APPLICATION OF MULTI-TEMPORAL SATELLITE DATA AND GIS FOR THE ENVIRONMENTAL CHANGE DETECTION

Ch. Bolorchuluun
School of Earth Sciences, National University of Mongolia,
Ikh Surguuliin gudamj, Ulaanbaatar-210646, MONGOLIA
Email: bolorchuluun@num.edu.mn

O. Batkhishig
Institute of Geography, Mongolian Academy of Sciences
P.O.Box-361, Ulaanbaatar-210620, MONGOLIA
Email: batkhishig@gmail.com

D.Amarsaikhan
Institute of Informatics and RS, Mongolian Academy of Sciences,
av.Enkhtaivan-54B, Ulaanbaatar-51, Mongolia
amar64@arvis.ac.mn

V. Battsengel
School of Earth Sciences, National University of Mongolia,
Ikh Surguuliin gudamj, Ulaanbaatar-210646, MONGOLIA
Email: battsengel@num.edu.mn

ABSTRACT

Change detection using land use and land cover maps is the basis of much land cover dynamics research. Specifically, a wide variety of remote sensing methods have been developed for detecting land use and land cover change in temporal categorical and multi-spectral. Maybe the simplest method of change detection is to sum the differences between the spectral values of every band of the temporal TM images. This method is available in almost all remote sensing processing software. The calculation result can precisely reflect the spectral change degree that is implicitly caused by the spatial object changes. However, because of the complexity of object reflection, the same object may reflect a different spectrum at different times, or different objects may reflect the same spectrum at different times. Therefore, in practice spectral difference is always taken to be a reference.

This paper describes a general overview and some methodologies to use RS and GIS techniques for change detection in some places of Mongolia. So far studies on this methodology were mainly concentrated on applying Landsat, Aster, Quick Birth satellite image data. The paper presents results of the works aimed at determination of optimal change detection methods for studying changes of environment.

KEYWORDS: change detection, environment, multi-temporal satellite data, GIS

1. INTRODUCTION

Natural resources are natural objects that are usually mapped for management or conservation purposes. These can belong to the domains of botany, soil science, geology, ecology, hydrology, oceanology and other environmental and Earth sciences. Conventional natural resource inventories aim at producing maps and databases of natural objects grouped as types or classes and attributed with sets of descriptive and analytical variables. Some natural objects are rather discrete and static and therefore easier to map, while others are continuous, complex, hidden or rather dynamic. Discrete objects, such as lakes, rivers or geological strata are modelled in a GIS using polygon or line objects. Usually human influence makes the semi-natural objects more discrete and therefore easier for inventorying.

Different land cover types of an agricultural area will be easier to delineate on an aerial photo or satellite image compared to different forest types of a tropical forest region. The discrete classes of natural resources are traditionally presented using sets of colours – the so called "choropleth", or more precisely "chorochromatic" map (Burrough and McDonnell, 1998). In GIS terms, this is a polygon map with defined topology and linked to attribute tables. This approach is also referred to as “double crisp”, since the surveyor uses sharp boundaries to delineate soil bodies and crisp classes to classify natural objects (Burrough et al., 1997). Forest vegetation types, geomorphologic classes, soil types and similar classes are in fact not always so crisp as the map indicates. In fact, these are often complex and continuous in their distribution (Hootsmans, 1996). Especially soils can be considered as poorly defined classes of hidden objects and are suitable for fuzzy set or continuous approaches to model their distribution in a more continuous way (Burrough, 1993).

In last decades, methods for quantifying taxonomic classes, such as fuzzy classification, have been developed (De Gruijter and McBratney, 1988). However, there is still a need for GIS methods to visually explore results of fuzzy classification (Burrough et al., 1997).
Moreover, visualisation techniques are needed to allow users to explore uncertainty in spatial data visually and to investigate the effects of different decisions in the classification process (MacEachren and Kraak, 1997). Some of the new interactive data exploration techniques such as the use of slide bars, point and click events, blinking and animations have proven to give a good impression of data uncertainty. In this paper we give insight into two relatively new visualisation techniques.

