

THE ROLE OF REMOTELY SENSED IMAGE TEXTURE IN ESTIMATING FOREST STAND STRUCTURAL COMPLEXITY

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ABSTRACT

Information on the structural complexity of forest stands is required to inform conservation priorities that guide the sustainable management of private native vegetation for multiple objectives of landowners. Whilst research into methods for the operational mapping of vegetation structure is expanding, the research is largely exploratory, and no methods have yet seen widespread acceptance. This research compares spectral (First principal component, Normalised Difference Vegetation Index, Enhanced Vegetation Index, Infrared Vegetation Index) and spatial transformations (Variance, Morans' I, and G*) of Landsat remotely-sensed imagery in combination with environmental attributes (Topographic derivatives and Soil Fertility) for estimating within-stand variations in forest structural complexity using linear regression analysis. Dry sclerophyll forests on the Southern Tablelands of New South Wales, Australia were used as a case study. Predictions were obtained for all structural attributes with the exception of Vegetation Cover 0-0.5m, and Overstorey regeneration. Errors of up to 31 percent of the field measured range of attributes accompanied predictions. Environmental attributes were more commonly selected as explanatory variables than derivatives of Landsat imagery, with NDVI and spatial autocorrelation measures (Moran's I and G*) the most commonly selected derivatives. Despite the moderate accuracy of predictions, the estimates of forest stand structural complexity are a useful information source for natural resource managers who require information on the relative structural complexity of native vegetation stands within the landscape. The utility of finer spatial resolution imagery is a key research priority since the moderate resolution of Landsat imagery limited the sensitivity of its derivatives in the current study.

1. INTRODUCTION

Well-managed native forests conserve biodiversity and maintain soil and water resources, whilst improving agricultural productivity and offering supplementary income for farmers from timber products (Parsons, 1999). The establishment of a "comprehensive, adequate and representative forest reserve system" is the key means identified for achieving long-term ecologically sustainable management of Australian forests regardless of land tenures (Commonwealth of Australia 1992). Due to poor representation in public reserves, the conservation of native vegetation is reliant on sympathetic management of stands occurring on private lands (NSW NPWS, 2003). Within Australia, an extensive legal and policy framework controls practices that could adversely affect the values of native vegetation. The complexity of current legislation and regulations creates uncertainty over the legality of management activities thus acting as disincentives to the management required to conserve native vegetation, (Dames and Moore, 1999; Parsons, 1999). Information on the type, quantity and condition of native forests on private tenure across Australia is limited and inconsistent, yet is required to inform conservation policy and prioritise management options for native vegetation (Dames and Moore, 1999; Parsons, 1999).

Traditional methods for estimating forest attributes (field surveys and air photo interpretation) remain the most accurate and comprehensive, but are costly where repeated measurements and/or measurement across large extents are required, and are limited where vegetation occurs on lands with restricted access (Musick and Grover, 1991). Digital analysis of, typically satellite, remotely sensed imagery offers a practical alternative for inventory and monitoring based on its compromise between detail and coverage. The exploration of

methods suitable for the operational monitoring of indices of forest structural complexity based on remotely sensed imagery is receiving increasing research attention, yet most research remains exploratory (Zerger *et al.*, 2006). Limitations of alternative approaches previously utilised nationally and internationally for estimating forest parameters from passive satellite imagery include, but are not limited to:

- An inability to estimate understorey attributes due to the omission of environmental variables (Geometric Optical/Sub-pixel modelling) (Lees and Ritman, 1991);
- Incorrect assumptions regarding the spatial distribution of trees and homogeneity of scene component reflectance (Geometric optical modelling) (Woodcock *et al.*, 1997);
- Immense field data requirements (decision trees) (Lees and Ritman, 1991);
- Limited output data types (decision trees, neural networks) (Lees and Ritman, 1991); and/or
- An inability to differentiate variations in biophysical parameters with similar spectral response (maximum likelihood classifiers) (Miller, 2005).

