CLASSIFICATION OF TREE AND SHRUB SPECIES IN KSU RESEARCH AND APPLICATION FOREST IN KAHRAMANMARAS, TURKEY

A. E. Akay [a, *], I. R. Karas [b], R. Gundogan [c]

[a] Department of Forest Engineering, Faculty of Forestry, KSU, 46100 Kahramanmaras, Turkey - akay@ksu.edu.tr
[b] Department of Geodetic and Photogrammetric Engineering, GYTE, 41400 Gebze, Kocaeli, Turkey -ragib@gyte.edu.tr
[c] Department of Soil Science, Faculty of Agriculture, KSU, 46100 Kahramanmaras, Turkey - rgundogan@ksu.edu.tr

Commission VIII, WG VII/1

KEY WORDS: Remote Sensing, Classification, Image processing, Vegetation Identification, Forestry

ABSTRACT

During the last few decades, remote sensing and Geographic Information Systems (GIS) technologies have become increasingly important tools for mapping, inventorying, and monitoring forest resources around the world. Using remotely sensed aerial images or digitized aerial photographs and GIS techniques to organize and analyze significant amount of spatial data, it is now becoming possible to analyze the number of variables (tree species, size and density, volume and height, growth, and etc.) for ecological and economic management of forests. Large-scale satellite images with good details are widely used in digital image processing and classification. The main purpose of this paper was using automated image processing and classification methods based on a satellite imagery to identify vegetation types in KSU Research and Application Forest in Kahramanmaras, Turkey.

KURZFASSUNG

Während der letzten Jahre hat die Bedeutung der Technologien im Bereich der Fernerkundung und des geographischen Informationssystems (GIS) für die Kartierung, Inventarisierung, und Beobachtung von Wäldern weltweit stark zugenommen. Die Nutzung von Luftbildaufnahmen oder digital bearbeiteten Luftbildaufnahmen und GIS Technik zur Erfassung und Analyse von Daten, die sich auf große Gebiete beziehen, ermöglicht es, verschiedene Variablen (z. B. Baumarten, Größe und Dichte, Volumen und Höhe, Wachstum) zur ökologischen und wirtschaftlichen Bewirtschaftung zu analysieren. Satellitenbilder in großem Maßstab mit guter Detailwiedergabe sind weit verbreitet bei der digitalen Bildverarbeitung und Klassifikation. Das Ziel dieser Arbeit bestand darin, unter Nutzung von automatisierter Bildbearbeitung und Methoden der Klassifizierung Satellitenbilder zur Identifizierung von Vegetationstypen im Versuchsforst der Universität Kahramanmaraş, Türkei, auszuwerten.

1. INTRODUCTION

Classification of the objects in natural resources has been recognized as one of the important tasks by natural scientists from wide range of disciplines. In remote sensing, the classification can be defined as a process of separating features into classes or areas in remotely sensed imagery (Raffy, 1994). Even though land classification dates back to early 1990's, it has received a great interest as compute-based remote sensing and Geographic Information Systems (GIS) technologies have advanced in last few decades. Due to capabilities of these technologies to provide, organize, and analyze vast amount of spatial data, land classifications have been used for mapping, inventorying, and monitoring purposes in the field of the natural resources (Carson et al. 2001).

In the field of forestry, digital interpretation procedures have been widely used for inventorying, and monitoring forested areas based on aerial photographs and satellite digital imagery (Gougeon, 1995). There have been studies on extracting single species stands from the interpretation of remotely sensed imagery with low spatial resolution (Beaubien 1983, Jano 1984, Gillis and Leckie 1993). Large-scale satellite images with high resolution and good details have been used in pixel-based classification of individual tree crowns (Leckie 1990, Beaubien 1994, Meyer et al.1996). However, the large amount of pixels may lead to potential classification problems. For example; one conifer tree crown can contain high number of pixels (e.g. over 5000 pixels), some pixels in a tree crown can be confused with shrub species, variation in background vegetation and soil material cause high frequency of data variability, and shadow within or around the tree crown effects the classification process.

In this study, automated image classification method was applied to identify vegetation types in KSU Research and Application Forest in Kahramanmaras-Turkey, based on satellite imagery. Different image processing techniques were evaluated and various problems and limitations with these techniques were discussed.

