CHARACTERISING UPLAND SWAMPS USING OBJECT-BASED CLASSIFICATION METHODS AND HYPER-SPATIAL RESOLUTION IMAGERY DERIVED FROM AN UNMANNED AERIAL VEHICLE

A.M. Lechner [a, *], A. Fletcher[a], K. Johansen,[b], P. Erskine[a]

[a] Centre for Mined Land Rehabilitation, Sustainable Minerals Institute, The University of Queensland, Brisbane, Australia - (a.lechner, a.fletcher,p.erskine)@cmlr.uq.edu.au
[b] Biophysical Remote Sensing Group / Joint Remote Sensing Research Program, Centre for Spatial Environmental Research, School of Geography, Planning and Environmental Management
The University of Queensland, Brisbane, Australia, k.johansen@uq.edu.au

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ABSTRACT:
Subsidence, resulting from underground coal mining can alter the structure of overlying rock formations changing hydrological conditions and potentially effecting ecological communities found on the surface. Of particular concern are impacts to endangered and/or protected swamp communities and swamp species sensitive to changes in hydrologic conditions. This paper describes a monitoring approach that uses UAVs with modified digital cameras and object-based image analysis methods to characterise swamp landcover on the Newnes plateau in the Blue Mountains near Sydney, Australia. The characterisation of swamp spatial distribution is key to identifying long term changes in swamp condition. In this paper we describe i) the characteristics of the UAV and the sensor, ii) the pre-processing of the remote sensing data with sub-decimeter pixel size to derive visible and near infrared multispectral imagery and a digital surface model (DSM), and iii) the application of object-based image analysis in eCognition using the multi-spectral data and DSM to map swamp extent. Finally, we conclude with a discussion of the potential application of remote sensing data derived from UAVs to conduct environmental monitoring.

1. INTRODUCTION

1.1 Overview

Subsidence, resulting from underground coal mining can alter the structure of overlying rock formations changing hydrological conditions (Booth et al., 1998; Karaman et al., 2001) potentially effecting ecological communities found on the surface. Of particular concern are impacts on endangered or protected swamp communities and swamp species sensitive to changes in hydrologic conditions. Vegetation communities are likely to undergo significant changes as a result of hydrological changes (Prosser and Melville, 1988). An additional focus of concern is on the supply security, quantity and quality of surface and groundwater sources. Monitoring to ensure appropriate management decisions for these environmental impacts is required with a high degree of confidence.

Changes to local hydrology resulting from underground mining is of particular concern in NSW, Australia, where coal is found in seams relatively close to the surface along the eastern and western edges of the Sydney-Gunnedah Basin (Australian Mine Atlas, 2011) underlying wetland communities of conservation value. These wetland communities include Montane bogs and fens and coastal heath swamps (Keith, 2004) found in high altitude temperate uplands. Upland swamp communities are often a focus of conservation effort due to their restricted geographic distributions and the wide range of vegetation species assemblages (Keith et al., 2010) resulting from the unique hydrologic and soil characteristics (Raulings et al., 2010). These broad floristic groups include communities that are listed by the federal government as endangered ecological communities and contain rare, threatened and endangered flora species.

Monitoring of potential impacts is currently undertaken by ecologists using plot based field ecological measurements of vegetation composition and condition. However, the biodiversity and spatial heterogeneity of these swamp communities results significant differences between plots within individual swamps as well as between swamps. Furthermore, these swamps undergo continual change as a result of the inflow of organic and inorganic material and erosion following disturbance (Keith et al., 2006; Tomkins and Humphreys, 2006) and drought and seasonal differences. This creates a constantly changing mosaic of vegetation cover and composition within and between swamps. Subsidence impacts can result in subtle shifts in topography or large visible impacts resulting from cracking in the bedrock and complete draining of swamps. As these swamps are highly heterogeneous both in space and time and the impacts tend to be spatially heterogeneous, often point source, the sample sizes required to identify impacts from natural variability using field based measurements can be very large and in some cases logistically impossible. Thus, field based monitoring by itself may not provide the degree of confidence required to monitor impacts on these communities.

