Mapping Moira grass location on a Murray River floodplain area using multispectral sensors on board of unmanned aerial platforms

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Report Citation:
BACKGROUND:

Barmah-Millewa Forest straddles the Murray River 35 km north-east of the town of Echuca (Victoria). It is an internationally-significant wetland reserve (Ramsar-listed) covering 66 000 hectares and home to the largest stand of river red gum (Eucalyptus camaldulensis) in the world (MDBC, 2007; Hale and Butcher, 2011). The vegetation dynamics in the reserve’s floodplain is highly dependent by the Murray river water regimes. This includes the aquatic grasses which go through different phenological stages along the year based on water availability and depth of the flood. Moira grass (Pseudoraphis spiniscens) is one of the iconic species of the area and representative of the floodplain landscape, especially during the flooding season. Moira grass tolerates flooding and drying and change aspects of their morphology under different water conditions (Abel et al., 2006; Colloff et al., 2014). It grows all the way to the water surface elongating its stems up to 3-4 m and develops floating leaves. When the water level decreases, the stems dry on the ground along the flow direction and re-root multiple times developing new specimens in the next wet season. To keep the recognised ecological character of the area, the extent of Moira grass needs to remain over 1350 hectares (Hale and Butcher, 2011). There is no current accurate assessment of the extent of Moira grass in the reserve, although some field mapping had been undertaken in the Barmah Forest (Victorian) component of the reserve in 1984 (Chesterfield, 1986) and 2012-13 (Vivian et al., 2015) asserting that the species distribution is being threatened by the extension of river red gum and giant rush (Juncus ingens) and impacted from grazing pressure of feral horses in Barmah Forest. A more accurate, rapid and repeatable measure of the species distribution in the forest, such as that potentially gained from aerial platforms, is therefore strongly required.

AREA SURVEY:

Two sites were selected to perform a classification of the main existing grass species: Hut Lake (35°54′46.23″, 144°59′44.82″), covering 26 ha approximately, and Little Rushy Swamp (35°53′24.09″, 145°02′28.92″), covering 4 ha. At the time of the survey, Hut Lake grass area was dry while Little Rushy Swamp was flooded, presenting different Moira grass conditions and phonological stages.

Multispectral data collection

Image acquisition was conducted by the Melbourne Unmanned Aerial System Integration Platform from the University of Melbourne (MUASIP) on two cloud-free days in January 2018. The conditions in the area after the heavy rains in December 2017 still allowed access to Hut Lake and to the entrance to Little Rushy Swamp that was still flooded with water depth up to 60 mm.
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Multispectral imagery was collected with a Micasense RedEdge sensor on board the X8 1000 platform operated by XM2 Industrial. Flight plans were designed to cover the whole area with an overlap of 80% between flight lines at 60m resulting in 5cm ground spectral resolution. The Micasense RedEdge imaging sensor (Micasense, Inc, California) collects information on 5 bands located at 475, 560, 668, 717 and 840 nm respectively. Blue (475 nm) and Green (560 nm) bands Full-Width-at-Half-Maximum (FWHM) is 20nm, Red (668 nm) and Red Edge (717 nm) 10 and Near Infrared (840 nm) 40nm.

![Figure 1. Multispectral imagery collected over the two sites: (a) Hut Lake and (b) Little Rushy Swamp. The images are the result of Near Infrared – Green – Blue false colour composites.](image)

**In-situ data collection**

A set of calibration targets was deployed on a levelled surface on the ground. Spectral data was collected on the targets simultaneous to sensor overpass using a ASD hand-held spectrometer (Malvern Panalytical Ltd, Spectris plc) covering the 400-1100nm spectral range. Imagery on the calibration targets was acquired at the centre of a flight line, minimising potential Bidirectional Reflectance Distribution Function (BRDF) effects (Pinter et al., 1990). Another set of reflective targets were distributed over the whole acquisition area. A differential GPS (Leica Geosystems, Hexagon) was used to measure accurate position of those targets, later used for geo-rectification of the imagery.