2. MATERIAL AND METHODS

2.1. Study Area

Baskonus Research and Application Forest of Kahramanmaras Sutcu Imam University was selected as a study area due to availability and accessibility of necessary spatial data such as aerial photos, satellite image, and thematic maps. The research

[*] Corresponding author.

forest is approximately 458 ha and located about 45 km west of Kahramanmaras, Turkey. The research forest is dominated by conifers; *Pinus brutia, Pinus nigra, Cedrus libani, and Abies cilicica*. The average side-slope and ground elevation were 73% and 1165 m, respectively. Figure 1 indicates the forest boundary, topography, streams, and road network.

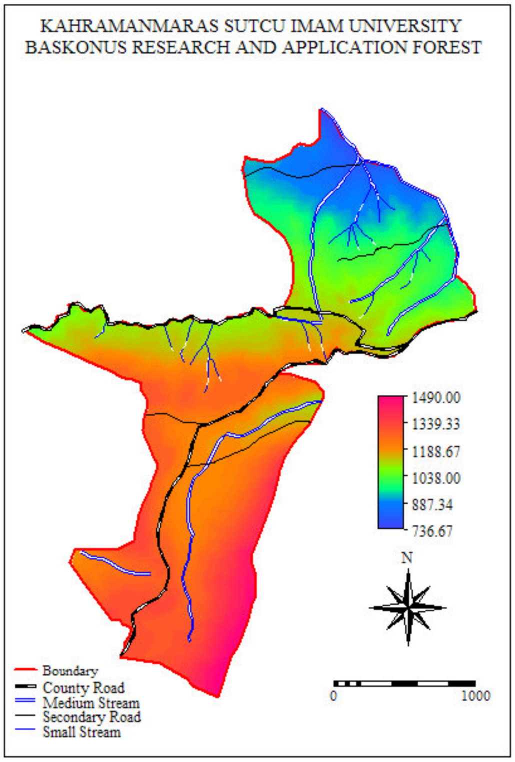

Figure 1. KSU Baskonus Research and Application Forest

2.2. Pre-Processing

In image processing, the September 2004 ASTER NIR satellite image (15 m) of Kahramanmaras region was used (Figure 2).

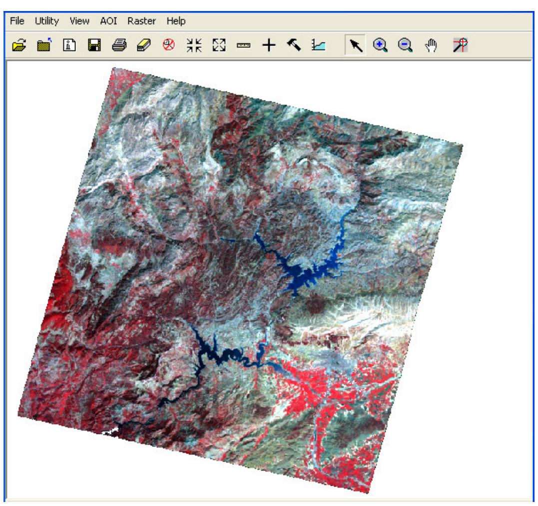

Figure 2. September 2004 ASTER NIR satellite image

The IR Aerial Photos (1:15000) taken in June 2000 and 1:25000 stand types map were used to perform accuracy assessment. The ERDAS Imagine 8.5 (Atlanta, GA, USA) was used to execute the pre-processing and classification tasks. In the first stage of pre-processing, research forest was clipped out from the satellite image by using "Mask" function in ERDAS 8.5, referencing forest boundary layer.

In subset image of the research forest, there was a high frequency of data variability due to stand density, shadow effect, background vegetation and ground materials. To reduce spatial frequency, low-pass filtering technique has been widely used (Lillesand and Kiefer, 2000). In this study, the performances of three different low-pass filtering standards (3x3, 5x5, and 7x7) were compared using "Convolution" function in ERDAS 8.5. The filtering process indicated that applying 7X7 low-pass filter maximized the filtering result and removed the data variation prior to classifications process (Figure 3).

