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ESTIMATION AND VALIDATION OF PASTURE ABOVEGROUND BIOMASS USING SENTINEL-2 AND ALOS PALSAR (A CASE STUDY IN BAYANDELGER SOUM, TUV PROVINCE)

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ABSTRACT: In Mongolia, accurate pasture aboveground biomass estimation and mapping is crucial for sustaining pasture and environmental processes. This study is aimed at estimating pasture biomass in Bayandelger soum, Tuv aimag, Mongolia using high resolution Sentinel-2-based vegetation indices, and ALOS PALSAR/DEM as well as some field biomass sampling dataset. A multiple linear regression model is used for the biomass estimation.The vegetation indices such as SAVI (R=0.72, p<0.01), NDVI (R=0.71, p<0.01) and NDI45 (R =0.67, p<0.01) show high correlations with field-measured biomass. The results indicate that the places with less than 10g/m2 biomass located in the southern part of the soum account for 10.2% of the total area, whereas the areas with 10-15 g/m2 biomass covered the entire steppe zone account for 56.5%. The areas with 15 – 20 g/m2 biomass mainly distributed in the central and northern parts of the river valley account for 13.4%, and the river floodplains and meadows of the central and northern parts with 20 – 25 g/m2 biomass account for 7.1%. The sites found in the meadows, wetlands, river valleys, and woodlands of the central and northern parts of the soum with more than 25 g/m2 biomass account for 12.8% of the total area.

1. INTRODUCTION

The pasture ecosystem covers 109645.6 thousand hectares of Mongolian territory, and it is an important source of livestock and livelihoods of herders in Mongolia. Pasture ecosystems play a key role in providing food, goods, and services for humans, and are crucial to livestock grazing (Boval and Dixon, 2012). Pastoralism plays the main role in the economy and livelihood of herders of Mongolia. Pasture biomass is one of the pasture health indicators in animal husbandry (Otgonbayar et al. 2018). Therefore, it is necessary to accurately investigate the biomass of pasture that comprise more than 70% of the territory of Mongolia. Moreover, determining the pasture yield in different geographical regions by pattern, type, and season is the main part of forming a pasture monitoring system (Gendaram et al. 2012).

Accurate estimation of the spatial distribution of the AGBs under different grazing pressures is indispensable for identifying the livestock carrying capacity and planning their appropriate management. (Primi et al. 2016). The biomass production, defined as the amount of dry matter content (DMC) per unit area produced (kg ha−1), is a key focus for monitoring grassland production for livestock (Quan et al. 2017). In addition, the AGB influences environmental processes, including carbon balance, soil nutrient dynamics, soil erosion, and water cycling (Anaya et al. 2009; Askar et al. 2018; Wen et al. 2013).

As it is known from the existing literature studies, pasture management has been widely used across the world since the 1980's. At the regional level with a lack of field data and large spatial areas are under consideration, the best way to estimate biomass is remote sensing (Kumar et al. 2015; Anaya et al. 2009). The most precise way to determine the grassland AGB is the field surveys, but they are too time-consuming and expensive for vast areas (Quan et al. 2017). The main principle of remote sensing is to make decisions based on spectral reflectance characteristics of any object (Nyamjargal et al. 2020). Based on spectral reflectance characteristics, the remote sensing images are analyzed and the outputs are used for mapping and biomass estimation (Baloloy et al. 2018; Wang et al. 2021; Huete, 1988).

Over the years, different biomass evaluation techniques have been developed, including linear regression models along with vegetation indices (Baloloy et al. 2018; Huete, 1988; Niu et al. 2019; Trautenmüller et al. 2021; Wang et al. 2021). For instance, Zheng et al. (2007) estimated the AGB from satellite data the using NDVI values. Baloloy et al. (2018) used NDVI, GNDVI, SAVI, SR, and SRre indices derived from Sentinel-2A, RapidEye, Planetscope satellite data along with a multivariate regression model for biomass evaluation. Niu et al. (2019) defined that NDI45 and MSR indices had a strong correlation compared to other indices when the 7 vegetation indices such as NDI45, MSR, SR, NDVI, GNDVI, EVI, and S2REP. The aim of this study is to estimate the AGB of the pasture area in Mongolia using high-resolution Sentinel-2 data, ALOS PALSAR/DEM and some field-measured biomass data.