Remote sensing provides an alternative or may be used in combination with field based methods as its total coverage can characterize spatial heterogeneity of the whole swamp and provides data describing the spatial extent of features unlike plot data. GPS guided Unmanned Aerial Vehicles (UAV) have the capacity to obtain very high spatial resolution / hyperspatial (<10cm) imagery of particular landscape features with revisit

* Corresponding author.

times determined by the operator as opposed to fixed satellite revisit time. While imagery is surficial in nature and provides less information than plot based field monitoring, UAV derived imagery can provide a total sample of a study area and thus describe spatial patterns outside of plots.

In recent years the application of unmanned vehicles by military organizations has resulted in the increasing availability of second tier vehicles and hardware for environmental research application (Hardin and Jensen, 2011; Hervoue et al., 2011; Lopez-Granados, 2011) and archaeology (Chiabrando et al., 2011). The advantages of UAV over existing remote sensing platforms is the potential to take site based imagery at near unlimited spatial (Laliberte and Rango, 2009, 2011) and temporal resolutions. Furthermore, the ability to capture imagery concurrently with field observation addresses a common remote sensing problem resulting from differences in the acquisition of ground and remote sensing data. Currently, the use of remote sensing with automated classification methods to classify small upland swamps is uncommon as the spatial resolution of common remote sensing sensors is too coarse for these communities because of they are often small with convoluted boundaries (Jenkins and Frazier, 2010). Mapping of swamp patches is commonly conducted with Aerial Photo Interpretation. This project utilised the hyperspatial resolution capacity provided by the UAV platform along with object based image analysis (OBIA) methods to investigate the utility of these two emerging remote sensing technologies for the classification of upland swamp communities.

Hyperspatial sub-decimetre imagery acquired using UAV platforms is commonly analysed using OBIA classification methods (e.g. Laliberte and Rango, 2009; Laliberte and Rango, 2011). When using hyperspatial resolution the target feature is usually larger than the pixel size, however the converse is true for medium and low spatial resolution imagery acquired by satellites such as Landsat or MODIS. Pixel based remote sensing classifiers (i.e. Maximum, likelihood classifiers) using spectral information are used with medium and low resolution imagery and are often unsuitable for classifying hyperspatial data. High spatial resolution data classified with pixel based classifiers can result in a lower overall classification accuracy (Blaschke and Strobl, 2003). As spatial resolution becomes finer, variance in observed spectral values within landcover classes increases making spectral separation between landcover classes more difficult (Blaschke and Strobl, 2003; Marceau and Hay, 1999). This is a result of the interrelationship of a number of scale dependent factors: the information classes desired, the method to extract the information and the spatial structure of the scene itself (Woodcock and Strahler, 1987). A key driver for the development of OBIA methods is addressing these scaling issues through segmenting high spatial resolution pixels into image objects made up of multiple neighbouring pixels sharing similar spectral values (Blaschke, 2009).

1.2 Aim

The aim of this study was to classify swamp vegetation derived from a UAV with modified digital cameras and OBIA remote sensing classification methods. In this paper we describe i) the characteristics of the UAV and the sensor, ii) the pre-processing of the remote sensing data to derive visible and near infrared multi-spectral imagery and a digital surface model (DSM), and iii) the derivation of swamp vegetation extent. Finally, we conclude with a discussion of the potential of remote sensing data derived from UAVs to conduct environmental monitoring with reference to upland swamps. We specifically focus on the characteristics of UAV remote sensing that distinguish it from other remote sensing platforms and sensors.

