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Mapping bugweed (*Solanum mauritianum)* infestations in *Pinus patula* plantations using hyperspectral imagery and support vector machines

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Declaration

I, Jonathan Tom Atkinson declare that the thesis/dissertation, which I hereby submit for the degree of Master of Science at the University of Pretoria, is my own work and has not previously been submitted by me for a degree at this or any other tertiary institution.

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Abstract

The invasive plant known as bugweed (*Solanum mauritianum)* is a notorious invader of forestry plantations in the eastern parts of South Africa. Not only is bugweed considered to be one of five most widespread invasive alien plant (IAP) species in the summer rainfall regions of South Africa but it is also one of the worst invasive alien plants in Africa. It forms dense infestations that not only impacts upon commercial forestry activities but also causes significant ecological and environment damage within natural ecotones. Effective weed management efforts therefore require new and robust approaches to accurately detect; map and monitor weed distribution in order to mitigate the impact on forestry operations. In this regard, support vector machines (SVM) offer a promising alternative to conventional machine learning and pattern recognition approaches to weed detection and mapping using remote sensing. The main objective of this research was to determine the utility of using a recursive feature elimination support vector machine (SVM-RFE) based approach with a 272-waveband AISA Eagle image to detect and map the presence of co-occuring bugweed within mature *Pinus patula* compartments in KwaZulu Natal. The SVM-RFE approach required only 17 optimal bands from the original 272 band image to produce a classification accuracy of 93% and True Skills Statistic of 0.83. Results from this study indicate that (1) there is definite potential for using SVMs for accurate detection and mapping of bugweed species in commercial plantations and (2) it is not necessary to use the entire 272-band dataset to accurately detect bugweed occurrence as the SVM-RFE approach will identify an optimal subset of wavebands for weed detection enabling substantially improved data processing and analysis.

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1. Introduction

The commercial forestry sector is recognised as a significant socio-economic force in South Africa, having a capital base of approximately R30 billion, an annual turnover of roughly R12 billion (Tewari, 2005) and contributing nearly two percent to the country's GDP (Nyoka, 2003). In this regard, commercial forestry is able to supply 95% of the country's wood-derived products whilst still achieving a positive trade balance of R2 billion/ annum enabling South Africa to become the 16th largest producer of pulp in the world (Pallet, 2005). In terms of its social contribution to the economy, the industry provides direct employment to some 75 000 people, 500 000 people indirectly in related industries with almost 2.1 million people reliant on the commercial forestry sector for their livelihoods (Forest Owners Association, 2000). Thus as far as its profit, foreign exchange and employment-generating potential is considered the commercial forestry industry is well established and forms an integral part of the landscape and economy (Le Maitre et al., 2004). However, in recent years there has been a rapid decline in the number of newly afforested areas in South Africa with the forestry industry largely limited to a fixed production area (Pallet, 2005). This is largely due to a decrease in the number of suitable sites for afforestation coupled with greater reluctance by the Department of Agriculture, Forestry and Fisheries (DAFF) in granting new water permit licences for afforestation (DWAF, 2005). Consequently, with fewer new areas being planted it is likely that the industry will have to either rely on timber and timber product imports to sustain the industry if current trends persist (Forestry South Africa, 2007) or embrace precision forestry activities which aim to increase and sustain the fibre supply from a fixed production area (Pallet, 2005).

It has therefore become increasingly important, not only from an environmental but also economically sustainable perspective, for forestry managers to ensure that forest productivity within existing planted areas are maximised. Thus any agents which present a significant threat to forest sustainability and could lead to a decline in productivity need to be identified and mitigated. One such threat is the occurrence of invasive alien plants (IAPs), or weeds, within the plantations which can negatively impact upon the growth and productivity of the commercial species (Little et al., 1997). One species of IAP which warrants concern, particularly in the province of KwaZulu-Natal (KZN) is S*olanum mauritianum* (bugweed).
The hardiness and resilience of this species has already established it as a major declared weed (Hanks, 2009) of natural ecosystems, forestry plantations, riverine areas and conservation

habitats and the weed can in fact become quite ubiquitous if not controlled (Witkowski and Garner, 2008). One of the major impacts of bugweed on any ecosystem is perhaps the ability of the weed to capitalize on the available natural resource pools to form dense stands and suppress the growth of other plant species through overcrowding and shading (ISSG, 2005). These dense stands not only have the potential to inhibit the re-establishment of commercial tree species but also prohibit the access to harvesting operations (Dobyn, 2009). Bugweed are also extremely resilient and opportunistic and compete fiercely for resources, often suppressing the growth or even displacing the surrounding vegetation (Richardson et al., 1996). This is particularly evident in commercial forest plantations where it has been reported to stunt the growth of certain *Pinus* species. (ISSG, 2005). In addition, studies have shown that bugweed is the most condensed IAP in KZN and at a national level is ranked ninth in terms of its affinity to consume water (Goodhall and Erasmus, 1996). From a fire management perspective, the presence of bugweed provides undesirable under canopy fuel loads within commercial forestry stands during extreme uncontrolled fire events. This can consequently lead to increased costs of fire protection and suppression and greater overall severity of wild fire damage as a result of additional fuel load material (Richardson and Van Wilgen, 2004).

Bugweed are insidious drivers of environmental change within managed forests and have the ability to compromise ecosystem services such as water purification, soil generation, organic matter decomposition and nutrient cycling (Le Maitre et al., 2004). Forestry managers therefore require accurate as well as timely spatial information on bugweed occurrence in order to ascertain the severity of invasion and contain small infestations before they get too large and expensive to eradicate. Additionally, the spread of IAPs usually follows three phases, namely colonization, establishment and spread (Kimothi, et al., 2010). Consequently, the ability to develop accurate and spatially explicit techniques for early invasive plant detection, mapping and monitoring (ideally at the colonization phase) is regarded as of high priority for commercial forestry management (Anderson, 1993). In light of these challenges the use of digitally analysed, remotely-sensed data for the early recognition and quantification of IAPs could not only result in a more time-efficient approach to classification, and thus weed detection, but the technology could also potentially reduce weed management costs (Haara and Nevalainen, 2002). Furthermore, since many resource management budgets now make provision for effective vegetation management there is a tangible need for practical methods of remotely detecting weeds, mapping their range, monitoring their spread and assessing the effectiveness of management strategies (Madden, 2004). Optical remote sensing technologies, more specifically hyperspectral sensors (Campbell, 2002; Lass et al., 2005), have the capacity to rapidly and synoptically exploit the unique spectral, phenological and structural characteristics of bugweed (Waske et al., 2010). Due to their excellent spectral resolution, hyperspectral sensors are extremely well suited to map the abundance of weed species over large spatial extents (Miao et al., 2006). Consequently, there has been an increase in the number of studies that have applied hyperspectral image analysis to detect invasive species including Brazilian pepper (Lass and Prather, 2004), leafy spurge (Glenn et al., 2005), spotted knapweed (Lawrence et al., 2006) and tamarisk (Hamada et al., 2007). More recently, Andrew and Ustin (2008) have shown that in diverse environments where areas are particularly susceptible to weed invasion, hyperspectral imagery is essential for weed detection and mapping. The study found that sensors that are less sensitive to varying spectral and environmental conditions will not be able to properly detect infestations resulting in classifications that may confound species invariability and detectability.