Predictive models based on empirical relationships between field inventory, abiotic environmental variables, remotely sensed imagery derived using regression analysis may provide an alternative method to measure and predict vegetation attributes over large areas and on lands with restricted access (Franklin *et al.*, 2000).

The objective of this research was to compare alternate spectral and spatial transformations of remotely sensed imagery, in addition to environmental variables for estimating a stand-level structural complexity index and its constituent attributes.

2. METHODS

2.1 Study Area

The Southern Tablelands of New South Wales is located largely in the South-Eastern Highlands Bioregion southeastern Australia (148° 35' 28" to 149° 45' 6" E and 35° 38' 46" to 34° 17' 8" S). The bioregion has a temperate climate with warm summers and no dry season. Mean annual rainfall ranges from 460 to 1883mm, and temperature from 6-16°C (NSW NPWS, 2003). Topography of Tablelands comprises the broken ranges and plateaus of the Great Dividing Range. Elevation within the Bioregion ranges from 500 to 1100m increasing in the southwest corner with the Australian Alps and in the east with the Great Escarpment (NSW NPWS, 2003). Palaeozoic granites, metamorphic sedimentary rocks and tertiary basalts are the main substrates occurring within the Murrumbidgee subregion of the Bioregion.

Dry sclerophyll forests have been extensively cleared or modified in the past. Dry sclerophyll forests now occur predominately on private or leasehold land, as disturbed regrowth and remnant patches on less fertile and steep terrain deemed unsuitable for agriculture. Remnant forest stands typically contain three discontinuous strata: an overstorey tree stratum dominated by eucalypts, an understorey sclerophyll shrub stratum, and a low herbaceous stratum (ACT, 2003).

The target community and study location were driven by a related project developing a decision support system to assist landowners to categorise and manage native vegetation, particular dry sclerophyll forests and woodland, on their properties for multiple values. Through the toolbox interface, spatially explicit estimates of the McElhinny Index (McElhinny, 2005) and structural attributes will be made available to landowners to extract approximations of the structural complexity of dry sclerophyll forest stands occurring on their land. The spatial predictions can be used by landowners to monitor the structural complexity of, and assess management alternatives for, forest stands, facilitating access to alternative policy instruments as incentives for conservation works.

2.2 Predictive Vegetation Modelling

Linear regression analysis was used to explore the estimation of a structural complexity index, as a function of textural and spectral derivatives of Landsat imagery and environmental attributes.

Response Variables: The primary intention of the research was the estimation of a structural complexity index for forest stands. McElhinny (2005) developed an index for determining the conservation value, based on the structural complexity, of open eucalypt forests and woodlands on the NSW Southern Tablelands. The McElhinny Index ranges from 1 to 100, the later indicating stands with high structural complexity, such as that likely to occur in an undisturbed remnant, the former indicating a stand with simplified structure, such as that in a disturbed regrowth stand where the forest profile has simplified (McElhinny, 2005).

The Index is calculated from thirteen core structural attributes including: Number of perennial species (sp./400m² plot); Lifeform richness (lifeforms/400m² plot); Basal area of live trees (m²/ha); Quadratic mean diameter at breast height (dbh) of live trees (cm); Vegetation cover 0-0.5m height (%); Vegetation cover 0.5-6.0m height (%); Overstorey regeneration (stems with

dbh <5cm) (stems/ha); Hollow bearing trees (stems/ha); Live trees with dbh>40cm (stems/ha); Number of dead trees (stems/ha); Length of fallen logs (>10cm diameter) (m/ha); Length of large (>30cm diameter) fallen logs (m/ha); and Litter dry weight (t/ha). Field samples for the thirteen core forest structural attributes were collected in a separate study (McElhinny, 2005), using a stratified sampling regime. Between winter 2002 to 2003, a representative set of 32 sites was established by locating two replicates within each of 24 stratum determined by: two vegetation communities (Broadleaved Peppermint-Brittle Gum (*Eucalyptus. dives-E. mannifera*) and Scribbly Gum-Red Stringybark (*E. rossii-E. macrorhyncha*)); two catchments (Murrumbidgee and Lachlan) and two levels of rainfall (600-700mm and 700-800mm) and two levels of vegetation condition (relatively undisturbed and disturbed). At each site, typically three, but up to six, plots 50 by 20 meters were established, providing estimates of stand level structural attributes for 100 plots.

