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Use of aerial remote sensing to detect pre-coning wilding conifers in a dry grassland environment

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Abstract

Wilding conifers pose significant threats to New Zealand's native ecosystems and water catchments and also increase the risk and intensity of wildfires. However, the detection and treatment of small, isolated, low-density infestations of pre-coning seedlings remains problematic and expensive. Very high resolution (VHR) imagery presents a potential solution to this, particularly where there is high contrast in spectral values between the target trees and the surrounding background vegetation. Therefore, we investigated whether VHR RGB and four-band multispectral imagery collected from a fixed-wing aircraft could be used to detect small pre-coning conifers within a dry grassland environment in the Mackenzie basin. Approximately 90% of conifer seedlings with a canopy diameter of > 30 cm were successfully detected using the RGB camera, but a higher proportion of these small trees was detected using the multispectral sensor, despite its lower spatial resolution. The construction of a semi-automated detection algorithm that was capable of taking relevant imagery and exporting the spatial coordinates of detected trees greatly improved the efficiency of the process but was also associated with higher errors of omission (false negatives) for larger size classes of trees with the multispectral imagery. Analysis of the associated costs indicated that the use of aerial remote sensing for detecting small trees would result in an approximately 10-fold reduction in treatment costs compared with current best practice control techniques (e.g. random search and destroy missions in helicopters) in similar environments. Therefore, the targeted application of remote sensing methods in conjunction with probabilistic seed spread models and density-dependent treatment regimes, will likely prove useful for managing wilding conifer infestations.

Keywords: multispectral imagery, spatial resolution, spectral resolution, detection, aerial photography, wilding conifer infestation, New Zealand

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1. Introduction

Wilding conifers have become a significant threat to New Zealand ecosystems, now covering more than 1.8 million hectares and continuing to spread at a rate of 5% per year (Howell 2016). Furthermore, these invasive trees are also affecting water availability in sensitive catchments, pose considerable fire risks and are visually changing landscapes (Froude 2011; Dickie et al. 2014). To address this, the New Zealand Government has invested in Phase 1 of the National Wilding Conifer Control Programme (2016–2019) to coordinate efforts by multiple agencies within the highest priority areas and to lay the ground work for a much larger programme (see www.mpi.govt.nz/protection-and-response/long-term-pest-management/wilding-conifers/). Funding for this initial response focused on:

- The species that are most prone to spreading
- Areas with the greatest vulnerability to invasion
- Areas where control is most cost effective
- Managing infestations over large areas
- The protection of farmland, biodiversity, iconic landscapes and sensitive water catchments.

Early detection and rapid response (EDRR) (Westbrooks 2004) are critical for the effective identification and eradication of early infestations of invasive plants (Bradley 2014). However, while the detection of larger wilding conifers across a landscape is relatively straightforward (Sprague et al. 2019), the detection and destruction of small, isolated, low-density conifer seedlings prior to cone production is far more challenging and consequently has become a pressing national issue for landscape management over significant areas. Unfortunately, the current approach of flying helicopters at low levels to locate trees over large areas is expensive, time consuming and fails to consistently locate smaller trees (Raal et al. 2009), resulting in a 2-year rather than a more cost-effective 3-year control cycle usually being required (Burns et al. 2001). In addition, the failure to properly stratify operational areas to allow the efficient selection of control options causes inefficiencies and can lead to wasted resources and under-budgeting for control costs.

Very high resolution (VHR) aerial remote sensing offers a potential solution to the detection of small conifers, particularly in environments where their spectral reflectance contrasts markedly with that of the surrounding background vegetation. Remote sensing has previously been used to detect invasive trees and has also proved capable of detecting individual tree canopies (Wang et al. 2004; Huang & Asner 2009; Ke & Quackenbush 2011; Bradley 2014; Sankey et al. 2016; Lehmann et al. 2017; Spring et al. 2017), and the remote characterisation of invasive plants is increasingly being used to understand their invasion ecology and to formulate a management response (e.g. Ge et al. 2006). (For a brief literature review of studies that have used aerial imagery to detect invasive trees and woody shrubs, see Appendix 1.) Furthermore, even where the detection of an early infestation is not possible or is uncertain, the acquisition of important information can still have a significant impact on EDRR efforts.

Two key attributes of the imagery that must be considered carefully in any study or practical application of remotely sensed data are the spatial and spectral resolution. In a remote sensing dataset, the electromagnetic energy that is reflected back from the Earth's surface is stored as grids of pixels. The spatial resolution of this dataset simply refers to the size of the pixels that are available for examination – the smaller the pixels, the more detail that can be differentiated. For example, VHR imagery (≤ 0.5–5 m) will allow individual houses or trees to be identified (indeed, even small plants can be detected using imagery with a high enough spatial resolution), whereas coarse-resolution imagery (e.g. 500–1000 m) will only show general landscape patterns (Bradley 2014). By contrast, the spectral resolution of a remote sensing dataset is defined by how a particular aerial or satellite sensor records different wavelengths of reflected electromagnetic energy. Each sensor detects and stores different slices of the electromagnetic spectrum as 'bands' of reflectance data – thus, the higher the number of bands, the larger the amount of information available and, therefore, the greater the ability to detect and differentiate surface properties. For example, RGB images only contain information from the red, green and blue portions of the electromagnetic spectrum, whereas multispectral sensors can provide reflectance information from four to eight discrete spectral bands, including parts of the spectrum that are not visible to the human eye, such as near-infrared (NIR) wavelengths, and hyperspectral sensors can have hundreds of very narrow bands, meaning that they come close to measuring the complete spectrum and can resolve species and even leaf chemistry differences (Bradley 2014). Therefore, any decision on which spatial or spectral resolution should be used will depend on the objective of the study, the size of the study area (VHR imagery may be impractical over large areas), the ecological background (i.e. the contrast between what needs to be detected and the background) and the cost of collecting the data (Wegmann et al. 2016).

The spatial and spectral resolutions of commercial satellite imagery have improved markedly over the last decade (Wegmann et al. 2016), and this imagery regularly has global coverage. However, the best commercially available multispectral satellite imagery has a pixel resolution of 'only' 1.3 m, which is still too coarse to detect pre-coning conifer seedlings. Alternatively, unmanned aerial vehicles (UAVs) can provide much more detailed imagery using an increasing variety of VHR sensors, but unfortunately are severely limited (particularly smaller UAVs) by their operational range, operating costs, regulatory restrictions and the difficulties in building extremely large photomosaics for what are often relatively small areas. Consequently, fixed-wing aircraft are a more traditional and flexible platform for collecting high-resolution imagery over moderately sized areas. Furthermore, high-resolution, full-frame digital SLR cameras are now capable of collecting RGB images with a ground resolution of < 5 cm depending on the flight altitude and lens focal length. Therefore, these, coupled with high-resolution multispectral sensors, can theoretically detect very small objects with considerable discrimination – for example, a target species can be detected from > 2000 ft above ground level (agl) where its spatial, spectral, textural, object-based and phenological properties permit its accurate detection. Therefore, remote systems have a high potential as efficient tools for the detection and location of invasive plants at the landscape scale, simultaneously meeting control requirements and allowing stratification of the operational area for planning and budgeting needs.

The aim of the present study was to determine whether aerial remote sensing imagery could be used to detect pre-coning seedling and sapling conifers in a high-contrast dry grassland landscape, with the overall objective of developing a practical detection tool that is suitable for operational deployment. To do this, we collected VHR RGB imagery (3–12 cm) and four-band multispectral imagery (10–40 cm) from a fixed-wing aircraft flying at three heights and compared this with ground-truth data collected in the field. In addition, we examined the costs and benefits of adopting such methods. We then used the findings to suggest improvements to the system and a process for integrating this form of remote sensing into an operational context.

2. Methods

2.1 Study areas

The main study area covered approximately 332 ha of relatively flat terrain between the western base of the Mary Range and Lake Pukaki in the Mackenzie basin (Fig. 1) and was part of the Wolds pastoral lease (DOC 2004). The landscape in this region is characterised by hummocky mounds of glacial debris separated by a network of depressions and troughs that are generally oriented along a north–south axis. At approximately 600 m above sea level (m asl), the climate here is considered cool and windy, with an annual rainfall of 800–1200 mm. The land is largely covered in grazed short tussockland, shrubs and rapidly increasing numbers of exotic plants, particularly pines (*Pinus* spp.) and sweet briar (*Rosa rubiginosa*). The areas of open, short tussockland (predominantly fescue tussock, *Festuca novae-zelandiae*) also contain some exotic pasture grasses and herbs, such as browntop (*Agrostis capillaris*), clover (*Trifolium* spp.) and hawkweed (*Hieracium* spp.), as well as several indigenous species, including cushion plants (*Raoulia* spp.), small daisies and ground orchids. The most abundant shrubs are matagouri (Discaria toumatou) and sweet briar, but tauhinu (*Ozothamnus leptophyllus*), brooms (*Cytisus scoparius* and *Carmichaelia* spp.) and small-leaved coprosmas (*Coprosma* spp.) are also common (DOC 2004). In terms of exotic species, the rapid invasion of conifers into the area in the last 10 years from the areas immediately adjacent to Lake Pukaki is of particular concern (P. Willemse, DOC, pers. comm.), with almost 40 ha of the study area now being estimated to be covered in dense stands of conifers up to 10 m in height. By far the most dominant of these conifers is lodgepole pine (*P. contorta*), which occurs as dense stands in places, while Corsican pine (*P. nigra*), ponderosa pine (*P. ponderosa*), cluster pine (*P. pinaster*) and Douglas fir (*Pseudotsuga menziesii*) are also present as scattered individuals (P. Raal, pers. obs.).

In addition, a second site known as the 'Quailburn' study area was used to test and further refine the initial aerial remote sensing method (Fig. 1). This study area covered 73.7 ha approximately 9 km northwest of Omarama and was part of a developed finishing farm with minimal ecological values that is owned by 'Greenfield' (New Zealand Pastures Ltd) (DOC 2000). The land here covers much of a large isolated hill at an altitude of approximately 500 to almost 900 m asl, and the vegetation consists largely of depleted short tussockland (*F. novae-zelandiae*), exotic pasture grasses and herbs such as browntop, clover and hawkweed, and increasing numbers of wilding conifers. This area formed part of a more extensive block that underwent wilding conifer control (following our surveys) by the Ministry of Primary Industries (MPI) in the Mackenzie basin during the 2017/18 financial year.

2.2 Equipment set-up

Preliminary trials were conducted in 2017 to assess whether suitable VHR RGB imagery for detecting woody weeds and birds could be collected from a fixed-wing aircraft. These trials used a Cessna 180 provided by Canterbury Aviation Ltd (www.canterburyaviation.co.nz) and allowed significant improvements to be made to the set-up by utilising the pre-existing 6-inch-diameter camera aperture in the floor of the aircraft, constructing a vibration-dampened mount for camera attachment to allow the collection of vertical imagery, purchasing a good quality, high-resolution camera and lens combination (Canon EOS 5DS r and Sigma 50-mm Art lens), and investing in flight planning and automated triggering software/hardware/GPS units. It was found that all this equipment could be relatively easily integrated with a four-band high resolution airborne multispectral sensor (HiRAMS) (provided by SpecTerra Services Pty Ltd, WA, Australia; www.specterra.com.au/) once a second aperture had been constructed within the airframe (Civil Aviation Authority approval required) and an additional 12-V power supply had been installed.

