



**THE 36TH**  
ASIAN CONFERENCE  
ON REMOTE SENSING

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QUEZON CITY, METRO MANILA, PHILIPPINES

## **APPLICATIONS OF MULTITEMPORAL RS IMAGES FOR LAND COVER CHANGE STUDIES IN CENTRAL MONGOLIA**

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**KEY WORDS:** Multitemporal images, Land cover, Change studies

**ABSTRACT:** The aim of this study is to conduct a study on land cover changes in Central part of Mongolian territory using multitemporal optical remote sensing (RS) data sets. As the data sources, Landsat images acquired in 1994, 2000, 2010 and 2014 are selected. To define the available land cover classes, the satellite images are classified using supervised (minimum distance, maximum likelihood and Mahalanobis distance) and unsupervised (isodata) classification methods and the results are compared. Of these methods, the better results are obtained through the use of the maximum likelihood method. Overall, the research indicates that in recent years, the land cover classes in the Central Mongolia have been changed.

### **1. INTRODUCTION**

Mongolian territory covers northeast and central Asia and has an area of 1.565,000 sq.km. The population of the country is about 3 million. The country is surrounded by dense forest in the north, Gobi desert in the south, plane steppe in the east and High Rocky Mountains in the west. Although, the country has different mineral deposits such as copper, coal, gold, molybdenum, fluorite, uranium, tin, and tungsten, they have not been properly exploited until recently. On the contrary, the main type of land use is pastureland for semi-nomadic livestock husbandry and it covers about 81% of total land of the country. Due to availability of large pastureland the economic activity in Mongolia has been mainly based on herding and agriculture. The actual availability of pasture is determined by rainfall, and access to fodder is determined by the availability of water during summer and of snow during winter. Compared to the pastureland, the use of agricultural land accounts for a very low percentage, because the presence of the Gobi desert and mountains in the west and northwest provide natural limits for its extended use (Amarsaikhan 2013).

The country has harsh continental climate. The winter low temperatures result in heavy snowfalls and the summer high temperatures often result in drought. Moreover, there are frequent forest and steppe fires during spring periods. These adverse climatic conditions often influence the country's fragile economy, specifically, agricultural crop production and animal husbandry. The drought and dzud also affect the productive capacity of the land. When there is drought, the fodder production is too low to feed all animals. As a result, extensive overgrazing occurs, because the increasing livestock numbers have degraded much of Mongolia's grasslands, especially those around major settlements. The drought and high temperatures decrease the cohesion of the exposed fertile topsoil and strong winds blow away the topsoil particles, resulting in dust storms, including yellow dust. Such sustained damage over a longer period of time will result in irreversible changes. With continued pressure of drought and overgrazing, the land degrades and may finally turn into desert (Amarsaikhan *et al.* 2008).

The drought, high temperature and high radiation decrease the cohesion of the exposed fertile topsoil and strong winds blow away the topsoil particles, resulting in dust storms, including yellow dust. Such sustained damage over a longer period of time will result in irreversible changes. With continued pressure of drought and overgrazing, the land degrades and may finally turn into desert, because even improved weather conditions might not immediately restore the old vegetation cover. Currently, in Mongolia the process of desertification is being strongly observed everywhere. For example, compared to 1960, a number of days with dust storms have been increased by a factor of more than four, while grasslands' productivity has been decreased by a factor of five. Many rivers and lakes are drying out. Soils are becoming more and more saline and lose their regenerative capacity. Meanwhile, the mobility of sand has been increased. A recent study has shown that, about 78% of

Mongolian total territory has been degraded. Thus, there are many problems related to the environment and natural resources in Mongolia which in turn influence the socio-economic sustainable development of the country (Jetten2009, Amarsaikhan 2011).

In the present research, we wanted to conduct a study on land cover changes in Central Mongolia using multitemporal optical RS images. To define the available land cover classes, the RS images have been classified using supervised and unsupervised classification methods and the results were compared. The analysis was carried out using ENVI system installed in a PC environment.