The varying combination of surrogates and resulting indices available for estimating stand structural complexity for conservation assessment is broad (for example McElhinny, 2005; Gibbons *et. al.*, 2004; Parks, Newell and Cheal, 2003; Oliver, 2002). To accommodate potential changes in the formulation of an index, or the index preferred by natural resource agencies, the scope of the research was widened to allow the exploration of the estimation of the set of stand attributes used to calculate the index, in addition to the estimation of the index.

The low number of samples at the site level (32 Sites) would have constrained analysis, particular the availability of samples to withhold for validation. A comparison of the variance in attribute values between plots at a site to the variance between plots across all sites indicated that the variance between plots at a site was not significantly smaller. Thus, the plots were determined not to be clustered and could be treated as independent samples.

Explanatory Variables: Forest stand structural complexity is an expression of the combined effect of deterministic and stochastic factors that influenced a stand during its development (Zerger, *et. al.*, 2006; Miller, 2005).

Variables accounting for deterministic factors: Abiotic GIS variables have been found to account for deterministic factors in predictive vegetation modelling (Austin, 2002; Guisan and Zimmermann, 2000). Environmental variables assist in the prediction of understorey attributes by models that otherwise utilise the spectral response in remotely sensed imagery that is hindered by the overstorey and the shadow it projects (Lees and Ritman, 1991).

Vegetation within the bioregion is known to vary in relation to changes in altitude, temperature and rainfall (NSW NPWS, 2003). Height, slope and aspect were extracted from a 25m digital elevation map. The cosine and sine of aspect were calculated to transform the circular measure of aspect linear variables depicting degree of 'north' and 'east', respectively.

The PCTL, an algorithm developed by Gallant and Wilson (2000) was used to calculate topographic position. The output from the algorithm ranges from 0 to 1. Values approaching 0 indicate that position is low in the landscape, such as in a valley, whilst values approaching 1 indicate that position is high in the landscape, such as on an upper slope or hilltop.

The plant productivity index (Kesteven, Landsberg, and URS Australia, 2004) is a 250m-resolution raster layer where each grid cell value is a relative index of plant productivity. The index is a measure of the amount of photosynthetically active radiation absorbed by plant canopies (APAR), modified by factors to account for soil fertility, atmospheric vapour pressure deficits, soil water content and temperature. (Kesteven, Landsberg and URS Australia, 2004).

Walker *et. al.* (2001) have found that substrate fertility can influence the type of successional process vegetation is subject to, and return its structural complexity. A layer representing substrate fertility was produced by combining a geology coverage grouped by origin (volcanic or sedimentary) with a topographic layer grouped by relative elevation (valley or ridge). Within the layer, substrates on which progressive succession would occur (valleys below ridges of volcanic origin) and those substrates on which regressive succession would occur (weathered volcanic ridges, those of sedimentary origin regardless of topographic position) are separated.

Variables accounting for stochastic factors: Variables derived from remotely sensed imagery have been found to account for deterministic and stochastic factors in predictive vegetation modelling (Miller, 2005). Within Australia, the Landsat 7 sensor provided the optimal compromise between spatial resolution and extent coverage with a relatively regular and short repeat capture cycle at a cost that allow repeated acquisition for operational monitoring (Wallace and Campbell, 1998). The relationship between Landsat spectral bands to Southern Tablelands dry sclerophyll forests has not been studied. Instead, research into the characterisation of wet sclerophyll forests in adjacent coastal areas (Lees and Ritman, 1991) utilising Landsat bands 2, 4, and 7 provided guidance on appropriate individual bands selection.

