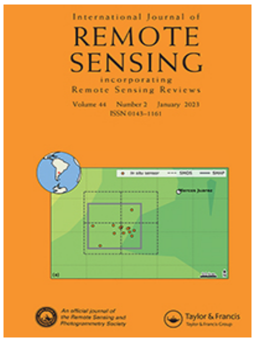

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Estimating fractional vegetation cover and aboveground biomass for land degradation assessment in eastern Mongolia steppe: combining ground vegetation data and remote sensing

Batnyambuu Dashpurev[a], Munkhtsetseg Dorj[b], Thanh Noi Phan[a], Jörg Bendix[c] and Lukas W. Lehnert[a]

[a]Department of Geography, Ludwig-Maximilians-University Munich, Munich, Germany; [b]Geodesy and Cartography, Agency of Land Administration and Management, Ulaanbaatar, Mongolia; [c]Faculty of Geography, Philipps-University of Marburg, Marburg, Germany

ABSTRACT

Fractional vegetation cover (FVC) and aboveground biomass (AGB) are critically important for monitoring grassland degradation, and their accurate estimation can be used as key proxies for assessing land degradation. The main purpose of this study was to estimate the FVC and AGB in the eastern Mongolian steppe using remote sensing and machine learning. In this context, spectral bands and vegetation indices were extracted from the processed Sentinel-2 data and used as predictors. The field vegetation data were derived from the Mongolian pasture-monitoring database, which consisted of 256 plots with FVC and AGB measurements. Consequently, we derived FVC and AGB from Sentinel-2 imagery using 256 field vegetation measurements in the vast eastern Mongolian steppe as a reference for random forest (RF) models ($R^2_{FVC} = 0.81$, $R^2_{AGB} = 0.76$). Among the variables, the predictor variables derived from spectral vegetation and soil indices, especially NDVI, Simple Ratio (SR), and OSAVI, were highly important for predicting FVC and AGB. As expected, a comparison among the map values showed that the spatial distribution of FVC and AGB was consistent with the landscapes and ecoregions in the study area. As the FVC and AGB maps only showed the current condition of vegetation cover, we also analysed NDVI trends to explain vegetation cover changes. We tested temporal trends in vegetation using Landsat NDVI time series data and the Mann-Kendall trend test. This revealed that in 7.3% of the area, the NDVI significantly increased, whereas a significant decrease was observed in 58% of the area.

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1. Introduction

Grasslands are critically important ecosystems, covering 26%–40% of the Earth's terrestrial surface (Suttie, Reynolds, and Batello 2005; Gholami Baghi and Oldeland 2019). Mongolia hosts an important part of the largest natural grassland region in the world, and is home

CONTACT Batnyambuu Dashpurev B.Dashpurev@iggf.geo.uni-muenchen.de Department of Geography, Ludwig-Maximilians-University Munich, Munich 80333, Germany

to one of the last intact steppe ecosystems with traditional land use and significant biodiversity (Batsaikhan et al. 2014; Pfeiffer, Dulamsuren, and Wesche 2020). In recent decades, grasslands in Mongolia have come under threat due to land degradation, climate change, aridity, grazing, and human activities (Reading, Bedunah, and Amgalanbaatar 2010). In particular, land degradation poses severe challenges to ecosystems and sustainable livelihoods in the eastern Mongolian steppes (Girvetz et al. 2014; Batnyambuu, Bendix, and Lehnert 2020a). Studies on land degradation use proxies for vegetation cover assessments that can directly be derived from both remote sensing data and field measurements (Quang Bao, Nkonya, and Mirzabaev 2015). For instance, fractional vegetation cover (FVC) and aboveground biomass (AGB) are important parameters that describe vegetation degradation and soil erosion, and are often used to evaluate and monitor land degradation status (Chu 2020; Liang and Wang 2020). Therefore, several previous studies have used estimates of vegetation cover and biomass as proxies for land degradation (Bai et al. 2008; Higginbottom and Symeonakis 2014; Quang Bao, Nkonya, and Mirzabaev 2015) Furthermore, approaches based on vegetation cover have been increasingly used in recent decades and have shown that the results of these studies effectively indicate the status and process of land degradation (Dubovyk 2017; Wessels, Prince, and Reshef 2008; Easdale et al. 2019; Dashpurev et al. 2021).

