OBJECT-BASED IMAGE ANALYSIS FOR FOREST SPECIES CLASSIFICATION USING WORLDVIEW-2 SATELLITE IMAGERY AND AIRBORNE LIDAR DATA

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ABSTRACT It has been shown that new remote sensing technologies have the potential to complement deficiencies of conventional methods such as aerial photograph interpretation and field sampling as well as improve the accuracy, reduce costs, and increase the number of applications within various forest environments. Newly available high resolution spatial data such as small footprint, multiple-return, discrete airborne LiDAR data and WorldView-2 satellite imagery offer excellent opportunities to develop new and efficient ways of solving conventional problems in forestry. However, the development of a comprehensive procedure for deployment of these new remote sensing data to create forest mapping products that are comparable and/or superior in accuracy to conventional photo-interpreted maps poses big challenges. Proper use of high spatial resolution data with object-based image analysis approach and nonparametric classification method such as decision trees may offer an alternative to aerial photograph interpretation in support of forest classification and mapping. This study presented ways of processing airborne LiDAR data and WorldView-2 satellite imagery for object-based forest species classification using decision trees in the Strzelecki Ranges, one of the four major Victorian areas of cool temperate rainforest in Australia. The results showed the contribution of four new WorldView-2 image bands to forest classifications, and demonstrated that the integration of airborne LiDAR and eight WorldView-2 bands significantly improved the classification accuracy.

KEY WORDS: Object-based image analysis, WorldView-2, LiDAR, decision tree, forest classification.

1. INTRODUCTION

Remotely sensed data have been widely explored for forest applications. Generally, passive remote sensing techniques are only able to provide information on horizontal (two-dimensional) forest extent (Riaño *et al.*, 2003). The vertical forest structure (or the interior of the canopy and understorey vegetation) cannot be mapped using these passive remote sensing techniques (Morsdorf *et al.*, 2010; Scanlan *et al.*, 2010). Therefore, passive remote sensing techniques are limited in their ability to capture forest structural complexity, particularly in uneven-aged, mixed species forests with multiple canopy layers (Lovell *et al.*, 2003). Fortunately, it has been shown that active remote sensing techniques via airborne LiDAR offer the capability for detailed description of the forest structure in three-dimensions (Evans *et al.*, 2006; Zhang *et al.*, 2011).

The LiDAR data have been shown to measure forest structure characteristics accurately in a variety of forest types. However, the LiDAR data may not discern tree species very well, especially for those with similar canopy structure and composition. There is a known complementary relationship between high spatial resolution images and LiDAR data. Images describe the spectral signatures of classes while LiDAR data provide details about the vertical structure. The synergy of multispectral and LiDAR data takes advantage of the information provided by LiDAR data on the vertical structure of the forest and the capability of multispectral data to capture different vegetation types based on their spectral response (García *et al.*, 2011).

The WorldView-2 is the first commercial satellite to provide high-resolution, 8 multispectral bands with 1.8 m spatial resolution (at nadir) (4 bands similar to those provided by QuickBird, and four new bands: coastal blue, yellow, red-edge and near-IR2) and 0.46 m spatial resolution (at nadir) panchromatic imagery. Each band is narrowly focused on a particular range of the electromagnetic spectrum that is sensitive to a particular feature on the ground. WorldView-2 is also the first commercial satellite to provide a red-edge band as part of its 8-band multispectral capabilities. Access to red-edge data is enabling novel remote sensing applications in forest classification that depends on the detection of subtle changes in plant communities (DigitalGlobe, 2009). The WorldView-2 satellite imagery is so new that few studies have been carried out to test its effectiveness in forest applications (Novichikhin, 2011; Ozdemir and Karnieli, 2011).

Increased spatial resolution provides opportunities for detecting small features and for mapping objects of interest in great detail (Blaschke *et al.*, 2010). However, high spatial resolution imagery poses challenges in image classification. In high spatial resolution images, individual pixels are typically smaller than the geographic objects of interest. Although this provides more details for visual interpretation, higher spectral variance within the classes of interest are also created (Chen *et al.*, 2011). Thus, traditional pixel based classification based solely on spectral data may not work successfully and can result in salt-and-pepper noise in the classification results (Benz *et al.*, 2004). To minimize the effect of high spectral variance, object based image analysis (OBIA) was introduced to remote sensing communities (Hay *et al.*, 1995; Baatz and Schäpe, 2000; Benz *et al.*, 2004).

The suitability of integration of airborne LiDAR data WorldView-2 satellite imagery for object-based forest classification, particularly in the Australian cool temperate rainforest environment has hitherto remained untested. This study presented ways of processing airborne LiDAR data and WorldView-2 satellite imagery for object-based forest species classification using decision trees in the Strzelecki Ranges, one of the four major Victorian areas of cool temperate rainforest in Australia.

