THE IMPACT OF FOREST FIRE ON FOREST COVER TYPES IN MONGOLIA

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ABSTRACT:

The objective of this study was the impact of forest fire on forest cover types. This study has identified non-forest and forest area that has seven forest class are included with cedar, pine, larch, birch, birch-pine mixed, birch-larch mixed and cedar-larch mixed, additionally, remote sensing imagery is applied. In contrast, Landsat imagery has been used several classification approaches. Moreover, the current classification has developments in segmentation and object-oriented techniques offer the suitable analysis to classify satellite data. In the object-oriented classification approach, images cluster to homogenous area as forest types by suitable parameters in some level. The accuracy analysis revealed that overall accuracy showed a good accuracy of determination (86.33 percent in 2000 and 93.75 percent in 2011) with regard to identify of the forest cover and type. Furthermore, these results suggest that the Landsat TM and ETM+ data can reliable detect the forest type based upon the segmentation and object-oriented techniques. In generally, our study area is high-risky region to forest fires. It is higher influence to forest cover and tree species and other ecosystems. Overall, wildfire of impact results showed that 25239 ha of forests were changed to burnt area and 52603 ha forests were changed to grassland.

1. INTRODUCTION

Mongolia is landlocked country between Russia and China, and a territory area is 1.56 million km2. It covers six climatic zones, including that desert, desert steppe, steppe, forest steppe, boreal forest and montane (World Bank, 2004). The forest of Mongolia is growing terrestrial dry and harsh climate, therefore forest capacity, natural growth, and resilience are absolutely low, and very easily lost ecological balance, because of natural and human impacts, including dryness, fire, pesticide and disease (Ch.Dorjsuren, 2007). According to the National Statistic Office, NSO (NSOSTAT data 2000), the boreal forest and forest steppe zones contain a coniferous component composed of Siberian larch (*Larix siberica*), Scotch pine (*Pinus sylvestris*) and Siberian pine or cedar (*Pinus siberica*), and a smaller broad-leafed component composed primarily of birch (*Betula platyphylla*), aspen (*Populus ttermula*) and poplar (*Populus diversifolia*). Over 90% of northern forests covers within seven provinces: Khuvsgul (29%), Selenge (16%), Bulgan (14%), Kentii (11%), Tuv (10%), Arkhangai (8.5%) and Zavkhan (5%). Mongolia has a typical continental climate, with hot summers (temperature up to 410C) and cold winters (temperatures to •530C) and rainfall is relatively low, varying from 50 mm in the southern desert region, to 450 mm in mountain areas, with 80% ~ 96% falling in the warm period from May to September (Erdenetuya, 2012). According to Erdenetuya (2012), about 56 per cent of the country's total area is located in a zone exposed to forest and grassland fires and a considerable fraction (98.5%) of the country's territories covered with forests are in a zone assessed as of highest fire risk. Wildfires constitute a major that determine spatial and temporal dynamics of forest ecosystems (Goldammer, 1999). Historically, fire was the most dominant disturbance factor in forests across the Mongolia, and strongly influenced spatial temporal dynamics of forest ecosystems (Chuluunbaatar, 1998).

Thus, fire is a natural and important component of these forest systems. The nature of wildfires may be changing in these systems, however, as a result of climate change, past management, and other anthropogenic causes (MNE, 2014). Moreover, the amount of wood available to meet demands by households and industry are increasing (NSOSTAT review, 2015). The government has recognized that wood imports are necessary to meet supply shortfalls and to discourage illegal logging. Hence customs duties on some types of wood and timber imports have been removed. The country's forest resource is not very rich in extent or quality, covering an area of 17.5 million ha on the southernmost fringe of the Great Siberian forest and some mountain ranges western and northwestern part of Mongolia territory (J. Tsogtbaatar, 2004). Although in the Law on Forests is required to implement detailed research again on the forest database which changes periodically every 10 years, we cannot monitor the forest areas' changes depending on current forest research equipment and technology, funds and capacity. For the Mongolian forest inventory a use of old aerial photography from 1970s to 1980s data and a visual estimation in the fieldwork are necessary.