The same GPS instrument was used to measure the location of existing end-members or later on classes present within the site. These include bare soil, Moira grass, water primrose (*Ludwigia peploides*) and water pepper (*Periscaria spp*). Moira grass was present in three stages of development: fresh abundant new growth, fresh scarce regrowth on stems lined on the ground from the previous season, and dry stem remnants from previous season. GPS position and spectral data was collected on selected areas covering all stages present. On the second site, the accessibility to the different grasses was more difficult, only reachable by
wading. The position of the grasses was measured in a second visit in May 2018 when the ground was fully dried. On the second site, the mixture of grass species was more apparent and the coverage lower.

**IMAGE PROCESSING AND CLASSIFICATION**

UAV image data was mosaicked producing a single stacked file for each site and calibrated to reflectance units using the calibration spectra collected on the targets. The calibration targets used in this study cover reflectance values between 0 and 32% and they are built to keep constant reflectance for varying illumination and sensor angle settings. Image calibration was performed using the empirical line method achieving an average error under 1% reflectance.

![Moira grass](image1)
![Moira grass](image2)
![Water primrose](image3)
![Water pepper](image4)

![Giant rush](image5)
![Wallaby grass](image6)
![Pond weed](image7)
![Wavy Marshwort](image8)

Figure 2. Main aquatic species found in the area: a&b) Moira grass (*Pseudoraphis spinescens*), c) water primrose (*Ludwigia peploides*), d) water pepper (*Persicaria hydropiper*), e) giant rush (*Juncus ingens*), f) swamp wallaby grass (*Amphibromus fluitans*), g) pond weed (*Potamogeton sulcatus*) and h) wavy marshwort (*Nymphoides crenata*).

A number of popular supervised classification techniques have been tested in both dry and flooded conditions to see which perform best at classifying the different grass species. For the supervised classifications, spectral ground samples (when available), and image end-members from the collected GPS locations were used. Due to grass mixture and inaccuracy
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of GPS measurements in water surfaces, the high resolution image was used to visually locate main species cohorts in the Little Rushy Swamp site. The supervised classification methods included: Maximum likelihood, Support Vector Machines and Spectral Angle Mapper. The Maximum likelihood classifier is one of the most popular methods and it is widely used to map vegetation species. It calculates the average signal of a pure class based on the input information and considers it to present a normal distribution in the multispectral space. The result is based on the distance to the theoretically built classes based on the average and covariance of the input data. It requires the input data to be very pure and representative of the existing population. Support Vector Machine classification is based on a machine learning algorithm trained with all input class values in the multidimensional spectral space (Suykens and Vandewalle, 1999). The classification result for each pixel is determined by the closest match in the input dataset. It is therefore dependent upon covering the complete class response in the input data although not necessarily in a representative (proportional) manner. The Spectral Angle Mapper classifier determines a class by the angular distance from the input cohort in the multidimensional spectral space. It is then not based on absolute signal values, but the relative position of the bands (Kruse et al., 1993). This classifier is then very successful in the cases where illumination differences affect the signal.

**CLASSIFICATION MAPS:**

A preliminary analysis of the dispersion of the signal for the different classes in both flooded and dry conditions showed that the spectral separability of the different plant types (forest, shrub, grasses) and the differences between the targeted grasses differed for both study areas (Figure 3). This preliminary study demonstrated how the spectral signal is highly affected by the background and grass phenological state. As a result, the most informative sensor bands varied between sites. We therefore used all spectral bands available as input for the classification.

Different classification methods were compared based on their performance classifying known areas like forest and known grass location based on the knowledge of the area. From the main supervised classification methods, the Support Vector Machine classifier (Drucker et al., 1996) performed the best for both sites. The Maximum Likelihood method was failing at assigning a class to areas where the data was not very close to the field data collected. Spectral Angle Mapper was not performing as good as expected either, most probably because we were applying the method to multispectral imagery, and the performance of this method improves considerably with the multidimensionality of the spectral space.
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Figure 3. Scatter plots for the band combination yielding the best spectral class separability in both study sites. The classes, represented in different colours, were more distinct when using Near-Infrared and Red-Edge reflectance in Hut Lake (a), for Little Rushy Swamp, NIR and Red bands were more informative in the discrimination of classes (b).

The classification performance was considerably improved using very high resolution imagery (5x5cm). This is due to two main reasons: the ability of selecting the different species for the classification training data; and the ability to detect grass species that are mixed with other broadleaf and would be mixed otherwise. The final output maps were however produced using 0.5x0.5m spatial resolution, to show better overall patches of the different species.