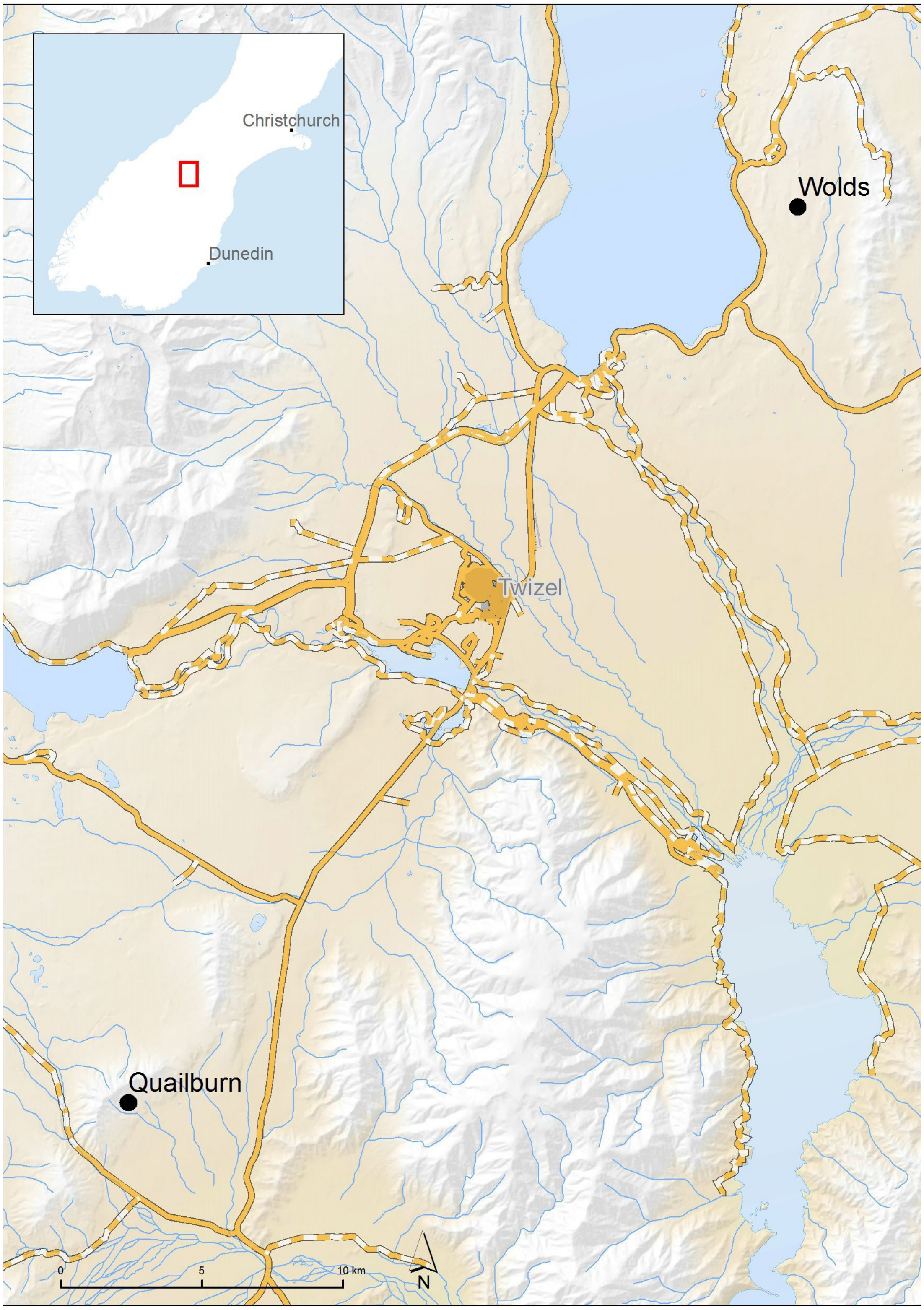

Figure 1. Locations of the Wolds and Quailburn study areas.

The spectral bands that were utilised by the HiRAMS in this trial and future data collection flights were categorised as 'vegetation red-edge' and are listed in Table 1. These significantly improved the spectral resolution of the imagery that was captured by the VHR RGB sensor alone. However, other bandpass combinations are also possible with this instrument. This sensor comprises four interline charge-coupled device (CCD) arrays with a pixel size of 7.4 µm, a corrected frame size of 2000 × 2000 and 14-bit (specified as 16-bit) digitisation with a focal length of 25 mm, and is particularly sensitive to wavelengths that are typically reflected from

Table 1. High resolution airborne multispectral sensor (HiRAMS) band pass configuration.

BAND	BAND DETAILS
1	710 ± 10 nm (red-edge)
2	550 ± 10 nm (green)
3	675 ± 10 nm (red)
4	780 ± 10 nm (near infrared)

plant matter, allowing for increased detection and differentiation of land surface properties in addition to those collected by 'standard' RGB sensors. Furthermore, in addition to the co-registered orthomosaics from the RGB and multispectral imagery, it is possible to derive a plant cell density (PCD) model and vegetation feature height model (VFHM) from the overlapped stereo imagery if required (see Fig. 2 for an example).

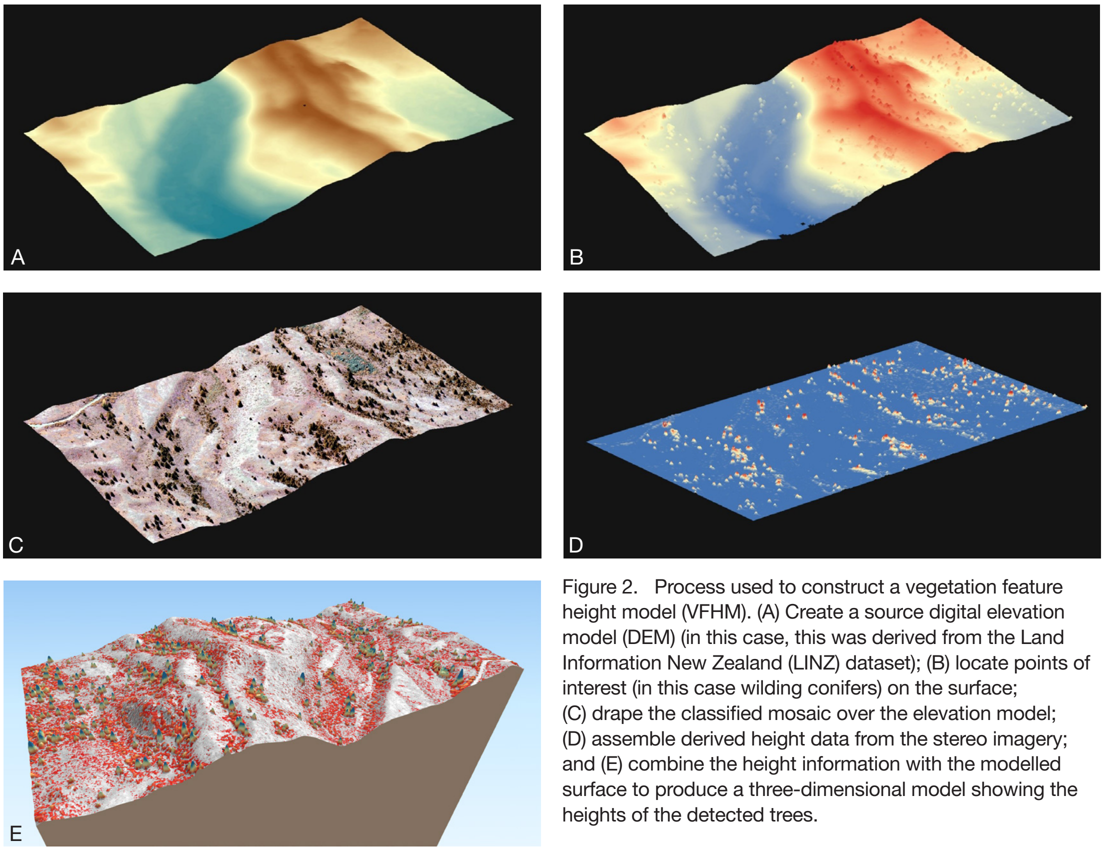

Figure 2. Process used to construct a vegetation feature height model (VFHM). (A) Create a source digital elevation model (DEM) (in this case, this was derived from the Land Information New Zealand (LINZ) dataset); (B) locate points of interest (in this case wilding conifers) on the surface; (C) drape the classified mosaic over the elevation model; (D) assemble derived height data from the stereo imagery; and (E) combine the height information with the modelled surface to produce a three-dimensional model showing the heights of the detected trees.

2.3 Data collection

Prior to flying over the Wolds study area, ground control points (GCPs) and seedling markers were established at six randomly located sites throughout the study area on 16 March 2017 (Fig. 3). GCPs are recognisable points within imagery that have known accurate locations and are used to increase the accuracy of the image's coordinate system in relation to the real world around it (Horning et al. 2012). The GCPs were high-contrast black and white Corflute squares (50 × 60 cm), and one GCP was left at each of the six sites to act as a marker for georeferencing the imagery. In addition, orange Corflute rectangles (40 × 60 cm) were used to mark up to six randomly selected seedlings of various sizes at each of the six sites (total n = 33 marked trees). These markers were placed approximately 1.5 m due south of each seedling to avoid any potential for 'pixel pollution' in the imagery (i.e. the colour from the marker boards influencing the pixel colour of the target trees). The GCPs and markers were weighed down with rocks to prevent them from being blown away and their locations were recorded using a Garmin 64 handheld GPS unit. The location of each marked seedling in each of the six sites was also recorded using the GPS unit, along with their respective heights, maximum 'crown' diameters, species identities, the slopes on which they were growing and the degrees of crowding by surrounding vegetation. Any seedlings that were growing in the deep shadow of larger trees were ignored. Where possible,

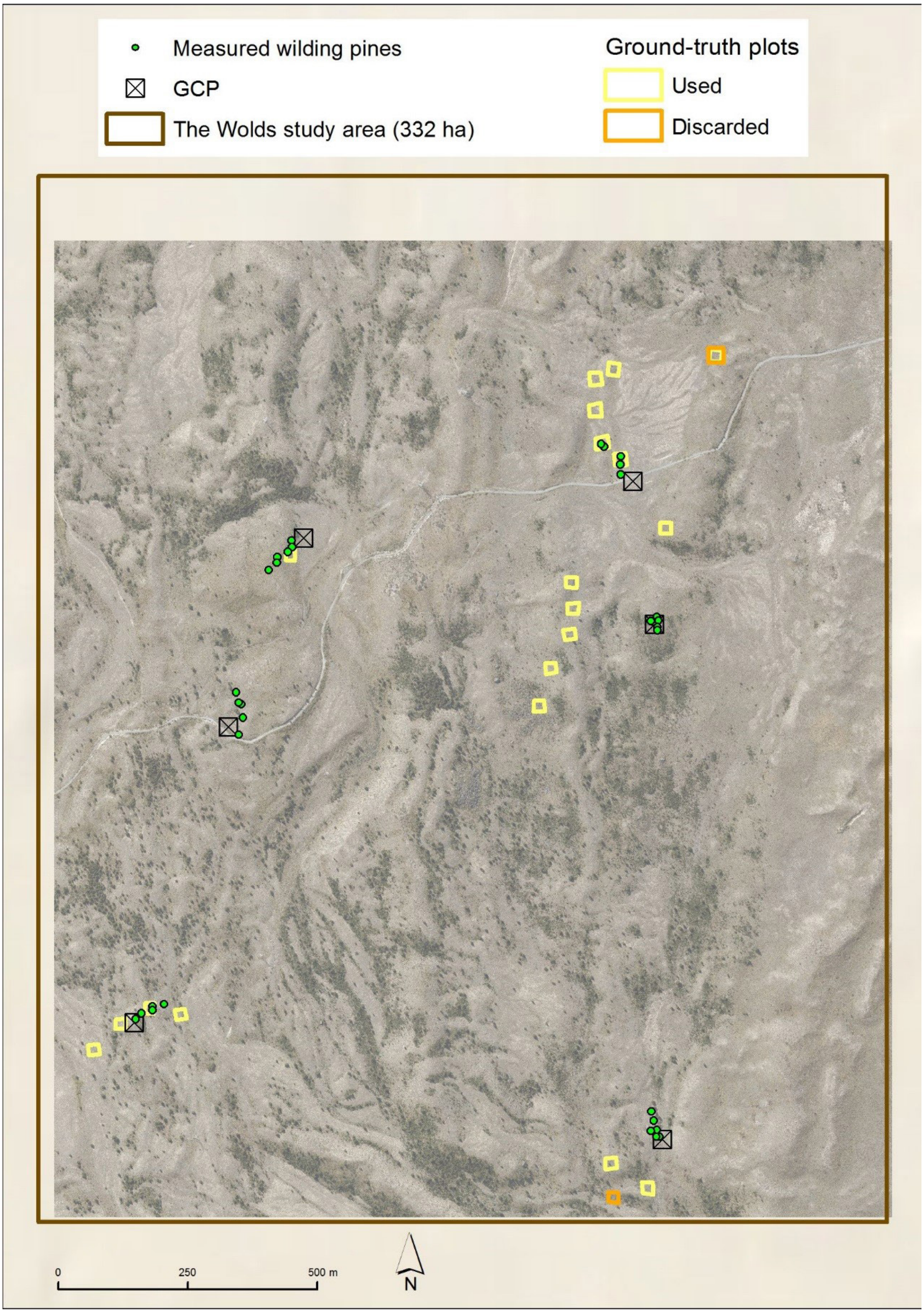

Figure 3. Locations of the ground control points (GCPs), 20 x 20 m plots and trees used for ground-truthing measurements in the Wolds study area.

the locations of individual trees of species other than the dominant lodgepole pine (e.g. Douglas fir, Corsican pine and ponderosa pine) were also recorded in the hope that they might be able to assist with the identification of conifers to species level.

