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Detecting canopy damage caused by *Uromycladium acaciae* on South African Black Wattle forest compartments using moderate resolution satellite imagery

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Abstract

Uromycladium acaciae, also known as wattle rust, is a rust fungus that has adversely impacted black wattle (Acacia mearnsii) in South Africa. This study assessed the potential of the Landsat 8 multispectral sensor to detect canopy damage caused by wattle rust on two plantation farms near Richmond, KwaZulu-Natal. The Landsat 8 bands and vegetation indices detected forest canopy damage caused by Uromycladium acaciae with an accuracy of 88.24% utilising seven bands and the Partial Least Squares Discriminate Analysis (PLS-DA) algorithm. Additionally, the model was optimised using the Variable Importance in Projection (VIP) method which only selected the most influential bands in the model. The coastal aerosol band (430nm-450nm), red band (640nm-670nm), near infrared (850nm-880nm) and NDVI were exclusively used in the optimised model and an accuracy of 82.35% was produced. The study highlighted the potential of remote sensing to detect canopy damage caused by a rust fungus and contributes towards a monitoring framework for analysing trends using freely available Landsat 8 imagery.

1. Introduction

Plantation forestry covers about 1.2 million hectares and predominantly occupies the Mpumalanga and KwaZulu-Natal provinces located in the eastern seaboard of the country. Softwood tree species include *Pinus* species while hard wood species are dominated by *Eucalyptus* and *Acacia* species *(Forestry South Africa*, *2017)*. One of the most common species grown by wattle growers in South Africa is *Acacia mearnsii*, which is also known as Black Wattle. Approximately 112 029 ha of land is planted with *Acacia mearnsii* which contributes 7.4% to the market for timber and pulp production (Meyers *et al.,* 2001). The bark of Black Wattle is considered to contain one of the richest sources of tannins which has various industrial uses, including that of leather tanning (Sherry, 1971). Apart from its characteristic in the bark, wattle trees are also utilised in soil reclamation, as wind breaks, fire fuel, mining timber and paper pulp (Rusk *et al.,* 1990; Sherry, 1971). In South Africa, Black Wattle is mostly grown for chip export and the production of charcoal (Crickmay and Associates, 2010). Furthermore, there are large areas of unmanaged wattle stands and woodlots which contributes towards the livelihoods of rural communities. Black Wattle is therefore an economically important tree species for plantations and is also socially important to the rural communities of South Africa. Nonetheless, with the constant increase in demand for timber products, forest production is under pressure and the future sustainability of the industry is at risk. One of the major threats identified by the South African National Forest Protection Strategy and adopted by the Department of Agriculture, Forestry and Fisheries (DAFF) is the escalating impact of pests and pathogens (Dyer *et al.,* 2010).

During 2013, an outbreak of a new disease has been observed in Black Wattle around the KwaZulu-Natal Midlands area, caused by a rust fungus. The pathogen has spread fast to all wattle growing areas in the country, becoming a major concern for wattle growers in the region (McTaggart *et al.,* 2015). A concerted research effort has been undertaken by the Tree Protection Co-operative Programme (TPCP) together with the Institute for Commercial Forestry Research (ICFR) and industry partners to develop an effective management strategy to reduce the impact of the rust. Recent DNA sequencing techniques have been used to identify the rust as *Uromycladium acaciae* (McTaggart *et al.,* 2015). Some of the symptoms of the affected trees include leaf spots, petiole and rachis deformation, defoliation, gummosis, stunting and dieback of seedlings (Figure 1). Fungicides are currently being tested for the control of *Uromycladium acaciae*. However, more research needs to be undertaken to understand the seasonal cycle of the rust and environmental triggers of outbreaks to optimise the timing of interventions.

Image	Picture	Symptom
Image A		The slime as seen on black wattle in Enon an Etterby plantations.
Image B		Leaf curl seen on a few trees.
Image C		Telia present on the leaves.
Image D		Uredinia present on leaves and stem.

Figure 1. *Uromycladium acaciae* impacts on *Acacia mearnsii* trees.

To effectively respond to the impact and spread of the rust, forest managers and researchers require up-to-date information related to the current spatial extent, variability and severity of such infestation. Monitoring and surveillance are in fact a key component of an effective pest and disease management strategy, however, there is currently no system in place in response to this need. More generally, the need for a forest health surveillance system has been identified as a priority for the South African forestry sector (Dyer *et al.,* 2010). Current capabilities are inadequate with conventional field-based methods being prohibitively expensive, labour intensive and time consuming. According to Oumar and Mutanga (2010) field-based assessments are the most accurate in determining forest health, however, this is not a feasible option when larger areas of forest health estimates are needed. Earth observation technologies such as satellites provide local to global coverage on larger areas where field measurements are unfeasible on a regular basis. Remote sensing technologies as an alternative, offer the potential to enhance forest management strategies by providing a synopsis of forest health rapidly and over vast geographic extents (Wanger *et al.,* 2010).

This study seeks to develop an impact detection methodology that can be used for mapping and monitoring the presence of wattle rust using remote sensing technologies. The development of such methodology will not only play a key role for the management of the wattle rust to ensure the sustainability of wattle resources into the future (Forestry South Africa, 2017) but will also contribute towards the development of a broad national forest health monitoring system.

