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CHANGES IN WETLAND COVERAGE IN THE KHURKH AND KHUITEN VALLEYS OF MONGOLIA BASED ON LANDSAT 8 OBSERVATIONS

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ABSTRACT

Globally, wetlands have an essential role in biodiversity, ecosystems and human well-being. Wetlands include peatlands, swamps, marshes, lakes and rivers which provide essential ecosystem services (Ramsar Convention on Wetland 2018). However, worldwide, wetlands have been deteriorated constantly in the last several centuries. Effective ways to solve problems related to wetland management and monitoring include change detection of wetlands by using remote sensing. Remote sensing involves the process of acquiring information associated with an object, area and phenomenon from a distance. This study aimed to detect wetland changes in the Khurkh and Khuiten valleys of Mongolia, using Maximum Likelihood Classification and change detection methods. The classification method was based on ground truth data and applied to Landsat datasets with the Normalized Difference Water Index (NDWI), and Landsat 8 images for the years 2014, 2017 and 2019. The result of classification illustrated that open water increased by 0.1% from 2014 to 2017 and by 1.9% from 2017 to 2019. On the other hand, wetland classified areas decreased by 2.2% from 2014 to 2017, but increased by 4.7% from 2017 to 2019 because NDWI was sensitive to rainfall in 2019. According to change detection analysis, most conversions during the study years occurred from both wetland and open water to non-vegetated area. Most of these changes were dominant along the edge of the open water, along the edge of the wetland area and around the cropland area. Furthermore, one of the observed results was that conversion of vegetated area to non-vegetated area mostly occurred in high areas located close to the mountains.

Key words: wetland change, Mongolia, NDWI, Landsat 8

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ABBREVIATIONS

DEM	Digital Elevation Model
GIS	Geographic Information System
MAS	Mongolian Academy of Sciences
IWRM	Integrated Water Resource Management
NDVI	Normalized Different Vegetation Index
NDWI	Normalized Different Wetness Index
NIR	Near infrared
OLI	Operational Land Imager
RAS	Russian Academy of Sciences
ROI	Regions of Interest
SWIR	Shortwave infrared
TIRS	Thermal Infrared Sensor
UNU-LRT	United Nations University Land Restoration Training Programme
USGS	United States Geological Survey

1. INTRODUCTION

Wetlands are one of the key components of conservation of worldwide biodiversity (Tiné et al. 2019). According to the Ramsar Convention on Wetland (2018), wetlands include peatlands, swamps, marshes, lakes and rivers which provide essential ecosystem services. Based on the findings of MEA [Millennium Ecosystem Assessment] (2005), wetlands' ecosystem services include supporting human well-being, flooding regulation, water supply, water purification, regulation of climate, fish life and recreational opportunities, among various other services. Wetlands play an essential part in the water cycle by receiving, accumulating, and releasing water, thereby controlling water flows. Although wetlands form storage sinks for a greater percentage of the world's soil carbon, they may become potential emitters of carbon, especially in permafrost areas, due to climate change (Ramsar Convention on Wetland 2018).

Worldwide, wetlands have been severely degraded with approximate 54-57% losses in the 20th and 21st centuries. The largest degradation of wetland areas has occurred in Europe and North America (56.3% and 56.0%, respectively), then in Asia 45.1% (Davidson 2014). Also, losses of inland wetlands worldwide have been higher than that of coastal wetlands (Davidson 2014).

Equally, Mongolian freshwater ecosystems are facing a lot of threats which include overgrazing, climate change impact, mining and gravel extraction, coupled with a lack of appropriate policies and institutional structures (Batnasan 2003). Furthermore, recently, Mongolian peatlands are considered to have suffered increasing degradation because of climate change, overgrazing and other anthropogenic impacts (Minayeva et al. 2018). The combination of climate change effects and overgrazing increases peatland losses in the Onon Balj River valley which includes the Khurkh and Khuiten valleys. One factor contributing to peatland loss is a lack of awareness and perception of stakeholders and local communities of peatlands being a part of the hydrological system (ADB 2017).

Peatland is an accumulation of decaying organic matter under saturated condition and its formation influences both the ecosystem and landscape water balance (Holden et al. 2004) having an impact on both water flow and retention (Hilbert et al. 2000). In Mongolia, peatlands are typically situated along rivers and are currently estimated to cover 27,000 km^2, or 2% of the total area of Mongolia (Minayeva et al. 2018).

The Khurkh-Khuiten basin, the study area, is situated between the Mongolian steppe zone and forest zones; and the Khurkh River is a tributary to the Onon River. In addition, the Khurkh and Khuiten valleys contain low lying slopes, flood plains, many small lakes and streams. The Khentii mountain is situated in the study area's west and north area (Jigj 1975). Also, in the Khurkh and Khuiten area, precipitation decreased by 18.9 mm, air temperature increased by 1.4°C and surface temperature increased by 2.5°C in the last decade (Tsogt-Erdene 2018). According to the Mongolian Statistical Information Service (2018), the overall domestic animal population reached 66,460,180 head in 2018. In the Khurkh and Khuiten valleys, the total population of domestic animals rapidly increased from 546,910 in 2014 to 748,320 head in 2017 and then 1,275,310 in 2018. Also, cultivated agricultural lands amounted to 10,686 ha in the Khurkh and Khuiten areas in 2018 (Mongolian Statistical Information Service 2018). Furthermore, citizens utilize peat as heating material and for building dwellings (ADB 2017).

The Khurkh and Khuiten valleys are essential to the ecosystem by harbouring rare and endangered fauna and flora (Oyungerel 2004). The following fauna and flora of the area have been registered in the "rare" and "very rare" category of the Mongolian Red Book

(Shiirevdamba 1997): *Anser albifrons, Haliaeetus leucoryphus, Haliaeetus albicilla, Grus grus, Otis tarda, Aquila clanga, and G.macrophylla Pall, S.hirculus L, C.selengensis Ivanova (ADB 2017).*

Mongolia is divided into 29 river basins (Dolgorsuren 2012) and all of them require policy instruments regarding Integrated Water Resource Management (IWRM) (Government of Mongolia 2012*a*). Unfortunately, the IWRM of river basins does not include peatlands and permafrost areas as water body components (ADB 2017). Furthermore, a widely used Mongolian policy on Environmental Impact Assessment does not mention peatlands and permafrost as a part of the fragile ecosystems (Government of Mongolia 2012*b*). Some Mongolian environmental laws indirectly regulate the management of wetland and peatland areas. These laws include the Law on environmental protection (Government of Mongolia 1995), Law on forests (Government of Mongolia 2012*c*) and Law on special area protection (Government of Mongolia 1994).

Remote sensing is one way of detecting changes, monitoring and managing wetlands (Owor et al. 2007). Timely acquisition of accurate information on wetland detection and changes can bring an understanding of the relationship and interactions between natural and anthropogenic impacts on wetlands in order to solve problems related to wetlands management (Owor et al. 2007). According to Lillesand et al. (2007), the term Remote Sensing involves the process of acquiring information associated with a particular object, area and phenomenon without coming in contact with it. Remote Sensing can be used in the monitoring and analysis of diverse natural studies such as wetland studies, land cover detection and change, hydrological survey and vegetation cover. Singh (1989) defines change detection as “the process of identifying differences in the state of an object or phenomenon by observing it at different times” (p. 989). Repeatable and precise mapping of wetland change is essential for people that depend on wetlands (Baker et al. 2007). Correct surveillance and precise identification of wetland characteristics are critical to avoid the loss of wetlands and to preserve them properly through change detection (Ashraf & Nawaz 2015). Because wetland ecosystems are very dynamic in nature and comprise a diversity of vegetative or hydrologic changes, there is a need for an equally robust change detection procedure (Whigham 1999; Mitsch & Gosselink 2000).

Landsat 8 imagery, which was employed in the study, supports moderate resolution (30 m) and repetitive acquisition (16 days) from earth’s surface. Landsat 8 sensors gather image data for nine shortwave spectral bands with cirrus and panchromatic bands (USGS 2015). In this study, two bands were employed, namely Near-Infrared (NIR) and Shortwave Infrared (SWIR). The NIR band is highly reflected and, hence, detects a healthy reflection of vegetation and dry soil. The SWIR band is used more productively for wet earth surfaces (Gao 1996). Because wetlands have features of both terrestrial and aquatic ecosystems, both NIR and SWIR are employed in the computation of NDWI for wetland change detection (Keddy 2010). NDWI is used in remote sensing to indicate change in leaf water content based on an estimation at canopy level.

The advantages of satellite data are that the data are in digital format and which is easy to integrate into a geographic information system (GIS). Furthermore, the use of satellite remotely sensed data to carry out land cover classification is relatively cheaper than the usage of conventional ways which mostly involve physical data collection on the ground for the whole area. Thus, satellite remote sensing is more suitable for conducting inventories and monitoring of wetlands in developing countries which, in most cases, experience financial limitations (Ozesmi & Bauer 2002).

Against this background this study aimed at detecting wetland change in the Khurkh and Khuiten valleys using remote sensing. Thus, the study is important in the sense that its findings will help various stakeholders, including those in Mongolia, in effective planning, monitoring and management of wetlands.

Overall goal

To detect wetland change in the Khurkh and Khuiten valleys in Mongolia for the years 2014, 2017 and 2019.

Project Objectives

1. To measure wetland cover change by using remote sensing and NDWI within a 5-year period;
2. To quantify the change between years in wetlands cover;
3. To identify areas of change and attempt to characterize these areas

2. BACKGROUND INFORMATION AND DATA

Mongolia is an arid country dominated by desert and steppe habitats; however, it is rich in wetlands that support breeding and migratory life of water birds and other species (BirdLife International 2005). Mongolia became a member of the Ramsar Convention in 1998 and since then more proactive measures have been taken in wetland conservation. There are 11 designated Ramsar sites to date with 1,439,530 ha, making Mongolia the sixth country with the highest number of Ramsar sites in Asia (After China, India, Pakistan, Japan and eastern Russia).

Peatlands exert influence on water flow and its retention, and peatlands also have an influence on permafrost existence and can, particularly, aid in the conserving of permafrost by preventing thawing (ADB 2017). Permafrost and peatlands are important components of the water cycle and biological processes in the permafrost area (Sjöberg et al. 2015). As defined by French (2007), permafrost is the earth material that remains at or below 0 degrees Celsius continuously for not less than two years. According to permafrost mapping of Mongolia in 2016, permafrost distribution is divided into five categories: continuous, discontinuous, sporadic, isolated patches and seasonally frozen ground (Jambaljav et al. 2016). The Khurkh and Khuiten valleys are situated in the zones of discontinuous and sporadic permafrost distribution, which are considered to be sharply decreasing (Fig. 1) (ADB 2017).

