Patch Metrics as Surrogates of Structural Complexity of Remnant Vegetation

Abdolrassoul S. Mahiny
Assistant Professor, College of the Environment
Gorgan University, Gorgan / IRAN
Tel: +981712245965
Fax:+981712245886
A_Mahini@yahoo.com

1. Introduction

In the Boorowa Region, northwest of Canberra, Australia, cumulative effects of development and human activities have significantly affected the structure, composition and function of native vegetation (Mahiny 2004). I used patch metrics as surrogates of patch internal complexity. To do so, the internal complexity of the remnant vegetation patches was assessed using the Habitat Complexity Score (HCS) method. Then, patch metrics were calculated using a classified TM image of the area in Fragstats software.

Neural networks and multiple regression analyses of the complexity as dependent variable against patch metrics as independent variables were conducted in this study. Use of patch metrics to map the complexity of vegetation structure over a large area was investigated.

2. Study Area

The Boorowa Catchment includes the town of Boorowa, northwest of Canberra, Australia. The catchment is located at around 110 kilometres distance from Canberra and covers almost 220 thousand hectares (Fig. 1).

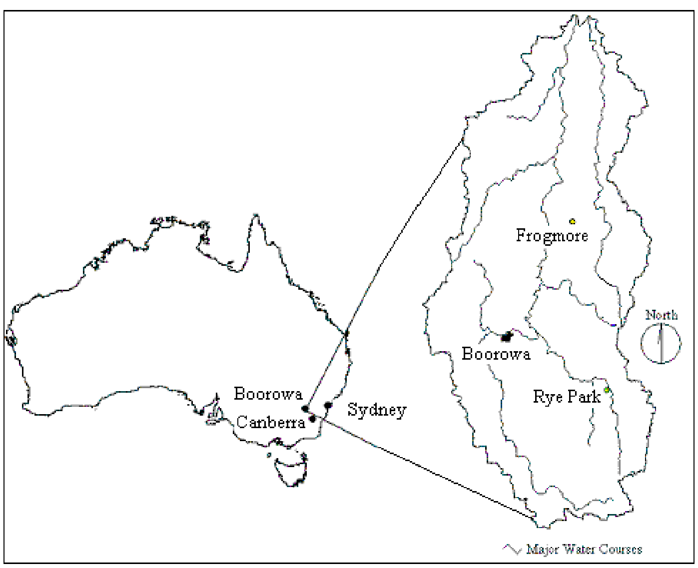

Figure 1. The Boorowa catchment location

3. Materials and Methods

The structure of vegetation patches was studied using the relationships between various raw and calculated image parameters on the one hand and the field data on the structure in a proper format on the other. Newsome and Catling (1979) developed and used an index called Habitat Complexity Score (HCS). HCS measures the structure of woodlands in the form of tree canopy cover, tall shrub cover, short shrub cover, ground herbage, logs, fallen trees and dead wood and rocks and litter in any vegetation patch (Fig. 2).

Figure 2. Habitats with high structural complexity (1), medium structural complexity (2) and low structural complexity (3)

Source: Coops and Catling (2001)

Freudenberger (2001) used data on 55 patches of different sizes in the Boorowa region sampled through a modified version of the HCS and was able to classify patches in terms of habitat complexity between 4 and 15. I used the same data in the present study. I first explored possible relationships between the HCS and the Landsat TM image for the year 2000. Then, the likely relationships between the external attributes of the patches and their internal structure were studied.

After screening the 55 data points available, 48 points were found useful for the analysis. Freudenberger (2001) suggested from his results that, an HCS score of 6 or less represents woodlands with poor structure, having no understorey shrubs and few logs on the ground though often a complete cover of pasture. A score of 7 - 12 represents grassy or shrubby woodlands with moderate structure comprising more than 20% shrubs and 10 - 50% cover of ground herbage, logs and litter. Finally, a score greater than 12 applies to a structurally complex woodland in good condition.

