THE USE OF HIGH RESOLUTION AIRBORNE IMAGERY FOR THE DETECTION OF FOREST CANOPY DAMAGE CAUSED BY *SIREX NOCTILIO*

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Abstract
More than a decade after its initial discovery in the Western Cape, the Eurasian woodwasp, *Sirex noctilio,* has spread to the southern parts of KwaZulu-Natal posing a serious threat to pine species in the region. Whilst foresters are able to provide broad scale assessments of *S. noctilio* infestation, there are no existing frameworks in place to provide quantifiable measurements of the spatial or temporal distributions of this damaging agent, and the impact it has on commercial pine forestry. Remote sensing technology offers an alternative to the current broad scale methods of assessing forest health. In this study, high resolution (50cm) imagery was acquired over commercial *Pinus patula* vegetation of varying age classes which had been ground assessed and ranked on an individual tree crown basis using a visual severity scale (i.e. healthy, green, red and grey). A series of ratio and linear based vegetation indices were calculated and compared to the different *S.noctilio* crown condition classes. Of the vegetation indices calculated, significant differences ($p<0.001$) between the pre-visual (healthy and green) and visual (red and grey) crown condition classes were obtained, using the normalised difference vegetation index (NDVI) and the green normalised difference vegetation index (GNDVI). Canonical variate analysis further revealed that greater discriminatory power between the different *S.noctilio* crown condition classes is obtained when using NDVI as compared to the other vegetation indices. Overall the study demonstrated the importance of using vegetation indices obtained from high resolution airborne imagery to discriminate between healthy trees and trees that were in the visual stage of infestation (red and grey stages).

Keywords: *Sirex noctilio*, high resolution imagery, vegetation indices, canonical variate analysis

Introduction

More than a decade after its initial discovery in the Western Cape (Tribe, 1995; Tribe & Cillie, 2004), the Eurasian woodwasp, *Sirex noctilio*, has spread to the southern parts of KwaZulu-Natal, posing a serious threat to pine species in the region. In an effort to minimise the potential threat to commercial pine production in the region, an integrated management strategy combining detailed detection and monitoring methods, silvicultural treatments and biological controls has been implemented on an industry wide basis in South Africa. The primary control of established *S.noctilio* populations is achieved by biological means using the nematode *Deladenus siricidicola* and parasitic wasps such as *Ibalia leucospoides* and *Megarhyssa nortoni; while* silvicultural methods such as thinning are carried out to improve tree vigour and thereby keep damage within acceptable levels. However, successful implementation, of the above control measures, depends on our ability to spatially quantify the severity and extent of infestation so that forest managers can adopt the most appropriate course of intervention before the stand reaches a point of non-recovery. For example, moderate *S.noctilio* infestations (<10%) require the inoculation of infested trees with nematodes whereas heavy infestations (between 10 and 50%) would require sanitization and salvage operations to be implemented. Additionally, Geographic Information Systems (GIS) and forest planning systems, which include harvesting schedules, timber volume analysis and species growth models have been developed to help foresters manage affected areas, and these systems require accurate spatial information on the severity and extent of *S.noctilio* damage.

Current methods used to identify the severity and extent of *S.noctilio* infestation include broad scale visual aerial reconnaissance, followed by field based exercises to verify the results. Although visual assessments of infestation are widely used to measure forest health (Haara & Nevalainen, 2002) the effectiveness of visual assessments are questionable because they are qualitative, subjective and dependent on the skill of the surveyor (McConnell *et al.*, 2000; Stone & Coops, 2004). Previous forest health studies have shown estimation errors between 25 and 75% (Belanger & Anderson, 1988). The ability of remote sensing technology to augment traditional forest health evaluation procedures has been demonstrated by researchers for a diverse range of pests and pathogens (Muchoney & Haack, 1994; Vogelmann & Rock, 1995; Majeed, 1999; Bonneau *et al.*, 1999a; Franklin *et al.*, 2003; Wulder & Dymond, 2004) and imagery types (Vogelmann & Rock, 1995; Bonneau *et al.*, 1999b; Coops *et al.*, 2003). Using remote sensing to detect infestations is based on the assumption that the canopy damage caused by the pest *S.noctilio* creates differences in foliar constituents, foliage amount and canopy structure (Entcheva *et al.*, 2004) thus affecting the absorption of light energy thereby altering the reflectance spectrum of the tree (Entcheva *et al.*, 1996; Stone *et al.*, 2001). Thus by reliably measuring the reflectance spectrum, the health status of the tree can be determined.