2. STUDY AREA

The study was conducted in Bayandelger soum's 2137.5 km2 area, Tuv aimag of Mongolia. As for the natural zone and region, Bayandelger soum belongs to the dry steppe of the steppe zone in the south, the steppe in the central, western, and eastern parts, the meadow steppe in some parts of the west, and forest-steppe in the northwestern, northern, and eastern parts of soum (Dash, 2009). The mean annual temperature is -1.1 ºC –(-3.8ºC), with a mean annual precipitation range of 250-400mm year^{-1} (Namkhaijantsan, 2009).

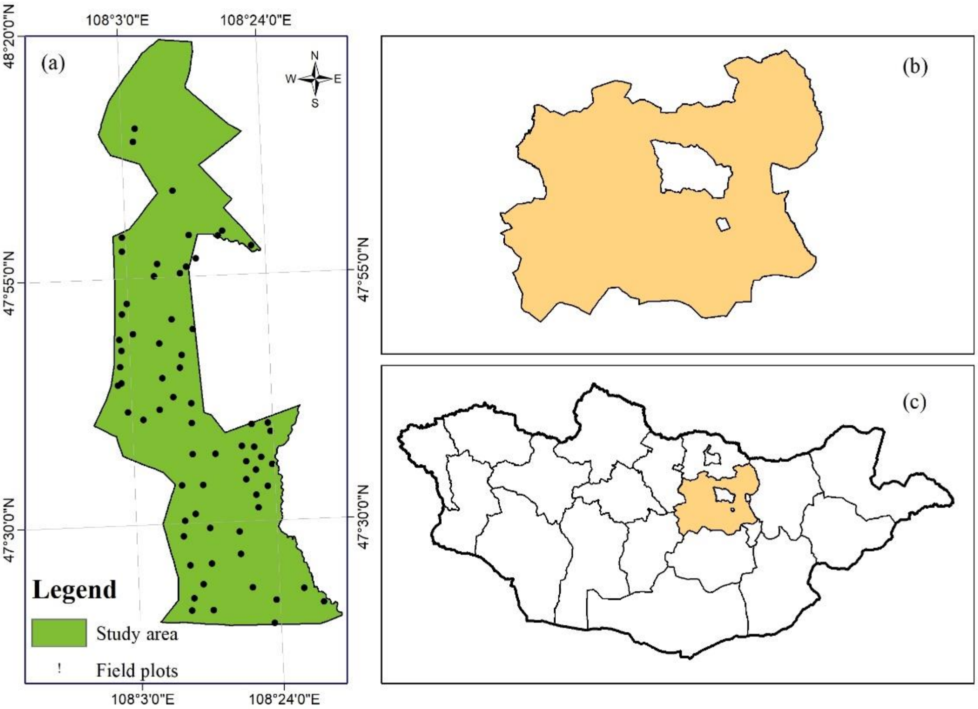


Figure 1. Location map of study area: (a) Bayandelger soum, (b) Tuv aimag, (c) Map of Mongolia

3. DATA AND METHODS

According to our research goal, field samplings of botanical composition were carried out at a total of 68 plots for 5 days between June 16-21, 2020 in Bayandelger soum. Our field study was conducted in preparatory and field measurement research. Transect and mowing methods were used to measure biomass from each plot. Plots are square, 50x50cm in size, and vegetation is harvested and sealed in plastic bags. In the laboratory, field-measured biomass was dried in 80ºC for 24 hours. Then, the dry biomass of pasture vegetation was calculated by weighing it with an accurate scale.

Three scenes of 48UYU of ALOS PALSAR with spatial resolutions of 12.5 meters were downloaded and used to calculate surface elevations for further studies of the study area. Two scenes of Sentinel-2 data acquired on 13 June in 2020 were downloaded from USGS site (https://earthexplorer.usgs.gov/). Sentinel-2 images were processed by the ENVI 5.1 and mapping of spatial distribution was performed in ArcGIS 10.8 software.
Sentinel-2 level 1-C processing includes radiometric correction. Atmospheric corrections were conducted using the SEN2COR plugin tool in Sentinel Application Platform (SNAP) software. Also, bands for classification algorithms and vegetation indices were conducted using SNAP software.

