

Biophysical Parameter Estimation of a Pine Plantation from Satellite Images Using Artificial Neural Networks

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Abstract- One non destructive method of biomass quantization involves exploiting biophysical parameters of trees such as diameter at breast height (DBH), height, basal area, volume and stocking. Generally, these parameters are estimated through model functions or algorithms which transform a set of remote sensing observations into biophysical measurements. Several studies have investigated the estimation of biomass parameters using low to high resolution optical digital images, but few studies have compared the performances of different advanced classification methods for estimating biomass variables. In this study, biophysical parameters including basal area, volume and stocking are estimated using different textural attributes calculated from SPOT 5 images over a *Pinus radiata* plantation in Australia. Two different neural networks including multilayer perceptron (MLP) with three different activation functions and radial basis function (RBF) neural networks are applied to analyze the relationship between the plot level biophysical information and the remotely sensed data. The results showed the capability of SPOT-5 data for use for biophysical parameters of *Pinus radiata* forest especially when MLP method is used.

Keywords: Biomass variables, SPOT-5, Neural Networks, Texture, *Pinus radiata*

1. INTRODUCTION

In recent decades, different remote sensing sensor data have been investigated for the quantization of biomass parameters including DBH, height, basal area, volume, stocking, etc. Several of these studies have analyzed and estimated biomass parameter using low to high resolution optical digital images such as MODIS, SPOT, Landsat and IKONOS (Makela and Pekkarinen, 2004; Lu, 2005; Sivanpillai et al., 2006; Kayitakire et al., 2006; Nelson et al., 2009; Wolter et al., 2009). These studies can be grouped in two classes; those that investigated the relationship between reflectance and spectral content of optical images and stand variables and those that focused on the advantages of using textural information derived from optical images to model and analyze forest structure. While several vegetation indices have been developed the most common one is normalize difference vegetation index or NDVI (Foody et al., 2001). Several studies have demonstrated the limitations of utilizing space borne spectral information for estimating stand volume, even over pine forests (Trotter et al., 1997; Kilpelainen and Tokola, 1999). Foody et al. (2001) suggested that vegetation indices are not reliable for quantizing biomass variables due to the following problems: (i) the asymptotic relationship between vegetation indices and biomass can lead to inaccurate evaluation of high biomass forests; (ii) the

radiometric calibration of remotely sensed data is applicable to radiance and not indices; (iii) the vegetation indices are environmentally dependent; and (iv) they often do not utilize all spectral data together.

Texture characterizes the spatial relationship between objects and varies with the spatial variability of image tone (Wulder et al., 1998). Since, spatial variation over a forest area is related to the spatial distribution of individual stands and their structures, textural information carries a wealth of information about stand structure. Several studies have shown that the textural analysis of remote sensing images can provide significant information in forest inventories (Ryherd and Woodcock, 1996; Hyyppa et al., 2000). Even, in heterogeneous stands, e.g. mixed-wood stands, textural attributes can provide more information than spectral data (Wulder, 1998). There are various methods that can be implemented to find the relationship between forest structure variables such as height, volume, DBH, basal area, crown closure, crown diameter, and textural information in digital images. Common methods include Semi-variogram, object-based methods, and Gray level Co-occurrence Matrix (GLCM). Using semi-variogram operationally in large scale applications is limited for two reasons: (i) data generated through this method can be too large and consequently difficult to manage (Kayitakire et al., 2006) and (ii) when analyzing inter-stand structure, it is necessary to construct separate semi-variograms for each stand and this can also be impractical (Cohen et al., 1990).

GLCM can be considered as a reliable method to find the relationship between biomass variables and remote sensing data. The most relevant textural features for remote sensing applications, according to the literature (Baraldi and Parmiggiani, 1995; Solberg, 1999; Lu, 2005; Tuominen and Pekkarinen, 2005; Kayitakire et al., 2006), are presented in table A. According to these studies, physical characteristics of objects, environmental conditions at the time of data acquisition, forest characteristics, spatial resolution and spectral characteristics of image and window size, are the most important parameters to determine the suitability of a textural feature for biomass classification or stand variables quantization.