Overview of vegetation indices

Researchers have studied the spectral effects of declining forest health (Ahern, 1988; Stone *et al.*, 2001; Entcheva *et al.*, 2004; Stone & Coops, 2004) and the various methods (Collins & Woodcock, 1996; Radeloff *et al.*, 1999; Levesque & King, 2003; Skakun *et al.*, 2003; Wulder & Dymond, 2004) which can be then used to detect the health status of trees. It has been reported that plants under stress display a decrease in canopy reflectance in the lower portion of the near infrared (NIR), a reduced absorption in the chlorophyll active band (red) and a consequent shift in the red edge (Carter & Knapp, 2001). For example, Entcheva *et al.*, (1996) found that reflectance at the 698 nm wavelength was significant in explaining needle reflectance response to southern pine beetle damage in *Pinus elliottii* while Ahern, (1988) found reflectance at 700 nm to be an indicator of needle stress in lodgepole pine caused by mountain beetles.

The most widely used vegetation indices (VI) exploit these spectral characteristics i.e. chlorophyll absorption by vegetation in the red portion of the spectrum and the high reflectance by vegetation in the NIR portion (Tucker, 1979; Treitz & Howarth, 1999). Additionally, the advantage of using remotely sensed VI includes the removal of variability caused by canopy geometry, soil background, sunview angles and atmospheric conditions (Gilabert *et al.*, 2002). Consequently, a number of narrow (Leckie *et al.*, 2004; Stone and Coops, 2004) and broad band vegetation indices (Vogelmann, 1990; Collins & Woodcock, 1996) have been successfully used to assess changes in the reflectance due to the declining health status of the tree. For the purpose of this study we have generally divided the broadband VI into two categories i.e. ratio based indices and linear based indices, although other categorisation may be appropriate for other purposes or imagery types (e.g. narrowband red edge indices). It is not our intent to provide a complete review of VI, for a complete review see Jackson & Huete (1991) and Thenkabail *et al.*, (2002), but we will review certain VI to the extent necessary to formulate our hypothesis regarding which indices would successfully detect and discriminate forest canopy damage caused by *S.noctilio* infestations.

Ratio based Indices

Ratio based indices operate by contrasting the intense chlorophyll pigment absorption in the red portion against the high reflectance, due to multiple scattering in the NIR portion of the electromagnetic spectrum (Elvidge & Chen, 1995). The most widely used ratio based indices such as the ratio vegetation index (RVI) (Jordan, 1969), normalized difference vegetation index (NDVI) (Rouse *et al.*, 1973), difference vegetation index (DVI) (Tucker, 1979) and green normalised difference vegetation index (GNDVI)(Gitelson & Merzlyak, 1998) respond to these differences in the near infrared and visible regions (Lillesand *et al.*, 2004).