To investigate likely relationships between HCS and the TM 2000 image attributes, the sampling points for the HCS were buffered and a surface area of 0.43 hectares was selected for each point. Initially, a total of 39 image variables were generated from the TM 2000 image bands. Then, the independent variables identified as most important and least correlated were used in the multiple regression analysis (Table 1). The R^2 of the regression analysis and an inspection of the plot in Figure 3 indicate a significant relationship between the dependent and independent variables (assuming a 5% level of significance).

Table 1. Multiple regression results for the original HCS values against independent variables derived from the TM 2000 image, all logarithmically transformed

MULTIPLE EGRESSION	Regression Summary for Dependent Variable: HCS R^2= .74 Adjusted R^2= .66 F(10,31)=9.2106 p<.00000 Std.Error of estimate: .07234					
N=42	BETA	St. Err. of BETA	B	St. Err. of B	t(31)	p-level
Intercpt			12.6961	7.425271	1.70985	.097287
MNDVMAX	-1.3625	.229504	-12.6556	2.131719	-5.93680	.000001
TM6CV	1.1814	.268283	1.1890	.270012	4.40360	.000118
GREENSD	-.2788	.178131	-.2953	.188708	-1.56493	.127753
TM4MEAN	-7.2831	1.589566	-30.5028	6.657366	-4.58180	.000071
NDVIMEAN	-5.0818	1.072230	-21.6490	4.567853	-4.73943	.000045
GREENMEA	5.8826	1.303959	22.1195	4.903056	4.51136	.000087
NDVIMAX	.8918	.216480	3.7976	.921800	4.11971	.000262
TM2VAR	14.4510	3.724348	6.8454	1.764219	3.8805	.000509
TM2CV	-11.2493	3.107915	-12.3201	3.403745	-3.61956	.001038
BRIGHTSD	-1.5285	. 543161	-1.2155	.431926	-2.81414	.008420

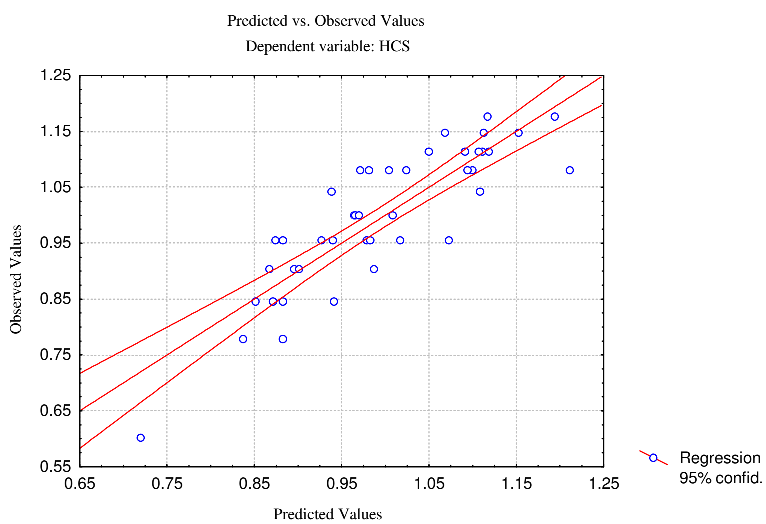

Figure 3. Plot of the regression analysis between the original Habitat Complexity Scores and the independent variables, all logarithmically transformed

The confirmed relationship was utilised to classify the image at the pixel scale using remote sensing data. The best subset of the independent variables was used as a general guide in defining the bands suitable for the classification. Neural network training and classification was conducted using the Silvics Ver. 1.1 software. A feed-forward MLP was used for the training. The files generated from the training were applied to the whole set of bundled bands in the image to classify the pixels into four categories of vegetation conditions. Using the test set of pixels, the classification accuracy was assessed and the output showed to have a high degree of accuracy (Table 2). The classified image is shown in Figure 4.