New generation, moderate resolution space-borne imagery can be an inexpensive, effective technology for the mapping, monitoring and risk assessment of new canopy pests and pathogens (Asner *et al.,* 2011; Wang *et al.,* 2010). This technology has been widely adopted for the monitoring of forest health and in support of integrated pest management strategies (Kennedy *et al.,* 2010; Meigs *et al.,* 2011; Verbesselt *et al.,* 2010; Wulder *et al.,* 2012). For example, the Landsat sensor is particularly sensitive to changes in forest structure in the near infrared and short-wave infrared channels (Wulder *et al.,* 2006). Image transformations in the near infrared and short-wave infrared regions have shown an 86% success rate in mapping subtle changes in canopy due to Mountain pine beetle red-attack damage. This result was achieved utilising a logistic regression approach (Wulder *et al.,* 2006). Ismail and Mutanga (2006) visually assessed damage to pine compartments triggered by *Sirex noctilio* attacks. The visual inspections were classed in a severity scale of damage. Using high resolution imagery (5m x 5m) they could show significant differences in the vegetation indices derived from the imagery between healthy and visually damaged pine compartments (Ismail and Mutanga, 2006). Oumar and Mutanga (2013) used the WorldView-2 sensor to detect *Thaumastocoris peregrinus* (Bronze Bug) damage in Eucalyptus plantations. Vegetation indices and environmental variables were entered separately into a Partial Least Squares (PLS) regression model and then combined in one model to test the collective strength of predicting *Thaumastocoris peregrinus* damage. An accuracy of 71% was achieved using the PLS regression model and bands in the red-edge and near infrared were identified as important predictors of damage (Oumar and Mutanga, 2013). Lottering and Mutanga (2015) successfully mapped levels of *Gonipterus scutellatus* damage in commercial Eucalyptus stands utilising a pan-sharpened WorldView-2 image. NDVI, Simple Ratio and Enhanced Vegetation Index were used as variables to detect damage. As with previous studies (e.g. Oumar and Mutanga, 2013) it was observed that NDVI values were most significant in detecting defoliation in forest plantations.

In summary, the sudden outbreak of *Uromycladium acaciae* has caused serious concerns towards the sustainability of the South African wattle industry. Black wattle is one of the most profitable tree species per hectare due to its bark and wood properties and requires urgent mitigation against the rust fungus. It is within this context, that this study aims to detect damage and map the current spatial extent of damaged plantations using medium resolution and cost-effective Landsat 8 operational land imager (OLI). The Landsat 8 sensor has seven spectral bands with a spatial resolution of 30 meters and would be advantageous for site interventions if successful in detecting disease defoliation in plantation forestry. A Partial Least Squares Discriminant Analysis (PLS-DA) framework is adopted in this study owing to the recent success in forest type applications globally (dos Santos *et al.,* 2017; Peerbhay *et al.,* 2013; Peerbhay *et al.,* 2014; Peerbhay *et al.,* 2016) and to the best of our knowledge the method has not being used for forest defoliation mapping using remotely sensed data in South Africa.

2. Methods and materials

2.1. Study area

The study area is located near Richmond (29.8667° S, 30.2667° E) in the KwaZulu-Natal province of South Africa. It covers an area of 875ha and is situated at an altitude range between 900m and 1400m above sea level. The area receives annual rainfall ranging from 800mm to 1280mm and has an average annual temperature of 17° Celsius. The area has deep well drained soils where timber and sugar cane are the primary resources planted across the arable land. *Acacia mearnsii* and *Eucalyptus smithii* are the most common tree species planted. The study area was chosen due to intense oubreaks of wattle rust and the noticable decline in tree health and productivity (Mucina and Rutherford, 2006).

