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THE ENVIRONMENTAL IMPACT IN THE ZAAMAR GOLD MINING ZONE OF MONGOLIA

Abstract

The mining sector is a major contributor to the Mongolian economy. Many ongoing operations are managed in a sub-optimal way leading to significant environmental damage and production losses.

Changes in hydrological regimes remain a significant problem, particularly for placer gold. On balance, current mining practices are inefficient and use excessive process water, thus overtaxing surface waters and underground supplies, and also generate excessive effluent, which is difficult to manage and poses a threat of uncontrolled discharges of slurry. In addition, where rivers are illegally dredged and where tailings are discharged into surface waters, turbidity of surface waters is a major concern. The water pumped from mines of all types and discharged into open surface water bodies may also cause flooding, leading to the formation of new, transient wetlands, which generally fall dry once the mine ceases to operate.

This paper describes a general overview and some methodologies to use remote sensing techniques for change detection in Zaamar gold mining district of Mongolia.

Keywords: change detection, environment, multi-temporal satellite data, mining activity

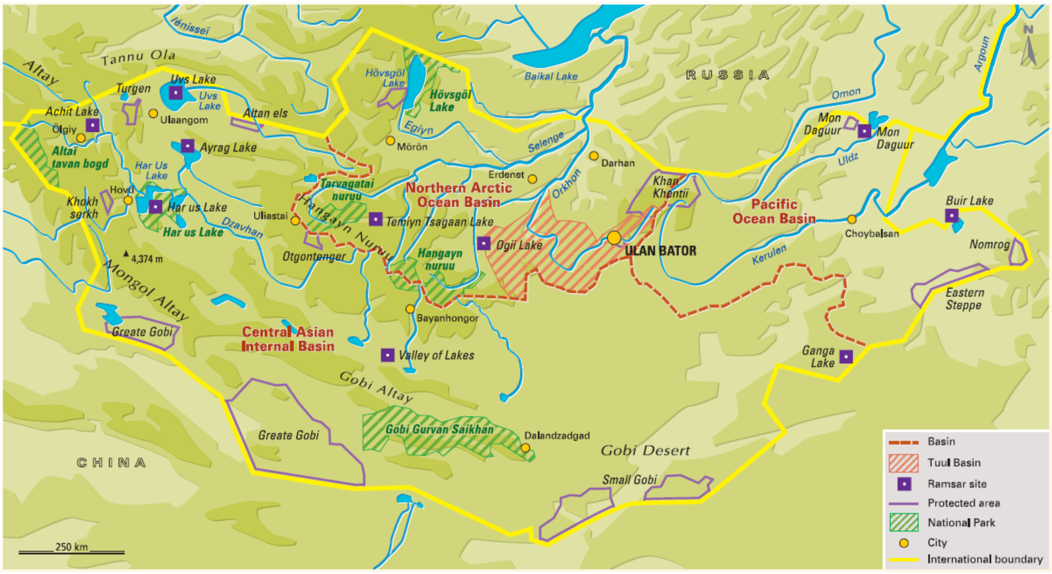
1. BACKGROUND

Mongolia is a mineral-rich country. According to the Ministry of Energy, Geology, and Mining, about 80 different minerals had been discovered in Mongolia. By 2000, 500 deposits (including uranium and rare earths) had been identified, of these about 200 were exploited, including 35 of construction materials. Since then, more deposits have been identified, and some are of global importance.

Gold mining industries, in particular, have expanded rapidly in the last fourteen years. At present, gold mining generates around 70% of total foreign currency. Although of great economic importance, it also has serious negative environmental and social impacts. Gold mining is leading to the destruction of the environment, consequently making life difficult for the local people, especially herders, who must compete for pastureland and water resources.(Mongolia,2006)

Most of the smaller industrial mines are open-cast operations using free digging shovels or hydraulic excavators and haul trucks that dump the ore near the wash plants. Oversize material remains on the screen and is blasted out via a tailgate by high pressure water from the water cannon. To provide process water for the placer wash plants, water is pumped from the Tuul River. No chemicals are added, gravitation methods being sufficient to recover the gold. The resulting effluent is directed to tailings ponds to settle out the coarsest material down to fine sand, and the still-turbid water is then recycled back to the wash plant or illegally discharged to the Tuul River. Water cannons consume large amounts of water, and the pumps are often left running even when the wash plant is idle. The settling ponds are unusually large and accordingly vulnerable to uncontrolled discharge by overtopping of the earth dam or its collapse. At least two mines discharge all effluent directly onto the floodplain, with frequent discharge of dirty water into the Tuul River. Overall, water use is very inefficient and is taxing surface water supplies and generating excessive volume of effluent that is more and more difficult to manage.

