A HIERARCHICAL CLASSIFICATON OF LANDSAT TM IMAGERY FOR LANDCOVER MAPPING

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ABSTRACT:

Information about current land-cover in forests is important for management and conservation of these areas. Up to the last decade traditional per pixel classification algorithms were used to be utilized in extracting land-cover information. However, they are poorly equipped to monitor land-cover in images acquired by current generation of satellite sensors with adequate accuracy. A good understanding and classification of an image can be done by gathering critical a priory knowledge about the study area and an effective use of channels involved in the procedure. It is important to make use additional spectral and spatial knowledge in order to improve the classification accuracy. In this study, a knowledge based hierarchical approach is proposed in order to classify and detect forest types in the Ömerli Dam Lake Region. The method makes use of the fact that land-cover types and their associated knowledge form a natural hierarchy. Hierarchical classification is a powerful approach in solving classification problems by decomposing the image into a hierarchical tree structure. This also results in sub-dividing the area into spectrally consistent regions and helps dealing with spectral variability within each subarea. Three types of knowledge were involved in the rule-based classification of the study area: Domain spectral knowledge, Spectral classification rules obtained from training data and Spatial knowledge. Sub-dividing the area into smaller homogeneous regions in hierarchical classification increased the accuracy, while supervised classification technique yielded 47 per cent in the same area. Spatial reclassification involved in the hierarchical classification method increased overall accuracy, yielding new classes like coast.

1. INTRODUCTION

1.1 Aim of the Study

Land-cover is one of the basic data layers in geographic information system for physical planning and environmental monitoring. Traditional multispectral image classification techniques are, however, insufficient for extraction of land-cover categories with required accuracy from high resolution imagery. Attempts to increase the overall classification accuracy, ranging from incorporation of ancillary data to use of expert systems and neural networks have proved to be successful when compared with traditional classification techniques. In this study, the classification accuracy problem was attacked using a knowledge-based hierarchical approach. In the context of Landsat imagery, domain spectral knowledge, spectral classification rules obtained from training data and spatial rules can be used to improve the quality of image classification (Anil, 1989). Since land-cover types present in Landsat imagery form a hierarchical structure, a top-down processing strategy was adopted in separate classes.

The research described in this study attempts to deal with the spectral variability within a landscape during image classification by subsetting large study areas into spectrally consistent geographic areas with the cooperation of spectral and spatial rules, classifying these areas independently and then rejoining them to form a final continuous classification. In essence, the hierarchical classification helps in reducing the classification confusion among land-cover classes, because the spectral variability present within each subset image is usually considerably less than that between different strata.

1.2 Background

There are numerous accounts of research where TM data were used to classify forest types, but few researchers have used a knowledge-based hierarchical approach. Anderson et al., (1976) Level I and II classifications (discrimination between deciduous and coniferous forests) from remotely sensed data have been produced with accuracy of greater than 80 percent. However, for Anderson Level III classifications (discrimination between forest types), mapping accuracy has been generally lower. Anil K. Jain (1989) proposed an image segmentation technique by extracting kernel information from the input image to provide hierarchical classifier to discriminate between major land-cover types in the study area. A more detailed interpretation of the image was then produced using a spatial clustering technique, the previously extracted kernel image information and spectral and spatial rules which make up the knowledge-base of the hierarchical classifier.

A rule-based expert system was developed by Skidmore (1989) to classify forest types. Relationships between forest type classes and terrain (ie gradient, aspect and topographic position) were quantified using the knowledge of local forest personnel. The expert system had a higher mapping accuracy than the maps produced by traditional classifiers. Bolstad and Lillesand (1991) designed a system of programs named CLASSMOD (Class Modeler) which allowed the integration of thematic data, satellite imagery and a rule-based, forward-chaining inference strategy in land-cover classification. Rules were used to describe feature types, data themes, the relationships among themes and feature types and to define the inference path. Barnsley and Bar (1992) used a kernel-based reclassification method, referred to as SPARK (Spatial Reclassification Kernel) which examined both the frequency and the spatial arrangement of class labels within a square kernel. It proved successful with 20 m. resolution SPOT XS data.