Spectral transformations reduce the dimensionality of the regression analysis by condensing the information content of multiple spectral bands into a reduced number of variables. Four spectral transformations were investigated. The Normalised Difference Vegetation Index (NDVI), is extensively used vegetation index in vegetation modelling studies (Asner *et. al.*2003) and is defined as

$$NDVI = \frac{(\rho_{NIR} - \rho_{red})}{(\rho_{NIR} + \rho_{red})}$$

(1)

Where ρ is reflectance in the near-infrared and red wavelengths of the electromagnetic spectrum.

The enhanced vegetation index, developed to address the susceptibility of the NDVI to background influences common in open-canopied vegetation such as dry sclerophyll forests (Asner *et. al.*2003), is defined as:

$$EVI = G \frac{\rho_{NIR} - \rho_{red}}{\rho_{NIR} + C_1 \times \rho_{red} - C_2 \times \rho_{blue} + L}$$

(2)

Where the coefficient L is approximated by 1, C_1 by 6, C_2 by 7.5, and G by 2.5.

The IFRI, found to detect variations in plant biomass better than the NDVI (Treitz and Howarth, 2003), is defined as:

$$IFRI = \frac{(\rho_{NIR} - \rho_{SWIR})}{(\rho_{NIR} + \rho_{SWIR})}$$

(3)

Where $SWIR$ is the reflectance in the short-wave infrared wavelengths of the electromagnetic spectrum.

The first principal component was also utilised, as a principal components analysis provides maximum preservation of the information from the original suite of Landsat bands, as compared to indices produced from only a few bands.

The spatial information content of remotely sensed imagery can assist in the differentiation of stands with different structures but common spectral response in remotely sensed imagery (Pearson, 2002). For examples, Nel, Wessman and Veblen (1994) used image texture to delineate regrowth from remnant vegetation, the latter having a higher gap size variance that is mirrored in the image texture. Texture measurements analyse the heterogeneity of raster images by characterising variations in reflectance between a focal pixel and its neighbouring pixels, indicating the degree to which any single pixel differs from its neighbouring pixels in terms of magnitude of difference and the direction of difference (Musick and Grover, 1991). Variance seeks to quantify the magnitude of difference between a pixel and its neighbourhood, regardless of the direction of the difference. It is defined as:

$$V = \frac{\sum (x_i - \bar{x})^2}{n-1}$$

(4)

Where x_i is the attribute value of i , \bar{x} is the mean and n is the number of samples

Local Indicators of Spatial Association (LISA) quantify the degree to which a phenomenon is clumped or dispersed in the local area (Anselin, 1995), such as that displayed by forest canopy texture. Moran's I and G^* are examples of LISA. Moran's I seeks to quantify the amount and direction by which a pixel differs from its neighbours, and is calculated as:

$$MI = (z_i / s^2) \sum_j w_{ij} z_j, j \neq i$$

(5)

Where z_i and z_j are deviations from the mean of i and j ; s^2 is the variance; and $w_{ij}(d)$ is the spatial weight matrix.

In addition to quantifying the magnitude and direction of difference between a pixel and its neighbourhood, like Moran's I, G^* seeks to also account for the intensity of spectral reflectance. G^* is defined as:

$$G^* = \frac{\sum_j w_{ij}(d) x_j - W_i \bar{x}(i)}{s(i) \sqrt{\frac{[(n-1)S_{ii}] - W_i^2}{n-2}}}$$

(6)

Where d is the lag distance considered; n is the number of samples; W_i is the sum of the weights; $S_{ii}=W_i$ for a binary weights case; and $x(i)$ is the mean of the entire sample. W_i , S_{ii} , $x(i)$, and $s(i)$ are calculated excluding i .

Each algorithm was applied using a moving windows with a radius of 3 or 5 pixels, or 75m 125m in Landsat 7 imagery to the spectral transformations.