Optical remote sensing approaches are becoming increasingly popular for estimating FVC and AGB (Chu 2020; Jin et al. 2014; Morais et al. 2021). In particular, advances in machine learning have enabled the accurate estimation of FVC and AGB by combining optical remote sensing data with data measured in the field (Zhang et al. 2020; Morais et al. 2021). Recently, a comprehensive review summarized different machine learning methods to estimate the AGB of grasslands from remote sensing data and found generally high accuracies for random forest (RF) technique (Morais et al. 2021). To improve the accuracy of FVC and AGB estimations, many previous studies have used spectral vegetation indices, such as the normalized difference vegetation index (NDVI), which is derived from the reflectance measured by remote sensing imagery (Morais et al. 2021). For reasons related to its strong correlation with FVC and AGB, NDVI is increasingly used to predict vegetation cover and biomass (Prabhakara, Hively, and Gregory 2015; Cabrera-Bosquet et al. 2011). In addition, field measurements are an important part of remote-sensing-based FVC and AGB modelling, which are often collected by traditional methods (Jin et al. 2014). However, surveying FVC and AGB using traditional vegetation sampling methods is costly, labour-intensive, and time-consuming, and it is impossible to cover large areas. For this reason, there have been very few efforts to estimate FCV and AGB in Mongolia using both field measurements and satellite imagery (Kim et al. 2020; Otgonbayar et al. 2019). More specifically, Otgonbayar et al. (2019) estimated the AGB using Landsat 8 and field survey data from Mongolia. Unfortunately, this study was not based on any field samples in the Eastern Mongolian Steppe area due to the low number of field vegetation plots. Fortunately, the continuous development of rangeland health monitoring systems in Mongolia has resulted in extensive databases that provide free-of-charge reference data on FVC and AGB (Densambuu et al. 2018). To our knowledge, there is no study on FVC and AGB which was conducted by combining in situ data from this rangeland health monitoring database as a field reference with remotely sensed data providing a vegetation cover product in Mongolia. The disadvantage of this new rangeland health monitoring data source is that the data have only become available in recent years. Therefore, changes in FVC and AGB over a longer timescale cannot be assessed. An alternative method for identifying the direction of change in vegetation cover is the analysis of NDVI trends based on a time series of remote sensing data (Huang et al. 2021). Several studies have demonstrated that changes in satellite-derived NDVI time series have the potential to serve as a proxy for land degradation assessments (Yengoh et al. 2015; Huang et al. 2021; Bai et al. 2008). As the NDVI correlates directly with vegetation productivity (Tucker and Sellers 1986), this index is easily calculated from spectral bands available over a long time period. Additionally, rapid advancements in remote sensing technology and applications have made the use of NDVI more popular for vegetation cover assessments (Yengoh et al. 2015; Huang et al. 2021)

Grasslands in the Mongolian steppe have long been used as pasturelands for nomadic pastoral systems (Sheehy 1993). Livestock grazing pressure largely influences grassland degradation in Mongolia (Sainnemekh et al. 2022), which leads to altered vegetation cover and AGB in the steppes (Munkhzul et al. 2021). Therefore, there is a high demand for FVC and AGB map products with reasonable accuracy at the regional-to-country scale for monitoring grasslands. The main aim of this study was to accurately estimate the FVC and AGB for grasslands and to determine the changes in vegetation cover over time in the eastern Mongolian steppe. To achieve this, we first derived FVC and AGB from Sentinel-2 imagery using data measured in the field as a reference for the RF regression models. We then performed a trend analysis to estimate the changes in NDVI over time in the eastern Mongolian steppe.

2. Materials and methods

2.1. Study area

Dornod aimag (or province) is the study area and is located in the easternmost part of Mongolia, bordering Russia to the north and China to the east and south (Figure 1). It occupies approximately 124,000 km^2 between 50°28′N and 46°25′ N in latitude and 112° 05′E and 119°56′ E longitude. The study area has three distinct ecoregions: Mongolian Daurian (or Mongol Daguur) forest steppe, Eastern Mongolian steppe, and Numrug forest steppe. The Mongolian Daurian forest steppe in the northern part of the study area covers the marginal branches of the Khentii Mountain Range and plains.

The eastern Mongolian steppe, the main part of the study area, mainly consists of broad plains and rolling hills, where the vegetation is dominated by bunch grasses such as *Stipa krylovii* and *Cleistogenes squarrosa*. The Numrug forest steppe, in the far eastern part of the study area, comprises marginal branches of the Greater Khingan Mountains, foot-hills, and plains. The study area is characterized by an extremely continental climate. The average monthly temperature minimum reaches −20 to −26°C in January, and the average maximum monthly temperature of 21°C occurs in July. The average annual precipitation amounts to 300–350 mm in the Mongolian Daurian forest steppe and 200–300 mm in the Eastern Mongolian steppe and Numrug forest steppe, with monthly maxima occurring mainly in summer (Girvetz et al. 2014; Pfeiffer et al. 2018; Shukherdorj et al. 2019; Yembuu 2021b). The study area has three strictly protected areas (SPA) and three nature reserves (NR). Traditionally, land use has been associated with livestock pastoralism, but mining- and oil extraction-related activities are becoming increasingly

