Estimation for forest biomass and coverage using Satellite data in small scale area, Mongolia

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Abstract. The estimation of forest biomass using satellite data has received increasing attention for several reason in Mongolia. Since forest in Mongolia is decreasing and it is important to estimate forest resources using satellite data. This research aims to apply recently launched Sentinel-1B Synthetic Aperture Radar (SAR) C-band and optical Sentinel-2B satellite data for estimation forest biomass and coverage and develop model for the study area. The study area is small scale forestry area named by Khanbuyan community, Bulgan province is situated in the Northern part of Mongolia. Boreal and montane forest belts of larch is dominated in this area. Sentinel-1B was used for estimation forest biomass and multispectral bands of Sentinel-2B applied for forest classification map. We used regression analysis to develop the model using Sentinel-1B and Sentinel-2B VV and VH polarizations for Sentinel-1B and Normalized Difference Vegetation Index (NDVI) for Sentinel-2B were applied in this research. Ground truth data was collected in July 2016 and September 2016 for forest coverage and biomass measurements. NDVI and backscatter coefficients for polarizations VV and VH of Sentinel-1B 2016 were related to ground truth biomass for modeling. Comparison of the model and ground truth measurements for above ground biomass have a good agreement.

1. Introduction

Forests are the dominant terrestrial ecosystem on Earth. Particularly forests depend directly with clean water, climate changes, global warming, valuable ecosystem goods and humanity [1].

However, as the day goes by, forest resources are shrinking quickly [2], in our country, the threat is also coming. Therefore, it is necessary to study the latest approaches. In the other countries methods of the world’s forests is advancing rapidly by improved global observation systems and analysis techniques [3]. The recent launched satellites, ecosystem models and improved land-based inventory systems providing high resolution, it allows to estimate forest canopy height,
estimate forest biomass and carbon stocks more than before methods [4-5]. Also, in the last decades using remote sensing data for estimation forest biomass is increased [6].

Different methods have been developed to estimate forest biomass with remote sensing and ground data, based on passive and/or active instruments [7]. Active sensors, such as light detection and ranging (LIDAR) and synthetic aperture radar (SAR), have the advantage to penetrate the canopy; for this reason, they are considered the most useful tools for providing vertical structure or volumetric forest measures [6,8]. There are several studies for classification forest using Sentinel-2 [9-12]. Sentinel-2 satellite imagery holds great potential for improving the classification of forest types at medium-large scales due to the concurrent availability of multispectral bands with high spatial resolution and quick revisit time [13]. Many studies developed models for forest biomass estimation and classification using SAR data. The recent launched satellites, ecosystem models and improved land-based inventory systems providing high resolution, it allows to estimate forest canopy height, estimate forest biomass and carbon stocks more than before methods [4, 5]. Also, in the last decades using remote sensing data for estimation forest biomass is increased [6].

There is less research using SAR data for forestry studies in Mongolia. The relationship between backscatter coefficient and forest biomass modelling for Mongolian forestry was developed [22]. Sentinel-1B is now devised as an effective SAR system to improve forest vegetation remote sensing, and studies exploring radar data potential for forestry applications can facilitate a wider use of SAR sensors [14].

The objective of this research is to develop model using Sentinel-1B SAR data for C-band and Sentinel-2B multispectral data for estimating forest biomass. Combination of VV, VH and NDVI data is important tool for forestry analysis in the study area. The innovation part of this research is to consider SAR polarizations and spectral NDVI for same time.

2. Study area and data sets

2.1. Study area
The study area is Khanbuyan community, Khangal soum, Bulgan province, which located in Northern part of Mongolia (Figure 1). High mountains of Bulgan, Burekghangai and Dulaankhaan dominate in the northern part of the province.

The soil type is sandy with semi desert features in the southern part while fertile land is mainly in the north for crop cultivation. The annual total precipitation is around 250–300 mm [26] in this study area. The north of the province is characterized by alpine forests, gradually blending in the arid steppe plains of the central Mongolian highland. According to the Holdridge life zones system of bioclimatic classification Bulgan is situated in the boreal dry scrub biome (larch, birch and shrub) where larch is 86.12 % and birch is 13.88 % (15). This area has a subarctic climate where the annual average temperature is 1.3 °C (29.7 °C). According to our research, the forest in Khanbuyan community covers an area of 11,750 hectares and its elevation is between 1,260 m and 1,570 m.

2.2. Data
Totally 161 sample stands were taken in this study. The sample stands differ for main type, leaf presence and type of field plots (size, shape, and number). All ground truth data were collected twice in July and September, 2017. Biomass growth is high in July. The ground truth data (Table 1) and data from the Forest resource development center, Ministry of Environment and Tourism (https://www.mne.mn/) were applied for the validation.

| Forest type | Number of samples | Mean   | SD      |
|-------------|-------------------|--------|---------|
| Larch       | 29                | 0.337550 | 0.041167 |
| Birch       | 20                | 0.407229 | 0.401080 |
Figure 1. The location of the study area, Khanbuyan community, Khangal soum, Bulgan province (N 49°15’–N 49°10’ and E 104°05’–E 104°15’).