The forest area has decreased by 1.2 million ha during the last 30 years from 1974 to 2006, but environmental and human impacts such as, burnt forests, logging, open forests are as increased by 3.2 million ha during the period (MNE, 2006). According to FAO statistics, present forest resources of the country indicate that Mongolia has a small amount of forest resources that have been decreased by human impacts, fires, insects and illegal logging (MNE, 2001). Moreover, it was noted that the occurrence of wildfire and distribution of forest pests were increased which statistic from 2010-2013 mention report of the nature and environmental of Mongolia (S. Bayarkhuu, 2014). The forest functions map, wildfire risk assessment and forest management plan. According to researchers, geospatial technology approaches and data are mapped the forest functions using GIS (B. Ochirsukh et al., 2011); wildfire risk map using decision support system (Elbegjargal and Ochirkhuyag, 2016) Therefore, we need to establish and expand a harmonized approach with application of geo-informatics for determination of forest resources in order to use for its management at decision making/planning and management level. However, the use of high-resolution data has a limit in the process of pixel orientated classification mainly adopted to medium spatial resolution image according to (Blaschke and Strobl, 2002; Hofmann, 2001; Limp, 2002; De Jong et al., 2000). Also, it was noted that new image classification approach, the method of object-oriented classification which thought as important the spatial-relations of the pixels which compose an image attracts attention. Since it has the classificatory function which gave the hierarchical structure that image analysis software, eCognition (Definiens Imaging, Germany) which has adopted this classification method in this object-oriented classified a forest and the classified object into a coniferous forest and a broadleaved forest further after classifying into a forest and non-forest first, it can be identify that it is suitable for the detailed classification of a forest area (Ursula et al., 2004). Also, we needed to identify immediate forest change detection. For this purpose, high spatial resolution satellite data is necessary and it would be used for forest inventory, for forest mapping and forest change detection. Forest cover types, disturbance regime maps and forest change detection maps will be developed in order to inform government agencies on the status of forest resources. Current image is very important for mapping and change detection analyze.

The objective of this study aimed to determine the fire impacts on forest types and forest cover changes using Landsat TM and ETM+ data. Moreover, to implement specific objective are that to develop forest cover classification scheme from satellite data interpretation and forest distribution scope, the evaluate forest cover change from different temporal scales and to determine how the forest fire influences the forest cover types and their changes.

2. STUDY AREA

The study area, Eruu soum, locates in the Selenge province in the northern part of Mongolia, approximately 360 km from capital of Ulaanbaatar. The Eruu soum's forest ecosystem is the sub- tundra and forest steppe zone (N 490-500, E 1060-1080), which covers approximately 839420 hectares, which forest area has covered about 96.1% of the land (Figure 1). The main forest types dominate by birch, aspen, cedar, fir, larch and pine. The study areas are in the elevation range of 573 to 2126 meters above sea level extracted from the 30-m resolution ASTER GDEM v2 was downloaded from. https://www.jspacesystems.or.jp/ersdac/GDEM/E/4.html.

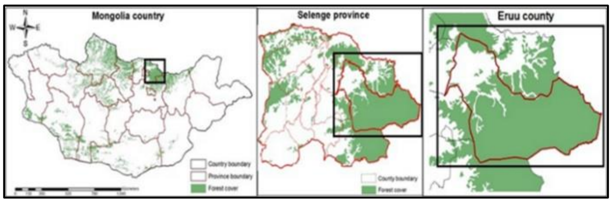

Figure 1. Study area

The mean annual temperature of about 7.00C while the mean monthly temperature ranges from -220C to 190C. A maximum temperature of 36.40C is recorded in June, and minimum temperature of -40.10C is recorded in January. Annual amount of precipitation is 276 mm and most of it falls between May and September. (Azzaya, D., Munkhzul, D., 2007).