Unlike broadband multispectral remote sensing platforms, the continuous nature of the spectra extracted from the hyperspectral imagery allows for discrimination of more subtle differences between individual species (Joshi et al., 2004). This not only provides more information about surface features but can be used to differentiate vegetation into taxonomic levels (Lawerence et al., 2006). This ultimately enables classification to occur at both an in-depth biochemical and structural level which would otherwise not be possible with the coarse bandwidths acquired by multispectral sensors (Lass and Prather, 2004). Ismail et al. (2008) points out that the inability of multispectral sensors to adequately detect canopy level diversity in complex, layered forested environments renders them especially ineffective in providing a biophysically-based approach for mapping diversity. Indeed, Ismail et al. (2008) endorses this assertion by showing that the generally high classification errors associated with the use of multispectral sensors for damage discrimination impose operational limitations on their use by forestry companies. Interestingly, studies of direct weed detection using hyperspectral sensors have often been limited to scenarios that do not necessarily require the spectral precision or fully utilise the capabilities offered by hyperspectral sensors (Joshi et al., 2004). For example, Govender, (2007) noted that weed locality and physiology within particular homogeneous landscapes would enable fairly accurate detection, discrimination and classification, even at a multispectral level. However, even though multispectral data may be more cost effective and more accessible than hyperspectral data, both classification and spatial resolution may be inadequate for regional or site-specific weed management activities (Zomer et al., 2009). Direct methods of detecting under canopy plant species is challenging given any image sensor platform (Joshi et al., 2004). That is, detecting bugweed within a commercial forestry environment presents a unique set of challenges. The often high degree of tree uniformity as well as dense canopy closure often results in the inability to distinguish small to medium co-occuring invasive trees, such as bugweed, that occur below the canopy or tree line. However, hyperspectral sensors possess the necessary spectral capacity to identify the unique spectral signatures of particular co-occurring invasive species relative to a backdrop of non-invasive vegetation (Hamada et al., 2007).

One of the fundamental processes of deriving land cover information from remotely sensed imagery is image classification (Huang et al., 2002), the outcome of which is a thematic map of the original image depicting the pixels assigned to a particular class (Kavzoglu and Colkesen, 2009). Recently, a new generation learning algorithm, namely support vector machines (SVM) (Vapnic, 1995), has increasingly been used for the classification of hyperspectral imagery. Support vector machines have not only been shown to improve overall image classification performance but also image data processing (Camps-Vells et al., 2004). Another attractive feature of SVMs are that they have proven to be particularly expedient when used in studies dealing with homogenous classes with a limited number of training samples available (Melgani and Bruzzone, 2004). Additionally, SVMs seem to be robust to the effects of the Hughes phenomenon (Camp-Valls and Bruzzone, 2005) or *curse of dimensionality*, that is with a limited number of training samples the classification rate decrease as the data dimensionality increases (Lennon et al., 2002). A difficult task even for techniques dedicated to processing hyperspectral data such as Spectral Angle Mapping or spectral unmixing (Mercier and Lennon, 2003).

It’s not surprising then that some studies have shown that SVMs are capable of producing higher classification accuracies than more widely used pattern recognition models such as maximum likelihood and neural network classifiers (Melgane and Bruzzone, 2004 and Pal and Mather, 2005). However, although SVMs are effective at classifying data, they do not directly provide the user with an indication of feature importance (Chen and Lin, 2006). Feature selection (FS) is a dimension reduction approach and while SVMs are known to be robust to dimensionality the application of FS with SVMs improves classification accuracy (Sanchez-Hernandez et al., 2007) and expedites subsequent data processing (Maio et al., 2006). FS does not alter the original representation of the variables but merely enables a model, such as SVMs, to selectively focus on relevant variables whilst ignoring the contribution of irrelevant or redundant (noisy) variables (Dunne et al., 2002). Advantages of FS include reduced data storage requirements, improved model prediction performance, reducing the costs of future measurements and improving data or model understanding (Guyon et al., 2002). Feature selection is therefore considered to be an integral component in bridging the gap between research and operational remote sensing applications (Van Aardt and Norris Rogers, 2008). For a review of feature selection see Kohavi, and John (1997) and Dunne et al., (2002). The aim of this research was to evaluate how advanced, machine learning techniques namely support vector machines (SVM) could be used to detect the presence of co-occurring bugweed trees within mature *Pinus patula* plantations using hyperspectral imagery. With regards to this study, the SVM algorithm and FS methods were used to produce the smallest subset of AISA Eagle wavelengths that would allow for the accurate classification of bugweed reflectance spectra. The overall objective of the study was to demonstrate, for the first time, the practicality and utility of using SVMs to identify the presence of bugweed in commercial *Pinus patula* plantations.

2. Methods and materials

2.1 Study site description

The study area is located in the Sappi Hodgsons plantation (Centroid: *30^{o}29'56 E* and *29^{o}13'42''S*), and is situated approximately 50 km north of Pietermaritzburg in the KwaZulu-Natal midlands (Figure 1.). The topography of the region ranges from gently sloping to moderately undulating with slopes between 1000-1400 m above sea level (Sappi Forests, 1993). The predominant underlying geology consists of shale from the Vryheid and Volksrust formation as well as dolerite. The major soil groups are deep red and yellow apedal subsoils as well as red structured subsoils towards the East and deep and shallow humic topsoils towards the North (Sappi Forests, 1993). The climates is cool with mean annual temperatures in the region of 15.9 ^{o}C and mean annual precipitation in the region of 1015 mm. Areas that are not occupied by commercial timber species are characterized by vegetation types such as the Ngongoni veld of the Natal mist-belt and Southern tall grassveld (Sappi Forests, 1993).
The majority of compartments within the site consist of *Pinus patula* trees which range in age from 1 to 22 years and form part of a pulpwood management regime. The prevalence of IAPs has become a serious problem in the plantation where invasive species such as bugweed have become increasingly prolific. Infestations are particularly evident along riparian zones, previously disturbed areas such as grasslands, and indigenous forest areas which border commercial compartment stands (Dobyn, 2009).