2.1 Field survey

In this study, ground truth data were gathered in the summer season 2019; from June 21 to June 26. This period is associated with rainy days and intensive vegetation growth. The sampling transects were gathered from different ecological sites characterized with natural heterogeneity. Each ground truth point was taken every 30 meters along each transect to cover the pixel size of the Landsat image. Ground truth data were gathered from 500 points because 100 to 120 ground truth points were planned to be used for each class for the calibration and validation sections. However, from the 500 points, 60 ground truth points were inappropriate for wetland study in the research area. Therefore, the study area was minimized based on the Digital Elevation Model (DEM) and hence the 60 ground truth points were found to be outside the target study area and they were excluded from all the calculations in the study. This was based on linking the ground truth data and the computed NDWI analysis. Thus, 7 transects and 440 ground truth data were utilized in the study. In this research, the data for the study area were classified into four categories which included open water, wetland, vegetated area and non-vegetated area.

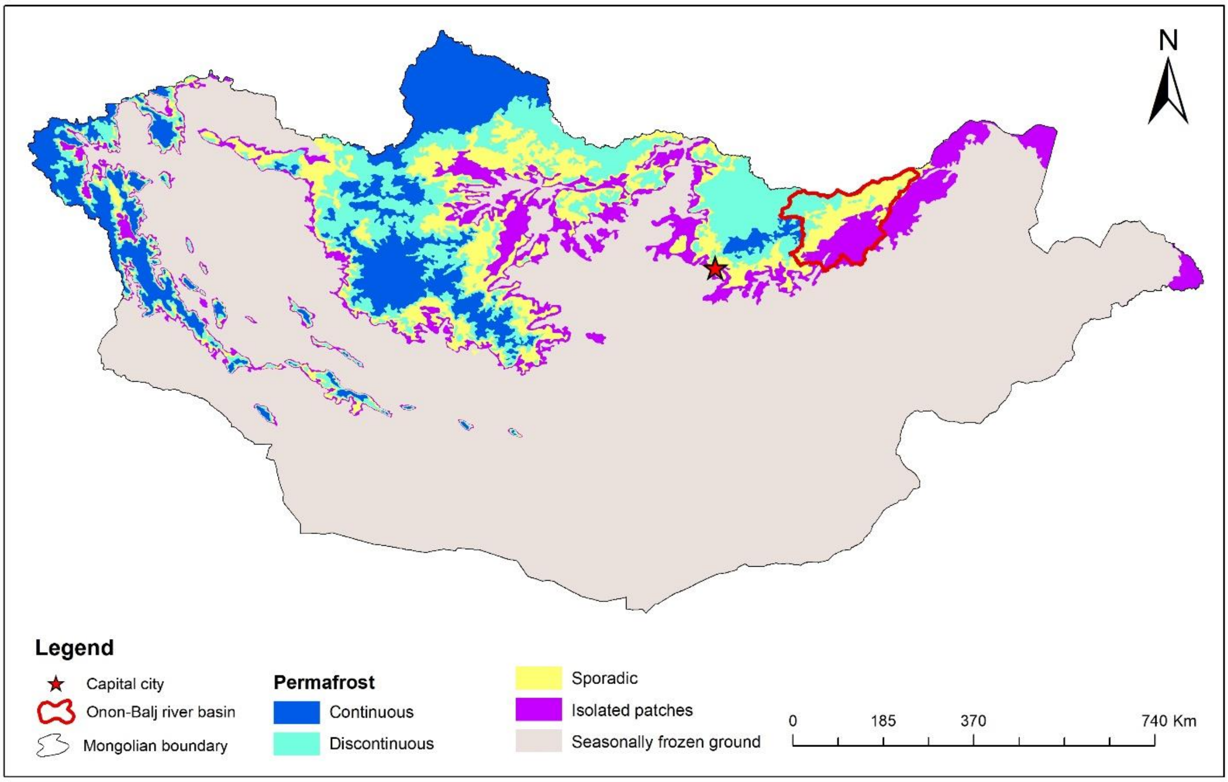

Figure 1. Permafrost distribution of Mongolia and location of the Onon-Balj river basin. (Source: adapted from Jambaljav et al. 2016).

2.2 Remote sensing

2.2.1 Imagery data

Landsat 8 satellite data is widely used for pixel-based classification of land cover and land use (Whiteside & Ahmad 2005; Berhane et al. 2018; Juniati & Arrofiqoh 2017; Chen et al. 2018; Piedelobo et al. 2019). Also, Landsat 8 satellite data are available free of charge. The satellite images' spatial resolution is 30 meters and temporal resolution is 16 days (USGS 2015). Units of absolute radiance are calculated in Landsat 8 data. The data originate from two sensors; these are the Operational Land Imager (OLI) and the Thermal Infrared Sensor (TIRS). The OLI and TIRS sensors are combined to create a single product. The single product is radiometrically and geometrically corrected, co-registered with correction and called the Level 1 product (USGS 2015). Landsat 8 provides a high quality product of standard data and has ground control points and digital elevation models. Also, level 1 of Landsat 8 data has units of Digital Numbers (DNs) that are easily established to the top of the atmosphere (TOA) reflectance and spectral radiance. Furthermore, it does not require costs for downloading from the Internet (USGS 2015). Landsat 8 satellite data collect values of spectral bands such as Near-Infrared (NIR) (0.85-0.88 µm), Short Wave Infrared imagery (SWIR) (1.57-1.65 µm) (USGS 2015), as was the case in this study. Furthermore, the NIR band detects a healthy reflect of vegetation, terrestrial plants and dry soil which are highly reflected. SWIR band is more widely used for wet earth surfaces (Gao 1996). Therefore, these two bands were chosen due to wetlands being characterised by both aquatic and terrestrial areas. The study used Landsat 8 data from 2014 because Landsat 8 data were launched in 2013. Therefore, Landsat 8 data could only be used after 2013. In this study, Landsat 8 data for the years 2014, 2017 and 2019 were utilized due to availability of data and cloud free images. Two to three year gaps were chosen due to the Mongolian harsh climate and change of amount of precipitation within the study years. Landsat 8 can support essential information related to monitoring, exploration, management and observation of Earth's surface (USGS 2015).

2.2.2 Atmospheric correction

Before data are collected by the sensors, solar radiation passes through the atmosphere. Because of this, atmospheric attenuation is crucial to pre-processing step (ENVI 2009). Therefore, the FLAASH model was utilized in this study as the first-principle atmospheric correction tool. In remote sensing, many scientists have done validation of a variety of studies regarding land cover dynamics by using remotely sensed imagery. However, most of the satellite imagery is affected by the effect of atmospheric particles through the Earth's surface emitted radiation scattering and absorption (Agapiou et al. 2011). Therefore, the Atmospheric Correction is used to remove the atmospheric effect by retrieving the atmospheric reflectance from the satellite imagery (ENVI 2009). Atmospheric correction is defined as real surface reflectance volume, by removing the scattering and absorption effects from the ground surface (Hadjimitsis et al. 2010) and it can increase the clarification of satellite data (Agapiou et al. 2011). Song and Civco (2002) suggested that "atmospheric correction is necessary to put multitemporal data on the same radiometric scale, in order to create an image data set with compatible scenes that are useful for classification and monitoring terrestrial surfaces over time" (p. 7).

2.2.3 Normalized difference water index (NDWI)

NDWI is widely used in remote sensing techniques for detecting wetland area, wetland inundation and wetland monitoring (Ashraf & Nawaz 2015; Gao et al. 2018). NDWI is a satellite-derived index based on the channels of the Near-Infrared (NIR) and Short-Wave Infrared (SWIR) (Gao 1996).

According to Gao (1996), NDWI was derived and successfully tested from Normalized Different Vegetation Index (NDVI). The NDVI was only able to determine green chlorophyll but not liquid water in vegetation. The introduction of the NDWI, which is more sensitives to liquid water in vegetation (Gao 1996), is aimed at identifying liquid water contained in plants from space using 0.86 µm (NIR) and 1.24 µm (SWIR) (Gao 1996). Also, NDWI is less susceptible to atmospheric scattering impacts than NDVI and is helpful in canopy water stress prediction and crop productivity assessment (Adam et al. 2010).

The NIR band detects a healthy reflection of vegetation, terrestrial plants and dry soil as they are highly reflected. SWIR band is more productively used for wet earth surfaces (Gao 1996). Therefore, this wetland detection study utilized methods of Gao (1996) that employed the NIR and SWIR bands for determining NDWI.

NDWI (Gao 1996) was calculated with formula 1. Range of NDWI is from -1 to +1.

$$NDWI = \frac{NIR - SWIR}{NIR + SWIR} \qquad (1)$$

where: NIR = Near infrared, SWIR = Short wave infrared imagery

Gao (1996) found that NDWI threshold pixels which are a combination of water and vegetation was -0.15, and dry vegetation of NDWI values were extracted -0.056 (negative) and bare soil of NDWI values were negative (-0.022). In a laboratory test of Gao (1996), water transmittance for thicknesses of water was tested at 0.05 cm, 0.1 cm and 0.4 cm. In line with findings of the laboratory test, the SWIR band has similar vegetation scattering characteristics as the NIR band. However, the SWIR band is sensitive to liquid water changes. Therefore, NDWI is indicated to be sensitive to total amounts of liquid water changes (Gao 1996).

2.2.4 Calibration

Calibration aims at bringing together all statistics that show spectral changes in each land cover type to be classified in an image, and it is the most important stage for successful classification and validation. The lowest number of pixels in a training set should always be n+1 with the use of any statistical classifier, regardless of how calibration data are defined, where n is the number of spectral bands. The number of pixels used is usually 10n to 100n to allow estimation of differences in calibration sets as it improves with number of pixels (Lillesand et al. 2007).

2.2.5 Classification

In order to deduce wetland cover change between years, the maximum likelihood classification method was utilized based on the ground truth data. The ground truth data were all collected at the same time as it is essential in remote sensing in order to obtain accurate results. The ground truth data were collected to relate to the calibration of image classification for accurate measurement of the wetland detection mapping result.

Image classification is the method of categorizing each pixel in an imagery dataset. In remote sensing, supervised and unsupervised approaches are used generally. In this study, supervised classification was used because in supervised classification, users can control the classification based on their knowledge and data. One of the examples of a supervised classification method is the Maximum Likelihood method that was employed in this study based on the water index for determining wetland detection.

When classifying data, the process involves a lot of computations as ample datasets on the class membership characteristics for a case are calculated. These data are made accessible for each situation in the standard output, which is merely the most probable class of affiliation (Foody et al. 1992). According to Lillesand et al. (2007) the Maximum Likelihood classification method defines a normal distribution of Digital Number (DN) values, allowing the function to determine the probability of a pixel belonging to a certain class of features and assigning each pixel to the highest class of probability.

Many researchers have agreed that it is one of the most productive approaches for satellite image classification (Bayarsaikhan et al. 2009, Berhane et al. 2018, Piedelobo et al. 2019). According to Richards and Jia (2006), a Maximum Likelihood Algorithm determines the probability distributions for the classes as per Bayes' theorem, thereby estimating whether a pixel belongs to a given land cover class. Furthermore, when using algorithms, the probability distributions for the classes assume the form of multivariate normal models. Therefore, a minimum number of pixels is required for each area in order to calculate the covariance matrix.