For example, using Landsat MSS data, Nelson (1983), examined image differencing, image ratioing and vegetation index differencing in detecting gypsy moth defoliation and found the NIR /red ratio to be more useful in detecting defoliated areas than any of the other examined VI. Results from a study using Landsat TM conducted by Vogelmann (1990) indicated that NDVI provided an accurate assessment of insect induced defoliation damage to deciduous trees. NDVI also appeared to be very good at discriminating between high, medium and low deciduous damage categories; however the NDVI was only partially successful in measuring conifer forest damage (Vogelmann, 1990). Ekstrand (1994) on the other hand, suggested that moderate defoliation damage in Norway spruce (*Picea abies*) could be estimated using Landsat TM band 4 (NIR) and classification accuracies of 80% were achieved in sites that were predominately spruce in composition. The study concluded that ratio based algorithms are more applicable to regions suffering from both chlorosis (yellowing) and defoliation and were inappropriate in areas where defoliation is the sole symptom of forest decline (Ekstrand, 1994).

Linear Based Combinations

Linear combinations of spectral bands have been used to develop physically significant indices (Jackson, 1983) such as the tasseled cap transformation (TCT) which was developed by Kauth and Thomas (1976). Using Landsat MSS bands, Kauth and Thomas (1976) established four new indices (brightness, greenness, yellowness and nonsuch) in the spectral data which could be useful for vegetation monitoring. Linear based VI are especially useful for the discrimination of vegetation from the soil background (Jackson, 1983) because linear VI are based on a predetermined soil line rather than the inherently assumed soil line underlying the ratio based NDVI (Lawrence & Ripple, 1998). Crist and Cicone (1984) later extended the transformation concept to Landsat TM data and more recently TCT have been calculated for high resolution, Ikonos (Horne, 2003) and QuickBird imagery (Yarbrough *et al.*, 2005). Several studies using broad band imagery (Collins & Woodcock, 1996; Price & Jakubauskas, 1998; Sharma & Murtha, 2001; Skakun *et al.*, 2003; Healey *et al.*, 2005; Jin & Sader, 2005) have shown the value of using the TCT when assessing forest health condition. According to Skakun *et al.* (2003) this is largely due to the fact that colour changes (chlorosis) associated with damaged trees are organized along the principal directions of brightness (TCB), greenness (TCG) and wetness (TCW) which are determined by the TCT. Additionally, Sharma & Murtha (2001) reported that differences between mean TCB, TCG and TCW of attacked stands and healthy *Pinus contorta* were statistically significant. Similar results were reported by Price & Jakubauskas (1998) who suggested that when using TCT components it was possible to distinguish stands that were progressively thinned as a result of beetle damage.

Research has shown that ratio and linear based vegetation indices have the potential to successfully quantify the severity and extent of infestation caused by various pests and pathogens. However, to date, no research has examined the benefits of using these vegetation indices to detect forest canopy damage caused by *S.noctilio*. Additionally, there is a need to identify small clusters or individual trees because pine plantations infested by *S.noctilio* have a scattering of dead and dying trees (Haugen *et al.*, 1990; Haugen & Underdown, 1990). This study intends to address these issues by firstly, using VI derived from high resolution imagery (50cm) to characterise *S.noctilio* induced stress in *Pinus patula* compartments. This allows for the identification of individual crown characteristics, thereby exploiting both spectral and spatial resolutions. Secondly, we intend to test the relative strength of various ratio and linear based vegetation indices in discriminating the crown condition classes associated with *S.noctilio* infestations. The overall objective of this study is to develop remote sensing techniques that will assist in the management of *S.noctilio* infestations. Once developed and tested, these techniques offer the potential to be applied operationally and should improve our ability to map those stands at high risk of infestation.

Materials and Methods

Description of the Study Area

The study area is approximately 1750 ha and forms part of the Sappi Pinewoods plantation which is dominated by *Pinus patula* compartments. The site is located approximately 30 km outside the town of Pietermaritzburg, KwaZulu-Natal. The average altitude for the site is 1190m with an average air temperature of 16.1° C. The mean annual rainfall of the area is 916mm.The terrain consists of low mountains and undulating hills. The geology of the area is a mixture of mudstone, sandstone, tillite, ampholite and basalt. Soils in the area are mostly sandy-clay and sand-clay loams (Macfarlane, 2004).

