Estimation of Grassland Biomass in Eastern Mongolia RS-Based Vegetation Indices

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Abstract. The aim of this study is to estimate above-ground biomass (AGB) in the eastern grassland area of Mongolia applying two machine learning methods, such as the support vector machine (SVM) and random forest (RF), and determine the appropriate method by comparing the results. For this purpose, 21 vegetation indices derived from MODIS data of August 2016 are used. As ground-truth information, reference biomass samples are available from 38 sites of a field survey. To select the appropriate prediction variables, the correlations between the measured biomass in the field and the defined indices are calculated. For further analysis, eight indices with correlation coefficients (r)>0.6 are selected. When the classification results are compared, the RF method demonstrates higher accuracy. Therefore, we can conclude that it can be used efficiently for the estimation of AGB in the selected grassland area of Mongolia.

Keywords: Eastern grassland area, biomass, MODIS data, vegetation indices

1 Introduction

Grasslands are the least protected and most transformed terrestrial ecosystem on our planet [1]. As grasslands are generally found in dry interior areas mainly between mountains and deserts, they have some significant ecological functions such as sand dune fixation, land degradation prevention, erosion control, water preservation and biodiversity conservation [2].

Most of the Mongolian territory is covered by extensive grasslands that reflect different natural and cultural diversities. They occupy more than 70% of the total land area in Mongolia and support the livelihoods of more than 200,000 herding families [3]. In recent years, the country's grasslands have been severely impacted by desertification and other undesired influences. The Gobi desert continues to expand northward and land degradation has intensified due to overgrazing, deforestation, and increased mining and other development activities [4]. The impacts of climate change also pose new threats to grassland ecosystems and livelihoods of herders in the country [5].

In Mongolia, grasslands have very high social, economic and cultural significances. Furthermore, they are the only shelter in Asia large enough to support universally significant wildlife, such as the Mongolian gazelle and many migratory birds that rely

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on these lands as a resting and refuelling stop during their long migrations [6]. Therefore, protecting Mongolia's vast grasslands is of vital importance. Recently, the status of the grassland condition in Mongolia has been debated with different discussions, including various advanced methods for monitoring and evaluating carrying capacity and some other indicators [7].

The carrying capacity is an important factor that influences the human environment and sustainable development in grassland areas [8]. One of the determinants of the carrying capacity is the AGB. Accurate and timely quantification of the AGB plays a substantial role in helping planners achieve effective management practice, because rational use of grassland resources is vitally important for the nation's economy.

Over the years, diverse machine learning techniques, including SVM, RF, neural networks, K-nearest neighbor, and regression models have been developed for AGB evaluation [9], due to their reliability and high accuracy compared to traditional methods. Many authors have used one or a combination of methods for biomass estimation and have made different judgments [3].

In this study, we wanted to compare the results of biomass estimation in the eastern grassland area of Mongolia using widely accepted SVM and RF methods. As data sources, visible and near infrared (NIR) bands of georeferenced MODIS data (WGS84 / UTM system) acquired in August 2016 and field-measured biomass sample values have been selected. Of the two techniques compared, the performance of the SVM method was worse than that of the RF technique.

2 Methods and Materials

2.1 Methods

In this study, we used the SVM and RF techniques for the estimation of pasture biomass in the selected test area. The SVM is one of the most vigorous prediction methods based on statistical learning frameworks. The method constructs a set of hyperplanes to classify all inputs in a high-dimensional space. An acceptable separation can be achieved by the hyperplane that has the largest distance to the nearest training data point of any class, since, generally, the larger the margin, the lower the error of the classifier [10].

The RF is an ensemble method that uses a large number of decision trees at training time. For classification tasks, the output of the technique is a class selected by most trees. The majority vote of all trees is used to assign a final class for each unknown. This directly overcomes the problem that any one tree may not be optimal, but by incorporating many trees, a global optimum should be obtained. The main advantage of RF is that due to the presence of multiple trees, individual trees do not need to be pruned [11].