**Hut Lake**

At the Hut Lake site, most of the surface was classified as Moira grass as expected (Figure 3, blue). The area of water pepper was overestimated in the classification, we believe this is because of the dominancy of broadleaf versus grass species in the overall signal. Grasses may be occluded by other species that grow taller in height, greater stem spread and have broad leaves. All classification methods underestimated the presence of lower grasses.
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Figure 3. Grass classification map for Hut Lake on Google Earth map background. Blue areas represent where Moira grass is present. Other existing grasses like water primrose and water pepper are represented in yellow.
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Little Rushy Swamp

Figure 4. Aquatic grass classification map for Little Rushy Swamp on Google Earth map background. Classes were defined based on a survey carried out in May 2018. Moira grass areas are represented in blue, swamp wallaby grass in dark yellow and other broadleaf species in purple.

At the Little Rushy Swamp site, the high resolution imagery allowed selecting dominant grass species as input to the classification. Nevertheless, similar species types that are visually grouped together may be underestimated. Grass and broadleaf species were in close proximity resulting in mixed areas. Similar to the classification in the Hut Lake, broadleaf species and tall ‘shrubs’ like the giant rush obscured the presence of Moira and other grass species, leading to underestimating the latter. Figure 4 presents the resulting classification map where Moira grass is represented in blue, swamp wallaby grass in yellow and broadleaf species like pond weed and wavy marshwort (*Nymhoides crenata*) in purple. We can see the effect of the heavy feral horse grazing on the western area of the exclusion fence (outside of the exclusion plot and hence exposed to horse grazing pressure) where grass cover has been removed to expose the lower-growing pondweed. On the contrary, the eastern side, not accessible by horses, has maintained strong grass cover.

The accurate classification of the area allows computing the approximate area covered by each of the iconic species. Moira grass accounts for a 92% of the herbaceous extension in the Hut Lake plain. Higher complexity is found in Little Rushy Swamp (Table 1).
Table 1. Summary of the extension calculated for each grass species (Moira, Wallaby grass and Giant rush) and for broadleaf aquatic species.

<table>
<thead>
<tr>
<th>Spp</th>
<th>Cover area (ha)</th>
<th>%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Moira grass</td>
<td>1.27</td>
<td>32.29</td>
</tr>
<tr>
<td>Wallaby grass</td>
<td>0.24</td>
<td>6.09</td>
</tr>
<tr>
<td>Giant rush</td>
<td>0.02</td>
<td>5.88</td>
</tr>
<tr>
<td>Broadleaf spp</td>
<td>0.95</td>
<td>24.07</td>
</tr>
</tbody>
</table>

**CONCLUSIONS AND FURTHER WORK:**

The high diversity of grass and other herbaceous species co-existing in Barmah Forest floodplains makes accurate species classification difficult, requiring high resolution multispectral imagery. For this purpose, high spatial-resolution multispectral imagery was collected by MUASIP from the University of Melbourne in early 2018 over two grassy wetland sites, one already dry and another still flooded.

The high resolution imagery allowed the visual identification of different species or species cohorts. Due to the coexistence of grass and taller herbaceous species, most classification techniques underestimate grass surface occluded by other species in emergent position. The high spatial resolution requirements limit the sensors that could be used to repeat similar work to unmanned or manned airborne platforms.

From the common supervised classification methods, the Support Vector Machine classifier trained with class spectral data extracted from the image performed best. The method resulted in a species distribution map that seemed more consistent with the knowledge of the species location. Due to the inaccuracy of GPS measurements above water, the image survey needed to be complemented with a second visit to the site once it was dry to collect the position of the most abundant species. The classification maps were then used to quantify the total area covered by Moira grass and other species of interest such as swamp wallaby grass and giant rush. The results also demonstrated how a fence had preserved the grass cover from heavy grazing, showing this an effective species management initiative.

We believe the mapping method could be improved over time by training the classifier using various phenological and water regime states, consolidating a technique to monitor Moira grass and other targeted plant species. Based on this study, we suggest the data acquisition should be complemented with spectral data collection for the main existing species over varied backgrounds in wet and dry conditions. This would allow for the creation of a more robust classification rule to apply over time. At this point, the classification methods to use are limited to very high resolution airborne imaging. In the future, techniques using pixel unmixing classifiers could be trained to attempt the classification using satellite imagery to provide an affordable large area assessment.
REFERENCES