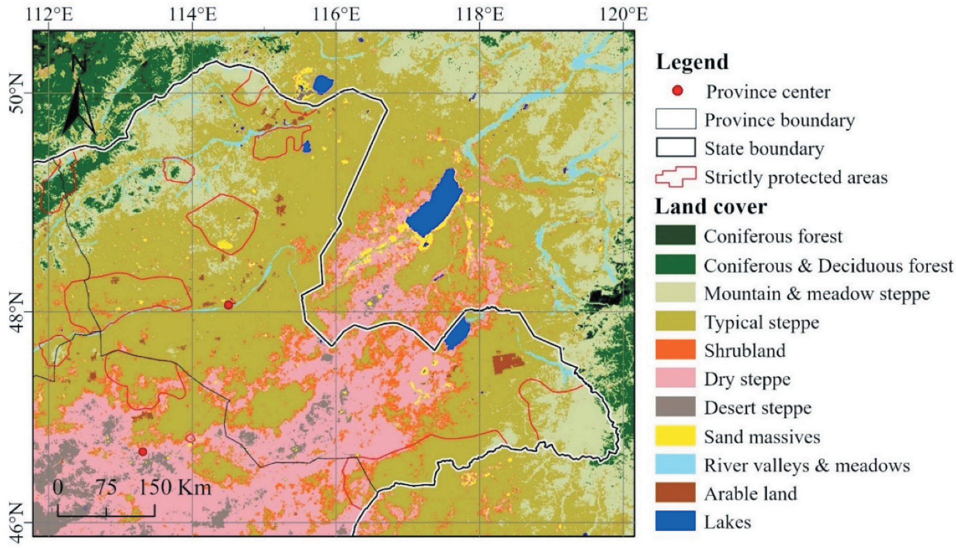

Figure 1. Location of study area and pasture photo-monitoring data. source: environmental information center Mongolia (NAMEM 2021).

important. Other land-use types in this area include settlements, agriculture, and infrastructure (Tsedev 2021).

2.2. Remote sensing of grassland vegetation cover

2.2.1. Data for FVC, AGB estimation and trend analysis

2.2.1.1. Remote sensing data. Multispectral imagery of Sentinel-2 was used to estimate the FVC and AGB, encompassing 13 spectral bands in the visible, near-infrared, and shortwave infrared regions of the spectrum with 10–60 m spatial resolution. The L1C images were downloaded free-of-charge from the United States Geological Survey's (USGS) website (https://earthexplorer.usgs.gov/). A set of 54 images with low cloud cover (25 tiles) of Sentinel-2 data acquired during 7– 17 July 2020 were used in this study. These images were atmospherically corrected and clouds were masked using the Sentinel Application Platform (SNAP) of the European Space Agency. Subsequently, single scenes of Sentinel-2 were merged into a mosaic to achieve a dataset covering the entire area of investigation. Finally, spectral indices were calculated from the spectral bands of Sentinel-2 imagery and used as an additional predictor for FVC and AGB estimation. The spectral indices and their corresponding descriptions are listed in Table 1.

For the trend analysis of vegetation cover, we used atmospherically corrected surface reflectance collections from Landsat 5 ETM and Landsat 8 OLI sensors on the Google Earth Engine platform. In these datasets, all satellite images were atmospherically corrected using the LEDAPS algorithms for Landsat 5 (Sayler 2020) and the LaSRC algorithms for Landsat 8 (USGS 2020) (USGS Landsat Surface Reflectance Tier 1). For all images acquired between 1st of June and 31st of August in the years 2010–2020, we employed the CFMask algorithm to identify and mask clouds and cloud shadows (Foga et al. 2017). Subsequently, the NDVI was calculated based on the red and near-infrared bands.

Table 1. Description of the spectral indices used in RF regression models for FVC and AGB.

Spectral indices	Abbreviation	Formula	Reference
Normalized difference vegetation index	NDVI	(NIR − Red)/(NIR + Red)	(Tucker 1979)
Red-Edge Normalized Difference Vegetation Index	$NDVI_{Red\text{-}edge}$	(NIR − RE)/(NIR + RE)	(Gitelson and Merzlyak 1994)
Green Normalized Difference Vegetation Index	$NDVI_{Green}$	(NIR - Green)/(NIR + Green)	(Gitelson, Kaufman, and Merzlyak 1996)
Simple Ratio	SR_{value}	NIR/Red	(Jordan 1969)
Red-Edge Simple Ratio	$SR_{Red\text{-}Edge}$	NIR/RedEdge	(Gitelson et al. 2002)
Green Chlorophyll Index	CL_{Green}	(NIR/Green) − 1	(Gitelson, Gritz, and Merzlyak 2003)
Red-Edge Chlorophyll Index	$CL_{Red\text{-}Edge}$	(NIR/RedEdge) − 1	(Gitelson et al. 2005)
Red-Edge Triangulated Vegetation Index	$RTVI_{Core}$	(100*(NIR – RedEdge) − 10*(NIR - Green))	(Haboudane et al. 2004)
Soil-Adjusted Vegetation Index	SAVI	1.5*(NIR – Red)/(NIR + Red + 0.5)	(Huete 1988)
Optimized Soil Adjusted Vegetation Index	OSAVI	(NIR – Red)/(NIR + Red + 0.16)	(Rondeaux, Steven, and Baret 1996)

Finally, the annual NDVI mosaics were produced by calculating the median NDVI value of all available images for the indicated time period within a year.