2. STUDY AREA

The study area is located in the step of Bituugiin-tal in Rinchinlhumbe subprovince of Hovsgol aimag/province, West-north Mongolia. It lies between $99^0$26’49.36”–$99^0$45’08.93” E longitudes; and $51^0$12’0.55”–$51^0$23’26.54” N latitudes in geographical coordinates. The total area is 499.84km^2. In this study all the maps georeferenced to UTM, WGS-84 map projection, and north zone of 47. By the UTM map projection system, the area covers 531150.0–552356.2 E, 5672144.6–5693543.0 N. This area is one of the one is beautiful places in the province.

3. METHODOLOGY

Supervised image classification is a technique that is often applied in analysis of remotely sensed data. The result of such a classification is a thematic map with a label for each pixel of the class with which it has the highest strength of membership. This hard or crisp classification is based on conventional crisp set theory. A conventional classification of remotely sensed imagery, models the study area as a number of unique, internally homogeneous classes that are mutually exclusive.

However, these assumptions are often invalid, especially in areas where transition zones and mixed pixels occur. Land cover types are rarely internally homogeneous and mutually exclusive, therefore, classes can hardly ever be separated by sharp or crisp boundaries, in feature space as well as geographic space. Furthermore, complex relationships exist between spectral responses recorded by the sensor and the situation on the ground, where similar classes, pixels or objects show varied spectral responses and similar spectral responses may relate to dissimilar classes, pixels or objects. Moreover, remotely sensed images contain many pixels where boundaries or sub-pixel objects cause pixel mixing, with several land covers occurring within a single pixel. Finally, classes are often hard to define resulting in vagueness and ambiguity in a classification scheme. Most, if not all, geographical phenomena are poorly defined to some extent and, therefore, fuzzy set theory as an expression of concepts of vagueness is an appropriate model for working with remotely sensed imagery (Fisher, 1999; Zhang and Foody, 2001). To adapt to the fuzziness characteristic of many natural phenomena, fuzzy classification approaches have been proposed (Foody, 1996; Zhang and Foody, 2001).

Fuzzy classification is based on the concept of fuzzy sets (Zadeh, 1965). Several techniques exist to derive fuzzy memberships. These techniques can be divided in two groups (Burrough and McDonnell, 1998):

- The Similarity Relation Model is data-driven. It involves searching for patterns within a dataset similar to traditional clustering. The most wide-spread method is the Fuzzy c-means algorithm (Bezdek, 1981).

- The Semantic Import Model is user-driven. An expert defines the membership functions (Evans, 1977).

Fuzzy-*k*-means uses an interactive procedure that usually starts with an initial random allocation of *N* objects to *K* clusters. Given the cluster-allocation (expressed in terms of the membership μ_{ic} in the range 0-1), and a weight of the attribute values, the cluster center *C* of the c^{th} cluster for the j^{th} attribute *x* is calculated:

$$C_{cj} = \frac{\sum_{j=1}^{N} (\mu_{ic})^q x_{ij}}{\sum_{j=1}^{N} (\mu_{ic})^q} \qquad (1)$$

where the fuzzy exponent *q* determines the amount of fuzziness or overlap.

In ordinary *k*-means, the membership μ of the i^{th} object to the c^{th} cluster is determined by:

$$\mu_{ic} = \frac{\left[(d_{ic})^2 \right]^{\frac{-1}{(q-1)}}}{\sum_{c=1}^{k} \left[(d_{ic})^2 \right]^{\frac{-1}{(q-1)}}} \qquad (3)$$

Burrough (Burrough et al., 1997) used the value $q = 1.5$ in this formula because stated that: ”appears to result in *k*-means classes mutually exclusive”.

The PARBAT software developed by Arko Lucieer (2004) was used to perform a non supervised fuzzy-c-mean classification. The algorithm used in this software complies with the procedures developed by Bezdek (Bezdek.J.C,1995) for the fuzzy-c-mean.

With the resulting images of membership values, confusion index and entropy computed with PARBAT, an analysis for the best parameters of overlapping and number of classes was carried out in order to obtain a significant classification.