2.2 Data sets

Field datasets have been obtained from the Institute of Information and Research on Meteorology, Hydrology and Environment of the Ministry of Environment and Tourism of Mongolia. This organization conducts nationwide rangeland biomass monitoring in different regions of the country. At our test site, biomass measured on 22 August 2016 was selected from 38 sample plots. The biomass of each plot was sealed in a plastic bag, sent to a meteorological station, and plotted for analysis. In the laboratory, each field-measured biomass was dried and the dry weight was calculated. The dry weight was divided by the surface area of the plot and then the weight was converted to c/ha.

As prediction variables for grassland biomass, we have applied 21 MODIS-based vegetation indices (Table 1) used for similar studies in Mongolia [3, 12].

Table 1. Vegetation indices used for the study

Vegetation indices	Name	Formula	Reference
Atmospherically Resistant Vegetation Index	ARVI$_2$	$-0.18 + 1.17 \times \left(\frac{NIR - Red}{NIR + Red}\right)$	[13]
Adjusted Transformed Soil Adjusted VI	ATSAVI	$\alpha \times \frac{(NIR - \alpha \times Red - b)}{(\alpha \times NIR + Red) - a \times b + X \times (1}$	[14]
Green chlorophyll index	CL$_{green}$	$\frac{NIR}{Red} - 1$	[15]
Chlorophyll Vegetation Index	CVI	$NIR \times \frac{NIR}{Red}$	[16]
Enhanced Vegetation Index 1	EV$_1$	$2.5 \times \frac{(NIR - Red)}{(1 + NIR + 6 \times Red - 7.5 \times Blue)}$	[17]
Enhanced Vegetation Index 2	EV$_2$	$2.5 \times \frac{(NIR - Red)}{(1 + NIR + 2.4 \times Red)}$	[18]
Green Atmospherically Resistant Vegetation Index	GARI	$\frac{NIR - (Green - (Blue - Red))}{NIR - (Green + (Blue - Red))}$	[19]
Top Grain Size Index	GSI	$\frac{(NIR - Blue)}{(NIR + Blue + Green)}$	[20]
Hue Index	HI	$\frac{(2 \times Red - Green - Blue)}{(Green + Blue)}$	[21]
Brightness Index	BI	$\frac{\sqrt{Green2 + Red2 + NIR2}}{3}$	[22]
Infrared Percentage Vegetation Index	IPVI	$\frac{NIR}{NIR + Red}$	[23]

Normalized Difference Vegetation Index	NDVI	$\frac{(NIR - Red)}{(NIR + Red)}$	[24]
Green Normalized Difference Vegetation Index	$NDVI_{green}$	$\frac{(NIR - Green)}{(NIR + Green)}$	[25]
Specific leaf area vegetation index	SLAVI	$\frac{NIR}{(Red + SWIR)}$	[26]
Simple Ratio	SR	$\frac{NIR}{Red}$	[27]
Wide Dynamic Range Vegetation Index	WDRVI	$\frac{(\alpha \times NIR - Red)}{(\alpha \times NIR + Red)}$	[28]
Redness Index	RI	$\frac{Red2}{(Blue + Green)}$	[29]
Soil Adjusted Total Vegetation Index	SATVI	$\frac{(SWIR1 - Red)}{(SWIR1 + Red + L)} x(1 + L) - \frac{SWIR2}{2}$	[30]
Soil Organic Carbon Concentration	SOC	$EXP(a + b \times Red + c \times Green + d \times Blue)$	[31]
Green Wide Dynamic Range Vegetation Index	WDRVI green	$\frac{(\alpha \times NIR - Green)}{(\alpha \times NIR + Green) + \frac{(1 - \alpha)}{(1 + \alpha)}}$	[32]
Moisture Stress Index	MSI	$\frac{SWIR}{(NIR)}$	[33]

2.3 Study site

As a test site, the eastern grassland area of Mongolia has been selected. It is part of an exceptional ecoregion within the vast Eurasian Steppes spanning from the European Pannonian Steppe to the Mongolian-Manchurian grasslands due to its intactness, relatively high altitude, and northern latitude. The main distinctive characteristic of the proposed property compared to other steppe ecosystems is that it is dominated by extensive grasslands with gently rolling hills, wetlands, and some species of bush and shrubs. The herds of millions of Mongolian white-tailed gazelles are an inseparable component of the ecosystem, both inhabiting and shaping it. Furthermore, the area has different types of grasses and endemic plants [34].