2. METHODS

2.1 Study Area

The study area is found on the Newnes plateau in the Blue Mountains west of Sydney (Figure 1). Development of flora monitoring methodology for assessing the impact of subsidence on swamp communities has been conducted by the Centre for Mined Land Rehabilitation at Centennial Coal’s operations on the Newnes Plateau since 2009 (Erskine et al. 2009). From this work a single swamp was selected: Barrier swamp. This swamp is larger than other swamps in the area and contains a wide diversity of species and hydrological features. Barrier swamp is found within the MU50 - Newnes Plateau Shrub Swamp floristic community (DEC, 2006). MU50 is of primary concern to regulators as it is federal and state listed and is considered an ecologically endangered community (DEC, 2006).

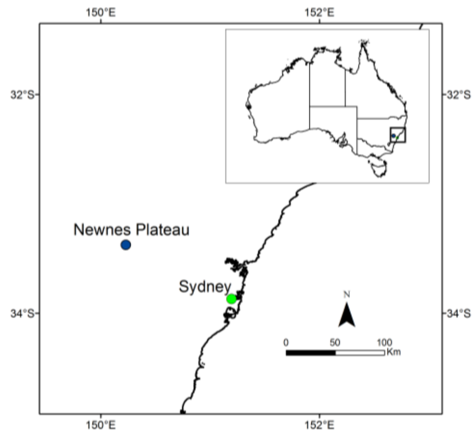

Figure 1. Location of Newnes plateau study location.

2.2 Characteristics of the UAV, sensor and acquired imagery

The unmanned aircraft system (UAS) used in this study includes a ground station and UAV with on board camera (Figure 2). The UAV is a GPS guided, electric powered Kahu Hawk with a 2m wingspan weighing approximately 3.9kg (www.kahunet.co.nz). It is controlled by a small ground station made up of a single laptop and transmitter allowing for communication and control of the UAV. Flight paths are commonly uploaded before take-off, however the UAV can be guided manually. Imagery is acquired using a single Sony NEX5 micro-DSLR camera with a 16mm lens. This system includes two cameras: i) a regular camera for acquiring imagery in the visible spectrum and ii) a modified full spectrum camera with a near infrared filter. The imagery in this study covered an area of approximately 26ha at 121m above ground level. It took approximately 45 minutes to complete this flight.

a)  **b)**  **c)** 

Figure 2. a) Kahu Hawk UAV. b) UAV ground station. c) Sony NEX5 micro-DSLR camera with 16mm.

2.3 Pre-processing

Pre-processing of remote sensing data was conducted using the pix-4D software in order to produce a digital surface model and orthophoto mosaic of both true colour and near infrared imagery (see www.pix4d.com). UAVs provide less stable platforms than manned flights and the orthorectification and mosaicing of these images with smaller extents can be difficult (Rango and Laliberte, 2010). Rango and Laliberte (2010) concluded that existing photogrammetric software is not commonly suited for this task. We tested the use of the pix-4D software that has been specifically developed with UAV imagery in mind.

The UAV took ~300 separate images that were then ortho-rectified and stitched together with the pix-4D software. Ortho-correction is required to correct for features that appear oblique due to the wide angle and low altitude photography. The first step in ortho-rectification requires the development of a digital surface model (DSM) made of a 3D point cloud from pixels matched in overlapping images. The DSM by-product produced as part of the development of the orthophoto mosaic was also used in the analysis. For this study we used 80% forward overlap and 50% side overlap. The pixel size of the final orthophoto mosaic was 4cm for the NIR and True colour imagery. The DSM used in the study was based on the NIR, as the NIR image had a higher contrast and thus resulted in high quality pixel matching required for the creation of a high quality DSM.

2.4 Object based image analysis

The image was classified using OBIA techniques with the eCognition v8 software. The first step in the process involved the segmentation of objects that could be used as the mapping unit to classify the image into two separate landcover classes: Eucalypt and Swamp (Figure 3). Two segmentation scales were used to segment the image using two different segmentation methods. First, a quadtree segmentation algorithm was used to divide the image into homogenous square objects of multiple sizes (at scale = 100). The second segmentation method was the multi-resolution region growing algorithm on the 'Fractal Net Evolution Approach' (Baatz et al., 2002) with the following parameters: scale = 100, shape = 0.1 and compactness = 0.5. Using this combination allowed for more compact objects than would have been produced using the multi-resolution segmentation approach alone. For both segmentation methods only the true colour imagery was used.

