Northern Australia Environmental Resources Hub

National Environmental Science Programme

Assessment of tools for monitoring savanna riparian vegetation: Fitzroy River case study

Report

Caroline A. Canham, Fiona L. Freestone, Shaun R. Levick, Nik Callow, Daniel Dixon, Michael M. Douglas and Samantha S. Setterfield

THE UNIVERSITY OF WESTERN AUSTRALIA

This report should be cited as: Canham CA, Freestone FL, Levick, SR, Callow N, Dixon D, Douglas MM, & Setterfield SA. 2021. *Assessment of tools for monitoring savanna riparian vegetation: Fitzroy River case study.* The University of Western Australia, Perth.

Front cover photograph: Fiona Freestone using a Leica BLK360 terrestrial laser scanner. Photo: Karen Dayman.

This report is available for download from the Northern Australia Environmental Resources (NAER) Hub website at nespnorthern.edu.au

The Hub is supported through funding from the Australian Government's National Environmental Science Program (NESP). The NESP NAER Hub is hosted by Charles Darwin University.

March, 2022

Printed by UniPrint

Contents

List of tables

List of figures

Abbreviations and acronyms

GCP .... ground control point

GNSS .... global navigation satellite system

LiDAR .... light detection and ranging

NESP .... National Environmental Science Program

NDVA .... normalised differential vegetation index

PBC .... Prescribed Body Corporate

RTK........... real-time kinematic

SME .... subject matter expert

TLS .... terrestrial laser scanning

TRARC ..... Tropical Rapid Appraisal of Riparian Condition

Acknowledgements

We thank the Walalakoo, Yungngora and Yanunijarra Prescribed Bodies Corporate for providing us with permission to undertake research on their country. We thank Traditional Owners and Indigenous rangers for accompanying us on Country, assisting with data collection and sharing knowledge about the land. We also thank Myroodah, Noonkanbah and Jubilee Downs pastoral stations for access to study sites. We acknowledge the assistance of the Kimberley Land Council in project facilitation, particularly Karen Dayman. Thank you to Joel Woodage from CR Kennedy for advice on using Cyclone Register. This project is supported through funding from the Australian Government's National Environmental Science Program through the Northern Australia Environmental Resources Hub.

Executive summary

Riparian vegetation in northern Australia is vulnerable to a number of processes that can alter its structure, composition and function, such as changes in water flows, fire, weed invasion and cattle grazing. Monitoring the condition of riparian zones is a critical component of adaptive management but it presents several challenges in northern Australia. Monitoring of riparian vegetation has traditionally used on-ground quadrats or transect methods to survey plant species and other parameters relating to the structure and health of vegetation. There is increasing interest in applying remote sensing techniques as methods of data collection become more affordable, including drone-based photogrammetry and terrestrial laser scanning.

This work, undertaken as part of the National Environmental Science Program's (NESP's) Northern Australia Environmental Resources Hub Project 2.6, reports on a comparison of two terrestrial laser scanning (TLS) sensors with contrasting price-points and capabilities, drone photogrammetry, and traditional vegetation transect methods to assess the structure of riparian vegetation in the lower Fitzroy River, Western Australia. We provide an overview of the techniques, focusing on the usability and application for management agencies, including associated costs (e.g. equipment and software) and the level of knowledge, skills and experience required to process and analyse the data collected.

We found that each of the tested methods has strengths and limitations in relation to scale (both detail/resolution and spatial coverage area), expertise, training and overall costs. Each of the methods have a potential to address specific questions in relation to the monitoring of riparian vegetation. TLS was found to be the most accurate and high-resolution method to investigate vegetation structure; however, the method covers a smaller spatial area than drone photogrammetry. Also, there are a number of potential barriers to the application of TLS methods, including equipment and software cost, advanced training expertise required, and field conditions. Drone photogrammetry provides TLS-like point-clouds, covers larger areas and has a lower cost to acquire data compared with TLS. However, drone photogrammetry provides less sub-canopy vegetation structure information and requires high levels of expertise for processing and data extraction. Each of the tested methods produced different types of data, from highly detailed 3D point clouds using TLS to estimated vegetation health scores using rapid vegetation transect assessments. There were also differences in the spatial scale assessed by each method and the opportunities for sampling frequency.

While the technology to collect remotely sensed data is becoming increasingly user-friendly and affordable, processing the data remains a specialised skill. To derive metrics from TLS and drone photogrammetry requires access to appropriate computer processors, software and specialised knowledge, skills and experience. Therefore, the application of TLS or drone photogrammetry should align with the specific aims of the monitoring program and the budget and human resources available.

1. Monitoring of riparian vegetation in northern Australia

Riparian vegetation in northern Australia faces multiple pressures, including flow alteration due to water development (Douglas et al., 2019; Canham et al., 2021), changed fire regime (Douglas et al., 2015) and impacts from cattle, feral pigs and weeds (Connor et al., 2018; Petty et al., 2012). Changes in riparian vegetation may be detected through targeted monitoring to address the specific concerns of relevant management groups, including government agencies and Indigenous ranger programs. An effective monitoring program requires clear objectives with research questions or hypotheses that can be quantified and tested to guide the selection of relevant indicators, and the method and frequency they are collected.

The riparian zone is often a narrow zone with great complexity in both species composition and vertical structure. Depending on the scale of impact and the design of the monitoring program, changes may be as dramatic as loss of whole areas of riparian tree species down to subtle changes such as no recruitment of riparian species, or a reduction in flowering and seed production (Douglas et al., 2015) Therefore, the selection of appropriate indicators or metrics should take into consideration the aim of monitoring and the spatial and temporal scales of interest for the detection of change (Lawley et al., 2016). Vegetation indicators may be categorised as:

- compositional e.g. alpha diversity of native trees, cover of native and exotic plants, litter cover, recruitment of native trees, tree health and evidence of grazing (Oliver et al., 2007).
- structural e.g. density of different plant forms, density of tree hollows, canopy cover and ground cover components and patch size. Structural indicators are linked to habitat provision for fauna and landscape-scale ecosystem function. Structural indicators have traditionally been observed using on-ground quadrat and transect surveys, but some may be suitable for remote sensing techniques.
- functional e.g. ecological processes, disturbance regime, and nutrient cycling (Lawley et al., 2015).

Measurement of vegetation indicators used in monitoring has traditionally favoured on-ground surveys using quadrats or transects. For example, the Tropical Rapid Appraisal of Riparian Condition (TRARC) method was developed for use by non-specialists to monitor vegetation condition (Dixon, 2006). Other on-ground methods used for assessing groundwater dependent ecosystems in northern Australia include measurement of predawn plant water potential and surveys of tree species composition and a visual assessment of health (DWER, 2017). However, there are very few examples of on-going programs monitoring riparian vegetation in northern Australia, despite the growing need for monitoring (Douglas et al., 2019). Furthermore, traditional on-ground survey methods are sometimes seen as time consuming and costly, and advances in technology have led to increased interest in using remote sensing to monitor riparian vegetation. There is therefore a need to identify appropriate and effective methods of data collection for monitoring riparian vegetation in northern Australia.

Recent advances in technology have seen increased uptake of remote sensing techniques for monitoring of vegetation, and there is often complementarity between remotely sensed data and traditional survey methods. For example, it is now commonplace to access satellite images to determine canopy cover and the width of the riparian zone, and this information may also assist with site selection. There are many options of remote sensing technologies, numerous ways of processing the outputs, and great potential for the types of research and management questions that might be answered. As high-quality remote sensing options become more affordable and user friendly, they are more appealing as a monitoring tool for land and water managers. The quality of off-the-shelf products, such as drones (e.g. the DJI Mavic Pro ~AUD$2,000) provides imagery sufficient for research or monitoring purposes and the ease of use of these products, such as advanced flight planning software, may make them appealing to managers. Terrestrial laser scanning (TLS) technology has been used in forestry and has been suggested for monitoring the structure of vegetation at a plot-scale (Campos et al., 2021); with a range of metrics developed to assess vegetation structure (Seidel et al., 2016). However, to our knowledge, there are few examples of drone and TLS technology being used routinely by managers to monitor riparian vegetation health in northern Australia.

TLS and drone photogrammetry methods generate very large and complex datasets that require significant processing and analysis, which may be a barrier to using these methods to monitor riparian vegetation. Research often assesses the application of these technologies but the researchers have a background in remote sensing and significant expertise in working with large spatial or 3D datasets. This experience and expertise may differ from that available at many agencies tasked with undertaking monitoring of riparian vegetation, such as natural resource management groups or Indigenous rangers. There is a need to understand the feasibility of using these technologies by non-subject matter experts (non-SMEs) if management staff have limited expertise, and also whether they provide data that is appropriate to their management questions. There is therefore a need to work through the process of data acquisition and analysis, informed by spatial data analysts, and then provide advice to managers.

1.1 Research scope and aims

This work, undertaken as part of the National Environmental Science Program's (NESP's) Northern Australia Environmental Resources Hub Project 2.6, aimed to evaluate the application of TLS and drone technology for monitoring of riparian vegetation and compare these results to traditional on-ground data collection methods.

The scope of this project was limited to assessing the use of TLS and drones in northern Australia. There are other data collection methods that may be considered by managers including analysis of satellite data, and LiDAR (light detection and ranging) collected from a helicopter (airborne LiDAR) or a drone, however these methods are beyond the scope of this study. The use of satellite data for assessing riparian vegetation has previously been reviewed (Levick, 2018) and demonstrated elsewhere in Australia (Melrose, 2013; Murray-Darling Basin Authority, 2020). Airborne LiDAR is a high-cost method that requires specialised analysis and was therefore not considered as feasible for monitoring riparian vegetation for most management agencies. Drone-based LiDAR is an emerging technique and was not considered when this study was conceived. However, the method may become viable to managers as the technology and data analysis develops.

We wanted to gain insight into how TLS and drone photogrammetry may be applied by managers, who may not necessarily have training and skills in spatial analysis. The professional experience of the main researchers involved in this project is in field-based ecology and plant water requirements with no experience in the analysis of 3D point clouds and drone imagery. Data acquisition and processing was informed and supported by researchers with expertise in the relevant areas of spatial data analysis.

In this report, we provide:

- details on the cost and expertise that was required to collect and analyse data collected using drone, TLS and transect ecological survey techniques
- a summary of the data collected and and metrics that were derived
- a discussion of the pros and cons of the techniques, with some comment on their suitability for managers and other agencies that monitor riparian vegetation.

1.2 Case study – Fitzroy River

This project was undertaken in the lower Fitzroy River in Western Australia (Figure 1), complementing work completed in the NESP 1.3.3 Environmental Water Needs project. Research has been targeted in this area as it is where water development potentially will occur as indicated by previous development proposals and the current state government water-planning documents (DWER, 2020). Future water planning and monitoring of the lower Fitzroy River will likely need to answer numerous questions about riparian vegetation health, cultural values, riparian weeds, fire disturbance and cattle (Douglas et al. 2019). Monitoring will form part of future water management decisions (DWER, 2020), and is a part of Healthy Country Plans (Walalakoo Aboriginal Corporation, 2016; Gooniyandi Aboriginal Corporation, 2015). Furthermore, a recent review of the literature identified that there is an increasing number of studies using remote sensing to characterise riparian vegetation; however, they highlighted a lack of studies in tropical regions (Huylenbroeck et al., 2020). There is therefore a need to identify monitoring tools that can be collected by people with a range of expertise and backgrounds and that provide ecologically relevant data.

The Fitzroy River catchment spans ~90,000 km^2 and is located on the south-western edge of Australia's tropical region. It experiences distinct summer wet and winter dry seasons with median monthly rainfall ranging from 0 mm (May to September) to 200 mm (January; 1991–2019 data collected at the Curtin Aero Gauge [-17.58, 123.83]; BoM 2019). The study area has high inter-annual variability in rainfall, with a median annual rainfall of 791 mm and a range between 397 mm and 1294 mm between 1991 and 2019 (BoM 2019). Mean monthly maximum temperatures are highest in November at 40.0 °C, with lowest maximum temperatures in June at 30.8 °C (BoM 2019).

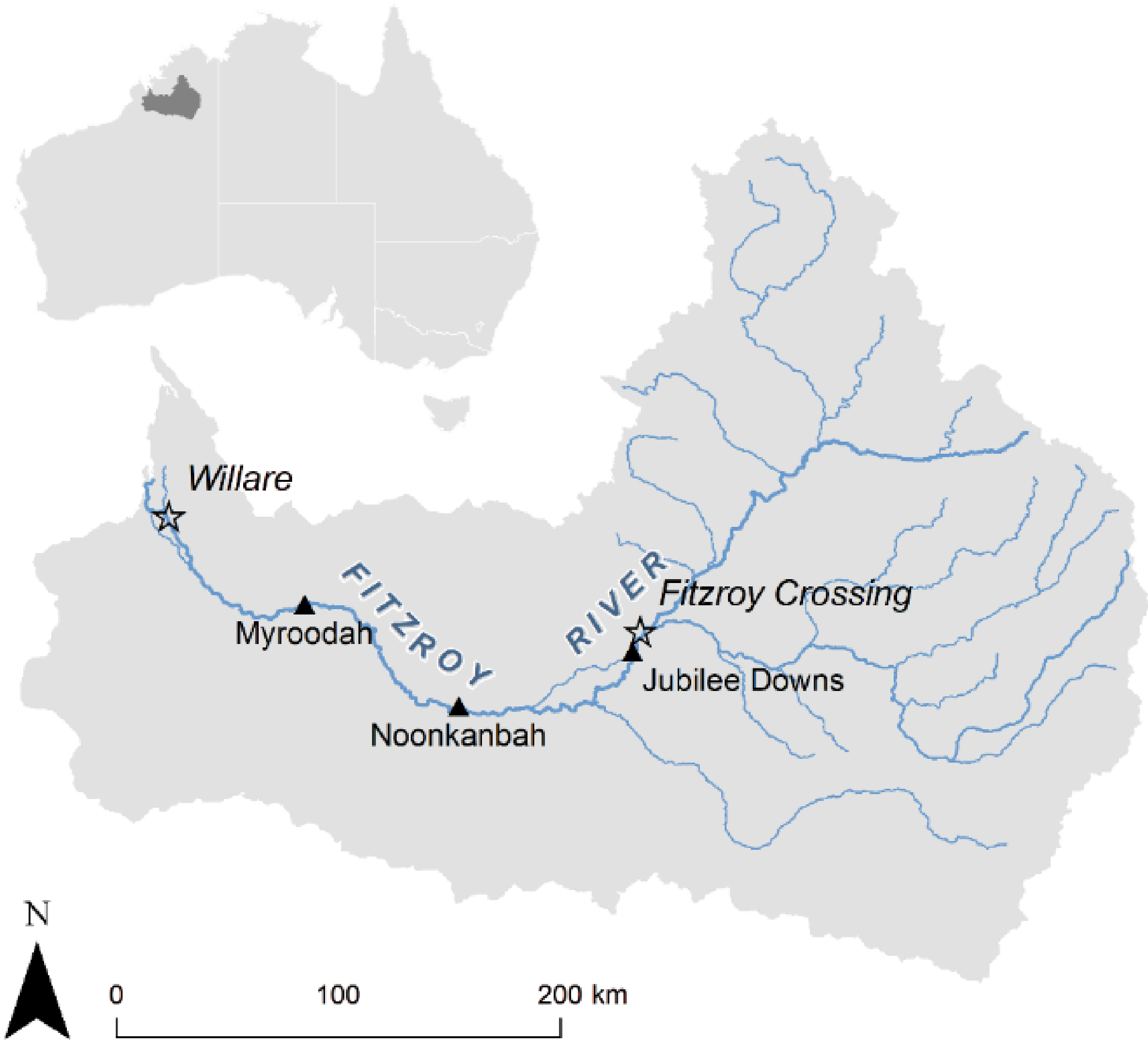
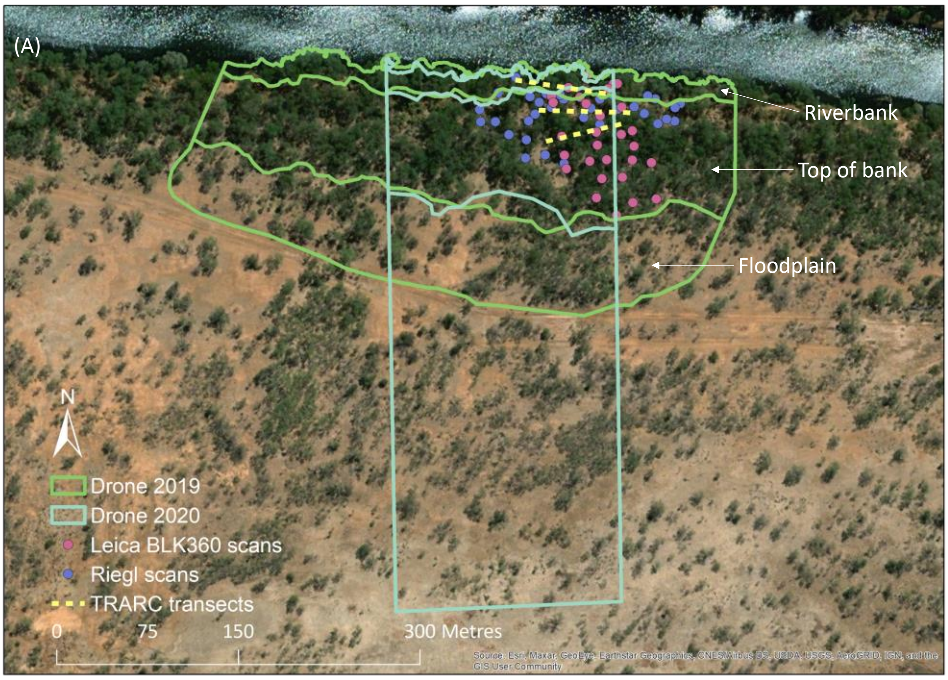