For a supervised remote sensing classification, reference data is used. An important step in a supervised classification of remote sensing imagery is the choice of reference pixels for the representation of classes. Usually, reference pixels are selected from the image or from external data like aerial photography or field data.

In this study, reference pixels are selected and extracted from the image by digitising polygons in the image display. Each polygon depicts a land cover class and is displayed in a unique class colour. Class statistics, extracted from the selected pixels, are used to classify all unlabelled pixels. Visualisation of class information in feature space gives a user valuable information about the location of classes and about possible overlap or vagueness between classes.

4. RESULTS

To illustrate the proposed α-shape class visualisation, the Landsat images of the selected areas was used. The following land cover classes can be found in the study area: water (lake), shrub, agricultural field, pasture, forest and other (open glade) area.

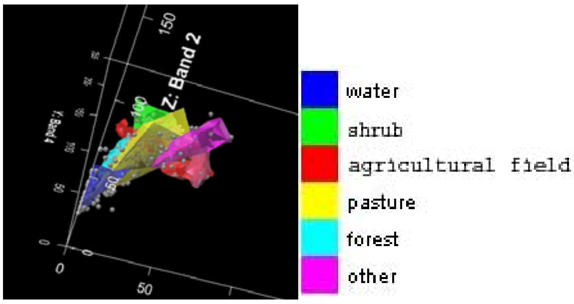

Figure 2: Comparison of class shape representation for the classes visualized as α-shapes

The classification in bands 7,4,2 from the Landsat images of the study area are used to test the α-shape based classifier. Figure 3 shows that classes. In Mongolia usually raining from end of July to beginning of September. Every year almost 80% of moisture going fall down in this season, and the agricultural fields moisture are increasing much more.

Figure 3 show that the agricultural class is over-classified and the pasture class is under-classified, compared to what has been observed in the field. It shows that there is considerable confusion in agricultural field and pasture. In addition, in regions collected by moisture (specially in September's image), confusion is high. Overall, the α-shape classifier gives good results with an overall classification average accuracy of 91.24%. Accuracy assessment results in table 1 show that the α-shape based classifier performs slightly better than standard supervised fuzzy c-means classifiers. The confusion matrix shows that the overlapping classes Pasture and Agriculture are difficult to separate.

5. CONCLUSION AND RECOMMENDATION

In this research work, multivariate texture segmentation had been successfully used for change detection identification. The segmentation accurately identification different objects on the images. The average of total accuracy is 91.24% in segmented images, using Confusing matrix, which is standards technique to assess the classification. It also detect many small objects, which make it difficult to compare the segmented image with reference image that does not contain those small objects. Uncertainty plays an important role in land cover classification of remotely sensed imagery.

