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Spectroscopic Determination of Aboveground Biomass in Grass using Hyperspectral Indices

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Abstract: Aboveground biomass (AGB) is a biophysical variable in vegetation studies .Biomass is considered as fresh matter weight or dry matter weight. The main objective of this study is to explore the potential of narrow band vegetation indices and band depth analysis method in biomass estimation. We will calculate three vegetation indices in this study i.e. soil adjusted vegetation indices (SAVI), normalized difference vegetation indices (NDVI), normalized difference water indices (NDWI) from field spectrometer data. We will use ASD field spec 4 for field spectrometer data. We will also apply band depth analysis method on field spectrometer data using continuum removed indices. The second objective of this study compares the performance of narrow band vegetation indices and band depth analysis method in aboveground biomass estimation by calculating root mean square error.

Keywords: Biomass, narrow band vegetation indices, band depth analysis, absorption features, continuum removal.

I. INTRODUCTION

Biomass is considered as fresh matter weight or dry matter weight, this both variables are strongly related with water content. We can measure biomass directly or indirectly. Measuring biomass directly for mapping grass is traditional method, which is time-consuming, destructive and expensive procedure and also requires extensive field work. So researchers and managers are looking for non-destructive and repeatable methods to monitor biomass [1].

Remote sensing techniques meet the two previous requirements, and provide the non destructive and repeatable methods to estimate biomass in grass, And in addition to this, remote sensing techniques allows both spatial and temporal analyses. Remote sensing technology also decreases the amount of labour needed for sampling, and reduce the cost associated with sampling and analysis. Hence, remote sensing is a very promising technology that allows collection of quantitative data over a landscape [2].

Thus, the objectives of this study will to 1) Study of biophysical properties of grass.2) Understand the relationship between aboveground biomass and spectral feature of reflectance from aboveground vegetation.3) Explore the potential of narrow band vegetation indices and band depth analysis method in aboveground biomass estimation using partial least square regression. 4) Compare the performance of narrow band vegetation indices and band depth analysis method in aboveground biomass estimation. To achieve these objectives, field hyperspectral data and corresponding aboveground green biomass measurements will conduct at the place where canopy cover is lower. Biophysical and chemical attributes of vegetation strongly determines their spectral properties such as leaf area index (LAI), the amount of live biomass and senesced biomass, moisture content, pigments (e.g., chlorophyll) and spatial arrangement of structures. The aim of narrow band vegetation indices in this study is to enhance the spectral contribution of green vegetation while minimizing contributions from soil background, solar irradiance, sun angle, senescent vegetation and the atmosphere. For the Normalized Difference Vegetation Index (NDVI) computation the visible and near infrared bands with the largest correlation with aboveground biomass will be use i.e. 654 and 877nm. Soil Adjusted Vegetation Index (SAVI) is similar to the NDVI, only an additive term in SAVI is to correct for soil background. NDVI is sensitive to variation of chlorophyll content and leaf area index (LAI), whereas NDWI is a spectral index sensitive to vegetation water content and LAI [3].

In this research we will build partial least square regression statistical technique to estimate aboveground biomass. Determine the appropriate absorption features was proved to be crucial to improve the performance of PLSR to estimate the aboveground biomass, by using the indices derived from those spectral regions. Partial least square regression provide small number of latent factors, small error in the prediction of the cross-validation, small adjusted error in the cross-validation and a coefficient of determination (R^2) as close to 1 as possible [4].

II. RELATED WORK

O.Mutanga & A. K. Skidmore proved that red edge position yielded comparable results to the narrow band vegetation indices involving the red edge bands. These results indicate that at high canopy density, pasture biomass may be more accurately estimated by vegetation indices based on wavelengths located in the red edge than the standard NDVI. The red edge contains more information on biomass quantity as compared to other parts of the electromagnetic spectrum.

The major limitation of using vegetation indices particularly NDVI based on the red and NIR portion of the electromagnetic spectrum is that they asymptotically approach a saturation level after a certain biomass density or LAI. Hyperspectral remote sensing offers possibilities of investigating vegetation indices based on narrow bands in the whole electromagnetic spectrum (350–2500nm), rather than focusing on the red and NIR bands alone. Narrow wavelengths offer potential to estimate biomass at high canopy density as compared to broadband indices computed using the red and NIR wavelengths [5].

