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MAPPING BIODIVERSITY AT THE LANDSCAPE LEVEL -TOWARDS A LANDSCAPE LOGIC

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ABSTRACT

Biodiversity assessments often use plot based assessments to measure key attributes or metrics. Our team at Landscape Logic have been working to determine the utility of remote sensing in producing landscape-level assessments of these variables.

This presentation gives an overview of this work and highlights projects underway to improve our quantification of landscape-level biodiversity. The first project explores landscape configuration and issues of data uncertainty. Remote sensing is widely used in ecology to measure and monitor patch size, shape and connectivity. However, choice of: satellite sensor, spatial and spectral resolution, classification technique and class description, can produce large differences in resultant predictions of extent and patchiness. Small and complex patches (relative to pixel size) are particularly sensitive to platform-sensor differences and often result in maps (and associated environmental management decisions) which are scale dependant. This has important implications particularly for long term land use change studies where there is often an implied change in sensor. Using a synthetic landscape we have modelled these phenomena and illustrate its implications using operational examples of woody vegetation and Carbon inventory mapping from the state of Victoria, Australia. Next, a landscape metric, termed patch resilience, which is able to encompass patch characteristics, including area, perimeter, edge complexity and internal perforation is presented. This tool has great utility in conservation priority mapping for example in distinguishing between systems that are large in terms of extent but highly fractured and other systems which are classified as rare or endangered because of their total area statistics but are in fact resilient because of their configuration. Finally some new LiDAR (airborne laser scanning) techniques for mapping the structural components of landscape level biodiversity are presented. Using full waveform LiDAR pulse range/distance information as well as intensity of reflection, half-pulse width, the number and sequence information a forest structure biodiversity scheme derived from LiDAR point clouds is proposed. A validation of the scheme is then presented using a network of field sites that recorded commonly used metrics of biodiversity.

INTRODUCTION

Vegetation condition assessment is an important part of landscape management. Vegetation attributes, used as surrogate measures of vegetation condition, typically have strong associations with a range of taxa or ecological functions relevant to policy and management objectives (Reinke and Jones, 2006). There are presently three broad approaches employed to assess vegetation condition: on-ground site assessment, spatial modelling and remote sensing (Gibbons et al., 2006). Remote sensing is a technology with great potential to deliver timely vegetation condition information at landscape and regional scales; offering standardised sampling units, synoptic data capture and regular repeat acquisition.

USING OPERATIONAL EARTH OBSERVING SATELLITES

Imagery from multi-spectral satellite remote sensing platforms is frequently used for vegetation assessment. Remote sensing based vegetation measures range from highly detailed fine scale assessments, to regional and global applications (Thomlinson et al. 1999, Defries et al. 2000, Huang et al. 2001, Armston et al. 2004, Johansen et al. 2007). Satellite remotely sensed data provide an efficient method to attribute large areas of vegetation in a timely manner (Coops and Culvenor 2000, Zawadzki et al. 2005). The spectral reflectance of an individual leaf will vary as a function of three parameters:

(i) leaf pigment (type and concentration);

(ii) leaf surface features; and

(iii) leaf cell(s) (arrangement, physiological structure and water content).

The relative contribution of each of these factors is wavelength dependent. Individual leaf signatures are characterised by low reflectance in the visible and middle infrared wavelengths (dominated by pigment and water dependant absorption features) and high reflectance in the near infrared (dominated by cell structural features). Key factors affecting image scale spectral reflectance characteristics include (a) leaf size and orientation, (b) the physical structure of the plant, (c) species distribution, (d) vegetation density, and (e) the influence of neighbouring land covers (Bannari et al. 1995, Armitage et al. 2000, Nagendra

2001). A common approach to vegetation assessments based on multi-spectral remotely sensed data is the use of vegetation indices (VI). Many different VIs have been developed to provide information on a range of vegetation characteristics such as vegetation cover, leaf density or leaf water content. The Normalized Difference Vegetation Index (NDVI) is widely used to derive estimates of vegetation cover (Bannari et al. 1995, Defries et al. 2000). Other routinely used vegetation indices include the Soil Adjusted Vegetation Index (SAVI) and the Enhanced Vegetation Index (EVI) (Huete 1988, Bannari et al. 1995, Huete et al. 2002).

