Grassland degradation patterns and causes, and the effectiveness of protected areas in Mongolia

Committee members:

Dr. Volker Radeloff

Dr. Anna Pidgeon

Dr. Mutlu Ozdogan

Dr. Randy Jackson

Dr. Philip Townsend

PhD candidate Elbegjargal Nasanbat,

Supervisor: Dr. Volker Radeloff

Date:04/20/2023

Summary

Mongolia has some of the most-intact grasslands remaining globally. However, Mongolia's grasslands are threatened by degradation due to climate change, overgrazing and other disturbances. Degradation can manifest itself both as a loss of vegetation cover, or as a change in vegetation communities. Monitoring degradation is challenging though and requires new remote sensing approaches, such as cumulative endmember fractions, and community classifications based on convolutional neural networks. Better degradation estimates - in turn - allow to identify the drivers of degradation. Protected areas can safeguard grassland biodiversity, but only if they are effective, and novel degradation measures can be used to measure their effectiveness.

The overarching goal of my proposed research is to map and assess the patterns of grassland degradation in Mongolia with medium-resolution Landsat imagery, both in terms of vegetation cover and vegetation communities, link the observed degradation to livestock numbers, climate drivers, and other disturbances such as Brandt's vole, and assess if protected area have been effective in stopping or even reversing grassland degradation.

My project has four major objectives:

a) estimate the long-term trends in grassland degradation from the full Landsat archive (1987 – 2022) based on cumulative endmember fractions parameterized with field spectroradiometer measurements and validated with biomass and vegetation cover field data.
b) quantify change in grassland vegetation communities based on convolutional neural networks (CNNs), by capitalizing on phenological differences of dry versus wet years.
c) identify the main drivers of grassland degradation (both long-term trends of cumulative endmember fractions and change in vegetation communities) focusing on climate, livestock numbers, and Brandt's vole distributions.
d) investigate the effectiveness of protected grassland areas, which are important for plant biodiversity and migrating ungulates, in stopping or even reverting grassland degradation.

Scientifically, I will contribute new knowledge by identifying the drivers of grassland degradation including climate, livestock grazing, and their interactions with other disturbances such as Brandt's voles, which are part of the natural ecosystems, but exacerbated by overgrazing.

Methodologically, my project will be the first to parameterize cumulative endmember fraction analyses with field Spectro-Radiometer data and validate fractions with field biomass and vegetation cover data. I will analyze data from a range of NASA assets, focusing on Landsat, but also MODIS data, and use advanced statistical and image analysis methods Spectral Unmixing, LandTrends, remotePARTS and Matching analysis for satellite data.

In terms of management and conservation, I will provide base-line data for sustainable livestock management and assess the effectiveness of Mongolia's growing protected area network, and of large herbivore habitat.

Timeline

My PhD started on 01/01/2021 and I am planning to finish in August of 2026.

Year	2021				2022				2023				2024				2025				2026	
Quarter	1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4	1	2
Objective 1	F	D	D	D	D	F	D	D	D	D	D	A	A	A	A	MP	MS					
Objective 2										F	D	D	D	D	D	A	A	MP	MS			
Objective 3														D	D	D	A	A	A	MP	MS	
Objective 4																D	D	D	A	A	MP	MS

D-Data processing, A-Analysis, MP-Manuscript preparation, MS- Manuscript submitting

Table of Contents

INTRODUCTION

Grassland biomes throughout the world are threatened by human activities and climate change (Scholtz and Twidwell 2022) even though these issues are strongly highlighted in the 15th of the United Nations Sustainable Development Goals for 2030 (Wang et al. 2020a), which focuses on land degradation, desertification, and biodiversity loss. Some of the most-intact grasslands remaining anywhere in the world are in Mongolia, including the montane grasslands of the Hentii and Hangai mountains, and the Daurian, Mongolian-Munchurian grasslands in eastern plains of Mongolia (Scholtz and Twidwell 2022). These steppe grasslands are important for wildlife conservation, biodiversity, and rural livelihoods (Chuluunkhuyag et al. 2021; Cromartie et al. 2020; He et al. 2018; Jürgensen et al. 2017; Lushchekina et al. 1999; Olson, Murray, and Fuller 2010; Shukherdorj et al. 2019; Zheng et al. 2008). However, Mongolia's grassland ecosystems are quite sensitive to overgrazing and climate variation (Li et al. 2005). In recent decades, Mongolia's grasslands have substantial declined in extent (Ykhanbai et al. 2004), and degradation resulted in a 70% decline in productivity (Hilker et al. 2014).

In addition to lower productivity and biomass, grassland degradation in Mongolia also resulted in a shift in plant community composition, from highly-productive perennial grass species (Agropyron cristatum, Cleistogenes squarrosa, Elymus chinensis, Stipa Krylovii, Stipa gobica/glareosa) to low productive or ruderal annual species, and higher proportions of forbs (Allium spp., Artemisia frigida, Artemisia sieversiana, Artemisia Adamsii, Chenopodium spp. species, Heteropappus hispidus, Caragana spp. species) (Jamiyansharav et al. 2018; G. Wang et al. 2019). The main causes for grassland degradation are increasing grazing pressure and changing climate condition (John et al. 2013; Sainnemekh et al. 2022a). Grazing intensity has increased because the number of livestock has gone up from about 25 million in 1990 to 67 million in 2020 (Hilker et al. 2014; Reading, Bedunah, and Amgalanbaatar 2010). Furthermore, there has been a shift towards more goats due to cashmere's increasing price, but goats are most detrimental to grasslands (Addison et al. 2012; John et al. 2016; Mundlak and Huang 1996; Xu et al. 2019). Particularly, when there is a lack of rotational grazing, this can exacerbate degradation, especially when combined with other disturbance (Chen et al. 2015; Hilker et al. 2014; John et al. 2016; Li, Wu, and Huang 2012; Liu et al. 2013; Ojima and Chuluun 2008), such as Brandt's vole (*Lasiopodomys brandtii)* (K. Li et al. 2017). Brandt's voles now occur on about 40 million ha in Mongolia (Munkhnasan 2019). These interactions of natural and human disturbances highlight that Mongolia's grasslands are coupled human natural system (Allington, Li, and Brown 2017; Chen et al. 2015; Liu et al. 2013; Qiongyu Huang et al. 2022).

Remote sensing data has been key to monitor changes in Mongolia's grasslands (Li et al. 2019; Meng et al. 2020a; Shao et al. 2017), identify the causes for these changes (Sternberg 2012), and assess the effects of grassland changes on rural livelihoods (Chen et al. 2018) and ecosystems (Z. Li et al. 2017; Yang and Du 2021). Nation-wide studies typically have relied on coarse-resolution MODIS and AVHRR imagery (de Beurs and Henebry 2004; Eckert et al. 2015), and focused on trends in vegetation indices (de Beurs and Henebry 2004; Eckert et al. 2015; Hill and Guerschman 2022; Hostert, Röder, and Hill 2003; Lamchin et al. 2020; Lewińska et al. 2021; Li, Fassnacht, and Bürgi 2021; Vermeulen, Munch, and Palmer 2021; Jie Wang et al. 2019; H. Yu et al. 2019; Zeng et al. 2003). However, surface fractions of green vegetation, non-photosynthetic vegetation, and soil offer advantages over vegetation indices when assessing degradation (Lewińska et al. 2020), and medium-resolution Landsat imagery may be better suited to identify grassland degradation and grazing effects (Lewińska et al. 2021). Furthermore, neither vegetation indices nor surface fractions can capture changes in plant species composition, and new approaches are needed to capture that aspect of grassland degradation. Such analyses require detailed field data though, including spectral measurements, biomass estimates and plant surveys.

One approach to safeguard grassland ecosystems is to establish protected areas, and Mongolia has greatly expanded its protected area network in recent decades (Jargal 2003). These protected areas are important for local flora (Shukherdorj et al. 2019) and for the iconic ungulate migrations of Mongolian gazelles (*Procapra gutturosa*), Goitered gazelle (*Gazella subgutturosa*), Saiga antelope (*Saiga tatarica mongolica*), and Onager (*Equus hemionus*) (Jürgensen et al. 2017; Lushchekina et al. 1999). However, it is unclear how effective Mongolia’s protected areas are in stopping, or even reverting, grassland degradation (Badarch et al. 2011). Globally, many protected areas are both directly and indirectly affected by human activities (Radeloff et al. 2010), including those in forested regions (Andam et al. 2008; Bragina et al. 2015; Butsic, Munteanu, et al. 2017a). Even land-use change and human activities in the surroundings of protected areas can cause harm by disrupting ecological processes and restricting organism’s movement (Hamilton et al. 2013). Econometric approaches (Butsic, Lewis, et al. 2017), such as propensity score matching, have been widely used to quantify the effectiveness of forested protected areas in stopping deforestation (Bragina et al. 2015; Brandt et al. 2019; Butsic, Munteanu, et al. 2017b; Sieber et al. 2013), and may also be valuable to assess the effectiveness of Mongolia’s protected grasslands (Jürgensen et al. 2017; Lushchekina et al. 1999).

1. Study area

My study area includes all of Mongolia (1,566,120 km^2) most of which is part of the central Asian temperate steppe’s grassland biome (Bliss 2016). Mongolia is a landlocked country at 42°–52° latitude and 88°–120° longitudes (Wang et al. 2020b), (Fig. 1.), bordered by China to the east, and south, and Russia to the north and west. Most of the country has a continental temperate climate, with pronounced seasonality (Batjargal 1997).

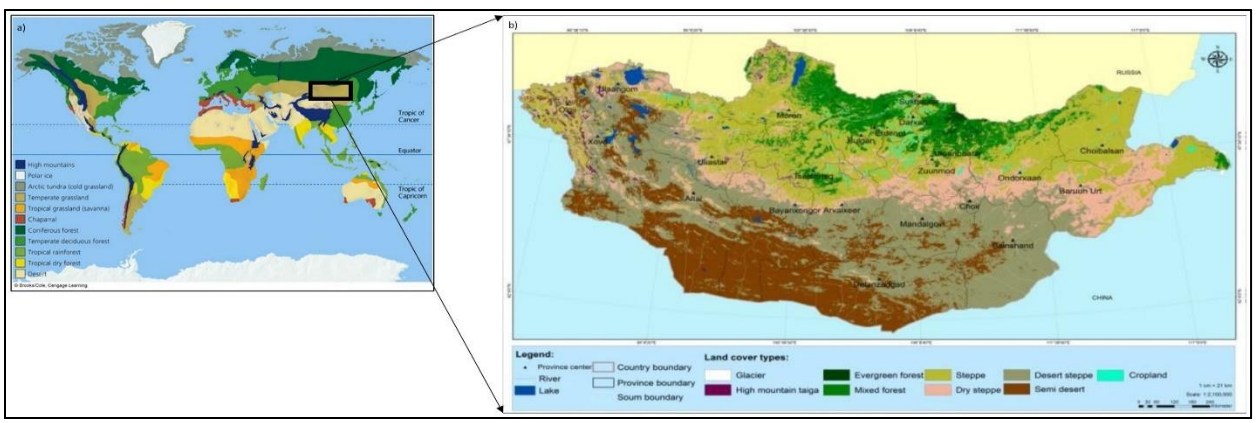

Figure 1. Study area (a) global biome map, and (b) Land cover map of Mongolia

Mongolia has a short growing season, high evaporation, and low precipitation, with an average precipitation of only about 120–250 mm, of which 70% falls during July and August (fig 2) (Dorjsuren, Liou, and Cheng 2016). During spring season there are often strong winds and unstable weather systems. This is also often the season when wild herbivores and livestock die due to the volatile weather conditions and because the animals are emaciated from the harsh winter season. Vegetation cover consists of Siberian coniferous forest in the north, and grasslands in the middle and central part transitioning to semi-deserts to the south (Wei et al. 2008).

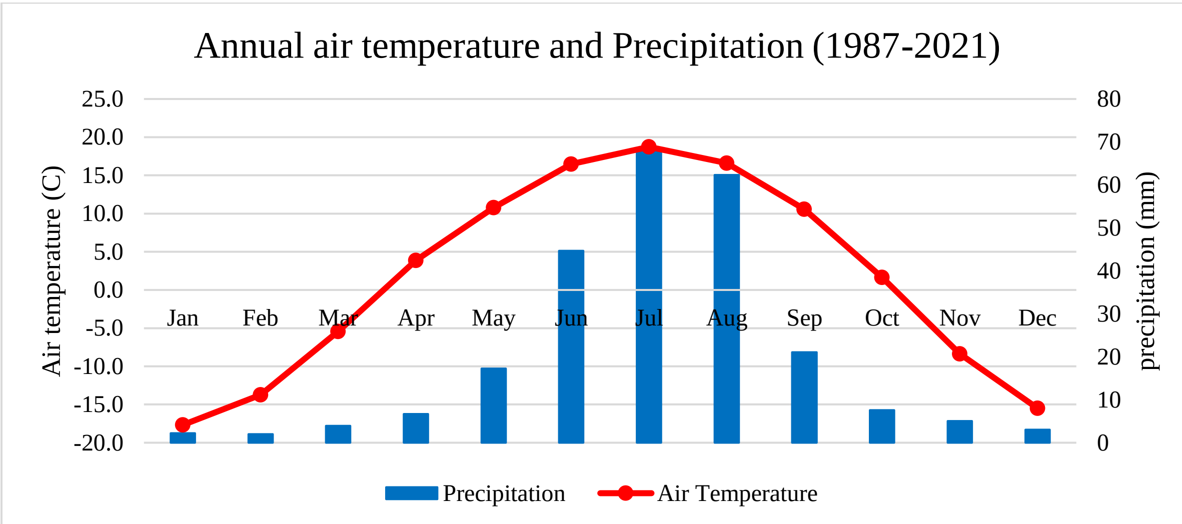

Figure 2. the annual time series of climate data (by average monthly between 1987-2021)

2. Goals and Objectives

The overarching goal of my proposed research is to assess the patterns of grassland degradation in Mongolia, identify its causes, and quantify protected area effectiveness.

Objective 1: To estimate long-term trends in grassland degradation based on annual cumulative endmember fractions parameterized with field spectroradiometer measurements and validated with biomass and vegetation cover field data.

Objective 2: To quantify change in grassland vegetation communities based on convolutional neural networks (CNNs), and phenological differences of dry versus wet years.

Objective 3: To identify the main drivers of grassland degradation (both long-term trends of cumulative endmember fractions and change in vegetation communities) focusing on climate, livestock numbers, and Brandt's vole distributions.

Objective 4: To investigate the effectiveness of protected areas in grasslands, which are important for plant biodiversity and migrating ungulates, in stopping or even reverting grassland degradation.

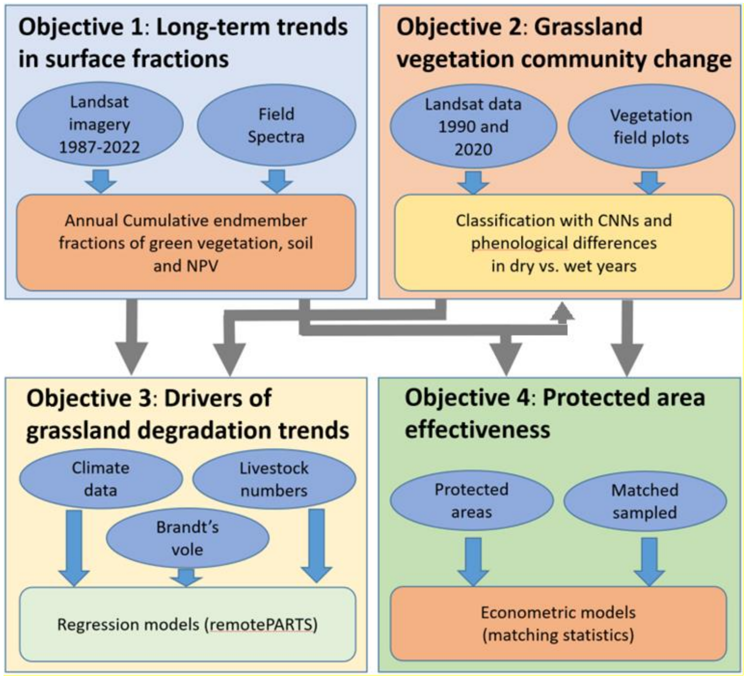

Figure 3. The framework of my research objectives and their linkages

CHAPTER 1: To estimate the long-term trends in grassland degradation based on cumulative endmember fractions parameterized with field spectroradiometer measurements and validated with biomass and vegetation cover field data.

1. Introduction

Grasslands cover about one-quarter of the Earth's land surface (Henebry 1993), making it important to monitor them accurately. In Mongolia, grasslands are widespread, and important parts of forest-steppe, steppe, desert steppe, and semi-desert ecosystems (Iwasaki 2006). However, during the 2010s, grasslands changed especially rapidly both in terms of species composition due to grazing but also in an increase of bare soil spots in the arid and semi-arid region due to the drought (Cao, Feng, and Wang 2016; Kang et al. 2021). Indeed, based on MODIS and AVHRR NDVI time series, grasslands have changed considerably (Chang et al. 2021; Chen et al. 2015, 2022; Enebish et al. 2020; Karnieli et al. 2006; Meng et al. 2020b, 2020a). However, vegetation indices can be affected by soil and rocks in areas with sparse vegetation, and MODIS data has coarse spatial resolution. Therefore, spectral unmixing of medium-resolution Landsat imagery based on field spectra may capture grassland degradation is probably better suited to assess grassland degradation (Okujeni et al. 2013, 2017; Schug et al. 2020; Vermeulen et al. 2021; Yue et al. 2021). Linear spectral unmixing models the reflectance curve of a given pixel as a linear combination of a set of field pure endmembers (green vegetation-GV, Non-photosynthesis vegetation-NPV and Soil) plus an error term (Hostert et al. 2003; Lewińska et al. 2021; Peddle, Hall, and Ledrew 1999; Radeloff, Mladenoff, and Boyce 1999). That is why Cumulative Endmembers Fractions can to overcome the limitation of analyses of NDVI at peak-greenness (Lewińska et al. 2020, 2021).

