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Exploratory Assessment of Lignum and Non-woody Riparian Vegetation using Drone Technology and Sentinel-2

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Executive Summary and Areas for Further Investigation

This project sought to explore practical methodologies to determine an extent baseline for lignum in the Murray-Darling Basin (MDB), to measure environmental outcomes, and to investigate options to measure condition of lignum shrublands and non-woody vegetation.

This offered a unique opportunity to undertake an exploratory assessment of novel methodologies for monitoring lignum and non-woody vegetation in the MDB.

The project explored the application and utility of unmanned 'drones' and Sentinel-2 (10 m) imagery by assessing:

- extent and condition of lignum stands (and understory vegetation) on Clarks Floodplain between Berri and Loxton in South Australia, based on remote sensing imagery, expert interpretation, field validation and GIS analysis of ground-truthed data;
- riparian vegetation 'corridor' mapping of the River Murray channel; and
- potential application and utility across the whole of the MDB and beyond.

Classification using drone-derived data is an important tool for environmental monitoring. How accurately vegetation is classified using drone-derived datasets depends on factors such as the complexity of the vegetation structure, the level of discrimination aimed for (i.e. species or cover type groupings), quality of training samples and timing with environmental conditions. It has been demonstrated repeatedly in the literature, that accurate classifications are achievable given the right combination of data capture and analysis methods.

Results from the current project indicate that lignum registers surprisingly low cover values when measured from above, due to its structure of multiple stems (many vertical) and usually no foliage or flowers. It was found that the most practical field measure of lignum condition is the percentage greenness of stems in a bush or stand. There was sufficient correlation between the various sensing technologies tested and the ground-truthing results to support the continuation of work to refine these methods.

Lignum is predominantly spread across shallow claypans or open floodplains. The results from this pilot study suggest that typical lignum stands rarely reach above 15% of vegetation cover in the field, unless a topographic feature exists (for example a terminal swamp) which enables water to pool for longer periods. It is suggested that the cover at Clarks Floodplain is quite typical for floodplain lignum in the MDB and is not considered unusually low relative to other locations, however further work at additional sites will confirm this.

As indicated above, the most effective parameter to measure lignum condition is the relative greenness of stems, so monitoring tools need to be able to identify stems and then classify the relative proportion of the colours green, yellow or brown. In seeking to measure stems and their greenness, another finding was that bushes which appear to have relatively dense stems when viewed horizontally visually do not necessarily translate to a similar assessment in the vertical view measured from a drone. Further testing is required to find ways to resolve these issues.

When collecting ground-truth data for lignum condition, it is recommended that further parameters such as age and size also be collected to potentially aid a closer correlation with remote sensing imagery. It was found in this project that the 50 cm radius polygon used to compute mean NDVI values was appropriate for larger bushes, however it was not appropriate for smaller individual bushes with sparse canopies, especially when accompanied with an emergent active vegetated understory (either annuals or chenopods). Similarly, a 25 cm radius polygon may not be sufficient for large bushes to represent the

footprint used in the on-ground scoring assessment. Further work in this area in combination with individual bush size and age class may result in a stronger correlation between ground survey field results and NDVI at the individual bush level. Options for testing groups of bushes rather than individual bushes should be considered, as well as testing groups of bushes by micro-topography and micro-habitats, as these factors influence local water availability, which is a major determinant of bush condition. Likewise, opportunity assessment of locations with denser areas of lignum coverage (e.g. greater than 15%) may make it possible to estimate lignum extent using workflows developed under the current project.

This study presumed that the ground survey methods for scoring vigour and greenness were the points of truth to compare multispectral imagery against. Consequently, experiments that investigate the spectral response of lignum due to physiological changes could yield interesting results. Experiments may include monitoring of active controlled watering projects and destructive sampling to establish relationships between plant physiology and spectral responses. Moreover, alternative spectral sensors and analysis methods may yield more compelling results. This study was limited to the use of NDVI, however alternative sensors (e.g. Micasense RedEdge MX Blue, hyperspectral sensors and LiDAR sensors to measure structure) and analysis techniques may be able to contribute to lignum extent and monitoring.

Whilst it was possible to upscale a drone image to resemble/simulate a Sentinel-2 image the low percent of lignum cover (largely less than 10% based on the Central lignum site used in the analysis) meant it was not possible using fractional cover techniques, to produce reliable outputs that express lignum cover at the Sentinel-2 pixel level with any confidence. It was however possible to get similar condition results based on mean NDVI values at the aggregated site level.

The above relates to lignum and floodplain area. In relation to riparian vegetation 'corridor' mapping of the River Murray channel, both RGB and multispectral imagery demonstrated the ability to detect understorey vegetation in a riparian system using oblique image capture. Generally, due to the projection plane and the position in the landscape, common reed (*Phragmites australis*) was most easily detected among non-woody riparian vegetation communities. The need for geo-tags in images was noted. While some of the methodology tested did not have geo-tags, new software is emerging which will cover this gap.

Table of Contents

Executive Summary and Areas for Further Investigation	ii
1 Introduction.....	1
Project Brief.....	1
Background and Context	2
2 Project Objectives.....	5
Workstream 1: Floodplain component	5
Workstream 2: Riparian Vegetation	6
Workstream 3: Occurrence Database.....	6
3 Methodology	7
Location of Field Sites	7
Assessment of Vegetation Condition	8
Floodplain condition monitoring using drones.....	8
Drone imagery capture.....	9
Ground-based field surveys	10
Data processing and preparation	10
Platform and sensor comparison.....	10
Broad-scale condition monitoring	11
Riparian Vegetation	13
Lignum Occurrence Database	13
Sentinel-2 condition and extent assessment.....	13
Condition and Extent.....	13
Fractional cover.....	13
4 Results and Findings.....	15
Drone data summary	15
Platform comparison and timeseries analysis.....	20
Broad-Scale Condition Monitoring and Comparison with Additional Lines of Evidence.....	26
Sentinel/drone comparison summary	28
Fractional cover.....	30
Lignum occurrence database	32
5 Discussion.....	34
Machine learning classification	35
Condition classification and learnings.....	36
Sentinel-2.....	36
Oblique Imagery.....	36
6 Summary and Future Assessment	37
7 References	39
Annex 1: Background information on Lignum.....	40

Annex 2: Classification of riparian vegetation using remote sensing and drone imagery	43
Annex 3: Oblique imaging of riparian vegetation	50
Annex 4: Archival multi-spectral imagery comparison	54

List of Figures

Figure 1 Hydrological connectivity and flows (Source: MDBA, 2019b)	2
Figure 2 Structural groups of Basin river and floodplain vegetation, their location on the floodplain and required watering frequency. (Source: MDBA, 2019b)	3
Figure 3 Workflow for lignum and non-woody vegetation monitoring tools project.....	6
Figure 4 Study area location	7
Figure 5 Study area map showing four sites utilised for high-resolution drone image capture and field surveys	8
Figure 6 Sample ground control points for a) high resolution RGB imagery and b) moderate resolution RGB imagery	9
Figure 7 Parrot Sequoia specifications reflectance and wavelength	12
Figure 8 Micasense RedEdge MX wavelength specifications – reflectance and wavelength	12
Figure 9 Sentinel-2 Wavelength specifications	14
Figure 10 Example of imagery and image products	17
Figure 11 NDVI and Greenness cluster by Vigour Score.....	18
Figure 12 Heatmap of NDVI central lignum	18
Figure 13 Box plots by greenness bin	19
Figure 14 Correlation between Greenness Score and NDVI central lignum a) Pearson and b) Loess method	19
Figure 15 RGB a) University of Adelaide and b) SA Water.....	20
Figure 16 NDVI a) University of Adelaide and b) SA Water	20
<i>Figure 17 Zonal stats processing engine at individual bush level – 25 cm radius</i>	<i>21</i>
<i>Figure 18 Zonal stats processing engine at individual bush level – 50 cm radius</i>	<i>21</i>
Figure 19 Illustration of overhead versus horizontal view of lignum, presence of active ground cover understory and spindly bushes	22
Figure 20 QQ Plot, buffer size and platform	22
Figure 21 Stacked QQ Plot, buffer size and platform.....	23
Figure 22 Box plot comparison greenness, NDVI and platform	23
Figure 23 NDVI and Greenness score clustered by vigour class	24
Figure 24 Time-series output by date	24
<i>Figure 25 Q-Q (quantile-quantile) plot for four separate capture dates.....</i>	<i>25</i>
Figure 26 central lignum mean NDVI, Loess smoothed regression and individual flag ids .	25
Figure 27 Image dates, mean NDVI timeseries, daily and rolling 90-day average rainfall...	26
Figure 28 Wetland Insights Tool (WITs) output for area covering the central lignum site....	27

Figure 29 Sentinel-2 and Drone-simulated band characteristics.....	28
Figure 30 NDVI, Greenness and Vigour Score – central lignum a) Sentinel-2 and b) Drone-simulated Sentinel-2	28
<i>Figure 31 Box plot comparison greenness, NDVI and platform</i>	<i>29</i>
Figure 32 Heatmap of NDVI and Greenness score a) Sentinel-2 and b) Drone-simulated Sentinel-2.....	29
Figure 33 Manually digitised tree (green) and lignum (yellow).....	30
Figure 34 Red- Lignum, Green -Tree, Blue – Bare ground/other	30
Figure 35 Fractional cover histograms for 2 and 15 ha locations.....	31
Figure 36 Estimate of cover based on manual digitising.....	31
Figure 37 National ALA distribution of various Lignum species. (Accessed 15 April 2021). 32	
Figure 38 Healthy lignum in flower on Chowilla floodplain in response to heavy spring rains in October 2005 (Photo A Jensen)	40
Figure 39 Male (left) and female (right) flowers of lignum, showing the distinctive extruding anthers of the male flower and star-shaped, low-set female flower (Automontage images A Jensen).....	41
<i>Figure 40 a, b, c and d. Examples of condition and vigour</i>	<i>42</i>
Figure 41 Classification output	48
<i>Figure 42 An area within the ortho-mosaic from the ‘shallow lake’ site, displaying a best-case</i>	<i>51</i>
<i>Figure 43 An area from the ‘shallow lake’ site, displaying a much more complex vegetation structure than Figure 42</i>	<i>51</i>
Figure 44 A segment of the riparian vegetation along the Murray River. The complex vegetation structure in both the overstory and understory contribute to warping in the ortho-mosaic. Top: RGB; Bottom: True colour multispectral composite	52
Figure 45 Scatter plot and regression - UoA and SAWater NDVI comparison	55

List of Tables

Table 1 UoA Flight parameters and coverage for all floodplain monitoring datasets*	9
Table 2 SA Water and UoA sensor comparison	11
Table 3 Summary of data captured at each site location	15
Table 4. Occurrence of lignum species by jurisdiction	32
Table 5 Duma florulenta occurrence within MDB.....	33
Table 6 Duma florulenta occurrence by ANAE system based on MDB ANAE Ver 3.0 dataset	33
Table 7 Southgate Condition Index (Southgate 1988) and Vigour scores (Jensen 2008)41	
Table 8. Summary of key findings from relevant research papers utilising drone-derived vegetation classification, including data type collected, image classification techniques implemented and reported accuracies of those classifications	45
Table 9. Classification reference data and accuracy assessment	49
Table 10. Sensor specification comparison	54

1 Introduction

Project Brief

Broad-scale measurement and monitoring of native floodplain shrubland, specifically lignum, and other non-woody riparian vegetation is currently limited or non-existent across the Murray-Darling Basin (MDB). However, these important water-dependent vegetation types are key indicators of the MDB Plan and relate to the Native Vegetation Theme of the Basin-wide Environmental Watering Strategy (BWS) (MDBA 2019a and b). This strategy is a key component of the adaptive management of environmental water to achieve Basin outcomes.

The outcomes of the most recent review of the BWS provided four related recommendations that need to be addressed (MDBA 2019b):

- Increase the specificity and measurability of lignum expected environmental outcomes (QEO), where possible;
- Specify an extent baseline for lignum shrublands;
- Explore options for describing the measures of condition for lignum shrublands, and quantifying these in relation to baseline data; and
- Increase the specificity and measurability of non-woody vegetation expected environmental outcomes, where possible.

In response to the above recommendations, this project offered a unique and innovative capability and opportunity to undertake an exploratory assessment of this novel methodology for monitoring non-woody vegetation in the MBD. While the primary focus was lignum, the projected aims included the common reed and other non-woody riverine species.

The project explored the application and utility of unmanned 'drones' and Sentinel-2 (10 m) imagery by assessing:

- extent and condition of lignum stands (and understory vegetation) on Clarks Floodplain between Berri and Loxton in South Australia, based on remote sensing imagery, expert interpretation, field validation and GIS analysis of ground-truthed data
- riparian vegetation 'corridor' mapping of the River Murray channel, and
- potential application and utility across the whole of the MDB and beyond.

Background and Context

The Murray-Darling Basin (MDB) is the largest river basin in Australia, covering more than one million square kilometres (or 14%) of Australia. It spans five States and Territories including Queensland, New South Wales, the Australian Capital Territory, Victoria and South Australia. The distribution, extent and condition of native vegetation over large areas of the MDB have been transformed significantly compared to pre-European status, with major changes to river flows and management of floodplain areas and wetlands for grazing, agriculture and forestry.

The extraction and regulation of water for consumptive use (human, irrigation and livestock needs), and the use of structures such as dams and weirs to facilitate a more reliable water supply have the collective effect of changing the pattern of river flows and frequency of floodplain and wetland water regimes. Coupled with climate change impacts in many areas throughout the Basin, this has resulted in decreased frequency, magnitude or duration of flows – especially as they relate to overbank flows and seasonality of flow resulting in higher summer flows compared to natural conditions. (MDBA 2019a).

It has also impacted river connectivity with the adjoining floodplain both longitudinally and laterally, as illustrated in Figure 1.

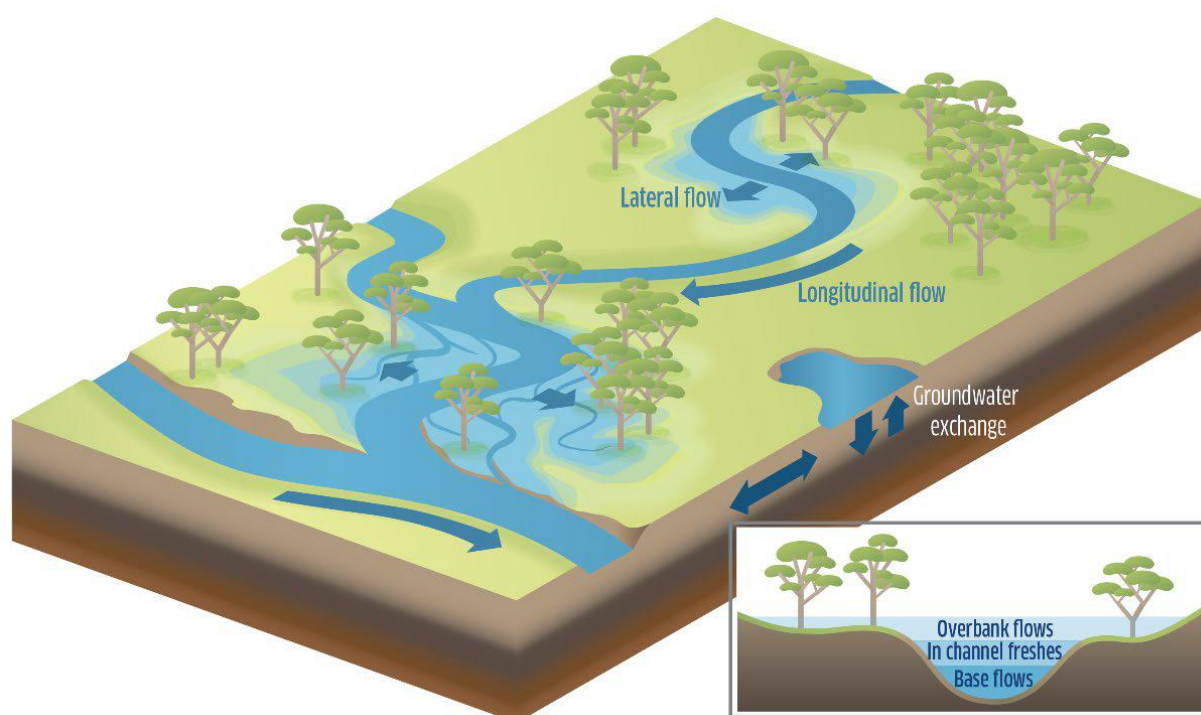


Figure 1 Hydrological connectivity and flows (Source: MDBA, 2019b)

The MDB contains numerous water-dependent ecosystems of international significance, listed under the Ramsar convention, and in various other international agreements for migratory waterbirds. Such water-dependent ecosystems also have important cultural value and significance. Of relevance to this project, the decline in the extent and condition of floodplain vegetation accelerated noticeably between 1990 and 2013 (Cunningham et al. 2013). Much of the change in condition was attributed to the lack of flooding as a result of reduced inflows. The restoration, maintenance and monitoring of these floodplain ecosystems, including the use of strategic environmental watering, has become a high priority for the Murray-Darling Basin Authority (MDBA) and Basin States and Territories. To this end, the Authority's 'Basin-wide Environmental Watering Strategy' provides the science-

policy context for establishing a long-term adaptive monitoring and management framework (MDBA 2019b).

Monitoring changes in the extent and condition of native vegetation (i.e. assets) in the short, medium and long-term is an accepted priority for natural resource management agencies in Australia and elsewhere. Condition information is needed to assess:

- which vegetation types and floodplains are in poor condition and require additional environmental watering,
- which vegetation types and respective condition states respond to the addition of environmental watering (expected ecological response),
- how much environmental water is sufficient to maintain vegetation in good condition over the longer term.

The Native Vegetation Theme within the BWS identifies four structural groups, namely, forests, woodland, shrubland and non-woody vegetation. In this context, native floodplain shrubland and non-woody vegetation are key water-dependent habitats within the Basin and form important indicators of floodplain health. The anticipated outcomes from the BWS (MDBA 2019b) for shrubland vegetation are as follows:

- to maintain the current extent of extensive lignum shrubland areas within the Basin
- by 2024, improvement in the condition of lignum shrublands.

Lignum, along with rushes, reeds, sedges and grasses fall within the shrubland and non-woody vegetation categories and occur on floodplains and riparian zones (Figure 2).

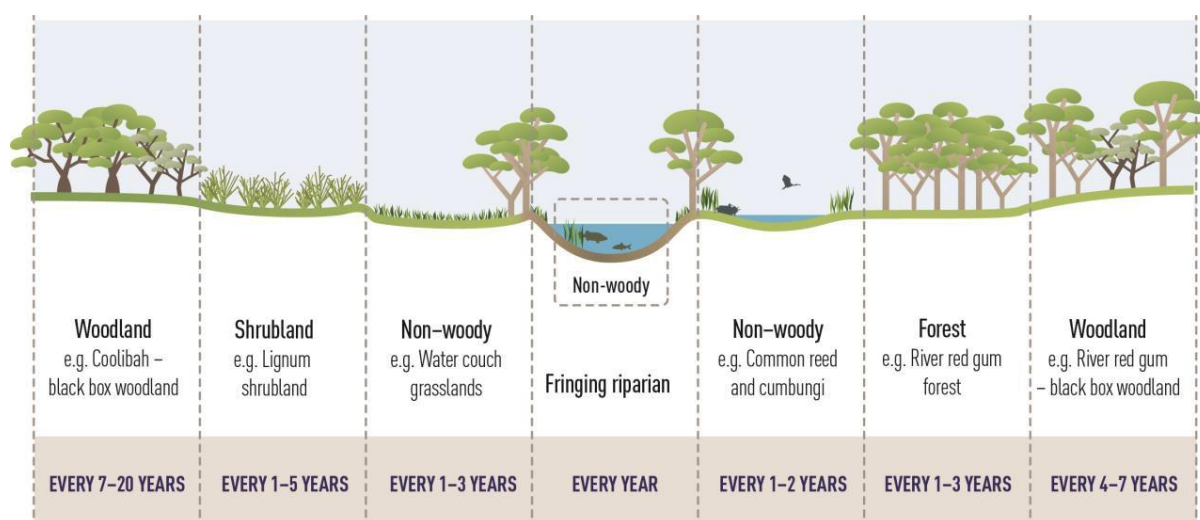


Figure 2 Structural groups of Basin river and floodplain vegetation, their location on the floodplain and required watering frequency. (Source: MDBA, 2019b)

The broad-scale measurement and monitoring of these habitats is currently limited (or non-existent) across the Basin. By contrast, methods for mapping the extent and distribution of forest and woodland vegetation types are well developed and underpin each State and Territories vegetation information systems and mapping programs (Thackway and Auricht, 2015).

To date, there has been significant investment in developing a *Stand Condition Tool* to monitor and assess floodplain forest and woodland trees within the Basin using satellite data and GIS (i.e. specifically red gum, black box and coolibah). However, the resolution of the Landsat imagery used in this methodology, whilst suitable for assessing overstorey trees, is

too coarse (30 m) to be of value for assessing shrubland and non-woody vegetation associated with floodplains and riparian habitats.

In order to develop operational methodologies applicable at broad scales, there is a need to explore the efficacy and value of using other forms of spectral imagery (e.g. drones and Sentinel-2 imagery) and their ability to assess shrubland (lignum) and riparian non-woody vegetation (e.g. reeds, sedges, etc.) on the floodplain and at the water-land interface.

This project seeks to address this gap.

2 Project Objectives

Following the initial phases of inception, clarification, consultation and collation of existing imagery and data, the project aimed to undertake activities based on three main work streams.

Workstream 1: Floodplain component

This component aimed to collaboratively explore the efficacy of using satellite imagery of a finer resolution with Geoscience Australia (GA; i.e. Sentinel-2; 10 m resolution) to map lignum extent and condition. The aim was to complement the existing imagery with:

- additional high-resolution NIR/RGB drone imagery captured at the site in South Australia in August and September 2021 performed by the University of Adelaide (UoA)
- analysis of Sentinel-2 data
- expert interpretation of drone imagery, field validation, and GIS analysis of ground-truthed data.

The drone imagery component involved:

- field work and drone flights over the floodplain. To the extent possible, this included sites where lignum occurred a) under red gum or black box overstorey, b) as part of the complex shrubland understory without overstorey, c) as a homogenous shrubland habitat
- assessment of nadir image capture along established transects (RGB and multispectral)
- investigation of feasibility of extraction of vegetation structure through image interpretation and classification, ground truthing and accuracy assessment (including comparison the GA's WIT based on Fractional Cover, Tasseled Cap Wetness and Water Observation from Space (WOfS) information products).

The remote sensing component of the work program also aimed in investigate the fusion of the drone and Sentinel-2 data, analysis of data from a Jupyter Notebook, and initial processing of data from the nadir images of the floodplain. Data from multiple sources, including Sentinel-2 time series, NDVI and GA's WIT products were to be explored to assess the feasibility of generating structural and vegetation species classifications.

The workflow is outlined in Figure 3.