Wolter et al. (1993) implemented a layered multitemporal approach to the classification of Landsat data, combined with a specific knowledge of cover type phenology and accuracy for forest classes aggregated to Anderson Level II (hardwood, conifer and mixed) was 93.6 percent. Johnson (1994) was one of those who implemented and applied a rule-based model to classification of built-up land from multispectral SPOT data. The technique she used addressed the specific problem of extraction of a spectrally heterogeneous land use category from SPOT XS satellite data. Stewart and Lillesand (1994) demonstrated the utility of pre-classification stratification of large study areas into spectrally consistent subareas or strata to deal with spectral variability among classes. Their study focused on classification of non-urban component of Lansat TM imagery using hybrid “guided” clustering methods for classification of individual strata. The results proved to be promising in terms of accuracy.

1.3 Hierarchical Approach for Classification of TM Image

The knowledge that can be used as rules in hierarchical classification procedures can be divided into two types: *Spectral and Spatial.* In remote sensing, spectral properties associated with different land-cover types have been extensively studied. This spectral knowledge plays an important role in Landsat image segmentation. Spatial knowledge, on the other hand, deals with the spatial relationships (e.g., proximity, connectivity and relative orientation) between various objects in the image. The spectral and spatial knowledge is used in three different ways in the classification procedure.

Domain knowledge is embedded in the region detection techniques. It is represented as spectral rules for region interpretation. These rules are used in interpreting and classifying different regions in the image. In Landsat images, water is the unique land-cover type such that the band reflectance values always decrease as the band number increases, ignoring the thermal band (band 6). In other words, if pixel (i, j) lies entirely within a water region, then

$$b_{ij}^1 > b_{ij}^2 > b_{ij}^3 > b_{ij}^4 > b_{ij}^5 > b_{ij}^7 \qquad (1)$$

except for some boundary pixels of water regions which may consist of both water and non-water areas, the band decreasing property holds for all water regions of the study area.

Spatial rules can be used in reclassification of pixels based on their spatial characteristics like the method implemented by Barnsley and Barr (1992). For example, a small vegetation area surrounded by urban pixels can be relabeled as an urban area. A tiny non-vegetation region surrounded by forest areas can be merged with the forest areas.

Landsat image consists of many regions which belong to different land-cover types. Since these land-cover types form a natural hierarchical structure, Hierarchical Classification is an appropriate strategy for land-cover classification. The procedure involves decomposing the image into hierarchical tree structure.

Once the hierarchical land-cover structure is defined, knowledge rules for each land-cover type have to be generated. Three types of information are considered in constructing the knowledge rules for each land-cover type in the hierarchy:

- *Domain spectral knowledge:* Spectral knowledge can be used to construct the hierarchical structure of land-cover classes, such as discrimination between vegetation and nonvegetation regions using indices and detecting water areas using band decreasing property. This domain knowledge is obtained from the remote sensing literature.

- *Spectral classification rules obtained from training data:* Qualitative spectral knowledge involved in Landsat TM imagery has to be transformed to more specific quantitative classification rules. Training data help to generate thresholds to be used later as rules for discriminating and classifying land-cover categories more accurately.

- *Spatial knowledge:* Since spectral knowledge alone is insufficient for classification of all land-cover types, spatial rules have to be used to increase the resultant accuracy.

2. STUDY AREA AND THE DATA

The study area is located approximately 20 km. east of Istanbul, centered on Latitude 40^0 58’ 48’’ N and Longtitude 29^0 22’ 51’’ E (Figure 1).