1.2. Analysis of objective

I will investigate grassland degradation trends across Mongolia over 35 years. To do so, I will combine remote sensing analysis (Lewińska et al. 2020, 2021) with statistical analyses (Alfonso Zamora Saiz et al. 2021; Ives et al. 2022; Tabachnick and Fidell 2019). My specific research question and hypotheses are:

1. How accurately can annual cumulative endmember fractions be generated based on field spectroradiometer data ?
2. What was the magnitude of grassland degradation change in steppe, dry steppe and desert steppe areas of Mongolia from 1987 to 2022?
   Hypothesis: *The magnitude of grassland degradation was greater in dry steppe areas then in other steppe areas*
3. What is the accuracy between the predicted endmember fraction and ground actual biomass and soil moisture?
   Hypothesis: *GV and NPV endmember fractions are positively correlated with biomass in steppe and dry steppe area.*

1.3. Sampling design

I selected my field sampling plots based on a stratified-random sample methods across Mongolia in 2021 and 2022, and my colleagues and I collected field spectra with an ASD-FieldSpec-4 Spectroradiometer (wavelength 350mn-2500mn) (Danner et al. 2015) in 330 samples, including spectra of green grass, Soil, and NPV grass, and also recorded corresponding GPS coordinates, and digital photos. In addition, I collected at the same locations soil moisture at 10 cm depth and clipped biomass (1x1 m plots) (Fig 4).

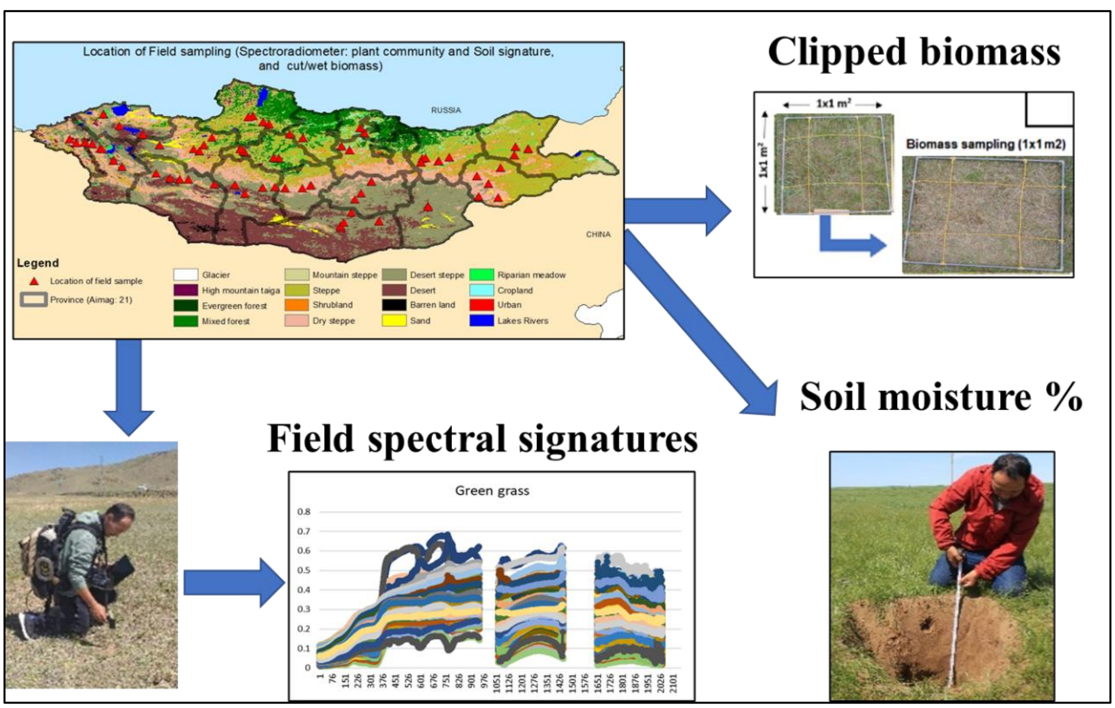

Figure 4. Study area (Mongolia) with locations of Spectro-radiometer (ASD 4) field samples of plant, and soils, plus measures of biomass, soil moisture, and photos.

2. Methods

I propose to conduct a spectral mixture analysis (Lewińska et al. 2020, 2021), based on field spectra, and analyze the entire Landsat archive for Mongolia from 1987 to 2022. I will conduct this analysis in four steps:

First, I will select endmember sets (GV, NPV and Soil) based on a collinearity and orthogonality analysis (van der Meera and Jia 2012). Specifically, I will calculate several statistical indicators including Pearson correlation coefficient, variance inflation factor and the singular value decomposition analysis to select the best endmember sets from field spectroradiometer signatures data across Mongolia.

Eq 1. Pearson correlation coefficient:

$$r = \frac{\sum x_i y_i - n\overline{xy}}{\sqrt{(\Sigma x_i^2 - nx^{-2})}\sqrt{(\Sigma y_i^2 - ny^{-2})}}$$

where: r is sample correlation coefficient, n is number of sample size, $x_i y_i$ are the individual samples with i, $\overline{xy}$ are mean of $x\ and\ y$ variables. In general, the value of correlation coefficients is represented between two or more variables below 0.7 is acceptable, but when the correlation is larger than 0.7 or even 0.9 is represents serious issue of multicollinearity among endmembers.

Eq 2.Variance of inflation factor (VIF):

$$VIF(i) = \frac{1}{1 - R_i^2}$$

where: R_i^2 is coefficient of determination of a regression. In generally values of VIF less than 3 are low and indicate no collinearity, less than 5 is moderate, and greater than 10 indicates severe collinearity (Becker 1999). The variance inflation factor-VIF (Fox and Monette 1992; van der Meera and Jia 2012; Senaviratna and A. Cooray 2019) has been widely applied in scientific literature to diagnose collinearity.

Eq 3.Singular Value Decomposition (SVD)

$$A = U\Sigma V^T$$

where: the columns of unitary matrices U and V are both square, and Σ is a diagonal matrix with an orthogonal singular value. The SVD analysis is commonly used in many applications including image compression, noise reduction of satellite images, and climate research (Baker 2005; Chitsaz et al. 2016; Ji and Fan 2019; C. Yu, Li, and Wang 2019). The singular value decomposition (SVD) converts a matrix A into a product of three matrices (fig 5).

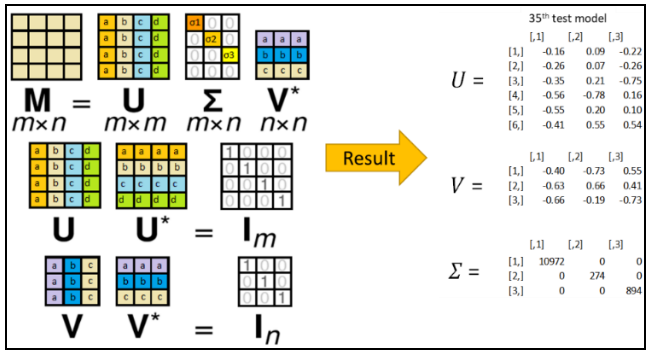

Figure 5. details of the Singular value decomposition (SVD)

Second, after I have selected my endmembers, I will apply a linear spectral unmixing for every Landsat image in the archive in Google Earth Engine, and calculate annual Cumulative Endmembers Fractions for each year (GV, NPV, soil and shade) following Lewinska et al., (Lewińska et al. 2020, 2021), which was developed by my research group in the SILVIS Lab. Linear spectral unmixing decomposes the measured spectrum of a mixed pixel into its constituent spectra, or endmembers, resulting in a set of corresponding image fractions that represent the proportion of each endmembers fractions present in the pixel (Uhrin and Townsend 2016). Different unmixing algorithms are based on variants of the linear mixture model (He, Yang, and Guo 2020; Uhrin and Townsend 2016). The formula is (Eq4):

Eq 4. linear spectral unmixing analysis *(LSMA)*

$$R_j = \sum_{i=0}^{n} f_i \cdot E_{i,j} + \varepsilon_j; \quad RMSE = \sqrt{\left(\sum_{j}^{m} \varepsilon_j^2\right)^{-m}}$$

where: R_j is the reflectance in wavelength band j, f_i fraction of field endmember i, $E_{i,j}$ is a reflectance of a spectrum of endmember i in satellite sensor band j, and ε_j is an error at the spectral bands j, and $RMSE$ is root mean square error of the ε_j, and n is number of endmember, and m is number of spectral bands in the discrete wavelength spectrum (Keshava and Mustard 2002; Lewińska et al. 2021). The cumulative endmembers provide annual estimates of the growing-season fractions of GV, NPV, Soil, Shade) for each Landsat Pixel, plus estimates of residual errors. I have already tested the linear spectral unmixing approach in Google Earth Engine for 126 different endmember sets derived from field spectral signatures, and for satellite data from July, 2021 to guide my endmember selection (fig 8 and 9).

Third, will estimate and identify the magnitude of short and long-term degradation trends of my cumulative endmember fractions using Landtrendr (Lewińska et al. 2021). If there are missing dates, which are not uncommon in the Landsat records, I will gap-fill them with a Whittaker filter (Lewinska et al. 2021 and Kong et al. 2019). Thus, the result of my Cumulative Endmember Fractions analysis will be an annual estimate of the fractions of growing season (GV, NPV, Soil, Shade) for each 30-meter Landsat Pixel, plus pixel-based estimates of residual errors and of uncertainties in the fraction, and the full time-series of grassland degradation trends as identified by LandTrendr. In generally, the LandTrendr's temporal segmentation involves repeated random-access calls to each pixel's time series in entire of frame image, resulting in a set of breakpoints that are "vertices" bounding straight-line segments, and "horizons" that represent magnitude of time duration over time series (Fig 6), (Kennedy et al. 2018). I also have implemented and tested the first three steps of my approach in western Mongolia (Fig 10).

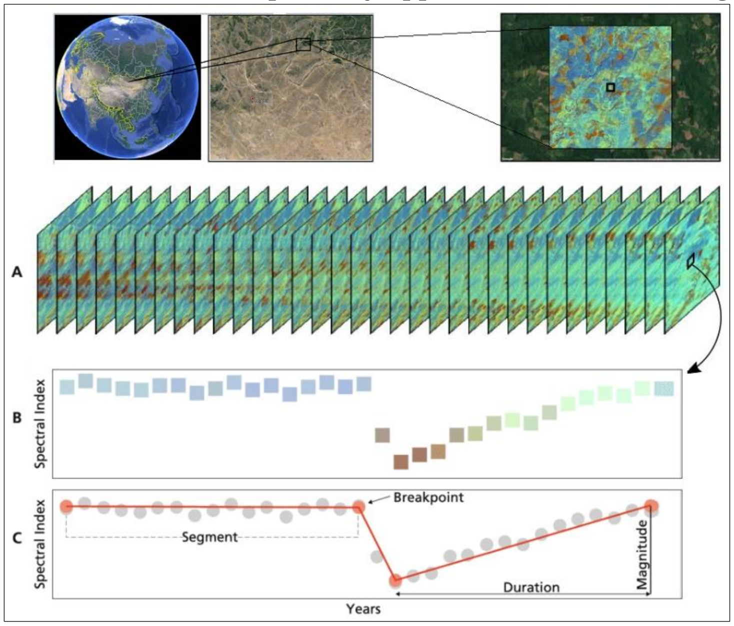

Figure 6. Overview of the change detection algorithm LandTrendr; a) contributions to a trajectory of a spectral index i.e cummulative endmember fractions, b) dectection of magnitude of LandTrendr, c) curve of magnitude of LandTrendr (de Jong et al. 2021; Lewińska et al. 2021), all implemented in Google Earth Engine (GEE).

Fourth, I will validate the long-term degradation LandTrendr based on vegetation cover and biomass field data from 1987 to 2022. Specifically, I will analyze dry biomass, soil moisture collected from 130 well-distributed Meteorological stations of the Mongolia Meteorological Agency for 10-day estimates during the growing season. I will conduct the Pearson correlation coefficient (r) for the relationship between my cumulative endmembers and the field estimates (Chang et al. 2017; Chen, Wang, and Fu 2020) (Eq1).

3. Expected results

The result of the analysis for my first chapter will be two primary products: first, the best spectral unmixing model field based to predict endmembers fractions maps such as GV, NPV, Soil and Shade (Fig 7, 8 and 10.); and second, long-term grassland degradation trend maps for the last 35 years derived from 30-m Landsat data. The maps will be accompanied by scatter plots to judge the linear relationship between the predicted variables (endmembers) and ground observation biomass (Fig 9).

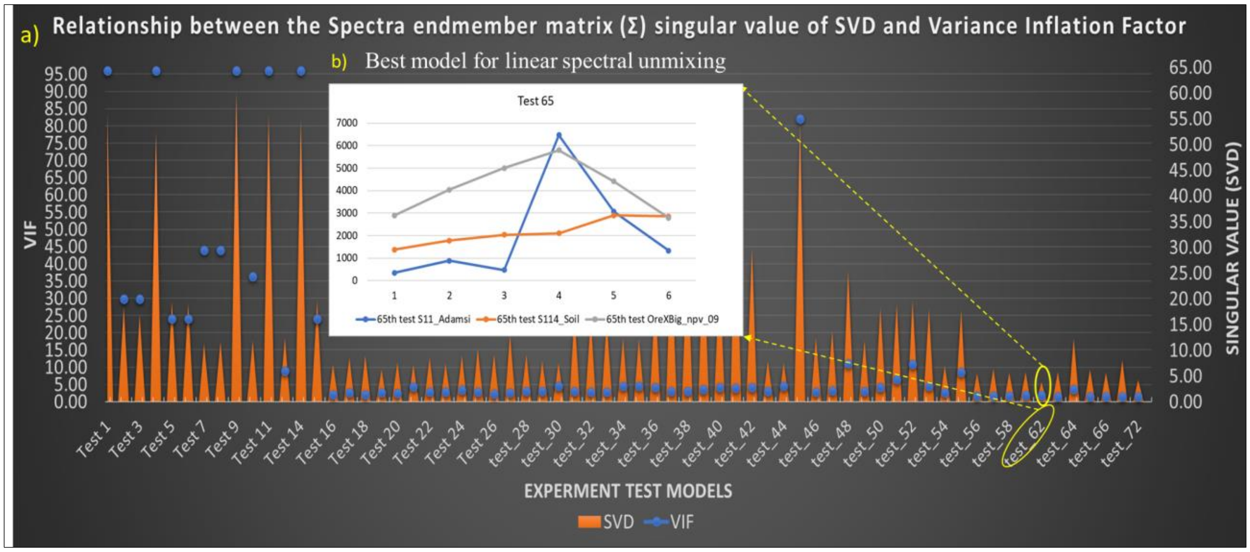

Figure 7. Preliminary result of the spectra endmember model selection by collinearity and orthogonality analysis; a) collinearity and orthogonality of the results; b) model selection.

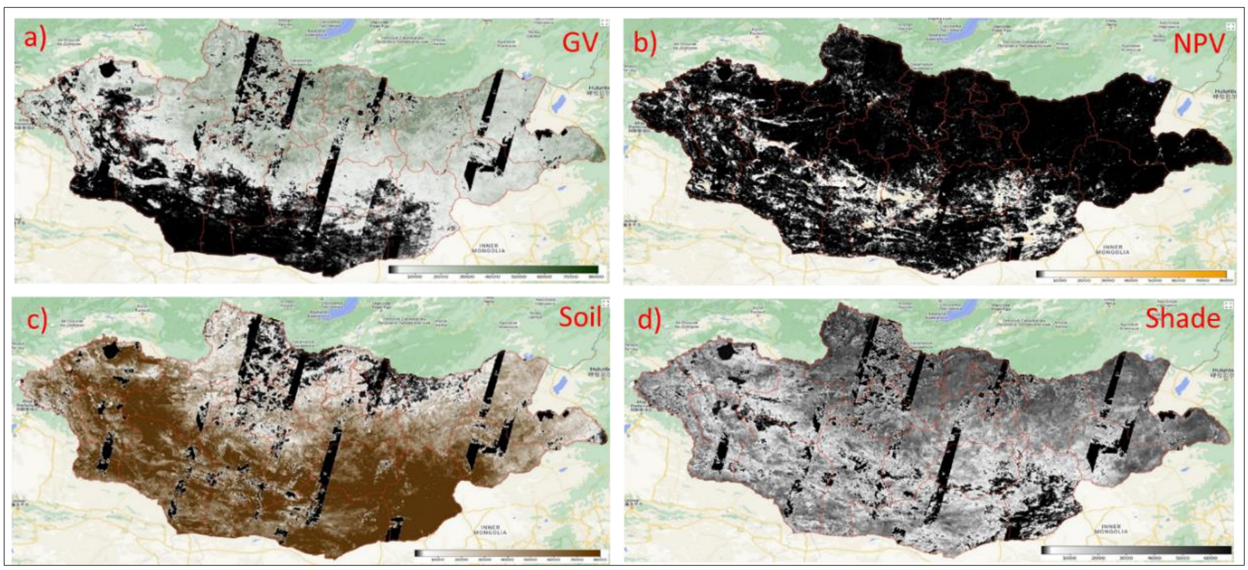

Figure 8. Preliminary result of the Spectral Unmixing model on July, 2021 (65th test model); a) GV map; GV fractions have a 63% correlation with biomass estimates, b) NPV map; 12% correlation, c) Soil map; 60% correlation, d) Shade map; 45% correlation, and e) RMSE ranging from 0-35%, and < 10% for most of Mongolia.

