

**Assessing the utility of Landsat 8 multispectral sensor and the MaxEnt
species distribution model to monitor *Uromycladium acaciae* damage in
KwaZulu-Natal, South Africa.**

By

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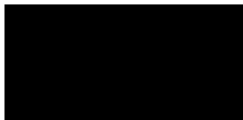
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DECLARATION

This study was undertaken in fulfilment of a Master of Science Degree and represents the original work of the author. Where use has been made of the work of others it is duly acknowledged in both the text and reference section of this dissertation.



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DECLARATION 2 – PUBLICATIONS

DETAILS OF CONTRIBUTION TO PUBLICATIONS that form part of and/or include the research presented in this thesis (includes publications in preparation and those that have been submitted, are in press or are published, and gives details of the contributions of each author to the experimental work and writing of each publication).

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ABSTRACT

South Africa has approximately 1.27 million hectares of plantation forests, with the forestry industry contributing 1% to the state's Gross Domestic Product (GDP). A major threat to the industry is an escalating number of tree-damaging insect pests and pathogens. *Uromycladium acaciae* is a pathogen which causes wattle rust in black wattle (*Acacia mearnsii*) plantation forests; after its first appearance in 2013 in KwaZulu-Natal, it has since spread to most areas in South Africa where suitable hosts are present, causing severe economic losses to the industry. Traditional field-based methods of assessing forest damage can be labour intensive and time consuming. The effective management of these biotic threats requires quick and efficient methods of assessing forest health. Remote sensing has the potential to assess vast areas of forest plantations in a timely and efficient manner. Therefore, the primary aim of this research is to assess *U. acaciae* canopy damage using freely available Landsat 8 multispectral satellite imagery and the partial least squares discriminant analysis algorithm (PLS-DA). The study was done on two plantation farms near Richmond, KwaZulu-Natal which are managed by NCT Forestry. The model detected forest canopy damage with an accuracy of 88.24% utilising seven bands and the PLS-DA algorithm. The Variable Importance in Projection (VIP) method was used to optimise the variables to be included in the model by selecting the most influential bands. These were identified as coastal aerosol band (430 nm - 450 nm), red band (640 nm - 670 nm), near infrared (850 nm - 880 nm) and NDVI. The model was run with only the VIP selected bands and an accuracy of 82.35% was produced. The study highlighted the potential of remote sensing to (1) detect canopy damage caused by *U. acaciae* and (2) provide a monitoring framework for analysing forest health using freely available Landsat 8 imagery.

The secondary aim of this study is to use the maximum entropy species distribution model (SDM) to determine potential forestry areas that may be at risk of *U. acaciae* infection. Species distribution modelling using bioclimatic predictors can define the climatic range associated with the disease caused by this pathogen. The climatic range will help identify high risk areas and forecast potential outbreaks. This study assessed the capacity of the MaxEnt species distribution model (SDM) and bioclimatic variables to estimate forestry areas that have a suitable climate for *U. acaciae* development. The model was developed using 19 bioclimatic variables sourced from WorldClim. The variables are used as predictors of risk for *U. acaciae* infection and are applied to the landscape occupied by black wattle plantations. The results

produced an area under the curve (AUC) value of = 0.97 suggesting strong discriminatory power of the model. The potential distribution of *U. acaciae* under future climate conditions was also assessed by applying the model to the bioclimatic variables developed from future climate surfaces acquired from WorldClim. The results emphasized (1) the usefulness of species distribution models for forest management and (2) highlighted how climate change can influence the distribution of *U. acaciae* due to the expansion and contraction of suitable climatic ranges.

Overall, the results from the study indicate (1) Landsat 8 multispectral imagery can be used to detect forest canopy damage caused by *U. acaciae*, (2) PLS-DA variable importance in the projection can successfully select the subset of multispectral bands that are most important in detecting damage caused by *U. acaciae*, (3) the MaxEnt species distribution model and bioclimatic variables can be used to identify geographic locations at risk of *U. acaciae* infection and (4) the variable permutation metric successfully identified the most important bioclimatic variables for *U. acaciae* development and highlighted the climatic patterns associated with the occurrence of the disease caused by this pathogen.