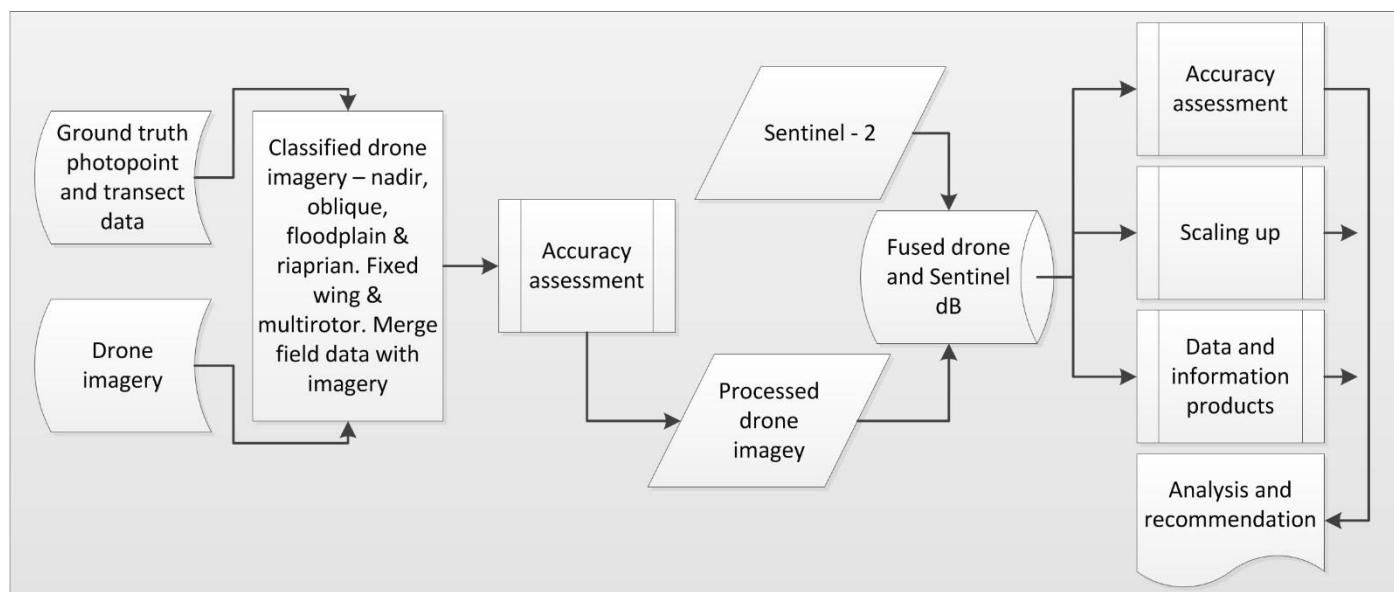


Figure 3 Workflow for lignum and non-woody vegetation monitoring tools project

Workstream 2: Riparian Vegetation

The river corridor non-woody vegetation component aimed to make use of the SA Water drone imagery for the MDBA Riparian and Assets programs. It offers a technique for 'corridor mapping' in 100-200 m band widths using a drone. This technique has been successfully used around the 40 km edge of Lake Victoria by SA Water. This component of the project explored the practical application of the drone corridor mapping technique for imaging non-woody riparian vegetation at the channel edge (water-land interface) for Clarks Floodplain near Lock 4 in South Australia. The use of a novel approach in using oblique (off-nadir) drone capture was also assessed as part of this component.¹

Workstream 3: Occurrence Database

Various records were collated for the preliminary development of a national lignum occurrence database, including lignum occurrence and distribution records throughout the MDB.

¹ The capture of oblique imagery requires a multi-rotor drone which was supplied by the University of Adelaide's Unmanned Research Aircraft Facility.

3 Methodology

Location of Field Sites

Clarks Floodplain is on the east bank of the River Murray, downstream of Weir and Lock No.4 at Bookpurnong, approximately 11 km north of Loxton and 6.5km south of Berri (Figure 4; Nature Foundation 2021). It lies at 505-515 km river distance from the Murray Mouth, in a river reach typified by extensive meanders and sand bars. This 271-ha floodplain complex is opposite the Murray River National Park (Katarapko Island).

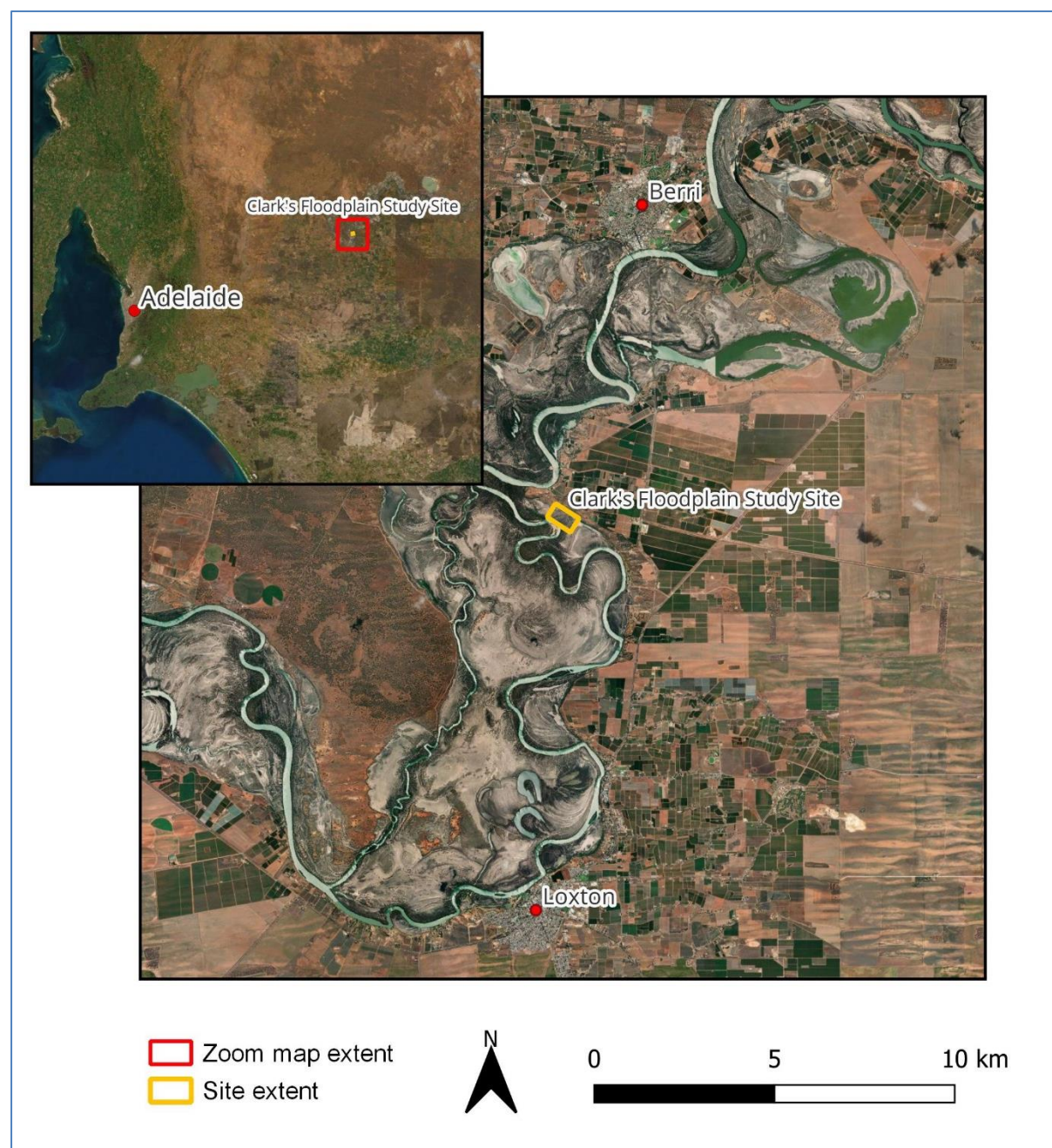


Figure 4 Study area location. Small inset map shows the location in relation to Adelaide. The larger map shows the location of the study area (yellow box) in relation to Berri and Loxton in the SA Riverland

Clarks Floodplain complex unusually incorporates four tight meander bends which creates a series of three sandy peninsulas with good connectivity between groundwater tables and the river mainstream. At higher elevations, the clay floodplain is bisected by several flood-runners and incised channels which allow flood flows to spread across the site.

Key vegetation communities are river red gum (*Eucalyptus camaldulensis*) forest and woodland, black box (*Eucalyptus largiflorens*) woodland and lignum (*Duma florulenta*) shrubland, which remain stressed as a result of the Millennium Drought and recent very dry years 2017-2020. There are significant gaps in age classes in vegetation communities through the Lower Murray, so it is a priority to sustain any germination events. The recommended environmental watering regime is designed to sustain to reproductive age the mass germination of river red gum and black box seedlings germinated at the peak of the 2010-12 floods. The Clarks Floodplain site includes one of few Riverland locations with surviving 1990s black box trees, so the survival of the 2011 cohort of black box saplings is of special value.

Assessment of Vegetation Condition

Background information on lignum and best practice in lignum monitoring is presented in Annex 1.

The following methodologies were applied within the major workstreams:

- Floodplain condition using drones (including platform comparison and the potential application of Sentinel-2 in determining lignum extent and condition)
- Assessment of riverine vegetation using oblique drone imagery, and
- Lignum occurrence database.

Floodplain condition monitoring using drones

Drone imagery and field vegetation surveys were performed at the Clarks Floodplain site between 31 August – 1 September 2021 (Figure 5).

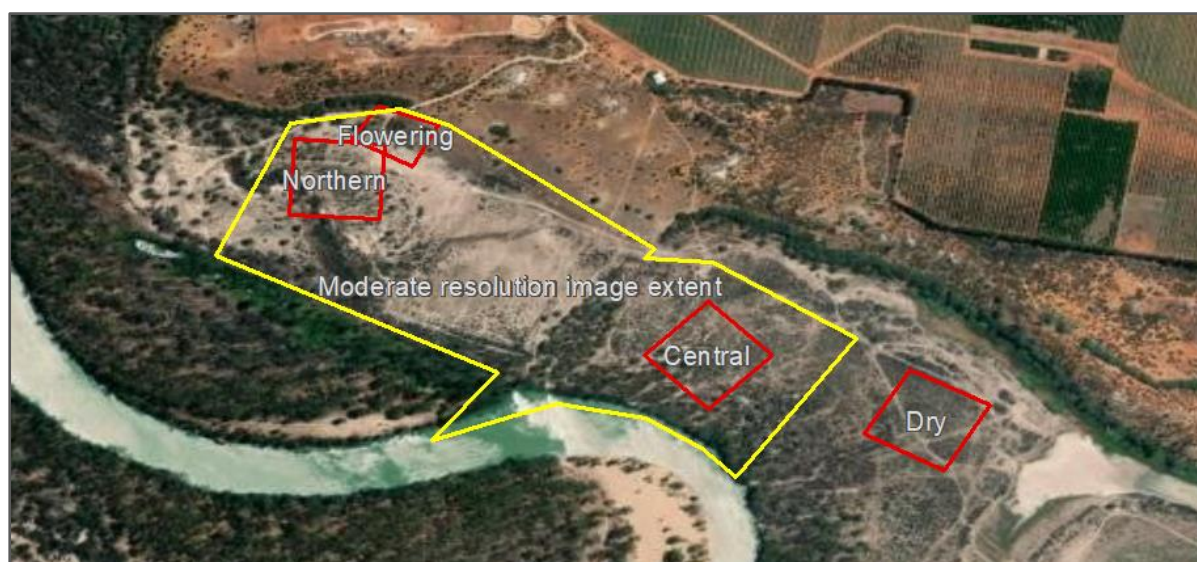


Figure 5 Study area map showing four sites utilised for high-resolution drone image capture and field surveys: Northern, Flowering, Central and Dry (red boxes). Also shown is mapping extent of moderate resolution drone image capture (yellow polygon). Approximate scale 1:15,000.

Drone imagery capture

High resolution red, green, blue (RGB) and multispectral imagery were collected over four site locations ('Northern', 'Flowering', 'Central' and 'Dry') within the study area (Figure 5). RGB and multispectral sensors were deployed simultaneously at a constant mapping altitude of 35 m above ground level (AGL) to obtain nominal pixel resolutions of approximately 0.6cm for RGB imagery and 2.8cm for multispectral (Table 1). The imagery was collected immediately following the completion of the ground-based field surveys for those sites. Moderate resolution imagery was also collected with both sensors deployed at 120 m AGL to provide increased coverage at a lower resolution of 2 cm per pixel for RGB and 9 cm for multispectral. Coverage extended across and between Central, Northern and Flowering Plots (Figure 5). Ground control points (GCPs) were distributed across the sites being mapped to enable co-registration of high and moderate resolution imagery (Figure 6).



Figure 6 Sample ground control points for a) high resolution RGB imagery and b) moderate resolution RGB imagery

Table 1 UoA Flight parameters and coverage for all floodplain monitoring datasets*

Site	Date	Area (ha)	Altitude (m)	Sensor**	Approx. GSD (cm)
Central	31-Aug	2.25	35	RGB	0.6
				Multispectral	2.8
Northern	31-Aug	2.25	35	RGB	0.6
				Multispectral	2.8
Dry	1-Sep	2.21	35	RGB	0.6
				Multispectral	2.8
Flowering	31-Aug	0.92	35	RGB	0.6
				Multispectral	2.8
Moderate Resolution (incl. Central, Northern, Flowering sites)	31-Aug / 1-Sep	36.20	120	RGB	2.0
				Multispectral	8.9
* All flights were flown with overlap of 75% and sidelap of 75%.					
** Technical specification for sensor wavelenaths are presented in Table 3 and Annex 3					

Ground-based field surveys

Ground-based field surveys were conducted across the same four sites ('Northern', 'Flowering', 'Central' and 'Dry') within the study area (Figure 5). The individual lignum plants identified for scoring were selected (where possible) using the following criteria: 1) maintaining even coverage across the site, 2) maintaining minimum 10 m distance between any other surveyed plant, 3) characterise site variability as much as practicable.

Prior to image acquisition, coloured tags were placed next to individual lignum plants. The tags are visible in the drone imagery and were subsequently used to identify individual plants that were scored by an expert on the ground. Greenness, number of leaves, number of flowers and a vigour score were recorded for each lignum individual marked with a tag. Each tag ID location was also recorded as a waypoint related to the field data sheet.

Data processing and preparation

The RGB and multispectral imagery was processed in Pix4D Mapper Pro to generate geo-rectified ortho-mosaics suitable to be imported for spatial analyses in a geographic information system (GIS). The processing techniques and outputs are similar to those for conventional aerial imaging surveys.

The multispectral imagery was processed to represent reflectance for each band using a calibration reflectance panel and downwelling sensor. Reflectance values range from 0 -1 and is the ratio between the reflected light from the surface and the incident light. Normalised Difference Vegetation Index (NDVI) products were computed using the red and near infrared bands for both high and moderate resolution multispectral image.

The surveyed lignum were identified in the RGB imagery using the handheld GPS coordinates and the coloured pin markers and related to the ground survey scores. Circular 50cm diameter polygons were placed at the approximate centre point of the plant², and the unique identifier was used to join the polygon to the field survey observations. Mean NDVI pixel values within each polygon were computed for each plant. Regression, correlation, box plot and heatmap analysis was used to compare drone derived NDVI values with greenness scores measured on the ground.

Platform and sensor comparison

The Assets monitoring program of the MDBA has a time series of three years' summer and winter multispectral (15 cm resolution) drone imagery (and complementary video transects) covering Clarks Floodplain, collected as part of the Salt Interception Scheme program. These datasets were captured by a 'Parrot Sequoia SenseFly eBee Plus' fixed wing drone capable of horizontal positional accuracy of +/- 4cm.

Geoscience Australia provided access to Sentinel 2 imagery within their Digital Earth Australia (DEA) platform, and also their fractional cover and Wetlands Insights Tool (WIT), which were collated along with 'geo-rectified .tif' drone imagery files from various MDBA monitoring programs e.g. the Assets and Riparian Programs. In combination with expert field validation and expert image interpretation, these datasets were used to help ground-truth the Sentinel 2 data and determine its efficacy for mapping lignum extent and condition.

Other data included the consultant team's extensive (20 years) field survey data collection and application-ready climate and flow data (e.g. daily temperature, rainfall and flow data). This component also explored the application and utility of SA Water's fixed winged drone (equipped with a Sequoia Camera) and the University of Adelaide's multirotor drone equipped with a high resolution RGB and Multispectral cameras in assessing lignum condition.

² A 100 cm polygon was also processed for the Central Lignum site to compare outputs between different geo-processing platforms e.g. ArcGIS compared to R Studio+

Observation of the sensor wavelength specifications revealed similarities in respect of various bands, thereby indicating it may be possible to undertake a platform comparison (Table 2 and Figures 7 and 8).

The actual comparison of sensors was based on the acquisition of the University of Adelaide (UoA) multi-rotor High-Resolution drone imagery fine (sub-centimetre) and medium (2-3 centimetre) resolution imagery (captured between 31 Aug and 1 September 2022), relative to the outputs of the courser 15cm SA Water Parrot Sequoia SenseFly fixed-wing imagery acquired on 19 August 2022.

The method involved processing similar statistics and plots for the SA Water multispectral normalized difference vegetation index (NDVI)³ outputs and comparing them with the UoA multispectral NDVI outputs for the same area (See also Annex 4).

A series of quality assessments comparing the results of various zonal statistics engines were also carried out in order to provide additional rigour and understanding.

Broad-scale condition monitoring

On the basis that the comparison between the UoA and SA Water drone outputs mentioned above produced comparable condition outputs, by logical extension it was hypothesised that the NDVI SA Water time-series dataset could be used to provide insights on condition for a broader floodplain area e.g. Central lignum site over time, and also a simple cross-check assessment related to the application and utility of other recently released operational condition type products. For example, Geoscience Australia's Wetland Insight Tool – WITs which identifies fractional percentage of green vegetation, dry vegetation, bare soil and water,⁴ i.e. the relationship between percentage of green vegetation in the WITs output and mean NDVI value from drone imagery.

Table 2 SA Water and UoA sensor comparison

Sensor	Wavelength
RedEdge MX (UoA Multispec) ⁵	Blue (475 nm center, 32 nm bandwidth), Green (560 nm center, 27 nm bandwidth), Red (668 nm center, 14 nm bandwidth), Red edge (717 nm center, 12 nm bandwidth), Near infrared (842 nm center, 57 nm bandwidth)
SenseFly Parrot Sequoia+ SA Water Multipsec ⁶	Green (550nm ± 40nm) Red (660nm ± 40nm) Red edge (735nm ± 10nm) Near infrared (790nm ± 40nm)

³ NDVI is calculated based on the following $NDVI = (NIR - Red) / (NIR + Red)$

⁴ Refer: https://auricht.com/awi/documents/Dunn_et_al_2019.pdf

⁵ <https://micasense.com/rededge-p/>

⁶ <https://www.sensefly.com/camera/parrot-sequoia/>

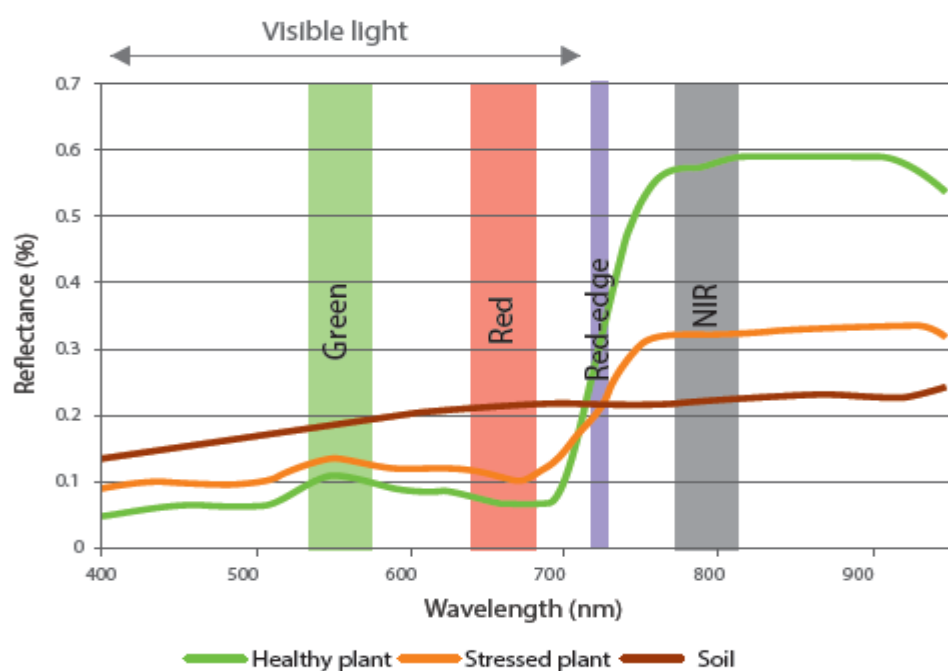


Figure 7 Parrot Sequoia specifications reflectance and wavelength

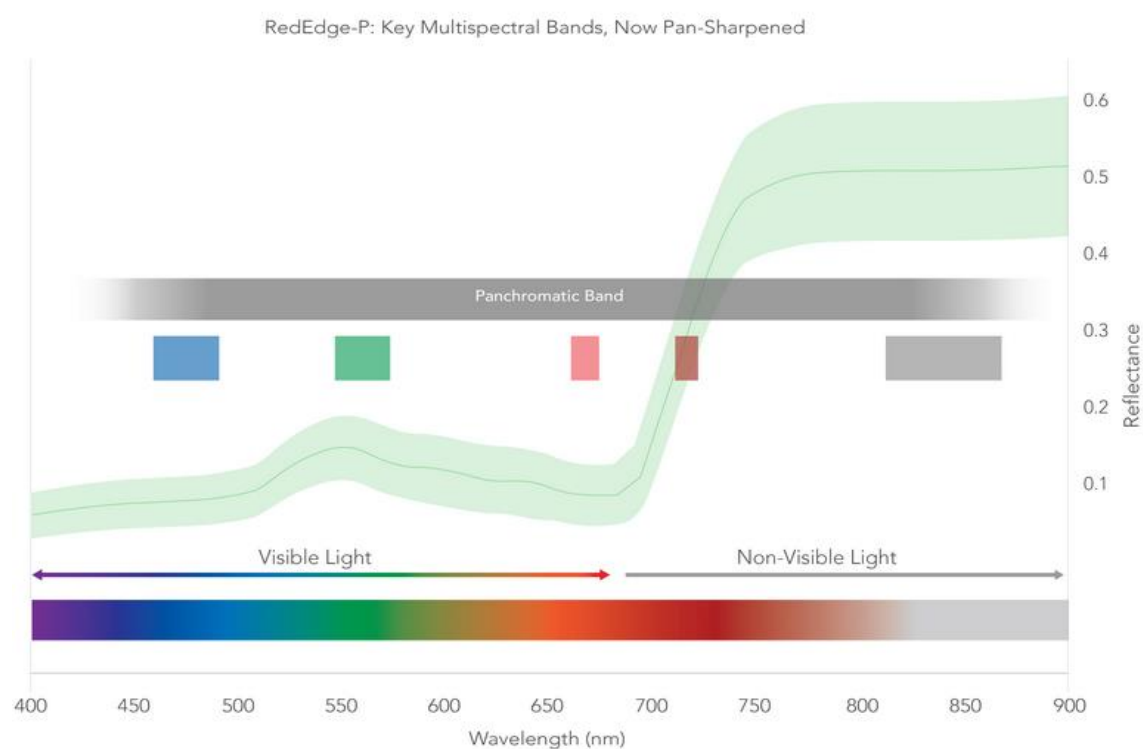


Figure 8 Micasense RedEdge MX wavelength specifications – reflectance and wavelength

Riparian Vegetation

The methodology used by SA Water for corridor mapping involves the use of SenseFly's linear mapping module which reportedly offers up to a 30% reduction in the number of images acquired over a linear area in comparison to other flight management procedures.

The SenseFly technical documentation states that it is fit-for-purpose and streamlines flight planning/post processing for corridors such as roads, rivers, coastlines and lake edges⁷.

On this basis there was no merit in further assessing this method as part of the current project, which instead focussed attention on the novel application of oblique image capture in developing insights into vegetation structure and health along a riparian area. The goal was to investigate the ability to detect understorey vegetation that would normally be obscured by overstorey tree cover under nadir imagery. Refer Annex 2.

Lignum Occurrence Database

This component involved extracting lignum records from the Atlas Living Australia (ALA), generating a spatial layer from coordinate attributes and subsequently stratifying sites into respective State / Territory and north and south MDB regions.

Sentinel-2 condition and extent assessment

Using GA's Digital Earth Australia platform, a Jupyter Notebook was developed to enable an assessment of the capability of Sentinel-2 imagery to support lignum condition and extent monitoring. An annotated copy of Notebook is available at the following GitHub location <https://gist.github.com/prl900/4d32f5b4088c78c963eb406102c7206b>

A summary of Sentinel-2 wavelength specifications is presented in Figure 9.