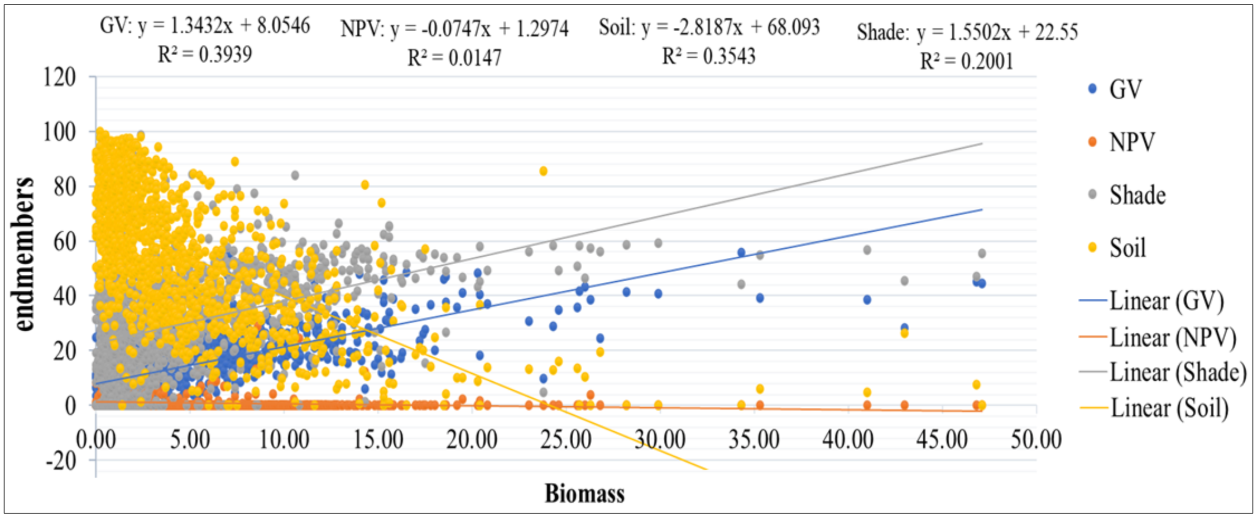

Figure 9. SMA's predicted variables (endmembers: GV, NPV, Shade and Soil) and ground observation biomass (Agrometeorological 1407 station)

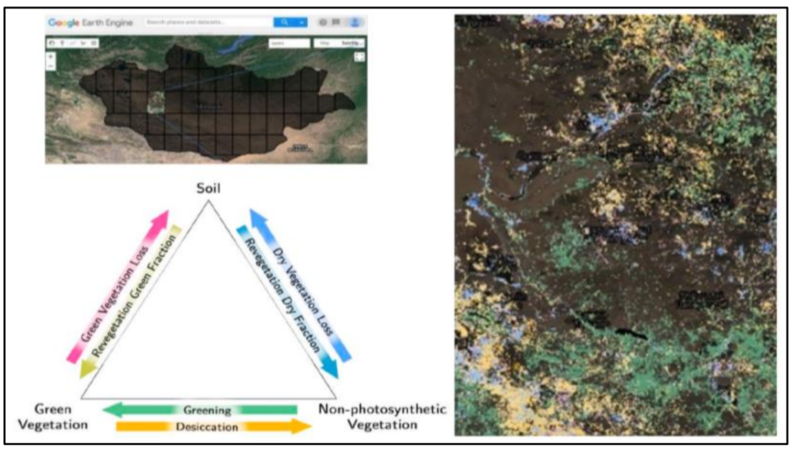

Figure 10. Preliminary analysis of one test area in west-Mongolia and the pathways of change among the different surface fractions from 1987 to 2020 (right).

4. Significance and contributions

My results will advance understanding of grassland degradation in Mongolia's 'steppe grassland ecosystem' because prior studies analyzed only coarse-resolution data, and they will be useful for pasture management, and desertification monitoring. Specifically, my datasets will be valuable for Mongolia's Desertification Center, the Geology Institute of the Academy of Science of Mongolia, and the Meteorological agency of Mongolia.

CHAPTER 2: To quantify change in grassland vegetation communities based on convolutional neural networks (CNNs), and on phenological differences of dry versus wet years.

1. Introduction

In Mongolia, a substantial increase in grazing intensity (Hilker et al. 2014; Khishigbayar et al. 2015), and drought (Chang et al. 2021) has led to a decrease in both the quality and quantity of grassland and pasture resources over the last few decades (Hilker et al. 2014; Li et al. 2019). Furthermore, grazing has caused significant loss of carbon from soil (Oates and Jackson 2014). There is substantial evidence that human activity and climate extremes both strongly affect the vegetation community composition in grassland ecosystems (Knick and Rotenberry 2002; Ma et al. 2010). Indeed, in Mongolia grassland degradation has resulted in lower productivity and biomass (Godde et al. 2020; Horie, Miyasaka, and Yoshihara 2023; Liu et al. 2019; Ma et al. 2010), but also resulted in a shift in plant community composition, from highly-productive perennial grass species (*Agropyron cristatum, Cleistogenes squarrosa, Elymus chinensis, Stipa Krylovii, Stipa gobica/glareosa*) to low productive or ruderal annual species, and higher proportions of forbs (*Allium spp. species, Artemisia frigida, Artemisia sieversiana, Artemisia Adamsii, Chenopodium spp. species, Heteropappus hispidus, Caragana spp.* species) (Jamiyansharav et al. 2018; G. Wang et al. 2019). That is important because for both grassland ecosystem services (Landis et al. 2018), and for grassland biodiversity changes in plant communities are just as important as changes in vegetation cover (Jamiyansharav et al. 2018; Lamchin et al. 2016; Yang et al. 2019).

However, classifying grassland plant communities from satellite imagery is challenging (Clark, Seyfried, and Harris 2001; Rapinel et al. 2019). So, while there is a large number of studies that focused on changes in vegetation communities in Mongolia (Aghababaei et al. 2021, Anon 2022; He et al. 2018; Jambal et al. 2012; Jamiyansharav et al. 2018; Lkhavgadorj, Iderzorig, and Kwon 2016; Oyundelger et al. 2020; Zemmrich, Hilbig, and Oyuunchimeg 2010), only a few studies used an integrated of remote sensing imagery with in situ measurements (Sainnemekh et al. 2022b). However, advances in machine learning, especially the development of CNNs, may offer an opportunity to classify plant communities and their changes over time shifts accurately (Chauhan and Ram 2018; Noi Phan, Kuch, and Lehnert 2020; Zhang et al. 2020). Particularly, deep neural networks (CNN) have ability to identify vegetation community changes (Kang et al. 2020). Furthermore, there are differences in phenology among communities during dry versus wet years, which may allow to distinguish them.

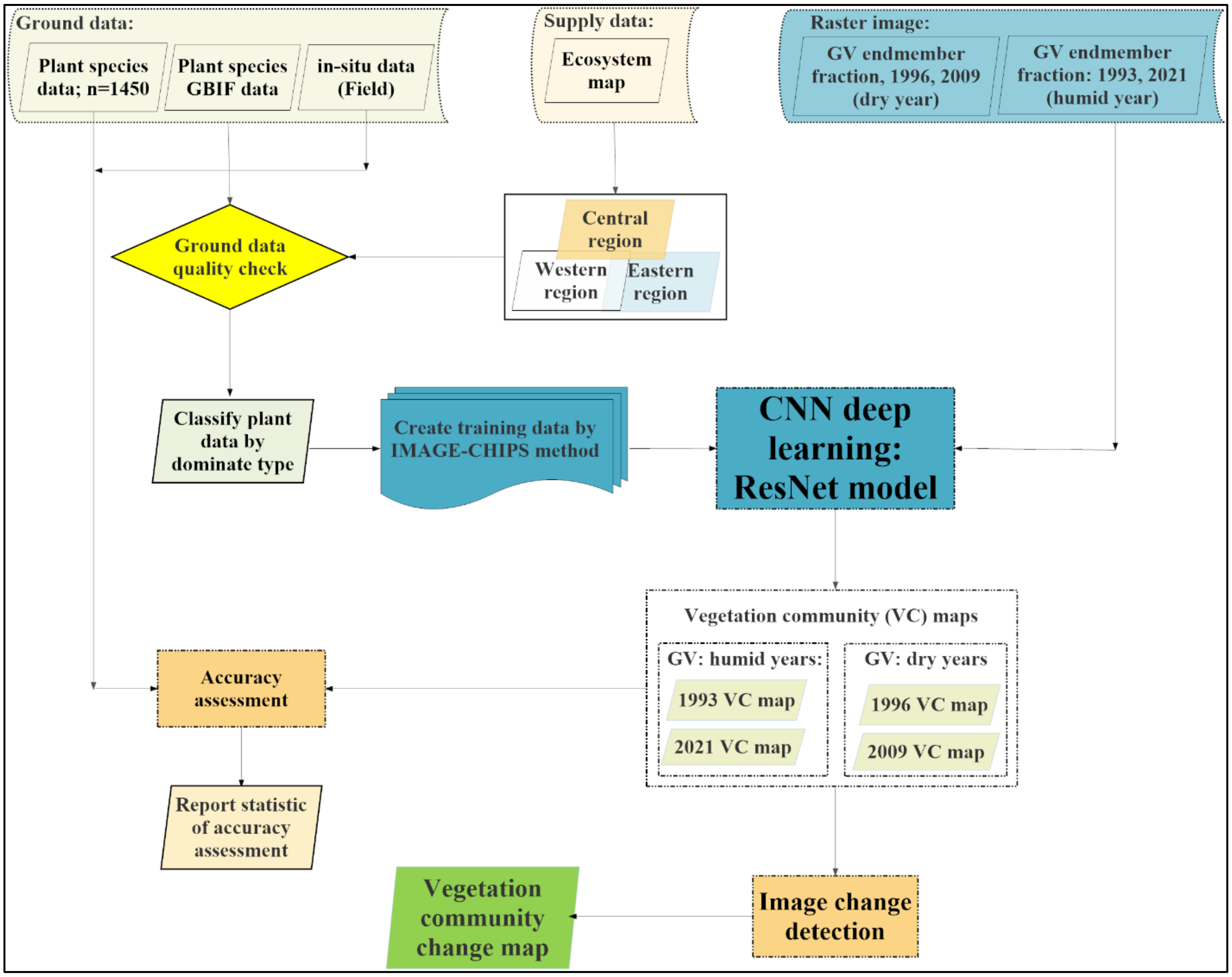

Figure 11. Flowchart of vegetation community classification

1.2. Analysis of objective

My goal is to determine vegetation community changes over 30 years, by deriving two vegetation maps that each use phenological differences between wet and dry years to capture vegetation communities accurately. I have two primary research questions and hypotheses:

1. Which type of vegetation community increases and declines in dry and humid years?

   Hypothesis: *In dry years, the perennial plant community mostly decreases, while the annual plant community increases*

2. How much have grassland communities in Mongolia changed?
   Hypothesis: There have been widespread changes from communities dominated by perennial grass species to those dominated by forbs

2. Methods

I propose to classify grassland vegetation community change from ca 1990 to ca. 2020. For each time point, I will implement four steps:

First, I will select a pair of years when climate extremes had a strong impact on the grassland vegetation community. For example, in drought years, grasslands are often dominated by unpalatable Artemisia spp, and Caraganna spp species that can adapt to the dry climate condition, while in wet years, palatable species of perennial grasses are more dominant in the semi-arid grassland region (Fig 12). In terms of the time points and data, 1993 and 1996 represent one nice pair of a wet and dry year, and so does 2020 and 2021. These different climate variations also affect plant phenology (Kariyeva and van Leeuwen 2012), which will help me to distinguish the dominant vegetation communities. The standardized precipitation evapotranspiration index (SPEI) (Stagge et al. 2016) is a good measure to identify wet and dry years (Beguería et al. 2014) (Fig 13) because three variables (precipitation, temperature, and evapotranspiration potential) are integrated in the SPEI (Nejadrekabi, Eslamian, and Zareian 2022). A global real-time drought monitoring system is operative, and provides global SPEI maps, time-series curve at 1^{o} resolution (Stagge et al. 2016).

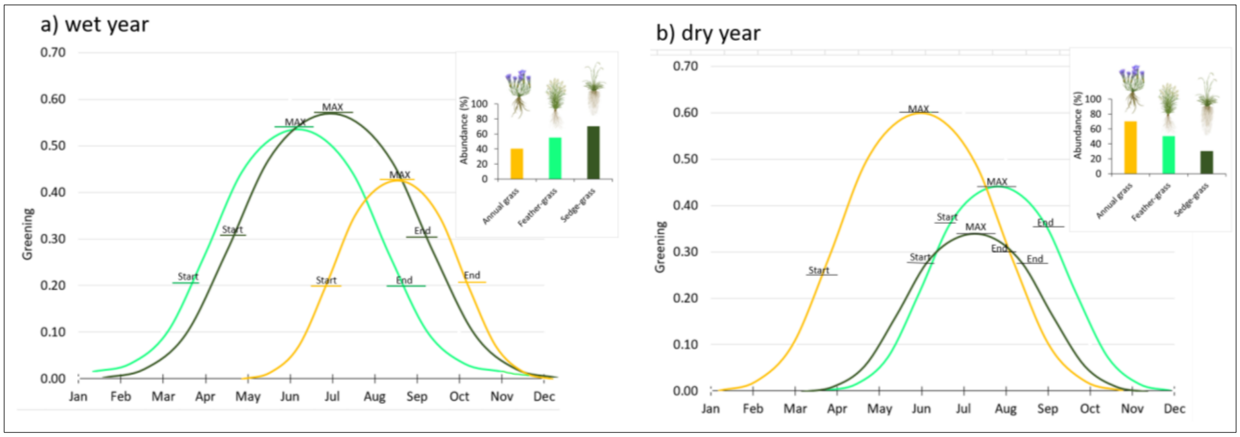

Figure 12. Semi-arid grassland of Mongolia (wet year and dry year's phenology metrics)

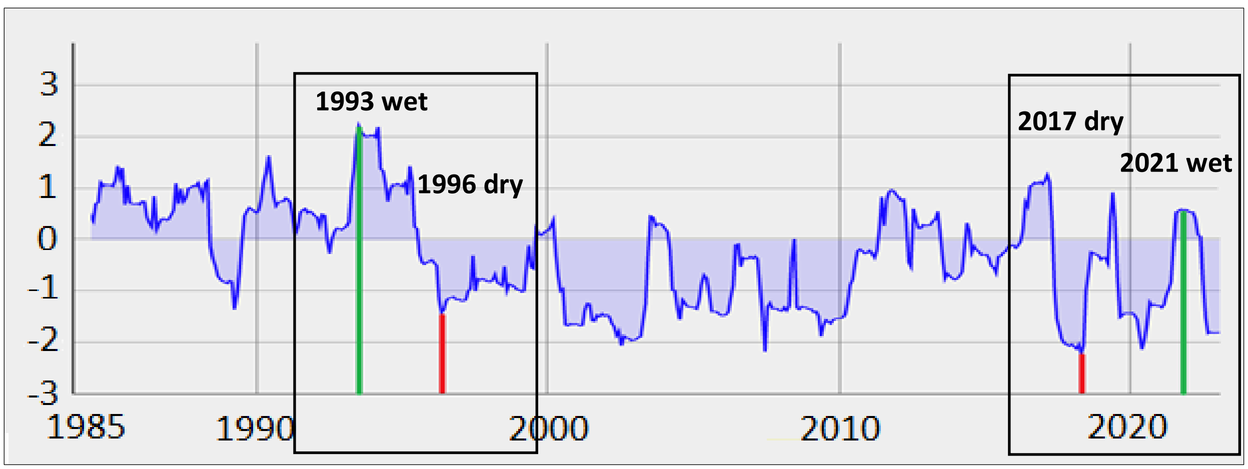

Figure 13. Time series SPEI drought index across Mongolia (1993, 1996, and 2017, 2021)

Second, I will develop a class catalog of the major grassland communities in Mongolia's dry, semi dry, and humid grassland regions, and select training samples based on plant species composition data collected by Mongolia's Meteorological Agency for 1450 sites for the national report on grazing impact monitoring of in Mongolia 2021(Sainnemekh et al. 2022b). For this survey, local meteorology technicians in 320 soum (counties) collect the primary data annually using a standardized methodology according to guide grassland management since 2012

(Sinclair et al. 2019). Aimag's (province) meteorological engineers ensure quality control and enter the monitoring data into the National Rangeland Monitoring Database.

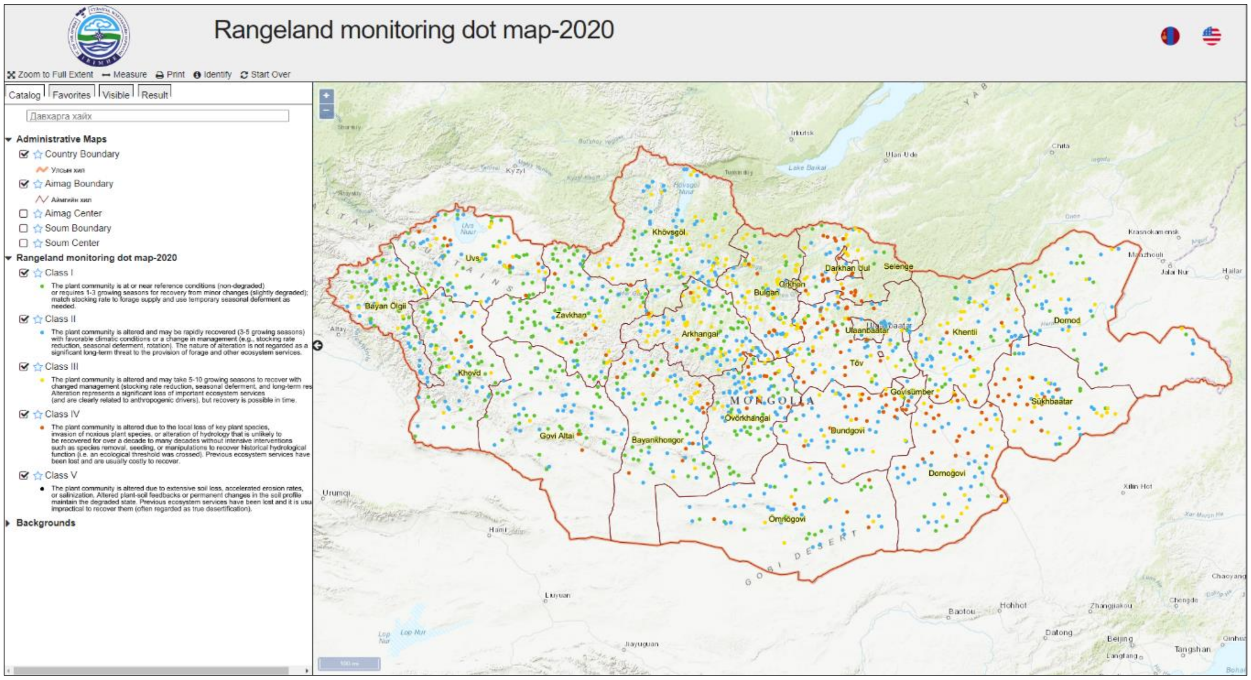

Figure 14. Mongolian rangeland monitoring sites (n = 1450).

Third, I will identify vegetation communities change by classifying the GV endmember fractions from my SMA, and apply the ResNet (He et al. 2016) model of CNNs deep learning algorithms (Saadeldin et al. 2022) on data for each of the paired year, and assess vegetation phenology metrics for the early 1990s and the late 2020 (Fig 12). For the CNN classification, I will use image chips (Hamer, Simms, and Waine 2021; Han et al. 2017) to create the training data surrounding the 1450 Mongolian rangeland monitoring sites, as well as in-situ data from vegetation community data in abandoned fields, which I will collect in 2023. In general, the CNN method is an artificial neural network that uses the local receptive field and shared weights (Sameen, M.I.; Pradhan and B.; Aziz, O.S. 2018). Deep learning methods can automatically learn the hierarchical contextual features from the input image and the ResNet architecture and provide a suitable platform to analyze satellite images (Bergado et al. 2016). In addition, information can be extracted at different levels including pixel-level, object-level, and patch-level. The architecture of CNN is based on several layers of operators (layers) in (Fig 15: 2D convolution layer, pooling layer (subsampling), and fully connected layer (Nahhas et al. 2018, and Husam et al. 2019).

