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Spectroscopic Determination of Aboveground Biomass in Grass using Partial Least Square Regression Model

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Abstract: Biomass is considered as fresh matter weight or dry matter weight. Biomass is regarded as an important indicator of ecological and management processes in the vegetation. This research aims to predict biomass of grass by using partial least square regression [PLSR] model. To build this PLSR model, we used two variables as an input for PLSR model, i.e. reflectance of aboveground grass and weight of grass [biomass]. For this research we used grass type **Cynodon dactylon*.We used ASD FieldSpec4 Spectroradiometer for measuring reflectance of aboveground biomass. For enhancing spectral properties of green vegetation we used five vegetation indices.We estimated aboveground biomass in grass with root mean square error [RMSE] 6.33 and R^2 = 0.9 per g/m^2 by using PLSR model.***

Keywords**: biomass, partial least square regression, vegetation indices, hyperspectral, red edge position.**

1. Introduction

Biomass is considered as fresh matter weight or dry matter weight. Estimation of biomass may be based on destructive or non-destructive methods. The first are usually not preferred as they are expensive, time-consuming, required extensive field work. Remote-sensing methods are becoming more prevalent in biomass estimation, because they provide non-destructive and repeatable methods for biomass estimation [i].

Biomass is a key biophysical variable influencing land surface processes such as photosynthesis, transpiration, and energy balance and is a required input for various ecological models [ii].

Computation of narrow banded indices from broadband can be inadequate to estimate biomass, due to variations in the soil colour, the canopy structure and/or atmospheric conditions [iii]. In contrast,indices computed from specific narrow-bands (hyperspectral data) improve biomass estimation [iv][v].

Hyperspectral measurements of vegetation canopies obtained from hand-held spectro- radiometer or airborne sensors contain useful information for the characterisation of vegetation, which could not be retrieved from multi-spectral imagery previously, Hyperspectral remote sensing allows the large-scale mapping of canopy biophysical properties [vi].

The red edge position yielded a slightly lower but significant correlation coefficient with biomass as compared to the narrow band vegetation indices. [vii].

Spectral vegetation indices are frequently used to estimate vegetation biophysical/biochemical characteristics. In general they have been proposed to reduce spectral effects caused by external factors such as the atmosphere and the soil background [viii].

2. Related work

Broadbands use the mean values of spectral information over broadband widths resulting in the loss of critical information that is available in narrowband. Thus, improvements in VIs are possible through the use of spectral data from distinct narrowband [ix].

The in situ hyperspectral data are of higher quality as compared with data from satellite-borne sensors since there is little atmospheric effect and the solar-view geometry is strictly controlled,Therefore, the relationships between AGB and spectral features based on ground measurements are more reliable. Such relationships are required for building Spectra-AGB models with inputs of satellite data, especially in vegetation index selection and model form selection [x].

Narrow bands located in the red edge (680–750 nm) are highly influenced by canopy biomass (LAI), and leaf chlorophyll content [11][12].

The red edge can be defined as the increase of reflectance at the boundary between the chlorophyll absorption feature in the red wavelengths and leaf scattering in the NIR wavelengths [13].

Red edge position (the point of maximum slope on the red infrared curve) appears to be sensitive to biomass variations for green vegetation as compared to senescing vegetation [14].

From this background, narrow wavelengths offer potential to estimate biomass at high canopy density as compared to broad band indices computed using the red and NIR wavelengths [15].

Narrow band vegetation indices are more promising to overcome spectral variability caused by canopy geometry, soil colour, sun view angles and atmospheric conditions for measuring biophysical properties [16].

The partial least squares (PLS) method has been recommended as an alternative approach to MLR to broaden the information contained in each model and thereby avoid over-fitting. As a full-spectral calibration method, PLS has an inherent capacity to deal with the over-fitting problem of full-spectrum calibration [17].

The PLS regression approach using ground-based canopy reflectance has been applied to estimation of pasture quality and Biomass [18].

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However, there is increasing evidence to indicate that wavelength selection can also refine the performance of PLS analysis [19][20].

