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Estimation of Forest Aboveground Carbon Storage Using Satellite Data and Stepwise regression

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Abstract

Aboveground carbon storage in forest resources is important for tracking ecosystem functionalities and climate change impacts. The main aim of this study is to develop a model for the estimation of Aboveground Carbon (AGC) for forests region using multi-factor regression analysis. Data-driven GGP methodology was applied to monitor AGC over Mongolia for 20 years. The study will be based on the remote sensing data and biomass data from ground truth measurements in 2018. The study area is the Eco-Khanbuyan community which is one of the most abundant forests in Bulgan province in Mongolia. The biomass data from ground truth measurements were collected in the Eco-Khanbuyan community. Vegetation indices, mean, variance, and entropy values from Landsat 8 satellite images were extracted for the forest in Eco-Khanbuyan. 80% of total ground truth points were used as training sets and 20% as test sets. The stepwise regression model shows that AGC depends on Normalized Different Vegetation Index (NDVI), mean, variance, homogeneity, contrast, dissimilarity, correlation, and entropy. It involves adding or removing potential explanatory variables in succession and testing for statistical significance after each iteration. Stepwise regression is the step-by-step iterative construction of a regression model that is applicable for carbon, biomass study, and vegetation change monitoring in the region.

Keywords: Aboveground Carbon (AGC), Normalized Different Vegetation Index (NDVI), Gross Primary Productivity (GPP)

Introduction

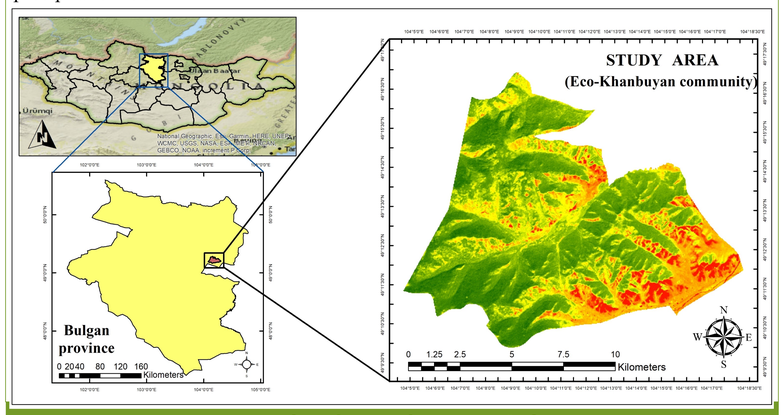
Forests are one of the biggest reservoirs of long-term storage of atmospheric carbon in the mitigation of global warming and climate change (Arasa-Gisbert et al., 2018). Globally, major elements of the forest ecosystems are declined and degraded due to industrialization, urbanization, and anthropogenic activities. Carbon dioxide (CO2) is one of the greenhouse gases, and its increasing concentration in the atmosphere leads to global warming and climate change. Forest ecosystems are the lifeline of the world's human population, which helps to mitigate the ever-increasing atmospheric CO2 concentration. Currently, climate change is a global concern, and forests play a vital role in climate change regulation and mitigation by reducing CO2 concentrations in the atmosphere (Streck and Scholz, 2006; Bracki, 2019; Ali et al., 2020; Burman et al., 2021). This kind of information also contributes toward atmospheric carbon reduction targets as part of international obligations (UNFCCC 2014; Sahu et al., 2016; Mayer et al., 2020).

Stepwise regression is different in that variables are either included or excluded from the model one at a time. In backward stepwise regression, we start with the full model and eliminate the least significant variable. This procedure is applied iteratively until all non-significant variables have been removed from the dataset. In forward stepwise regression, we start with no variables in the model and add the most significant variable. This is repeated until a new variable does not sufficiently improve the fit of the model to justify its inclusion. GPP (Gross Primary Productivity) represents the total carbon fixed through photosynthesis in an ecosystem.

The objective of this research is to use Landsat 8 satellite 1, 2, 3, 4, 5, 6, and 7 bands multispectral data for estimating forest aboveground carbon stocks in the Eco-Khanbuyan community, Bulgan province of Mongolia. The combination of Landsat data is being an important tool for forestry analysis and studies. The research is an approach to developing a model for estimating the carbon stocks of the upper part of the forest in the study area and constructing a map using the results.

Study area

The study area is the Eco-Khanbuyan community, Bulgan province is one of the northern parts of Mongolia. This area has a subarctic climate where the absolute temperature is +34,8 °C in summer, absolute temperature is -45°C during winter. The average annual precipitation is 324 mm in this area.



Methods and Materials

30-m multispectral data of Landsat8 OLI (2018) were downloaded from the United States Geological Survey (USGS). We used the ground truth measurement data in august 2018 by the Eco-Khanbuyan community, Bulgan province. In Mongolia, the ground truth measurement is suitable in August. We applied the stepwise linear regression. The basic idea of stepwise regression is to introduce the variables one by one into the model.

The stepwise regression screening variables method, one of the most widely used methods in regression models [67,68], was used to establish collinearity in the accuracy of models. The remote sensing information model of AGC in forests. The advantage of stepwise regression is to determine the importance of explanatory variables and eliminate the influence.