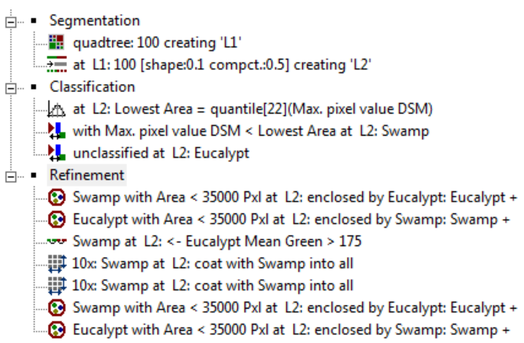

Figure 3. OBIA ruleset created in eCognition.

In the next step objects were classified into swamp and eucalypt landcover classes to determine swamp extent:

i) Swamp: This wetland landcover class is dominated by a combination of shrubs and sedges. It does not include large trees such as Eucalypts.

ii) Eucalypt: Barrier swamp is surrounded by tall closed Eucalypt woodlands with tree height often greater than 20m.

The boundary between swamp vegetation for Barrier swamp is represented by the interface between the surrounding Eucalypt woodlands and the swamp. For the majority of its perimeter this boundary is quite discrete.

A classification ruleset was developed based on the surface height determined by the DSM. The classification was conducted using a tiling approach. Within each tile a quantile value was calculated based on the maximum DSM pixel value within each object. In tile 1 the quantile value was 22 and in tile two it was 25. Areas with objects with a maximum DSM pixel value less than the quantile value were classified as swamp and objects above the quantile value were classified as Eucalypt.

After the initial classification based on the DSM further refinement of the classification was conducted. Single objects or small clusters (less than 30,000 pixels) of objects in the minority were reclassified to the enclosing class objects. Next, neighbouring objects classed as Eucalypt next to the already classified swamp objects were merged based on a mean object green pixel value greater than 175. Finally a 10 pixel buffer was applied to the swamp classes then applied to the eucalypt class to smooth the edge between eucalypt and swamp classes. In the final refinement steps single objects or small clusters of objects in the minority surrounded reclassified to the enclosing class again.

A global accuracy assessment was conducted using a point based method with 20 randomly located points for each tile to confirm the quality of the classification. At each point the accuracy of the classified imagery was assessed visually using the original true colour UAV imagery. Due to the high spatial resolution of the imagery visual inspection is very reliable for assessing accuracy.

3. RESULTS

For this paper we will describe the results of OBIA of two tiles which represent two subsets from upstream and downstream areas within the Barrier Swamp (Area 1 and 2 Figure 4). Figure 4 describes the two orthophoto mosaic products created by the pix-4D software.

In study area 1 the classified areas of Eucalypt and Swamp qualitatively demonstrated a good match between classified landcover and the original aerial imagery (Figure 5) and the classification accuracy was 95%. The inset demonstrates that large trees that include spectrally different features such as trunks, branches and leaves have been successfully segmented into a single image object and finally classified correctly as Eucalypt.

