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ASSESSMENT OF RANGELAND CONDITION USING REMOTE SENSING TECHNOLOGY: A CASE STUDY OF FOREST STEPPE ZONE IN MONGOLIA

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ABSTRACT

Rangelands play an essential role in providing humankind with varied ecosystem services such as water and food production. Recent studies have shown that the rangelands are under serious threat of land degradation caused by global warming, overgrazing and land conversion. Mongolia is no exception. However, current classification and change detection analysis by remote sensing mostly focus on land cover and land use. Furthermore, there is a substantial gap in the studies on classifications of rangeland condition in the Mongolian context. To fill this gap, this study aimed at assessing the condition and changes in rangeland condition in the forest-steppe zone in Mongolia with the use of remote sensing technique. The Bornuur soum of Tuv aimag in Mongolia was selected as the study area. A quantitative methodology with a remote sensing tool was employed to assess rangeland condition. The results of the study showed an overall accuracy of 53.5%. This accuracy level, despite being low, indicates the possibility of refining the remote sensing methodology applied in this research to acquire more reliable results for Mongolia. The study provided an insight into possible improvements of the methodology of rangeland monitoring and sustainable land management, as well as environmental studies.

Key words: rangeland condition, NDVI, Landsat, Mongolia

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ABBREVIATIONS

ALAGAC	Administration of Land Affairs, Geodesy, and Cartography
CE	Commission Error
EVI	Enhanced vegetation index
FLAASH	Fast Line-of-sight Atmospheric Analysis of Hypercubes
MEA	Millennium Ecosystem Assessment
MLC	Maximum Likelihood Classification
MODIS	Moderate Resolution Imaging Spectroradiometer
MODTRAN	Moderate Resolution Atmospheric Transmission
NAMEM	National Agency for Meteorology and Environmental Monitoring
NDVI	Normalized Difference Vegetation Index
OA	Overall accuracy
OE	Omission Errors
OLI	Operational Land Imager
PA	Producer's accuracy
ROI	Region of Interest
SDC	Swiss Agency for Development and Cooperation
SPOT	Systeme Pour l'Observation de la Terre
TM	Thematic Mapper
UA	User's accuracy

1. INTRODUCTION

Rangeland is narrowly defined as "uncultivated land that provides the necessities of life for grazing and browsing animals" (Holechek et al. 2011, p. 1). On a broader scale, rangeland, which accounts for 69 percent of the total drylands on Earth, is crucial to support livelihoods for 2 billion people and 50 percent of global livestock (MEA [Millennium Ecosystem Assessment] 2005). Moreover, rangeland provides multiple ecological services, including, among others, biodiversity preservation, carbon stock, forage for animals and social-cultural values (Briske 2017). Therefore, rangeland degradation represents a problem for the global environment causing negative impact on climate, natural habitats and hydrology (Harris 2010; Reeves & Baggett 2014; Eddy et al. 2017). Harris (2010) and Mariano et al. (2018) indicated that the growing headage and overgrazing, as well as land management without scientific knowledge and proper policy framework, have greatly affected rangeland condition around the world. Developing nations such as Mongolia can greatly contribute to the global efforts on carbon sequestration through better rangeland management and thereby mitigate negative impacts of global warming (Safriel et al. 2005; Coppock et al. 2017).

Mongolia is a vast landlocked country which covers an area of 1,564,116 square kilometres between Russia to the north and China to the south. Mongolian rangeland covers 70% of the total area (ALAGAC [Administration of Land Affairs, Geodesy, and Cartography] 2016) with animal husbandry as a primary source of income for Mongolian herders (Meurs et al. 2017). Needless to say, rangelands play a vital role, not only in the agricultural sector of Mongolia, but also for the economy in general by providing livelihoods for the local communities (Ulambayar & Fernández-Giménez 2013; Bestelmeyer et al. 2017). However, there are manifold factors affecting rangeland condition in Mongolia, for instance, the number of livestock and overgrazing (Baatar 2008), climate and land-use conversion, i.e. mining, urban area, cropland and poor roads (Damdinsuren et al. 2008).

According to the Mongolian Statistical Information Service (2018), the number of animals has significantly increased over the past decade in Mongolia, especially in the forest-steppe zone. In 2018, the number of animals was estimated to 66.4 million head, which is 33.7 million more than in 2010, or with an average annual increase of 4.2 million head of livestock (MSIS [Mongolian Statistical Information Service] 2018).

Based on the assessment and monitoring of rangeland health of Mongolia, 57 percent of 1516 long-term monitoring sites were significantly degraded in relation to the ecological and land potential (reference condition) of the soils and respective climatic zones (Densambuu et al. 2018*b*).

Thus, given the increase in rangeland degradation, it is imperative to take prompt measures before the rangeland condition deteriorates further in the forest-steppe zone (Densambuu et al. 2018*b*). Therefore, accurate and timely information on rangelands is a key issue for monitoring their current condition, supporting effective land management, and halting rangeland degradation.

Currently, Mongolia has two national monitoring programs to assess rangeland condition based on networks of the National Agency for Meteorology and Environmental Monitoring (NAMEM), and The Agency for Land Management, Geodesy and Cartography (ALAGAC). NAMEM provides the information on the long-term trends in vegetation and rangeland condition on national level whereas ALAGAC proposed to assess impacts of grazing management on the local level (Densambuu et al. 2018*b*).

Since 2011, meteorological technicians at NAMEM in 320 soums (territorial units) have been manually collecting the data at 1516 long-term monitoring sites using the new measurement methods including line-point intercept, gap intercept, transect and air-dry biomass at 1 cm clipping height, and photo points. These methods use core indicators such as foliar canopy cover, species composition, and basal gaps of perennial plants, plant height, and biomass. ALAGAC collects data from 4200 sites and implements a photo-monitoring system that provides information about vegetation cover. This method is faster than NAMEM's approach for data collection (Densambuu et al. 2018*b*). The national monitoring programs are valuable sources of information to support decision-making processes in land management and project the scenarios of rangeland condition into the future. Nevertheless, these approaches for rangeland assessment require considerable amounts of time, finance and labour (Boschetti et al. 2007; Karnieli et al. 2013).

Although the existing national monitoring system for rangeland assessment can provide accurate information on rangeland condition, there is still a pressing need for a better system to meet the higher criteria of time- and cost-effectiveness and capable of depicting polygon features to evaluate the current state of rangelands. This was the main reason for conducting the current research; to evaluate rangeland conditions with a more cost-effective method.

Remote sensing is one way to evaluate rangeland condition timely and effectively (Purevdorj et al. 1998; Svoray et al. 2013) because it can provide temporal and spatial information on rangeland monitoring and management on a broader scale (Tueller 1989; Hunt et al. 2003; Booth & Tueller 2003). Vegetation indices derived from satellite data have been widely used for evaluation of rangelands, for example assessment of rangeland and pasture condition (Vanderpost et al. 2011; Fava et al. 2012); indication of vegetation degradation (Karnieli et al. 2013); investigation of changes in vegetation dynamics (Hilker et al. 2014); and evaluation of pasture production (Boschetti et al. 2007).

Taking into account all the aforementioned, this study posed the following goal and objectives:

Goal

The major goal of this study was to assess the condition and changes in rangelands in the forest-steppe zone in Mongolia with the use of remote sensing.

Objectives

Based on the goal of the study, the objectives were formulated as follows:

1. To evaluate the current rangeland condition based on NDVI in the Bornuur soum of Tuv aimag in Mongolia.
2. To describe the changes in rangeland health in the Bornuur soum of Tuv aimag in Mongolia.

2. BACKGROUND INFORMATION

2.1 Rangeland

2.1.1 Definition

Allen et al. (2011) stipulated that “rangelands may include natural grasslands, savannas, shrublands, many deserts, steppes, tundras, alpine communities and marshes” (p. 5).

Holechek et al. (2011) suggested that “rangelands include desert and forest and all natural grasslands” (p. 1)

In Mongolia, "pastureland" means rural agricultural land covered with natural and cultivated vegetation for grazing of livestock and other animals (Law of Mongolia "On Land", 2002).

2.1.2 Land categorization in Mongolia and research area

According to the Law of Mongolia “On land”, the territory of Mongolia is divided into six categories, namely: (1) agricultural land, (2) cities, villages and other settlements, (3) transportation and network, (4) forest area, (5) water area, and (6) specially protected land. These six categories are further sub-divided into sub-classes. For instance, agricultural land is classified into five sub-classes: rangeland, cropland, haymaking land, abandoned area, lands under agricultural constructions and other land for agricultural production. Rangeland is divided into sub-groups based on utilization, namely winter-spring and summer-autumn utilization (Law of Mongolia “On Land”, 2002).

In the field survey for this study, the first transect was in a summer-autumn utilization area and the second and fourth transects were in the winter-spring rangelands. The third transect was in the four seasonal rangelands. For the fifth and seventh transects, the points were mainly in the winter-spring utilization area, and the rest were in the summer-autumn rangelands, whereas the sixth transect had most of points in the summer-autumn area and the remainder in the winter-spring rangelands.

2.1.3 Importance of rangeland

Rangelands, which support 2 billion people on Earth, are essential sources of water and food for humankind (MEA [Millennium Ecosystem Assessment] 2005; Holechek et al. 2011). Moreover, they help to absorb carbon dioxide from the atmosphere and, thereby, contribute to mitigation of the negative consequences of climate change (Holechek et al. 2011).