Table 2. Accuracy assessment for the classified image shown in Figure 7.6

A. Individual category accuracies (%)				
ID	Producer	User	Overall	Kappa Index
1	89.47	94.44		
2	93.60	92.85		
3	100	96.89	95.78	94.30
4	97.60	98.38		

B. Error Matrix					
Reference					
		1	2	3	4
Classified	1	68	3	0	1
	2	7	117	0	2
	3	1	3	125	0
	4	0	2	0	122

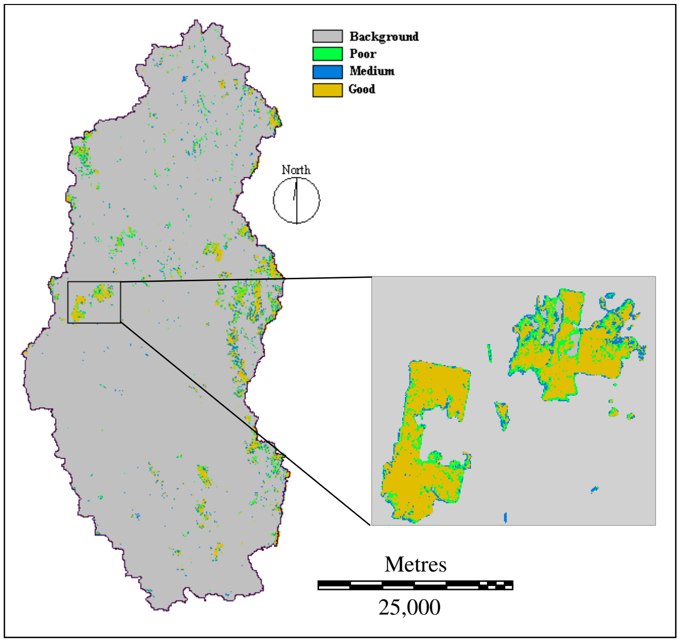

Figure 4. The result of classification using three classes of low, medium and high structural complexity conditions and the background areas

Filters were created for each condition of vegetation structure, and used for extracting the proportion of pixels in each of these conditions for each patch. Fragstats software (Ver. 3.3) was used to quantify various metrics for the remnant vegetation patches. The general linear model with response surface design was used for the multivariate regression analysis. The *Medium* and *High* dependent variables were used against the 9 independent variables: *Area, Perim, Para, Shape, Gyrate, Contig, Enn, Elevave*, and *Riverave.* The significance of the full model was very high (Table 3).

Table 3. Result of the multivariate regression analysis on the two selected dependent variables

Statistica Visual GLM Test of SS Whole Model vs. SS Residual				Response Surface Regression Design	
Dependent Variable	**Multiple R**	**Multiple R^2**	**Adjusted R^2**	**SS Model**	**Df Model**
Medium	0.95*	0.91*	0.91*	4477513	54*
High	0.96*	0.92*	0.92*	7911567	54*
Dependent Variable	**SS Residual**	**Df Residual**	**MS Residual**	**F**	**P**
Medium	423606*	1346*	341.71*	263.46*	0.00*
High	636330*	1346*	742.75*	309.60*	0.00*

For better predictions of the dependent variables, neural network was used which offered the possibility of including nonlinear relationships and describing them by example and iteration.

Evaluation of the plots of observed against predicted dependent variables in the two categories of medium and high structural complexity vegetation demonstrated that the neural networks have modelled the relationships between the independent and dependent variables well (Fig. 5)

