Land cover classification using maximum likelihood method (2000 and 2019) at Khandgait valley in Mongolia

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Abstract. Promoting the recovery of forest management has been identified as a key priority by the Government of Mongolia. The objective of this paper is to define land cover classification and land cover change in Khandgait valley between 2000 and 2019. The study area is located in the North central part of Mongolia in Bulgan province. Landsat satellite images with 30m resolution were applied. For the validation, we used ground truth measurements. Maximum-likelihood method was applied in this study. The output map of land cover classification was analyzed and compared with the ground truth measurements. The results showed an overall accuracy of 86.5% and 89.0% for the 2000 and 2019 images, respectively. Land cover changes were quantitatively presented with the results of accuracy assessments between 2000 and 2019. In the future, we need to improve forest monitoring and analyze forest management using satellite images.

1. Introduction
Mongolia is the seventh largest country and one of the biggest land-locked nations in Asia. Forest resources management of Mongolia suffers from several weaknesses such as unregulated use, overuse, and inadequate protection [1]. Forest is most important part for soften extreme weather and absorption of the greenhouse gases. Most windy period is April and May. January is the coldest month and July the warmest [2]. The boreal forests accounting for 14.2 million hectares (87%) dominated by larch and birch in north side of Mongolia and 2.0 million hectares of saxaul forests (13%) in the south side of Mongolia. Forestry is an important industry for Mongolia, and has a great potential nowadays as a source of sustainable livelihoods for those in forested provinces. Forest sector uses satellite data from 1990, and started to produce forest cover map by using remote sensing. Nowadays, many researches
consider the forest cover mapping, forest type, forest degradation, forest fire. Mongolian forests have low productivity, growth, and are vulnerable to disturbance from drought, fire, illegal logging and pests.

However, gradually, forest resources are reducing quickly, and the threat is also coming in our country. In general, intensive and effective forest management requires reliable inventory data and maps indicating the current state of the forest. The aim of this research is to conduct land cover classification and change in forested area. Our study is a case study of forest cover changes; therefore, we have different forest cover classification approaches, and have been adopted in producing land cover map with satellite data, including the maximum likelihood approaches, accuracy assessment, and change detection.

2. Study area

Study area is in Khandgait valley in the North central part of Mongolia (figure 1). It is located at the alpine forests, gradually blending in the arid steppe mountains-region (about 50 km northeast of the mining city Erdenet). High mountains of Bulgan, Buregkhangai and Dulaankhaan are dominated in the northern part of the province.

Soil type is sandy with semi desert features in the southern part while fertile land is mainly in the north for crop cultivation. Climate surrounding consists of a mean annual temperature is about +0.29°C and yearly precipitation is about 270 mm [3, 4] in the study area. According to the Holdridge life zones system of bioclimatic classification Bulgan is situated in the boreal dry scrub biome (larch, birch and shrub) where larch is 86.12% and birch is 13.88%.

In this study, we used over several remote sensing imageries, which are downloaded the Landsat data from (http://glovis.usgs.gov). These images were clear of cloud cover. Assessment processed with the layer of the data such as Forest taxation data of the FRDC, Topographic maps of region, Google Earth Pro and Bing map used ENVI 5.2 software. The Landsat ETM+ image data has consisted of eight spectral bands, with the same spatial resolution as the first five bands of the Landsat TM image. The characteristics of the Landsat data used in the current study are shown in (table 1).

![Khandgait valley of Mongolia](image)

**Figure 1.** The location of the study area, topography.

| Satellite       | Date  | Resolution | Spectral bands used        |
|-----------------|-------|------------|----------------------------|
| Landsat ETM     | Path 133,134 Row 26 | 2000 | 30m | Blue, Green, Red, NIR |
| Landsat OLI     |       |            |                            |
Field measurement has been operated on the selected points of study area and forest area unintentionally. All ground truth data were collected in summer 2019.

3. Methodology
Optical satellite images were applied in this research. Landsat image preprocessing is necessary for quantifying meaningful information from remotely sensed data [5]. We completed three types of corrections; geometric, radiometric and atmospheric. Firstly, the geometric correction of the image is an important prerequisite, which must have performed prior to using images in geographic information systems (GIS) and other image processing programs. Secondly, radiometric correction is to avoid radiometric errors or distortions, while the geometric correction is to remove geometric distortion. Finally, atmospheric correction was used to remove the target, and it is also absorbed or scattered effects.