To estimate AGB using optical satellite data, the essential methods including regression (Rouse et al. 1973; Delegido et al. 2011; Huete, 1988), artificial neural networks (ANN) (Xie et al. 2009), partial least squares regression (PLSR) (Rivera-Caicedo et al. 2017), and machine learning algorithms (Clevers et al. 2007). To develop a robust methodology to estimate pastureland biomass from Sentinel-2 data, field-measured biomass samples were analysed together with spectral information derived from Sentinel-2. In order to validate estimated biomass, a total of 68 field-measured biomass samples were available in Bayandelger soum (Figure 1).

NDVI, NDI45, SAVI, and NDMI vegetation indices were calculated from the Sentinel-2 imagery to estimate biomass. In addition, topographic variables were calculated using ALOS PALSAR digital elevation model to surface condition. A combination of a multiple linear regression model (MLR) and remote sensing techniques was used to develop the biomass estimation model of vegetation and its mapping. A flowchart of the processes to obtain the spatial distribution map is shown in Figure 2.

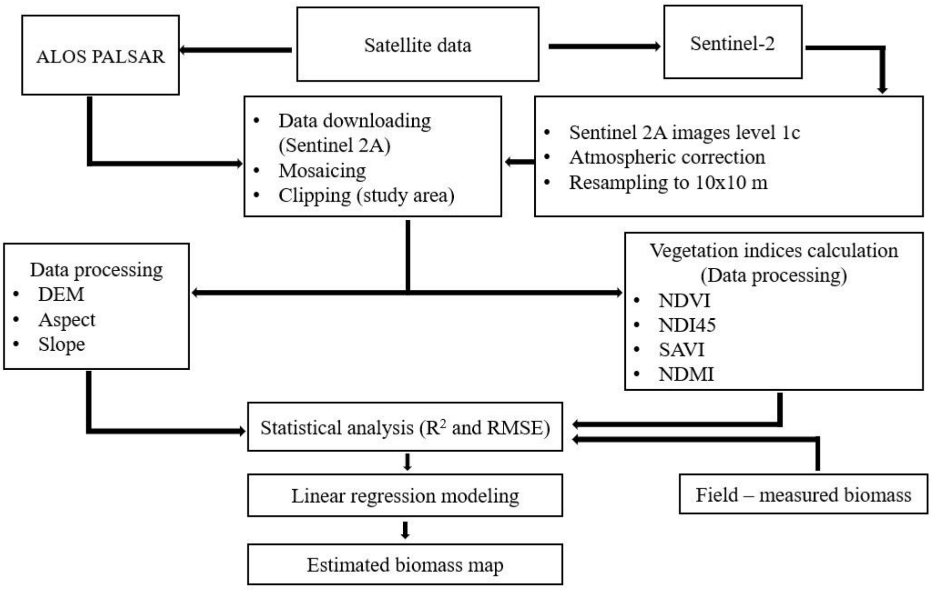


Figure 2. Flowchart for estimating pasture biomass using Sentinel-2 and ALOS PALSAR (DEM) and for generating a biomass map.

The NDVI is one the most commonly used indices (Rouse et al. 1973), and a sample indicator of vegetation health. Many researchers have shown its great correlation with biomass. NDVI value for live plants range between 0 to 1, with 1 being the healthiest and 0 being the least healthy. Formula to calculate NDVI is shown below:

$$NDVI = \frac{(NIR-RED)}{(NIR+RED)} \tag{1}$$

The (NDI45) is an index which is related to NDVI. However, it is characterized by greater linearity and shows less saturation at higher values than NDVI index (Delegido et al. 2010). The formula of this index is also very similar to NDVI, and it uses band 5 in the mathematical equation.

$$NDI45 = \frac{(NIR-RED)}{(NIR+RED)} \tag{2}$$

The SAVI index uses a transformation technique that minimizes soil brightness influence from spectral vegetation indices. Apart from NIR and Red bands it uses also L parameter which stands for soil brightness correction factor (Huete, 1988). For Sentinel image this factor takes usually value of 0.428. The formula is more complicated, but also the value of SAVI needs to be normalized to the scale -1 to +1, as in our case it takes value > 1.0.