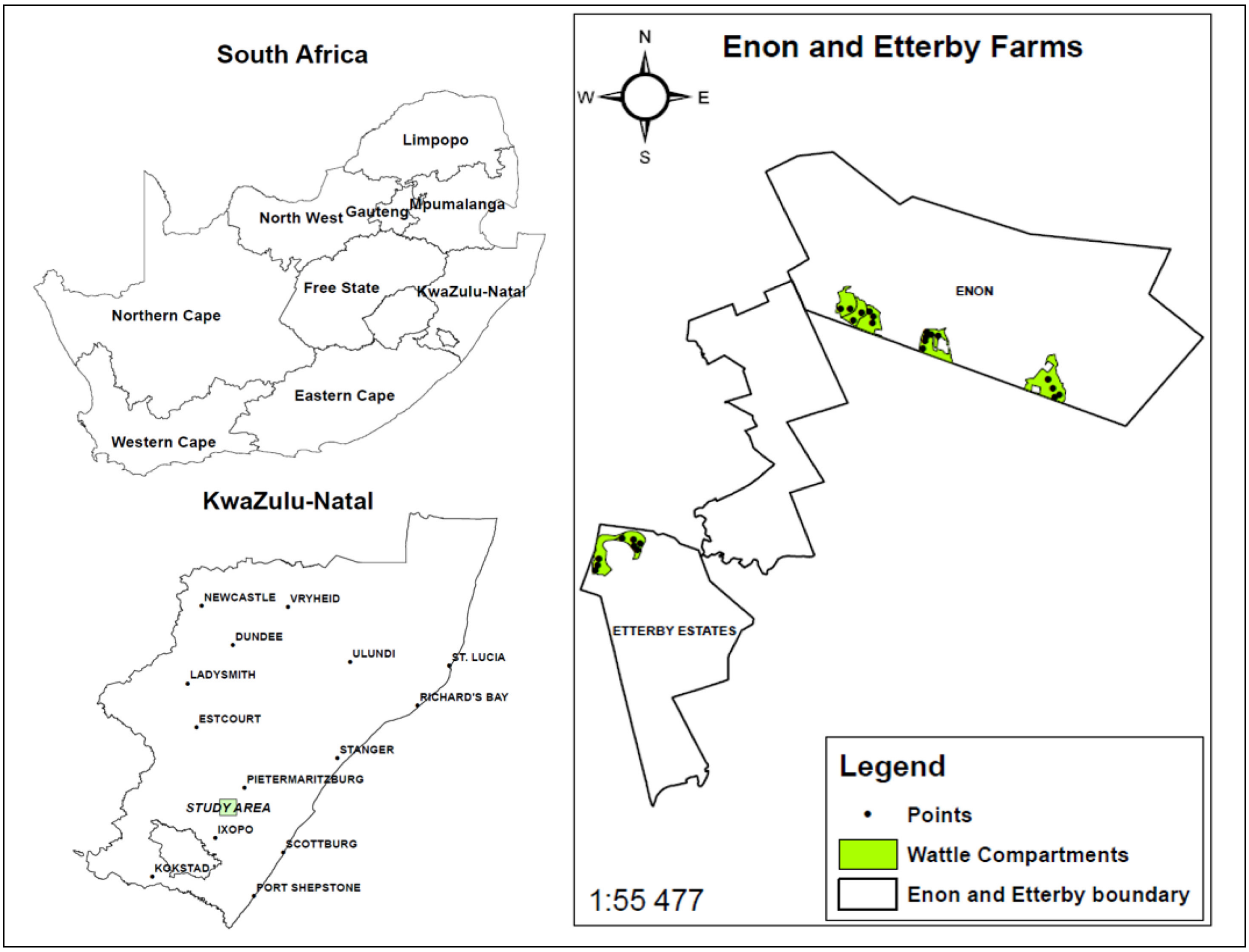

Figure 2. Location of the study area with the boundary of Enon and Etterby forest plantations.

2.2. Landsat 8

The Landsat 8 image has a scene size of 170km north-south by 180km east-west. The image consists of seven spectral bands and 30 meters' resolution (Table 1). NDVI values were also calculated due to the success in previous studies to detect forest defoliation (Oumar and Mutanga, 2013). The image area under investigation was acquired from the United States Geological Survey website (www.usgs.com) and prepared for image processing. The image was atmospherically converted to radiance and then surface reflectance using the dark image subtraction method (Chavez, 1988). Using the field survey plots, image spectra were extracted using ENVI 4.8 to develop an input dataset into the PLS-DA model for discrimination (Congalton and Green, 1999).

Table 1. Landsat 8 Operational Land Imager (OLI) bands and wavelength

Bands	Wavelength (nanometres)	Resolution (meters)
Band 1 - Coastal aerosol	430-450	30
Band 2 - Blue	450-510	30
Band 3 - Green	530-590	30
Band 4 - Red	640-670	30
Band 5 - Near Infrared (NIR)	850-880	30
Band 6 - SWIR	1570-1650	30
Band 7 - SWIR	2110-2290	30

2.3. Field data collection

Following the industry protocol developed in conjunction with the TPCP and Forest Agricultural Biotechnology Institute (FABI), 79 field plots were set in wattle compartments between the ages of 7 and 9 years and which were greater than 7ha (approximately 9 pixels) to avoid spectral noise from adjacent land cover. Each field plot was surveyed to determine the presence, level of infestation and impact of the rust, *Uromycladium acaciae,* on the forest canopy. Each field plot consisted of a rectangular plot of 30m x 30m consisting of 100 trees planted at a spacing of 3m x 3m. A differentially corrected handheld GPS was used and recordings were taken at each plot centre. Since the presence of the rust was surveyed to be widespread with no clear identification of a non-infected wattle stand, 31 plots showing no symptoms of the wattle rust were used as control plots and were located in the Mpumalanga region.

3. Statistical Analysis

3.1. Partial Least Squares Discriminant Analysis (PLS-DA)

PLS-DA is a regression based prediction model that identifies a correlation between the predictor variable (X = spectral bands) and the response variable (Y = wattle rust) (Wold *et al.,* 2001). The goal of using PLS is to provide dimension reduction in the dataset. In this study, the response variable was the wattle rust which is binary and classed into presence of damage and absence of damage. The PLS-DA model creates a few eigenvectors which explain the variance of the spectral reflectance as well as the correlation with the response variable (Peerbhay *et al.,* 2013).

Due to the large number of correlated variables in a PLS-DA model, a cross validation analysis was performed to test the significance of each component using Tanagra statistical software (Rakotomalala *et al.,* 2005). Components were added numerically until the lowest coefficient of variation (CV) error rate was obtained. The purpose of cross-validation is to avoid using too many low order components which may reduce the model accuracy (Peerbhay *et al*., 2013).

