ANALYSIS OF VEGETATION INDICES FOR PASTURE BIOMASS EVALUATION USING MULTI-TEMPORAL SATELLITE IMAGES AND UAV DATA

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ABSTRACT: In general, remote sensing (RS) has been proved to be an effective way of monitoring pasture biomass. Recently, near-ground sensing using a Unmanned Aerial Vehicles (UAV) has witnessed to have wide applications in obtaining accurate field information. RS in the pasture biomass that is achieved by using the UAV allows us to measure both the plant vigor and the water stress effect on the vegetation. In comparison with many other sensing technologies, the UAVs have the advantages of very high resolution to obtain very detailed information about vegetation cover. The aim of this research is to conduct a pasture biomass study in the central area of Selenge aimag using 10m resolution optical satellite data and very high-resolution UAV images. The datasets selected for the study consisted of Sentinel-2a images and UAV images acquired in 2021. We investigated the relationship of satellite and UAV images by calculating such indices as a normalized difference vegetation index (NDVI), soil-adjusted vegetation index (SAVI), transformed soil adjusted vegetation index (TSAVI), simple ratio (SR), modified triangular vegetation index (MTVI), red-edge triangular vegetation index (RTVI), and perpendicular vegetation index (PVI). The correlation analysis between the spectral indices was conducted using a partial least square regression method.

1. INTRODUCTION

Mongolia is situated at the Central Asian highland and borders with Russia in the north and with China in the south. The geography of Mongolia is characterized by great diversity and is divided into such zones as forest taiga, forest steppe, steppe, dry steppe, Rocky Mountains and Gobi. The country is mainly mountainous with an average altitude of 1,580m above sea level. The principal mountains are concentrated in the west, with much of the region having elevations above 2,000m and the country's highest peaks permanently snow-capped land covered with glaciers. The country stretches about 2,400km from the west to the east and about 1,260km from the north to the south. The total area of the country is about 1,565,000sq.km and the length of the country's borders is 8,158km (Amarsaikhan, 2017).

Pastureland plays an important role for Mongolian animal husbandry because it provides grazing for over 60 million livestock and is used by more than 200,000 herding families. Pastureland makes up about 82% of the total land area of the country and represents the largest remaining contiguous area of common pastureland in the world. In recent years, the Mongolian pastureland has been seriously deteriorated. Severe droughts and a growing number of livestock have been the main factors for pastureland degradation in many parts of the country (Amarsaikhan, 2014). Over the past years, RS has provided an important source of information for determination of the pasture condition and biomass. Different RS techniques along with a variety of datasets have been used for this purpose (Amarsaikhan et al. 2012).

Accurate estimation of biomass can provide significant improvement in the productivity of agricultural industries that utilize pasture (Beukes et al. 2019). Biomass may be measured by cutting, drying, and weighing quadrants of pasture. However, this is a time-consuming and not practical option for farmers. An emerging area of research is the use of satellite or areal based RS technologies for biomass estimation (Clarke et al. 2006, Ali et al. 2016). There are various methods for the assessment of the available pasture biomass and its quality, including (Johnston et al. 2010) manual collections of pasture biomass (Department of Agriculture and Fisheries. 2014), collecting well-calibrated rising-plate measurements along established transects (Stockdale. 1984), through simulation modeling of pasture biomass, and hybrid satellite-pasture simulation approaches (Wang et al. 2019). Although there are many techniques, at local level UAVs alone or in combination with other techniques promise to be a major enabling technology. The recent studies have shown the emerging benefits of the UAV-captured multispectral imaging for pasture biomass conditions in the USA, Brazil, Europe, Australia, and South Africa (Wijesingha et al. 2020).

The aim of this study is to investigate the relationship between satellite and UAV images in relation to the biomass description. For this purpose, the NDVI, SAVI, TSAVI, SR, MTVI, RTVI, and PVI indices have been used. As an analysis method to study the relationship between the determined spectral indices, a partial least square regression method was applied.