2.2.6 Validation and accuracy assessment

One of the most common classification accuracy methods is the error matrix. The error matrix compares the relationships between the ground truth data and the corresponding result of classification on a class by class basis (Lillesand et al. 2007). In the study, the wetland images created for the study area included the points for the ground truth dataset used in the error and accuracy assessment. The wetland classification was then compared to the ground truth information collected at particular points. Accuracy assessment is the calculation of the overall accuracy (OA), user's accuracy (UA), producer's accuracy (PA) and error matrix (Story & Congalton 1986). According to Story and Congalton (1986), the OA is defined as the ratio between the number of correctly classified validation pixels and the number of validations pixels that have been used for all classes, presented as a percentage.

2.2.7 Change detection

In order to define wetland change and to characterize the areas in 2014, 2017 and 2019, a post classification method was utilized based on the computed Maximum Likelihood Classification method for the study area. In this study, change detection showed percentage of area in the year of study converted to each class from the four classes. For example, the wetland class can be converted to each of the following classes: conversion from wetland to wetland, from wetland to open water, from wetland to vegetated area, and from wetland to non-vegetated area. Furthermore, each class conversion resulted in total of 16 conversion variants. Singh (1989) defined change detection as the process of defining differences in the state of a phenomenon or object based on the different year's satellite images. Data on land cover change and land use change are essential to all the stakeholders for effective monitoring, management assessment and planning (Hussain et al. 2013). According to Ross and Bhadauria (2015) change detection is applied in a variety of fields including land use changes, deforestation rate, habitat fragmentation, coastal change and urban sprawl. Furthermore, there are several change detection techniques, each with its own advantages and disadvantages, and it is therefore important to consider several factors before performing change detection using a given method in order to improve accuracy of the results. In addition, Al-doski et al. (2013) describe six procedures that need to be taken into account when performing land cover change detection and these are: nature of detection change problem, selection of remotely-sensed data, image processing, image classification, selection of change detection algorithms and evaluation of change detection results.

There are two broad categories of change detection techniques, and these are pre-classification and post-classification. Pre-classification techniques just obtain minimal information about changes whereas post-classification techniques separate changes in detail comprising appropriate attributes (Ross & Bhadauria 2015). Therefore, in change detection analysis, the post-classification technique has proved to be the most popular method as it involves the comparison of classified images that are independently produced.

2.3 Research area

The study area lies to the east of the Khentii, Bayankhaan, Shuvuut, and Ereen mountain ranges. All the main rivers within the study area – Ulz, Onon, Balj – have their source in the Khentii mountains. The eastern part of the Khentii Mountains consists of medium altitude mountain ridges, piedmonts and a broad river valley. The highest point of the study area is Mt Khetsuu (1568 m elevation) while the lowest point is the junction of the Onon and Balj rivers (840 m elevation). Furthermore, the study area is situated within the rapidly shrinking zones of discontinuous and sporadic permafrost distribution. Also, within the study area there is a national park named Onon-Balj (Myagmarsuren et al. 2012). The area hosts several biogeographic zones – Siberian taiga, Dahurian-Manchurian forest steppe and Eastern Mongolian steppe regions. The types of mire massifs found in the study area include transitional peatlands, spring fens, transitional mires of the freshwater lake chains, the sporadic permafrost, highland valley meadow fens and saline marshes of salty steppe lake chains. In addition, the study area is a part of a Ramsar site named "Lakes in the Khurkh-Khuiten river valley" that was categorized as a wetland of international importance in 2004. The total area of the Ramsar site is 429.4 km^2 (BirdLife International 2005).

2.4 Research area definition

The research area was defined based on two steps. First, the Khurkh and Khuiten sub-basins were created using the Geospatial Hydrologic Modelling Extension named HEC-GeoHMS tool in ArcGIS10.5 based on Digital Elevation model (DEM). The HEC-GeoHMS tool has been developed as a geospatial hydrology toolkit for hydrologists and engineers. Also, it delineates the basin and sub-basin of the watershed (Fleming & Doan 2009). Second, after creating a sub-basin, the study area named the Khurkh and Khuiten valleys was defined based on DEM from 945-1200 meters above sea level in ArcGIS 10.5.

2.5 Meteorological information

Precipitation data were obtained from the closest meteorological station of the Khurkh and Khuiten valleys and were acquired from the Mongolian Information and Research Institute of Meteorology, Hydrology and Environment.

In Mongolia, out of the total precipitation approximately 85% falls during the period from April to September, with most of the precipitation falling in July and August or around 50-60% of total precipitation (Batima et al. 2005). In this study, monthly average precipitation data for the study years were examined because NDWI is sensitive to total amounts of liquid water changes (Gao 1996). Therefore, monthly average precipitation data and 10-day period prior to image capture in each year of chosen satellite data were computed in this study.

According to the rainfall data for the study years presented in Figure 2, the highest rainfall for the study was observed in July 2019 compared to the other years. The results show that the differences between the highest rainfall in 2019 and the two other study months, respectively, were very large.

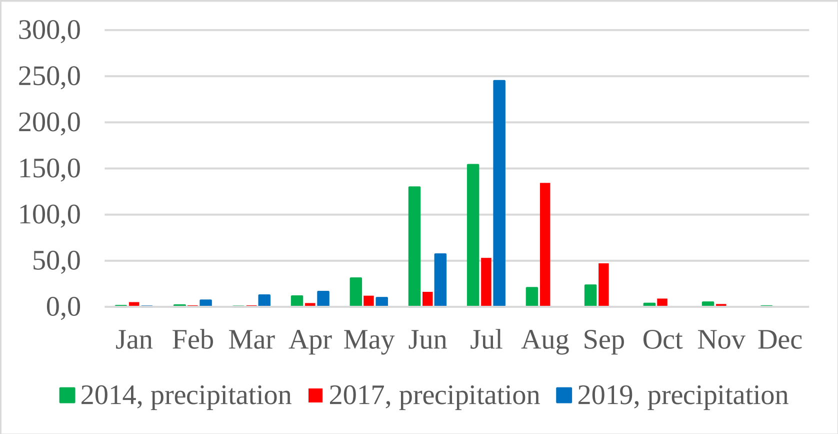

Figure 2. Monthly average precipitation of the meteorological station in 2014, 2017 and 2019. (Source: National Meteorological Agency 2019).

Also, precipitation data presented in Figure 3 below were compared within the 10-day period prior to image capture in each year of chosen satellite data. The 10-day periods are from 2nd to 12th July in 2014, 24th June - 4th July in 2017, and 1st - 11th July in 2019. Considerably more precipitation fell during the 10-day period of July 1st - 11th in 2019, than in 2014 and in 2017. The highest rainfall, 32.1 mm, was registered on the 6th of July 2019.

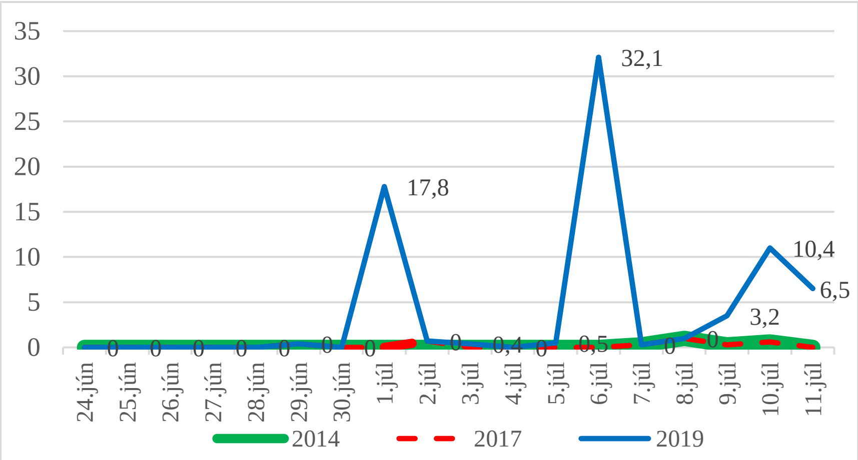

Figure 3. Comparison of rainfall patterns during 10-day periods preceding the date of respective satellite image in 2014, 2017 and 2019. (Source: National Meteorological Agency 2019).

3. METHODOLOGY

3.1 Description of study area

The study area is situated in the north-eastern part of Mongolia named the Khurkh and Khuiten valleys, within the Onon River basin, and it borders with Russia in the north (Fig. 4). The Onon River basin is one of the origins of the Amur River, which is one of the biggest rivers in the world. (ADB 2017). When the study area was delineated, two steps were used in determining the study area.

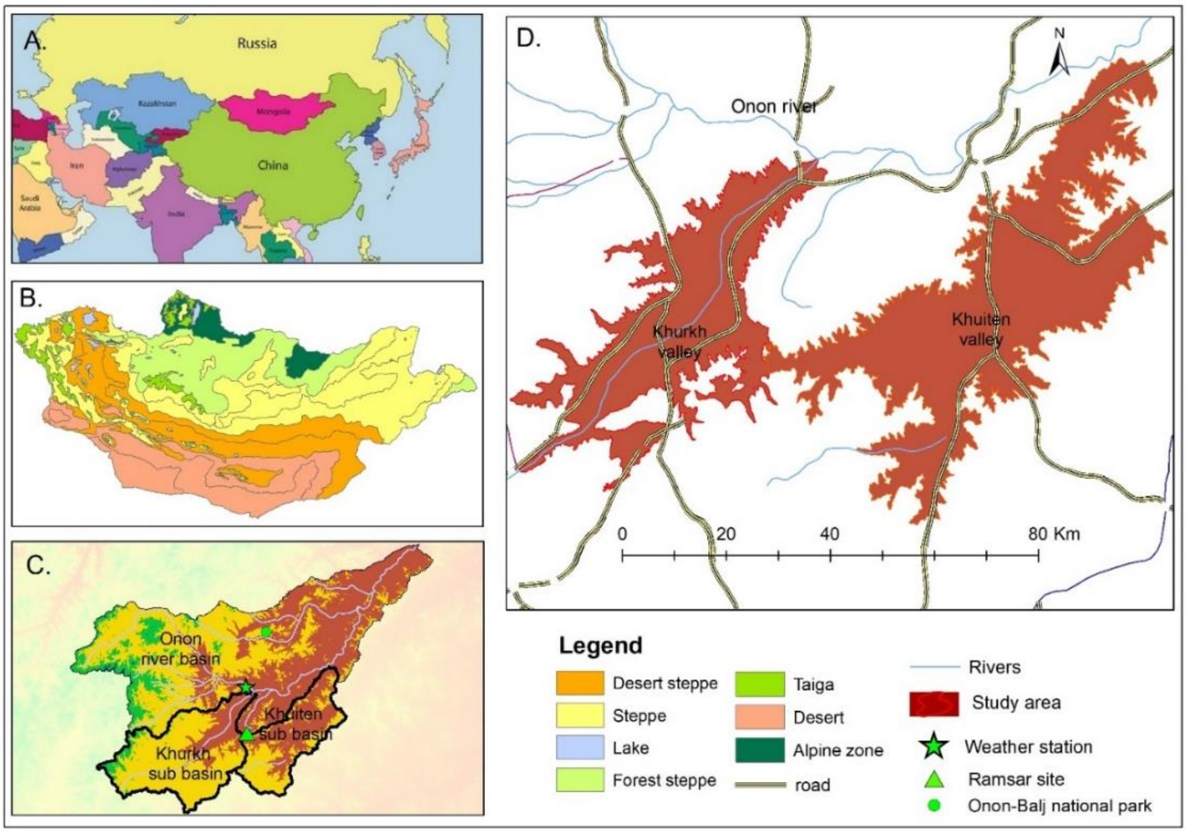

Figure 4. Study area A. Location of Mongolia on the world map (Source: goway.com); B. Mongolian territory (Source: Mongolian Land Information System); C. Onon-Balj river basin that includes the Khurkh and Khuiten sub-basin which were highlighted (Source: SRTM Digital Elevation Model); D. The Khurkh and Khuiten valleys study area (Source: SRTM Digital Elevation Model).