2.3 Predictive Model Development

Values in each explanatory variable corresponding to the location of the field plots were extracted and compiled into a database for modelling. Within JMP IN 4.0.4 (SAS Institute Inc., 2001), stepwise least squares regression was used to establishing the empirical relationship between vegetation attributes and explanatory variables, and build models for predicting the McElhinny Index and the biophysical attributes used to calculate the index. Data for 59 randomly selected plots was utilised to train the regression models, whilst the remaining 41 plots were withheld from the analysis for later use in validating the model predictions. A significance criterion of 0.05 was placed on explanatory variable entry and exit during the stepwise regression analysis process. The regression analysis also assisted in identifying the biophysical attributes that could be predicted with sufficient confidence, and which explanatory variables were useful for accounting for variations in each forest stand attribute.

2.4 Model Validation

The models were subsequently inverted, by applying the empirical relationships to the continuous explanatory variables, using the Model Maker function in Imagine 8.6 to produce spatial predictions of the structural complexity index and each attribute over the study region. The root mean square error (RMSE) was calculated to assess the accuracy of the resulting spatial predictions against the independent validation set withheld from the field data. RMSE is the appropriate measure for determining the accuracy of predictions of continuous spatial attributes. An indication of the generality of the models can be obtained by comparing the RMSE for plots used to train the models to those used to validate the models.

3. RESULTS

The amount of variance in response variables that was explained by the models was low. The models accounted for only 15 per cent of the variation in the McElhinny Index, whilst up to 38 per cent of variation in some individual biophysical attributes were accounted for (Refer Table 1). The average error associated with estimates was reasonable for the McElhinny Index (+/- 13 per cent for test data), but was quite large for some biophysical attributes (+/- 31 per cent for Vegetation Cover 0.5m-6.0m) (Refer Table 2). No models with sufficient significance (<0.05) were obtained for Vegetation Cover 0-0.5m, and Overstorey regeneration.

Environmental variables dominated the explanatory variables, but were commonly accompanied by variables derived from remotely sensed imagery. Measures of remotely sensed image texture were less commonly utilised than had been anticipated. Where texture measures were utilised, Moran's I and G* were more commonly selected over the variance measure, and were most commonly calculated using a 5-pixel moving window.

Typically, RMSE values for validation plots were typically lower than for training plots. Exceptions included: Number of perennial species; Quadratic mean diameter at breast height of live trees; Vegetation cover 0.5-6.0m height; Number of dead trees; Length of large fallen logs (Refer Table 2).

Table 1: Environmental attributes were common selected over variables derived from remotely sensed imagery as explanatory variables in models providing the most accurate predictions of the McElhinny Index and dry sclerophyll forest biophysical attributes.

Response Variable	R ²	RMSE	Prob >F	Explanatory Variables
McElhinny Index	0.15	11.09	<0.01	NDVI M5
Basal Area	0.32	7.555	<0.01	PC1, Substrate , NIR, PI
DBH	0.18	5.57	0.03	Substrate, SWIR, IFRI G3, Green
Large Log Length	0.21	55.65	<0.01	Slope, NDVI M5
Litter Dry Weight	0.32	4.25	<0.01	SWIR, NDVI G5, North, NDVI
Log Length	0.38	331.71	<0.01	Slope, Green, Elevation
No. Dead Trees	0.12	70.84	0.03	East, Elevation
No. Hollow Trees	0.22	45.26	<0.01	PI, EVI V5
No. Large Trees	0.14	30.82	0.04	NDVI, SWIR, Substrate
No. Lifeforms	0.12	0.92	0.02	IFRI M5, Slope
No. Perennial Sp.	0.19	4.80	<0.01	PI, NDVI G5
Shrub Cover	0.11	2.86	0.01	North

Table 2: The similar errors associated with model estimates of the McElhinny Index and biophysical attributes for validation as compared to training plots, indicating the generality of the regression models.