The methodology involved re-processing University of Adelaide drone imagery to conform to Sentinel-2 specifications as outlined in the following workflow using data from on the Central lignum site:

Condition and Extent

1. Resample the 2.7 cm multispectral drone image to 1 metre
2. Apply Gaussian kernel to simulate Sentinel-2 characteristics
3. Resample above output to 10 metre to align with Sentinel-2 resolution i.e. produce a Drone-based Sentinel-2 image.
4. Load and clean DEA Sentinel-2 image from 24 Aug 2021 (to approximate date of drone imagery)
5. Review DEA Sentinel-2 spectral characteristics
6. Compute histogram comparisons for individual bands (RGB and NIR)
7. Generate NDVI for Sentinel-2 and simulated Drone-based Sentinel-2 imagery
8. Compute statistics and plots based on NDVI and field survey data

Fractional cover

9. Development of an on-line tool to capture tree and lignum area
10. Estimate of percent cover at site level
11. Determination of fractional percent lignum estimate

⁷ Refer: <https://www.sensefly.com/camera/sensefly-corridor/>

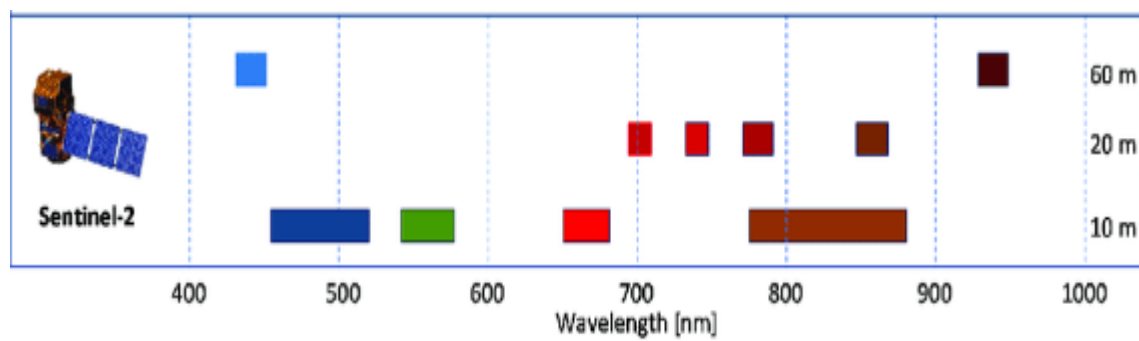


Figure 9 Sentinel-2 Wavelength specifications

4 Results and Findings

Drone data summary

Thirty field survey observations were made at each of the Central and Northern sites, with 28 plants surveyed at the dry site. Only eight observations were made at the Flowering site, as it was an opportunistic site with exceptional greenness and flowering occurring due to local run-off channelled from adjacent high ground (Table 3). With the exception of the Flowering site, all sites were all approximately 2 ha. The Dry site was opportunistically surveyed following successfully surveying of the priority North and Central sites. However, time limitations prevented the opportunity to perform the moderate resolution imaging.

Table 3 Summary of data captured at each site location⁸

Site	Area (Ha)	Observations Made	Observations Used	Mean % Greenness	Mean NDVI (High Res)	Mean NDVI (Low Res)
Central	2.25	30	29	47.41	0.41	0.41
Dry	2.21	28	24	31.67	0.33	-
Flowering	0.92	8	8	56.25	0.54	0.48
Northern	2.25	30	26	24.62	0.36	0.35
Totals	7.63	96	87	37.07	0.39	0.28

Not surprisingly, maximum greenness occurred at the Flowering site, which receives significant additional water from every local rainfall event. The Central site was closer to mature black box woodland which appeared to retain higher soil moisture and the lignum bushes were generally larger, with more growth phases creating a larger 'tangle' mass. The Dry and Northern sites were more exposed and appeared to have relatively drier soil moisture, and bushes tended to be smaller with less dense overall mass. The Flowering and Central sites had the highest mean NDVI, suggesting a correlation between mean NDVI and % greenness at the site scale.

The multispectral imagery at High Resolution (2.8 cm) and Moderate Resolution (8.9 cm) are both comparable for spectral / NDVI analysis. The High Resolution data does offer greater visual detail at the fine scale (Figure 10). Data capture time and volume are considerably greater per unit area for the High Resolution vs Moderate Resolution. The High-Resolution imagery is used for subsequent analysis as it was collected over all ground surveyed sites (the Dry site was opportunistically collected and was not planned for coverage during the earlier Moderate Resolution capture).

A comparison of the field surveyed Greenness Score and mean NDVI values for the polygons over the related lignum was performed. The Greenness Score was binned into 10 percent increments to conform the data to the majority of data values. Mean NDVI values for the related lignum were computed using the High-Resolution 2 ha data.

Using a range of statistical assessment methods e.g. box plot and heatmap analysis etc, a preliminary assessment to determine separation between the groups suggests that although a broad trend of increasing Greenness Score is accompanied by both a higher NDVI value and Vigour Score, the large variance within the majority of the groups indicates that more testing is required to establish meaningful relationships between NDVI values, greenness scores and vigour classes at the individual bush level (Figures 11-14). Figure 11 presents greenness and NDVI values clustered by vigour class and demonstrates the wide range of values within any one vigour class. Further testing should seek to standardise the area to be measured or scored in individual bushes, both by instruments and field observers, since the

⁸ Mean NDVI based on 50 cm diameter buffer for each lignum bush

area of any individual bush is highly variable due to opportunistic growth in response to short term favourable conditions of available soil moisture.

The results of a correlation between Greenness Score and NDVI using both the Pearson and Loess (Local regression) correlation methods further illustrate the variation in Greenness Score and corresponding NDVI value at the individual plant level. However, it also demonstrates a relationship between the overall general increase in NDVI and Greenness Score (Figure 14).

On this basis it was concluded that further testing and refinement of parameters is required to be able to use drone imagery to confidently determine the condition of an individual bush based on NDVI value. A critical factor is the choice of the size of the polygon applied to generate the NDVI at the bush level and bush size. Options for testing groups of bushes rather than individual bushes should be considered, as well as testing groups of bushes by micro-topography and micro-habitats, as these factors influence local water availability, which is a major determinant of bush condition.

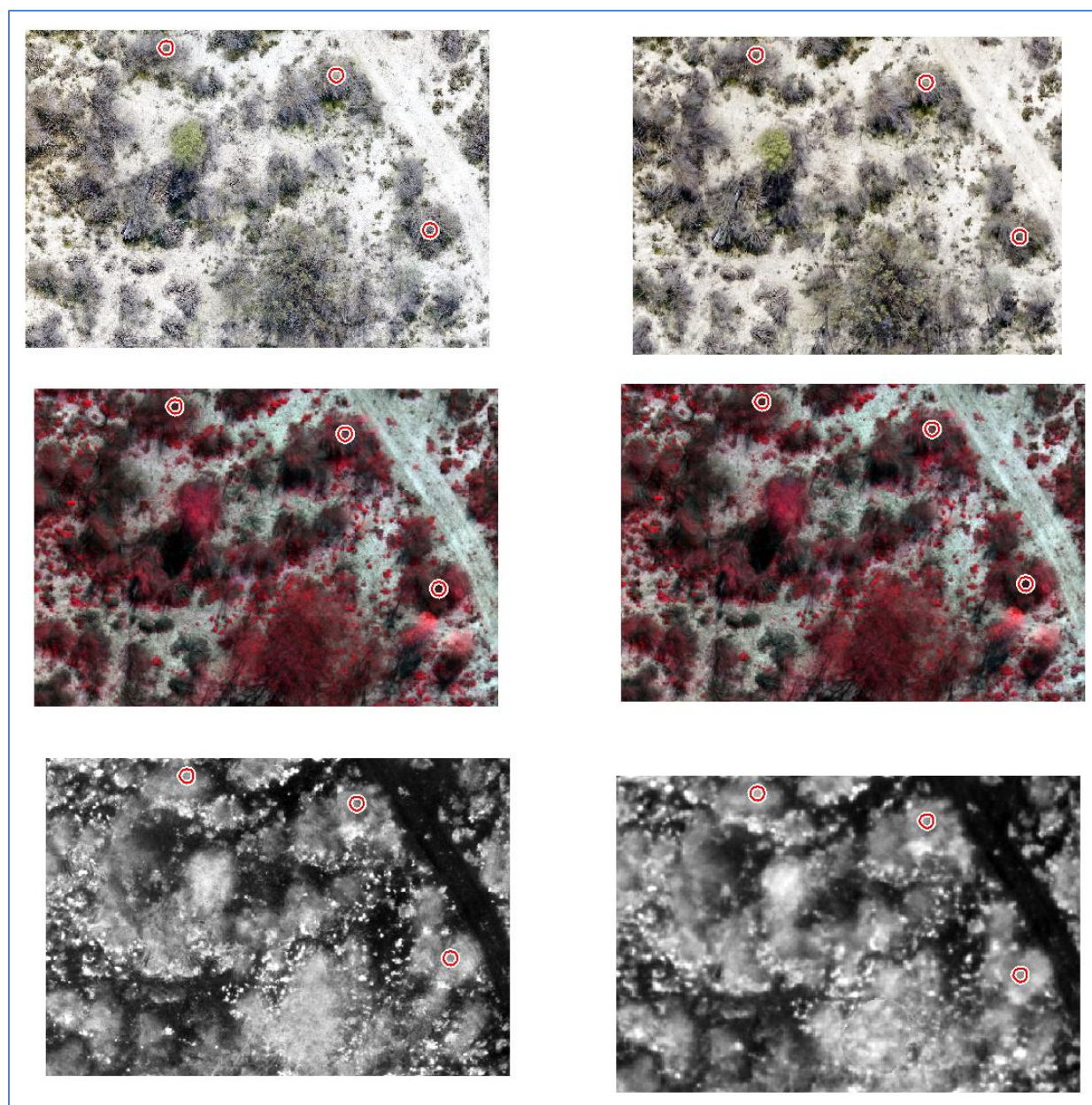


Figure 10 Example of imagery and image products. Left column are outputs from High Resolution imagery, right column are outputs from Moderate Resolution imagery. Top row: RGB imagery. Middle row: multispectral imagery visualised using a false colour band combination. Bottom row: NDVI, in these images greater plant vigour is represented by lighter shades of grey. Red circles in all images are polygons utilised to extract NDVI values from the imagery.

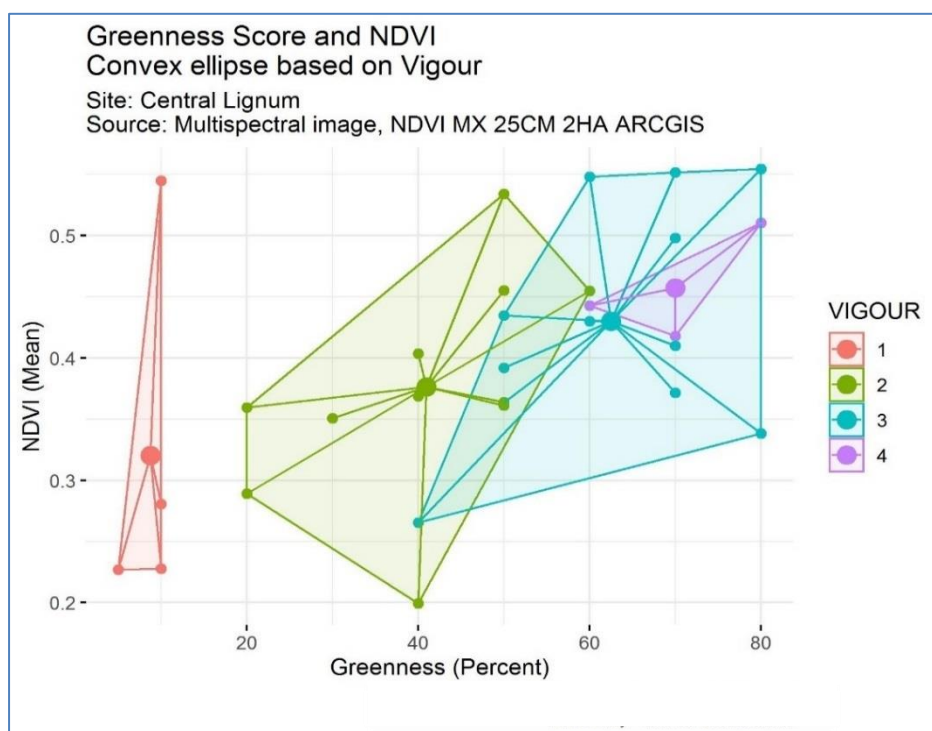


Figure 11 NDVI and Greenness cluster by Vigour Score

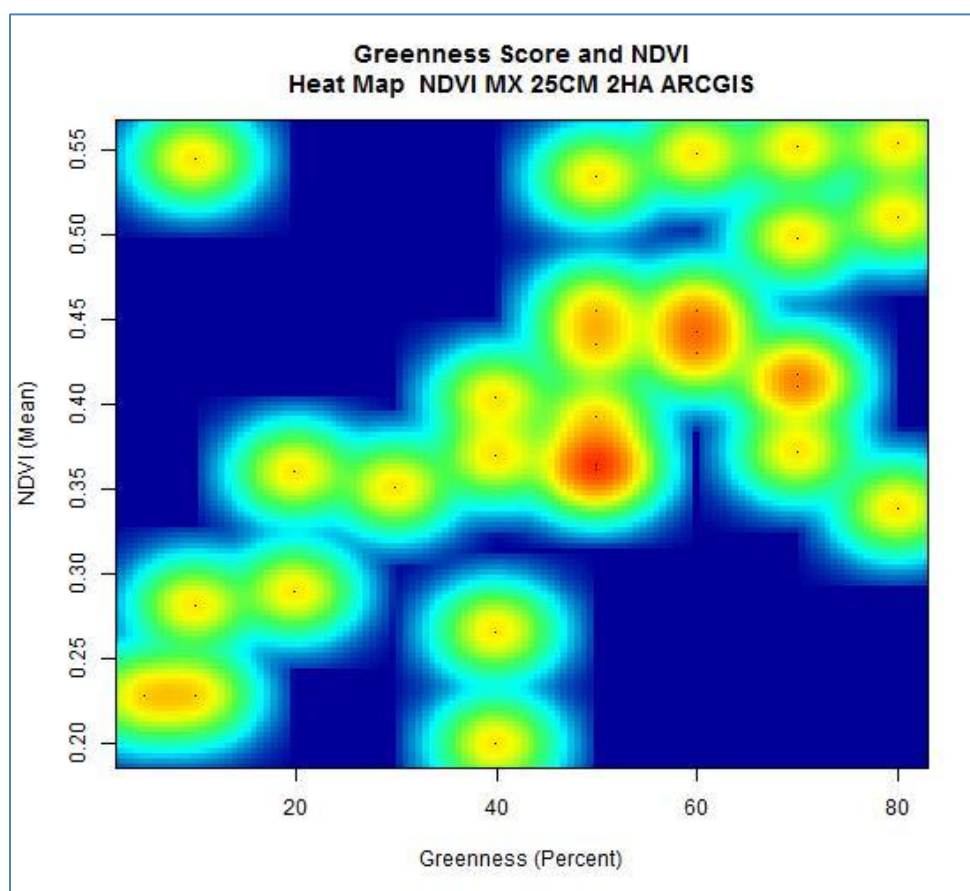


Figure 12 Heatmap of NDVI central lignum

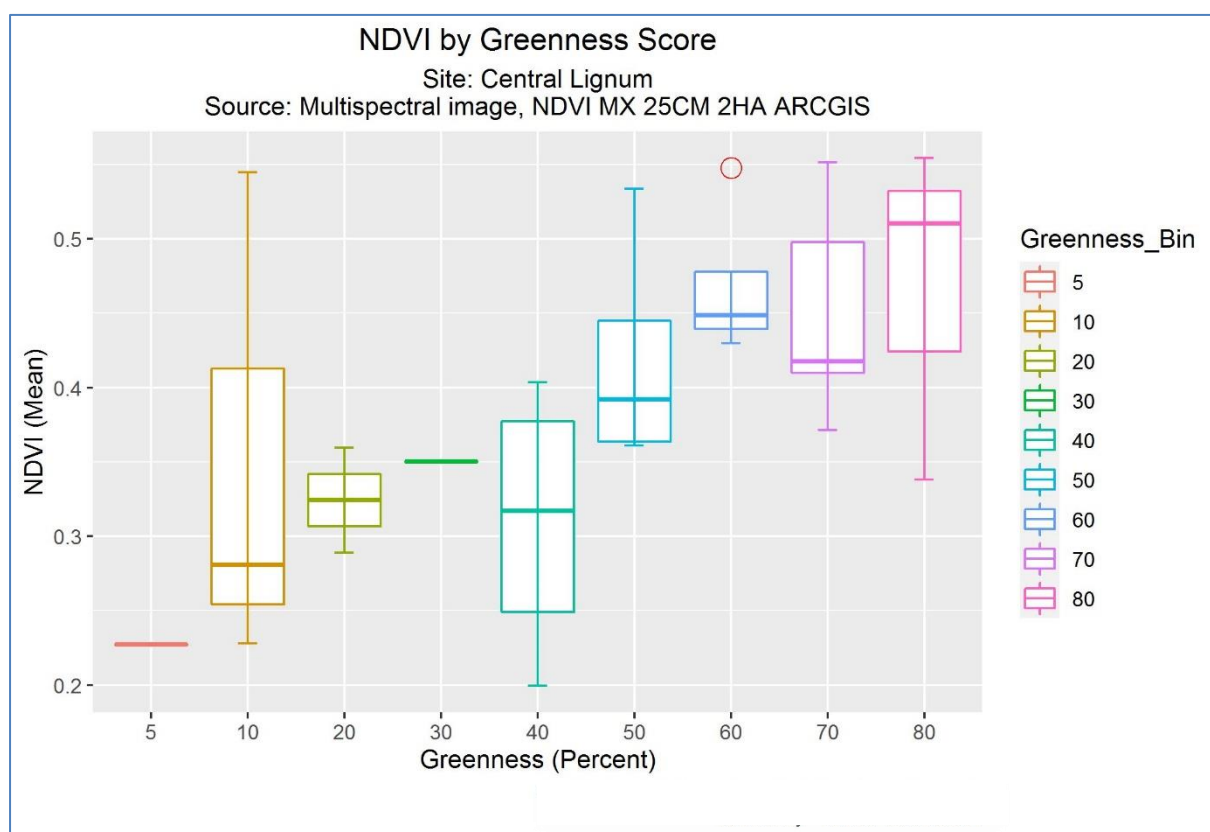


Figure 13 Box plots by greenness bin

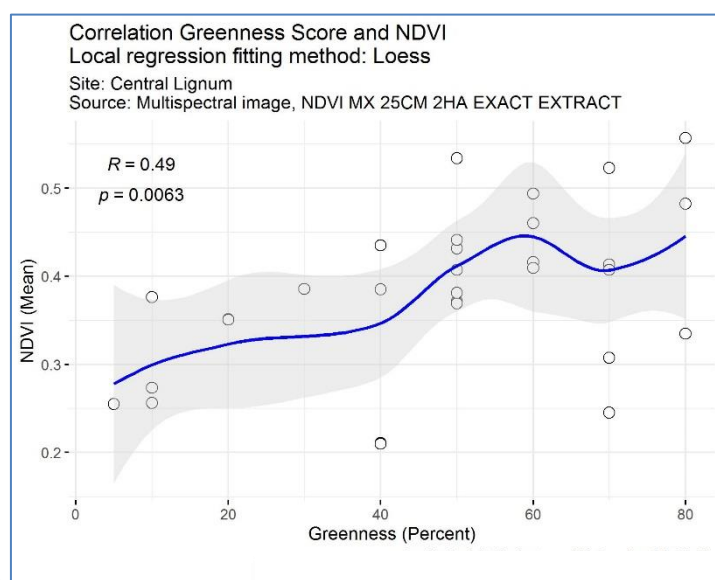
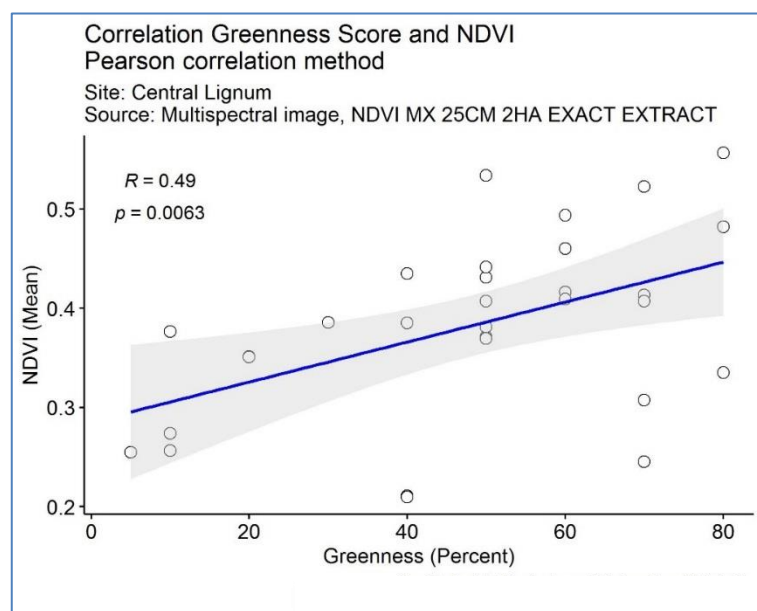


Figure 14 Correlation between Greenness Score and NDVI central lignum a) Pearson and b) Loess method

Platform comparison and timeseries analysis

A visual appreciation of the difference in resolution between the UoA (High-Resolution multirotor drone imagery) and SA Water imagery (Moderate-Resolution fixed wing drone imagery) can be obtained from Figures 15 and 16 with the NDVI outputs clearly illustrating the increased level of detail in the finer resolution data (but also an increase in greenness due to prevailing seasonal conditions).



Figure 15 RGB a) University of Adelaide and b) SA Water

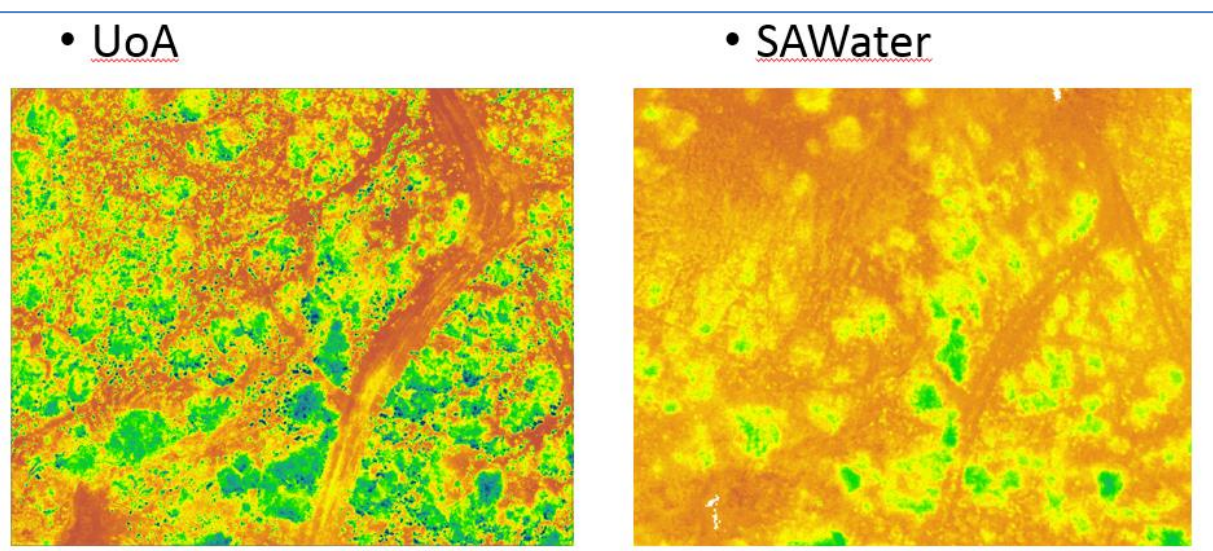


Figure 16 NDVI a) University of Adelaide and b) SA Water

As part of the platform assessment process a comparison of zonal statistics outputs for differing buffer sizes (i.e. 25cm radius / 50 cm diameter and 50 cm radius / 100cm diameter) using a range of processing engines (ArcGIS and R extract and R exact-extract) was undertaken. This demonstrated a difference in outputs for the fine resolution imagery when using a 25 cm radius point buffer, however this was largely removed when using a 50cm radius buffer polygon. This result is an artefact of the way in which each engine processes pixels that fall on the boundary of the polygon- i.e. whether they are included or excluded from the analysis and the resultant impact on the mean NDVI value for the individual lignum bush. Interestingly when considered at the aggregate site level there was no significant difference with all processing engines producing an output within 2% (Figures 17 and 18).