2.2 Remote sensing approach for rangeland evaluation

Remote sensing is a widely used method for assessing rangeland condition which has proved its effectiveness. Several studies have addressed the Mongolian rangelands using remote sensing, but few studies have focused on the current state of rangeland condition, utilizing this technique (Sankey et al. 2009).

Karnieli et al. (2013) proposed to investigate the ability of remote sensing technique to assess degradation in the steppe zone in Mongolia using vegetation indices and Landsat-7 data and demonstrated that unpalatable species could explain the enhanced vegetation index (EVI) in the grazed areas. Landsat-7 images were selected during the final stage of the growing season, i.e.

the end of July and August and the middle of September. This area is included in the forest-steppe zone and characterized by plains topography. Palatable and unpalatable plants are distinguished in terms of the leaf cell structure and phenological stage for the spectral curve, and EVI values of the fenced area are less than those of grazed area.

2.3 Study area

The study area is characterized by mountains covered with forest and steppe zone. In the mountain area, rainfall is 250-300 mm, and 150-200 mm in the steppe. Most of the precipitation falls during the growing period for vegetation. The average temperature ranges from 15-20°C in the region.

2.4 Field data

State and transition models of Mongolian rangeland are divided into forest-steppe, steppe, desert steppe, desert and high mountain zones. For the forest-steppe zone, the state and transition model has three categories including (1) gravelly hills and fan, (2) loamy fan and mountain valley, and (3) riparian. Furthermore, this model is subdivided into five sub-classes, and each sub-class, in turn, is divided into five- and four-stage and transient dynamics such as reference state, sub-dominant changed state, dominant changed state, and degraded state. Dominant vegetation and cover are essential indicators for the state and transition model of Mongolian rangeland (Densambuu et al. 2018*a*). The Braun-Blanquet method, which was developed in the 20th century, is a robust tool for monitoring vegetation (Wikum & Shanholtzer 1978). In this study, it was initially planned to get at least 100 points from each class, but the number of points in each class ended up being different. For example, very good and very poor classes had less than 30 points to use for the classification of rangeland condition.

2.5 Landsat satellite data

Each set of satellite data had different spatial, radiometric, spectral and temporal resolution due to sensor type. It is important to understand the advantages and disadvantages of various types of sensors in selecting the image data for classification (Lu et al. 2011), and this is dependent on the purpose and scale of the study.

Landsat satellite data is widely used in rangeland application, especially in estimating biomass, assessing vegetation cover, detecting degradation and assessing land condition because of easy access and capacity to monitor vast areas. It also has a fine resolution compared to MODIS satellite data which can provide rangeland information on a large area, but it has challenges in assessing rangeland condition of vegetation community at the local level (Eddy et al. 2017). Landsat data is free of charge, whereas high-resolution data, which is suitable for specific vegetation change monitoring, is not readily affordable, which therefore limits data acquisition (Willis 2015).

Landsat-8 (OLI) and Landsat (TM) Level-1 data with a spatial resolution of 30 m are radiometrically calibrated and orthorectified using ground control points and a digital elevation model for terrain correction. Radiometric calibration decreases the background noises and converts the raw data DN to radiance (in W/m2sr μm). Orthorectified images and geometric correction minimize errors that can be misclassified due to location (Wulder et al. 2019). Also, the satellite has a 16-day revisit time. The temporal resolution provides an opportunity to revisit the location, and it helps to detect changes and monitor the rangeland condition.

The Landsat TM sensor consists of seven spectral bands, including blue, green, red, near-infrared, middle infrared, thermal infrared, and Landsat OLI, which was launched on 13 February 2013, and additionally collects data for two new bands, a coastal band and a cirrus band (Wulder et al. 2019). Spectrally, the most important bands to calculate the NDVI are the near-infrared and red portions of the spectrum because of chlorophyll and water content. The vegetation reflects the near-infrared band but absorbs the red band. The reflection and absorption depend on natural materials, including water content, pigment, as well as carbon and nitrogen content. Therefore, plants have different spectral curves. A combination of these bands and their relationship are marked out as vegetation indices (Asner 1998; Ceccato et al. 2001).

2.6 Atmospheric correction

This research project used the FLAASH (Fast Line-of-sight Atmospheric Analysis of Hypercubes) module, which is an atmospheric correction tool within the ENVI program to transfer the digital number values of pixels from the top of the atmosphere to surface reflectance. Atmospheric correction uses remote sensing data for quantitative surface parameters and removes or decreases the influence of scattering and absorption of atmospheric molecules and the object reflectance of aerosols (Yuan & Niu 2008).

The method of atmospheric correction is mainly based on a radiation transfer model. The advantage of atmospheric correction is that it removes or decreases the influence of the atmosphere on object reflectance and separates the characteristics of land objects from atmospheric-land mixed signal. There is a selection standard of MODTRAN model atmosphere and aerosol types to represent the scene (Yuan & Niu 2008).

2.7 NDVI

There are many different vegetation indices in the world, one of which is the normalized difference vegetation index (NDVI). It is widely used in the assessment of rangeland condition (Fava et al. 2012; Karnieli et al. 2013; Ünal et al. 2014). NDVI is a band combination to measure the difference between the near-infrared and red bands. NDVI ranges from -1 to 1. If the NDVI is around 0, it could represent no vegetation cover, but if it has negative values, it could be non-vegetation surfaces, i.e. water and asphalt roads. Additionally, healthy vegetation shows higher NDVI values because of higher reflection of the near-infrared band. On the other hand, stressed plants may have lower NDVI values (Tucker 1979; Xue & Su 2017).

2.8 Calibration

A total of 502 samples from the field survey (70%) were used for calibration. The pixel-based approach requires training data with an equal number for each class and large enough sample sizes to ensure classification accuracy. Also, the training data need more representative samples for the region and each class and a well-defined classification scheme. Practically, at least one class uses between 10 and 100 pixels, but it is appropriate to use more pixels to help differentiate the classes. Besides, collection of samples across the study area would increase representation of the classes (Lillesand et al. 2008).

2.9 Image classification

A pixel-based classification is a traditional classification approach in remote sensing. The method is based upon the spectral characteristic of pixels to detect land cover, and measures change mostly without considering the spatial context. The commonly used pixel-based technique has been implemented successfully in many areas to measure changes using remote sensing (Hussain et al. 2013).

Maximum likelihood classification is based on Gaussian (being normally distributed) and Bayes' theorem. The Bayesian classifier uses two factors to estimate the probability. The factors can explain the same a priori probability or proportional to the number of pixels for each class. The maximum likelihood classifier considers the mean vector and covariances of the class and calculates the statistical probability which belongs to a pixel value for each category. It means that all pixels are classified as having the highest probability, but if the highest probability is less than a threshold set, it remains unclassified. The main disadvantage of the classifier is that it requires a large number of computations to differentiate each pixel. Hence, it is slower than other classifiers such as the minimum distance classifier and parallelepiped classifier (Lillesand et al. 2008).

2.10 Change detection

The change detection technique, using satellite data, is an efficient way to detect the changes between two images in a time series. This technique requires the same sensor, resolution, and accurate registration for location. Furthermore, it performs different methods, including image differencing, principal component analysis, post-classification and spectral-temporal combined analysis. The spectral-temporal combined analysis was used in this study, and the multi-date images were combined to obtain a single dataset. The advantages of this method are time-effectiveness and simplicity (Lu et al. 2004).

2.11 Validation and accuracy assessment

Validation is the most important part of the classification, and Lillesand et al. (2008) argue that "A classification is not complete until its accuracy is assessed" (p. 585). Accuracy assessment is a tool that is useful for evaluating the result of classification by an explaining error, or confusion matrix. In the confusion matrix, each class is represented by a comparison of ground truth data and the corresponding results of classification. There are several parameters to assess how good the classification is, such as overall accuracy, user's and producer's accuracy, omission and commission errors. Pixels along the diagonal are correctly classified pixels in the confusion matrix. The overall accuracy is calculated by dividing the total number of corresponding pixels (along the major diagonal) by the total number of ground truth data for validation. In the matrix, there are two types of errors such as omission (underestimation) and commission (overestimation). User's accuracy, which is the number of omission errors, is calculated by dividing the number of the correctly identified pixels in each class by the total number of pixels of the class in the classified image. Producer's accuracy, which is the number of commission errors, is calculated by dividing the number of the correctly identified pixels in each class by total number of pixels in the ground truth data (Lillesand et al. 2008). The confusion matrix is presented in Table 1. All equations are described below.

Table 1. Error and confusion matrix. (Source: Story & Congalton 1986).

		Ground truth data					
		A	B	C	Total	Omission	User's accuracy (%)
Classified image	a	20	1	2	∑a=23	0.13	87
	b	4	32	6	∑b= 42	0.24	76
	c	3	7	50	∑c=60	0.17	83
	Total	∑A=27	∑B=40	∑C=58	N=125		
	Commission	0.41	0.2	0.14			
	Producer's accuracy (%)	59	80	86			
		Overall accuracy=82%					

$$OA = \frac{aA+bB+cC}{N} = (20+32+50)/125 \approx 0.82 \quad (1)$$

Equation 1. OA-Overall accuracy, aA, bB and cC-corresponding values, N- total number of ground truth data

$$OE = \frac{(aB+aC)}{\sum a} = (1+2)/23 \approx 0.13 \quad (2)$$

Equation 2. OE-omission error, aB and aC-values of the class omission, ∑a-total number of class pixels in the classified image

$$CE = \frac{(bA+cA)}{\sum A} = (4+7)/27 \approx 0.41 \quad (3)$$

Equation 3. CE-commission error, bA and cA-values of the class commission, ∑A-total number of pixels in the ground truth data

$$UA = 1 - OE \quad (4)$$

Equation 4. UA-user’s accuracy, OE-omission error

$$PA = 1 - CE \quad (5)$$

Equation 5. PA-producer’s accuracy, CE-commission error

3. METHODS

3.1 Study area

Mongolia is characterized by a continental climate with extreme daily and yearly temperature fluctuations. Due to the climate, mountainous terrain and geographical location, winters are long and cold with minimal precipitation, whereas summers are hot. Most of the annual precipitation (approximately 85 percent) falls during the growing season and ranges from 50 mm in the desert area to more than 300 mm in the mountain areas of Khangai and Khentii (Badarch 1971).