GROUND DATA

Vegetation assessments based on remotely sensed data require some form of ground data with which to establish relationships between multi-spectral response (as recorded at the satellite) and vegetation characteristics/attributes (as recorded during field survey). The collection of ground or reference data for remote sensing studies is a well-established but often under-resourced process. There are, however, numerous issues that require consideration to produce a well designed and flexible field survey that will ensure the collection of appropriate ground data for a given study.

Ground data quality issues are an important consideration in any study involving geographic information, including remotely sensed data. Ground data, and specifically spatial data, quality elements identified within existing geographic data guidelines include what are termed the ‘Big 5’ issues: (1) positional accuracy, (2) attribute accuracy, (3) logical consistency, (4) data completeness, and (5) data lineage (Hunter et al. 2003, Reinke and Jones 2006). While some issues are generic to all spatial data, such as the ‘Big 5’, other issues such as spatial scale, temporal resolution, and site homogeneity are particularly relevant to remote sensing applications (Figure 1).

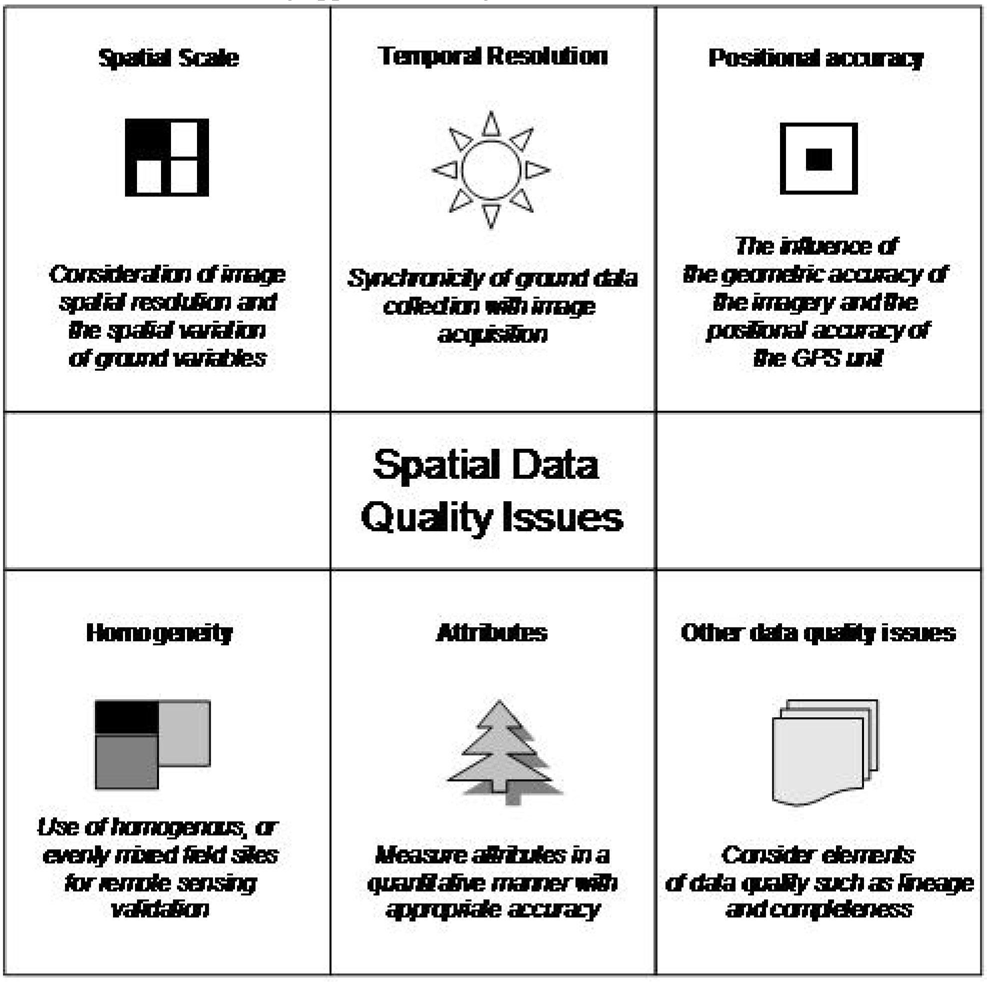

Fig. 1. A summary of ground data quality issues, based on those identified in Reinke and Jones (2006)