First, the Khurkh and Khuiten sub-basins were created by using the HEC-GeoHMS10.1 tool in Arc-GIS10.5. Secondly, the study area was extracted based on the Digital Elevation Model (DEM) that is located at 945-1200 meters above sea level in the Khurkh and Khuiten valleys in ArcGIS10.5. The size of the study area is 2925.8 km^2 (Fig. 5).

3.2 Flow chart

Wetland detection consisted of the following steps: (1) image acquisition; (2) image pre-processing; (3) calculation of NDWI; (4) classification process (5) validation (6) change detection. Obtaining an appropriate pixel-based classification requires the following 6 steps to utilize together multispectral remote sensing images from Landsat, as illustrated in Figure 5.

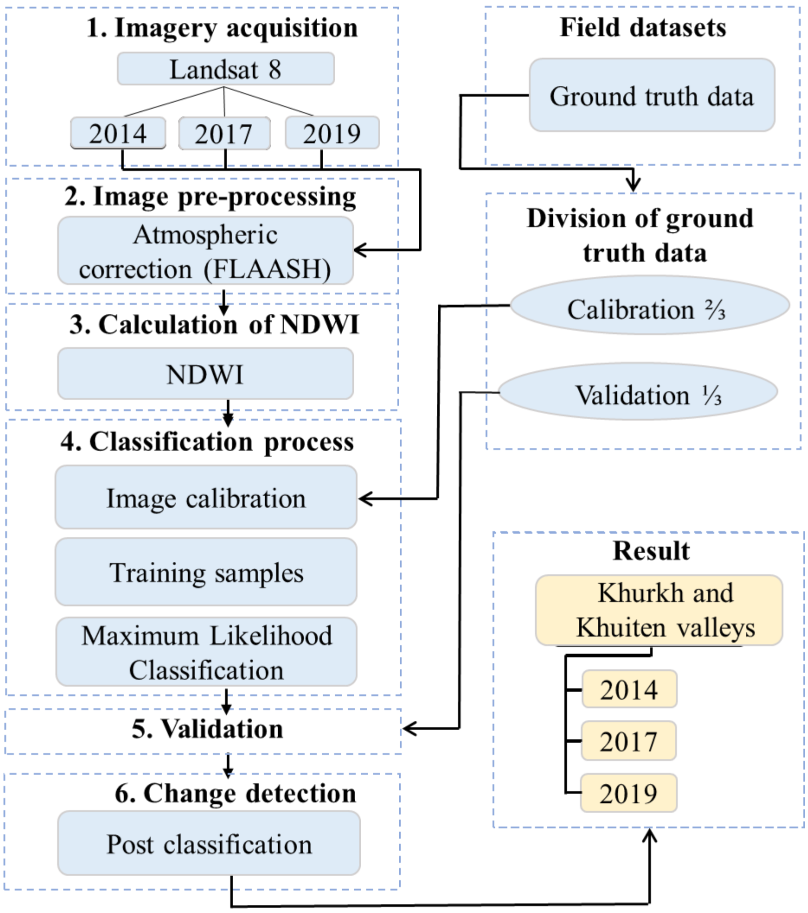

Figure 5. Research methodology flow chart.

3.3 Data collection

3.3.1 Imagery acquisition

Landsat 8 satellite data were obtained through the Earth Explorer of the United States Geological Survey (Fig. 6) (USGS 2019). In the study, the NIR and SWIR bands of Landsat 8 were utilized (Table 1). In remotely sensed imagery, obtaining satellite images that are not affected by the effect of clouds is difficult (Zhu et al. 2015). However, satellite data of the years 2014 and 2017 were cloud-free, but the 2019 image had cloud effect in some sections of the study area. Landsat 8 sensors have a cirrus band that has a wavelength range from 1.36 to 1.38. Cirrus and multispectral bands were calibrated automatically to the reflectance of the top of the atmosphere (Zhu et al. 2015). The cloud cover effect for the 2019 satellite image was erased by using extract by mask tool in ArcGIS10.5. Data in this study included 3 satellite images from Landsat 8 (provided by USGS 2019). Imageries acquisition times were selected on 12 July 2014 (path: 129, row: 26), 04 July 2017 (path: 129, row: 26) and 10 July 2019 (path: 129, row: 26) and field surveys were conducted within four weeks of satellite data acquisition.

Table 1. Spectral characteristic of Landsat 8 satellite data.

Landsat 8			
Band name	Bands	Wavelength (micrometers)	Resolution (meters)
NIR	Band 5	0.85 - 0.88	30
SWIR	Band 6	1.57 - 1.65	30

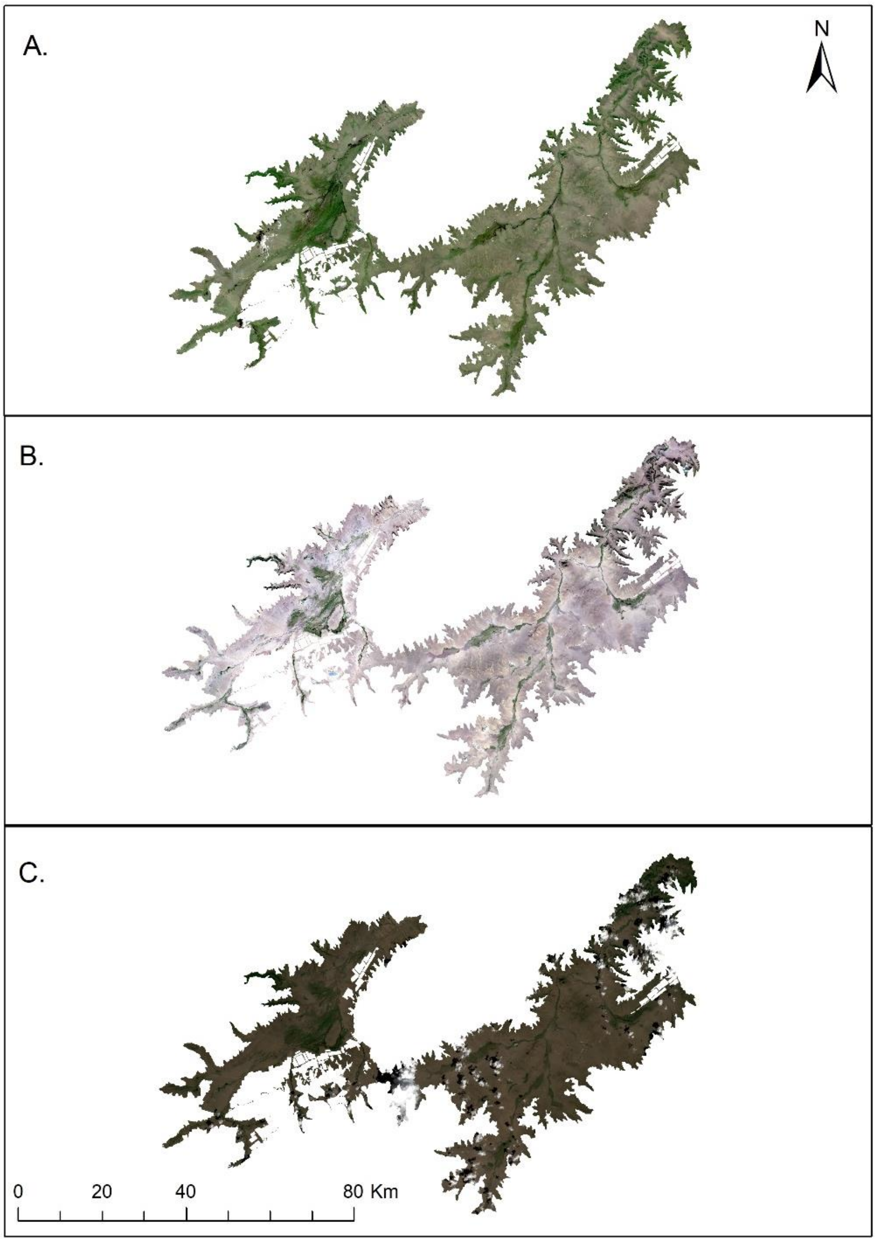

Figure 6. RGB of raw data in study area A. Raw data in 2014, B. Raw data in 2017, C. Raw data in 2019.

3.3.2 Field survey

Field data from 500 ground truth points along 8 transects were collected in the Khurkh and Khuiten valleys of Mongolia using the systematic sampling method (Fig. 7). The systematic sampling method is a selection of random points from the ground at a specific interval from the selected area (Yates 1948). The field data were gathered at a similar time and different land conditions such as from valleys, open water area, shallow water, grassland, peatland, wet meadow and riverbank. Four classes were categorized; open water (lake, river, stream), wetland (shallow water, wet meadow and peatland), vegetated zone (grass, meadow and dry meadow) and non-vegetated zone (bare soil, rocks, tilled land and dry clay). Data were collected in the period June 21-26 2019. Ground truth data were taken at 30-meter intervals through transects based on the resolution of the satellite data (Fig. 7). All 500 ground truth points were linked to GPS coordinates (Garmin ~3-5 m accuracy)

3.4 Image pre-processing

In this study for each satellite image calibrated radiance was calculated by using the FLAASH module that is an atmospheric correction method in ENVI 5.2 software for finding surface reflectance. The FLAASH Atmospheric Correction tool was selected from the Radiometric correction toolbox. The FLAASH toolbox requires input parameters. For entering sensor type information, Landsat 8 OLI was chosen. Mid-Latitude summer was selected in the model atmosphere setting based on Mongolian surface air temperature. This represented aerosols in the study area that are not strongly affected by industrial and urban sources due to using the rural selection in aerosol mode. Initial visibility value was selected based on weather conditions that indicate scene visibility in kilometres. The study area showed clear weather conditions, hence the selected scene visibility was from 40 km to 100 km.