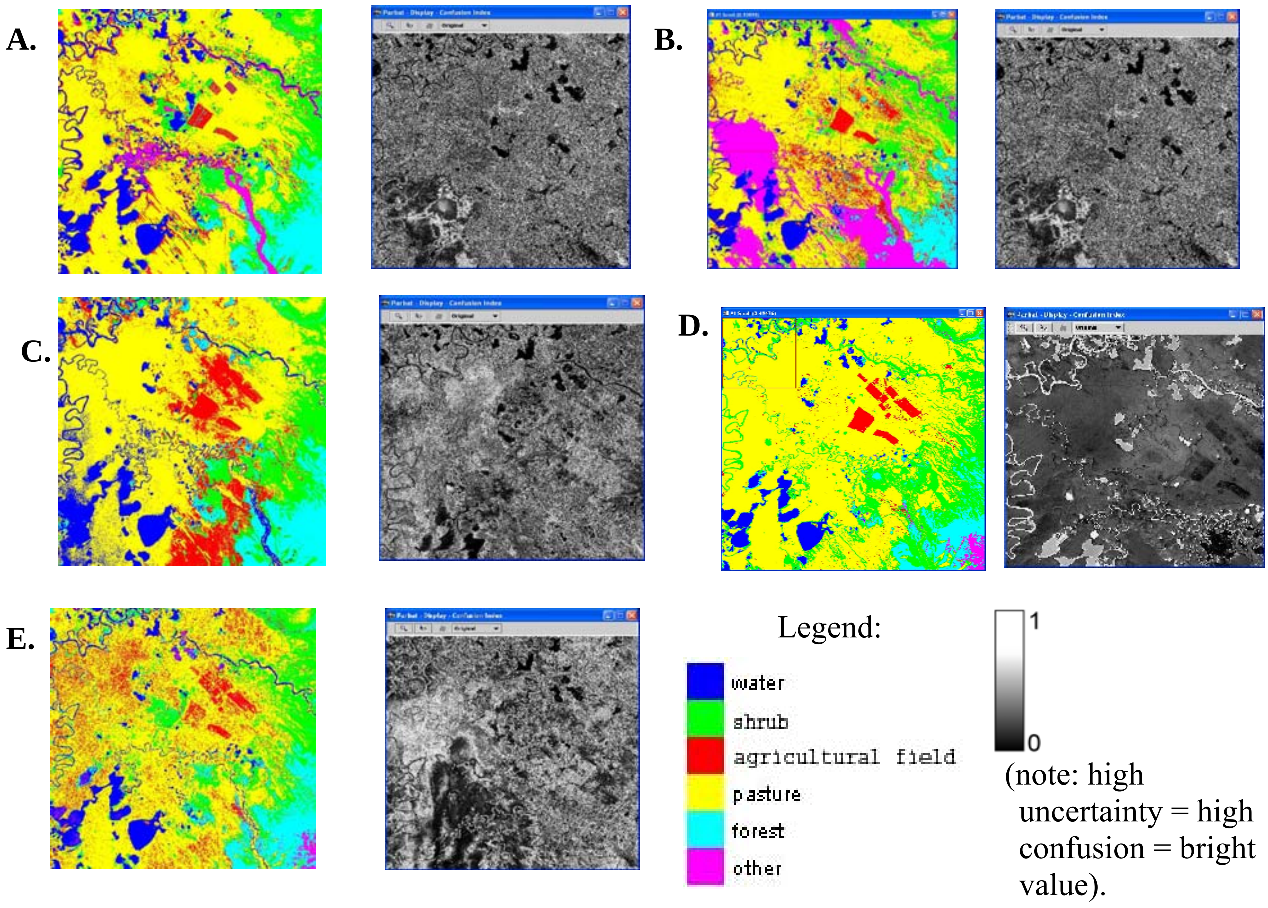

Figure 3: α-shape based fuzzy classification result of **A.** - 23 July 1986; **B.** - 10 September 1992; **C.** - 05 September 1999; **D.** - 28 June 2000 and **E.**- 09 August 2001 (left) 'defuzzified' classification result; (right) image with the confusion index.

Table 1: Classification accuracy percent for a classification based on α-shapes

Data of source		*Reference*						
	Class	Water	Shrub	Agricultural field	Pasture	Forest	Other	Total
22 July 1986	Water	99.94	0.00	0.00	0.02	0.00	0.00	0.00
	Shrub	0.00	99.03	7.96	0.12	0.89	0.00	0.00
	Agricultural field	0.00	0.39	77.84	3.66	0.00	6.39	95.75
	Pasture	0.06	0.52	9.02	96.19	0.00	6.38	1.95
	Forest	0.00	0.06	4.74	0.00	99.11	0.00	0.00
	Other	0.00	0.00	0.44	0.01	0.00	87.23	2.30
	Total	100.00	100.00	100.00	100.00	100.00	100.00	100.00
10 September 1992	Water	98.39	0.00	0.00	0.00	0.00	0.00	18.68
	Shrub	0.00	97.39	0.05	0.76	0.91	1.92	7.32
	Agricultural field	1.57	0.34	91.15	4.91	2.55	0.55	13.75
	Pasture	0.03	1.94	8.80	93.66	0.04	8.24	44.58
	Forest	0.00	0.04	0.00	0.00	96.50	0.55	14.38
	Other	0.02	0.29	0.00	0.68	0.00	88.74	1.29
	Total	100.00	100.00	100.00	100.00	100.00	100.00	100.00