Table 2. Acquired satellite remote sensing dataa.

| Satellite       | Acquisition Date | Resolution | Level | Spectral/ Polarizations Used |
|-----------------|------------------|------------|-------|-----------------------------|
| Sentinel-1B SAR | August 2016      | 10m        | C-band| VV, VH                      |
| Sentinel-2B     | August 2016      | 10m        | -     | Blue, Green, Red, NIR       |

a Source: Japan Aerospace Exploration Agency (JAXA), Japan, and European Space Agency (ESA).

The Sentinel-1 is an imaging radar mission providing continuous all weather, day and night imagery at C-band (Table 2). Sentinel-1B SAR C-band data interferometric wide swath mode was used, with a 250 km swath width at 5 × 20 m spatial resolution, an incidence angle between 29.1 degree and 46.0 degree, and VV and VH dual polarizations. Scenes were multilooked (one look in range and four azimuth), geocoded based on Shuttle Radar Topography Mission (SRTM) data, and radiometrically calibrated with a final pixel spacing of 10 × 10 m [16].

The Sentinel-2B MSI Level 1C data was acquired on August 2016 (Table 2). The multispectral bands with spatial resolution of 10 m were used. These are four visible bands; Blue (490 nm), Green (560 nm), Red (665 nm), and Near-Infrared (NIR) (842 nm) [17].

3. Methodology and analysis

3.1 Methodology
Synergy of two satellites was applied in this research. Figure 2 explains the schema methodology for this study. First, Sentinel-1B used for estimation forest biomass. A backscatter coefficient from VV, VH polarizations was estimated for larch and birch biomass. Relationship between backscattering coefficients and ground truth biomass was obtained.
In order to find backscatter, we used SNAP v. 4.0.0 (Sentinel Application Platform) software developed by ESA (European Space Agency). Radiometric calibration to the sigma 0 values, spekkel filter, calibration, range-doppler terrain correction using SRTM digital elevation model and conversion from linear to decibel scale was used from Alena, et al. (2018).

To determine backscatter coefficients, we used VV and VH polarizations. The intensity values for the polarizations pixels values were converted to the normalized radar backscattering coefficients ($\sigma_0$), measured in decibel (dB) using Equation (1) in [10] and [18].

$$\sigma_0 \text{ dB} = 10 \log 10 \sigma_0$$

In which $\sigma \text{ dB}$ is the normalized radar cross section and $\sigma_0$ is the backscatter for a specific polarization. Secondly, NDVI Equation (2) vegetation biomass has been successfully estimated based on the normalized difference vegetation index (NDVI) (18), which is derived from the visible red (RED) and near-infrared (NIR) channels of the Sentinel-2B.

$$\text{NDVI} = \frac{\text{NIR-RED}}{\text{NIR+RED}}$$

Third, the allometric Equation (3) was derived from [24] on the relationship between ABG and diameter at breast height ($D_{bh}$) and total height of tree ($H_{tot}$) measurements.

$$\text{AGB} = \alpha \ast D_{bh}^\beta \ast H_{tot}^\gamma$$
The species specific coefficients; α, β, γ which are previously used for forestry in northern region in Mongolia were used for the allometric equation (Table 3).

| Forest type      | α      | β      | γ     |
|------------------|--------|--------|-------|
| Siberian Larch   | 0.0534 | 2.0332 | 0.5996|
| Asian white Birch| 0.0735 | 2.1950 | 0.4053|

In order to develop the model of biomass using satellite data, we used the regression analysis. We assume that AGB is related to VV and VH from Sentinel-1B and NDVI from Sentinel-2B (Equation 4).

\[ AGB_{\text{prediction}} = F(VV, VH, NDVI) \]  

(Equation 4)

For the assumption, the multidimensional linear regression analysis was selected. From the assumption, we developed the model for forest biomass estimation (AGB prediction) which can be described in the Equation 5. The Equation 5 was used for the development of biomass model (AGB prediction) in this research. The output of this model is described in the Figure 3. The relationship between AGB prediction and ground AGB biomass is in the figure 4.

\[ AGB_{\text{prediction}} = 3.35 + 3.13 \cdot VV + 0.21 \cdot VH + 1.53 \cdot NDVI \]  

(Equation 5)

where:
- \( VV \) – the backscatter coefficients for a specific polarization;
- \( VH \) – the backscatter coefficients for a specific polarization;
- \( NDVI \) – normalized difference vegetation index.
Figure 5. Land cover classification map using Sentinel-2B for August 2016.