The Variable Importance in the Projection (VIP) method was used to select bands that have the highest importance in a PLS-DA model:

$$VIP_k = \sqrt{K \sum_{a=1}^{A} [(q_a^2 t_a^T t_a)(w_{ak} / ||w_k||^2)] / \sum_{a=1}^{A} (q_a^2 t_a^T t_a)} \quad [1]$$

Where *VIPk* is the importance of the *k*th waveband based on a model with α components. *Wαk* is the corresponding loading weight of the *k*th waveband in the *αth* PLS-DA component. *t*a, *wa* and *qa* are the *a*th column vectors, and *K* is the total number of wavebands of X (Gomez *et al.,* 2008).

This method scores each waveband in the dataset and ranks them in order of importance. Bands that score higher than one have the highest influence in the model. The model was then re-run using the VIP bands to test if the classification accuracy improved or regressed (Peerbhay *et al.,* 2013).

3.2. Accuracy assessment

Approximately, 70% of the data was used for model training and 30% for model testing. A confusion matrix was used to validate the accuracy. The overall accuracy was tested using kappa (KHAT) statistic which is a measure of how well the classifier predicts the reference data. KHAT values range from -1 to +1, where +1 represents perfect accuracy between training and test datasets (Congalton and Green, 1999)

4. Results

4.1. Mean *Uromycladium acaciae* reflectance

The mean reflectance of *Uromycladium acaciae* infected trees is shown in Figure 3. The reflectance indicates a normal spectral vegetation curve with low reflectance in the visible spectrum and a sharp spike in the Red and Near Infrared regions.

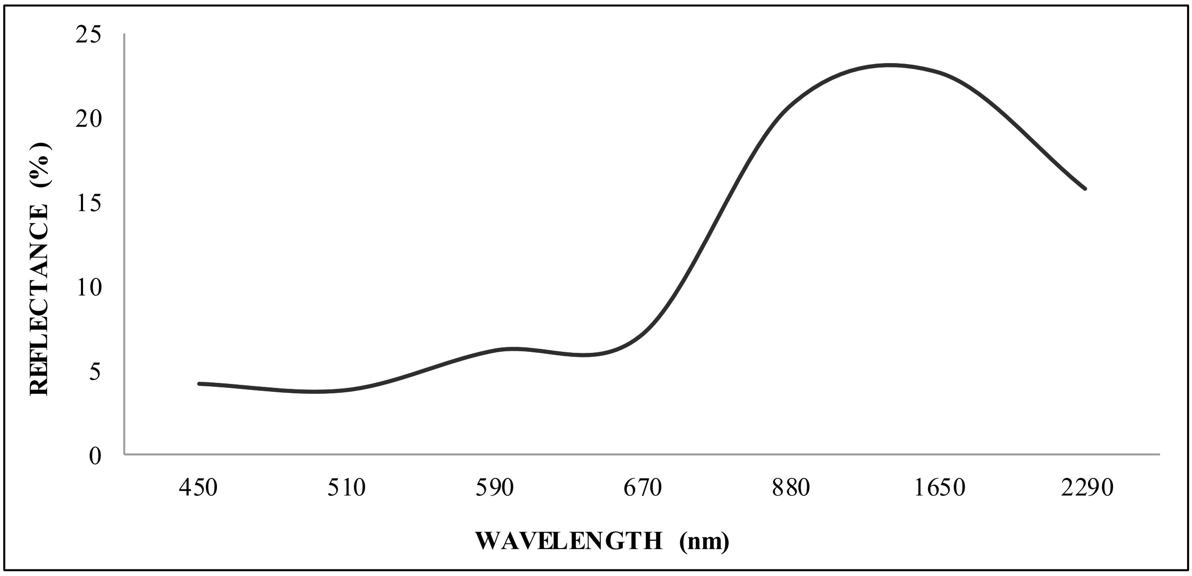

Figure 3. Reflectance of *Uromycladium acaciae* infected trees from Landsat 8 bands (*n* =7)

4.2. PLS-DA model optimization

The addition of components to the PLS-DA model reduced the error rate as depicted in Figure 4. Using the first component which produced an error rate of 17.89. However, as more components were progressively added to the model, the error began to decrease with the lowest error recorded by 6 components at 4.09%. The model thereafter stabilised on the 7th and 8th component. Using 6 components, the PLS-DA model was then developed with all 7 bands including NDVI.