Figure 1: Location of the study area

Inoculation, clear felling and thinning operations have been carried out in Pinewoods since 2003, in an effort to reduce the high S.*noctilio* infestation rates present within certain stands.

These management interventions are carried out based on age stratification guidelines i.e. less than 7 years, from 8 to 9 years, 10 to12 years and older than 13 years .The age strata have been developed to account for insect-tree dynamics. S.*noctilio* typically attacks older stressed trees however as the insect population increases , an increasing percentage of healthy pine trees are attacked (Haugen *et al.*, 1990; Ciesla, 2003). Therefore intervention measures such as clear felling operations would be implemented in older compartments (> 13 years) in order to salvage “utilizable” trees, while inoculations would be carried out in stands that are between 10 to 12 years old to reduce S.*noctilio* populations from reaching epidemic proportions.

Data acquisition

High Resolution (50cm) multispectral imagery was acquired on the 9th September 2005 by Land Resources International (LRI) Inc, Pietermaritzburg (South Africa) with their manufactured LrEye aerial imaging system. The LrEye sensor is composed of a series of four monochrome Sony cameras. Each camera collects data for one of the bands shown in Table 1.The resulting four bands are registered to form an image with four co-registered bands that are referenced to the Gauss conformal projection (central meridian: 31). To minimise bidirectional reflectance and to cover the study area, flight lines were oriented away from the sun and flown as a series of north-south strips. Field data collection took place one week after the image was acquired.

Table 1: Spectral range of Landsat TM compared to the LrEye sensor

Band	TM spectral range (nm)	LREye spectral range (nm)	Colour
1	0.45-0.52	450 to 480nm with the peak at 465.88nm	Blue
2	0.52-0.60	550 to 580nm with the peak at 568.42nm	Green
3	0.63-0.69	650 to 680nm with the peak at 664.67nm	Red
4	0.76-0.90	850 to 900nm with the peak at 870.53nm	Near Infrared

Field Data Collection

A stratified random sampling technique was adopted for this study. Pine compartments that were harvested, or that were recently planted, were excluded from the sample. A 50 m x 50 m grid was generated over the study area and 10 grid cells were randomly selected from each predetermined age stratum (i.e. less than 7 years, from 8 to 9 years, 10 to12 years and older than 13 years). This age stratification was adopted because it reflects current *S.noctilio* management guidelines. At the centre point of each grid cell, a 10 meter radius plot was created. Tree crowns located within each plot were manually identified on the LrEye data and subsequently located in the field using a Global Position System (GPS). In total, 782 trees were assessed for *S.noctilio* infections based on a visual severity scale that is shown in Table 2.This process was undertaken with the assistance of Sappi forest planners and technical staff who have a detailed understanding of the identification and classification of *S.noctilio* infestations. Additionally, trees that were classified as ‘red’ were destructively sampled to evaluate the presence of *S.noctilio* larvae.

Table 2: The crown condition classes assessed in the ground survey

Class	Stages	Visual Symptoms
1	Healthy	No signs of S.*noctilio* infestation
2	Green	Green crown, presence of resin droplets, cambium stain, ovipositors found on the trunk and no needle loss
3	Red	Severe chlorosis , reddish brown canopy and high needle loss
4	Grey	Emergence holes, no canopy , most branches intact and 100% needle loss

Vegetation Indices

According to Coops *et al.*, (2004) the method used to obtain the spectral reflectance of individual trees when using high resolution imagery is important because significant variation in brightness exists depending on the pixel position within the crown. In a study conducted by Leckie *et al.*, (1992) to account for effects of the variation on individual crown delineation it was concluded that either the whole tree or the sunlit tree sampling methods were the most suitable methods to derive consistent and representative spectral response. In this study, the whole crown method was used, each of the selected crowns was manually delineated on the LrEye imagery and the crown spectral response extracted for the VI used in this study (Table 3).

Table 3: Ratio based vegetation indices used in this study.