Cho, M.A.; Skidmore, A.K.; Corsi, F.; van Wieren,showed that spaceborne hyperspectral data are more promising for more accurate monitoring for complex landsurfaces. But many efforts have been made to classify different land-cover types using Landsat data, crops, second growth and green pasture are not spectrally distinct in the broad-band system. This spectral ambiguity can be reduced using hyperspectral data. The presence of multiple wavelengths in the SWIR region in Hyperion contributes to minimize the problem of spectral ambiguity between vegetation and Soil, which is a common problem with broad-band systems.Extracting meaningful and accurate measures to quantitatively characterize vegetation still remains a challenge in remote sensing. In part, the accuracy of the retrieval of vegetation properties using remote sensing depends upon sensor spectral and spatial resolutions. Although broad-band remote sensing has been widely used, this system has limited capability for accurate estimation of vegetation because its coarse spectral resolution leads to ambiguous differentiation between senesced vegetation and soil backgrounds. Hyperspectral remote sensing has the ability of overcoming some of these problems [6].

Zhang, Miaogen Shen, Yanhong Tang et al carried out field survey to collect hyperspectral reflectance and AGB for five major grassland ecosystems on the Tibetan Plateau and calculated seven narrow-band vegetation indices and the vegetation index based on universal pattern decomposition (VIUPD) from the spectra to estimate AGB.When they considered each ecosystem type separately, all eight vegetation indices provided good estimates of AGB, with the best predictor of AGB varying among different ecosystems. When AGB of all the five ecosystems was estimated together using a simple linear model, VIUPD showed the lowest root mean square error among the eight vegetation indices. The regression models containing dummy variables predicted AGB with higher accuracy as compared to simple models, which could be attributed to the dummy variables accounting for the effects of ecosystem type on the relationship between AGB and vegetation index (VI). These results suggest that vegetation index based on universal pattern decomposition (VIUPD) is the best predictor of AGB among simple regression models. Moreover, both vegetation index based on universal pattern decomposition (VIUPD) and the soil-adjusted vegetation index could provide accurate estimates of aboveground biomass with dummy variables integrated in regression models. Therefore, ground-based hyperspectral measurements are useful for estimating aboveground biomass, which indicates the potential of applying satellite/ airborne remote sensing techniques to aboveground biomass estimation of these grasslands on the Tibetan Plateau.The in situ hyperspectral data are of higher quality 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 (VI) selection and model form selection [7].

Wang Xiaoping ,Guo Ni, uses three kinds of indices in their study, 1) based on the position of hyperspectral variables 2) based on the areas of hyperspectral variables 3) based of the hyperspectral vegetation index. Based on the field experiment, the relationship between the hyperspectral spectral reflectance and aboveground biomass for four kinds of grass types in Gannan rangelands were analyzed, using the parameters of the canopy spectral reflectance absorbed character and the vegetation indices and the biomass analysis by single variable linear and non-linear regression analysis indicated that the biomass estimation model based on the spectral vegetation indices is better than the models based on the spectral position variable. Results show that the regression of quadratic model using ratio vegetation index (RVI) provide a better univariate regression involving hyperspectral indices for grass aboveground fresh biomass estimation compared other models in Gannan rangelands [8].

Pearson proved that *i*nformation contained in a single spectral band is usually not sufficient to characterize crop properties fully or to identify causal factors and their relationships with the host or the environment. So far, the most common technique to extract information content from spectral measurements is the computation of spectral vegetation indices (VIs). In particular, these vegetation indices were found to be quantitatively and functionally related to several vegetation parameters such as leaf area index (LAI), percent vegetation cover, intercepted photosynthetically active radiation (IPAR), and green biomass The normalized difference vegetation index (NDVI) and ratio vegetation index (RVI) have been used extensively in correlating remote sensing observations with the characteristics of vegetation [9].

D.H. Zhao, J.L. Li, J.G. Qi used vegetation indices constructed with red and NIR spectral measure-ments have been shown to be significantly correlated with crop agronomic variables such as LAI, aboveground biomass, and chlorophyll content. Broadband and narrowband based vegetation indices have been compared for their ability to estimate crop agronomic variables such as green vegetation cover, LAI and CCD .In general, the narrowband VIs may be slightly better than their broadband versions for estimating crop variables. Many VIs were developed in the past three decades with the primary purposes of (1) Enhancing their sensitivities to green vegetation signals and (2) reducing external effects such as those from soil and atmospheric variations [10].

