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Multitemporal Satellite Image Database Classification for Land Cover Inventory and Mapping

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Abstract: A raster Geographic Information System (GIS) database file created whit 12 satellite remote sensing image layers of test area. A widely recognized characteristic of these image layers is correlated that exists between image channels. The Principle Component Analysis (PCA) was used to reduce the dimensionality of the input database and to produce new uncorrelated image layers. The first, second and third principle component analysis eigen-channels (PCA1, PCA2 and PCA3), accounted for 93.42% of the variance from the 12 input Landsat TM image channels. Total accuracy of this classification was 80.63%. The results of classified of land cover of the study area by PCA eigen-channels are satisfactory. This methodology may will allow the greater application of satellite remote sensing image databases in land cover type in the future.

Key words: Eigen-channels, GIS, principle component, raster, remote sensing

INTRODUCTION

Land-use data are compiled in order to determine trends in land utilization required to make production, marketing and policy decisions. The usual method used to obtain this data is by national census, which produces a detailed classification. High-resolution satellite remote sensing technology and digital image processing may supplement this method. The reason for using satellite remote sensing is the ease and rapidity with which data can be obtained from the time of image acquisition using digital image processing[1]. The Principle Component Analysis (PCA) is a reducing technique that leads to a description of correlated multitemporal satellite image data in which the new variables are uncorrelated. The statistical PCA technique has several practical advantages from a classification pint of view and can be compared to the usual supervised and unsupervised methods into various[2]. It is likely that improvement in the accuracy of the land cover, agriculture and forest land classification. The main aim of this study was to investigation the potential of the analysis of multi-data Landsat TM satellite image database, for land cover classification. A more general aim of the study was to demonstrate the powerful capabilities of an integrated raster Geographic Information System (GIS) and statistical Principle Component Analysis (PCA) techniques.

MATERIALS AND METHODS

The basis for the method of multitemporal classification of relevance to this report is Principle Component Analysis (PCA). The principle component analysis is a reducing technique that leads to a description of multidimensional data in which the new axis or new variables are uncorrelated. The first component containing most variance of the input variables. In the image processing PCA is a linear transform, which rotates the axis of image space along lines of maximum variance and used to minimize the number of image data channels[3,4]. Multitemporal satellite image database corresponding of the same area obtained at different dates. There will be compared with one another a pixel by pixel basis. There will be a high correlation between the Digital Numbers (DNs) from those parts of the image representing land cover types that have remained constant between the imaging dates[5]. Those pixels, which are uncorrelated, have change over the same period. The results of the analysis of PCA carry out on the two n-band single-date image database, will be 2n PCA eigen-channels image database. The new variables are the principal components of the multitemporal satellite image database[4,6]. The major variation, which is usually not due to change, has been concentrated in the higher principle components. The minor, small

Table 1: The layers of the raster GIS database

Input GIS layer	Sensor/band	Imaging data	Input GIS layer	Sensor/band	Imaging data
1	TM band 1	02.05.90	7	TM band 1	17.10.93
2	TM band 2	02.05.90	8	TM band 2	17.10.93
3	TM band 3	02.05.90	9	TM band 3	17.10.93
4	TM band 4	02.05.90	10	TM band 4	17.10.93
5	TM band 5	02.05.90	11	TM band 5	17.10.93
6	TM band 7	02.05.90	12	TM band 7	17.10.93

area variation can be seen in the lower components[7]. The PCA is one of the multivariate statistical analysis techniques and has several practical advantages from a classification pint of view and can be compared to the usual supervised and unsupervised methods into various[8,9].

Satellite image database: The specific test site area was 20.52×26.15 km and was covered two Landsat TM imaging dates.

Landsat	TM 02.05.90
Landsat	TM 17.10.93

With 684 x 871 pixels, 684 pixels in rows and 871 in columns, with pixel size 30×30 m were available of test area. In this study six TM bands λ_1, λ_2, λ_3, λ_4, λ_5 and λ_7 corresponding to TM band 1, 2, 3, 4, 5 and 7 were used for each imaging dates. A raster Geographic Information System (GIS) database file was created with 15 layers. Twelve of these layers stored image data of TM image dates 02.05.90 and 17.10.93 of study area. The layers of the raster GIS database are presented in Table 1.

