Evaluating the Use of Remote-Sensing to Locate Weeds in Kosciuszko National Park

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DECLARATION

I, Chad Ajamian, declare that this Master of Research thesis entitled “Evaluating the Use of Remote Sensing to Locate Weeds in Kosciuszko National Park” is of no more than 20,000 words in length, including quotes, and exclusive of tables, figures, appendices, bibliography, references, and footnotes.

Additionally, in accordance with the Department of Environmental Sciences, and Masters of Research guidelines, this thesis contains 50 pages (or less) of assessable material, of which excludes front matter, references, and appendices.

This thesis contains no material that has been submitted previously, in part or whole, to any university or institution for any academic degree, diploma, or other qualification.

Except where otherwise indicated and stated, the entirety of this thesis is wholly of my own work and efforts.

Signed: 

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ABSTRACT

The spread of invasive species in sensitive ecosystems is a major environmental problem, resulting in significant hazards to local and regional environmental and socioeconomic facets. Traditional field-survey based management, particularly in adverse terrain, is difficult – inhibited by climactic conditions, worker safety, and time. There is a strong demand for remote-sensing to mitigate these issues, improving efficiency and effectiveness, and increasing coverage ability.

The aims of this thesis are to investigate the potential use of remote-sensing in weed management and specifically evaluate the use of it to two locate weed species in Kosciuszko National Park (KNP). The evaluation was performed through the collection and processing of floral spectra to formulate a spectral library, which was then analysed for statistical uniqueness, utilising machine-learning classification algorithms.

Results of the Random Forest (RF) discriminability analysis presented an overall separability accuracy of 70%. This was then resampled to simulate the discriminability for commercial drone and multi-spectral satellite sensors, giving accuracies of 59% and 63%, respectively.

This preliminary analysis is promising, and builds the foundation for future multispectral research for weed management in KNP, and provides a foundational methodology for spectral pre-assessment in general.

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Chad Ajamian

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1 INTRODUCTION

Aided by the proliferation of high-quality data access and computing power, remote sensing is proving to be a valuable tool that is being increasingly utilised in multiple disciplines. Its ability to obtain vast quantities of information about the environment, at details and parameters previously unavailable, have seen its growing presence in innovative transdisciplinary studies (Easton, 1991; Xie, Sha, & Yu, 2008). One common example of this is the use of remote sensing imagery for ecological vegetation mapping – a rapidly advancing field through the expansion of imagery sources, classification algorithms, computing power, and other technological advancements (W. Turner et al., 2003; Xie et al., 2008). With various imagery sources now available – with differing spectral, spatial, radiometric, temporal, and financial characteristics – the suitability for remote sensing across varying aspects of ecology has increased (W. Turner et al., 2003; Xie et al., 2008).

The major challenges lie in the classification of this imagery, which are significantly more variable in their effectiveness, where the accuracy of distinguishing and mapping vegetation classes can vary significantly (Shang & Chisholm, 2014). One method may be exceptionally successful for one community and area, but comparingly ineffective in another (Shang & Chisholm, 2014). Searching for improved classification methods and ascertaining the best ones for particular cases, is one of the major research frontiers of vegetation remote sensing (Kerr & Ostrovsky, 2003; Lass et al., 2005). These cases, and demands, for vegetation remote sensing are ever-increasing across a broad range of areas.

Invasions by non-indigenous floral and faunal species are considered one of the most formidable of threats and risk factors to ecosystems, and socioeconomic conditions – particularly in Australia (Sinden et al., 2004). The direct annual impact of invasive species in Australia is estimated to be as high as $6.4 Billion per annum – $3.3 Billion alone for the grain industry, adjusted for inflation (Llewellyn et al., 2016; Sinden et al., 2004). This excludes other flow-on impacts on the environment including: native species extinctions; reduction of biodiversity; damage to ecosystem services; reduced aesthetics; impacts on fire regimes; and potential feedback influences (DiTomaso et al., 2013; Huang & Asner, 2009; Sinden et al., 2004). Remote sensing is a tool that is being used for the detection, classification, and monitoring of invasive species to assist in addressing these issues (Lass et al., 2005).

With the variable effectiveness of remote sensing in weed management scenarios, it useful to perform primary studies to ascertain potential benefits and results of implementing such systems in particular and specific weed management scenarios (Carson, Lass, & Callihan, 1995; O'Neill, Ustin, Hager, & Root, 2000). Assessing the suitability of classification algorithms before a full-scale deployment and analysis can assist in facilitating business cases for expenditures, as well as providing preliminary expectations of usefulness (Nidamanuri & Zbell, 2011). One method for this is to perform a statistical analysis on the separability of the spectral profiles of plants, essentially determining their contrast in general, and then re-performing this classification as to the specific capture parameters of imagery capture devices chosen (Nidamanuri & Zbell, 2011).

This thesis aims to assess the potential effectiveness of remote sensing utilisation for invasive species management through literature review, and a focused case study of two noxious weeds in Kosciuszko National Park, NSW, Australia. This thesis is presented in several chapters, which starts with a literature review, which then opens to the main results presented as a journal article prepared for latter submission, and concludes with a synthesis of the research.

2 LITERATURE REVIEW

2.1 Noxious Weeds

Infestations of invasive species in the Australian landscape has the potential to cause significant environmental, social, and economic effects. The presence of two concerning weeds, ox-eye daisy (*Leucanthemum vulgare* Lam.) and orange hawkweed (*Heiracium aurantiacum* L), in the already stressed alpine regions of Australia, particularly in Kosciuszko National Park (KNP), is a great concern to regional biodiversity and health of the environment (NSW DPI, 2012; NSW OEH, 2015b).

Detecting, and determining, the distribution and extent of specific floral species is key to environmental scientists and managers, providing significant knowledge regarding the growth, health, productivity, disturbances, and issues across an ecosystem (Franklin, 2010; Sanchirico & Mumby, 2009). The increase of human-induced climate change, as well as the intensification of species movements through globalisation and other anthropogenic activities, has made critical the need for knowledge for invasive species management, to assist with conservation efforts and sustainable practices (Beaumont et al., 2009; Clements & Ditommaso, 2011; Hulme, 2009; Westphal, Browne, MacKinnon, & Noble, 2008).

2.1.1 Ox-Eye Daisy

2.1.1.1 Description

Ox-eye daisy, *Leucanthemum vulgare* Lam. (Asteraceae), is a native European diploid rhizomatous perennial herb, an introduced species in Australia, generally for ornamental purposes (Chaujar, 2010; McConnachie et al., 2015). It is shallow-rooted, and spreads by rhizomes, but primarily by seed (NSW OEH, 2015b). The plants are capable of growing to 1m tall, but generally range from 30cm to 90cm, with a combination of prostrating basal stems capable of rooting, as well as simple stems (McConnachie et al., 2015). Seeding is highly prolific, with a single mature plant being able to produce 26,000 high longevity seeds annually, with as much as 80% still viable after six years, and some able to germinate after 39 years (McConnachie et al., 2015; Toole & Brown, 1946).

2.1.1.2 Distribution

The daisy is a worldwide problem, considered a weed in over forty countries (NSW OEH, 2015b). The weed is an established issue in southern Canada and the United States of America, as well as New Zealand, and is spreading in Australia (NSW OEH, 2015b). The species thrives in neglected and poor conditions such as roadside verges, and has a tendency to aggressively invade areas of high conservation importance (Chaujar, 2010; McConnachie et al., 2015). Ox-eye daisy is found in Victoria and New South Wales (NSW), with the most alarming infestation in KNP. The densest concentrations are near Tantangara Road, Providence Portal, and the Snowy Mountains Highway, as well as along trails such as Nungar Creek Trail and Bullocks Hill Trail (Atlas of Living Australia, 2016a). Other hotspots in Australia include: Llangothlin, 50km north of Armidale; Mount Lofty, Adelaide; minor scattered records in Hobart, and the western edge of Kanangra-Boyd National Park (Atlas of Living Australia, 2016a).

2.1.1.3 Issues

Ox-eye daisy is rapidly proliferating as an invasive species of concern throughout NSW, as it poses a significant threat to the local environment (NSW OEH, 2015b). Additionally, there is the strong potential for negative effects in the grazing industry, as witnessed in Canada, and the United States of America (USA) (Benson, 2012). The daisy is recognised as a significant pasture weed as it is: non-palatable for cattle; significantly reduces livestock carrying capacity; and makes the taste of dairy produced unpalatable for human consumption (Benson, 2012). The daisy is also a host for many viral diseases affecting crops (Benson, 2012). Infestations, especially dense ones, are recognised to exclude other plant species including natives, reducing native species diversity, as well as exacerbating soil erosion and depleting soil organic matter (McConnachie et al., 2015). In NSW, there is a *"very high risk"* to alpine, sub-alpine, open bushland and grassland areas (McConnachie et al., 2015, p. 104).

2.1.2 Orange Hawkweed

2.1.2.1 Description

Orange hawkweed, *Heiracium aurantiacum* L, also known as *Pilosella aurantiaca* (L.) F.W.Schultz & Sch.Bip. is part of the *Hieracium* species, commonly known as hawkweeds (Atlas of Living Australia, 2016b). The species is native to mountainous regions in Europe, is a major weed in USA, Canada, Japan, and New Zealand. It is in the establishment stage in Australia, having been listed on the State Prohibited Weeds list (NSW DPI, 2012). It is a perennial flowering plant, producing 5-30 flower head clusters each, and seeds without the need of pollination (Morgan, 2000). One square meter of an infection region produces up to 40,000 seeds during the summer season, spreading via adhesion to human and animal activity, as well as hydrological and aeolian movement (NSW DPI, 2012). Initially starting as a rosette, orange hawkweed spreads though stolons and rhizomes, which become daughter rosettes (NSW DPI, 2012). Its serious threat to the environment, combined with a small spatial distribution, provides the potential for an early-in-the-chain eradication. As such, the plant is listed on the 'Alert List for Environmental Weeds'.

2.1.2.2 Distribution

Infestations of orange hawkweed are currently limited to small pockets in Victoria, Tasmania and NSW (Atlas of Living Australia, 2016b). Hawkweed is present in two separate regions in Tasmania, as it was sold there from the 1950's as an ornamental garden plant (NSW DPI, 2012). Whilst being sold in NSW up to 2005, its first recorded naturalisation was in 2003 at Toolong Range in KNP (Atlas of Living Australia, 2016b). In 2011 surveys, the weed is contained to 135 discrete patches to a total of 7.43ha, in a sphere of 8,165 ha of parkland, limited to the park boundary (NSW DPI, 2012). In NSW, the weed is currently constrained to the KNP region. The hotspot is partly within the Jagungal Wilderness Area, and near Round Mountain (Atlas of Living Australia, 2016b). Minor limited infestations are also present in the Victorian Highlands, believed to spread by travellers. The Cabramurra infestations are roughly 50km from the Tantangara Road infestations of ox-eye daisy (Atlas of Living Australia, 2016b). The areas of invasive species infestations are presented in a figure in *appendix one*. The weed tends to habituate along ridges and other areas where winds may be 'blocked' (Jones, 2017). This section of KNP would be an ideal study area for sampling, which can be specified as the region encompassing the northern extent – between Tantangara Dam and Jagumba. Therefore, it is selected as the study site area for this project.

2.1.2.3 Issues

Categorised as a 'sleeper weed', orange hawkweed is flagged for having the potential to undergo an exponential growth and spread, with modelling suggesting the potential for NSW, Victoria, and Tasmania to be at risk of a 27 million hectare infestation (NSW DPI, 2012). Orange hawkweed can have significant environmental impacts through loss of botanical biodiversity (Morgan, 2000). Additionally, the plant increases the acidity of the soil below it, modifying the lithographic environment and impacting the growth of other species (NSW DPI, 2012). Orange hawkweed has displaced inter-tussock vegetation in New Zealand and there is potential for a similar issue to occur in Australia, destroying rare and threatened native vegetation (Morgan, 2000). The weed is unpalatable to livestock and aggressively competes with pasture, with potential modelled impacts to Australia being $48 million p.a. (NSW DPI, 2012). Additionally, there is the potential for damage to native vegetation reducing the natural iconic aesthetics of the region, impacting the local $280 million tourism industry (NSW DPI, 2012).

2.1.3 Current Weed Management Approaches in Kosciuszko N.P.

A variety of approaches are used for controlling the weeds, sorted into different weed management categories, which are organised based on the level of weed invasion, and their history (NSW DPI, 2012). For ox-eye daisy, the category is containment – where eradication is assumed to now be impossible, and the focus is instead on reducing the severity, and spread, of the already established infestations (NSW DPI, 2008). This can include, for example, ensuring the weed does not reach more pristine parts of the ecosystem, whilst confining its existence to road verges. However, orange hawkweed is different and has a considerably higher management effort, as it is classed in the eradication category, where the focus is to obliterate the weed entirely (Hamilton, Cherry, & Turner, 2015). No weed eradication programs have been entirely successful in mainland NSW to date (Hamilton et al., 2015). Globally, no orange hawkweed eradication programs have reached completion successfully (Jones, 2017).

The relatively contained distribution, low populations, and lesser chance of reinvasion, provides the opportunity for eradication of orange hawkweed to occur, in contrast to ox-eye daisy which is already considerably spread (Caldwell & Wright, 2014). The eradication program can be summarised as consisting of: strategic detection programs; coupled with rapid and repeated control initiatives; as well as monitoring, and evaluation, to provide an integrated and adaptive environmental management response (Caldwell & Wright, 2011, 2014; Cherry, Constantine, Primrose, Hauser, & Tasker, 2016; Hamilton et al., 2015). The main challenge is detecting the remaining hawkweed plants in the extensive, topographically-challenging, difficult, alpine terrain. A combination of conventional and innovative approaches are being utilised. Extensive ground surveillance surveys are undertaken by a combination of field staff, contractors, and volunteer programs to detect weed infestations (Cherry et al., 2016;

Hamilton et al., 2015). Volunteer programs are large, involving over three hundred people (Cherry et al., 2016; Jones, 2017). Whilst useful, human surveys are estimated to have up to an 80% success rate, requiring further search methods (C. Hauser et al., 2012).

As such, these methods are accompanied by innovative programs including helicopter-insertion surveys, sniffer dog training and deployment programs, and wind spread modelling (Cherry et al., 2016). Cousens and Williams (2011), as well as Cousens et. al. (2012) predicted future hawkweed locations in KNP by modelling wind dispersal and habitat suitability, where habitat was calculated by a combination of ground-cover disturbance, vegetation community types, and soil moisture conditions. Potential spread changes under climate change scenarios was also determined in Beuamont et. al. (2009). The feasibility of using dogs to identify hawkweed was determined to be effective by Hanigan and Smith (2014), which encouraged its use as a management technique. The dogs are able to cover five times more than human operators, but may do this along an esoteric route, which is mitigated through in-field GPS trackers which can alert a trainer where a gap in a search grid may have occurred for re-evaluation (Jones, 2017). Weed eradication detector dogs are now being used successfully to 'verify' and detect hawkweed plants (Cherry et al., 2016). *"Robotic aircraft and intelligent surveillance systems"* – or drones – were used to map and detect orange hawkweed in KNP (Hung & Sukkarieh, 2015, p. 100). This system used image processing algorithms to search for the orange colour provided by the flower of orange hawkweed (Hung & Sukkarieh, 2015). Flowers were successfully detected, albeit with considerable rates of false-positive returns (Hung & Sukkarieh, 2015). This system is able to provide a coverage of 25 hectares a day (Jones, 2017). In the 2016-17 season, this colour based approach was used, by coupling the service with helicopter insertion surveys. The demand for an additional method that can cover a large area, accurately, and outside of the flowering season, is significant (Jones, 2017).

In order to most effectively contain and control weed infestations, alternative methods need to be utilized in addition to the conventional field survey and manual image analysis approach. Classification of optical remote sensing images can provide a suitable approach to mapping the spatial extent and distribution of weed outbreaks (Carson et al., 1995). This process can save thousands of worker hours, increasing efficiencies and allowing resources to be greater utilised (Carson et al., 1995). Crucially, this process will provide a greater spatial coverage than is possible by field surveying, as well as providing a much higher rate of successful detection than what has been achieved using RGB image analysis of the orange hawkweed flowers.

2.2 Remote Sensing

2.2.1 Remote Sensing and Species Detection

A wide variety of remote sensing applications have been used for general ecological management and species detection, as they are more efficient than traditional field-survey methods (Franklin, 2010; Mumby, Green, Edwards, & Clark, 1999). Early use of remote-sensing systems typically produced analysis that averaged information over tens or hundreds of square meters, a limitation of previous spectral resolution availability, which is far too generalised and coarse for most scientific purposes (Franklin, 2010; W. Turner et al., 2003; Underwood, Ustin, & Ramirez, 2006). However, advances in the spatial and spectral resolutions of modern sensors, as well as in processing abilities, has allowed for direct remote sensing to be of a further benefit to the biodiversity field (W. Turner et al., 2003).

Determining the species, quantities, characteristics, and distribution of vegetation is a significant aspect of remote sensing research (Adam, Mutanga, & Rugege, 2010; Kerr & Ostrovsky, 2003; W. Turner et al., 2003). There are two major themes that occur here. The first is an *indirect* biodiversity-remote sensing approach, where environmental parameters and factors are used to determine potential distributions by proxy (Joshi et al., 2006; Kerr & Ostrovsky, 2003; Lobitz et al., 2000; W. Turner et al., 2003). Species are often restricted to specific habitats, where certain factors need to be optimal for them to survive, or thrive (Cañadas, Sagarminaga, De Stephanis, Urquiola, & Hammond, 2005). These habitat requirement factors include temperature, distance to streams, rainfall, soil moisture, topography, and terrain (Joshi et al., 2006; Kerr & Ostrovsky, 2003). These elements are then often combined with other spatial information such as general land cover, and other ecological variables including chlorophyll, phenology, and vertical canopy structure (Joshi et al., 2006; Kerr & Ostrovsky, 2003). These can all be identified remotely and then used to develop models to precisely estimate potential distribution and patterns of species (Cañadas et al., 2005; Joshi et al., 2006; Kerr & Ostrovsky, 2003; Lobitz et al., 2000; Osborne, Alonso, & Bryant, 2001; W. Turner et al., 2003).

The secondary application theme, and the one utilised by this thesis, is the *direct* biodiversity-remote sensing approach, whereby individual organisms, species groups, or ecological communities are remotely sensed through airborne or satellite sensors (Adam et al., 2010; Kerr & Ostrovsky, 2003; Nidamanuri & Zbell, 2011; Shang & Chisholm, 2014; W. Turner et al., 2003). Satellite systems with high spectral and spatial resolutions allow for the direct remote sensing of larger flora, and ecological communities through spaceborne imagery (Franklin, 2010; Kerr & Ostrovsky, 2003; W. Turner et al., 2003). Likewise, cameras mounted to aerial systems such as drones and fixed-wing aircraft allow for even higher resolutions at the compromise of coverage and cost, with the ability to detect smaller plants (Anderson & Gaston, 2013; Colomina & Molina, 2014; Tang & Shao, 2015; Watts, Ambrosia, & Hinkley, 2012). These systems, combined with multispectral sensors which contain many more discrete spectral bands of the electromagnetic spectrum, allow for the recognition of plant species or communities based on their representative spectral signatures (Anderson & Gaston, 2013; Colomina & Molina, 2014; Tang & Shao, 2015; W. Turner et al., 2003; Watts et al., 2012).

Individual spectral signatures are based upon the chemical composition of the target species, species physiology, plant architecture and geometry, morphology, and external factors – including climate, solar angle, and soil characteristics (Barrett & Curtis, 1992). Primarily, reflectance profiles are influenced by the plant materials that have optical influences – lignin, cellulose, sugar, starch, and proteins – mostly composed of nitrogen, carbon, oxygen, and hydrogen (Barrett & Curtis, 1992). Along the electromagnetic profile spectrum, different factors influence the reflectance of wavelengths. The photosynthetically influenced region, 400 to 700 nm, is characterised by leaf pigments (Tucker & Garratt, 1977). Healthy green vegetation has a higher reflectance in the green wavelengths (490 – 520 nm), and less in the blue and red regions (Tucker & Garratt, 1977). There is generally a large increase in reflectance between 680 to 780 nm, due to red absorption (Slaton, Hunt, & Smith, 2001). Near-infrared (NIR) (750 – 1300 nm) is controlled by cell structure, such as the structure of leaves, and air spaces within it – influencing scattering and absorption (Slaton et al., 2001). Mid-infrared (1300 – 2500 nm) is influenced mainly by water content, especially at 1400 – 1900 nm, and reflectance peaks generally occur at 1600 and 2200 nm (Pfitzner, Bartolo, Carr, Esparon, & Bollhofer, 2011). These are summarised in *figure 1*.