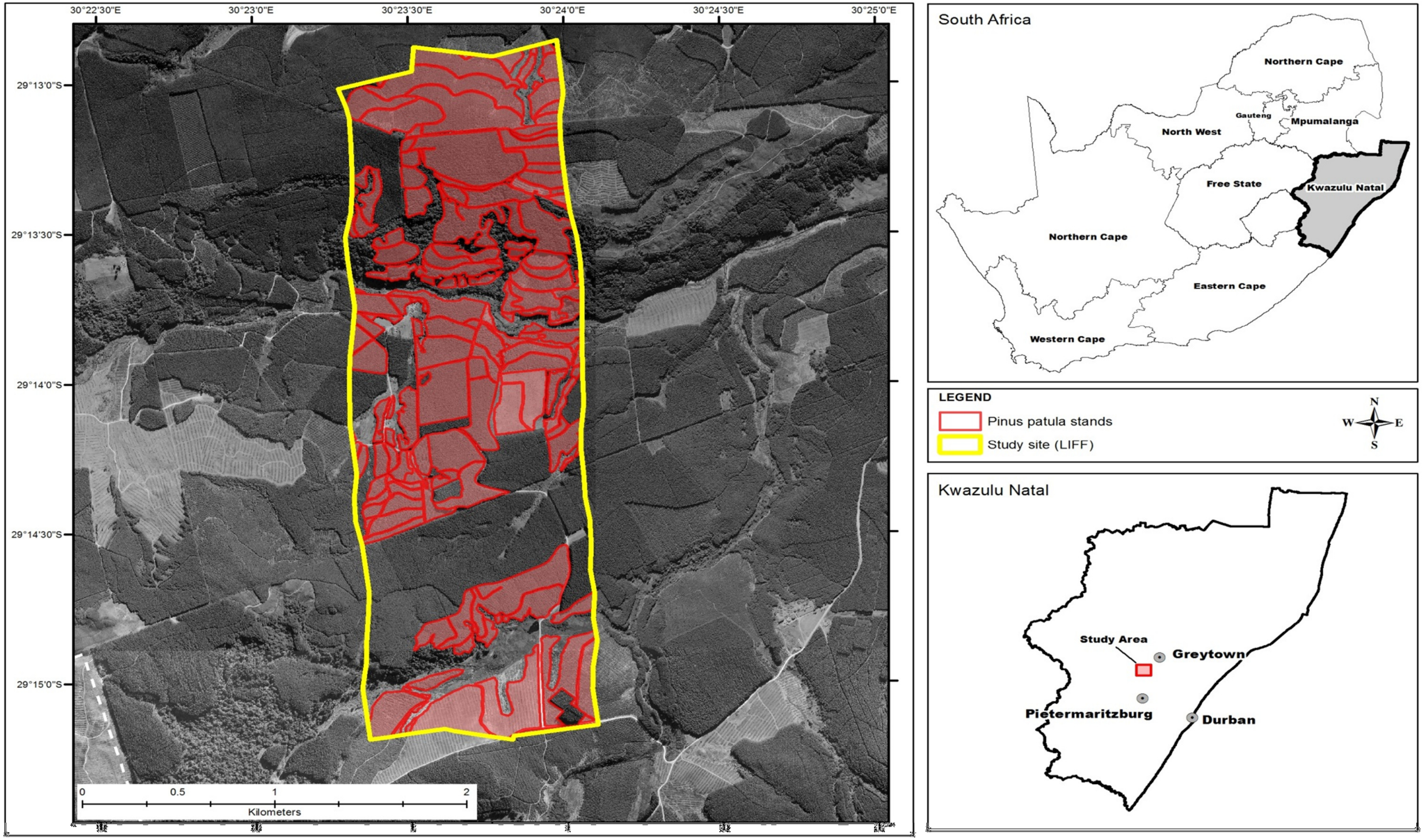

Figure 1: Location of study area. The red areas in the 2009 panchromatic aerial imagery represent the *Pinus patula* compartments where samples were collected.

Bugweed can be identified as shrubs or small trees ranging in height from 2-12 m with rounded canopies and trunks reaching a diameter of 20 cm (ISSG, 2005). According to the National Environmental Management: Biodiversity Act of 2003, (NEMBA) bugweed is a declared category 1b invader weed (DAFF, 2009). As such, one of the directives of NEMBA regarding the regulation of category 1b invader weeds is that, due to their high invasive potential, these plants require compulsory control as part of an invasive species control programme. NEMBA thus imposes a legal obligation upon all landowners to actively locate and regulate the predominance and limit the spreading of category 1b species such as bugweed occurring on their land.

2.2 Image acquisition

The hyperspectral imagery was acquired using the Airborne Imaging Spectrometer for Applications (AISA). The AISA Eagle sensor is a pushbroom sensor consisting of a hyperspectral sensor head, data logger, GPS unit and irradiance sensor. The sensor operates in the visible (400 nm – 700 nm) as well as the near-IR portion (701 nm – 2000 nm) of the spectrum (Jan *et al.*, 2008). The AISA Eagle sensor samples wavelengths 400-900 nm using 272 bands at a spectral resolution (bandwidth) of 2-4 nm and spatial resolution of 2.4 m (http://www.gallieo-gp.com). The imagery was acquired on 11 March 2009 under cloudless conditions at 07:38 a.m. A fixed wing, light aircraft was used to collect the imagery at a mean GPS flight altitude of 2728.42 m. The 272 band image dataset, with an initial spectral range of 393.23 nm – 994.09 nm, was spectrally resampled to 4.9 nm in line with the spectral binning options identified from the technical specifications for the AISA Eagle sensor (http://www.gallieo-gp.com). Spectral binning (Johnson et al. 1999 and Klerk et al. 2007) was employed as a resampling method to eliminate redundant and damaged variables in the dataset and spectrally resampling the imagery allowed (a) for rapid image analysis by reducing data redundancy and (b) removed bands which contained a high degree of noise. After binning, the resulting dataset had been reduced to 110 bands with a spectral range of 400.00 nm – 901.40 nm eliminating bands greater than 905 nm due to excessive noise.

The AISA imagery was geometrically registered (RMSE < 1.0 pixels with 3rd order polynomial approximation) using 20 ground control points (GCPs) (Andrew and Ustin, 2008). The GCPs were selected from high resolution colour (RGB) aerial photographs of the same region collected in April 2009 (Sanchez-Hernandez et al. 2007). The aerial photographs, having an estimated ground accuracy of 10 cm (RMSE < 1.0 pixels with 1st order polynomial approximation) were geometrically registered using topographical features such as roads, streams and cadastral boundaries (Goodall and Naude, 1998) provided by Sappi Forests and were referenced to the Universal Transverse Mercator projection (WGS 84 datum, UTM Zone 36S) using the Environment for Visualization software (ENVI, ITT Visual Solutions). The AISA imagery was atmospherically corrected from radiance to apparent surface reflectance using the empirical line method (Roberts et al., 1985; Kruse et al., 1990). The empirical line method matches the image data to field reflectance spectra of two materials with contrasting albedo (bright and dark targets). The image reflectance spectra are then regressed with field reflectance spectra to determine a linear transformation from radiance to reflectance. The gain and offset curves for the image spectra are then used to derive the average ground reflectance for the entire image (Gao et al., 2009).

2.3 Bugweed reference data

A purposive sampling approach (Tashakkori and Teddie, 2003) was used for the identification of bugweed within forest compartments using the high resolution colour (RGB) imagery. Bugweed occurrence was based on photographic interpretation of the high resolution airborne imagery (Hamada, 2007; Lass et al., 2005 and, Kavzoglu and Colkesen, 2009) and subsequent field verification was carried out using a GPS. More specifically, a 20 m x 20 m digital grid was transposed onto the high resolution imagery (Clay et al., 1999) and bugweed occurring within mature *P. patula* stands, having a canopy greater than 5.7 m^2 (1 pixel) and ranging in age from 7 to 20 years, were then visually assessed (Lass et al., 2005). Figure 2 illustrates how successful bugweed samples were identified within the *P. Patula* stands and located at least 20 m from other bugweed samples (Hestir et al., 2008). Juvenile patula trees, or trees younger than seven years, were excluded from the sampling procedure because the bugweed occurrence within these young compartments was both limited and infrequent. Two point features per grid cell were recorded with the first point representing the bugweed and the second point representing the pine trees. Subsequently, a total of 240 tree samples were collected (120 bugweed samples and 120 *Pinus patula* samples). The spectral reflectance signatures for the 240 tree sample points were then extracted in a GIS using ArcMap (version 10.1, ESRI Inc., Redlands CA) with the resampled imagery then input into the R Project for Statistical Computing (http://www.R-project.org) and used in the classification process. Field visits were also conducted between June 2009 and July 2009 to confirm that bugweed from the imagery was present within the study site. In order to develop the model, sample data were partitioned to provide training (50 %, n = 60) and testing (50 %, n = 60) datasets.