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Chapter One

Introduction

1.1. Background

Forests are home to much of the earth's biodiversity and can help mitigate climate change by acting as net carbon sinks (Sturrock *et al.*, 2011). Economically, the commercial forestry industry contributes 1% to South Africa's GDP and employs over 165 000 people (DAFF, 2020). Additionally, planted forests play an important role in preserving natural forests, as they provide an alternative source of timber. In the last three decades, global forest area decreased by 40%. This is predominately due to the conversion of forested land to agricultural practice (Shvidenko *et al.*, 2005). Disturbance agents such as insect pests, pathogens and fire escalate strain on forest resources (Sturrock *et al.*, 2011). Therefore, acute forest management strategies are needed to help conserve forest resources and sustain the forestry industry.

Black Wattle (*Acacia mearnsii*) is one of the most common species commercially grown in South Africa. A recent threat to black wattle plantations is the occurrence of a wattle rust disease caused by the fungus known as *Uromykladium acaciae*. In an effort to manage wattle rust outbreaks, remote sensing technologies and species distribution modelling were investigated to garner more knowledge about the distribution and environmental conditions associated with the presence of *U. acaciae* and the expression of the disease it causes.

Monitoring and risk assessment of pests and pathogens are essential to an integrated pest management strategy. There is a pressing need for monitoring and risk assessment in commercial forests due to larger social, environmental and economic impacts. Disease and pest management strategies vary among damage-causing agents, hence the need to develop species-specific systematic monitoring and risk assessment tools. Broader understanding of pests and pathogens will encourage more precise management interventions and limit the social, environmental and economic impacts (Talgo *et al.*, 2020).

Traditional methods of assessing forest damage require field visits and, in some cases, destructive sampling of trees to determine the level of damage. This is not a practical solution when large areas of forest plantations are exposed to diseases and pests. Remote sensing has been used extensively to monitor forest stress caused by pests and diseases (Hall *et al.*, 2016;

Kaiser *et al.*, 2016; Heim *et al.*, 2019). Multispectral remote sensing products are cost effective and easily accessible. The sensors collect data in three to six spectral bands within the visible and mid-infrared bands (Oumar, 2016) which have been used to map tree health with varying levels of accuracy. For example, Xiao and McPherson (2005) used Landsat 8 multispectral data to map tree health in the University of California, Davis with accuracies ranging between 86% and 88%. Wang *et al.* (2015) used the Landsat 8 OLI to map health levels of Black locust (*Robinia pseudoacacia*) in the Yellow River Delta in China using a maximum likelihood classifier and produced an accuracy of 74%.

The application of remote sensing for mapping tree health relies on advanced statistical methods to help interpret the data and improve classification accuracy. Partial Least Squares-Discriminant Analysis (PLS-DA) is a multivariate statistical technique that allows for the comparison between multiple response variables as well as multiple explanatory variables (Peerbhay *et al.*, 2013). It is based on binary coding and uses sample characteristics and the variable of interest. This method generates fewer components and improves classification accuracy (Peerbhay *et al.*, 2013). Several studies have used multispectral and hyperspectral imagery together with PLS-DA to map biotic and abiotic stresses in commercial crops and forest plantations, most of which achieved satisfactory classification accuracies. For example, Zovko *et al.* (2019) assessed grapevine drought stress in Croatia by using hyperspectral images taken by two spectral-radiance calibrated cameras covering wavelengths from 409 nm to 988 nm and 950 nm to 2509 nm. Using the PLS-DA algorithm, the study produced an accuracy of 97%. Dos Santos *et al.* (2017) used multispectral Landsat 8 imagery and PLS-DA to map *Thaumastocoris peregrinus* damage on *Eucalyptus* forests in Brazil and achieved an accuracy of 76.7%.