In the case of the burnt area statistic, during 2007-2009 that period has high frequently in region of study area illustrated in figure 2.

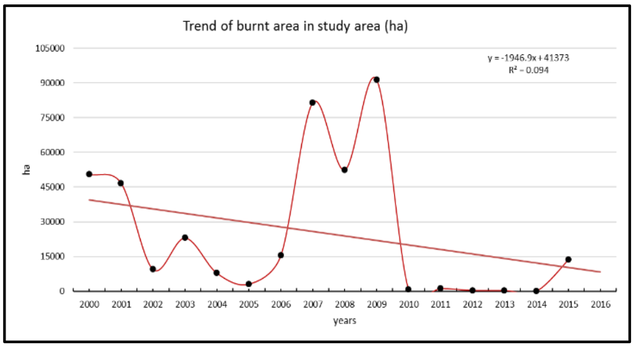

Figure 2. Burnt area trend of study area

In figure 2, during 15 years' number of burned area has been decreasing that period. However, in the whole territory has steppe fire occurrence is higher than forest fire.

3. MATERIALS AND METHODS

We have been used Definiens Developer software (formerly eCognition) to clusters and post-classification objects in the satellite image.

3.1. Object-oriented image analysis

The object-oriented classification does not operate directly on single pixels, but image objects which refer to homogeneous, spatially contiguous regions obtained by dividing image, namely image segmentation. Image segmentation is a preliminary step in object-oriented image classification, and the segmentation technique can be grouped into three types: thresholding/clustering, region based, and edge based. That techniques can be found in according to (Jing Quian, Qiming Zhou and Quan Hou, 2007) and (Fu and Mui, 1981; Haralick and Shapiro, 1985).

Overall, the object-oriented approach and the image analysis process are divided into the two principal workflow steps, segmentation and classification methods have been intensively used for a large number of environmental applications. Examples for such applications includes: image classification based on higher resolution satellite image (Kanta Tamta et al. 2015 and Sun Xiaoxia et al. 2005) and land cover change (Michael J. et al. 2012); forest types classification (S.Shataee et al. 2004); Productive Fossil Localities (Charles Emerson et al. 2015) and many more. These applications have mostly been implemented using high resolution remote sensing imagery (Stanislaw Lewinski et al. 2014). The different spatial working steps for the image classification and with burned area time series analysis of remote sensing data are represented in figure 3.

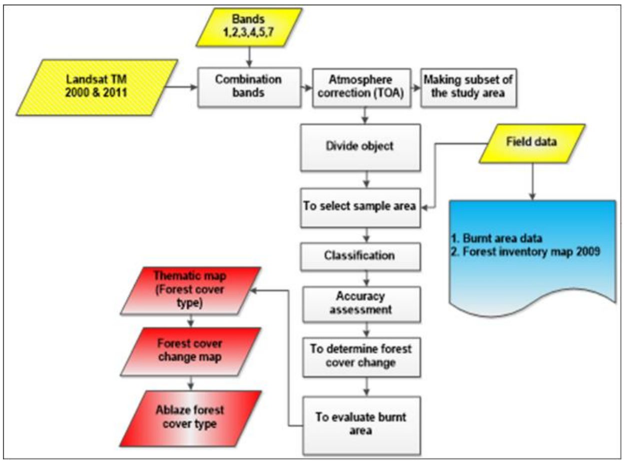

Figure 3. Diagram of the methodological workflows

3.2. Datasets

In order to investigate the Landsat-5 Thematic Mapper (TM) and Landsat-7 Enhanced Thematic Mapper Plus (ETM+) images were acquired in the early 2000s and 2011 were used (14 April 2000, 13 September 2000 and 20 September 2011) for path 131-row 25-26, respectively. In order to reduce scene-to-scene variation related to sun angle, differences in atmospheric condition. In addition, cloud cover of images is minimal in all scenes. Digital number values of data converted to radiance, and ground-leaving reflectance translated from radiance using the 6S algorithm (Vermote et al. 1997).