$$SAVI = \frac{(NIR-RED)}{(NIR+RED+L)} * (1+L) \tag{3}$$

The normalized difference moisture index (NDMI) is very robust vegetation moisture sensitive index (Gao and Goetzt, 1995) which enables to access the information about water content in plants and spongy mesophyll structure in the vegetation canopy. For this calculation SWIR band is used together with NIR band. This index is very commonly used to evaluate vegetation moisture decline during the drought monitoring. The index has variety of applications: from agriculture and ecological applications to water bodies characteristics, vegetation water stress and wetlands monitoring.

$$NDMI = \frac{(NIR-SWIR1)}{(NIR+SWIR1)} \tag{4}$$

The two widely used statistics, coefficient of determination and the root-mean-square error (RMSE) (6), have been calculated to assess the quality of the models.

$$RMSE = \sqrt{(\widehat{k_i} - k_i)^2} \qquad (5)$$

Where $\widehat{k_i}$ is predicted values
k_i is observation values
n is number of observations
RMSE is the root mean square error

4. **RESULTS AND DISCUSSION**

A spatial map of pasture biomass covering Mongolia at a spatial solution of 8x 8 across Mongolia was generated using remote sensing data, based on NOAA satellite NDVI (Erdenetuya, 2004). In addition, data from the MODIS satellite was combined with ground data to map the vegetation condition and summer situation in the country in 2002 by Information and Research Institute of Meteorology, Hydrology, and Environment. Otgonbayar et al. (2018) calculated pasture biomass with a spatial resolution of 30 meters across Mongolia based on a total of 17 indices using Landsat 8 multi-temporal satellite imagery.

In this study, we calculated the following vegetation indices: NDVI (a), NDI45 (b), SAVI (c), and NDMI (d) from the Sentinel-2 at a spatial resolution of 10 meters to estimate pasture vegetation biomass. Also, elevation (e), slope (f), and aspect were derived for the study area (Figure 3).

