THE USE OF MULTITEMPORAL LANDSAT MSS DATA FOR STUDYING FOREST COVER TYPES.

by: D. Fabian Lozano-Garcia & Roger M. Hoffer

Department of Forestry & Natural Resources and
Laboratory for Applications of Remote Sensing.
Purdue University, West Lafayette, Indiana 47907

AUTHOR BIOGRAPHICAL DATA

D. Fabian Lozano-Garcia received his B.S. degree in biological sciences, with emphasis on remote sensing of natural resources from the Universidad Nacional Autonoma de Mexico. He received his M.S. in Forestry and Natural Resources from Purdue University in 1984, and presently he is working on his doctoral degree in applications of digital remote sensing for natural resources inventories. Fabian was a research staff member of the Instituto Nacional de Investigaciones sobre Recursos Bioticos in Xalapa, Mexico until 1981.

Roger M. Hoffer is a Professor of Forestry and also Senior Scientist, at LARS, Purdue University. He was co-founder of LARS in 1966, and has served as a principal investigator on Landsat, Skylab, Shuttle Imaging Radar, and other major remote sensing projects. Roger is a Certified Photogrammetrist and has served as National Director of the Remote Sensing Applications Division and President of the Western Great Lakes Region of ASP, and as Associate Editor of Photogrammetric Engineering and Remote Sensing. He was recipient of the 1978 Alan Gordon Memorial Award from ASP.

ABSTRACT

Considerable interest has been generated in recent years concerning the destruction of forests in many countries of the world. There has been speculation concerning possible relationships between the increased level of carbon dioxide in the earth´s atmosphere. Landsat multispectral scanner data provides a unique opportunity to study the earth´s surface and the extent and condition of various cover types, including forest. Many different computer-aided analysis techniques have been developed to classify Landsat multispectral scanner (MSS) data. However, most of these techniques are designed to utilze a single data set. To determine changes in the extent or condition of the forest canopy that may occur over time requires overlaying multiple data sets and a different approach to the analysis of such a multi-temporal data set. This research examines the effectiveness of tha Layered Classifier as a possible technique for analyzing multi-temporal Landsat data. The test site was near the Monroe Reservoir in the Hoosier National Forest, Indiana. Landsat satellite data, obtained on four dates throughout the year were digitally registered

and analyzed. The results show that the Layered Classification technique enabled more accurate classification results to be obtained, and at far less cost (in terms of computer time needed) than were obtained by simply combining the data from two dates and applying a standard maximum likelihood classification algorithm. These results provide significant insights into effective techniques for using satellite data to monitor changes in forest canopy conditions or areal extent.

INTRODUCTION

The need for accurate information related to the location, extent and condition of the natural resources of an area is of great importance due to the pressure that man is imposing on the environment. Cities are growing and taking over agricultural areas, areas of primary forest lands are giving way to urban and agricultural fields, and the landscape is being altered by the construction of dams. These are only a few examples of human effects on the environment.

The specific type of information needed is dependent upon the requirements of individual users or user groups, but some basic characteristics can be defined. Talbot (1981), in discussing the forest resources of the world, listed the following key questions with respect of our knowledge of these resources: How much area does it cover? How fast does it grow? How fast is being utilized? How fast will it came back once cut? How much biomass does it contain? How much carbon does it absorb, store, or release when burned? Similar question can be raised for other types of natural resources. How we answer these questions and how accurately we make our assessments is dependent upon our understanding of the environmental characteristics of the natural resources.

The natural environment is in continuous change, although the rate of variation for different components of the environment can vary a great deal. The environmental variations could be grouped into the following categories (Dethier, 1974; Jensen, 1984; Thompson, 1982; Todd, 1977)

1) Man-made alterations -- Man-induced alterations may be intentional or unintentional. Examples of the first case are the development of urban settlements or the clear-cuting of the forest. Accidental changes are the increase of soil erosion that occurs after the vegetative cover has been removed and the subsequent alterations of the hydrologic regime of a river. Monitoring man-induced variations is very important in order to be able to observe any adverse effect of man's activities on the environment.