3.5 Calculation of Normalized Difference Water Index

In this study, ENVI 5.2 software was utilized to prepare the NDWI maps using Gao's (1996) formula (2) in 2014, 2017 and 2019. The NDWI was identified from the band math tool of ENVI5.2. The band math tool is an appropriate mathematical description. It requires band math expression and expression valid IDL function. In this study (ENVI 2009), both NIR and SWIR bands were calculated using the following equation in the band math tool (Fig. 8).

$$NDWI = (\text{float}(b1) - \text{float}(b2)) / (\text{float}(b1) + \text{float}(b2)) \quad (2)$$

where: b1 = NIR band; b2 = SWIR band

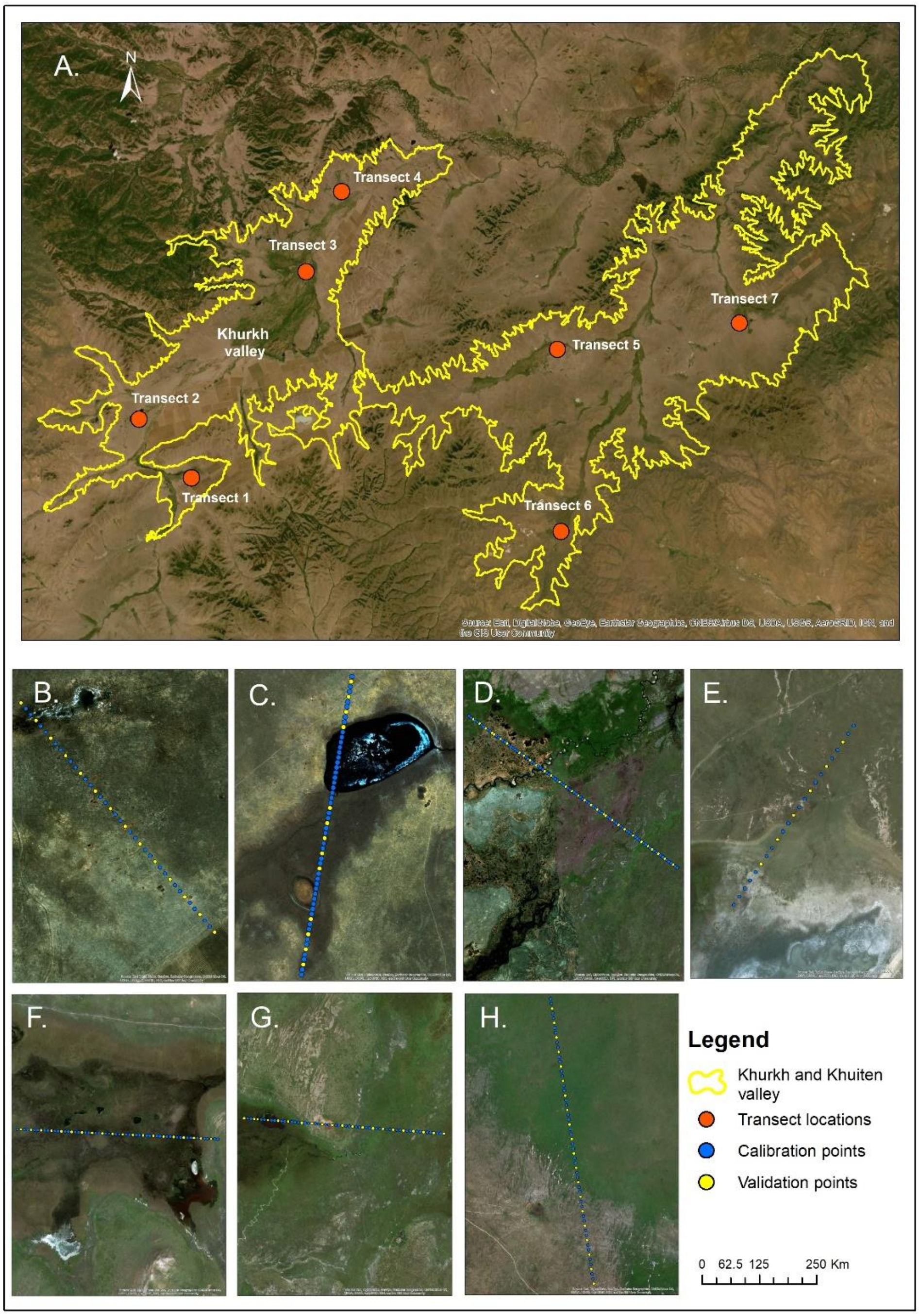

Figure 7. Distribution of ground truth data in the Khurkh and Khuiten valleys of Mongolia; A. Transects' locations; B. Transect 1 (60 points, Khurkh valley); C. Transect 2 (60 points, Khurkh valley); D. Transect 3 (100 points, Khurkh valley); E. Transect 4 (40points, Khurkh valley); F. Transect 5 (60 points, Khuiten valley); G. Transect 6 (60 points, Khuiten valley); and H. Transect 7 (60 points, Khuiten valley). (Source of base map: Esri, DigitalGlobe, GeoEye, Earthstar Geographis, CNES/Airbus DS, USDA, USGS, AeroGRID, IGN and the GIS user Community).

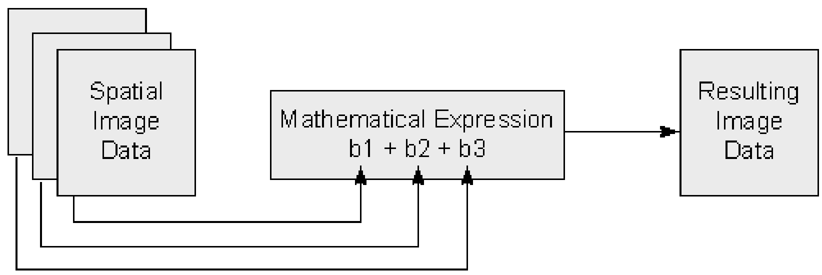

Figure 8. Band math tool's calculation in NDWI (Source: ENVI 2009).

3.6 Calibration

In this research, 70% of the ground truth data were computed with the calibration of image classification. The field data constituted a proportional representation of the class in the study area. A total of 500 ground truth data samples had originally been proposed to be gathered in the field survey. Collection of around 100 to 120 ground truth data for each class was an initial goal. However, 33 points were gathered for the open water class, 108 points for the wetland class, 275 points for the vegetated area class and 24 points for the non-vegetated area class. Thus, 70% of the wetland class (72 points) and 70% of the vegetated area class (183 points), all points of the open water class (33 points) and all points for the non-vegetated class (24 points) were employed in the calibration section. Therefore, a total of 312 ground truth points were used in the calibration section for this study. Then Region of Interest (ROI) was delineated based on the calibration of ground truth points for the classification process.

3.7 Classification process

In this study, Region of Interest (ROI) was used in the classification process. Before classification, firstly ROI for each of the 4 classes was identified by using ground truth data. A total of 166 pixels of ROI were created based on ground truth data from the calibration. In remote sensing, the ROI comprises selected raster samples, such as water, that are usually identified for a particular use. ROI was created using conversion tools in ArcGIS 10.5. Furthermore, point features of ground truth data were converted to raster dataset using the point to raster conversion tool. Then the raster data were converted to polygon features using the raster to polygon tool for creating ROI.

Secondly, training samples were created using ROI. A training sample was created based on satellite data of the year 2019 for each class. The training Sample Manager tool in ArcGIS 10.5 was utilized for preparation of classification. Image classification was determined as using the pixel-based Maximum Likelihood Classification method by using ArcMap 10.5. That is a traditional approach to detect land cover and measure changes based on the spectral characteristics of pixels.

3.8 Validation/ classification accuracy assessment

In the validation section, accuracy assessment was quantitatively evaluated based on ⅓ of the ground truth data. For the reasons explained in sub-section 3.6, two classes were used in the validation section, the wetland class (36 points) and vegetated area class (92 points). Open water and non-vegetation areas were not utilized in the validation section due to the small number of ground truth data. Therefore, a total of 128 points were computed from the ground truth data for the accuracy assessment. The data for accuracy assessment were selected randomly from the classes of wetland and vegetated area from the ground truth data. Overall accuracy and the error matrix were calculated in Excel software (formula 3). Overall accuracy (OA), Producer's and User's Accuracy values were calculated using formulas 4 and 5 (Story & Congalton 1986). The diagonal elements indicate the pixels that have been correctly classified, while off-diagonal elements indicate errors of omission or commission (formulas 6 to 9). On the other hand, Producer's Accuracy (PA) indicates the probability with which an image pixel has been correctly labelled by a classifier, while User's Accuracy (UA) indicates the probability with which a pixel belongs to a particular class and the pixel in that given class has been correctly labelled by the classifier.

$$\text{OA} = \frac{Total\ number\ of\ correctly\ classified\ pixels\ (diagonal)}{Total\ number\ of\ reference\ pixel} * 100 \qquad (3)$$

$$\text{UA} = \frac{Number\ of\ correctly\ classified\ pixels\ in\ each\ category}{Total\ number\ of\ reference\ pixels\ in\ that\ category\ (the\ row\ total)} * 100 \qquad (4)$$

$$\text{PA} = \frac{Number\ of\ correctly\ classified\ pixels\ in\ each\ category}{Total\ number\ of\ reference\ pixels\ in\ that\ category\ (the\ column\ total)} * 100 \qquad (5)$$

$$Sensitivity = \frac{a}{a+b}\ (equivalent\ to\ Producer's\ Accuracy) \qquad (6)$$

$$\text{Specificity} = \frac{d}{b+d} \qquad (7)$$

$$Commission\ error\ =\ 1 - Specificity \qquad (8)$$

$$Omission\ error\ =\ 1 - Sensitivity \qquad (9)$$

where:
a = number of times a classification agreed with the observed value
b = number of times a point was classified as X when it was observed to not be X.
c = number of times a point was not classified as X when it was observed to be X.
d = number of times a point was not classified as X when it was not observed

3.9 Change detection

The wetland's change detection in the Khurkh and Khuiten valleys was calculated by utilizing the post classification method in the ArcMap 10.5 software. The results of NDWI were determined by employing a change detection method based on the years 2014, 2017 and 2019. The change detection method uses multi-temporal datasets for identifying differences in land cover change based on dates of satellite images. With change detection, multi-temporal datasets are used to distinguish areas showing different land cover between image dates. One way of doing this is to use post classification comparison whereby two dates (2014-2017 and 2017-2019) of imagery are individually categorised and registered. An algorithm can be used to identify changes in pixel classification between the dates (2014-2017 and 2017-2019). Maps can be used to display the exact class of changes between the dates of imagery (Lillesand et al. 2007).