Figure 1. Map of the Fitzroy River catchment showing the location of the study sites, Jubilee Downs, Noonkanbah and Myroodah. The towns/settlements of Fitzroy Crossing and Willare are also indicated.

1.3 Sampling design

Data was collected at two times – November 2019 and September 2020 – and at two locations – Myroodah and Jubilee Downs pastoral stations (Figure 1). Sites were located on Nyikina-Mangala and Yi-martuwarra country, and Traditional Owners and rangers from each area accompanied us as directed by the respective Prescribed Bodies Corporate (PBCs). There was an effort to ensure overlap between the plots sampled to allow for comparison between the techniques. Sample points for each method is shown in Figure 2.



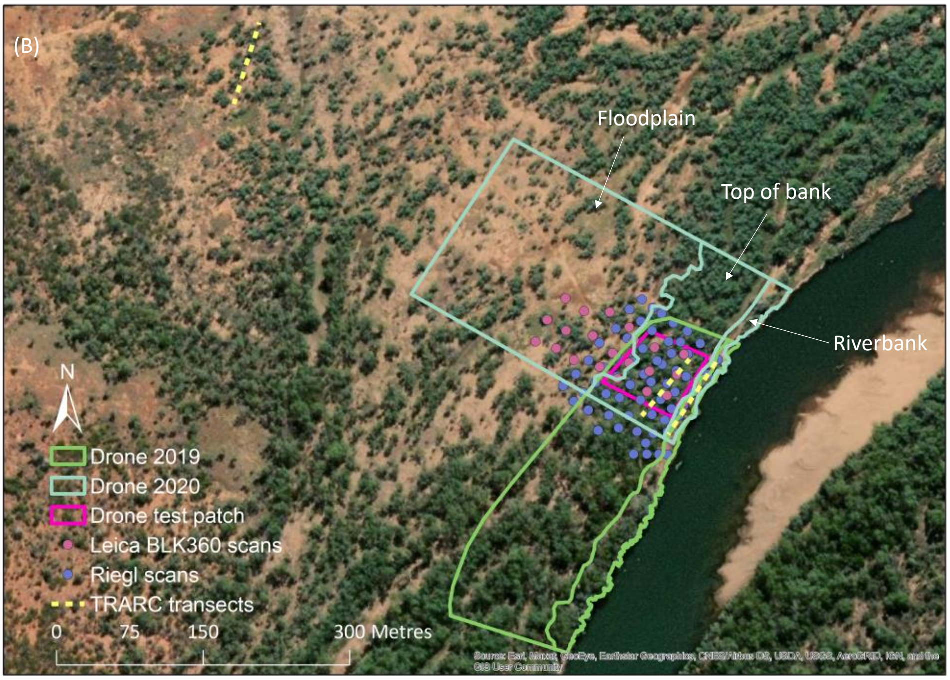


Figure 2. Map of data collection points for Myroodah (A) and Jubilee Downs (B), showing points of terrestrial laser scans using the Reigl VZ 2000i and Leica BLK360, the areas flown by drones in 2019 and 2020, and transects surveyed using the TRARC (Tropical Rapid Appraisal of Riparian Condition) method.

2. Assessment of techniques

TLS instruments use LiDAR sensors on a ground-based instrument. They record the time taken for a laser pulse to hit an object and return to the sensor, which can be used to build a 3D point cloud (Watt & Donoghue, 2005). The method has been demonstrated for assessing vegetation structure in a variety of ecosystem types including temperate and tropical forests (Calders et al., 2020; Muumbe et al., 2021; Newnham et al., 2015).

There are different laser scanners available with a wide range in price, with the main differences between the models being the nature and strength of the laser. In open areas, the time-of-flight laser of a top-of-the-range scanner, such as the Reigl VZ-2000i can travel up to 2.5 km, collecting a lot of information without having to complete as many scans. The Leica BLK360 is also a time-of-flight scanner but has a weaker laser meaning the area covered is much smaller than that covered by the Reigl in a single scan. However, in more closed, complex environments, such as dense mangroves or riparian vegetation, smaller, cheaper models with a smaller laser range may be effective as the laser does not need to travel far before encountering an object. The Leica BLK360 also does not include inbuilt GPS and inertial sensors, meaning that a dGPS is required to georeference scans.

We chose to test two different laser scanning systems: (i) the more powerful, more expensive Riegl VZ 2000i along with a specialist to collect this data, and (ii) the Leica BLK360, which is more affordable, more portable and easily operated by almost anyone to collect data in the field. We sought to use both TLS systems to:

1. determine tree height
2. calculate stand canopy cover
3. assess vertical complexity.

We also assessed drone photogrammetry techniques and vegetation transect surveys.

2.1 Terrestrial laser scanning – Riegl VZ-2000i

2.1.1 Data collection

The workflow used for the collection, processing and data analysis is shown in Figure 3. Scans were collected in November 2019. TLS was conducted from a surveying tripod at 1.8 m above ground level, using a Riegl VZ-2000i laser measurement system with integrated RTK-GNSS (real-time kinematic global navigation satellite system; Figure 4). The scanner and tripod are larger than the Leica scanner and two people are required to move it around the site. Scan positions were arranged to minimise occlusion, and spacing varied from 10 m to 30 m in dense riparian areas and 30 m to 50 m in the more open sites. The scanner was operated at 600 kHz with an angular sampling resolution of 0.03 deg, providing enough power for canopy penetration and a narrow beam footprint (4 cm at 100 m) for fine-scale vegetation characterisation. The scan pattern was set to 360 × 100 degrees. To georeference scans, the scanner communicated with a RTK base station (Emlid RS2) established at the site and operating over a LoRa network. Real-time positioning error of the scanner at each scan location was < 0.05 m.

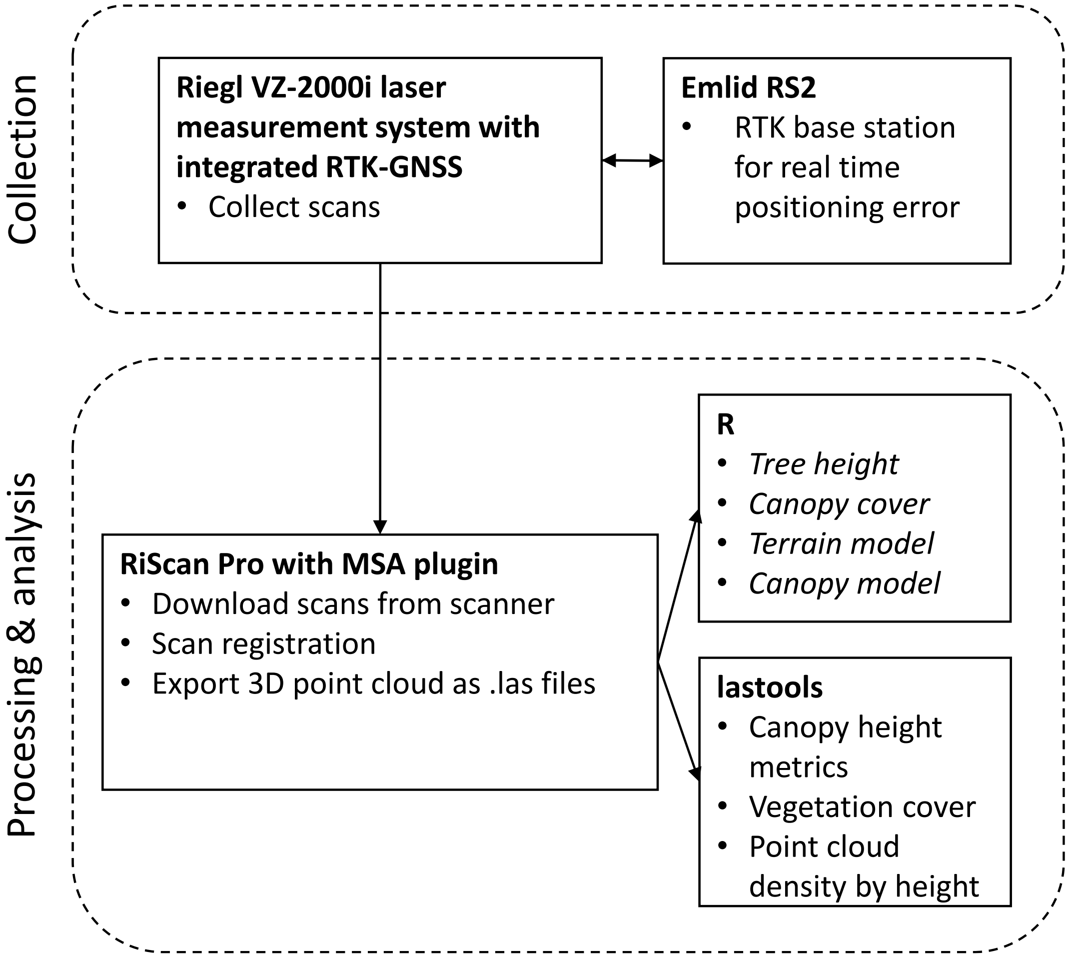


Figure 3. Workflow for data collection and processing using the Riegl TLS.

Figure 4. The Riegl VZ-2000i terrestrial laser scanner in use.

2.1.2 Processing and analysis

Raw processing of the TLS datasets was conducted in Riegl's RiSCAN Pro software suite (v2.11). Scan data were projected into the WGS84 coordinate system (UTM Zone 51S) and filtered for noise based on reflectance and deviation characteristics. User input is required to define the filter settings, which included deleting any points with a reflectance value lower than -25 and pulse deviation value for greater than 60. The Multi-Station Adjustment (MSA) plugin was used to finely co-register the individual scans, which were already well positioned given the integrated GNSS with real-time correction. The MSA adjustment approach is iterative – starting with a 5 m search radius, then 3 m, then 1 m, then 0.5 m, and finally 0.2 m. Final root mean square error of the co-registration was 0.018 m. Co-registered scans were merged and homogenised with a 0.03 m octree filter prior to export the industry standard ASPRS .las (1.4) format for further analysis.Thus, a merged point-cloud dataset was produced for each of the three scanned sites. The process of producing the merged scans in RiSCAN Pro was completed by an expert in spatial analysis, with further analysis attempted by non-SMEs to determine what could be completed by a non-expert.

To derive metrics from the scan data, the point clouds were further analysed using R, a free, code-based statistics program, using the LidR package (Roussel & Auty, 2021; Roussel et al., 2020). The package allows for metrics to be extracted from the 3D point cloud and was designed to be used for vegetation datasets. To reduce processing time and requirements, the .las files were imported using the first returns. Attempts were made to compute terrain and canopy models; however, this was not able to be completed on the merged scans due to processing limitations and inexperience.

Collaborators with TLS expertise derived metrics from the point cloud data for Jubilee Downs and Myroodah at the riverbank and top-of-bank landscape positions. In each habitat and landscape position 20 × 20 m subplots were selected for analysis. The program 'lastools' (cost EUR 2000; https://rapidlasso.com/pricing/) was used, running the function 'lascanopy', after normalising for height above ground. Open source options for the derivation of canopy metrics are FUSION (http://forsys.cfr.washington.edu/fusion/fusion_overview.html), lidR (https://rdrr.io/cran/lidR/man/cloud_metrics.html) or laserchicken (https://laserchicken.readthedocs.io/en/latest/#features). Metrics derived include average canopy height, canopy cover and point-cloud density at different heights and a full list of metrics is provided in Appendix 1.

2.1.3 Results and discussion

Costs and expertise

The Riegl VZ-2000i is a high-end laser measurement system. Data collection requires minimal training to ensure scan settings are correct, but data handling and processing required expertise and specialised training. Co-registered and geolocated point clouds were provided by our collaborators for further analysis. Collaborators also provided plot-based metrics of canopy height and vertical complexity as determined through point density at different heights.

We found that the team members with expertise and experience in processing and analysing scan outputs were needed to deliver metrics, with only limited analysis able to be completed by the non-SMEs who found significant difficulties due to inexperience with analysing 3D spatial data. For example, an attempt was made to derive a canopy height model in LidR, however this was unsuccessful as the model ran for 12 days, and then the computer reset itself, losing any progress. To overcome this, the model was then run on a reduced point cloud, however this resulted in limited metrics (Appendix 2). In contrast, the analysis of the point cloud dataset by our expert collaborators using RiScan Pro and lastools resulted in a range of plot-scale metrics (Appendix 3). This demonstrated that a team seeking to use this technology will require training in appropriate programming languages (either in R, C++ or Python), and workflows (e.g. using las_catalogue in the LidR package to tile the large file to process it in useable chunks).

The upfront costs for scanning with the Riegl system is high, with the scanner costing approximately $200K and RiSCAN Pro software required for processing data, based on prices provided by collaborators that have previously purchased the TLS system. Estimated costs of equipment are provided in Table 1.

Table 1. Costs for equipment and software required for the collection of TLS data using the Reigl Scanner. Total shows the estimated up-front cost, excluding labour and ongoing license fees.