Response Variable	Actual		% Field Range	
	Training	Validation	Training	Validation
McElhinny Index	10.71	10.57	13.39	13.21
Basal Area	8.04	7.22	16.10	14.46
DBH	5.62	7.33	14.55	18.99
Large Log Length	58.08	72.32	20.74	25.83
Litter Dry Weight	5.39	4.95	14.73	13.52
Log Length	336.20	327.58	20.25	19.73
No. Dead Trees	92.68	100.50	14.95	16.21
No. Hollow Trees	42.77	41.68	17.82	17.36
No. Large Trees	40.56	30.79	28.97	21.99
No. Lifeforms	1.00	0.91	10.03	9.12
No. Perennial Sp.	4.60	5.23	14.82	16.87
Shrub Cover	2.93	4.26	21.52	31.26

4. DISCUSSION

A comparison of the RMSE for plots used to train the models to those used to validate the models reveals the generality of the models. The similarity in RMSE values for test plots as compared to RMSE values for validation plots indicates the potential robustness and wider applicability of the predictive models to situations other than that in which the models were parameterized. This indicates that alternative modelling

methodologies and/or explanatory variables derived from the same base abiotic and remotely sensed data sets are unlikely to achieve superior model performance.

The uncommon selection of image texture measures may be linked to the spatial resolution of Landsat imagery relative to the size of tree canopies in the target vegetation community. The spatial resolution of the Landsat imagery may have reduced the utility of the measure of image texture to differentiate within-stand variations in structure that produce similar spectral reflectance. Woodcock and Strahler (1987) confirmed through exploration of image local variance that spectral separability is maximised when the resolution-cell size of imagery is less than half, and no more than three-quarters, the size of the target object. Landsat imagery is unlikely to meet this criterion for optimal spatial resolution. With the exception of stands where regrowth was significantly overstocked, and thus the forest cover homogeneous, the generalisations in moderate spectral and spatial resolution imagery suppress inter-pixel variations and thus texture (Wulder *et al.*, 1998). Imagery from finer spatial resolution sensors, particularly SPOT 5, should increasingly become a viable alternative if the cost of imagery for covering regional extents continues to decline, and the capacity of computers to store and process the larger data sets associated with finer spatial resolution imagery continue to increase. Regardless, if the methodology presented in this paper is to be utilised for operation monitoring alternative imagery will need to be sourced given the demise of the Landsat 7 sensor following the commencement of this research.

The common selection of abiotic environmental attributes as explanatory variables, particularly for models of structural attributes associated with the understorey, suggests that despite an open canopy, the overstorey is still interfering with the spectral reflectance of understorey vegetation reaching the remote sensors (Nagendra, 2001). This also reinforces the value of environmental attributes in explaining variations in attributes of the understorey whose spectral reflectance contributes little to the information in remotely sensed imagery due to interference by the overstorey.

The more common utilisation of environmental variables as predictor variables in the regression models does not diminish the value of variables derived from remotely sensed imagery as explanatory variables in predictive vegetation modelling. Zerber *et al.*, (2006) and Pressey *et al.* (2000) have already identified that environmental variables are unsuitable data on which to base a system for the operational monitoring of vegetation due to: a) the comparatively coarse resolution, inconsistent coverage and infrequent temporal updates of environmental variables and b) since environmental variables do not account for changes in vegetation attributes due to random factors, such as competition, human or natural disturbance, land use management and vegetation enhancement activities. Since future changes in vegetation structural complexity are likely to result from the latter factors as opposed to changes in environmental characteristics (Zerber *et al.*, 2006), data used as the basis of an operational monitoring system of vegetation structure must be capable of accounting for random factors. Miller (2005) found that, in contrast to abiotic environmental variables, variables derived from remotely sensed imagery, particularly measures of image texture, have the potential to account for random factors in predictive vegetation modelling.

Although the model fit was low, the spatial estimates of the McElhinny structural complexity index and forest stand attributes are still useful for management and monitoring.

Natural resource managers are more flexible in their information requirements than, for example forest scientists or forest managers. Forest scientists or managers require accurate and precise measurements of the attributes of a native vegetation stand to support research and estimate harvesting yields, respectively. In contrast, natural resource managers are more concerned with the relative value of attributes of a native vegetation stand and comparing and contrasting the attributes to other stands of native vegetation within the landscape that may differ in location, type or condition (Parkes, Newell, and Cheal, 2004).