2.2.1.2. Pasture monitoring data.

Pasture monitoring data were downloaded free-of-charge from the Agency for Land Administration and Management, Geodesy, and Cartography in Mongolia (https://egazar.gov.mn). The database contains FVC and AGB with corresponding land cover photos of 256 plots in Eastern Mongolia (Figure 1). Field data were collected during the vegetation growing season of August 2020. Each sampling plot in the pasture-monitoring database consisted of nine photos taken in the nadir with a footprint of approximately 1 m^2. Each image was 5 m from the next image. Therefore, all images were aligned along a 50 m transect. The FVC values for each sampling plot are the mean values of nine different image locations. Monitoring images were collected annually at 5 metre intervals along two parallel 50 m long tapes by land management authorities. Analysis was performed using the Sample Point software that facilitates manual, pixel-based image analysis from nadir digital images of any scale, and automatically records data to a spreadsheet (Cagney, Cox, and Booth 2011). The AGB in each plot was sampled using a 1 × 1 m quadrat. The plants in each quadrat were harvested at the ground surface and dried at 80°C to obtain the dry weight. A rangeland-monitoring network was established and developed for grazing management and to report vegetation trends in Mongolian pasturelands.

2.2.2. Random forest regression

In this study, two regression models were separately applied to Sentinel-2 data using the RF algorithm (Breiman 2001). RF, a representative 'ensemble learning' method (Saini and Ghosh 2017), is widely used for regression and classification tasks in remote sensing. In the estimation of FVC and AGB, the spectral bands and indices of the Sentinel-2 data were used as predictors (Table 1). Training and validation data for both RF regression models were selected from the Mongolian pasture-monitoring data. For each model, 256 field vegetation measurements were randomly divided into training and independent validation datasets (90% and 10% of the data, respectively). Consequently, 230 samples were used as the training dataset. For the validation dataset, 26 samples were used. The models were validated and their accuracies were estimated using 10-fold cross-validation. R-squared values were calculated from the independent estimates to evaluate the performance of the RF regression models (Belgiu and Drăgu 2016; Sheykhmousa et al. 2020).

2.2.3. Mann-Kendall trend test

A Mann-Kendall trend test and Sen's slope test were applied for each pixel in the time series to analyse NDVI trends for significance and slope of change, respectively. The Mann-Kendall test determines whether there is a monotonic trend (upward or downward) in the multidimensional time series data of NDVI. It compares the two sets of ranks given by the same datasets. The trend values range between −1 (negative trend) and +1 (positive trend). The slope of the trend for each pixel was calculated using the nonparametric coefficient developed by Sen (Sen 1968). The Sen's slope test detects the magnitude of the slope based on the assumption of a linear trend (significance levels of 0.01 (high), 0.05 (medium), and 0.1 (low)).

3. Results

3.1. Estimation of fractional vegetation cover and aboveground biomass

The RF regression model was applied to the spectral bands and indices of Sentinel-2 data to estimate FVC and AGB in the eastern Mongolian steppe in 2020 (Figure 2(a,b)). The training and validation data for the RF model were prepared from Mongolian pasture-monitoring data. The validation results showed that the RF regression models performed well at R-squared values of 0.81 for FVC and 0.76 for AGB (Table A1). Supplementary Figure A1 shows the variable importance values for the RF models. According to the ranks, the important variables in the FVC and AGB regressions were similar. To estimate FVC, the most important variables were spectral vegetation indices, including the simple ratio (SR) vegetation index, NDVI, and NDVI red-edge. For the spectral bands, the red and vegetation red-edge bands were also considered very important for model performance. For AGB, the most important predictor variables were NDVI, SR vegetation index, OSAVI, SAVI, red-edge chlorophyll index (CI red-edge), NDVI red-edge, red band, and vegetation red-edge band. The spectral vegetation and soil indices were generally dominant in promoting the performance of the model.