4. RESULTS

4.1 Normalized Different Water Index analysis

In this study, NDWI values were extracted for the years 2014, 2017 and 2019 (Fig. 10) (Table 2). The lowest NDWI value was -0.27 in 2019 and the largest values were 1.0 in 2014 and 2019, respectively. The variation in NDWI values is shown in Figure 9.

Table 2. NDWI values in 2014, 2017 and 2019.

Date	Min	Max
2014	-0.32	1.0
2017	-0.34	0.69
2019	-0.27	1.0

In remote sensing, the Region of Interest (ROI) comprises selected samples of raster. ROIs were created based on ground truth data. The results presented in Table 3 and Figure 10 are the computed NDWI values extracted by ROI in 2019.

Table 3. NDWI values from ROI in 2019.

Classes	Min	Max	Mean	Std.dev.
Open water	0.42	0.64	0.51	0.20
Wetland	-0.07	0.34	0.07	0.06
Vegetated area	-0.13	0.39	0.06	0.13
Non vegetated area	-0.03	0.40	0.11	0.19

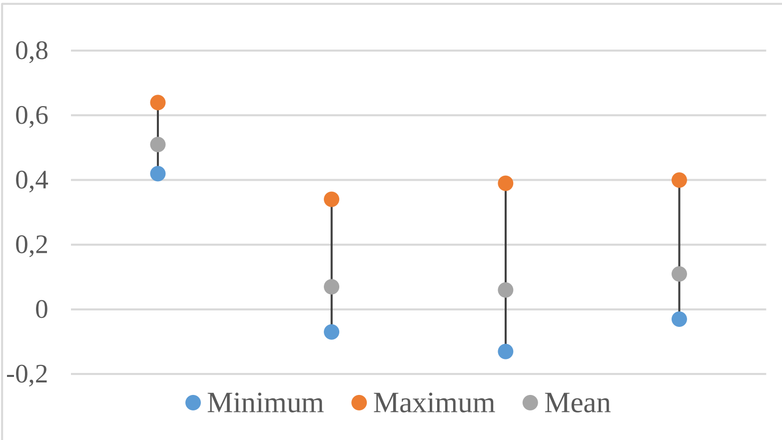

Figure 9. Variation of NDWI values in class for ROI.

From the results, positive values were extracted for open water, while the wetland, vegetated area and non-vegetated area had both positive and negative values. From the results of ROI extraction of NDWI, the highest value occurred in the open water class at 0.64 and the minimum value was -0.03 in a non-vegetated area.

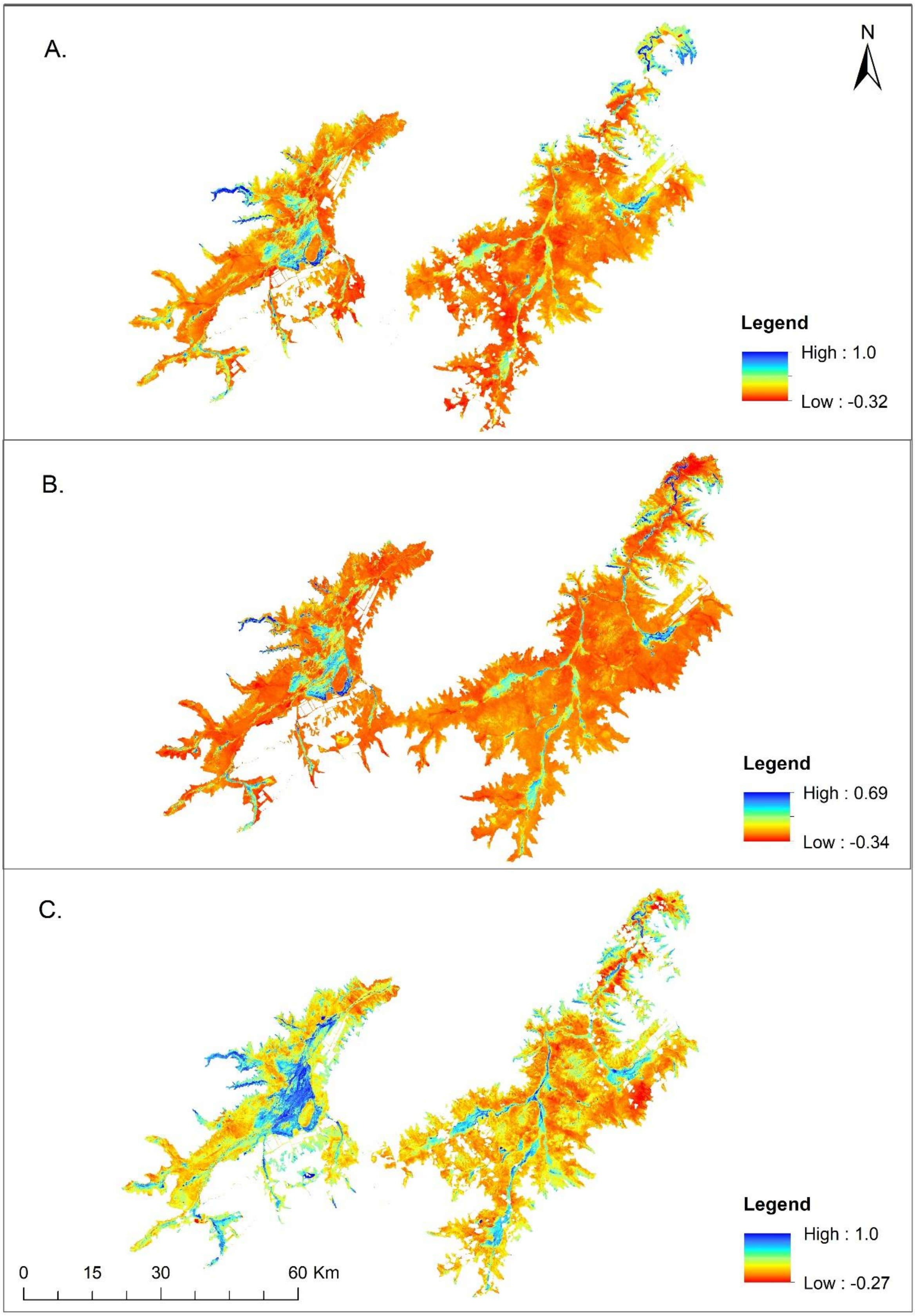

Figure 10. NDWI values for the study area. A. NDWI value in 2014. B. NDWI value in 2017. C. NDWI value in 2019.

4.2 Image classification

According to the ground truth data, data for the vegetated area class were most commonly found (275 sites). There were also 33 sites of open water area, 108 sites of wetland area and 24 sites of non-vegetated area (Table 4).

The 440 ground truth data served two purposes: for calibration and validation. Two thirds (70%) of the ground truth data was selected randomly for image calibration. One third (30%) was selected randomly from the ground truth data for validation of the classification accuracy assessment (Table 4).

Table 4. Classes of ground truth data.

Classes of field data	Total points	Calibration points, ⅔	Validation points, ⅓
1. Open water (rivers, lakes, streams)	33	33	
2. Wetland (shallow water, wet meadow, peatland)	108	72	36
3. Vegetated area (dry meadow and grass)	275	183	92
4. Non-vegetated area (bare soil, rocks and tilled land and dry clay)	24	24	
Total	**440**	**312**	**128**

Image classification results in the years 2014, 2017 and 2019 in the Khurkh and Khuiten valleys are shown in Figure 11. The surface area of each class is presented in Table ***5***. Classification of open water areas showed an increase to 0.6% in total area (292580.3 ha) in 2014 and to 0.7% and 2.6% in the years 2017 and 2019, respectively. The wetland area covered 7.9% in 2014, then decreased by 2.2% in 2017 and increased again by 4.7% in 2019. Comparing open water and wetland coverage in the classification, it was 0.6% and 7.9% in 2014, and 0.7% and 5.7% in 2017, respectively. However, both open water and wetland increased at 2.6% and 10.4%, respectively, in 2019.

The vegetated area showed an inverse correlation compared to the wetland during the study years. The non-vegetated area increased through each of the study years. It was 0.2% in 2014, 0.9% in 2017 and 2.4% in 2019.

Table 5. Changes in the classes for the Khurkh and Khuiten valleys between 2014, 2017 and 2019.

Classes	2014	2017	2019	2014	2017	2019
	Area (ha)	Area (ha)	Area (ha)	%	%	%
Open water	1645.3	2109.9	6645.6	0.6	0.7	2.6
Wetland	23252.3	16538.1	26620.5	7.9	5.7	10.4
Vegetated area	267042.2	271378.3	216331.3	91.3	92.7	84.6
Non vegetated area	640.6	2582.3	6099.7	0.2	0.9	2.4