2) Phenological changes.- These variations are a sequence of predictable, natural events that occur in a known and logical order. The period of time involved in this type of change is one year or part of the year. An

example of this type of change is the development of crops or the seasonal variations of foliage in a deciduous forest.

3) Long-term changes.- Many of the naturally occurring modifications in the landscape take place over periods of time greater than one year. These phenomena often have a periodic component and their effects are observed as small, relatively permanent changes from one observation to the next. The movements of sediment by a river, the slow progress of a glacier, or the desertification process represent typical examples of these types of change.

4) Short-term changes.- These are naturally occurring changes that take place over small periods of time and usually over a relatively small area. Depending on their nature it may or may not be possible to monitor such changes by means of remote sensing techniques. Examples of these situations are landslides and river flooding.

One of the tools that is available to monitor environmental variations is the series of Landsat satellites. Since July 1972, these satellites have provided useful data over the entire world. The Landsat program is experimental and was intended to establish the value of relatively coarse-resolution, large area, synoptic, reflective multispectral imagery for earth resources analysis (Lintz and Simonett,1976).

These satellites offer the possibility of periodic coverage, a synoptic view and digital multispectral scanner data availability. Thus, the resource manager has the potential for monitoring the areas where ground cover is subjected to alterations either by natural or human activities, or analyzing the phenological development of natural and cultivated vegetation.

OBJECTIVES

The overall objective of this work is to compare the accuracy and cost-effectiveness of three multitemporal analysis methods, based computer-aided analysis techniques and Landsat satellite multispectral scanner data.

Methods to be compared will include:

a) Comparison of single scene classifications. Landsat data taken on different dates is classified one date at a time and the results are compared.

b) Multitemporal/Multispectral classification. A two date (eight channels) data set is generated and a single step classification is performed using all eight channels.

c) Layered Multitemporal/Multispectral approach. A two (or more) date data set is generated, and a step-wise hierarchical classification approach, involving various subsets of spectral bands is used to classify the data.

METHODS AND MATERIALS

Study Area Description

The test site is located in the south-central portion of the state of Indiana, about 50 miles south-southwest of Indianapolis. It is located in the Interior Low Plateau province, in the unglaciated portion of Indiana. The area is well drained by a medium-fine dendritic drainage system (Lindsay et al. 1969). The study area is covered in a high proportion by forest stands, mostly composed of Tulip Poplar, Oak, Maple, Hickory, Ash, Walnut and Sycamore. Small stands of Pine are scattered in the study area. The steep slopes and heavily dissected topography have discouraged the extensive clearing of this area for agriculture, although selective logging has altered the composition of most stands. A significant portion of the Hoosier National Forest is represented by this association. On the valley bottoms in the western, south-western and east central portion of the area, the forest has been cleared for crops and pasture. Some portions of sub-urban Bloomington occur on the north-western corner of the area. Monroe Reservoir, Lemon Lake, Yellowood Lake and Grandview Lake are the major water bodies in the area.

Available Data

Seven dates of registered multispectral scanner images of the Landsat-1 satellite were available for a portion of the Hoosier National Forest including the Monroe Reservoir and surrounding areas. Table 1 shows the available data.

Table 1. Available Landsat-1 Multispectral Scanner Images.

Scene ID	Date	Season
1285-16001	May 4, 1973	Early spring
1320-15541	June 8, 1973	Late spring
1392-15531	August 19, 1973	Summer
1411-15584	September 7, 1973	Late summer
1482-15514	November 17, 1973	Late fall
1572-15493	February 15, 1974	Winter
1591-15550	March 8, 1974	Late winter

An evaluation of the quality, cloud cover and similarity of seasonal conditions was made to select the best sets of imagery for the digital analysis.

RESULTS

A visual interpretation of the standard MSS color composite indicates that summer data, primarily June or September, is required to adequately separate the deciduous forest from the other classes. A winter data set is required to distinguish between the coniferous forest and all other cover types. Therefore, a combination of a summer and winter data set would be adequate to obtain good differentiation of all of the cover types in the area.