As shown in Figure 2, the FVC and AGB had similar spatial distributions. Large values of both maps were concentrated in the northwestern and far eastern parts, where FVC ranged between 67%–90%, whereas AGB ranged between 1800–2604 kg/ha. These areas are covered by mountains and meadow steppes. According to the histogram charts in Figure 2, a larger FVC value occupied 20% of the total area, while AGB accounted for 11% of the total area. The intermediate values of both maps, 44%–67% and 1000–1800 kg/ha, were located in the transition zone of high and low fractions of vegetation value, which accounted for 47% of the total area in FVC, while AGB accounted for 22% of the total area. The low values of both maps, 20%–44% and 198–1000 kg/ha, were clustered in the central and northeastern parts of the study area, where the land is composed of moderately dry steppe and dry steppe. The histogram charts of both maps show that the low FVC values accounted for 33% of the study area, while AGB accounted for 67% of study area.

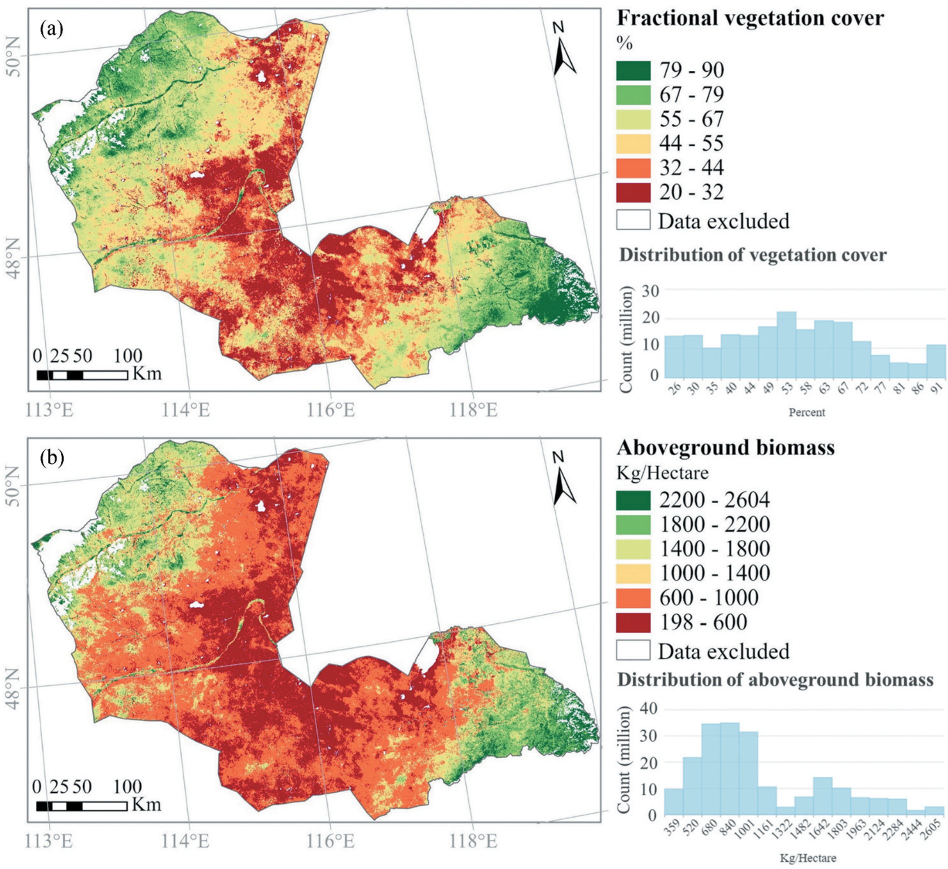

Figure 2. Maps of FVC (a) and AGB (b) for year 2020 using sentinel-2 data in eastern Mongolian steppe. Water surface and forest area were excluded for FVC and AGB.

3.2. The result of Mann-Kendall trend test

The Mann-Kendall trend test statistics were obtained from the median NDVI value of Landsat time series during the vegetation period of 2010–2020 at a spatial resolution of 30 m. Based on Sen's slope, positive and negative NDVI trends were observed in different ecological regions, which are presented in Figure 3. According to the trend magnitude of the Mann-Kendall analysis, the NDVI values in 29% of all pixels in the study area increased (Figure 4).

Regarding spatial distribution, these areas tended to be clustered along the northern and far eastern parts of the study area, where the landscape mainly consisted of forest steppe. Of these, only 25% gained a statistically significant trend, with a maximum magnitude of 0.15. In other words, 7.3% of the study area experienced statistically significant positive trends. In contrast, the NDVI in 71% of the study area exhibited a decreasing trend. Of those, 84% had a statistically significant trend that was most concentrated in the middle-eastern, central, and northeastern boundaries of the study area. These areas were composed of moderately dry steppes and dry steppes. Figure 3(b) shows that significantly