The area includes various types of land use. Southern half of the Ömerli Dam Lake covers 5,2% of the region, approximately 28% of the area is built-up land, mostly residential composed of apartment buildings and more than 44% is occupied by forest types. The most common tree species are black pine (Pinus nigra), red pine (Pinus brutia), oak, spruce and plane tree. Destructive logging practices and urban sprawl took place in the late years but the region is still a good place for the classification analysis.

The Landsat TM image acquired 18 July 1997 was used mainly for the analysis. Spectral contrast between vegetated surfaces and cultural surfaces such as pavement, bare soil, construction areas and buildings were optimized due to the fact that it is a summer scene. 6 bands of the TM image were used. Thermal Band (Band 6) was not used because of its coarse spatial resolution.

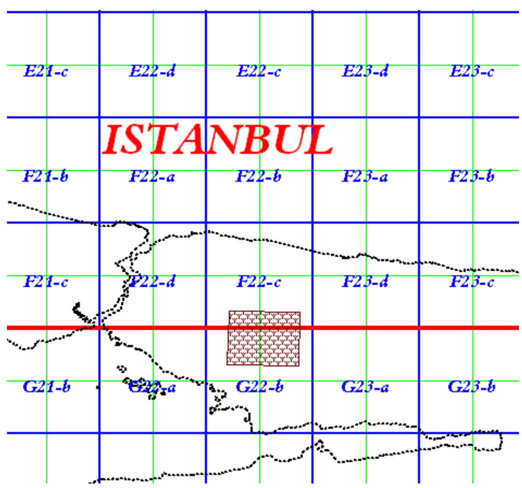

Figure 1. Location of the study area

1/25 000 scaled forestry map sheets of Omerli Dam Lake and neighborhood, acquired from the General Directorate Of Forestry, provided valuable information about the forest types, tree ages, trunk diameter and density as well as other features like the road types, water boundaries and rivers.

The data set also includes a 1/5 000 scaled orthophoto. It proved to be a valuable ancillary data in terms of spatial resolution (50 cm.), date of acquisition (September 1999) and the level of detail.

3. METHOD

3.1 Contruction of hierarchy

The study area consists of both man-made and natural regions. Forestry areas include deciduous (mostly oak groves) and coniferous types (red-pine, black-pine). Nonforested areas, on the other hand, are composed of orchards, shrubs, agricultural fields and grass. Remaining regions are covered with water (Omerli Dam Lake), roads and urban areas. So it would be a good strategy to divide whole study area first into two classes as vegetation and nonvegetation due to the heterogeneous nature of it. This is the first level of the hierarchical classification. Decomposing the area into such two classes as a first level would help to eliminate errors arising from mixed pixels in urban and residential regions from further levels.

The second level of proposed hierarchical classification involves further decomposition of both vegetated and non-vegetated areas and masking operations. Forest types, agricultural areas, shrub and grasslands like open forest floor would be separated from each other using thresholds. Masking helps to extract image pixel values which satisfy the criteria and create new images which consist of target classes for further analysis. Each type of region is further decomposed into smaller regions recursively for detailed interpretation until regions cannot be further subdivided.

The Figure 2 illustrates the structure of the proposed hierarchical classification for the test region. It contains 3 levels and 13 nodes.

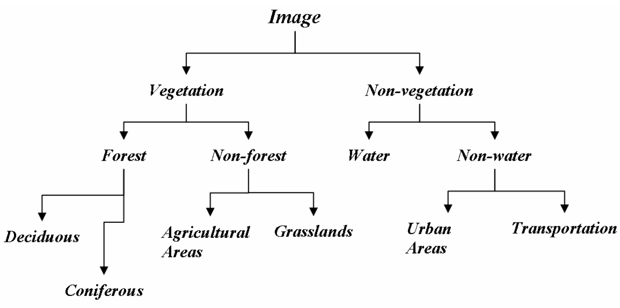

Figure 2. Proposed Hierarchical Tree Structure

3.2 Spectral Rule Generation

There are a few ways to increase the knowledge of the researcher about the spectral properties of the features in the TM image. Domain spectral knowledge – as described above – is hardly sufficient to generate rules in order to progress in such hierarchical methods, especially when seasonal variations of the vegetation is considered, so additional information has to be generated. This was done by examining training data containing regions of the various types with the correct types being known.