2. MATERIALS AND METHODS

2.1 Study Area

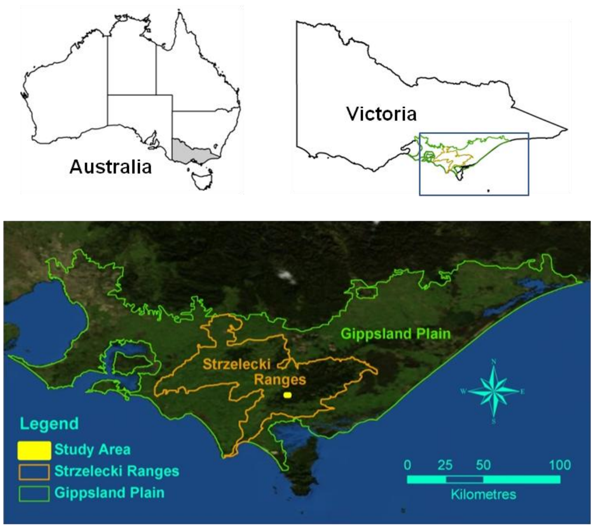

Figure 1. Location of the study area.

The study area is in the eastern Strzelecki Ranges, southeast Victoria, Australia (Figure 1). The Strzelecki Ranges experienced wide scale land clearing since European settlement. Subsequent abandonment of agricultural areas and several bush fires resulted in severe landscape disturbance in the Ranges. Land use and land cover have undergone further significant changes with the establishment of large scale plantations in the area over the last four decades (Noble, 1978; Legg, 1986). Currently, areas bordering small patches of cool temperate rainforest in the eastern Strzeleckis are a mosaic of different land use histories involving both natural and human disturbances, and so a very complex forest structure in the remnant patches of cool temperate rainforest and adjacent forests including wet sclerophyll and plantation forests prevails. This study focuses on an area with cool temperate rainforest distribution in the eastern Strzeleckis, which covers an area of 3.10 km^2 with elevations ranging between 300 and 458 m.

2.2 Data

LiDAR data were collected using an Optech ALTM Gemini LiDAR system at a flying height of 1,100 m above ground between 11 and 23 October 2009 (for the whole Strzelecki Ranges). The laser pulse repetition frequency is 70 kHz. The wavelength of the LiDAR laser is 1.064 µm. The laser scanner was configured to record up to 4 returns for one laser pulse. The LiDAR data used for this project was documented as 0.20 m for vertical accuracy and 0.25 m for horizontal accuracy. The LiDAR data were classified into ground and non-ground points by the vendor and were delivered in binary LAS 1.2 file format. WorldView-2 satellite imagery over the study area was acquired on 3 December 2010. Images were orthorectified by the vendor and delivered at spatial resolution of 0.5 m and 2.0 m for panchromatic and multispectral images respectively. Images were checked and georeferenced with the LiDAR data. Ecological Vegetation Classes (EVCs), which describe the spatial extent of native vegetation species and plantation forests, provided by the HVP Plantations Pty Ltd were used as ground reference data.

2.3 Methods

Using the LiDAR ground data, a digital elevation model (DEM) with two-metre horizontal resolution (grid size) was generated. A canopy surface model (CSM) was also generated using only the highest points of the first returns of non-ground LiDAR data within grid cells. A canopy height model (CHM) was then computed by subtracting the DEM from the CSM. A grid of square columns with four-metre horizontal resolution covering the study area were generated using Python programming language in ArcGIS 10.0 software. It is the non-ground LiDAR points within each of these square columns that were used to quantify the vertical distribution of LiDAR points by calculating the variables of mean, standard deviation, coefficient of variation (CV), skewness, and kurtosis. The values of each of these variables over the study area were then represented with a raster image. These five raster 'images', together with CHM and eight WorldView-2 multispectral bands were used as input data layers for the object-based image analysis in the eCognition Developer 8.7 software.

Object-based variables were derived from all data layers including six LiDAR-derived layers and eight spectral bands for the classifications. In addition to the mean and standard deviation of each object in a layer, GLCM (grey level co-occurrence matrix) textures (homogeneity, contrast, dissimilarity, and correlation) were also calculated in the eCognition for all data layers. The segmentation using different input data including LiDAR data only, four WorldView-2 bands only, eight WorldView-2 bands, LiDAR data and four WorldView-2 bands, and LiDAR data and eight WorldView-2 bands were conducted in the eCognition software. Object-based classification was implemented with decision trees in CART 6.0 software (Steinberg and Golovnya 2006) to classify the forests to cool temperate rainforest dominated by Myrtle Beech (*Nothofagus cunninghamii*) , Mountain Ash (*Eucalyptus regnans*), mixed forest consisting of overstorey Mountain Ash and understorey Myrtle Beech, Silver Wattle (*Acacia dealbata*), and plantation dominated by Shining Gum (*Eucalyptus nitens*). The overall accuracy, Kappa values, producer's accuracy and user's accuracy were then calculated from confusion matrix (Congalton and Green, 2009) to assess the accuracy of each of the classification results.