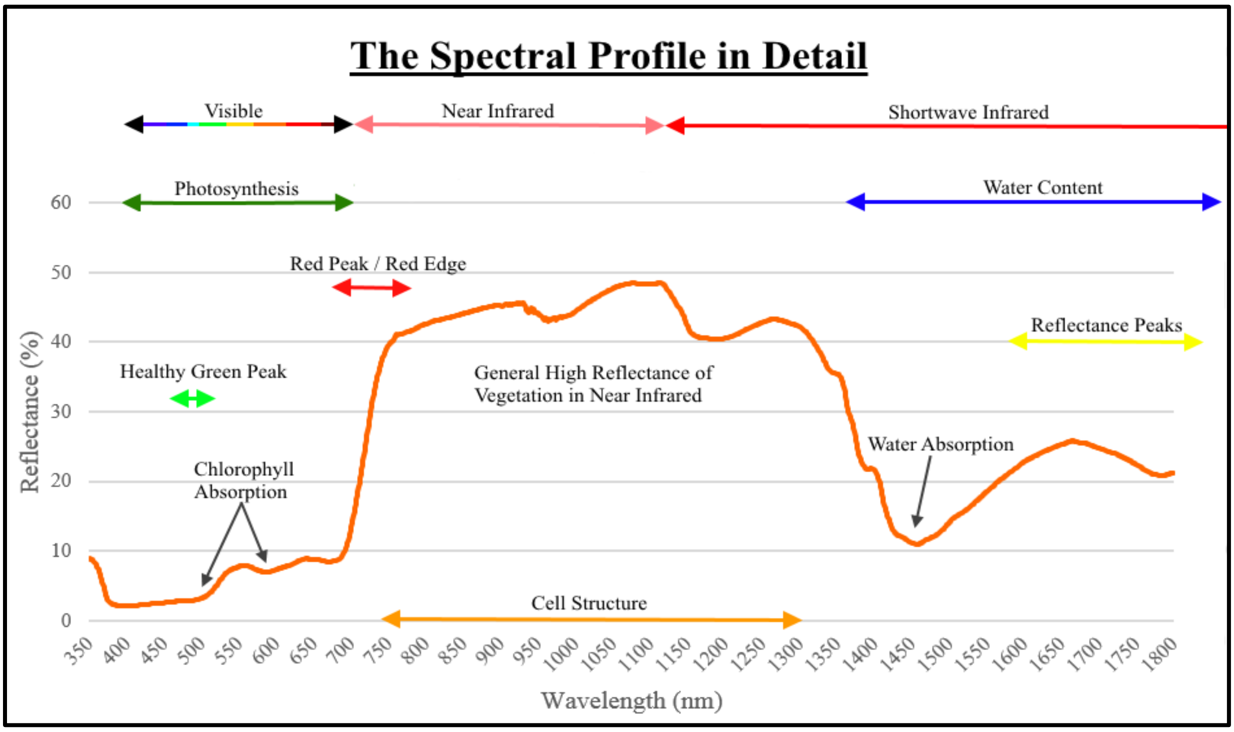

Figure 1. The Spectral Profile in Detail (Barrett & Curtis, 1992; Slaton et al., 2001; Tucker & Garratt, 1977)

2.2.2 Remote Sensing and Weed Management

Geographic Information Science (GIS) and remote sensing have been used through a variety of methods to detect weeds globally, and locally. Multi-attribute distribution modelling is commonly used to target where species are most likely to occur (C. E. Hauser & McCarthy, 2009). For orange hawkweed, Williams et al. (2008) constructed a dispersal habitat suitability model considering disturbance level, moisture, vegetation community, wind dispersal probability, and current infestation locations. This was used to target surveillance locations, to reduce management costs, with a predicted saving of 120,000 management hours (Williams, Hahs, & Morgan, 2008). Whilst it is useful to determine the potential spread regions of infesting weeds, another beneficial technique is determining the specific locations of weeds currently growing, so a highly targeted management program can be implemented.

In order to combat infestations of ox-eye daisy and yellow hawkweed (*Hieracium caespitosum)* in Idaho, USA, high resolution multispectral satellite imagery was used to locate regions containing flowering plants (Carson et al., 1995). Supervised and unsupervised classifications were first performed, with multispectral LANDSAT 5 imagery with a 30m by 30m resolution, and French SPOT 1-3 satellite imagery of a 20m by 20m resolution (Carson et al., 1995). However, the spectral and spatial resolutions of these were too coarse for the detection of weed species due to wavelength averaging in each band (Carson et al., 1995). Instead, an 'airborne data acquisition and registration' (ADAR) system was used to improve spatial resolution to 1 m^2 and specify wavelengths further (Carson et al., 1995). The supervised classification method of this imagery had a 68% success rate of classifying the weeds at 95-100% densities, a 2-6% success rate in classifying 20-95% densities, and a 97% success rate in classifying areas clear of weeds (Carson et al., 1995). The unsupervised classification method had a 55% success rate for high densities, 4-17% for the other range, and a 98% rate for weed free areas (Carson et al., 1995). Overall both were fairly accurate, but had low accuracies for lower densities, potentially due to confusion with other classes and spectral mixing.

Classification of imagery, based on field spectrometry, has also been hypothesised as an effective method for law enforcement agencies in detecting illegal *Cannabis* plantations in nature reserves (Azaria, Goldschleger, & Ben-Dor, 2012). Classification of hyperspectral remote sensing imagery is a potential method of detecting plantations of weed species, but is dependent on how unique the individual plants spectral profile is, compared to its surrounding ecology (Azaria et al., 2012). To tackle weed invasions of Leafy Spurge *(Euphorbia esula* L.) at Theodore Roosevelt National Park, a combination of field spectroscopy and the Airborne Visible / Infrared Imaging Spectrometer (AVIRIS), was used for detecting and mapping the species (O'Neill et al., 2000). Here, supervised classification of AVIRIS imagery, combined with field measurements, were used to obtain spectral profiles of both invasive and native species (O'Neill et al., 2000). Then, after image processing, supervised classification techniques were used to determine estimated locations, which was compared to the previously recorded locations for ground truthing (O'Neill et al., 2000). Depending on the mixing of species in a location, accuracy results here ranged between 73% and 99% (O'Neill et al., 2000).

2.2.3 Spectroradiometry and Remote Sensing – Factors to Consider

Successful weed management practices require an intricate understanding of the foundational biological and ecological principles of the weeds themselves, and the environment they are contained within (Tooke & Battey, 2010). Flowering phenology, attuned to environmental cues such as temperature and photoperiods, are important to note when searching for the presence of a particular plant species (Tooke & Battey, 2010). Spectroradiometric measurements of yellow hawkweed has determined that their spectral signature is significantly more distinct during the flowering stage, allowing it to be detected and classified easier and more accurately (Lass & Callihan, 1997). When not flowering, the weed had a similar spectral pattern from other plants that grew in the area, making it difficult to delineate (Carson et al., 1995). The highest error rates occurred when the yellow hawkweed was in the post-bloom stage. The observable distribution of the hawkweed was highly dependent on the stage of the plants phenology, with the full bloom stage being most accurate - whilst ox-eye daisy was strictly limited to this stage (Lass & Callihan, 1997). The most appropriate phenological stage appropriate to detection of the species via remote sensing, i.e. when it is most spectrally 'unique', must be considered to ensure the most effective and efficient classification, delineation, and mapping of areas affected by weed infestations (Lass & Callihan, 1997). This notion was echoed in Hestir et al. (2008), where the different spectral characteristics at different life stages were emphasised in their detection ability of three different weeds – perennial pepperweed (*Lepidium latifolium*), water hyacinth (*Eichhornia crassipes)*, and Brazilian waterweed (*Egeria densa)* – suggesting that the timing of the acquisition of data should coincide with the peak occurrence of growth and/or the most unique spectral profile phase. Multispectral remote sensing is a powerful set of tools that can be utilised to determine the spatial characteristics of invasive species. The methods of using these tools need to account for potential variability in spectral profiles across phenological stages (Hestir et al., 2008).

2.3 Spectral Profiling

2.3.1 Spectral Reflectance

Hand-held *(in-situ)* spectroradiometers collect reflected wavelengths from sources in a series of spectral wavelengths through the electromagnetic radiation spectrum,

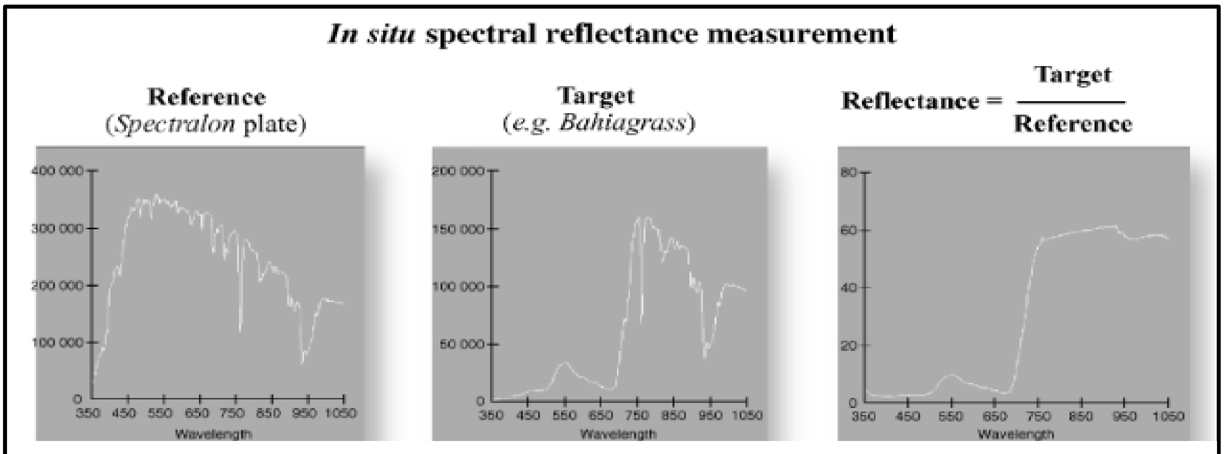

Figure 2. In situ spectral reflectance measurement. (Im and Jensen, 2008)

specifically within the visible, and/or near-infrared and infrared regions (Im & Jensen, 2008; Jensen, 2006). This works similarly to the ex-situ, spectral remote sensing methods (Jensen, 2006). Hand-held spectroradiometers are designed to collect the radiant flux from samples in the laboratory or field. These in-situ measurements are generally done up to a 1m range from the sample (Im & Jensen, 2008). An in-situ spectroradiometer system generally consists of four parts: an input optics, such as a lens, which gathers radiation from a measured field of view angle; a monochromator, which disseminates this radiation into its component wavelengths; a detector, which then determines the quantity of radiation per individual wavelength; and then a logging and control system to define, process, store, and gather the information (Bentham Instruments Ltd, 2014). Spectral information can be collated to constitute a profile for a particular species, often referred to as a spectral signature or fingerprint (Jensen, 2006). These are also known as reflectance profiles, and are the resultant of the reflectance across different wavelengths, calculated by dividing the target reflectance by a reference 'spectralon' plate, as in *figure 2* (Im & Jensen, 2008).

The spectral signatures acquired from these in-situ measurements can be used to document and record the individual spectral reflectance characteristics of different materials, such as unique types of vegetation (Goetz, 2002; Jensen, 2006). Furthermore, they can be used to calibrate future hyperspectral or multispectral remote sensing information to mitigate against the influence of absorption and atmospheric scattering (Goetz, 2002). Most notably for this project is the use of matched-filtering, where collected spectral profiles can be cross-referenced against samples of unknown constituents, to identify them from a wider coverage region (Goetz, 2002).

2.3.2 Developing a Spectral Profile

Determining spectral signatures through ground-based reflectance spectra is a critical aspect of this research. The measurements obtained must be accurate, and be representative of their target. However, these measurements are highly influenced by the methodology of their capture, environmental conditions, equipment responses, and calibration quality. Whilst collection of this data is highly tenuous, and susceptible to experiment design, there are no international or national standards for the in-situ collection of spectral signatures (Pfitzner et al., 2011). Supervising Scientist Report 195 by the Australian Government Department of Environment and Energy aimed to collate literature regarding this issue, in order to collect data for a national spectral database (Pfitzner et al., 2011).

Critical issues need to be considered in undertaking in-situ spectral measurements, including atmospheric properties, measurement timing, height, orientation of measurement, field of view of the lens, calibration, and spectral averaging (Milton, Schaepman, Anderson, Kneubühler, & Fox, 2009; Rollin, Milton, & Emery, 2000). There are several influences that must be at least considered when creating a spectral profile of a vegetation species. These include: general experimental design, calibration, reference testing frequency, time of day, environmental aspects, spatial viewing characteristics and illumination specificities (Barrett & Curtis, 1992; Im & Jensen, 2008; Milton et al., 2009; Pfitzner et al., 2011; Rollin et al., 2000). These factors are further analysed in *table 1*.

Table 1. Field Spectroradiometry Consideration Factors (Barrett & Curtis, 1992; Im & Jensen, 2008; Milton et al., 2009; Pfitzner et al., 2011; Rollin et al., 2000)

Field Spectroradiometry Factors to Consider	
Experimental Design	Timing, method, geometry, scale, number of samples (variability across temporal and spatial scales)
Calibration	Calibration panel, spectrometer
Instrument Settings	Number of samples, white reference, dark current considerations
Illumination	Date, time, solar zenith and azimuth angles, location
Viewing Geometry	Field of view, capture height (from target and ground), capture angle
Enviro. Conditions	Air pressure, visibility, humidity, temperature, cloud cover, wind vector
Vegetation	Texture, phenology, form, cover, conditions, homogeneity, health, species, layering.
Photographs	Site setup, target, sky.

Whilst this list is extremely large, field analyst undertakings and experimental design can be used to mitigate a multiplicity of these factors, particularly those due to viewing geometry, timing, and calibration (Pfitzner et al., 2011). Consistent in-situ methodologies increases accuracy and the effectiveness of analysis by allowing for better identification of outliers (Pfitzner et al., 2011).

2.3.3 Analysing and Comparing Spectral Profiles

A wide variety of applications utilise the spectral profiles measured from imaged pixels or objects to retrieve useful information. The analysis of these profiles, however, varies substantially, as a wide variety of mathematical and statistical approaches are available. Supervised classification algorithms are machine learning techniques that allow for a detailed analysis and comparison of spectral profiles. Random Forest (RF) is one of the most popular, and accurate, techniques for classifying large datasets (Belgiu & Drăguţ, 2016; Breiman, 2001; Pal, 2005). RFs work by generating a large collection of decision trees, of which each is constructed from a subset of the original data, sampled by random, with replacement (Breiman, 2001). These are then processed as an ensemble, to identify a consensus across of classification based on the most common output (Breiman, 2001).

A study performed RF classification on manually delineated sun-lit regions of tree crowns to classify ten different species with an 82% accuracy (Immitzer, Atzberger, & Koukal, 2012). The algorithm was also used to see if *Cyperus papyrus* L. was spectrally unique in comparison to its co-existent species, yielding ten optimal wavelengths where the separation was most significant, with an overall accuracy of 90% (Adam & Mutanga, 2009). Another study utilised this method to discriminate specific grass species which indicate the degradation of rangeland ecosystems, which could then be used to assess the areas overall health (Mansour, Mutanga, Everson, & Adam, 2012). Ground-level hyperspectral scans, in conjunction with a RF analysis, was used to determine the separability of native and invasive species in Virginia, USA to identify if remote sensing could be a potential approach in resolving weed management issues (I. Aneece & Epstein, 2017). Aneece and Epstein (2017) found this to be successful, with accuracies for individual species ranging from 23% to 88%. Supervised classification methods through machine learning, such as the RF method, allow for accurate and comprehensive insights into spectral profiles and datasets.

3 Journal Paper

Evaluating the Use of Remote-Sensing to Locate Weeds in Kosciuszko National Park

3.1 Abstract

This study establishes a proof-of-concept insight into the use of multispectral remote sensing techniques to detect, and determine, the spatial distribution of selected noxious weeds, using orange hawkweed and ox-eye daisy in Kosciuszko National Park (KNP) as a case study. This involved collecting spectral profiles of the weeds *in-situ* and *ex-situ* with a field spectroradiometer, in addition to surrounding native vegetation. These profiles were then processed and analysed to determine their uniqueness and to estimate the potential effectiveness of multispectral and hyperspectral remote sensing in separating these signatures. Spectral analysis was performed by a series of methods through the statistical suite 'R', primarily through machine learning algorithm, Random Forest (RF). The overall accuracy of separating all measured species types from each other was 70% accuracy overall, with a 59% accuracy when averaged to the bands of a multispectral drone camera, and 63% for the same process applied to a multispectral satellite WorldView-3. Our results demonstrate that there is a significant potential for multispectral remote sensing to be utilised as a detection method for orange hawkweed and ox-eye daisy in KNP.

3.2 Introduction

The natural qualities of the Australian Alps are a quintessential part of Indigenous and European Australian heritage and culture, with their landscape and features presented in numerous art forms (NSW DE&C, 2006). The Alps are protected by a chain of national parks, the largest and most famous of which being KNP, situated in the south-eastern corner of mainland Australia, along the Snowy Mountains (NSW DE&C, 2006). The region contains a unique ecosystem, including one of the only seasonally snow-covered regions on the continent. Therefore, it is home to a large array of rare and unique floral and faunal species, accentuating a criticality to preserve the biodiversity of the park (NSW DE&C, 2006). The presence of noxious weeds in the KNP and surrounding regions, is a key threat to the local biodiversity, and health of the environment – with a significant potential to cause negative environmental, social, and economic impacts (Benson, 2012; Caldwell & Wright, 2014; Dehaan, Louis, Wilson, Hall, &

Rumbachs, 2007; McConnachie et al., 2015; NSW DPI, 2012; NSW OEH, 2015a, 2015b). The noxious weeds that are a focus of this study are species of the daisy family (Asteraceae) and are being targeted by multiple government agencies (NSW DPI, 2012; NSW OEH, 2015b). These plants are orange hawkweed (*Hieracium aurantiacum)* and ox-eye daisy (*Leucanthemum vulgare* Lam. (Asteraceae)). Whilst hawkweeds are yet to reach past the early stages of establishment, they pose a major threat to ecosystems – particularly grasslands, alpine, and temperate areas – as well as an unbearable cost to the grazing industry (Benson, 2012; Caldwell & Wright, 2014; Morgan, 2000).

Orange hawkweed was first discovered in the KNP region in late-2003 (NSW DPI, 2012). Listed as a State Prohibited Matter in NSW (previously known as a class one noxious weed), it is internationally regarded for displacing native vegetation, and harming agricultural productivity – particularly in New Zealand, Canada, and USA (Caldwell & Wright, 2014; Wilson, McCaffrey, Paul C. Quimby, & Birdsall, 1997). Its current containment in NSW to within the national park (barring one outlier recently discovered early-2017 in a neighbouring farm), as well as its high risk factor, makes it an ideal candidate for a targeted eradication program (P. J. Turner, Hamilton, Caldwell, & Johnson, 2013). Ox-eye daisy is a more prevalent introduced species, which is difficult to control with eradication and control programs (Benson, 2012; McConnachie et al., 2015). Much more common and widespread than the hawkweeds, control programs are now aimed towards containment rather than eradication (NSW OEH, 2015b). It also reduces the productivity of grazing lands, and is a host for several crop-affecting viral diseases, such as the yellow dwarf virus (DiTomaso et al., 2013).

There is an urgent need for prevention of these weeds spreading, particularly orange hawkweed, as it disperses easily and prolifically, and is hazardous to the environment. This prevention process traditionally involves monitoring existing infestations and scouting for additional infestations using field survey approaches (NSW DPI, 2012). However the demand and urgency to control the plants domination has led to a more diverse range of control techniques, including: sniffer dogs; volunteer programs; visible-colour drones; helicopter insertion surveys; and spread-modelling systems (Caldwell & Wright, 2014; Cherry et al., 2016; Hanigan & Smith, 2014; Hung & Sukkarieh, 2015; Williams et al., 2008). The difficulty in weed management is further increased by the exceptionally difficult topography - creating lengthy travel times by forcing the use charted helicopters, off-road vehicles, and off-track hiking – reducing the amount of time that can be used for searches, increasing costs, and lowering search coverage potential (Hamilton et al., 2015; Hanigan & Smith, 2014). Time is a strong constraint in this project - as the flowering period, which makes the plants significantly easier to spot by officers and volunteers, is quite short (1-2 months) (Lass & Callihan, 1997). Time constraints are further inhibited by climatic conditions, as snowfall reduces the visibility of surface vegetation, as well as creating occupational hazards and discomfort to employees and sniffer dogs. A remote sensing method has previously been trialled, which involves flying drones with a RGB camera over known sites, and seeking the orange colour value of orange hawkweed in the image (Hung & Sukkarieh, 2015). This method relies on the phonological stage of the plant to be appropriate (Hung & Sukkarieh, 2015). Additionally, the geographic coverage of these drone flights are fairly limited (Hung & Sukkarieh, 2015).

Therefore, in order to mitigate some of the issues addressed with current methods, there is a demand for an alternative process to be developed. This process should: determine the location of noxious weeds throughout different stages their phenological cycle; be able to be operated remotely; cover a reasonable amount of area efficiently; and more importantly – provide effective output results. A proposed process that fits these criteria is multispectral remote sensing. This preliminary study aims to establish the spectral profiles of the noxious weeds and prevalent native vegetation, and statistically define their separability at ground level. This will ascertain if these methods can accurately, and effectively, assist in the determination of the spatial distribution of noxious weeds in the Australian Alpine environment using airborne or spaceborne sensors.

3.3 Methods

3.3.1 Methodology Overview

A series of methods were used for this project. This included general training and testing, sampling of the spectral profiles of the weeds in the field as well as in the greenhouse, data entry, multiple pre-processing steps, and multiple RF classifications of spectral profiles. A summary of the methodology process used is presented in *figure 3*.