Once the equipment had been installed in the aircraft, predetermined flight plans for designated altitudes, camera/lens combinations, and forward and side image overlap were imported into the GPS-integrated triggering electronics (Flight Planner Pro software and Aviatrix hardware;

www.aeroscientific.com.au). Three flight heights were selected for this trial: 1100, 2200 and 4400 ft agl. The expected mosaic accuracy was ± 5 m (from ground control). The expected spatial resolutions at each of these heights for RGB and multispectral images are provided in Table 2.

Flying and image collection were conducted on 17 March 2017, commencing at around 12:00 pm to minimise sun angles. On this date, the pilot flew to the designated area and followed the predetermined flight paths, during which time the two cameras were automatically triggered simultaneously at specific locations and the images were saved to memory (SD/CF cards for the RGB sensor or HD for the HiRAMS). The area was flown over in approximately 2 hours under a cloudless and sunny sky. An increasing northwesterly wind made the maintenance of consistent headings increasingly difficult towards the end of the flight, but this did not appear to have a significant impact on the accuracy of the resulting orthomosaics (see Figs 4 & 5).

Table 2. Expected spatial resolutions of the two sensors at each of the three flight heights.

CAMERA	FLIGHT HEIGHT (FEET ABOVE GROUND LEVEL)		
	1100	2200	4400
Canon 5DS r (50 mm)	3.0 cm	6.0 cm	12.0 cm
High resolution airborne multispectral sensor (HiRAMS)	10.0 cm	20.0 cm	40.0 cm

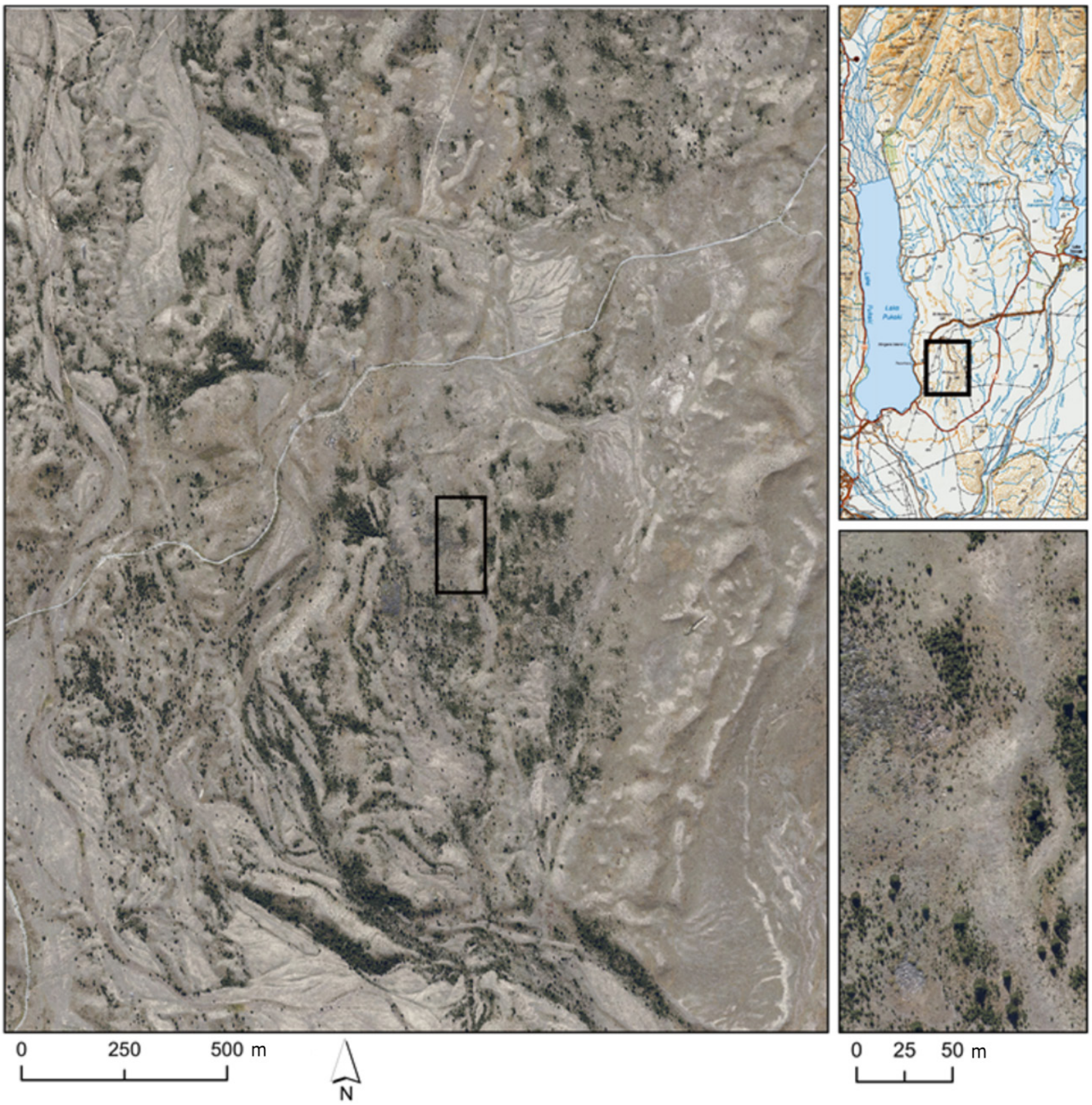

Figure 4. Very high resolution RGB image of the Wolds study area and a magnified subsection.

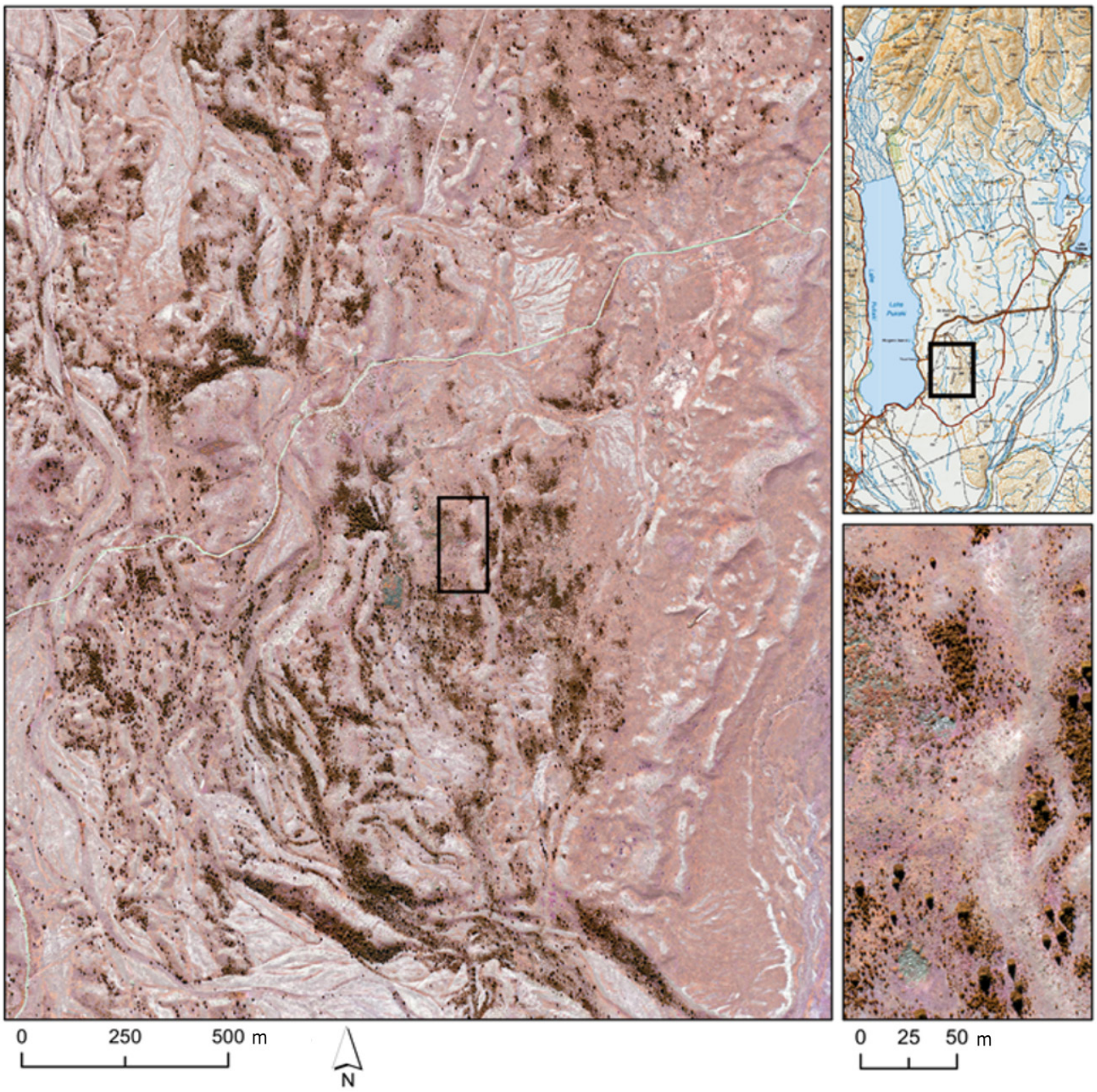

Figure 5. High resolution airborne multispectral sensor (HiRAMS) four-band (near infrared (NIR), red, red-edge) image of the Wolds study area and a magnified subsection.

Since the indicative results from the above trial were promising, a more rigorous ground-truthing exercise with a much larger sample size was conducted within the core study area on 10–11 May 2017. Twenty 20 × 20 m plots were distributed throughout the imaged area in areas of moderate to low seedling density and on a variety of slopes and aspects (Fig. 3). The corners of each plot and all the conifers that occurred within each plot were recorded using a Trimble Catalyst GNSS receiver, which had a spatial accuracy of 1–2 m in the field. In addition, the species identity, height (cm), maximum crown diameter (cm), status (alive/dead), level of shade (deep shade or not) and degree to which the canopy was crowded by other vegetation were recorded for each conifer within each plot irrespective of tree size. This resulted in a further 407 trees being located and measured within the 20 field plots. However, one of the plots was found to have a very high seedling density and high levels of GPS precision error and so was subsequently removed from the analysis. The remaining 380 trees from 19 plots were then used for the accuracy assessment, 61% of which had a canopy diameter of < 50 cm.

2.4 Data processing, model building and data analysis

2.4.1 Image processing, classification and accuracy assessment

SpecTerra Services Pty Ltd (Perth, Australia) was contracted to construct a comprehensive data package of co-registered RGB (Fig. 4) and four-band multispectral (Fig. 5) orthomosaics for all three flight heights and ground resolutions, which were used for all further analyses. In addition, an associated three-dimensional (3D) VFHM for the main study area that was derived from the imagery collected at 2200 ft agl was also requested.

The collected imagery was first classified using the initial small sample set of ground-truth data and user-defined regions of interest (ROIs). Common pixel values were used to identify all of the conifers within the Wolds study area using the ENVI image interpretation software (ENVI v.5.2.1; Exelis Visual Information Solutions Inc., Broomfield, Colorado, USA). A maximum likelihood (ML) algorithm was initially used but subsequently abandoned in favour of a more robust neural network (NN) machine learning algorithm, as this did not require a priori assumptions of the statistical distribution of pixels within the feature space and also provided a supervised thematic classification of the study area. Once an accurate classification (i.e. there was strong separation of pixels classified as conifers from non-conifer pixels using the spectral profile plots computed in ENVI) had been obtained for all three flight heights, the detection/non-detection of seedling and sapling conifers was assessed manually by directly overlaying the known locations of trees and the plot corners with the classified imagery (i.e. pixels that were defined as conifers) within either the ENVI or ArcGIS software. The initial small sample size of marked trees was then increased substantially by using the plot data collected in May 2017. Detection/non-detection was primarily assessed according to the flight height (i.e. the spatial resolution) and the canopy diameter, with the latter being grouped into six size classes (0–9 cm, 10–20 cm, 21–30 cm, 31–40 cm, 41–50 cm and 50+ cm). The number of trees within each canopy size class is shown in Fig. 6.