Description	Equipment/software	Cost
Scanner	Riegl VZ-2000i	$200,000
Ground control	Emlid Reach RS2	$3,000
Data processing	RiScan Pro with MSA plugin	$25,000 upfront & $4,000 annual fee
Processing PC	Dell Xeon 4210 CPU with 128GB RAM and NVIDIA GeoForce RTX 2080 with 8 GB VRAM	$10,000
Total		**$238,000**

Data and metrics outputs

Registered point clouds provided high-definition 3D representations of the sites. The TLS point cloud can be visualised at different angles, for example Figure 5 shows a sideview of a transect, which highlights the height of trees. The cover and distribution of vegetation may be better viewed from above, as shown in Figure 6a, with the colourscale also showing height (above sea level).

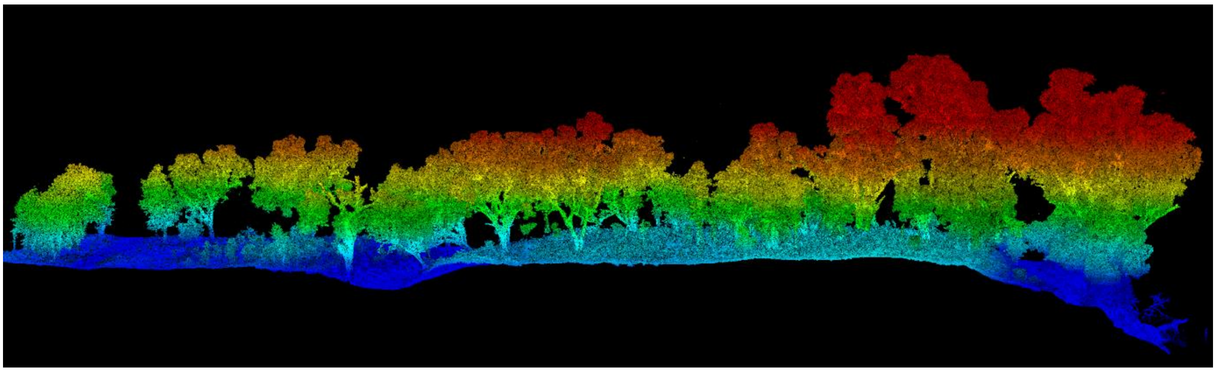
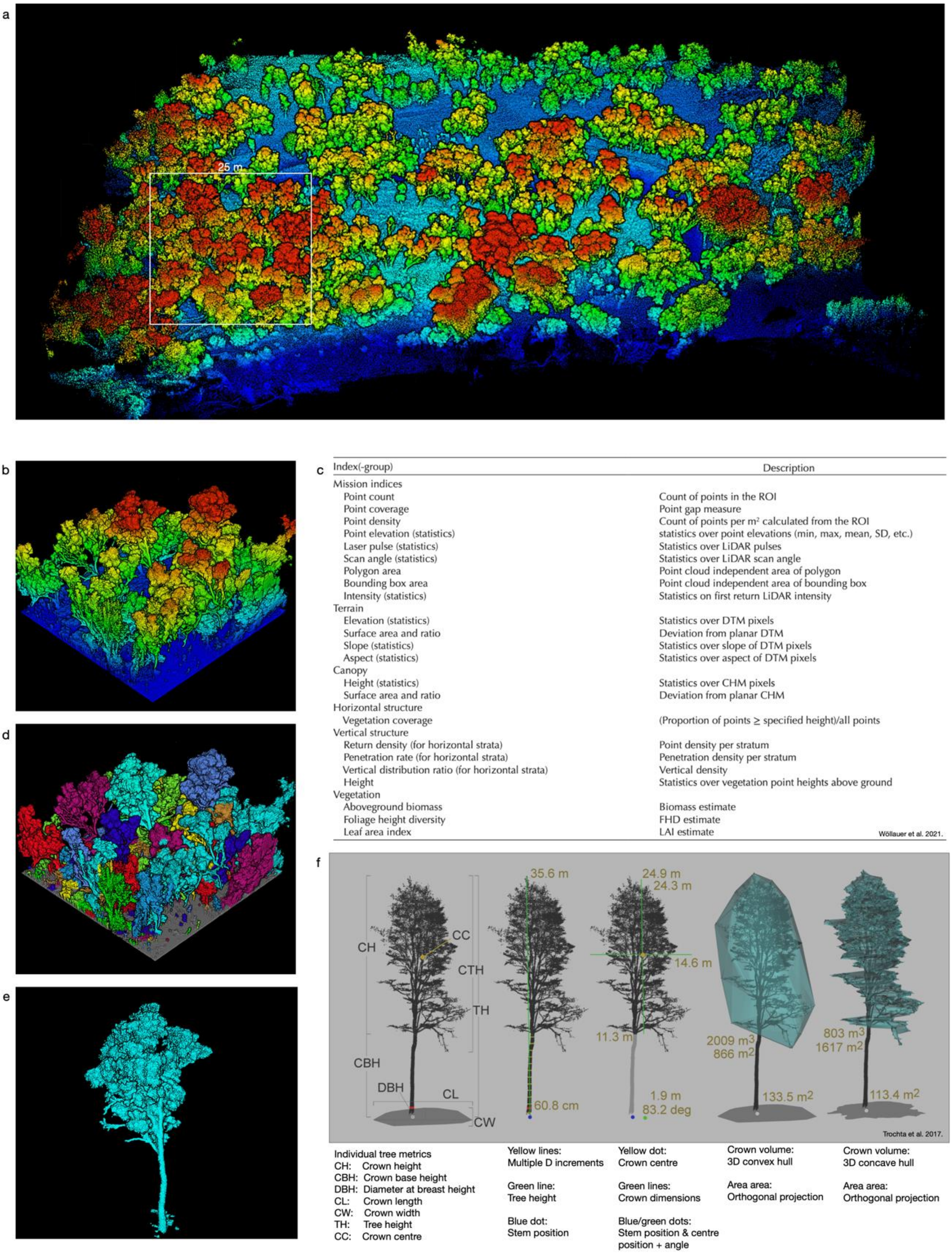


Figure 5. A 3D representation of a 10m wide belt-transect through the middle of the merged point cloud for the Jubilee Downs site. Image was produced in CloudCompare, colour scale indicates height above sea level.



Index(-group)	Description
Mission indices	
Point count	Count of points in the ROI
Point coverage	Point gap measure
Point density	Count of points per m² calculated from the ROI
Point elevation (statistics)	statistics over point elevations (min, max, mean, SD, etc.)
Laser pulse (statistics)	Statistics over LiDAR pulses
Scan angle (statistics)	Statistics over LiDAR scan angle
Polygon area	Point cloud independent area of polygon
Bounding box area	Point cloud independent area of bounding box
Intensity (statistics)	Statistics on first return LiDAR intensity
Terrain	
Elevation (statistics)	Statistics over DTM pixels
Surface area and ratio	Deviation from planar DTM
Slope (statistics)	Statistics over slope of DTM pixels
Aspect (statistics)	Statistics over aspect of DTM pixels
Canopy	
Height (statistics)	Statistics over CHM pixels
Surface area and ratio	Deviation from planar CHM
Horizontal structure	
Vegetation coverage	(Proportion of points ≥ specified height)/all points
Vertical structure	
Return density (for horizontal strata)	Point density per stratum
Penetration rate (for horizontal strata)	Penetration density per stratum
Vertical distribution ratio (for horizontal strata)	Vertical density
Height	Statistics over vegetation point heights above ground
Vegetation	
Aboveground biomass	Biomass estimate
Foliage height diversity	FHD estimate
Leaf area index	LAI estimate

Wöllauer et al. 2021.

Figure 6. Overview of TLS point cloud metric derivation. (a) Full spatial extent of the Jubilee Downs dataset clipped to the area that was the focus of the scanning survey; colour scale is height above sea level. (b) A 25 m × 25 m quadrat of points are clipped out and normalised by height above ground; colour scale is height above ground level. (c) List of plot-scale metrics that can be automatically extracted from the plot-scale data from (Wöllauer et al., 2021). (d) Individual trees are segmented from the plot-level dataset; colours represent individual trees. (e) Single trees are extracted from the plot-scale data for further analysis. (f) List of the types of metrics than can automatically calculated on an individual tree basis (Trochta et al., 2017).

Plot-scale data calculated by TLS experts included average canopy height, canopy height percentiles and canopy cover (Figure 7). To run these analyses, subplots were selected, with examples shown in Figure 6b & d. This provided comparative metrics between sites. For example, vegetative cover (inclusive of all plant material) was greatest at Myroodah, with less cover and greater variability in cover found at Jubilee Downs (Figure 7c). Canopy cover was considered in three different metrics: the 90th and 99th percentile (i.e. the 90th percentile is the height below which 90% of the vegetation occurs (Walter et al., 2021), and average canopy height (calculated from the height of each point in the point cloud). Vegetation structure can also be assessed by considering the density of the point cloud, which shows the density of vegetation at different height classes (Figure 8). This showed that there was a greater density of vegetation in the 0.5 m to 5 m height classes at Myroodah compared to Jubilee Downs. However, at greater heights vegetation was denser at Jubilee Downs compared to Myroodah for the subplots assessed.

Examples of other plot-scale metrics that may be derived from the TLS point cloud data are summarised in Figure 6c (Wöllauer et al., 2021), and these may be considered by managers to determine the most relevant metric for their monitoring question. Similarly, managers may be interested in assessing individual trees and examples of tree-scale metrics are provided in Figure 6f.

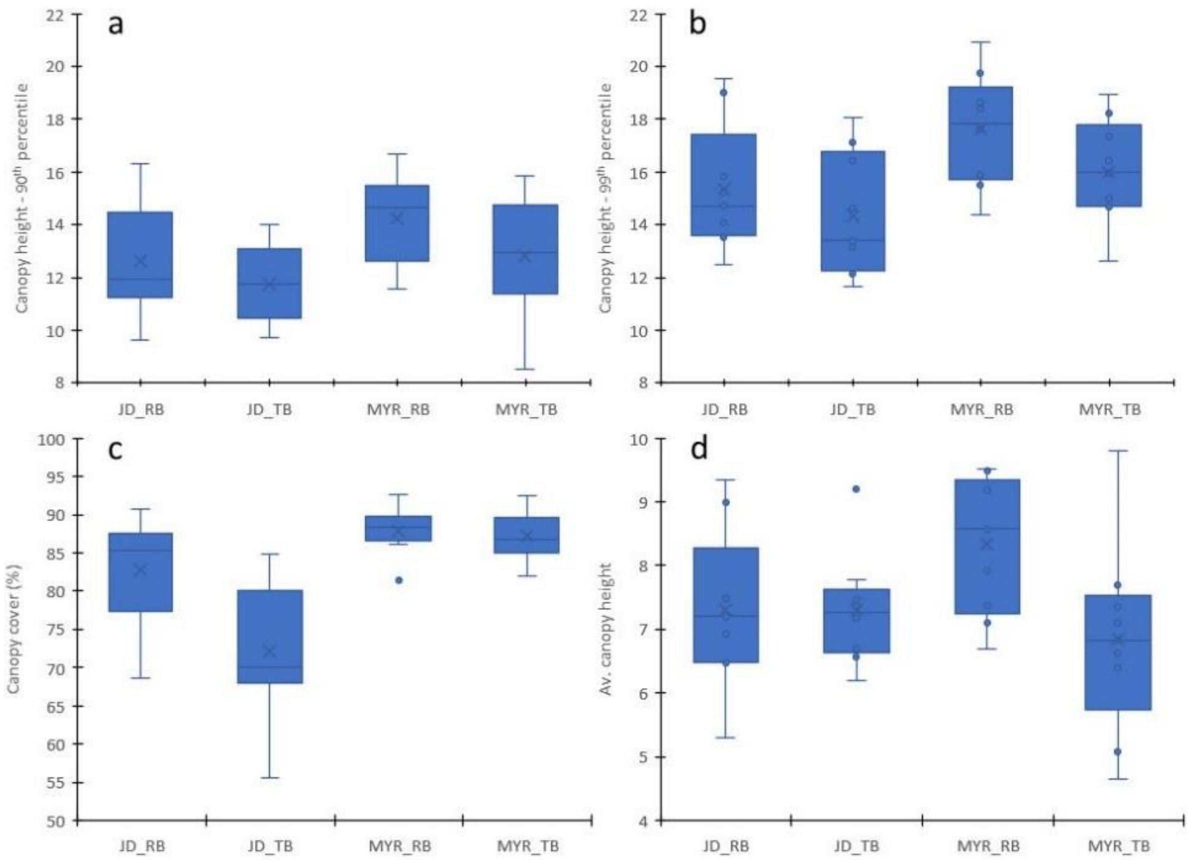


Figure 7. Boxplots summarising metrics derived from TLS data collected using the Reigl scanner at Jubilee Downs (JD) and Myroodah (MYR) sites and riverbank (RB) and top-of-bank (TB) landscape positions.

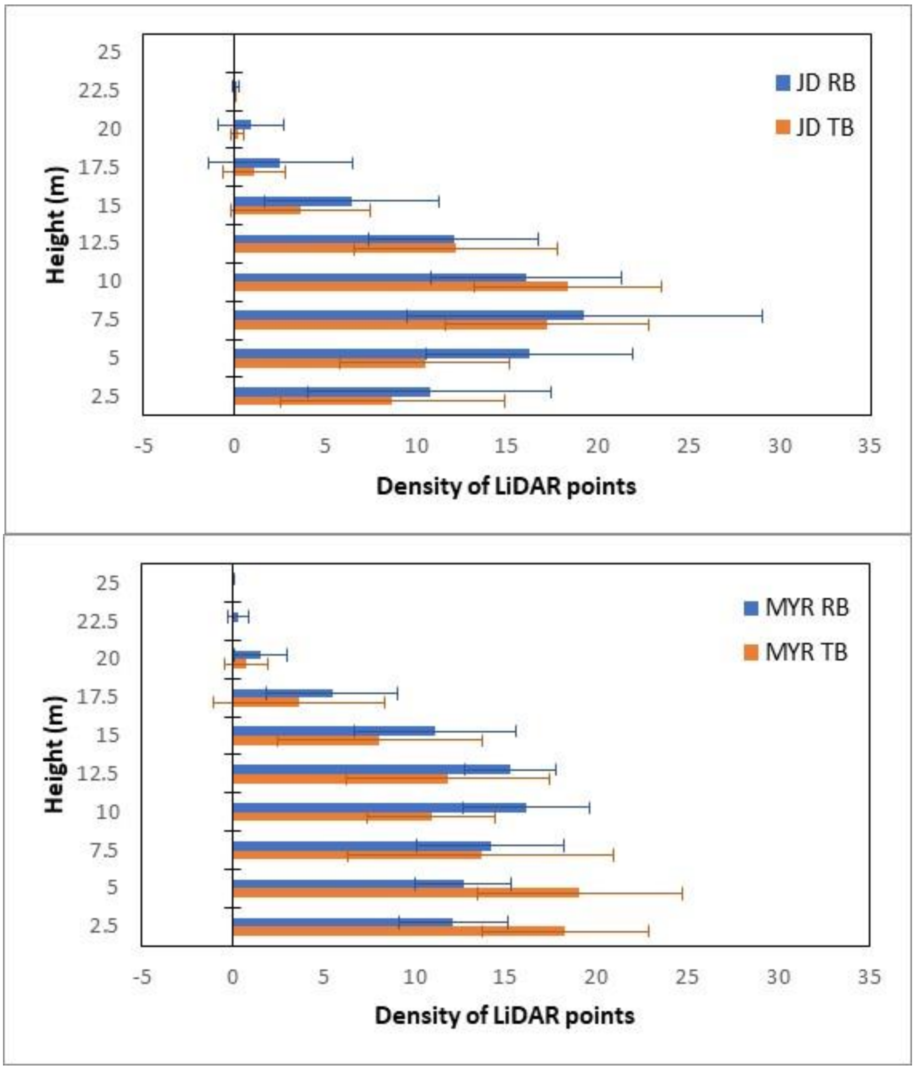


Figure 8. Density of LiDAR points at 2.5 m increments at Jubilee Downs and Myroodah riverbank and top-of-bank landscape positions. Values are the mean (with standard deviation bars) for 9 subplots within each area of interest.