05 September 1999	Water	82.13	0.00	0.00	0.15	0.00	0.00	13.77
	Shrub	0.78	97.96	0.86	1.41	5.74	0.00	3.65
	Agricultural field	1.17	0.09	80.20	17.80	0.29	0.00	19.09
	Pasture	12.47	0.74	18.02	78.20	0.23	0.67	54.71
	Forest	0.09	1.21	0.63	0.03	93.74	1.00	6.03
	Other	3.36	0.00	0.29	2.41	0.00	98.33	2.76
	Total	100.00	100.00	100.00	100.00	100.00	100.00	100.00
28 June 2000	Water	100.00	0.00	0.00	0.00	0.00	0.00	16.69
	Shrub	0.00	94.62	0.00	0.08	0.13	0.00	2.15
	Agricultural field	0.00	0.00	90.41	7.74	0.26	0.56	13.29
	Pasture	0.00	0.74	9.57	92.18	0.29	0.00	61.13
	Forest	0.00	4.64	0.00	0.00	99.32	0.00	6.37
	Other	0.00	0.00	0.02	0.00	0.00	99.44	0.37
	Total	100.00	100.00	100.00	100.00	100.00	100.00	100.00
09 August 2001	Water	99.86	0.00	0.00	0.00	0.00	0.00	18.07
	Shrub	0.00	100.00	0.02	0.07	0.00	0.00	4.03
	Agricultural field	0.00	0.00	78.57	14.26	0.00	0.00	24.29
	Pasture	0.00	0.00	21.41	85.67	0.00	0.00	49.91
	Forest	0.00	0.00	0.00	0.00	100.00	0.00	3.19
	Other	0.14	0.00	0.00	0.00	0.00	100.00	0.50
	Total	100.00	100.00	100.00	100.00	100.00	100.00	100.00

REFERENCE:

Bezdek, J. C., 1981. Pattern Recognition with Fuzzy Objective Function Algortihms, Plenum Press, New York.

Bezdek,J.C.,1995. Fuzzy and neural pattern recognition: video short course: Parts 1-2 and Parts 3-4 and Part 5 and Course notes. The International Society for Optical Engineering (SPIE)

Burrough, P. A. and McDonnell, R. A., 1998. Principles of Geographical Information Systems, Spatial Information Systems and Geostatistics, Oxford University Press. pp.327

Burrough, P.A., Gaans, P.F.M. and van Hootsmans, R., 1997. "Continuous classification in soil survey: spatial correlation, confusion and boundaries". Geoderma, 77 (Fuzzy sets in Soil systems): pp.115-135.

De Gruijter, J.J. and McBratney, A.B., 1988. "A modified fuzzy k-means method for predictive classification". In: H.H. Bock (Editor), Classification and Related Methods of Data Analysis. Elsevier Science Publishers B.V., pp. 97-105.

Evans, I., 1977. The selection of class intervals, Transactions of the Institute of British Geographers (NS) 2: pp. 98–124.

Fisher, P. F., 1999. Geographical Information Systems: Vol. 1 Principles and Technical Issues, Vol. 2 Management Issues and Applications, second edition edn, Wiley & Sons, New York, chapter Models of Uncertainty in Spatial Data, pp. 191–205.

Foody, G. M., 1996. Approaches for the production and evaluation of fuzzy land cover classifications from remotely sensed data, International Journal of Remote Sensing 17(1). pp. 1317–1340.

Hootsmans, R.M., 1996. Fuzzy sets and series analysis for visual decision support in spatial data exploration. PhD Thesis, University of Utrecht, Utrecht, pp.167

Luceer,A., 2004. Uncertainties in segmentation and their visualisation, Enshede, pp. 43-56

MacEachren, A.M. and Kraak, M.J., 1997. "Exploratory cartographic visualization: advancing the agenda". Computers & Geosciences, 23(4): pp. 335-344.

Zadeh, L. A., 1965. Fuzzy sets, Information and Control 8, pp. 338–353.

Zhang,J. and Foody,G. M., 2001. Fully-fuzzy supervised classification of suburban land cover from remotely sensed imagery: Statistical and artificial neural network approaches, International Journal of Remote Sensing 22(4). pp. 615–628.