RESULTS

The raster GIS database file created contained 15 image layers as previously outlined. The analysis presented to data was derived from single image data subsets of the raster GIS database file that by default was based on correlated datasets. Principle component analysis was used to reduce the dimensionally of the input database and to produce new uncorrelated image layers for further analysis. Twelve image layers were selected and used as input to PCA on EASI/PACE™. Thus the input correlated multitemporal subset had dimension of 12, λ_1, λ_2, ….λ_{12}. The PCA identifies the minimum number of new uncorrelated variables or principle components through variance maximizing of each component. The preliminary and final PCA results are presented in Table 2 and 3, respectively.

Table 2: Preliminary PCA results of multitemporal data subject

Input layers	Sensor/imaging data	Mean reflection	SD
1	TM 02.05.90	71.25	5.74
2	TM 02.05.90	29.57	3.85
3	TM 02.05.90	26.48	5.68
4	TM 02.05.90	85.77	27.79
5	TM 02.05.90	70.33	17.90
6	TM 02.05.90	25.22	10.69
7	TM 17.10.93	40.32	3.52
8	TM 17.10.93	16.69	2.50
9	TM 17.10.93	15.31	2.94
10	TM 17.10.93	44.54	12.91
11	TM 17.10.93	37.23	12.19
12	TM 17.10.93	100.35	13.33

Table 3: Final PCA results of multitemporal data subject

PCA layers	Eigen value	SD	Percent variance	Cumulative % variance
1	981.71	31.33	58.79	58.79
2	474.75	21.79	28.43	87.22
3	103.57	10.17	6.20	93.42
4	39.63	6.29	2.37	95.79
5	31.07	5.57	1.86	97.65
6	21.77	4.66	1.30	98.95
7	8.56	2.92	0.51	99.46
8	3.47	1.86	0.21	99.67
9	2.83	1.68	0.17	99.84
10	1.17	1.08	0.07	99.91
11	0.89	0.95	0.05	99.96
12	0.44	0.67	0.04	100.00

The first principle component accounted for 58.79% of the total variance in the new uncorrelated data. The first, second and third principle components, eigen-channels accounted for 93.42% of the variance from the 12 input channels. These three eigen-channels were added to the raster GIS database as layers 13, 14 and 15 and are referred to as PCA eigen-channels and are used for the analysis presented below. The new uncorrelated PCA layers were displayed using the following band combination: RGB: PCA1, PCA2, PCA3.

The multitemporal, unsupervised Classification (KCLUS) was carried out on the EASI/PACE™ image processing soft ware using the first three principle component analysis eigen-channels (PCA1, PCA2 and PCA3) of study area. The results of this classification are presented in Fig. 1.

The classified area estimates, in hectares, for the major classes in the test area. As can be seen major classes namely coniferous, broadleaves forest, grassland,