The region features warm summers with decreasing rainfall from east to west, along with frigid dry winters. In winter, the grass becomes dry and very flammable, making wildfires more common. Grass recovers quickly from the fire, but trees do not. This partially explains the absence of a sufficient number of trees in the area. There are also seasonal droughts in grasslands that occur during summer [35].

The study area and its MODIS image of 21 August 2016 are shown in Fig.1. There are extensive green areas (green colour), areas with sparse vegetation, soil of different types, and other land cover classes. The selected sample plots for biomass estimation are shown by points.

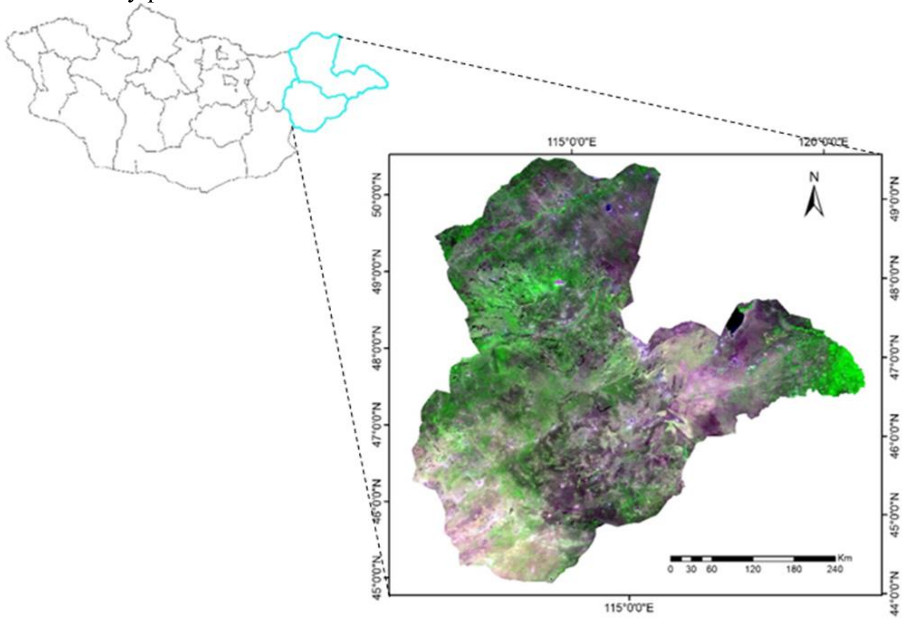

Fig. 1. Location of the study area and its MODIS image.

3 Results and Discussion

Initially, the 21 selected spectral indices were calculated using the R software. Then the correlations between the field-measured biomass and calculated vegetation indices were estimated. The correlation coefficients (r) estimated for the RS-based indices are presented in Table 2. As seen in Table 2, there is only 1 index (i.e. SOC) with a relatively high correlation coefficient (i.e. r ≥0.67). Furthermore, it is seen that there are 7 indices (i.e. ARVI2, ATSAVI, GARI, IPVI, NDVI, SATVI, and WDRVI) with high correlation coefficients (i.e. r ≥0.60). Therefore, among the vegetation indices, the SOC can be considered the best index to explain ground biomass. Compared to other indices, GARI (r =0.647) has the second highest correlation with AGB. However, CI (r =-0.704) and HI (r =-0.701) showed the lowest performance in estimating the measured biomass, which means that they are not appropriate for estimating biomass in the study area.

Table 2. The results of correlation analysis.

