Weed managers guide to Remote Detection: Understanding opportunities and limitations of technologies for remote detection of weeds

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Summary Remote detection is an influential tool for weed management, however accessing current technology can be costly, heterogeneous and unattainable for land managers. A new project aims to break down these barriers by investigating the limitations of this technology for remote weed detection in complex landscapes and create a *Community of Practice* for knowledge and information sharing that is accessible to all land managers. This paper presents an overview of the project methods and objectives, together with preliminary results and conclusions drawn from early analyses of recently acquired red, green, blue (RGB) and multispectral hawkweed imagery. Initial results emphasise the promise of RGB and multispectral sensors mounted on Remotely Piloted Aircraft Systems (RPAS), and supervised machine learning (ML) models for detecting hawkweed flowers with high accuracy in a rich set of landscapes.

Keywords remote sensing, Hieracium pilosella, Remotely Piloted Aircraft Systems (RPAS), machine learning (ML), object detection, community

INTRODUCTION

Conventional surveillance methods (e.g. field surveys) for invasive plant species, or weeds are time-consuming, dangerous and expensive, resulting in a lack of quantitative information about weed distribution in Australia (Campbell 1991). Such a lack of updated data hampers effective weed management (Coutts-Smith and Downey 2006). Traditional remote sensing efforts to detect weeds using aerial photography and multispectral imagery have obtained mixed success, with low spatial (from 10 to 30 m/pixel) and spectral (~100 nm) resolutions (e.g., Spot, Landsat) (Lamb and Brown 2001, Thorp and Tian 2004). Even with higher spatial resolution, satellite multispectral sensors (e.g., IKONOS and WorldView) have low instrument signal to noise ratios (SNRs), limiting their use to only large-scale weed infestations.

Hyperspectral imaging is a cutting-edge remote sensing tool that can obtain many spectral measurements (from 50 to 400 bands) in one pass. The resulting images allow separation of weeds from desirable vegetation and provide semi-quantitative abundances in plant and soil mixtures (Boardman 1998), showing considerable promise for identifying and mapping weed abundance (Miao *et al.* 2006, Dehaan *et al.* 2007). However, analysis using airborne and satellite systems can be costly and resolution is not always acceptable. Further, previous trials have demonstrated the deployment of active optical sensors in aerial platforms (Lamb *et al.* 2009), where detection of greenness by multispectral sensors typically worked well in crops when weeds are easily differentiated. In landscapes where weeds are mixed with other vegetation in heterogeneous situations, multispectral systems have shown less detection reliability.

Remotely Piloted Aircraft Systems (RPAS) and sensor technologies are now commercially available, achieving spatial resolutions from 2 to 50 cm/pixel, and with an increased flexibility to collect quantitative data at lower costs than traditional methods. In addition, machine learning (ML) may offer the ability to model relationships between low-resolution satellite imagery and corresponding higher-resolution images. This will allow enhancement of low-resolution satellite imagery, improving ability to detect weeds using this lower cost imagery.

Research in this space has traditionally been widespread and segregated across Australia, with no existing mechanism to bring findings and resources together to improve uptake. This paper describes a new research project that aims to address this gap by investigating the limitations and opportunities of existing remote sensing technologies now available for detecting weeds in heterogeneous landscapes. The paper also presents preliminary results of recent hawkweed imagery analysis in the sections below.

MATERIALS AND METHODS

Project description The project, entitled *"The weed managers guide to Remote Detection: Understanding the opportunities and limitations of multi-resolution and multi-modal technologies for remote detection of weeds in heterogeneous landscapes"* aims to investigate opportunities for cost-effective use of high-resolution red, green, blue (RGB), or colour, multispectral and hyperspectral technologies across various airborne platforms (drone, aircraft, satellite), paired with multi-modal ML analyses to detect weeds in heterogeneous landscapes. Three nationally significant 'model' weeds: 1) (hawkweed, (*Pilosella aurantiaca*); 2) African lovegrass (*Eragrostis curvula*); and 3) bitou bush (*Chrysanthemoides monilifera* subsp *rotundata*) will be used to test each technology, with the objective of determining practicable methods for land managers to use remote sensing for weed detection, aiding different management objectives (i.e. eradication, containment, asset protection). The project aims to grow extensive national partner networks, and to develop a national community of practice and portal to share learnings and advice on remote detection of weeds.

RPAS-mounted RGB, multispectral and hyperspectral imagery will be collected for each weed species. Field sites have been established in complex ecological landscapes where the weeds are present in varying densities. Sites will be sampled over 18 months in accordance with physiological or phenological changes that may allow improved detection of target species.

Analysis with multispectral and hyperspectral imagery will comprise the discrimination of key spectral bands and vegetation indices per weed species against other vegetation, as well as developing a pipeline to autonomously detect and map such weeds for a range of landscape ecosystems applying digital image processing, and supervised ML techniques such as gradient boosting and convolutional neural networks (CNNs). The development and outcomes of these pipelines will be validated with ground-based, or on-site data from experts. The first data capture for this project was at orange hawkweed sites in December 2021.