According to Yunatov (1977), the Mongolian plateau is divided into six natural zones: alpine, mountain taiga, forest steppe, steppe, Gobi and desert. The forest-steppe zone, which is the main resource of Mongolian rangeland, amounts to 25 percent of the total territory.

The study area was the Bornuur sub-province (E105º58'-106º33', N48º15'-48º42'), Tuv province. The area is located approximately 100 km north of Ulaanbaatar and belongs to the forest-steppe natural zone (Figure 1).

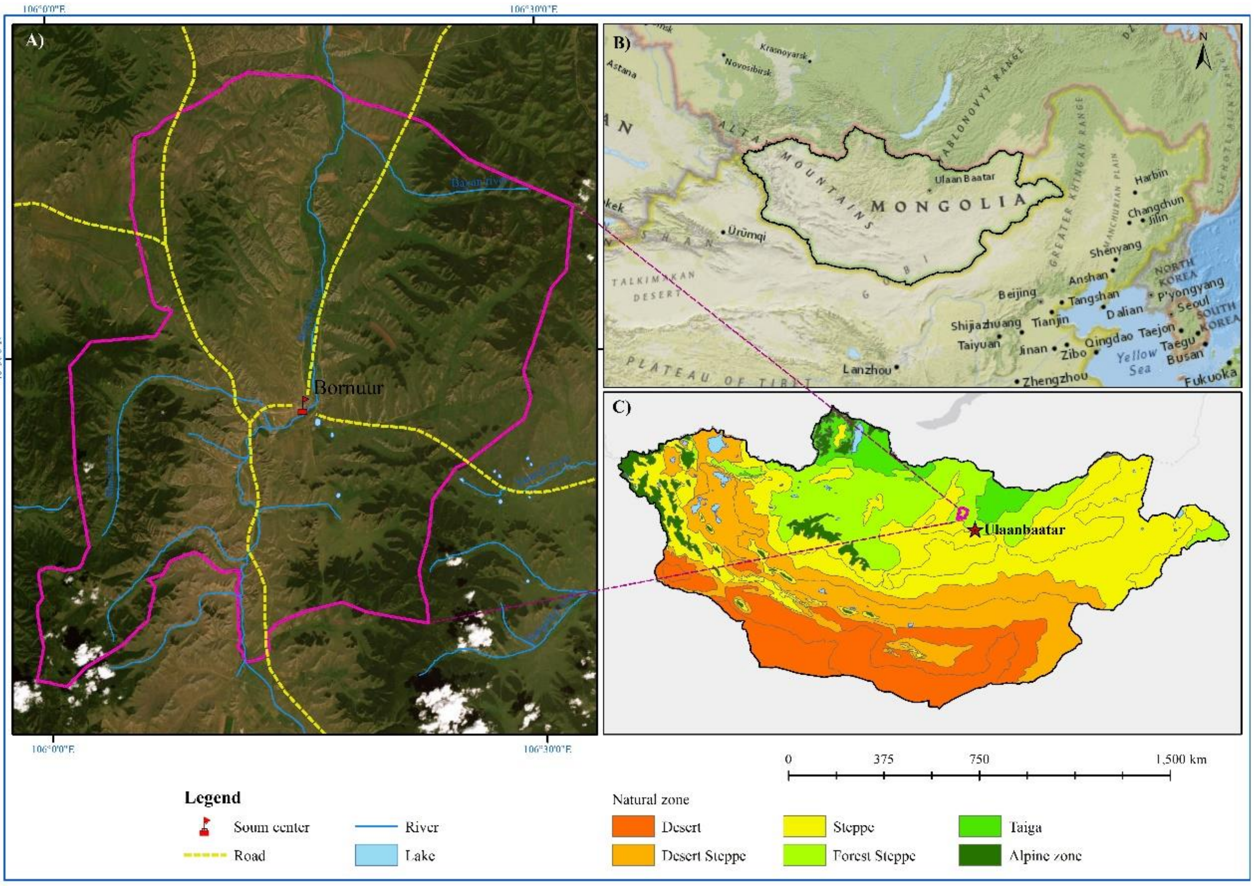

Figure 1. The study area, A) Bornuur soum of Tuv aimag, B) National Geographic map, C) Natural zones in Mongolia. (Sources: Mongolian Land Information Database and Esri, Digital Globe, Geo Eye, Earthstar Geographics, CNES/Airbus DS, USDA, USGS, AeroGRID, IGN, and the GIS User).

3.2 Flow chart

The data analysis included the following steps: (1) selection and download of image data; (2) atmospheric correction for Landsat TM/OLI images; (3) calculation of the normalized difference vegetation index (NDVI) and extraction of training sample based upon field survey; (4 and 5) image classification and change detection; validation of the results (Figure 2).

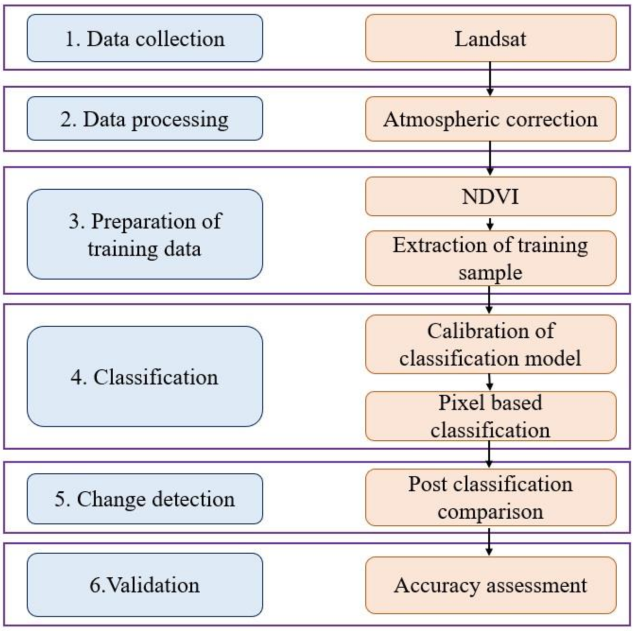

Figure 2. Methodology for pixel-based classification of rangeland condition.

3.3 Data collection

3.3.1 Field survey

A field survey was conducted to evaluate rangeland condition for the research area. The rangeland condition is divided into five classes (Figure 3), namely very good, good, moderate, poor and very poor (Chognii 2001). The state and transition model of Mongolian rangeland was used to evaluate rangeland condition, especially in the forest-steppe zone (Densambuu et al. 2018a). According to the model, the selected samples with transects were taken from the mountain, mountain meadow and river valley to represent varied rangeland conditions. All points were evaluated based on the various rangeland conditions such as reference state, a sub-dominant changed state, a dominant changed state, and degraded state (Table 2). Also, the Braun-Blanquet (BB) was utilized to determine vegetation cover for every point (Wikum & Shanholtzer 1978).

Field data collection was carried out in the first half of July 2019 along seven transects (each approximately 3 km long). The sampling transects were set up in a rolling topography to gather all the points from different ecological sites characterized by natural heterogeneity and variability of species (Figure 4). Point measurements were taken every 30 meters along each transect to cover the pixel size of the Landsat image data. The 700 samples were collected using quadrats (50 cm x 50 cm). The exact geographic coordinates of the points were identified through the GPS system (Garmin III plus, ~5 m accuracy). This field survey was conducted based on different types of landforms (Table 3).

Table 2. Classification of rangeland condition.

Rangeland condition	**State Transition Model**	**Description**	**Transient dynamics**
Very good	Reference state	Healthy rangeland	None to slight
Good	Sub-dominant changed state	Slight sub-dominant changed	Slight to Moderate
Moderate	Sub-dominant changed state	Moderate sub-dominant changed	Moderate
Poor	Dominant changed state	Main dominant changed	Moderate to Extreme
Very poor	Degraded state	Severely degraded	Extreme to Total

Table 3. Number of points for data sampling.