Maximum-likelihood classifier assumes that each class in each band can be described by a normal distribution (1). Maximum-likelihood is a supervised classification method derived from the Bayes theorem, which states a posteriori distribution P(𝑖|ω), i.e., the probability which is a pixel with feature vector ω belongs to class 𝑖 is given by:

\[
P(𝐶𝑖|𝑥) = P(𝑥|𝐶𝑖)∗P(𝐶𝑖)/P(𝑥)
\]  

Where \(P(𝐶𝑖|𝑥)\) – testing most probability; \(P(𝑥|𝐶𝑖)\) – conditional probability; \(P(𝐶𝑖)\) - prior probability, the probability that 𝑖 is observed; \(P(𝑥)\) – probability of pixel for any class; \(𝐶𝑖\) – that class; \(𝑥\) – pixel. This method is better than other methodology due to measuring shape, size and navigation not only the location.

Present method for the change detection used in this study classifies adjusted images which is obtained at different times, and compares and analyzes these images using a change-detecting matrix for the construction of the final change map. The acquired land cover classification map in 2000 and 2019, respectively for this study (figure 2).

Figure 2. Distribution of the land cover classification in the study area: derived from (a) Landsat TM 2000 and derived from (b) Landsat ETM + 2019.

4. Analysis
The accuracy assessment for land cover classification map and ground truth measurements were assessed by using confusion matrices approach [6] and calculated by using (2).

\[
OA = \frac{∑A}{∑B} × 100
\]  

(2)
Where; $A$ is the number of pixels assigned to the correct class and $B$ is the number of pixels that actually belongs to that class.

We randomly overlaid our ground truth measurements on the land cover classification map and made validation. In the table, we show the matrix evaluation for the validation. Overall accuracy was 86% in the table 2. Bare land, forest, shrubland, and degraded classes area were selected as ground truth classes.

**Table 2.** Accuracy assignment of land cover classification.

| Landsat data | Ground truth data | Bare land | Forest | Shrubland | Pasture | Degraded area | River |
|--------------|-------------------|-----------|--------|-----------|---------|----------------|-------|
| Bare land    |                   | 8         | 3      | 2         | 1       | 9              | 11    |
| Forest       |                   | 3         | 15     | 2         | 0       | 5              | 5     |
| Shrubland    |                   | 0         | 1      | 10        | 3       | 7              | 8     |
| Pasture      |                   | 0         | 0      | 1         | 10      | 9              | 5     |
| Degraded area|                   | 9         | 0      | 2         | 7       | 11             | 1     |
| River        |                   | 0         | 0      | 1         | 10      | 0              | 6     |
| Overall accuracy (%) |       |           |         |           |         | 86             |       |

During the 20 years, the degraded area has increased by 8.6 km$^2$. In contrast, the shrubland and forest areas have decreased by 17.4 km$^2$ and 2.6 km$^2$, respectively (figure 3).

**Figure 3.** The changes of the land cover classification 2000 and 2019 (km$^2$).

We have calculated land cover changes between 2000 and 2019 that was used maximum probability classification method for the study area (figure 4).

**5. Conclusion and discussion**

In this study, we defined land cover classification which is dominant of forested area. The Khandgait valley, Bulgan province was selected for the study area. We used Landsat satellite images and ground truth measurements for this study and it was analyzed land cover classification and land cover change between 2000 and 2019. The changes of the assessment were compared between these two years data from the satellite images and with ground truth data measured from fieldwork (2018) in the study area.
The maximum likelihood method was selected for this study. The land cover classification was classified as 42% forest, 23% shrubland, 13% pasture, 4% river and 10% degraded. The forested area is degraded by 5%. The Khandgait valley, greatest area is with the forest and next shrub area by supervised classification. However, it was only suitable with the small area. Forest is more distinctive on any vegetation index during the growing season. The local community partnerships are possible to analyze on forest pest, fire, logging, shortage area and long-term monitoring through LANDSAT satellite data. Forest boundary made possible to mapping on Landsat or other high-resolution satellite data. In the future, there should be improved forest monitoring and improve forest management using satellite images and ground truth measurements.

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