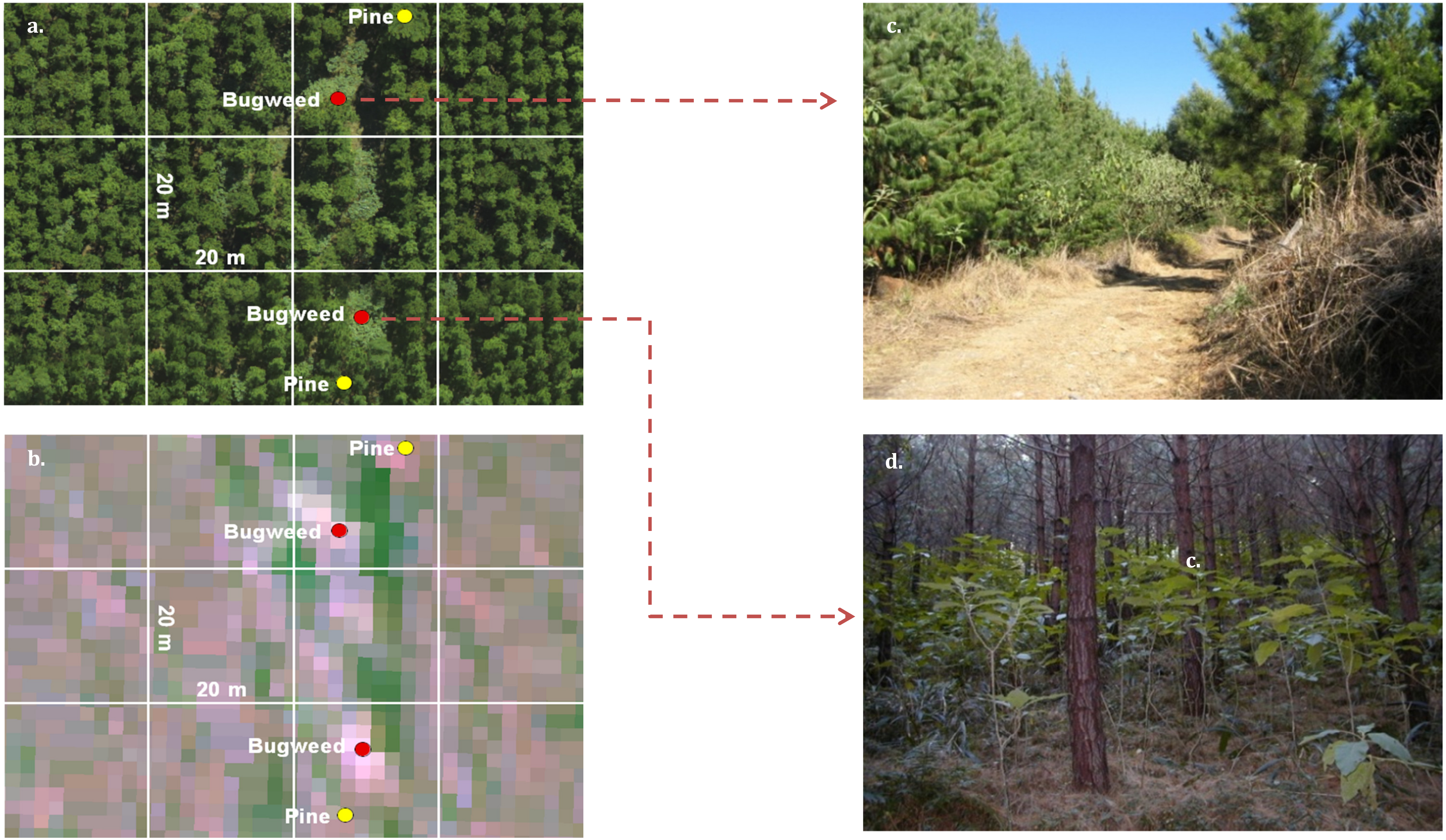

Figure 2: 10 cm resolution aerial imagery (a) and 2.4-m AISA Eagle imagery (b). The photographs show the bugweed present between (c) and within compartments (d).

2.4 Support Vector Machines

The support vector machine (SVM) algorithm uses a supervised machine learning technique that is based on statistical learning theory (Vapnik, 1998) and Vapnik's Structural Risk Minimization principle (Vapnik, 1995) to determine the locality of decision boundaries, or the maximum margin (hyperplane) of optimal separation, between classes (Pal and Mather, 2004). SVM's strength lie in their ability to exploit a margin-based geometrical criterion rather than a purely statistical criterion for classification (Melgane and Bruzzone, 2004). SVMs are essentially a type of linear binary classifier that assigns image pixels, or vectors, from a known training sample to one of two possible class labels (Mountrakis et al., 2011). SVMs used for classification are based on finding the optimal separation surface, referred to as a hyperplane, between classes by identifying the most representative training samples, or support vectors, on either side of the hyperplane (Mercier and Lennon, 2003). The optimal hyperplane is therefore the one that separates the classes with the maximum distance between the separating margin and the data points (support vectors) on the plane with the least generalization error and is known as the optimum separating hyperplane (Huang et al., 2002). In the case of a two-class linearly separable classification problem SVM employs an optimization technique to select the optimal separating boundary (hyperplane) from the infinite number of linear decision hyperplanes (Fig. 3), that can separate two classes (Karimi et al., 2006). SVMs are therefore especially popular amongst researchers since they can handle large input spaces and are not drastically affected by the curse of dimensionality, which is of particular importance when analysing and processing hyperspectral data (Camps-Vells et al., 2005).

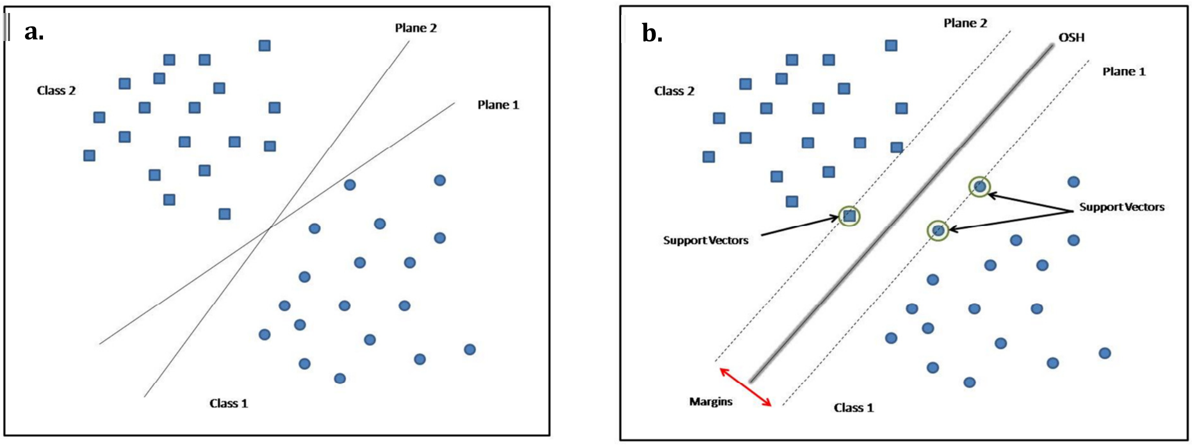

Figure 3: (a) Linear separating planes between two classes and (b) the optimal separating hyperplane between the two classes of data determined by the SVM

In cases where the training data are not linearly separable a "kernel trick" is used to project the data into a hyper dimension, or feature space, where the kernel can then simulate the optimal separation of the classes (Kavzoglu and Colkesen, 2009). The kernel trick not only orientates the data in a way that facilitates smooth and reliable classification of the data by means of a linear function (Noor and Sap, 2008) but also enables efficient computation of the optimization problem (Boser et al., 1992). There are a large number of standard and customised kernels available and two most commonly cited kernels in remote sensing literature are the radial basis function (RBF) and polynomial kernels, (Kavzoglu and Colkesen, 2009) However, for this study the linear kernel function was employed to classify the occurrence of bugweed within mature pines stands. The decision was based on results obtained from a preliminary run of the SVM model using the polynomial, RBF and linear kernel functions (Pal and Mather, 2004) and after comparing the computational time of each model as well as the classification accuracies it was observed that the linear model produced the highest overall accuracy in the fastest computational time. For a review of suitable kernel selection and parameter optimization of SVMs, see Cherkassky and Ma (2004) and Noor and Sap (2008).

The process of training the SVM model for this study was adapted from the procedure outlined by Hsu et al. (2010). For training the SVM classifier using the linear kernel only the regularization parameter *C* (a penalty parameter) requires optimization. The parameter is selected by the user to balance out the competing criteria of margin maximization and error minimization (Kavzoglu and Colkesen, 2009). The higher the value of *C*, the higher the penalty associated with misclassified samples (Pal and Mather, 2004). In order to determine which *C* values will produce the best classification result an optimum parameter search must be performed on the training dataset (Hsu et al., 2010). Common approaches of determining the optimal value(s) of *C* is to implement a combined grid search utilising *k-fold* cross validation (Pal, 2009). The grid search method exhaustively searches for the optimal *C* parameters over a defined parameter range and reports the *k-fold* cross validation classification error for each parameter (Wu and Wang, 2009). The grid points are usually based on a logarithmic scale (e.g. C = 10^{-5}, 10^{-4}, 10^{-3}, …..10^{3}, 10^{4}, 10^{5}) and the classifier accuracy is estimated for each point occurring within the grid (Ben-Hur and Weston, 2010). Consequently, each instance of the entire training subset is predicted at least once so that cross validation accuracy is the percentage of data correctly classified (Hsu et al., 2010). Naturally the *C* parameter with the lowest cross validated error is then selected.