	ARVI2	ATSAVI	BI	CI	CL	EV_1	EV_2	GARI
Biomass	0.632	0.609	-0.539	-0.704	0.586	0.573	0.553	0.647
	GSI	HI	I	IPVI	NDVI	$NDVI_g$	RI	SATVI

Biomass	0.513	-0.701	-0.654	0.632	0.632	0.54	-0.674	0.604
	SLAVI	SOC	SR	WDRVI	$WDRVI_g$			
Biomass	0.52	0.675	0.586	0.625	0.597			

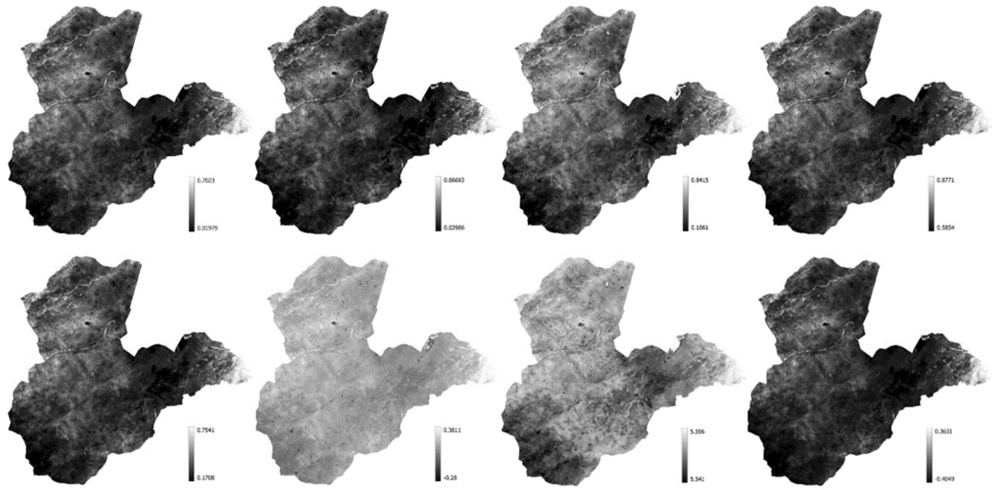

Fig. 2. The indices selected for the final classifications: (a) ARVI2, (b) ATSAVI, (c) GARI, (d) IPVI, (e) NDVI, (f) SATVI, (g) SOC, and (h) WDRVI.

After investigating the relationships among dependent and independent variables (i.e. AGB and spectral indices), the selected SVM and RF methods have been used to classify 8 vegetation indices (Fig.2) with the r>0.6. The classification outputs (i.e. biomass maps) to predict the AGB are shown in Fig.3.
Furthermore, in order to illustrate the differences between actual and predicted AGB values in both classification techniques, quantitative comparisons have been made (Fig. 4). As seen in Fig. 4, there are 19 sample plots (i.e. 3, 4, 9, 10, 16, 20, 22-27, 30-33, 36-38) where the measured biomass values correspond to the predicted values very well. Meanwhile, in eight sample plots (i.e. 1, 6, 8, 18, 19, 29, 35) they have high differences between the measured and predicted biomass values. Consequently, it is possible to judge that there are 11 sample plots indicating moderate differences between the actual and predicted AGB values.
For the evaluation of the quality of the applied models, two widely used statistical measurements, the coefficient of determination (R2) and the root mean square error (RMSE) [36] have been used. The most common interpretation of R2 is how well the model fits the observed data, and a higher coefficient indicates a better fit for the model. The RMSE provides information about the performance of a model by allowing a comparison of the actual difference between the estimated and observed values.

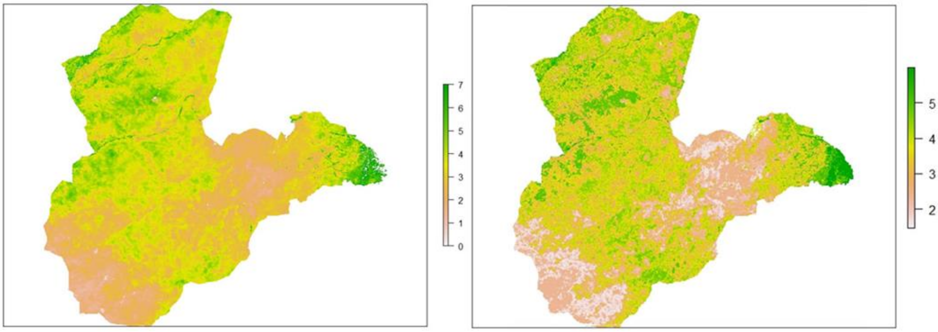

Fig. 3. The predicted biomass maps using: (a) the SVM, (b) the RF model.