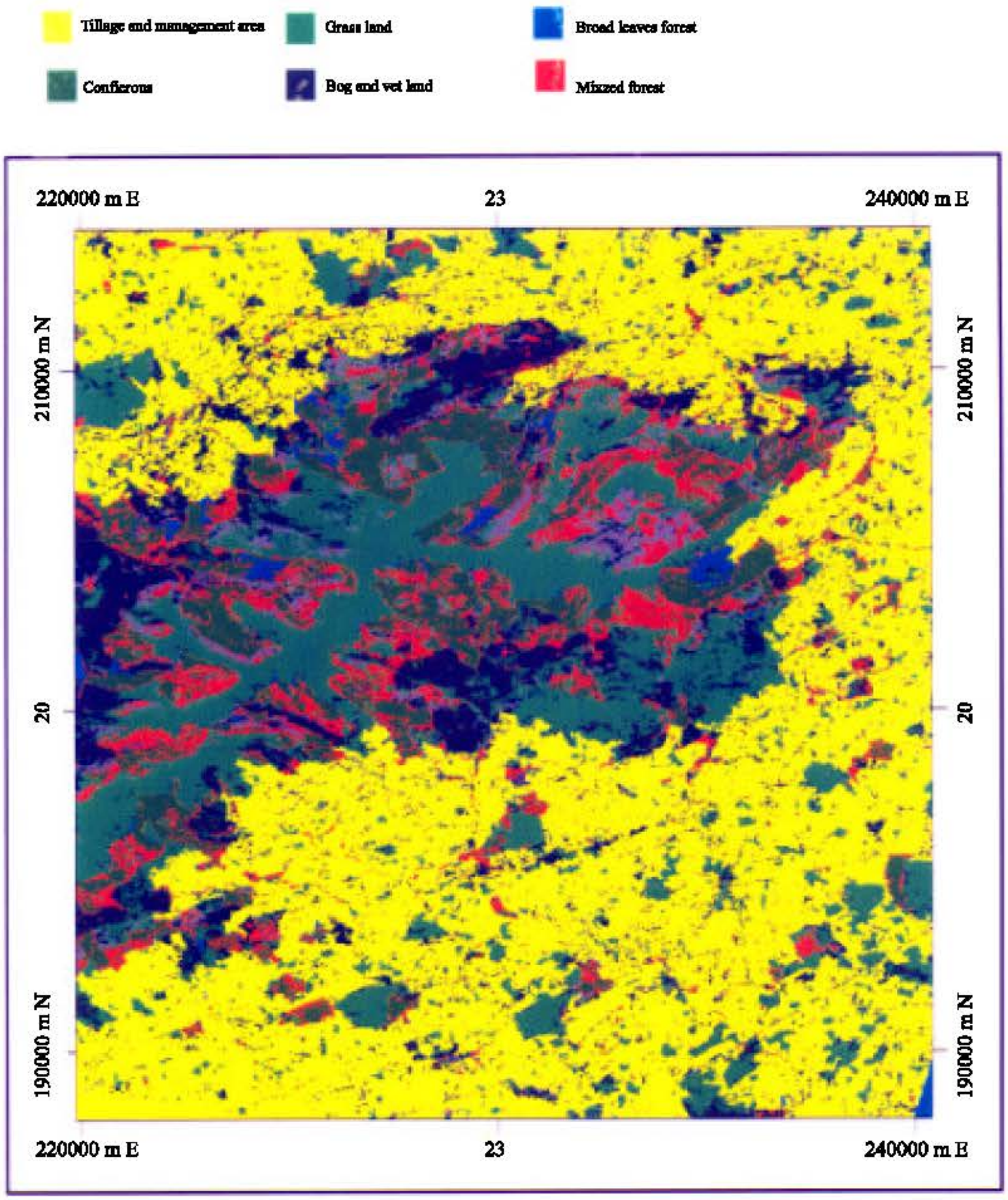

Fig. 1: Results of the KCLUS classification on the PCA eigen-channels database

tillage, pasture, bog, vet land and mixed forest. Total accuracy of this classification was 80.63%. The results of this classification in forest area were satisfactory corresponding with forest serves inventory.

CONCLUSIONS

The Landsat TM satellite imagery from two different dates was successfully used for the raster GIS for the test area. The first, second and third principle component analysis eigen-channels (PCA1, PCA2 and PCA3), accounted for 93.42% of the variance from the 12 input image channels. It means, the three new uncorrelated PCA eigen-channels (PCA1, PCA2, PCA3) can be replacement with the 12 input Landsat TM satellite correlated image channels for classification in this study. This classification technique was found to be an interesting and useful means of extracting information on long term change in land cover type occurring between two multitemporal images, based on a single date satellite image classification. Total accuracy of this classification was 80.63%. The results of classified of land cover of the study area by PCA are satisfactory. It is likely that improvement in the accuracy of the classification. This image processing and classification technique is potentially of great benefit to Agriculture and Forest inventory, mapping and management in particular and resource management and land cover type in general. This methodology will allow the greater application of satellite remote sensing image databases in land cover type in the future.

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