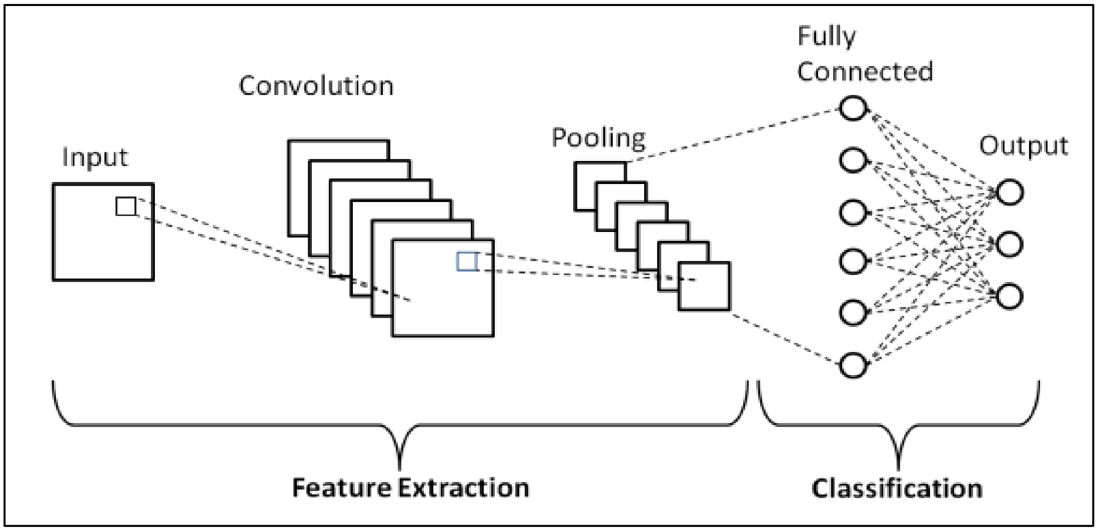

Figure 15. Workflow of the CNN Model (Phung and Rhee 2019)

Fourth, I will conduct a state-of-the-art accuracy assessment (Olofsson et al. 2013, 2014). For this, I will create a confusion matrix, which plays a central role for both the accuracy assessment and area adjustments (Foody 2013), and is commonly used in land cover change detection (Anderson et al. 1976; Knorn et al. 2009; Liu et al. 2016; Olofsson et al. 2013; Juanle Wang et al. 2019). The error matrix is an ordinary cross-tabulation of the class labels allocated by the classification of the Satellite based data against the reference data for the sample plots (Table 1). The main diagonal of the error matrix represents correct classifications while the off-diagonal elements show omission and commission errors. The accuracy assessment of formula was given by (Eq 5, 6 and 7) are estimator overall, user's, producer's accuracies, and confidence interval (Olofsson et al. 2013, 2014).

Table 1. Population error matrix with the rows (i) representing the map classification and the columns (j) representing the reference classification; (Pij) is the population proportion of area with map class (i) and reference class(i). The row (P_{i+}) and column $\left(P_{+j}\right)$ marginal totals are the sum of the (Pij) values in each row and column.

		Reference class						**Total**
		1	**2**	**…**	**j**	**…**	**q**	
	1	P11	P12	…	P1j	…	P1q	P1+
	2	P21	P22	…	P2j	…	P1q	P2+
	:	:	:		:		:	:
	:	:	:		:		:	:
Map class	j	Pj1	Pj2	…	Pjj	…	Pjq	Pj+
	:	:	:		:		:	:
	q	Pq1	Pq2	…	Pqj	…	Pqq	Pq+
	Total	**P+1**	**P+2**	**…**	**P+j**	**…**	**P+q**	**1**

Eq 5. Error matrix of q classes include overall accuracy.

$$0 = \sum_{j=1}^{q} p_{jj}$$

where: pij is the proportion of the area for the map class i and reference class j, "population" is defined as the full region of interest, and pij is the value that would result if a census of the population was obtained reference classification.

Eq 6. Commission error of matrix.

$$Ui = p_{ii}/p_{i}\cdot$$

where: i is the user's error of class, $1 - p_{ii}/p_{i\cdot}$, and j is the producer's accuracy of class which the proportion of the area of reference class j that is mapped as class j.

Eq 7. Omission error of matrix.

$$P_j = p_{jj}/p_{\cdot j}$$

where: j is omission error of class, $1 - p_{jj}/p_{\cdot j}$.

In addition, sampling design is used the stratified random sampling in which the strata correspond to the map classes,

Eq 8. Strata sampling design.

$$\hat{p}_{ij} = W_i \, \frac{n_{ij}}{n_{i\cdot}}$$

where: $\hat{p}_{ij}$ is available of each element of the error matrix, W_i is the proportion of area mapped as class i, n_{ij} is the sampling counts.

To estimate the confidence intervals for the overall accuracy I will use the following equations.

Eq 9. Variance of overall accuracy.

$$\hat{V}(\hat{O}) = \sum_{i=1}^{q} W_i^2 \hat{U}_i(1 - \hat{U}_i) \Big/ (n_i - 1)$$

Eq 10. Calculation of confidence interval.

$$\pm 1.96\sqrt{\hat{V}(\hat{U}_i)}$$

where: $\hat{U}_i$ is replaced with $\hat{P}_j$ and $\hat{O}$for the producer's and overall accuracies. In terms of calculation, the estimate user's accuracy will confidence intervals at the 95% confidence level.

3. Expected results

The result of this analysis will produce three primary outcomes: 1) an assessment of the ability of CNNs to map Mongolia's vegetation communities, 2) an assessment of the value of combining data from wet and dry years to map vegetation communities, 3) vegetation community change maps for Mongolia's grasslands.

4. Significance and contributions

My result will provide important information to understand how much grasslands have degraded due to change in plant communities. In doing so, I will assess an aspect of grassland degradation overlooked by vegetation indices or surface fractions. For management, my results will the valuable because different plant communities differ in forage quality. Finally, my results could be useful for grassland vegetation restoration.

CHAPTER 3: To identify the main drivers of grassland degradation (both long-term trends of cumulative endmember fractions and change in vegetation communities) focusing on climate, livestock numbers, Brandt's vole distributions.

1. Introduction

Climate change and grazing are the two main driers of grassland degradation (Allington et al. 2017). In Mongolia, droughts have increased in frequency in recent decades, and especially summer rainfall has declined (Lioubimtseva and Henebry 2009), which greatly affected grasslands (Allington et al. 2017; Chen et al. 2018; John et al. 2013; Kang et al. 2021). Also, livestock grazing is a major threat to Mongolian grassland ecosystems, due to the rapid increase in livestock numbers (Allington et al. 2017; Gong Li et al. 2000) from 22 million in the late 1980s to 71 million today (Fig 10.) (Allington et al. 2017; Gong Li et al. 2000). Furthermore, there is a positive feedback loop in that overgrazing increases Brandt's vole populations (*Lasiopodomys brandtii*), which degrade pastures further (K. Li et al. 2017). Brandt's voles are native but expanded their range to > 40 million ha in Mongolia (Fig 18) (Munkhnasan 2019; Shenbrot and Krasnov 2005). They prefer freshly grazed areas, eat the roots of grasses, and destroy the soil surface (Zhong et al. 2022). Furthermore, Brandt's voles are highly detrimental to livestock because their burrowing brings infertile soils to the top and fosters the spread of low-nutritious weeds (K. Li et al. 2017).

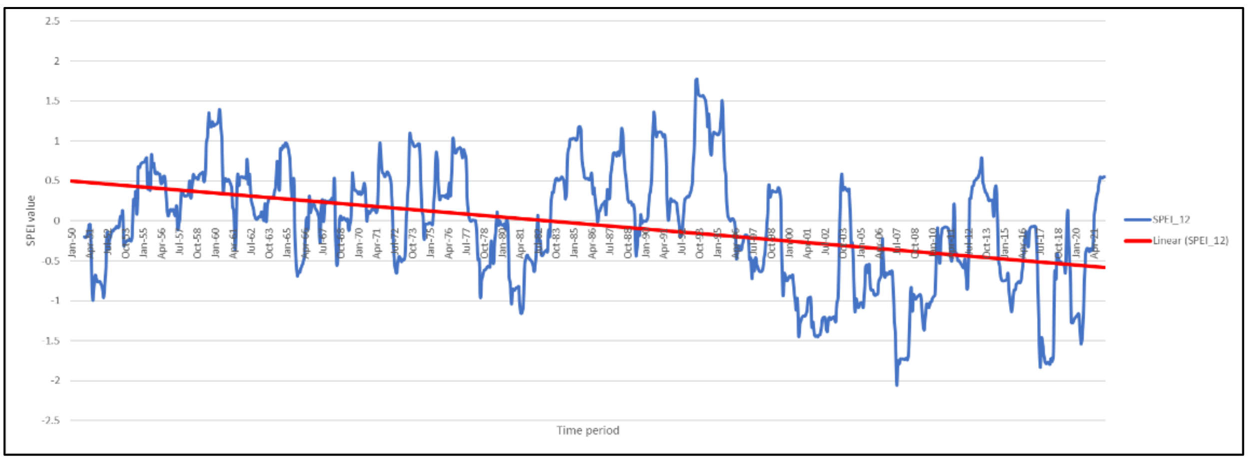

Figure 16. SPEI Drought index (1950-2021)

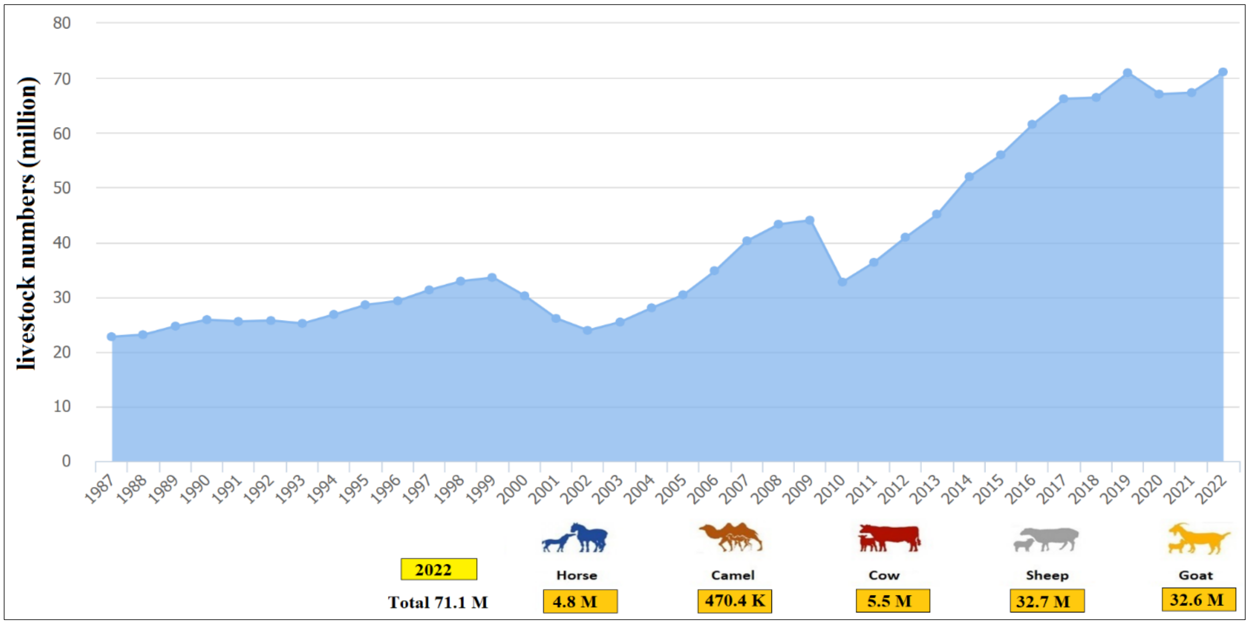

Figure 17. Time-series of livestock numbers, five species (1987-2022) such as; horse, camel, cow, sheep and goat

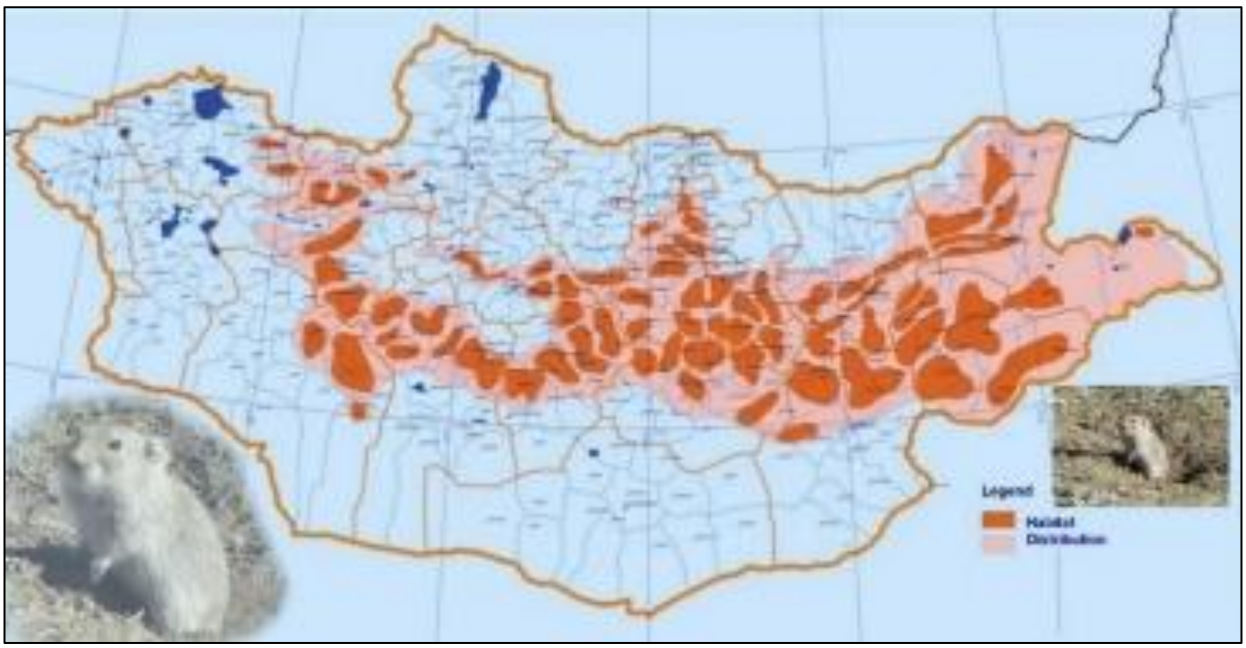

Figure 18. The distribution of Brandt's vole (orange color is represented habitat, pink color is showed distribution colonization area)

1.2. Analysis of objective

I propose to identify the drivers of grassland degradation parameter for both trends in annual endmember fractions and changes in vegetation communities thereby building directly on my 1st and 2nd objectives. In the analysis for chapter 3, I will address three primary research questions and test corresponding hypotheses:

1. Which factors are causing grassland degradation both in terms of vegetation cover, and in vegetation community composition?
   Hypothesis: *the frequency of drought is main cause of grassland degradation.*
2. How does livestock density affect grassland degradation?
   Hypothesis: *Density of sheep and goats are strong predictors of grassland degradation.*
3. Why are Brandt's vole numbers increasing, and do they pose a threat to grasslands?
   Hypothesis: *Higher livestock numbers are leading to an increase into the number of voles, and voles are contributing to grassland degradation.*

2. Methods

I propose to identify the main drivers of grassland degradation, both in terms of changes in annual endmember fractions (my 1st objective), and grassland communities (2nd objective). I will focus on a few drivers of grassland degradation such as climate change, livestock numbers, and Brandt's vole. I will analyze long-term data from of the national Standard Meteorological Station Datasets of Mongolia (130 stations) for the last 35-years, which include precipitation, air temperature, soil moisture, unfenced biomass, wind speed, as well as Brandt's vole abundance data from 2005 to 2020. I will also analyze long-term of annual livestock numbers, which I have already obtained from the National Statistical Office of Mongolia for each of the 1500 sub-villages ("Bag level") and for five species from 1987-2022 (fig 15).

First, I will conduct regression analyses at both the pixel-level, and using sub-villages as my unit of analysis, because some information is only available at that level. For this, will summarize all datasets (climate variables, Brandt's vole, and livestock numbers) by conducting spatial interpolations via universal kriging and zonal statistics to calculate mean values within the surveyed sub-villages/bags (Wang, Brown, and Agrawal 2013). In terms of geostatistical interpolation, will use ordinary kriging as implemented in the ArcGIS packages of geostatistical techniques to interpolate between point-based meteorological stations. To summarize my vegetation data, will calculate zonal statistics, and the livestock data is available at the sub-village level. Kriging and zonal statistical estimation are defined by the following equation (Belkhiri, Tiri, and Mouni 2020; Charles et al. 2022):

Eq 11. Calculation of ordinary kriging interpolation.

$$\hat{Z}(x_p) = \sum_{i=1}^{n} \lambda_i Z(x_i)$$

where: $\hat{Z}(x_p)$ is the estimated value of variable Z at location x_p; $Z(x_i)$ is the known value at location x_i; λ_i is the weight associated with the data.

Eq 12. Calculation of zonal statistics in a given spatial unit.

$$\bar{x} = \frac{1}{N}\sum_{i=1}^{N} x_i$$

where: $\bar{x}$ is the mean of observed value, x_i is observed values and N is number of observation of data. The GIS zonal statistic operation is commonly used in a raster analysis performed on the two rasters, in which one is the zone and other is the value (Fig 19) (Hyndman and Fan 1996).