Transect	**Landform**	**Number of points**
1	Hill, river, and uphill	100
2	Hill down, mountain, and foot of mountain	100
3	Foot of the mountain and foot slope	100
4	Mountain and hill	100
5	Mountain slope, hill, and mountain	100
6	River valley	100
7	Mountain valley	100
	Total number of points	700

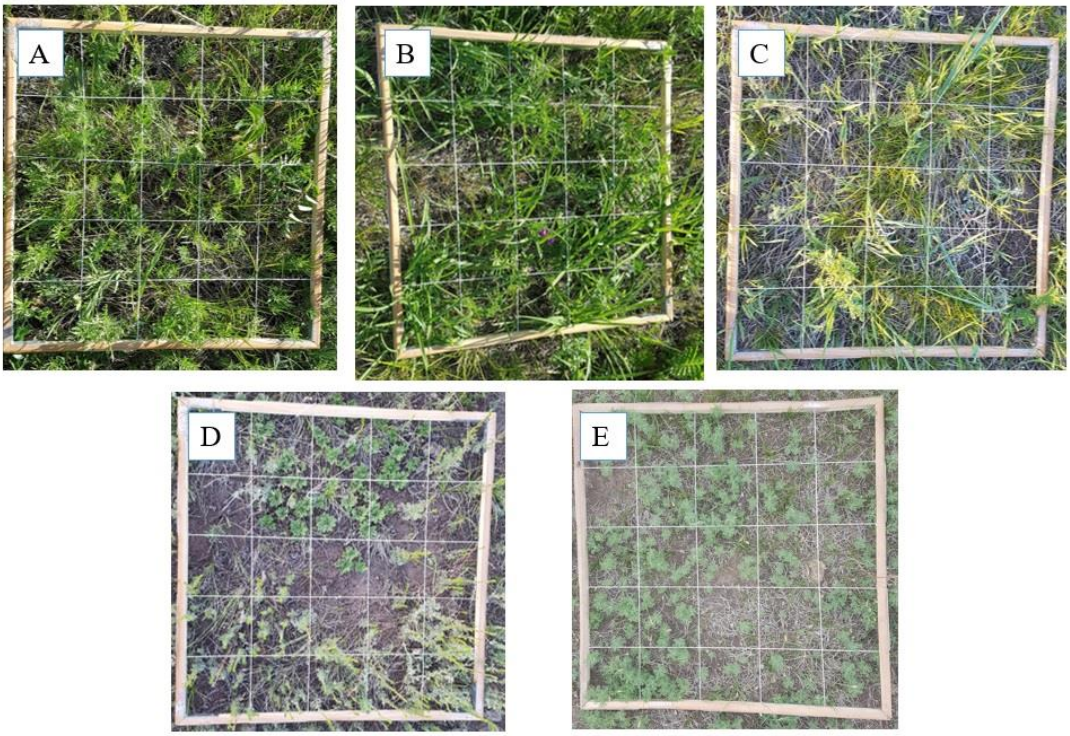

Figure 3. Photos of rangeland condition for ground truth, A) Very good, B) Good, C) Moderate, D) Poor, E) Very poor.

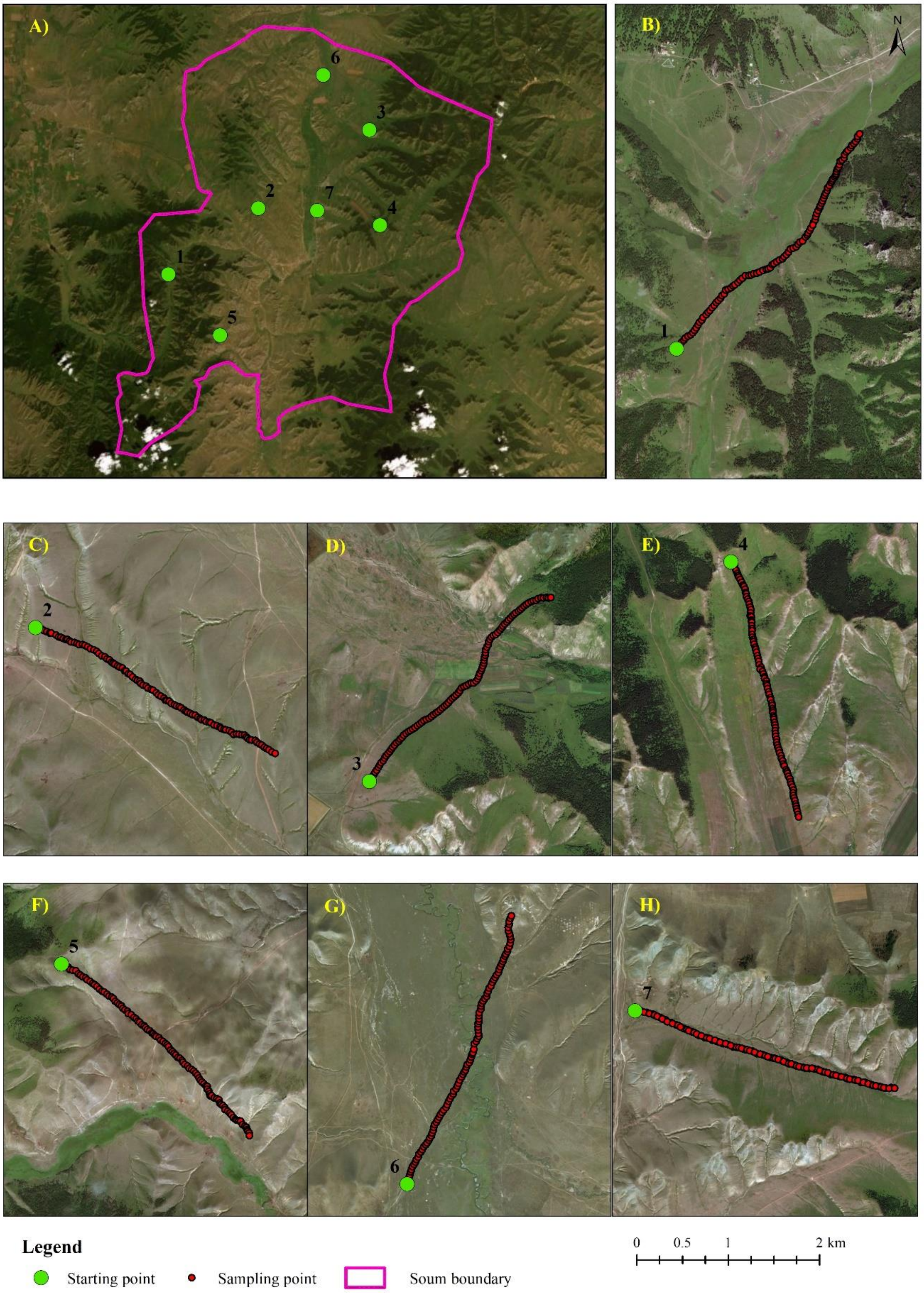

Figure 4. Sampling points using satellite data. A) All transects, B-H) Transect 1-7. (Sources: Mongolian Land Information Database and Esri, Digital Globe, Geo Eye, Earthstar Geographics, CNES/Airbus DS, USDA, USGS, AeroGRID, IGN, and the GIS User).

All samples of ground data were observed in the seven transects during the field campaigns and are presented in Table 4.

Table 4. Sampling points of data collection.

Transect	Rangeland condition					Total points
	1-Very good	2-Good	3-Moderate	4-Poor	5-Very poor	
1		24	67	9		100
2		10	65	24	1	100
3		13	17	70		100
4	13	34	35	18		100
5		2	36	50	12	100
6			22	61	17	100
7			60	40		100
Total	13	83	302	272	30	700

3.3.2 Image data collection

In order to evaluate rangeland condition in the study area over several years, the three years of 2010, 2015 and 2019 and dates during the growing season (July 6, July 4 and July 8 respectively) were selected and downloaded from the website http://earthexplorer.usgs.gov. The images were selected from the same period in July because of spectral differences and inter-annual variability of NDVI, and were almost not affected by clouds (Figure 5). It was deemed appropriate for differentiating of rangeland condition classes and reducing the effects of seasonal changes in NDVI. As shown in Table 5, the near-infrared and red bands were used in this study.

Table 5. Spectral characteristic of Landsat satellite data.

Landsat-5 TM			Landsat-8 OLI		
Bands	Band name	Wavelength, (μm)	Bands	Band name	Wavelength, (μm)
Band 3	Red	0.63-0.69	Band 4	Red	0.636-0.673
Band 4	NIR	0.76-0.90	Band 5	NIR	0.851-0.879

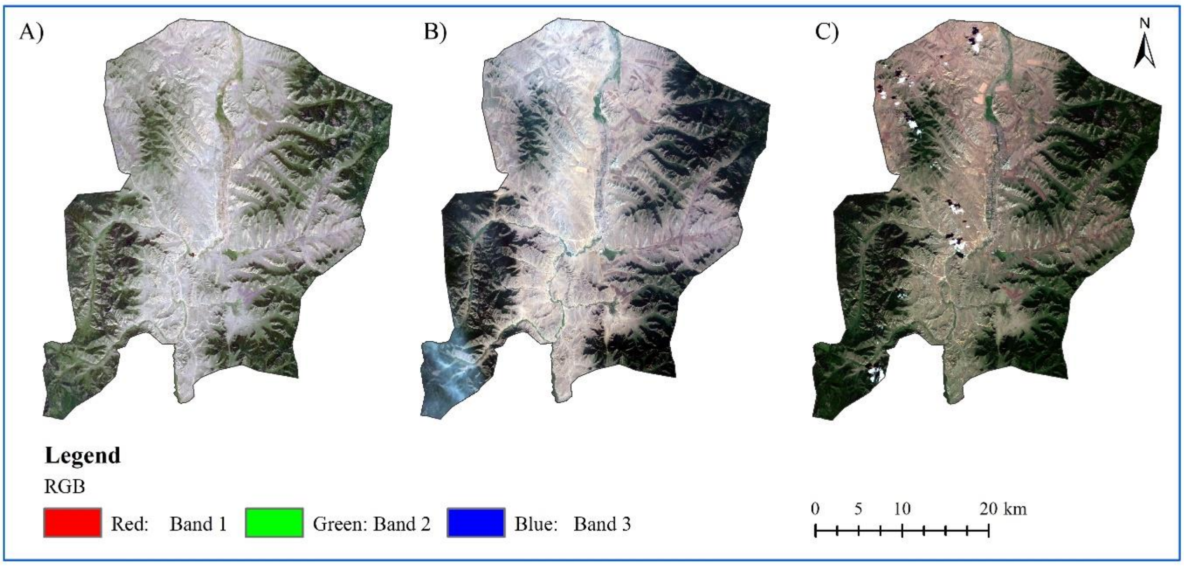

Figure 5. RGB images of Landsat datasets, A) 2010, B) 2015, C) 2019.

