Science for Saving Species

An update for Parks Victoria

Project 1.2.2

Threatened Species Recovery Hub

National Environmental Science Programme

Can remote sensing be used to estimate biomass for the management of grazing pressure in buloke woodlands?

Summary

Buloke woodlands of the Riverina and Murray-Darling depression bioregions (also called buloke woodlands or pine-buloke woodlands) is an EPBC Act-listed Endangered ecological community. The community was heavily cleared and degraded for pastoral and cropping uses. The restoration, and conservation, of remnant patches of this semi-arid woodland is tied to the management of the threat of grazing and browsing by native and feral vertebrate species. The risk of grazing damage to palatable herbs, shrubs, and seedlings is related to the availability of forage (biomass). Therefore, understanding how understorey biomass (particularly grass) varies over the landscape and over time is essential for herbivore management. Clipping and weighing vegetation samples is an accurate and direct way of determining aboveground understorey biomass, but it is time-consuming and labour-intensive. As such, it is unlikely to be integrated into regular management practice. Another way to do this is by using remote sensing, which has the potential to estimate biomass frequently and over large areas. However, the performance of remote sensing in semi-arid areas has been less reliable due to sparse vegetation cover, soil background, as well as dead vegetation and litter. We investigated the ability of remote sensing data to predict understorey biomass variation, and therefore forage, to inform the management of herbivore populations.

Research methods

- We sampled the biomass at 40 sites in different vegetation types across Pine Plains, Wyperfeld National Park (see Figure 1): buloke woodland (n = 10), open grassland (cleared buloke woodland) (n = 10), black box woodland (n = 10), and lakebed (n = 10). In 2019, we sampled an additional 6 sites in each vegetation type (total: 64 sites).
- Each site measured 90 × 90m, corresponding to a 3 × 3 Landsat satellite image pixel arrangement. We focused sampling in the centre pixel, though a larger area of homogeneous vegetation was chosen to account for any satellite or GPS registration errors.

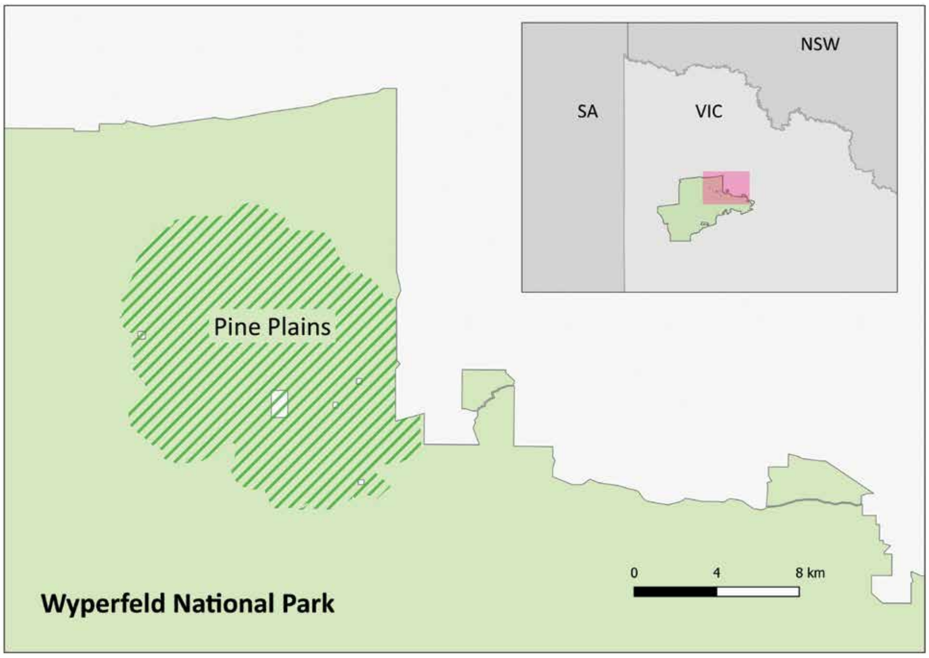

Figure 1. This research was undertaken at Pine Plains, Wyperfeld National Park.