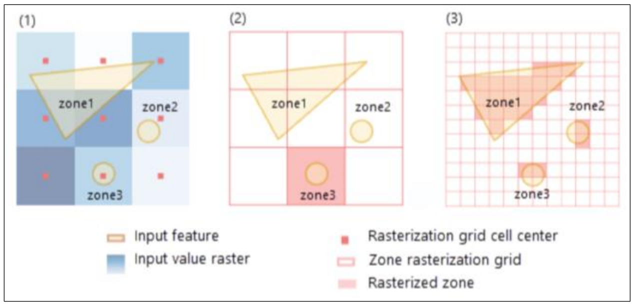

Figure 19. The zonal statistic GIS tool

Second, will analyze long-term trends in the annual surface fractions via a regression that accounts for temporal and spatial autocorrelation by applying remotePARTS (Ives et al. 2022; Radeloff et al. 2000). Large datasets with time-series of autocorrelated data are frequently encountered in remote sensing where both temporal and spatial autocorrelation is common (Ives et al. 2022). RemotePARTS first estimates the trend for each pixel using an autoregressive model that accounts for temporal autocorrelation. Second, it conducts a generalized least square regression that accounts for spatial autocorrelation. If the dataset is too large to parameterize a single GLS, remotePARTS partitions the data into subsets, parameterizes each regression, and then combines the results from each model into one estimate. Because remotePARTS is fundamentally a regression analysis, it is very amenable to hypothesis testing, either of the trends themselves (e.g., there is a significant negative trend in greenness), or in terms of explanatory variables (e.g., there is a stronger negative trend where droughts are more severe). For my analyses of trends at the sub-village level, partitioning will not be necessary, but for analyses at the pixel-level, it will be.

Third, I will explain changes in vegetation communities using remote PARTS. In this case my response variable is different because I have only two time steps, and cannot estimate the slope of a trend. Instead, I will estimate absolute measures of change, such as the decrease in percent cover of feather grass. remotePARTS allows me to analyze all pixels across Mongolia's grasslands while accounting for spatial autocorrelation to test for significance of drivers of changes in vegetation community.

3. Expected results

The result of this analysis will be the identification of the drivers of grassland degradation parameters for both trends in surface fractions and changes in vegetation communities thereby building directly on my 1st and 2nd objectives. In addition, the temporal spatial regression analysis will produce partial p-values for the relationships between grassland degradation versus, air temperature, precipitation, biomass, soil moisture, wind, Brandt's vole and livestock.

4. Significance and contributions

My result will be broadly relevant given that climate change is affecting grasslands throughout the world. However, climate change also interacts with other drivers of degradation, which is why I will analyse livestock and Brandt's vole as well. In Mongolia, my results will be useful for regional administrations when deciding on pasture carrying capacity plans. Furthermore, this is analysis will be a good reference for governmental and non-governmental organizations, such as the State Emergency Commission of Mongolia, when making decisions about drought response and herder assistance.

CHAPTER 4: To investigate the effectiveness of protected areas in grasslands that are important for plant biodiversity and migrating ungulates in stopping or even reverting grassland degradation.

1. Introduction

Globally, only 4.1% of the world's temperate grasslands are in protected areas (Henwood 2010). That is unfortunate because grasslands harbor unique biodiversity and play important roles in global carbon cycling and climate regulation (Poulter et al. 2014). The biodiversity and plant species (biota) within protected areas are often affected by both land use within the protected areas themselves and habitat loss and fragmentation in the surrounding landscape (Townsend et al. 2009). However, protected areas are crucial for the conservation of species threatened by human activity, land use change and wildlife habitat loss (Radeloff et al. 2010). Especially, many grasslands have been converted to agriculture, or are used for livestock herding, resulting in biodiversity losses (Terrado et al. 2016). Protected areas in grassland biomes can provide refugia for threatened species, including migratory ungulates, for which vegetation cover, biomass, and forage quality is important, as well as endangered plant species, which are threatened by vegetation composition changes (Hannah et al. 2007; Parmesan 1996).

Mongolia has many protected areas: 21% of the country is protected, and 10 new protected area have been established since 2010. Furthermore, the national program on Special Protected Areas was enacted in April 1998 by the Parliament of Mongolia (act number 29) to extend the protected area network of high ecological importance and biodiversity value so that 30% are protected by 2030 (Jargal 2003). However, these protected areas face growing pressure stemming from human activities that could lead to biodiversity losses, habitats fragmentation, and especially of rare plants (Jamsran et al. 2019; Reading, Bedunah, and Amgalanbaatar 2006; Terrado et al. 2016) of which there is a high concentration in the grasslands of eastern Mongolia (Shukherdorj et al. 2019). In the meantime, overgrazing and climate change impacts have increased in the areas surrounding national protected areas (Bayartogtokh et al. 2021; Girvetz et al. 2014; Liu et al. 2013). Moreover, the mobility of ungulate migration is changing due to irregular and unpredictable spatial and temporal patterns of rainfall (Mueller et al. 2008). The effectiveness of protected areas depends on their ability to stop habitat loss within boundaries zone (Radeloff et al. 2010), which makes grassland degradation is a good indicator of conservation effectiveness for grassland protected areas.

1.2. Analysis of objective

I propose to quantify the effectiveness of protected areas in Mongolia's grasslands, both those that have a long history, and those established recently. The effectiveness estimates will utilize my results from my 1st and 2nd objectives and will be informed by my analysis of drivers for my 3rd objective. Overall, my goal is to better understand relationship between grassland degradation, wildlife conservation and PAs effectiveness in grassland ecosystem. My specific research question and hypothesis are:

1. How effective have Mongolia's protected areas been in terms of stopping grassland degradation?

Hypothesis: protected areas have been effective in stopping grassland degradation within them

2. How does climate change affect Protected areas and their effectiveness?
   Hypothesis: if climate change is the main driver of degradation, effectiveness of protected areas is limed
3. How does livestock grazing interact with Protected area effectiveness?
   Hypothesis: if grazing is a main driver of degradation, protected areas may have been highly effective in those parts of Mongolia where livestock numbers are generally high
4. Have protected areas limited grassland degradation especially in those areas where degradation is a threat to ungulate's habitat?
   Hypothesis: due to the importance of protected areas for migratory ungulates, they have been more effective in areas where wild herbivores are concentrated

2. Methods

I propose to investigate the effectiveness of protected areas in stemming grassland degradation and vegetation community changes as quantified in my objectives 1 and 2 using econometric methods. I will analyze all protected areas in Mongolia's grassland (Fig 21), and areas where wild large herbivores are concentrated (Fig 22).

I propose to conduct my analyses in three steps. First, will select a sample of matched pairs of sites inside and outside of protected areas and wildlife habitats based on propensity scores (Brandt et al. 2019; Butsic, Lewis, et al. 2017). In generally, propensity score matching is a quasi-experimental approach in which pairs of samples are analyzed. In each pair, one sample is in the protected area (the 'treated' area), and one is outside, and samples are paired so that they have similar characteristics. Moreover, in propensity score matching treatments are non-random but all relevant variables are observed by researchers (Brandt et al. 2019; Butsic, Lewis, et al. 2017). In addition, propensity scores are generally calculated using Logistic regression approaches, which value (x-axis) ranges from 0 (zero probability) to 1.0 (100%) (Powell, Hull, and Beaujean 2020): equations are given below.

Eq 13. Logistic regression and propensity score.

$$In \frac{e(x_i)}{1-e(x_i)} = In \frac{\Pr(z_i = 1|x_i)}{1-\Pr(z_i = 1|x_i)} = a + \beta^T x_i$$

where: $e(x_i) = \Pr(z_i = 1|x_i)$, and $e(X_i) = b_0 + b_1X_1 + b_2X_2 + b_3X_{3+\dots+}b_1X_1$, and b_0 is the intercept, b_1 is the regression coefficient, X_i the treatment variables and covariates (random variables), x_i is observed value of variables. In logistic regression, the dependent variable is binary, $Z_i = 1$ is the value for the treatment and the value for the control is $Z_i = 0$.

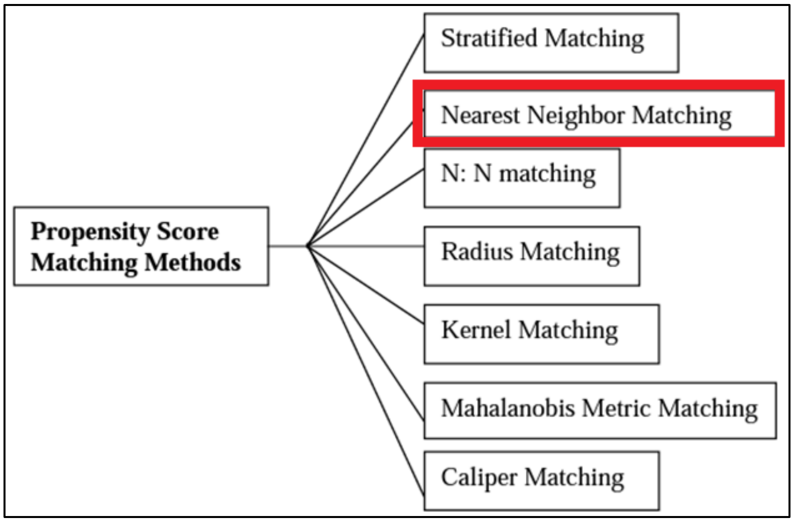

Figure 20. Propensity score Matching method (Nearest Neighbor).

There are different approaches to identify the best matches. I will use the absolute difference between the estimate propensity scores for the control and treatment groups and minimize that by Nearest Neighbor Matching (Equation 14)

Eq 14. Nearest Neighbor matching.

$$C(P_i) = \min_j \left| P_i - P_j \right|$$

where: $C(P_i)$ is presented the group of control subjects j matched to treated subjects i (on the estimated propensity score), P_i is the estimated propensity score for the treated subjects i, P_j is the estimated propensity score for the control subjects j. The control and treatment subjects are randomly ordered but the first $\boldsymbol{n}$ treatments are matched to $\boldsymbol{n}$ control subjects with the closest propensity score. The commonly used matches are $1{:}\,1, 1{:}\,N \text{ or } N{:}\,1$ matches.

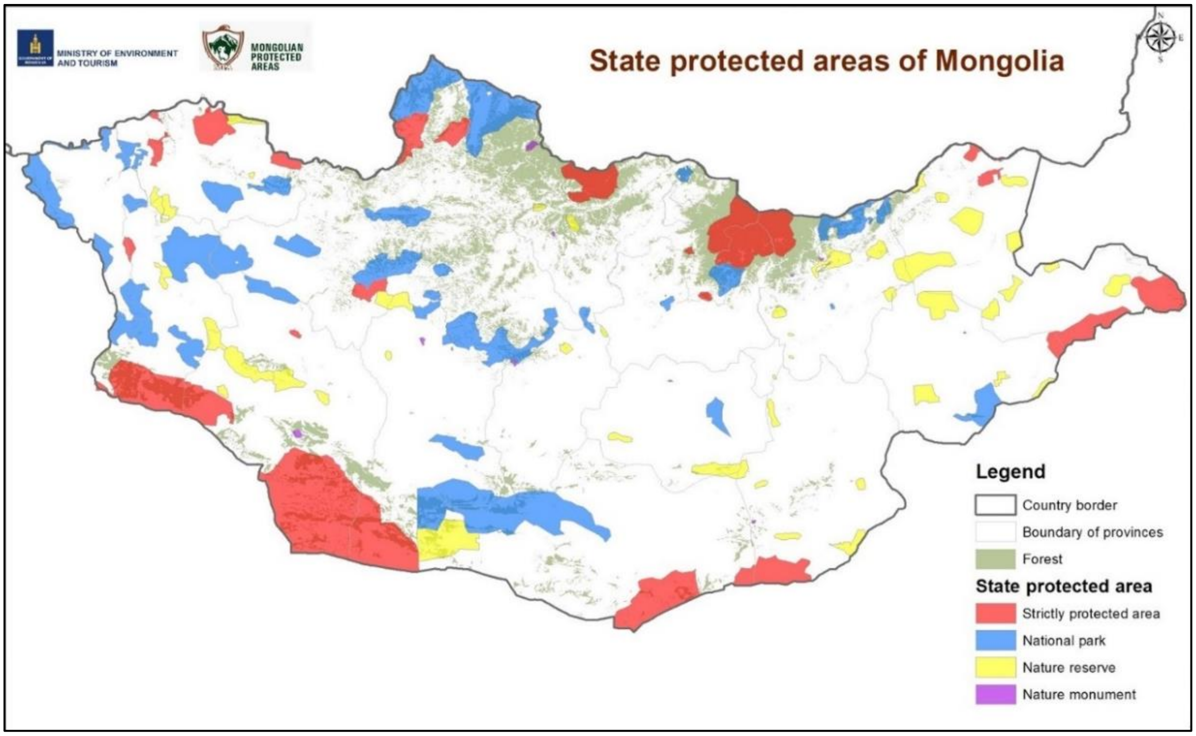

Figure 21. State protected area of Mongolia (red: strict PA; blue: National Park; yellow: Nature reserve; pink: Nature monument), in which I will randomly distributed pair samples inside and outside PAs boundaries.

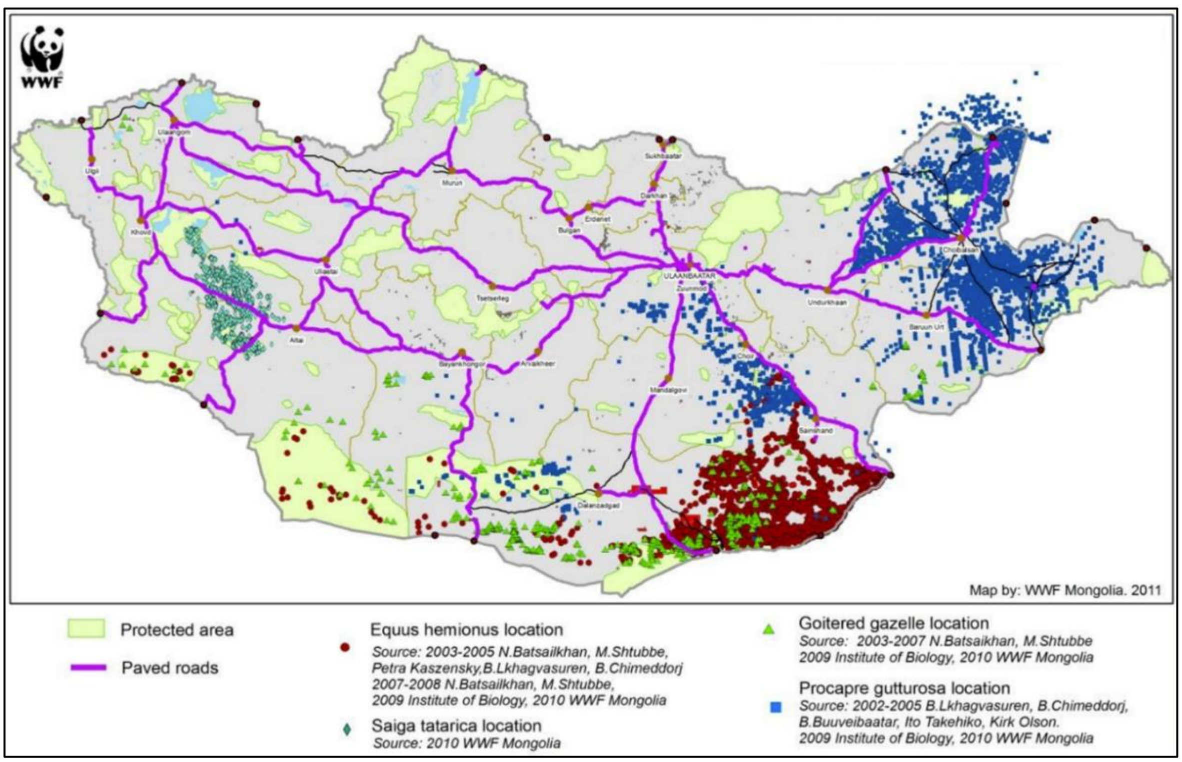

Figure 22. Wild large herbivore locations (red: Onager; cyan: Saiga antelope; green: Goitered gazelle; blue: Mongolian gazelle).

Second, once I have my matched sample sites, will identify the effectiveness of protected areas in reducing vegetation cover declines (Brandt et al. 2019; Butsic, Lewis, et al. 2017) by combining matching statistics with fixed-effects linear probability models for my panel data of cumulative endmember fraction trends (Butsic, Munteanu, et al. 2017b; Sieber et al. 2013).

Third, will conduct similar analyses to assess protected area effectiveness to limit grassland community changes (Brandt et al. 2019; Butsic, Lewis, et al. 2017).

3. Expected results

The result of this analysis will produce three primary research outcomes: 1) an assessment of the effectiveness of protected areas in Mongolia's grasslands throughout the Landsat record; 2) an indication on the relative importance on climate versus livestock on protected area effectiveness; 3) a detailed examination if protected areas in core areas of wild herbivores are effective.

4. Significance and contributions

My result will be broadly relevant given that grassland degradation may be affecting protected area effectiveness, wildlife habitat, and conservation management throughout the world. In Mongolia, my results will be useful for regional administrations when deciding about nature conservation plans, manage protected area usage and protected zones, and for the selection of new protected areas. As such, my results will be relevant for the Mongolia Program of the Wildlife Conservation Society (WCS), World Wildlife Fund (WWF), and the Ministry of the Environment and Tourism of Mongolia.

EXPECTED OUTCOMES AND DELIVERABLES

In my PhD research and in my future career, I plan to conduct interdisciplinary research at the interface of remote sensing, land use science, and conservation biology in my home country of Mongolia. Based on my dissertation chapters, I plan to publish four journal articles in Remote Sensing of Environment (Obj. 1), Global Change Biology (Obj. 2), Global Environmental Change (Obj. 3), and Conservation Biology (Obj. 4). In addition, my research will generate important datasets, which I will make openly and freely available, including: (1) plant species community and Spectro-radiometer library for Mongolia for 2021/22; (2) grassland degradation trends based on annual cumulative endmember fractions from by Landsat for 1987-2022, (3) grassland community maps for ca. 1990 and 2020, and (4) Protected area effectiveness data. Throughout my project, I will collaborate closely with my network of partners in the country, many of which I have worked with closely already in my prior position as the Chief technologist of GIS and Remote Sensing, National Remote Sensing Center of Mongolia, thereby building capacity and strengthening international collaborations.

OVERALL SIGNIFICANCE

Mongolia's steppe grasslands are vast and among the most-intact grasslands remaining globally. The grasslands are mostly dominated by various grasses including feather grass, wheatgrass, and needlegrass as well as forbs, shrubs, and small trees. The steppe grasslands provide important habitat for a number of endangered and threatened species, and for the migrations of Mongolian gazelles (*Procapra gutturosa*), Goitered gazelle (*Gazella subgutturosa*), Saiga antelope (*Saiga tatarica mongolica*), Onager (*Equus hemionus*), the wild Bactrian camels, and Argali sheep. It is also home to a variety of predators, such as wolves, foxes, and eagles.