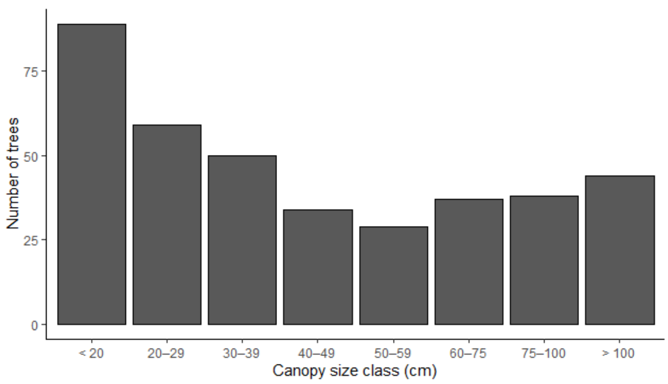

Figure 6. Number of trees per canopy size class in the 19 study plots included in this analysis.

2.4.2 Automated classification and accuracy assessment

The manual detection of individual trees from imagery covering large geographic areas is unlikely to be efficient or sustainable. Therefore, a literature review was undertaken (Appendix 1) to assess a range of potential classifiers and their likely applicability for the effective detection of wilding conifers in general and within different size classes. An 'automated' detection algorithm using the most appropriate classifier was then constructed using the R statistical software (R Development Core Team 2017).

Imagery that was collected at 2200 ft agl was determined to be at the optimal resolution in the manual classification outlined in section 2.4.1. Therefore, to reduce costs and increase the processing efficiency while maximising the likely detectability of small trees, only data from the VHR RGB and four-band multispectral imagery that was collected at 2200 ft agl were used in this analysis, alongside data on the tree sizes and locations collected from the nineteen 20 × 20 m plots (see above). These data were imported into ArcGIS and the imagery for each plot was then clipped from the full-site imagery, resulting in 19 TIF files of plots for each of the RGB and multispectral datasets. In addition, the locations of all marked trees within each plot were mapped. Sets of identified tree pixels and non-tree pixels were then extracted from each plot and withheld for use as training data for the image classification algorithm (Fig. 7).

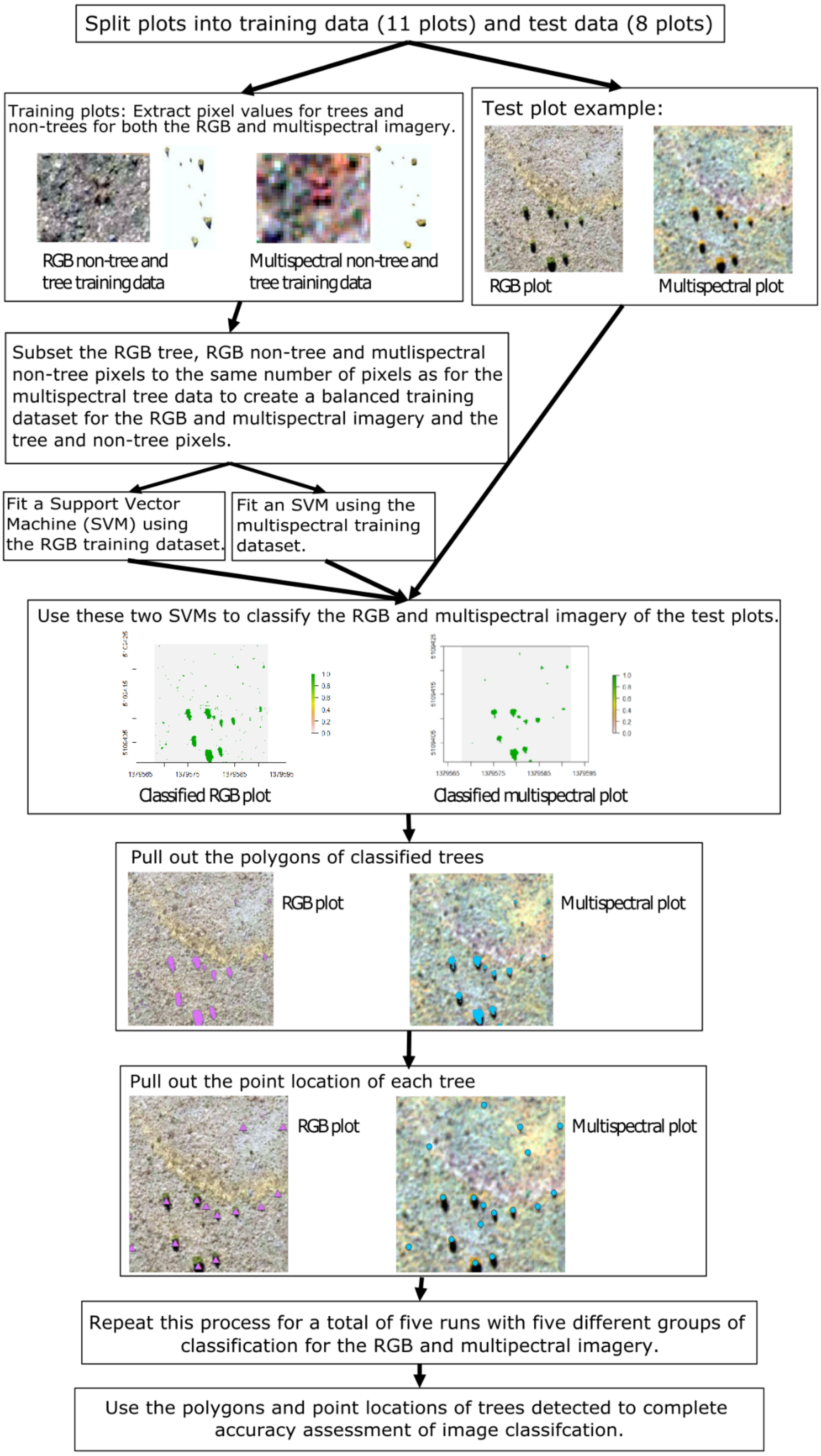

Figure 7. Generalised methodological workflow for image classification using support vector machine (SVM) models.

Following the testing of several classification algorithms (see Table 3 and Appendix 1), a support vector machine (SVM) image classification method was selected and run using the 'e1071' and 'raster' packages in the R statistical software. This method uses 'machine learning' (Blaschke 2010) to train an SVM model to distinguish between different defined classes within images and has proven particularly effective for identifying trees that are expanding into adjacent shrubland and grassland (Weisberg et al. 2007). For this analysis, only two classes needed to be defined: trees (wilding conifers) and non-trees. The image classification procedure was pixel-based and supervised meaning that the SVM algorithm assessed each pixel and determined whether it was a tree or not using the set of training pixels.

Table 3. Success of the various imagery classification methods that were trialled.

CLASSIFICATION METHOD	TYPE	SUCCESSFUL?
Thresholding and watershedding	Pixel-based, unsupervised	Yes
Support vector machines	Pixel-based, supervised	Yes
Convoluted neural networks	Object-based, supervised	No
Random forest	Pixel-based, supervised	Yes
Fuzzy segmentation	Image segmentation	No
Image smoothing	Pixel-based	Yes, but file formats not compatible

In total, 60% of the plots (n = 11) were used to train the model, while the remaining 40% (n = 8) were used to assess the accuracy of the image classification. Since there were significantly fewer pixels for the multispectral imagery than for the VHR RGB imagery (due to the relative size of the pixels; Table 2) and for the tree pixels than for the non-tree pixels (trees were less common than the background vegetation), the same numbers of pixels were used for the training data from the RGB and multispectral datasets to eliminate potential bias for both trees and non-trees. The respective RGB and multispectral SVMs were then used to classify the imagery of the test plots. Any trees that were detected in the classified imagery were converted into polygons and the centroid of each tree polygon was extracted. Both the tree polygons and the centroid point locations of the trees (as NZTM coordinates) were then exported for the RGB and multispectral datasets.

This entire process was repeated four more times using randomly selected training and test plots and resampled from the same pool of data (using a 'jack knife' procedure) to improve the variance estimates for the SVMs (see Fig. 7 for an illustration of the general workflow). The resultant locations of trees (as defined within the shapefiles and point location files) from each run of the process were then compared with the locations of trees that had been detected within the same plots by the SVMs in ArcGIS using a similar process to that for manual classification and accuracy assessment (see section 2.4.1). The success (or otherwise) of tree detection was summarised for each of the size classes separately and cumulatively for both the RGB and multispectral datasets and for each of the five classification runs.

Finally, the errors of omission (false negatives) and commission (false positives) (Horning et al. 2012) were calculated by determining the number of trees that were not detected and the number of 'objects' or pixel groups that were misidentified as trees, respectively. These errors were calculated using the following formulae (Congalton 1991):

2.4.3 Application to Quailburn

The SVM classification algorithm was also tested in a hilly area close to the old Quailburn Station (Fig. 1), which was scheduled for conifer control by MPI in March 2018. VHR RGB (Fig. 8) and multispectral (Fig. 9) imagery was collected using the same flight and image capture specifications as were used in the Wolds study area (i.e. imagery was captured at 2200 ft agl in 2017; see section 2.2 and Table 2).

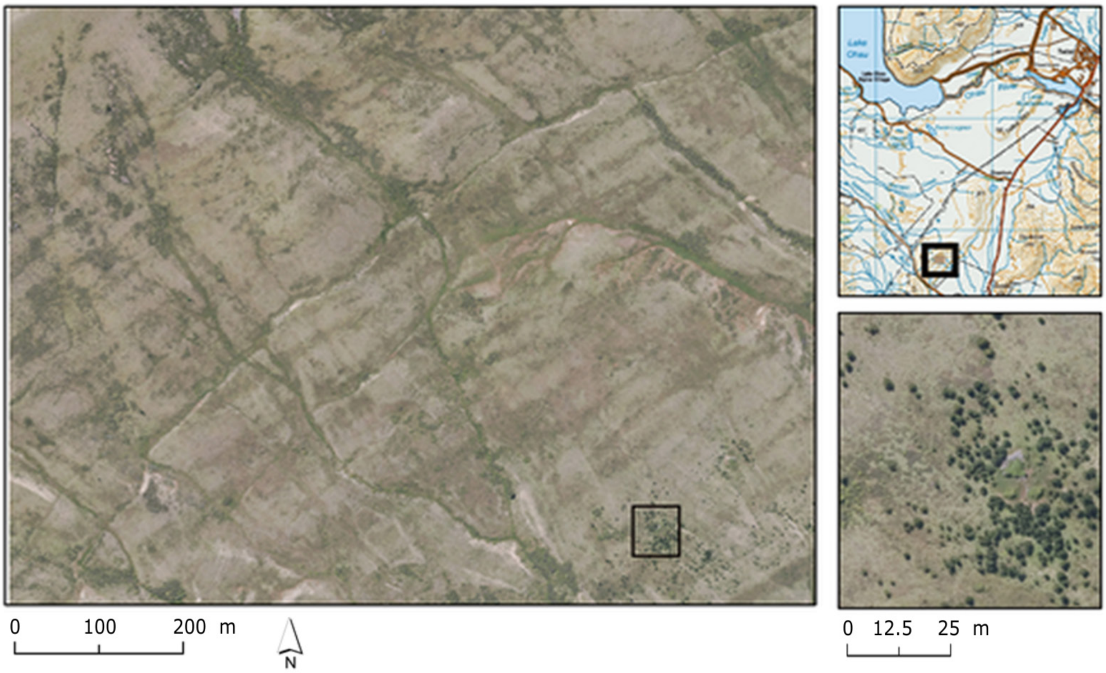

Figure 8. Very high resolution RGB image of the Quailburn study area and a magnified subsection.