2.5 Feature selection and variable ranking

The AISA Eagle hyperspectral sensor is capable of simultaneously acquiring data from more than a hundred narrow spectral bands (data channels) ranging from the visible to infrared portions of the electromagnetic spectrum (Tarabalka et al., 2010). More spectral bands include more information. However, as Serpico and Moser, (2007) point out, dealing with such a large number of narrow band channels presents problems in the acquisition phase (noise), storage and transmission phases (data size) and processing phase (complexity). Consequently, this limits robust statistical estimations and often results in overfitting of the training data leading to poor generalization capabilities of the classifier (Camps-Valls and Bruzzone, 2005). Machine learning approaches that are therefore able to circumvent these challenges by processing a subset of relevant bands which best characterize a particular feature whilst limiting the effects of dimensionality, are essential to remote sensing. One such approach is feature selection. For this study an adaptation of the SVM Recursive Feature Extraction (RFE) algorithm proposed by Guyon and Elisseeff (2003) was utilized to select the most important subset of bands that provided the best classification accuracy.

The SVM-RFE utilizes all the hyperspectral bands and then successfully eliminates bands from the dataset based on their influence on the SVM algorithm. As the SVM is trained using the linear kernel, each iteration of the model eliminates bands with the smallest ranking criterion. The ranking criterion corresponds to the vector weights of the decision hyperplane assigned by the SVM algorithm (see Guyon et al., 2002 for a detailed discussion on SVM-RFE). However, the SVM-RFE approach outlined in this study uses forward feature selection (FFS) instead of backward feature elimination (BFE) proposed by Guyon et al. (2002) as a search strategy. FFS begins with an empty subset of variables and progressively adds relevant variables into larger and larger subsets. BFE starts with the set of all variables and progressively eliminates the least relevant variables (Dunne et al, 2002). Since BFE starts by evaluating all bands in the dataset, it is computational more demanding than FFS. Consequently, using FFS to building classifiers, when there are a large number of features (for example hyperspectral bands) in the dataset, is much faster (Kohavi and John, 1997). Additionally, the SVM-RFE algorithm was modified so that at each stage of the FFS process, the *C* parameter of the SVM linear kernel is optimized as well. The optimal subset of band's are then selected based on the prediction error as calculated by a 10-fold cross validation (CV).

Once the bands with the highest accuracy are identified using the modified SVM-RFE procedure they are utilized in the LIBSVM library (e1017) within the R statistical software (R Development Core Team 2008) to implement the SVM algorithm.

2.6 Accuracy assessment

The most widely accepted, and perhaps most effective, way to represent classification accuracy is by means of a presence/ absence model (Allouche et al., 2006 and, Fielding and Bell, 1997). The performance of the model is usually summarized in an error matrix that cross tabulates the observed and predicted presence/ absence patterns (Fielding and Bell, 1997) (Table 1). With reference to this study the performance of the optimal subset of bands was evaluated both numerically (overall accuracy) as well as statistically (true skills statistic, specificity and sensitivity). The overall accuracy is interpreted as the total number of correctly classified pixels divided by the total number of sample pixels analysed within the error matrix. In a similar way, the accuracies of individual categories can also be represented. The sensitivity (*sens)* represents the probability that a sample pixel will be correctly classified to a particular category and includes the error of omission which occurs when a pixel is not included into a category it does belong to i.e. false negative (Allouche et al., 2006). The sensitivity can be defined as:

$$\boldsymbol{sens} = \boldsymbol{TP}/(\boldsymbol{TP}+\boldsymbol{FN}) \qquad (1)$$

The specificity (*spec)* is a measure of how reliable the classified map actually is and represents the probability that a sample pixel classified on the image represents the same category on the ground and includes the error of commission which occurs when a pixel is classified to a category that it does not belong to (false positive) (Banko, 1998). The specificity may be represented as:

$$\boldsymbol{spec} = \boldsymbol{FP}//(\boldsymbol{FP}+\boldsymbol{TN}) \qquad (2)$$

Table 1: The error matrix used in the study

		validation dataset		
		presence	**absence**	**row total**
model	**presence**	True Positive (TP)	False Positive (FP)	*TP + FP*
	absence	False Negative (FN)	True Negative (TN)	*FN + TN*
	column total	*TP + FN*	*FP + TN*	Total

Additionally, the True Skill Statistic (TSS) (Allouche et al., 2006) was used as a measure to evaluate the model's agreement with the reference data and can be defined as:

$$\boldsymbol{TSS = (sens + spec) - 1} \qquad (3)$$

The TSS is very similar to Cohen's kappa statistic but has the advantage of correcting for dependency on prevalence whilst still maintaining all the advantages of kappa. Consequently, the TSS is able to account for errors of commission and omission in one statistic, and just like kappa, the TSS values also range from -1 to + 1. The TSS provides a good indication of the extent to which the percentage of correctly classified pixels in the error matrix is as a result of true agreement or chance agreement, with TSS values approaching one indicating true agreement and values approaching zero, chance agreements (Karimi et al., 2006). The presence absence models contained a total of 120 samples each and a 50/50 hold-out sampling approach would be used on the entire 240 sample dataset. The 120 samples that were used for testing the model were also used for model cross-validation. Although cross validation was performed on the test data set, a separate dataset was not used for overall model validation or tuning. Instead all data was used to develop the overall classification rule.

3. Results

3.1 Band selection and ranking

The modified SVM-RFE method was able to identify the optimal subset of variables with the lowest cross-validated error for bugweed detection as shown is Figure 4. Results showed that best accuracy (CV accuracy = 97%) was achieved by using a subset of 17 bands from the original 110 bands resulting in a 85 % decrease in the number of bands required for analyses. As shown in Figure 4, model accuracy subsequently decreased and remained constant from 17 bands onwards. By evaluating the CV error for each band combination in Figure 4, it is evident that using all the bands does not improve the model's predictive accuracy. Rather there is an optimal subset of bands that produce the best accuracy. In fact, the use of more than 17 bands would subsequently result in an ensuing decrease in predictive accuracy up until 69 bands where the accuracy would again improve to 97%. Ranked variable importance also showed that of the 17 bands selected by the model, wavelengths that had the potential to discriminate bugweed were located in the visible and near-infrared (NIR) regions of the electromagnetic spectrum (fig. 5). One band (b_5: 419.6 nm) occurred within the blue range (350 - 450 nm), eight bands (b_{21}: 498.0.1 nm, b_{22}: 502.9 nm, b_{31}: 547.0 nm, b_{45}: 615.6 nm, b_{54}: 659.7 nm, b_{55}: 664.6 nm, b_{56}: 669.5 nm, b_{57}: 674.4 nm) occurred within the chlorophyll absorption regions (450 – 675 nm) and one band (b_{35}: 566.8 nm) was located within the yellow edge (550 – 582 nm). Five bands (b_{58}: 679.3 nm, b_{59}: 684.2 nm, b_{63}: 703.8 nm, b_{64}: 708.7 nm, b_{74}: 757.7 nm) were in the red-edge portion of the spectrum (670 – 753 nm) with the remaining two NIR bands occurring at b_{87}: 821.4 nm and b_{108}: 924.3 respectively.