## 2. STUDY AREA AND DATA SOURCES

As a test site, Undur shireet soum located in Tuv aimag (province) has been selected. The area of the Tuv aimag is considered as part of the Khentii-Khangai Mountain Range and Eastern Mongolian plains and most of its territory is elevated in between 1200m and 1500m above sea level. Large mountains and valleys lie in the north and a steppe with small hills and mound sit in the south (as forthe selected test area) of the aimag. The Undur shireet soumis bordered with the Bulgan aimag to the west and with other soums of the aimag in all other directions. Steppe brown and light brown soil is dominated in most of the test site. The area has a harsh mainland climate and the annual average temperature usually drops below 0 degree.

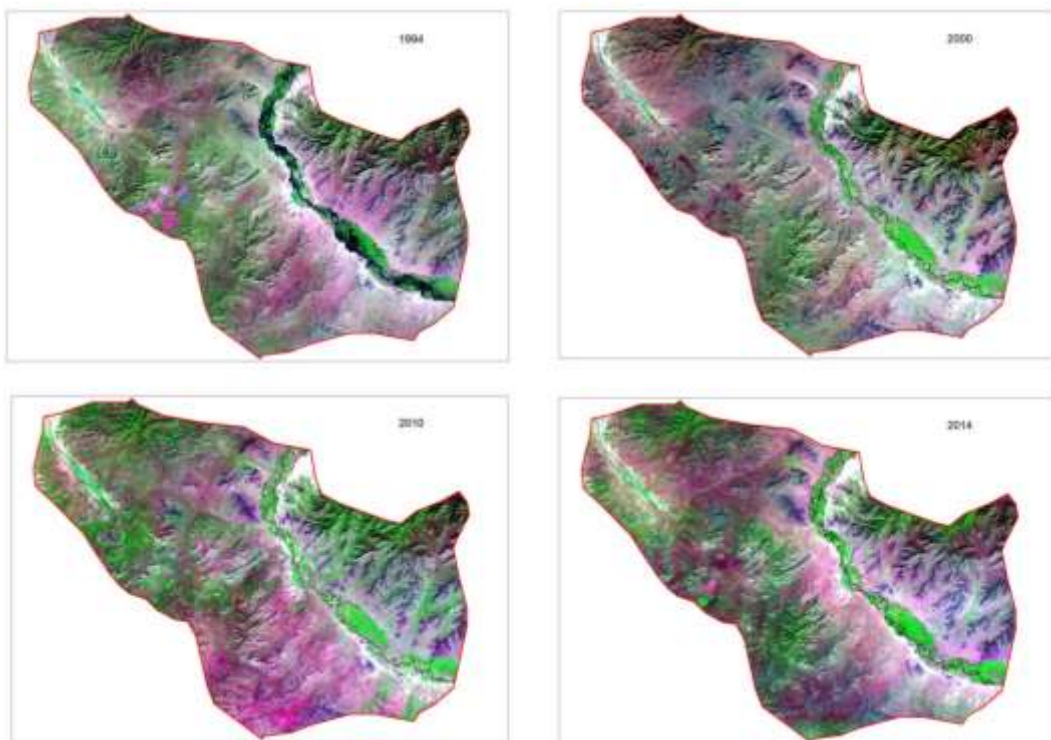


Figure 1. MultitemporalLandsatimages of the Undur shireet soum, Tuv aimag.

The data used consisted of seriesof Landsat data sets acquired during summer period of1994, 2000, 2010 and 2014. The Landsat images have seven multispectral bands and the spatial resolution is 30 m for the reflective bands, while it is 120 m for the thermal band of the TM and 60m for the band 6 of the ETM. In the present study, channels 2,3,4,5 and 7 have been used. In addition, a topographic map of 1986, scale 1:50,000 and a general land use map of 1985, scale 1:100,000 were available, accordingly. Figure 1 shows the study area in multitemporal Landsat images.