Considerations for application of method

The Reigl scanner records a very accurate 3D representation of a site and allows for the analysis of structural metrics that are not otherwise able to be determined accurately in the field. Also, once the data has been collected in the field, it provides a snapshot of the state of the system at that given point in time, which may be analysed further in the future as methods develop. However, we recommend that potential users are aware of the skills and computing power needed to undertake processing; in our case study, input was required from an expert spatial analyst as the non-SMEs to were unable to process the point cloud and therefore couldn't derive vegetation metrics in a reasonable timeframe. The Reigl scanner was also the most expensive option that we assessed, with the scanner itself costing $200K with additional high expenses (~$40K) for processing software.

Reigl TLS data may be considered by pracitioners if they are undertaking a comprehensive program monitoring riparian vegetation. The method is particularly suited to assessing vegetation structure, which may be relevant to a range of important management needs such as habitat qualities for terrestrial fauna, through the change in horizontal or vertical structural vegetation components over time.

Due to the complexity of the dataset and the difficulty with processing the data, it is important that users understand the metrics that are available and how they will be applied to their management question. Furthermore, to address specific monitoring questions a period of research would be required to develop the best protocol for collecting data before committing to an ongoing monitoring program. This would have to be factored into the management budget and will require good working relationships between the non-SMEs who will use the data and the spatial analyst collecting and processing the data.

Overall, if a management agency has a monitoring question that requires very accurate, highly detailed information about vegetation at the site, then the TLS method should be considered. The caveats are ensuring appropriate specialist skills in the team (or through external consultation) to process and analyse data and be clear in how the detailed information would be used to inform management decisions.

2.2 Terrestrial laser scanning – Leica BLK360

2.2.1 Data collection

Scans using a Leica BLK360 were collected in September 2020, overlapping the location of the Riegl scans from the previous year (Figure 2). Ideally all data would have been collected in the same year, however this was not possible due to limitations with equipment access and staff availability. At Jubilee Downs, 24 Leica scans were collected approximately 20–25 m apart, 50 m along the riverbank and extending 175 m from the riverbank to the floodplain (Figure 9Figure 9). Within the scan area, 6 round red-and-white ground control points (GCPs) were laid out and 14 ground control trees were identified to species level. At Myroodah, 27 scans were collected approximately 10 to 20 m apart, 50 m along the riverbank and extending 125 m from the riverbank to the floodplain, with 5 GCPs and 10 ground control trees.

Figure 9. The Leica BLK360 in use. Photo: Karen Dayman.

The coordinates for GCPs and trees were collected with a Trimble R10 GNSS System base and rover, paired with a Trimble TSC3 handheld controller, with the intention of georeferencing the scan data. Coordinates of all scan stations were recorded using a handheld Garmin GPSMap 64st GPS and a mud map was hand drawn for each site, documenting which scans, trees and GCPs were adjacent to each other. The workflow for data collection, processing and analysis is shown in Figure 10.

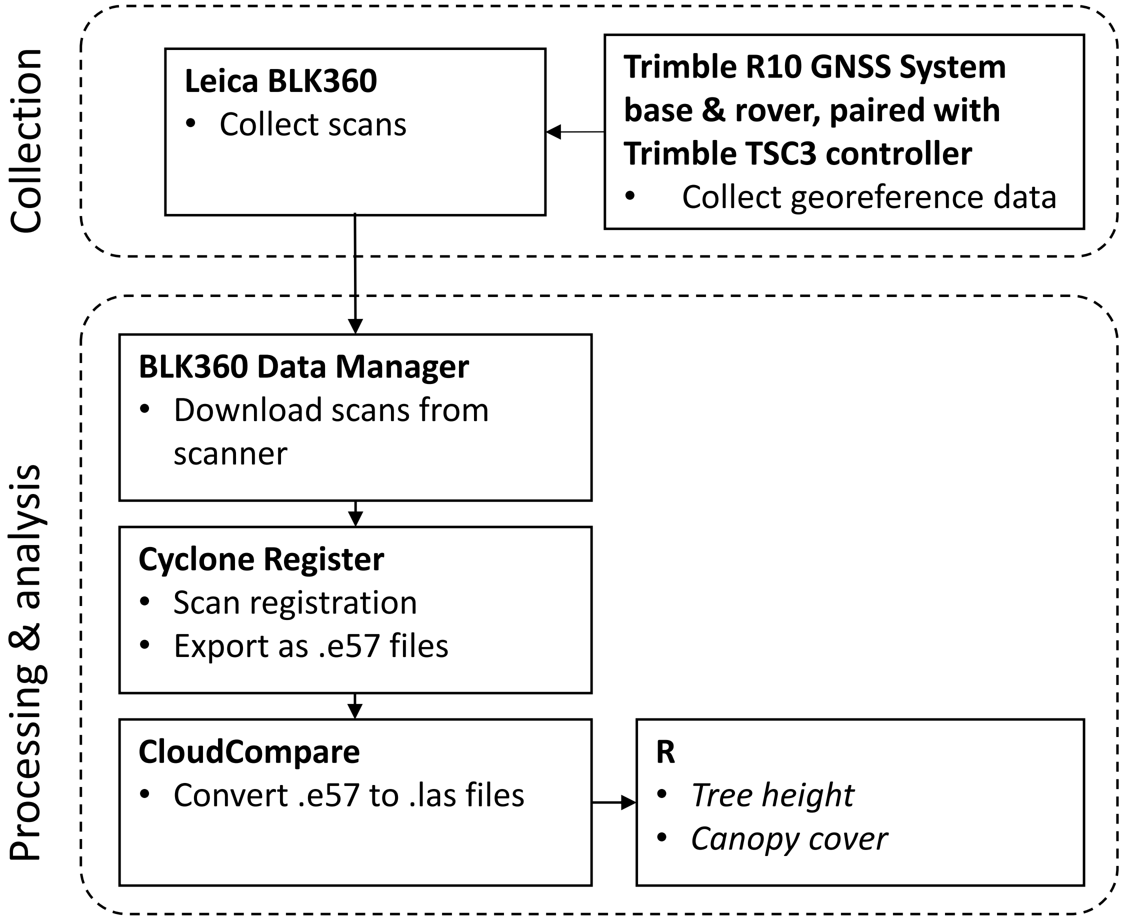


Figure 10. Workflow diagram showing the process for data collection and processing for the Leica BLK360.

2.2.2 Analysis

Scans (point clouds) were registered (aligned) manually in Cyclone Register (Leica Geosystems) using the point-cloud to point-cloud method. This method involves visually matching features of adjacent scans, using the field mud map as a reference. It was not possible to georeference the site using this method as the GCP targets were not visibile in the point-cloud view. While georeferencing the site might be important for repeat surveys, this was not deemed essential for the one-off metrics being assessed for this project. Once the scans were registered, the completed site point clouds were exported as .e57 files. The .las format is not supported by Cyclone Register, therefore files were exported as .las in CloudCompare (https://www.cloudcompare.org), which is a free program. Due to issues with registering the point cloud and analysing the large dataset, there was no further data processing or analysis for the Leica data.

2.2.3 Results and discussion

Costs and expertise

The Leica BLK360 scanner is a lower cost option for the collection of TLS data that requires less expertise for operation compared to the Reigl scanner. It has a single push button for operation, limited customised options, and downloading images from the scanner to the computer was simple. The Leica BLK360 data was collected by non-SMEs, although experts provided advice on the sampling design. Processing of data was completed in Cyclone Register, again by non-SMEs, although the registration (lining-up) of images was improved by an expert using the more expensive RiSCAN Pro software (Figure 11). The Leica BLK360 scanner costs considerably less that the Reigl scanner, at $30k (Table 2).

Table 2. Costs for equipment and software required for the collection of TLS data using the Leica BLK360 scanner. Total shows the estimated up-front cost, excluding labour and ongoing license fee.

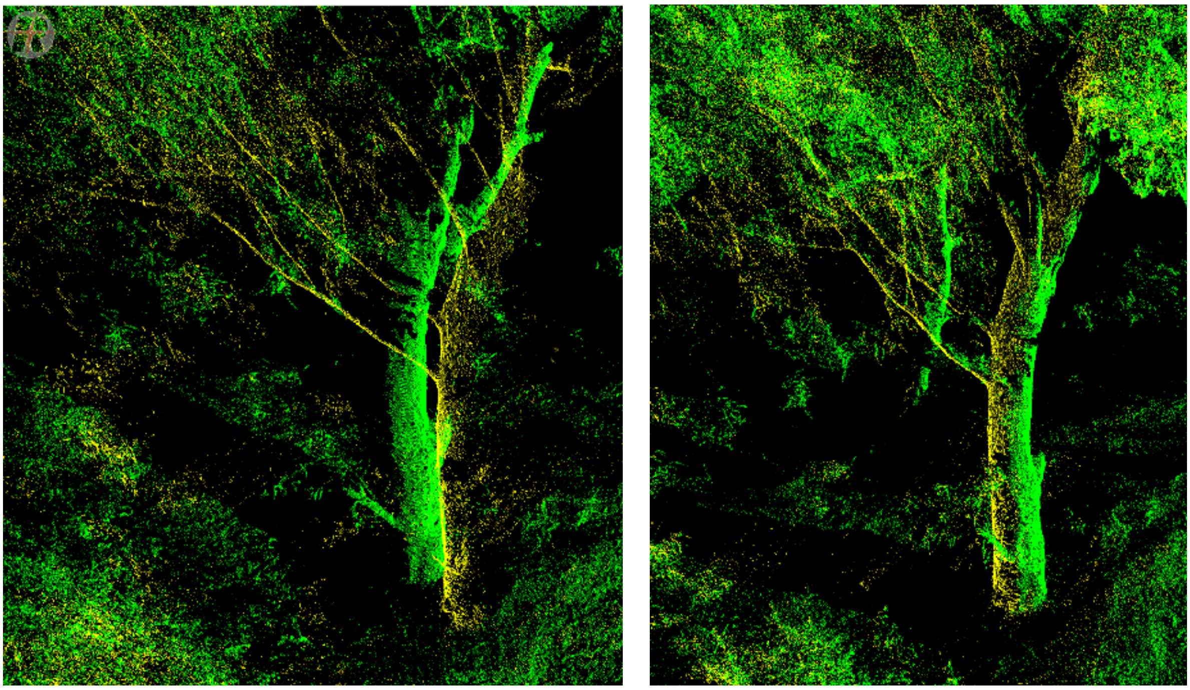
Task	Equipment/ software	Cost	Notes
Scanner	Leica BLK360	$30,000	
Software	BLK360 Data Manager	Nil	
	Cyclone Register	$850	Annual educational license
	Cloud Compare	Nil	
	R	Nil	
Processing PC	Dell Xeon 4210 CPU with 128GB RAM and NVIDIA GeoForce RTX 2080 with 8 GB VRAM	10,000	
Total		**$30,850**	

Outputs

We encountered problems with processing the data, particularly registering the scans. Problems with registering images mostly arose from the insufficient scan position density and distribution in the field. The Leica scanner has a range of approximately 60 m, significantly less than that of the Reigl. We had implemented a sampling design to account for this, collecting scans approximately every 20 m, along a grid, which should have allowed for overlap between the points. However, due to the high density of tree trunks and thick lower- and midstorey, the scanner did not measure all vegetation between sample points, making it difficult to register a point cloud, and it was not possible to register all scans at Myroodah due to the density of trees. At Jubilee Downs, where the vegetation was sparser, it was possible to use the river, car tracks, rocks, fences and other land features to help with scan registration. At Myroodah, where vegetation was denser, only the riverbank was of use in registering adjacent scans – it is not practical to use tree-tops in the alignment process as tree tops tend to look similar in 3D space.

Further improvements may be made in the processing of scan data. We used the point-cloud to point-cloud method to register scans, which is relatively straightforward for scans of geometric objects, like buildings. However, we found the method problematic when applied to point-cloud data of dense, complex riparian vegetation as there were few clear objects to align scans to. Another limitation of using this method is that it was not possible to georeference the scans as ground targets were not visible in the point-cloud view. Future studies are recommended to use a high number of black-and-white targets, make sure they are visible in at least 3 scans and have scans positioned much closer together. This should enable georeferenced scans in Cyclone using the ground control points for registration, however it will require additional time in the field to place targets at each location.

Due to difficulties with processing the data, there was no further analysis of the point-cloud data collected using the Leica. Methods have been developed to assess vegetation structure from single scans rather than registering them into a merged point cloud, which may be useful for monitoring. For example, Seidel et al. (2016) and Walter et al. (2021) derived metrics of vegetation structure using single scans. Future research should investigate the use of single-scan data and how it may be applied by managers.



a) Initial registration in Cyclone (note yellow 'ghost' is a misaligned scan)

b) A better alignment was achieved using RiScan Pro

Figure 11. Example images showing the differences in alignment using point-cloud to point-cloud registration in Cyclone software and improved registration in RiScan Pro.

Considerations for application of method

The Leica has a much lower price point than the Reigl, which may make it an appealing option for managers. The data collection is slower than the Reigl due to having to place scans closer together. Managers that wish to use the Leica scanner are advised to test the collection method in a variety of stands to determine an optimal sampling protocol, starting with a grid with either 10 m or 5 m spacing (as recommended by (Wilkes et al., 2017). There is potential for improving the methods for registering point clouds in Cyclone, as registration in RiScan Pro had better alignment of data. Also, since our data collection a newer version of Leica software has become available which allows for registration in the field using an iPad, where data can be aligned on-screen after each scan. This may help with checking that scan data is collected correctly while in the field, rather than not knowing until it is processed later.

The derivation of metrics from the processed scan data is similar to the Reigl, and therefore the same level of expertise is required. Managers that wish to use TLS data, collected using either scanner, are advised to work closely with experts in the analysis of these datasets, be clear in the metrics that they require and check if the method can provide it, and be aware of the costs involved.

2.3 Drone photogrammetry

Perhaps the most commonly suggested new technology for environmental management has been the use of drones (Cruzan et al., 2016; Dunford et al., 2009). Modern photogrammetry software uses Structure-from-Motion, where multiple overlapping photos have locations co-matched between images and used to create three-dimensional (3D) scenes. There are two main types of outputs – a TLS or LiDAR-like point-cloud of RGB colour points that represents the 3D structure of the scene, and orthophotomosaics, where the software uses this 3D scene to project and then merge the individual images to create a seamless mosaiced image of an area of interest.