A key component within an integrated management approach and which forms part of the risk assessment is predicting the distribution of pest species. Species distribution modelling (SDM) is a popular technique for estimating the potential distribution of species based on presence data and environmental predictors at the relevant site (McCune, 2016). The maximum entropy species distribution model (Philips *et al.*, 2006) has been used extensively to estimate species distributions and to predict current and future distributions; it has also been used for large-scale biodiversity mapping by government and non-government organisations (Elith *et al.*, 2011). One of the key advantages of MaxEnt is that it requires presence data only, overcoming the problem of unreliable absence data (Elith *et al.*, 2010). Several studies have shown the usefulness of SDMs to predict species distribution based on presence-only data and bioclimatic

variables (Evangelista *et al.*, 2011; Barredo *et al.*, 2015; Germishuizen *et al.*, 2017) and to evaluate the potential impact of climate change on the distribution of economically important species or species that are of conservation interest (Qin *et al.*, 2017; Li *et al.*, 2020; Çoban *et al.*, 2020). Yang *et al.* (2013) used the MaxEnt model and bioclimatic variables to estimate the distribution of the Malabar nut (*Justicia adhatoda* L) in the lesser Himalayan foothills and produced an AUC value of 92.3 which indicates strong predictive power of the model. Remya *et al.* (2015) used bioclimatic variables and the MaxEnt model to predict the habitat suitability for the *Myristica dactyloides* (Gaertn.) tree. Current and future climate scenarios were evaluated and using the Jackknife test, the study found the most important variables to be annual temperature, annual precipitation and precipitation of wettest month. Elith *et al.* (2013) utilized bioclimatic variables and the MaxEnt model to highlight the differences in geographic distribution of myrtle rust (*Uredo rangelii*) and guava rust (*Puccinia psidii*). The study noted the importance of correct disease classification as taxonomic differences in rust species can influence the results of modelled distributions. Moreover, the study emphasized the robustness of the MaxEnt technique by differentiating the predicted distributions of two rust species. Ikegami and Jenkins (2018) evaluated the global distribution of Pine Wilt Disease which is caused by the pine wood nematode (*Bursaphelenchus xylophilus*). The study used bioclimatic variables and the MaxEnt model to assess the climatic conditions which are suitable for Pine Wilt Disease occurrence and found the environmental variables which most likely correlate with the current distribution of Pine Wilt Disease are the warmest three months and aridity. Additionally, the study modelled the future climate using the WorldClim dataset and found the suitable geographic area for Pine Wilt Disease will increase based on current climate change projections.

Based on the success of the above-mentioned studies, the present study investigated wattle rust using a twofold approach. The first was to assess wattle rust damage using Landsat 8 multispectral imagery and PLS-DA. The second was to use the bioclimatic variables and the MaxEnt model to better understand the climatic niche of *U. acaciae*.

1.2. Aims and objectives

The aim of this research was to assess the utility of Landsat 8 multispectral imagery and machine learning techniques to monitor the occurrence of the wattle rust disease caused by the fungus *U. acacia* in black wattle plantation forests. Specifically, the objectives are:

- To assess the capability of Landsat 8 multispectral satellite imagery to detect wattle rust damage on black wattle using the PLS-DA algorithm.
- To test the effectiveness of PLS variable importance in the projection (VIP) to select the most influential wavebands to detect wattle rust damage.
- To identify the potential occurrence of wattle rust within the black wattle plantations landscape based on bioclimatic variables and the MaxEnt model.
- To use the variable permutation metric to identify the most important climatic variables for *U. acaciae* development.
- To create a wattle rust risk map based on the current and future climate.

The first paper in this thesis assessed the efficacy of the Landsat 8 multispectral sensor and the PLS-DA technique to detect damage caused by the wattle rust. The VIP method was then used to identify the bands that are most important for verifying damage on black wattle. The second paper focuses on species distribution modelling. The MaxEnt model and bioclimatic variables were used to identify areas that may be at risk of *U. acaciae* infection. A risk map was created to highlight areas that may potentially have outbreaks of wattle rust based on the location and surrounding climate. Finally, the results from the two studies are summarised and applied to develop a framework to monitor wattle rust outbreaks and screen new areas for possible *U. acaciae* infection.

1.3. Thesis outline

This thesis is compiled in to four chapters. It is mainly structured around two core chapters (Chapters Two and Three). These chapters have been written specifically for publication. Chapter Two has been published and Chapter Three is currently in review. Both these chapters have detailed sections covering the study area, literature review and methodology. Therefore, these sections will not be covered in the introduction of the thesis to avoid repetition.

Chapter Two assesses the capabilities of the Landsat 8 multispectral sensor to detect wattle rust damage using partial least squares discriminant analysis (PLS-DA). The variable importance in the projection (VIP) method was used to identify the wavebands that are most likely to detect wattle rust damage. The model detected forest canopy damage with an accuracy of 88.24% utilising seven bands and the PLS-DA algorithm. The model was run with only the VIP selected bands and an accuracy of 82.35% was produced.