3.4 Atmospheric correction

The images were atmospherically corrected using the FLAASH (Fast Line-of-sight Atmospheric Analysis of Hypercubes) module, which is an atmospheric correction tool to get surface reflectance in ENVI 5.2 software. For performing the FLAASH module, the radiometrically calibrated radiance image with interleaved-by-line (BIL) was used, and represented the floating-point, and selected the use single factors of all bands with a 1.0 of the single scale factors. Then, multispectral Landsat TM5 and Landsat-8 OLI in sensor type were used. Flight date and time were entered manually. The ground elevation was filled out at 1.3 km above sea level.

Moreover, for selecting atmospheric model settings, the mid-latitude summer in the atmospheric model was chosen based on a seasonal altitude surface temperature model and selected the rural in an aerosol model that is one of the standard MODTRAN aerosol and haze types. The over-land retrieval standard (660:2100 nm) in Kaufman-rate aerosol retrieval tabs was selected for multispectral settings, and the use of adjacency correction in the FLAASH advanced settings, an option was set to YES in the study.

3.5 Normalized Difference Vegetation Index

The NDVI was calculated to evaluate rangeland condition using ENVI 5.2. NDVI was calculated from the red and near-infrared bands (Tucker 1979). NDVI is shown in Equation 6.

$$\mathrm{NDVI} = \frac{\mathrm{NIR-RED}}{\mathrm{NIR+RED}} \qquad \textbf{(6)}$$

Equation 6. NDVI-Normalized Difference Vegetation Index, NIR-near-infrared spectral reflectance value, Red- visible spectral reflectance value.

To open the atmospherically corrected images, the open image file in the File menu was used to find the NDVI tool from the toolbox. Next, the image in the NDVI calculation input file was selected and the Landsat TM or OLI in input file type for NDVI calculation parameters was chosen. Finally, the output file was stored in a new NDVI file.

3.6 Calibration

The samples from the field survey in July 2019 were divided into calibration and validation datasets. A total of 502 samples were randomly selected to calibrate the maximum likelihood classifiers using ArcGIS 10.5 software (Table 6).

Table 6. Calibration points.

Transect	Rangeland condition					
	Very good	Good	Moderate	Poor	Very poor	Total points
1		17	47	6		70
2		7	46	17	1	71
3		10	12	49		71
4	13	22	24	12		71
5		2	25	35	12	74
6		0	15	43	17	75
7		0	42	28		70
Total	13	58	211	190	30	502

The region of interest (ROI) was created using the ROI tool in ENVI to calculate the areas of ROI for each class. The information on ROI illustrated that 30 pixels of samples were in the very good class, 183 pixels in the good class, 602 pixels in the moderate class, 558 pixels in the poor and 90 pixels in the very poor class (Table 7).

Table 7. Information on ROI.

Classes	Pixel	Area		Average size (ha)	Standard deviation
		m^2	ha		
Very good	12	10800	1.08	0.22	0.07
Good	57	51300	5.13	0.13	0.06
Moderate	195	175500	17.55	0.14	0.07
Poor	182	163800	16.38	0.14	0.08
Very poor	26	23400	2.34	0.12	0.07
Total	472	424800	42.48		

3.7 Classification process and final classification

The pixel-based maximum likelihood classification (MLC) was conducted using ArcGIS 10.5 software. MLC was selected to perform the classification of rangeland condition based on spectral signatures (ROI) from the classification menu in the image classification toolbar. Next, the calculated NDVI image was set in input raster bands, and the spectral signatures (ROI) were selected in the input signature file from the ROI results folder. The sample option in a priori probability weighting was used, and the final image was saved in the output classified raster in the MLC window.

3.8 Change detection

Changes in rangeland condition were analysed with the combined use of local-spatial analyst tools-arc toolbox in ArcMap. Two classified images were selected in the input raster in the combine window.

3.9 Validation

In the case study, classification accuracy was calculated in Excel software based upon ground truth samples (n=198) to ensure the classification results. The samples were divided into two categories. The first category was for calibration of classification, and the second category was for validation and accuracy assessment. A total of 198 samples from the field survey were computed for the validation and accuracy assessment. These samples for validation were selected randomly (Table 8), and each class included a different number of ground truth regions of interest (ROI) because of the rangeland conditions in the field survey.

Table 8. Samples for validation.

Transect	Validation			
	Good	**Moderate**	**Poor**	**Total points**
1	7	20	3	30
2	3	19	7	29
3	3	5	21	29
4	12	11	6	29
5		11	15	26
6		7	18	25
7		18	12	30
Total	25	91	82	198

4. RESULTS

4.1 Evaluation of spectral separability

The ROI for each class was computed using the compute statistics button in the ROI tool and analysed visually to identify the separability of classes utilizing the send ROIs to n-D visualizer in the options menu (Figure 6 and Figure 7).

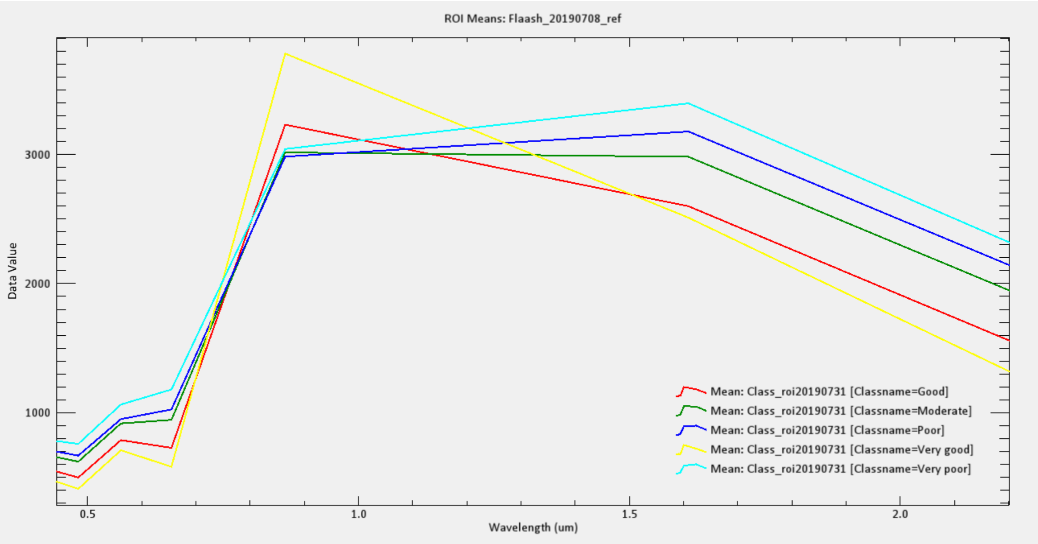

Figure 6. Viewing multiple histograms on a single chart.

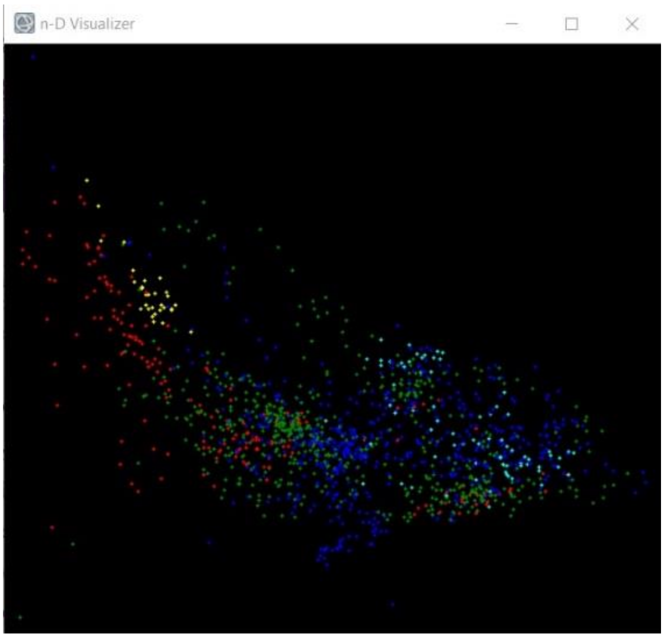

Figure 7. Visualization of the 2-dimension space of spectral features in ENVI (red and near-infrared).

4.2 NDVI analysis

In this study, NDVI was calculated to use the classification of rangeland condition based on ENVI. The results and map of the NDVI for the years 2010, 2015, and 2019 are shown in Table 9 and Figure 8. The variation in NDVI values fluctuated during the following periods.

Table 9. The temporal variation in NDVI values from 2010 to 2019.

Year	Maximum	Minimum
2010	0.90	-0.003
2015	0.88	-0.02
2019	0.91	-0.39

The maximum in the NDVI was observed in the good class, whereas the minimum was observed in the poor class. The obtained results showed that in the Bornuur in 2019, the NDVI value was between 0.72 and 0.79 for the very good class. NDVI values for the good class were between 0.36 and 0.80, for the moderate class between 0.31 and 0.73, for the poor class between 0.29 and 0.78, and for the very poor class between 0.35 and 0.54 (Table 10 and Figure 8).