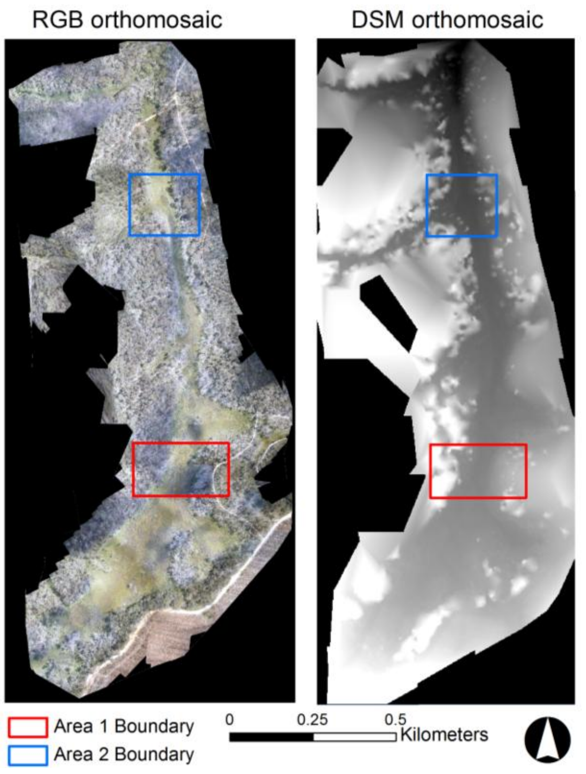

Figure 4. Study area

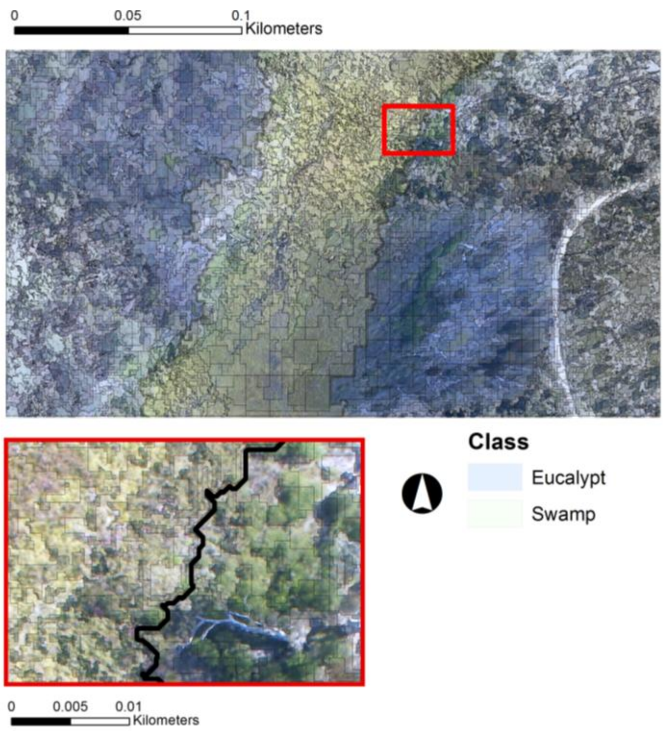

Figure 5. Segmentation and classification of Area 1.

A similar level classification success could be seen in Area 2 (Figure 6). The classification accuracy for this tile was 100%. The inset shows an area within the image where tree canopy cover is sparse but has been correctly classified as Eucalypt. Also within the inset, tree trunks on an angle can be clearly seen indicating that the orthorectification did not perform so well in this part of the image.