The general model of the regression:

$$AGC = F(Vegetation\ Indexs,\ Mean, Var, Hom, Con, Diss, En, Sec,\ Corr\ )$$

Table 1. Information of variables

Type	Name	Calculate Model	Abbreviation	
Vegetation Index	Normalized Different Vegetation Index	(NIR-R)/(NIR+R)	NDVI	NIR, R, and B represent Near-Infrared Reflectivity, Red reflectivity, Blue reflectivity, and L take value for 0.5
	Simple Ratio Index	NIR/R	SR	
	Soil-Adjusted Vegetation Index	(NIR-R)*(1+L)/(NIR+R+L)	SAVI	
	Enhanced Vegetation Index	2.5(NIR-R)/(NIR+6R-7.5B+1)	EVI	
Texture	Mean	$\sum_{i=0}^{N-1}\sum_{j=0}^{N-1} i \cdot P_{(i,j)}$	Mean	$P_{(i,j)} = \frac{V_{(i,j)}}{\sum_{i=0}^{N-1}\sum_{j=0}^{N-1}(V_{(i,j)})}$ V(i, j) is the ith row of the jth column in the Nth moving window; $\mu_x = \sum_{i=0}^{N-1} i \sum_{j=0}^{N-1} P_{(i,j)}$ $\mu_y = \sum_{i=0}^{N-1} i \sum_{j=0}^{N-1} P_{(i,j)}$ $\sigma_x = \sum_{i=0}^{N-1} (i-\mu_i)^2 \sum_{j=0}^{N-1} P_{(i,j)}$ $\sigma_y = \sum_{i=0}^{N-1} (i-\mu_j)^2 \sum_{j=0}^{N-1} P_{(i,j)}$
	Variance	$\sum_{i=0}^{N-1}\sum_{j=0}^{N-1} (i-mean)^2 \cdot P_{(i,j)}$	Var	
	Homogeneity	$\sum_{i=0}^{N-1}\sum_{j=0}^{N-1} \frac{P_{(i,j)}}{1+(i-j)^2}$	Hom	
	Contrast	$\sum_{\lvert i-j\rvert=0}^{N-1} \lvert i-j\rvert^2 \left\{\sum_{i=0}^{N-1}\sum_{j=0}^{N-1} i \cdot P_{(i,j)}\right\}$	Con	
	Dissimilarity	$\sum_{\lvert i-j\rvert=0}^{N-1} \lvert i-j\rvert \left\{\sum_{i=0}^{N-1}\sum_{j=0}^{N-1} i \cdot P_{(i,j)}\right\}$	Diss	
	Entropy	$-\sum_{i=0}^{N-1}\sum_{j=0}^{N-1} P_{(i,j)} \cdot \log(P_{(i,j)})$	En	
	Angular second moment	$\sum_{i=0}^{N-1}\sum_{j=0}^{N-1} {P_{(i,j)}}^2$	Sec	
	Correlation	$\frac{\sum_{i=0}^{N-1}\sum_{j=0}^{N-1}(i,j) \cdot P_{(i,j)} - \mu_x\mu_y}{\sigma_x\sigma_y}$	Corr	

Results

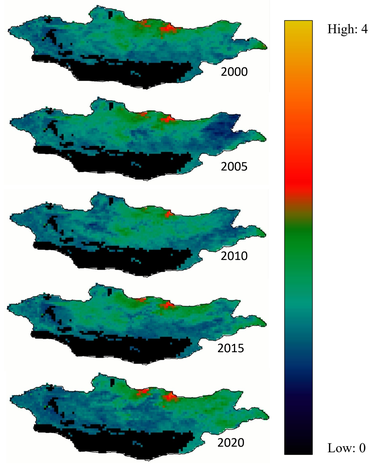


Figure 2. GPP in Mongolia

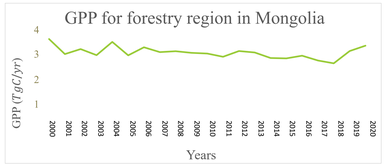


Figure 3. GPP for forestry region in Mongolia

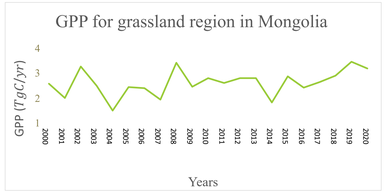
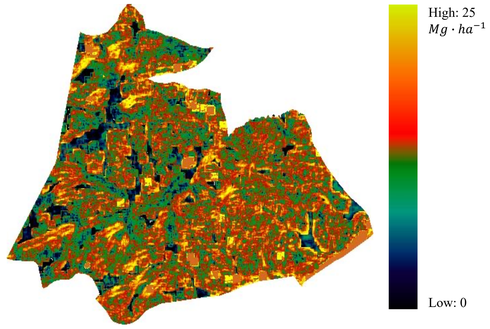


Figure 4. GPP for grassland region in Mongolia



Data-driven GPP for 2000-2020 data were used to estimate the present AGC in Mongolia. (Figure 2-4)

Stepwise regression analysis is the AGC estimation approach used in Figure 5.

Figure 5. Outputs from Aboveground Carbon (AGC) estimation for the study area

Discussion and Conclusions

This study used different satellite data to monitor carbon C storage in Mongolia over years 2000-2020. Outputs of the small local area contributed to understanding the dynamics of carbon stocks in relation to the key factors for sustainable management of forest carbon. Monitoring aboveground carbon storage in forests and grassland resources is important for tracking ecosystem functionalities and climate change impacts. Applied Mathematics and machine learning techniques can provide excellent modeling for Carbon research and global warming issues.

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