



ШИНЖЛЭХ УХААНЫ АКАДЕМИ
ИНФОРМАТИКИЙН ХҮРЭЭЛЭН

ЭРДЭМ ШИНЖИЛГЭЭНИЙ
БҮТЭЭЛ №11

УЛААНБААТАР
2011ОН

EVALUATION OF FOREST CHANGES USING MULTITEMPORAL LANDSAT IMAGES

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Abstract: The aim of this study is to demonstrate how multitemporal optical satellite images can be used for forest change study in Mongolia. For the analysis, multispectral Landsat images from the years of 1989, 2001 and 2011 as well as some other maps were used and different digital image processing techniques were applied.

1. Introduction

In general, forests are managed for an evolving constellation of objectives: timber and other commodities production; recreation; maintenance of wildlife habitat; water quality protection; wilderness and open space preservation; and, in the coming years, as a buffer against climatic change, and effective management of these resources, requires reliable and timely information about their status and trends. For this end, different government and private sector organizations around the world spend hundreds of millions of dollars on thorough forest monitoring activities [8].

Forests cover approximately 30 percent of the land area of the planet, however, estimates suggest that deforestation is occurring at a rate of between 15-17 millions ha per year, predominantly because of human-induced land-use changes. Over 45 per cent of the Earth's original forests have been cleared during the past century [10]. These human-induced changes in forest extent and condition impact biodiversity, climate, biochemical cycles and economic development [6]. Therefore, it is very important to protect forests, as they contain the majority of the planet's land-based species. Nature's products support such diverse industries as agriculture, cosmetics, pharmaceuticals, pulp and paper, horticulture, construction and waste treatment. In addition, forests regulate the global atmospheric cycles that make biological life possible on earth [10].

As it is known, remote sensing (RS) technology has a great potential to estimate different forest parameters, including canopy as well as stand on spatio-temporal scale. These parameters have a good relation with remote-sensor retrieved signature and empirical models are used to find a relation. Moreover, satellite RS is useful for effective forest monitoring and management and it is less labour intensive and cost-effective. In addition, historical satellite data provides useful information about forest cover changes from local to global scales [3].

The aim of this study is to demonstrate how multitemporal optical satellite images can be used for forest change study of Bogdkhan Mountain. For the analysis, multispectral Landsat images of 1989, 2001 and 2011 as well as topographic and forest taxonomy maps have been used.

2. Test site and data sources

The Bogdkhan Mountain is situated in central part of Mongolia, near the city of Ulaanbaatar. The mountain is a protected area and has a territory of 41651ha, of which 55% is covered by forest.

The mountain has 588 species of high plants, which are related to 256 genres of 70 families. 135 species such as carex, artemisa, oxytropis that relate to 11 main genres comprise 22.9% of all species distributed on the mountain. Forest is distributed on the altitude range of 1400m (1450m)- 2100m (2150m) above sea level and consists of 3 sub zones such as mountain plateau, taiga and taiga type.

The optical remotely sensed images used in the present study consisted of Landsat TM image acquired on 31 August 1989, Landsat ETM image of September 2001, and Landsat TM image of August 2011. In addition, a topographic map of 1984, scale 1:50.000 and a forest taxonomy map of 1997, scale 1:100.000 were available, accordingly. Figure 1 shows forest map of the test area[1].

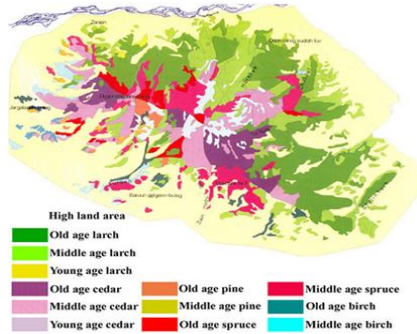


Figure 1. Forest taxonomy map of the test area.

3. Georeferencing of Landsat images

In order to carry out multitemporal forest analysis, initially, the optical images were thoroughly analyzed in terms of brightness and geometric distortion. The images were of a good quality. Then, the Landsat images were successively geometrically corrected to a Gauss-Kruger map projection using a topographic map of the study area, scale 1:50.000.

The ground control points were selected on clearly delineated sites and in total 12 regularly distributed points were chosen. For the actual transformation, a second order transformation and nearest neighbour resampling approach have been applied and the related root mean square errors were 0.61 pixel, 0.68 pixel, and 0.57 pixel, respectively. Figure 2 shows false colour composite images of the multitemporal Landsat images.