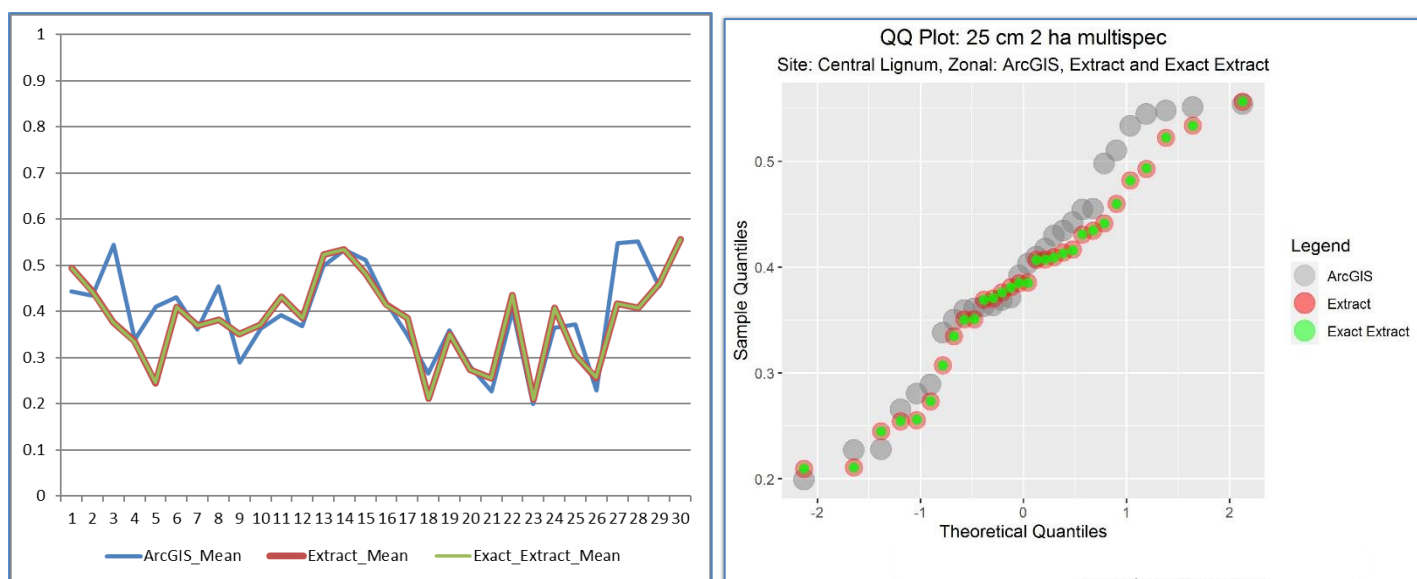


Figure 17 Zonal stats processing engine at individual bush level – 25 cm radius

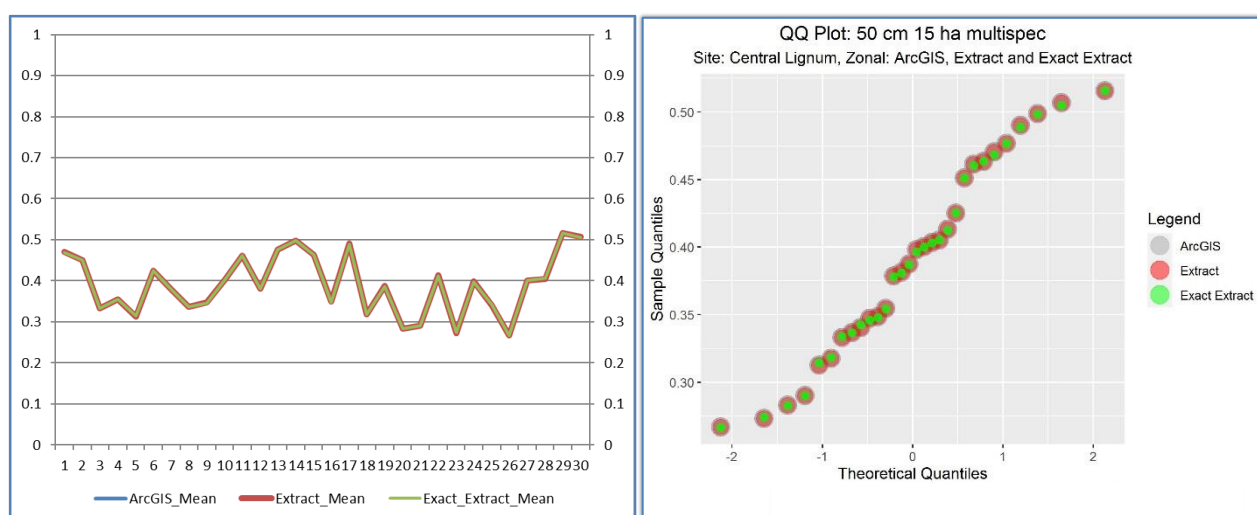


Figure 18 Zonal stats processing engine at individual bush level – 50 cm radius

It should however be noted that a complicating factor exists in that the footprint of many of the lignum bushes recorded in the Dry and Northern sites related to smaller/low density type bushes with only limited cover (Figure 19). This in turn limits the ability of the 50cm radius diameter polygon buffer to reflect actual lignum footprint i.e. small and spindly bushes with a low density coverage results in a 50 cm radius buffer picking up a significant area of bare ground or annual active groundcover plants which in turn has potential to significantly skew results i.e. non-lignum signal.

On this basis, whilst the 50cm radius diameter was appropriate for the Central lignum site (which had a higher percentage of larger bushes), it was not appropriate for the other sites at the individual bush level.

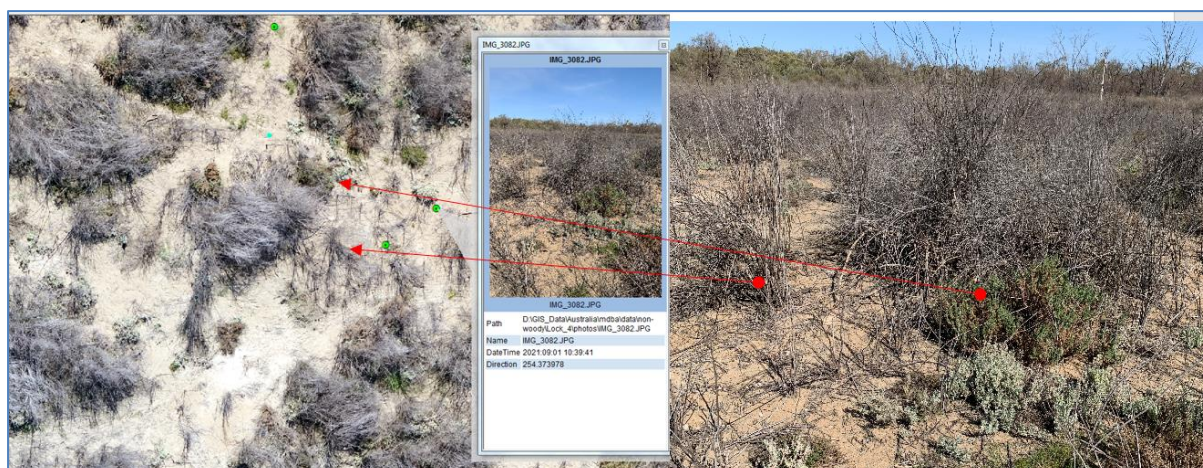


Figure 19 Illustration of overhead versus horizontal view of lignum, presence of active ground cover understory and spindly bushes

Interestingly a comparison between the UoA and SA Water multispectral NDVI imagery resulted in similar results for linear regression, Q-Q (quantile-quantile), and box plots comparing field survey Greenness Scores with NDVI values, where the slightly higher NDVI values of the UoA imagery likely being a result of increased vigour and greenness due to prevailing seasonal conditions (Figures 20-23)

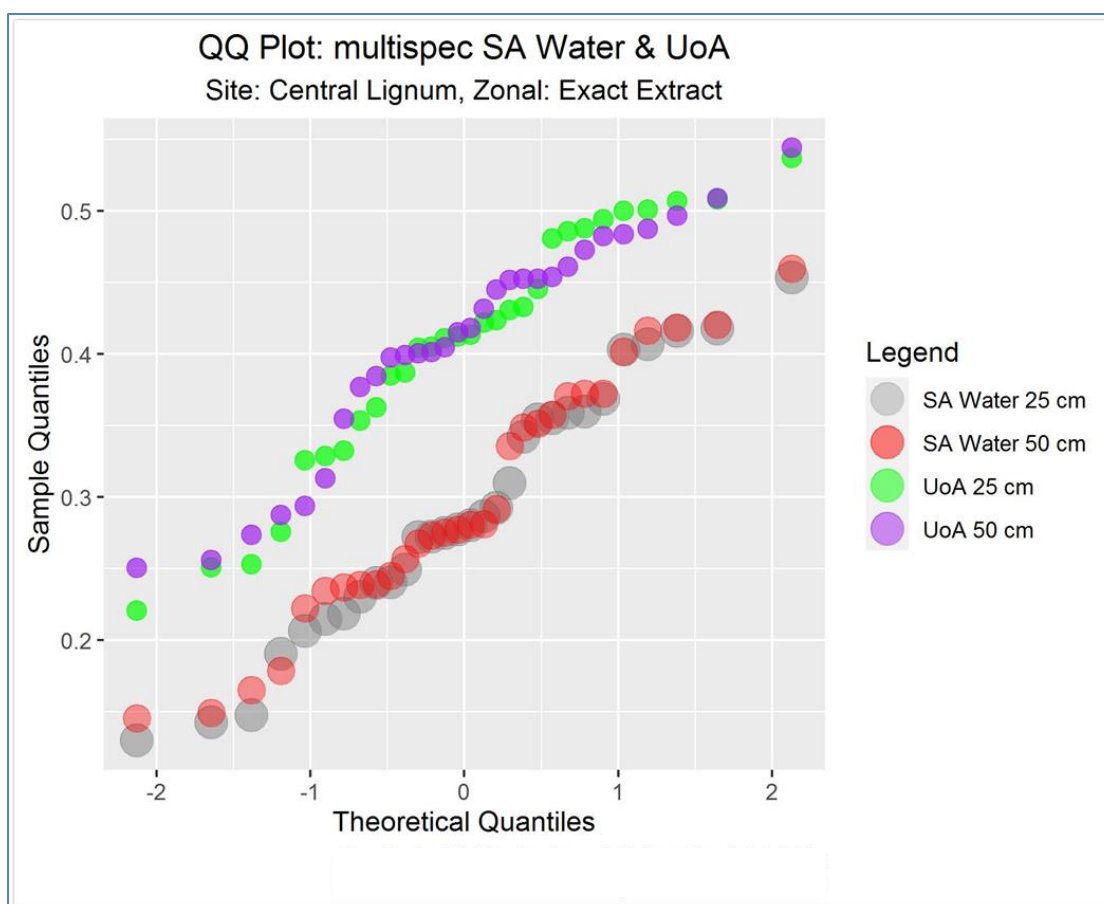


Figure 20 QQ Plot, buffer size and platform

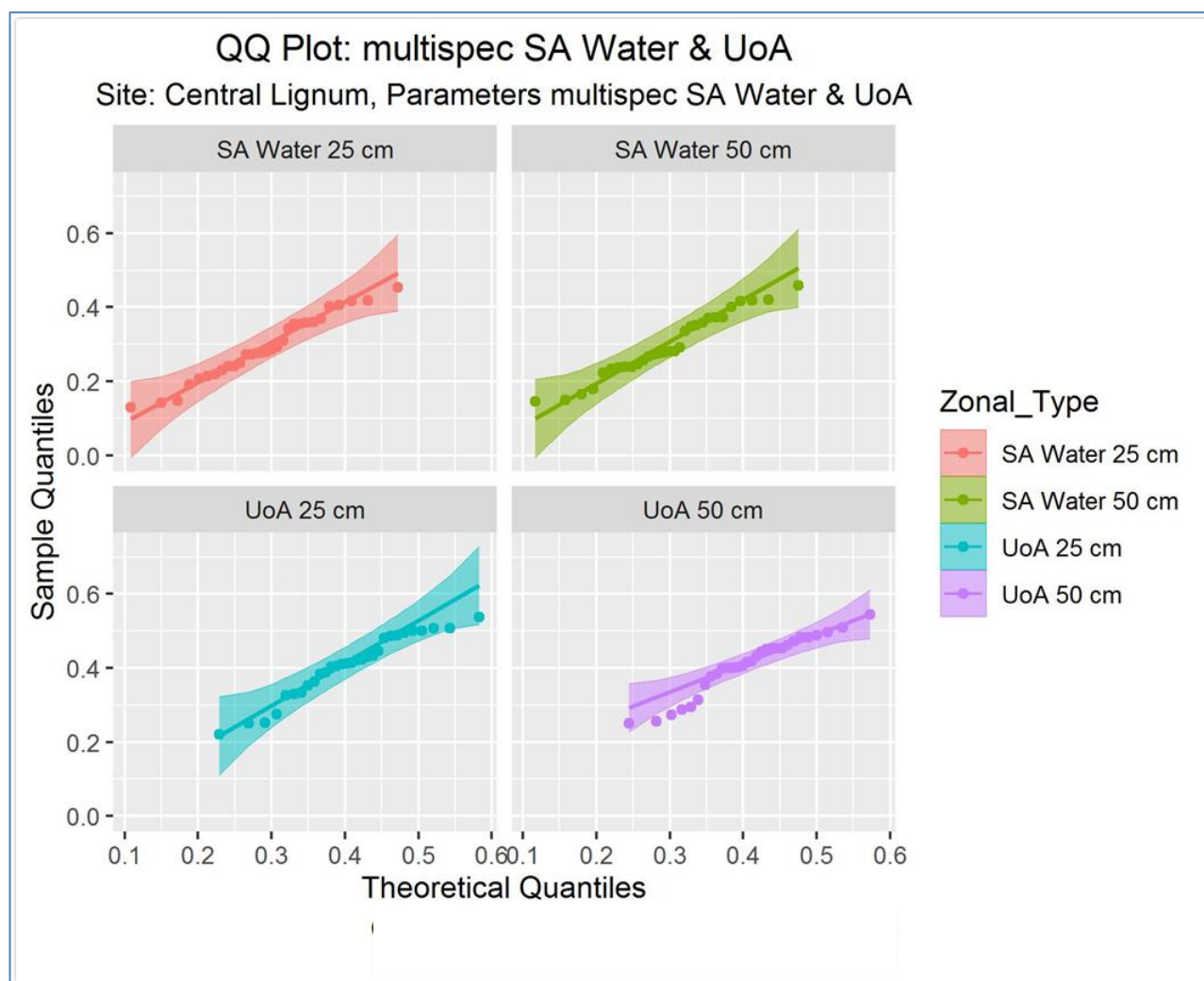


Figure 21 Stacked QQ Plot, buffer size and platform

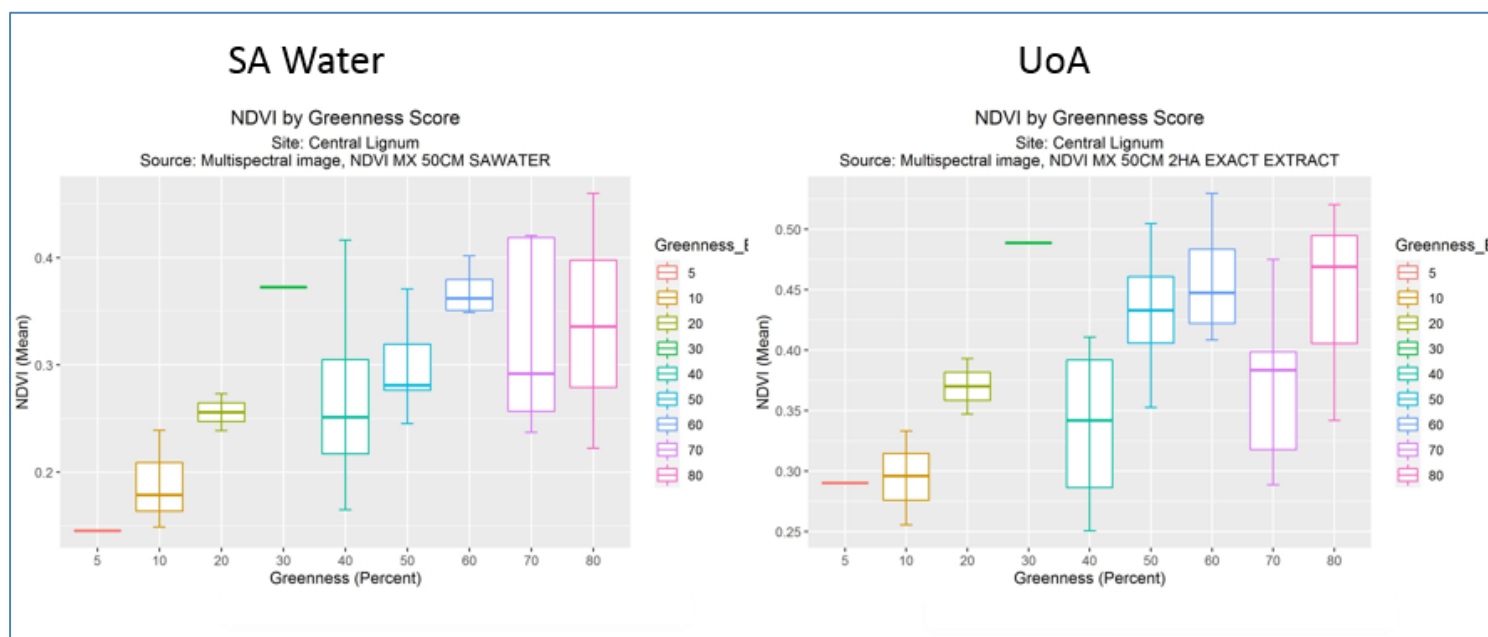


Figure 22 Box plot comparison greenness, NDVI and platform

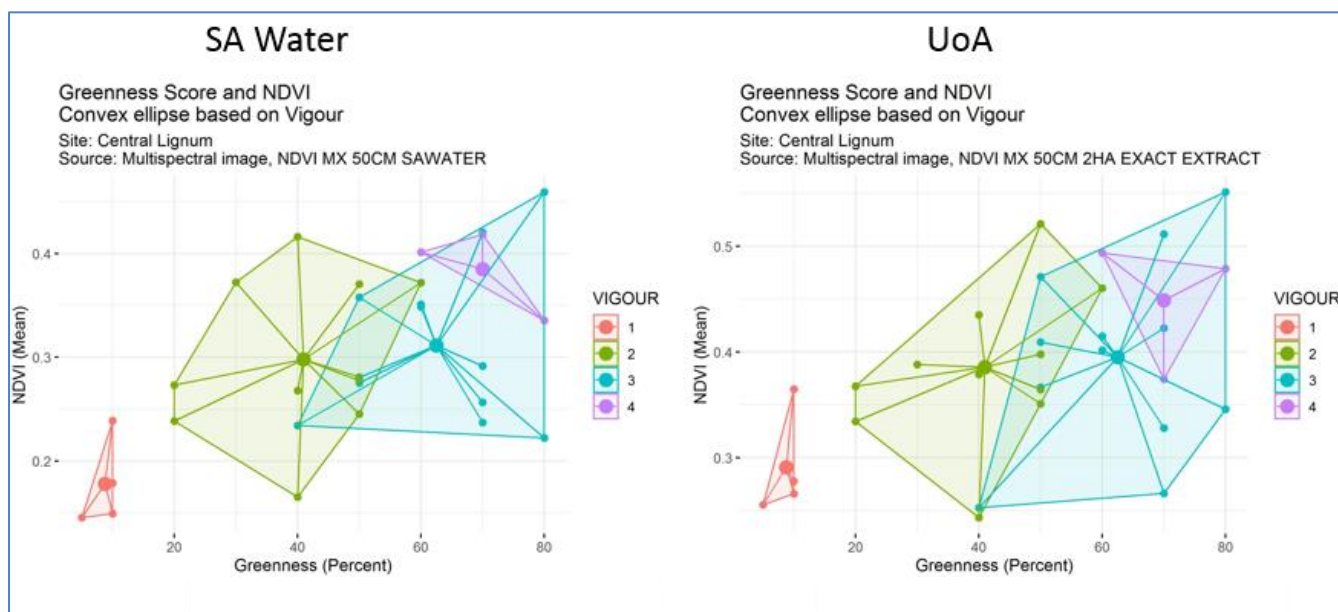


Figure 23 NDVI and Greenness score clustered by vigour class

The findings above indicate some promise in processing the SA Water data stack (plus the UoA NDVI imagery) to develop a timeseries analysis. Although unverified by field observation, the results of this processing are presented below using a range of statistical methods. Findings demonstrate some potential relationship between outputs and seasonal conditions over time at the overall site level (Figures 24-26).

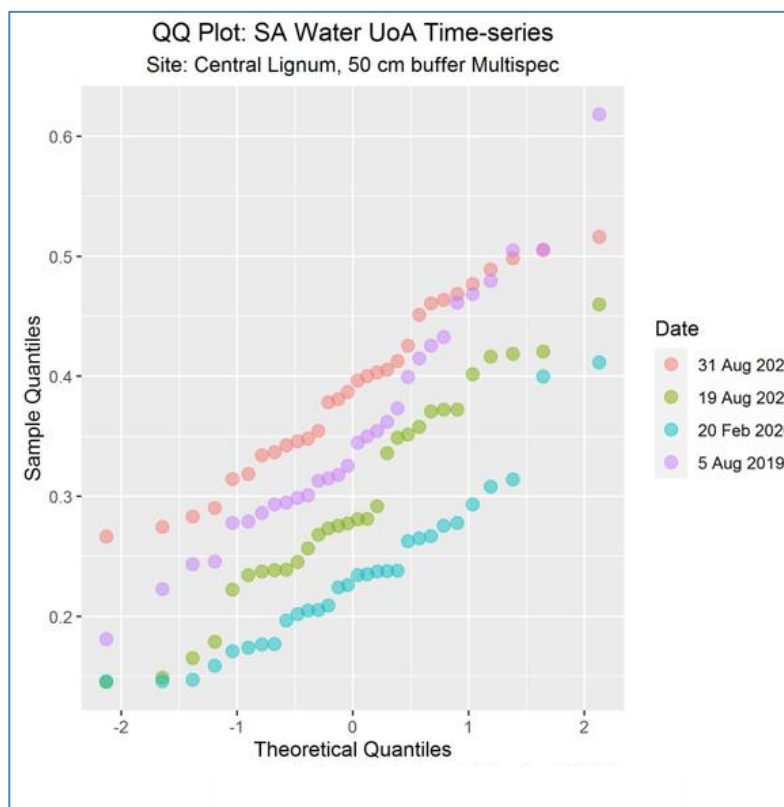


Figure 24 Time-series output by date

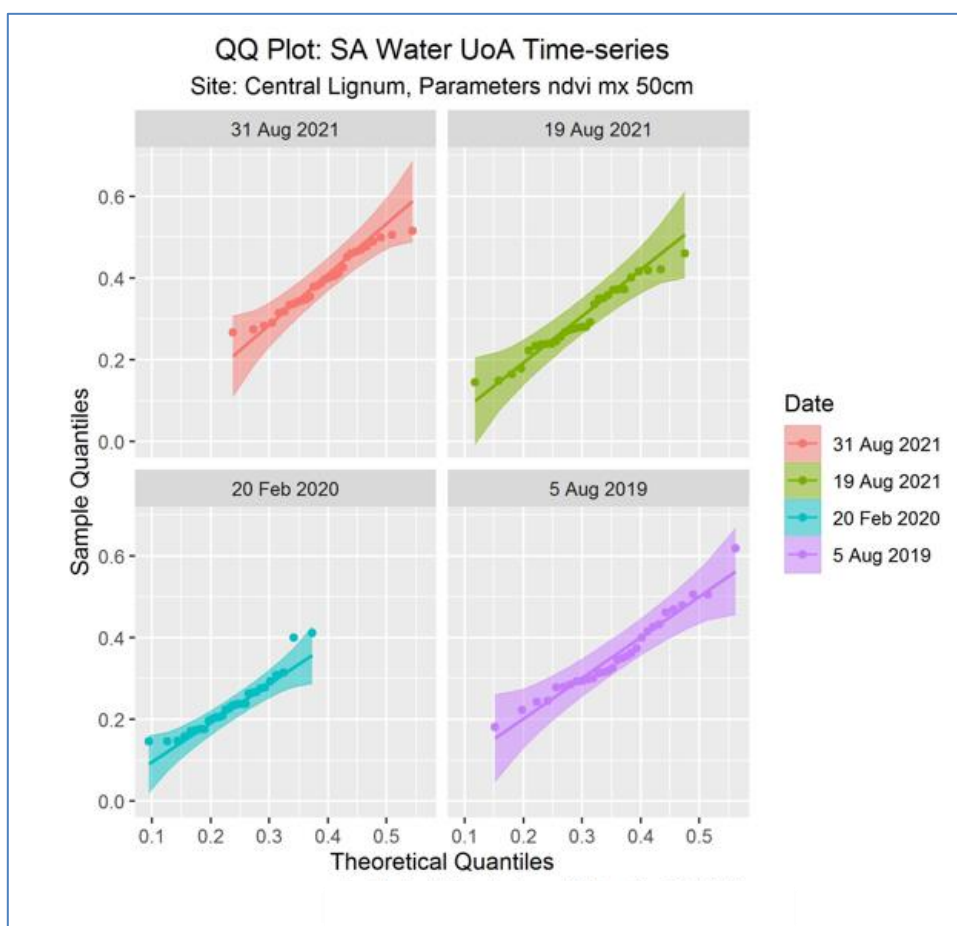


Figure 25 Q-Q (quantile-quantile) plot for four separate capture dates

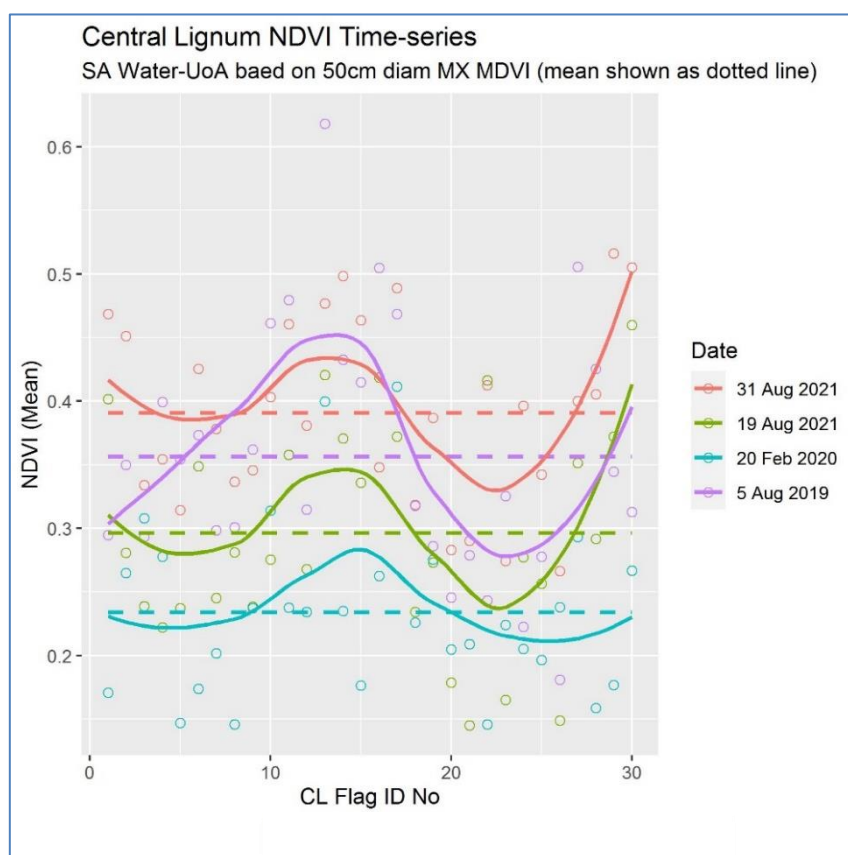


Figure 26 central lignum mean NDVI, Loess smoothed regression and individual flag ids