The digital classification was performed to test three multitemporal classification schemes: 1) to provide a better understanding of the complexities involved in any multitemporal analysis of multispectral scanner data; 2) to define the best set of data for this type of application; and 3) to provide a guideline for the methodology to be used in this type of study.

Four out of seven available dates were selected to carry out the digital classification comparison. It was considered that these four data sets were representative of different phenological conditions of the vegetative cover. The selected dates were May, June, September and February.

Table 2 shows the classification techniques utilized in this work. They can be divided into single date, single stage two dates, and layered classifiers. In the single date approach, each data set is classified independently. In the single stage two dates approach, two methods were tested --one with all 8 channels and the other with the four best channels. The layered approach was first tested using the same training statistics generated for the 8 channel, single stage approach. The second generating two sets of independent training statistics --one for each date.

Table 2. Classification Techniques Used.

Classification Technique	Single Date	Single Stage		Layered	
Statistics used for training	Independently Generated for each Date: May, June, Sept. & February	All 8	"Best" 4	Combined Dates (All 8	Separate Dates (4 June, 4 Feb.)
Algorithm used for classification	GML	GML	GML	GML	GML

The first analysis conducted in this study involved the classification of each single date. Training statistics were generated using a "multi-cluster block" approach similar to the one described by Fleming et al (1975), using transformed divergence as a measure of interclass separability along with calibrated spectral curves, coincident spectral plots, bi-spectral plots and aerial photography as an aid in class identification.

The second analysis involved classifications of a two date, eight channel data set. The selected dates were June of 1973 and February of 1974. These dates were selected on the basis of the reference data (primarily used for the interpretation and evaluation procedures). Training statistics were generated using also a "multi-cluster blocks" approach.

Two different classifications were performed with this data set. The first used all the channels of both dates (Multitemporal/Multispectral 8 channels). For the second classification, four channels were selected based upon the minimum and average transformed divergence value, calculated by the SEPARABILITY processor of LARSYS.

One of the characteristics of the layered classifier is that it permits the analyst to optimize the decisions (use of certain spectral bands) in the separation of a class or group of classes. In a Multitemporal/Multispectral scanner classification, this algorithm also permits the use of the best season (represented by a set of spectral channels) for the identification and separation of cover types.

The first approach used with this classifier involved using the same 8 channel training statistics developed for the single stage Multitemporal/Multispectral classification. Next, a set of training statistics was developed independently for each of the two dates and used as part of the input to the layered classifier.

The selection of the classes that will constitute a particular node, and the set of spectral channels to be used to separate this node were based on the separability information. This was obtained by calculating the transformed divergence (Dt) values of the training classes for all possible combinations of spectral channels. The best set of features to be used in each particular node was also defined using the separability information, based on a threshold of Dt=1750.

The classification results were quantitatively evaluated using a set of test fields. These test fields were defined using a grid sampling technique. The same set of test field were used to evaluate all of the classification results. The cover types were pooled for the evaluation into 5 major groups: Deciduous Forest, Coniferous Forest, Grassland, Water and Soils. For the Deciduous Forest, 11 fields with 1512 pixels were identified; for Coniferous Forest, 8 fields with 152 pixels; for Grasslands, 5 fields with 197 pixels; for Water, 5 fields with 320 pixels; and for Soils, 5 fields with 238 pixels.

It can be seen in Figure 1, that June presented the most consistent performances, with percentage values above 70 % except for the Coniferous Forest class. In the other three single date classifications, the Pasture, Coniferous Forest and Deciduous Forest classes showed considerable variability in performance.

The classification performances by cover type for the two Multitemporal/Multispectral classifications and the Layered classification are shown in Figure 2. These approaches provided relatively more consistent results, except for the Pasture class.

Following the suggestions of Anderson (1974) and Landgrebe (1976) the statistical evaluation of the classification performance was carried out using the arcsine transformation of the % accuracy. An ANOVA and Newman-Keuls Range test was performed to compare cover type accuracy within each classification scheme and the overall classification performances of the eight schemes.