However, some studies have used different methods such as regression and multiple regression models, neural network, classification methods and empirical methods to define the relationship between optical data and different biomass parameters in forest mapping (Hyyppa et al., 2000; Gemmell et al., 2001; Cohen et al., 2003; Ingram et al., 2005; Labrecque et al., 2006; Luther et al., 2006). Among these methods, neural networks have the capacity to build reliable regression models between optical data and vegetation variables provided enough training data is available (Kimes et al., 1998). There are

different types of neural networks which can be applied in biomass variable estimation such as MLP and RBF (Foody et al., 2001).

Table A. Most Relevant Textural Features for Remote Sensing Applications

| Textural feature | Equation |
|-----------------------------|---|
| Mean (ME) | $\sum_{i=0}^{Ng-1} \sum_{j=0}^{Ng-1} ip(i, j)$ |
| Dissimilarity (DISS) | $\sum_{i=0}^{Ng-1} \sum_{j=0}^{Ng-1} Abs(i - j)p(i, j)$ |
| Entropy (EN) | $\sum_{i=0}^{Ng-1} \sum_{j=0}^{Ng-1} p(i, j) \log(p(i, j))$ |
| Variance (VAR, σ^2) | $\sum_{i=0}^{Ng-1} \sum_{j=0}^{Ng-1} (i - MEAN)^2 p(i, j)$ |
| Angular Second Moment (ASM) | $\sum_{i=0}^{Ng-1} \sum_{j=0}^{Ng-1} p(i, j)^2$ |
| Correlation (COR) | $\sum_{i=0}^{Ng-1} \sum_{j=0}^{Ng-1} \frac{(i - MEAN)(j - MEAN)p(i, j)}{\sigma_i \sigma_j}$ |
| Contrast (CON) | $\sum_{i=0}^{Ng-1} \sum_{j=0}^{Ng-1} p(i, j) (i - j)^2$ |
| Homogeneity (HOM) | $\sum_{i=0}^{Ng-1} \sum_{j=0}^{Ng-1} \frac{p(i, j)}{1 + (i - j)^2}$ |

Where Ng is the number of gray levels, and p(i, j) represents the probability of co-occurrence of gray levels i and j.

Hyppa et al. (2000) compared the value of various spectral data derived from different sources including SPOT Pan, SPOT XS and Landsat TM to estimate stem volume, mean tree height and basal area using regression and neural network models. The results showed better accuracy is derived for higher spatial resolution data using a neural network model. Moreover, the best estimation of the error of stand mean height using optical data was more than 30% of measured mean height whereas estimations of stem volume and basal area parameters were not reliable, especially using space borne data. Foody et al. (2001) compared three different types of neural networks including MLP, RBF and generalized regression neural networks (GRNN) to estimate biomass using spectral attributes of TM data. MLP was shown to be the best method with a correlation coefficient between test data and biomass of 0.64 compared to 0.21 for NDVI.

This study aims to investigate the relationship between GLCM in different window sizes and three biomass variables including basal area, volume and stocking. Moreover, different types of neural network methods were also evaluated for all biomass variables.

2. STUDY AREA AND DATA

The study area contained a 5,000ha *Pinus radiata* plantation near to the town of Batlow in New South Wales, Australia. Field data from 63 plots (measured by the New South Wales Department of Industry and Investment (IINNSW) and Forests NSW in September 2008) included DBH and height measurements for each tree. After buffering these plots with a 30m radius it became evident that some plots contained road edge effects or incorporate mixed age classes and consequently 21 plots were removed from the field dataset for the rest of study. Basal area, volume and stocking were calculated per

hectare for each plot. Table B summarises information related to the 42 plots used in this study.

Table B. Summary of the Used Plot Data in This Study

| Age | Basal (m ² /ha) | Volume (m ³ /ha) | Stocking (tree/ha) |
|----------------------------|----------------------------|-----------------------------|--------------------|
| Less than10 to more than30 | 21 to 65 | 106 to 545 | 121 to 1150 |

Multispectral SPOT-5 data acquired in April, 2008 was used in four bands including green, red, infra red (NIR) and short wave infra red (SWIR). The first three bands were acquired in 10m resolution, while SWIR was originally 20m. We resampled SWIR to 10m resolution, the same as the other bands. This image was radiometrically corrected in level 1A and orthorectified. For this study, DN values were used to calculate different GLCM layers, whereas researchers usually use reflectance conversion before building regression model. It can be argued that, as long as band ratio is not applied, as in this study, DN values are applicable to generate GLCM for biomass variable estimations.