This study calculated a number of different types of remotely sensed variables including mean spectral reflectance values, VIs, and image texture measures. Mean spectral reflectance values and VIs were strongly correlated with vegetation condition attributes. Of the suite of VIs calculated three ratio based indices were found to have the highest correlation with stem density and the diameter at breast height

(DBH) of plants greater than 5 cm (adjusted r2 values ranging from 0.60 to 0.70, $p < 0.05$). However, adjusted r2 values for overall site vegetation composite condition, were 0.47 (SPOT 5 data) and 0.51 (IKONOS data). This lower correlation was a consequence of vegetation attributes that were not strongly correlated (r2 <0.40) with any remotely sensed variables. These attributes included: (a) the proportion of grass species, bare ground and exposed rock, (b) the presence of an understorey and exotic species cover, (c) the proportion of organic litter cover, (d) the presence of hollow-bearing trees, and (e) other structural attributes. A comprehensive presentation of these results is given in Sheffield et al., (2009).

CONFIGURATION AND PIXEL SIZE

Thematic maps are frequently used to characterise (a) configuration and composition of a landscape, and (b) its relationship to landscape processes or landscape change (for example, Nagendra et al., 2006). Small/linear vegetation patches are a common feature of fragmented landscape being found as roadside vegetation, hedgerows, scattered trees, riparian areas and greenways. Despite their small size, these landscape features have an ecological value significantly greater than their areal extent. The accurate mapping of such small/linear patches is essential as (a) their presence/absence substantially modifies landscape configuration, connectivity and fragmentation, and (b) the physical attributes of these features, such as width and length, influences their ecological role. However, as a consequence of their relatively small size and narrow width, these features may be under-represented in remotely sensed and traditional field based mapping. Understanding the process of mapping these ecologically significant patches is critical.

Fundamental to remote sensing devices is the sensing array, that is, the grid of sensors at which multi-spectral measurements are made and from which an image is constructed. This sensing array plays a fundamental role in the detection of small/linear patches. The accurate mapping (delineation and classification) of a feature, from remotely sensed imagery, is a function of the: (a) size and shape of the feature; (b) position of the feature with respect to the sensors array; (c) multi-spectral characteristics of the feature relative to surrounding objects; (d) properties of the remote sensing image (image registration, view angle, radiometric calibration, image acquisition time); and (e) characteristics of the sensor, for example, the spatial, spectral and radiometric resolution (Cracknell, 1998; Townshend et al., 1991).

Since a features' position is random relative to the position of the imaging sensors grid small features may be lost when they only make up a portion of a cell or are found at the intersection of several cells (Cunningham, 2006). The grid position effect can be a significant source of mapping error for individual map features.

This case study utilised simulated imagery in order to test the effect of grid position and feature size/shape in isolation. Thus, the accuracy with which a feature was mapped was a consequence of grid position alone. This allowed: 1) determination of the effect of grid position on classification of small and linear landscape features, 2) calculation of the appropriate spatial resolution required to extract features of varying elongation and area and 3) examination of the effect of differing spectral contributions of the object and its surrounding on classification.

Using a statistical simulation model the effect of patch size and shape, classification threshold and grid location on the classification of small and linear features using remote sensing data was tested. A computer model considered rectangles of a variety of lengths, widths and total areas with different classification thresholds and orientations to simulate the mapping of small and linear patches. We found that small and/or elongated patches have a reduced probability of extraction, a reduced mapping accuracy and an increased variability in accuracy due to the effects of grid position. To extract those patches accurately, the grid spatial resolution should be many times finer. Full details of the model and simulations are given in Lechner et al., 2009.