2. STUDY AREA



Map 1: Overview of the river basins in Mongolia

Source: Prepared for the World Water Assessment Programme by AFDEC, 2006.

The selected target area, Zaamar soum, is located in one of the biggest gold mining regions in the central part of the country. There are a number of different sized enterprises involved in mining activities.

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 (Wang, 1990; 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).

The fuzzy c-means classifier (FCM) uses an iterative procedure that starts with an initial random allocation of the objects to be classified into c clusters. Given the cluster allocation, the centre of each cluster (in terms of attribute values) is calculated as the weighted average of the attributes of the objects. In the next step, objects are reallocated among the classes according to the relative similarity between objects and clusters based on a well-known distance measure: the Euclidean, Diagonal (attributes are scaled to have equal variance) or Mahalanobis (both variance and covariance are used for distance scaling) metrics are frequently used. Reallocation proceeds by iteration until a stable solution is reached where similar objects are grouped together in a cluster. Their membership value gives their degree of affinity with the centroid of the class (Bezdek, 1981). Membership μ of the ith object to the cth cluster of n number of classes in ordinary *k*-means, the membership μ of the i^{th} object to the c^{th} cluster is determined by:

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

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”.

For our application the thematic maps included in the stochastic model constitutes the attributes and the computation was done using all the pixel values in the image, with the exception of the cluster center itself to avoid null distances. Then as a difference from the method used by Burrough (Burrough et al., 1997), where only a sample of pixels from a large image was used in order to reduce computations, the distance calculated in equation 1.5 is simplified to:

$$d_{ic}{}^{2} = x_{ij} - c_{cj}{}^{2} \qquad (1.4)$$

themes to a 8 bit format.

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

In 1994 only one gold mining company-Khailaast worked in Zaamar gold mining district. And the east side of Zaamar gold mining district where around 239.2 million sq.km floodplain.

But in 2000 worked 15 gold mining company. The floodplain size decreased up to 5.7 million sq.km.

To illustrate the proposed α-shape class visualisation, the Landsat images of the selected areas was used. The classification in bands 7,4,2 from the Landsat 7 images (Figure 1) of the study area are used to test the α-shape based classifier. Figure 3 shows that classes.

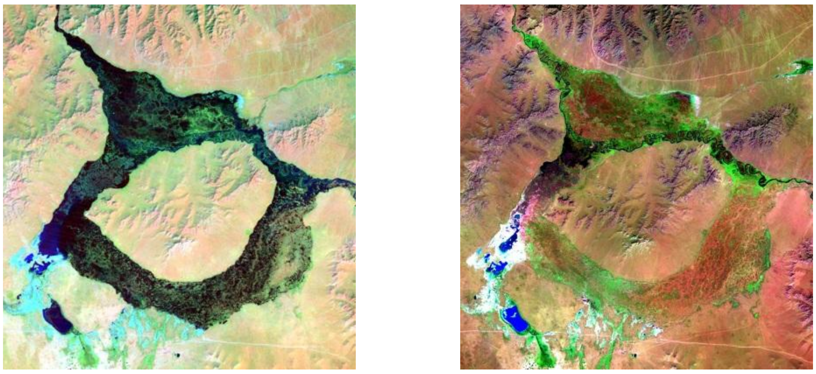


Figure 2. Landsat image 742

(Left – image of 12 September 1994; right –image of 20 September 2000)