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Research methods (continued)

- Several quadrats were sampled within each site. At each quadrat, species were visually ranked in terms of biomass to estimate understorey species composition. We clipped biomass to just above ground-level, then separated into live and dead. Samples were dried and weighed. We collected biomass during seven field trips between December 2016 and May 2019.
- Landsat 7 and 8 imagery (freely available online) was downloaded for the same period. We developed semi-automated routines to integrate data from both Landsat sources, interpolate to daily values, and then calculate vegetation indices (Table 1).
- We modelled the relationships between these indices and understorey biomass. Soil moisture, canopy type (open or wooded), and dominant understorey growth form (annual grass, perennial grass, herb, shrub) were also included in the statistical models.

Figure 2. Clipping biomass at a lakebed site in April 2017. Image: Linda Riquelme

Table 1. Vegetation indices tested, with an overview of the sensitivities of each (USGS 2019, Baig et al. 2014).

Vegetation Index	Description
Normalized Difference Vegetation Index (NDVI)	Used to quantify vegetation greenness and vegetation density. Higher values indicate denser green vegetation. Values 0.1 and below correspond to areas of rock, sand, or snow.
Enhanced Vegetation Index (EVI)	Like NDVI, but EVI corrects for some atmospheric conditions and canopy background noise. Higher values indicate denser green vegetation.
Soil Adjusted Vegetation Index (SAVI)	Minimises the influence of soil brightness in areas with low vegetation cover. Higher values indicate denser green vegetation.
Modified Soil Adjusted Vegetation Index (MSAVI)	Also minimises the influence of soil brightness, but more sensitive to vegetation signals than SAVI. Higher values indicate denser green vegetation.
Normalized Difference Moisture Index (NDMI)	Used to determine vegetation water content. Less sensitive to atmospheric effects than NDVI. Positive values represent green vegetation, while negative values indicate bright surfaces with dry or no vegetation.
Tasseled Cap Brightness	Measures total reflectance in an image. It's associated with bare or partially covered soil, natural and built features, and variations in topography. Higher values indicate bare ground, or minimal or dry vegetation.
Tasseled Cap Greenness	Measures vegetation density and cover. Higher values indicate denser green vegetation.
Tasseled Cap Wetness	Sensitive to soil moisture, canopy moisture, and water.

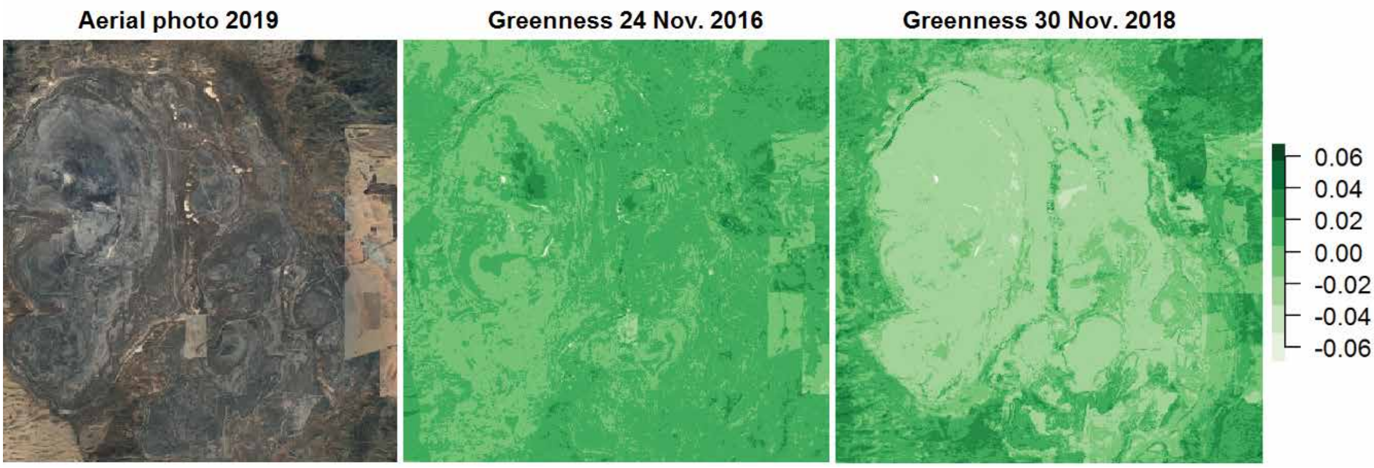

Figure 3. Recent Google Maps aerial image of Pine Plains (left); Tasseled Cap Greenness during wet (centre) and dry (right) periods. Higher values indicate higher amounts of green vegetation.