The dimensionality was increased to 10, six of which correspond to the TM bands; the remaining four were band transforms, namely Normalized Difference Vegetation Index *(NDVI)* and TM Tasseled Cap Transformations *(Brightness, Greenness, Wetness).*

NDVI values, ranging from –1 to +1, stretched to unsigned 8-bit data. Examination of training sites, in cooperation with the orthophoto of the region, proved that a normalized difference vegetation index threshold of 135 was a critical value for discriminating between vegetation and non-vegetation. The value was found by using region growing tool, and examining the statistics generated from the DN values of the area of interest (AOI).

Further investigation of the vegetated areas revealed that NDVI and greenness components are good indicators of forest type discrimination. The vegetation image which was created by masking the non-vegetated areas from the original image, was again decomposed into sub-levels as deciduous forest, coniferous forest and non-forest regions using these two indicators. Non-vegetation image was then divided into two more sub-classes as urban and transportation.

3.3 Road Extraction

The extraction of roads from images has received considerable attention in the past. Several schemes have been proposed to solve this problem at resolutions that range from satellite images to low altitude aerial images. The strategies proposed fall into two broad categories. The work described in Gruen and Li (1994), Heipke et al. (1995), and McKeown et al. (1988) deal with the semi-automatic extraction of roads. The human operator has to select a certain number of points of the road which is then extracted. On the other hand, the work presented in Ruskone et al. (1994) is concerned with the automatic extraction of roads. Most of the studies referred above used fine resolution aerial images in information extraction about roads.

These models, despite their success with aerial imagery, can hardly be applied to satellite images with coarser spatial resolutions. In this study, the roads were extracted using the vector coverages digitized from the orthophoto map. The 1:5000 scale-orthophoto of the study area proved to be an excellent ancillary data for extraction of roads. An ARC/INFO coverage was created by digitizing roads and used to extract the road pixels from the image. A thematic roads image was created using the vector coverage and these regions were extracted and masked from the original image.

3.4 Hierarchical Classification

3.4.1 First Level: Domain spectral knowledge and spectral classification rules obtained from training data were used as input to the model created using *Spatial Modeler Language* (SML) ERDAS IMAGINE version 8.3.1. For later applications the software was customized and a user-friendly graphical user interface was created using Erdas Macro Language (EML) (Figure 3).

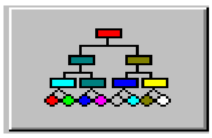

Figure 3. Hierarchical classification module access button

It is a known fact that healthy vegetation areas have high reflectance in the near-infrared region and low reflectance in the red-light region of the electromagnetic spectrum. This domain knowledge was transformed to quantitative rules using the training areas of the known classes.

A NDVI threshold of 135 was used in the first level of the hierarchical classification process. Both vegetation and non-vegetation areas were masked from the original TM image sequentially yielding two new thematic images in the first level as vegetation.img and non-vegetation.img. The output thematic images of the first level can be seen in Figure 4. Both of the new image files were used as inputs to the second level of the technique.

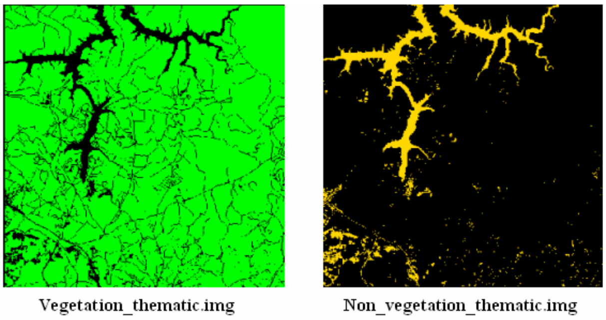

Figure 4. Resultant images of the first level classification

3.4.2 Second Level: The second level of the model involves decomposition of the vegetation image into forest and non-forest images, and decomposition of the non-vegetation image into water and non-water images. Both procedures are described below:

The vegetation image was divided into further sub-classes in the land-cover hierarchy. The rules generated during the examination of the training data were used as thresholds (Table 1).