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Site description Hawkweed drone imagery was obtained from the Port Phillip hawkweed study site during December 2021 in Kosciuszko National Park (148.5875990°E 35.6923769°S), NSW, Australia. Much of the infestation at this site is enclosed within an approximate 20 m x 20 m area, which encompassed the flight region for data capture.

Ground truthing To facilitate the validation of all species captured within imagery, white plastic reference quadrats (1 m x 1 m) were placed across the site in areas representing variable botanical composition and hawkweed density. Ground images (Nikon D600 DSLR camera) of each quadrat were captured as reference images and quadrat features were recorded, including GPS location, plant species composition, plant height, species phenological stage and percentage ground disturbance. Cloud cover, wind speed, humidity, temperature and altitude were also recorded.

Imagery acquisition Imagery was captured on the 16th and 17th of December 2021 using DJI M300 and M600 drones. A number of different camera systems were mounted to these drones including high-resolution RGB cameras (Phase One-100MP, DJI P1-45MP and Fuji GFX 100s-100MP), multispectral (Micasense Altum) and hyperspectral (Specim AFX VNIR covering 400-1000nm of the electromagnetic spectrum) cameras. Each payload configuration was flown at different heights (20 m to 120 m) to facilitate various ground sampling distance (GSD) resolutions (0.22 to 5 cm/pixel). Ground calibration panels were placed in the field to help with spectral calibration for the multispectral and hyperspectral data. Various ML models were applied to the captured images, establishing separate processing pipelines for high-resolution RGB, and multi/hyperspectral data.

RGB imagery analysis

1.Training and optimisation To provide reasonable accuracy, 128 sample images from the RGB dataset were selected for model training, beginning with those of highest resolution (0.22 cm/ pixel). Bounding-box annotations were generated for each hawkweed flower appearing per sampled image. Several parameters such as the initial learning rate, final OneCycle learning rate, momentum, weight decay, obj loss gain, focal loss gamma, batch size, epoch, and confidence were optimised to obtain the maximum accuracy of the selected deep models.

2.Testing and Prediction Model performance was evaluated using several metrics, including precision, recall, and mean average precision (mAP) for an intersection over union (IOU) of 0.5 (50%). Precision measures the number of correctly predicted boxes, while recall measures the number of true boxes correctly predicted.

Flower detections of hawkweed within images were validated by weed experts. Detected hawkweeds within the ten ground-truthed reference quadrats were counted and visually cross-checked with ground images. Accuracies of all quadrats were subsequently averaged, producing the overall accuracy of the hawkweed detector model. An illustration of detected flowers is shown in Fig. 1.

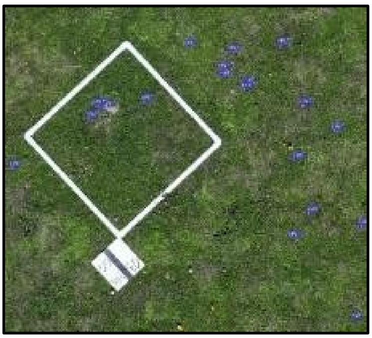


Fig. 1.Visual outlook of a tested high-resolution RGB image with hawkweed (quadrat dimensions 1m x 1m). Spatial resolution 11648 x 8736 pixels, and GSD 0.22 cm/pixel.

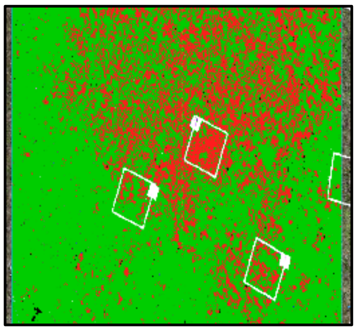
Multispectral imagery analysis Spectral signatures of hawkweed flowers and rosettes were identified, and a ML-based supervised model was tuned to map the weed using a data fusion approach between high-resolution RGB and multispectral orthomosaic rasters.

1. Orthomosaics and raster alignment
Initial image processing consisted of generating an orthomosaic for the site, georeferencing the resulting raster using ground control points (GCPs) and overlaying the multispectral orthomosaic to achieve pixel-level alignment between both rasters.

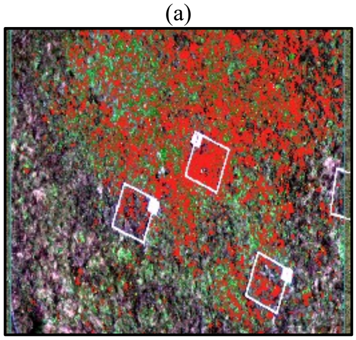
2. Data labelling Pixel-wise image labelling was performed over the reference quadrats containing hawkweed presence. Given that the spatial resolution of the multispectral raster is considerably lower than the high-resolution RGB imagery, the labelling task was supervised by on-ground weed experts. Challenges in labelling the data were addressed by applying a data-fusion approach. To simplify the spectral analysis, a total of four classes were compiled for hawkweed assessments, namely hawkweed rosettes, flowers, other vegetation, and non-vegetation.