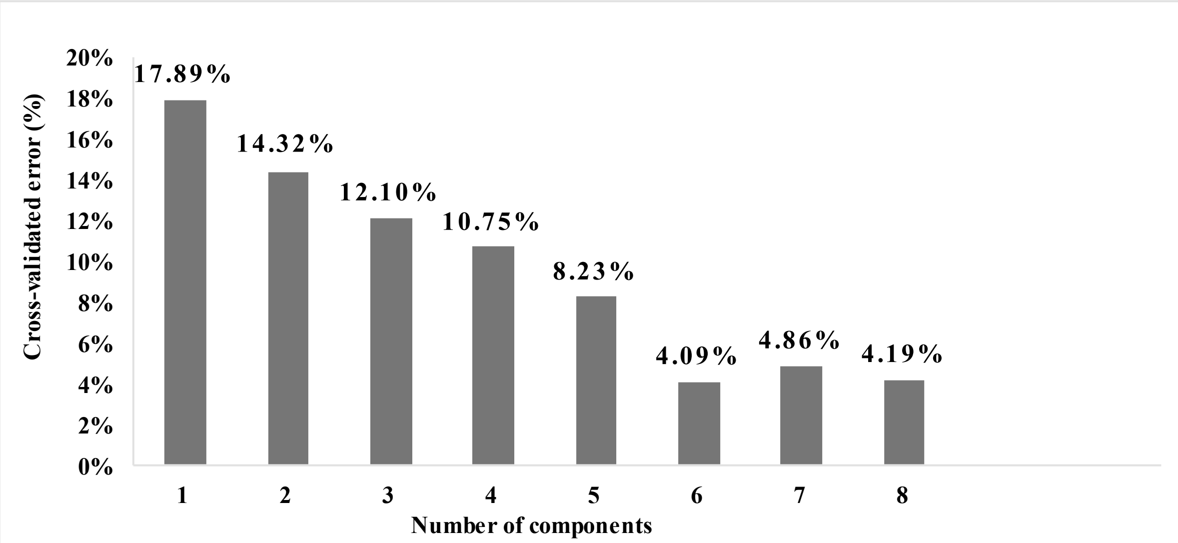

Figure 4. Testing PLS-DA components to determine the lowest CV error with 7 bands and NDVI using tenfold cross-validation.

4.3. PLS-DA Classification

The confusion matrix in Table 2 below indicates the performance of PLS-DA in classifying the presence and absence of *Uromycladium acaciae* damage on *Acacia mearnsii*. The PLS-DA model classified the presence of damage and absence of damage with an overall accuracy of 88.24% with a KHAT value of 0.76.

Table 2. Confusion matrix using 7 Landsat bands.

Class	Absence of damage	Presence of damage	Row total
Absence of damage	60	0	60
Presence of damage	20	90	110
Column total	80	90	170
Producer accuracy	75%	100%	Overall accuracy 88.24%
User accuracy	100%	82%	Kappa 0.76

4.4. PLS-DA model optimization using VIP bands

The next step was to determine the VIP scores for the 7 bands including the NDVI variable. PLS-DA provides a hierarchal scoring system which lists wavebands which are most relevant in the model. Costal Aerosol (1.05), Red (1.03), Near Infrared (1.23) and NDVI (1.14) were selected by the VIP method. Band 5 Near Infrared had the highest significance.

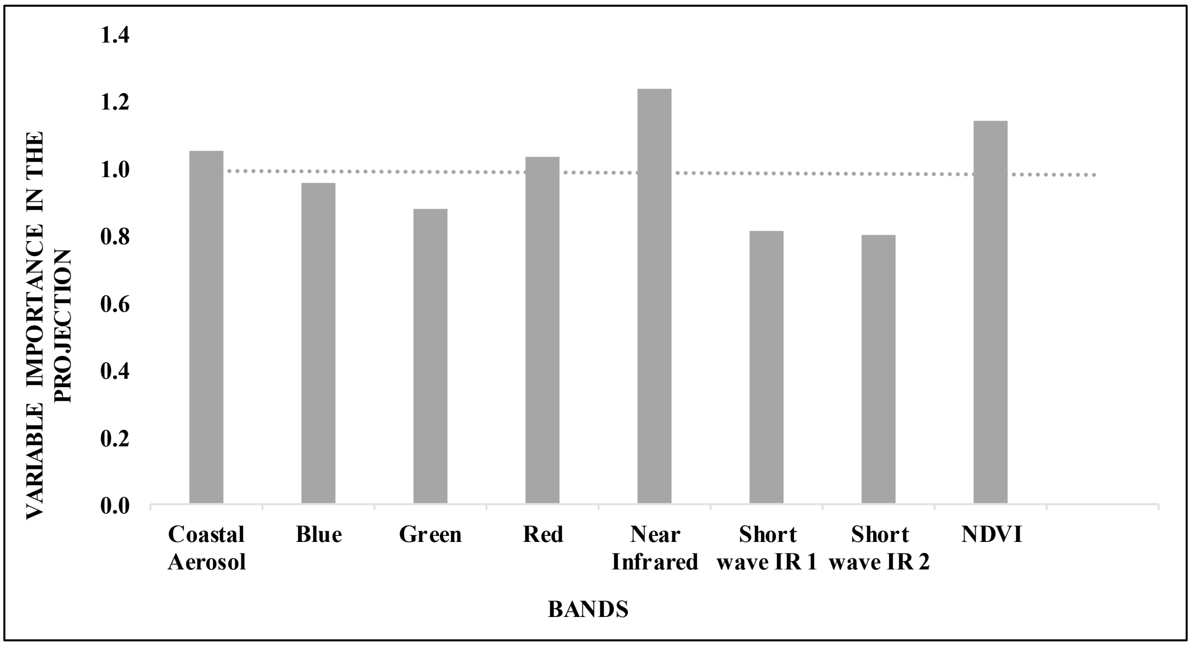

Figure 5. Waveband importance as determined by the VIP method. The important wavebands are those with VIP values greater than one.

The model was then run again using only the VIP bands as depicted in Figure 6. When optimising the model, four components yielded the lowest CV error rate of 6.88% as seen below in Figure 6.