3. Material and methodology:

3.1 Study Area

30 sample plots of homogeneous part of the grassy area are placed in the study area in order to estimate their biomass and to be characterizing radiometrically. Each sample plot is of size 30cm*30cm. In these sample plots, aboveground biomass collected and spectral data are recorded.

3.2 Canopy Reflectance Measurements

For each 30 cm × 30 cm plot the top of the canopy reflectance are measured. Spectral data are gathered in a spectral range of 350–2,500 nm using an ASD FieldSpec®4 spectroradiometer. For each plot, 15 reflectance readings are recorded, each one representing the average of 25 individual readings in each subplot, the spectroradiometer calibrated against a reference panel of known measurements of 100 ms. before taking the spectral reflectivity (Labsphere Spectralon®) in order to be able to convert the readings into absolute reflectance.
In this research, for data collection RS3 software is used and ViewSpecPro software is used for data analysis

3.3AbovegroundBiomass Measurements

All of the aboveground biomass in each 30 × 30 cm subplot located in the NE corner of each plot harvested right after the spectral measurements is taken.To avoid a loss of water in the samples, they put individually into hermetic plastics bags. The samples are weighted in the lab using a digital precision scale, therefore obtaining the total biomass weight. The aboveground biomass determined by dividing the weight of the harvest grass by the surface area of the plots (expressed as g/m2).

3.4 Narrow band vegetation indices:

Table 1: narrow-band vegetation indices from reflectance used in estimating AGB.

VI (Vegetation Index)	**Equation**	**Referances**
NDVI (Normalized Difference Vegetation Index)	NDVI = $(R_{875} - R_{680})/(R_{875} + R_{680})$	[21]
SAVI (Soil Adjusted Vegetation Index)	SAVI = 1.5 * $(R_{875} - R_{680})/(R_{875} + R_{680} + 0.5)$	[22]
NDWI (Normalized difference Water Index)	NDWI=$(R_{864} - R_{1245})/(R_{864} + R_{1245})$	[23]
DVI (difference vegetation index)	$R_{875} - R_{680}$	[24]
SR (Simple ratio)	R_{875} / R_{680}	[25] [26]

3.5 Partial least square regression (PLSR):

We build PLSR model by using matlab 2010a, version 7.10.In this research we tested partial least squares regression statistical methods for developing models to estimate biomass from the grass/clover spectra.

4. Result and discussion:

A spectral reflectance graph is the plot of the reflectance as a function of wavelength in nanometer. Each spectral reflectance is a mean of 15 reflectance reading of each plot. Figure I shows spectral reflectance curve of 30 plots.

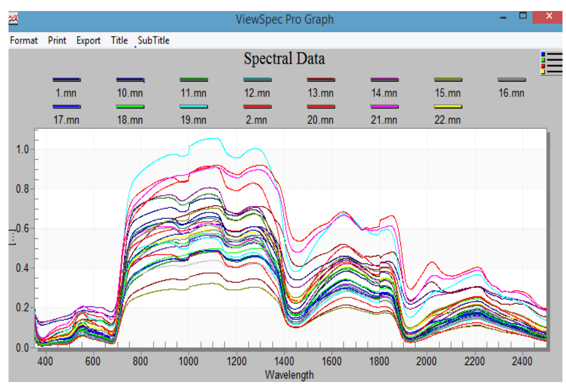

Figure 1: Reflectance curve of 30 sample plots.

Aboveground Biomass in grass estimation using Partial least square regression:

We used three datasets in this research i.e. training dataset, testing dataset, and dataset for biomass prediction. In each dataset we used two variables .Y for aboveground biomass weight ,and X for spectral reflectance .Training and testing dataset were provided with X and Y.Whereas prediction dataset is only provided with X .