	NDVI		Greenness	
	Low	High	Low	High
Coniferous	180	220	-3	20
Deciduous	220	255	20	255
Other	135	180	-255	20

Table 1. Forest classification rules

The model created using Spatial Modeler Language created two new images using the threshold values given in Table 1. The forest.img image consists of two forest types and the nonforest.img consists of other vegetation including grass and agricultural areas (Figure 5).

The non-vegetation image was sub-divided into water and non-water images using the band decreasing property of the Landsat bands for the water regions. The spatial modeler language script was created for extraction of water areas from any Landsat scene and a user interface (Figure 6) linked to it was used at this node. The water statistics created before were used by the model as default values in water extraction. The resultant water and non-water images are shown in Figure 7.

3.4.3 Third Level: The third level of the hierarchical classification model involves further classification of each image (forest image, non-forest image, and non-water image) and then merging the resultant images to create one thematic map.

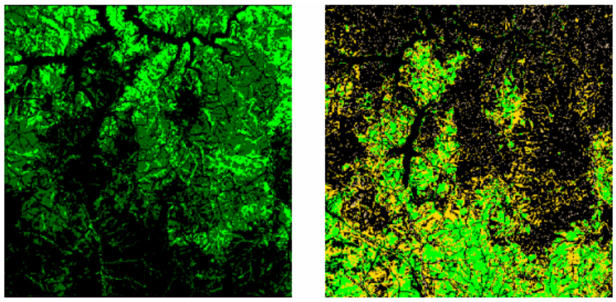

Figure 5. Second level results (Forest/Non-Forest images)

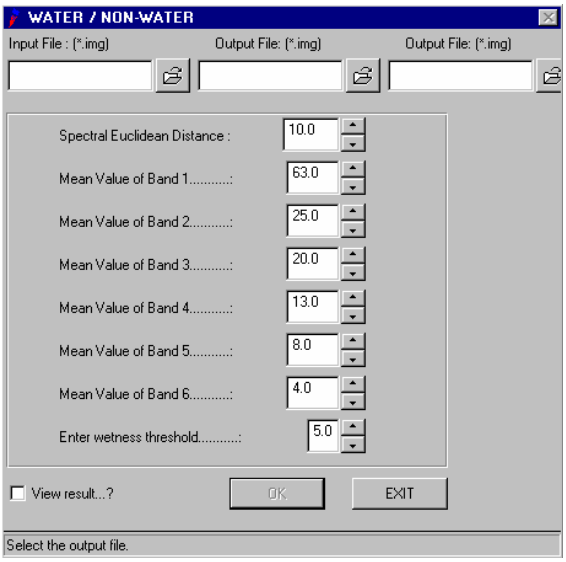

Figure 6. User interface for water rule

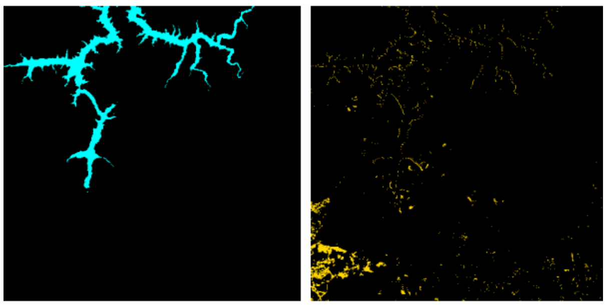

Figure 7. Second level results (Water/Non-water images)

The forest.img (thematic image) was recoded using the threshold values and divided into two forest types as coniferous and deciduous. Non-forest image was decomposed into agricultural areas and grass/open forest floor classes

A new thematic image was created with 7 classes after rejoining separate thematic images. All of these categories (except for the road data which was extracted using the vector coverage) were generated using thresholds as rules in the hierarchical classification procedure. The final image and classes are illustrated in Figure 8.