In addition, we were collected thematic maps and ancillary datasets (Table1.) A combination of image processing software: ArcMap, ERDAS Imagine, ENVI and Definiens developer software applied throughout the all process.

Table 1. data collection

Satellite	Sensor	Date acquired	Spatial resolution (m)
Landsat	ETM+	14 April 2000	30
Landsat	ETM+	13 September 2000	30
Landsat	TM	20 September 2011	30
Thematic data			
Topographic maps			
Forest inventory map 2009			
Ancillary data			
Forest fire information by MODIS 2000 – 2016 (burnt area)			
Forest statistic data 2007			

We have been used burnt area distribution image by MODIS and hectares in each year from 2000 to 2011 for data analysis in this study has been shown in figure 4.

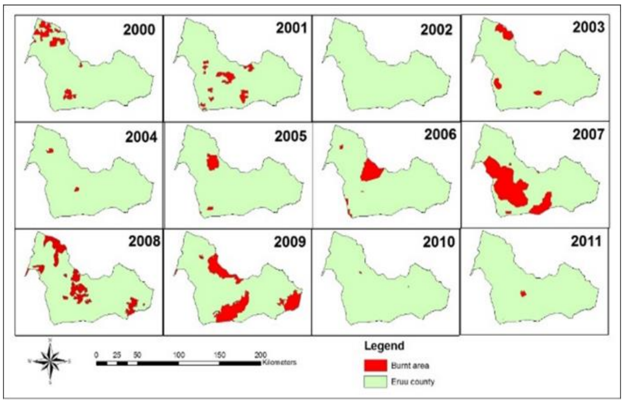

Figure 4. Burnt area distribution image by MODIS image of study area (2000 to 2011)

According to the fire statistics of 2000-2011, biggest fires of 106500-197200 hectares in the range between 2007-2009 were occurred in study area.

4. RESULT AND DISCUSSION

Overall, the study area is representative of the southern boreal forest of Serbia. We have been generated their forest type of distribution map highlighted two year 2000 and 2011.
That classified maps were based on nearest neighbor of object-oriented classification approaches. It will be more realistic that it is accuracy be compared to the traditional pixel-based classification (Akif Mohammed Al Fugara et al. 2009). Figure 5 and 6 shows the result of the classified satellite images in 2000 and 2011. These images identified about 14 cover classes with a description of 9 vegetation cover including 8 forest cover types cedar, pine, larch, birch, shrub and three types of mixed forest have been used 30 meter spatial resolution Landsat TM and ETM+ data.

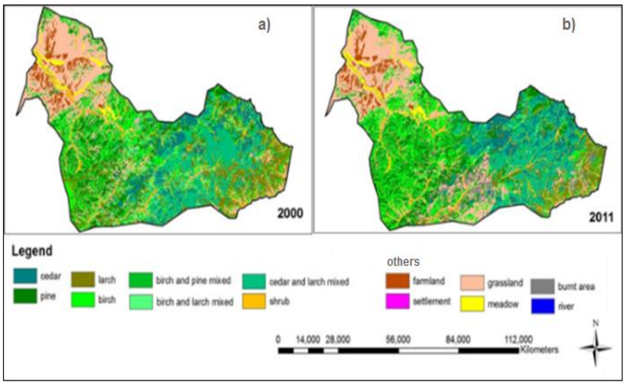

Figure 5. Classified for the forest types using satellite imagery a) forest type 2000 and b) forest type 2011. Which represented forest types (cedar, pine, larch, birch, shrub, birch-pine mixed, birch-larch mixed and cedar-larch mixed. In general, pine is dominant in birch and pine mixed forest, larch is dominant in birch and larch mixed forest. After the burning pine and larch, they can be replaced by birch in naturally and rapidly. In addition, occurrence of forest fires depends on forest types, precipitation distribution and availability of fire sources. (Goldammer., 2007).