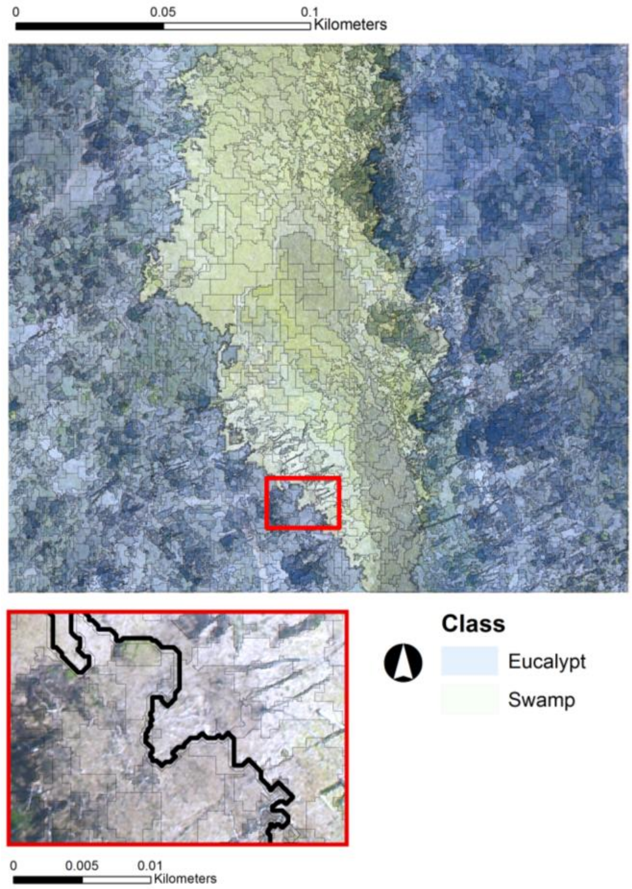

Figure 6. Segmentation and classification of Area 2.

4. DISCUSSION

4.1 Discussion

Hyperspatial resolution remote sensing data classified using OBIA approach has the potential to provide solutions for monitoring environments which contain features that are potentially difficult to classify using spectral information contained within the pixel alone. A key issue with high spatial resolution data is that the components that make up the feature class can be found as separate pixels. For example, eucalypt trees are made up of branches, trunk, and leaves each with unique spectral characteristics. At the fine scales described by UAV imagery variance in observed spectral values within landcover classes increase in proportion to variance between classes making spectral separation between landcover classes more difficult (Blaschke and Strobl, 2003; Marceau and Hay, 1999). Segmenting pixels into objects that correspond with landcover classes is a key part of the solution to classifying high spatial resolution imagery for the derivation of vegetation landcover classes. In this study there are numerous examples of where eucalypt tree canopies could be discerned within a single object containing both canopy, branch and ground cover.

A range of classification methods were trialled, but only the OBIA ruleset was presented in this paper, as it was able to accurately classify the swamp boundary. Other OBIA classification methods using texture based information derived from the imagery, thresholds based on mean object spectral values and supervised classification using spectral information within objects were trialled unsuccessfully. Eucalypt versus swamp could not be classified with these methods in the study site. The final classification ruleset relied on global context information from the DSM. Further, refinement of the ruleset to identify plant assemblages within swamps is likely to rely on the use of such context information along with spectral and textural information.

Classification of swamp areas is difficult because of the lack of spectral contrast between different vegetation types within and between swamp vegetation and the surrounding vegetation. Swamp mapping is unlike other remote sensing mapping tasks where there are large spectral differences between landcover classes e.g. urban versus agriculture or forest versus desert. In the Barrier swamp environment there were no distinct peaks in the distribution of intensity values for each band (Figure 7). Peaks in the distribution are a good indication that landcover classes may be identified spectrally, where each peak corresponds potentially to a different landcover class. Homogeneity in spectral signatures of landcover of vegetation in swamps potentially may be overcome through gathering data at other wavelengths, especially infrared wavelengths. Hyperspectral data have been shown to be successful in identifying different vegetation species from each other (e.g. Martin et al., 1998).

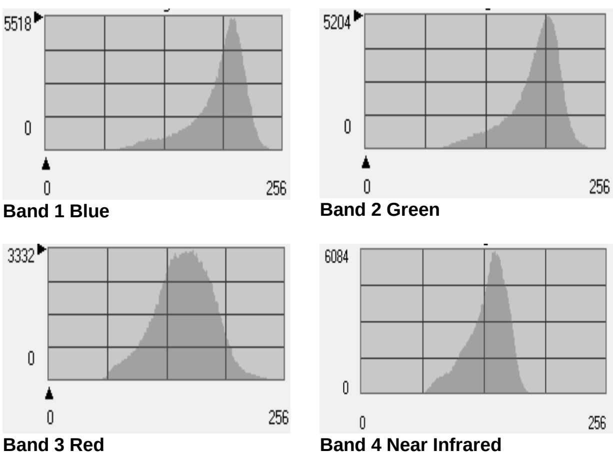

Figure 7. Histogram of distribution of pixel intensity values (0-255) for the whole orthophoto mosaic for each band.