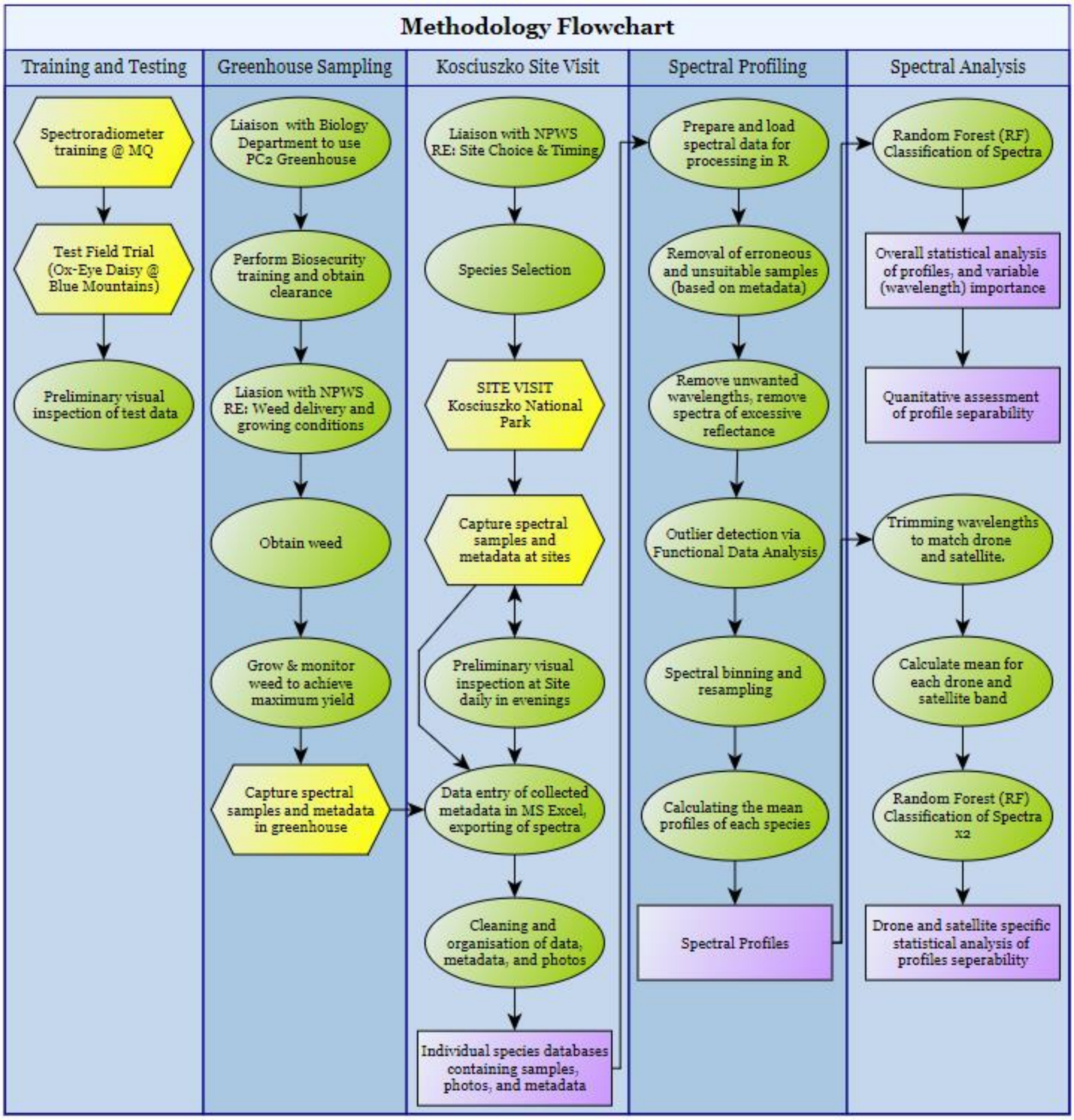

Figure 3. Methodology Flowchart

3.3.2 Study Area

KNP is located in the Snowy Mountains of New South Wales (NSW), in south-eastern Australia (latitude: 35°30'S to 37°02'S; longitude: 148°10'E to 148°52'E). Covering much of the Australian Alps Bioregion, it is the largest national park in NSW at 673,542 ha. (NSW DE&C, 2006). The region is highly biodiverse, and unique, which makes it an important region for environmental protection (NSW DE&C, 2006). However, the proliferation of noxious weeds, particularly ox-eye daisy and hawkweed varieties, are a considerable risk to this alpine environment. Orange hawkweed is almost exclusively recorded in the Southern Ranges, with the majority of recordings located between the Tooma River and Cabramurra (Caldwell & Wright, 2011, 2012, 2014).

Seven sites were chosen, in liaison with officers of the NSW National Parks and Wildlife Service (NPWS), as depicted in *figure 4.* Six of these were used to measure orange hawkweed, which due to an NPWS eradication project, currently has a very sparse, and patchy distribution. One site was used to measure ox-eye daisy, which is much more widespread and abundant throughout the region.

Several sites - Ogilvie's Quarry, Ogilvie's Creek Picnic Area, and Ogilvie's Airstrip (sites 1-3) represent the potential 'ground-zero' source of orange hawkweed infestations, whilst also being the most accessible sites in this region of the park, and containing a wide variety of native species (Caldwell & Wright, 2011, 2012, 2014). Doubtful Gap (site 4), is one of the more eastern locations of orange hawkweed and represents recently recorded infestations (Caldwell & Wright, 2014). At opposite sides of a valley, Farm Ridge and Round Mountain Trail (sites 5 and 6), are some of the heavier infestation sites in the Jagungal Wilderness (Caldwell & Wright, 2011, 2012, 2014). Tantangara Road (site 7) was selected as the final site because it contained a significant and widespread infestation of ox-eye daisy for several kilometres, as well as a substantial variety of representative native species.

As infestations of orange hawkweed were less prevalent than expected due to highly effective control, it was decided that some ex-situ sampling would be useful for enhancing the accuracy of the spectral profile. As such, several plants were grown on-site at the university greenhouse and routinely sampled.

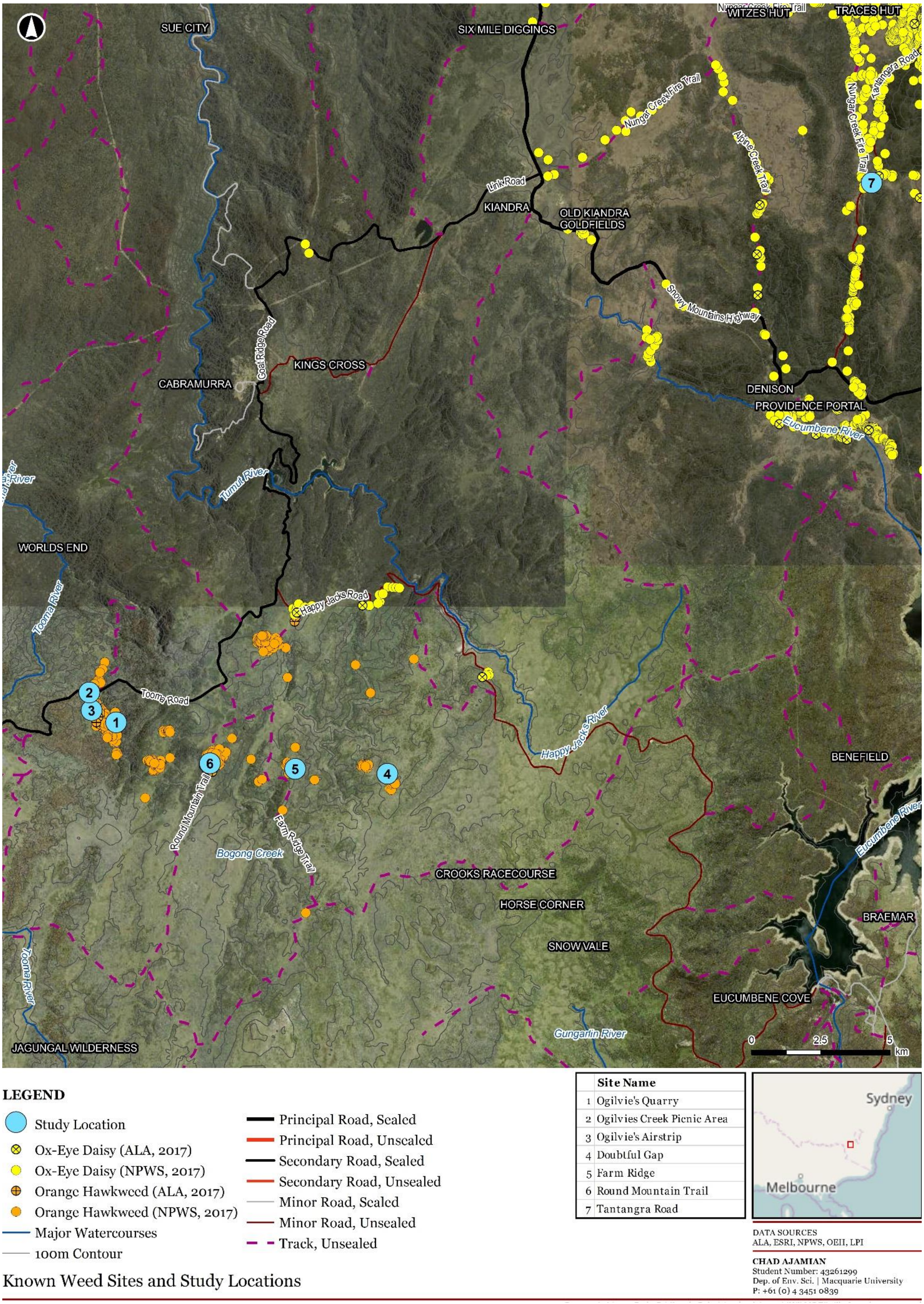

Figure 4. Study Sites in Kosciuszko National Park

3.3.3 Selecting Species for Scanning

In addition to a detailed site selection method, the floral species that were scanned were carefully chosen through a systematic nomination process. This process involved identifying species that were: most prevalent at the field survey sites; known to have some correlation of cohabitation with the weed species; were of a similar colour flower to the weed species (to reduce potential for false positives in later applications); and had enough quantities available to collect a robust spectral database. These parameters ensure that the spectral signatures collected are indicative of the typical environment that orange hawkweed and ox-eye daisy could be found in, contain a wide variety of plant families, and have sufficient interspecies diversity to provide a fair and reasonable statistical analysis and better represent aerial imagery application outcomes.

The local knowledge of the Khancoban NPWS, in conjunction with field observations and literature, were used to assist with selecting the most suitable native species for scanning. Nine species were finally selected for spectral comparison with the weeds, and photographs of them are shown in *figure 5*. The species selected were: alpine daisy bush *(Olearia phlogopappa)*; leafy bossiaea *(Bossiaea foliosa)*; alpine grevillea *(Grevillea australis)*; sticky cassinia (*Cassinia uncata)*; snow grass *(Poa sieberiana)*; alpine shaggy-pea *(Podolobium alpestre)*; kangaroo grass *(Themeda triandra)*; alpine everlasting *(Xerochrysum subundulatum)* – in particular due to the colour of its flower being similar to that of orange hawkweed; and black sally *(Eucalyptus stellulata)*. These species provide a concise, yet comprehensive, selection of species suitable for spectral comparison and analysis.

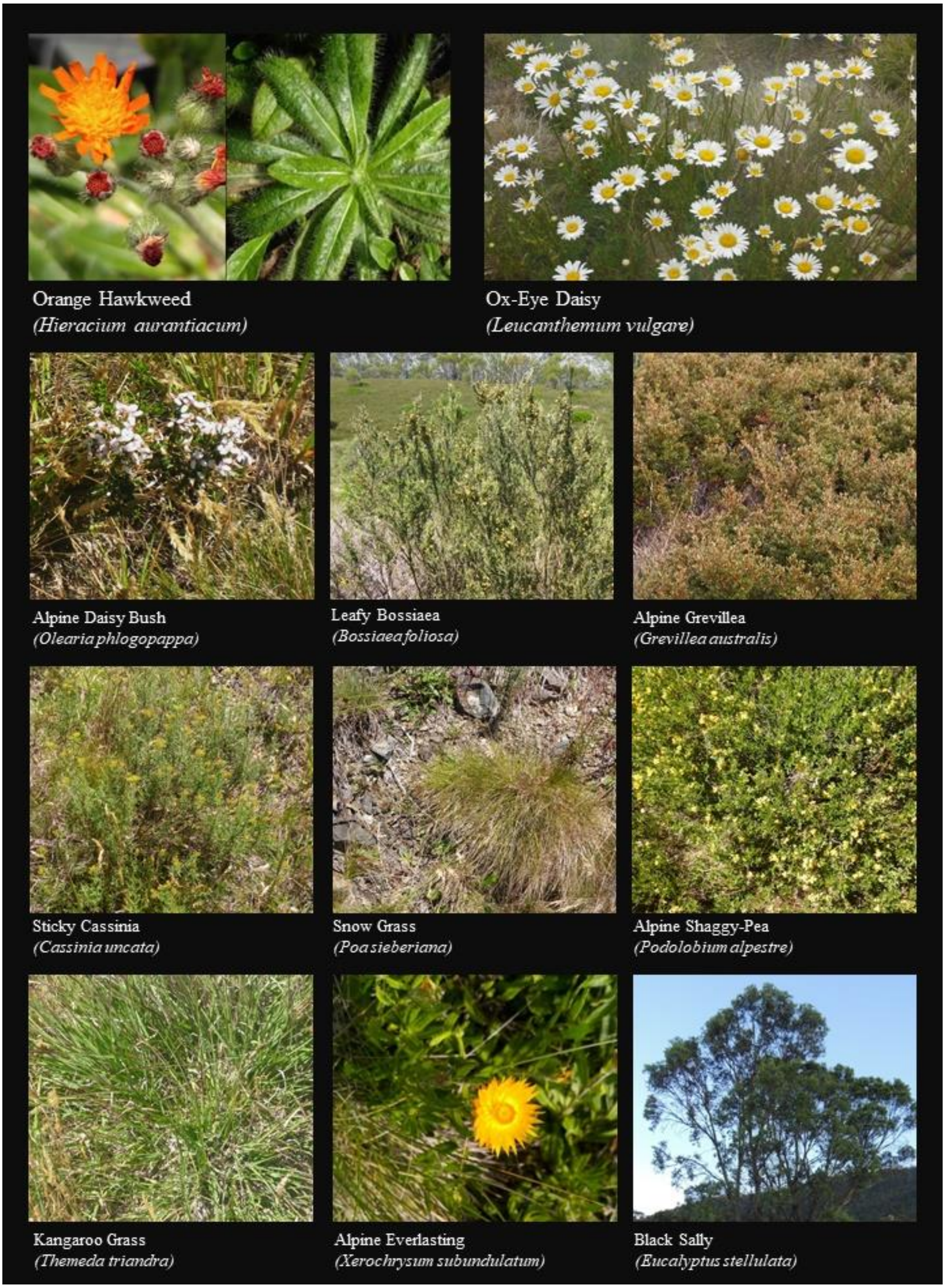

Figure 5. Species Selected for Spectral Analysis

3.3.4 Spectral Sampling

To collect spectral profiles in-situ and ex-situ, a Spectral Evolution RS-3500 spectroradiometer was utilised for the field measurements. The device has a spectral range of 350-2500nm, output in 1nm increments at an accuracy of ± 4-7% (Spectral Evolution, 2016). This covers a vast portion of the electromagnetic spectrum that is influenced by vegetation cover (Japan Aerospace Exploration Agency, 2008).

The measurement process involved first sampling a control plate, to calibrate the data against the general lighting conditions of the region, then taking multiple measurements of each weed and native species located at each site. A photograph taken on site of this process is presented in *figure 6.* This was done to capture the range of variability in reflectance associated with different parts of the plant (i.e. leaves, stems, flowers) as well as between individuals of the same species. The target measurements were divided by the reference measurements to adjust for the general environmental conditions present at the time.

Figure 6. Field Spectral Sampling Process

The critical issues that need to be, and were, considered in undertaking in-situ spectral measurements are presented in *table 2* (Barrett & Curtis, 1992; Im & Jensen, 2008; Milton et al., 2009; Pfitzner et al., 2011; Rollin et al., 2000). In this study, all controllable factors were mitigated where possible. This included: standardising field of view; performing reference sample scans every ten minutes, and after changes in light; ensuring proper warm-up time; only performing measurements at as close to noon as possible for solar angles; and ensuring a suitable number of samples were collected. Each sample is the average of ten measurements, and each target was sampled three times. A minimum of fifteen targets were measured for each plant, providing a *minimum* of 450 total samples per species.

Table 2. Field Spectroradiometry Factors Considered in Experimental Design (Barrett & Curtis, 1992; Im & Jensen, 2008; Milton et al., 2009; Pfitzner et al., 2011; Rollin et al., 2000)

Field Spectroradiometry Factors Considered in Experimental Design	
Experimental Design	Timing, method, geometry, scale, number of samples (variability across temporal and spatial scales)
Calibration	Calibration panel, spectrometer
Instrument Settings	Number of samples, white reference, dark current considerations
Illumination	Date, time, solar altitude and azimuth, location
Viewing Geometry	Field of view, capture height (from target and ground), capture angle
Environmental Conditions	Air pressure, visibility, humidity, temperature, cloud cover, wind vector
Vegetation	Texture, phenology, form, cover, conditions, homogeneity, health, species, layering.
Photographs	Site setup, target, azimuth, sky.

The data were recorded in field metadata sheets, which were adapted from Pfitzner et. al. (2011). After a significant number of samples are collected, they can be then collated, and processed, to develop a profile for a particular species, often referred to as a spectral signature or fingerprint (Jensen, 2006). These signatures require caution in their creation, as vast variabilities can occur in nature (Im & Jensen, 2008). Preliminary visual inspection of samples during and after field surveys can provide rapid, indicative, and qualitative estimates of profiles – allowing exceptional errors to be rectified during surveys, avoiding post-survey failures. These were regularly performed after each site visit, and during sample collection. On returning, metadata sheets were manually entered into a spreadsheet, along with links to photographs, and scan file paths. This then facilitated the organisation of scan samples, photographs, data, and metadata into individual folders by species level.

3.3.5 Spectral Processing

Once the database for each species was developed, the process of converting spectral samples to profiles was undertaken. Initially, the metadata and field notes were manually cross-referenced to samples, to identify those which were erroneous and unsuitable. This included accidental triggers, variable weather conditions, and other environmental influences. Following this manual process, sorted spectral samples were again converted to .csv for use in R, with one spreadsheet per species. These spreadsheets were then concatenated and transposed into a single sheet, with labels abbreviate to avoid errors that were occurring from large field names.

Following, this a variety of pre-processing steps were implemented to refine the data prior to analysis. Multiple analyses in the statistical package 'R' were performed to execute the pre-processing, as well as determining the quantitative and qualitative evaluations of the uniqueness of the spectral profiles. These packages included: caret, e1701, fda, fda.usc, gdata, hsdar, propsectr, tidyverse, and VSURF (Febrero-Bande & Oviedo de la Fuente, 2012; Genuer, Poggi, & Tuleau-Malot, 2016; Gregory R. et al., 2017; Khun et al., 2017; Lehnert, Meyer, & Bendix, 2016; Meyer, Dimitriadou, Hornik, Weingessel, & Leisch, 2017; R Core Team, 2017; Ramsay, Wickham, Graves, & Hooker, 2017; RStudio, Inc., 2016; Stevens & Ramirez-Lopez, 2013; Wickham, 2017).

The first step in the pre-processing involved trimming the ends of the profiles, keeping the data between the wavelengths 400 nm to 1300 nm. This ensured that the 'noisy' ends of the electromagnetic spectrum – due to water vapour absorption – were avoided in the analysis, which would potentially tarnish the results (Pfitzner et al., 2011). Additionally, the 400-1300 nm range was the most important for us to study, as they are the ones that would be most likely to be used in the future by imagery capture and analysis. The next process involved automatic removal of outlier spectral profiles. Erroneous samples, such as those with reflectance values greater than 100% were removed from the study, as these impossibly high values were an artefact of changing weather conditions on site. Whilst calibration occurred very frequently, the strong breeze and scattered cloud cover during the field sampling caused light conditions to change rapidly.

Further outlier detection was performed using the Functional Data Analysis (FDA) technique 'depth.mode' in the packages fda and fda.usc (Febrero-Bande & Oviedo de la Fuente, 2012; Ramsay et al., 2017). This is an exploratory analysis function which determines outliers by considering the profile curve that is the most densely surrounded by others as the 'deepest' one – which is then used by a likelihood ratio test to trim the data based on further parameters that are set (Febrero-Bande & Oviedo de la Fuente, 2012) (see *appendix two* for specific code and values utilised). Next, spectral binning and resampling was performed to average individual wavelengths to groups of 10 nm. This quantization reduces the effects of minor errors, as well as assisting in mitigating the 'curse of dimensionality' (Hughes, 1968). For machine-learning, the predictive ability is reduced as the number of dimensions, or in this instance wavelength classes, increases - a concept known as the Hughes phenomenon (Hughes, 1968). By mildly simplifying the number of factors, we assist the machine learning analysis. This procedure ensured that the profiles are as clean and representative as possible for determining overall profiles, as well as input for the RF process.

3.3.6 Spectral Profiling

Once the spectral processing was complete, the spectral profiles for each species was determined. The output spectral profiles for individual plants that had undergone the pre-processing steps mentioned prior were separated. The mean for each wavelength across the species was then calculated and reassembled, providing an average spectral profile for each class. This then delivered the spectral profiles for each of the noxious weed and native species.

3.3.7 Spectral Classification

The RF classification is a machine learning algorithm that was utilised to perform statistical analysis on the separability of the spectral profiles. This was performed mostly within the caret function in R (Khun et al., 2017). Firstly, the dataset of profiles was randomly split at a ratio of 80:20 into training and testing datasets. This allowed for 80% of the spectral profiles to be used to develop training algorithms, which would then be 'tested' against the 20% control datasets to verify the classification. One thousand decision 'trees' were selected for the RF method, which provides a good balance between accuracy, processing time, and memory usage. The accuracy of more trees than this is rather asymptotic, where larger values than this exceptionally increases computational cost with little tangible benefit (Oshiro et al., 2012). Similarly, the number of repeats – one hundred – was selected to balance results and computation time. The Kappa statistical value was used to specify the most optimal model. This can be described as a value between 0 and 1 which represents the amount of 'agreement' that is correct in comparison to the amount of 'agreement' that could occur by chance (Viera & Garrett, 2005). Essentially, the higher the value, the less likely the data is to be assigned by chance, and the better the classification (Viera & Garrett, 2005). A variety of results were chosen to be outputted by the algorithm, including: confusion matrix and statistics; overall statistics; statistics by class (by plant); and variable importance (key wavelengths for separability). This process provided the overall statistical analysis of the spectral profiles.

