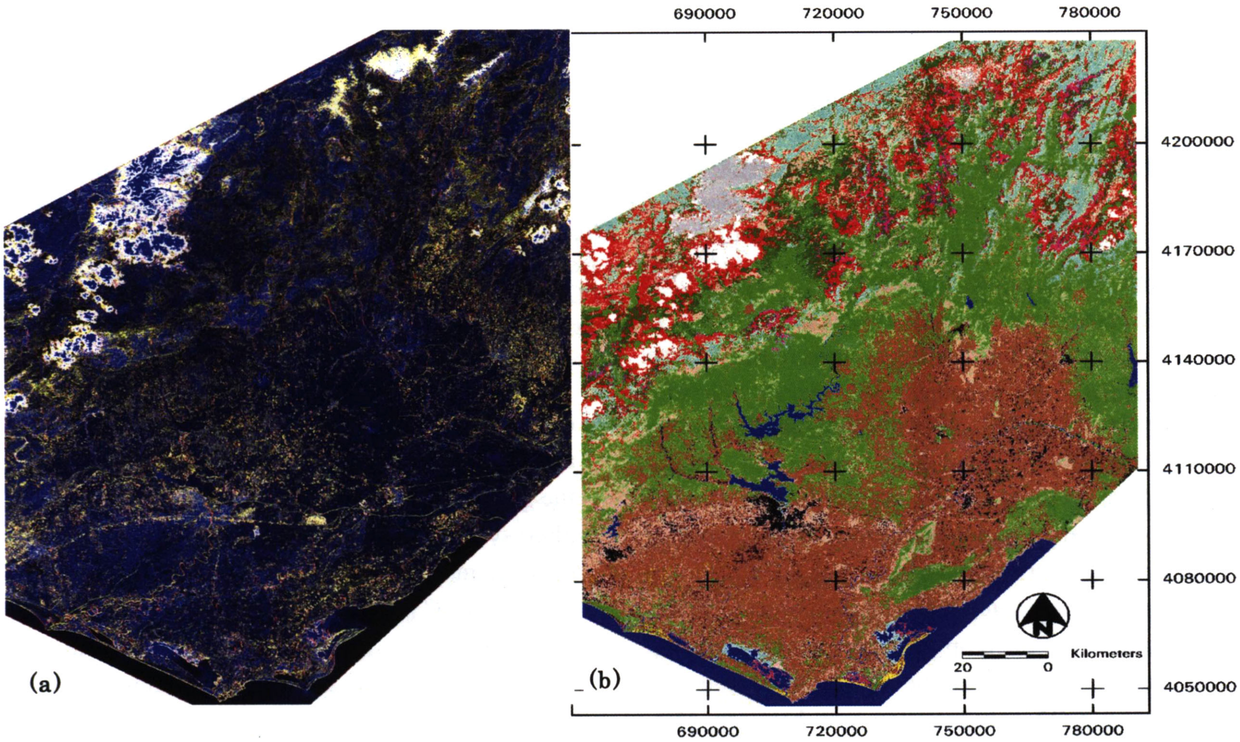

Figure 6. Variogram lags of 5 pixel and variance image (a); classified image incorporating texture measures, DEM and spectral bands within a maximum likelihood classification (b).

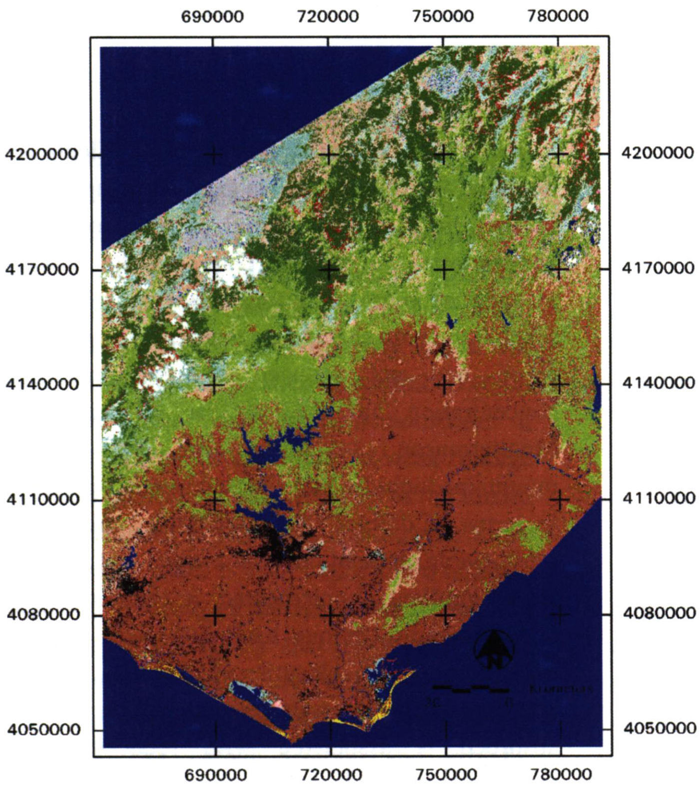

Figure 7. Classification result using ANN incorporating variance, variogram 5 lags, DEM and spectral bands.