A. Psomas, M. Kneubühler explored the potential of hyperspectral remote sensing for mapping aboveground biomass in grassland habitats along a dry-mesic gradient, independent of a specific type or phenological period.They were developed Statistical models between biomass samples and spectral reflectance collected with a field spectroradiometer. They were collected grassland samples at four time steps during the growing season to capture normally occurring variation due to canopy growth stage and management factors. They were investigated relationship between biomass and (1) existing broad- and narrowband vegetation indices, (2) narrowband normalized difference vegetation index (NDVI) type indices, and (3) multiple linear regression (MLR) with individual spectral bands. Best models were obtained from the multiple linear regression (MLR) and narrowband NDVI-type indices. Spectral regions related to plant water content were estimate biomass with lower prediction error.

Even though MLR models using spectral bands gave better estimates and predictions on the field level, they could not be scaled easily to the sensor level. Therefore, for up-scaling field-developed models and for better estimation of grassland biomass, they propose using narrowband NDVI type vegetation indices, constructed with bands in spectral regions related to canopy water content[11].

III. METHODOLOGY

Clark, r. n., and Roush, t. l., applied a refined method (band depth analysis of absorption features)Spectral variability is independent of biochemical concentration. The effect of spectral variability is minimized by enhancing and standardizing known chemical absorption features. However, the effect of overfitting arises using stepwise regression technique is minimized by concentrating on known absorption pits that are enhanced by continuum removal [12].

Kokaly, R.F.; Clark, R.N, Continuum Removal Transformation and Derived Indices technique is use to minimise the noise effects and to enhance the absorption characteristics of the spectrum, In order to apply this method, it was necessary to identify the limits of the regions where it is going to be perform. These regions will be determine empirically by taking account of the locations of the local spectral maxima of the grass, as long as those areas are sensitive to changes in the variable of interest (in this case, AGB)[13].

Onisimo Mutanga and Andrew K. Skidmore determined CR transformation is obtained by dividing the original reflectance values by the corresponding values in the continuum (*i.e.*, the segment which represents the trend). For comparison of individual absorption features from a common baseline, continuum removal method normalizes reflectance spectra. The continuum is simply a convex hull fitted over the upper level of a spectrum to connect local spectrum maxima. The first spectral data value and last spectral data values are on the hull and therefore the first and last values of continuum removed spectrum are equal to 1[14].

Huang, Z.; Turner, B.J.; Dury, S.J.; Wallis, I.R.; Foley, W.J states that,in addition to the continuous spectra derived from the continuum removed reflectance (CRR), the absorption features were characterised by two indices: the maximum band depth (MBD) and the area over the minimum (AOM) [15]. Pu, R.; Ge, S.; Kelly, N.M.; Gong, P.described area over the minimum (AOM) as the product between the depth and the width (*i.e.*, width measured at half of the depth) [16].

Hongrui Ren , Guangsheng Zhou defined the maximum band depth (MBD) is the magnitude of the maximum difference between the spectrum and the continuum [17] and Clevers, J.G.P.W.; Kooistra, L.; Schaepman, M.E. shows that it is related with the intensity of the absorption in that region. Both indices have succeeded in the estimation of biomass [18].

Miguel Marabel and Flor Alvarez-Taboada compared statistical model to predict aboveground biomass.and they prove that the most accurate model to predict the total AGB is partial least squares regression (PLSR). PLSR is a generalisation of linear multiple regression which is able to reduce the large number of measured collinear spectral variables to a few noncorrelated latent variables or factors[19].

Kensuke Kawamura uses partial least square regression with waveband selection for estimating forage biomass. Thus, this method builds a linear model based on the latent variables of the mean-centred matrix containing the predictor variables (the spectral bands).Partial least squares regression (PLS regression) is a type of statistical method which finds a linear regression model by projecting the predicted variables and the observable variables to a new space [20].