Table 10. NDVI values for ROI for the period 2019.

Class	Max	Min	Mean	Standard deviation	Standard error
Very good	**0.79**	0.72	0.73	0.02	0.01
Good	0.8	0.36	0.63	0.13	0.02
Moderate	0.73	0.31	0.52	0.1	0.01
Poor	0.78	**0.29**	0.49	0.08	0.01
Very poor	0.54	0.35	0.43	0.07	0.01

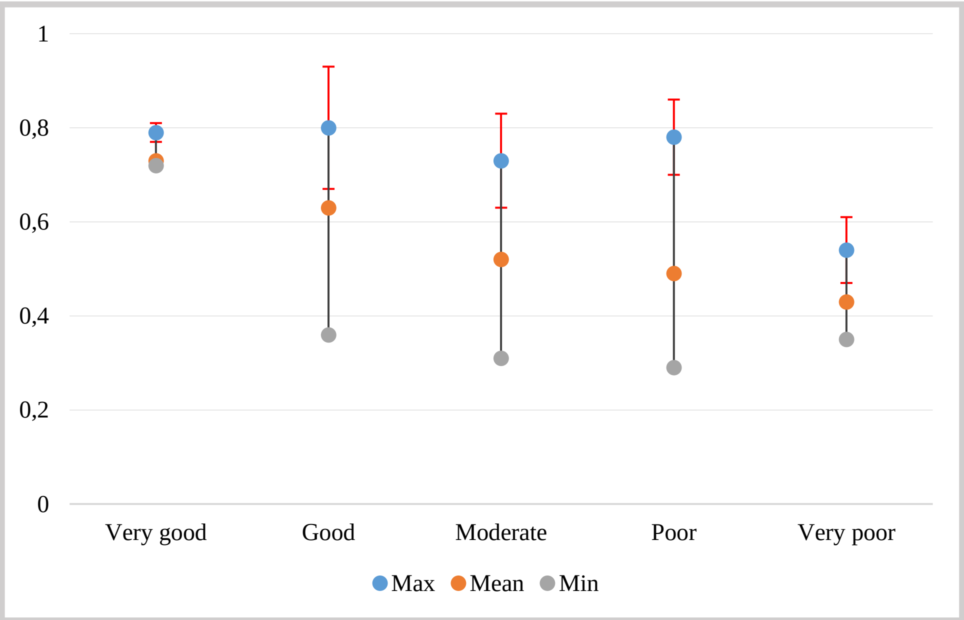

Figure 8. Variation of NDVI in classes for ROI.

4.3 Image classification

The pixel-based approach was conducted with the use of the maximum likelihood classification method. Based on the flow chart (see Figure 2), three classification maps of rangeland condition by the images were produced for the years 2010, 2015, and 2019. The rangeland condition was classified according to the four classes, including very good, good, moderate, and poor because of the number of sampling points.

The classified rangeland condition maps of the years 2010, 2015 and 2019 are given in Figure 9, and the classification results are summarized in Table 11. The results of image classification demonstrated that 3.29% of the total area was in a very good, 5.64% in a good, 28.83% in a moderate and 62.23% in a poor class in 2010. In 2015, 0.66% of the total area was in a very good, 0.90% in a good, 73.86% in a moderate and 24.58% in a poor class. In 2019, 3.35% of the total area was in a very good, 6.46% in a good, 34.0% in a moderate and 56.18% in a poor class (Figure 10).

Table 11. Statistical results of rangeland condition.

Pasture condition	2010		2015		2019	
	Area (ha)	Area (%)	Area (ha)	Area (%)	Area (ha)	Area (%)
Very good	2157.57	3.29	435.33	0.66	2197.71	3.35
Good	3694.86	5.64	589.41	0.90	4231.98	6.46
Moderate	18890.73	28.83	48385.35	73.86	22277.07	34.00
Poor	40770.81	62.23	16103.88	24.58	36807.21	56.18
Total	65513.97	100	65513.97	100	65513.97	100

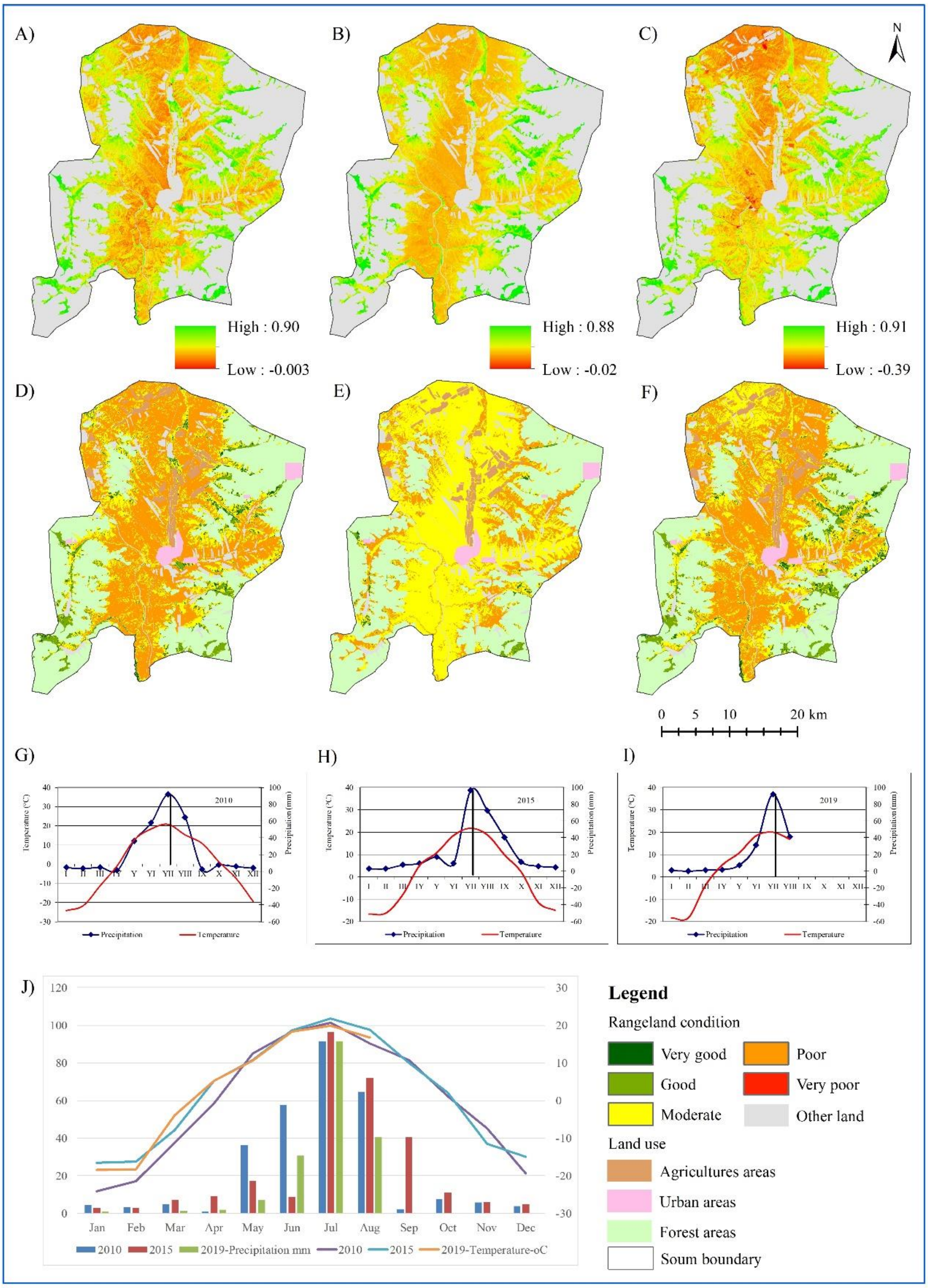

Figure 9. A) NDVI 2010, B) NDVI 2015, C) NDVI 2019, D) Supervised image 2010, E) Supervised image 2015, F) Supervised image 2019, G-J) Climatic features: precipitation and temperature. (Source: National Agency for Meteorology and Environmental Monitoring, unpublished data).