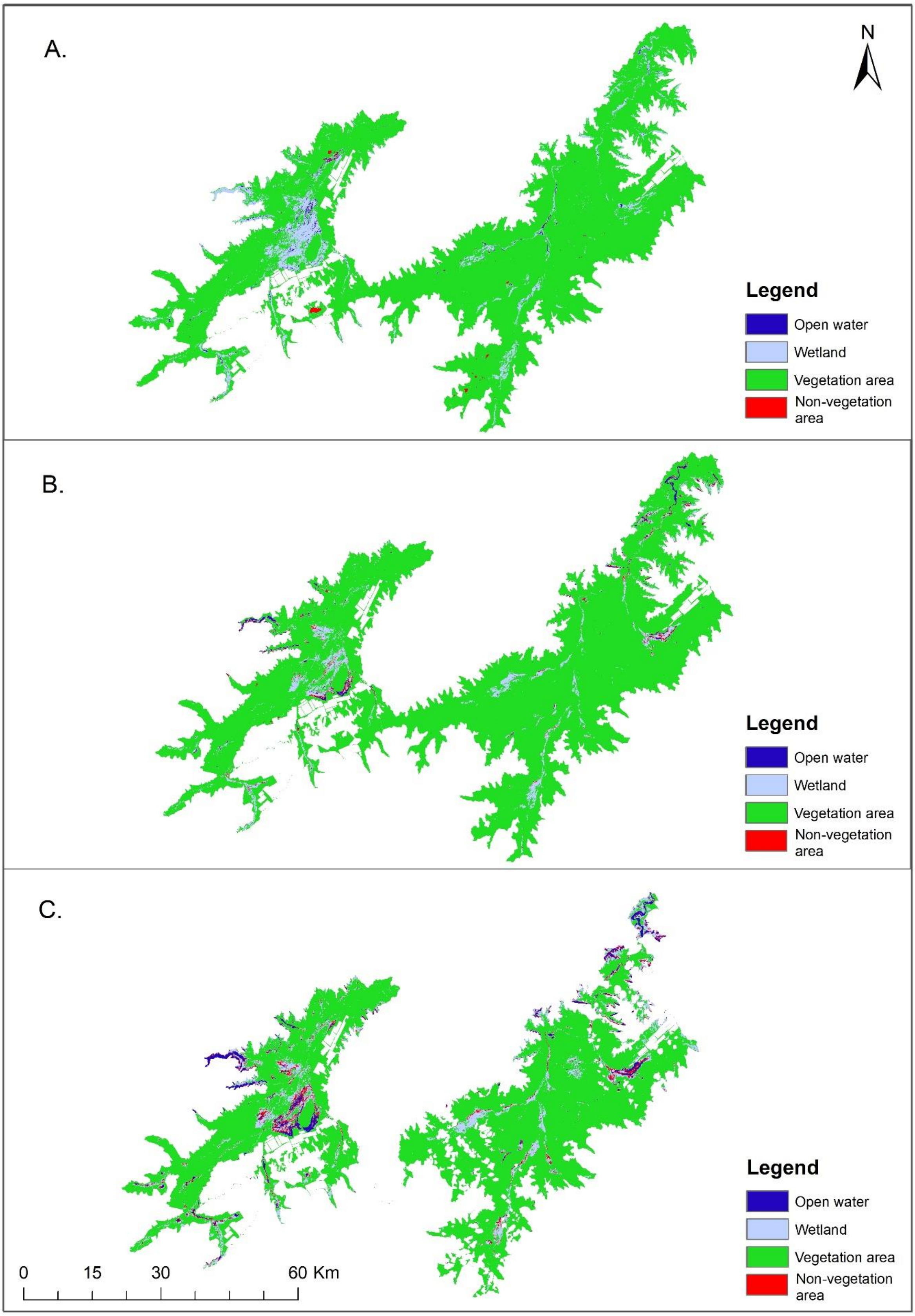

Figure 11. Maximum Likelihood classification results in the Khurkh and Khuiten valleys. A. Classification result in 2014, B. Classification result in 2017, C. Classification result in 2019.

4.3 Accuracy assessment of classification

Table 6 shows the results of the accuracy assessment. The identified commission error for the vegetated area (0.52) was higher than that of the wetland class (0.36). However, the omission error for the vegetative area (0.20) was lower than that of the wetland class (0.53).

The Producer's Accuracy (PA) was 63.8% for the wetland class which was relatively higher that for the vegetated class (48.3%). User's accuracy for the vegetated class was also relatively higher (79.6%) compared to that of the wetland class (46.9%).

Overall accuracy of the classification was 52.8%, which is acceptable.

Table 6. Accuracy assessment of the classification.

		Classes derived from satellite data						
		Open water	Wetland	Vegetated area	Non-vegetated area	Sum	Commission error	Producer's Accuracy (PA) (%)
Ground truth measurement	Open water	0	0	0	0	0	1	0
	Wetland	0	23	11	2	36	0.36	63.8
	Vegetated area	3	26	43	17	89	0.52	48.3
	Non-vegetated area	0	0	0	0	0	1	0
	Sum	3	49	54	19	**125**		
Omission error		1	0.53	0.20	1			
User's Accuracy (UA), (%)		0	46.9	79.6	0			
Overall accuracy		**52.8%**						

4.4 Change detection

Figure 13 illustrates change detection through conversion of classes between 2014-2017 and 2017-2019, respectively. Also, Table 7 shows conversion of classes in percent between 2014 and 2017. According to the findings, the most frequent changes were related to the conversion of open water and wetland to vegetated area (47.2% and 47.9%, respectively). A total of 35.4% of open water had changed to wetland area. Furthermore, between 2014 and 2017, 4.7% of the open water class changed to non-vegetated area along the river in the north-east and south-west Khuiten valley which is within the wetland area. Of the wetland area, 7.4% was converted to open water while another 7.4% was converted to non-vegetated area. Conversion of wetland to open water mostly occurred in the middle and western part of the Khurkh valley and the north-west part of the Khuiten valley, whereas, conversion of wetland to non-vegetated area mostly occurred along the edge of the rivers for both the Khurkh and Khuiten valleys. The vegetated area did not indicate any changes into the open water class between 2014 and 2017. The changes from vegetated area to wetland occurred around 2.7%, and the changes mostly appeared along the rivers and wetland areas of both the Khurkh and Khuiten valleys. Between 2014 and 2017, the changes from vegetated area into non-vegetated area amounted to 0.3%, mostly in the middle of the Khurkh area, which is within the open water and wetland areas. However, the conversion of vegetated area into non-vegetated area was more dominant in areas closer to cropland, in the edge of the open water area and edge of the wetland area. Furthermore, conversion of vegetated area to non-vegetated area also occurred in the north-east of the Khuiten valley located in a higher area and close to the mountain area (around 1183 m above sea level). Approximately 2.2% of the non-vegetated area was converted to open water and it was more significant along the edge of the open water for both the Khurkh and Khuiten valleys. In the same period, 9.7% of the non-vegetated area was changed into wetland, more significantly in the middle of the Khurkh valley. Furthermore, in the same period, there were no significant changes in conversion of non-vegetated areas to vegetated area.

Table 7. Changes in classes between 2014 and 2017.

	Classes	2017, percent			
		Open water	Wetland	Vegetated area	Non vegetated area
2014, percent	Open water	12.7	35.4	47.2	4.7
	Wetland	7.4	37.3	47.9	7.4
	Vegetated area	0.0	2.7	97	0.3
	Non vegetated area	2.2	9.7	0.0	88.0

Table 8 shows percentage of class conversions between 2017 and 2019. The most frequent changes were observed for wetland to vegetated area with 70.3% in the south-east of the Khurkh valley and in the Khuiten valley; the change mostly occurred in the south-east and north-west. Also, around 64.8% of the non-vegetated area was changed to wetland, mostly in the north-east of the Khurkh valley. Furthermore, part of the change from non-vegetative area to wetland occurred at the edge of the wetland in the Khurkh valley. As to open water, around 37.4% was converted to wetland, mostly in the middle of the Khurkh valley close to the wetland area. At the same time, approximately 14.9% of the open water class was changed to vegetated area. A total of 21.6% of open water was converted to non-vegetated area, mostly in between the north-east and middle of the Khuiten valley between 2017 and 2019. Around 0.2% of wetland was converted to open water, mostly along the rivers in both the Khurkh and Khuiten valleys as well as the middle of the Khurkh valley. Also, from 2017 to 2019, around 0.4% of wetland in the study area was changed to non-vegetated area, mostly along the rivers' edge, wetland area edge and cropland area edge. Furthermore, there was also no significant change between vegetated area to open water class (Fig. 12).

Table 8. Changes in classes between 2017 and 2019.

	Classes	2019, percent			
		Open water	Wetland	Vegetated area	Non vegetated area
2017, percent	Open water	26.1	37.4	14.9	21.6
	Wetland	0.2	29.1	70.3	0.4
	Vegetated area	0.0	0.15	98.4	1.4
	Non vegetated area	0.9	64.8	26.1	8.2

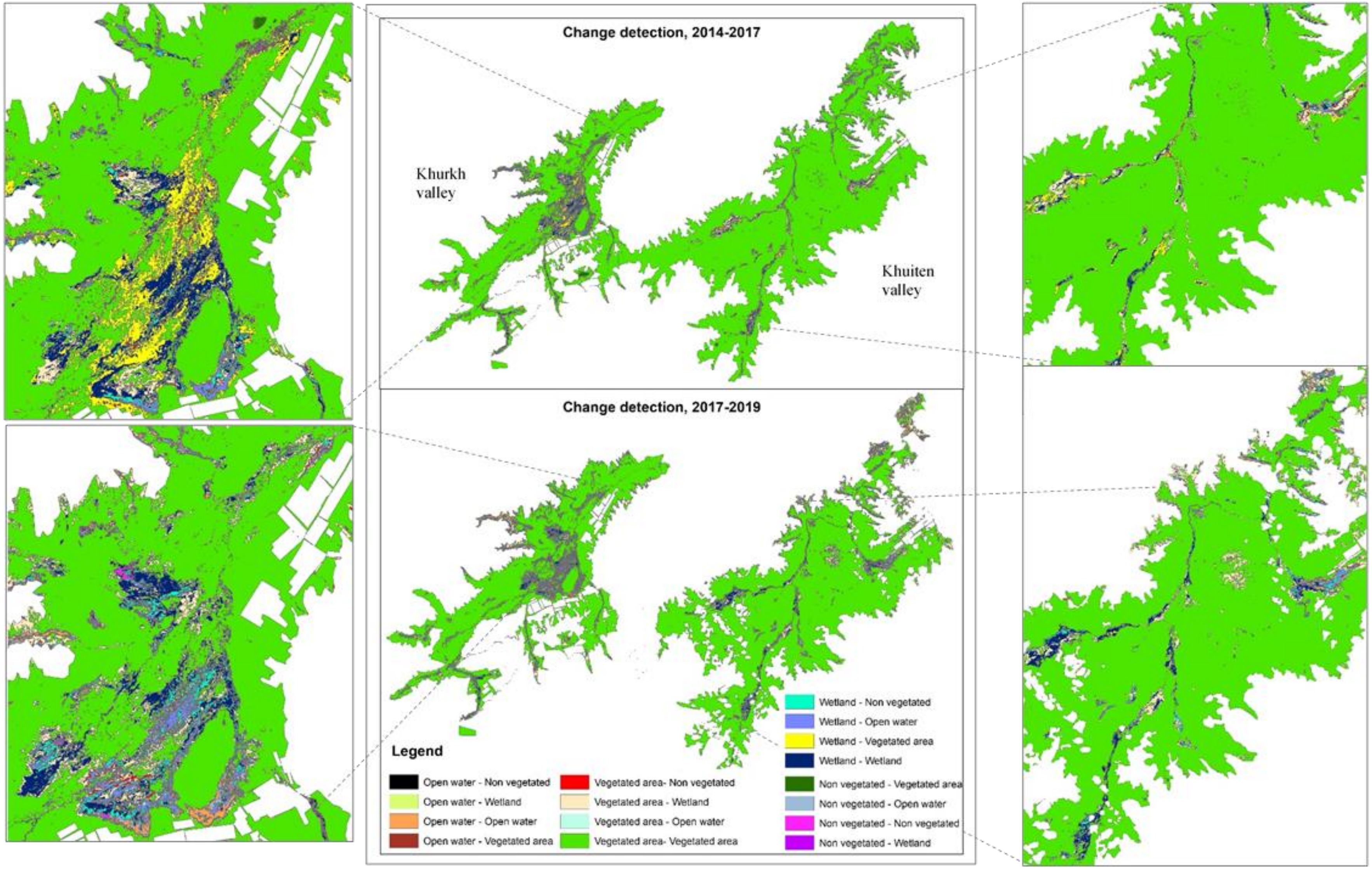

Figure 12. Change detection in the classes from 2014 to 2017, and from 2017 to 2019.