5. CONCLUSIONS

This research has explored the use of spectral and spatial derivatives of remotely-sensed imagery, combined with environmental attributes, for estimating the structural complexity of open forest stands using linear regression analysis. Although the strength of the predictions are moderate, information on the structural complexity of stands provided by the estimates are still useful for natural resource managers who are interested in the relative structural complexity to others in the landscape. Nevertheless, the similarity of error in predictions of training and validation field samples suggest that stronger and more accurate predictions are unlikely to be achieved regardless of further research effort.

The research has also provided valuable insights into which structural attributes can be estimated with the methodology and the utility of alternate explanatory variables. The clarification that environmental variables provide in estimating understorey attributes and the role of variables derived from remotely-sensed imagery in accounting for variations in forest stand structure that is the consequence of random disturbance as opposed to environmental characteristics, findings consistent with others in the research literature. The results of this research, although preliminary, point to the utility of the normalised difference vegetation index and spatial autocorrelation (Moran's I and G*) variables derived from remotely-sensed imagery combined with environmental variables of site fertility in addition to topographic measures of elevation, slope, and aspect.

The demise of the Landsat sensor, combined with the identification that the coarse spatial resolution of Landsat imagery relative to the target vegetation may be limiting the accuracy of textural and spectral explanatory variables; suggests that a key future step in achieving an operational methodology for monitoring vegetation structural complexity, is the testing of finer spatial resolution imagery.