	Vegetation Index Name	Index	Equation	Reference
1	Normalized difference vegetation index	NDVI	NDVI = (NIR−red)/(NIR + red)	Rouse et al, 1973; Jackson, 1983
2	Ratio vegetation index	RVI	RVI = NIR/red	Jordan, 1969
3	Difference vegetation index	DVI	DVI = NIR−red	(Tucker, 1979)
4	Green normalised difference vegetation index	GNDVI	GNDVI = (NIR – green)/ (NIR + green)	Gitelson and Merzlyak, 1998

Tasseled cap transformation

The Gram-Schmidt orthogonalization process was used to derive the tasselled cap transformation (TCT) coefficients. Initially, a soil line and the vector in the “brightness” direction are determined; subsequently from the “brightness” vector all other vectors (i.e. greenness and yellowness) are orthogonally calculated. Yarbrough *et al.*, (2005) and Jackson (1983) provide a mathematical description for calculating coefficients for *n* space indices using the Gram-Schmidt orthogonalization process .Coefficients (Table 4) are based on the grey level values (DN) of the LrEye imagery of the four land cover types i.e. wet soil, dry soil, green vegetation and senesced vegetation. Water was used to represent wet soil values because pixels representing wet soils were not found in the imagery. Dry soil values were collected from dirt roads while tree crowns represented green vegetation.Dry grass values were used to represent senesced vegetation.

Table 4: Gram-Schmidt coefficients

	B	G	R	NIR
Brightness (TCB)	0.337663	0.586272	0.638220	0.367348
Greenness (TCG)	-0.227113	-0.131965	-0.288569	0.920724
Yellowness(TCY)	0.097931	-0.781721	0.607311	0.102451

The resulting linear equations for brightness, greenness and yellowness are as follows:

Brightness (TCB) = 0.337663 (blue) + 0.586272 (green) + 0.638220 (red) + 0.367348 (NIR)
Greenness (TCG) = -0.227113 (blue) -0.131965 (green) -0.288569 (red) + 0.920724 (NIR)
Yellowness (TCY) = 0.097931 (blue) -0.781721 (green) 0.607311 (red) + 0.102451 (NIR)

Statistical Analysis

We tested the hypothesis that ratio and linear based vegetation indices could differentiate among the various stages of infestation (i.e. healthy, green red and grey) caused by *S.noctilio*. Analysis was undertaken to compare the crown condition classes for each of the indices in order to determine which of the VI consistently discriminated at least some of the classes as determined by the visual severity scale (Table 2). This was tested using an analysis of variance (ANOVA) with a Tukey's HSD post hoc test.

Canonical variate analysis (CVA) is a multivariate statistical technique which discriminates among prespecified groups of sampling entities based on a suite of characteristics (McGarigal *et al.*, 2000). The technique involves deriving linear combinations (i.e. canonical functions) of two or more discriminating variables that will best discriminate among the *a priori* defined groups (Mutanga, 2005). In this study vegetation indices (VI) are entered into the analysis based on their ability to increase group separation (i.e. crown condition classes). This reduces the number of indices to a subset that provides the best discrimination among classes. The best linear combination of VI is achieved by the statistical decision rule of maximising the among group variance, relative to the within group variance (Mutanga, 2005). The first discriminant function provides the best separation among classes, while the second function separates classes using information not used in the first function and so forth. Additionally, the functions will be independent or orthogonal, that is, their contributions to the discrimination between groups will not overlap (Lawrence & Labus, 2003). Based on this background, we used CVA to exhibit optimal separation of the crown condition classes based on the linear transformation of the calculated VI, and establish which VI are most related to the separation of these classes.