3.2. Analysis
The accuracy assessment for land cover classification map and ground truth measurements were assessed by using confusion matrices approach (20) and calculated by using Equation 6.

\[ OA = \frac{\sum A}{\sum B} \times 100 \]  

where \( A \) is the number of pixels assigned to the correct class and \( B \) is the number of pixels that actually belongs to that class. Validation has been done for land cover classification map. Output map was compared with ground truth data (Figure 6). Overall accuracy assess is 92 % in the Table 4 and Figure 6. Birch, larch, grassland, mixed shrub were selected as ground truth classes.

Table 4. Accuracy assignment of land cover classification.

| Sentinel-2B forest type | Larch | Birch | Shrub | Grassland | Sum | Accuracy |
|------------------------|-------|-------|-------|-----------|-----|----------|
| Larch                  | 87    | 3     | 2     | 0         | 92  | 94.6%    |
| Birch                  | 3     | 36    | 2     | 0         | 41  | 87.8%    |
| Shrub                  | 0     | 1     | 15    | 1         | 17  | 88.2%    |
| Grassland              | 0     | 0     | 1     | 10        | 11  | 90.9%    |
| Sum                    | 90    | 40    | 20    | 11        | 161 |         |

Detailed information for ground truth data which obtained in 2016 year was used for the accuracy assessments.
Figure 6. Land cover classification map with the ground truth samples.

For the forest biomass analysis, backscatter coefficients from VV and VH polarizations were related to ground truth biomass in the study area. Figure 7 and 8 describe relationship between VH and AGB while figure 9 and 10 show relationships between VV and AGB.

Figure 7. VH backscattering values for forest using Sentinel-1B for August 2016.
Figure 8. The relationship between VH backscattering and ground truth AGB.

There is reasonable relationship between VH and AGB (Figure 8) while there is less relationship between VV and AGB (Figure 10) for the forestry in the study area.

Figure 9. VV backscattering values for forest using Sentinel-1B for August 2016.
Figure 10. The relationship between VV backscattering for biomass.

For the validation of the model (AGB prediction), we compared output map with ground truth measurements from Forest resource development center (FRDC), Ministry of Environment and Tourism in Mongolia [15]. There were 19 points from the FRDC randomly selected for the validation. There is a good agreement between model output (AGB prediction) and ground AGB measurement ($R^2=0.66$) (Figure 11).

Figure 11. Relationship between AGB prediction and ground AGB measurement.

4. Conclusions and discussions
Almost 70% of the study area is larch forest. The detailed description of the sampled stands (Table 4) was used as ground truth validation for the land cover classification. The results showed that the land cover classification map had the highest accuracy which is 92%. From the analysis there is high biomass for the sampled stands where heights are 20 m or higher for the larch forest. In this research, we developed new model (AGB prediction) which combined data from Sentinel-1B and Sentinel-2B. The developed model important for the forest biomass study in small scale area. Using this model, we can find forest biomass in the same small scale region which has same climate condition. Some models have only one Sentinel-1 or Sentinel-2 data for forest biomass estimation. We extended the model using both Sentinel satellites which are VV, VH and NDVI for our research. Output model from the study was compared with ground truth measurement of the Forest resource development center and agreement was high. NDVI was a good factor for AGB. The results of using VV, VH polarizations and NDVI has a good agreement which ground measurement (regression was 0.7).

The average of AGB resource is 41 tonn/ha over Mongolia. There are 5 different zones in Mongolian forest which are Altai, Khangai, Khuvsigul, Khentii and forest buffer zone. Our study area included in Khangai forest zone which has average AGB which is 35.1 tonn/ha [21]. According to the model of this research average AGB is 37.4 tonn/ha.
The validation of this study, we compared between output of the model and ground truth measurement which was collected from the Forest resource development center of Ministry of Environment and Tourism ($R^2=0.66$). It means there is good agreement between these two data. The outputs that at C-band the availability of multi-temporal information is very important for improved characterization of Mongolian forest. The integration of optical Sentinel-2B (NDVI) data and to Sentinel-1B (VV, VH) showed results that could lead to estimation of forest biomass.

The model contributes estimation forest coverage in small areas in Mongolia and forestry economics.