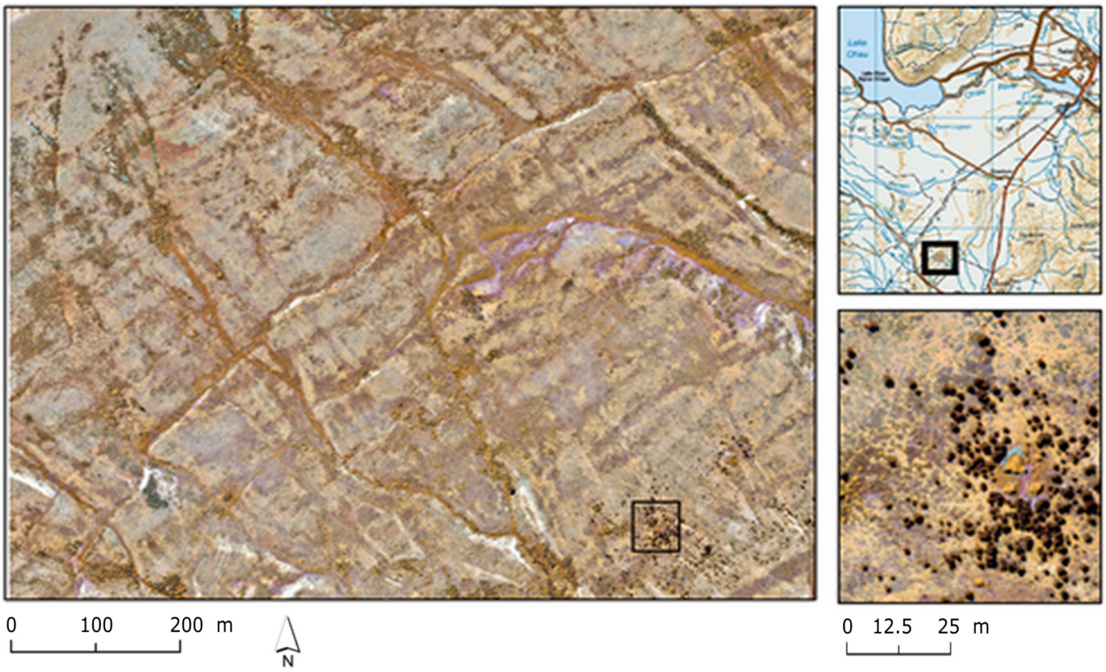

Figure 9. High resolution airbourne multispectral sensor (HiRAMS) four-band (near infrared (NIR), red, red-edge) image of the Quailburn study area and a magnified subsection.

In this instance, it was not possible to undertake ground-truthing fieldwork to train the SVM algorithm, as operators were killing trees as soon as they were located (see below). Therefore, the detection algorithm that had been trained using the Wolds imagery data was initially used instead. However, this algorithm produced a high degree of pixel pollution and resulted in numerous misclassifications. Therefore, subsets of the Quailburn imagery from areas in which we were either confident that no conifer trees were present or knew that conifer trees were present were used to train a new SVM detection algorithm. This was undertaken for both the RGB and multispectral imagery, using the same large training areas (relative to those used for the Wolds imagery) for both imagery types. The SVM detection algorithm was trained and run using the same methods as for the Wolds data (see section 2.4.2). For the purposes of this test, only a subset of the Quailburn imagery was classified due to the large area that was covered and the long processing time that would have been required.

Following the collection of the imagery, a conifer control operation was carried out over the entire block. Using a Garmin 64 handheld GPS unit, the operators recorded the location of every tree that was treated. These data were then used as an independent sample to assess the accuracy of the image classification by comparing what had been classified as a conifer with trees that had been identified and controlled on the ground. While a formal assessment of the image classification was not conducted in this instance because we were unable to confirm whether the GPS locations represented all of the conifer trees in the area (it appeared that the contractors had simply GPS tagged a single point for each cluster of trees) and the contractors did not measure the diameter of the trees they controlled, the GPS points provided a rough approximation of the performance of the image classification procedure.

2.5 Cost assessment

The costs associated with collecting VHR RGB and multispectral imagery (i.e. aircraft deployment and imagery processing) are significant, so it is worth examining and comparing these with current operational expenditure (e.g. for helicopter-based search and destroy missions) and examining how this expenditure might change if the remote sensing methods described here are adopted in the future. Therefore, the costs associated with both current control methods and the remote sensing methods developed here were defined as at 2017/18, with the aim of providing additional information and context for land managers.

3. Results

Manual assessment and classification of the orthomosaics that were constructed from the VHR RGB and multispectral imagery (see section 2.4.1) was superseded by the custom-built classification algorithm (see section 2.4.2). Since the two approaches gave very similar results, we only report on those from the automated algorithm that was applied to the 2200-ft orthomosaic in conjunction with the manual assessment of the detection accuracy using tree location data from the 19 plots.

3.1 Classification of the Wolds study area

Classification of both the RGB and multispectral imagery was relatively straightforward due to the high level of contrast in pixel values between the conifers and the remaining background vegetation types (Fig. 10). Image classification computed a wilding conifer coverage of 38.2 ha across the 332-ha Wolds study area (i.e. 11.5% of the total area). Tree density was highly variable across the study area, with most trees, particularly larger individuals and/or stands, being concentrated within the wetter bases of gullies or shallow drainages (Fig. 5). Most of the conifers that were detected in the Wolds study area were lodgepole pines. Although other species were present, we were unable to find sufficient of these to attempt to classify conifers by species with any confidence. However, preliminary results did suggest that it would be possible to separate Douglas fir from other conifers using multispectral imagery providing that sufficient samples of suitable pixels could be found and used to train the classifier.

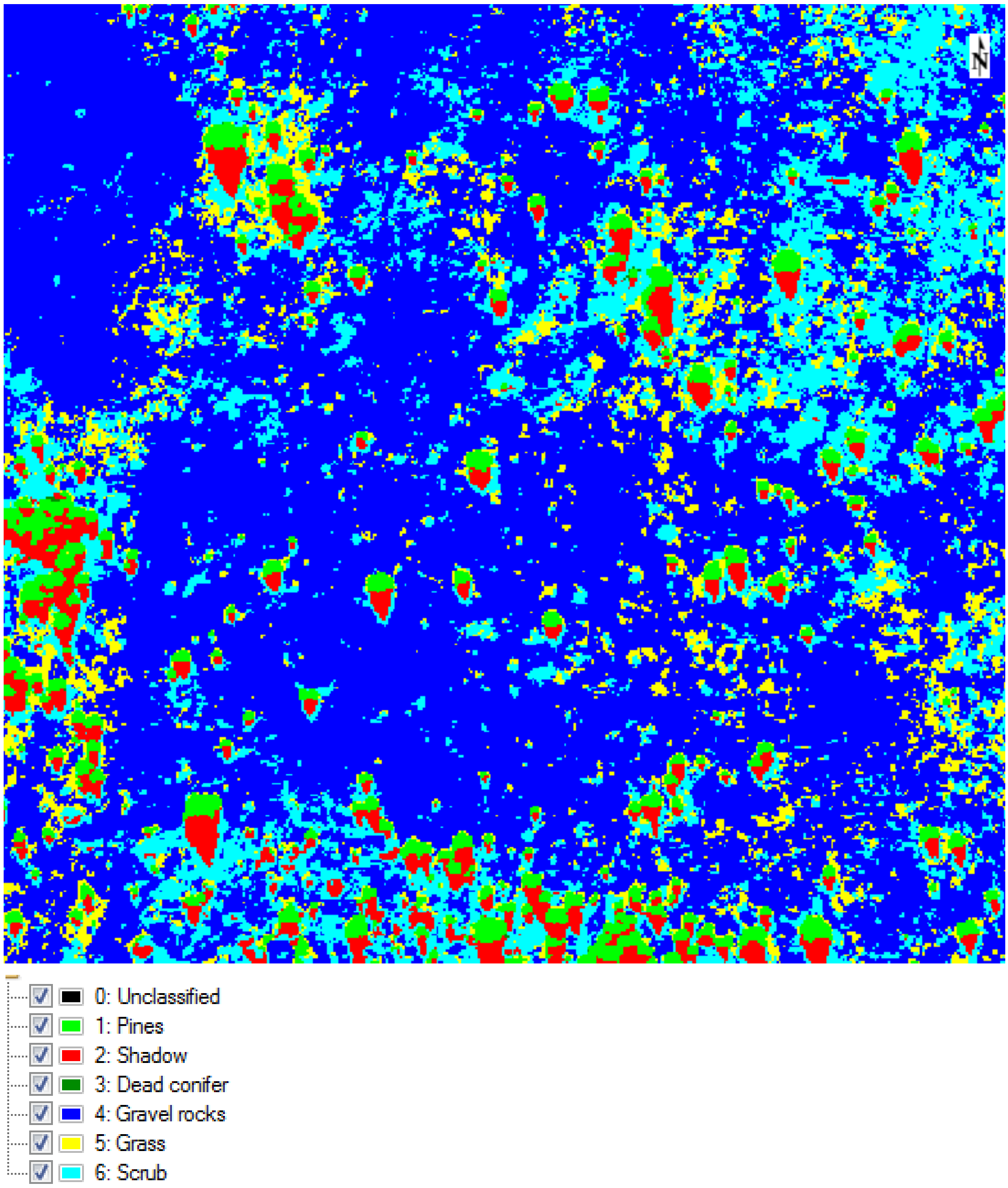

Figure 10. Example of the imagery from the Wolds study area that was classified using neural networks within ENVI.

3.2 Detection of size classes

In the Wolds study area, a higher percentage of trees in the 20–29 cm, 30–39 cm and 40–49 cm canopy size classes were detected in the multispectral imagery than the RGB imagery, whereas the reverse was true for trees in the 50–59 cm, 60–69 cm and 70–79 cm size classes (Fig. 11A). The greatest difference in the detectability of trees between the RGB and multispectral imagery occurred in the 30–39 cm size class, where approximately 90% of the trees were detected with the multispectral imagery compared with only around 65% with the RGB imagery. However, despite these discrepancies, the cumulative detection rates for trees were very high overall for both sets of imagery, with 95–100% of trees with crown diameters of >40 cm being detected (Fig. 11B).

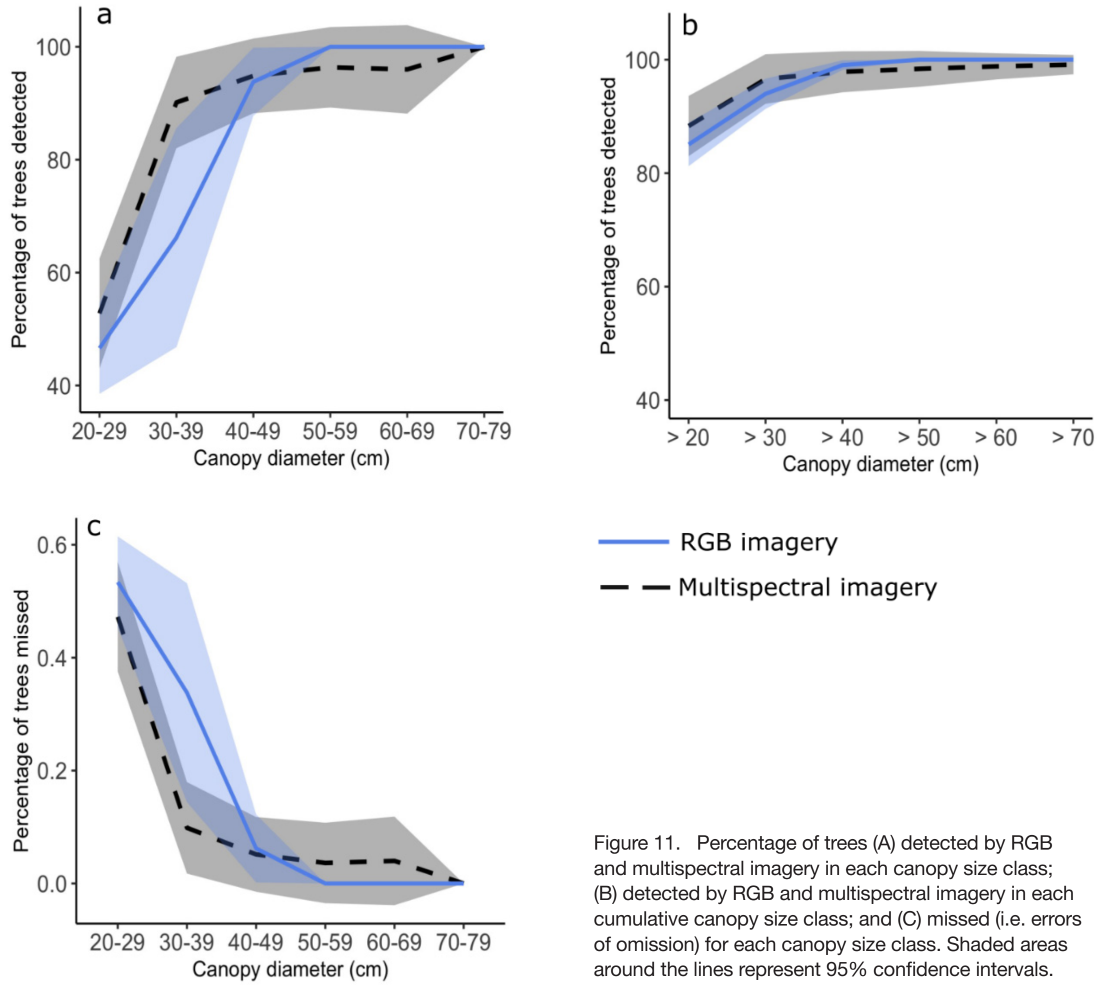

Figure 11. Percentage of trees (A) detected by RGB and multispectral imagery in each canopy size class; (B) detected by RGB and multispectral imagery in each cumulative canopy size class; and (C) missed (i.e. errors of omission) for each canopy size class. Shaded areas around the lines represent 95% confidence intervals.