3.3.8 Multispectral Drone Emulation

Whilst the spectral classification method provides significant insights into the separability of species spectral profiles across the hyperspectral wavelength range, it is important to determine if the key discriminate wavelengths are in a range that is available in the current multispectral cameras. To do this, a downsampling approach was performed on the data. For this paper, the Parrot Sequoia was hypothesised as a potential sensor for detecting the invasive weed species (Parrot Drones S.A.S., 2017b). This was due to the affordability, small size and weight, compatibility with both fixed-wing and multi-rotor drones, as well as the capacity for selfcalibration (Parrot Drones S.A.S., 2017b). In order to ascertain usability of this sensor to discriminate the weed species, a new classification was performed. For this step, processed scans were trimmed into the wavelengths that were available for capture on the Parrot Sequoia. These wavelengths were: 550nm ± 10 (green); 660nm ± 10 (red); 735nm ± 5 (red-edge); and 790nm ± 10 (near-infrared). The individual wavelengths within these bands were then binned, to assume the mean across the entire range, simulating the data captured within each pixel band. This is visualised in *figure seven*, where the average reflectance across the band is represented as a point feature. These mean bands were then run the RF classification, with the same parameters set as before. This provides an indicative insight into the potential ability of the Parrot Sequoia in detecting the invasive species.

3.3.9 Multispectral Satellite Emulation

To further evaluate weed discriminability, the ability for detection by satellite based on spectral resolution was assessed. The WorldView-3 multispectral high-resolution satellite operated by DigitalGlobe was selected for this estimation. The satellite has a 31cm panchromatic spatial resolution and a 1.23m multispectral resolution – making it the highest available at its launch date in November, 2016 (DigitalGlobe, Inc., 2014). Similar to the multispectral drone process, the processed scans were trimmed and binned to simulate the data captured by each band, and presented in *figure 7*. These wavelengths were: 400-452 nm, 448-510 nm, 518-586 nm, 590-630 nm, 632-692 nm, 706-746 nm, 772-890 nm, 866-954 nm, and 1195-1225 nm.

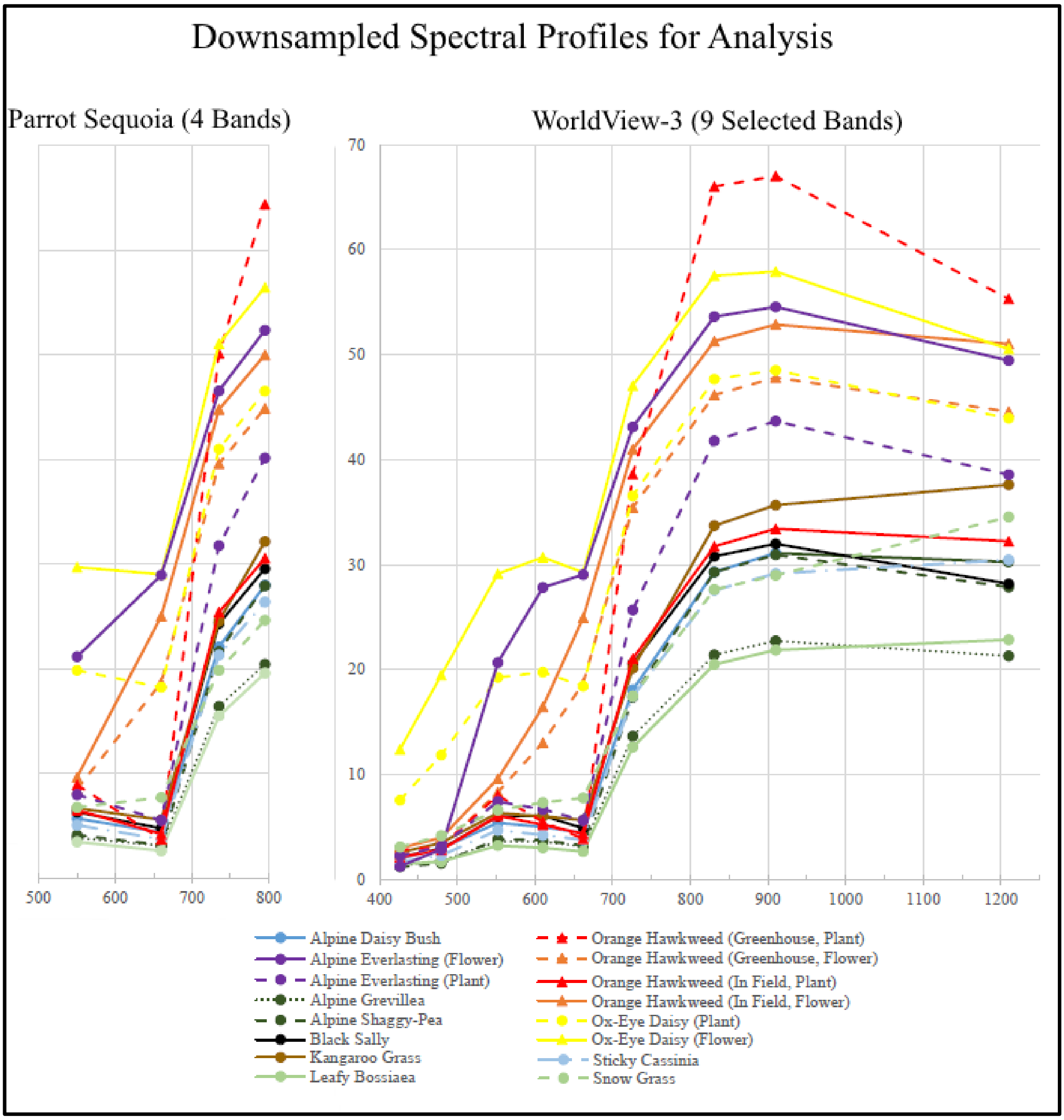

Figure 7. Downsampled Spectral Profiles for Analysis. Point features represent the mean reflectance across the spectral band.

3.4 Results

3.4.1 Pre-Processing

A before and after comparison, displaying the spectral profiles separated by species, is presented in *figure 8*. Abbreviations for plant names have been used in R to reduce the codes susceptibility to errors, and are presented in *table 3*.

Table 3. Abbreviations and Plant Names used in Results and Discussion. **Indicates targeted invasive species.*

Abbreviation	Proper Common Name *(Scientific Name)*
ADB	Alpine daisy bush *(Olearia phlogopappa)*
AGR	Alpine grevillea *(Grevillea australis)*
ASP	Alpine shaggy-pea *(Podolobium alpestre)*
BOS	Leafy bossiaea *(Bossiaea foliosa)*
BSE	Black sally *(Eucalyptus stellulata)*
CAS	Sticky cassinia *(Cassinia uncata)*
KAG	Kangaroo grass *(Themeda triandra)*
***OH_**	Orange hawkweed *(Hieracium aurantiacum)* [OHff = In Field, Flower; OHfp = In Field, Plant; OHgf = Greenhouse, Flower; OHfp = Greenhouse, Plant]
***OX_**	Ox-eye daisy *(Leucanthemum vulgare)* [OXf = Flower; OXf = Plant]
PD_	Alpine everlasting (*Xerochrysum subundulatum)* [PDf = Flower; PDp = Plant]
SGR	Snow grass *(Poa sieberiana)*

The pre-processing stages produced data that was trimmed, cleaned, and with the number of outliers minimised. Noisy and erroneous profiles were removed. This increased the effectiveness, accuracy, and efficiency of the later analyses.

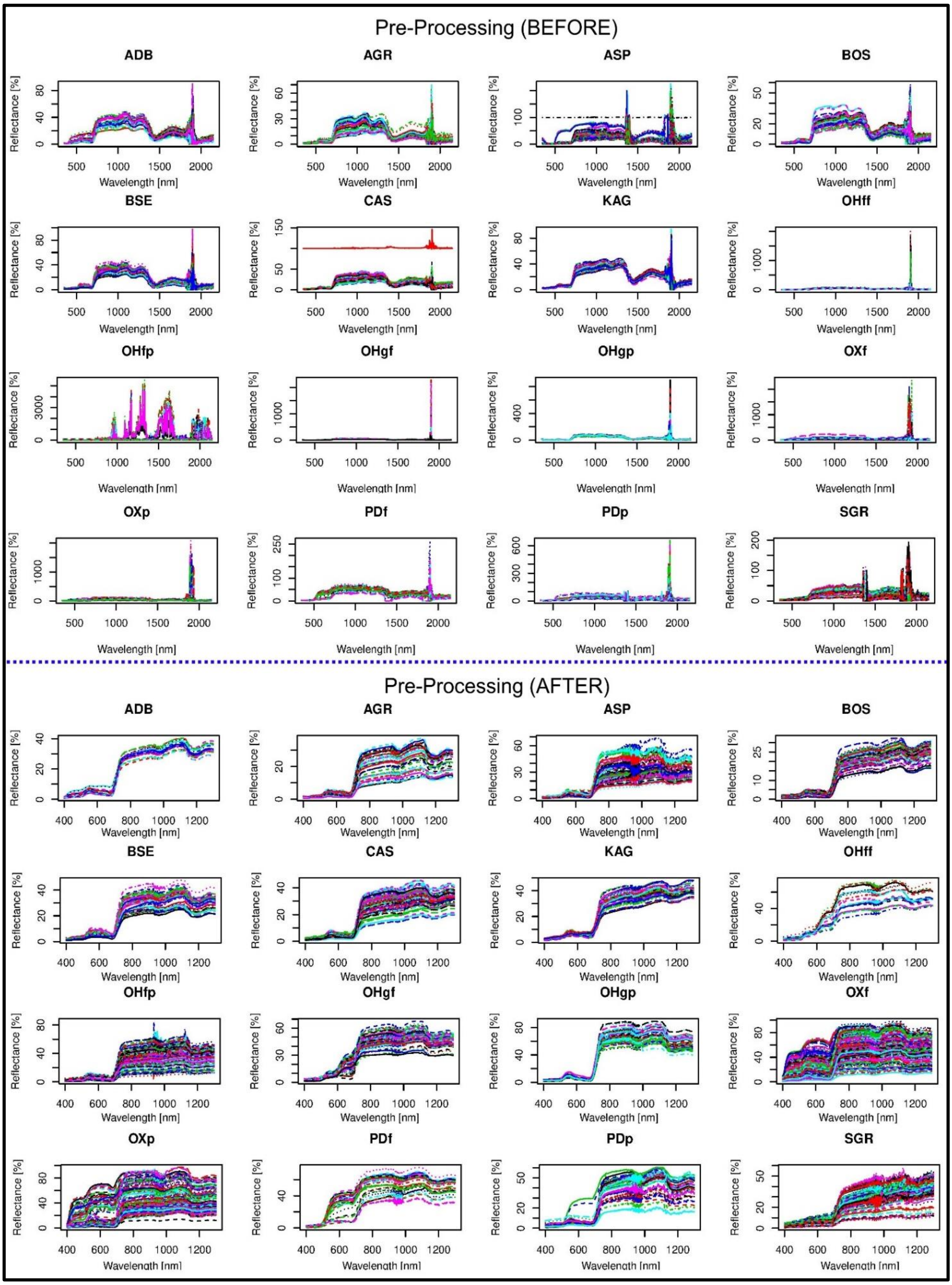

Figure 8. Spectral Profiles Before and After Pre-Processing

3.4.2 Average Spectral Profiles

The average spectral profiles by species - subset by flower and plant, and field or greenhouse sources (if applicable) are presented in *figure 9*. It is visually evident that there are some distinct differences across the mean profiles. Orange hawkweed, alpine everlasting, and ox-eye daisy have a significantly higher reflectance overall. Ox-eye daisy uniquely peaks in the 420 nm – 500 nm range, whilst the same occurs for orange hawkweed flower samples between 575 nm and 675 nm. Notably, the greenhouse samples for orange hawkweed plants have the highest reflectance, and are significantly higher than field samples.

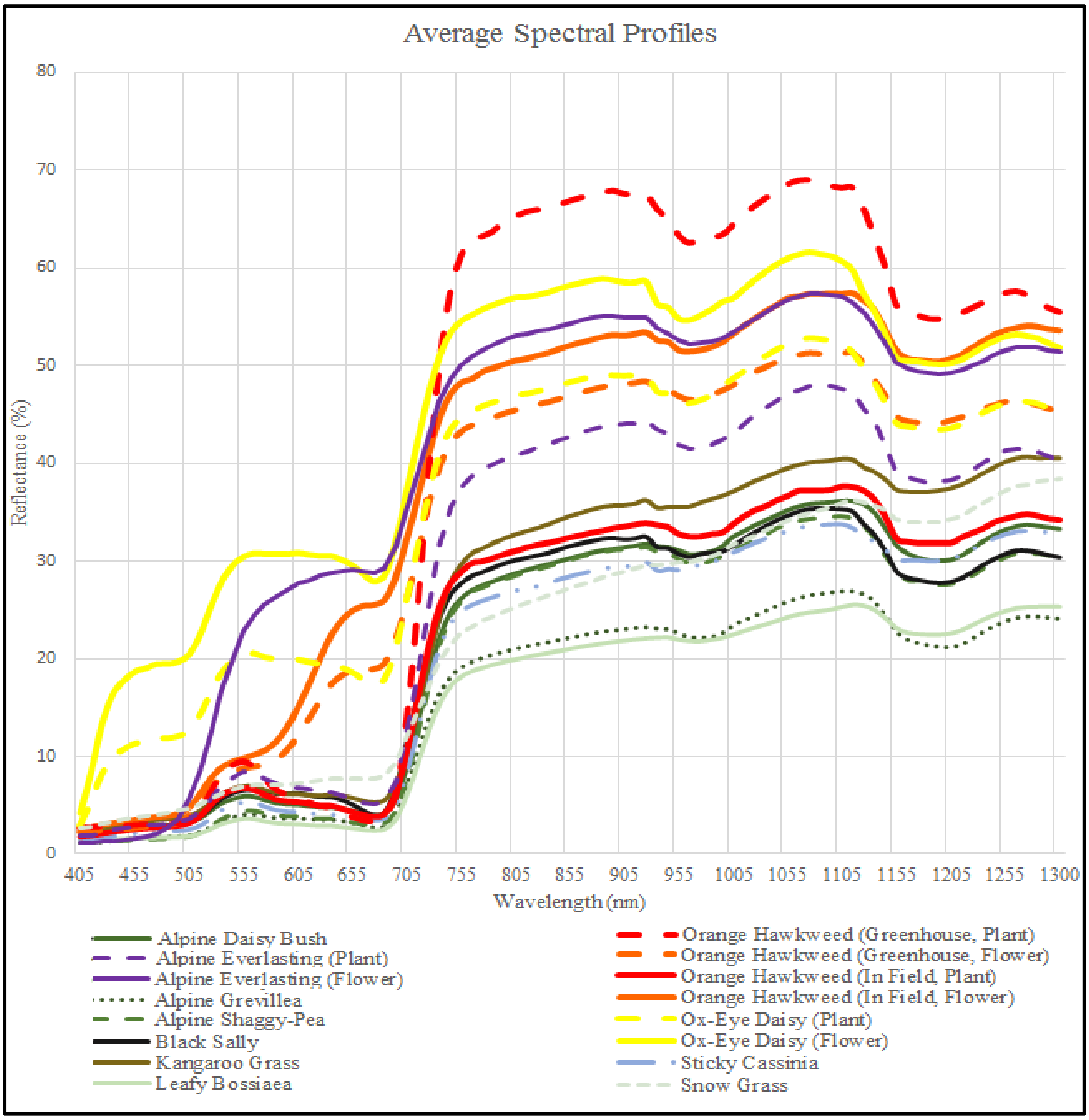

Figure 9. Average Spectral Profiles of Selected Vegetation

3.4.3 Spectral Analysis - Overall

3.4.3.1 Confusion Matrix

The confusion matrix of the RF classification is presented below in *table 4*. Higher values here represent a lower ability to clearly discriminate the classes. Most of the confusion seems to be between the subsets of ox-eye daisy, otherwise confusion is rather low across the classes, representing a stronger separability accuracy.

Table 4. Confusion Matrix - Overall

PREDICTION \ REFERENCE	ADB	AGR	ASP	BOS	BSE	CAS	KAG	OHff	OHfp	OHgf	OHgp	OXf	OXp	PDf	PDP	SGR	*Total*
ADB	2	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	*3*
AGR	0	3	3	0	0	0	0	0	0	0	0	0	0	0	0	1	*7*
ASP	0	1	13	0	0	1	0	0	0	0	1	0	1	0	0	0	*17*
BOS	0	0	0	11	2	1	0	0	0	0	0	0	0	0	0	3	*17*
BSE	0	2	0	0	7	0	0	0	0	0	0	0	1	0	1	0	*11*
CAS	0	0	0	0	0	6	1	0	1	0	0	0	4	0	0	0	*12*
KAG	0	0	0	0	0	1	4	0	0	0	0	0	0	0	1	4	*10*
OHff	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	*2*
OHfp	0	0	0	0	0	0	1	0	14	0	0	0	0	0	1	0	*16*
OHgf	0	0	0	0	0	0	0	1	0	12	0	0	0	0	0	0	*13*
OHgp	0	0	0	0	0	0	0	0	0	0	7	0	1	0	0	0	*8*
OXf	0	0	0	0	0	0	1	0	0	0	0	30	7	0	1	0	*39*
OXp	0	1	0	0	0	3	1	0	2	0	0	11	13	0	0	0	*31*
PDf	0	0	0	0	0	0	0	0	0	0	0	0	0	5	1	0	*6*
PDp	0	0	0	0	0	0	0	0	1	0	0	0	0	0	3	0	*4*
SGR	1	0	0	0	0	0	1	0	1	0	0	0	0	0	0	22	*25*
Total	3	7	16	11	9	12	9	3	19	12	8	41	27	6	8	30	*222*

3.4.3.2 Overall Statistics

The confusion matrix assists in determining the overall accuracy of the classification. Displayed in *table 5* the overall accuracy across all species is very positive, with the Kappa value of 0.67 representing a *"substantial"* strength of agreement (Landis & Koch, 1977, p. 165).

Table 5. Overall Random Forest Statistics - Overall

Overall Random Forest Statistics	
Accuracy	0.6968
95% Confidence Interval (of the accuracy)	0.6316, 0.7567
No Information Rate (NIR)	0.1855
P-Value [Accuracy > NIR]	< 2.2e-16
Kappa	0.6651

3.4.3.3 Statistics by Class

The statistics by class provides a detailed breakdown of the classification accuracy and detection ability. The sensitivity, specificity, prediction value, prevalence, detection rate, detection prevalence, and balanced accuracy are shown in *table 6*. These provide the discrimination ability statistics at a detailed, species specific level. Overall balanced accuracies for classes ranged from 69.4% to 99.8%. Accuracy for orange hawkweed was high, ranging from 83.3% and 86.3% for field samples, and 93.5% to 99.8% for greenhouse samples. Ox-eye daisy was rather variable, with the plant having an accuracy of 69.4%, and 84.1% for the flower.

Table 6. Random Forest Statistics by Class - Overall

	ADB	AGR	ASP	BOS	BSE	CAS	KAG	OHff	OHfp	OHgf
Sensitivity	0.667	0.429	0.813	1.000	0.778	0.500	0.444	0.667	0.737	1.000
Specificity	0.995	0.981	0.980	0.971	0.981	0.971	0.972	1.000	0.990	0.995
Pos. Pred. Value	0.667	0.429	0.765	0.647	0.636	0.500	0.400	1.000	0.875	0.923
Neg. Pred. Value	0.995	0.981	0.985	1.000	0.990	0.971	0.976	0.995	0.976	1.000
Prevalence	0.014	0.032	0.072	0.050	0.041	0.054	0.041	0.014	0.086	0.054
Detection Rate	0.009	0.014	0.059	0.050	0.032	0.027	0.018	0.009	0.063	0.054
Detection Prevalence	0.014	0.032	0.077	0.077	0.050	0.054	0.045	0.009	0.072	0.059
Balanced Accuracy	0.831	0.705	0.896	0.986	0.879	0.736	0.708	0.833	0.863	0.998

	OHgp	OXf	OXp	PDf	PDp	SGR
Sensitivity	0.875	0.732	0.481	0.833	0.375	0.733
Specificity	0.995	0.950	0.907	0.995	0.995	0.984
Pos. Pred. Value	0.875	0.769	0.419	0.833	0.750	0.880
Neg. Pred. Value	0.995	0.940	0.926	0.995	0.977	0.959
Prevalence	0.036	0.186	0.122	0.027	0.036	0.136
Detection Rate	0.032	0.136	0.059	0.023	0.014	0.100
Detection Prevalence	0.036	0.177	0.140	0.027	0.018	0.113
Balanced Accuracy	0.935	0.841	0.694	0.914	0.685	0.859

3.4.3.4 Wavelength Importance

The variable importance output of the RF classification provides an indicative insight into wavelengths where the discriminability of the weed species is maximised. The higher the value, the more important this band is for detecting this species. Negative values indicate that this band is actually harmful, and causes more confusion than benefit for the specific class. The 20 most important wavelength regions are depicted by order of importance in *table 7*. The most useful wavelength regions for spectral discrimination are: 400-420nm, 440-480nm, 510-550nm, 570-580nm, 640-690nm, 710-750nm & 1295-1305nm.