Broad-Scale Condition Monitoring and Comparison with Additional Lines of Evidence

The mean NDVI values for the timeseries data stack for the Central lignum site were plotted against daily and rolling 90-day average rainfall to determine if any relationship existed thereby providing increased insights at the overall site level (e.g. Central lignum) and an indication of the rigour of such an approach for determining condition based on greenness (Figure 27).

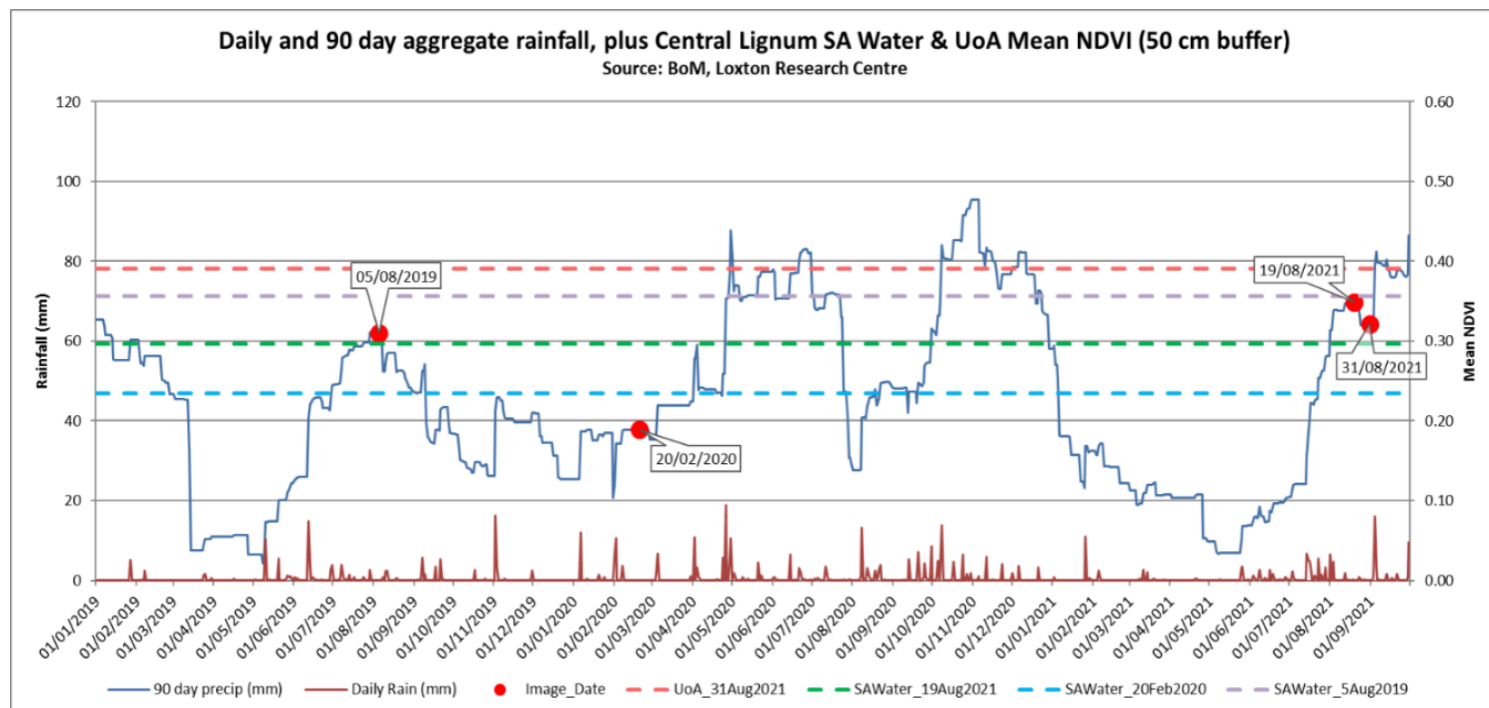


Figure 27 Image dates, mean NDVI timeseries, daily and rolling 90-day average rainfall

Assessment of outputs of Geoscience Australia's Wetland Insight Tool for an area that covers the central lignum site also demonstrates a similar finding based on the relative amount of greenness for each date that imagery was available (Figure 28). In this respect the period around August 2019 had a higher percent greenness related to the period between the end of January and mid-March 2020, indicating consistency with the mean NDVI values reported in Figure 27 above.

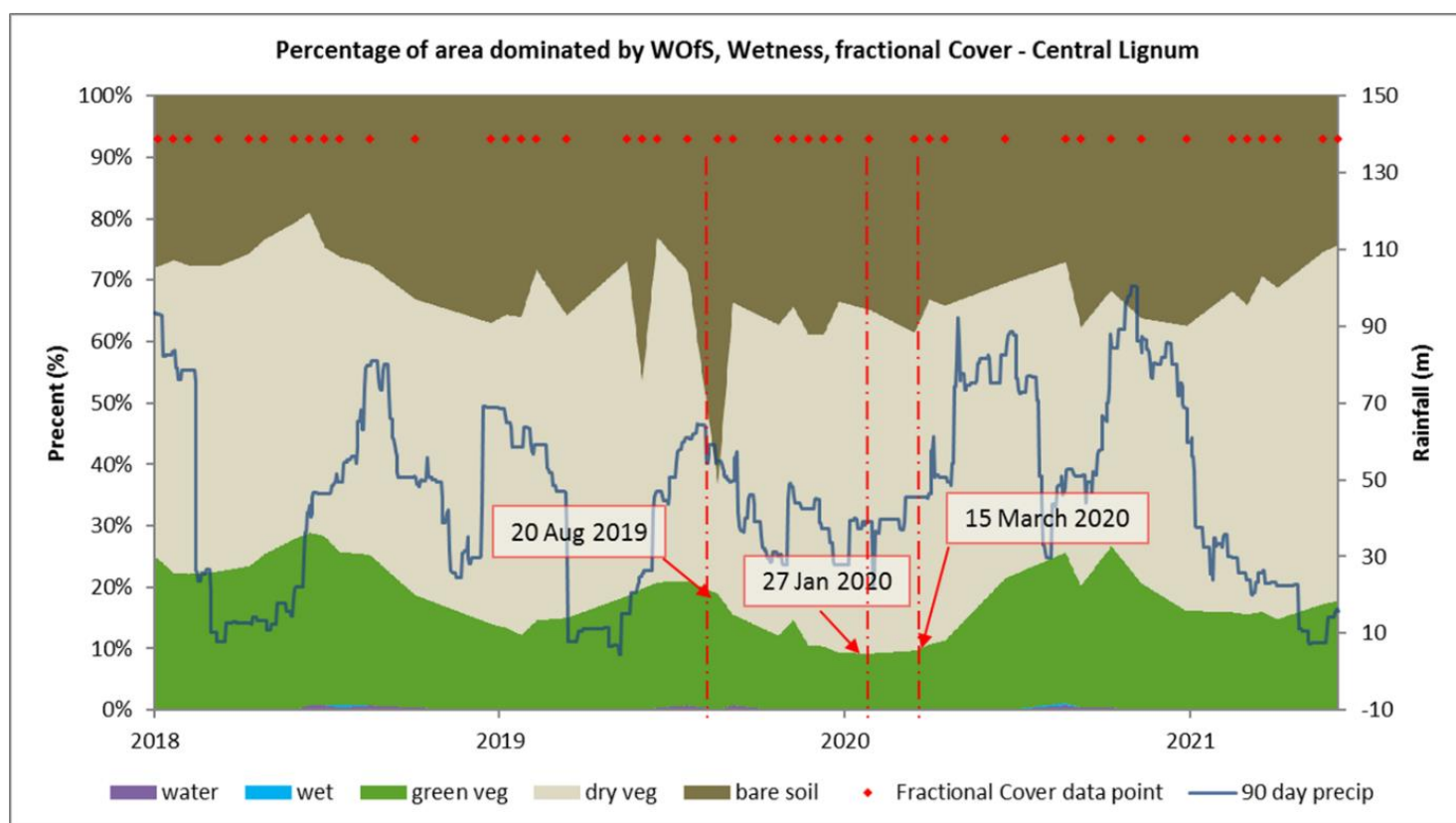


Figure 28 Wetland Insights Tool (WITs) output for area covering the central lignum site

Sentinel/drone comparison summary

The results of the Drone-simulated Sentinel-2 imagery and subsequent comparison with the original Sentinel-2 image demonstrated that it was possible to develop a credible up-scaled drone output as evidenced by histogram outputs for individual bands (Figure 29).

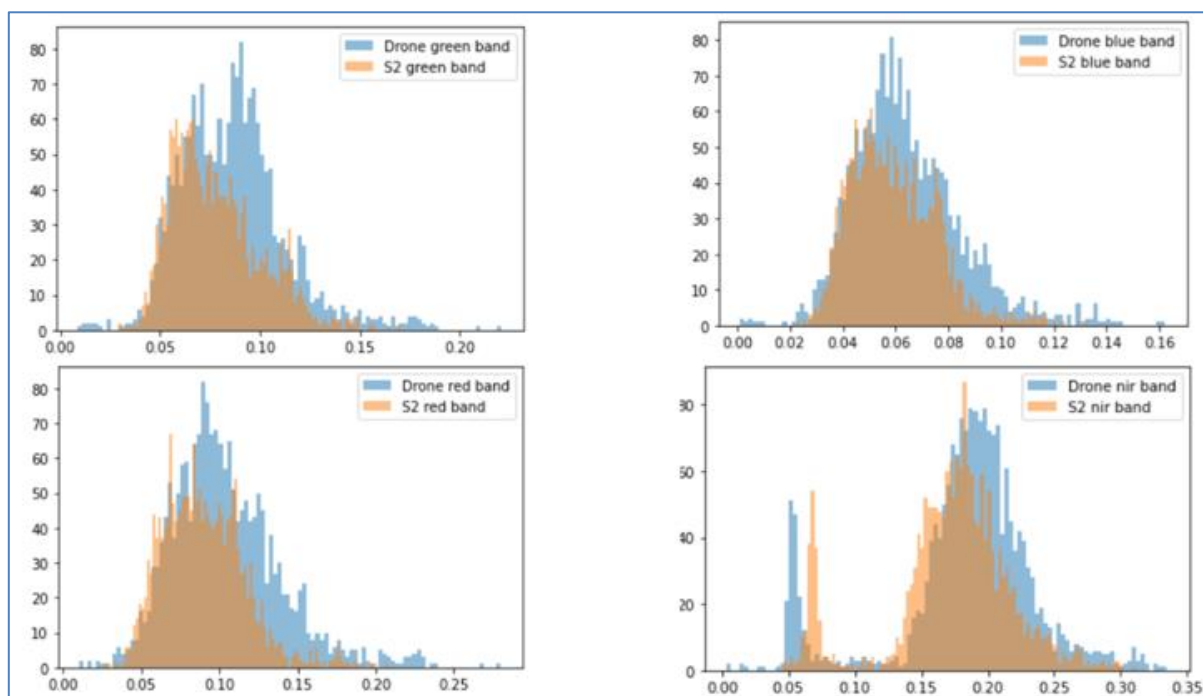


Figure 29 Sentinel-2 and Drone-simulated band characteristics

Subsequent QQ plots, box plots, heat maps NDVI comparisons between the two image outputs confirmed this similarity, as did the wide range for NDVI values compared with Greenness Scores, consistent with the findings of the finer scale drone imagery reported above (Figures 30-32).

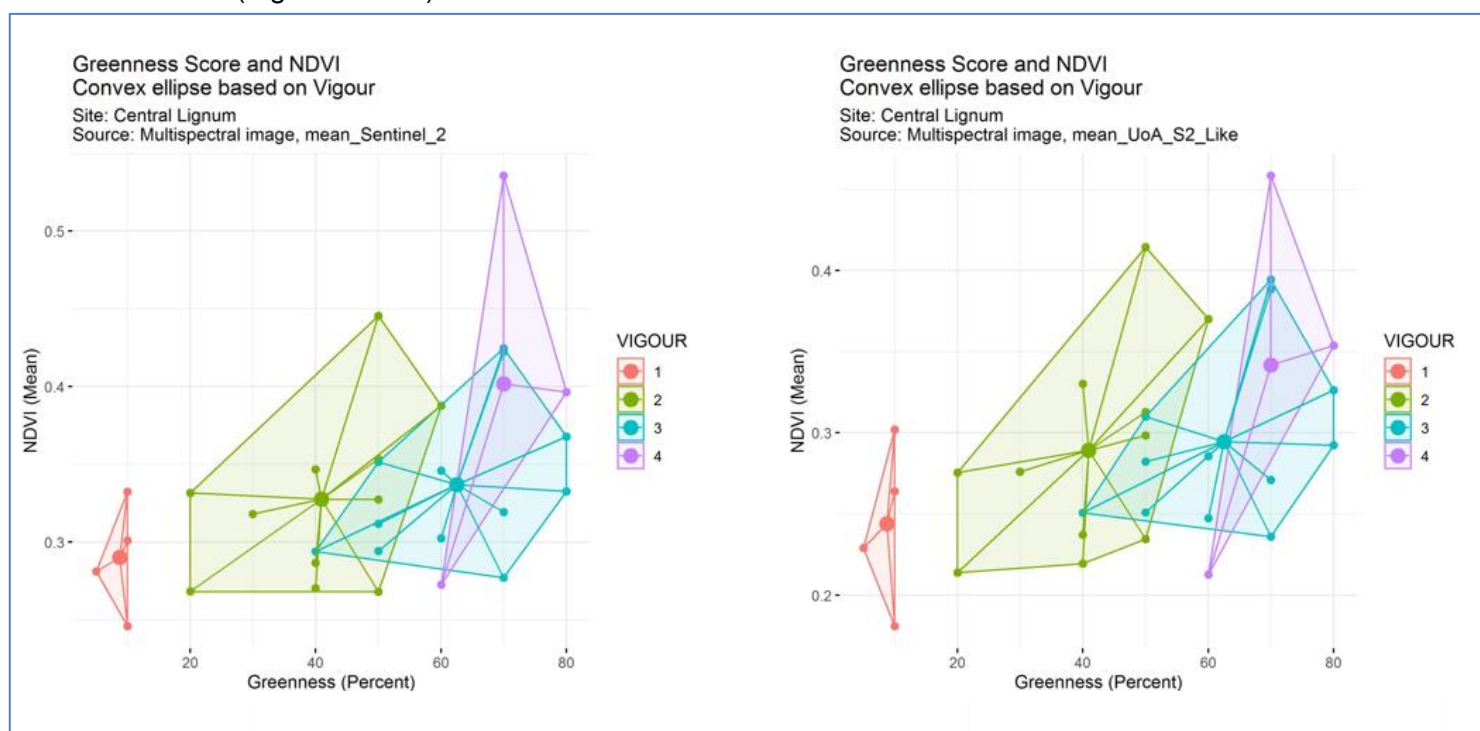


Figure 30 NDVI, Greenness and Vigour Score – central lignum a) Sentinel-2 and b) Drone-simulated Sentinel-2

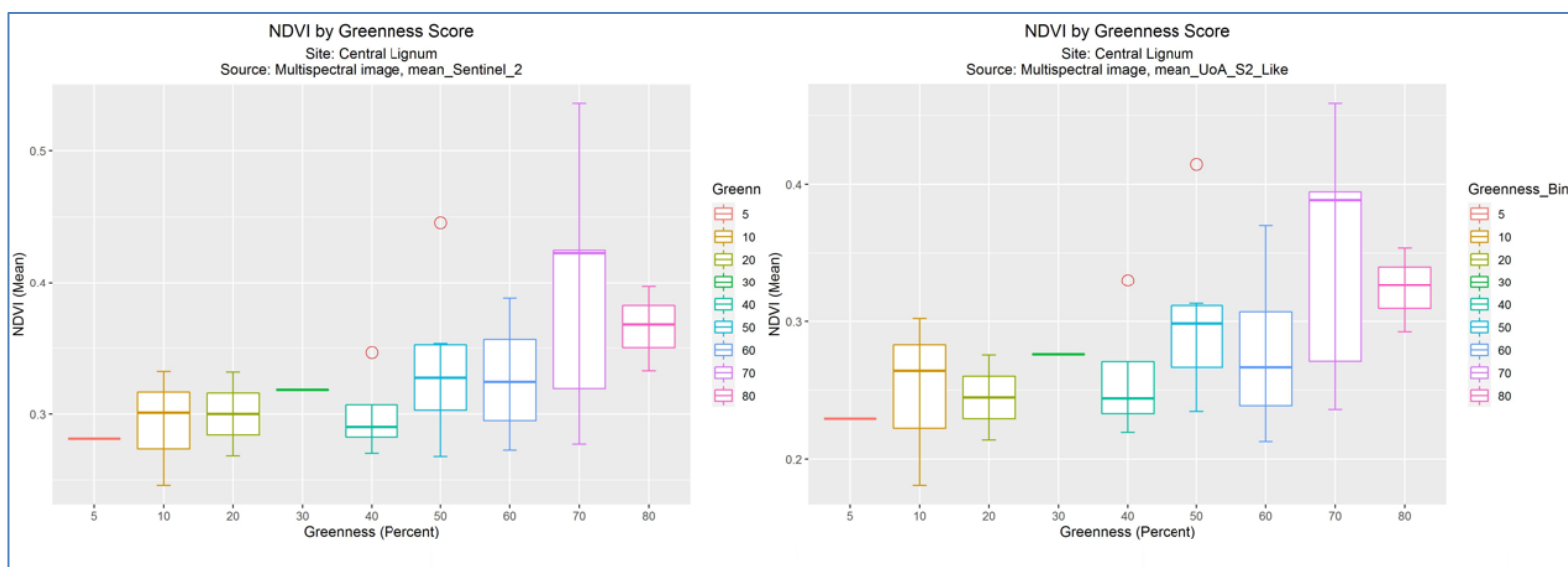


Figure 31 Box plot comparison greenness, NDVI and platform

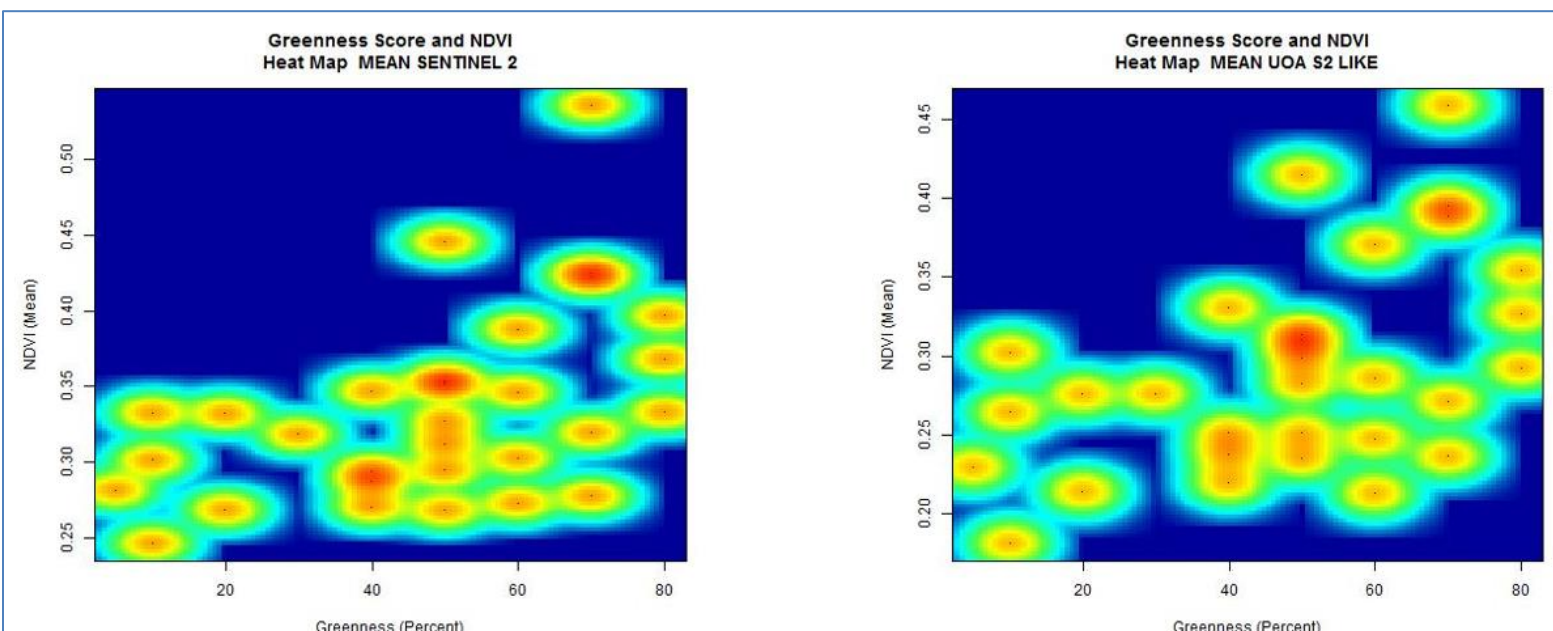


Figure 32 Heatmap of NDVI and Greenness score a) Sentinel-2 and b) Drone-simulated Sentinel-2

Fractional cover

Training material was developed to differentiate lignum and tree profiles (Figure 33).