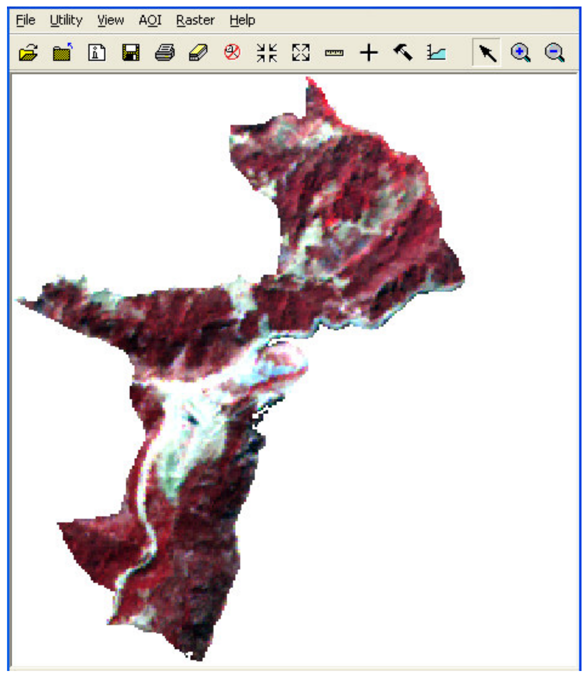

Figure 3. 7x7 low-pass filtered image of the research forest

2.3. Classifications

In classification process, firstly, Unsupervised Classification method was applied by using ten classes to identify the forest vegetation in the research forest. In ERDAS 8.5, the "Isodata" algorithm was used to perform classification repeatedly and form clusters using the minimum spectral distance formula. The result of unsupervised classification was indicated in Figure 4 (with 10 classes).

Supervised Classification method was then performed based on a set of user-defined classes, by creating the appropriate spectral signatures from the data. "User-Defined Polygon" function was employed to lower the chance of underestimating class variance since it involved a high degree of user control. To generate a signature file that accurately represents the classes to be identified, over 200 samples were repeatedly selected from the

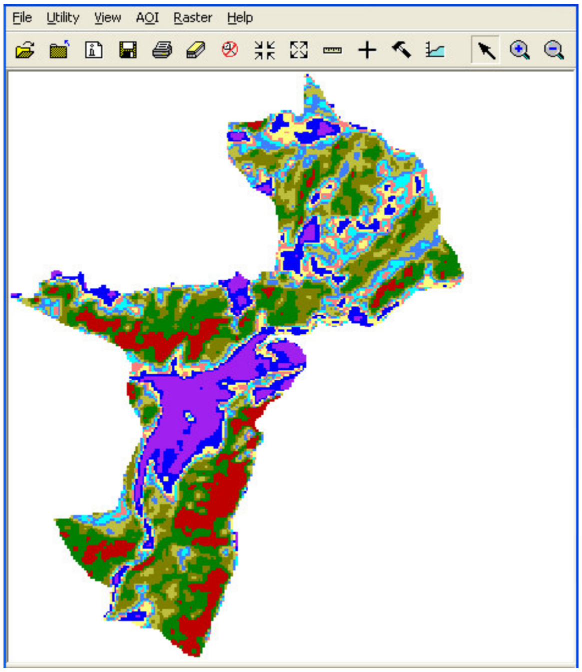

Figure 4. The image of research forest after unsupervised classification

image by drawing a polygon around training sites of interests. Once a set of reliable signatures were created, supervised classification was performed using the Maximum Likelihood (statistically-based classifier) technique provided by ERDAS 8.5 (Figure 5).