Wang Xiaoping ,Guo Ni,Zhang Kai ,Wang Jing, carried out a field survey to collect hyperspectral reflectance and aboveground biomass for five major grassland ecosystems on the Tibetan Plateau and calculated seven narrow-band vegetation indices and the vegetation index based on universal pattern decomposition (VIUPD) from the spectra to estimate aboveground biomass. First, they investigated correlations between aboveground biomass and each of these vegetation indices to identify the best estimator of aboveground biomass for each ecosystem type. Next, they estimated aboveground biomass for the five pooled ecosystem types by developing models containing dummy variables. At last, they compared the predictions of simple regression models and the models containing dummy variables to seek an ecosystem type-independent model to improve prediction of aboveground biomass for these various grassland ecosystems from hyperspectral measurements[8].

IV. RESULT AND DISCUSSION

The results suggest that 640–660 nm and 800–870 nm, the centers of the red and NIR channels of several multi-spectral sensors on the current generation of earth-orbiting satellites, were not always the optimum wavelength position of red-NIR bands for VIs. Although different in formula, both the NDVI and RVI calculated from narrow bands at 690-710 nm and 750-900 nm were closely correlated with LAI and CCD [2].

Hyperspectral absorption features were shown to be the best measures for pasture biomass at canopy scale, i.e., above ground biomass, live biomass, dry biomass and canopy water content. Water absorption features (i.e., water absorption depth and water absorption area) had the highest correlations with above ground biomass, live biomass, and canopy water content, and ligno-cellulose absorption features (i.e., ligno-cellulose absorption depth and ligno-cellulose absorption area) had the highest correlations for senesced biomass. These findings shows possible improvement for estimating grass measures using spectral absorption features derived from hyperspectral sensors [3].

We conclude that There is a issue of saturation problem in biomass estimation when the Modified Normalized Difference Index (MNDVI) calculated from a combination of narrow channels in the shorter wavelengths of the red edge(700–750 nm) and longer wavelengths of the red edge (750–780 nm). SR yields the highest correlation coefficients with biomass as compared to narrow band NDVI and triangular vegetation index(TVI). We therefore recommend the use of a SR based on a waveband located in the shorter red edge portion (706 nm) and a band located in the longer red edge portion (755 nm) for a better estimation of biomass at high canopy density[5].

Effectiveness of explanatory variables for AGB estimation relies on the radiation absorption in the red band by pigments such as chlorophyll and various types of carotenoid and energy reflection as well as mesophyll multi scattering in the NIR region [7].

Sampled grasslands represent a dry-mesic gradient having different level of water and nutrients, which eventually lead to different rates of growth and biomass accumulation. Lower biomass variability observed later in the season could be partly attributed to the management practices applied to these fields.Furthermore, analyses on the individual biomass samples collected showed that the average standard deviation of the three samples was 21% of the mean biomass measured within each grassland field [11].

PLSR models produced lower ranges of RMSE than SVM or OLSR when the same input data were considered. The most accurate model to predict TAGB involved PLSR and the MBD index derived from the continuum removed reflectance in the absorption feature between 916 and 1120 nm (Z3) and 1079 and 1297 nm (Z4) (RMSE = 7.120 g/m2, 15.81% of the mean value). The combination of PLSR and continuum removed spectra produced lower ranges of error for the cross validation analyses (RMSE = 7.120 to 7.136 g/m2) compared to the PLSR and the spectra transformed by other techniques (Normalization or Multiplicative Scatter Correction) (RMSE = 7.443 to 7.640 g/m2).However, transformations yielded more accurate PLSR models than non-transformed data. The comparative analysis of the performance of PLSR models and SVM models showed higher R2 and smaller RMSE for the PLSR models, regardless of the non-transformed spectral subset used as input data [19].

The use of Partial Least Square with waveband selection is promising for spectral assessment of a wide range of ecosystem parameters. Further, waveband selection procedures in Partial Least Squarewill improve the accuracy and robustness of the method [20].

V. CONCLUSION

The red edge contains more information on biomass quantity as compared to other parts of the electromagnetic spectrum. Narrow wavelengths have advantage of offering higher potential to estimate biomass at high canopy density as compared to broadband indices computed using the red and NIR wavelengths. Band depth analysis method of absorption features is useful to minimize effect of spectral variability. More accurate statistical model for estimating aboveground biomass is partial least square regression. Narrow band vegetation indices are more promising to overcome spectral variability caused by canopy geometry, soil background, sun view angles and atmospheric conditions when measuring biophysical properties.

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