3.3 Accuracy and errors

The multispectral imagery was associated with lower errors of commission (classification of pixels as trees when they were something else) but higher errors of omission (incorrectly classifying tree pixels as something else) than the RGB imagery (Table 4). Further analysis of the errors of omission by canopy size classes clearly showed that there was a much greater likelihood that RGB imagery would miss more trees in the 20–29 cm, 30–39 cm and 40–49 cm size classes than the multispectral imagery (Fig. 11C).

3.4 Testing the method in the Quailburn study area

There appeared to be a high degree of overlap between the GPS locations of wilding conifers provided by contractors undertaking ground control work and the classified multispectral imagery from the Quailburn study area (Fig. 12A). However, there were a number of areas where either contractors had missed trees (or not tagged every tree, particularly in higher density areas), pixels had been classified incorrectly (false positives) or there were spatial inaccuracies between the GPS locations and the orthomosaic. This apparent offset can be seen in Fig. 12B & C, where a significant number of the GPS points (dark blue) appear to be offset from the light blue conifers that were classified from the multispectral imagery. It is also useful to note the substantial areas of vegetation that were misclassified as conifers when the SVM algorithm was applied to the RGB imagery and to a lesser extent the multispectral imagery (lower left). These areas may represent false positives and artefacts of the classification process or may have simply been missed or not recorded by the contractors, particularly in areas of denser vegetation.

Table 4. Errors of commission and omission for the RGB and multispectral imagery. Values are means ± 95% confidence intervals for the five iterations.

	RGB (natural colour) imagery	Multispectral imagery
Errors of commission (false positives)	27% ± 4%	17% ± 10%
Errors of omission (false negatives)	16% ± 7%	23% ± 7%

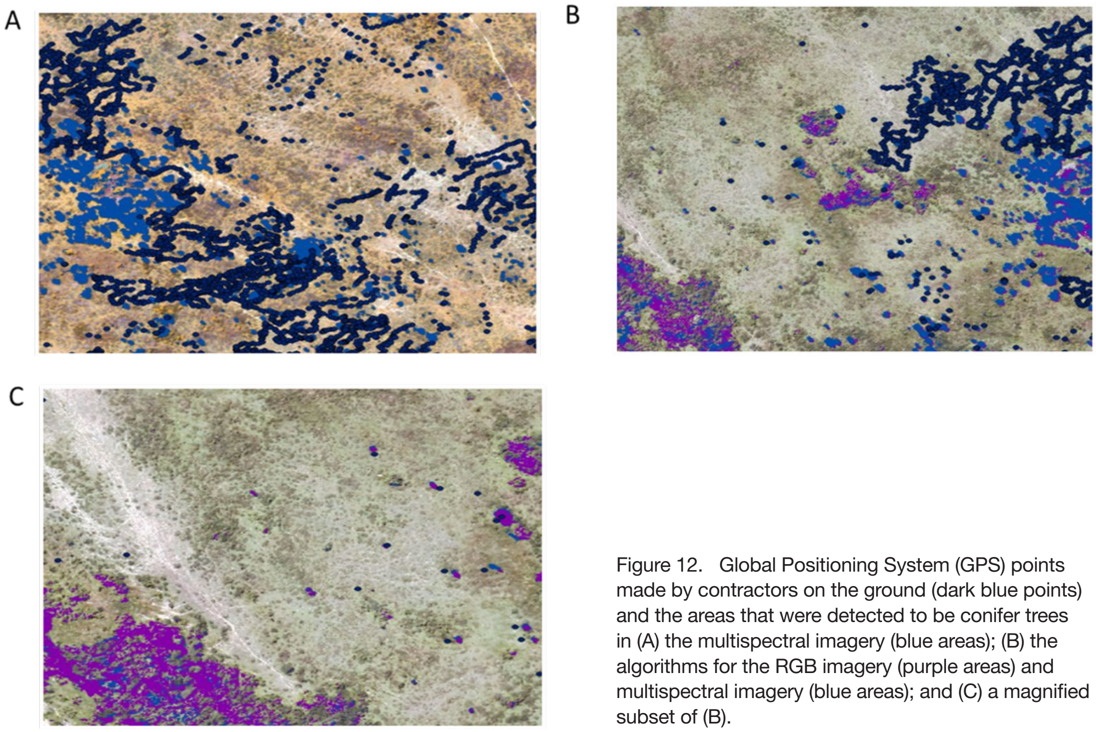

Figure 12. Global Positioning System (GPS) points made by contractors on the ground (dark blue points) and the areas that were detected to be conifer trees in (A) the multispectral imagery (blue areas); (B) the algorithms for the RGB imagery (purple areas) and multispectral imagery (blue areas); and (C) a magnified subset of (B).

3.5 Cost assessment

Although many of the establishment costs can be considered 'one-off', they were significant (Table 5) and so need to be considered, particularly if the current set-up is to be replicated. In comparison, the operational costs were relatively minor (Table 5), being dominated by the cost of hiring the aircraft (suitably modified) for the period required to cover the area of interest, hiring a pilot trained in operating the equipment, and any costs associated with setting up the aircraft and equipment. The most significant costs were associated with processing the captured RGB and multispectral imagery and the derivation of additional imaging products from these. The schedule of costs as at October 2018 for three levels of ground resolution and at rates per hectare depending on the size of the area being covered is outlined in Table 6. Higher costs per hectare reflect the increased ground resolution (i.e. smaller pixel size) required, the smaller size of the area covered in each frame, and the larger number of derived models and indices. For example, the image processing cost is in the order of $7.70/ha for areas < 2500 ha where imagery is collected at the highest RGB and multispectral resolution (20–30 cm) at 2200 ft agl with the addition of derived indices and vegetation feature height models. However, this cost decreases dramatically (i.e. to $1.87–$2.20) as the multispectral ground resolution decreases to 55–70 cm and the coverage area increases to > 10 000 ha.

To put these costs into some sort of context, we also attempted to estimate the current operational costs for 'search and destroy' missions in an open grassland environment and to compare these with the predicted cost once our recommended remote sensing approach is added

Table 5. Establishment costs for the equipment, software and aircraft fit-out required to develop a fit-for-purpose image collection system, and operational costs for the flight and annual software lease.

DESCRIPTION	COST (NZ$)
Establishment costs*	
Aircraft fit-out (installation of a second sensor aperture)	$5000
Very high resolution RGB camera (Canon 5DS r)	$5790
50-mm Sigma lens	$1549
Canon Camera Global Positioning System (GPS) device	$379
CF and SD cards	$1000
External camera power adapter	$239
Basic camera mount	$1000
Gyro camera mount	$10,000
System laptop	$1830
Pilot screen (MS Surface)	$976
Screen mount	$186
12-V rechargeable power pack	$612
External hard drives	$600
Flight planning, flight control and after-flight data manipulation software	$10,300
Software training and installation	$1100
Sundry cables and other fittings	$300
Software development (automated processing algorithm)	$10,000
Total	**$50,861**
Operational costs†	
Aircraft platform (Cessna 180 fixed-wing aircraft and pilot; Canterbury Aviation)	$775/hour
Aircraft/equipment set up, image transfer and storage, etc.	$80/hour (dependent on imaging requirements)
Annual software license fees (flight planning, control and image labelling)	$1000/year

* Note: This does not include the costs of developing an operations-ready tool that is capable of utilising the analytical output.

† Costs assessed for an area of < 2500 ha.

for the various categories of tree densities (Table 7). This showed that for scattered and sparse infestations of wilding conifers, the addition of remote sensing methods to direct helicopter-based control operations (in conjunction with good seed-spread models) may confer significant cost savings (i.e. up to ten times less than current operational costs). However, as stem density increases beyond 20 stems/ha, control measures other than helicopter-based spraying operations become less economically viable or necessary because infestations become more visible in other more readily available imagery, such as Land Information New Zealand (LINZ) aerial photographs or satellite imagery.

Table 6. Cost of capturing and processing the very high resolution RGB imagery, four-band high resolution airborne multispectral sensor (HiRAMS) imagery, vegetation feature height model (VFHM) and additional indices by ground resolution and area of spatial coverage. Prices are in NZ$ and are accurate as at October 2018.

PROCESSING COST 2018–2019*	RATE REDUCTION (%)	VERY HIGH RESOLUTION RGB ($/ha)	HiRAMS (CO-REGISTERED) ($/ha)	VFHM ($/ha)	PCD†/ NDVI‡/ OTHER INDICES ($/ha)	TOTAL RGB-HiRAMS-PCD ($/ha)	TOTAL RGB-HiRAMS-PCD-VFHM ($/ha)
20–30 cm HiRAMS§ (price per ha)							
First 2500 ha	–	$2.60	$2.70	$2.20	$0.20	**$5.50**	**$7.70**
Next 2500 ha	5.00%	$2.47	$2.57	$2.09	$0.19	**$5.23**	**$7.32**
Next 5000 ha	10.00%	$2.34	$2.43	$1.98	$0.18	**$4.95**	**$6.93**
All over 10,000 ha	15.00%	$2.21	$2.30	$1.87	$0.17	**$4.68**	**$6.55**
35–50 cm HiRAMS§ (price per ha)							
First 2500 ha	–	$2.05	$2.00	$2.10	$0.20	**$4.25**	**$6.35**
Next 2500 ha	5.00%	$1.95	$1.90	$2.00	$0.19	**$4.04**	**$6.04**
Next 5000 ha	10.00%	$1.85	$1.80	$1.89	$0.18	**$3.83**	**$5.72**
All over 10,000 ha	15.00%	$1.74	$1.70	$1.79	$0.17	**$3.61**	**$5.40**
55–70 cm HiRAMS§ (price per ha)							
First 2500 ha	–	$0.90	$1.10	N/A	$0.20	**$2.20**	
Next 2500 ha	5.00%	$0.86	$1.05	N/A	$0.19	**$2.10**	
Next 5000 ha	10.00%	$0.81	$0.99	N/A	$0.18	**$1.98**	
All over 10,000 ha	15.00%	$0.77	$0.94	N/A	$0.17	**$1.88**	

* Note: The processing costs do not include flight costs and there was a $240 processing start-up fee per contiguous survey area.

† Plant cell density model – there is an extra charge for additional indices.

‡ Normalised difference vegetation index.

§ Refers to the required ground resolution (i.e. pixel size).

Table 7. Current operational costs for the detection and control of wilding conifers and the anticipated savings expected with the addition of remote sensing methods.