3. METHODOLOGY

Four different neural networks including multi-layer perceptron (MLP) with three different activation functions, comprising of sigmoid, Gaussian and hyperbolic functions, and radial basis function (RBF), were compared to determine which one is better for estimating each biomass variable. In this study, these methods were used in an architecture comprising an input layer, one hidden layer and an output layer. In MLP, the inputs are related to the output nodes through two types of input and output weighting coefficients, which are calculated during the training process. In the hidden part that can comprise more than one layer, different activation functions can be exploited to convert the input values. In RBF neural networks, there is one set of weighting coefficients and the input weighting coefficients have been replaced by radial units. The hidden layer is usually one layer in the RBF neural networks. Further details related to neural networks are beyond the scope of this paper and can be found in the computer science literatures (e.g. Benoudjit and Verleysen, 2003).

In addition to the GLCM features presented in table A, three GLCM features including maximum probability (MP) within window, energy (EN) or the square root of ASM and standard deviation (ST) which is the square root of variance, have been generated in 6 different window sizes including 3×3, 5×5, 7×7, 9×9, 11×11 and 13×13. A subset of 30 plots was randomly selected as training data and 12 plots were used as test data. Then, in order to find attributes to be used as inputs for neural networks, a linear regression between each GLCM feature and each biomass variable was tested for the training dataset, and features whose correlations were higher than for the others for different window sizes were selected for the input to the neural network. Moreover, in order to avoid multicollinearity, high correlation among the selected attributes, the interdependency of selected features was tested and highly correlated features were removed. The selected attributes were used in the neural networks. As the number of samples was insufficient for selecting validation data, a 5-fold cross validation method was used to adjust the neural networks parameters including the number of neurons and the number of iteration. The results of each method are reported using RMSE and correlation coefficients between the actual value of the test data and the predicted value for each biomass variable.

4. RESULTS

As mentioned above, only those GLCM attributes which were not highly correlated were generated for 6 different window sizes and different multispectral bands. Table C shows the selected attributes of each band for the training dataset for use in the neural networks, as well as their correlations with each biomass parameter. The highest correlation coefficients for each biomass variable are shown in bold text.

Table C. The Selected GLCM Features to Be Used in Neural Networks

| Biomass variable | Band | GLCM feature | R ² |
|------------------|-----------|--------------|----------------|
| Basal area | Green | COR 9×9 | 0.43 |
| | Red | HOM 13×13 | 0.63 |
| | NIR | MP 7×7 | -0.25 |
| | | ENT 3×3 | -0.11 |
| | | ME 13×13 | -0.68 |
| SWIR | ----- | ----- | |
| Volume | Green | COR 7×7 | 0.25 |
| | Red | HOM 13×13 | 0.65 |
| | NIR | MP 7×7 | -0.19 |
| | | ENT 3×3 | -0.24 |
| | | ME 11×11 | -0.72 |
| COR 3×3 | 0.10 | | |
| SWIR | COR 13×13 | -0.20 | |
| Stocking | Green | ----- | ----- |
| | Red | EN 5×5 | 0.62 |
| | NIR | MP 3×3 | -0.28 |
| | | ME 13×13 | -0.14 |
| | | COR 13×13 | 0.57 |
| SWIR | ----- | ----- | |

As table C shows there are significant relationships between multispectral SPOT-5 image and biophysical attributes of this plantation. This table demonstrates that ME, COR, ENT, HOM, EN and MP are the most suitable GLCM attributes for this study; however, it is not possible to recommend a certain size of window as the most efficient for the GLCM calculation.

