Evaluating integrated multi-scale frameworks for strategic forest inventory and monitoring in Australian heterogenous woodlands

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IGARSS TOPIC – A.15 Forest Monitoring & Classification

Abstract – This paper evaluates the use of multi-scale sampling frameworks for improved forest and woodland inventory. The representative sampling strategy integrating field and remotely sensed data provided more detailed information than is currently available, allowing improved understanding of forest and woodland composition and structure, and improved biomass estimations.

INTRODUCTION

As a signatory to international agreements that include the United Nations Framework Convention on Climate Change (UNFCCC), the Kyoto Protocol and the Montreal Process, Australia is increasingly obliged to provide spatial and temporal information on ecosystem species/community composition and structure. Such information is necessary for providing regional assessments of biological diversity and forest condition, supporting sustainable utilisation of ecosystems, and calculating greenhouse gas emissions associated with land use change and forestry. To date, most agencies in Australia have necessarily relied upon either air photography or spaceborne optical data (namely Landsat MSS, TM and ETM+) for such assessments. Due to the large costs involved, effective monitoring at the species/community level has not been achieved, nor does existing mapping provide all the information that scientists and policy makers increasingly need.

This paper demonstrates the integrated use of a sample-based assessment and monitoring strategy, for maximising the potential of ground-truth data combined with various remotely sensed data for strategic forest inventory and monitoring. The multi-scale inventory framework uses sampling with fine resolution data to calibrate and validate coarser wall-to-wall sensors. It continues work previously described in [1, 2, 3, 4].

METHODS

The study was undertaken over a 220,000 hectare area containing diverse multi-aged forests and woodlands located near Injune, central Queensland, Australia. Key components of the project design include:

a) Wall-to-wall mapping systems. For regional assessment, Landsat Thematic Mapper from 1991 to 2000 [5], [6], [7], and existing regional level vegetation datasets [8], [9].

b) A systematic sampling scheme consisting of 150 Primary Sampling Units (PSU’s), arranged on a 4km grid over the entire 220,000 hectare study area. Each PSU is 500 by 150 metres (7.5 hectares), where one metre resolution first/last return airborne lidar was collected. Centred on each PSU, 1:4000 colour stereo large scale photography (LSP) covering 81 hectares was also obtained.

A stratified random field-sampling scheme within 13 selected PSU’s, based on an informed interpretation of LSP. Detailed field surveys were undertaken in 33 ½ hectare fixed area ground plots with complete tree maps.

Core attributes collected with the various methods were species composition, forest structure, condition, biomass, disturbance, land use and broad land cover change over the last 10 years. The area of 150 PSU’s constitute 0.5% of study area, and the area of the 13 PSU’s containing field plots is approx 1% of the total PSU area. The area covered by LSP is approximately 4.3% of the study area. A more detailed description of the sampling methods can be found in [1], and [2].

Fig. 1 illustrates the different sampling design methods for one PSU. Blue lines are polygon boundaries for interpreted broad vegetation and cover classes. Green grid lines indicate the 1 hectare polygon sampling areas, which cover the full extent of the photo (8x8 1 hectare cells). The lidar PSU area is bounded by the yellow rectangle. Within the lidar PSU the two field plots are shown with red outlines. There were 2 to 4 field plots per lidar sample area, for the 13 samples with field plots. Lidar derived contours can be generated at one metre height intervals, and this example shows portions of vegetation that are 5 metres above ground in yellow, and
Vegetation areas 15 metres above ground in pink.

Existing national datasets include those collated by Australia’s National Forest Inventory (NFI), with the data used in this project obtained in 2000 for Montreal Process reporting commitments, and consisted of broad forest types, including cover, at the nominal scale of 1:500,000 for Queensland [9]. The other dataset used was National Vegetation Information System (NVIS) [8] data, which provided more detailed structural and floristic data than the NFI, though at the regional scale (nominally 1:100,000). NVIS data was further updated with more recent Queensland Herbarium data. Both NFI and NVIS are able to provide near complete continental coverage of Australia’s forests and woodlands.