The statistical comparison among the eight classifications indicates that there are two separate groups. The first group consists of the two Layered classifications, the Multitemporal/Multispectral classifications both with 8 and 4 channels, and the June classification. The overall classification performance for these classifications show no significant difference between them at a 0.1 level. The other group, formed by the May, September and February classifications, had much lower classification performances and the statistical comparison indicated significant differences between the classifications. If the comparison is made using the average performance by class (Sum of the percent correct in each class/No. of classes), the Layered classifier 2 set of 4 channels is statistically better than the other schemes. The June, the Multitemporal/Multispectral 8 channels, the Multitemporal/Multispectral 4 channels and the Layered 1 set of 8 channels formed a group that it is statisticaly similar. February and May formed another group, and the September classification stands alone with the lowest value.

DISCUSSION

The May classification overall performance was relatively high. However, it was difficult to define a good set of training statistics for the Coniferous Forest, both the clustering and supervised fields methods failed to define separable training statistics for this class. Other confusion problems were due to the high spectral variability of the deciduous forest.

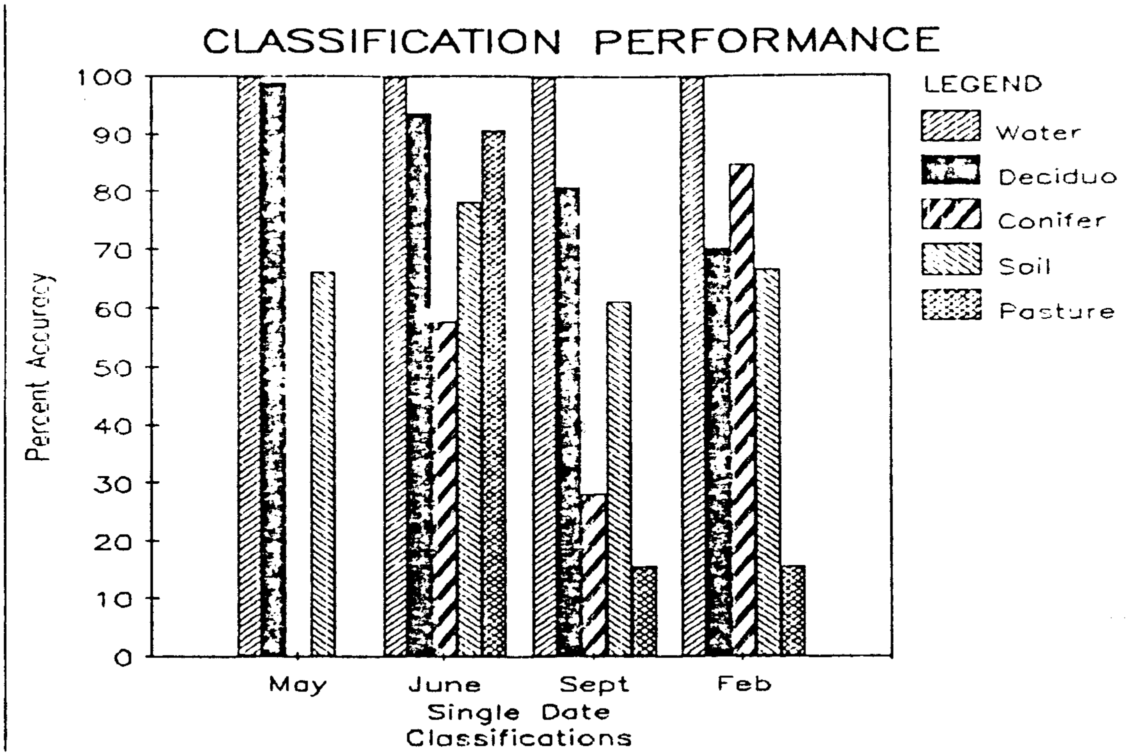

Figure 1. Classification Performance of the Single Date Classifications