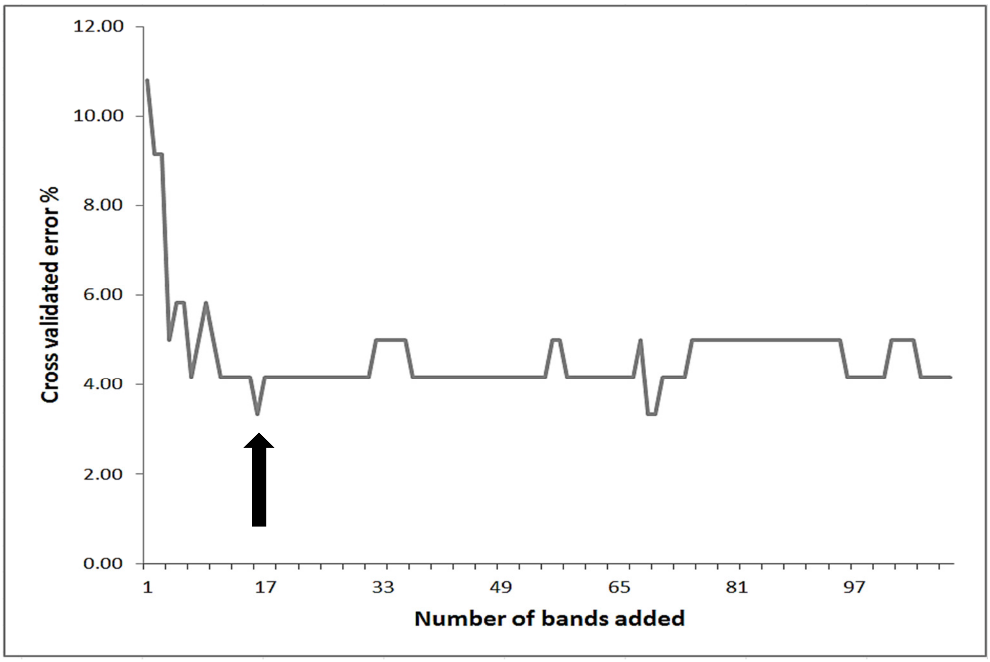

Figure 4: Results of the forward feature selection method for selecting the optimal number of bands from the 110 band dataset. The arrow indicates the lowest error of 4 % obtained using a linear SVM model with cost parameter of 10.

The shaded areas in Fig. 5 exhibit the reflectance wavelengths of the 17 bands that are significant for the classification of bugweed as determined by the modified SVM-RFE method. Based on the analysis, it is clear that there is a dominance of optimal of bands occurring in the red edge region of the electromagnetic spectrum.

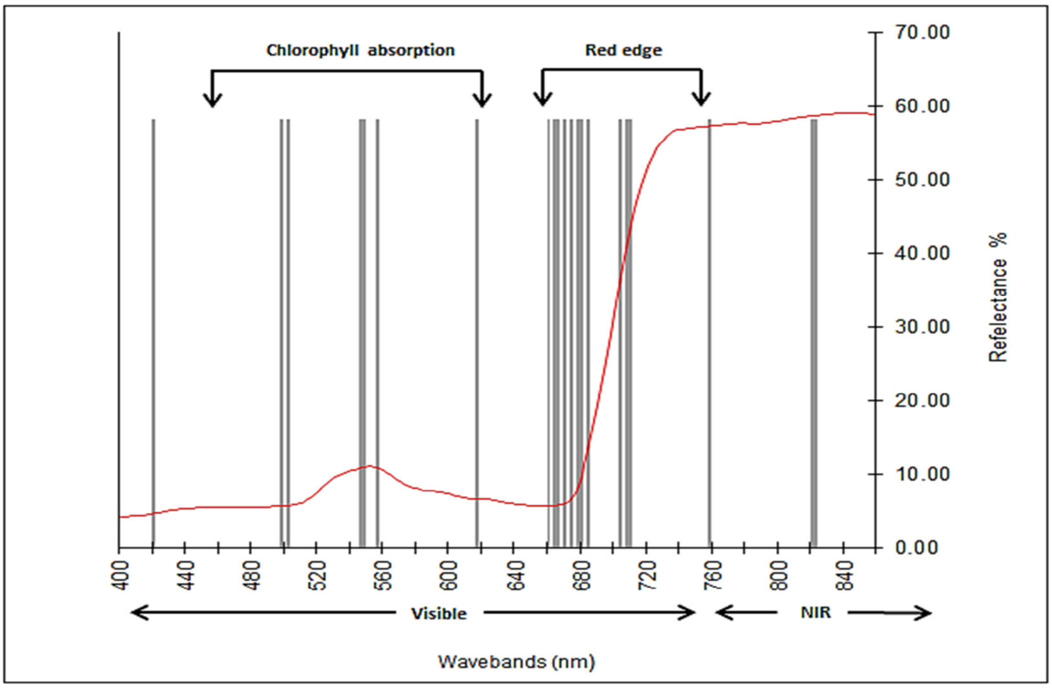

Figure 5: Spectral distribution of 17 optimal AISA Eagle bands selected using the SVM-RFE

3.2 Classification accuracy

Table 2 shows the results of the linear SVM model using the 110 and 17 band models. The regularization parameters for the 110 and 17 band datasets which yielded the best results were 10 and 100 respectively. The sensitivity of both datasets was high ranging from 90 % for the 110 band model and 95 % for the 17 band model. This indicates that the proportion of correctly classified reference bugweed trees in relation to all the classified trees in the test data set was very high.

Table 2: Error matrices showing overall and class accuracies using independent test samples for (a) 110 band and (b) 17 band datasets

(a) Error matrix of bugweed occurrence (Presence or absence)

		REFERENCE DATA		
		Bugweed	**Pine**	**Row Total**
CLASSIFIED DATA	**Bugweed**	54	5	59
	Pine	6	55	61
Column Total		60	60	120
Overall Accuracy (%)		90.83		
TSS		0.82		
Sensititvity (%)		90.00		
Specificity (%)		92.00		

(b) Error matrix of bugweed occurrence (Presence or absence)

		REFERENCE DATA		
		Bugweed	**Pine**	**Row Total**
CLASSIFIED DATA	**Bugweed**	57	5	62
	Pine	3	55	58
Column Total		60	60	120
Overall Accuracy (%)		93.33		
TSS		0.87		
Sensititvity (%)		95.00		
Specificity (%)		92.00		

The specificity for both models was also very high at 92 % signifying a low errors of commision for both the 17 and 110 models and indicating a high probability that a classified pixel in the image was actually represented on the ground. The high values obtained for the TSS statistics (0.82 – 0.87) in both datasets approaching 1 and are an indication of good model performance showing strong agreement between the actual and predicted values for bugweed, particularly for the 17 band model. Overall accuracy for the 17 band model was slightly higher (93.3 %) than the 110 band model (90.8 %) indicating an increase in classification accuracy with a smaller subset of bands compared with the original 110 bands.

3.3 Mapping bugweed occurrence

After testing the performance of the SVM classifier utilizing the SVM-RFE reduced band dataset the methodology described above was applied to the entire AISA Eagle imagery to produce a classified thematic map showing the occurrence of bugweed in the study area. Visual interpretation of the image classification indicated some important observations. Firstly, the results showed that there was a predominance of bugweed to the north and south of the study area. Towards the north, there were fairly uniform dense bugweed present between certain compartments separated by an open or natural area as well as smaller pockets along roads between certain compartments in the south. The results of the image classification for one compartment located in the south of the study area are presented in Figure 6. Unsurprisingly, the distinctive light-green canopy's of well-developed bugweed clusters, with canopy's greater than 5.7 m^2, were easily identifiable. However, in some instances the model was even able to isolate individual bugweed trees with canopies of 5.7 m^2 within the pine compartments. What is interesting is that the model was able to accurately detect 152 instances of bugweed within this compartment alone and of the 152 cases detected, 55 instances (fig. 6b) were of bugweed having a canopy smaller than 5.7 m^2 (1 pixel). This result is quite significant considering that it has been suggested that weed eradication programs should also target small satellite infestations (Moody and Mack, 1988) in view that no early detection system can truly be operational unless it is able to detect small as well as large infestations (Andrew and Ustin, 2008).