Key findings

- Pine Plains is a mosaic of wooded stands and open plains. As you might expect, the main driver of understorey biomass variation is tree cover. We sought to understand this and other drivers of biomass over space and time, before modelling and predicting understorey biomass. Although wooded sites had greater total aboveground biomass, they had significantly less understorey biomass than open sites (especially grass; Figure 4). There was a lot of site variation in understorey biomass even within vegetation types, however.
- Above average rain fell during winter and spring 2016. Conditions became drier during 2018 and 2019, leading to an overall drop in understorey biomass. Both total understorey and grass biomass peaked in spring 2017, but otherwise remained quite stable during the study period until May 2019, where it dropped in open areas (Figure 4). Live biomass was at its highest in winter 2017, then consistently declined over the next year. There was a very slight increase in live biomass between May 2018 and May 2019 (Figure 4).
- Grass tended to fall close to or below the proposed forage switch threshold in wooded areas during the summer and autumn months (Figure 4).

BELOW: Buloke woodland. Image: Linda Riquelme

Key findings (continued)

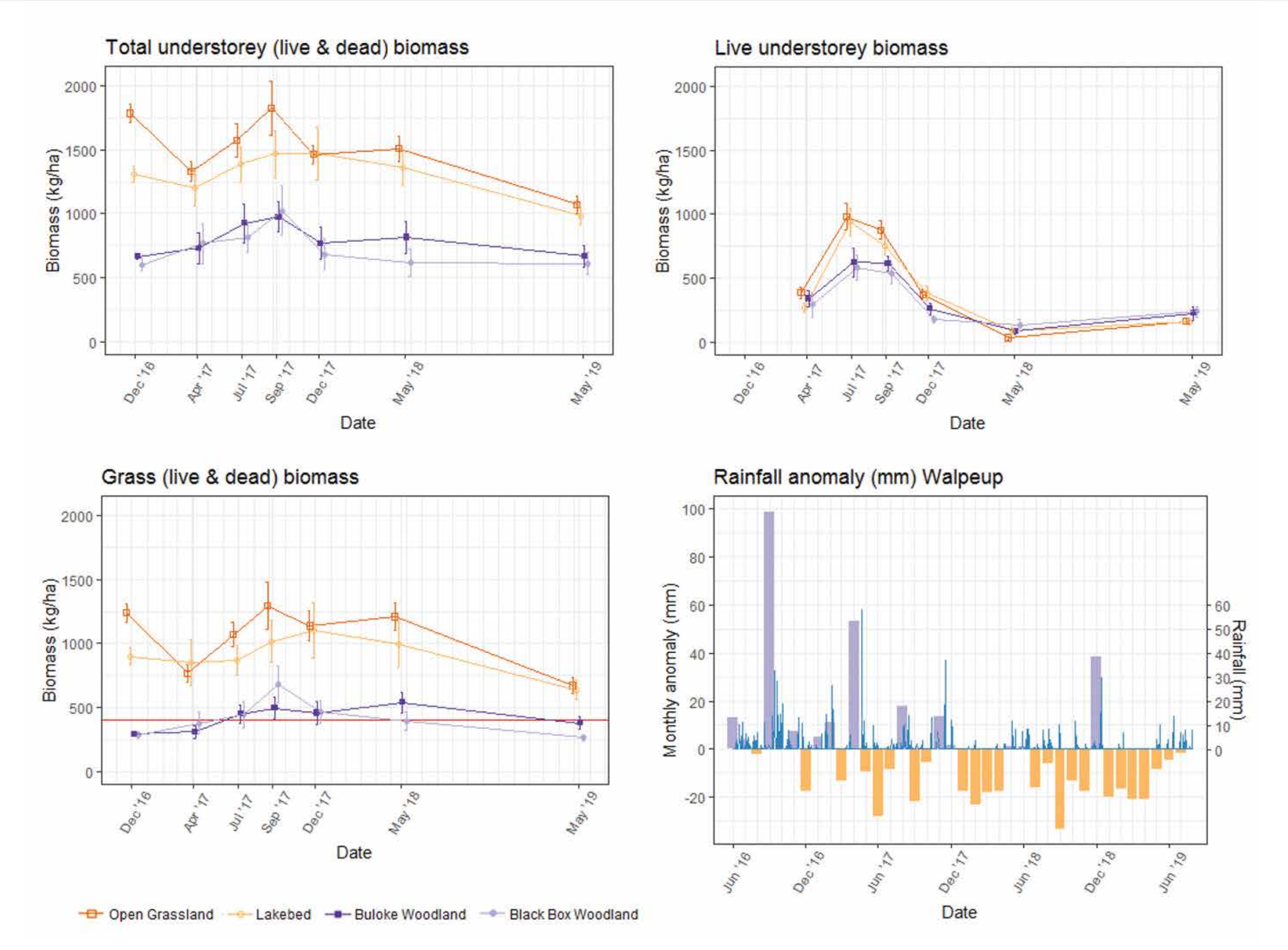

Figure 4. Total understorey (live and dead, all growth forms) (top left); live understorey (all growth forms) (top right), and grass (live and dead) (bottom left) biomass over the sampling period (Dec. 2016 – May 2019). Red line (bottom left) represents Norbury's (1987) 400 kg ha-1 forage switch threshold. Daily rainfall and mean monthly rainfall anomaly for Walpeup (BoM station 76065) for June 2016 – June 2019 (bottom right).