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References
[1] Yude P, Richard A B, Oliver L P and Robert B J 2013 The Structure, Distribution and Biomass of the World’s Annual Review of Ecology, Evolution, and Systematics 533-4
[2] Lauren 2017 Deforestation and Climate Change (Washington: Climate Change Institute)
[3] Gregory P A, Joseph M, Helene C M, Ghislain V, Romuald V, Maminainina R et al. 2012 A universal airborne LiDAR approach for tropical forest carbon mapping Oecologia 1147–60
[4] Stewen W R, Ramakrishna R N, Faith Ann H, Maosheng Z, Matt R and Hirofumi H A 2004 Continuous Satellite-Derived Measure of Global Terrestrial Primary Production BioScience 548-60
[5] Micheal A L 2010 A global forest canopy height map from the Moderate Resolution Imaging Spectroradiometer and the Geoscience Laser Altimeter System Geophysical Research Letters 37 L15401
[6] Laurin GV, Balling J, Corona P, Mattioli W, Papale D, Puletti N et al. 2018 Above-ground biomass prediction by Sentinel-1 multitemporal data in central Italy with integration of ALOS2 and Sentinel-2 data Journal of Applied Remote Sensing 12(1), 1-17
[7] Georgia G, Dimitris Z, Ioannis G, Kalliopi R, Vassilia K, Maria T et al. 2016 Vegetation biomass estimation with remote sensing: focus on forest and other wooded land over the Mediterranean ecosystem Int. J. of Remote Sensing (38) 7 1940-66
[8] Arun D and Kulkarni B L 2016 Random Forest Algorithm for Land Cover Classification. Int. J. on Recent and Innovation Trends in Computing and Communication 58-63
[9] Çolak E and Sunar AF 2018 Remote sensing & GIS integration for monitoring the areas affected by forest fires: a case study in Izmir, Turkey The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences XLII-3/W4 165-70
[10] Sasan V, Javad S, Kamran A, Hadi F, Hamed N, Tien D P et al. 2018 Improving Accuracy Estimation of Forest Aboveground Biomass Based on Incorporation of ALOS-2 PALSAR-2 and Sentinel-2AImagery and Machine Learning: A Case Study of the Hyrcanian Forest Area (Iran) Remote Sensing 10 (172) 1-21
[11] Borràs J, Delegido J, Pezzola A, Pereira M, Morassi G and Camps-Valls G 2017 Land use classification from Sentinel-2 imagery Revista de Teledetección 55-66
[12] Immitzer, Vuolo , Einzmann K, Ng WT, Böck S and Atzberger C 2016 Suitability of Sentinel-2 Data for Tree Species Classification in Central Europe ESA Living Planet Symposium Prague
[13] Nicola P, Francesco C and Cristiano C 2017 Use of Sentinel-2 for forest classification in Mediterranean environments Annals of silvicultural research 42 1-7
[14] Gaia Vaglio Laurin 2018 Above-ground biomass prediction by Sentinel-1 multitemporal data in central Italy with integration of ALOS2 and Sentinel-2 data Journal of Applied Remote Sensing 16008 1-17
[15] FRDC FRaDCiM 2016 Forest management report from Khanbuyan community Planning of forest management
[16] Tsyganskaya V, Sandro M, Philip M and Ralf L 2018 SAR-based detection of flooded vegetation – a review of characteristics and approaches Int. J. of Remote Sensing 39 (8), 2255-93

[17] Korhonen L, Hadi H, Packalen P, Rautiainen M 2017 Comparison of Sentinel-2 and Landsat 8 in the estimation of boreal forest canopy cover and leaf area index Remote Sensing of Environment 195 259-74

[18] Yunxiang Jin 2014 Remote Sensing-Based Biomass Estimation and Its Spatio-Temporal Variations in Temperate Grassland, Northern China Remote sensing 6 1496-513

[19] Arun D K and Barrett L 2016 Random Forest Algorithm for Land Cover Classification International Journal on Recent and Innovation Trends in Computing and Communication 2321-8169 58 - 63

[20] Mohammad H T and Majid H THR 2011 Mapping salt diapirs and salt diapir-affected areas using MLP neural network model and ASTER data International Journal of Digital Earth 6:2 143-57

[21] Ministry of Environment and Tourism M 2016 Mongolian multipurpose national forest inventory 2014-2016 (Ulaanbaatar)

[22] Tsolmon R, Tateishi R and Tetuko J 2002 A method to estimate forest biomass and its application to monitor Mongolian Taiga using JERS-1 SAR data International Journal of Digital Earth 23 (22) 4971-8

[23] Alena D, Markus H, Milutin M and Wolfgang W 2018 Forest area Derivation from Sentinel-1 data Photogramm Remote Sensing 111-7 227-33

[24] Dorjsuren C 2017 Estimation of aboveground biomass and carbon stock in Mongolian Boreal forest (Ulaanbaatar:GIZ)

[25] Natsagdorj E, Renchin T, Martin K, Tseveen B, Dari C, Tsend O et al. 2017 An integrated methodology for soil moisture analysis using multispectral data in Mongolia Geo-spatial Information science 46-55

[26] Natsagdorj E, Renchin, Philippe DM, Dari C and Tseveen B 2018 Long-term soil moisture content estimation using satellite and climate data in agricultural area of Mongolia Geocarto International 34:7 722-34