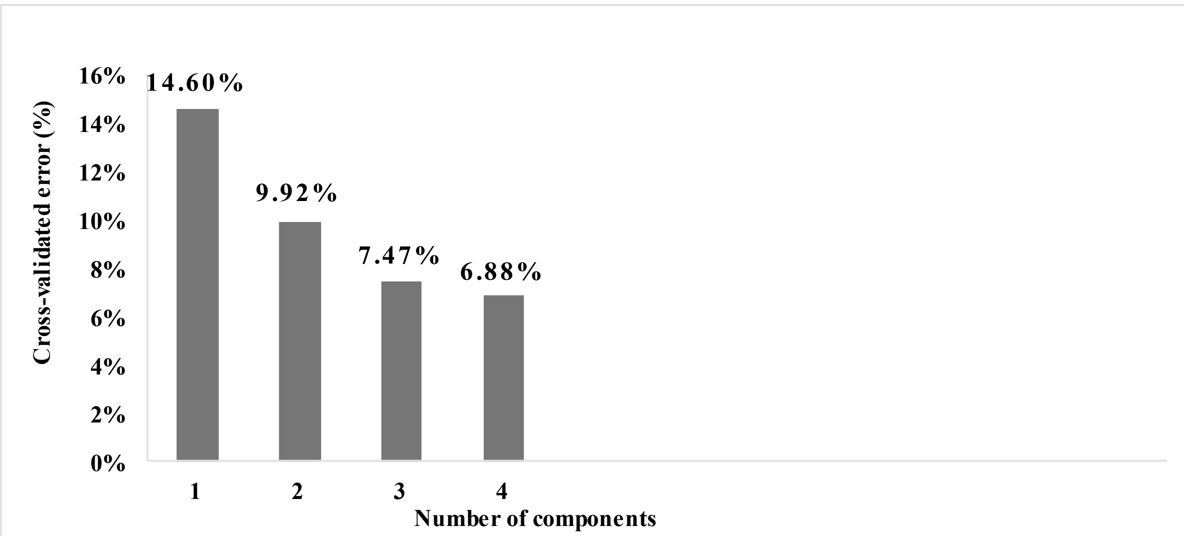

Figure 6. Testing PLS-DA components to determine the lowest CV error using the four VIP bands and NDVI.

The confusion matrix in Table 3 below indicates the performance of PLS-DA in classifying the presence and absence of *Uromycladium acaciae* damage with only the four VIP bands. The PLS-DA model classified the presence of damage and absence of damage with an overall accuracy of 82.35% and with a KHAT value of 0.66.

Table 3. Confusion Matrix based on PLS-DA algorithm and variables selected by the VIP.

Class	Absence of damage	Presence of damage	Row total
Absence of damage	70	30	100
Presence of damage	0	70	70
Column total	70	100	170
Producer accuracy	100%	70%	Overall accuracy 82.35%
User accuracy	70%	100%	Kappa 0.66

5. Discussion

This study has shown the potential of the freely available multispectral Landsat 8 satellite to detect the impact on trees infected with *Uromycladium acaciae*, in South African wattle plantations. The results show the success of the PLS-DA technique combined with remote sensed variables for disease damage detection in plantation forestry and contributes towards developing a routine monitoring system for repeated *Uromycladium acaciae* monitoring. Moreover, this study has shown that in addition to recent remote sensing techniques, utilizing PLS for pest detection (Oumar and Mutanga, 2010) and species classification (Peerbhay *et al.,* 2013), the algorithm can also be successfully utilized for disease damage detection.

5.1. Mapping *Uromycladium acaciae* damage using Landsat 8 and PLS-DA

The ability to detect *Uromycladium acaciae* damage remotely provides a practical tool for identifying outbreaks thus contributing to mapping trends and the continuous monitoring of the disease. The freely available imagery of Landsat 8 and revisit time of 16 days make it a cost effective solution for monitoring *Uromycladium acaciae* damage (Oumar, 2016). Using the Landsat 8 bands, PLS-DA successfully used 6 components to detect defoliation caused by *Uromycladium acaciae* and produced an accuracy of 88.24% and kappa value of 0.76. The accuracy obtained in this study is comparable to that of other studies which have identified other forest pathogens in South Africa using remotely sensed information (Poona and Ismail, 2013; Poona and Ismail, 2014). For example, Poona and Ismail (2013) used Quickbird imagery and artificial neural networks to detect pitch canker disease in *Pinus radiata* forests. Several vegetation indices were used to discriminate healthy tree crowns from infected tree crowns. The neural network model managed to produce an overall accuracy of 82.15%. Similarly, Poona and Ismail (2014) used a handheld field spectrometer to detect asymptomatic *Fusarium circinatum* stress in 3 months old *Pinus radiata* seedlings. The random forest algorithm and the Boruta algorithm were used for classification and dimension reduction respectively. The Boruta algorithm highlighted the most important bands as well as the least important to discriminate between infected and healthy seedlings. Between the various classes of seedlings sampled in the study, the KHAT values ranged from 0.79 to 0.84. Additionally, by utilising only the most significant wavebands, the classification accuracy improved.