We used the leave-one-out cross validation technique for estimating the error rate conditioned on the training data. The advantage of using the leave-one-out cross validation technique is that all the data is used for estimating error. Using this cross validation technique, each observation is systematically removed, the canonical function re-estimated and the excluded observation classified (Mutanga, 2005). A confusion matrix is then constructed to compare the field (true) crown condition classes with the class assigned by the VI to the sample dataset. It depicts accuracies of the crown condition classes (producer's and user's accuracies). Producer's accuracies are calculated by dividing the number of correctly classified trees in each crown condition class by the number of training data used for that class (i.e. column total in the confusion matrix). User accuracies are computed by dividing the number of correctly classified trees by the total number of trees that were classified in that crown condition class (i.e. row total in the confusion matrix). Additionally a discrete multivariate technique called kappa analysis that uses the *k* ("KHAT") statistic as a measure of agreement with the reference data was calculated (Congalton & Green, 1999; Skidmore, 1999). This statistic serves as an indicator of the extent to which the percentage correct values of an error matrix are due to “true” agreement versus “chance” agreement (Lillesand *et al.*, 2004). If the kappa coefficients is one or close to one then there is perfect agreement between training and test data. Conceptually *k* can be defined as:

$$k = \frac{\text{observed accuracy} - \text{chance agreement}}{1 - \text{chance agreement}} \quad (1)$$

Results

We tested the hypothesis that ratio and linear based vegetation indices would discriminate among the various crown condition classes by conducting a one-way ANOVA. Of the vegetation indices calculated, significant differences ($p<0.001$) were obtained using NDVI, GNDVI, DVI, RVI, TCG and TCB. A one-way ANOVA shows that there is a significant difference between the vegetation indices and the *S.noctilio* crown condition classes, but it does not show which crown condition classes are different. We therefore executed a Tukey’s HSD post hoc test in order to establish differences between each of the crown condition classes (i.e. healthy, green, red and grey). Results with their respective level of significance are shown in the table below.

Table 5: Analysis of variance results with a Tukey’s HSD post hoc test. Class 1 (healthy), class 2 (green), class 3 (red) and class 4 (grey).

NDVI	1	2	3	4	TCG	1	2	3	4
1	..	**	*	*	1	..	**	*	*
2	**	..	*	*	2	**	..	*	*
3	*	*	..	*	3	*	*	..	*
4	*	*	*	..	4	*	*	*	..
GNDVI	1	2	3	4	TCB	1	2	3	4
1	..	**	*	*	1	..	**	**	*
2	**	..	*	*	2	**	..	**	*
3	*	*	..	*	3	**	**	..	**
4	*	*	*	..	4	*	*	**	..
DVI	1	2	3	4	NIR	1	2	3	4
1	..	**	*	*	1	..	**	*	*
2	**	..	*	*	2	**	..	*	*
3	*	*	..	*	3	*	*	..	*
4	*	*	*	..	4	*	*	*	..

P< 0.001 =*, Not Significant =**

The results indicate that both ratio and linear based indices are poor at discriminating between class 1 (healthy) and class 2 (green stage). However, the VI tested are capable of discriminating between the previsual (classes 1 and 2) and visual crown condition classes (classes 3 and 4). The most significant degree of separation occurs between class 1 and classes 3 and 4 and between class 2 and classes 3 and 4. All indices are capable of discriminating between these classes except for TCB which can only discriminate between class 1 and class 4 and between class 2 and class 4. Based on the results from ANOVA, it is difficult to determine which index has the best discriminatory power. Therefore, we carried out a canonical variate analysis and included all indices (discriminatory variables) except for the TCB component. Additionally, to improve the discriminatory power of the VI, class 2 (green stage) was grouped with class 1 (healthy trees) while the rest of the classes remained the same i.e. class 3 (red stage) and class 4 (grey stage)