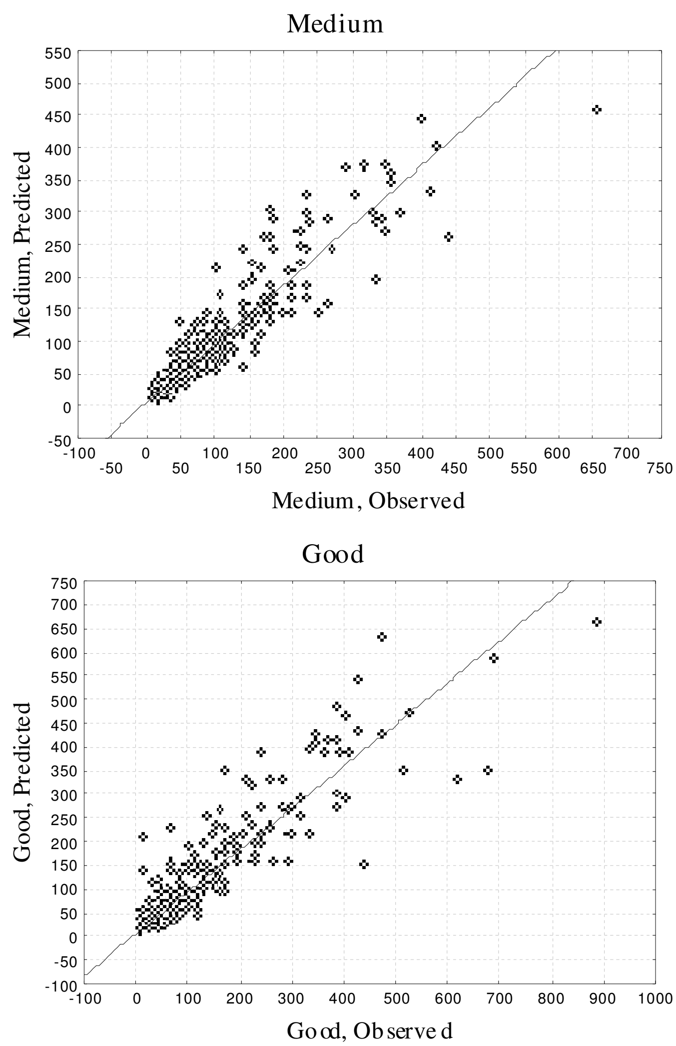

Figure 5. Plots of observed against predicted values of medium and high structural complexity conditions

4. Conclusion

Vegetation structure is an important indicator of vegetation condition or health. The HCS provides information on the structural complexity of vegetation patches. It is possible to use airborne or space-borne remotely sensed imagery to establish relationships between the scores of habitat structure and the image attributes. Thus, the information from sampled areas can be extrapolated to the catchment.

External patch attributes such as shape and size were extracted and their relationships with the three categories of vegetation condition explored. The multivariate regression analysis showed the possibility of modelling the relationships between vegetation condition categories and the independent variables. The neural network analysis of two categories of vegetation condition and the same independent variables with the MLP type was also implemented to compare the results with that of the multivariate regression. This was successful, with the neural network producing smaller residuals.

5. Acknowledgement

I wish to acknowledge the help and support provided by the authorities of the Gorgan University of Agriculture and Natural Resources Sciences for conducting this researcg as part of my Ph.D. thesis. Suggestions made by anonymus reviewers were very much helpful.

6. References

Freudenberger, D., 2001. *Bush for the Birds: Biodiversity Enhancement Guidelines for the Saltshaker Project, Boorowa, NSW,* CSIRO Sustainable Ecosystems. from:http://www.cse.csiro.au/research/Program2/Resources/Saltshaker.pdf (Accessed August 2001)

Mahiny, A. S. 2004. A Modelling Approach to Cumulative Effects Assessment for Rehabilitation of Remnant Vegetation. Ph.D. Thesis. SRES, ANU, Australia

McCormick, N., 1999. *Silvics, version 1.1*, Space Applications Institute, Ispra, Italy, Ispra. Available from:http://eurolandscape.jrc.it/forest/silvics/

McGarigal, K., and Marks, B. J., 1995. *FRAGSTATS: Spatial pattern analysis program for quantifying landscape structure,* USDA Forest Service. Available from:http://www.srs.fs.usda.gov/pubs/viewpub.jsp?index=3064 (Accessed 11 January 2001)

Newsome, A. E., and Catling, P. C., 1979. Habitat preferences of mammals inhabiting heathlands of warm temperate coastal, montane and alpine regions of southeastern Australia, in *Ecosystems of the World. Vol. 9A. Heathlands and Related Shrublands of the World*, ed Specht, R. L., Elsevier Scientific Publishing Co., Amsterdam.