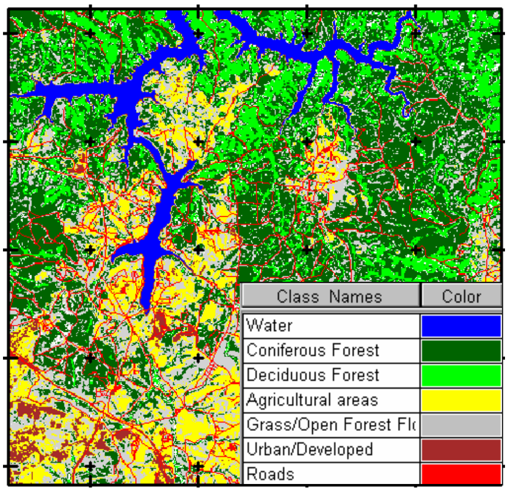

Figure 8. Final image created by using Hierarchical approach

3.4.5 Spatial Reclassification: Spatial reclassification represents a comparatively simple way to examine the spatial variation in land-cover in remotely sensed images, and is easy to implement in most image processing systems. It can be performed in one of two ways. The first, named as *kernel-based spatial reclassification* (Barnsley and Barr, 1992), involves passing a simple convolution kernel across the land-cover image. In the second, referred to as *object-based spatial reclassification,* discrete objects (i.e., groups of adjacent pixels with the same class label) are identified within the initial image segmentation: information on the size, shape and spatial arrangement of these objects is subsequently used to determine the nature of the land-use in different parts of the image.

In this study kernel-based procedure was applied to resultant land-cover image created using the hierarchical approach. Following contextual rules were used during spatial reclassification :

- Pixels labeled as urban due to the spectral similarities can be reclassified and labeled as coast if they share a border with the lake.
- Agriculture and forest pixels can be reclassified as urban if they are surrounded by a user-defined number of urban pixels.
- Urban/developed pixels can be reclassified as forest if they are surrounded by a user-defined rate of forest area.

A 3 X 3 kernel was used to detect the urban pixels neighboring water as the first step of the spatial reclassification and 940 coast pixels mislabeled as urban were detected. The thematic image was corrected and a new class was added to the classification scheme after these pixels were relabeled as "coast".

The second step of the spatial reclassification was to detect pixels labeled as any kind of forest or agricultural area in dense urban regions. A 5 X 5 kernel was used to find out forest or agricultural areas surrounded by urban pixels (Figure 9) because a 150 m. X 150m. area was found to be suitable for such a region which contains various land cover types with small parcel sizes.

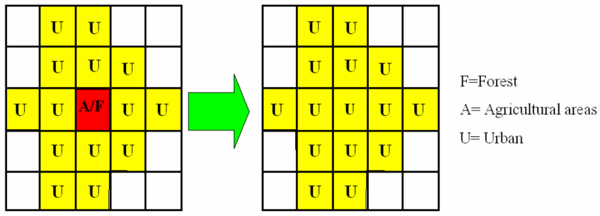

Figure 9. Spatial reclassification kernel

The central forest (or agricultural) pixel was relabeled as urban if more than 14 of 24 neighboring pixels (almost 60 percent of the area) were labeled as urban. This threshold was found after comparing the thematic image and the orthophoto.

Final 5 x 5 kernel was used to detect urban pixels within forested area but a negligible amount of pixels satisfied the criteria to relabel as forest.