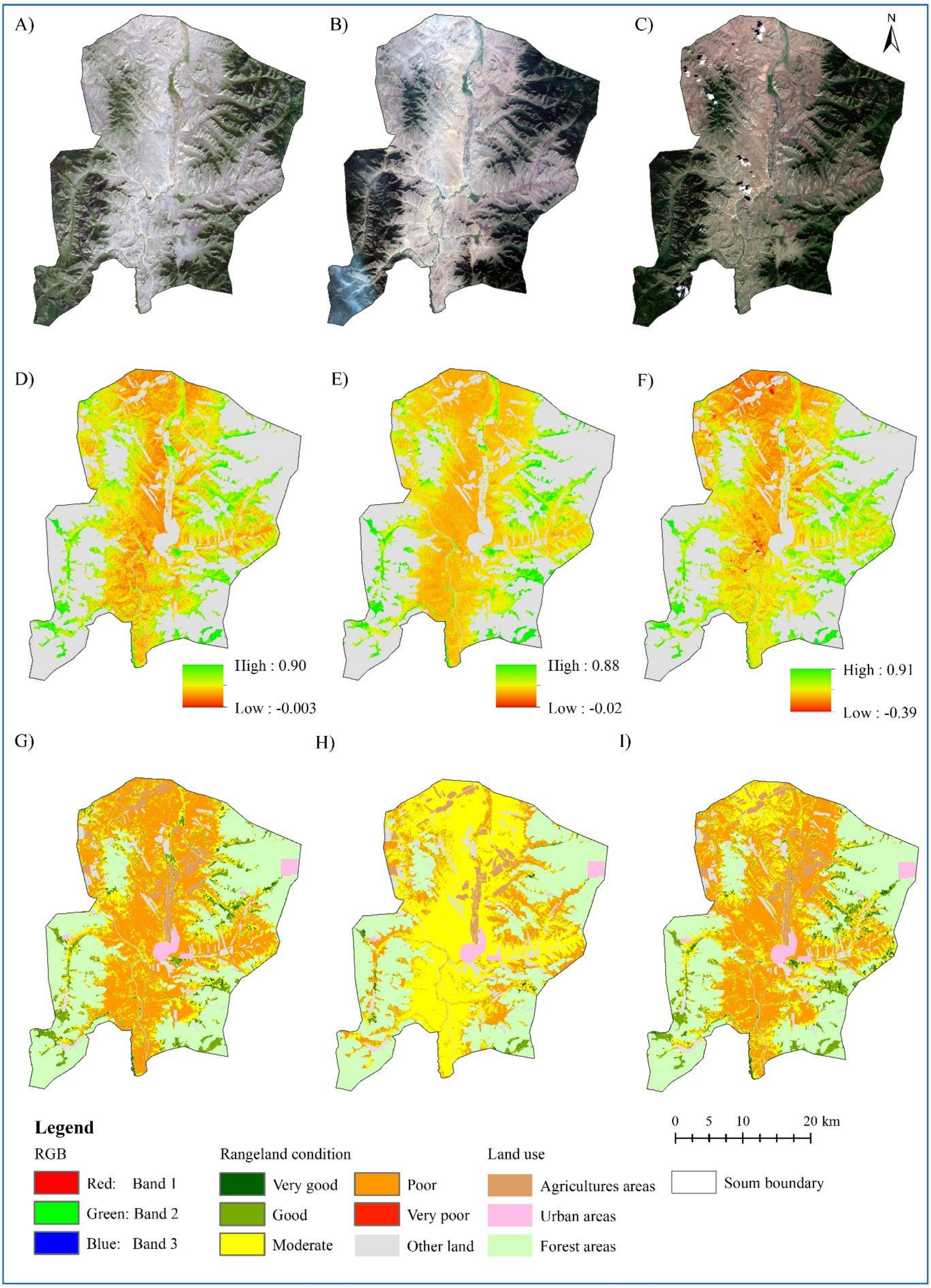

Figure 10. A-C) Raw data, D-F) NDVI, G-I) Supervised images (2010, 2015 and 2019).

4.4 Change detection

In this section, the classes of the two maps were compared. The difference map of the classification image was colour-coded to indicate the magnitude of the changes between the two images (Figure 11). The change detection analysis showed that the percentage of changes varied from each rangeland condition to another. Changes were mostly related to the conversion of poor rangeland to moderate class (57.01%), moderate land to poor class (17.25%), and good class to moderate (3.27%) from 2010 to 2015. Changes in other classes in Bornuur soum were less than 2%. For the same period, changes from poor to very good and from poor to good were not identified (Table 12). For the poor and moderate classes, the biggest changes were found in the centre and around the agricultural area of the region. The changes in the moderate to poor class were widely distributed around the forest edge of the area. The spatial distribution of good to moderate class was similar to that of the years 2015-2019 (Figure 11). In Table 12, unchanged pixels are located along the major diagonal of the confusion matrix.

Table 12. Results of the monitoring of changes in rangeland condition classes during the years 2010-2015 (%).

	Class	2015				
		Very good	**Good**	**Moderate**	**Poor**	**Total**
2010	Very good	0.02	0.01	1.99	1.27	3.29
	Good	0.64	0.89	**3.27**	0.84	5.64
	Moderate	0.001	0.001	11.58	**17.25**	28.83
	Poor	0	0	**57.01**	5.22	62.23
	Total	0.66	0.90	73.86	24.58	100

Table 13 illustrates a change matrix of the rangeland condition from 2015 to 2019 in percentage (%). As can be seen, change from the moderate class to poor rangeland was mainly detected (49.5%) in the centre of the province. Additionally, poor rangeland changed to moderate class (15.37%). The changes in poor to moderate class occurred around the forest area. In other words, moderate class was replaced by good class (3.96%) in the forest edge of the region (Figure 11).

Table 13. Results of the monitoring of changes in rangeland condition classes during the years 2015-2019 (%).

	Class	2019				
		Very good	**Good**	**Moderate**	**Poor**	**Total**
2015	Very good	0.002	0.66	0.002	0.001	0.66
	Good	0.001	0.90	0.001	0.001	0.90
	Moderate	1.77	**3.96**	18.63	**49.50**	73.86
	Poor	1.59	0.94	**15.37**	6.68	24.58
	Total	3.35	6.46	34.00	56.18	100

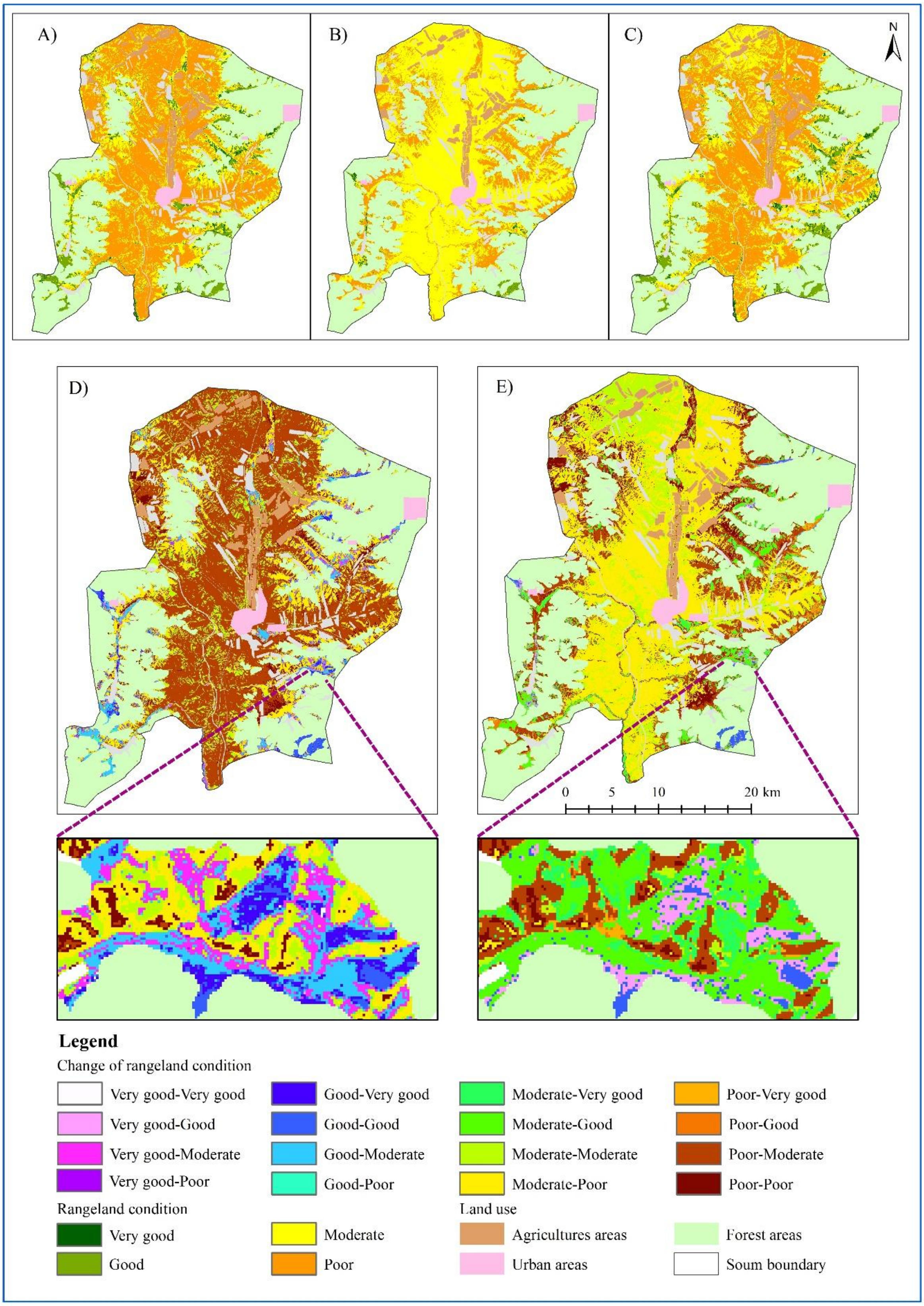

Figure 11. A-C) Supervised classification of rangeland condition (from left 2010, 2015 and 2019), D) 2010-2015 change detection map, E) 2015-2019 change detection map.

4.5 Validation and accuracy assessment

The good, moderate and poor classes included the highest number of ROI's compared to those of the very good and very poor classes for calibration, but the very good and very poor class ROI were not calculated on this assessment. The average number of pixels per ROI was 94.4 for the 2019 image.

4.5.1 Overall accuracy

The producer's and user's overall accuracies are shown in Table 14. The achieved overall accuracy of the supervised classification was 53.5% for 2019.

4.5.2 User and producer accuracy

According to the findings, it was observed that the lowest and highest accuracy of the producer and user were related to the good rangeland class. For this class the producer's and user's accuracies were 28% and 87.5%, respectively. The producer's accuracies fell into the moderate class with 48.35%, and poor rangeland with 67.07%. The value of the user's accuracy was found to be 55% for the moderate class, and 52.88% for the poor class.