## 3. GEOREFERENCING OF THE LANDSAT DATA SETS

In the beginning, the Landsatseries imagesweregeoreferenced to aUTM map projection usingmore regularly distributed ground control points (GCP)s defined from different sites on the topographic and general land use maps of the test area. Generally, the GCPs have been selected on clearly delineated sites such as river valleys, morphological structures and roads. For the transformation, a second-order transformation and nearest-neighbour resampling approach (ERDAS 2010) were applied and the related root mean square (RMS) errors werein between 0.63pixel and 0.96 pixel.

#### 4. CLASSIFICATION OF THE IMAGES AND LAND COVER CHANGE STUDIES

After the georeferencing, the images have been classified using such supervised and unsupervised classification techniques as the minimum distance, maximum likelihood, Mahalanobis distance and isodata clustering. The minimum distance rule calculates the spectral distance between the measurement vector for the candidate pixel and the mean vector for each signature (ENVI 2004). The maximum likelihood classification is the most widely used supervised classification technique, because a pixel classified by this method has the maximum probability of correct assignment, while the Mahalanobis distance classifier is a parametric method, in which the criterion to determine the class membership of a pixel is the minimum Mahalanobis distance between the pixel and the class centre (Amarsaikhan *et al.* 2010). Unlike these methods, the isodata is iterative in that it repeatedly performs an entire classification and recalculates statistics. It uses minimum spectral distance to assign a cluster for each candidate pixel (Mather 1999). The process begins with a specified number of arbitrary cluster means or the means of existing signatures, and then it processes repetitively, so that those means shift to the means of the clusters in the data (ERDAS 2010).

In the present study, as the features for the classification, for all data sets green, red, near infrared and two middle infrared bands have been selected. To define the sites for the training signature selection, from the images of different years, several areas of interest (AOI) have been selected for the available classes such as soil, water, green vegetation and pastureland using the local knowledge and land use map. Then, the separabilities of the selected training signatures were evaluated using Jeffries–Matusita distance (Richards 1999) and the samples which demonstrated the best possible separabilities were chosen to form the signatures. The final signatures included about 95-484 pixels.

In the case of 1994 data, after the visual inspection, it was seen that the best result has been obtained by the use of the maximum likelihood decision rule. On the classified image, there were very little mixtures among the statistically similar classes such as green vegetation and pastureland. As could be seen from the results, the worst classification result has been obtained by the use of the unsupervised classification method, because there were very high mixtures among the classes: green vegetation, soil and pastureland. In addition there were many areas classified as water. Unlike other methods, the second better result has been obtained by the use of the Mahalanobis distance classifier, although, the result had some mixtures between the pastureland and soil classes. The results of the classifications of 1994 data are shown in Figure 2.