Table 7. Wavelength Importance – Overall

Wavelength (nm)	ADB	AGR	ASP	BOS	BSE	CAS	KAG	OHff	OHfp	OHgf	OHgp	OXf	OXp	PDf	PDp	SGR
#1. 670-680	10.40	17.40	13.40	24.41	21.68	18.94	9.44	18.49	25.92	24.31	18.90	0.13	19.59	20.49	17.89	26.70
#2. 400-410	8.99	8.71	20.32	5.29	8.34	15.31	10.12	3.19	26.32	9.07	7.67	4.99	16.75	3.82	18.43	15.05
#3. 530-540	6.25	14.64	25.82	20.12	9.93	12.88	11.62	0.52	7.15	7.38	5.74	7.40	0.98	6.36	10.99	15.60
#4. 520-530	5.40	11.29	24.15	18.64	9.02	15.36	11.48	3.45	6.47	6.86	6.11	3.90	4.89	6.77	9.36	14.28
#5. 680-690	7.34	13.57	9.50	20.12	19.29	15.99	5.50	16.28	20.40	21.46	16.36	1.51	15.59	16.69	14.69	23.13
#6. 510-520	6.17	11.82	22.80	14.94	7.65	13.86	10.87	3.75	7.54	8.33	5.85	3.09	4.46	6.68	9.03	10.10
#7. 450-460	6.77	9.38	22.07	13.60	12.40	10.59	13.85	7.72	17.05	16.66	14.61	21.37	8.36	13.32	12.76	18.44
#8. 410-420	8.52	9.83	17.89	5.91	5.73	14.80	8.73	3.53	18.99	5.01	6.47	8.58	6.88	4.35	21.78	9.12
#9. 660-670	7.02	9.22	10.40	17.80	15.12	15.15	8.50	14.08	20.10	18.96	13.95	-0.91	16.64	14.51	12.86	20.35
#10. 710-720	6.40	1.78	7.56	9.92	10.52	9.51	19.15	10.92	16.14	19.17	5.41	3.79	3.14	11.98	10.81	15.69
#11. 460-470	4.98	9.34	19.04	12.88	10.75	10.66	14.58	5.69	14.69	15.18	12.77	16.38	4.69	11.26	11.77	15.99
#12. 1295-1305	1.07	9.76	6.15	3.06	12.53	5.94	11.68	3.45	12.24	4.00	3.47	3.60	6.13	1.91	4.33	18.54
#13. 740-750	4.06	5.49	5.58	7.85	8.39	7.39	7.40	6.32	11.06	13.20	7.70	5.78	2.21	11.05	8.02	18.42
#14. 540-550	6.83	10.80	18.12	15.89	7.66	8.59	8.72	1.94	8.05	8.49	5.27	5.69	0.82	7.03	8.16	12.95
#15. 570-580	1.94	1.26	6.53	8.04	4.08	4.06	3.97	2.41	4.66	17.84	3.32	9.45	-5.47	15.52	5.13	9.23
#16. 440-450	6.37	7.61	17.49	11.41	10.65	10.49	12.30	7.14	15.17	14.49	11.61	16.78	2.84	11.48	11.60	15.69
#17. 650-660	5.86	7.23	11.56	17.41	11.49	15.51	9.95	13.92	16.95	17.44	12.17	-0.88	16.79	13.05	11.35	16.70
#18. 730-740	5.80	1.43	3.39	4.96	6.57	7.03	9.79	7.22	9.85	14.88	4.55	3.62	3.32	10.49	7.43	17.13
#19. 470-480	3.21	8.57	16.48	12.09	9.30	7.57	13.64	2.42	12.81	14.52	10.23	13.48	6.59	10.69	9.98	14.31
#20. 640-650	5.34	7.41	10.28	13.54	10.12	13.19	10.55	11.07	14.61	12.66	9.48	-2.54	16.28	11.34	8.03	12.54

3.4.4 Spectral Analysis - Multispectral Drone Emulation

3.4.4.1 Confusion Matrix

The confusion matrix of the RF classification is presented below in *table 8*. Confusion between native species is significantly higher when simplified to the multispectral bands of the Parrot Sequoia camera, yet noxious species seem not to differ to the original classification. This may be due to a stronger similarity between native species when downsampled to the multispectral drone bands.

Table 8. Confusion Matrix – Multispectral Drone Emulation

		REFERENCE																
		ADB	AGR	ASP	BOS	BSE	CAS	KAG	OHff	OHfp	OHgf	OHgp	OXf	OXp	PDf	PDP	SGR	*Total*
PREDICTION	ADB	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	*1*
	AGR	0	0	2	2	0	2	0	0	1	0	0	0	0	0	0	1	*8*
	ASP	0	0	9	1	0	0	0	0	2	0	1	0	1	0	1	0	*15*
	BOS	0	1	0	8	2	3	0	0	1	0	0	0	1	0	0	0	*16*
	BSE	0	0	0	0	1	0	0	0	1	0	0	0	1	0	0	0	*3*
	CAS	1	3	0	0	1	4	0	0	1	0	0	0	0	0	1	0	*11*
	KAG	0	0	0	0	0	0	3	0	0	0	0	0	0	0	1	1	*5*
	OHff	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	*2*
	OHfp	0	1	0	0	2	0	0	0	7	0	0	1	1	0	1	0	*13*
	OHgf	0	0	0	0	0	0	0	0	0	12	0	0	0	0	0	0	*12*
	OHgp	0	0	0	0	0	0	0	0	0	0	8	0	2	0	0	0	*10*
	OXf	0	0	0	0	1	0	0	1	2	0	0	34	9	0	0	1	*48*
	OXp	0	0	3	0	1	2	0	0	2	0	0	5	8	0	0	0	*21*
	PDf	0	0	0	0	0	0	0	0	0	0	0	0	0	5	0	0	*5*
	PDp	0	0	0	0	0	0	0	0	0	0	0	1	3	0	3	0	*7*
	SGR	2	1	2	0	1	1	6	0	2	0	0	0	1	1	1	27	*45*
Total		*3*	*7*	*16*	*11*	*9*	*12*	*9*	*3*	*19*	*12*	*9*	*41*	*27*	*6*	*8*	*30*	*222*

3.4.4.2 Overall Statistics

The overall accuracy, even whilst reduced to multispectral drone bands is high, with the Kappa value of 0.54 representing a *"moderate"* strength of agreement (Landis & Koch, 1977, p. 165). Detailed statistics are presented in *table 9.*

Table 9. Random Forest Statistics – Multispectral Drone Emulation

Random Forest Statistics – Multispectral Drone Emulation	
Accuracy	0.5928
95% Confidence Interval (of the accuracy)	0.5248, 0.6582
No Information Rate (NIR)	0.1855
P-Value [Accuracy > NIR]	< 2.2e-16
Kappa	0.5452

3.4.4.3 Statistics by Class

Overall balanced accuracies for classes ranged from 48.1% to 100%. Accuracy for Orange Hawkweed was high, ranging from 67% and 83% for field samples, and 99.5% to 100% for greenhouse samples. Ox-Eye Daisy was rather variable however, with the plant having an accuracy of 61.5%, and the flower being 87.6%. The statistics by class for the multispectral drone emulation are presented in *table 10.*

Table 10. Random Forest Statistics by Class – Multispectral Drone Emulation

	ADB	AGR	ASP	BOS	BSE	CAS	KAG	OHff	OHfp	OHgf
Sensitivity	0.000	0.000	0.563	0.727	0.111	0.333	0.333	0.667	0.368	1.000
Specificity	0.995	0.963	0.976	0.961	0.991	0.967	0.991	1.000	0.970	1.000
Pos. Pred. Value	0.000	0.000	0.643	0.500	0.333	0.364	0.600	1.000	0.538	1.000
Neg. Pred. Value	0.986	0.967	0.967	0.985	0.963	0.962	0.972	0.995	0.942	1.000
Prevalence	0.014	0.032	0.072	0.050	0.041	0.054	0.041	0.014	0.086	0.054
Detection Rate	0.000	0.000	0.041	0.036	0.005	0.018	0.014	0.009	0.032	0.054
Detection Prevalence	0.005	0.036	0.063	0.072	0.014	0.050	0.023	0.009	0.059	0.054
Balanced Accuracy	0.498	0.481	0.769	0.845	0.551	0.650	0.662	0.833	0.669	1.000

	OHgp	OXf	OXp	PDf	PDp	SGR
Sensitivity	1.000	0.829	0.296	0.833	0.375	0.900
Specificity	0.991	0.922	0.933	1.000	0.981	0.906
Pos. Pred. Value	0.800	0.708	0.381	1.000	0.429	0.600
Neg. Pred. Value	1.000	0.960	0.905	0.995	0.977	0.983
Prevalence	0.036	0.186	0.122	0.027	0.036	0.136
Detection Rate	0.036	0.154	0.036	0.023	0.014	0.122
Detection Prevalence	0.045	0.217	0.095	0.023	0.032	0.204
Balanced Accuracy	0.995	0.876	0.615	0.917	0.678	0.903

3.4.4.4 Band Importance

Whilst the Parrot Sequoia only covers four distinct ranges, it is useful to determine the order of importance for these bands. The most important wavelengths are presented by order of importance in *table 11***.** The near-infrared band, 780 – 810nm, seems to be the least crucial of the four, with green, red, and red-edge classes being more substantially more important for species classification.

Table 11. Band Importance - Multispectral Drone Emulation

Wavelength (nm)	ADB	AGR	ASP	BOS	BSE	CAS	KAG	OHff	OHfp	OHgf	OHgp	OXf	OXp	PDf	PDp	SGR
#1. 540-560 (Green)	18.79	26.09	60.60	46.16	12.14	32.99	29.37	19.52	28.83	39.19	27.42	93.06	26.51	33.11	26.25	61.21
#2. 650-670 (Red)	16.41	17.17	33.96	45.07	25.61	38.69	25.00	34.91	65.56	71.43	49.39	39.54	10.88	45.92	26.35	68.17
#3. 730-740 (Red-Edge)	16.95	9.38	6.18	31.10	20.32	24.15	22.88	17.03	32.68	42.01	35.99	2.36	15.50	16.56	27.60	59.30
#4. 780-810 (NIR)	14.31	18.72	-4.0	46.19	21.83	28.35	27.30	16.00	39.15	28.85	53.73	-1.7	12.26	18.97	38.05	51.40

3.4.5 Spectral Analysis - Satellite Emulation

3.4.5.1 Confusion Matrix

In *table 12*, the RF classification confusion matrix of the data simplified to the WorldView-3 spectral resolution is presented. There is notable confusion between ox-eye daisy (plant) and orange hawkweed (in field, plant), as well as between the ox-eye daisy classes, and within the native species.

		REFERENCE																
		ADB	AGR	ASP	BOS	BSE	CAS	KAG	OHff	OHfp	OHgf	OHgp	OXf	OXp	PDf	PDP	SGR	*Total*
PREDICTION	ADB	1	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0	*3*
	AGR	0	3	0	0	0	0	0	0	1	0	0	0	0	0	0	1	*5*
	ASP	0	1	10	0	2	0	0	0	0	0	0	0	0	0	0	0	*13*
	BOS	0	2	0	9	0	2	0	0	0	0	0	0	1	0	0	0	*14*
	BSE	0	0	0	0	5	0	0	0	0	0	0	0	0	0	0	0	*5*
	CAS	0	0	3	0	0	8	0	0	4	0	0	0	3	0	0	1	*19*
	KAG	0	0	0	0	0	0	8	0	0	0	0	0	0	0	0	1	*9*
	OHff	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	*1*
	OHfp	1	0	0	0	0	0	0	0	12	0	0	2	5	0	0	1	*21*
	OHgf	0	0	0	0	0	0	0	2	0	11	0	0	0	1	0	1	*15*
	OHgp	0	0	0	0	0	0	0	0	0	0	8	0	2	0	0	0	*10*
	OXf	0	0	0	0	0	0	0	0	0	0	0	30	9	0	2	0	*41*
	OXp	0	0	1	2	0	2	0	0	2	1	0	8	6	0	0	0	*22*
	PDf	0	0	0	0	0	0	0	0	0	0	0	0	0	3	1	0	*4*
	PDp	0	0	0	0	0	0	0	0	0	0	0	1	0	0	5	0	*6*
	SGR	1	1	2	0	2	0	1	0	0	0	0	0	0	2	0	25	*34*
Total		*3*	*8*	*16*	*11*	*9*	*12*	*9*	*3*	*19*	*12*	*8*	*41*	*27*	*6*	*8*	*30*	*222*

Table 12. Confusion Matrix - Satellite Emulation

3.4.5.2 Overall Statistics

The overall statistics of emulating the spectral resolution of the multispectral satellite is moderately positive, with overall accuracy at 65.61%. The Kappa value is sufficient at 0.62. Overall statistics are presented in *table 13.*

Table 13. Random Forest Statistics - Satellite Emulation

Random Forest Statistics – Satellite Emulation	
Accuracy	0.6561
95% Confidence Interval (of the accuracy)	0.5894, 0.7185
No Information Rate (NIR)	0.1855
P-Value [Accuracy > NIR]	< 2.2e-16
Kappa	0.6187

3.4.5.3 Statistics by Class

The statistics by class for the satellite emulation is presented in *table 14*. Overall balanced accuracies ranged from 57.0% to 99.5%. Orange Hawkweed's balanced accuracy ranged from 67% to 100%, whilst Ox-Eye Daisy ranged from 57% to 80%.

Table 14. Random Forest Statistics by Class – Satellite Emulation

	ADB	AGR	ASP	BOS	BSE	CAS	KAG	OHff	OHfp	OHgf
Sensitivity	0.333	0.429	0.625	0.818	0.556	0.667	0.889	0.333	0.632	0.917
Specificity	0.995	0.991	0.985	0.976	1.000	0.947	0.995	1.000	0.955	0.981
Pos. Pred. Value	0.500	0.600	0.769	0.643	1.000	0.421	0.889	1.000	0.571	0.733
Neg. Pred. Value	0.991	0.981	0.971	0.990	0.981	0.980	0.995	0.991	0.965	0.995
Prevalence	0.014	0.032	0.072	0.050	0.041	0.054	0.041	0.014	0.086	0.054
Detection Rate	0.005	0.014	0.045	0.041	0.023	0.036	0.036	0.005	0.054	0.050
Detection Prevalence	0.009	0.023	0.059	0.063	0.023	0.086	0.041	0.005	0.095	0.068
Balanced Accuracy	0.664	0.710	0.805	0.897	0.778	0.807	0.942	0.667	0.794	0.949

	OHgp	OXf	OXp	PDf	PDp	SGR
Sensitivity	1.000	0.732	0.222	0.500	0.625	0.833
Specificity	0.991	0.939	0.918	0.995	0.995	0.953
Pos. Pred. Value	0.800	0.732	0.273	0.750	0.833	0.735
Neg. Pred. Value	1.000	0.939	0.894	0.986	0.986	0.973
Prevalence	0.036	0.186	0.122	0.271	0.036	0.136
Detection Rate	0.036	0.136	0.027	0.014	0.022	0.113
Detection Prevalence	0.045	0.186	0.100	0.018	0.027	0.154
Balanced Accuracy	0.995	0.835	0.570	0.748	0.810	0.893

3.4.5.4 Band Importance

For the satellite bands, the order of importance, and importance per species, was determined, as shown in *table 15*.

Wavelength (nm)	ADB	AGR	ASP	BOS	BSE	CAS	KAG	OHff	OHfp	OHgf	OHgp	OXf	OXp	PDf	PDp	SGR
#1. 448-510 (Blue)	12.13	31.36	72.05	42.41	32.51	30.31	27.54	13.29	40.63	41.37	30.98	103.7	33.84	25.61	27.64	51.40
#2. 632-692 (Red)	17.49	30.76	15.46	65.29	40.49	39.99	15.09	35.35	61.78	71.22	54.01	5.53	51.12	47.97	37.21	80.11
#3. 706-746 (Red-Edge)	13.52	6.13	7.19	29.92	21.65	21.07	17.48	19.75	27.07	45.19	18.21	-2.6	15.52	24.95	19.56	56.81
#4. 1195-1225 (SWIR1)	7.85	48.87	22.36	38.58	50.05	12.37	28.81	7.23	42.35	11.20	10.43	1.38	22.70	2.93	19.98	40.48
#5. 772-890 (NIR1)	12.22	15.28	9.87	38.45	26.91	25.95	11.66	6.38	29.20	24.60	41.50	17.83	10.37	13.69	28.39	49.11
#6. 400-452 (Coastal)	15.45	29.92	45.94	9.51	17.07	27.97	14.87	8.82	36.64	22.49	16.56	27.02	14.78	17.12	21.07	26.82
#7. 518-586 (Green)	13.39	21.54	43.19	38.81	11.79	35.73	12.32	9.11	8.67	28.42	12.16	21.07	5.77	34.63	16.40	33.67
#8. 590-630 (Yellow)	12.62	3.65	10.94	36.51	20.68	24.80	11.23	16.65	21.77	25.08	15.60	8.97	18.17	29.03	16.27	25.09
#9. 866-954 (NIR-2)	10.06	14.30	-4.9	65.34	20.73	24.20	12.72	3.89	26.60	18.08	22.97	18.86	3.37	6.84	24.93	23.38

Table 15. Band Importance - Satellite Emulation

3.4.6 Summary of Results

The scanning, and analysis, of the spectral profiles for the nine native and two invasive species, across the seven sites in KNP, provides a representative quantitative assessment of the potential use of remote sensing to locate weeds in the region. The average spectral profiles provides an indicative insight into the potential discriminability of the species. Analysis found that the most important wavelength ranges for separability are 400-420nm, 440-480nm, 510-550nm, 570-580nm, 640nm-690nm, 710nm-750nm & 1300nm. The relationship between important wavelength ranges, sensor ranges of the chosen cameras, and average spectral profiles are presented graphically in *figure 10*. Finally, the RF classification provided a range of separability statistics, with 70% accuracy overall, 59% accuracy when averaged to the bands of the multispectral drone, and 66% for the same process performed for the multispectral satellite. Similarly, Kappa values were 0.67, 0.55, and 0.62, respectively.

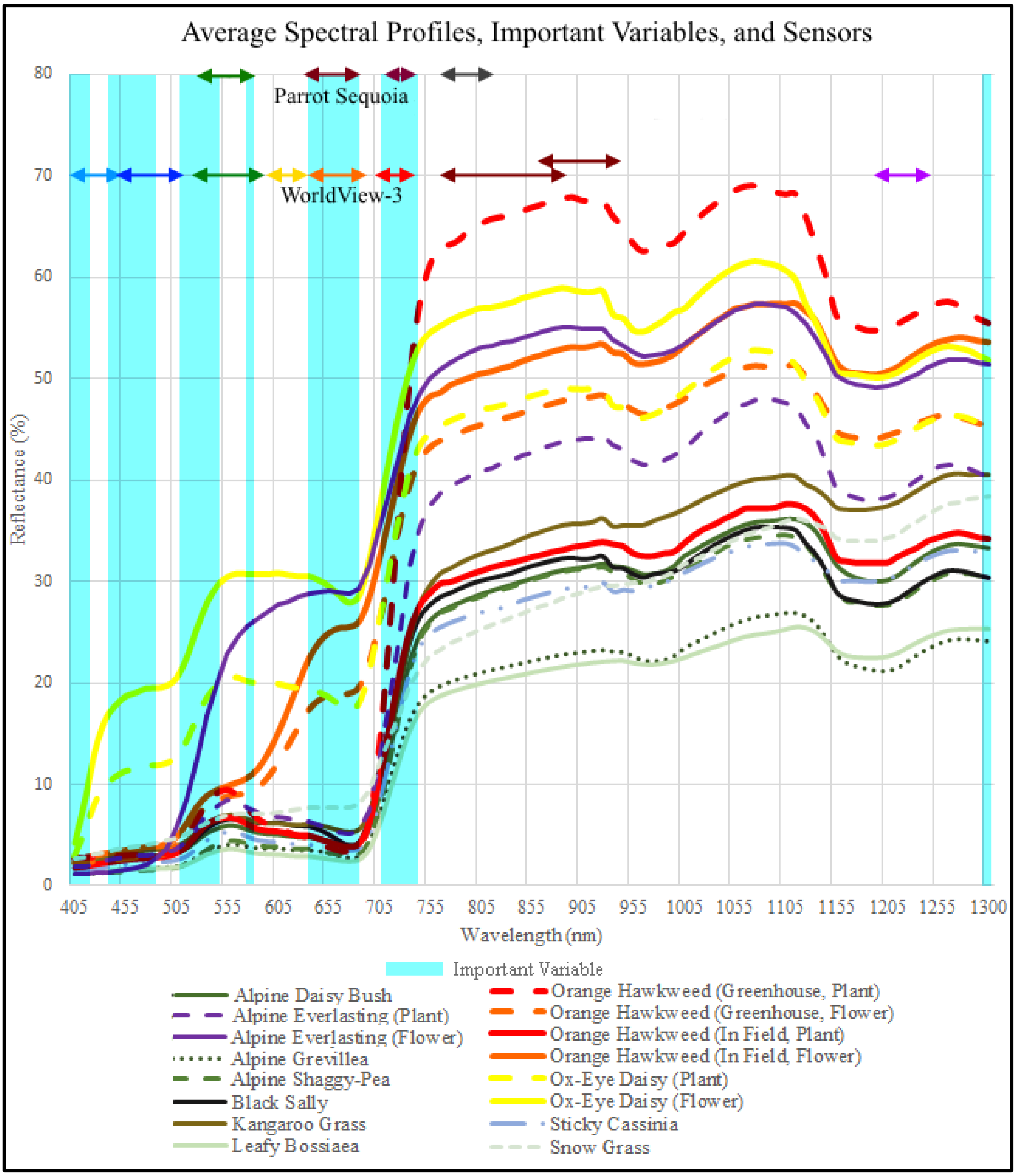

Figure 10. Average Spectral Profiles, Important Variables, and Sensors

3.5 Discussion

3.5.1 Remote Sensing

Determining the average spectral profiles, discrimination ability, and key wavelengths provided significant insights into the potential use of remote-sensing to locate the two species of noxious weeds in KNP . There are many notable differences and similarities between the native and invasive species, as well as across the individual species themselves. Alpine grevillea (*Grevillea australis*) and leafy bossiaea (*Bossiaea foliosa*) shared a fairly similar reflectance pattern across the spectral profile. Snow grass (*Poa sieberiana*) had a fairly different spectrum, with reflectance varying from the usual pattern between 700 and 1300 nm. Sticky cassinia (*Cassinia uncata*) shared a very similar curve to alpine shaggy pea *(Podolobium alpestre)* up to 1100 nm, diverging afterwards. A similar occurrence was observed between black sally *(Eucalyptus stellulata)* and alpine daisy bush *(Olearia phlogopappa).* Most notably in these results, is the strong visual separation of the two weeds, orange hawkweed and ox-eye daisy, from the rest of the native species. The alpine everlasting (*Xerochrysum subundulatum*) resides between both weeds spectral profiles. Ox-eye daisy seems the most different, especially between 400 and 650 nm, where it has a substantially higher reflectance in comparison to all other species – potentially an effect of its white flowers. Notably, the two weeds have a very similar shaped curve following 700 nm, seemingly running parallel to each other for the rest of the spectrum. Orange hawkweed values ranged significantly between plant, greenhouse, flowering, and non-flowering classes. However, all classes of the invasive species had positive balanced classification accuracies. Invasive classes with lower classification accuracies (orange hawkweed (field, flower) and ox-eye daisy (plant)) seemed to be attributed to inter-species class confusion according to the confusion matrix. Plant-only samples and flower-only samples seemed to have been similar, increasing confusion, and reducing separability and classification accuracy.