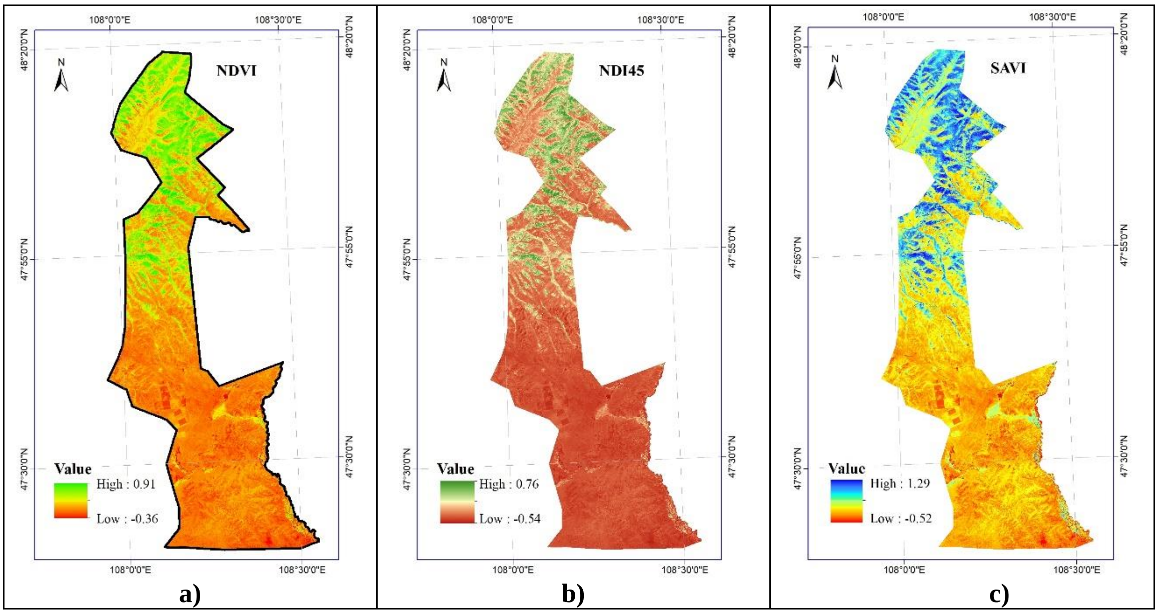


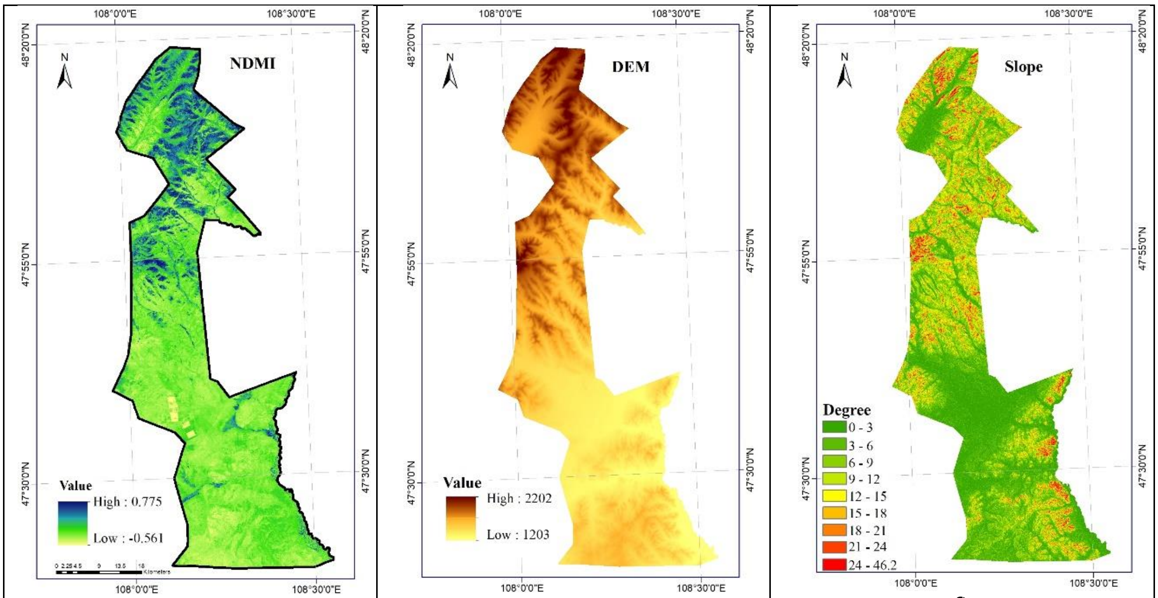
Figure 3. Spatial distribution of variables of study area.

Table 1 shows the statistical correlation of the parameters selected for biomass calculation. Topographic variables (slope and aspect) were not included in the regression analysis due to their low statistical significance for biomass estimation.

Table 1. Correlation matrix of variables.

	biomass	*NDVI*	*NDI45*	*SAVI*	*NDMI*	*DEM*
biomass	1					
NDVI	0.71**	1				
NDI45	0.67**	0.86**	1			
SAVI	0.72**	0.98**	0.91**	1		
NDMI	0.57*	0.60**	0.59*	0.60**	1	
DEM	0.33	0.44*	0.32	0.40*	0.02	1

**p<0.05, *p<0.01



d) e) f)

Table 2.

Regression Statistics	
Multiple R	0.739
R Square	0.546
Adjusted R Square	0.483
Standard Error	2.150
Observations	34

Table 2 shows that soil-adjusted vegetation index 0.72 (SAVI), normalized difference vegetation index 0.71 (NDVI), and normalized difference index 0.67 (NDI45) had high statistical correlations with selected variables, while normalized difference moisture index 0.57 (NDVI) and digital elevation model 0.33 (DEM) are weakly correlated with selected variables.

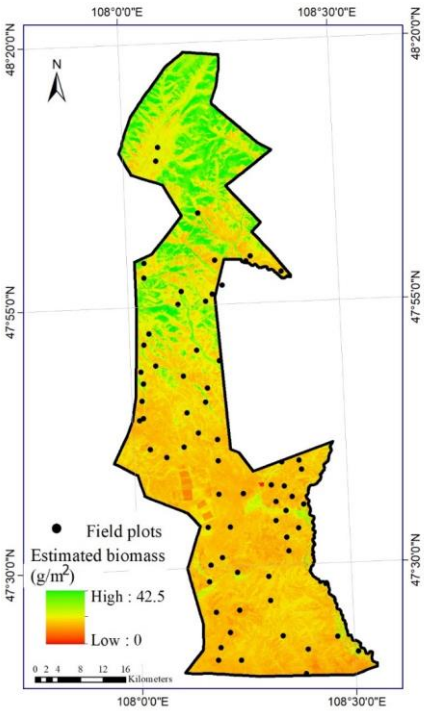


Figure 4. Estimated biomass using Sentinel-2 spectral vegetation indices (NDVI, NDI45, NDMI, and SAVI), DEM in ALOS PALSAR and PLSR model.