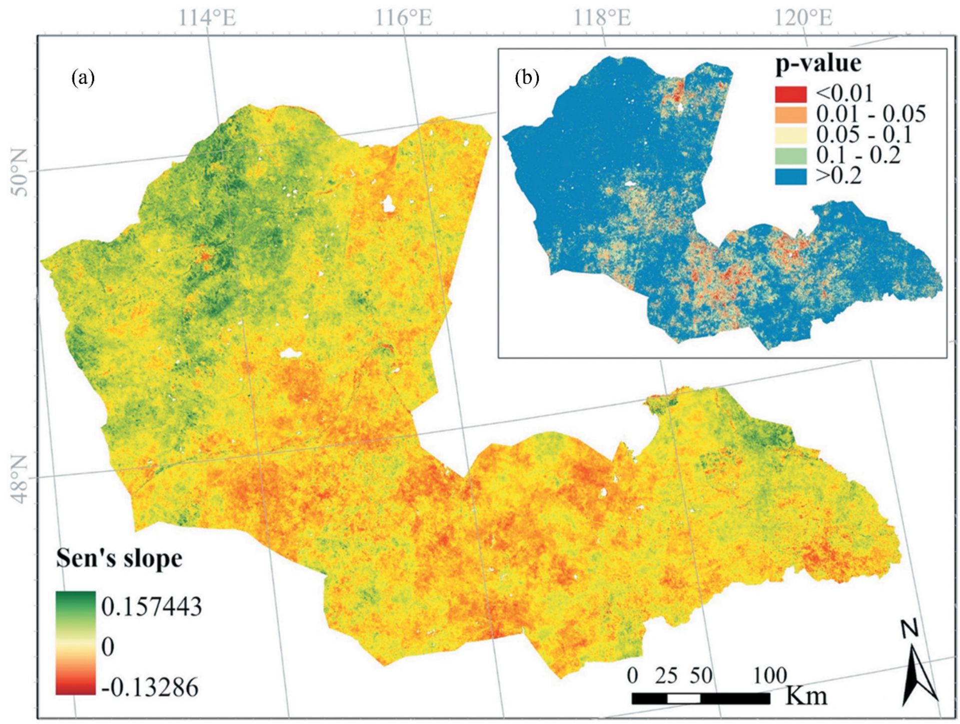

Figure 3. Mann-Kendall trend test results of NDVI time series 2010–2020. Magnitude of trend is shown in (a) and (b) and represents significant levels. Water surface was excluded.

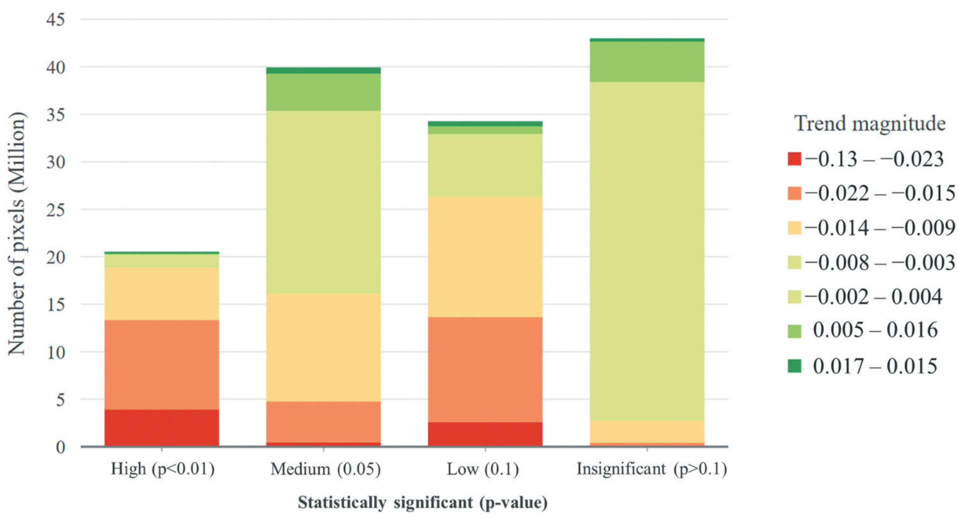

Figure 4. Comparison of Sen's slope and significance level (p-value).

decreasing trends were located in areas that are mostly used for oil exploration and exploitation around the middle-eastern cluster, the centre of the province, and areas along the northeastern country borders.