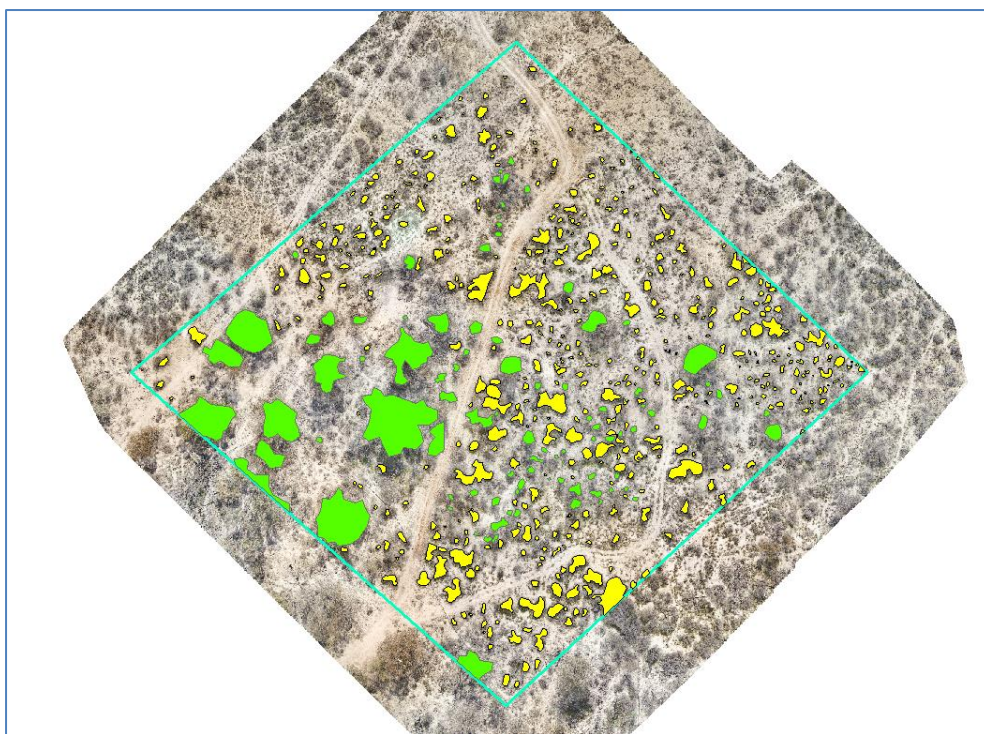


Figure 33 Manually digitised tree (green) and lignum (yellow)

The above training data were then used as input to determine fractional cover estimates, with Individual bands applied to lignum, tree (black box or coobah) and bare ground. (Figure 34).

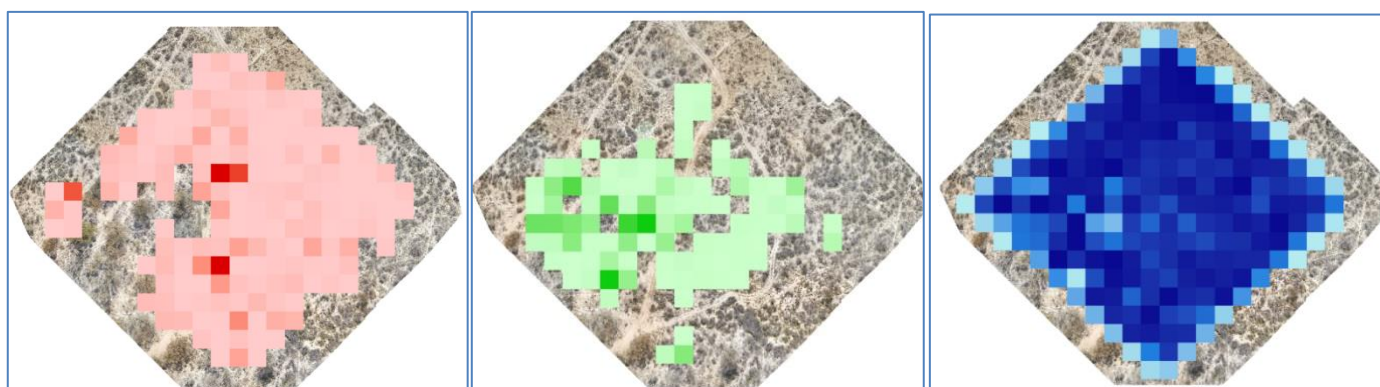


Figure 34 Red- Lignum, Green -Tree, Blue – Bare ground/other

The lignum fractional cover histogram shows % cover on the x-axis (Figure 35) and reveals the majority of sites recorded less than 10% cover. With such low estimates it was not possible to get a reliable output that expresses lignum cover at the cell level with any confidence.

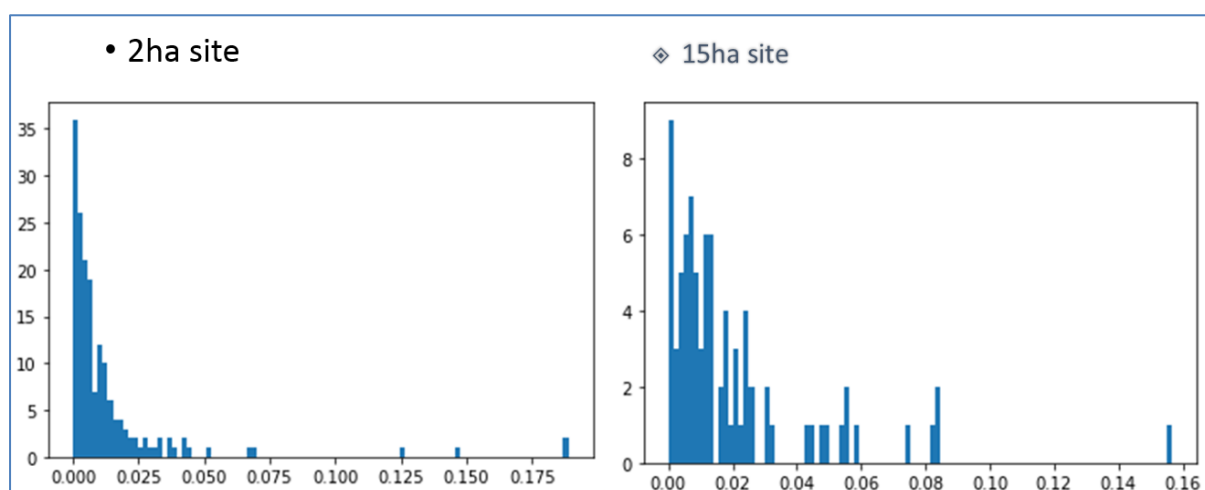
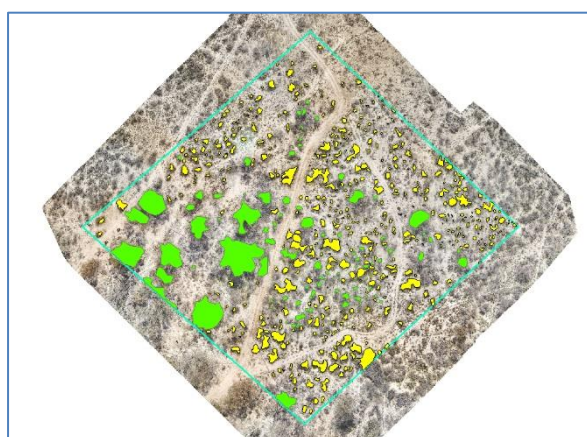


Figure 35 Fractional cover histograms for 2 and 15 ha locations

Overall area calculations based on manual interpretation indicate that this is reasonably consistent with ground observations, e.g. 7.5 % lignum cover in central lignum site (Figure 36). Note that estimates of canopy cover and density when viewed horizontally on ground by the human eye can be misleading, due to the minimal physical area taken up by lignum stems and the difficulties in determining the area covered by an individual bush (Refer Figure 19).



Class	AREA m2	% Area
Other	15,261	84.94%
Tree	1,367	7.61%
Lignum	1,340	7.46%
Grand Total	17,968	100%

Figure 36 Estimate of cover based on manual digitising

Lignum occurrence database

Occurrence records for three species of lignum (*Duma florulenta*, *Muehlenbeckia adpressa* and *Muehlenbeckia axillaris*) were downloaded from the Atlas of Living Australia portal, with counts subsequently analysed by State and MDB region returning 13,336 records (Figure 37 and Table 4).

Figure 37 below reveals the dominance and inland occurrence of *D. florulenta*, relative to other species. Further, its association with temporary floodplain wetlands is clear in the Murray-Darling Basin and Diamantina-Cooper catchments. There is a noticeable concentration in the Upper Darling floodplains and the western floodplains of the Murray tributaries and Lower Murray and Lower Darling valleys.

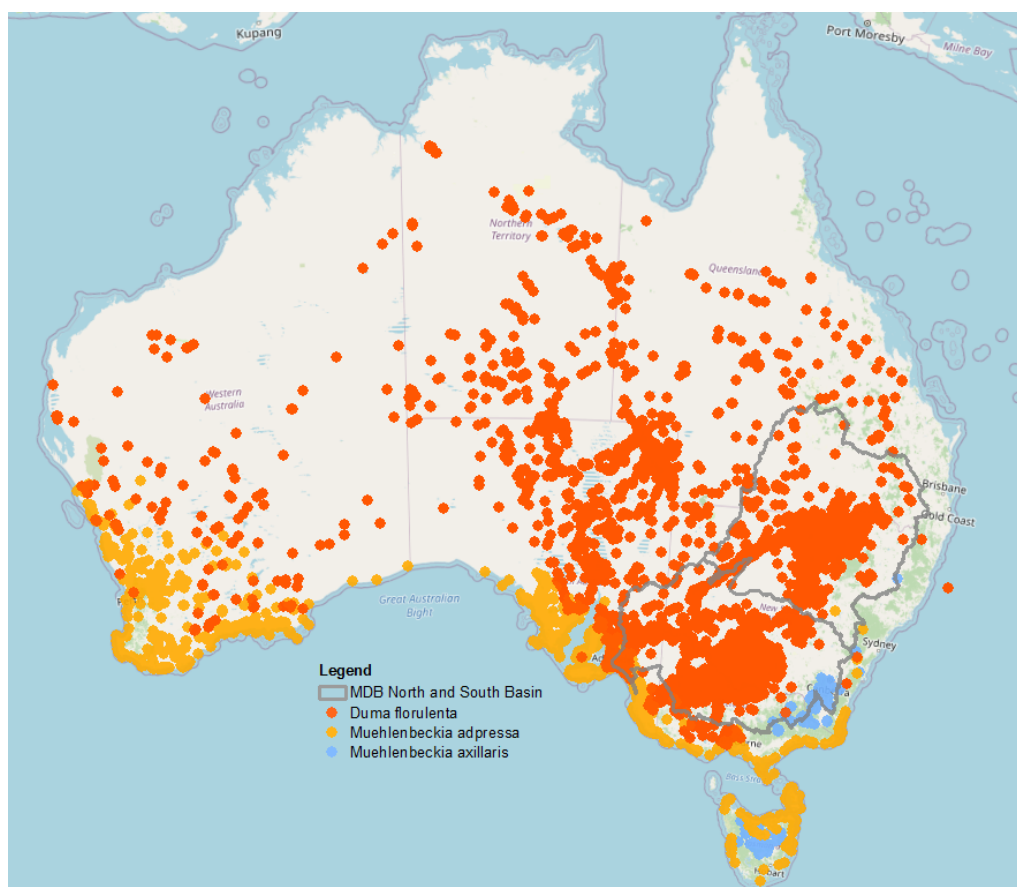


Figure 37 National ALA distribution of various Lignum species. (Accessed 15 April 2021)

Table 4. Occurrence of lignum species by jurisdiction

Jurisdiction	<i>Duma florulenta</i>	<i>Muehlenbeckia adpressa</i>	<i>Muehlenbeckia axillaris</i>	Grand Total	%
Australian Capital Territory			13	13	0.1%
New South Wales	5,092	110	63	5,265	39.5%
Northern Territory	315			315	2.4%
Queensland	431			431	3.2%
South Australia	3,145	894		4,039	30.3%
Tasmania		355	227	582	4.4%
Victoria	1,907	132	27	2,066	15.5%
Western Australia	168	456		624	4.7%
Unassigned	1			1	0.0%
Grand Total	11,059	1,947	330	13,336	100%
Percent of Total	83%	15%	2%	1	-

The MDB contains 8,921 or 67% of the national records (for total lignum), while the southern MDB contains 6,071 or 68% of the total MDB records. Likewise, the MDB contains a total of 8,773 or 79 % of the national records of *D. florulenta* in the ALA database. Of these 68% occur in the Southern MDB and 32% in the Northern Basin. (Table 5).

Table 5 *Duma florulenta* occurrence within MDB

n-sMDB	Count	%
Northern Basin	2,849	32%
Southern Basin	5,924	68%
Grand Total	8,773	100%

Similarly, an integrated analysis of the *D. florulenta* occurrence with the MDB ANAE Ver 3.0 wetland mapping layer for the MDB reveals the majority of records (as to be expected) occur on floodplains (approx. 55%), however a significant number (24%) do not intersect with the Ver 3.0 wetland layer (Table 7).

Table 6 *Duma florulenta* occurrence by ANAE system based on MDB ANAE Ver 3.0 dataset

ANAE System <input type="checkbox"/>	Northern Basin		Southern Basin		Total Count	Total Percent
	Count	Percent	Count	Percent		
Estuarine		0.00%	16	0%	16	0.2%
Floodplain	1,882	66.06%	2,890	49%	4,772	54.4%
Lacustrine	36	1.26%	410	7%	446	5.1%
Palustrine	135	4.74%	965	16%	1,100	12.5%
Riverine	107	3.76%	209	4%	316	3.6%
(blank)	689	24.18%	1,434	24%	2,123	24.2%
Grand Total	2,849	100.00%	5,924	100%	8,773	100.0%

5 Discussion

Challenges were experienced in operating the various sensing technologies in the field and analysis of the data recorded – for example, the need to schedule the field work to coincide as closely as possible with a cloud free Sentinel-2 image of the location. There were also challenges in the process of obtaining suitable images for assessment of the condition of the two target species for this project, tangled lignum (*D. florulenta*) and common reed (*Phragmites australis*) due to the environmental and plant conditions prevailing at the time, e.g. *Phragmites* was largely senescent (dormant).

Tangled lignum forms its habit through initial vertical growth of tall stems which then arch over to a horizontal position and new vertical stems grow from each node (Jensen *et al.* 2006). Over time, this process produces a tangle with older brown branches at the centre and new green branches on the outer areas of the bush. Formation of leaves and flowers is of very short duration (<4 weeks), usually at low densities unless there is a significant period of high-water availability from either flood or a large rainfall event. Previous studies have shown that actual measurements of height or width of lignum bushes, or records of leaf growth or flowering, do not provide reliable measures of condition, owing to the characteristic bending and spreading of taller stems as they grow heavier, and the very short time span to capture flowering and leaf production (e.g. Jensen 2008). Assessment of the relative percentage of green stems (relative to yellow or brown stems) in total bush stems has been found to be the most effective and consistent parameter to indicate plant health (Southgate 1998, Chong & Walker 2005, Jensen 2008).

Lignum is a complex plant at the individual bush level, as well as being affected by seasonal conditions. The condition of an individual bush is informed by age and size of the plant, how many growth cycles it has experienced and then seasonal conditions which determine water availability. As a result, two individual plants adjacent to each other can produce a range of condition scores for greenness and vigour. Situations also exist where two plants may have similar greenness but differing vigour scores and vice-versa.

Field observations during this study suggested that plant condition in lignum tended to be assessed at a higher vigour status from a horizontal view when compared with a vertical view, thought to be due to the large component of vertical stems which are not readily visible in the vertical plane, compared to the horizontal plane.

However, this assumption was not tested in this study and this factor requires further testing to determine how to achieve more consistent measurements. The apparent lack of agreement may be attributed to the disparity between the visual and horizontal observations and the vertical visible and (invisible) near infrared spectral measurements. Although both are viewing the same plant, they are also likely observations of differing phenological characteristics, and are therefore not necessarily intrinsically comparable. Further testing is also required to establish the contribution to the NDVI reading from groundcover plants under the lignum bushes.

This trial also demonstrated that estimating condition in the field for ground-truthing selected lignum plants is not an exact science that is readily repeatable by individual field assessors. As noted above, previous experience suggests the most consistent results are obtained from an assessment of trends in condition via a scoring system, e.g. scores for percentage greenness, rather than precise measurements of height, width or flowering (Jensen 2008, Jensen *et al.* 2006).

From a remote sensing perspective, we suggest that monitoring trends in condition using robust drone based multispectral imaging is worth further investigation due to recent advances in commercially available high precision positioning systems such as RTK. With high precision positioning systems, spectral time series data can be captured to measure per shrub spectral changes (including and beyond NDVI) to decouple the demonstrated

variability of individual lignum shrub habit, age and condition. These structural factors may be controlled by monitoring the change in condition per groups of shrubs at local scales related to local water availability, e.g. in a clay swale.

Moreover, alternative spectral sensors and analysis methods may yield more compelling results. The study was limited to the use of NDVI, however alternative sensors (e.g. Micasense RedEdge MX Blue, hyperspectral sensors and LiDAR sensors to measure structure) and analysis techniques may be able to contribute to lignum monitoring.

In the current study, based on comparison with field observations of greenness and vigour metrics, it was concluded that it would be difficult to use drone imagery to confidently determine the condition of an individual bush based on NDVI value. In the drone imagery, there was a large variation in NDVI value compared to field-based Greenness and Vigour Scores. Further refinement should consider alternative parameters to be modelled, increased sample size and the effect of scale (single bushes vs groups and size of bush etc).

It was possible however, at the aggregate plot scale, to demonstrate a general increase in NDVI with corresponding Greenness and Vigour using regression values and coefficients. The monitoring techniques tested appear to have very positive potential for assessing lignum condition at field scales, but further refinement and testing is needed to identify parameters which will produce the most consistent results.

The presence of low green understorey shrubs was a potential confounding factor in NDVI reading. The field test was undertaken about six weeks after a major local rainfall event, which had triggered extensive growth of groundcover plants under the lignum stands. Vertical assessment scores appeared to be falsely inflated if any green groundcover was visible under lignum bushes in response to local rainfall events.

For lignum, the introduction of additional metrics such as plant size and age classes may help in improving the correlation between NDVI and field observation of plant condition and is worthy of further exploration.

It was also possible to use different drone platforms and resolutions to get similar NDVI outputs at the site scale when using multispectral imagery. This has been demonstrated in comparisons between images from UoA and SA Water drones acquired on similar dates.

From the project results, it was possible to obtain an indication of the overall greenness at the site level that reflects condition over time, as demonstrated using time-series drone data and relationship to prevailing seasonal conditions.

These findings were further confirmed using GAs Wetland Insights Tool (based on Landsat archive) and rainfall data.

For common reed, it was found that the results along the main river channel were limited by inundation of the riparian zone due to elevated river levels during a high flow. In addition, the plants are senescent in autumn and winter, so sampling should be timed to occur in the warmer seasons. For example, late summer would usually be a suitable time for both active growth in plants and normal river levels.

Machine learning classification

The Support Vector Machine (SVM) classifier was used to produce an extent map, where the lignum class had an accuracy of 57% with an overall accuracy of 65%. (Annex 2). Additional image collection under different environmental conditions may be useful, including development of a multi-temporal stack of multi-band images to train the classifier to assist in greater differentiation between lignum, tree, ground cover vegetation and bare ground. Accuracy could be improved by using alternative machine learning approaches such as Convolutional Neural Networks (CNN), as done for UoA waterbird nesting results developed

for MDBA⁹. The software developed for the project has the potential to be used to detect and map lignum occurrence and extent in a similar manner to detecting bird nests using RGB imagery. The raw RGB imagery supplied for this project is suitable to perform preliminary trials for lignum detection and may offer an alternative method to estimating lignum shrub number, coverage and density. Further refinement could develop capacity to add condition to the parameters monitored.

Condition classification and learnings

For condition monitoring, zonal statistics show some differences due to the processing engine at the individual bush level when using a 25cm radius buffer. However, there is no difference when considering overall mean NDVI value for the site using this metric. No differences occur in the zonal statistics engine when using a 50cm radius buffer. However, the larger buffer standard distorts results when applied to smaller, less dense lignum bushes due to the impact of bare ground and other groundcover influencing the NDVI score. This was an issue for the northern and dry lignum sites.

Sentinel-2

Using the UoA imagery, it was possible to develop a Sentinel-2 equivalent output and produce a credible estimate of greenness at the overall 'site' or plot level, e.g. for the whole central lignum site. However, due to the low percent lignum cover values (based on the low density of lignum bushes when viewed from above, even at the central lignum site which mostly comprised larger bushes relative to other sites), it was not possible to obtain an 'accurate' estimate of percent lignum cover using fractional cover techniques. The majority of Sentinel-2 pixels had considerably less than 10% cover. This figure is consistent with manual interpretation methods which estimated the overall lignum cover at less than 8% for the central lignum site. Viewing lignum cover horizontally gives an impression of higher densities, when compared to nadir view and can lead to an over-estimate. However, the horizontal view appears more accurate for estimating greenness and vigour at the bush level.

Oblique Imagery

RGB ortho-mosaics were generally much cleaner than multispectral imagery (Refer Annex 3). Phragmites was detectable on both RGB and multispectral images. A major limitation of RGB ortho-mosaics (based on video) is the lack of geotags and subsequent ability to develop 'real' world scaling.

The signal from the NIR band did not reveal any additional insights into condition, largely as a result of the Phragmites being dormant or senescent at the time of image capture. High river flows meant that much of the riparian vegetation was underwater and therefore not visible at the time of capture using oblique imagery of the riverbank area.

Additional issues identified when capturing oblique imagery included difficulties associated with sky in the background, highly variable surfaces and warping of pixels.

⁹ Refer – MDBA Drone Waterbird and Innovation Sweep MD-WERP Tactical Project

6 Summary and Future Assessment

This project sought to explore practical methodologies to determine an extent baseline for lignum in the Murray-Darling Basin (MDB), to measure environmental outcomes, and to investigate options to measure condition of lignum shrublands and non-woody vegetation.

This offered a unique opportunity to undertake an exploratory assessment of novel methodologies for monitoring lignum and non-woody vegetation in the MDB.

The project explored the application and utility of unmanned 'drones' and Sentinel-2 (10 m) imagery by assessing:

- extent and condition of lignum stands (and understory vegetation) on Clarks Floodplain between Berri and Loxton in South Australia, based on remote sensing imagery, expert interpretation, field validation and GIS analysis of ground-truthed data;
- riparian vegetation 'corridor' mapping of the River Murray channel; and
- potential application and utility across the whole of the MDB and beyond.

Classification using drone-derived data is an important tool for environmental monitoring. How accurately vegetation is classified using drone-derived datasets depends on factors such as the complexity of the vegetation structure, the level of discrimination aimed for (i.e. species or cover type groupings), quality of training samples and timing with environmental conditions. It has been demonstrated repeatedly in the literature, that accurate classifications are achievable given the right combination of data capture and analysis methods.

Results from the current project indicate that lignum registers surprisingly low cover values when measured from above, due to its structure of multiple stems (many vertical) and usually no foliage or flowers. It was found that the most practical field measure of lignum condition is the percentage greenness of stems in a bush or stand. There was sufficient correlation between the various sensing technologies tested and the ground-truthing results to support the continuation of work to refine these methods.

Lignum is predominantly spread across shallow claypans or open floodplains. The results from this pilot study suggest that typical lignum stands rarely reach above 15% of vegetation cover in the field, unless a topographic feature exists (for example a terminal swamp) which enables water to pool for longer periods. It is suggested that the cover at Clarks Floodplain is quite typical for floodplain lignum in the MDB and is not considered unusually low relative to other locations, however further work at additional sites will confirm this.