3. RESULTS AND DISCUSSION

The overall accuracy and Kappa values from five classifications were listed in Table 1. An overall classification accuracy of 61.39% was achieved using only the LiDAR data. The overall accuracy obtained from the classification using four conventional WorldView-2 bands was nearly same to the accuracy from using LiDAR data. The use of eight image bands increased the overall accuracy to 70.40%, implying the contribution of four new WorldView-2 bands to the classification. With the inclusion of LiDAR data to spectral bands, the overall classification accuracy was improved. For example, the overall accuracy increased from 61.42% (using only four image bands) to 73.50%. The combined use of the LiDAR data and eight image bands produced the highest overall accuracy. This indicated that the integration of the LiDAR data with eight WorldView-2 bands has more discriminatory power in object-based forest classification. The Kappa values in Table 1 show the similar trend of classification accuracy when using different data sets.

Table 1. Overall accuracy and Kappa values

Data source	Overall accuracy (%)	Kappa
LiDAR data	61.39	0.51
4 Image bands	61.42	0.49
8 Image bands	70.40	0.62
LiDAR and 4 Image bands	73.50	0.66
LiDAR and 8 Image bands	82.35	0.77

Figure 2 (a) shows that four image bands or eight image bands alone cannot achieve a producer's accuracy better than 50% for mixed forest and Silver Wattle. The producer's accuracies resulted from the LiDAR data for mixed forest and Silver Wattle were higher than those from image bands. Four image bands, LiDAR data, or even the combination of these two data sets cannot create a higher producer's accuracy for Mountain Ash. However, eight image bands alone did produce a higher producer's accuracy, indicating the strong capability of new WorldView-2 bands for capturing spectral characteristics of Mountain Ash. The WorldView-2 data (four bands or eight bands) also showed strong capability of identifying the rainforest. Integration of the LiDAR data and eight image bands produced higher producer's accuracies for all forest types. It is seen that a high producer's accuracy for plantation forests can be achieved using any of the data sets, implying that the characteristics of spectral reflection and vertical structure of plantation forests can be discriminated from other forests by LiDAR and/or WorldView-2 image data.

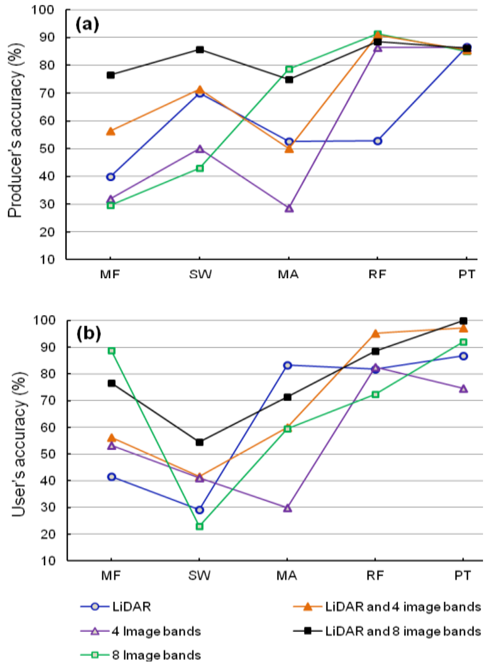

Figure 2. Producer's and user's accuracies of the classifications using different input data sets.
Notes: MF, mixed forest; SW, Silver Wattle; MA, Mountain Ash; RF, rainforest; and PT, plantation.

Similar to producer's accuracies, user's accuracies varied with forest types as shown in Figure 2 (b). The highest user's accuracies were achieved for rainforest and plantation forests by integration of the LiDAR data with either four image bands or eight image bands. Combined use of the LiDAR data and WorldView-2 image data produced both high producer's accuracies and high user's accuracies for rainforest and plantation forests. Therefore, the classified rainforest and plantation forest in this study are considered to be very reliable. Although Figure 2 (a) showed the higher producer's accuracies for Silver Wattle using the LiDAR and image data, relative low user's accuracies were observed. It indicated that over 85% of test sampling objects of Silver Wattle were correctly classified. On the other hand, however, only 55% of the objects that were classified into Silver Wattle were Silver Wattle. Considering all forest types, it is evident that the integration of the LiDAR data and eight WorldView-2 bands produced overall better user's accuracies.

4. CONCLUSIONS

This study explored the application of airborne LiDAR data and WorldView-2 satellite imagery data in object-based forest species classifications in an Australian cool temperate rainforest environment. New WorldView-2 multispectral bands, in particular the red-edge, yellow, and near infrared-2 bands did show their contributions to the classifications. Based on overall accuracies and Kappa values of the classifications, it is evident that integration of the LiDAR data and eight WorldView-2 multispectral bands produced significantly higher classification accuracy than using any one of the data sets alone. In addition, producer's and user's accuracies showed that combined use of the LiDAR data and eight WorldView-2 multispectral bands exhibited more discriminatory power for all five forest species in the study area.

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