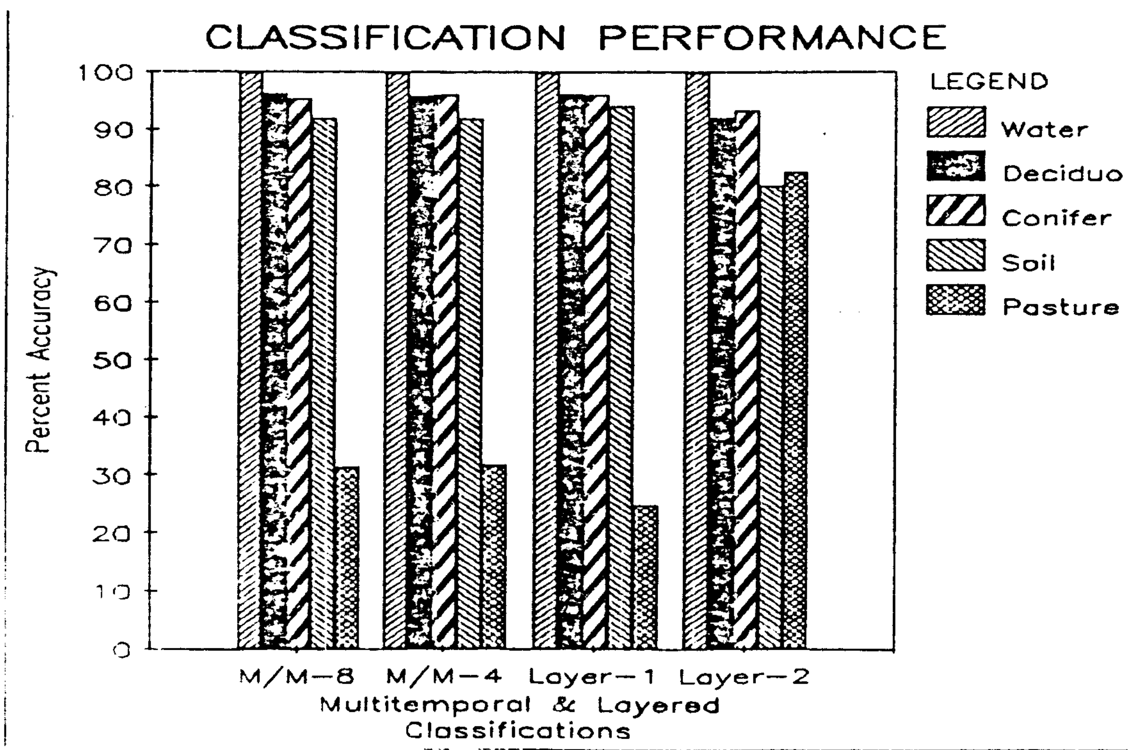

Figure 2. Classification Perfornces of the Multitemporal/Multispectral Classifications and the Layered Classifications

June classification was the best of the four single date classifications, with 90.6 % overall performance and 84.1 % average performance. Both the Deciduous Forest and the Grassland classes had high accuracy (90 %); no significant difference was found between the percent accuracy of these two classes. Soils tended to be confused with Grasslands, but this was a logical confusion since some grassland or pasture areas did not have a fully developed vegetative cover that could separate them from the Soil classes. This was observed in the aerial photography and could also be confirmed by some overlap between the Soils and Grasslands training classes.

The September classification was the lowest in the statistical comparison of overall performances. Several problems were found in this data set. During the clustering process, it was not possible to obtain training classes representing the Coniferous Forest. Therefore, a set of supervised training areas were selected to represent this class. However, even this approach was only partially successful because low separability values were found between one of the Deciduous Forest classes and one of the coniferous forest classes in the final set of training statistics. Another confusion occurred between the Soil and Grassland classes. Almost 61 % of the samples identified as pasture in the test fields were classified as Soils; conversely, 24 % of the test pixels of the soil classes were classified as Grassland.