4. Discussion

4.1. Relevance of the FVC and AGB estimation

The main objective of this study was to produce FVC and AGB maps that have been estimated based on Mongolian pasture-monitoring data and Sentinel 2 satellite imagery using RF algorithms. The results of the FVC and AGB estimation models provide the following new contributions compared to the existing literature. First, the pasture-monitoring system in Mongolia has been newly developed; however, its platform has already accumulated an unprecedented amount of vegetation data. Nevertheless, no studies have prepared vegetation cover maps using the aforementioned large vegetation cover data over Mongolia and our study region. Therefore, our models and their results provide an effective way to use this pasture monitoring data for producing vegetation maps over Mongolia and the eastern Mongolian steppe regions. Very few studies have mapped the FVC and AGB over Mongolia and steppe regions (Yamamoto, Kajiwara, and Honda 2000; Nyamsuren et al. 2019), and even these have used very limited field measurement data. For instance, Otgonbayar et al (2019) recently mapped AGB using an RF model and Landsat imagery over Mongolia that used 553 field measurement sites as training data for the RF model for over 1.56 million km^2 area. A recent comprehensive review suggested that the accuracy of AGB estimation in grasslands using RF algorithms is strongly dependent on the number of field sites (Morais et al. 2021). For this study, we used 256 field measurement sites as the training and validation data of the RF model for 123.5 thousand km^2 area. Third, our results showed that the spectral indices and characteristics of Sentinel-2 data enabled the derivation of FVC and AGB maps with a spatial resolution of 20 m in Mongolian grasslands. Sentinel-2 imagery is one of the most widely used remote sensing data for vegetation cover mapping worldwide (Bareth and Waldhoff 2017; Phiri et al. 2020). However, no study has thus far been conducted to derive FVC and AGB from Sentinel-2 data in Mongolian grasslands, except for forest AGB estimation at small spatial scales (Norovsuren et al. 2019). As expected, the spectral indices and channels ranging from visible red to near-infrared were the most influential variables in the RF models. In particular, NDVI, SR, and red and vegetation red-edge channels have been ranked as the most important for the estimation of FVC and AGB, which confirms the findings of other studies (Wang et al. 2018; Jie et al. 2019). Regarding the map products, a comparison between the higher and lower vegetation values shows that the spatial distribution of FVC and AGB is highly correlated to landscapes and ecoregions. The northwestern and far eastern parts are at higher altitudes, with high vegetation coverage and less human interference, while the conditions in the central and northeast areas are the opposite.

The application of Sentinel-2 data in modelling FVC and AGB in semi-arid grasslands still faces challenges due to soil factors and sparse vegetation. For instance, high soil reflectance significantly reduces the capabilities of vegetation indices to estimate FVC and AGB in sparsely vegetated areas (Montandon and Small 2008; Ren, Zhou, and Zhang 2011). To reduce the effects of soil reflectance, previous studies used a combination of both spectral vegetation and soil indices in FVC and AGB estimations and achieved varying degrees of success. Recent comparative studies have reported that OSAVI is one of the most appropriate soil indices for estimating FVC and AGB in semi-arid regions (Fern et al. 2018; Gholami Baghi and Oldeland 2019). In our models, the OSAVI contributed significantly to the estimation of FVC and AGB, which is consistent with the findings of these comparative studies. In addition, cloud cover and shadows strongly affect FCV and AGB estimation. Although Sentinel-2 has a higher temporal resolution (5 days) than other medium spatial and temporal resolution satellites (e.g. Landsat OLI), it is hardly possible to find cloud-free satellite imagery during the vegetation growing season in the eastern Mongolian steppe. Cloud cover and its shadows on optical images typically result in the absence of vegetation reflectance information at phenological stages. Consequently, it limits FVC and AGB prediction accuracy (Whitcraft et al. 2015). Therefore, further studies on FVC and AGB monitoring should use integrated satellite data such as the harmonized Landsat and Sentinel-2 data (Claverie et al. 2018) which could improve vegetation cover and biomass monitoring by increasing the temporal resolution. Such integrated data increases the chances of obtaining satellite data with little or no cloud cover. Therefore, these data are suitable for monitoring changes in vegetation cover, biomass, and phenology.

4.2. Relevance of the NDVI trend

The majority of similar studies for NDVI trend analysis usually considered that the significantly increasing trends could be a proxy for vegetation cover restoration, while significantly decreasing trends are interpreted as ongoing degradation. Thus, NDVI trends have been commonly used to detect areas of ecological vulnerability (Easdale et al. 2019; Lamchin et al. 2019; Jiani et al. 2020; Deng, Yin, and Han 2020). Likewise, the results of the Mann-Kendall trend test showed that both vegetation cover restoration and degradation spatially varied over the study area. Focusing on statistically significant parts, a large cluster of decreasing NDVI trends has been observed in the central part of the study area over the past decades. This observation is generally similar to those found by (Wang et al. 2020; Meng et al. 2021), who used classification methods on the same NDVI dataset in different years (1990–2015 and 1990–2020) to estimate the vegetation cover trends over Mongolia. In addition, Nasanbat et al. (2018) found that the moderately dry and dry steppes of Eastern Mongolia experienced decreasing NDVI trends in 2000–2016 based on the Mann-Kendall trend analysis through NDVI time series. Decreasing trends were particularly observed in June and July during the same period (Nasanbat et al. 2018). The significant decreasing trend can be related to an increase in human activities. For example, the central part of the study area is under high human pressure which is mostly related to oil exploration, exploitation, and mining. In this area, our previous spatio-temporal analysis showed that land use for dirt roads, oil exploration, and exploitation infrastructure has increased by 75% in the past decade (Batnyambuu, Bendix, and Lehnert 2020b). In addition to land-use change, several studies have confirmed that the aridity of semi-arid ecosystems is one of the driving forces behind land degradation, potentially accelerating the degradation process due to climate change in Mongolian grasslands (Yembuu 2021a; Nandintsetseg et al. 2021; Miao et al. 2017). For instance, air temperatures have increased by approximately 1.4–2.4°C in Mongolia since the 1960s, while the warm season precipitation has rapidly declined in the central and eastern parts of Mongolia (Yembuu 2021a). In addition, our literature review confirms that livestock grazing pressure largely influences land degradation in Mongolia (Tuvshintogtokh and Ariungerel 2013; Batkhishig 2013; Yintai et al. 2018; Sainnemekh et al. 2022). However, a recent livestock-caused land degradation assessment showed that Eastern Mongolian steppe grazing has been consistently low compared to other parts of Mongolia (Jamsranjav et al. 2018).