The central and south area of Eruu soum was affected by fires in 2007-2008 and this burnt area was clearly detected by satellite imagery. The forest cover type changes replaced by other forest cover types after burning. Also, vegetation cover types were replaced with grass land and barren land in 2011. The results shown in figures 6 and 7.

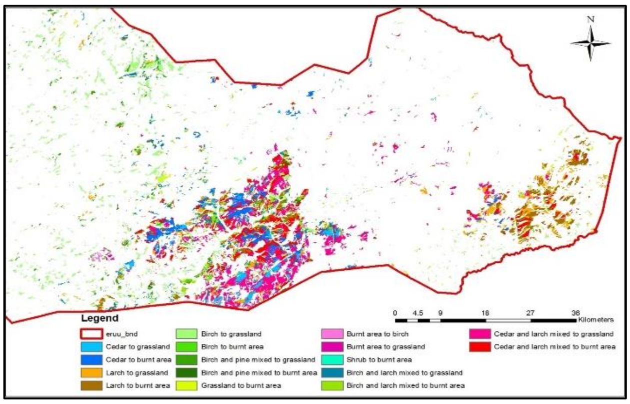

Figure 6. Forest type changes 2000 and 2011

About 17211-hectare area covered by birch and 16128-hectare cedar and larch mixed area were replaced by grassland area. Its illustrated in figure 7.

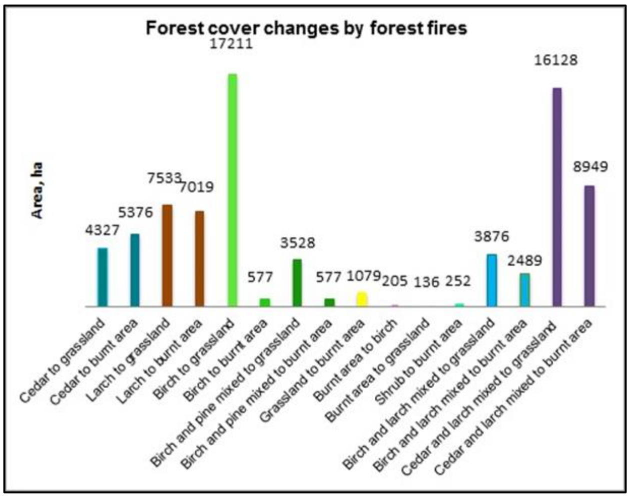

Figure 7. Forest cover and type change by forest fire

Totally 25239 ha of forests were changed to burnt area and 52603 ha forests were changed to grassland. Therefore, forest type in central and east parts of study area in 2000 was changed to grassland and birch area in 2011 due to forest fires. The forest cover area has decreased by 5.03% and non-forested area has increased by 11.9% in 2011 compared to 2000. According to our study results, larch was extremely decreased by 10.4% due to forest fires in Eruu soum area. However, readers can pay attention on an accuracy of our used methodology that is approximately 80%. Increases in cedar by 22.4% may relate with classification methodology because cedar can be mixed with other class type. It has represented change of forest types shown in table 2.

Table 2. Change of forest types

Land classes	2000	2011	Change %
	Area unit (hectares)		
Cedar	51439	66353	22.4
Pine	96925	104137	6.9
Larch	98232	88672	-10.4
Birch	110734	127771	13.3
Birch and pine mixed	36868	64532	42.8
Farmland	20976	20829	-0.7
Settlement	236	284	16.8
Grassland	184172	188676	2.3
Meadow	14982	16875	11.2
Burnt area	617	27744	97.7
Barren land	4651	4205	-10.9
River	2210	2097	-5.3
Shrub	45635	41413	-9.2
Birch and larch mixed	31895	30214	-11.1
Cedar and larch mixed	140196	118997	-15.1

4.1. Accuracy assessment

Accuracy assessment is very important for verification of classification results. In mathematics, the computation of probable error of classification is very complicated. But in practice, we often assess the classification accuracy by means of examining samples and computing the error matrix from the statistical comparison between each interpretation and the ground data. The result of the object-oriented classification of the Landsat imagery were compared, used a forest inventory map of 2009, higher resolution satellite image in Google-Earth, digital elevation model and burnt areas statistic data. Also, we used a random method of systematic, then 256 points were selected into study area. The results of the accuracy assessments and the Kappa statistics of both image classifications are presented in table 3 and table 4. In order to evaluate the usefulness of geographic data for forest cover type classification, we also used object-oriented classification method to Landsat images.