The best relationships between training data and biophysical attributes were obtained for the NIR and red bands, which are the most suitable bands for vegetation studies. The best correlation was obtained for the NIR band and volume and basal area with correlation coefficients of -0.72 and -0.68, respectively, while the highest correlation between multispectral bands and stocking occurred for the red band, with a correlation coefficient of 0.62. SWIR makes the lowest contribution for biomass variables predictions. One of the main reasons for this weak relationship is the coarser resolution of this band compared to the others.

After selection of the most suitable GLCM attributes for use as inputs in neural networks, it was required to select the most important neural networks parameters, including the required number of iteration for the training process and the number of neurons in the hidden layer. These parameters were obtained through 5-fold cross validation. The rest of the parameters such as learning rate were set according to the literature. Table D gives the results for the 5-fold cross validation method. Table D shows that the number of iterations and neurons will change as the biomass variable and neural network method alter.

Using four adjusted neural networks, three different biomass variables were predicted separately as shown in table E. Again,

the highest values are in bold text. As table E shows the neural network methods, regardless of which method is used, were able to build a regression model with higher correlation compared to the linear relationships between training datasets and biomass variables. MLP methods can perform better than RBF neural networks for prediction of all biomass attributes.

Table D. Neural Networks Parameters Derived from 5-Fold Cross Validation

| Method | Biomass Variable | Iteration | Neuron |
|------------------|------------------|-----------|--------|
| MLP (Gaussian) | Basal area | 100 | 15 |
| | Volume | 100 | 4 |
| | Stocking | 100 | 8 |
| MLP (Hyperbolic) | Basal area | 1000 | 6 |
| | Volume | 100 | 5 |
| | Stocking | 10 | 11 |
| MLP (Sigmoid) | Basal area | 100 | 5 |
| | Volume | 100 | 5 |
| | Stocking | 100 | 3 |
| RBF | Basal area | 100 | 7 |
| | Volume | 100 | 11 |
| | Stocking | 100 | 13 |

Regarding the type of activation function, Gaussian function seems to be better (but has not tested statistically yet) than the other functions with lower RMSE, 4.12m²/ha for basal area and 91.5m³/ha for volume, and higher correlations, especially for basal area. Hyperbolic function has higher efficiency compared to the other functions for predicting stocking.

Table E. RMSE and correlation between input data and each biomass variable derived from different methods

| Method | Biomass Variable | RMSE | R ² |
|------------------|---------------------------------|-------------|----------------|
| MLP (Gaussian) | Basal area (m ² /ha) | 4.12 | 0.91 |
| | Volume (m ³ /ha) | 91.5 | 0.83 |
| | Stocking (trees/ha) | 203 | 0.78 |
| MLP (Hyperbolic) | Basal area (m ² /ha) | 6.58 | 0.85 |
| | Volume (m ³ /ha) | 96.5 | 0.81 |
| | Stocking (trees/ha) | 168 | 0.84 |
| MLP (Sigmoid) | Basal area (m ² /ha) | 5.74 | 0.88 |
| | Volume (m ³ /ha) | 99.9 | 0.79 |
| | Stocking (trees/ha) | 206 | 0.73 |
| RBF | Basal area (m ² /ha) | 6.5 | 0.80 |
| | Volume (m ³ /ha) | 119.7 | 0.68 |
| | Stocking (trees/ha) | 216 | 0.73 |

5. CONCLUSION

The capability of GLCM attributes derived from SPOT-5 multispectral image DN values, for estimation of biophysical variables including basal area, volume and stocking in plot level was investigated. MLP neural networks with three different activation functions and RBF neural network were compared for this task. The results showed GLCM attributes derived from DN values are efficient for use as predictors for biophysical parameters. According to the linear regression between different GLCM attributes and biophysical parameters, NIR and red bands were the most suitable bands for this task; however, the other bands should not be neglected. This paper shows no specific window size is superior for GLCM calculation. Moreover, it was shown that not all GLCM attributes are useful for biophysical parameter prediction. Generally, neural networks can perform efficiently to build regression models

between textural attributes derived from SPOT-5 multispectral image and biophysical parameters. MLP methods seem to perform better than RBF for biophysical parameter prediction, especially when Gaussian activation function is used for basal area and volume prediction and hyperbolic activation function is applied for stocking.

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