Biochemical and biophysical properties of plants, and their leaves, are responsible for differing spectral signatures (Heim, Jürgens, Große-Stoltenberg, & Oldeland, 2015). These properties are also often inherently different based on the species habitat, and source region (I. P. Aneece, Epstein, & Lerdau, 2017). Whilst it is important to note that there are differences in the spectral profiles, it is critical to understand the electromagnetic regions where these disparities greater occur. The main discriminatory wavelengths were found to be in the visible blue, green, and red light regions, as well as the non-visible regions in the red-edge, and in one small area of the near-infrared region. The red-edge contains a significant amount of properties, enhancing the differences normally visible. Using specialised photographic equipment, a visual representation of this in orange hawkweed is presented in *figure 11*.

Figure 11. Orange Hawkeed, photographed in (A) the full visible light spectrum, (B) at 720nm red-edge infrared using specialised photographic equipment at the same angle, and (C) at an acute angle, accentuating hairs. An Australian $20 note is used as a colour reference across images (A) and (B).

This modified camera is designed to capture images at the 720 nm wavelength, which is in the 'red-edge' range of the electromagnetic spectrum. *Figure 11, image A*, shows the plant in standard RGB form. *Image B*, is captured at 720nm at the same angle, and the reflectance and texture is visually different. This is enhanced in *image C*, captured at 720nm from a more acute angle, where it is apparent the 'hairs' on the leaves is significantly more apparent, as well as the overall texture. The greater visibility of the hairs here may be partially responsible for the spectral differentiability in this region.

Interestingly, there were no bands selected for discriminability in the large range between 750nm and 1295nm. Whilst there is a strong difference in the mean profiles in this range, a re-examination of the raw data accentuates a significant intraspecies variability of samples for this region. Values in this range is generally considered to be influenced by cell structure, and could also be impacted by variable weather conditions (Slaton et al., 2001). This difference can potentially be explained by biological and lighting factors.

For orange hawkweed, both field and greenhouse samples were analysed, to increase sample size. However, greenhouse growing conditions generally differ from those in the field, increasing growth rates and manipulating cell structures, which creates more delicate and thin leaves, causing differences in reflectance spectra (Fletcher, Johnson, & McFarlane, 1990; Keyhaninejad, Richins, & O'Connell, 2012; Vigneau, Rabatel, Roumet, & Ecarnot, 2010). Findings from Vigneau et al. (2010, pg. 9) using hyperspectral imagery for wheat crop monitoring determined that spectral profiles obtained *"greenhouse plant leaves can not be applied directly to field leaves"*. Additionally, due to the controlled nature of the orange hawkweed, the greenhouse plants were not legally permitted to be scanned outside of the facility. The increased diffusion and scattering of the greenhouse may have affected results, even with appropriate calibration. Additionally, diffuse light from greenhouse scattering is more efficiently used by plants, due to a deeper penetration of light into the canopy – affecting plant structure, and in turn their profiles (Li & Yang, 2015). When training the sniffer dogs, it was noted by NPWS that scent of the weed in the greenhouse was notably different to those in field (Jones, 2017). It has been hypothesised that this is due to the harsh weather conditions in KNP requiring the plant to grow in a more hardy matter, whilst greenhouse plants are able to thrive in more ideal conditions (Jones, 2017). It is important to ascertain the difference between greenhouse and in-situ samples of orange hawkweed, due to its rapid removal in the field, reducing the availability of plants for sampling on site. Whilst it is useful to supplement the scarce quantities of field samples of orange hawkweed using the greenhouse species, these may be too different to those collected in the field to be of high usability.

In order to determine the potential practicability of these discrimination results, the statistical analysis was repeated with the wavelengths trimmed and averaged, to represent and emulate a hypothetical response from a multispectral, drone-mountable, camera. The bands of the Parrot Sequoia, nominated as an indicative example, was selected for this purpose. Overall, the error in the confusion matrix was higher than the non-reduced data, as expected. However, the vast majority of confusion, as per the matrix, is between native species, and within the different sub-divisions of noxious weed species. Whilst overall accuracy is moderate at 59%, this is between all species and classes, and a binary classification of alien versus native species may be higher. This is further accentuated with some native classes, with alpine daisy bush and alpine grevillea having balanced accuracies of less than 50%, whilst the average balanced accuracy of the invasive species was 83.1% - not accounting for intraspecies class confusion. The RGB sensor on the Parrot Sequoia is coupled with four spectral cameras: 'Green' (540-560nm); 'Red' (650-670nm); 'Red-Edge' (730-740nm): and 'Near Infrared' (780-810nm) (Parrot Drones S.A.S., 2017b). Interestingly, the visible light portions were considered the most important for overall classification, with the 'Green' band being best for detecting ox-eye daisy, and the 'Red' band being the best for orange hawkweed. This is in contrast to weed detection performed with this camera in a Californian vineyard, where formulas utilising the red-edge band was considered the most useful (MicaSense, 2016). Generally, the classification results with data binned and trimmed to emulate a multispectral drone-mountable camera, i.e. the Parrot Sequoia, are promising, and provides solid justification for further investigation.

Similarly, the above process was repeated for the hyperspectral satellite, WorldView-3. This presented improved results on a spectral basis than the Parrot Sequoia. Less misclassification across classes, and better individual accuracies, resulted in a better overall accuracy of 66%. With nine main spectral bands that include the range of our spectral data, there is a significantly higher coverage of the key discrimination regions by the WorldView-3 sensor. Based on the band importance order, the addition of a blue band increased the accuracy here, as well as the change in wavelengths covered by these red and red-edge bands in comparison to the Parrot Sequoia. The improved accuracy of WorldView-4 to the Parrot Sequoia can be attributed to it being able to sense data in more of the key spectral bands determined. Paradoxically, however, whilst the spectral resolution may be more suitable for the discrimination of profiles, the spatial resolution is significantly worse than the Parrot Sequoia. With improving technology, higher resolution imagery will hopefully be available in the future.

Determining the multispectral discriminability of orange hawkweed and ox-eye daisy from their cohabitant native species – and the assuring results provided – demonstrates the ability of the process, and its practicability. Remote sensing weed management approaches utilising the spectral signatures of target species have experienced a diverse range of accuracies globally. With studies ranging from as low as 2-6% accuracy, to 73-99%, it is crucial to perform this statistical analysis for each potential application (Carson et al., 1995; O'Neill et al., 2000). This variation in results, caused by an axiomatic nexus of confounding factors, accentuates the demands for introductory studies, and highlights the positive results found in this trial (Azaria et al., 2012). Confusion with other plant species in the processing of imagery seems to be largest hurdle for utilising multispectral methods for weed detection – an issue which is worsened considerably with lower spectral discriminability, and vice versa (Carson et al., 1995). As such, the overall RF classification accuracy of 70% in this study provides confidence for pursuing further investigation of using remote sensing as an environmental management method for locating weeds in KNP, particularly the next stage which is to perform field validation in the summer season.

Statistical analysis of multispectral discriminability allows for a preliminary assessment of imagery classification ability. As such, this process provides evidence for (or against) the use of remote sensing image capture and analysis – prior to undertaking a large-scale operation (Immitzer et al., 2012). Whilst these external and passive methods are more affordable in the long-run to perform than wide-scale field surveys, it is necessary to prove their potential worth – to obtain appropriate budgets, evoke interest in future research, and so forth. This method of analysing the spectral profiles themselves first, allows for estimates of potential accuracies to be gathered – prior to procurement of multispectral capture equipment, hiring of drone operators, purchase of imagery and training of staff, etc (Immitzer et al., 2012).

It is crucial for emerging technologies to undergo preliminary assessments prior to pitching their use as a management option. Orange hawkweed is noted as a problematic invasive species on the National Environmental Alert List, and as a National Agricultural Sleeper Weed (Cherry et al., 2016). Its containment to KNP, relative limited spread, and strongest demand for eradication made it the key target of this study. Nevertheless, the magnitude and variety of other national weed management target species, will benefit from multispectral remote sensing methods. Unfortunately, implementing nation-wide extremely high-resolution aerial remote sensing efforts for weed management is unfeasible. However, this statistical spectral discrimination method can be utilised for preliminary studies on other weeds in the alert list, to determine the best potential uses for these technologies, and allocate a potential budget for this method in the most effective and efficient manner.

This approach will benefit more in smaller regions, as it will be easier to obtain and compute high resolution imagery – as well as them having a less diverse range of native species that have similar spectral profiles. For example, it would be useful to reapply the methods of this study to other high priority weed management regions, such as Lord Howe Island. Sites which have an open-sky view, in order to allow the weeds to be seen by sensors, are ideal. Known for having one of the most intensive invasive species eradication programs in Australia, Lord Howe Island may benefit from using these methods to quickly determine the potential of spectral applications for the 68 targeted weeds there (Lord Howe Island Board, 2016). The high priority species for investigation – ground asparagus *(Asparagus aethiopicus)*, bitu bush *(Chrysanthemoides monilifera* subsp. *rotundata)*, and cherry guava *(Psidium cattleyanum)* – would benefit the most from a preliminary spectroradiometric assessment (H. Cherry, personal communication, 10th July 2017). This acts as an example of one of the many ways this process could be applied to other sites and weeds, and as an illustration of how an assessment of spectral separability prior to full scale imagery capture operations is required to provide an indication of potential benefits.

3.5.2 Invasive Species Management

This spectral profiling and classification of invasive and native species has proven to be useful as an assessment tool for determining prospective use of remote sensing imagery capture and classification. The ability to ascertain potential classification accuracies prior to full-scale deployment increases the productivity and effectiveness of future efforts. Specifically, for orange hawkweed and ox-eye daisy, the results of this analysis has provided substantial benefits to current and future eradication efforts. Obtaining the spectral profiles of the invasive species, and their native cohabitants, through field and greenhouse sampling and post-processing already allows for significant future work in this space. Any future operations – from small-scale drone applications, to large-scale aircraft-mounted or satellite capture systems for larger patches, will utilise the spectra determined in this study.

There are a variety of ways of practically implementing the results found. As is common in RS deliberations, a paradox emerges of balancing spectral, spatial and temporal resolutions with spatial coverage, expenditure, and potential accuracies (Atkinson & Aplin, 2004; Rocchini, 2007). Consequently, a careful determination of the implementation technique for KNP needs to be addressed. Two main paradigms emerge: firstly, a multispectral camera mounted to a drone or other low-flying unmanned aerial vehicle; and secondly, purchase and analysis of WorldView-3 high-resolution multispectral satellite imagery of the region.

The first option provides a significantly higher spatial resolution, increasing potential accuracy, at the cost of a high coverage region. The Parrot Pro AG Drone Package, containing a Parrot Sequoia camera mounted onto a Parrot Disco-Pro, provides 80 hectares of coverage per flight, at a resolution of < 15cm/px from a 120 m flight altitude, with included basic software (Parrot Drones S.A.S., 2017a). This system, available for $6,875 AUD, is a suitable device for implementing this spectral analysis, as determined in the second part of the statistical analysis. The higher resolution of the drone will be more suitable for orange hawkweed, where plants exist in very small patches, which may be missed by a coarser spatial resolution. Conversely, the spatial coverage provided by this system is small relative to the extent of KNP. For example, at 80 hectares per flight, it would take over two flights to cover the extent of Tooma Reservoir. However, this would be more time effective than manual ground surveys, and would be useful for targeting key sites.

Secondly, using satellite imagery that is high resolution and multispectral is another method for remotely searching the landscape for these targeted spectral profiles. WorldView-3 is a commercial remote sensing satellite launched in 2014, with a maximum spatial resolution of 31 cm/px (panchromatic), and a maximum multispectral spatial resolution of 124 cm/px. Imagery is available to purchase from this system at $24/km^2 (AUD), with academic discounts also available (Land Info Worldwide Mapping, LLC, 2016). This can be a much more affordable method of collecting imagery and searching for the weeds across the park. However, the resolution of the satellite would be a strong limitation, as it would not be able to pick up small, dispersed, infestations. Instead, it would be more useful for detecting large patches such as the 3600m^2 patch of orange hawkweed found near Fifteen Mile Ridge in the 2010/2011 season, or the large swaths of ox-eye daisy that were seen during the field surveys. However, utilising satellite imagery would allow for an exceptional coverage of the parks extent, at a significantly more affordable level than drone, or physical surveys. Both options have important uses, benefits, and limitations. Overall, use of the Parrot Sequoia provides a more spatially detailed analysis, at the expense of coverage and a mild decrease in accuracy – whilst use of the WorldView-3 system covers a significantly greater region, yet would only be able to detect large patches of the invasive species, due to resolution constraints. As such, it is evident that both systems are rather dichotomous in their abilities to locate weeds, and choosing either system would result in a strong compromise of coverage or precision. Consequently, it is useful to contemplate the notion of a multifaceted and heterogeneous approach, combining both systems in conjunction with field assessments to mitigate these issues, represented in *figure 12.*

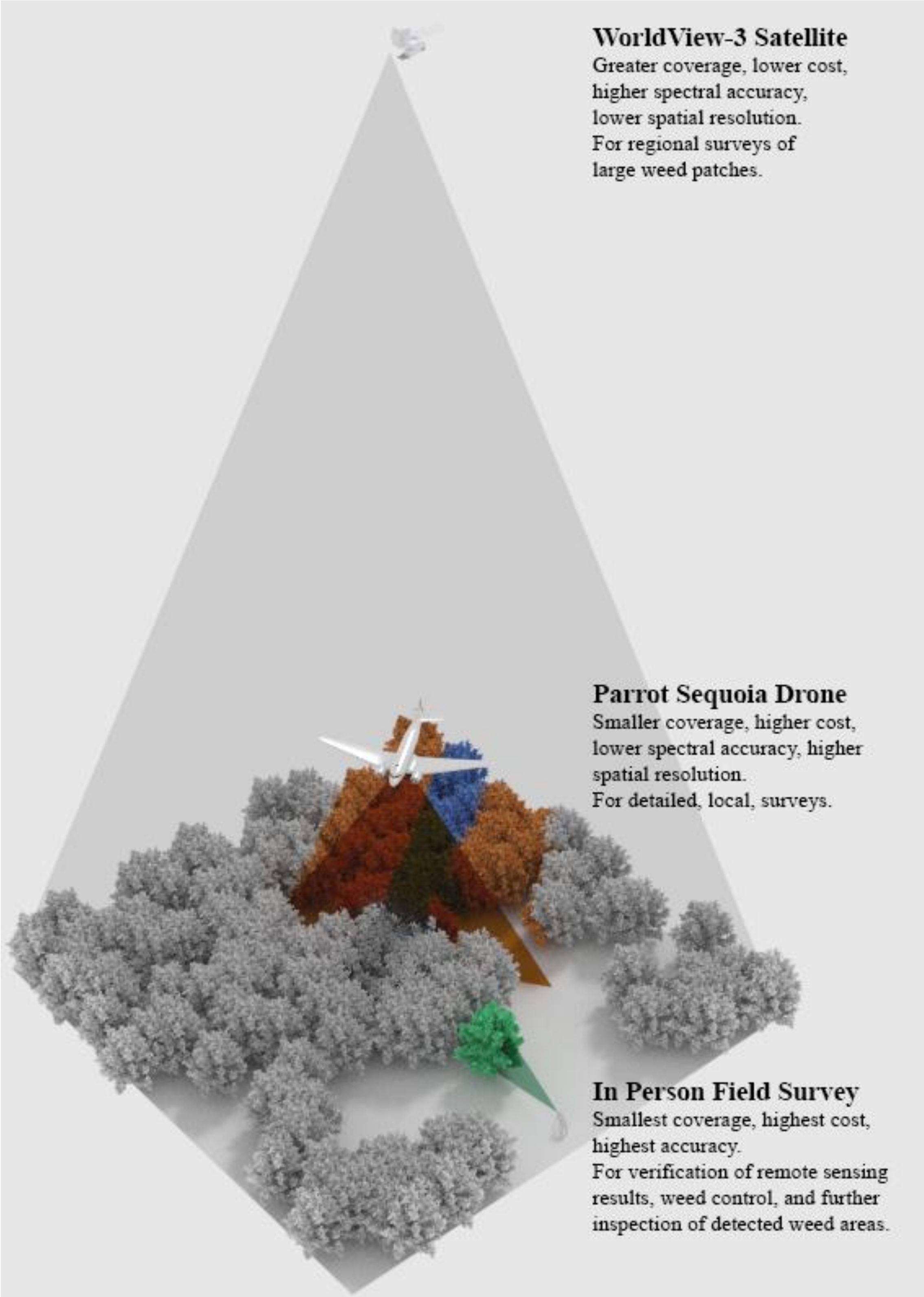

Figure 18. Potential multifaceted remote sensing approach for KNP. (Diagram created from individual sprites in Carbomap, 2014)

Hot-spot regions – which could be assessed through GIS analysis of known plant locations, or simply expert knowledge – could be inspected using the drone surveys to perform a detailed assessment across smaller regions. This would then operate in conjunction with satellite remote sensing to search other, previously unassessed regions of the park, for large patches of weeds that would have previously been unknown. If one of these regions are then flagged via satellite, a further drone analysis could be performed there to find smaller patches that may have occurred in these new-found sectors of weed growth. In all cases, these newly found weed locations would then be field-verified by the expert NPWS team members and treated accordingly. A false positive from remote sensing is easily verifiable in the field, taking a maximum of a day to check, but a manual search could take entire seasons to even be able to search that area (Jones, 2017).This multidimensional tactic reduces the disadvantages of both methods, and would provide a significantly more useful approach.

Specifically, for invasive species in KNP, a multi-dimensional remote sensing approach will be an effective, efficient, and useful environmental management practice. Tying into a ‘search and destroy’ eradication program, utilising both drone and satellite spectral analysis will help in determining the potential locations of weed species, with the two methods having a diverse implementation across small and large scales. Remote sensing will provide a significantly larger detection coverage in contrast to traditional methods, in a significantly shorter timeframe, and more affordable manner to complement existing management strategies.

3.5.3 Limitations

Whilst the results of this study are positive, it is important to discuss the limitations of our method. Firstly, this study looked specifically into the discriminability and separability through a statistical machine-learning analysis of the plant species based on their spectral profiles alone. Finding that this is indeed possible and effective, it is then necessary to assess this based on trials analysing imagery of known infestations and control samples, and verifying them on the ground. Unfortunately, this was out of the scope for the timeframe and funding of the Master of Research. However, this research and its results acts as a facilitator to secure budget and interest for further research, and procurement of imagery. Additionally, another constraint of this study was acquiring enough samples of orange hawkweed. Due to the extreme demand for controlling the invasive species, most samples that were found had already been treated, were in isolated forms and not in patches, and were blended with the local native vegetation. As such, a lower diversity of individual plants was collected than was desired. Whilst this was addressed by acquiring several individuals and growing them in a secure greenhouse facility, the profiles collected were significantly different, requiring them to be analysed separately. In addition, the wavelength variability was the main assessment criteria of this study, which does not account for later imagery analysis constraints, including signal-to-noise ratios of sensors, and spectral un-mixing. These limitations considered in the context of an initial pilot study are easily addressable in the next stage of research, which will build into a robust management system in the park.

3.5.4 Future Directions

Providing foundational evidence for the spectral discriminability of invasive and native species in KNP, this study has opened up a number of future research questions. Firstly, the next stage of this research should be to cross-validate the statistical analysis with imagery captured from both drone and satellite sources of both control and known infestation areas, in conjunction with ground surveys. Additionally, it would be useful to collect more spectral samples of orange hawkweed, ox-eye daisy, and the native species. Furthermore, other invasive species in the KNP, such as other hawkweeds, should also be scanned and studied to see if this method could be expanded further. In terms of expansion, it would also be useful for researchers to trial this in other national parks or areas that are tackling localised weed management issues, such as Lord Howe Island.

3.6 Conclusion

The aim of this study was to evaluate the use of remote sensing to determine and discriminate the spectral profiles of invasive and native plant species. Specific to orange hawkweed and ox-eye daisy in KNP, this study determined that there is a significant separability between these invasive species and their native co-habitants. Through analysing and assessing both multispectral satellite and drone imagery potential, a comprehensive implementation plan was established that would utilise remote sensing to assist in the eradication process. The consequences of untampered weed proliferation in KNP are significant, risking its significant cultural and heritage values and biodiversity, as well as causing significant environmental and socioeconomic impacts. Through utilising remote sensing in a multi-faceted approach combining drone and satellite capture and analysis with ground surveys, weed management in the park will see significant benefits. Overall spectral separability accuracy of 70%, with 59% for the Parrot Sequoia drone camera, and 63% for the WorldView-3 satellite, emphasises the potential ability of this process. If established, orange hawkweed provides a significant threat, resulting in unbearable costs to the ecosystem and grazing industry. By conducting a focused analysis of the spectral detection abilities in KNP this paper provided insights into the application potential of this discipline, determining its specific use in relation to orange hawkweed and ox-eye daisy to the Australian alpine natives. Ultimately, in conclusion, this paper finds that the use of remote-sensing to locate and eradicate weeds in KNP through determining and discriminating spectra is effective, and should be used as part of a multidisciplinary environmental management approach.