These variables from Sentinel-2 data are used in multiple regression models for estimating pasture biomass. The multiple linear regression equation (6) for the spatial distribution of biomass is written as follows:

$$\text{Biomass}=5.63+11.7\text{NDVI}+13.2\text{NDI45}+8.75\text{SAVI}+15.17\text{NDMI}+0.46*\text{DEM} \quad (6)$$

The AGB map was interpreted by five classes in the study area (Figure 4): Places with less than 10g/m2 biomass are located in the southern part of Bayandelger soum and accounted for 10.2% of the total area (218.9 km2), places with 10-15 g/m2 biomass covered the entire steppe zone (56.5% or 1206.7 km2). Also, areas with 15 – 20 g/м2 biomass were mainly distributed in the central and northern parts of the river valley (13.4% or 286.4 km2), 20 – 25 g/m2 biomass was in the river floodplains and meadows in the central and northern parts of this area (7.1% or 152.5 km2). An area that included more than 25 g/m2 biomass was found in the meadows, wetlands, river valleys, and woodlands in the central and northern parts of the soum and accounted for 12.8% (272.9 km2) of the total area. A correlation between estimated and measured biomass is shown Figure 5.

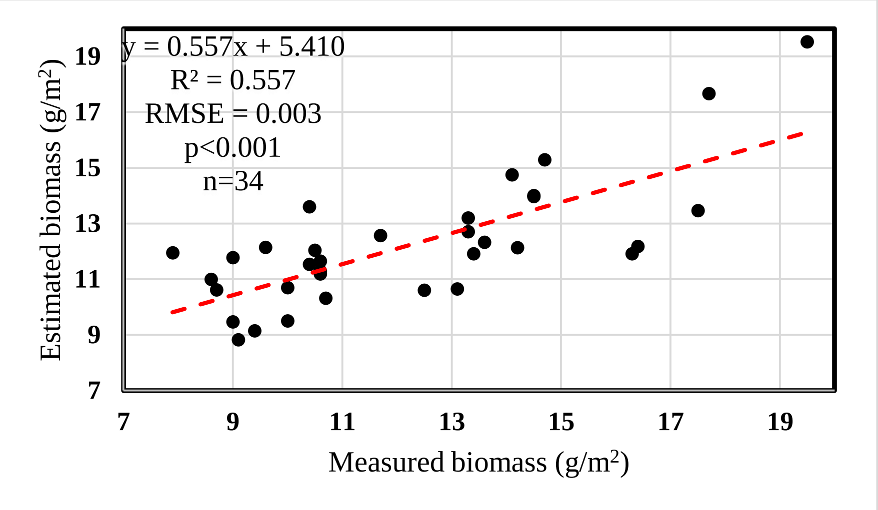


Figure 5. Correlation between estimated and measured biomass.

5. CONCLUSION

In this study, we wanted to evaluate biomass in Bayandelger soum of Tuv aimag, Mongolia using vegetation indices derived from Sentinel-2 satellite data, along with PALSAR derived DEM. Research indicated that SAVI (R=0.72, p<0.01), NDVI (R=0.71, p<0.01), and NDI45 (R =0.67, p<0.01) showed a high correlation with field-measured biomass. However, NDMI (R=0.57, p<0.05) болон DEM (R=0.33, p<0.05) vegetation indices exhibited weak correlation with field-measurement of biomass. Multiple linear regression between selected variables from vegetation indices and field measurement biomass data showed a significant correlation (R2 = 0.546, p<0.05, RMSE = 2.150 g/m2) for biomass estimation. Statistics between measured and estimated biomass indicated a good accuracy (R2 = 0.557 and RMSE = 0.003 g/m2). Moreover, the study revealed that the places with 10-15 g/m2 biomass covered the entire steppe zone (56.5%). The places with less than 10g/m2 biomass located in the southern part of the study area accounted for 10.2%, while theareas with 15 – 20 g/м2 biomass distributed in the central and northern parts of river valley accounted for 13.4%. Overall, the study indicated that the estimation of pasture AGB using high-resolution remote sensing satellite imagery is crucial for pasture studies and monitoring in Mongolia.

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