- We used biomass and remote sensing data collected between December 2016 and May 2018 to train Generalised Linear Mixed Models (GLMM) to explain and predict biomass variation across Pine Plains and over the sampled seasons. Remote sensing models explained 24% of total, 44% of live, and 40% of grass biomass variation (R^2m values); when taking site differences into account (R^2c values), models explained 56%, 53%, and 87% respectively (Table 2). Although vegetation indices performed similarly, different indices worked best for different types of biomass (Table 2).
- Including dominant understorey growth form did little, if anything, to improve models.

RIGHT: A grazed buloke sapling. Image: Linda Riquelme

Table 2. Biomass models. "Soil moisture" refers to mean soil moisture for a one-month period, with a two-week lag. The "ε_i" term captures unexplained variation attributable to differences in sampling locations, otherwise known as "random" site variation.

Biomass	Model	R^2m	R^2c
Total	biomass ~ **Greenness** + soil moisture + canopy + ε_i	0.24	0.56
Live	biomass ~ **EVI** + soil moisture + canopy + ε_i	0.44	0.53
Grass	biomass ~ **Brightness + Greenness + Wetness** + soil moisture + canopy + ε_i	0.40	0.87

- Making explanatory models is one thing, but for a model to be useful for future management, its capacity to predict to new data is crucial. We predicted biomass to a new set of samples from May 2019. Some of these sites were in the training data set, some were new.
- We then compared model predictions to the observed biomass for that period (Figure 5).
- Predictions from remote sensing did better for "known" (resampled) sites (Figure 5(a)) than to sites that the model had never "seen" (new and anonymised resampled sites) (Figure 5(b)). Observed grass biomass tended to be lower than the model predicted, however. Although grass is highlighted here (Figure 5), models for all understorey biomass types predicted better to "known" than to "new" sites.
- Variation in understorey biomass across the landscape, even within the same canopy type, was not captured using remote sensing (Figure 5).