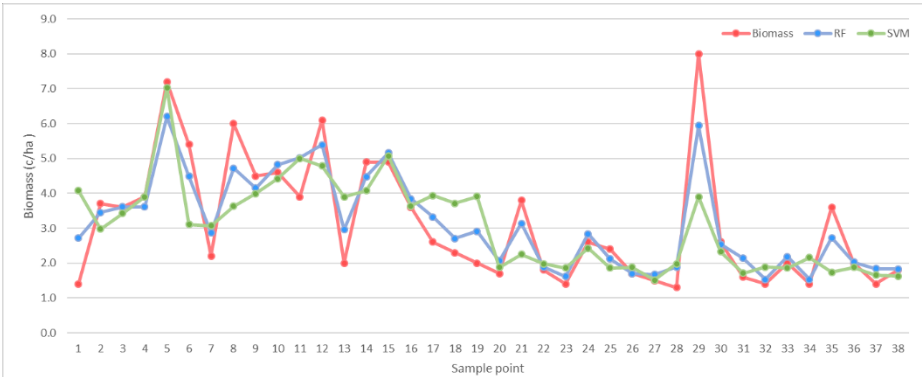

Fig. 4. Comparisons between the actual and predicted AGB values in both classifications.

As can be seen from the quality evaluation of the models, the coefficients of determination (R2) of SVM and RF were 0.22 and 0.77, respectively. Meanwhile, the corresponding RMSEs were 1.58c/ha and 0.82 c/ha, accordingly. Therefore, in the case of the selected test site, the result of the RF method is superior to that of the SVM technique and the final biomass output map could be used accurately for grassland-related planning and management.

In general, biomass estimation is a challenging task, especially in areas with varying landscapes and environmental conditions, such as Mongolia, and requires accurate and timely measurement methods. In Mongolia, pasture biomass studies based on RS have been conducted since the mid-1980s. One of the first satellite-based investigations was conducted by [37], and therefore many investigations related to Mongolian pasture and its conditions have been carried out [3].

Recently, [38] applied partial least squares regression and RF models along with the selected spectral indices to estimate pasture biomass in entire Mongolia. In their study, the PLSR result showed a satisfactory correlation between the biomass measured in the field and the estimated biomass with R2= 0.750 and RMSE = 101.10 kg ha - 1. The RF regression gave slightly better results with R2=0.764 and RMSE = 98.00 kg ha−1. Moreover, [39] compared the performance of various vegetation indices computed using in situ spectral data for AGB estimations in order to determine the most suitable index for use in the north-central Mongolian grassland. The results showed that seven indices were correlated with the biomass of the above ground plant, with r values ranging from 0.57 to 0.79. Additionally, the study indicated that the atmospherically resistant vegetation index performed best compared to the other indices.

4 Conclusions

The appropriate model for predicting grassland biomass in the eastern grassland area of Mongolia was defined by comparing the RF and SVM methods. To determine the ultimate predictor variables, initially 21 spectral indices were calculated using the 2016 MODIS spectral bands. For the evaluation of these indices, a correlation analysis was conducted. For training, reference biomass data sets collected from 38 sample points at the study site were used. The correlation analysis revealed 8 indices with r >0.60 and the SOC index indicated the highest correlation (r ≥0.67). After the evaluation of the indices, the high performing 8 spectral indices were classified by the RF and SVM. When the results were compared, the RF method showed a much higher accuracy (R2=0.77 and RMSE=0.82 c/ha) compared to the SVM (R2=0.22 and RMSE=1.58c/ha c/ha). Overall, the research indicated that the RF technique could be effectively used for the estimation of grassland biomass in eastern Mongolia.

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