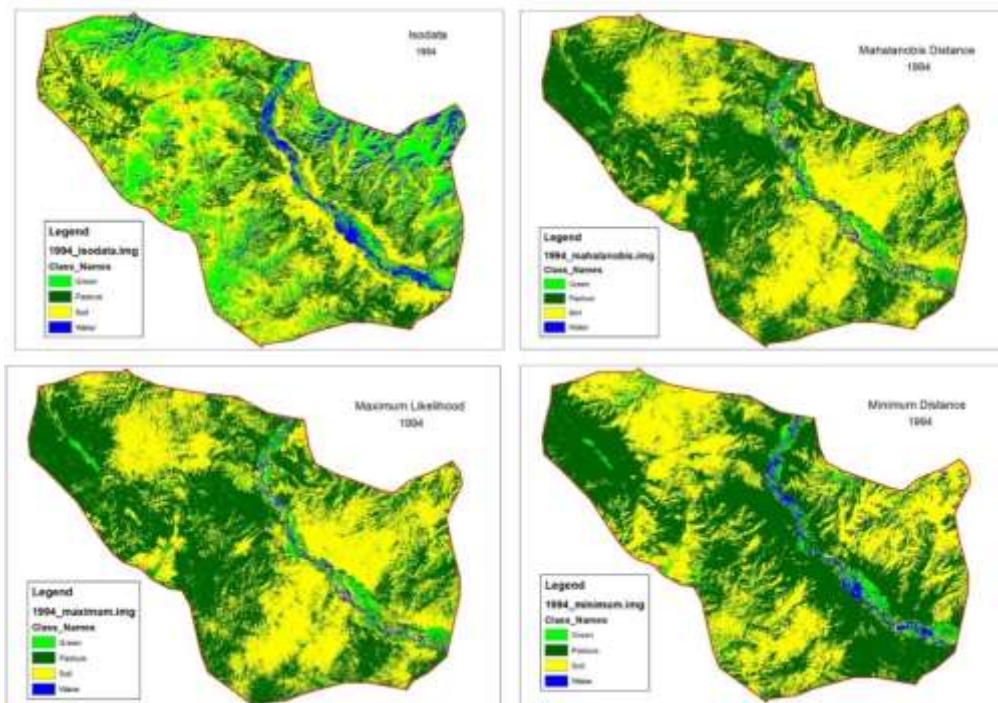


Figure 2. The results of the classifications of the Undur shireet soum, Tuv aimag (1994).

As could be seen from the results of the classification of 2000 image, the best result has been obtained by the use of the Mahalanobis distance classifier. On this image, there were very little mixtures among the statistically overlapping classes: green vegetation and pastureland. Moreover, it is seen that the worst classification result has been obtained by the use of the isodata clustering method as in the previous case, because there were high mixtures among the classes as green vegetation, soil and pastureland. Again there were many areas misclassified as water.

In the case of this classification, the second better result has been obtained by the use of the maximum likelihood classification, although, the result had different mixtures between the pastureland and soil classes. The results of the classifications of the 2000 data are shown in Figure 3.