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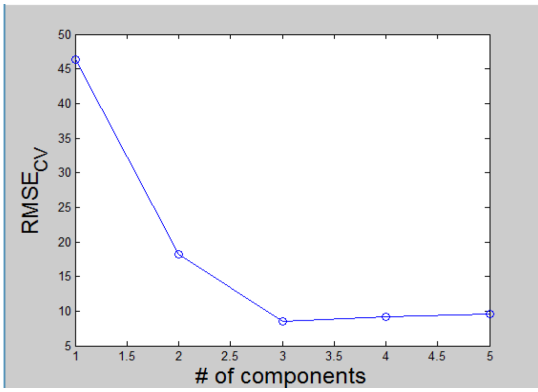

Figure 2: Graph between RMSE with cross validation and component

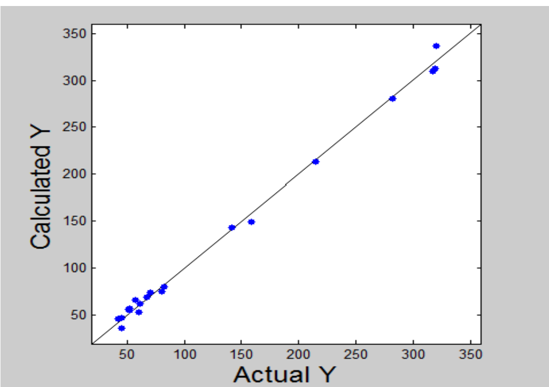

Figure 3: Graph between calculated Y and actual Y

Prediction dataset predict Y by using partial least square regression model. We build PLSR model by using training dataset.

We predicted aboveground biomass in grass by using PLSR model with root mean square error. The PLSR model predictions were compared using root mean square error in prediction (RMSE) calculated from the test data set.

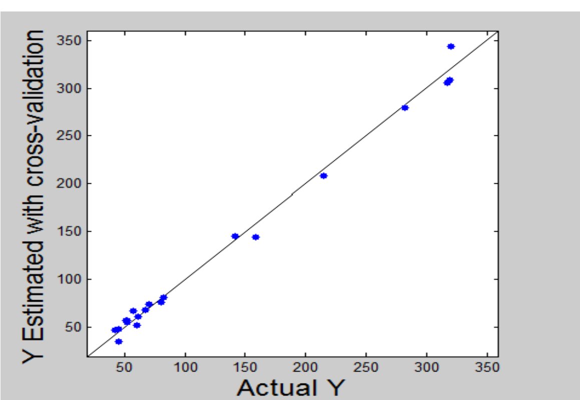

Figure 4: Graph between Y estimated with cross validation and actual Y.

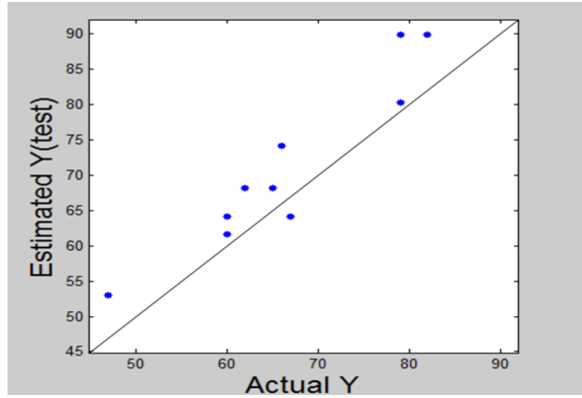

Figure 5: Graph between estimated Y and actual Y.

Table 2: Partial least square regression models between each VI and AGB using the data set for building model and the predictions of each model using an independent test data set.

VI (vegetation index)	RMSE
DVI	46.29
SAVI	18.24
NDWI	8.52
RVI	9.12
NDVI	9.62

5. Conclusion:

It is concluded that aboveground biomass of grass predicted by using PLSR model with RMSE (root mean square error) = 6.33 and R^2 =0.9 per g/m^2.Partial least square regression model between normalized difference water index (NDWI) and aboveground biomass of grass shows minimum error of prediction of biomass as compared to DVI, SAVI, NDVI, and RVI. This result shows water content in grass has higher influence on estimation of biomass in grass.

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