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REFERENCES

- ACT Government, 2003. *Draft ACT Lowland Woodland Conservation Strategy Action Plan No. 27*. Environment ACT, Canberra.
- Anselin, L., 1995. Local indicators of spatial association – LISA. *Geographical Analysis*, 27, pp. 93-115.
- Austin, M.P., 2002. Spatial prediction of species distribution: an interface between ecological theory and statistical modelling. *Ecological Modelling*, 157, pp. 101-118.
- Asner, G.P., Hicke, J.A., and Lobell, D.B. 2003. Per-pixel analysis of forest structure in Wulder, M.A., and Franklin, S.E., (eds), *Remote Sensing of Forest Environments: Concepts and Case Studies*, Chapter 8 Kulwer Academic Publishers, Massachusetts, USA, pp.209-254
- Commonwealth of Australia, 1992. *National Forest Policy Statement*. Commonwealth of Australia, Canberra.
- Dames and Moore, 1999. *Integrating Farm Forestry and Biodiversity*. Rural Industries Research and Development Corporation, Canberra.
- Franklin, S.E., Hall, R.J., Moskal, L.M., Maudie, A.J., Lavigne, M.B., 2000. Incorporating texture into classification of forest species composition from airborne multispectral images. *International Journal of Remote Sensing*, 21, pp. 61-79.
- Gallant, J.C., and Wilson, J.P., 2000. Primary Topographic Attributes in Wilson, J.P., and Gallant, J.C. (eds), *Terrain Analysis: Principles and Applications*, Chapter 4, John Wiley and Sons, New York, pp. 51-85.
- Gibbons, P., Ayers, D., Seddon, J., Doyle, S. and Briggs, S., 2004. *BioMetric Decision Support Tool, Version 1.4*. NSW Department of Environment and Conservation, Canberra, pp. 51.
- Guisan, A., and Zimmermann, N.E., 2000. Predictive habitat distribution models in ecology. *Ecological Modelling* 135, pp. 147-186.
- Kesteven, J., Landsberg, J., and URS Australia, 2004. *Developing a National Forest Productivity Model*. Australian Greenhouse Office, Canberra ACT, pp. 104.
- Lees, B.G., and Ritman, K., 1991. Decision-Tree and Rule-Induction Approach to Integration of Remotely Sensed and GIS Data in Mapping Vegetation in Disturbed or Hilly Environments. *Environmental Management*, 15, pp. 50-71.
- McElhinny, C., 2005. *Quantifying Stand Structural Complexity in Woodland and Dry Sclerophyll Forests, South-Eastern Australia*. Ph.D Thesis, School of Resources, Environment and Society, The Australian National University, Canberra.
- Miller J., 2005. Incorporating Spatial Dependence in Predictive Vegetation Models: Residual Interpolation Methods. *The Professional Geographer*, 57, pp. 169-184.
- Musick, H.B., and Grover, H.D., 1991. Image texture measures as indices of landscape pattern, in Turner, M.G., and Gardner, R.H. (eds.), *Quantitative Methods in Landscape Ecology*. Springer-Verlag, New York. pp. 77-103
- Nagendra, H., 2001. Using remote sensing to assess biodiversity. *International Journal of Remote Sensing*, 22(12), pp. 2377-2400.
- Nel, E.M., Wessman, C.A., and Veblen, T.T., 1994. Digital and Visual Analysis of Thematic Mapper Imagery for Differentiating Old Growth from Younger Spruce-Fir Stands. *Remote Sensing of Environment*, 48, pp. 291-301.
- New South Wales National Parks and Wildlife Service (NSW NPWS). 2003. The South Eastern Highlands Bioregion in *The bioregions of New South Wales: their biodiversity, conservation and history*, Chapter 16. NSW National Parks and Wildlife Service, Hurstville, NSW. pp. 203-210.
- Oliver, I., 2002. An expert panel approach to the assessment of vegetation condition within the context of biodiversity conservation. *Ecological Indicators*, 2, pp. 223-237.
- Parkes, D., Newell, G. and Cheal, D., 2003. Assessing the quality of native vegetation: The 'habitat hectares' approach. *Ecological Management and Restoration*, 4, pp. S29-S38.
- Parsons, M., 1999. *Native Forests on Farms*. Rural Industries Research and Development Corporation, Canberra, Australia.
- Pearson, D.M., 2002. The application of local measures of spatial autocorrelation for describing pattern in north Australian landscapes, *Journal of Environmental Management*, 64, pp. 85-95.
- Pressey R.L., Hager T.C., Ryan K.M., Schwarz J., Wall S., Ferrier S. and Creaser, P.M. 2000. Using abiotic data for conservation assessments over extensive regions: quantitative methods applied across New South Wales, Australia. *Biological Conservation*, 96, pp. 55-82.
- SAS Institute Inc., 2001. *JMPIN 4.0.4*. SAS Institute Inc. Cary, NC, USA.
- Treitz, P., and Howarth, P. 1996. *Remote Sensing for Forest Ecosystem Characterisation: a Review*. Great Lakes Forestry Centre, Ontario.
- Walker, J., Thompson, C.H., Reddell, P., and Rapport, D.J., 2001. The Importance of Landscape Age in Influencing Landscape Health. *Ecosystem Health*, 7(1), pp. 7-14.
- Woodcock, C.E., and Strahler, A.H., 1987. The Factor of Scale in Remote Sensing. *Remote Sensing of Environment*, 21, pp. 311-287.
- Woodcock, C.E., Collins, J.B., Jakabhazy, V.D., Li, X., Macomber, S.A., and Wu., 1997. Inversion of the Li-Strahler Canopy Reflectance Model for Mapping Forest Structure. *IEEE Transactions on Geoscience and Remote Sensing*, 35, pp. 405-414.
- Wulder, M.A., LeDrew, E.F., Franklin, S.E., and Lavigne, M.B., 1998. Aerial image texture information in the estimation of northern deciduous and mixed wood forest leaf area index (LAI). *Remote Sensing of the Environment*, 64, pp. 64-76.
- Zerger A., Gibbons, P., Jones, S., Doyle, S., Seddon, J., Briggs, S. & Freudenberger, D., 2006. Spatially modelling native vegetation condition, *Ecological Management and Restoration* 7 (in-press).