Small aerial multi-rotor drones with 4–8 rotors or small fixed-wing aircraft are equipped with small standard RGB camera on a gimbal, or with miniturised multispectral sensors that typically work across the visible (RGB) and near infra-red (NIR) parts of the spectrum. Drones can be programmed to fly a set path, collecting overlapping imagery. Two common outputs from drone photogrammetry are point-cloud data (similar to point-cloud data derived from LiDAR) and high-resolution orthomosaics (which are stitched-together images to produce one large image). Orthomosaics may then be classified into mapping units or vegetation metrics calculated. We used a method modified from (Callow et al., 2018) to determine vegetation cover at two sites. This approach uses overlapping images in combination with surveyed ground control points to process a 3-dimensional model of the terrain and canopy. We tested two drones: (i) DJI Mavic 2 Pro (M2; small and light) and (ii) Phantom 4 Advanced (PH4; small and light, but slightly more powerful). We sought to:

1. calculate tree canopy cover
2. investigate data collection methods, comparing different flight paths and camera angles to determine the influence they have on data processing
3. calculate normalised differential vegetation index values using a RGB-NIR sensor (RedEdge-MX Kit; MicaSense Inc., Seattle, WA, USA).

2.3.1 Data collection

Images were captured using the standard cameras on-board the M2 and PH4 (Figure 13). A RedEdge sensor that provides near infrared data was trialled; however, no data were successfully collected due to a camera malfunction during fieldwork. Further comment on this sensor is provided in the Considerations for application of method section. Data from the standard cameras were collected in November 2019 and September 2020 and flight paths overlapped the area covered using the terrestrial laser scans (Figure 2).

Different flight heights, flight paths and gimbal angles were trialled in both 2019 and 2020, as detailed in Tables 1 and 2 in Appendix 4. Cameras were set to capture 20-megapixel images every 2 seconds and images had a 90 % forward overlap and 75–80 % side overlap.

GCPs were used to spatially align drone images (Figure 12). Twelve red-and-white round targets were placed within and along the boundary of each drone flight. To be effective, GCPs are required at regular intervals across the study area, must be visible to the drone and broadly represent the range of topography within the flight path. This was sometimes difficult to achieve in areas with dense vegetation or rough terrain along riverbanks. The coordinates for each GCP were collected using a Trimble R10 GNSS system base and rover, paired with a Trimble TSC3 handheld controller (GCP point survey accuracy 0.012m). The base station was set up in an open area and run for a minimum of four hours to optimise satellite data collection.

Data were collected by a RePL trained pilot and under The University of Western Australia Remote Operators Certificate (ReOC) licence with the Civil Aviation Safety Authority (CASA.ReOC.0628).

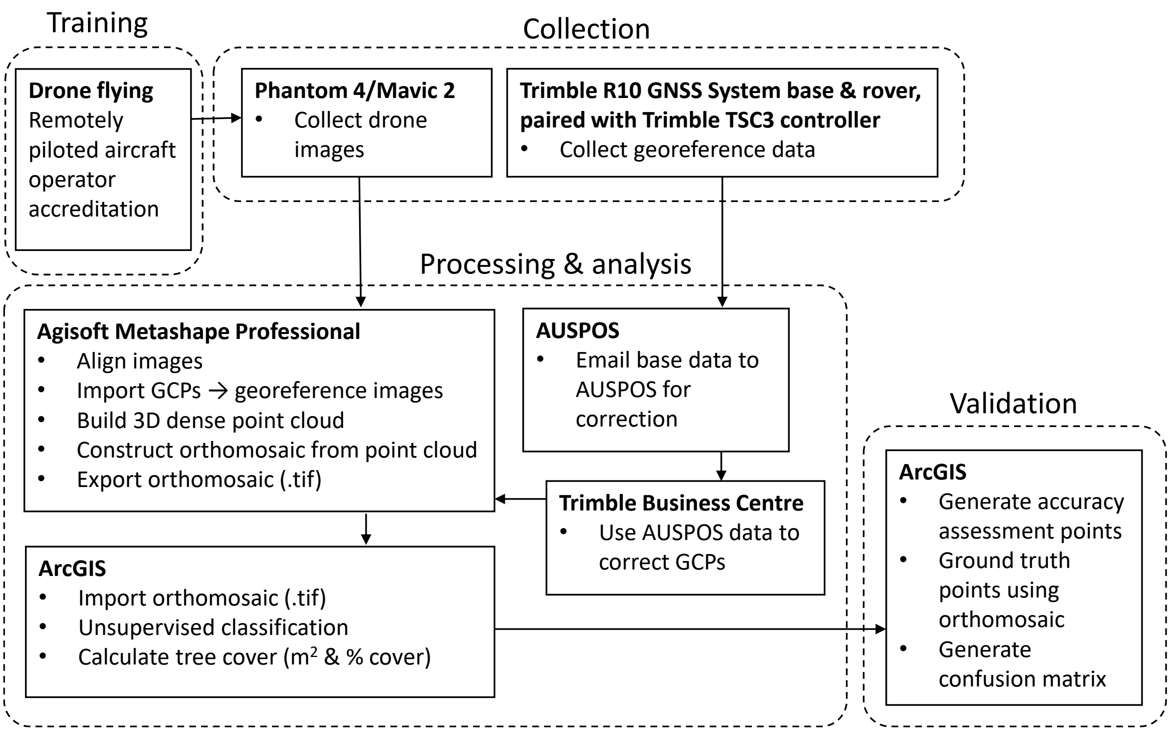


Figure 12. Workflow diagram showing the process used for the collection and analysis of drone data.

Figure 13. Collection of data using the Mavic drone.

2.3.2 Analysis

Trimble base station files were downloaded and emailed to the Geoscience Australia AUSPOS service for post-processing to increase accuracy of the global positioning data. This information was then used to correct the GCP data.

To create an orthomosaic, drone images were processed in AgiSoft Metashape Professional v1.6.5 (hereafter called Metashape). There are many different methods for creating orthomosaics in Metashape, and many manual decisions to be made at each processing step. The methods we used largely followed those described in Callow et al. (2018) and James et al. (2017). Briefly, images were aligned and then georeferenced using the GCPs. During this registration process, Metashape begins to construct a sparse point cloud of the site. To create the most realistic point cloud from overlapped images, bundle adjustments were performed using camera optimisation settings as recommended in James et al. (2017) and Callow et al. (2018); Camera Model C settings were used (f, cx, cy, k1, k2, k3, p1 and p2). Point-cloud filtering was then performed by manually inspecting the sparse point cloud and identifying low-precision points (i.e. outliers) for removal, so that only high-accuracy points are included in the 3D model and for creating outputs.

To assess how different collection methods influence data processing, we trialled different flight patterns and gimbal angles. For example, in 2020, 5 flights were flown to collect data at Jubilee Downs; 4 flights covered the same 6-ha area using a cross-hatch (i.e. north-south and east-west) pattern with the gimbal at 2 different angles; and one single flight covered an area of 18 ha (Table 2 in Appendix 4). Images from the 18-ha single flight were registered but the point cloud had a large spatial error (i.e. > 2m; Table 3). The point cloud derived from stitching four cross-hatched flights together had a smaller error of 0.08 m (Table 3). This sampling design meant that the study area was covered from multiple angles which improved image registration and reduced the spatial error in the sparse point cloud.

Table 3. Summary of data collected using the Phantom 4 (PH4) and Mavic 2 (M2) drones.

Year	Site	Drone/ camera	Flight method	Flight height (m)	Area (ha)	Ortho-mosaic?	Check point error (m)	Ortho resolution (cm)
2019	Jubilee Downs	PH4	4 flights, 2 orientations, 2 gimbal angles	70	4.98	Yes	NA	NA
	Myroodah	M2	1 flight	50	2.26	No	NA	NA
		M2	1 flight	80	8.62	Yes	NA	NA
		PH4 (RedEdge)	1 flight	80	8.62	No	NA	NA
2020	Jubilee Downs	PH4	4 flights, 2 orientations, 2 gimbal angles	60	6	Yes	0.08	1
		M2	1 flight	80	18	Yes	2.37	2
	Myroodah	PH4	4 flights, 2 orientations, 2 gimbal angles	60	6	Yes	0.05	1
		M2	1 flight	80	18	No	NA	NA

In Metashape, the refined sparse point clouds were used to build a dense point cloud for each site, from which a mesh was created. The mesh was then used to build a 2D orthorectified aerial image of the site (orthomosaic), which was then exported from Metashape as a .tiff file.

Site orthomosaics were imported into ArcMap 10.5.1 to assess vegetation for defined areas of interest: (i) riverbank, (ii) top of bank and (iii) floodplain. These defined areas were manually clipped using polygons created in ArcMap. For each area of interest an unsupervised classification was used to categorise pixels into 30 classes, which were then then manually assigned to 1 of 4 broad themes: land, live vegetation cover, shadow and litter (e.g. senesced vegetation and leaf litter). The area (m^2) for each theme was calculated using the tabulate area function in ArcGIS and vegetation cover was calculated as a percentage of the total area of interest.

Unsupervised classifications were validated using a 5,000 m^2 test patch at Jubilee Downs. The test patch was clipped from the 2019 and 2020 datasets and 400 points were generated using a stratified random approach. Each point was visually assessed and assigned to 1 of the 4 broad themes. A confusion matrix was then generated in ArcMap, comparing accuracy points (user accuracy) with the unsupervised classification (predicted accuracy).

2.3.3 Results and discussion

Costs and expertise

Drone data were collected by a researcher with a current drone pilot license and expertise in the collection and analysis of drone imagery for vegetation. Images were processed and and analysed by a non-SME with input and assistance from an expert in geographic information systems.

The drones trialled are relatively inexpensive, consumer-level models at a cost of approximately $2,000. Georeferencing is required to register (stitch together) images, which required a dGPS. We used a Trimble system, which cost an estimated $100,000, however the Emlid Reach RS2 is available for approximately $8,000 and may be suitable for georeferencing drone images. After the project conception and data collection new RTK drones have become available. These drones avoid the need for such an extensive array of ground control points as the drone photo position is corrected from the RTK base station. Processing and analysis required specific software (Agisoft Metashape Professional and ArcMap) and a high-specifications computer (Table 4).

Table 4. Costs for equipment and software required for the collection of drone data. Total shows the estimated up-front cost, excluding labour and ongoing license fee.

Task	Equipment/ software	Cost	Notes
Image collection	Phantom 4 Advanced (or similar, e.g. DJI Mavic 2 Pro)	$2,000	
Image collection	CASA license, drone registration and pilot training	$0–$3,000	• Drones < 2kg and standard conditions, operater accreditation is free, online. Drones (including <2kg) must be registered for use as part of a job ($40 annually) • > 2kg or not standard conditions, a remote pilot license (RePL) is required ($1500-3000) • Subject to change, for current rules check: www.casa.gov.au/drones/register
Image collection	Tablet/ phone	$1,000	
Georeferencing (field)	Trimble R10 GNSS System base and rover, paired with a Trimble TSC3 hand-held controller	$100,000	Trimble cost not included in total cost as these systems are often available to managers. An alternative dGPS is the Emlid Reach RS2 for ~$8,000
Georeferencing (lab)	Trimble business software	-	Included in Trimble dGPS package
Georeferencing (lab)	AUSPOS	-	Online GPS processing service – request results via email (free service from Geoscience Australia)
Build 3D point cloud	Agisoft Metashape Professional (educational license)	~$805	Agisoft Metashape Professional Edition Educational license (rehostable node-locked) One-off $USD549 Agisoft Metashape Professional Edition (node-locked license) One-off $USD3499
Data anlaysis	ArcMap	~$250/year	Annual academic license
Processing PC	Dell Xeon 4210 CPU with 128GB RAM and NVIDIA GeoForce RTX 2080 with 8 GB VRAM	$10,000	
Total		**$17,555**	**Excludes dGPS for georeferencing**

Data and metrics outputs

The total area covered by the flights ranged from 4 to 18 ha and data were collected at both Myroodah and Jubilee Downs study sites (Table 3). We trialled methods for collecting drone images, using different flight paths and gimbal angles. We found that a single flight did not provide an accurate orthomosaic, as indicated by large error values (e.g. 2.37 m) at points checked for spatial accuracy (Table 3). Orthomosaics derived from 4 flights using the cross-hatch flight path and with two gimbal angles had smaller error values, at approximately 0.08 m. Further analysis was therefore only completed on orthomosaics produced from the four flight cross-hatch method.

Using the cross-hatch method, we produced orthomosaics with a high resolution of 1 cm pixels (Figure 14). Unsupervised classification of the orthomosaics produced a spatial dataset which may be displayed as a 2D visual representation (Figure 14).

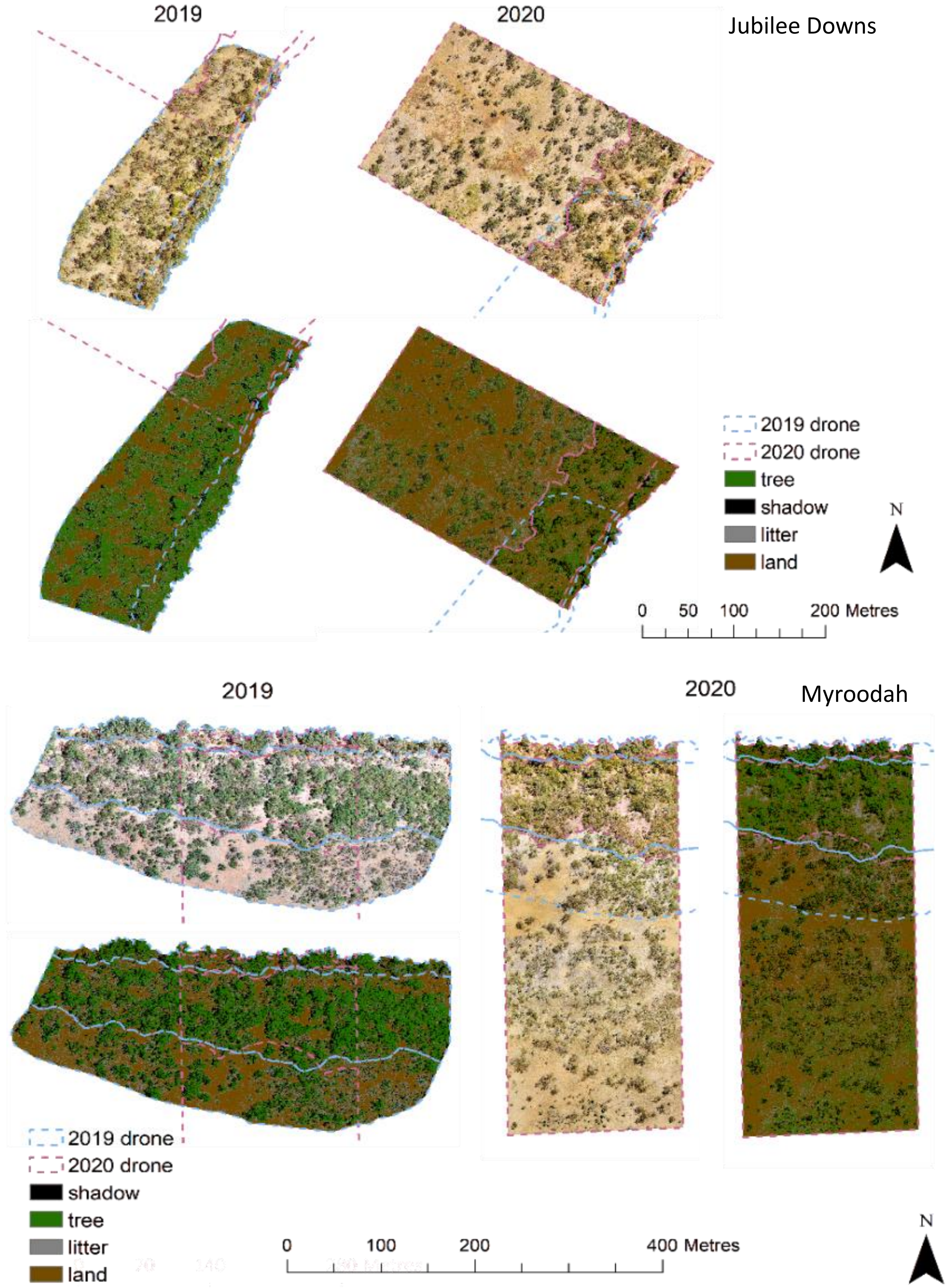


Figure 14. RGB orthomosaics and classified orthomosaics for Myroodah and Jubilee Downs in 2019 and 2020 from data collected using the Phantom 4 drone. Orthomosaics were stitched together in Metashape and the unsupervised classifications were done in ArcMap.