CLASS	STEM DENSITY	CURRENT OPERATIONAL COST (NZ$/ha)	ESTIMATED OPERATIONAL COST WITH REMOTE SENSING* (NZ$/ha)
Scattered	<1 stem/ha	$10	$1
Sparse	1–20 stems/ha	$100	$10
Medium	20–400 stems/ha	$600 ($900 if repeats required)	$600 (only if use of ground crews unsuitable and helicopter is the only option)
Dense	>400 stems/ha	$2200	Boom sprayed

* Remote sensing using a very high resolution RGB camera and a high resolution airborne multispectral sensor (HiRAMS) deployed at 2200 ft above ground level at a baseline cost of $5.50/ha.

Table 8. Resources required to develop the three geographic information system (GIS)-based data capture options.

OPTION	TIME AND EFFORT NEEDED FOR DEVELOPMENT	GIS STAFF INVOLVEMENT
Option 1: Manual	**N/A** – can be implemented straight away	**High** – highly dependent on the involvement/ availability of a GIS staff member to create and map gpx points or density polygons
Option 2: Online web maps	**Medium** – need to investigate which web tool is most suitable	**Medium** – required initially when the data are transferred from the R model into the online mapping system; some GIS/user intervention is also likely to be required to check the quality of any updates to existing data
Option 3: Customised stand-alone system	**High** – collaboration needed between engineering/technology technique development and GIS	**Medium** – some GIS/user intervention is likely to be required to check the quality of any updates to existing data; the system may also require ongoing maintenance/updates

4. Discussion

4.1 Accuracy of the remote sensing methods

The remote sensing methods outlined in this report could reliably detect approximately 90% of the pre-coning wilding conifer seedlings with a crown diameter of >30 cm in the Wolds study area at a flight height of 2200 ft agl. This result is very encouraging, as large numbers of small seedlings and saplings are often missed during current aerial search and destroy operations. This increased detection ability means that areas that are surveyed and treated using remote sensing data may only need to be revisited on a 3-year cycle, at most, compared with the current 2-year cycle that is used, indicating that this approach has considerable potential for reducing both the return rates and the costs of control (Raal et al. 2009). However, it should be noted that these results are only applicable to the specific environments, flight parameters and sensors that were trialled in this study. Thus, changes in the composition and structure of the background vegetation (particularly the contrast in reflectance between the background vegetation and conifers), the topography (i.e. the slope, aspect and resultant hill shade anomalies) and the desired ground resolution will likely result in further trials or changes to the training of the classification algorithms being required, as highlighted by the need to retrain the classification algorithm that was constructed using data from the Wolds study area to provide a classification that was better suited to the Quailburn study area, despite the relative proximity of the two sites and similarities in the vegetation cover (although the vegetation was more depleted at the latter site).

We also found that the RGB and HiRAMS sensors had similar classification accuracies for seedling conifers with canopy diameters of >40 cm, indicating that processing costs could be reduced by using RGB imagery alone (see Table 6). However, the inclusion of an NIR band within the multispectral imagery greatly assisted in the differentiation of species, as well as the accurate detection of smaller pre-coning seedlings, indicating that the use of RGB imagery would greatly impair the detection of smaller seedlings and increase the likelihood of false positives, as clearly indicated by the overestimation of areas covered by conifer trees in the Quailburn study area using RGB imagery. However, work that is currently underway suggests that the use of RGB imagery in conjunction with much larger training sets (i.e. imagery obtained from a 15 000-ha block at Molesworth Station) and more complex AI-based classifiers is likely to return similar accuracies to the multispectral imagery used in the current study (K. Joy, Orbica, pers. comm.). Further improvements are also likely as the geographic spread of trial sites increases and the variability in image illumination is better controlled.

Although it was relatively easy to distinguish conifers as a group from the surrounding vegetation using the remote sensing methods developed in this study, it was much more difficult to distinguish between different species of conifer, particularly those within the genus *Pinus*. This was likely a consequence of having too few training samples to allow the accurate differentiation of what appeared to be relatively subtle differences in the reflectance signatures of different species. Therefore, it would be useful to explore whether, with further verified training samples, it would be possible to distinguish between some species (such as Douglas fir from the *Pinus* species) using the current sensor array. However, it may only be possible to differentiate between *Pinus* species using a hyperspectral sensor with much greater spectral resolution (i.e. hundreds of bands vs. four bands) (e.g. Mackereth 2017), which would be associated with considerable deployment and analytical overheads. In most cases, the application of such technology is likely to be unnecessary for wilding conifer control, as all conifers are usually removed regardless of species. However, this may be useful where conifers need to be differentiated from background vegetation with much less contrast than dry open shrubland and grassland (e.g. secondary regrowth or forested areas). One solution to this issue would be to collect reference hyperspectral imagery and then incorporate the specific reflectance bands that differentiate conifers particularly well within a customised, high-resolution multispectral sensor. Therefore, further trials will clearly be required in such habitats before we can be confident of detecting conifers, and even if we can detect target trees in such habitats, the height structure of the vegetation is likely to preclude the detection of pre-coning seedling conifers.

4.2 Limitations

The creation of a semi-automated detection algorithm that is capable of processing VHR RGB and multispectral imagery and reporting the spatial coordinates of any conifers detected is likely to be very useful. However, orthomosaics of such imagery at the landscape scale are extremely large and difficult to manipulate. Fortunately, these can be broken down into much smaller tiles and batch processed, but even so, file sizes remain large, so computers with fast processors and graphics cards are required to process jobs in a timely fashion and reduce the chance of crashes. Although the current algorithm could detect most lodgepole pine trees that were at or above coning size (i.e. canopy diameter > 50 cm), as well as significant numbers of pre-coning trees of ≤ 30 cm in canopy diameter, there are several areas where it could be improved.

While it is likely that suitable training data will always be required for a new location, improvements in the classification methods should be examined, particularly with regard to performing image segmentation as a pre-processing step prior to the object-based image analysis (OBIA) and classification (Blaschke 2010). The inherently high level of small-scale variability in VHR vegetation imagery often results in the incorrect classification of individual pixels (producing a more 'speckled' classification than expected). However, image segmentation uses an algorithm to group neighbouring pixels into segments (or objects) that are then used for classification, which can be particularly effective in reducing the number of false positives and the amount of pixel speckle (Weisberg et al. 2007; Blaschke 2010; Bradley 2014; Wegmann et al. 2016). Although attempts were made to incorporate segmentation as part of the classification algorithm in this study (Table 3), we were unable to get this process to work within the R-based algorithm. Therefore, semi-automating such procedures within the Python scripting language or utilising specialist OBIA software packages (e.g. eCognition and ENVI FX) that allow for the development of detailed 'rule-sets' and batch processing (Dronova 2015) are currently being examined (K. Joy, Orbica, pers. comm.).

The presence of false positives in a classified image is not considered a major issue, as the need to check areas in which false positives have occurred would seem worth the additional cost to ensure that an area is covered as thoroughly as possible. However, false negatives are far more problematic, particularly if larger seedlings are being missed. Consequently, the higher rate of false negatives (i.e. errors of omission) that occurred in the classification of multispectral imagery compared with RGB imagery was initially concerning, as this is an important type of error when trying to detect small, pre-coning trees. However, these higher errors of omission only appeared to occur for the larger size classes (i.e. trees with crown diameters of 50–59 cm and 60–69 cm), presumably reflecting the proportional effect of misidentifying the sometimes highly variable 'tree pixels' within each of these larger diameter crowns (i.e. the result of variable solar reflectance resulting from variable crown aspect and crown surface irregularities). Nonetheless, significant improvements could likely be made if the spatial and spectral resolutions were increased. Improvements in the spatial resolution would require lower flight altitudes (e.g. dropping the aircraft flight height to 1100 ft agl) and a reduced field of view, with consequent increases in flight times and image processing to cover the same area. Increasing the spectral resolution would require an improvement in the number of bands that could be captured by the sensor, as well as more complex data handling and analysis routines, particularly if hyperspectral data (i.e. hundreds of spectral bands) were collected. While the collection and processing of such data would be more complex and have higher costs, it is more likely to be able to discriminate between different species and determine their state of health should this be considered important.

Improvements to the quality of the training data would also be of some benefit. Accurate in-field assessments of spectral reflectance (from adequate samples of individuals) using a portable spectrometer would assist in the accurate identification of the smaller size classes of conifers and may also contribute to the differentiation of conifer species. Consequently, the construction of a 'spectral library' containing robust reflectance signatures for all species of concern and incorporating any variations that are likely for different size classes coupled with hyperspectral or bespoke multispectral aerial data would be a useful objective. Furthermore, although the training data used for this study were sufficient to accurately distinguish conifers from the short tussockland background, it seems likely that additional training data would be needed for adequate discrimination within other habitat types (e.g. areas of native secondary regrowth).

The spatial accuracy of the collected imagery and derived orthomosaics within the Wolds study area was reasonably good, and this was certainly helped by the distribution of GCPs prior to collection of the imagery, as indicated by the lower accuracy in the Quailburn study area where no GCPs were used. Although the spatial accuracy could have been increased by using accurately located GCPs, the deployment of these over large spatial areas prior to imagery collection is often problematic. The present system was also reliant on the accuracy of the GPS that triggered the sensor(s) shutter within the aircraft, which was moving at speed and at relatively low altitudes. Greater spatial accuracy would also have been possible with the use of more accurate Global Navigation Satellite System (GNSS) GPS units and post processed kinematic (PPK) correction to fix these point locations. Further improvements may also be achieved by improving the sensors that were used. For instance, improvements have since been made to the RGB system by introducing a gyroscopically stabilised camera mount, and we continue to investigate the use of alternative higher resolution sensors and the integration of inertial measurement units (IMUs).

There was also an obvious spatial offset between the imagery and the location of trees used for training purposes, which caused considerable confusion at times when trying to reconcile the locations of trees in the imagery (particularly the smaller seedlings) with the GPS locations of trees within the 20 × 20 m plots in the Wolds study area and the locations of treated confers in the Quailburn study area. For the most part, these discrepancies could be resolved due to the high contrast between conifers and the background vegetation. However, the ability to make these comparisons was significantly compromised for plots or areas containing higher densities of trees and seedlings. This indicates that a GNSS-capable GPS receiver with a much higher spatial accuracy (real-time satellite-based augmentation system (SBAS) correction, real-time kinematic (RTK) or PPK post-processing) is required for such comparative work both on the ground and in the air, and will be essential when trying to locate conifers in areas with far less background contrast and/or greater structural diversity.

It should also be noted, however, that most of the identifiable offsets were only in the order of 1–2 m, which would be unlikely to have significant impacts on locating trees for chemical control using helicopters due to the relative height of aerial operators and the targeted search of specific coordinates for detected trees. It can also be assumed that any small trees that are masked by the presence of other larger trees (due to them being directly adjacent to these trees or hidden in the image shadows) would also be detected and treated by aerial operators. As mentioned previously, some false positives are likely, which will lead to unavoidable visits to trees or other vegetation that are not conifers. Therefore, it will be important to capture these data and feed them back into the classification algorithm to enable future improvements.

4.3 Associated costs

The deployment of remote sensing methods for the detection of wilding conifers requires careful consideration, as this may be associated with significant additional costs to current operational practices if appropriate flight areas are not carefully selected. Therefore, to make the inclusion of remote sensing detection methods worthwhile, there must be clear advantages in terms of the overall cost and efficiency, and the most appropriate situations for such technologies to be deployed must be clearly understood.

The remote sensing procedure that was developed in the present study was found to result in an approximately 10-fold reduction in treatment costs compared with current methodologies, indicating that the potential savings could be significant. However, it is worth noting that the financial viability of this remote sensing approach is only appropriate for use with the 'scattered' and 'sparse' stem density categories – areas of higher stem density may be better dealt with using alternative methods if allowed by the stratification of operational control and budgetary constraints. Furthermore, any discussion around costs and benefits must consider the desired ground sample distance (GSD) or spatial resolution of the imagery. As the GSD decreases and the spatial resolution increases, the field of view (FOV) also decreases, which then requires an increased flying time to cover the same area, the collection and processing of an increased number of images and, ultimately, increased costs. Therefore, it is important to determine the optimal resolution that allows the greatest proportion of small pre-coning trees to be detected with the maximum efficiency and for which the cost of collecting the imagery is more than offset by either the reduction in frequency with which the area requires treatment (e.g. a reduction in the treatment cycle from 3 years to 2 years) or a substantial reduction in costs compared with current methodologies. Such cost calculations are likely to vary depending on the size of the targeted area and the type of habitat over which wilding conifers are being searched for (e.g. high/low contrast, flat/steep terrain). Therefore, our findings will only apply to the grassland habitat from which the data were collected and the specific flight parameters that were used. Furthermore, these savings will only be realised in the long term if sensible consideration is given to the most appropriate survey design for the habitats being flown over, the size of trees that need to be detected and the density at which these occur, along with the 'cost' of failing to locate pre-coning trees when using other detection methods.