Table 3. Error matrix for the overall classification in 2000

Class	Cedar	Pine	Larch	Birch	Birch and pine	Farmland	Settlement.	Grassland	Meadow	Burnt area	Barren land	River	Shrub	Birch and larch	Cedar and larch	Row Total	User's accuracy
Cedar	15	1														16	93.7%
Pine	1	21	3	4												29	72.4%
Larch	2		27	1												30	90.0%
Birch		1		33												34	97.0%
Birch and pine			1		10											11	90.9%
Farmland						6										6	100%
Settlement																0	
Grassland			2	6		1		46					1			56	82.1%
Meadow									5							5	100%
Burnt area																0	
Barren land											1					1	100%
River																1	100%
Shrub		2	1										11			14	78.5%
Birch and larch					1									9		10	90.0%
Cedar and larch	1	4	1										1		36	43	83.7%
Producer's Accuracy	78.9%	72.4%	77.1%	76.7%	83.3%	85.7%		100%	100%		100%	100%	84.6%	100%	100%		
Overall Classification Accuracy = 86.33%										Overall Kappa Statistics = 0.8436							

Table 4. Error matrix for the overall classification in 2011

Class	Cedar	Pine	Larch	Birch	Birch and pine	Farmland	Settlement	Grassland	Meadow	Burnt area	Barren land	River	Shrub	Birch and larch	Cedar and larch	Row Total	User' s accuracy
Cedar	20															20	100%
Pine		27	2	3												32	84.3%
Larch		1	14													15	93.3%
Birch				39												39	100%
Birch and pine	1				18											20	90%
Farmland						6										6	100%
Settlement																0	
Grassland			3	1				53								57	92.9%
Meadow									5							5	100%
Burnt area										8						8	100%
Barren land											1					1	100%
River												1				1	100%
Shrub		1											13			13	100%
Birch and larch														2		3	66.6%
Cedar and larch		3													33	43	91.7%
Producer's Accuracy	95.2%	84.3%	73.6%	90.7%	100%	100%		100%	100%		100%	100%	100%	100%	97.0%		
Overall Classification Accuracy = 93.75%										Overall Kappa Statistics = 0.9284							

The overall accuracy achieved by the object-oriented classifications are 86.33% in 2000 and 93.75% in 2011. The kappa coefficients are found to be 0.8436 in 2000 and 0.9284 in 2011 which are high, especially for a classification containing as many as fourteen types of land covers.

5. CONCLUTIONS

The study operates the ability of remote sensing technology, Landsat TM and ETM+ data, to classify forest cover types in the two-different date imagery using object-oriented image analysis methods. Consequently, nearest neighbor approach is appropriate the results of forest types in the study area. Moreover, the study is identified non-forest and forest area that has seven forest class are included with cedar, pine, larch, birch, birch-pine mixed, birch-larch mixed and cedar-larch mixed. The overall accuracy of the forest type maps was 86.33% in 2000 and 93.75% in 2011. The kappa coefficients have been found to be 0.8436 in 2000 and 0.9284 in 2011 which are highly significant, especially for a classification containing as many as fourteen types of land covers.

According to the fire statistics of 2000-2016, biggest fires of 106500-197200 hectares' area occurred over study area during 2007-2009. In generally, our study area is high-risky region to forest fires. It is very higher influence to forest cover and tree species and other ecosystems. Overall, wildfire of impact results showed that 25239 ha of forests were changed to burnt area and 52603 ha forests were changed to grassland.

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