Canonical variate analysis (CVA) results

We tested the relative strength of various ratio and linear based vegetation indices in detecting *S.noctilio* infestations by conducting a canonical variate analysis (CVA). Table 6 shows the eigenvalues as well as the factor structure matrix from the canonical variate analysis using 3 crown condition classes (i.e. healthy, red and grey stages). The measure of information contained in the functions is represented by the eigenvalues corresponding to those functions. The eigenvalues are interpreted as the ratio of variances along each function (Richards, 1993). The largest portion of the explained variance (97.5%) is contained in the first canonical function while the reminder is contained in the second function (2.5%). The factor structure coefficients contained in the matrix below represent the correlations between the variables and the canonical functions and are used to interpret the canonical functions (McGarigal *et al.*, 2000). Results indicate that the highest factor structure coefficients are contained in the NDVI (0.633) and the GNDVI (0.629). The second canonical function also shows that one of the largest contributions is contained in the GNDVI (0.605) and to a lesser extent NDVI (0.369), however the magnitude for the second canonical function is much smaller that that of the first canonical function. The scatter plot in Figure 2 shows the position of the crown condition classes in canonical space.

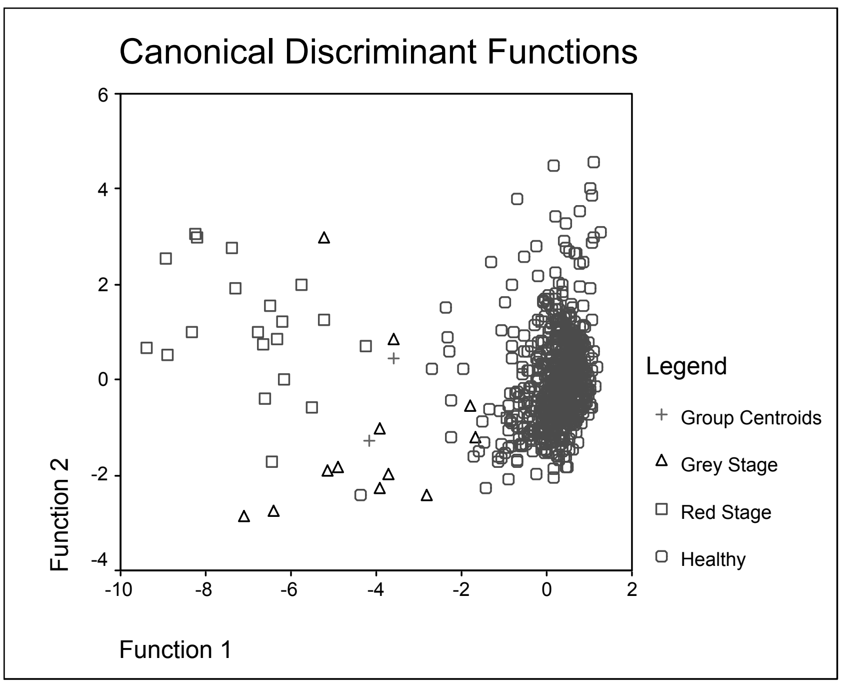

Figure 2: Scatterplot of two canonical functions produced by canonical variate analysis

Table 6: Factor structure matrix representing the correlation between variables and canonical functions (3 classes)

	Function 1	Function 2
NDVI	.633	.369
GNDVI	.629	.605
DVI	.559	.550
TCG	.500	.669
NIRR	.484	.463
Eigenvalue	0.961	0.025
% Variance	97.5	2.5

Classification

To further investigate the effectiveness of high resolution airborne imagery to discriminate between crown condition classes we classified the samples using Fisher's linear discriminant functions(McGarigal *et al.*, 2000; Mutanga, 2005).To test the predictive discriminatory power of the canonical functions we used the leave-out-one technique for estimating the error rate conditioned on the training data. In the leave-out-one technique each observation is systematically dropped and the canonical function re-estimated and the excluded observation classified. The confusion matrix including the kappa statistic, user accuracy and producer accuracies are shown in Table 7.