Our validation of the unsupervised classification found that trees were correctly classified the majority of the time, although with greater accuracy in 2020 (0.78 compared with 0.62 in 2019; Tables 3 and 4 in Appendix 4). However, Kappa values indicated that overall there was a weak to moderate agreement between the unsupervised classification and the manually checked points (Kappa values of 0.58 for 2019 and 0.61 for 2020).

The unsupervised classification of vegetation cover broadly agreed with our expectations of the patterns of vegetation cover at the different locations. The floodplain landscape position had the smallest vegetation cover, with greater cover on the riverbank and the top of banks, which is consistent with general observed trends (Figure 16). However, it was difficult to make comparisons between the years, as changes were made to the collection method. The 2019 flight path (6 ha) focussed on thick vegetation closer to the river. After reviewing the data, it was decided in 2020 to also test the method on sparser floodplain vegetation, and the flight area shape was changed to reflect this (Figure 2). Thus, the percent vegetation cover values outside of the test patch should not be compared between the years. Also, the classification process where the unsupervised classification categories are manually placed into broad themes may have also contributed to differences between the years due to user bias or error.

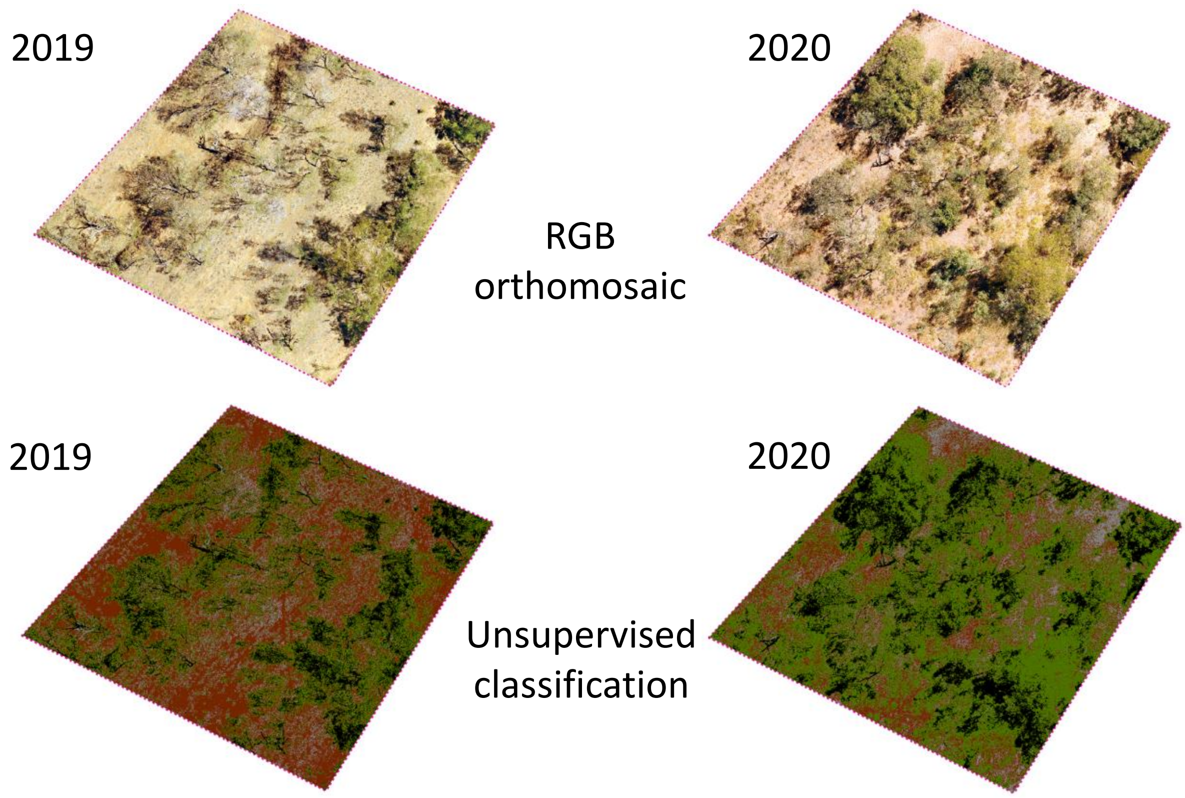


Figure 15. Orthomosaic and unsupervised classification for a test patch at Jubilee Downs in 2019 and 2020. The unsupervised classification was manually grouped into 4 themes as pictured; green = tree, brown = land, grey = other vegetation (e.g. grasses, senesced vegetation, understorey), black = shadow.

Figure 16. Percent cover from unsupervised classification of drone derived orthomosaics, stitched together from 4 flights for Jubilee Downs in 2019 and 2020 and Myroodah in 2020, and 1 flight for Myr 2019. Sites were separated into 3 landscape positions: riverbank (RB), top-of-bank (TB) and floodplain (FP) as shown in Figure 2.

Considerations for application of method

The lower cost and apparent ease of data collection may make the use of drones increasingly appealing to managers for monitoring riparian vegetation; however, there are costs associated with the software and expertise for processing and analysis which must be considered. For our study, the drones were flown by someone with extensive experience (and a license); however, it would be relatively straightforward for a non-expert to fly the drone as off-the-shelf drones come with flight planning software, although a remote pilot license is required (Table 4). It is necessary for the user to ensure that they follow CASA (Civil Aviation Safety Authority) guidelines, as well as any other policy that is required by their organisation or the groups they are working with and the areas they plan to fly within. Although flying the drone was relatively easy, there were issues with the collection of scientific-grade data and the processing of raw data, these are summarised below.

Field conditions. The timing of flights is important, with images ideally collected over solar noon to minimise shadows. We experienced problems with windy, hot (40+ °C) field conditions. When we attempted to collect data around midday, the equipment overheated, which limited data collection. Therefore, the majority of the data was collected earlier in the day but this then had implications for the processing of the data due to shadows. The operational temperature limit of many drones (e.g. DJI Mavic & Phantom) is 40 °C.

Flight path. We tested different flight patterns to investigate the effect on the images collected and our ability to stitch the images together. We found that the cross-hatch method, with multiple flights collecting images from different angles and with a high percentage of overlap between images provided the best results in terms of being able to stitch images together, and as a result spatial accuracy (Table 3). Therefore, we would recommend a cross-hatch flight path with 90 % front overlap and 75–80% sidelap to collect the most accurate data; however, there is trade-off as a smaller area is covered due to battery life and time in the field.

Sensors. We used drones with standard RGB cameras; however, drone-acquired LiDAR data may be more effective for assessing vegetation structure. We had also aimed to collect near-infrared data using a RedEdge sensor to calculate normalised differential vegetation index (NDVI) values; however, we encountered several problems with this method in addition to malfunction due to heat (the manufacturer confirmed that a circuit board capacitor failed, likely due to excess heat). Primarily, surface reflectance values are required for accurate near-infrared values. Our expert collaborator has repeatedly trialled calibration panels, however it was not possible to get the drone, RedEdge and calibration panels all working together. It is likely that satellite-derived NDVI would be a better option if managers are interested in that metric and have skills in geographic information systems; however, there would need to be a period of research to determine the best way to collect this data. Drone-collected NDVI data may be particularly useful for high resolution and sub-pixel calibration of multispectral satellite imagery.

Data processing and analysis. Processing and analysis of the photogrammetry data was completed by non-SMEs; however, due to limited prior experience, there was a steep learning curve and a significant investment in time. Final outputs were also probably limited due to user inexperience, for example there is uncertainty around the accuracy of the orthomosaic classifications. Similar to the TLS data, there were many steps to processing the data, and different proprietary software were required. The level of expertise required is high, with user inputs requiring knowledge of the process. The method also requires specialised software and a high specifications computer, which adds to the cost of using this method. It is likely that advancements in cloud computing and open-source tools will increase the accessibility of future drone monitoring applications by reducing the costs of expensive computers and software. However, such applications will still require technological professionals to handle data processing and management.

Precision and accuracy requirements. For precise and accurate assessments of metrics such as canopy cover, it is likely necessary that RTK is required to geolocate each image to provide high-resolution data. However, if the management question does not require such resolution (for example counting individual trees in a given area) then it may be appropriate to create a lower-resolution orthomosaic without RTK, instead relying on GPS data from the drone.

The outputs we were able to derive (the orthomosaic and estimates of vegetation cover) may not be pertinent metrics for managers monitoring riparian vegetation. Canopy cover data may be better assessed using satellite imagery, although the coarser resolution of these images must be taken into account to ensure the expected changes are able to be detected. There is potential for other sensors to provide data that may be used by managers, such as NDVI measured using a RedEdge sensor, but further work is required to successfully apply this method, and again it should be determined if this would be better assessed using satellite data. Furthermore, data collection requires ground control points across the studied area, and repeated flights over the same area are recommended. We found this resulted in a smaller study area than we were expecting using this technique.

2.4 Vegetation transect surveys – TRARC

There are many methods used for the monitoring of riparian vegetation using traditional on-ground transect survey. For this study, we assessed the Tropical Rapid Appraisal of Riparian Condition (TRARC) method (Dixon, 2006), which has previously been used by Indigenous ranger groups in the Kimberley region. TRARC provides a rapid assessment of vegetation condition, with a focus on the key threatening processes to riparian vegetation, including weeds and erosion from cattle. Another reason for including TRARC was because researchers undertaking the assessment had not used it before, and so, just like the remote sensing technologies, they had to learn how to collect and analyse the data from scratch. We also collected canopy cover data using a forest densiometer at each point that was scanned by the Leica scanner. We sought to:

1. assess riparian vegetation canopy health
2. calculate canopy cover using the densiometer.

2.4.1 Data collection

The TRARC method provides an overall health assessment score, derived from observational assessments of canopy cover, canopy health, tree size classes, regeneration, plant and weed cover, soil properties, logs, erosion and environmental stressors such as fire and animal impacts (Dixon, 2006). For our assessment we did not include scores for erosion and environmental stressors, as we were not considering these using the TLS and drone techniques. Data were collected along 100 m transects, with three points of observation along each transect (e.g. 0 m, 50 m and 100 m). At each point, the prompts on the datasheet were used to record data, following the guide by Dixon et al. (2006; Figure 17). Three transects were completed at Jubilee Downs (positioned on the riverbank, top-of-bank and the floodplain) and 4 at Myroodah (riverbank, 2 at the top of the bank and 1 on the floodplain; Figure 18).

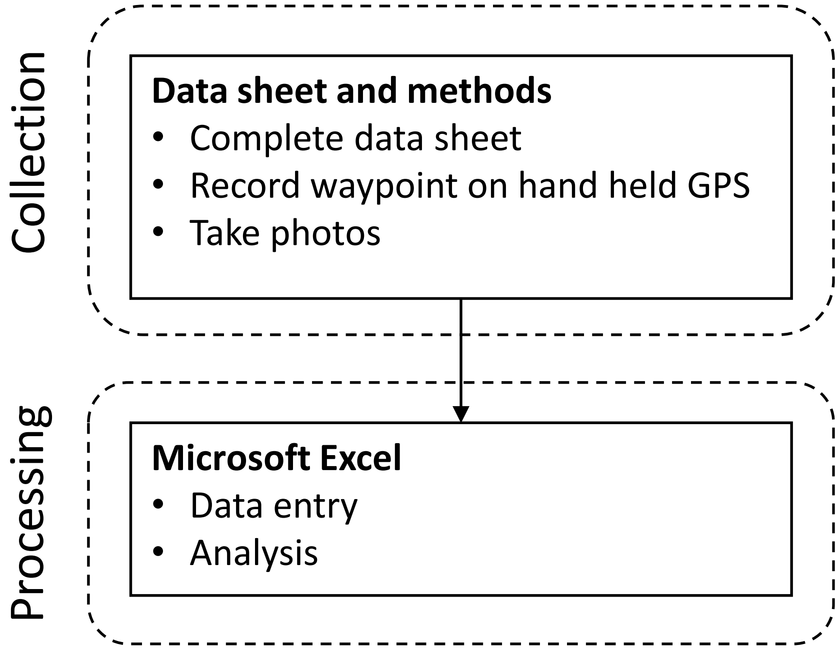


Figure 17. Workflow diagram for the collection and processing of data using the TRARC method.

2.4.2 Analysis

The analysis followed that by Dixon et al. (2006), using an Excel datasheet that was made to support the method. Data was entered into the spreadsheet, which autocalculated values. Each category had a total maximum score of 25, and the categories are summed to get a 'condition' score. For our assessment, we did not include the erosion category as it was not directly applicable to the top-of-bank and floodplain transects. We also did not include the scores for 'pressure', which includes details about the effect of fire, grazing and other threatening processes. As not all parameters were included in our assessment, we show the total out of 75 rather than 100.

Figure 18. Completing surveys using the TRARC method.

2.4.3 Results and discussion

Costs and expertise

The TRARC method required very little equipment, with the method completed using a measuring tape and datasheets (Table 5), with the instructions on the assessment/scoring system also printed for reference in the field. It required the researchers to run through the method before the trip but it was familiar to them due to their backgrounds in ecology and plant science. More training would be required for a non-ecologist. Data processing required experience in using Excel to enter the data and to summarise the outputs.

Table 5. Costs for equipment and software required for the collection of drone data. Total shows the estimated up-front cost, excluding labour and ongoing license fees.

Task	Equipment/ software	Cost	Notes
Survey vegetation – TRARC method	Clipboards, measuring tape etc	~$100	Requires an understanding/training to record data
Data processing	Computer		Standard work computer
Total		**$100**	

Data and metrics outputs

Overall, scores for plant cover were low, with the greatest value at Myroodah riverbank which had a plant cover score of 12 out of 25 (Table 6). The floodplains at both sites had very low scores of 0.5–1 out of 25. Across the whole site, plant cover was lower at Jubilee Downs compared to Myroodah. The regeneration category includes canopy health, tree size classes, large trees and regeneration of trees. The scores were relatively consistent across all of the transects, ranging from 14–16 out of 25, except for Jubilee Downs floodplain, which had a score of 8. Although it wasn't a key aim of our study, we included scores for assessing weeds at the sites. A high score for weeds indicates fewer weeds. Jubilee Downs was less impacted by weeds, compared with Myroodah, with high scores at the riverbank and floodplain landscape positions. The overall condition scores reflected our impressions of the site, based on our field observations as well as reviewing photographs of the site.

Table 6. Summary table of vegetation condition assessed using TRARC method. The last column shows the total for the four vegetation condition categories, with the second number showing the maximum value. Note that we did not include erosion in our assessment (it is in the original version of the TRARC method). RB= riverbank, TB = Top of bank, FP = floodplain landscape positions.