4 SYNTHESIS

Through the coupled examination of literature, and a case-study analysis of potential spectral weed management approaches in KNP, this dissertation has provided an assessment of the potential effectiveness of remote sensing utilisation for invasive species control in NSW, and in general. The construction of a spectral library of orange hawkweed, ox-eye daisy, and their key common co-habitual species, followed by a statistical spectral discriminability assessment, has clearly determined favourable capacity and capability for weed control in the region. With a 70% separability overall – and 59% for drone and 63% for satellite – the benefits of a dual approach in targeting these weeds was highlighted, and recommended for implementation as part of a multidisciplinary management approach.

This spectral machine-learning analysis approach augments and supplements previous RF vegetation discriminability methods and assessments, such as those by Immitzer et al., 2012; Mansour et al., 2012; Pal, 2005; Pouteau, Meyer, Taputuarai, & Stoll, 2012; and Shang & Chisholm, 2014. Current applications are mostly foreign to Australia, or focus on general vegetation classification and quantification, or are weed focused but performed in monocultures – such as agricultural crops. As such, a clear research frontier has emerged for testing these methods for weed management, particularly in an Australian context, and in a natural, diverse, native environment. This investigation demonstrates that remote sensing for the detection of noxious weed locations is effective in the Australian landscape, through the positive results in the KNP case study. Additionally, comparing and contrasting the spectra of the weed species to nine native species substantiates the use of this technology, adding and expanding to remote-sensing based weed management studies such as (Tamouridou et al., 2017) which focused on agricultural, monoculture based environments. Analysing orange hawkweed and ox-eye daisy spectrally in KNP expands on previous remote-sensing efforts in the region, including Hung and Sukkarieh's (2015) work using RGB drones for surveillance and detection of orange hawkweed, as well as hyperspectral discrimination of Blackberry (*Rubus fruticosus* sp. agg.) by Dehaan et al. (2007). Furthermore, this expands further the work of Mcintyre (2015), where the utility of three remote sensing sources was used to determine the most important factors in the capture and analysis process of high resolution multispectral data for mapping and detecting the pasture weed Paterson's curse (*Echium plantafineum).*

This analysis ameliorates prior remote sensing research through facilitating an examination for noxious weeds in a diverse, Australian, environment.

For invasive species management in particular, it has been determined through spectral profiling and classification that this method can, and will be, useful for both determining potential results from remote sensing analysis approaches for weed management in KNP, and as a preliminary assessment tool in general. The methods presented here can be used to perform pilot studies for other small-scale invasive species cases in an affordable manner. Additionally, they provide quantitative measures of effectiveness of full-scale operations, prior to, and providing evidence for, significant investment. It was found that satellite and drone sensors varied considerably in their respective benefits and shortcomings, and as such a multifaceted approach in combination with already established and developing methods was suggested as a management method.

Acting as a proof-of-concept study, the statistical method is limited in that it did not yet perform analysis on ground imagery sources. This constraint however, enables future research into cross-validation of this analysis with captured imagery from both sources of control and known infestation areas, as well as searching new, unknown, areas for weed species. Furthermore, the number of noxious weeds and invasive species of which spectral profiles were developed and analysed could be further expanded.

Ultimately, this review of literature and case study analysis has found that the remote sensing is an effective technique to be utilised for invasive species management in Kosciuszko National Park.

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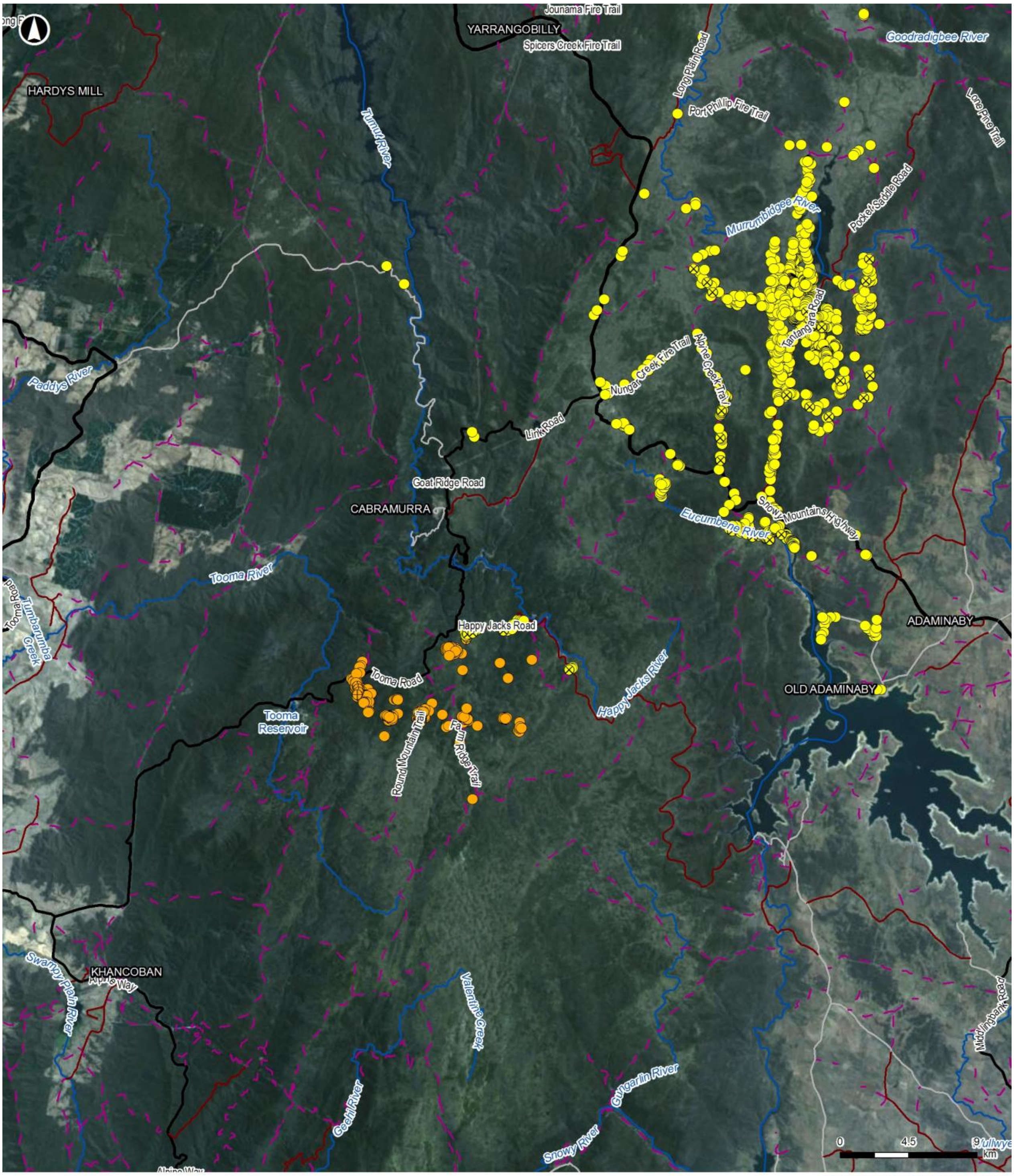
6 Appendices

Appendix 1. Areas of Invasive Species



LEGEND

- Ox-Eye Daisy (ALA, 2017)
- Ox-Eye Daisy (NPWS, 2017)
- Orange Hawkweed (ALA, 2017)
- Orange Hawkweed (NPWS, 2017)
- Major Watercourses
- Principal Road, Sealed
- Principal Road, Unsealed
- Secondary Road, Sealed
- Secondary Road, Unsealed
- Minor Road, Sealed
- Minor Road, Unsealed
- Track, Unsealed

DATA SOURCES
ALA, ESRI, NPWS, OEH, LPI

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Areas of Invasive Species Infestation

Date: 18/09/2017 Path: C:\Users\43261299\Google Drive\Academia\2017\GIS\MRES_WeedLocations_r1v1.mxd
Created by : Chad Ajamian. 43261299
Masters of Research in Environmental Sciences

INFESTATION

APPENDIX 2. R CODE USED FOR METHODS AND RESULTS

```
##################################################################################################
##################################################################################################
#######     This script, was developed by Chad Ajamian with significant         ##################
#######     assistance from Rene Heim. It is used for performing spectral       ##################
#######     discrimination analysis for Orange Hawkweed and Ox-Eye Daisy against ##################
#######     native cohabitating species.                                        ##################
#######     All following steps will be commented.                              ##################
##################################################################################################
##################################################################################################
#                                                                                                #
#                                                                                                #
#                              _(_)_                          wWWW    _                          #
#                  @@@@       (_)@(_)   vVVVv     _     @@@@  (___) _(_)_                         #
#                 @@()@@ wWWWw  (_)\    (___)   _(_)_  @@()@@  Y   (_)@(_)                       #
#                  @@@@  (___)     `|/    Y    (_)@(_)  @@@@  \|/   (_)\                         #
#                   /      Y       \|    \|/    /(_)    \|     |/       |                        #
#                \ |     \ |/       | / \ | /  \|/       |/   \|      \|/                        #
#                \\|//   \\|///  \\\|//\\\|///  \|///  \\\|//  \\|//  \\\|//                      #
#               ^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^                     #
#                                                                                                #
##################################################################################################
# 1. Preparation Steps                                                                           #
##################################################################################################

##################################################################################################
## 1.1. Install the required packages.                                                           #
##################################################################################################

install.packages(c("hsdar", "fda", "fda.usc", "propectr", "gdata", "caret",
"reshape2", "gridExtra", "cowplot", "VSURF", "colourpicker",
"png", "grid", "qpcR", "tidyverse", "dplyr"))
install.packages('e1071', dependencies=TRUE)

##################################################################################################
##  1.2. Loading Packages                                                                         #
##################################################################################################

library(hsdar)
library(fda) # For Outlier detection
library(fda.usc) # For Outlier detection
library(prospectr) # For spectral binning
library(gdata) #To drop levels of a df
library(caret)
library(reshape2)
library(cowplot)
library(VSURF)
library(colourpicker)
library(tidyverse)
library(e1071)

####################################################################################################  2.
Load Spectral Data, Remove Unwanted Wavelengths , Remove Spectra >100%                    #
##################################################################################################

setwd("C:/Users/43261299/Google Drive/Academia/2017/R/FINAL")
data.original <- read.csv("data/SpectralProfilesMergedJuly.csv", check.names = FALSE)
data.original$Type <- drop.levels(data.original$Type)
as.vector(unique(data.original$Type))
data.rmv.noise <- data.original[,match('400', names(data.original)):match('1300', names(data.original))]
#this removes the unwanted bands
names(data.rmv.noise[,c(1,901)]) #Check bands after removal

#Final df after noisy end are removed
data.wo.noise <- cbind(data.original['Type'],data.rmv.noise)# Final df after noisy end are removed

#create a list of subsets based on the factor value.
subsets <- split(data.wo.noise, data.wo.noise$Type)

##Remove Spectra with reflectance values above 100%
subsets$OHff <- subsets$OHff[apply(subsets$OHff[, -1], MARGIN = 1, function(x) all(x < 100)), ]
subsets$OHfp <- subsets$OHfp[apply(subsets$OHfp[, -1], MARGIN = 1, function(x) all(x < 100)), ]
subsets$OHgf <- subsets$OHgf[apply(subsets$OHgf[, -1], MARGIN = 1, function(x) all(x < 100)), ]
subsets$OHgp <- subsets$OHgp[apply(subsets$OHgp[, -1], MARGIN = 1, function(x) all(x < 100)), ]
subsets$ASP <- subsets$ASP[apply(subsets$ASP[, -1], MARGIN = 1, function(x) all(x < 100)), ]
subsets$CAS <- subsets$CAS[apply(subsets$CAS[, -1], MARGIN = 1, function(x) all(x < 100)), ]
subsets$OXp <- subsets$OXp[apply(subsets$OXp[, -1], MARGIN = 1, function(x) all(x < 100)), ]
subsets$OXf <- subsets$OXf[apply(subsets$OXf[, -1], MARGIN = 1, function(x) all(x < 100)), ]

##################################################################################################
##  3. Manually Screen and Remove Obvious Outliers                                               #
##################################################################################################

##Essentially, manually print the pdf, look for outliers, and continually remove max
```

```
##until it is clean.

## PDF Before
pdf("output/all.before.manual.august.pdf", width = 32, height =18)
par(mfrow=c(4,7))
for (i in 1:length(subsets)){

labnames <- list(main="Width", xlab="Wavelength [nm]", ylab="Reflectance [%]")
set <- subsets[[i]]
set.2 <- as.matrix(set[,2:902])
f.res <- fdata(set.2, argvals = as.integer(names(set[,2:902])), names = labnames)

plot(f.res, main = names(subsets)[i])

}
dev.off()

####ASP
which.max(subsets$ASP[,'1000'] )
subsets$ASP <- subsets$ASP[-72,] # use multiple times and check plot if spectra are gone
subsets$ASP <- subsets$ASP[-70,]
subsets$ASP <- subsets$ASP[-70,]
subsets$ASP <- subsets$ASP[-70,]
subsets$ASP <- subsets$ASP[-70,]
subsets$ASP <- subsets$ASP[-70,]
subsets$ASP <- subsets$ASP[-64,]

####BOS
which.max(subsets$BOS[,'1000'] )
subsets$BOS <- subsets$BOS[-11,] # use multiple times and check plot if spectra are gone
subsets$BOS <- subsets$BOS[-71,]
subsets$BOS <- subsets$BOS[-69,]
subsets$BOS <- subsets$BOS[-11,]

####OHff
which.max(subsets$OHff[,'1000'])
subsets$OHff <- subsets$OHff[-13,]

####PDp
which.max(subsets$PDp[,'1000'])
subsets$PDp <- subsets$PDp[-24,]
subsets$PDp <- subsets$PDp[-24,]
subsets$PDp <- subsets$PDp[-22,]
subsets$PDp <- subsets$PDp[-22,]
subsets$PDp <- subsets$PDp[-2,]
subsets$PDp <- subsets$PDp[-34,]
subsets$PDp <- subsets$PDp[-35,]

##PDF After
pdf("output/all.after.manual.august.pdf", width = 32, height =18)
par(mfrow=c(4,7))
for (i in 1:length(subsets)){

labnames <- list(main="Width", xlab="Wavelength [nm]", ylab="Reflectance [%]")
set <- subsets[[i]]
set.2 <- as.matrix(set[,2:902])
f.res <- fdata(set.2, argvals = as.integer(names(set[,2:902])), names = labnames)

plot(f.res, main = names(subsets)[i])

}
dev.off()

####################################################################################################
##  4. Outlier Detection via Functional Data Analysis                                              #
####################################################################################################

source('script/Remove_Functional_Outlier_June2017.R')

cleaned_data <- lapply(subsets, rmv.funct.outlier)

pdf("output/all.after.automatic.august.pdf", width = 32, height =18)
par(mfrow=c(4,7))
for (i in 1:length(cleaned_data)){

labnames <- list(main="Width", xlab="Wavelength [nm]", ylab="Reflectance [%]")
set <- cleaned_data[[i]]
set.2 <- as.matrix(set[,2:902])
f.res <- fdata(set.2, argvals = as.integer(names(set[,2:902])), names = labnames)

plot(f.res, main = names(cleaned_data)[i])

}
dev.off()

cleaned.df <- bind_rows(cleaned_data)
write.csv(cleaned.df,"output/data_after_outlierdetection.august.csv")

####################################################################################################
##  5. Spectral Binning and Resampling                                                             #
```

```
##############################################################################################

Type <- cleaned.df[,1]

data.resamp <- cleaned.df[,2:902] #removing Type column
data.bin <- binning(data.resamp, bin.size=10)

data.after.bin <- cbind(Type, as.data.frame(data.bin))

write.csv(data.after.bin,"output/data_after_preprocessing.august.csv", row.names = FALSE)
data.classif <- read.csv('output/data_after_preprocessing.august.csv', check.names = FALSE)

##############################################################################################
##  6. Random Forest Classification  (note: this takes 24-72hrs to run)                      #
##############################################################################################

source('script/RandomForest_May2017.R')

Classification_Results <- list()

Classification_Results[['Run1']] <- RFapply(data.classif,repeats=100,trees=1000,seq(1,70,5))

tmp <- lapply(Classification_Results, function(i){  capture.output( print(i) ,
file="output/20170815_Results_RandomForest_August.txt", append=TRUE)})

##############################################################################################
##  7. Figure: Comparison Before and After all Classification                                #
##############################################################################################

subsets_unfiltered <- split(data.original, data.original$Type)

pdf("ComparisonBeforeandAfterAllPreProcessingAugust.pdf", width = 10, height = 15)
par(mfrow=c(8,4))

for (i in 1:length(subsets_unfiltered)){

labnames <- list(main="Width", xlab="Wavelength [nm]", ylab="Reflectance [%]")
set <- subsets_unfiltered[[i]]
set.2 <- as.matrix(set[,2:1800])
f.res <- fdata(set.2, argvals = as.integer(names(set[,2:1800])), names = labnames)

plot(f.res, main = names(subsets_unfiltered)[i])

}
for (i in 1:length(cleaned_data)){

labnames <- list(main="Width", xlab="Wavelength [nm]", ylab="Reflectance [%]")
set <- cleaned_data[[i]]
set.2 <- as.matrix(set[,2:902])
f.res <- fdata(set.2, argvals = as.integer(names(set[,2:902])), names = labnames)

plot(f.res, main = names(cleaned_data)[i])
}

dev.off()


##############################################################################################
##  8. Analysis based on Drone Camera Bands (Parrot Sequioa)                                 #
##############################################################################################

##Outside R, remove values in data_after_outlierdetection.august.csv that cannot be used
##For parrot sequoia, useable bands are 530-570, 640-680, 730-740, and 770-810
##Excel also then used to calculate the means for each of these bands

dataclipdrone <- read.csv('output/data_after_outlierdetection_august_clipped_mean_parrot.csv', check.names
= FALSE)[-1]
names(dataclipdrone)

source('script/RandomForest_May2017.R')

Clipped_Classification_Results <- list()

Clipped_Classification_Results[['Run1']] <- RFapply(dataclipdrone,repeats=100,trees=1000,seq(1,70,5))

tmp <- lapply(Clipped_Classification_Results, function(i){  capture.output( print(i) ,
file="output/20170815_Results_Clipped_RandomForest_August.txt", append=TRUE)})


##############################################################################################
##  9. Analysis based on WorldView-3 Camera Bands                                            #
##############################################################################################

##Outside R, remove values in data_after_outlierdetection.august.csv that cannot be used
##For WorldView-3, useable bands are 400-452, 448-510, 518-586, 590-630, 632-692, 706-746, 772-890, 866-
954, 1195-1225
##Excel also then used to calculate the means for each of these bands

dataclipworldview3 <- read.csv('output/data_after_outlierdetection_august_clipped_mean_worldview3.csv',
check.names = FALSE)[-1]
```

```
names(dataclipworldview3)

source('script/RandomForest_May2017.R')

Clipped_Classification_Results <- list()

Clipped_Classification_Results[['Run1']] <- RFapply(dataclipworldview3,repeats=100,trees=1000,seq(1,70,5))

tmp <- lapply(Clipped_Classification_Results, function(i){  capture.output( print(i) ,
file="output/20170815_Results_RandomForest_August_WorldView3.txt", append=TRUE)})
```

FUNCTION ONE: REMOVE FUCTIONAL OUTLIER

```
rmv.funct.outlier <- function(data){

        require(fda)
        require(fda.usc)

        #data <- subsets[[1]]

        i <- seq(2, ncol(data))
        data.wo.noise.mat <- as.matrix(data[,i]) #As matrix to be able to transform the object (1452-52=1400)

        labnames <- list(main="Width", xlab="Wavelength [nm]", ylab="Reflectance [%]") #labnames to have plot
information within fdata object
        myfdata <- fdata(data.wo.noise.mat, argvals = as.integer(names(data[,i])), names = labnames) #Why as
integer??

        outlier.mat <- outliers.depth.trim(myfdata, dfunc = depth.mode, nb = 10, smo = 0.2, trim = 0.1, ns =
0.5) #Smoothing variables here are a guess

        outlier.vector <- as.numeric(outlier.mat$outliers)

        as.data.frame(data[-outlier.vector, ])

}
```

FUNCTION TWO: RANDOM FOREST

```
RFapply <- function(data, repeats, trees, mtry){
#data must have a first col named "Type" including the response and further cols containing the predictors
  require(caret)

  learning <- createDataPartition(data$Type, p = .8,
                          list = FALSE,
                          times = 1)

  myRFTrain <- data[ learning ,  ]
  myRFTest  <- data[-learning ,  ]

  testing<-as.integer(row.names(myRFTest))

  # Random Forest - Caret - Fit Model #

  rfControl <- trainControl(method = "repeatedcv",
                            number = 10, repeats = repeats,
                            classProbs = TRUE,
                            allowParallel = TRUE,
                            selectionFunction = "oneSE",
                            returnResamp = "final")

  rfGrid <- expand.grid(mtry = mtry)

  rfFit <- train(Type ~ ., data = myRFTrain,
                method = "rf",
                importance = TRUE, ntree=trees,
                trControl = rfControl, tuneGrid = rfGrid,
                metric = "Kappa", maximize = TRUE)

  rfPred <- predict.train(rfFit, myRFTest[,-1], type = "raw")

  list(fit = rfFit,
       pred = predict.train(rfFit, myRFTest[,-1], type = "raw"),
       confusion = confusionMatrix(rfPred, myRFTest$Type),
       varImp = varImp(rfFit, scale = FALSE))
}
```

Appendix 3. Conference Paper

Accepted for Submission – August, 2017.