As indicated above, the most effective parameter to measure lignum condition is the relative greenness of stems, so monitoring tools need to be able to identify stems and then classify the relative proportion of the colours green, yellow or brown. In seeking to measure stems and their greenness, another finding was that bushes which appear to have relatively dense stems when viewed horizontally visually do not necessarily translate to a similar assessment in the vertical view measured from a drone. Further testing is required to find ways to resolve these issues.

When collecting ground-truth data for lignum condition, it is recommended that further parameters such as age and size also be collected to potentially aid a closer correlation with remote sensing imagery. It was found in this project that the 50 cm radius polygon used to compute mean NDVI values was appropriate for larger bushes, however it was not appropriate for smaller individual bushes with sparse canopies, especially when accompanied with an emergent active vegetated understory (either annuals or chenopods). Similarly, a 25 cm radius polygon may not be sufficient for large bushes to represent the footprint used in the on-ground scoring assessment. Further work in this area in combination with individual bush size and age class may result in a stronger correlation between ground

survey field results and NDVI at the individual bush level. Options for testing groups of bushes rather than individual bushes should be considered, as well as testing groups of bushes by micro-topography and micro-habitats, as these factors influence local water availability, which is a major determinant of bush condition. Likewise, opportunity assessment of locations with denser areas of lignum coverage (e.g. greater than 15%) may make it possible to estimate lignum extent using workflows developed under the current project.

This study presumed that the ground survey methods for scoring vigour and greenness were the points of truth to compare multispectral imagery against. Consequently, experiments that investigate the spectral response of lignum due to physiological changes could yield interesting results. Experiments may include monitoring of active controlled watering projects and destructive sampling to establish relationships between plant physiology and spectral responses. Moreover, alternative spectral sensors and analysis methods may yield more compelling results. This study was limited to the use of NDVI, however alternative sensors (e.g. Micasense RedEdge MX Blue, hyperspectral sensors and LiDAR sensors to measure structure) and analysis techniques may be able to contribute to lignum extent and monitoring.

Whilst it was possible to upscale a drone image to resemble/simulate a Sentinel-2 image the low percent of lignum cover (largely less than 10% based on the Central lignum site used in the analysis) meant it was not possible using fractional cover techniques, to produce reliable outputs that express lignum cover at the Sentinel-2 pixel level with any confidence. It was however possible to get similar condition results based on mean NDVI values at the aggregated site level.

The above relates to lignum and floodplain area. In relation to riparian vegetation 'corridor' mapping of the River Murray channel, both RGB and multispectral imagery demonstrated the ability to detect understorey vegetation in a riparian system using oblique image capture. Generally, due to the projection plane and the position in the landscape, common reed (*Phragmites australis*) was most easily detected among non-woody riparian vegetation communities. The need for geo-tags in images was noted. While some of the methodology tested did not have geo-tags, new software is emerging which will cover this gap.

7 References

- Chong C. & Walker K. F. (2005) Does lignum rely on a soil seed bank? Germination and reproductive phenology of *Muehlenbeckia florulenta* (Polygonaceae). Australian Journal of Botany 53, 1-9.
- Craig A. E., Walker K. F. & Boulton A. J. (1991) Effects of edaphic factors and flood frequency on the abundance of lignum *Muehlenbeckia florulenta* Meissner: Polygonaceae on the River Murray floodplain, South Australia. Australian Journal of Botany 39, 431-443.
- Cunningham SC, White M, Griffioen P, Newell G and Mac Nally R, (2013). Mapping Floodplain Vegetation Types across the Murray-Darling Basin Using Remote Sensing. Murray-Darling Basin Authority, Canberra. (unpublished report and spatial data layer).
- MDBA (2019a). *Basin-wide environmental watering strategy*. Second edition – Revised February 2020. Murray-Darling Basin Authority, Canberra.
- MDBA (2019b). Review of the Basin-wide environmental watering strategy. MDBA publication no: 39/19. Murray–Darling Basin Authority, Canberra. CC BY 4.0
- Jensen, A.E. (2008). The roles of seed banks and soil moisture in recruitment of semi-arid floodplain plants: the River Murray, Australia. PhD thesis, University of Adelaide, Adelaide. <http://digital.library.adelaide.edu.au/dspace/handle/2440/49169>
- <http://digital.library.adelaide.edu.au/dspace/handle/2440/49169>
- Jensen, A.E., Walker, K.F., & Paton, D.C. (2006). The Secret Life of Tangled Lignum, *Muehlenbeckia florulenta* (Polygonaceae): little known plant of the floodplains. In Wetlands of the Murrumbidgee River Catchment (eds I. Taylor, P. Murray & S. Taylor), 79-85. Murrumbidgee Catchment Management Authority, Leeton, NSW.
- Nature Foundation (2021). *2021-2026 Water for Nature Long-term Watering Plan*. Nature Foundation, Prospect, South Australia.
- Roberts J. & Marston F. (2000) Water regime of wetland and floodplain plants in the Murray-Darling Basin. Tech Rep 30/00, CSIRO Land & Water, Canberra.
- Southgate, A. (1988). A Reconnaissance of the Ecology of Lignum (*Muehlenbeckia cunninghamii* (Meissner) F Muell.) on the River Murray Floodplain. Honours thesis, University of Adelaide, Adelaide.
- Thackway, R, and Auricht, CM, (2015). Vegetation Monitoring and Evaluation Scoping Study. Final Report prepared for the Murray-Darling Basin Authority, 19 June 2015. Auricht Projects, Adelaide.

Annex 1: Background information on Lignum

An Introduction to Lignum

Lignum is a long-lived, deep-rooted perennial shrub that can attain 3 m height (Figure 5, Roberts & Marston, 2000). Lignum grows in characteristic shrublands on floodplains of the western Murray-Darling Basin, often in shallow clay pans. It grows best in local habitats subject to temporary ponding of water, after rain or flooding (Roberts & Marston, 2000). Lignum is typically found on swamps, river-flats, gilgais and other intermittently flooded areas. It is particularly common in the Murray-Darling Basin, including on grey cracking clays on the River Murray floodplain in South Australia, in zones with flood frequencies of approximately 3 in 10 y (Craig *et al.*, 1991).

The habit is distinctive, with multiple tangled woody stems (hence the common name Tangled Lignum), which remain leafless except when new growth occurs in response to significant local rains or river flooding (Roberts & Marston, 2000). The small leaves are shed again after flowering. Lignum appears to be opportunistic, ready to respond rapidly to either significant rains or floods (Figure 38; Southgate, 1988).



Figure 38 Healthy lignum in flower on Chowilla floodplain in response to heavy spring rains in October 2005 (Photo A Jensen)

Lignum reproduces sexually and vegetatively, with new plants striking from nodes on roots or on branches contacting the soil. Lignum is dioecious, with male and female bushes which feature small, yellow-green flowers of five petals clustered in interrupted racemes (Southgate 1988; Chong & Walker 2005). The female flowers are smallest, with a tri-branched style and eight barren filaments, and are held close to the branch; the male flowers, with eight fertile stamens and a residual stigma, are more obvious (Figure 39).



Figure 39 Male (left) and female (right) flowers of lignum, showing the distinctive extruding anthers of the male flower and star-shaped, low-set female flower (Automontage images A Jensen)

Best Practice Lignum Condition Scoring

Previous assessments of lignum health included a range of variables, including Southgate's condition index (Southgate 1988), which assesses the degree of greenness through the plant (Table 1; Jensen 2008, Jensen et al 2006). Height and width were found not to be reliable parameters for measuring change in lignum condition because of the random nature of growth.

For the purpose of this project, it was concluded that the most useful biological variables to be monitored in assessing lignum condition were percent greenness, percent leaf cover and relative abundance of flowers. Scores were also recorded on the relative number of vertical and horizontal branches (0-4) and plant vigour (0-4) (Table 7). The dominant colour of branches was noted, also whether there was groundcover present and the plant types, as well as general comments on the phenological stage and health status of the plant. Gender was noted where flowers occurred.

Table 7 Southgate Condition Index (Southgate 1988) and Vigour scores (Jensen 2008)

Lignum condition	greenness score	Lignum Vigour	Vigour score
>50% green/rest yellow	6	>75% green growth	4
>50% green/rest brown	5	50 – 75%	3
<50% green/rest yellow	4	25 – 50%	2
<50% green/rest brown	3	<25%	1
no green/mainly yellow	2	No green growth	0
no green/mainly brown	1		
all brown	0		

Examples of different lignum condition are presented in Figures 40 a-d.

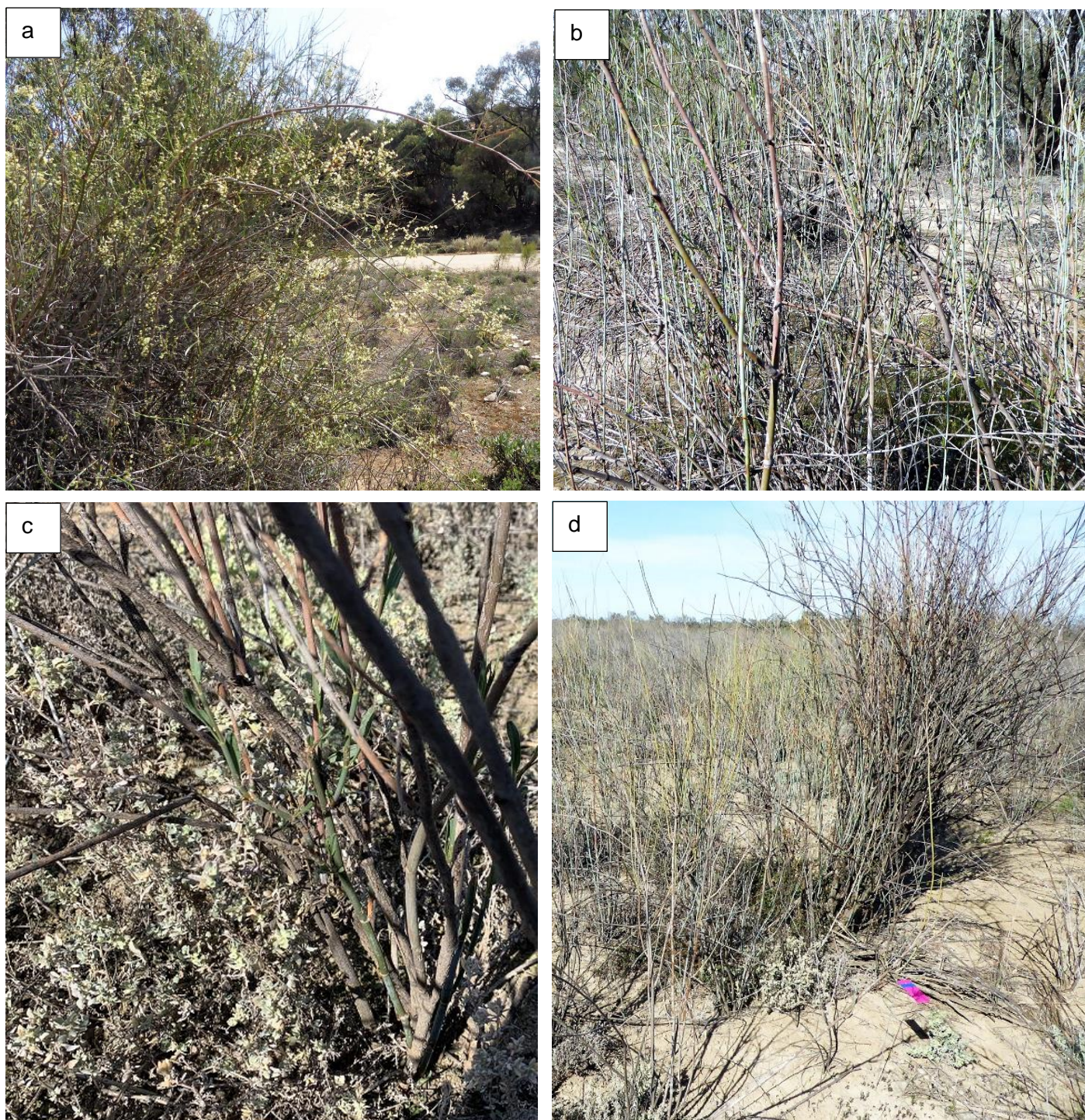


Figure 40 a, b, c and d. Examples of condition and vigour, showing vigour class 4, a very healthy bush with >75% green stems, plus leaves and flowers present (Figure 40a), vigour class 3, a healthy bush with green and vigorous vertical stem growth, 50-75% green stems (Figure 40b), vigour class 2, a bush with less vigour and mixed green and brown stems, 25-50% green stems (Figure 40c) and vigour class 1, a dormant bush with <25% green stems, mostly brown and dry stems with little active growth (Figure 40d)

Annex 2: Classification of riparian vegetation using remote sensing and drone imagery

Introduction

Vegetation monitoring within natural systems is essential for environmental decision-making and land management. Conventional ground-based methods for vegetation condition monitoring are often laborious, expensive and limited in the area of land covered. In recent decades, remote sensing methods have developed to enable broader areas to be surveyed as well as the collection of additional data to complement ground-based efforts.

Remote sensing of vegetation traditionally utilises satellite imagery, however there have been rapid increases in the use of drones over the last decade as a result of improving technologies that provide benefits in scale, resolution and capture times (Huylensbroeck, Laslier et al. 2020). Classification of land cover is a key remote sensing technique employed to monitor vegetation. After the initial training process, it allows users to automatically divide vegetation into classes at a level they decide on, often grouping multiple species based on their genus, family or cover type (i.e. low ground cover, shrubs, overstory). In some cases these classifications can be made at finer scales, with potential for even species level classifications to be achieved with high accuracy (Lu and He 2018, Durgan, Zhang et al. 2020).

This review will briefly discuss the advantages and limitations of drones and satellites as the two commonly used remote sensing platforms for vegetation monitoring. It will then highlight recent efforts in vegetation classification using RGB and multispectral sensors on a drone, with a focus on floodplain, riparian and semi-arid ecosystems. Ultimately, the aim of the review is to provide a summary of classification techniques which may be suitable for use in semi-automated monitoring of vegetation at Clark's floodplain.

Evolution of technology – from satellites to drones

The applications of satellites for environmental monitoring include land cover classification, vegetation health estimates using vegetation indices (such as NDVI) and aboveground biomass estimates (Dillabaugh and King 2008, Lawley, Lewis et al. 2016). Often this type of analysis is performed at the regional to global scale and is insufficient for monitoring at the local-scale due to the limitations in spatial resolution of satellite remote sensing (Anderson and Gaston 2013). The advances in structure from motion (SfM) software to generate very high resolution ortho-mosaics has accommodated the use drone data for monitoring purposes (Wich and Koh 2018). Many of the classification techniques that are currently implemented using drone data are based upon, or are directly transferrable from, satellite-derived classification techniques.

The increase in accessibility and development in drone-based remote sensing has lifted some of the temporal and spatial limitations of satellite products. Drones provide the ability to acquire repeated, georeferenced, very high-resolution spatial data on demand with minimal cost (Kattenborn, Leitloff et al. 2021 (Manfreda, McCabe et al. 2018)). As such, drones are not limited by the temporal resolutions determined by the orbit repeat times of satellites.

Vegetation classification from drone imagery

For simplicity, this review will break classification techniques down into three broad categories – pixel-based spectral classification, object-based classification and classification using deep learning methods.

Pixel-based (spectral)

Unsupervised

Unsupervised classification utilises clustering algorithms such as ArcGIS Pro's Isocluster algorithm which uses statistical methods to separate individual pixels into classes based on spectral similarity (Villoslada, Bergamo et al. 2020). Therefore, unsupervised classification algorithms do not require any human intervention in order to train the classifier. There are many studies which have used unsupervised classifications in attempt to characterise composition of vegetation communities, with mixed results (Gini, Passoni et al. 2014). In a number of cases (see Table. 1), unsupervised classification techniques were outperformed by supervised for classification of vegetation. A significant drawback to unsupervised classification is that the resulting classes from the clustering algorithms do not directly correlate with the classes of plant communities seen in reality (Jones and Vaughan 2010).

Supervised

Supervised classification techniques utilise human intervention to decide which pixels should make up a training class. This is done by selecting training sample areas in the form of digitised polygons that relate to vegetation types in reality. The training samples can then be fed into spectral or machine learning classifiers to produce classified outputs. The most widely used classifiers for supervised classification are Maximum Likelihood, Support Vector Machine and Random Forest.

Object based image analysis

Object based image analysis (OBIA) refers to classification techniques which use shape, texture and context rather than just pixel-level spectral characteristics (Liu and Xia 2010). In a number of cases (Ahmed, Shemrock et al. 2017) (van Iersel, Straatsma et al. 2018, Gomez-Sapiens, Schlatter et al. 2021), a combination of OBIA to first segment images, followed by spectral classification is used to improve the accuracy of the classification of vegetation. Very high-resolution imagery is subject to a lot of spectral mixing. For example, a tree can be made up of thousands of pixels with large variation in reflectance values due to signals being received from within the canopy, such as the ground beneath, therefore accuracy can be improved by using pixel and object based classification together (Wich and Koh 2018).

Deep learning

Studies utilising neural networks to classify vegetation from drone acquired data often report very high accuracy from trained models. However, these usually require the most input (labelling or manually segmenting thousands of images) during the training process, as well as high computational power. Furthermore, a significant amount of variable training data is required to reduce the chance of over-fitting, whereby models may become un-generalizable across datasets and location (Kattenborn, Leitloff et al. 2021). The success of the classification using neural networks may also vary with complexity in vegetation composition and structure. For example, Higgsisson et al. 2021, used a convolutional neural network (CNN) using 50,000 training images to classify *Phragmites australis* in a semi-arid wetland using RGB data. They reported an overall accuracy of 0.947, however had only acquired training data from a single site. It is also worth noting the authors acknowledge that the high accuracy is likely to be attributed to very few species in their chosen site having similar morphology to *Phragmites australis*.

Choosing classifiers – drone case studies

Table 8 features a selection of research papers which contain drone-derived vegetation classification methods and reported accuracies. Papers which had similar vegetation types to Clarks floodplain were most desirable and prioritised, however, there are a limited number of studies based in that vegetation type and climate so others with somewhat more diverse habitats were also included.

Table 8. Summary of key findings from relevant research papers utilising drone-derived vegetation classification, including data type collected, image classification techniques implemented and reported accuracies of those classifications

Source	Vegetation type	Aim	Data type	Classifier	Reported Accuracy
(Al-Ali, Abdullah et al. 2020)	Arid shrublands and grasslands	Assess vegetation cover of aridland shrubs and grasses and distinguish between them	4 band multispectral – Parrot Sequoia	Unsupervised: k-mean and ISODATA Supervised: SVM, MDM, ML and Parallelepiped Random Forest Object based	Unsupervised: 73 – 91% Supervised: SVM - 93% ML – 93% Random Forest: 55% Object-based: 86 – 94%
(Long, Kettenring et al. 2017)	Semi arid-wetlands – <i>Phragmites australis</i>	Classify raster data into nine major vegetation types	3 band multispectral	Supervised: Maximum Likelihood	Overall accuracy: 81.1%
(Gomez-Sapiens, Schlatter et al. 2021)	Arid riparian vegetation	Initially to classify by species but unable to. Reduced grouping to 7 cover types.	5 band multispectral	Supervised: Combination of pixel and object based using Support Vector Machine (SVM) on segmented image.	Overall accuracy across 3 sites: 87-96%
(Ahmed, Shemrock et al. 2017)	Mixed forest, wetlands, managed croplands	Classify raster data into 3 different vegetation classes 2 classes for surrounding environment – soil and built-up	4 band multispectral	Object-based classification	Overall accuracy: 95%
(Gini, Passoni et al. 2014)		Classify 4 species of tree and surrounding environment including soil, grass and concrete	RGB and modified RGB camera to record infrared information	Unsupervised: ISODATA Supervised: Maximum Likelihood	Unsupervised: 50% Supervised: 79%
(Villoslada, Bergamo et al. 2020)	Coastal meadow	Classify raster data from 3 sites into 5 land cover types.	4 band multispectral converted into 13 different vegetation indices	Unsupervised: ISODATA clustering, PCA on vegetation indices and spectral bands Supervised:	Unsupervised: Kappa = 0.58 Supervised: Kappa = 0.89

				Random Forest	
(van Iersel, Straatsma et al. 2018)	Floodplain	Use time series (6 captures over 11 months) raster data into a single raster containing 10 classes. 6 vegetation, 4 ground classes (sand, water, road, rock)	RGB and modified RGB camera to record infrared fusing elevation data and vegetation indices.	Object based segmentation with Random Forest Classifier	Overall accuracy 92 – 94%
(Prosek and Simova 2019)	Temperate shrubland	Classify multispectral raster data into six vegetation types. 4 woody plant species and two meadow veg types.	Fusion of 6 band multispectral and elevation data. Comparison with only using multispectral data without elevation.	Object based segmentation with supervised nearest neighbour classifier	Fused Overall accuracy: 88% Multispec only overall accuracy: 73.3%
(Higginson, Cobb et al. 2021)	Semi-arid wetland – <i>Phragmites australis</i>	Estimate cover of <i>Phragmites australis</i> , leaf litter, water and bareground	Cosumer grade RGB camera	Convolutional neural network	Overall accuracy: 95%
(Hamylton, Morris et al. 2020)	Temperate dune system	Detecting extent of <i>Lomandra longifolia</i>	Integrated RGB Phantom 4 Pro Camera	Convolutional neural network	Overall accuracy: 85%

Based on the variability in reported accuracies, it is likely that the choice of classification algorithms is not entirely responsible for the how well vegetation is classified using drone-derived datasets. Factors such as the complexity of the vegetation structure, the level of discriminability aimed for (i.e. species or cover type groupings), quality of training samples and timing with environmental conditions are likely to play a role in accuracy of classification. (Al-Ali, Abdullah et al. 2020) state that reflectance of soil backgrounds, and a mixture of green and senescing shrubs are likely factors for misclassifying vegetation extents. Classifying to the individual species level with currently available drone sensors is a challenging task and is likely due to species diversity not always correlating well with spectral diversity as demonstrated by (Villoslada, Bergamo et al. 2020). (Lu and He 2018) found that spatial resolution has a significant impact on classification at the species level. Furthermore, (van Iersel, Straatsma et al. 2018) state that similar vegetation types such as grassland and low herbaceous vegetation often have low classification accuracy. This is most likely due to having spectral characteristics that are too similar to be separated given the spectral and radiometric resolution of available multispectral cameras. Difficulties aside, it has demonstrated repeatedly in the literature, that accurate classifications are achievable given the right combination of data capture and analysis methods.

RGB vs Multispectral

The increase in accessibility and usability of drones with integrated RGB cameras over the past decade has been a primary driver for research based upon using RGB cameras for vegetation monitoring. However, multispectral sensors are now widely available and are being readily developed, as well as dropping significantly in price. The advantage of a multispectral sensor is a discrete spectral response and the inclusion of a near-infrared band which offers benefits in spectral discriminability of vegetation (Assmann, Kerby et al. 2019).

Fusion of spectral and height data

A number of studies have employed a data fusion method which combines height information as well as spectral data into the classification algorithm (Straatsma et al. 2018, Prosek and Simova, 2019, (Durgan, Zhang et al. 2020, Fernandez-Guisuraga, Calvo et al. 2022)). However, the outcome is ultimately dependent on the accuracy of the height data. The quality of SfM derived elevation models is highly dependent on the capture conditions, whereby high winds may cause too much movement in the vegetation canopy for the height of canopies to be reconstructed accurately. Furthermore, the fine, spindly characteristics of vegetation in Australia's low rainfall areas can be difficult to reconstruct using photogrammetry techniques, even with little movement caused by wind. In this case, inaccurate height data from SfM derived models may have a confounding effect rather than improving the accuracy of the classification. To avoid some of the drawbacks of SfM, LiDAR sensors can be employed to capture height data, however it comes at additional cost.

Conclusion

Classification using drone-derived data is an important tool for environmental monitoring. Successful classification can result from a number of different techniques, whereby accuracy is often influenced by the complexity of the landscape in terms of both structure and spectral discernibility. The literature reports success using a number of different techniques, and the end goal, as well as resource availability is likely an important factor is determining which technique to utilise.

Classification of Lignum extent and condition at Clarks Floodplain

A Support Vector Machine (SVM) classifier was chosen to classify the 5-band multispectral composite imagery into four classes. A total of 61 training samples across the four classes were created to train the SVM. Polygons were used for the training samples and were designed to capture the spectral variability that is present in each of the classes. The output produced and overall accuracy of 65%. (Refer Figure 41 and Table 9).