5.2. Mapping *Uromycladium Acaciae* using VIP variables and PLS-DA

PLS-DA provides valuable information on important variables based on the VIP method. The analysis of important variables selected by VIP has shown that the highest scores in the PLS-DA model were the Coastal Aerosol (430nm - 450nm), Red (640nm - 670nm) and NIR (850nm - 880nm) regions of the electromagnetic spectrum respectively. The results obtained by the VIP model produced a slightly reduced overall classification accuracy of 82.35%. This is a reduction of 5.89% when compared to using all seven bands. However, this process shows the capability of using fewer important bands to produce a high classification accuracy greater than 80%.

The results of this study were in contrast to the study conducted by Peerbhay and Mutanga (2013), whereby the VIP analysis improved the classification of forest species. Peerbhay *et al.,* (2013) found the accuracy improved to 88.78% utilising VIP bands (n =78) compared to utilising all AISA Eagle bands (n =230) which produced an overall accuracy of 80.61%. A possible reason for the different results between the two studies is the number of bands utilised. Landsat 8 has 7 bands whereas AISA Eagle has a total of 230. The many bands of AISA Eagle may have caused over-fitting of the model and therefore reduced the overall accuracy. Landsat 8 has a fewer number of bands thus reducing the number of bands from 7 to 4 (VIP) lowers the sensors ability to detect spectral variation. Future work should consider the utility of employing higher spectral resolution multispectral sensors such as Sentinel, with 13 bands or WoldView-3 with 16 bands, to improve on detection results.

The Near Infrared and NDVI indices calculated from Landsat 8 were classified as the most important variables for detecting *Uromycladium acaciae* damage. Vegetation indices calculated from Red and Near Infrared are sensitive to plant phenology and thus provide a good measure of forest health (Oumar, 2016). This highlights the potential to detect forest damage using the visible wavebands. Furthermore, this study illustrates the usefulness of PLS-DA in managing spatial data as well as successfully classifying areas that have been damaged by *Uromycladium acaciae*.

5.3. Future work

One of the disadvantages of broad band sensors is the discreet changes in spectral reflectance by stressed vegetation which can be hidden by field geometry, lighting and the density of the canopy (Ismail, Mutanga and Bob, 2007). Hence, the results of this study may be influenced by such factors and thus opens up the possibility of analysing the impacts of Uromycladium acaciae under a hyperspectral sensor and using a finer spatial resolution to investigate the changes in reflectance throughout the entire electromagnetic spectrum. The narrow bands may reduce the aforementioned limiting effects of multispectral sensors and may be capable of distinguishing stages of the impacts evident in the life cycle of the rust such as the leaf curl or the occurrence and intensity of the teleospores which hold infected spores for dispersal. Such information may be valuable in detecting risk before an outbreak occurs and plan for precautionary interventions. Nonetheless, the opportunity exists to investigate higher spatial and spectral multispectral sensors combined with ancillary information related to the surrounding environment of the pathogen. These may include bioclimatic, topographic and edaphic factors in the landscape for an in-depth spatial mapping framework.

6. Conclusion

The aim of this study was to assess the potential of Landsat 8 multispectral imagery in conjunction with PLS-DA to detect damaged caused by *Uromycladium acaciae* at farm level in two KwaZulu-Natal forest plantations. The results revealed that the Landsat 8 multispectral sensor successfully detected the trees which were under stress by *Uromycladium acaciae* and that the methodology developed in this study may be adopted to implement a monitoring system for the wattle rust at a landscape level. Additionally, the VIP PLS-DA method was successful in determining the subset of bands which are most useful to detect *Uromycladium acaciae canopy* impact. In this case, bands within the 430nm - 880nm range were most effective. This opens up the possibility to investigate *Uromycladium acaciae* under a higher resolution sensor to bolster monitoring efforts as well assess the pathogen at different lifecycles, where smaller symptoms of the pest are not detectable using multispectral imagery.

7. Acknowledgments

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8. References

Asner, GP & Hicke JA & Lobell DB, 2003, “Per-Pixel Analysis of Forest Structure”, in Wulder MA & Franklin SE (eds.), *Remote Sensing of Forest Environments*, Springer, Boston, MA.

Breiman, L. 2001, “Random forests”. *Machine Learning*, vol. 45, no. 129, pp. 15-32.

Chavez, Jr. 1988, “An improved dark-object subtraction technique for atmospheric scattering correction of multispectral data”, *Remote Sensing of Environment*, vol. 24, no. 3, pp. 459-479.

Congalton, RG & Green, K 1999, *Assessing the Accuracy of Remotely Sensed Data: Principles and Practices,* Lewis Publishers, Boca Raton.

dos Santos, A & Oumar, Z & Arnhold, A & da Silva, N & Silva, CO & Zanetti, R 2017, "Multispectral characterization, prediction and mapping of Thaumastocoris peregrinus (Hemiptera: Thamascoridae) attack in Eucalyptus plantations using remote sensing*", Journal of Spatial Science*, vol. 62, no. 1, pp. 127-137.

Dyer C, Upfold S, Edwards M, Smith C, Roux J, Wingfield M, Peter M and Heath R. 2010, "The development of an integrated national forest protection strategy for South Africa", Draft Report N. 42731. Department of Agriculture, Forestry and Fisheries (DAFF), South Africa.

FAO 2007, "Overview of forest pests, South Africa" Forest Health & Biosecurity Working Papers, Working Paper FBS/30E. Forest Resources Development Service, Forest Resources Division. FAO, Rome.