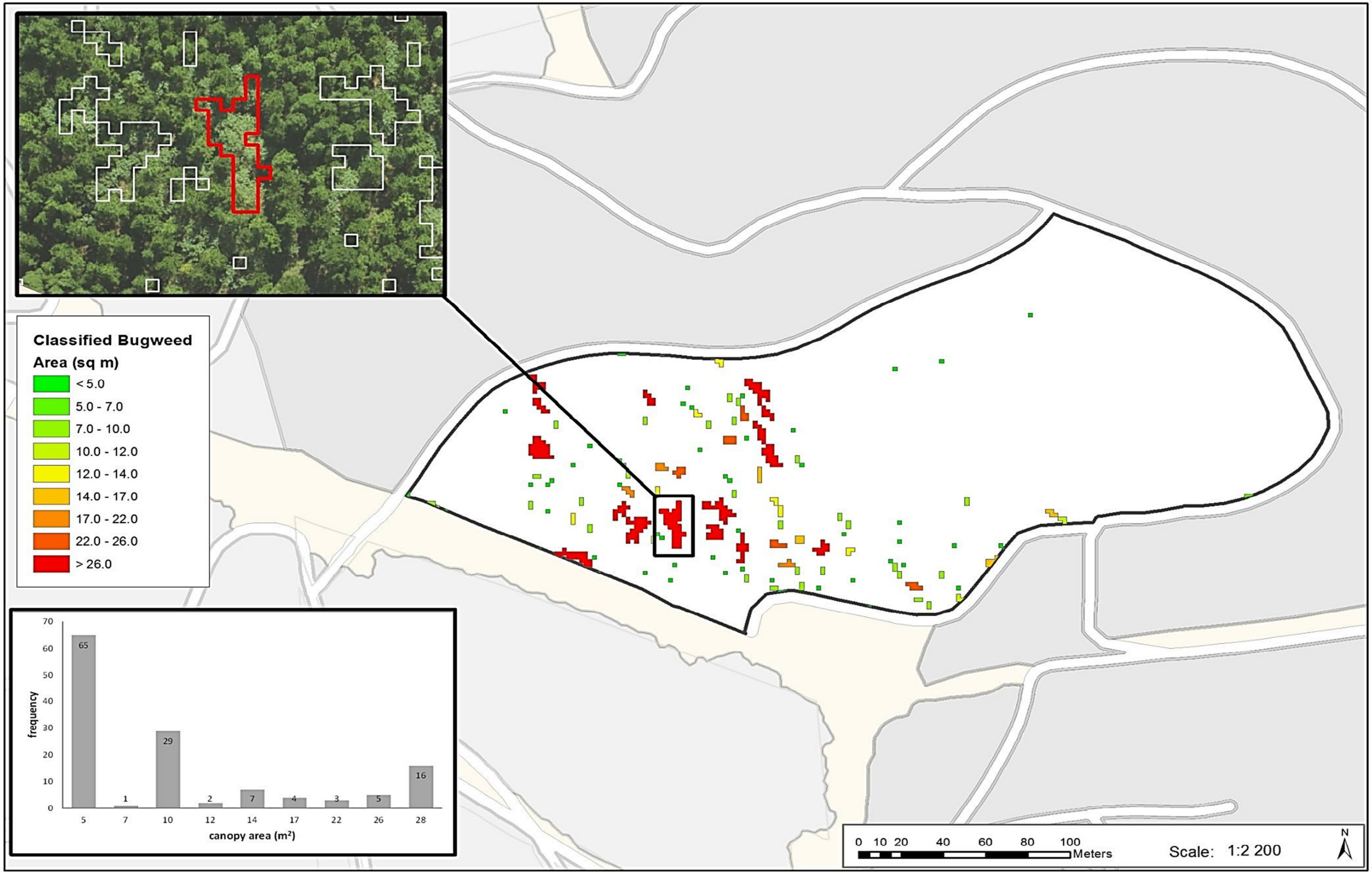

Figure 6: Classified map of detected bugweed with varying canopy size after applying the SVM-RFE algorithm to the 17 band AISA Eagle dataset.

4 Discussion

4.1 Modelling bugweed using support vector machines

The SVM algorithm applied in this study proved to be a powerful classifier and thus seems promising for hyperspectral image classification within homogenous semi-natural ecosystems, such as forestry plantations. The method allowed for the automated detection, classification and successful mapping of bugweed using the AISA Eagle image data. SVMs were theoretically developed for binary classification scenarios (Melgane and Bruzzone, 2004) and therefore their application in remote sensing, where a large majority of the land cover classifications involve more than one class (multiclass), are usually limited (Pal, 2009). However, the binary classification used in the study produced satisfactory classification results. This is not surprising as Karimi et al (2006) have also shown that SVMs can perform better when the number of classifiers, and therefore complexity of the classification problem is reduced. Furthermore, Sanchez-Hernandez et al (2007) were able to show that a binary SVM with an overall classification accuracy of 92 % outperformed the standard maximum likelihood classifier having an overall accuracy of 65 % when classifying eight habitat types in a Californian coastal saltmarsh.

The critical issue is the accuracy of the bugweed classification within the study area. Accuracy assessments show that the SVM algorithm is a robust and accurate method for bugweed image classification using high resolution hyperspecral imagery. Overall classification accuracies ranged from 91 to 93 % whilst the TSS, an indication of model performance, ranged from 0.82 to 0.87 for all datasets tested further confirming the model's applicability within an operational environment. Previous works using SVMs have also shown successful classification performance for hyperspecttral data (Chi et al., 2008; Watanachaturaporn et al., 2004; Bazi and Melgani, 2006; Huang et al., 2002; Pal and Mather, 2004; Guo et al., 2005; Karimi et al., 2006; Melgani and Bruzzone, 2004; Camps-Vells and Bruzone, 2005). Moreover, the overall accuracies from this study seem to be superior in relation to other invasive species classification studies applying different classification methodologies. Among these, studies which used Gaussian Maximum Likelihood and linear discriminant analysis (Dalponte et al., 2009), Mixture Tuned Match Filtering (Glenn et al., 2005), RandomForest (Lawrence et al., 2006) as well as Minimum Noise Fraction, continuum removal and band ratio indices (Underwood et al., 2003) all yielded lower overall classification accuracies than the current study. The potential to use a spatially explicit model for bugweed detection, as well as other nuisance species, is further strengthened if one considers the relatively high specificity and sensitivity accuracies obtained. The sensitivity and specificity accuracies obtained for both the 110 and 17 band datasets are a good indication that the SVM model is not only capable of producing an accurate map of more than one vegetation class, but that the model is also suited for differentiating one particular species with distinctive sets of features, such as bugweed, from other unique species such as pine. However, particular attention was placed on the specificity, which reflects errors of commision, as this illustrates how well the model was able to detect bugweed in the study site. The low specificity consequently confirms the SVMs potential for use as a decision support tool within a vegetation management programme since the extent of bugweed would be adequately detected and mapped. However, caution is advised, as Damasevicius (2008) points out that SVM training as well as generalisation performance is highly dependent on the type of kernel function and associated hyper-parameters used for classification. Since the accuracy of the SVM depends on the proper setting of the hyper-parameters, the main challenge for researchers is determining how best to optomize the hyper-parameters for a given application (Chercaskky and Ma, 2004).

4.2 Optimal waveband selection for bugweed detection

An interesting result from this study was that the SVM-RFE methods selected 17 optimal bands that yielded better classification accuracies than the original 110 band dataset. The results are in contrast to both Pal and Mather (2004) and Ceamanos et al., (2009) who reported improved SVM importance with increased number of bands. The reason for the better performance of the 17 band dataset is that the fewer bands resulted in less noise, enabling the model to limit the use of redundant bands thus improving overall classification accuracy (Melgani and Bruzzone, 2004). More importantly, the study has shown that the 17 band dataset consists of an optimal subset of hyperspectral bands at defined wavelengths within specific regions of the electromagnetic spectrum. Variable importance also showed that of the 17 bands selected from the model, thirteen bands occurred in the visible region (400 – 700 nm) and four bands were in located the near-infrared portion (NIR) (700 – 2500 nm) of the electromagnetic spectrum. Ceccato et al 2002 points out these regions of the spectrum are defined by (i) vegetation pigment content and by (ii) plant internal structure and the importance of reflectance and shape of individual plant spectral signatures within these regions is in keeping with our understanding of the basis of spectral uniqueness between plant species (Andrew and Ustin, 2008). Indeed, Scotford and Miller (2005) comment that a large majority of agricultural studies (which include weed management) use spectral measurements in these regions to detect both physiological and biological differences between plant species and other surface features.