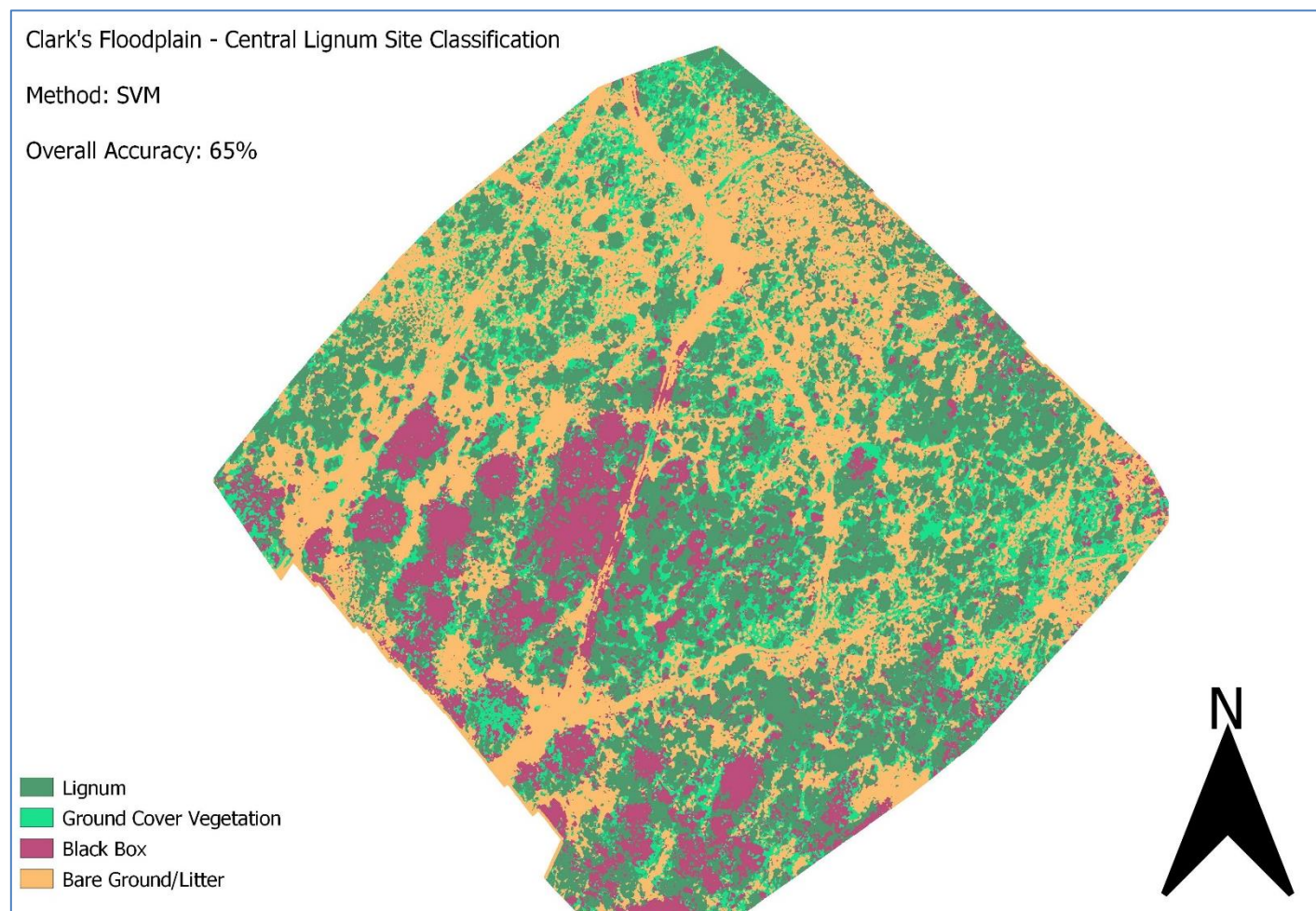


Figure 41 Classification output

Table 9. Classification reference data and accuracy assessment

	Reference Data						
Class	Lignum	Ground Cover Veg	Black Box	Bare Soil and Litter	Total	Users Accuracy	Kappa
Lignum	93	21	8	39	161	0.57764	0
Ground Cover Veg	17	33	10	19	79	0.417722	0
Black Box	10	14	43	8	75	0.573333	0
Bare Soil and Litter	7	19	0	147	173	0.849711	0
Total	127	87	61	213	488	0	0
Producer's Accuracy	0.732283	0.379310345	0.704918	0.690140845	0	0.647541	0
Kappa	0	0	0	0	0	0	0.50451

It is likely that classification accuracy will vary with timing of image acquisition respective changes in environmental conditions. In this case, an increase in water availability prior to image acquisition resulted in the growth of annual ground cover vegetation at time of imaging. The spectral discriminability between new growth in Lignum, Black Box and this new ground cover was reduced. Furthermore, there may be additional confusion between bare ground/litter and Lignum, due to much of the plant, especially when less vigorous, presenting grey, dry looking stems, with a potentially similar signature to the surrounding litter.

In order to improve the classification, additional image collection under different environmental conditions may be useful. In doing so, a multi-temporal stack of multiband rasters could be used train the classifier to further assist differentiation between classes as they change independently throughout time. For example, Black Box vegetation is likely to have less fluctuation in its spectral signature in comparison to Lignum after environmental watering events due to differences in water uptake capabilities. We would expect to see an increase in vigour and greenness of the Lignum as water uptake increases, however the black box woodland is more likely to have had access to groundwater and therefore water uptake may have little relative increase.

Another consideration for improving the classification is to supplement the spectral training data with canopy height data. In our case, this was not viable as due to time constraints flights were not intentionally designed to produce a precision 3D reconstruction of the landscape and therefore the canopy height derived from the datasets was not reliable. Including non-precise canopy height data into the training stack would have had a confounding effect on the classification.

Annex 3: Oblique imaging of riparian vegetation

Aims

The purpose of data collection at the riparian sites was to determine how much information could be acquired with regards to vegetation structure and health along the bank of the river using a novel method – oblique multispectral and RGB imagery. The goal behind using oblique imagery is the ability to detect vegetation which would usually be obscured by the canopy of red gum and black box woodland when capturing images from nadir.

Methods

Imagery was captured using a Zenmuse X7 and a Micasense Red edge MX mounted onto a Matrice M210 aircraft. Imagery was captured at two sites – a shallow lake with *Phragmites australis* on the northern side and a separate section of riverbank along the Murray, downstream of lock 4. The direction of flight was parallel to the riverbank with the drone facing inwards towards the riparian vegetation. RGB and multispectral imagery was captured along a stretch of approximately 500m at each site. To ensure there was sufficient overlap within the oblique image datasets, the flight path was repeated at 4 altitudes; 10, 15, 20 and 25m AGL. Due to differences in hardware and software between sensors, each sensor required different image capture methodology.

The RGB capture technique involved capturing imagery in video format at 30 frames per second and then extracting a subset of still images in post processing. To ensure sufficient overlap for SfM to stitch images together, 1 frame per second was extracted from the video using Agisoft Metashape. Agisoft Metashape was then used to align and stitch individual frames to produce an orthomosaic.

To capture multispectral imagery, the aircraft followed the same flight transects as the RGB image capture, however, the Micasense Red edge MX was set up on a timed interval to capture images each second for the duration of the flight. Both, RGB and multispectral datasets were processed using Agisoft Metashape.

Results

Both RGB and multispectral imagery demonstrated the ability to detect understorey vegetation in a riparian system. Generally, due to the projection plane and the position in the landscape, *Phragmites australis* was most easily detected, and in some cases, especially at the shallow lake site, blocked the view of other small understorey shrubs and grasses (Figures 42 to 44).

RGB ortho-mosaics were generally much cleaner, containing fewer artefacts from the ortho-mosaicking process.

The multispectral imagery did not provide any additional information in comparison to the RGB imagery, as much of it presented warping. As a result, in most cases, only the foreground (usually *Phragmites*) is represented sensibly; however, it is ultimately dependent on the structural complexity of the vegetation at any particular location along the ortho-mosaic.

Phragmites is just as easily detectable in the RGB ortho-mosaic as it is in the multispectral ortho-mosaic. Furthermore, the imagery was captured at a time when much of the understorey vegetation had senesced, therefore the signal from the NIR band of the multispectral sensor was not able to reveal any additional information about the health of the vegetation.

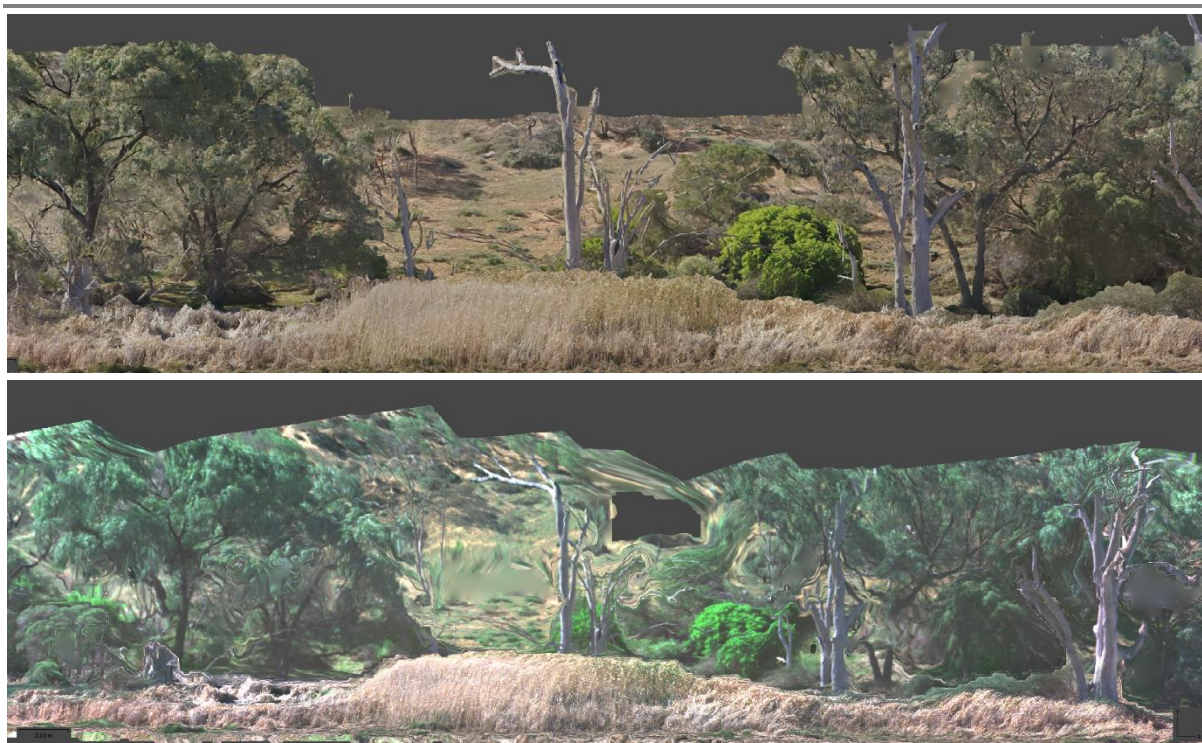


Figure 42 An area within the ortho-mosaic from the 'shallow lake' site, displaying a best-case. There are fewer artefacts in this particular section of the ortho-mosaic due to a relatively simple vegetation structure in the foreground and background. Top: RGB; Bottom: True colour multispectral composite

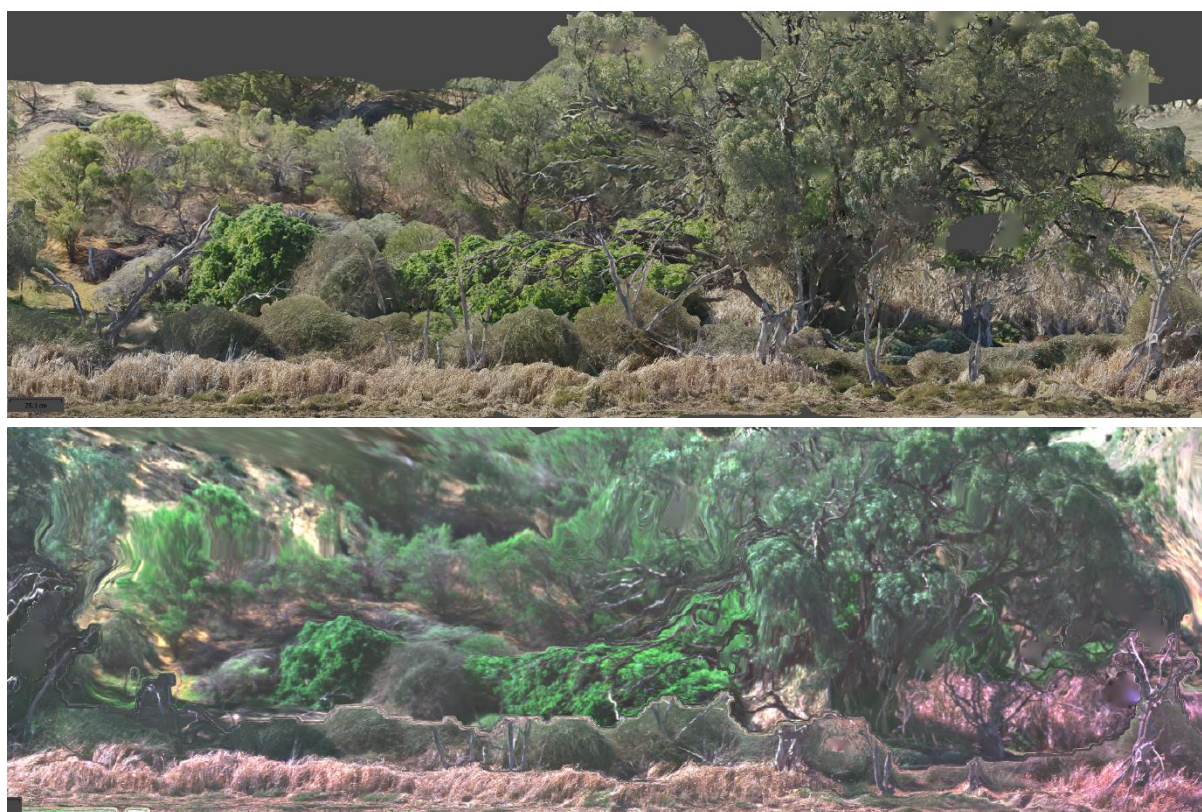


Figure 43 An area from the 'shallow lake' site, displaying a much more complex vegetation structure than Figure 42. The *Phragmites australis* is relatively well reconstructed, however, the vegetation in the background is particularly warped in the multispectral ortho-mosaic. Top: RGB; Bottom: True colour multispectral composite

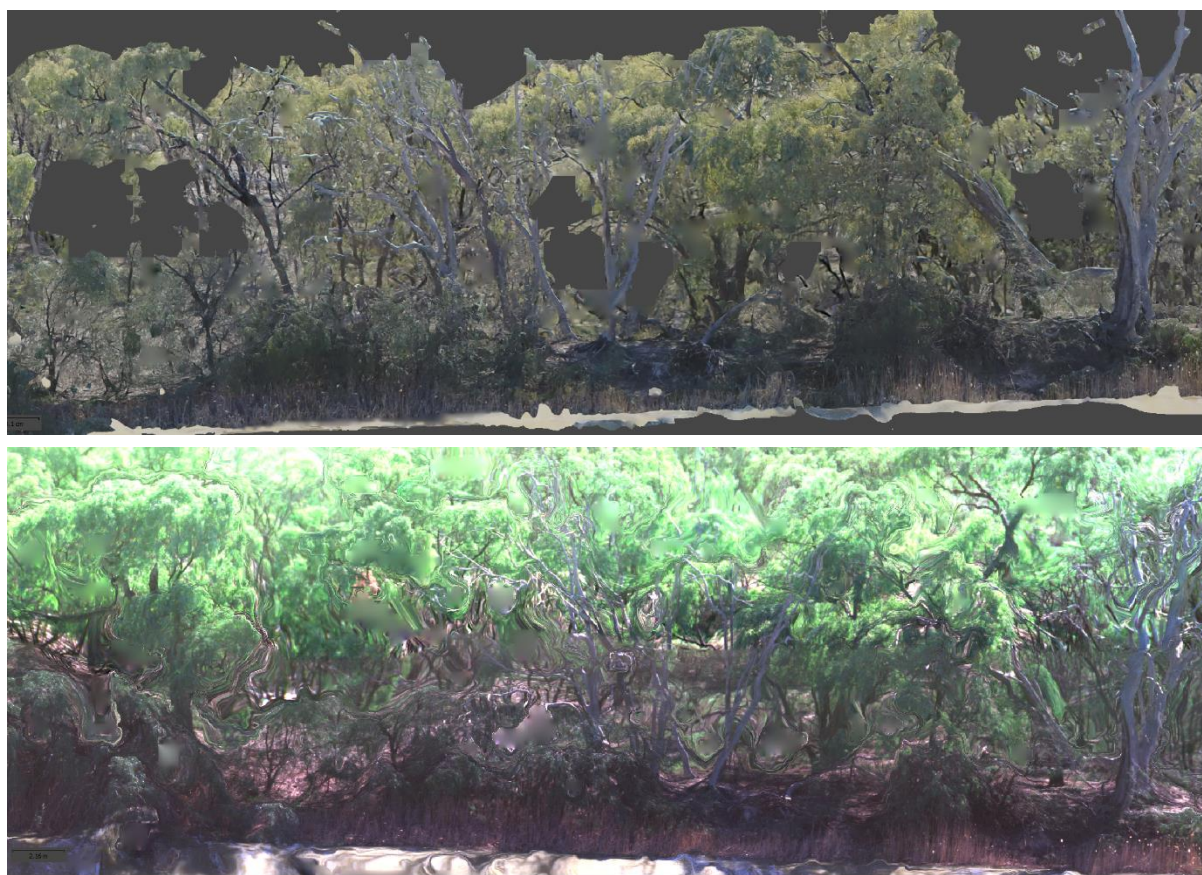


Figure 44 A segment of the riparian vegetation along the Murray River. The complex vegetation structure in both the overstory and understory contribute to warping in the ortho-mosaic. Top: RGB; Bottom: True colour multispectral composite

Both sensors had more success at the shallow lake site rather than on the river. The vegetation structure at the river site was more complex and 'busy', as well as the occurrence of deep water in the imagery. As a result, the quality of the ortho-mosaics were lower at the river site, whereby both ortho-mosaics presented more warping and missing information. Generally, the riparian vegetation was also less visible at the river site due an increase in flow preceding the imaging run and therefore much of it was submerged.

A significant benefit to the multispectral sensor is the automatic geo-tagging of imagery using the GPS connected the Red edge MX sensor. This provides a significant advantage during the ortho-mosaicking process, as Metashape uses the information to geo-reference and scale the imagery with high precision. Although the RGB ortho-mosaics are 'cleaner', containing fewer artefacts, a major limitation of RGB capture by video is the lack of geo-tags, as positional metadata is unable to be obtained and written into individual frames. As a result, the RGB ortho-mosaic is not geo-referenced and lacks real world scaling, so is therefore unable to be used to measure the establishment of *Phragmites* along the riverbank in absolute terms.

The lack of RGB geo-tags may be resolved by placing markers along the edge of the riverbank with known distances between them, thereby allowing distances to be measured to conduct presence/absence surveys. However, recent developments in RGB hardware and mission planning software now allow still geotagged images to be obtained fast enough without having to capture video. For example, the Zenmuse P1 allows images to be taken at sub-second intervals whilst writing geo-tags into image metadata. The drawback in this case, is the additional cost to purchase new hardware; ground surveys may be cheaper in the short term.

Issues with ortho-mosaicking oblique riverbank images which need further investigation and resolution include:

- difficulties associated with sky in background
- highly variable surface parallel to the projection plane
- causes warping of pixels to 'flatten' the image as if being viewed from front on
- movement of vegetation along the riverbank.

Annex 4: Archival multispectral imagery comparison

Data Analysis

Table 10. Sensor specification comparison

	Band widths and spectral resolution (nm)				
Sensor	Blue	Green	Red	Red Edge	Near Infrared
Parrot Sequoia	-	530-570	640-680	730-740	770-810
Micasense Rededge MX	459-481	546.5-573.5	661-675	711-723	813.5-870.5

Radiometric resolution

Parrot Sequoia: 10-bit output – dynamic range of 1024

Micasense Red edge MX: 12-bit output – dynamic range of 4096

The red edge has 4 bins, to every sequoia bin.

Due to the 10-bit output, the Sequoia's dynamic range is limited in comparison to the red edge. In turn, some of the variation that is detected in the red edge may not be detected in the Sequoia. This may be especially important where differences in condition of vegetation is subtle.

Spatial resolution

The Parrot Sequoia on a fixed wing platform is unable to fly any lower due to the speed of flight requirements to obtain sufficient overlap. However, the potential coverage is much larger than that of a multi-rotor drone. It is a good option to use for broad scale change, but is less viable for detecting change in individual plants.

Influence of altitude/GSD – as GSD increases, the proportion of pixels over vegetation increases, therefore attenuating some of the NIR signal from the Lignum.

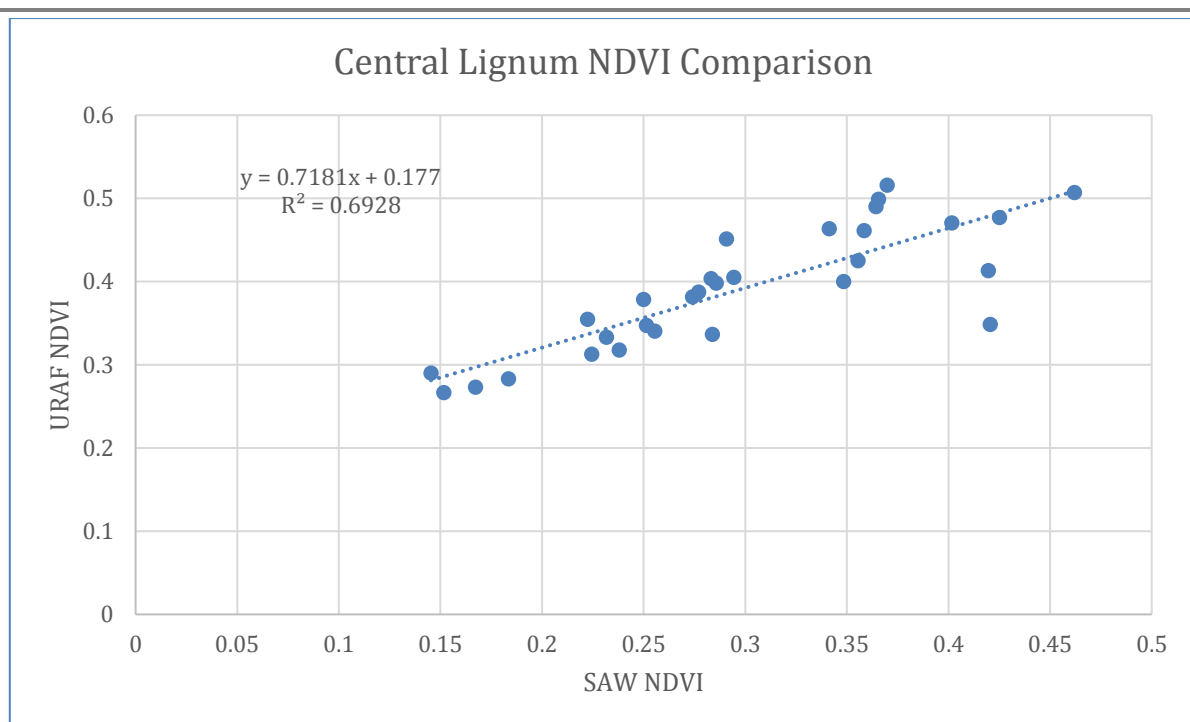


Figure 45 Scatter plot and regression - UoA and SAWater NDVI comparison

A comparison of NDVI values presented some differences between datasets captured two weeks apart. Values captured by SA Water with a Sequoia multispectral sensor tended to be low than those captured by URAF with a Micasense Rededge MX multispectral sensor. The SA Water data was captured 12 days prior to the URAF datasets and therefore changes in environmental conditions over that period of may have resulted in lower NDVI values in the SA Water dataset. (Figure 45).