The extensive use of freely available satellite imagery to identify large, dense stands of conifers and of seed spread models to identify priority areas for the application of these remote sensing methods would be useful first steps. Further cost savings could also likely be made if the imagery classification algorithm could be improved (perhaps by utilising an alternative segmentation or object-based classification method) so that it could run without the input of significant technical expertise. This will require the development of a user-friendly interface that is capable of taking in the imagery as well as classifying and detecting pre-coning sized conifers down to a canopy diameter of 30–50 cm. Integration of the resultant conifer location coordinates with a GPS-based unit that is not only capable of locating these trees but also of recording whether they are conifers that could be treated with herbicide will further increase the value of this system.

4.4 Future directions

In this study, the use of VHR multispectral imagery and a semi-automated classification algorithm was shown to be effective for the detection of small pre-coning wilding conifer seedlings and saplings in a dry grassland environment. However, as suggested by Jensen (2005), the detection of a useful proportion of small conifers was only found to be possible if the ground resolution of the sensor system was less than or equal to one-half the size of the object measured across its smallest dimension. The question of whether the resolution and cost formula that are currently applied are operationally adequate (i.e. sufficient numbers of small seedling are being detected) should also be further discussed and, if necessary, revisited. There is also obvious room for improvement in both the classification method that was used and the detection algorithm that was developed to further reduce associated errors and make this a more user-friendly and practical detection system. Current work is focussed on improving the detection rate of seedlings using VHR RGB imagery, object-based image classification (OBIA) and machine learning classification algorithms through the use of much expanded training data sets within a Python programming environment. An additional key component of this will be the development of a suitable geographic information systems (GIS) tool that can utilise the output of the detection process and incorporate it within operational GPS-based software. Such a tool would not only be able to provide accurate point location data but would also be capable of recording whether a tree/seedling was indeed present and, if so, whether it was a conifer, allowing it to be treated with an appropriate quantity of herbicide.

This procedure would require data from the classification process to be supplied in a specific and standardised format and held in a central location to provide a 'single source of truth', and a backed-up copy of the information to be stored. The current automated algorithm produces an output that shows the centre points of trees and density polygons of groups of trees. These data would need to be exported as either GPX files or shapefiles, which could then be handled in one of the following three ways (providing that the explicit user requirements are met), each of which is associated with increasing complexity and cost (see Table 8):

- **Manual**: A GIS analyst would map the GPX files and density polygons for use in operational planning. The GPX points/shapefile would then be provided for use in the helicopter's GPS system or other device that can be used by a ranger. Any activity data would need to be fed back to the system that is used by the operator (e.g. DOC Weeds or the Wilding Conifer Information System (WCIS)) to record the work.
- **Online web maps**: The data could be introduced to a stand-alone or existing web mapping application (e.g. DOC Weeds and WCIS) in a read-only or editable format to be viewed in context with other operational data. If it is read-only (to preserve the source accuracy), it could be used to refine/improve the accuracy of the data that are held in existing systems.
- **Customised stand-alone system**: This would require the production of both online web maps (as above) for operational planning and an offline solution for use in the helicopter. The GPS data would link in with the spray equipment in the helicopter such that when a helicopter flies to a tree, the action of spraying would capture the treatment point either by changing the attributes/colour of the existing point on the map or by providing a treatment 'overlay' to track progress. The activity/infestation outputs would then need to be fed back into the existing systems (e.g. DOC Weeds and WCIS).

If there is any intention to update existing infestation geometries (i.e. options 2 and 3 above), it would be desirable to introduce some measure of 'confidence' into the infestation polygons so that they receive a 'higher' score if they are captured by this method. This capability would also need to be added to the current data capture system.

It is not desirable to collect VHR remote sensing data of this quality for all sites due to the associated costs. Therefore, we suggest that the following process is followed for the appropriate application of these methods (see Fig. 13). Areas of interest should first be evaluated using available satellite or aerial imagery, and any areas with readily identifiable wilding conifer infestations should be assessed and stratified by density for appropriate control measures. Areas that are adjacent to these significant infestations or other areas that are known or likely to be infested with low-density seed sources (e.g. through seed spread modelling) can then be prioritised for the collection of VHR RGB and multispectral imagery (if necessary) using a fixed-wing aircraft, and the resultant tree and seedling location data can be used for control purposes or as a tool to audit earlier control operations. Even if it is not possible to identify the smallest of plants, accurate maps of larger and denser infestations will be extremely valuable for modelling the invasion risk and understanding the invasion process. It would therefore seem unwise to ignore the potential of remote sensing tools simply because they cannot detect the earliest signs of infestation.

Significant challenges remain for the detection of pre-coning wilding conifers using the remote sensing techniques outlined above. Other than the obvious issues of converting remote sensing data into information that is operationally useful, the biggest challenge will be the detection of conifers in habitats containing much lower contrast background vegetation types (Pearlstine et al. 2005; but see Gil et al. 2013). To address this, a similar programme of research will need to be conducted, which may well require the use of more complicated and expensive equipment (i.e. hyperspectral sensors) that is theoretically more capable of identifying vegetation to the individual species level. Furthermore, even if this level of spectral resolution is not required, serious consideration should be given to the development of a robust reference library of spectral signatures for all wilding conifer species of interest, as this would be of significant assistance during the imagery classification process, particularly in areas where there is low spectral contrast or when assessing the efficacy of previous control operations.

Finally, it may be possible to derive other products from these data that may be of benefit. Obvious candidates include the array of vegetation indices (VIs) that have been formulated to highlight specific traits of vegetation (Jones & Vaughan 2010; Horning et al. 2012; Wegmann et al. 2016). The best known of these is the normalised difference vegetation index (NDVI – not used in this study as it didn't provide the necessary separation to address specific questions around identification of small pre-coning trees), which utilises the NIR band and is strongly linked to vegetation cover, biomass and net primary productivity, allowing the level of 'vegetation greenness' of a scene to be assessed on a scale of −1 to +1. This may be of benefit when assessing the success (or otherwise) of a control operation, particularly in areas where stands are relatively dense, or the control operation was only partially successful. In addition, some VIs are particularly sensitive to the presence of dead wood or lignin, or can correct for soil reflectance (Jones & Vaughan 2010; Horning et al. 2012). SpecTerra Ltd is also able to provide a surface model of plant cell density (PCD), which indicates the level of water and/or fertility stress in the canopy vegetation. This type of index is used extensively in the horticultural industry and may have some application when assessing the effectiveness of wilding conifer control regimes. It is also worth noting that given the amount of overlap (both forward and side) that can occur during the collection of imagery, very accurate models of vegetation height can be computed using the stereoscopic information, allowing an accurate soil surface elevation model to be sourced via light detection and ranging (LiDAR) or, if LiDAR data are not available, a canopy height model to be produced that shows the relative heights of trees relative to each other. This type of product may be worth considering if there are questions around the relative heights of conifers, the density of the trees and the impacts these parameters may have on the type of control required.

4.5 Summary of benefits

The present study showed that remote sensing using VHR RGB and multispectral imagery:

- Is an efficient and accurate means of locating small pre-coning wilding conifers in high-contrast environments.
- May be associated with considerable reduction in labour costs compared with current ground or aerial search and destroy operations.
- Would bring cost efficiencies through reductions in the control frequency (from every 2 years to every 3 years).
- Is a useful tool for the accurate planning and costing of control operations in a given area, as it allows optimisation of the control method for the tree density that is present.
- Provides greater certainty of detecting wilding conifers, reducing the need to monitor or audit the effectiveness of control operations. Furthermore, where an audit is required, remote sensing is an effective tool for detecting dead and dying stems.
- Has broader applications to control programmes for other environmental weeds.

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Appendix 1

Summary of previous studies that have used aerial imagery to detect woody and invasive woody plants

SPECIES/SYSTEM	TYPE OF REMOTE SENSING USED	RESOLUTION	IMAGERY CLASSIFICATION PROCEDURE	REFERENCE
Ponderosa pine (*Pinus ponderosa*) invading grasslands in Colorado's Front Range	Digitised aerial photographs (historic from 1937 to 1990)	2.5-m spatial resolution, panchromatic film	Pixel-based, density slicing	Mast et al. 1997
Two South African savannas in which *Acacia* spp., *Grewia* spp. and *Dichrostachys cinerea* were the dominant encroaching species	Aerial photographs	2 m, RGB	Textural analysis using semi-variograms	Hudak & Wessman 1998
Palestine oak (*Quercus calliprinos*; dominant tree) and mastic tree (*Pistacia lentiscus*; dominant shrub) at a site in northern Israel; no invasive species studied	Aerial photographs from 1960 and 1992	0.75 m	Pixel-based supervised classification with maximum likelihood classifier	Kadmon & Harari-Kremer 1999
Weedy species (*Senna obtusifolia*, *Ipomoea lacunose* and *Solanum carolinense*) in Mississippi	Aerial multispectral images	1-m spatial resolution, three bands: RG + near infrared (NIR)	Pixel-based step-wise discriminant analysis to classify as weed-infested or not weed-infested	Medlin et al. 2000
Mapping and measuring the tree cover and density of pinyon (*Pinus* spp.) and juniper (*Juniperus* spp.) in rangelands in Utah	RGB digital aerial photographs	25 cm, RGB	Feature extraction using Feature Analyst (extension of ArcGIS) – supervised image segmentation (training datasets of piñon-juniper cover and non-piñon-juniper cover)	Madsen et al. 2011
Pinyon and juniper encroaching in rangelands of the western USA	High-resolution aerial imagery	0.06-m pixel resolution, four bands: RGB + NIR	Used eCognition for object-based image analysis (OBIA) – supervised, so used both training and test plot data	Hulet et al. 2013
Relating individually detected redberry junipers (*J. pinchotii*) to field measurements of the aboveground biomass in two counties in Texas	Aerial imagery from the National Agricultural Imagery Program (NAIP)	1 m, three bands: RG + NIR	Used support vector machines (SVMs) in ENVI	Mirik et al. 2013
Western juniper (*J. occidentalis*) cover in rangelands in the western USA (Oregon, Idaho, California and Nevada); a comparison of imagery classification techniques (OBIA v. pixel-based methods) is also presented		Imagery at 0.5 m and 1 m, four bands: RGB + NIR	OBIA: • Wavelet analysis: Two-dimensional Mexican hat wavelet analysis in Matlab • Image segmentation: used region of growth and undertaken in spring Pixel-based: • ISODATA: used a clustering algorithm in ArcGIS • Random forests: used the random forest package in R • Maximum likelihood: undertaken in ERDAS Imagine Results: The Wavelet analysis performed best, followed by image segmentation, ISODATA, random forests and finally maximum likelihood	Poznanovic et al. 2014

Continued on next page

Appendix 1 continued

SPECIES/SYSTEM	TYPE OF REMOTE SENSING USED	RESOLUTION	IMAGERY CLASSIFICATION PROCEDURE	REFERENCE
Jeffrey pine (*Pinus jeffreyi*), Douglas fir (*Pseudotsuga menziesii*) and Port-Orford cedar (*Chamaecyparis lawsoniana*) encroaching on savanna in Little Bald Hills, California	Aerial photographs and digital imagery	1-m spatial resolution; black/white for earlier historic imagery and RGB for recent images	Pixel-based; unsupervised to divide imagery into classes and then supervised to select for tree vegetation	Sahara et al. 2015
Mapping *Acacia mangium* in Brazilian savanna	RGB and colour infrared (CIR) imagery acquired from an unmanned aerial system (UAS)	3 cm for RGB camera and 2.6 cm for CIR camera	Feature detection and mapping using the free VisualSfM software (to pre-process the imagery); then semi-automated classification in QGIS using the minimum distance classification algorithm (supervised and pixel-based)	Lehmann et al. 2017

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