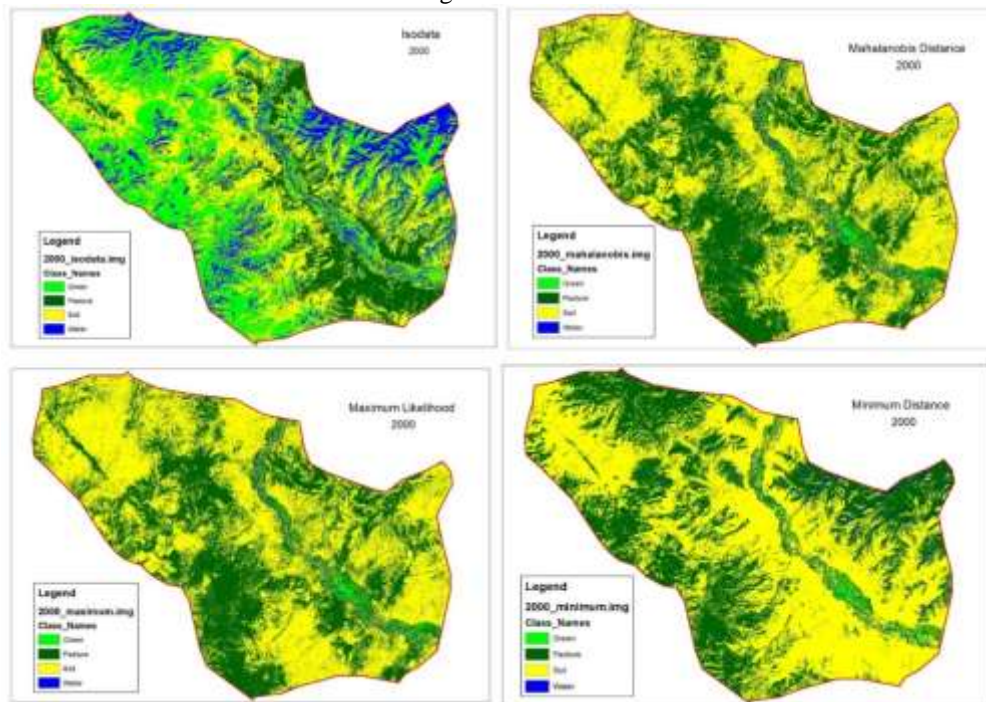


Figure 3. The results of the classifications of the Undur shireet soum, Tuv aimag (2000).

In the case of 2010 data, it was seen that the best result has been obtained by the use of the maximum likelihood method, because there were very little mixtures among the green vegetation and pastureland classes. Unlike the previous classification results, the second better result has been obtained by the use of both minimum distance and Mahalanobis distance classifiers. Moreover, it is seen from the results of the classification decision rules, the worst classification result has been obtained by the use of the unsupervised classification method, because there were very high mixtures among the green vegetation, soil, water and pastureland classes. The results of the classifications of 2010 image are shown in Figure 4.

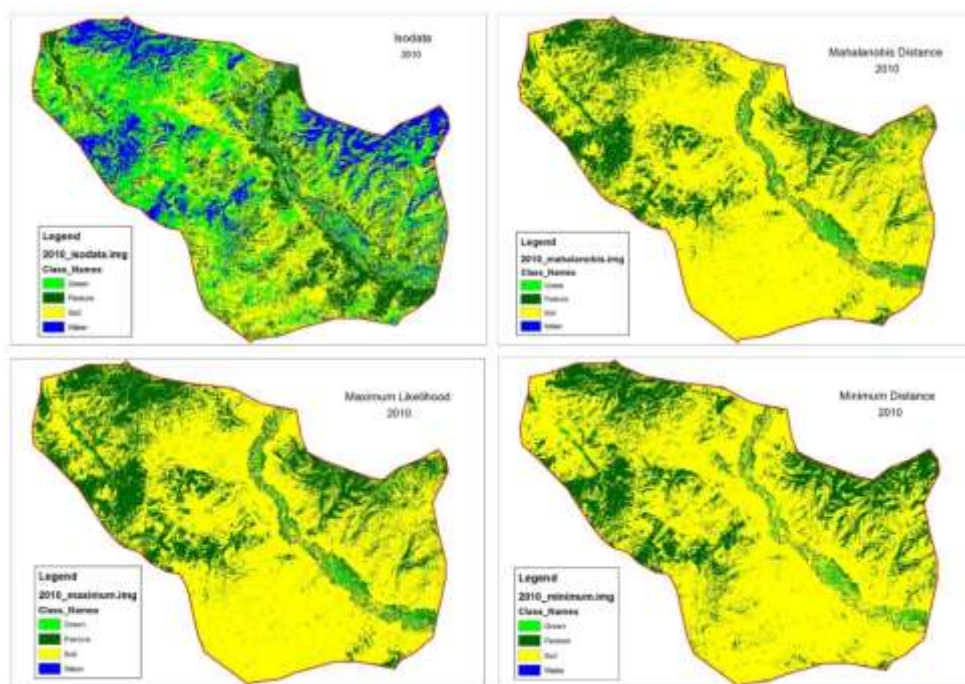


Figure 4. The results of the classifications of the Undur shireet soum, Tuv aimag (2010).

As seen from the results of the classification of 2014 image, the best result has been obtained by the use of the Mahalanobis distance classifier, because there were very little mixtures among the statistically overlapping classes such as green vegetation and pastureland. Moreover, it is seen that the worst classification result has been obtained again by the use of the isodata clustering method, because there were high mixtures among all classes. For the 2014 image, the second better result has been obtained by the use of the maximum likelihood and minimum distance classification methods, because these results looked very similar to the result of the Mahalanobis distance method. The results of the classifications of the 2014 data are shown in Figure 5.