In Mongolia's long history, herders have relied on the grasslands for their livelihoods, using a nomadic seasonal rotation system for grazing livestock, hunting, and gathering. However, in recent decades the grasslands are facing a large number of threats including grassland degradation and soil nutrient losses due to overgrazing, climate change, mining, and natural disturbance. Degradation can manifest itself both as a loss of vegetation cover, or as a change in vegetation communities. In order to support the conservation of Mongolia's grassland ecosystems, both in terms of general biodiversity, and of rare plant species, there is a need to conduct the kind of remote sensing assessments that I am proposing here.

In terms of its scientific contribution, my research will advance the understanding of the magnitude of grassland degradation, and of the core drivers of grassland degradation including climate, grazing, and the positive feedback loop between grazing and Brandt's voles. Furthermore, I will examine multiple dimensions of grassland degradation including changes in surface fractions of the cumulative endmembers, as well as vegetation community changes.

Methodologically, I will contribute to remote sensing, by analyzing cumulative endmember fractions with field spectra, by processing the full Landsat archive for Mongolia, and by developing new methods to map grassland communities based on CNNs as a deep learning approach and on phenological differences between dry and wet years.

For biodiversity conservation and grassland management, I will provide new datasets depicting Mongolia's grasslands and their changes with 30-m Landsat imagery. This enables my detailed assessment of grassland degradation from 1987 to 2022 and provides change trend information in local and regional level. I will identify the main drivers of degradation, which is the necessary first step to limit it. Related, I will quantify if protected areas are effective in stemming grassland degradation, thereby protecting the grassland vegetation communities, and the habitat for Mongolia's herds of wild ungulates.

Grassland degradation and vegetation community change maps are useful source information for local and regional policy making, pasture management, land-use planning and desertification process, and nature conservation action management. Furthermore, my results will provide reference maps for grassland vegetation restoration, and local decision makers, as well State Emergency Commission of Mongolia, state and local PAs organization, the Ministry of the Environment and Tourism of Mongolia and non-governmental organizations, and nature conservation NGOs such as the Wildlife Conservation Society (WCS), World Wildlife Fund (WWF) in Mongolia.

REFERENCES

Addison, J., M. Friedel, C. Brown, J. Davies, and S. Waldron. 2012. "A Critical Review of Degradation Assumptions Applied to Mongolia's Gobi Desert." *Rangeland Journal* 34(2):125–37.

Aghababaei, Masoumeh, Ataollah Ebrahimi, Ali Asghar Naghipour, Esmaeil Asadi, and Jochem Verrelst. 2021. "Classification of Plant Ecological Units in Heterogeneous Semi-Steppe Rangelands: Performance Assessment of Four Classification Algorithms." *Remote Sensing* 13(17). doi: 10.3390/rs13173433.

Alfonso Zamora Saiz, Carlos Quesada González, Lluís Hurtado Gil, and Diego Mondéjar Ruiz. 2021. "An Introduction to Data Analysis in R." Pp. 1–276 in *Hands-on Coding, Data Mining, Visualization and Statistics from Scratch*. Vol. vol. Switzerland AG: Springer, Cham.

Allington, Ginger R. H., Wei Li, and Daniel G. Brown. 2017. "Urbanization and Environmental Policy Effects on the Future Availability of Grazing Resources on the Mongolian Plateau: Modeling Socio-Environmental System Dynamics." *Environmental Science and Policy* 68:35–46. doi: 10.1016/j.envsci.2016.11.005.

Andam, Kwaw S., Paul J. Ferraro, Alexander Pfaff, G. Arturo Sanchez-Azofeifa, and Juan A. Robalino. 2008. "Measuring the Effectiveness of Protected Area Networks in Reducing Deforestation." *Proceedings of the National Academy of Sciences of the United States of America* 105(42):16089–94. doi: 10.1073/pnas.0800437105.

Anderson, James R., Ernest E. Hardy, John T. Roach, and Richard E. Witmer. 1976. "LAND USE AND LAND COVER CLASSIFICATION SYSTEM FOR USE WITH REMOTE SENSOR DATA." *U S Geol Surv, Prof Pap* (964).

Anon. 2022. "Changes in Plant Community and Soil Properties Mediated by Grazing in Semi-Desert of Mongolia." *Mongolian Journal of Biological Sciences* 20(1):49–60. doi: 10.22353/mjbs.2022.20.05.

Badarch, Ochirsukh, Woo Kyun Lee, Doo Ahn Kwak, Sungho Choi, Khitlaxay Kokmila, Jae Gyun Byun, and Seong Jin Yoo. 2011. "Mapping Forest Functions Using GIS in Selenge Province, Mongolia." *Forest Science and Technology* 7(1):23–29. doi: 10.1080/21580103.2011.559938.

Baker, Kirk. 2005. "Singular Value Decomposition Tutorial." *The Ohio State University* 2005:24. doi: 10.1021/jo0008901.

Batjargal, Zambyn. 1997. "Desertification in Mongolia." *RALA Report* 200(7):107–13.

Bayartogtokh, Badamdorj, Basan Munkhchuluun, Purevdorj Jargalsaikhan, and Uudus Bayarsaikhan. 2021. "Khar Yamaat Nature Reserve: Biodiversity, Ecosystem Features, Threats and Conservation Management." *Mongolian Journal of Biological Sciences* 19(2):3–15.

Becker, William E. 1999. "Peter Kennedy, A Guide to Econometrics. 4th Ed. Cambridge: MIT Press, 1998. Xii + 468 Pp." *The Journal of Economic Education* 30(1):89–90. doi: 10.1080/00220489909595943.

Beguería, Santiago, Sergio M. Vicente-Serrano, Fergus Reig, and Borja Latorre. 2014. "Standardized Precipitation Evapotranspiration Index (SPEI) Revisited: Parameter Fitting, Evapotranspiration Models, Tools, Datasets and Drought Monitoring." *International Journal of Climatology* 34(10):3001–23. doi: 10.1002/joc.3887.

Belkhiri, Lazhar, Ammar Tiri, and Lotfi Mouni. 2020. "Spatial Distribution of the Groundwater Quality Using Kriging and Co-Kriging Interpolations." *Groundwater for Sustainable Development* 11:100473. doi: 10.1016/J.GSD.2020.100473.

de Beurs, Kirsten M., and Geoffrey M. Henebry. 2004. "Trend Analysis of the Pathfinder AVHRR Land (PAL) NDVI Data for the Deserts of Central Asia." *IEEE Geoscience and Remote Sensing Letters* 1(4):282–86. doi: 10.1109/LGRS.2004.834805.

Bliss, Susan. 2016. "Mongolia: Grassland Landscape and Biome." *Geography Bulletin* 48(1):10–17.

Bragina, E. v., V. C. Radeloff, M. Baumann, K. Wendland, T. Kuemmerle, and A. M. Pidgeon. 2015. "Effectiveness of Protected Areas in the Western Caucasus before and after the Transition to Post-Socialism." *Biological Conservation* 184:456–64. doi: 10.1016/j.biocon.2015.02.013.

Brandt, Jodi S., Volker Radeloff, Teri Allendorf, Van Butsic, and Anand Roopsind. 2019. "Effects of Ecotourism on Forest Loss in the Himalayan Biodiversity Hotspot Based on Counterfactual Analyses." *Conservation Biology* 33(6):1318–28. doi: 10.1111/cobi.13341.

Butsic, Van, David J. Lewis, Volker C. Radeloff, Matthias Baumann, and Tobias Kuemmerle. 2017. "Quasi-Experimental Methods Enable Stronger Inferences from Observational Data in Ecology." *Basic and Applied Ecology* 19:1–10.

Butsic, Van, Catalina Munteanu, Patrick Griffiths, Jan Knorn, Volker C. Radeloff, Juraj Lieskovský, Daniel Mueller, and Tobias Kuemmerle. 2017a. "The Effect of Protected Areas on Forest Disturbance in the Carpathian Mountains 1985–2010." *Conservation Biology* 31(3):570–80. doi: 10.1111/cobi.12835.

Butsic, Van, Catalina Munteanu, Patrick Griffiths, Jan Knorn, Volker C. Radeloff, Juraj Lieskovský, Daniel Mueller, and Tobias Kuemmerle. 2017b. "The Effect of Protected Areas on Forest Disturbance in the Carpathian Mountains 1985–2010." *Conservation Biology* 31(3):570–80. doi: 10.1111/cobi.12835.

Cao, Xiaoming, Yiming Feng, and Juanle Wang. 2016. "An Improvement of the Ts-NDVI Space Drought Monitoring Method and Its Applications in the Mongolian Plateau with MODIS, 2000–2012." *Arabian Journal of Geosciences* 9(6). doi: 10.1007/s12517-016-2451-5.

Chang, S., H. Chen, B. Wu, E. Nasanbat, N. Yan, and B. Davdai. 2021. "A Practical Satellite-Derived Vegetation Drought Index for Arid and Semi-Arid Grassland Drought Monitoring." *Remote Sensing* 13(3):414. doi: 10.3390/rs13030414.

Chang, S., B. Wu, N. Yan, B. Davdai, and E. Nasanbat. 2017. "Suitability Assessment of Satellite-Derived Drought Indices for Mongolian Grassland." *Remote Sensing* 9(7). doi: 10.3390/rs9070650.

Charles, Thaís da Silva, Tárcio Rocha Lopes, Sergio Nascimento Duarte, Jéssica Garcia Nascimento, Hugo de Carvalho Ricardo, and Adriano Bicioni Pacheco. 2022. "Estimating Average Annual Rainfall by Ordinary Kriging and TRMM Precipitation Products in Midwestern Brazil." *Journal of South American Earth Sciences* 118:103937. doi: 10.1016/J.JSAMES.2022.103937.

Chauhan, Karan, and Shrwan Ram. 2018. "Image Classification with Deep Learning and Comparison between Different Convolutional Neural Network Structures Using Tensorflow and Keras." *International Journal of Advance Engineering and Research Development* 5(02):533–38.

Chen, Jiquan, Ranjeet John, Ge Sun, Peilei Fan, Geoffrey M. Henebry, María E. Fernández-Giménez, Yaoqi Zhang, Hogeun Park, Li Tian, Pavel Groisman, Zutao Ouyang, Ginger Allington, Jianguo Wu, Changliang Shao, Amartuvshin Amarjargal, Gang Dong, Garik Gutman, Falk Huettmann, Raffaele Lafortezza, Connor Crank, and Jiaguo Qi. 2018. "Prospects for the Sustainability of Social-Ecological Systems (SES) on the Mongolian Plateau: Five Critical Issues." *Environmental Research Letters* 13(12). doi: 10.1088/1748-9326/aaf27b.

Chen, Jiquan, Ranjeet John, Yaoqi Zhang, Changliang Shao, Daniel G. Brown, Ochirbat Batkhishig, Amartuvshin Amarjargal, Zutao Ouyang, Gang Dong, Dan Wang, and Jiaguo Qi. 2015. "Divergences of Two Coupled Human and Natural Systems on the Mongolian Plateau." *BioScience* 65(6):559–70. doi: 10.1093/biosci/biv050.

Chen, Kuan, Genbatu Ge, Gang Bao, Liga Bai, Siqin Tong, Yuhai Bao, and Luomeng Chao. 2022. "Impact of Extreme Climate on the NDVI of Different Steppe Areas in Inner Mongolia, China." *Remote Sensing* 14(7). doi: 10.3390/rs14071530.

Chen, Zefeng, Weiguang Wang, and Jianyu Fu. 2020. "Vegetation Response to Precipitation Anomalies under Different Climatic and Biogeographical Conditions in China." *Scientific Reports* 10(1). doi: 10.1038/s41598-020-57910-1.

Chitsaz, Nastaran, Ali Azarnivand, Shahab Araghinejad, and E. Volpi. 2016. "Pre-Processing of Data-Driven River Flow Forecasting Models by Singular Value Decomposition (SVD) Technique." *Hydrological Sciences Journal* 61:2164–78. doi: 10.1080/02626667.2015.1085991.

Chuluunkhuyag, Oyundari, Lv Chaoyan, Jan Treiber, Oyuntsetseg Batlai, Henrik von Wehrden, Robert Feller, and Karsten Wesche. 2021. "Influence of Altitude and Longitude on Vegetation in the Dzungarian Gobi and the South-Western Mongolian Altai." *Phytocoenologia* 50(4):339–69. doi: 10.1127/phyto/2021/0371.

Clark, P. E., M. S. Seyfried, and B. Harris. 2001. "Intermountain Plant Community Classification Using Landsat TM and SPOT HRV Data." *Journal of Range Management* 54(2):152–60. doi: 10.2307/4003176.

Cromartie, Amy, Claire Blanchet, Chéïma Barhoumi, Erwan Messager, Odile Peyron, Vincent Ollivier, Pierre Sabatier, David Etienne, Arkady Karakhanyan, Lori Khatchadourian, Adam T. Smith, Ruben Badalyan, Bérengère Perello, Ian Lindsay, and Sébastien Joannin. 2020. "The Vegetation, Climate, and Fire History of a Mountain Steppe: A Holocene Reconstruction from the South Caucasus, Shenkani, Armenia." *Quaternary Science Reviews* 246. doi: 10.1016/j.quascirev.2020.106485.

Danner, Martin, Matthias Locherer, Tobas Hank, and Katja Richter. 2015. "Spectral Sampling with the ASD FIELDSPEC 4." doi: http://doi.org/10.2312/enmap.2015.008.

Dorjsuren, Munkhzul, Yuei An Liou, and Chi Han Cheng. 2016. "Time Series MODIS and in Situ Data Analysis for Mongolia Drought." *Remote Sensing* 8(6). doi: 10.3390/rs8060509.

Eckert, Sandra, Fabia Hüsler, Hanspeter Liniger, and Elias Hodel. 2015. "Trend Analysis of MODIS NDVI Time Series for Detecting Land Degradation and Regeneration in Mongolia." *Journal of Arid Environments* 113:16–28. doi: 10.1016/j.jaridenv.2014.09.001.

Enebish, Bayarjargal, Dulamsuren Dashkhuu, Mijiddorj Renchin, Michael Russell, and Piyush Singh. 2020. "Impact of Climate on the NDVI of Northern Mongolia." *Journal of the Indian Society of Remote Sensing* 48(2). doi: 10.1007/s12524-019-01080-9.

Foody, Giles M. 2013. "Ground Reference Data Error and the Mis-Estimation of the Area of Land Cover Change as a Function of Its Abundance." *Remote Sensing Letters* 4(8):783–92. doi: 10.1080/2150704X.2013.798708.

Fox, John, and Georges Monette. 1992. "Generalized Collinearity Diagnostics." *Journal of the American Statistical Association* 87(417). doi: 10.1080/01621459.1992.10475190.

Girvetz, Evan H., Robert McDonald, Michael Heiner, Joseph Kiesecker, Galbadrakh Davaa, Chris Pague, Matthew Durnin, and Enkhtuya Oidov. 2014. "Eastern Mongolian Grassland Steppe." Pp. 92–103 in *Climate and Conservation: Landscape and Seascape Science, Planning, and Action*. Island Press-Center for Resource Economics .

Godde, C. M., R. B. Boone, A. J. Ash, K. Waha, L. L. Sloat, P. K. Thornton, and M. Herrero. 2020. "Global Rangeland Production Systems and Livelihoods at Threat under Climate Change and Variability." *Environmental Research Letters* 15(4). doi: 10.1088/1748-9326/ab7395.

Gong Li, Sheng, Yoshinobu Harazono, Takehisa Oikawa, Ha Lin Zhao, Zong Ying He, and Xue Li Chang. 2000. "Grassland Desertification by Grazing and the Resulting Micrometeorological Changes in Inner Mongolia." *Agricultural and Forest Meteorology* 102(2–3):125–37. doi: 10.1016/S0168-1923(00)00101-5.

Hamer, A. M., D. M. Simms, and T. W. Waine. 2021. "Replacing Human Interpretation of Agricultural Land in Afghanistan with a Deep Convolutional Neural Network." *International Journal of Remote Sensing* 42(8):3017–38. doi: 10.1080/01431161.2020.1864059.

Hamilton, Christopher M., Sebastian Martinuzzi, Andrew J. Plantinga, Volker C. Radeloff, David J. Lewis, Wayne E. Thogmartin, Patricia J. Heglund, and Anna M. Pidgeon. 2013. "Current and Future Land Use around a Nationwide Protected Area Network." *PLoS ONE* 8(1). doi: 10.1371/journal.pone.0055737.

Han, Sanghui, Alex Fafard, John Kerekes, Michael Gartley, Emmett Ientilucci, Andreas Savakis, Charles Law, Jason Parhan, Matt Turek, Keith Fieldhouse, and Todd Rovito. 2017. "Efficient Generation of Image Chips for Training Deep Learning Algorithms." P. 1020203 in *Automatic Target Recognition XXVII*. Vol. 10202. SPIE.

Hannah, Lee, Guy Midgley, Sandy Andelman, Miguel Araújo, Greg Hughes, Enrique Martinez-Meyer, Richard Pearson, and Paul Williams. 2007. "Protected Area Needs in a Changing Climate." *Frontiers in Ecology and the Environment* 5(3):131–38. doi: 10.1890/1540-9295(2007)5[131:PANIAC]2.0.CO;2.

He, Feng, Zongyong Tong, Lixue Wang, Guiliang Zheng, and Xianglin Li. 2018. "Effect of Fertilizer Additions on Plant Communities and Soil Properties in a Temperate Grassland Steppe." *Polish Journal of Environmental Studies* 27(4):1533–40. doi: 10.15244/pjoes/78040.

He, Kaiming, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. 2016. "Deep Residual Learning for Image Recognition." Pp. 770–78 in *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*. Vols. 2016-December. IEEE Computer Society.

He, Yuhong, Jian Yang, and Xulin Guo. 2020. "Green Vegetation Cover Dynamics in a Heterogeneous Grassland: Spectral Unmixing of Landsat Time Series from 1999 to 2014." *Remote Sensing* 12(22):1–20. doi: 10.3390/rs12223826.

Henebry, Geoffrey M. 1993. "Detecting Change in Grasslands Using Measures of Spatial Dependence with Landsat TM Data." *Remote Sensing of Environment* 46(2):223–34. doi: 10.1016/0034-4257(93)90097-H.

Henwood, William D. 2010. "Toward a Strategy for the Conservation and Protection of the World's Temperate Grasslands." *Great Plains Research* 20(1):121–34.

Hilker, Thomas, Enkhjargal Natsagdorj, Richard H. Waring, Alexei Lyapustin, and Yujie Wang. 2014. "Satellite Observed Widespread Decline in Mongolian Grasslands Largely Due to Overgrazing." *Global Change Biology* 20(2):418–28. doi: 10.1111/gcb.12365.