This data set provided an interesting representation of the phenological variations of the Deciduous Forest. In general, three stages of the forest were recognized: a) fully developed leaves, b) intermediate stage and c) begining Autumn coloration. Several spectral classes were found representing these forest conditions. A relation between topography and these spectral subclasses of deciduous forest was found. The green vegetation occurred at the high elevations. The classes with autumn coloration were found in the narrow valleys that have not been cleared of forest cover. However, no test fields were defined for these subclasses due to the lack of aerial photos taken at the same time as the Landsat data, so the consistency of this relationship cannot be shown quantitatively.

The February data, as would be expected, resulted in confusion between the soils and pasture classes. More than 72 % of the test pixels of the Grassland classes were erroneously classified as soils and almost 29 % of the test pixels of the Soils class were assigned to the Grasslands. The 84 % accuracy of the Coniferous Forest was the best of the four single dates classifications. This improvement in accuracy was statistically significant in relation to the other three single date classifications. The Coniferous Forest class showed some degree of confusion only with the Deciduous Forest classes.

The Multitemporal/Multispectral classifications used an eight channel data set, based on a combination of the June and February dates. Two classifications were performed with this data set. The first used all the channels of both dates (Multitemporal/Multispectral 8 channels). For the second classification, four channels were selected based upon the minimum and average transformed divergence value, calculated by the SEPARABILITY processor of LARSYS. The selected channels were:

Waveband m	Date	Spectral Region
0.6-0.7	June	Visible (red)
0.7-0.8	June	Reflective IR
0.6-0.7	February	Visible (red)
0.7-0.8	February	Reflective IR

It is important to point out that one channel in each major portion of the spectrum covered by Landsat-MSS was selected for this classification.

Both overall performance and the performances by class were very good, except for the class "Pasture" which had an accuracy of 31.5 % for the 8 channel classification and 32 % for the 4 channel classification, due to confusions between the Pasture and Soil classes. 58 % of the Pasture test pixels were classified as soils in the 8 channel classification, and 50 % of the Pasture test pixels of the 4 channel classification were assigned to the soils classes. This was an interesting result, since the June data alone had an accuracy of 90 % for the pasture class, while the February data set had only a 15 % accuracy for the same class. The Soil class had and accuracy of 78% and 66 % in the June and February classification respectively, it show an improvment in the accuracy in this classification up to 92.0 %. Thus, the combined data resulted in an intermediate accuracy for the pasture class, rather than the high performance of the June data set alone, while the soils class show an adequate increase in accuracy.

In the Layered classifier 2 dates, the primary concern in the design of the decision tree was to obtain an adequate separation of the Coniferous Forest from all other classes, since the June data resulted in low accuracy for this class but was good for all other, and the February data had good accuracy for the Coniferous class.

The two date layered classification had the best overall performance of all four classifications, with 91.8 %. Both Deciduous and Coniferous forest cover types had over 90 % correct classification. Most of the misclassifications in each of these forest classes were actually due to confusion occurring between them rather than between forest and non-forest categories.

Also, a more consistent classification was obtained for the other classes --over 80 % as can be seen on Figure 2. The statistical comparisons of the percent correct classification for the five classes show three groups (Water, Forest and Soils-Grasslands) in which there were no significant differences in the classification accuracy.

It was clear that the classification was improved due to the capabilities of the layered classifier. Using this classification processor, the analyst can select the best set of features to separate a class or group of classes.

The second classification using the Layered techniques (i.e. training statistics based on one set of 8 channels) showed no significant difference from the results obtained in the single stage Multitemporal/Multispectral classifications. A small decrease in the percent accuracy for the Pasture class was found, but this difference was not statisticaly significant. The primary difficulty in classification of Pasture was again due to confusion with the soil class. However, the CPU time required was only 60 % (10 minutes less) of that required for the single stage Multitemporal/Multispectral 4 channel classification.

As shown in Table 3, the overall classification performance varied from 70.4 % to 91.8 %. Also, in the classification results shown in Table 2, the average performance values indicate an important variability in relation to the overall performance values.