These spectral characteristics are of more importance in the red-edge region as this region represents absorption spectra of the visible and reflectance spectra of the NIR portions (Dalponte et al., 2009) and subtle differences between species in crown characteristics can show up as large differences in infrared reflectance (Butler and Schlaepfer, 2004). The red-edge refers to the point of maximum slope between the red chlorophyll absorption region (680 nm) and the region of high near-infrared reflectance (750 nm) (Scotford and Miller, 2005). The red-edge is of significance to researchers as its exact wavelength and strength varies depending on the species considered and as such bands in this region are pivotal to plant species separation and therefore potentially essential for weed identification. Moreover, the spectral reflectance of at least two wavelength bands, usually on either side of the red-edge, enables a variety of vegetation indices to be calculated. Future studies could therefore utilise the normalized differential vegetation index (Stafford and Bollam, 1998), the red ratio vegetation index (Biller, 1998), the green ratio vegetation index (Oberti & Baerdemaeker, 2000) or the chlorophyll vegetation index (Gitelson et al., 1996) to investigate additional weed spectral and physical characteristics. These indices could be used to determine canopy characteristics and even specific weed properties (Scotford & Miller, 2005) within a forest compartment. Reducing the dimensionality of the AISA Eagle imagery and isolating a subset of optimal bands may offer an affordable and robust alternative to multispectral systems for both airborne and satellite applications of forestry assessment. Identifying these optimal spectral bands could help forestry managers exploit other optical remote sensing platforms, such as digital multispectral imagers (DMSI), or other commercially accessible hyperspectral sensors, which operate in the desired spectral range for bugweed discrimination.

4.3 Forest management implications

Mapping any understory invasive species is a challenging exercise. So the occurrence of understory bugweed makes detection with direct optical remote sensing techniques very difficult especially in areas with closed canopies (Joshi et al, 2004). However, in open canopies that have bugweed growing in the understory, the results from this study have demonstrated that where bugweed dominates the spectral signature, detection is possible. One of the most likely uses for regional bugweed thematic maps from a weed management approach would be to locate and track bugweed infestations and distribution within plantations. Furthermore, the methods described in this study could be used to supplement existing weeding programs or be used as a decision support tool for long term integrated weed control programs (Goodhall & Naude, 1998, Goodhall & Erasmus, 1996). More specifically, vegetation management within commercial plantations are generally categorised into three phase's namely pre-plant weeding, post-plant weeding and noxious weeding. The most immediate benefit of applying the methods from this study would be to formulate a framework that prioritizes weeding activities at both the pre-plant and noxious weeding phases. Dobyn (2009) sates that pre-plant weeding occurs before tree establishment and if carried out effectively, will not only save costs on future weeding operations but will also promote the sustainable protection of future timber plantations. Conversely, noxious weeding is necessary to mitigate IAPs that have already become established within mature plantations after post-plant weeding and require regular targeted eradication.

The synoptic identification and classification of plantation bugweed could undoubtedly be used to prioritize areas of high infestation on which to focus management and monitoring efforts. This could be done by firstly identifying the bugweed by pinpointing their locality in the plantation, establishing their extent and abundance (single trees or clusters) and then deciding on their potential impact to not only forestry resources but also forestry operations and surrounding ecotones, such as riparian areas (Dobyn, 2009). From an ecological stand point, riparian ecosystems (the border of streams and rivers) are extremely vital for fulfilling a variety of ecosystem functions within the plantation yet they are particularly susceptible to weed invasion due to their low-lying position in the landscape and because rivers act as conduits for the dispersal of seeds (Du Toit et al, 2003, Richardson et al, 2007). These areas act as focal points for further encroachment and potential spreading within the timber plantations and therefore need to be managed just as proactively as the plantation weeding regimes. Whether or not the results of this study prompts a more concerted effort to consider remote sensing technologies as operationally viable for weed management depends on the capacity and will of forestry institutions and resource managers to exploit the availability as well as access to the technology and employ the knowledge for effective use of the tools (Chornesky, et al, 2005).

4.4 Challenges to mapping the occurrence of bugweed using hyperspectral data

Results from this study indicate that bugweed within forest stands can be accurately mapped with hyperspectral images acquired at both a high spatial and spectral resolution. However, this comes at the expense of increased computational time and increased classification complexity due to augmented data hyper-dimensionality (Dalponte et al., 2009). Currently, data availability and data cost combined with technical and specialised methodological approaches are the major limitations that persist with regards to operational hyperspectral applications in South Africa (Ismail et al, 2008). The result is that very few local studies have actually explored the potential of using hyperspectral imagery for classification (Mutanga and Skidmore, 2005, Mutanga and Skidmore 2004). These factors have played a crucial role in limiting the success of developing an operational framework for weed detection in a commercial forestry environment. As Ismail et al. (2008), points out for remote sensing technologies to be widely accepted by forest companies and the tools to be operationally feasible, methods must allow for the efficient and cost effective mapping of infestations. It should be noted however, the question is not whether one data source is superior to another (e.g. hyperspectral vs multispectral or airborne vs spaceborne) but rather under what conditions a particular sensor can provide the desired information to meet the mapping objective. Evaluating the suitability of remote sensing data for a specific mapping task should include an evaluation of geometric integrity, spatial resolution, spectral resolution, area coverage and image acquisition costs. Furthermore, each of these considerations needs to be evaluated relative to the mapping task at hand (Madden, 2004). Indeed, Ismail et al. (2008) was able to show that the generally high classification errors associated with damage discrimination of pine species by *Sirex noctilio* (Eurasian woodwasp) imposes operational limitations on the use of broad band multispectral sensors by forestry companies. For that reason, even though hyperspectral image acquisition may be costly, in certain circumstances, the potential economic benefits gained from having a reliable and repeatable data source to accurately detect invasive species are more important than the image and processing costs (Glenn et al., 2005).

5. Conclusion

The primary goal of this study was to demonstrate the utility of SVM methods to analyse high resolution hyperspectral imagery for detecting bugweed, one of the most problematic invasive species within commercial plantations. It is well documented that the early detection of IAPs within plantations, whilst their spatial extent is still localized or small, reduces the cost of control and consequently improves eradication efforts. Using hyperspectral data with superior machine learning algorithms to detect and map bugweed would be a valuable tool for recording bugweed distribution and infestation levels in commercial forests. Furthermore, SVM's superior generalization ability and capacity to utilize small training datasets and still produce higher classification accuracies than more conventional methods should make them more appealing amongst spatial researchers and possibly even resource managers. From an operational perspective, classification methods which are able to focus training activities on a desired species of interest whilst only requiring small and inexpensive training sets to derive the required information are highly favourable. Overall, the results of the study showed that the modified SVM-RFE approach is an efficient as well as accurate method for (i) optimal band selection and (ii) detecting the presence of bugweed within mature *Pinus patula* compartments.

The SVM-RFE approach was able to produce high overall and class accuracies in excess of 90 % by using only 17 of the original 272 AISA Eagle spectral bands. A large majority of these bands were situated within the visible and red-edge portion of the electromagnetic spectrum signifying the importance of these regions in detecting the occurrence of bugweed within commercial forestry compartments using hyperspectral imagery. The results from the study have reiterated why SVMs are particularly appealing in classifying remote sensing data. That is, they provide a timely and repeatable product for developing a framework for effective weed management in commercial forestry focusing on weed monitoring, prioritization and eradication. Considering the high overall and class classification accuracies obtained from the study the use of high spatial resolution image data for the classification of nuisance plant species as part of an integrated weed management program should be further pursued by commercial forestry institutions. There are definite management and financial benefits of high resolution weed mapping and monitoring in support of forestry management activities. Yet very few, if any, real-world methods exist to quantify weed diversity occurrence at high spatial resolution in regional commercial forest plantations. Lower image acquisition costs combined with some hyperspectral image platforms becoming more commercially accessible should hopefully reinforce hyperspectral sensors as a viable long term management tool for a variety of forestry applications.

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