Hill, Michael J., and Juan P. Guerschman. 2022. "Global Trends in Vegetation Fractional Cover: Hotspots for Change in Bare Soil and Non-Photosynthetic Vegetation." *Agriculture, Ecosystems & Environment* 324:107719. doi: 10.1016/j.agee.2021.107719.

Horie, Rentaro, Takafumi Miyasaka, and Yu Yoshihara. 2023. "Grazing Behavior of Mongolian Sheep under Different Climatic Conditions." *Journal of Arid Environments* 209. doi: 10.1016/j.jaridenv.2022.104890.

Hostert, Patrick, Achim Röder, and Joachim Hill. 2003. "Coupling Spectral Unmixing and Trend Analysis for Monitoring of Long-Term Vegetation Dynamics in Mediterranean Rangelands." *Remote Sensing of Environment* 87(2–3):183–97. doi: 10.1016/80034-4257(03)00145-7.

Hyndman, Rob J., and Yanan Fan. 1996. "Sample Quantiles in Statistical Packages." *American Statistician* 50(4):361–65. doi: 10.1080/00031305.1996.10473566.

Ives, Anthony R., Likai Zhu, Fangfang Wang, Jun Zhu, Clay J. Morrow, and Volker C. Radeloff. 2022. "Statistical Tests for Non-Independent Partitions of Large Autocorrelated Datasets." *MethodsX* 9. doi: 10.1016/j.mex.2022.101660.

Iwasaki, Hiroyuki. 2006. "Impact of Interannual Variability of Meteorological Parameters on Vegetation Activity over Mongolia." *Journal of the Meteorological Society of Japan* 84(4):745–62. doi: 10.2151/jmsj.84.745.

Jackson, Randall D. 2020. “Soil Nitrate Leaching under Grazed Cool-Season Grass Pastures of the North Central US.” *Journal of the Science of Food and Agriculture* 100(15):5307–12.

Jambal, Sergelenkhuu, Nachinshonhor G. Urianhai, Takashi Otoda, Yoshihiro Yamada, Undarmaa Jamsran, Keiji Sakamoto, and Ken Yoshikawa. 2012. “Effect of Grazing Pressure on the Structure of Rangeland Plant Community in Mongolia.” *Journal of Arid Land Studies* 22(1):235–38.

Jamiyansharav, Khishigbayar, María E. Fernández-Giménez, Jay P. Angerer, Baasandorj Yadamsuren, and Zumberelmaa Dash. 2018. “Plant Community Change in Three Mongolian Steppe Ecosystems 1994-2013: Applications to State-and-Transition Models.” *Ecosphere* 9(3). doi: 10.1002/ecs2.2145.

Jamsran, Buyan Erdene, Chinsu Lin, Ishgaldan Byambakhuu, Jamsran Raash, and Khaulenbek Akhmadi. 2019. “Applying a Support Vector Model to Assess Land Cover Changes in the Uvs Lake Basin Ecoregion in Mongolia.” *Information Processing in Agriculture* 6(1). doi: 10.1016/j.inpa.2018.07.007.

Jargal, Jamsranjav. 2003. “Protected Area Status in Mongolia.” *Mongolian Journal of Biological Sciences* 1(2):49–54. doi: 10.22353/mjbs.2003.01.18.

Ji, Liuqing, and Ke Fan. 2019. “Climate Prediction of Satellite-Based Spring Eurasian Vegetation Index (NDVI) Using Coupled Singular Value Decomposition (SVD) Patterns.” *Remote Sensing* 11(18). doi: 10.3390/rs11182123.

John, Ranjeet, Jiquan Chen, Youngwook Kim, Zu tao Ou-yang, Jingfeng Xiao, Hoguen Park, Changliang Shao, Yaoqi Zhang, Amartuvshin Amarjargal, Ochirbat Batkhshig, and Jiaguo Qi. 2016. “Differentiating Anthropogenic Modification and Precipitation-Driven Change on Vegetation Productivity on the Mongolian Plateau.” *Landscape Ecology* 31(3):547–66. doi: 10.1007/s10980-015-0261-x.

John, Ranjeet, Jiquan Chen, Zu Tao Ou-Yang, Jingfeng Xiao, Richard Becker, Arindam Samanta, Sangram Ganguly, Wenping Yuan, and Ochirbat Batkhishig. 2013. “Vegetation Response to Extreme Climate Events on the Mongolian Plateau from 2000 to 2010.” *Environmental Research Letters* 8(3):035033. doi: 10.1088/1748-9326/8/3/035033.

de Jong, Steven M., Youchen Shen, Job de Vries, Ginny Bijnaar, Barend van Maanen, Pieter Augustinus, and Pita Verweij. 2021. “Mapping Mangrove Dynamics and Colonization Patterns at the Suriname Coast Using Historic Satellite Data and the LandTrendr Algorithm.” *International Journal of Applied Earth Observation and Geoinformation* 97. doi: 10.1016/j.jag.2020.102293.

Jürgensen, Jonathan, Dorothée G. Drucker, Anthony J. Stuart, Matthias Schneider, Bayarbaatar Buuveibaatar, and Hervé Bocherens. 2017. “Diet and Habitat of the Saiga Antelope during the Late Quaternary Using Stable Carbon and Nitrogen Isotope Ratios.” *Quaternary Science Reviews* 160:150–61. doi: 10.1016/j.quascirev.2017.01.022.

Kang, Yanghui, Mutlu Ozdogan, Xiaojin Zhu, Zhiwei Ye, Christopher Hain, and Martha Anderson. 2020. “Comparative Assessment of Environmental Variables and Machine Learning Algorithms for Maize Yield Prediction in the US Midwest.” *Environmental Research Letters* 15(6). doi: 10.1088/1748-9326/ab7df9.

Kang, Yao, En Liang Guo, Yong Fang Wang, Yu Long Bao, Yu Hai Bao, and Ren Mandula Na. 2021. “Application of Temperature Vegetation Dryness Index for Drought Monitoring in Mongolian Plateau.” *Chinese Journal of Applied Ecology* 32(7):2534–44. doi: 10.13287/j.1001-9332.202107.018.

Kariyeva, Jahan, and Willem J. D. van Leeuwen. 2012. “Phenological Dynamics of Irrigated and Natural Drylands in Central Asia before and after the USSR Collapse.” *Agriculture, Ecosystems & Environment* 162:77–89. doi: 10.1016/J.AGEE.2012.08.006.

Karnieli, A., M. Bayasgalan, Y. Bayarjargal, N. Agam, S. Khudulmur, and C. J. Tucker. 2006. “Comments on the Use of the Vegetation Health Index over Mongolia.” *International Journal of Remote Sensing* 27(10):2017–24.

Kennedy, Robert E., Zhiqiang Yang, Noel Gorelick, Justin Braaten, Lucas Cavalcante, Warren B. Cohen, and Sean Healey. 2018. “Implementation of the LandTrendr Algorithm on Google Earth Engine.” *Remote Sensing* 10(5).

Keshava, Nirmal, and John F. Mustard. 2002. “Spectral Unmixing.” *IEEE Signal Processing Magazine* 19(1):44–57. doi: 10.1109/79.974727.

Khishigbayar, J., María E. Fernández-Giménez, Jay P. Angerer, R. S. Reid, J. Chantsallkham, Ya Baasandorj, and D. Zumberelmaa. 2015. “Mongolian Rangelands at a Tipping Point? Biomass and Cover Are Stable but Composition Shifts and Richness Declines after 20years of Grazing and Increasing Temperatures.” *Journal of Arid Environments* 115. doi: 10.1016/j.jaridenv.2015.01.007.

Knick, Steven T., and John T. Rotenberry. 2002. “Effects of Habitat Fragmentation on Passerine Birds Breeding in Intermountain Shrubsteppe.” Pp. 130–40 in *Studies in Avian Biology*.

Knorn, Jan, Andreas Rabe, Volker C. Radeloff, Tobias Kuemmerle, Jacek Kozak, and Patrick Hostert. 2009. “Land Cover Mapping of Large Areas Using Chain Classification of Neighboring Landsat Satellite Images.” *Remote Sensing of Environment* 113(5). doi: 10.1016/j.rse.2009.01.010.

Lamchin, Munkhnasan, Jong Yeol Lee, Woo Kyun Lee, Eun Jung Lee, Moonil Kim, Chul Hee Lim, Hyun Ah Choi, and So Ra Kim. 2016. “Assessment of Land Cover Change and Desertification Using Remote Sensing Technology in a Local Region of Mongolia.” *Advances in Space Research* 57(1). doi: 10.1016/j.asr.2015.10.006.

Lamchin, Munkhnasan, Sonam Wangyel Wang, Chul Hee Lim, Altansukh Ochir, Ukrainskiy Pavel, Belay Manju Gebru, Yuyoung Choi, Seong Woo Jeon, and Woo Kyun Lee. 2020. “Understanding Global Spatio-Temporal Trends and the Relationship between Vegetation Greenness and Climate Factors by Land Cover during 1982–2014.” *Global Ecology and Conservation* 24:e01299. doi: 10.1016/j.gecco.2020.e01299.

Landis, Douglas A., Claudio Gratton, Randall D. Jackson, Katherine L. Gross, David S. Duncan, Chao Liang, Timothy D. Meehan, Bruce A. Robertson, Thomas M. Schmidt, Karen A. Stahlheber, James M. Tiedje, and Benjamin P. Werling. 2018. “Biomass and Biofuel Crop Effects on Biodiversity and Ecosystem Services in the North Central US.” *Biomass and Bioenergy* 114:18–29. doi: 10.1016/j.biombioe.2017.02.003.

Lewińska, Katarzyna Ewa, Johanna Buchner, Benjamin Bleyhl, Patrick Hostert, He Yin, Tobias Kuemmerle, and Volker C. Radeloff. 2021. “Changes in the Grasslands of the Caucasus Based on Cumulative Endmember Fractions from the Full 1987–2019 Landsat Record.” *Science of Remote Sensing* 4:100035. doi: 10.1016/J.SRS.2021.100035.

Lewińska, Katarzyna Ewa, Patrick Hostert, Johanna Buchner, Benjamin Bleyhl, and Volker C. Radeloff. 2020. “Short-Term Vegetation Loss versus Decadal Degradation of Grasslands in the Caucasus Based on Cumulative Endmember Fractions.” *Remote Sensing of Environment* 248:111969. doi: 10.1016/j.rse.2020.111969.

Li, Ang, Jianguo Wu, and Jianhui Huang. 2012. “Distinguishing between Human-Induced and Climate-Driven Vegetation Changes: A Critical Application of RESTREND in Inner Mongolia.” *Landscape Ecology* 27(7):969–82. doi: 10.1007/s10980-012-9751-2.

Li, G., J. Wang, Y. Wang, H. Wei, A. Ochir, D. Davaasuren, S. Chonokhuu, and E. Nasanbat. 2019. “Spatial and Temporal Variations in Grassland Production from 2006 to 2015 in Mongolia along the China-Mongolia Railway.” *Sustainability (Switzerland)* 11(7). doi: 10.3390/su10022177.

Li, Ke, Michael H. Kohn, Songmei Zhang, Xinrong Wan, Dazhao Shi, and Deng Wang. 2017. “The Colonization and Divergence Patterns of Brandt’s Vole (Lasiopodomys Brandtii) Populations

Reveal Evidence of Genetic Surfing." *BMC Evolutionary Biology* 17(1):1–17. doi: 10.1186/s12862-017-0995-y.
Li, Li, Fabian Ewald Fassnacht, and Matthias Bürgi. 2021. "Using a Landscape Ecological Perspective to Analyze Regime Shifts in Social–Ecological Systems: A Case Study on Grassland Degradation of the Tibetan Plateau." *Landscape Ecology* 36(8):2277–93. doi: 10.1007/s10980-021-01191-0.
Li, S. G., J. Asanuma, W. Eugster, A. Kotani, J. J. Liu, T. Urano, T. Oikawa, G. Davaa, D. Oyunbaatar, and M. Sugita. 2005. "Net Ecosystem Carbon Dioxide Exchange over Grazed Steppe in Central Mongolia." *Global Change Biology* 0(0):1944–55. doi: 10.1111/j.1365-2486.2005.01047.x.
Li, Zhouyuan, Wenzhao Wu, Xuehua Liu, Brian D. Fath, Hailian Sun, Xinchao Liu, Xinru Xiao, and Jun Cao. 2017. "Land Use/Cover Change and Regional Climate Change in an Arid Grassland Ecosystem of Inner Mongolia, China." *Ecological Modelling* 353:86–94. doi: 10.1016/j.ecolmodel.2016.07.019.
Lioubimtseva, E., and G. M. Henebry. 2009. "Climate and Environmental Change in Arid Central Asia: Impacts, Vulnerability, and Adaptations." *Journal of Arid Environments* 73(11):963–77. doi: 10.1016/j.jaridenv.2009.04.022.
Liu, Jiyuan, Quanqin Shao, Xiaodong Yan, Jiangwen Fan, Jinyan Zhan, Xiangzheng Deng, Wenhui Kuang, and Lin Huang. 2016. "The Climatic Impacts of Land Use and Land Cover Change Compared among Countries." *Journal of Geographical Sciences* 26(7):889–903. doi: 10.1007/s11442-016-1305-0.
Liu, Yanshu, Zhongjie Shi, Liyan Gong, Richun Cong, Xiaohui Yang, and David J. Eldridge. 2019. "Is the Removal of Aboveground Shrub Biomass an Effective Technique to Restore a Shrub-Encroached Grassland?" *Restoration Ecology* 27(6):1348–56. doi: 10.1111/rec.13012.
Liu, Yi Y., Jason P. Evans, Matthew F. McCabe, Richard A. M. de Jeu, Albert I. J. M. van Dijk, Albertus J. Dolman, and Izuru Saizen. 2013. "Changing Climate and Overgrazing Are Decimating Mongolian Steppes." *PLoS ONE* 8(2):e57599. doi: 10.1371/journal.pone.0057599.
Lkhavgadorj, Khureltsetseg, Badamnyambuu Iderzorig, and Ohseok Kwon. 2016. "Changes in Plant Community Structure in Relation to Climate Change and Restoration Plot Areas in Mongolia." *Journal of Ecology and Environment* 39(1):119–25.
Lushchekina, Anna A., S. Dulamtseren, L. Amgalan, and Valery M. Neronov. 1999. "The Status and Prospects for Conservation of the Mongolian Saiga Saiga Tatarica Mongolica." *ORYX* 33(1):21–30.
Ma, Wenhong, Jin Sheng He, Yuanhe Yang, Xiangping Wang, Cunzhu Liang, Mohammat Anwar, Hui Zeng, Jingyun Fang, and Bernhard Schmid. 2010. "Environmental Factors Covary with Plant Diversity-Productivity Relationships among Chinese Grassland Sites." *Global Ecology and Biogeography* 19(2):233–43. doi: 10.1111/j.1466-8238.2009.00508.x.
van der Meera, Freek D., and Xiuping Jia. 2012. "Collinearity and Orthogonality of Endmembers in Linear Spectral Unmixing." *International Journal of Applied Earth Observation and Geoinformation* 18(1):491–503. doi: 10.1016/j.jag.2011.10.004.
Meng, Xiaoyu, Xin Gao, Shengyu Li, and Jiaqiang Lei. 2020a. "Spatial and Temporal Characteristics of Vegetation NDVI Changes and the Driving Forces in Mongolia during 1982-2015." *Remote Sensing* 12(4). doi: 10.3390/rs12040604.
Meng, Xiaoyu, Xin Gao, Shengyu Li, and Jiaqiang Lei. 2020b. "Spatial and Temporal Characteristics of Vegetation NDVI Changes and the Driving Forces in Mongolia during 1982–2015." *Remote Sensing* 12(4). doi: 10.3390/rs12040603.
Mueller, Thomas, Kirk A. Olson, Todd K. Fuller, George B. Schaller, Martyn G. Murray, and Peter Leimgruber. 2008. "In Search of Forage: Predicting Dynamic Habitats of Mongolian Gazelles Using Satellite-Based Estimates of Vegetation Productivity." *Journal of Applied Ecology* 45(2):649–58. doi: 10.1111/j.1365-2664.2007.01371.x.

Mundlak, Yair, and He Huang. 1996. “International Comparisons of Cattle Cycles.” *American Journal of Agricultural Economics* 78(4):855–68. doi: 10.2307/1243843.

Munkhnasan, Tsevegmed. 2019. *The Biology of Microtus Brandii /Vole/ in the Mongolian Steppe and Their Population, Impacts on Natural Rangeland Welfare and Controlling Management*.

Nejadrekabi, M., S. Eslamian, and M. J. Zareian. 2022. “Spatial Statistics Techniques for SPEI and NDVI Drought Indices: A Case Study of Khuzestan Province.” *International Journal of Environmental Science and Technology* 19(7):6573–94. doi: 10.1007/s13762-021-03852-8.

Noi Phan, Thanh, Verena Kuch, and Lukas W. Lehnert. 2020. “Land Cover Classification Using Google Earth Engine and Random Forest Classifier-the Role of Image Composition.” *Remote Sensing* 12(15). doi: 10.3390/RS12152411.

Oates, Lawrence G., and Randall D. Jackson. 2014. “Livestock Management Strategy Affects Net Ecosystem Carbon Balance of Subhumid Pasture.” *Rangeland Ecology and Management* 67(1):19–29. doi: 10.2111/REM-D-12-00151.1.

Ojima, Dennis, and Togtohyn Chuluun. 2008. “Policy Changes in Mongolia: Implications for Land Use and Landscapes.” Pp. 179–93 in *Fragmentation in Semi-Arid and Arid Landscapes: Consequences for Human and Natural Systems*. Vol. 9781402049064.

Okujeni, Akpona, Sebastian van der Linden, Stefan Suess, and Patrick Hostert. 2017. “Ensemble Learning from Synthetically Mixed Training Data for Quantifying Urban Land Cover with Support Vector Regression.” *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing* 10(4):1640–50. doi: 10.1109/JSTARS.2016.2634859.

Okujeni, Akpona, Sebastian van der Linden, Laurent Tits, Ben Somers, and Patrick Hostert. 2013. “Support Vector Regression and Synthetically Mixed Training Data for Quantifying Urban Land Cover.” *Remote Sensing of Environment* 137:184–97. doi: 10.1016/j.rse.2013.06.007.