As show in Table 3, the overall classification performance varies from 70.4 % for the February classification to 91.8 % for the Layered 2 set of 4 channels classification. The average performance values indicate an important variability in relation to the overall performance values, except for the Layered 2 set of 4 channels classification.

Of the five best classifications, according to the ANOVA and Newman-Keuls tests, the Multitemporal/Multispectral 8 channel classification required the highest amount of CPU time, followed by the June classification, then the Multitemporal/Multispectral 4 channels, then the Layered 1 set of 8 channels and with the lowest value of all five, the Layered 2 sets of 4 channels classification. This approach

Table 3.- CPU Time and Overall Classification Performance.

	CPU Time	No. of Spectral Classes	Overall Performance	Average Performance
MAY	23.1 min	10	81.7 %	66.4 %
JUNE	39.1 min	22	90.6 %	84.1 %
SEPTEMBER	43.5 min	25	72.9 %	57.3 %
FEBRUARY	23.2 min	12	70.4 %	67.6 %
MULTITEMPORAL/ MULTISPECTRAL 8 Channels	77.3 min	14	91.0 %	83.0 %
MULTITEMPORAL/ MULTISPECTRAL 4 channels	25.4 min	14	90.8 %	83.2 %
LAYERED 1 set of 8 channels	16.5 min	14	90.8 %	82.3 %
Layered 2 sets of 4 channels	9.1 min	20	91.8 %	89.9 %

resulted in the best method since it required only less than one fourth of the time required for the June classification, it used one eight of the time of the Multitemporal/Multispectral 8 channels, only more than one third of the time required for the Multitemporal/Multispectral 4 channels classification and one half of the CPU time required for the Layered 1 set of 8 channels classification.

CONCLUSIONS AND RECOMMENDATIONS

The results of this research show the advantage of the Layered Multitemporal/Multispectral classification approach over the Multitemporal/Multispectral classification and the Single Date classification approaches in the analysis of Multitemporal MSS data.

Single Date Classifications

Considering the available dates for this work and that some times it is difficult to obtain more than one Landsat-MSS image, the use of a data set representing the summer season is the most suitable for classifying major cover types.

Multitemporal/Multispectral Classification

The Multitemporal/Multispectral approach provided an accuracy over 98 % in the differentiation of forest versus non-forest classes. In addition, an accuracy of over 95 % was obtained in the separation between Coniferous and Deciduous Forest. The weak points of this scheme are: The complexity in the development and interpretation of the training statistics and the CPU time required to perform the classification. The eight channel classification required 8.5 more CPU time than Layered classifier, and even the four channel Multitemporal/Multispectral classification required 2.8 times more CPU time than the Layered classifier. The selection of the four best channels of this data set indicates that one channesl of each of the available regions of the electromagentic spectrum in the MSS for each date, are required to perform a multitemporal classification.

Layered Classification

The layered Classification procedure proved to be the best in terms of classification accuracy, with 99 % for the forest classes combined and 90 % for the non-forest classes (excluding water), for both the Layered 2 sets of 4 channels and Layered 1 set of 8 channels. Although percent accuracies in the Layered 2 sets of 4 channels for the individual forest cover types were slightly lower in relation to the Multitemporal/Multispectral Classifications, these differences were not statistically significant. Pasture classes showed an improvement, using the same comparison between techniques. The layered technique also provided more consistent results, since all accuracies were over 80 %. The design of the decision tree for the classification is one of the most important and difficult tasks in this approach.

There were no significant differences in the overall classification accuracy between the June classification, the Multitemporal/Multispectral classification and the Layered classification; however, refering to Table 3 the amount of CPU required to classify the same area (considering the CPU time of the Multitemporal/Multispectral scheme as 100 %) was 50 % with the June data and 11 % with the Layered classifier. Therefore, the combination of high classification accuracy, low CPU time requirements and flexibility in handeling multitemporal data sets makes the Layered classifier a very useful tool in multitemporal analysis of remotely sensed data.

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