Table 7: Confusion matrix showing the predicted accuracy of Sirex noctilio using a 3 level classification system: class 1 (healthy), class 2 (red), and class 3 (grey)

Class	1	2	3	UA
1	695	2	2	99.43
2	8	26	3	70.27
3	2	3	11	68.75
PA	98.58	83.87	68.75	
KHAT	0.79			

Discussion

High resolution remote sensing provides a reasonable and robust tool to improve our ability to spatially quantify the severity and extent of *Sirex noctilio* infestations while not excluding the importance of visual assessments made by forest health experts. Both ratios and linear based vegetation indices are able to significantly ($p < 0.001$) discriminate between the previsual (healthy and green) and the visual stages of infestations (red and grey).Canonical variate analysis further reveals that greater discriminatory power between the different crown condition classes is obtained when using NDVI as compared to the other vegetation indices. Accuracy assessments show that NDVI is successful in locating and predicting the condition of tree canopies on the imagery when crown condition classes are reduced to a three classification system, in which case producer accuracies range from 84% (red stage) to 69% (grey stage) . The results obtained from this study are comparable to previous studies on declining forest health (Vogelmann, 1990; Leckie *et al.*, 2004; Wulder *et al.*, 2004; Leckie *et al.*, 2005) and emphasize the importance of the visible and NIR bands when studying the effects of declining forest health especially when infestation results in foliar discolouration.

Mapping the red stage of infestation is regarded as a priority among forest managers because it gives an accurate indication of the severity and extent that is taking place that year (current infestation) (Leckie *et al.*, 2005). Additionally, the depiction of infestation levels by mapping out the red stage of infestation meets current operational requirements. Forest managers can now quantify the potential effects of S*.noctilio* infestation on fibre supply and stand vulnerability, thereby allowing for the design of the most appropriate intervention measures.

The difficulty in discriminating the green stage of infestation is in consistent with other studies that have attempted to classify light to moderate symptoms using high resolution remotely sensed imagery (Leckie *et al.*, 2004; Leckie *et al.*, 2005).The success of discriminating green stage infestation is dependent on the detection of subtle changes in the spectral reflectance of the tree (Ekstrand, 1994). Slight changes in the spectral reflectance of stressed vegetation, when measured by various broad band sensors, are often masked by the high degree of variation in reflectance caused by factors such as varying view geometry, illumination, and canopy density (Runesson, 1991).Given this limitation, hyperspectral remote sensing offers possibilities to investigate the early stages of infestations based on narrow bands using the entire electromagnetic spectrum. These narrow bands allow for the detection of detailed features which would otherwise have been masked (Schmidt & Skidmore, 2001).

The performance of linear based indices as compared to ratio based indices was disappointing. However, previous studies (Collins & Woodcock, 1996; Skakun *et al.*, 2003) found changes in the tasseled cap wetness component (TCW) to be a good indicator of conifer mortality and the most consistent indicator of forest change due to the inclusion of the short wave infrared (SWIR) band. However in this study, the calculations of the tasselled coefficients were limited to the visible and NIR parts of the spectrum (400-900nm) and included only the tasselled cap brightness (TCB) and greenness (TCG) components. Additionally, spectrometer research conducted by (Leckie *et al.*, 1988) regarding discolouration caused by the spruce budworm indicated that the SWIR regions are better than the visible and NIR for discrimination. Similarly, initial attack by *Sirex noctilio* changes the water balance of the attacked tree, (Neumann & Minko, 1981; Slippers *et al.*, 2003) ,so using a sensor that captures SWIR wavelength has the potential to improve overall classification accuracy as well as discrimination between crown condition classes.

Conclusion

The use of ratio and linear based indices calculated from high resolution imagery has resulted in the successful detection and mapping of canopy damage caused by Sirex *noctilio*. Although it is difficult to discriminate between the healthy and green stages of infestation, classification accuracies are improved when using a three class crown condition index that differentiates between the healthy and the visual stages of infestation. More importantly, this has lead to the development of a detection and mapping framework that augments current management initiatives designed to reduce *Sirex noctilio* infestations.

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