Site and landscape position	Plant cover (score out of 25)	Regeneration (score out of 25)	Weeds (score out of 25)	Total (condition)
Jubilee Downs RB	2	16	23	65% (49/75)
Jubilee Downs TB	4	14	15	44% (33/75)
Jubilee Downs FP	0.5	8	24	45% (34/75)
Myroodah RB	12	14	18	81% (61/75)
Myroodah TB 1	7	15	12	45% (34/75)
Myroodah TB 2	5	16	17	57% (43/75)
Myroodah FP	1	9	16	37% (28/75)

Usability of the method for managers

The TRARC method was the least expensive data collection method that we trialled, with very low equipment costs (clipboards, measuring tapes and datasheets), and the main investment being in training in the method. Similar to the other tested methods, surveys were somewhat limited by the heat, with work generally halted in the middle to avoid heat exhaustion. Surveys were instead completed either at the beginning or the end of each day. The time required for each transect was relatively low, particularly after completing the method several times. The first couple of transects took more time, as the researchers discussed the scores that they would give, following the supplied instructions. This discussion was useful as it helped with consistency between transects and sites.

Limitations of the method are that it is based on scores, which limit the sensitivity of the data collected. For example, if the metric of interest for monitoring is canopy cover, the TRARC method gives scores based on categories at 25% cover increments, and scores are based on a visual assessment rather than a more quantitative measure. However, if the aim of the monitoring program is to have a broad assessment of vegetation 'health' across sites, this method may be applied. As the method relies on scoring, there may be significant differences in the scores based on the observer; therefore, it is important that observers are trained in using the method and that there is discussion and feedback between observers to ensure consistency across observations. The method includes a photo for each transect, but a more formal photo-point monitoring method may also be considered to support observations.

The TRARC method did not include detail on the species present, although it did include a list of high-impact weed species. The TRARC method can be adapted to include a list of species of interest to a monitoring program. For example, if the monitoring is aiming to assess the impact of water-take on riparian tree species, then species that are most likely to be impacted could be included as part of the score card. Species that are culturally important could also be added for monitoring.

3. General discussion

We focused this project on the utility of approaches for managers that will seek specific metrics to inform adaptive management of riparian zones in northern Australia. We found that there is potential for the techniques tested to be used to address specific questions. In particular, TLS can be used to investigate vegetation structure more thoroughly than traditional on-ground survey methods. However, there are a number of barriers to the application of these technologies.

1. **Cost**. Upfront costs are significant for tools such as the Reigl TLS (~$200,000 purchase price). The drones trialled in our study were less expensive in their upfront costs, at approximately $25,000, although if the data is to be repeatedly collected for monitoring purposes then georeferencing is required. Options for georeferencing range from ~$100,000 for a Trimble dGPS system to ~$8,000 for the Emlid Reach RS2.
2. **Expertise**. The processing and analysis of data collected using remote sensing techniques required significant time and input from remote sensing experts. Both the TLS and drone photogrammetry methods generate large and complex datasets that require experts with knowledge in the appropriate software to process. Problems with data analyses resulted from user inexperience in computer programming and analysis of large spatial datasets. Significant training or the employment of someone with appropriate skills is required to plan, collect and analyse data.
3. **Field conditions**. Remote areas in northern Australia present challenges in the application of each of the techniques. Our data collection trips occurred late in the dry season, when midday temperatures were very high (generally 40° C plus). All of the equipment had functionality issues at these high temperatures. For example, both the Riegl and Leica scanners overheated and shutdown during data collection and could not be used again until they had cooled down. The iPad running the drone also malfunctioned due to overheating. Collecting data using on-ground ecological methods was also challenging in the heat and to avoid heat stress, work was carried out either at the beginning or the end of the day to avoid the full sun. The timing of data collection may therefore be limited to the coolest times of the year (June and July in northern Australia).
4. **Vegetation type**. The density and structure of riparian vegetation is highly variable and often complex, which may limit the application of TLS and drone techniques. Occlusion is a problem in dense, complex stands, where the scanner is unable to detect trees hidden behind other trees. Some studies report problems with occlusion (Bogdanovich et al., 2021), but problems may be overcome if the sampling design is appropriate (Wilkes et al., 2017), such as increasing the number of scans and using a regular grid pattern to facilitate registration. A monitoring program would benefit from a preliminary study with planning and testing to develop a protocol to guide time-effective and feasible routines for data collection.

Usability of output data

Each of the tested methods produced data in distinctly different formats, and this should be taken into consideration by managers (see Table 7 for a summary of the output formats). Key considerations for each method are provided below.

Reigl scanner. The raw scans are in a proprietry data format that had to be processed in the RiSCAN Pro software by an expert collaborator. The pointcloud data is difficult for a non-SME to process and analyse, and requires high computing power. We recommend managers clearly articulate the metrics of interest for their monitoring requirement and their expectations about the format of data delivered.

Leica scanner. The Leica scanner has similar issues as the Reigl scanner, with data processing limited by the need for specialised software, expert input and high computing power. However, there may be potential for scans to be registered in Leica Cyclone Register software, which is significantly cheaper than RiSCAN Pro (although we found the alignment of scans was improved using RiSCAN Pro software). We recommend the development of a protocol for data collection and processing of data in Cyclone Register. The derivation of metrics is similar to the analysis of point cloud data collected using the Reigl scanner, and the previous comments about expert input apply here.

Drone photogrammetry. Images collected using the drone were processed by a non-SME with support from expert collaborators. However, there was a very steep learning curve and a significant investment in time to be able to stitch the images together to create an orthomosaic and classify tree cover. Few metrics were derived using the drone photogrammetry method, and there is uncertainty around the accuracy of the canopy-cover data. Managers that wish to use drone photogrammetry should be aware of the limited metrics that the method provides, and that they may not be the best metrics for monitoring riparian vegetation, depending on the changes that managers aim to detect.

TRARC method. The on-ground methods provided data in a format that would be most familiar to natural resource managers, with data in an Excel spreadsheet using the format supplied with the TRARC manual. The data is very coarse, with each indicator assigned a categorical value, and condition for the site is summed across indicators. Managers that use this method should be aware that it may not collect data in enough detail to detect subtle changes. We recommend that the method by modified to specific monitoring needs, with additional prompts in the survey to ensure that these indicators are assessed.

4. Recommendations and conclusions

While the technology to collect remotely sensed data is becoming increasingly user-friendly and affordable, processing the data remains a specialised skill. Application of the technologies to monitor riparian vegetation would require significant financial investment and access to appropriate computer processors, software and specialised knowledge, skills and experience (Table 7). Furthermore, spatial analysis requires a very different skill set to on-ground ecology. It is important that spatial analysis for environmental management occurs with oversight by an ecologist, or that an ecologist completes the training required to effectively undertake the analysis.

It is possible that our approach was inhibited by existing on-ground method paradigms. For example, riparian vegetation health is typically assessed by measuring metrics like tree diameter, tree canopy health and species composition. While remote sensing may not be the ideal method to answer these specific questions, these technologies may be able to answer other questions about tree health (Table 7).

The costs associated with the processing and analysis of remotely sensed TLS and drone data are often not made explicit and may not be immediately obvious to managers. Our experience was that considerable time and experience was required to complete the processing of remotely sensed datasets when returning from the field. The cost in staff time as well as the software and hardware required for the processing of data needs to be taken into account when considering the use of TLS and drone technologies.

Table 7. Summary of the pros and cons and suggestions for possible monitoring applications of terrestrial laser scanning (TLS), drone photogrammetry and the TRARC rapid on-ground assessement methods.

Approach	Pros	Cons	Possible applications
TLS	• Extremely high resolution (<5 mm) • High structural detail • 3D snapshot of site	• Expensive • Processing and analysis is highly specialised • Covers a relatively small area (~4ha) • Poor performance in hot (>40 °C) temperatures.	• Tree or plot-scale assessment of vertical structure
Drone photogrammetry	• Data collection is relatively inexpensive • Covers a larger area (~6 ha)	• Limited vegetation indices • Processing and analysis are specialised • Uncertainty around repeatability • Poor performance in hot (>40 °C)	• Assessment of vegetation cover and width of vegetation zones • Geomorphological and fluvial processes
TRARC	• Inexpensive • Minimal training required	• Semi-quantitative (uses a scale from user observations)	• Monitoring by community groups, indigenous rangers, land managers

References

Bogdanovich, E., Perez-Priego, O., El-Madany, T. S., Guderle, M., Pacheco-Labrador, J., Levick, S. R., . . . Migliavacca, M. (2021). Using terrestrial laser scanning for characterizing tree structural parameters and their changes under different management in a Mediterranean open woodland. *Forest Ecology and Management, 486*, 118945. doi:https://doi.org/10.1016/j.foreco.2021.118945

Calders, K., Adams, J., Armston, J., Bartholomeus, H., Bauwens, S., Bentley, L. P., . . . Verbeeck, H. (2020). Terrestrial laser scanning in forest ecology: Expanding the horizon. *Remote Sensing of Environment, 251*, 112102. doi:https://doi.org/10.1016/j.rse.2020.112102

Callow, J. N., May, S. M., & Leopold, M. (2018). Drone photogrammetry and KMeans point cloud filtering to create high resolution topographic and inundation models of coastal sediment archives. *Earth Surface Processes and Landforms, 43*(12), 2603-2615. doi:https://doi.org/10.1002/esp.4419

Campos, M. B., Litkey, P., Wang, Y., Chen, Y., Hyyti, H., Hyyppä, J., & Puttonen, E. (2021). A Long-Term Terrestrial Laser Scanning Measurement Station to Continuously Monitor Structural and Phenological Dynamics of Boreal Forest Canopy. *Frontiers in Plant Science, 11*(2132). doi:10.3389/fpls.2020.606752

Connor, S. E., Schneider, L., Trezise, J., Rule, S., Barrett, R. L., Zawadzki, A., & Haberle, S. G. (2018). Forgotten impacts of European land-use on riparian and savanna vegetation in northwest Australia. *Journal of Vegetation Science, 29*(3), 427-437. doi:https://doi.org/10.1111/jvs.12591

Cruzan, M. B., Weinstein, B. G., Grasty, M. R., Kohrn, B. F., Hendrickson, E. C., Arredondo, T. M., & Thompson, P. G. (2016). Small unmanned aerial vehicles (micro-UAVs, drones) in plant ecology. *Applications in Plant Sciences, 4*(9), 1600041. doi:https://doi.org/10.3732/apps.1600041

Dixon, I., Douglas, M., Dowe, J., Burrows, D. (2006). *Rapid appraisal of riparian condition: Version 1 (for use in tropical savannas)*. River Managment Technical Guideline No. 7. Land and Water Australia. Canberra.

Douglas, M. M., Jackson, S., Canham, C. A., Laborde, S., Beesley, L., Kennard, M. J., . . . Setterfield, S. A. (2019). Conceptualizing Hydro-socio-ecological Relationships to Enable More Integrated and Inclusive Water Allocation Planning. *One Earth, 1*(3), 361-373. doi:https://doi.org/10.1016/j.oneear.2019.10.021

Douglas, M. M., Setterfield, S. A., McGuinness, K., & Lake, P. S. (2015). The impact of fire on riparian vegetation in Australia’s tropical savanna. *Freshwater Science, 34*(4), 1351-1365. doi:10.1086/684074

Dunford, R., Michel, K., Gagnage, M., Piégay, H., & Trémelo, M. L. (2009). Potential and constraints of Unmanned Aerial Vehicle technology for the characterization of Mediterranean riparian forest. *International Journal of Remote Sensing, 30*(19), 4915-4935. doi:10.1080/01431160903023025

DWER. (2017). *Groundwater-dependent ecosystems of the Dampier Peninsula: Royalties for Regions groundwater investigation*. Department of Water and Environmental Regulation (DWER). Perth, Western Australia.

DWER. (2020). *Managing water in the Fitzroy River Catchment: Discussion paper for stakeholder consultation*. Perth, Western Australia, Australia: Department of Water and Environmental Regulation, Government of Western Australia.

Gooniyandi Aboriginal Corporation. (2015). *Gooniyandi Healthy Country Plan*. Gooniyandi Aboriginal Corporation/Kimberley Land Council.

Huylenbroeck, L., Laslier, M., Dufour, S., Georges, B., Lejeune, P., & Michez, A. (2020). Using remote sensing to characterize riparian vegetation: A review of available tools and perspectives for managers. *Journal of Environmental Management, 267*, 110652. doi:https://doi.org/10.1016/j.jenvman.2020.110652

James, M. R., Robson, S., d'Oleire-Oltmanns, S., & Niethammer, U. (2017). Optimising UAV topographic surveys processed with structure-from-motion: Ground control quality, quantity and bundle adjustment. *Geomorphology, 280*, 51-66. doi:https://doi.org/10.1016/j.geomorph.2016.11.021

Lawley, V., Lewis, M., Clarke, K., & Ostendorf, B. (2016). Site-based and remote sensing methods for monitoring indicators of vegetation condition: An Australian review. *Ecological Indicators, 60*, 1273-1283. doi:https://doi.org/10.1016/j.ecolind.2015.03.021

Levick, S. R., Shendryk, Y., Setterfield, S.A. and Rossiter-Rachor, N.A. (2018). Evaluation of satellite remote sensing pathways for mapping and monitoring of gamba grass for the Savanna Fire Management Methodology. CSIRO and Charles Darwin University, Darwin. (2018). *Evaluation of satellite remote sensing pathways for mapping and monitoring of gamba grass for the Savanna Fire Management Methodology.* CSIRO and Charles Darwin University, Darwin.

Melrose, R., Kingwell, J., Lymburner, L. & Coghlan, R. (2013). *Murray Darling Basin Vegetation Monitoring Project: Using time-series Landsat satellite data for the*

assessment of vegetation. Record 2013/37. Geoscience Australia. Canberra.

Murray-Darling Basin Authority. (2020). *The Murray–Darling Basin Tree Stand Condition Tool Hindcast Report*. Canberra, Australia.

Muumbe, T. P., Baade, J., Singh, J., Schmullius, C., & Thau, C. (2021). Terrestrial Laser Scanning for Vegetation Analyses with a Special Focus on Savannas. *Remote Sensing, 13*(3). doi:10.3390/rs13030507

Newnham, G. J., Armston, J. D., Calders, K., Disney, M. I., Lovell, J. L., Schaaf, C. B., . . . Danson, F. M. (2015). Terrestrial Laser Scanning for Plot-Scale Forest Measurement. *Current Forestry Reports, 1*(4), 239-251. doi:10.1007/s40725-015-0025-5

Oliver, I. A. N., Jones, H., & Schmoldt, D. L. (2007). Expert panel assessment of attributes for natural variability benchmarks for biodiversity. *Austral Ecology, 32*(4), 453-475. doi:https://doi.org/10.1111/j.1442-9993.2007.01718.x

Petty, A. M., Setterfield, S. A., Ferdinands, K. B., & Barrow, P. (2012). Inferring habitat suitability and spread patterns from large-scale distributions of an exotic invasive pasture grass in north Australia. *Journal of Applied Ecology, 49*(3), 742-752. doi:https://doi.org/10.1111/j.1365-2664.2012.02128.x

Roussel, J., & Auty, D. (2021). *Airborne LiDAR Data Manipulation and Visualization for Forestry Applications.* . R package version 3.1.4. . Retrieved from https://cran.r-project.org/package=lidR.