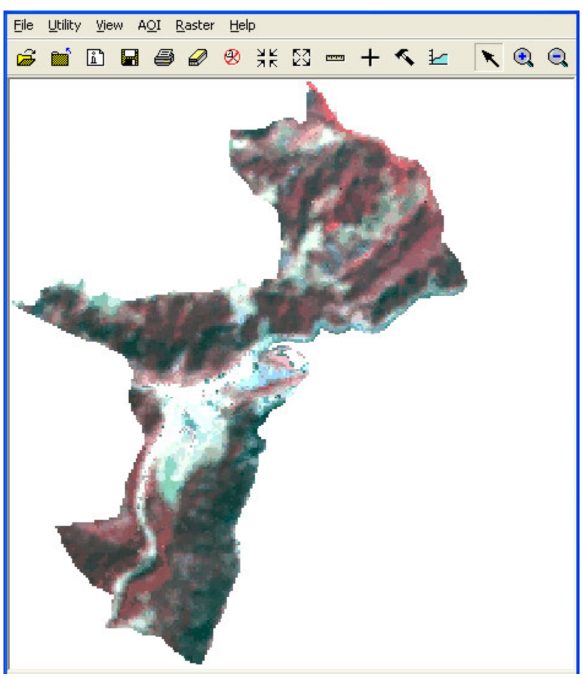

Figure 5. The image of research forest after supervised classification

After both classification methods, "Recode" function in ERDAS 8.5 was applied to combine the classes into six main classes including conifer trees, deciduous trees, shrubs, grass, agricultural vegetations, and others. In the recoding process, open grounds and roads were assigned into the same class with the name of "others".

3. RESULTS AND DISCUSSION

In image filtering stage, spatial frequency was successfully reduced by applying 7x7 low-pass filtering. The results from classification stage indicated that unsupervised classification was not satisfactory to classify vegetation types in the research forest. Figure 6 indicated the recoded image after the unsupervised classification process.

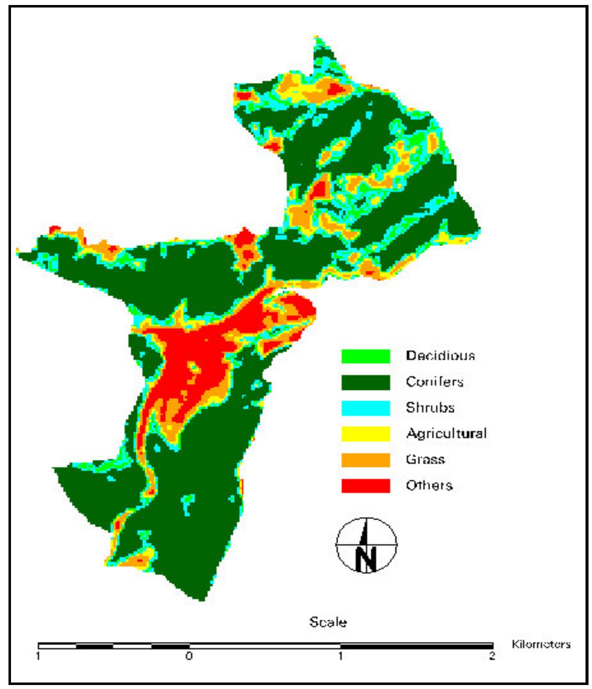

Figure 6. Recoded image after the unsupervised classification

Unsupervised classification process could not distinguishing grass from agricultural vegetation and underestimated the grass because dry grass was confused with stubble left on the agricultural fields. Conifers were generally well identified by unsupervised classification; however, deciduous trees were mixed with shrubs. In some parts of the images, open grounds and roads were also mixed with grass and agricultural vegetations.

Supervised classification, however, provided better results in terms of distinguishing forest vegetation. The recoded image after supervised classification process was indicated in Figure 7. By systematically selecting 250 sample points from the recoded image, the accuracy assessment of the supervised classification was performed by using aerial photos and stand type map as reference sources. The results indicated that, the overall classification accuracy and Kappa values were 69% and 0.55, respectively.