4.5.3 Commission and omission error

Commission and omission errors (CE and OE) per class were computed for individual rangeland condition classes. The omission error of the very good class was equal to 100% (OE=1) due to the lack of a field survey representing this class. CE errors in the maximum likelihood analyses occurred with the good class (72% error), moderate class (52% error), and poor class (33% error). OE errors from the classes good, moderate and poor were 87.5%, 55%, and 52.88%, respectively.

Table 14. Confusion matrix obtained with Maximum Likelihood Classifier for the 2019 rangeland condition classification in the Bornuur of Tuv aimag.

		Classes derived from satellites							
		Very good	Good	Moderate	Poor	Very poor	Sum	Commission	Producer's accuracy (%)
Ground truth measurements	Very good	0	0	0	0	0	0		
	Good	4	7	10	4	0	25	0.72	28.00
	Moderate	2	0	44	45	0	91	0.52	48.35
	Poor	0	1	26	55	0	82	0.33	67.07
	Very poor	0	0	0	0	0	0		
	Sum	6	8	80	104	0	**198**		
Omission		1.00	0.13	0.45	0.47				
User's accuracy (%)		0.00	87.50	55.00	52.88				
Overall accuracy: 53.5%									

5. DISCUSSION

5.1 Interpretation of main findings

5.1.1 NDVI

The results of this research demonstrate that the good, moderate and poor classes were difficult to differentiate due to spectral overlapping of NDVI values. As shown in Figure 8, the very good and very poor classes can be easily identified. Although Fathizad et al. (2018) employed a different method based on object-oriented classification, they found that NDVI values for poor rangeland were -0.34 and 0.67. This is consistent with the findings of this research.

According to theory of remote sensing, the reflectance values of plants which are healthy and stressed are different. Hence, the spectral overlapping on the classes of rangeland condition would most likely have a different source. Field data focuses on the assessment of plant type and cover rather than considering soil moisture, plant chlorophyll content and other factors that have significant effects on the spectral characteristics examined in the NDVI. In addition, the study used the state and transition models of Mongolian rangeland to evaluate the condition of rangeland in the region. For example, in this field survey, for the festuca-forbs which dominate the mountain steppe rangeland on hills and slopes, festuca > 20% or small bunch grass > 15% were identified in the very good class, small bunch grass > 20% and artemisia frigida < 30% in the good and moderate classes, artemisia frigida > 30% and small bunch grass < 15% in the poor class, and artemisia frigida > 40% in the very poor class using the state and transition models for Mongolian rangeland. Summarizing this specific information, it can be argued that the good and moderate classes are very similar in the field. For these two classes, the vegetation community is the same, but the cover is slightly different within the quadrats (50 cm x 50 cm). Despite the vegetation cover, a carex community appears in the moderate class. From this context, the very good and very poor classes are dominated by the festuca and artemisia, and these could be different values of spectral reflectance compared to the other classes due to chlorophyll and water content. However, the good, moderate and poor classes can be overlapped on the spectral ranges of NDVI because of having similar plant communities.

Lamchin et al. (2016) showed that NDVI values were 0.50-0.75 in the non-degraded, 0.40-0.50 in low degraded, 0.25-0.40 in moderate degraded, 0.15-0.25 in highly degraded, and 0-0.15 in severely degraded rangelands using Landsat in Mongolia. Although the classification used in this study is close to the above-mentioned classes of rangeland based on degradation level, the NDVI values are unlikely to be comparable.

5.1.2 Classification

The results of the study showed that the overall accuracy of maximum likelihood classification was 53.5%. Due to the spectral overlapping, the classified images based on NDVI were not reliable for distinguishing between the good, moderate and poor conditions of rangeland.

This study indicated that the most significant changes were seen on the map from 2015. The image data indicated extreme fluctuations in environmental change of the rangeland health, which are very unlikely. The comparison of each class for the years 2010 and 2015 showed that the moderate class increased from 28.83% to 73.86%, but the very good, good and poor classes decreased to 2.63%, 4.74% and 37.65%, respectively. During 2015 and 2019, the very good,

good and poor classes in rangeland increased by 2.69%, 5.56% and 31.6%, but the moderate class decreased from 73.86% to 34% in the study area.

Comparative analysis of the results showed that the rangeland condition improved in the period from 2010 to 2015 but tended to decrease between 2015 and 2019. Variations of such magnitude between years are improbable and could be because of the colour imbalance of the raw data. If the image of 2015 is removed and processed better, more natural and expected results for the region could be obtained.

On the other hand, the images were pre-processed and classified with the same method. Furthermore, the fluctuations between years may depend on the sensor types of Landsat data, but the 2015 and 2019 images are a similar source of Landsat OLI. Therefore, the error of classification can be related to the digital image processing.

Melville et al. (2018) mapped lowland native grassland communities using the random forest classification technique and evaluated rangeland condition based on plant species and vegetation. As a result, the accuracy of grassland complex class was estimated to be approximately 54.82% for Landsat, which is in agreement with the results of this study. Alternative approaches to the use of NDVI to evaluate rangeland condition produced noticeable results too (Minor et al. 1999; Fava et al. 2012). However, rangeland still remains one of the most difficult ecosystems to be classified with remote sensing data (Melville et al. 2018; Xu et al. 2019) due to spectral properties and species diversity.

5.1.3 Evaluation of the current condition of the rangeland

This research found that currently 56.18% (Table 11) of the rangeland in Bornuur soum could be classified as poor. For the poor class, producer's accuracy had higher values (67.07%) than other classes. These results suggest that the poor condition represented half of the total rangeland. However, the results are not reliable due to errors of spectral overlapping on the NDVI values range. This means that the poor class may actually be the good and moderate class.

Results of the field survey on rangeland condition for 700 randomly selected samples demonstrated that 42.4 % of samples were in the very good class, 11.86% in the good class, 43.14% in the moderate class, 38.86% in the poor class and 4.29% in the very poor class. But the very poor class was not classified in the image classification because of the limitation of ground truth data.

5.1.4 Change detection

In general, the results of change detection analysis showed the transition between rangeland condition classes in the study area through replacing the very good class by the good and moderate, as well as the poor class. This research demonstrated that changes occurred mainly between poor and moderate classes, moderate and poor classes, as well as between good and moderate classes during 2010-2015. In contrast, the moderate class altered to poor class between 2015-2019.

Change detection analysis indicated that rangeland was highly sensitive to climate and human impacts without the consideration of classification errors. Hilker et al. (2014) and Vandandorj et al. (2015) reported that rangeland condition is highly dependent on precipitation, especially in the forest-steppe zone of Mongolia.

Natsagdorj et al. (2019) found that rainfall in the study area increased slightly between 2000 and 2013, and changes in NDVI tended to increase for this period in the Bornuur. As illustrated in Figure 9, the rainfall in July 2015 was more intensive than in July in other years. The rainfall could affect the supervised image of rangeland condition for the year 2015 due to the NDVI's sensitivity to water content. In addition, rangeland condition may be affected by inter-annual variability in precipitation and temperature. Because of these factors, the NDVI can show varied values for healthy and stressed plants.

5.2 Evaluation

5.2.1 Limitations of the study and recommendations for future research

The literature on the evaluation of current rangeland condition in the forest-steppe zone in Mongolia at this scale and usage of moderate resolution image is limited because of the complexity of rangeland systems.

The overall accuracy demonstrated inconsistency and difference in the datasets, which may illustrate classification error and a significant imbalance in the amount of calibration and validation points for each class. Additionally, the good class was a high user's accuracy, but low producer's accuracy, which may result in low classification overall accuracy. The main reason for the high variation in CE and OE errors per class was most likely the limited sample size. The number of training and validation points was relatively small compared to the moderate and poor classes.

In this study, 100 points per class were planned as a minimum for calibration and validation of classification to achieve good results. However, the very good, good and very poor classes did not reach the minimum size. Therefore, the use of an equal number of points for each class and an increase in the number of training samples that represent the most significant rangeland condition classes would ensure further improvement of the accuracy of classification.

Also, this is highly problematic when performing rangeland condition classification, regardless of sensor, spectral and temporal resolution. Taking into account the complexity of rangeland systems, high resolution can be a potential solution to improve the classification and input dataset. But the latter does not meet the set criterion of effectiveness due to its high cost.

Varied landforms and ecological sites remained the main challenges in rangeland condition classification of the study area. For this reason, the maximum likelihood classification technique could be insufficient. Therefore, it is advisable to identify landform types of rangeland and assess their condition separately. Because of the landform type, different plants with various characteristics can grow together. It may, however, cause difficulty in distinguishing between classes due to inclusion of different plants in one class.

6. CONCLUSIONS

This research aimed at assessing rangeland condition based on NDVI and analysing change detection in the Bornuur soum of Tuv aimag. There were several issues with this research and as a result the data gathered is not reliable enough to draw significant conclusions on the current state of vegetation cover health or the change detection between years. It has, however, been a great learning experience and there are several indicators of areas of interest that will require further analysis and a refinement in methodology and analysis.

Despite manifold limitations, this research showed that remote sensing can be a relatively fast method for evaluation of rangeland condition and changes in large areas. This study demonstrated that further refinement of the methodology and data analysis could lead to a significantly better analysis of this land cover type. The data also showed several interesting features that could be explored more profoundly in further studies. This includes the possible correlation between areas of negative change in NDVI values over time with recognised areas of human activities and agriculture and more detailed description of the research area.

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