Ajamian, C., Chang M., Tomkins, K., 2017. "Preliminary Assessment of the Uses of Sensors and the Spectral Properties of Weed and Native Species in Kosciuszko National Park, NSW, Australia" in *The Eleventh International Conference on Sensing Technology: Remote Sensing, 2017, Sydney*.

Preliminary Assessment of the Uses of Sensors and the Spectral Properties of Weed and Native Species

In Kosciusko National Park, NSW, Australia

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Abstract—**This study aims to establish a proof-of-concept of using optical sensors to detect and determine the spectral properties of weed and native species in Kosciusko National Park (KNP), Australia. This involves interpretation of the spectral profile of the two weeds, namely Orange Hawkweed and Ox-Eye Daisy (in field and in lab), in contrast to their surrounding native vegetation. This paper presents a case study into the applicability of hyperspectral sensors, and discusses the collected spectral profiles. The preliminary results indicate that difference in profiles between the weeds and natives is large, and opens further research into determining if the profile is unique enough to then pick-up with remotely-sensed imagery collected by drones, aircraft, or satellites.**

Keywords: Hyperspectral; Spectroradiometry; Remote Sensing; Weed Management; Invasive Species; Multispectral

I. Introduction

The natural environment of the Australian Alps is an important part of Indigenous and European Australian heritage and culture [1]. The Alps are protected by a chain of national parks, the largest and most well-known of which being Kosciusko National Park (KNP), situated in the south-eastern corner of mainland Australia, along the Snowy Mountains [1]. The region contains unique ecosystems, being one of the only seasonally snow-covered regions on the continent, and as such is home to a large array of rare, and unique floral and faunal species [1]. The presence of noxious weeds in the KNP and surrounding regions, is of a deep concern particularly in terms of threats to the local biodiversity, and health of the environment – with a significant potential to cause deleterious and significant environmental, social, and economic impacts [2]–[8].

The noxious, state prohibited, weeds investigated in this study are species of the daisy family (Asteraceae) – Orange Hawkweed (*Hieracium aurantiacum*), Ox-eye daisy (*Leucanthemum vulgare* Lam. (Asteraceae)). Their occurrence in KNP is being targeted by multiple government agencies, for example, the NSW National Park and Wildlife Service [5], [8]. Whilst Orange Hawkweed is yet to reach past the early stages of establishment, they pose a major threat to ecosystems – particularly grasslands, alpine, and temperate areas [2], [3], [9].

Orange Hawkweed was first discovered in the Kosciusko National Park region in late-2003 [8]. Listed as a Class 1 Noxious Weed, the highest threat level in NSW, it is internationally recognised for displacing native vegetation, and harming agricultural productivity – particularly in New Zealand, Canada, and USA [3], [10]. Its current containment within the national park (barring one outlier recently discovered early-2017 in a neighbouring farm), as well as its high risk factor, makes it an ideal candidate for a targeted eradication program [11]. Ox-eye daisy is a more prevalent introduced species, which is difficult to control with eradication and control programs [2], [7]. Much more common and widespread than the Hawkweeds, control programs are now aimed towards containment rather than eradication [5]. It also reduces the productivity of grazing lands, and is a host for several crop-affecting viral diseases, such as the yellow dwarf virus [12].

There is an urgent need to develop methods to prevent these weeds spreading, particularly Orange Hawkweed, as it spreads easily and prolifically, and is hazardous to the environment. The prevention process traditionally involves monitoring existing infestations and scouting for additional infestations using field survey approaches [8]. However, the demand, and urgency, to mitigate the plants distribution has led to a more diverse range of control techniques, including sniffer dogs, volunteer programs, visible-colour drones, helicopter insertion surveys, and spread-modelling systems [3], [13]–[16]. The difficulty in weed management in KNP is further increased by the exceptionally difficult topography - creating lengthy travel times by forcing the use charted helicopters, off-road vehicles, and off-track hiking – reducing the amount of time that can be used for searches and increasing costs [14], [17]. Time is a strong constraint in this project - as the flowering period for Orange Hawkweed, which makes the plants significantly easier to spot by officers and volunteers, is quite short in spring [18]. Time constraints are further inhibited by climatic conditions, as snowfall in winter blankets the surface vegetation, as well as creating occupational hazards and discomfort to employees and sniffer dogs. A remote sensing method that has previously been trialled, involves flying drones with a RGB camera over known sites, and seeking the orange colour value of Orange Hawkweed in the image [15]. This method relies on the phonological stage of the plant to be appropriate [15]. Additionally, the geographic coverage of these drone flights are fairly limited [15].

Therefore, in order to mitigate some of the issues addressed with current methods, there is a demand for an alternative process to be developed. This process should: determine the location of noxious weeds throughout different stages their phenological cycle; be able to be operated remotely; cover a reasonable amount of area efficiently; and importantly – provide effective output results. A proposed tool that fits these criteria is hyperspectral remote sensing, and this preliminary study aims to establish the spectral profiles of the noxious weeds and prevalent native vegetation – which will then be able to be used to determine if these methods can accurately, and effectively, assist in the determination of the spatial distribution of noxious weeds in the Australian Alpine environment.

II. Methods

A. *Study Area*

Kosciuszko National Park is located in the Snowy Mountains in the state of New South Wales (NSW), in south-eastern Australia (latitude: 35°30'S to 37°02'S; longitude: 148°10'E to 148°52'E). Covering much of the Australian Alps Bioregion, it is the largest national park in NSW at 673,542 ha. [1]. Seven sites were chosen, in liaison with NSW National Parks officers. Six of these were used to measure Orange Hawkweed, which due to an NPWS eradication project, currently has a very sparse, and patchy distribution. One site was used to measure Ox-Eye Daisy, which is much more widespread and abundant throughout the park.

Several sites - Ogilvie's Quarry, Ogilvie's Creek Picnic Area, and Ogilvie's Airstrip (sites 1-3) represent the potential 'ground-zero' source of Orange Hawkweed infestations, whilst also being the most accessible sites in the park, and containing a wide variety of native species [3], [19], [20]. Doubtful Gap (site 4), is one of the more eastern locations of Orange Hawkweed and represents recently recorded infestations [3]. At opposite sides of a valley, Farm Ridge and Round Mountain Trail (sites 5 and 6), are some of the heavier infestation sites in the Jagungal Wilderness [3], [19], [20]. Tantangara Road (site 7) was selected as the final site because it contained a significant and widespread infestation of Ox-Eye Daisy for several kilometres, as well as a substantial amount of representative native species.

As infestations of Orange Hawkweed were less prevalent than expected, it was decided that some lab sampling would be useful for enhancing the accuracy of the spectral profile. As such, after liaising with the Macquarie University Department of Biology, access to use 'Physical Containment Level 2 Laboratory' was obtained. The weed was then delivered by NPWS, and monitored over 12 months to collect spectral samples.

B. *Spectral Sampling*

To develop spectral profiles of target weed species, and their surrounding vegetation communities, sample spectral profiles, in the field and lab, using a hand-held spectroradiometer, were collected.

In this study, a Spectral Evolution RS-3500 Spectroradiometer was utilised for the field measurements. The device has a spectral range of 350-2500nm, output in 1nm increments at an accuracy of ± 4-7% [21]. This covers a vast portion of the electromagnetic spectrum that is influenced by vegetation cover [22].

The measurement process involved first sampling a control plate, to calibrate the data against the general lighting conditions of the region, then taking multiple measurements of each weed and native species located at each site. This was to capture the range of variability in reflectance associated with the plant canopy, as well as between individuals of the same species. The target measurements were divided by the reference measurements to adjust for the general environmental conditions present at the time, which provides a reflectance value in percent for each wavelength in the spectroradiometer range.

One of the key challenges in determining spectral signatures through ground-based reflectance spectra is that these measurements are highly influenced by the methodology of their capture, environmental conditions, equipment responses, and calibration quality. Whilst collection of this data is highly tenuous, and susceptible to poor experiment design, there are no international or national standards for the field collection of spectral signatures [23]. The most comprehensive document on this topic is the Supervising Scientist Report 195, which was used extensively in experiment design and metadata tables [23].

The critical issues that need to be considered in undertaking in-situ spectral measurements are presented in *table 1* [23]–[27]. In this study, all controllable factors were mitigated where possible. This included: standardising field of view; performing reference sample scans regularly and after changes in light; ensuring proper warm-up time; only performing measurements at ideal times for solar angles; and ensuring a suitable number of samples were collected. Each sample is the average of ten measurements, and each target was sampled three times. A minimum of fifteen targets were measured for each plant, providing a *minimum* of 450 samples per species. The data were recorded in field metadata sheets, which were adapted from [23].

TABLE I. Field Spectroradimetry Consideration Factors [23-27]

Field Spectroradiometry Consideration Factors	
Experimental Design	Timing, method, geometry, scale, number of samples (variability across temporal and spatial scales)
Calibration	Calibration panel, spectrometer
Instrument Settings	Number of samples, white reference, dark current considerations
Illumination	Date, time, solar altitude and azimuth, location
Viewing Geometry	Field of view, capture height (from target and ground), capture angle
Environmental Conditions	Air pressure, visibility, humidity, temperature, cloud cover, wind vector
Vegetation	Texture, phenology, form, cover, conditions, homogeneity, health, species, layering.
Photographs	Site setup, target, azimuth, sky.

C. *Spectral Profiling*

After a significant number of samples are collected, they can be then collated, and processed, to develop a profile for a particular species, often referred to as a spectral signature or

Partnerships: NSW Adaptation Research Hub – Biodiversity Node; NSW Office of Environment and Heritage; NSW National Parks and Wildlife Service; Macquarie University – Department of Biological Sciences.

fingerprint [28]. These signatures require significant caution in their creation, as vast variabilities can occur in nature [25]. Preliminary visual inspection of samples during and after field surveys can provide rapid, indicative, and qualitative estimates of profiles – allowing exceptional errors to be rectified during surveys, avoiding post-survey failures. These were regularly performed after each site visit, and during sample collection. On returning, metadata sheets were manually entered into a spreadsheet, along with links to photographs, and scan file paths. This then facilitated the organization of scan samples, photographs, data, and metadata into individual folders by species level.

Once this database for each species was developed, the process of converting spectral samples to profiles was undertaken. Initially, the metadata and field notes were manually cross-referenced to samples, to identify those which were erroneous and unsuitable. This included accidental triggers, dynamic weather conditions, and other environmental influences. Following this, species-by-species samples were loaded into the software package DarWIN for a visual inspection of spectral samples, where outliers were removed - if justified by metadata and their reflectance values. For example, occasionally samples had wavelengths with reflectance values beyond 200% due to changing light conditions, which is not possible, indicating an erroneous sample. This processing then provided an assemblage of good, usable samples for each species. Using the 'calculate' feature in DarWIN, basic statistics were then computed for each species, which included the minimum, maximum, mean, and standard deviation of each wavelength. The mean of each species was then uniformly smoothed in DarWIN using the same parameters to ensure reliability. These were then exported and brought into MS Excel for further visualization. This process resulted in the preliminary spectral profiles for the species.

III. Results

The resultant spectral profiles of the two noxious weeds, and their co-habituating native plants, are presented in fig. 1. There are many notable differences and similarities between the native and invasive species, as well as across the individual species themselves. Across the species, as expected, the profiles seemed to be 'grouped', depending on their vegetation type.

Alpine Grevillea *(Grevillea australis)* and Leafy Bossiaea *(Bossiaea foliosa)* shared a fairly similar reflectance pattern across the spectral profile. Snow Grass *(Poa sieberiana)* had a fairly different spectrum, with reflectance varying from the usual pattern between 700 and 1300 nm. Cassinia *(Cassinia uncata)* shared a very similar curve to Alpine Shaggy Pea *(Podolobium alpestre)* up to 1100 nm, diverging afterwards. A similar occurrence was observed between Black Sally *(Eucalyptus stellulata)* and Alpine Daisy Bush *(Olearia phlogopappa).*

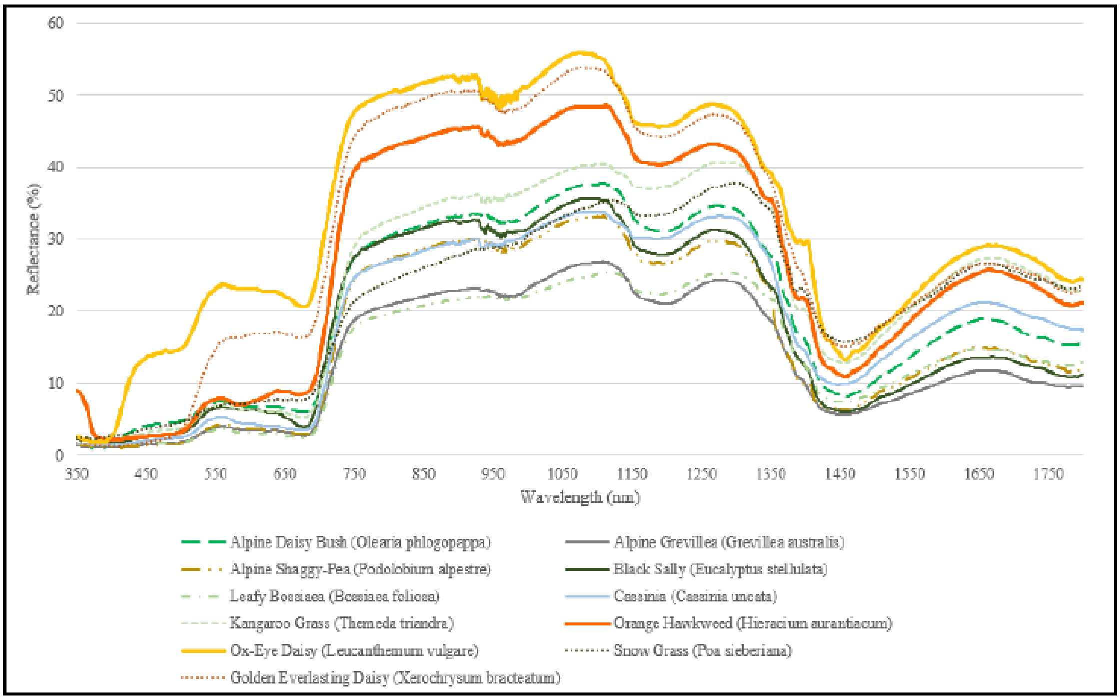

Figure 1. Spectral profiles of the study weeds and native species

Kangaroo Grass *(Themeda triandra)* had the 2nd highest reflectance of the native species.

Most notably in these results, is the strong visual separation of the two weeds, Orange Hawkweed and Ox-Eye Daisy, from the rest of the natives. The Golden Everlasting Daisy *(Xerochrysum bracteatum)* resides between both weeds spectral profiles. Ox-Eye Daisy seems the most different, especially between 400 and 650 nm, where it has a substantially higher reflectance in comparison to all other species. Notably, the two weeds have a very similar shaped curve following 700 nm, seemingly running parallel to each other for the rest of the spectrum. The difference between the native and invasive species spectral profiles here seems to be considerable, and worth investigating further.

IV. Discussion and Conclusions

Differences between the spectral profiles of Orange Hawkweed and Ox-Eye Daisy do seem to differ from native species in this preliminary assessment. The weeds tend to have a greater reflectance than the native species. These are particularly apparent for Ox-Eye Daisy between 400 and 700 nm, and for both weeds between 700 and 1300 nm. This is likely to be the result of a variety of factors, as spectral signatures are based on the chemical composition of individual target samples, as well as the physiology of species, plant architecture and geometry, morphology – and external factors including weather conditions, solar angle, and soil characteristics [28], [29]. Differences are most apparent in the near infrared segment of the electromagnetic spectrum, which is generally attributed to the cell structure of the plants. A dissimilarity in cell structures between the native and invasive species, provides the potential for hyperspectral remote sensing to be utilized to search for these weeds.

This proof-of-concept insight provides a noteworthy understanding into the spectral properties of plants and weeds in the Australian Alpine Region. The difference in spectra between weeds and native species presented here accentuate the need for a more detailed statistical analysis of the profiles, due to promising potential results. With further research and developments, multispectral and/or hyperspectral remote sensing methods, may be used to search for these weeds through their profiles. This application of sensing technology may then greatly assist in preserving the unique and crucial biodiversity of Kosciuszko National Park, through eradication of Orange Hawkweed, and containment of Ox-Eye Daisy.

Acknowledgment

I would like to thank and acknowledge the hard-working, extremely friendly, and knowledgeable staff of the Khancoban NPWS Office in their assistance with this project.

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Appendix 4. ABC News Article

Corrigan, L., 2017, 'Man, beast and machine work together to eradicate a weed infestation in Kosciusko National Park', *ABC News*, 1st March 2017, last accessed 19th September 2017, <http://www.abc.net.au/news/2017-03-01/man-beast-and-machine-fight-killer-kosciusko-weed/8316144>

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Man, beast and machine work together to eradicate a weed infestation in Kosciusko National Park

ABC South East NSW By Laura Corrigan

Posted 1 Mar 2017, 6:59pm

PHOTO: An orange hawkweed plant in Kosciusko National Park. (Supplied: Andrew McConncachie, DPI)

MAP: Jindabyne 2627

A multi-agency operation to eradicate a noxious weed from New South Wales has been looking into innovative ways to combat the plant, with helicopters, drones and sniffer dogs all part of the fight.

Hawkweed is an invasive member of the daisy family.

The European weed changes the soil chemistry around it killing native plants and agricultural pasture. It also impacts on native fauna by reducing their habitat, and food supply.

ABC South East

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- Sean Spicer dismisses fury over surprise Emmys appearance
- Flurry of military drills on Korean peninsula in show of force against North
- CBS increases bid for Channel Ten ahead of creditors' meeting
- The Dally M will go ahead, even

There are two infestations of hawkweed in the Kosciusko National Park. Mouse-ear Hawkweed is in the main range and Orange Hawkweed is in the Jagungal wilderness.

There has also been one reported sighting of the weed on a nearby private property.

NSW National Parks and Wildlife Services (NPWS), ACT Parks and NSW Department of Primary Industries (DPI) are working together to control the small infestation before it spreads.

PHOTO: Mouse-ear hawkweed devastating New Zealand High Country. (Supplied: Dr Peter Espie)

The weeds have caused a significant impact in New Zealand where they have become widespread, threatening diversity.

NPWS Senior Weeds Officer Dr Peter Turner said biological control was tested in New Zealand.

"And at this stage it's not looking too promising.

"One of the reasons is because these plants have been grown as garden plants over 400 odd years they've been bred and bred and bred. So biological control is a very difficult option."

Sniffer dogs used to find hidden weeds

But there are other weapons at their disposal, including two specially-trained sniffer dogs, Sally and Connor.

> "They're very cute, they love their tennis balls, that's how they get rewarded. They're doing a great job.

"We need all those tools to actually get the job done," Dr Turner said

The first line of defence are the volunteers and agency workers who do line surveys.

They are assisted by helicopters that drop them in and out of hot spots.

NPWS Weed Management Coordinator Hillary Cherry said the dogs were then sent in, and they often found hidden plants the humans missed.

"We did an assessment last year of the dogs and we found some volunteers found some plants, and our surveyors found some plants and the dogs found some plants. They didn't all find the same plants."

"So there's space for everyone in this and if everyone can contribute hopefully we can get all of them."

VIDEO: Sally the Dog Searches for Noxious Weeds (ABC News)

Special drones pick up things human eyes cannot see

Drones have also been used to detect the weeds and researchers at Macquarie University are looking into how they can be better utilised.

Masters of Research Student Chad Ajamian has been trailing drones to detect more than the visual light — red, yellow, blue — emitted by the weeds.

He wants them to detect non-visible light bands like infrared.

PHOTO: Chad Ajamian collecting sample hyperspectral profiles of native vegetation with a field spectroradiometer in Kosciusko National Park. (Supplied: Chad Ajamian)

"Currently they are using drones in the area and they are focusing on the bright orange colour of the orange hawkweed.

"But with hyperspectral remote sensing using, these other bands, we're hoping that we can target the leaves themselves so we don't have to rely on the plant flowering," Mr Ajamian said.

The use of fire is also being tested in trial plots.

But Ms Cherry said the volunteers were the core of the program.

"We're still at the stage where we have to have our humans but the complementary nature of the dogs, the drones and anything else we can throw at it are certainly going to get us over the top of it," she said.

If you see this plant contact your council weeds officer, the NSW Invasive Plants & Animals Enquiry Line 1800 680 244 or email to weeds@dpi.nsw.gov.au

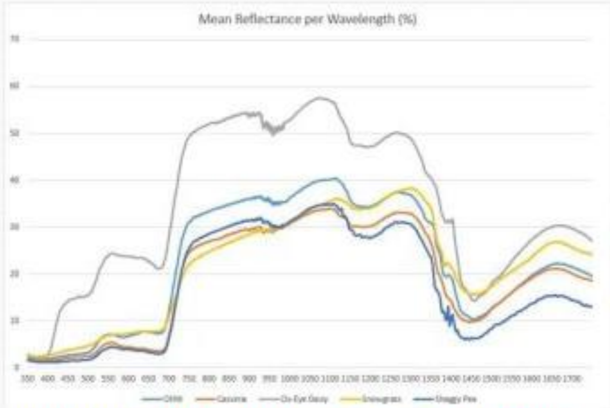

PHOTO: Graph of the spectral profile of weeds with orange hawkweed in light blue
(Supplied: Chad Ajamian, Macquarie University)

Topics: environmental-management, environmental-health, weeds, national-parks, jindabyne-2627, bega-2550

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Appendix 5. ABC Radio National Program

Jones, A. (2017, October 7). Sniffer spaniels get the doggone weeds on Off Track. Off Track. Australia: ABC Radio National. Retrieved from http://www.abc.net.au/radionational/programs/offtrack/weed-sniffing-dogs/8884950

Description: ABC Radio National Program on the importance of this project in conjunction with sniffer dogs and other management methods for orange hawkweed eradication in KNP.