2. TEST SITE AND DATA SOURCES

In this study, an area situated near the Baruunburen sum of Selenge Province in the northern part of Mongolia was selected. The soum is situated 260 km toward the north of the capital city of Ulaanbaatar. Figure 1 shows location of the study area. In terms of physical geography, the selected test site belongs to a forest-steppe zone and its altitude ranges from 1000m to 1500m above sea level. The mean annual precipitation is between 300mm and 350mm and the mean annual temperature in July is +25°C, while it is -26°C in January.

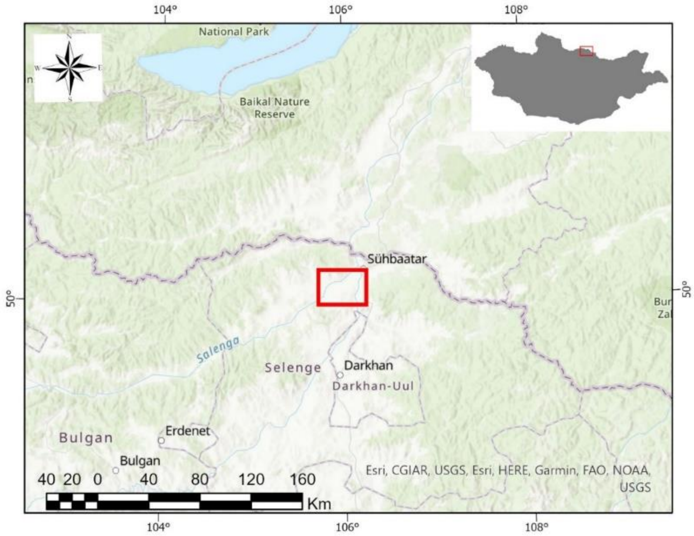

Figure 1. Location map of the test site.

In our study, for the pasture biomass studies, a Sentinel-2a image of 12 July 2021 and a UAV orthophoto image of 18 July 2021 have been used. The Sentinel 2a data has 12 spectral bands (Sentinel-2 User Handbook, 2015) with 10, 20, and 60m spatial resolutions, while the UAV image has 5 channels with a pixel resolution of 2.5cm. The characteristics of multispectral bands of the Sentinel 2a are presented in Table 1. In the current study, blue, green, red, red-edge, and near-infrared bands of the Sentinel 2a, and UAV-based Sentera 4k multispectral camera (Blue band: 0.44–0.54 µm, Green band: 0.54–0.65 µm, Red band: 0.65–0.72 µm, Red-edge: 0.72–0.84 µm, and Nir: 0.84–0.89 µm) datasets have been used.

Table 1. Characteristics of spectral bands of Sentinel-2A.

Band	Wavelength (µm)	Spatial resolution (m)	Bandwidth (nm)
Band 1	0.443	60	27/45 (2A/2B)
Band 2	0.490	10	98
Band 3	0.560	10	45/46 (2A/2B)
Band 4	0.665	10	38/39 (2A/2B)
Band 5	0.705	20	19/20 (2A/2B)
Band 6	0.740	20	18
Band 7	0.783	20	28
Band 8	0.842	10	115
Band 8A	0.865	20	20
Band 9	0.945	60	20
Band 10	1.375	60	20
Band 11	1.610	20	90
Band 12	2.190	20	180