5. DISCUSSION

5.1 Normalized Difference Water Index values

In order to distinguish the four classes of features in this study, the NDWI for each of the classes was computed. Both the wetland and vegetated areas' NDWI extracted positive and negative values, due to a lack of clear distinguishing values between them. Certain vegetation characteristics of wetlands could be another possible reason, too. Some vegetation that extracted negative NDWI values in these classes might have indicated the NDWI values of dry vegetation which has negative values as wetlands consist of both aquatic and terrestrial characteristics. The study found that bare soil had also both positive and negative values (see Table 3). The NDWI values for bare soil were both negative and positive because some areas of the bare soil were previously under the open water body class and as such spectral differences between the classes could not be significantly distinguished. According to the result of the NDWI values, the data could clearly distinguish open water. On the other hand, classes of wetland, vegetated area and non-vegetated area were not clearly distinguished (Fig. 9). According to Ozesmi and Bauer (2002), wetland types were difficult to classify based on spectral characteristics because of a mix of water and vegetation. However, the class of open water was spectrally very clear. Thus, the findings of the NDWI values between some classes did not show spectral differences such as wetland, vegetated area and non-vegetated area.

5.2 Classification overview

According to the results, the classified area for open water increased by 0.1% from 2014 to 2017 and by 1.9% from 2017 to 2019 (Table 5). On the other hand, the wetland classified area decreased by 2.2% from 2014 to 2017 but increased by 4.7% from 2017 to 2019. The expectation of the researcher was that the wetland cover in the study area would decrease from 2014 to 2017 and 2019. Instead, the findings revealed that wetland cover increased from 2017 to 2019. The reason for this increase might be related to the fact that the study area experienced a huge rainfall amount in 2019 (figures 2 and 3). The high rainfall might have boosted the wetland cover. Yuan et al. (2005) found that magnitude of wetlands may change from year to year because of different amounts of precipitation. Also, these changes can be influenced by the spectral characteristics of the SWIR band that is one of the bands for defining an NDWI. As defined by Gao (1996), the SWIR band is sensitive to water change due to the NDWI, as indicated, and should therefore be sensitive to total amounts of liquid water changes.

With regards to vegetation area, the findings revealed that the area increased by 1.4% from 2014 to 2017 and then decreased by 8.1% from 2017 to 2019 (see Table 5). The decrease in vegetation area from 2017 to 2019 might be a result of too high rainfall which caused floods in the study area, based on the information gathered. The high rainfall might have caused fluctuations in the vegetated area class from 2017 to 2019. This is supported by the fact that the changes were more prominent in the low-lying areas of the research area. The occurrence of these floods might have affected the vegetation cover in 2019. However, the non-vegetated area increased during the study period. The increase in the non-vegetated area might have been a result of the high rainfall experienced in 2019 which might have caused landslides and a lot of eroded soils to be washed over the riverbanks and therefore increased the non-vegetated area.

5.3 Accuracy assessment

The classification achieved 52.8% overall accuracy which might be a result of a relatively small number of points for collecting ground truth data (440 points) and validation points compared to the size of the study area (292580.3 ha). Another reason for the overall accuracy would be the fact that the accuracy assessment used only two classes instead of four. Only two classes were used because there was limited ground truth data for the other two classes. Producer's accuracy reflects the accuracy of classes derived from satellite data. According to the study findings, the producer's accuracy was 63.8% for the wetland class. The producer's accuracy was not greater as wetland and vegetated area could not be distinguished from each other's class because of the spectral mixing of the classes (Fig. 9). The user's accuracy for the vegetated area was found more reliable with 79.6%; however, this again was based on input data that were flawed.

5.4 Change detection overview

According to the results, the most frequent changes in both time periods between 2014 and 2017 and between 2017 and 2019 involved conversion of wetland to vegetated area (47.9% and 70.3%, respectively). From the results, the detected changes from wetland to vegetated area appeared to be quite high. These changes might have been influenced by the fact that wetland consists of both terrestrial and aquatic characteristics which may have affected the accuracy of the results. Similarly, the open water class indicated high changes to the non-vegetated area, wetland and vegetated area between the study years. In both cases, misclassification and the sensitive characteristics of the NDWI might have also affected determination of the change. Also, relatively rare and unlikely types of conversions were revealed in this study, such as wetland to open water and non-vegetated to wetland. Thus, it is suggested that this might have been caused by the high rainfall in the study area in 2019.

According to the results presented in Table 5, the classified area for open water increased by 0.1% from 2014 to 2017 and by 1.9% from 2017 to 2019. On the other hand, wetland classified area decreased by 2.2% from 2014 to 2017 and increased by 4.7% from 2017 to 2019. The expectation of the researcher was that the wetland cover in the study area would decrease from 2014 to 2017 and 2019. Instead, the findings revealed that wetland cover increased from 2017 to 2019. The reason for this increase might be related to the fact that the study area experienced high rainfall in 2019. The high rainfall might have boosted the wetland cover in the sense that it might have caused a lot of down pools and flooding causing an increase in the surface area of wetland classes sensitive to the amount of water.

Also, the classification results revealed that the open water class increased only a small percent of around 0.1% from 2014 to 2017 and it also indicated a small number of changes of approximately 1.9% from 2017 to 2019 (Table 5). However, findings of the change detection showed that that there was a high number of conversions of open water to open water class, or 12.7% from 2014 to 2017. From 2017 to 2019, the open water class conversion also indicated a high number of conversions that was 26.1%. (Table 7 and 8). This high number of conversions in the open water class could have been caused by similarity in spectral ranges of classes and could also have been influenced by high rainfall. This is supported by the argument of Gao (1996) that the SWIR band has similar vegetation scattering characteristics as the NIR band. However, the SWIR band is sensitive to liquid water changes. Therefore, the NDWI is sensitive to changes in vegetation water content.

According to the study findings, between 2014 and 2017, and between 2017 and 2019, the vegetated area was changed to non-vegetated area, mostly in areas closer to cropland, at the edge of open water and edge of the wetland area. Furthermore, conversion of vegetated area to non-vegetated area mostly occurred in higher areas (around 1183 m above sea level), that is, situated close to mountain area. The lowest point of the study area was 945 meters above sea level, while the highest point was 1200 meters above sea level. Also, conversion of wetland to non-vegetated area was 7.4% between 2014 and 2017, while between 2017 and 2019, it decreased to 0.4%. Between the same periods the wetland change to non-vegetated area mostly occurred along the edges of the rivers, edge of wetland and close to cropland. According to statistical data of Mongolia, the total area of cropland in 2018 was 10,686 ha (Mongolian Statistical Information Service 2018).

In addition, some of the conversions of the vegetated area to non-vegetated area mostly occurred in high areas located close to mountain areas. The vegetation area changes in the high areas might have been the result of high rainfall that washed away soil particles into the valleys, thereby creating bare soil. The high rainfall might also have resulted in huge soil deposits at the lower elevations along the mountains causing an increase in bare soils in those areas.

5.5 Evaluation of study findings

5.5.1 Limitations

Ground truth data were gathered from 500 points because 100 to 120 ground truth points were planned to be used for each of the four classes for calibration and validation sections. Thus, 500 points were the minimal number of points that were needed in order to have an equal distribution of points between each class. Out of the 500 data collection points, 440 points were used in the study. The data from 60 points could not be used because the research area was altered. Ground truth data were categorized into 4 classes, which were open water, wetland, vegetated area and non-vegetated area. In the calibration section, all 4 classes were employed. However, in the validation section, only 2 of the 4 classes were used (wetland and vegetated area) because data from the open water and non-vegetated area were too limited to separate validation and calibration sections. As a result, overall accuracy was not very high because of the limitation of validation points. Thus, increasing the number of points for ground truth data could have improved the overall accuracy. Furthermore, there was an issue on how the data points were placed in each class in the field data classification which might have resulted in inconsistency between field and satellite data. In addition, there was a minimal number of calibration and validation points for all classes, which might have affected the overall accuracy in this study. The research period chosen might also have influenced the results of this study in the sense that this study might have shown very different results at different times of the year when wetland would be more easily detected and outlined. Also, there are several other issues that might have affected the overall accuracy and findings of this study which include: spectral mixing of classes, issues with the spatial characteristics of Landsat, the temporal resolution and the meteorology of the study area.

Open water, wetland and non-vegetated area were distinguished based on NDWI value. Most researchers use several indices in wetland change detection studies that can indicate high overall accuracy such as NDWI, NDVI and WRI (Berhane et al. 2018; Gao 2018). In addition, NDWI was sensitive to rainfall based on station data. There were limited previous studies on wetland and wetland mapping using remote sensing from Mongolia. This was one of the limitations in sourcing secondary data related to this study.

5.6 Further research

In this study, NDWI was utilized for determining wetland changes within 5 years. One of the advantages of using NDWI is that it is appropriate for detecting wetland location and changes. NDWI can be used for detecting aquatic changes when a researcher has limited time, limited financial resources and cannot manage to go to large areas for monitoring. Elimination of these obstacles would allow the use of both NDWI and NDVI. Using more than one index in this study could have improved the overall findings of the study. Therefore, it is recommendable to conduct further research with a focus on the following areas: further work at different temporal scales, at high spatial resolutions with differently defined research areas, and studies looking for a correlation between areas of negative and positive change at various scales and attempting to identify key factors related to both. It is highly advisable to improve the methodology in order to obtain more accurate results.

6. CONCLUSIONS AND RECOMMENDATIONS

6.1 Conclusions

The findings of this study suggest that remote sensing can be a relatively reliable method to evaluate wetland condition and changes in large areas. Furthermore, the results indicate that further improvement in methodology and data analysis can significantly improve the analysis of wetland condition. Also, the findings from this study revealed several interesting features requiring more detailed further research. These include the possibility of correlation between areas of negative change in NDWI values over time in relation to human activities in the study area including increased livestock production. In addition, improvements in the definition of the research area by dividing it into smaller and more detailed areas would significantly improve the results.

Furthermore, several issues came up in this research, therefore, the results were not sufficient to draw more accurate conclusions on the current state of wetlands or the change detection between the study years in the study area. However, this study has managed to identify areas of interest which require further research. Lastly, refinement of methodology and analysis of this study would improve the results.

6.2 Recommendations

Wetlands are important to human life, biodiversity and landscape processes. However, through this study, it was discovered that previous wetland studies were limited in Mongolia with the exception of one report on strategic planning for peatlands in Mongolia (ADB 2017). For example, in Mongolia, wetland studies are not well recognized. Therefore, there is an urgent need for conducting more wetland studies in Mongolia. Also, there is a need for designing a proper wetland map of Mongolia.

Social studies awareness and conception of local communities that are related to wetlands are essential in wetland management, monitoring and sustainable existence of wetland (Shrestha 2013). Therefore, there is a need to conduct further studies focusing on local communities and their understanding of wetlands. Such studies can greatly contribute to sustainable wetland management.

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