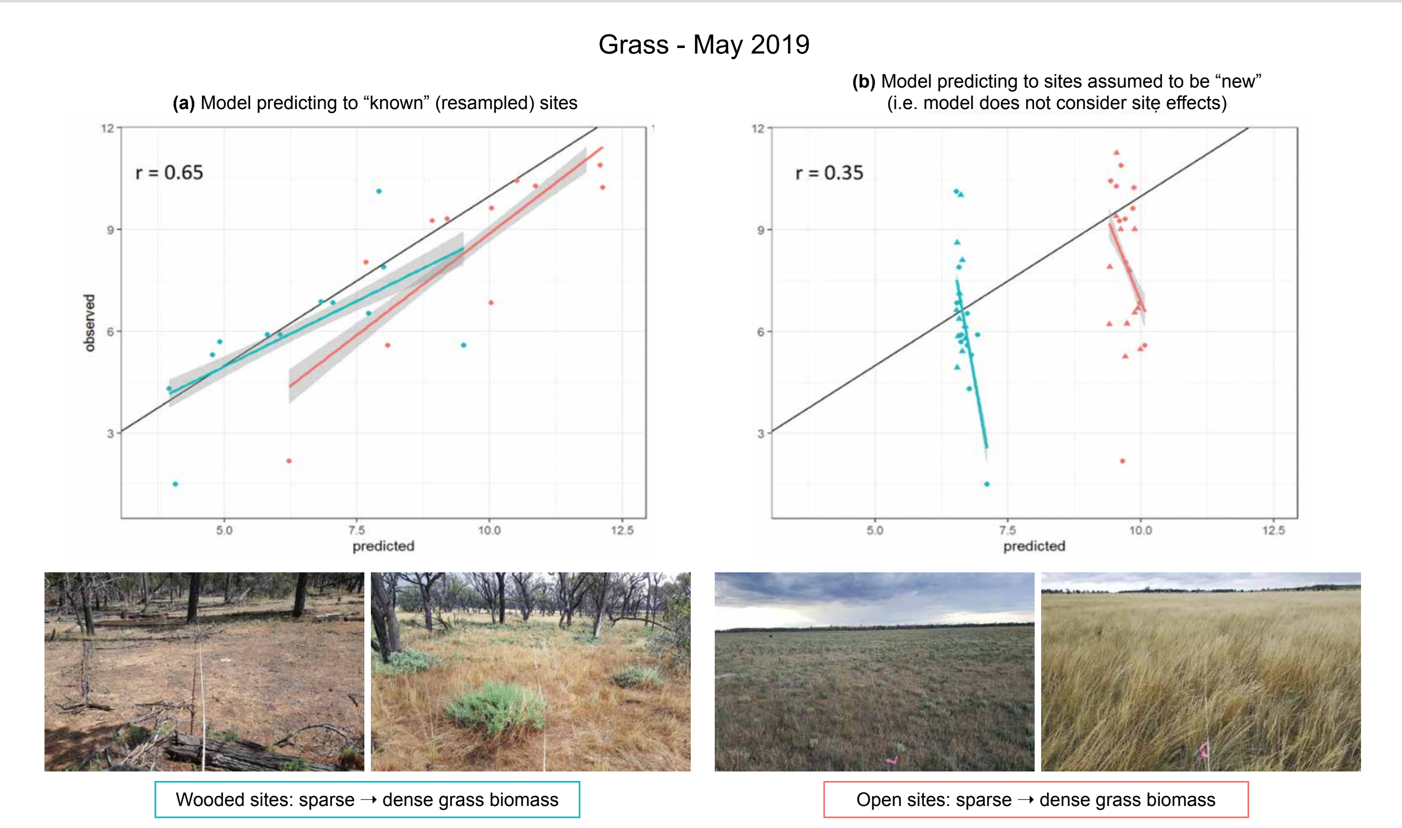

Figure 5. Predicted vs observed (field measured) grass biomass. Predictions to "known" (resampled) sites (a), and when all sites assumed to be "new" (b). r values indicate strength of correlation between "observed" and "predicted" values. Images show the range of biomass within wooded (left) and open (right) sites within a single season.

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Main points and future work

- The model was reasonably skilled at predicting grass biomass to new observations from known (previously sampled) sites (r = 0.65; Figure 5(a)).
- The model was unskilled when predicting to new or anonymised sites (r = 0.35; Fig. 5(b)). This indicates that biomass variation is responding to factors that have not been included in the model, such as small-scale variations in topography, soil type, soil moisture, or nutrient availability, for example.
- The model tended to overpredict grass biomass at known sites. This would need to be taken into account to avoid grass biomass dropping below the forage switch threshold and not being detected, thereby increasing the over-grazing risk.
- Although total understorey biomass remained relatively stable over time, the amount of live understorey biomass dropped with decreasing rainfall (Figure 4). The forage switch threshold (Norbury 1987) is based on total (live and dead) grass biomass. However, the relative importance of live and dead forage may differ, as forage availability decreases in the field: kangaroos generally prefer green grass, but will also eat dry grass, forbs and shrubs during times of drought (e.g. Dawson et al. 1975, Dawson & Munn 2007). It is unclear how changes in live forage availability might alter the threshold.
- The biomass models use soil moisture data with a 5 × 5 km resolution. Rainfall events can be patchy, which could influence soil moisture at a smaller scale. As existing soil moisture data does not capture this variation, estimates could potentially be improved by installing multiple weather stations across forage monitoring sites.
- We suggest that other methods are needed to obtain reliable large-scale estimates of biomass. Some preliminary work indicates a Rising Plate Meter or a drone with a multispectral scanner may be a more useful alternative for monitoring forage than satellite remote sensing.
- Future work will compare different biomass estimation models in terms of cost, suitability and precision. A biomass production model based on the Pine Plains data, will then be developed to predict forage over time.

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Further Information

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