RESULTS

The hawkweed detector model achieved an overall accuracy of 98.67% in the detection of hawkweed flowers within RGB imagery (0.22cm/pixel resolution) acquired at the Port Phillip site. Similarly, preliminary results on labelled data with the multispectral ML model reported a pixel-wise classification accuracy of 98.67% in the detection of hawkweed rosettes, and an overall accuracy of 98% percent for all hawkweed classes labelled. An example of the mapped classes extrapolated to the entire multispectral imagery is shown in Fig. 2.



(a)



(b)

Fig. 2. Image preview of predicted areas of hawkweed rosettes using multispectral imagery. **(a)** Highlighted areas of hawkweed rosettes in red, other vegetation in green, and non-vegetation in white. **(b)** Highlighted areas with the presence of

hawkweed rosettes in red. Quadrat dimensions 1m x 1m.

High precision, recall and mAP values for hawkweed detection from RGB imagery were of 93%, 97% and 97.3% respectively. Similarly, high precision and recall values were also achieved from multispectral imagery, at 97% and 99% respectively.

DISCUSSION

Study results support the value of RPAS-mounted RGB and multispectral sensors for detecting hawkweed plants at flowering stages within an alpine heterogeneous landscape. Findings are consistent with other studies investigating RGB and multispectral sensors for hawkweed detection (Hamilton *et al*., 2018; Ajamain *et al*., 2021). The accuracy metrics on the ML model are preliminary and indicate that further validation on prediction of hawkweed using multispectral imagery with a wider range of vegetation is required. Results also highlight the significance of image resolution in relation to image clarity and detection accuracy when applying deep learning models to remotely sensed data. Since high resolution imagery acquisition can be costly, there remains a need to identify models capable of improving clarity and detecting species within lower resolution imagery.

Despite the potential for detection at flowering stages, optimal control of weeds largely relies on detection during the vegetative stage, a goal historically less successful using RGB and multispectral technology (Hamilton *et al*., 2018; Ajamain *et al*., 2021). Such challenges point to the potential of RPAS-borne hyperspectral sensors as demonstrated by the capacity for spectroradiometers to distinguish hyperspectral profiles of hawkweed leaves to an accuracy of 80% (Ajamain *et al.*, 2021).

Future project work will continue to investigate remote sensing technologies and their application to each model weed system, including: 1) the development of detection models for low-resolution images; 2) the development of image pre-processing pipelines and models to improve image quality, and 3) the development of an image super-resolution method to upscale low resolution imagery for improved weed detection. Project methodologies, imagery and results will be collated into a set of guidelines, an online portal and community of practice for the sharing of resources associated with the Remote Detection of Weeds.

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REFERENCES

Ajamian, C.; Chang, H.-C.; Tomkins, K.; Farebrother, W.; Heim, R.; Rahman, S. (2021). Identifying Invasive Weed Species in Alpine Vegetation Communities Based on Spectral Profiles. *Geomatics* 1, 177–191.

Boardman, J.W. (1998). Leveraging the high dimensionality of AVIRIS data for improved sub-pixel target unmixing and rejection of false positives: mixture tuned matched filtering. Proceedings of the. 7th Annual JPL Airborne Geoscience Workshop, Pasadena, California, 12–14 January 1998, pp. 55–56.

Campbell, M.H. (1991). Weed control in pastures — are we winning? *Plant Protection Quarterly* 6 (2), 55–63.

Coutts-Smith A. & Downey, P. (2006). Impact of Weeds on Threatened Biodiversity in NSW, Technical Series 11, CRC for Australian Weed Management, Adelaide

Dehaan, R. Louis, J. Wilson, A. Hall, A. & Rumbachs, R. (2007). Discrimination of blackberry (*Rubus fruticosus* sp agg.) using hyperspectral imagery in Kosciuszko National Park, NSW, Australia, ISPRS *Journal of Photogrammetry and Remote Sensing* 62, 13–24.

Hamilton, M., Matthews, R. and Caldwell, J., (2018). Needle in a haystack–detecting hawkweeds using drones. Proceedings of the 21st Australasian Weeds Conference, pp. 9-13 (Weeds Society of NSW, Sydney).

Lamb, W. & Brown, B. (2001) PA -Precision Agriculture: Remote-Sensing and Mapping of Weeds in Crops, *Agricultural Engineering Research*, 78 (2), 117-125.

Lamb, D.W., Trotter, M.G. and Schneider D.A. (2009) "Ultra low-level airborne (ULLA) sensing of crop canopy reflectance: A case study using a CropCircleTM sensor". *Computers and Electronics in Agriculture* 69, 86-91.

Miao, X. Gong, P. Swope, S.M. Pu, R. Carruthers,

R.I. & Anderson, G.L. (2006). Estimation of yellow starthistle abundance through CASI-2 hyperspectral imagery using linear spectral mixture models, *Remote Sensing of Environment* 101 (3), 329–341.
Thorp, K.R. & Tian, L.F. (2004). A review on remote sensing of weeds in agriculture, *Precision Agriculture* 5, 477–508.