Ismail, R & Mutanga, O & Bob, U 2007, "Forest health and vitality: The detection and monitoring of *Pinus patula* trees infected by *Sirex noctilio* using digital multispectral imagery (DMSI)", *Southern Hemisphere Forestry Journal*, vol. 69, no. 1, pp. 39-47.

Kennedy, RE & Yank, Z & Cohen, WB 2010, "Detecting trends in forest disturbance and recovery using yearly Landsat time series: 1. LandTRendr - Temporal segmentation algorithm", *Remote Sensing of Environment*, vol. 114, no. 1, pp. 2897-2910.

Kumar, KK & Nagai, M & Witayangkurn, A & Kritiyutanant, K & Nakamura, S 2016, "Above Ground Biomass Assessment from Combined Optical and SAR Remote Sensing Data in Surat Thani Province, Thailand", *Journal of Geographic Information System*, vol. 8, no. 1, pp. 506-516.

Lottering, R & Mutanga, O 2016, "Optimising the spatial resolution of World View-2- pan-sharpened imagery for predicting levels of Gonipterus scutellatus in KwaZulu-Natal, South Africa", *ISPRS Journal of Photogrammetry and Remote Sensing*, vol. 112, no. 1, pp. 112, 13-22.

McTaggart, AR & Doungsa-ard, C & Wingfield, MJ 2015, "*Uromycladium acaciae*, the cause of a sudden, severe disease epidemic on *Acacia mearnsii* in South Africa". *Australian Plant Pathology,* vol. 44, no. 6, pp. 637-645.

Mucina, L and Rutherford, M.C. 2006 (eds.), *The Vegetation of South Africa, Lesotho and Swaziland*. Strelitzia 19, South African National Biodiversity Institute, Pretoria.

Peerbhay, K & Mutanga, O & Ismail, R 2013, "Commercial tree species discrimination using airborne AISA Eagle". *ISPRS Journal of Photogrammetry and Remote Sensing*, vol. 79, no. 1, pp. 19–28.

Peerbhay, K & Mutanga, O & Ismail, R 2014, "Does simultaneous variable selection and dimension reduction improve the classification of Pinus forest species?", *Journal of Applied Remote Sensing,* vol. 8, no. 1, DOI: 10.1117/1.JRS.8.085194

Poona, NK & Ismail, R 2013, "Discriminating the occurrence of pitch canker fungus in Pinus radiata trees using QuickBird imagery and artificial neural networks", *Southern Forests: A Journal of Forest Science,* vol. 75, no. 1, pp. 29-40.

Poona, NK & Ismail R 2014, "Using Boruta-selected spectroscopic wavebands for the asymptomatic detection of Fusarium circinatum stress", *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing,* vol. 7, no. 1, pp. 3765-3772.

Mayers, J & Evans, J & Foy, T 2001, *Raising the stakes: impacts of privatisation, certification and partnerships in South African forestry*, IIED, London.

Meigs, GW & Kennedy, RE & Cohen, WB 2011, "A Landsat time series approach to characterise bark beetle and defoliator impacts on tree mortality and surface fuels in conifer forests". *Remote Sensing of Environment*, vol. 115, no. 12, pp. 3703-3718.

Mucina, L & Rutherford, MC 2011, *The Vegetation of South Africa, Lesotho and Swaziland. Strelitzia 19*, South African National Biodiversity Institute, Pretoria. ISBN: 978-1919976-21-1

Oumar, Z & Mutanga, O 2010, "Predicting plant water content in Eucalyptus grandis forest stands in KwaZulu-Natal, South Africa using field spectra resampled to the Sumbandila Satellite Sensor", *International Journal of Applied Earth Observation and Geoinformation*, vol. 12, no. 1, pp. 158-164.

Oumar, Z 2016, "Assessing the Utility of the SPOT 6 Sensor in Detecting and Mapping Lantana camara for a Community Clearing Project in KwaZulu-Natal, South Africa", *South African Journal of Geomatics*, vol. 12, no. 2, pp. 214-226.

Rusk, GD & Pennefather, M & Cronje, C 1990, "Forestry costs in South Africa. In: South African Timber Growers Association Economics Division", Pietermaritzburg. Document no. 74/1990.

Sherry, SP 1971, *The Black Wattle (Acacia mearnsii de Wild)*, University of Natal Press, Pietermaritzburg.

Verbesselt, J & Hyndman, R & Newham, G & Culvenor, D 2010, "Detecting trend and seasonal changes in satellite image time series", *Remote Sensing of Environment*, vol. 114, no. 1, pp. 106-115.

The United States Geological Survey 2015, The United States Geological Survey, Reston, USA, viewed 31 July 2015, https://www.usgs.gov/.

Wang, J & Sammis, TW & Gutschick, VP & Gebremichael, M & Dennis, SO & Harrison, RE 2010, "Review of satellite remote sensing use in forest health studies", *The Open Geography Journal*, vol. 3, no. 1, pp. 28-42.

Wulder, MA & Masek, JG & Cohen, WB & Loveland, TR & Woodcock, CE 2012, "Opening the archive: How free data has enabled the science and monitoring promise of Landsat", *Remote Sensing of Environment*, vol. 122, no. 1, pp. 2-10.