USING LiDAR TO DETERMINE FOREST STRUCTURE

Forest structure, the architectural arrangement of plant material, has received less attention than species composition in terms of description and/or classification, yet diagnostically structure is considered just as important in characterizing a forest as its composition (Florence, 1996; Spies, 1998; Stone and Porter, 1998). This analogy was used by Noss (1990) who suggested that vegetation condition, when assessed in the context of biodiversity, should be considered in terms of: structure, composition, and function. Spies (1998) described the essential attributes of forest structure as structural type, size, shape, and spatial distribution (vertical and horizontal) of components and examined their roles and importance to the functioning and diversity of ecosystems. For example, foliage layering or vertical foliage distribution is a component of forest structure that plays important roles in the absorption of solar radiation, the microclimate of the forest and in providing wildlife habitat. Many authors have noted the association between biodiversity and measures of the variety and/or complexity of arrangement of structural components within an ecosystem (Mac Nally et al., 2001; Sullivan et al., 2001). Most forest stand structure descriptors are based on measures easily obtainable from the ground level (e.g. diameter at breast height (DBH), stem density or ground assessed canopy cover). Currently, appraisal or scoring methods for structural complexity require a laborious process that involves site visits and many logistically expensive point based measurements. An automated, more consistent, semi-automated method is required.

Airborne laser scanning (LiDAR; Light Detection and Ranging) has been recognised as a powerful tool for forest structure characterization. Numerous papers have documented the utility of LiDAR for the estimation of forest attributes in forestry (e.g. Lefsky et al., 1999; Means et al., 1999; Nilsson, 1996). Næsset (1997) showed the potential of LiDAR to estimate fractional cover. Similar methods utilising the point density of LiDAR returns to estimate fractional cover were presented in other studies (Coops et al., 2007; Hopkinson and Chasmer, 2007, 2009; Morsdorf et al., 2006; Solberg et al., 2006) and showed promising results. While the majority of previous LiDAR research focuses on its application for forestry, the purpose of this case study is to report on a protocol for characterizing the ecological structure of a (dry Eucalypt) forest landscape using LiDAR data alone for the assessment of vegetation condition. LiDAR data was acquired over the study area using a RIEGL LMS-Q560 sensor. The full forest characterization scheme is presented in Miura and Jones (2010).

The forest structural characterisation scheme is derived from both the range, i.e. the distance information from the LiDAR system (how long it takes for a pulse of energy to travel from the sensor to the object and return to the sensor) and the nature of the return type. Distance information is utilised to describe the height of the reflecting surface (i.e. ground, low, medium and high). Additionally, four return types are distinguished:

• Type 1 are singular returns, that is only one return was recorded from each emitted pulse of energy.

• Type 2 are first of many returns, that is, part of the pulse of incident energy has interacted with a plant facet and been reflected back to the sensor but much of the energy has continued through the tree interacting with other structural elements along its path.

• Type 3 are intermediate returns, which are the subsequent interactions of the pulse described in Type 2.

• Type 4 are the last of many returns, that is the last returned pulse back to the sensor from an incident pulse.

From these the Forest Classification Scheme is derived (table 1) and validated against field derived equivalents of these metrics. The implications of these data correlations are discussed further in Miura and Jones (2010).

Category	Description	LiDAR return ratio
1 *OG*	opening above the ground	*Ground* Type 1
2 *OL*	opening above low vegetation	*Low veg* Types 1 and 2
3 *VL*	presence of understorey vegetation	*Low veg* total (Types 1, 2, 3 and 4)
4 *CC*	canopy cover	*Medium veg* Types 1 and 2 and *High veg* Types 1 and 2
5 *OM*	opening above medium vegetation	*Medium veg* Types 1 and 2
6 *VM*	presence of mid-storey vegetation	*Medium veg* total (Types 1, 2, 3 and 4)
7 *VH*	presence of high trees	*High veg* total (Types 1, 2, 3 and 4)
8 *DH*	vertically dense canopy of high trees	*High veg* Types 3 and 4

Table 1 LiDAR derived Forest Classification Scheme

CONCLUSION

New developments in remote sensing technology and classification methods will result in increased attribution accuracy and the ability to measure a greater number of vegetation condition metrics. Research remains ongoing on methods to take advantage of new high spatial resolution, hyperspectral and LiDAR datasets for vegetation condition assessment. These new technologies will play an increasingly important role in the future. Remote sensing systems have the ability to provide total coverage of vegetation condition at the site, landscape, regional, and perhaps one day, global scales. Operational remote sensing is indispensable for natural resource management allowing for the detection of change in vegetation condition as result of human disturbances ranging from habitat fragmentation, introduced species to climate change. While remote sensing shows great promise it is important that significant effort is not only devoted to developing new technologies and attribution methods but also to understanding the uncertainties that result from using these technologies and methods.

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