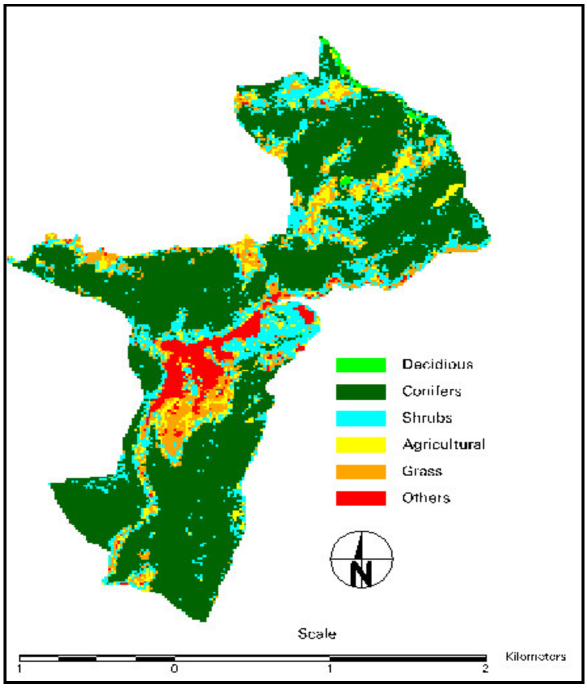

Figure 7. Recoded image after the supervised classification

Supervised classification method worked well for identifying conifers, but accuracy for deciduous trees and shrubs were relatively low due to large variation of spectral signatures. It was difficult to identify young stands due to shadow effect. The total areas for six main classes determined by both supervised and unsupervised classification methods were shown in Table 1. The results indicated that unsupervised classification overestimated three classes including deciduous, others, and grass, while underestimated conifers, shrubs, and grass.

Class Number	Class Names	Areas (%)	
		Unsupervised	Supervised
1	Decidious	6.2	0.5
2	Conifers	55.4	62.5
3	Shrubs	13.7	17.3
4	Agricultural	6.7	7.0
5	Grass	9.3	8.1
6	Others	8.7	4.7

Table 1. Total areas of six main classes after both classifications

4. CONCLUSIONS

In this study, pre-processing and classification techniques were applied and their performances were assessed in classifying vegetation types in KSU Research and Application Forest in Kahramanmaras, Turkey. For a better accurate assessment of the results, high-resolution orthophotos might be more useful to get accurate corresponding locations to the satellite image. Conducting field verification would also be helpful to eliminate ambiguities from interpretation of reference sources. In this study, it was not intended to delineate individual trees since it was not possible using ASTER NIR image with coarse resolution of 15 m x 15 m. In future studies, satellite imagery with better spatial resolution (e.g. 1 m or less) would be used to test the results from this study and to attempt identify individual tree crowns.

REFERENCES

Beaubien, J., 1983. Une methode de rehaussement d'images Landsat pour la classification du couvert vegetal. Proceedings, *8th Canadian Symposium on Remote Sensing*, Montreal, Quebec, pp. 559-566.

Beaubien, J., 1994. Landsat TM satellite images of forests: from enhancements to classification. *Canadian Journal of Remote Sensing*. 20(1): 17-26.

Carson, W.W., A.E. Akay, and D. Weyerman, 2001. An inventory of juniper through the automated interpretation of aerial digital imagery. *First International Precision Forestry Symposium*, University of Washington, College of Forest Resources, Seattle, Washington, USA

Gillis, M.D. and D.G. Leckie., 1993. *Forest inventory mapping procedures across Canada*, Inf. Rep. PI-X-114. Chalk River, Ontario: Petawawa National Forestry Institute. 79 p.

Gougeon, F., 1995. A crown-following approach to the automatic delineation of individual tree crowns in high spatial resolution aerial images. *Canadian Journal of Remote Sensing*. 21(3): 274-284.

Jano, A.P., 1984. Comparison of Landsat, MEIS II and Airborne MSS Data for Forest Classification in the Boreal Region of Ontaria. Proceedings, *9th Canadian Symposium on Remote Sensing*, Halifax, Nova Scotia, August 14-17, pp. 627-632.

Leckie, D.G., 1990. Advanced in remote sensing technologies for forest surveys and management. *Canadian Journal of Forestry Research*. 20: 464-483.

Lillesand, T.M. and R.W. Kiefer., 2000. *Remote sensing and image interpretation*. Fourth edition. John Wiley and Sons, Inc. New York. 724 p.

Meyer, P., K. Staenz, K.I. Itten., 1996. Semi-automated procedures for tree species identification spatial resolution data from digitized colour infrared-aerial photography. *ISPRS Journal of Photogrammetry and Remote Sensing*. 51: 5-16.

Raffy, M., 1994. The role of spatial resolution in quantification problems: spatialization method. *Int. J. Remote Sensing*. 15(12): 2381-2392.