Several other issues arise from using hyperspatial resolution imagery that are related to the small pixel size of the imagery affecting the spectral response from features within segmented objects. Firstly, there is problem when the conceptual boundaries of the information class is inconsistent with boundaries found on the ground (Lang, 2008). The sparse canopy of Australian native eucalypt trees means proportionally more ground is visible through the canopy than European trees and denser shrubby ground cover. Thus, while the object being classified might be a tree vegetation class, the feature that dominates the area on the ground is often the ground cover (e.g. Figure 5 inset). A similar phenomenon was exhibited by the swamp vegetation where within object spectral reflectance was affected by the ground water and soil moisture. In some areas the visual patterns in the swamp that could readily be discerned in the image was the result of differences in soil moisture not differences in vegetation cover. For the development of the OBIA ruleset we initially trialled a multiresolution segmentation approach in the first step of the segmentation process instead of quadtree segmentation. This resulted in the creation of numerous sinuous objects that followed patterns visible in the image unrelated to the information class we were trying to extract, such as shadows between tree crowns and hydrological features such as small streams, rills and subsurface ground water movement. Finally, in high spatial resolution data each pixel within an information class bounded by an object may not be related directly to the information class, as pixels within objects will always show some heterogeneity as a result of irregular shadows and shade (Ehlers et al., 2006). The shadow effect was especially obvious between tree canopies. In this study we were able to address many of these problems through the use of the quadtree segmentation. It is likely, however, that these issues would have been significantly worse if a pixel based classifier would have been used. The "salt and pepper" classification effect, for example, is common to pixel-based classification methods (Ivits and Koch, 2002).

4.2 Implications for monitoring

The boundary between the swamp and surrounding Eucalypt woodlands can be used as a key indicator for monitoring swamp condition and thus the impacts of underground mining. As hydrological conditions change, this can in some cases result in a drying out of swamps with less drought tolerant swamp vegetation making way for eucalypt trees. Changes in boundaries of swamps can be used as a key indicator of wetland health (Keith et al., 2010). Thus the accurate mapping of swamp extent through the classification technique developed in this study is key to monitoring long-term changes in wetland condition.

While there are still many hurdles to overcome in demonstrating the operational capabilities of UAV derived hyperspatial imagery and OBIA methods for upland swamp monitoring, there are many other practical reasons why such methods are useful and need to be pursued. Firstly, monitoring using UAVs is more practical and cost effective than field methods. For example it takes half a day to conduct field sampling of two 20m x 20m plots in the barrier swamp due to access issues compared to the 1 hour flight time of the UAV. These plots only cover a small fraction of the total swamp area. Remote sensing technologies also remove physical interaction with the study site, minimising the risk of impacts resulting from the monitoring activities and potentially improved access to remote and rugged sites. Small UAVs require minimal baggage and thus are very portable. This allows for the collection of suitable imagery at near real time, coinciding with field surveys or in response to irregular events such as flooding. Finally, the successful capture of imagery is maximized as image collection can occur under cloud cover due to low flight altitude.

5. CONCLUSION

The results of this study demonstrate how the combination of two new remote sensing technologies in the form of UAVs and OBIA methods can be successfully combined to classify swamp vegetation extents. These more recent remote sensing technological developments show great promise. Further work on Barrier swamp and other swamps on the Newnes plateau will continue with the aim of developing a suitable remote sensing platform, orthophoto-mosaicing techniques and classification method that can provide the appropriate spatial and temporal resolutions for effective monitoring of swamp vegetation communities. Successful development of these techniques will provide confidence to miners, regulators and the public that impacts are identified in a timely manner across all potentially impacted sites.

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