Olofsson, Pontus, Giles M. Foody, Martin Herold, Stephen v. Stehman, Curtis E. Woodcock, and Michael A. Wulder. 2014. “Good Practices for Estimating Area and Assessing Accuracy of Land Change.” *Remote Sensing of Environment* 148.

Olofsson, Pontus, Giles M. Foody, Stephen v. Stehman, and Curtis E. Woodcock. 2013. “Making Better Use of Accuracy Data in Land Change Studies: Estimating Accuracy and Area and Quantifying Uncertainty Using Stratified Estimation.” *Remote Sensing of Environment* 129. doi: 10.1016/j.rse.2012.10.031.

Olson, Kirk A., Martyn G. Murray, and Todd K. Fuller. 2010. “Vegetation Composition and Nutritional Quality of Forage for Gazelles in Eastern Mongolia.” *Rangeland Ecology and Management* 63(5):593–98. doi: 10.2111/REM-D-09-00122.1.

Oyundelger, Khurelpurev, Christiane M. Ritz, Oyunbileg Munkhzul, Birgit Lang, Julian Ahlborn, Batlai Oyuntsetseg, Christine Römermann, and Karsten Wesche. 2020. “Climate and Land Use Affect Genetic Structure of Stipa Glareosa P. A. Smirn. in Mongolia.” *Flora: Morphology, Distribution, Functional Ecology of Plants* 266. doi: 10.1016/j.flora.2020.151572.

Parmesan, C. 1996. “Climate and Species’ Range [1].” *Nature* 382(6594):765–66.

Peddle, Derek R., Forrest G. Hall, and Ellsworth F. Ledrew. 1999. “Spectral Mixture Analysis and Geometric-Optical Reflectance Modeling of Boreal Forest Biophysical Structure.” *Remote Sensing of Environment* 67(3):288–97. doi: 10.1016/S0034-4257(98)00090-X.

Phung, Van Hiep, and Eun Joo Rhee. 2019. “A High-Accuracy Model Average Ensemble of Convolutional Neural Networks for Classification of Cloud Image Patches on Small Datasets.” *Applied Sciences (Switzerland)* 9(21). doi: 10.3390/app9214500.

Poulter, Benjamin, David Frank, Philippe Ciais, Ranga B. Myneni, Niels Andela, Jian Bi, Gregoire Broquet, Josep G. Canadell, Frederic Chevallier, Yi Y. Liu, Steven W. Running, Stephen Sitch, and

Guido R. van der Werf. 2014. “Contribution of Semi-Arid Ecosystems to Interannual Variability of the Global Carbon Cycle.” *Nature* 509(7502):600–603. doi: 10.1038/nature13376.
Powell, Marvin G., Darrell M. Hull, and A. Alexander Beaujean. 2020. “Propensity Score Matching for Education Data: Worked Examples.” *Journal of Experimental Education* 88(1):145–64. doi: 10.1080/00220973.2018.1541850.
Qiongyu Huang, Nicole Motzer, Ginger Allington, Kirk Olson, Melissa Songer, Peter Leimgruber, and Tungalag Ulambayar. 2022. “Untangling the Interactions Between Rural Outmigration, Grassland Degradation, and Sustainable Land Use in Mongolia.”
Radeloff, Volker C., Todd F. Miller, Hong S. He, and David J. Mladenoff. 2000. “Periodicity in Spatial Data and Geostatistical Models: Autocorrelation between Patches.” *Ecography* 23(1):81–91. doi: 10.1111/j.1600-0587.2000.tb00263.x.
Radeloff, Volker C., David J. Mladenoff, and Mark S. Boyce. 1999. “Detecting Jack Pine Budworm Defoliation Using Spectral Mixture Analysis: Separating Effects from Determinants.” *Remote Sensing of Environment* 69(2):156–69. doi: 10.1016/S0034-4257(99)00008-5.
Radeloff, Volker C., Susan I. Stewart, Todd J. Hawbaker, Urs Gimmi, Anna M. Pidgeon, Curtis H. Flather, Roger B. Hammer, and David P. Helmers. 2010. “Housing Growth in and near United States Protected Areas Limits Their Conservation Value.” *Proceedings of the National Academy of Sciences of the United States of America* 107(2):940–45. doi: 10.1073/pnas.0911131107.
Rapinel, Sébastien, Cendrine Mony, Lucie Lecoq, Bernard Clément, Alban Thomas, and Laurence Hubert-Moy. 2019. “Evaluation of Sentinel-2 Time-Series for Mapping Floodplain Grassland Plant Communities.” *Remote Sensing of Environment* 223:115–29. doi: 10.1016/j.rse.2019.01.018.
Reading, Richard P., Don Bedunah, and Sukh Amgalanbaatar. 2010. “Conserving Mongolia’s Grasslands, with Challenges, Opportunities, and Lessons for North America’s Great Plains.” *Great Plains Research* 20(1):85–107.
Reading, Richard P., Donald J. Bedunah, and Sukhiin Amgalanbaatar. 2006. “Conserving Biodiversity on Mongolian Rangelands: Implications for Protected Area Development and Pastoral Uses.” *Rangelands of Central Asia: Proceedings of the Conference on Transformations, Issues, and Future Challenges* 1–17.
Saadeldin, Mohamed, Rob O’Hara, Jesko Zimmermann, Brian Mac Namee, and Stuart Green. 2022. “Using Deep Learning to Classify Grassland Management Intensity in Ground-Level Photographs for More Automated Production of Satellite Land Use Maps.” *Remote Sensing Applications: Society and Environment* 26. doi: 10.1016/j.rsase.2022.100741.
Sainnemekh, Sumjidmaa, Isabel C. Barrio, Bulgamaa Densambuu, Brandon Bestelmeyer, and Ása L. Aradóttir. 2022a. “Rangeland Degradation in Mongolia: A Systematic Review of the Evidence.” *Journal of Arid Environments* 196.
Sainnemekh, Sumjidmaa, Isabel C. Barrio, Bulgamaa Densambuu, Brandon Bestelmeyer, and Ása L. Aradóttir. 2022b. “Rangeland Degradation in Mongolia: A Systematic Review of the Evidence.” *Journal of Arid Environments* 196.
Scholtz, Rheinhardt, and Dirac Twidwell. 2022. “The Last Continuous Grasslands on Earth: Identification and Conservation Importance.” *Conservation Science and Practice* 4(3). doi: 10.1111/csp2.626.
Schug, Franz, David Frantz, Akpona Okujeni, Sebastian van der Linden, and Patrick Hostert. 2020. “Mapping Urban-Rural Gradients of Settlements and Vegetation at National Scale Using Sentinel-2 Spectral-Temporal Metrics and Regression-Based Unmixing with Synthetic Training Data.” *Remote Sensing of Environment* 246:111810. doi: 10.1016/j.rse.2020.111810.
Senaviratna, N. A. M. R., and T. M. J. A. Cooray. 2019. “Diagnosing Multicollinearity of Logistic Regression Model.” *Asian Journal of Probability and Statistics*. doi: 10.9734/ajpas/2019/v5i230132.

Shao, Changliang, Jiquan Chen, Housen Chu, Raffaele Lafortezza, Gang Dong, Michael Abraha, Ochirbat Batkhishig, Ranjeet John, Zutao Ouyang, Yaoqi Zhang, and Jiaguo Qi. 2017. "Grassland Productivity and Carbon Sequestration in Mongolian Grasslands: The Underlying Mechanisms and Nomadic Implications." *Environmental Research* 159:124–34. doi: https://doi.org/10.1016/j.envres.2017.08.001.

Shenbrot, Georgy I., and Boris R. Krasnov. 2005. *Atlas of the Geographic Distribution of the Arvicoline Rodents of the World (Rodentia, Muridae: Arvicolinae)*. Vol. 45. 1st ed. Pensoft Pub.

Shukherdorj, Baasanmunkh, Takashi Shiga, Oyuntsetseg Batlai, Karsten Wesche, Christiane M. Ritz, Khaliunaa Khurelbaatar, Jae Young Kim, Hyeong Jun Jo, Batkhuu Nyam-Osor, Gyu Young Chung, and Hyeok Jae Choi. 2019. "Contribution to the Knowledge on the Flora of Numrug Strictly Protected Area and Some Parts of East Mongolia." *Journal of Asia-Pacific Biodiversity* 12(2):284–301. doi: 10.1016/J.JAPB.2019.01.005.

Sieber, Anika, Tobias Kuemmerle, Alexander v. Prishchepov, Kelly J. Wendland, Matthias Baumann, Volker C. Radeloff, Leonid M. Baskin, and Patrick Hostert. 2013. "Landsat-Based Mapping of Post-Soviet Land-Use Change to Assess the Effectiveness of the Oksky and Mordovsky Protected Areas in European Russia." *Remote Sensing of Environment* 133:38–51. doi: 10.1016/j.rse.2013.01.021.

Sinclair, Steve J., Tara Zamin, Paul Gibson-Roy, Joshua Dorrough, Nathan Wong, Vanessa Craigie, Georgia E. Garrard, and Joslin L. Moore. 2019. "A State-and-Transition Model to Guide Grassland Management." *Australian Journal of Botany* 67(5):437–53. doi: 10.1071/BT18167.

Stagge, James H., Lena M. Tallaksen, Lukas Gudmundsson, Anne F. van Loon, and Kerstin Stahl. 2016. "Response to Comment on 'Candidate Distributions for Climatological Drought Indices (SPI and SPEI).'" *International Journal of Climatology* 36(4):2132–38. doi: 10.1002/joc.4564.

Sternberg, Troy. 2012. "Piospheres and Pastoralists: Vegetation and Degradation in Steppe Grasslands." *Human Ecology* 40(6):811–20. doi: 10.1007/s10745-012-9539-7.

Tabachnick, Barbara G., and Linda S. Fidell. 2019. "Using Multivariate Statistics (7th Edition)." Pp. 1–815 in *Pearson*. New York: Pearson Allyn and Bacon.

Terrado, Marta, Sergi Sabater, Becky Chaplin-Kramer, Lisa Mandle, Guy Ziv, and Vicenç Acuña. 2016. "Model Development for the Assessment of Terrestrial and Aquatic Habitat Quality in Conservation Planning." *Science of the Total Environment* 540:63–70. doi: 10.1016/j.scitotenv.2015.03.064.

Townsend, Philip A., Todd R. Lookingbill, Clayton C. Kingdon, and Robert H. Gardner. 2009. "Spatial Pattern Analysis for Monitoring Protected Areas." *Remote Sensing of Environment* 113(7):1410–20. doi: 10.1016/j.rse.2008.05.023.

Uhrin, Amy v., and Philip A. Townsend. 2016. "Improved Seagrass Mapping Using Linear Spectral Unmixing of Aerial Photographs." *Estuarine, Coastal and Shelf Science* 171:11–22. doi: 10.1016/j.ecss.2016.01.021.

Vermeulen, L. M., Z. Munch, and A. Palmer. 2021. "Fractional Vegetation Cover Estimation in Southern African Rangelands Using Spectral Mixture Analysis and Google Earth Engine." *Computers and Electronics in Agriculture* 182:105980. doi: 10.1016/j.compag.2020.105980.

Wang, Guocheng, Yao Huang, Yurong Wei, Wen Zhang, Tingting Li, and Qing Zhang. 2019. "Inner Mongolian Grassland Plant Phenological Changes and Their Climatic Drivers." *Science of the Total Environment* 683:1–8. doi: 10.1016/j.scitotenv.2019.05.125.

Wang, Jie, Xiangming Xiao, Rajen Bajgain, Patrick Starks, Jean Steiner, Russell B. Doughty, and Qing Chang. 2019. "Estimating Leaf Area Index and Aboveground Biomass of Grazing Pastures Using Sentinel-1, Sentinel-2 and Landsat Images." *ISPRS Journal of Photogrammetry and Remote Sensing* 154:189–201. doi: 10.1016/j.isprsjprs.2019.06.007.

Wang, Juanle, Kai Cheng, Qing Liu, Junxiang Zhu, Altansukh Ochir, Davaadorj Davaasuren, Ge Li, Haishuo Wei, Sonomdagva Chonokhuu, Oyunchimeg Namsrai, and Ariunsanaa Bat-Erdene. 2019.

“Land Cover Patterns in Mongolia and Their Spatiotemporal Changes from 1990 to 2010.” *Arabian Journal of Geosciences* 12(24). doi: 10.1007/s12517-019-4893-z.

Wang, Juanle, Haishuo Wei, Kai Cheng, Altansukh Ochir, Davaadorj Davaasuren, Pengfei Li, Faith Ka Shun Chan, and Elbegjargal Nasanbat. 2020a. “Spatio-Temporal Pattern of Land Degradation from 1990 to 2015 in Mongolia.” *Environmental Development* 34. doi: 10.1016/j.envdev.2020.100497.

Wang, Juanle, Haishuo Wei, Kai Cheng, Altansukh Ochir, Davaadorj Davaasuren, Pengfei Li, Faith Ka Shun Chan, and Elbegjargal Nasanbat. 2020b. “Spatio-Temporal Pattern of Land Degradation from 1990 to 2015 in Mongolia.” *Environmental Development* 34:100497. doi: https://doi.org/10.1016/j.envdev.2020.100497.

Wang, Jun, Daniel G. Brown, and Arun Agrawal. 2013. “Climate Adaptation, Local Institutions, and Rural Livelihoods: A Comparative Study of Herder Communities in Mongolia and Inner Mongolia, China.” *Global Environmental Change* 23(6). doi: 10.1016/j.gloenvcha.2013.08.014.

Wei, Yun Jie, Lin Zhen, Xue Lin Liu, and Ochirbat Batkhishig. 2008. “Land Use Change and Its Driving Factors in Mongolia from 1992 to 2005.” *Chinese Journal of Applied Ecology* 19(9):1992–2002.

Xu, Yecheng, Y. Zhang, Jiquan Chen, and Ranjeet John. 2019. “Livestock Dynamics under Changing Economy and Climate in Mongolia.” *Land Use Policy* 88:104120. doi: 10.1016/j.landusepol.2019.104120.

Yang, Hongyan, and Jianmin Du. 2021. “Classification of Desert Steppe Species Based on Unmanned Aerial Vehicle Hyperspectral Remote Sensing and Continuum Removal Vegetation Indices.” *Optik* 247:167877. doi: 10.1016/J.IJLEO.2021.167877.

Yang, Hongyan, Jianmin Du, Yuan Wang, Yanbin Zhang, Xipeng Zhang, and Yongchao Kang. 2019. “Classification Method of Grassland Species Based on Unmanned Aerial Vehicle Remote Sensing and Convolutional Neural Network.” *Nongye Jixie Xuebao/Transactions of the Chinese Society for Agricultural Machinery* 50(4). doi: 10.6041/j.issn.1000-1298.2019.04.021.

Ykhanbai, Hijaba, Enkhbat Bulgan, Ulipkan Beket, Ronnie Vernooy, and John Graham. 2004. “Reversing Grassland Degradation and Improving Herders’ Livelihoods in the Altai Mountains of Mongolia.” *Mountain Research and Development* 24(2):96–100. doi: 10.1659/0276-4741(2004)024[0096:RGDAIH]2.0.CO;2.

Yu, Changzhi, Hengjian Li, and Xiyu Wang. 2019. “IET Image Processing SVD-Based Image Compression, Encryption, and Identity Authentication Algorithm on Cloud.” doi: 10.1049/iet-ipr.2018.5912.

Yu, Hao, Lei Wang, Zongming Wang, Chunying Ren, and Bai Zhang. 2019. “Using Landsat OLI and Random Forest to Assess Grassland Degradation with Aboveground Net Primary Production and Electrical Conductivity Data.” *ISPRS International Journal of Geo-Information* 8(11):511. doi: 10.3390/ijgi8110511.

Yue, Jibo, Jia Tian, Nianxu Xu, and Qingjiu Tian. 2021. “Vegetation-Shadow Indices Based on Differences in Effect of Atmospheric-Path Radiation between Optical Bands.” *International Journal of Applied Earth Observation and Geoinformation* 104:102579. doi: 10.1016/j.jag.2021.102579.

Zemmrich, Anne, Werner Hilbig, and Damdinsürengiyn Oyuunchimeg. 2010. “Plant Communities along an Elevation Gradient under Special Consideration of Grazing in Western Mongolia.” *Phytocoenologia* 40(2–3):91–115. doi: 10.1127/0340-269X/2010/0040-0443.

Zeng, Xubin, Praveen Rao, Ruth S. DeFries, and Matthew C. Hansen. 2003. “Interannual Variability and Decadal Trend of Global Fractional Vegetation Cover from 1982 to 2000.” *Journal of Applied Meteorology* 42(10):1525–30. doi: 10.1175/1520-0450(2003)042<1525:IVADTO>2.0.CO;2.

Zhang, Xin, Liangxiu Han, Lianghao Han, and Liang Zhu. 2020. “How Well Do Deep Learning-Based Methods for Land Cover Classification and Object Detection Perform on High Resolution Remote Sensing Imagery?” *Remote Sensing* 12(3). doi: 10.3390/rs12030417.

Zheng, Xiao Xuan, Rui Dong Wang, Tian Tian Jin, Li Fen Mu, and Guo Hua Liu. 2008. “Relationships between Biodiversity and Biomass under Different Regimes of Grassland Use in Hulunbeir, Inner Mongolia.” *Shengtai Xuebao/ Acta Ecologica Sinica* 28(11).

Zhong, Zhiwei, Guoliang Li, Dirk Sanders, Deli Wang, Robert D. Holt, and Zhibin Zhang. 2022. “A Rodent Herbivore Reduces Its Predation Risk through Ecosystem Engineering.” *Current Biology*. doi: 10.1016/j.cub.2022.02.074.

ACKNOWLEDGEMENT

This proposal, the research ideas, questions and writing is my work but I am very thankful to my advisor Prof Volker Radeloff for his guidance, advice, productive discussions, and editorial support that allowed me to improve the proposal. I would also like to thank my dear professors who are my thesis committee members Prof Anna Pidgeon, Prof Philip Townsend, Prof Randy Jackson and Prof Mutlu Ozdogan, for giving me valuable commend and suggestion. I would like to also thank the Institute of Geography, Mongolian Academy of Sciences, and Mongolian Geospatial Association for providing field tools, and team of field campaign to complete my field work. Similarly, I greatly appreciate support by the National Agency for Meteorology and Environmental Monitoring, which is providing the long-term climate datasets. I would like to thank Wildlife Conservation Society of Mongolia (WCS), World Wildlife Fund (WWF) for providing ungulates habitat GIS data. Lastly, I am thankful to Dr K. Lewinska, who pioneered the cumulative endmember approach for grassland degradation monitoring.