RESULTS AND DISCUSSION

While more detailed results have been presented in [1] and [2], a summary of key findings is presented here, and the vegetation type, cover and biomass results are introduced. Height measurements showed good consistency between field and lidar, and lidar and LSP. Due to the multi-age structure of the forest and woodlands it was found that a mean stand height was not a suitable descriptor.

Foliage cover results indicated that field based transects did not capture the amount of variation observed in lidar data. LSP estimates tended to under-estimate cover with respect to lidar, mainly due to operators interpreting tree crowns rather than all vegetation over 2 metres in height. Landsat forest cover estimates were poorer in open woodland environments, and in general tended to under-estimate the amount of variation in cover types across the landscape. Statistical analysis of Landsat foliage projective cover indicates that cover could range from ± 2-6% of the initial estimate. This could indicate that care should be taken with forest and non-forest change assessments that fall within this range as any change may be due to measurement error rather than actual loss of woodland, particularly when climatic influences are considered.

Fig. 2 illustrates the differences in forest type estimation between existing data, sampling, and wall-to-wall mapping methods. Landsat broad forest type and cover classification were trained with 40% of the LSP polygon PSU’s. Areas of regrowth were identified from prior Landsat assessments of foliage cover and clearing [5, 6, 7], and classified accordingly. When the classification was tested against all LSP 1 hectare grid polygons (9600) error in area for species classification ranged ± 9% depending on dominant genus. Existing mapping of the study area tended to over-estimate the amount of eucalypts by up to 20%, when compared to the LSP and Landsat estimates, and consequently under-represent less common species. The lack of identification of regrowth areas and less common species is likely to account for the increased area of eucalypt forest or woodland. Percentage counts of tree species in field plots compared favourably to LSP and Landsat area estimates, and this improved when only trees higher than 10 metres were considered.

Above ground biomass estimates at the plot level were generated from field data using a combination of existing allometric equations and mapped tree data, augmented with destructive harvesting across the diameter range of representative species. Lidar derived biomass was estimated by slicing lidar data horizontally in 5 metre increments to produce foliage cover surfaces (ie the vertical distribution of foliage). A step-wise linear regression tested the multiple input surfaces against the plot level biomass estimates. This resulted in a strong linear relationship with an adjusted $r^2$ of 0.89 and SE of 11.01tha$^{-1}$.
As field derived biomass estimates are not without error, further analysis between field and lidar biomass estimations found that 69% of the lidar estimates fell within the 95% confidence limits of field data, and a t-test revealed no significant difference between the two estimation methods [2].

Lidar biomass estimates were then combined with both LSP and Landsat mapped forest type and cover to test relationships between these variables and biomass. Biomass and LSP interpreted forest type and cover produced the strongest relationships, shown in Fig. 3. There are distinct trends with increasing biomass and increasing forest cover. Canopy cover (CC) classes are 2 (10-30% CC), 3 (30-50% CC), 4 (50-80% CC), and 5 (80-100% CC). The broad forest types used (callitris, eucalypt, acacia, and mixed/other) have much overlap with biomass estimates due to the heterogeneous nature of the environment. Examination of median and quartile biomass values identified differences between broad genus groups. Relationships between Landsat vegetation cover types and biomass were less distinct, though improvements in training data used for classification should enhance this.

Further analysis will be required to test these apparent differences, however initial results indicate the robustness of the lidar biomass estimation methods, when compared to existing site based, and broader continental scale biomass estimates, for example [10], [11], and [12].

**CONCLUSIONS**

Results indicate that significant improvements in quality, cost-effectiveness, and efficiency of many satellite based mapping programs for regional and national level reporting such as Montreal Criteria and Indicators could be made using an integrated framework that includes large-scale photography and airborne scanning lidar. The study has demonstrated the potential of LSP and laser scanner data for characterising the floristic composition, structure and biomass of woodland environments, although the scale of interpretation between remotely sensed data and interpreted data explains much of the difference between datasets. Based on these results, the next step will use such fine spatial resolution datasets to provide a basis for expanding to a catchment scale e.g. [13], or for wider characterisation of forest and woodland environments in many areas of Australia.

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