4. ACCURACY ASSESSMENT

A number of randomly selected 265 reference points measured in the field survey were used in the accuracy assessment of the classification. The class values of the reference points were assigned during the field survey, except for the water class. The overall accuracy of the proposed hierarchical and maximum likelihood classifications were found to be 91.32% and 47.55% respectively. In order to compare different classification methods namely Hierarchical and Maximum Likelihood Classification techniques, Kappa coefficient of agreement as an accuracy measure for remote sensing classification is used.

As it is given in Table 2, Kappa coefficients are obtained as 0.94 for Hierarchical Classification and 0.37 for Maximum Likelihood Classification. This implies that the accuracy of the Hierarchical Classification, 91.32 percent, and the accuracy of the supervised classification, 47.55 percent, are better than the accuracy that would result from a random assignment. This result indicates the Hierarchical Classification is better than supervised classification in identifying the forestry areas from Landsat image.

Classes	***Hierarchical Classification***		***Supervised Classification***	
	Accuracy (%)	***Kappa***	***Accuracy (%)***	***Kappa***
Water	100.00	1.0000	70.59	0.6919
Coniferous	95.60	0.8430	30.77	0.8985
Deciduous	97.06	0.9044	94.12	0.9325
Agricultural	90.24	0.9132	82.93	0.2902
Grass	77.36	0.8619	16.98	0.0959
Urban	90.91	1.0000	90.91	0.4103
Roads	94.74	1.0000	5.26	0.2818
Coast	100.00	1.0000	0.00	0.0000
OVERALL RESULT	***91.32***	***0.9403***	***47.55***	***0.3700***

Table 2. Overall classification results

The hierarchical classification method was more successful in detecting agricultural, grass and urban areas. Except for the road pixels which were extracted using vector coverage, the superiority of hierarchical approach has been proved, since the area was sub-divided into spectrally homogeneous region, minimizing the risk of spectral confusion among classes.

5. CONCLUSIONS

Compared to the traditional multispectral classification methods, the knowledge-based hierarchical classification did improve the classification results. The water was found to be the unique class, generated by both techniques, with similar thematic output. All other classes involved some confusion due to the spectral similarities (i.e., agricultural areas and urban, roads and urban). No class with "coast" label was generated with the maximum likelihood classification method because it was created by spatial reclassification step of the hierarchical method. Coastal regions were not included in the starting classification scheme because high risk of confusion between actual shore and urban and/or road pixels which would cause some inland urban pixels to be labeled as coast and affect resultant accuracy. Maximum likelihood classification detected one fourth of the coniferous area, which are detected by hierarchical classification.

The results showed the proposed hierarchical classification approach is promising and has several advantages in comparison to standard approaches:

- The domain spectral knowledge and other spectral knowledge obtained from training data are provided in an easily modified and understandable rules.
- Computationally expensive operations can be avoided by restricting the channels involved in the classification procedure. Although the dimensionality was increased in the beginning of the approach, only those with the least correlation and which would best define the target classes were used in the rules.
- Integration of spatial characteristics of features with the classification procedure helps to increase the understanding of some classes confusable with others.
- It is flexible when applying to geographically different areas. Higher level, more general categories in the hierarchy would remain constant across different types of terrain; only the lower level nodes would be variable from one type of region to another.

The disadvantage of the proposed hierarchical classification approach is the requirement of the reliable training data. The rules are extracted using the statistical information of the training data so these statistics should be carefully examined since gathering enough training statistics to adequate account in order to be used as rules, is a difficult task.

Although the classification technique presented in this study generally worked well, there is potential for improvement and refinement:

- Additional ancillary data like detailed land use and land cover maps would not only decrease omission and commission errors for the forest cover type classifications, but also increase the levels of classification, like classifying the types of trees in the forest areas
- Multitemporal TM image of the study area, if combined with additional channels like band ratios and transforms, would help generating more reliable rules for hierarchical classification method.
- More spatial rules should be generated. Most of the frequently used spatial rules can be collected and transformed into computer-accessible format.

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