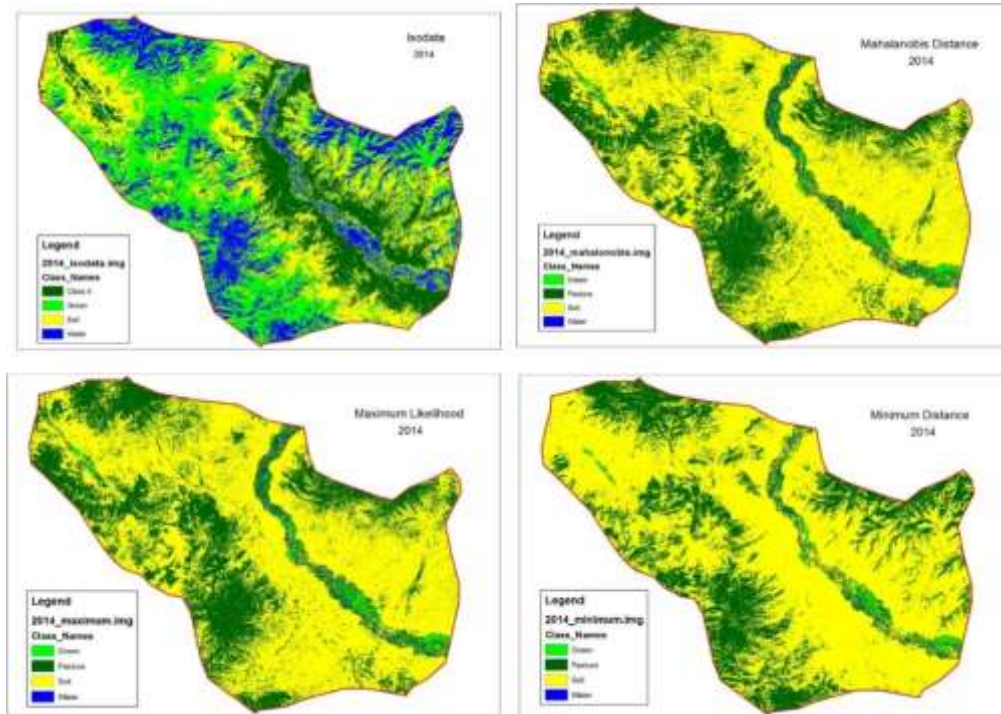


Figure 5. The results of the classifications of the Undur shireet soum, Tuv aimag (2014).

The areas related to theselected classes evaluated from RS images obtained at different years are shown in table 1. As could be seen from Table 1, in recent decades the test site has faced many changes and the areas of the classes have been significantly changed since 1994. In order to define the areas related to land cover changes, the total areas related to each class were defined by calculating statistical parameters of the classified multitemporal RS images.

Nº	Landsat image	Water (ha)	Soil (ha)	Green vegetation (ha)	Pastureland (ha)
1	1994	2711.8	126854	10019.6	142958
2	2000	1935.3	155079	2687.1	122822
3	2010	1718.5	198606	3185.0	79033
4	2014	1751.0	181888	3669.6	95234

Table 1. The total areas for the available classes in different years, evaluated from multitemporal Landsat data sets.

## 5. CONCLUSION

The aim of this research was to carry out a study on land cover changes in Central Mongolia using multitemporal remotely sensed data sets. As the data sources, Landsat images from 1994, 2000, 2010 and 2014 were selected. To classify the available land cover classes such as soil, water, green vegetation and pastureland, minimum distance, maximum likelihood, Mahalanobis distance and isodata classification methods were used and the results were compared. Among the applied techniques, the better results were obtained by the use of the maximum likelihood decision rule and Mahalanobis distance classifier. Overall, the study indicated that over recent years, the land cover classes in the selected test site have been significantly changed.

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