5. Conclusion

This study mapped the current land degradation that involved the estimation of FVC, AGB, and NDVI trends. In this study, we used 256 field vegetation measurement sites as training and validation data for 124,000 km^2 of area. As a result, we obtained maps of FVC and AGB with good accuracy (R-squared = 0.76–0.81). Additionally, we found that a statistically significant decreasing trend in NDVI occurred in 59% of the study area, which was mostly clustered around the central, middle-eastern, and northeastern parts. These results are particularly important for policymakers to counteract land degradation and improve land management. Furthermore, our models and results show the best practice for using Mongolian pasture-monitoring data to produce land degradation and vegetation maps at regional to country-wide scales.

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Disclosure statement

No potential conflict of interest was reported by the authors.

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ORCID

Batnyambuu Dashpurev http://orcid.org/0000-0003-0410-9508
Thanh Noi Phan http://orcid.org/0000-0002-2747-5028

Author contributions

Batnyambuu Dashpurev: Conceptualization, methodology, software, data preparation, formal analysis, investigation, visualization, writing – original draft preparation, and editing. **Munkhtsetseg Dorj**: Field data preparation. **Thanh Noi Phan**: Methodology and Review. **Jörg Bendix**: Conceptualization, methodology, supervision, and review **Lukas W. Lehnert**: conceptualization, methodology, software, statistical analysis, Supervision, Writing- Reviewing and Editing.

Availability of data

The data supporting the findings of this study are available from the corresponding author upon reasonable request.

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Appendix A

Table A1. Evaluation of RF regression performance for Sentinel-2 data. In performance, 10% of reference data excluded for validation.

	Out of Bag (OOB) Errors		Validation data for regression		
Land cover types	Number of Trees	Percentage of variation explained	R-Squared	p-value	Standard Error
Fractional vegetation cover	250	57.85	0.81	<0.01	0.12
Aboveground biomass	250	50.9	0.76	<0.01	0.11

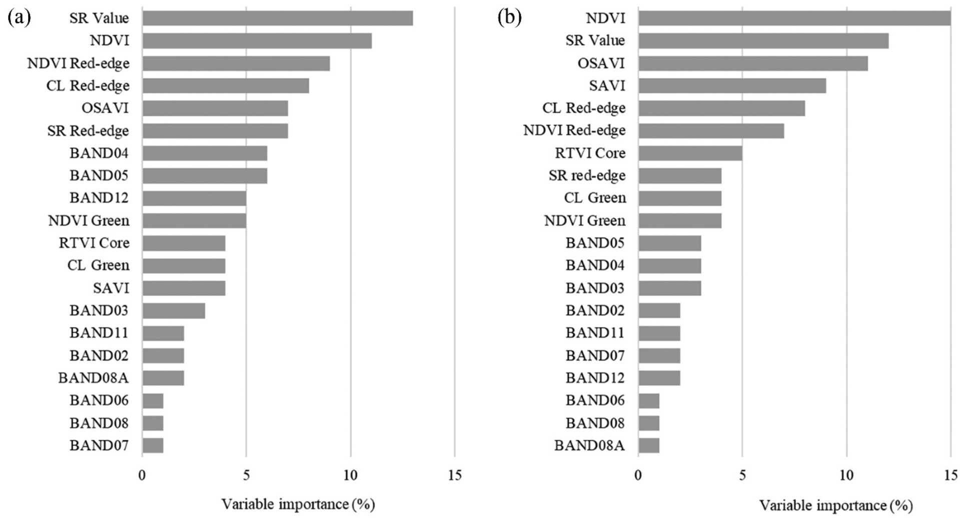

Figure A1. Variable importance of FVC (a) and AGB estimation (b).