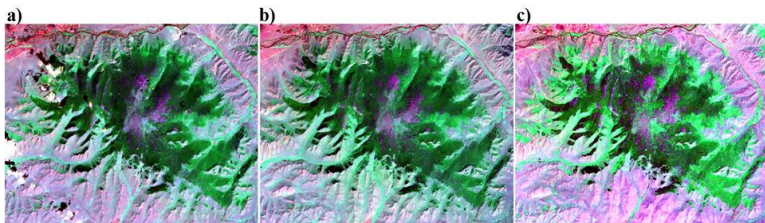


Figure 2. a) Landsat TM image of 1989, b) Landsat ETM image of 2001, c) Landsat TM image of 2011.

4. Feature selection and Bayesian classification

To define the forest changes, multitemporal Landsat images have been classified into forest and non-forest classes. For this purpose, training signatures had to be formed and two to three areas of interest representing the available two classes (ie, forest and non-forest) have been selected.

Separability of the training signatures was firstly checked in feature space and then evaluated using Jeffries–Matusita distance. The values of Jeffries–Matusita distance range from 0 to 2.0 and indicate how well the selected pairs are statistically separate. The values greater than 1.9 indicate that the pairs have good separability [4,7]. After the investigation, the samples that demonstrated the greatest separability were chosen to form the final signatures. The final signatures included about 528-895 pixels. As the classification features, the combinations of Landsat bands 3, 4 and 5 were used.

For the actual classification, Bayesian maximum likelihood classification (MLC) has been used assuming that the training samples have the Gaussian distribution. The MLC is the most widely used statistical classification technique, because a pixel classified by this method has the maximum probability of correct assignment [2,5,9]. The decision rule assuming Bayes' rule can be written as follows:

$$P(C_i|x) = P(x|C_i) * P(C_i) / P(x)$$

where $P(C_i|x)$ -posterior probability, $P(x|C_i)$ -conditional probability, $P(C_i)$ -prior probability, $P(x)$ -probability of finding a pixel from any class. The actual classification is performed according to $P(C_i|x) > P(C_j|x)$ for all $j \neq i$.

In the present study, for the available classes the equal prior probabilities have been used. To increase the reliability of the classification, to the initially classified images, a fuzzy convolution with a 3x3 size window was applied. The fuzzy convolution creates a thematic layer by calculating the total weighted inverse distance of all the classes in a determined window of pixels and assigning the centre pixel the class with

the largest total inverse distance summed over the entire set of fuzzy classification layers, i.e. classes with a very small distance value will remain unchanged while the classes with higher distance values might change to a neighboring value if there are a sufficient number of neighboring pixels with class values and small corresponding distance values [7].

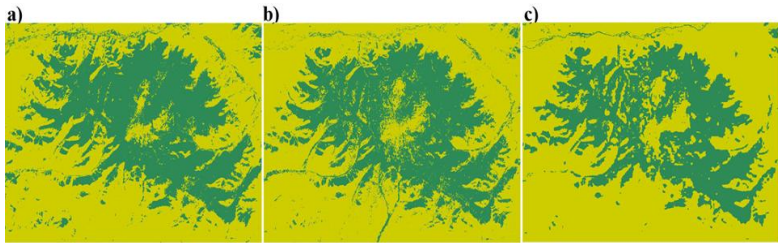


Figure 3. a) Classified image of 1989, b) Classified image of 2001, c) Classified image of 2011.

The visual inspection of the fuzzy convolved images indicated that there are some improvements on the borders of the neighboring classes that significantly influence the separation of the decision boundaries in multidimensional feature space. The final classified images are shown in figure 3(a–c). Looking at the classified images, one can observe what kind of changes had occurred in those periods in the forest cover of the Bogdkhan Mountain.

5. Conclusions

The aim of this research was to demonstrate how multitemporal optical RS images could be used for forest change study in Mongolia. For this purpose, Bogdkhan Mountain was taken as a test area and as data sources, multispectral Landsat images of 1989, 2001 and 2011 as well as topographic and forest taxonomy maps were used. To discriminate between forest and non-forest classes, the Bayesian classification was applied. Overall, the study demonstrated that RS is a good source that could be easily and successfully used for forest change studies.

6. References

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