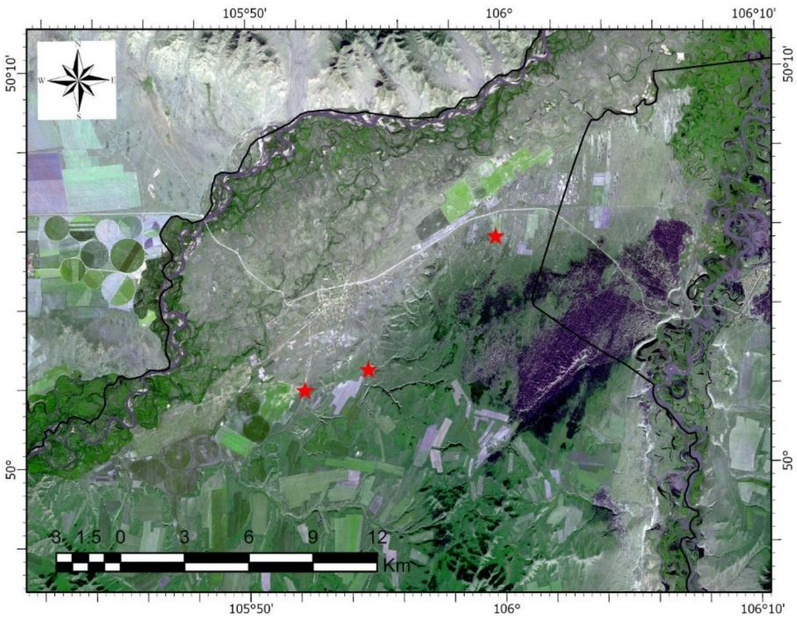

Figure 2. Location of field measurement UAV's

3. RESEARCH METHODS AND RESULTS

Generally, vegetation indices have been found to be useful in minimizing spectral variability caused by canopy geometry, soil background, sun view angles, and atmospheric conditions when measuring biophysical properties (Elvidge et al. 1995). In many cases, researchers exploit vegetation reflectance changes in different spectral bands to obtain some useful information. As it is known, vegetation reflectance is low in both blue and red regions of the visible spectrum compared to the green portion, and it is the highest in the near infrared (NIR) range. Vegetation and soil indices obtained by algebraically combining these bands allow researchers to enhance different spectral signatures for different vegetation properties concerning size, vigour, shape, and colours (Salamí et al. 2014).

The NDVI is a standardized index allowing us to generate an image displaying greenness (relative biomass). This index takes advantage of the contrast of the characteristics of two bands from a multispectral dataset—the chlorophyll pigment absorptions in the red band and the high reflectivity of plant materials in the NIR band. Healthy vegetation absorbs most of the visible light and reflects a large portion of the NIR light. Unhealthy or sparse vegetation reflects more visible light and less NIR light (Hamideh et al. 2017). The formula is written as follows:

$$NDVI = (NIR - R)/(NIR + R) \quad (1)$$

The SAVI is a vegetation index that attempts to minimize soil brightness influences using a soil-brightness correction factor. This is often used in arid regions where vegetative cover is low, and it outputs values between -1.0 and 1.0. The formula is written as follows:

$$SAVI = ((NIR - Red)/(NIR + Red + L)) * (1 + L) \quad (2)$$

The TSAVI is a vegetation index that minimizes soil brightness influences by assuming the soil line has an arbitrary slope and intercept. The formula is written as follows:

$$TSAVI = (s *(NIR - s * Red - a)) / (a * NIR + Red - a * s + X * (1 + s2)) \quad (3)$$

The SR is a common vegetation index for estimating the amount of vegetation. It is the ratio of light scattered in the NIR and absorbed in red bands, which reduces the effects of atmosphere and topography. Values are high for vegetation with a large leaf area index, or high canopy closure, and low for soil, water, and non-vegetated features. The range of values is from 0 to approximately 30, where healthy vegetation generally falls between values of 2 and 8. The formula is written as follows:

$$SR = NIR / Red \quad (4)$$

The MTV is a vegetation index for detecting leaf chlorophyll content at the canopy scale while being relatively insensitive to leaf area index. It uses reflectance in the green, red, and NIR bands. The formula is written as follows:

$$MTVI=1.5*(1.2 * (NIR - Green) - 2.5 * (Red - Green))\sqrt{((2 * NIR + 1)^2-(6 * NIR - 5\sqrt{(Red)}) - 0.5)} \quad (5)$$

The RTVI is a vegetation index for estimating leaf area index and biomass. This index uses reflectance in the NIR, red-edge, and green spectral bands. The formula is written as follows:

$$RTVI = (100*(NIR - RedEdge) - 10*(NIR - Green)) \quad (6)$$

The PVI is similar to a difference vegetation index; however, it is sensitive to atmospheric variations. When using this method to compare images, it should only be used on images that have been atmospherically corrected. The formula is written as follows:

$$PVI = (NIR - a * Red - b) / (\sqrt{(1 + a2)}) \quad (7)$$

Different vegetation and soil indices from the Sentinel-2a and UAV surface reflectance products were calculated by ArcGIS Pro 3.0.1 software and the results are presented in Figure 3.