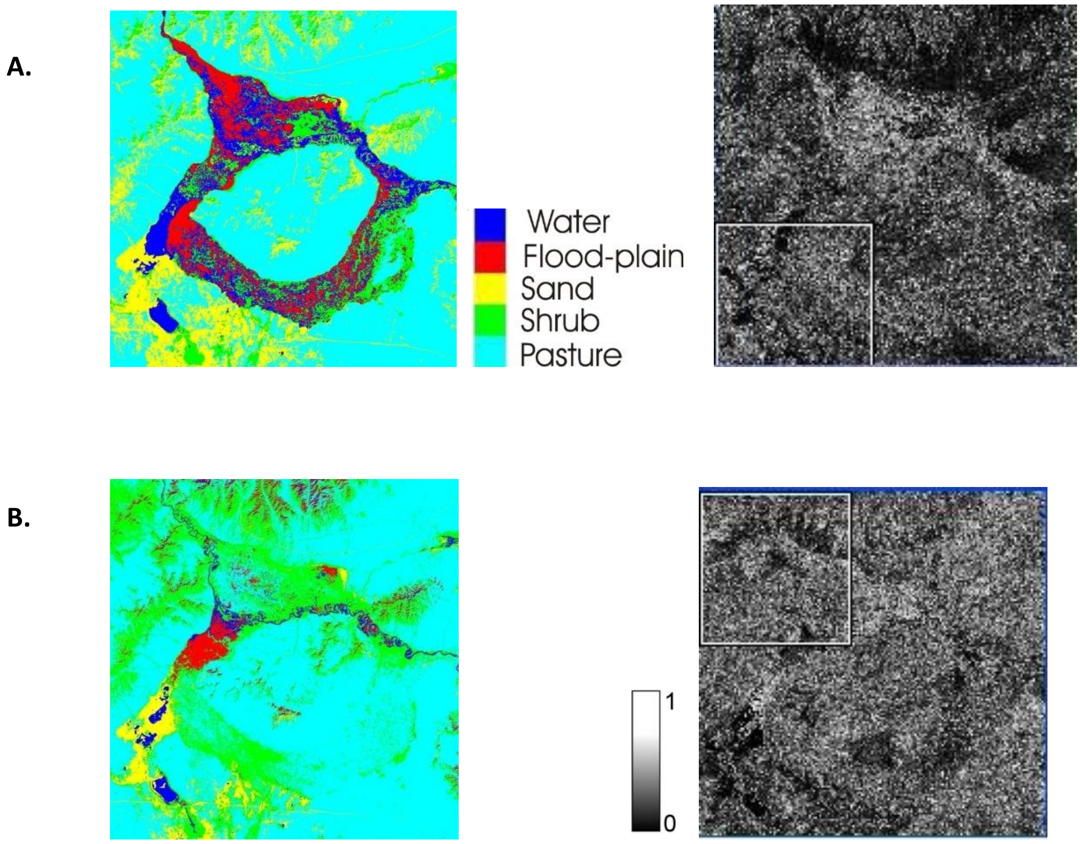


Figure 3: α-shape based fuzzy classification result of A. – 12 September 1994; B. – 20 September 2000

(left) 'defuzzified' classification result; (right) image with the confusion index.

Confusion image display shows areas where confusion in classification occurs (bright areas). Pasture and shrub's areas overlap in feature space, as can be seen in figures 3. Pixels in this overlap zone show high confusion values in the image display (note: high uncertainty = high confusion = bright value).

Overall, the α-shape classifier gives good results with an overall classification average accuracy of 94.35%. Accuracy assessment results in table 1 show that the α-shape based classifier performs slightly better than standard supervised fuzzy c-means classifiers.

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

Data of source	Class	Reference					
		Water	Shrub	Flood Plain	Sand	Pasture	Total
12 July 1994	Water	96.14	0	1.67	0	0	29.14
	Shrub	0	98.65	0.22	0	0	5.99
	Flood Plain	3.86	0	98.11	0	0.19	6.06
	Sand	0	0	0	98.65	0.01	7.49
	Pasture	0	1.35	0	1.35	99.8	51.32
	Total	100	100	100	100	100	100
20 September 2000	Water	89.13	0	0	0.61	0	6.78
	Shrub	1.66	95.26	8.87	1.8	0.42	4.48
	Flood Plain	1.01	2.57	86.43	0.47	7.9	10.36
	Sand	7.28	0	0	90.05	0.35	18.24
	Pasture	0.92	2.17	4.7	7.16	91.33	60.15
	Total	100	100	100	100	100	100

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 94.35% 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.

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