Roussel, J., Auty, D., Coops, N. C., Tompalski, P., Goodbody, T. R. H., Meador, A. S., . . . Achim, A. (2020). lidR: An R package for analysis of Airborne Laser Scanning (ALS) data. *Remote Sensing of Environment, 251*, 112061. doi:https://doi.org/10.1016/j.rse.2020.112061

Seidel, D., Ehbrecht, M., & Puettmann, K. (2016). Assessing different components of three-dimensional forest structure with single-scan terrestrial laser scanning: A case study. *Forest Ecology and Management, 381*, 196-208. doi:https://doi.org/10.1016/j.foreco.2016.09.036

Trochta, J., Krůček, M., Vrška, T., & Král, K. (2017). 3D Forest: An application for descriptions of three-dimensional forest structures using terrestrial LiDAR. *PLOS ONE, 12*(5), e0176871.

Walalakoo Aboriginal Corporation, W. A. (2016). *Walalakoo Healthy Country Plan 2017-2027*. Walalakoo Aboriginal Corporation RNTBC.

Walter, J. A., Stovall, A. E. L., & Atkins, J. W. (2021). Vegetation structural complexity and biodiversity in the Great Smoky Mountains. *Ecosphere, 12*(3), e03390. doi:https://doi.org/10.1002/ecs2.3390

Watt, P. J., & Donoghue, D. N. M. (2005). Measuring forest structure with terrestrial laser scanning. *International Journal of Remote Sensing, 26*(7), 1437-1446. doi:10.1080/01431160512331337961

Wilkes, P., Lau, A., Disney, M., Calders, K., Burt, A., Gonzalez de Tanago, J., . . . Herold, M. (2017). Data acquisition considerations for Terrestrial Laser Scanning of forest plots. *Remote Sensing of Environment, 196*, 140-153. doi:https://doi.org/10.1016/j.rse.2017.04.030

Wöllauer, S., Zeuss, D., Magdon, P., & Nauss, T. (2021). RSDB: an easy to deploy open-source web platform for remote sensing raster and point cloud data management, exploration and processing. *Ecography, 44*(3), 414-426. doi:https://doi.org/10.1111/ecog.05266

Appendix 1: TLS metrics

A list of the metrics derived from TLS point cloud data at Myroodah and Jubilee Downs study sites.

abv: total points in subplot

min: min canopy height

max: max canopy height

avg: average canopy height

qav: quadratic mean height

std: standard deviation of height

ske: skewness of height

kur: kurtosis of height

hom: height of median energy

cov: canopy cover

p01: 1st percentile of canopy height

p05: 5th percentile of canopy height

p10: 10th percentile of canopy height

p25: 25th percentile of canopy height

p50: 50th percentile of canopy height

p75: 75th percentile of canopy height

p90: 90th percentile of canopy height

p95: 95th percentile of canopy height

p99: 99th percentile of canopy height

c00: number of lidar points between 0.5 – 2.5 m

c01: number of lidar points between 2.5 – 5 m

c02: number of lidar points between 5 – 7.5 m

c03: number of lidar points between 7.5 – 10 m

c04: number of lidar points between 10 – 12.5 m

c05: number of lidar points between 12.5 – 15 m

c06: number of lidar points between 15 – 17.5 m

c07: number of lidar points between 17.5 – 20 m c08: number of lidar points between 20 – 22.5 m

c09: number of lidar points between 22.5 – 25 m

d00: density of lidar points between 0.5 – 2.5 m

d01: density of lidar points between 2.5 – 5 m

d02: density of lidar points between 5 – 7.5 m

d03: density of lidar points between 7.5 – 10 m

d04: density of lidar points between 10 – 12.5 m

d05: density of lidar points between 12.5 – 15 m

d06: density of lidar points between 15 – 17.5 m

d07: density of lidar points between 17.5 – 20 m

d08: density of lidar points between 20 – 22.5 m

d09: density of lidar points between 22.5 – 25 m

vc0: vertical complexity of lidar points between 0.5 – 2.5 m

vc1: vertical complexity of lidar points between 2.5 – 5 m

vc2: vertical complexity of lidar points between 5 – 7.5 m

vc3: vertical complexity of lidar points between 7.5 – 10 m

vc4: vertical complexity of lidar points between 10 – 12.5 m

vc5: vertical complexity of lidar points between 12.5 – 15 m

vc6: vertical complexity of lidar points between 15 – 17.5 m

vc7: vertical complexity of lidar points between 17.5 – 20 m

vc8: vertical complexity of lidar points between 20 – 22.5 m

vc9: vertical complexity of lidar points between 22.5 – 25 m

Appendix 2: Outputs from LiDAR analysis

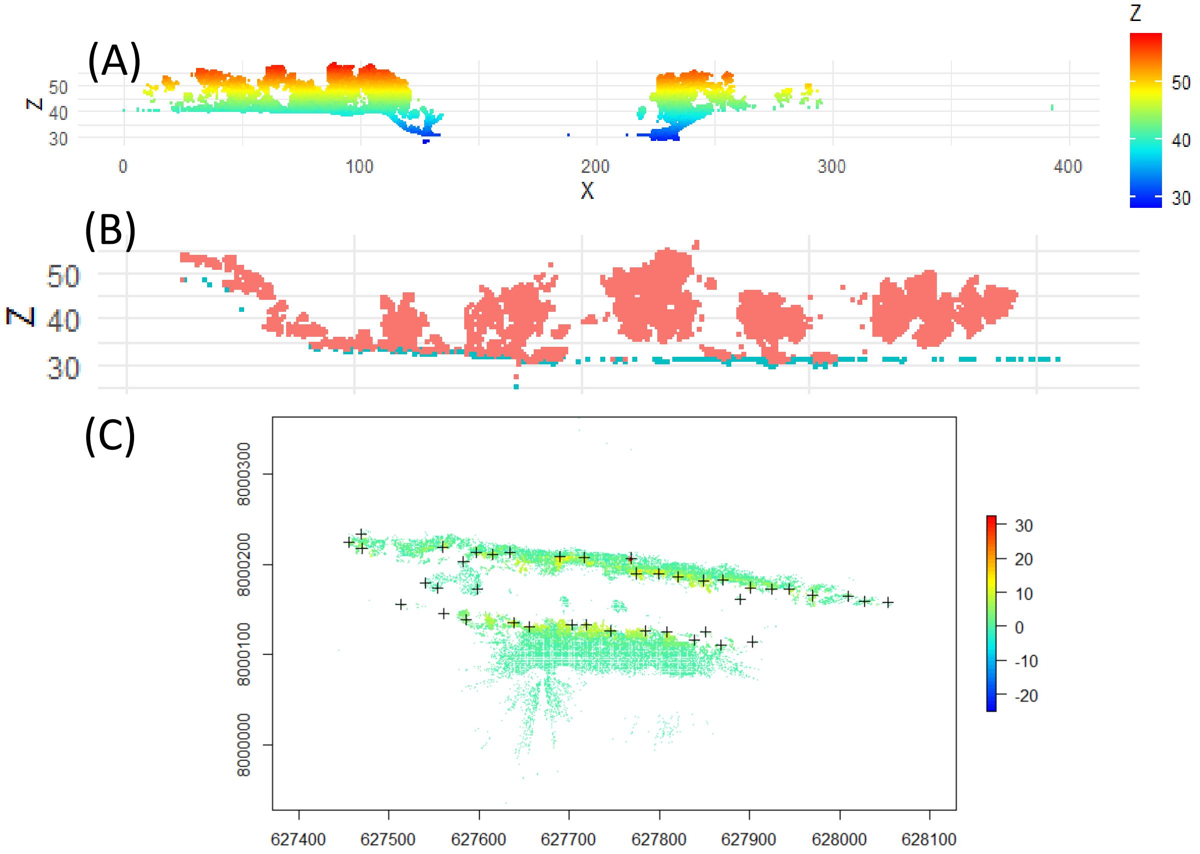


Figure 1. Examples of outputs from analysis of Reigl-derived TLS data using the LiDR package in R. Data is from Myroodah. Panel A shows a 2D transect through the middle of the merged point cloud (note that the scans were collected on the left bank of the river, but the scanner reached the other side too). Panel B shows a 2D profile view of a ground classification on a reduce point cloud (pink indicates vegetation, green is ground). Panel C shows output from a tree detection function as an aerial view, with crosses indicating tree tops.

Appendix 3: Reigl outputs from RiSCAN Pro

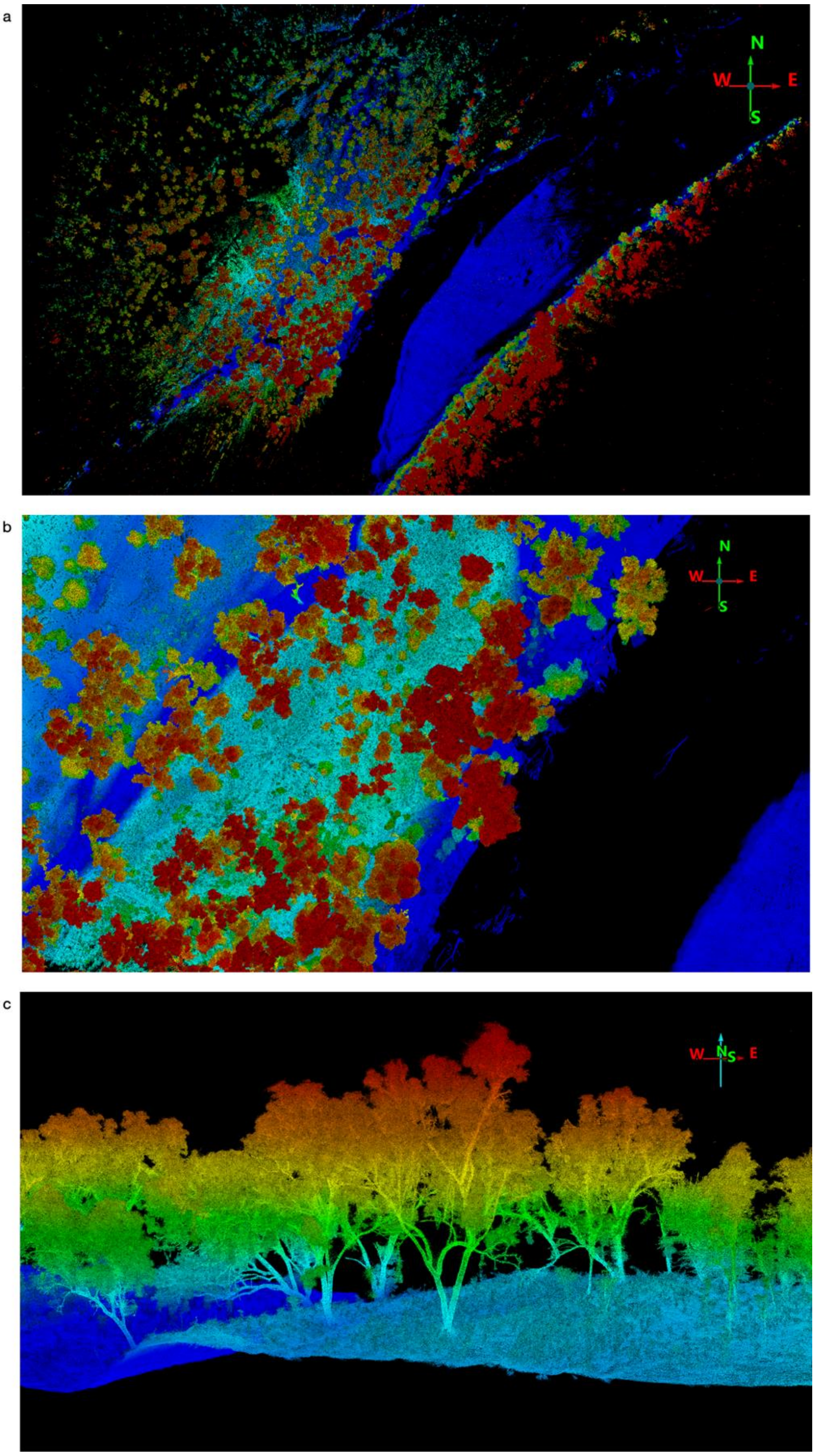


Figure 2. An example of the 3D point cloud data collected using the Riegl scanner, showing the riverbank and riparian trees at Jubilee downs. The data shown was processed in RiScan Pro from multiple scan positions. (a) Full spatial extent of the data (note that scan positions were on the western bank of the river, but the laser reached aross to the eastern bank). (b) Zoomed in aerial view of the TLS data – ground returns are shown in blue shades, greens and reds indicate tree canopy height. (c) Oblique view of a 10m wise belt transect cut through the TLS point cloud showing individual stem and canopy detail for each tree.

Appendix 4: Drone flight details

Table 1. Details of the drone imagery capture in November 2019. Key: PH4 = Phantom 4; M2 = Mavic Pro 2.

Location	Area flow (ha)	Drone/ camera	Flight number	Flight orientation	Above ground level (m)	Gimbal angle (degrees)	No. photos
Jubilee	4.98	PH4	1	270	70	0	302
Jubilee	4.98	PH4	2	270	70	-85	300
Jubilee	4.98	PH4	3	180	70	0	180
Jubilee	4.98	PH4	4	180	70	-85	285
Myroodah	2.26	M2	1	238	50	0	349*
Myroodah	8.62	M2	1	236	80	0	551
Myroodah	8.62	PH4 & RedEdge	1	236	80	0	248+

* Images were not successfully registered.

+ Attempted to use the RedEdge sensor but it malfunctioned. RGB images were not successfully registered.

Table 2. Details of the drone imagery capture in September 2020. Key: PH4 = Phantom 4; M2 = Mavic pro 2.

Location	Area flow (ha)	Drone/ camera	Flight number	Flight orientation	Above ground level (m)	Gimbal angle (degrees)
Jubilee	6	PH4	1	NE-SW	60	0
Jubilee	6	PH4	2	NE-SW	60	5
Jubilee	6	PH4	3	NW-SE	60	0
Jubilee	6	PH4	4	NW-SE	60	5
Jubilee	18	M2	1	NW-SE	80	0
Myroodah	6	PH4	1	NE-SW	60	0
Myroodah	6	PH4	2	NE-SW	60	5
Myroodah	6	PH4	3	NW-SE	60	0
Myroodah	6	PH4	4	NW-SE	60	5
Myroodah	18	M2	1	N-S	80	0

Table 3. Results of classification validation at Jubilee Downs using a confusion matrix to assess the accuracy of the unsupervised classification compared with user defined points. Data shown is for the 2019 data collection.

Class Value	tree	land	litter	shadow	Total	User Accuracy	Kappa
tree	75	10	20	16	121	0.62	0
land	27	116	34	0	177	0.66	0
litter	3	6	32	0	41	0.78	0
shadow	4	0	1	56	61	0.92	0
Total	109	132	87	72	400	0	0
Predicted Accuracy	0.69	0.88	0.37	0.78	0	0.70	0
Kappa	0	0	0	0	0	0	0.58

Tabl 4. Results of classification validation at Jubilee Downs using a confusion matrix to assess the accuracy of the unsupervised classification compared with user defined points. Data shown is for the 2020 data collection

Class Value	tree	land	litter	shadow	Total	User Accuracy	Kappa
tree	164	24	5	16	209	0.78	0
land	17	62	2	0	81	0.77	0
litter	4	14	18	0	36	0.5	0
shadow	16	3	0	55	74	0.74	0
Total	201	103	25	71	400	0	0
Predicted Accuracy	0.82	0.60	0.72	0.77	0	0.75	0
Kappa	0	0	0	0	0	0	0.61