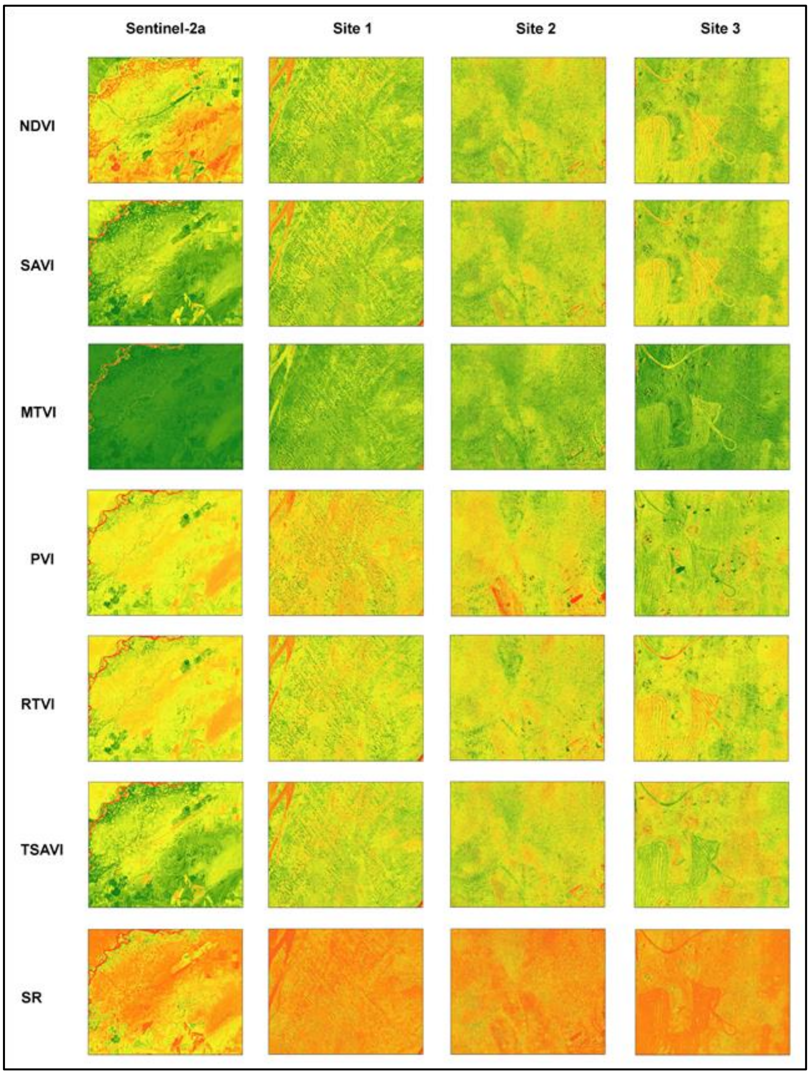

Figure 3. Sentinel 2a and UAV index results.

The correlation coefficients of vegetation and soil indices, calculated from satellite data and UAV images are shown in Table 1. For all vegetation indices, NDVI (r=0.934) yielded the highest correlation coefficient value for site 1 UAV image, TSAVI (r=0.934) was for site 2 UAV image, while TSAVI (r=0.934) was considered the highest correlation index for site 3 UAV image.

Index	Site 1	Site 2	Site 3
NDVI	0.934	0.916	0.928
SAVI	0.912	0.924	0.927
MTVI	0.625	0.738	0.697
PVI	0.834	0.859	0.867
RTVI	0.857	0.846	0.813
TSAVI	0.925	0.934	0.934
SR	0.864	0.842	0.835

Table 1. Correlation coefficients in satellite and UAV images.

4. CONCLUSIONS

The aim of this research was to conduct a pasture biomass study using the optical satellite images and UAV's based multispectral camera. As could be seen from the study, the pasture biomass and different vegetation indices had a significant correlation with each other. The highest correlation coefficients were found in NDVI (r=0.934, 0.916, 0.928) and TSAVI (r=0.925, 0.934, 0.934) from seven different vegetation and soil indices used to find the relationship between satellite and UAV images. Overall, the study showed that UAV with multispectral camera can help evaluating vegetation land cover conditions. However, the validation of the test area and other conducted fieldwork measurements should be highly recommended for the study.

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