Chapter Three utilizes the bioclimatic variables and MaxEnt algorithm to model the distribution of *U. acaciae* in the current and predicted future climate. The variable permutation metric was used to determine which environmental variables are most suitable for the development of *U. acaciae*. The variable permutation metric identified the minimum temperature of coldest month (Bio6), precipitation of wettest month (Bio13), annual mean temperature (Bio1) and precipitation seasonality (Bio15) as the climatic variables which have the highest correlation with *U. acaciae* occurrence.

Chapter Four is a synopsis of the study. The aims and objectives of the study are further discussed together with the findings and results. The chapter also discusses how the methodology used in this study can be used to develop a wattle rust monitoring system. Lastly, limitations of this study are examined and recommendations for future research are presented.

The next chapter in this thesis addresses the first two objectives of this study. These are i) to assess Landsat 8 multispectral satellite imagery to detect wattle rust damage on black wattle using the PLS-DA algorithm and ii) to test the effectiveness of PLS variable importance in the projection (VIP) to select the most influential wavebands to detect wattle rust damage. This forms the first research paper which has been published.

Oumar, M.S., Peerbhay, K., Germishuizen, I., Mutanga, O. and Oumar, Z., 2019. Detecting canopy damage caused by *Uromycladium acaciae* on South African Black Wattle forest compartments using moderate resolution satellite imagery. *South African Journal of Geomatics*, 8 (1), 69-83.

Chapter Two

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

2.1 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 (430 nm - 450 nm), red band (640 nm - 670 nm), near infrared (850 nm - 880 nm) and the normalized difference vegetation index (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.

2.2 Introduction

Plantation forestry covers about 1.27 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 (FSA, 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 (Sherry, 1971; Rusk *et al.*, 1990). 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 predominantly located in KwaZulu-Natal 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 insect pests and pathogens (Dyer *et al.*, 2010).

During 2013, an outbreak of a new disease had been observed in Black Wattle around the KwaZulu-Natal Midlands area, caused by a rust fungus. The pathogen had spread fast to all wattle growing areas in the country, becoming a major concern for wattle growers in the region. A concerted research effort had 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 *U. acaciae*. However, more research is needed to understand the seasonal cycle of the rust and environmental triggers of outbreaks to optimise the timing of interventions.





Image	Picture	Symptom
Images 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 key components of an effective pest and disease management strategy, however, there is currently no system in place locally to respond 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 but will also contribute towards the development of a broad national forest health monitoring system.

New generation, moderate resolution space-borne imagery such as Landsat 8 can be an inexpensive, effective technology for the mapping, monitoring and risk assessment of new canopy pests and pathogens (Wang *et al.* 2010; Asner *et al.* 2011). Remote sensing has been widely adopted for the monitoring of forest health and in support of integrated pest management strategies (Kennedy *et al.*, 2010; Verbesselt *et al.*, 2010; Meigs *et al.*, 2011; 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 in southern KwaZulu-Natal. The visual inspections were classed in a severity scale of damage. Using high resolution digital multispectral imagery (0.5 m x 0.5 m) they showed significant differences in the vegetation indices derived from the imagery between

healthy and visually damaged pine compartments. 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 with bands in the red-edge and near infrared being the most important in the prediction 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. The 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 *U. 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 (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.

2.3 Methods and materials

2.3.1 Study area

Enon and Etterby farms which are managed by NCT Forestry were chosen as the study area. The study area was chosen due to intense outbreaks of wattle rust and the noticable decline in tree health and productivity. The farms are located near Richmond (29.8667°S, 30.2667°E) in the KwaZulu-Natal province of South Africa and covers an area of 875 ha. The farms are situated at an altitude range between 900 m and 1400 m above sea level. The area receives annual rainfall ranging from 800 mm to 1280 mm and has an average annual temperature of

17°C. The area has deep well drained soils where timber and sugar cane farming are the primary activities across the arable land. *Acacia mearnsii* and *Eucalyptus smithii* are the dominant tree species planted (Mucina and Rutherford, 2006).

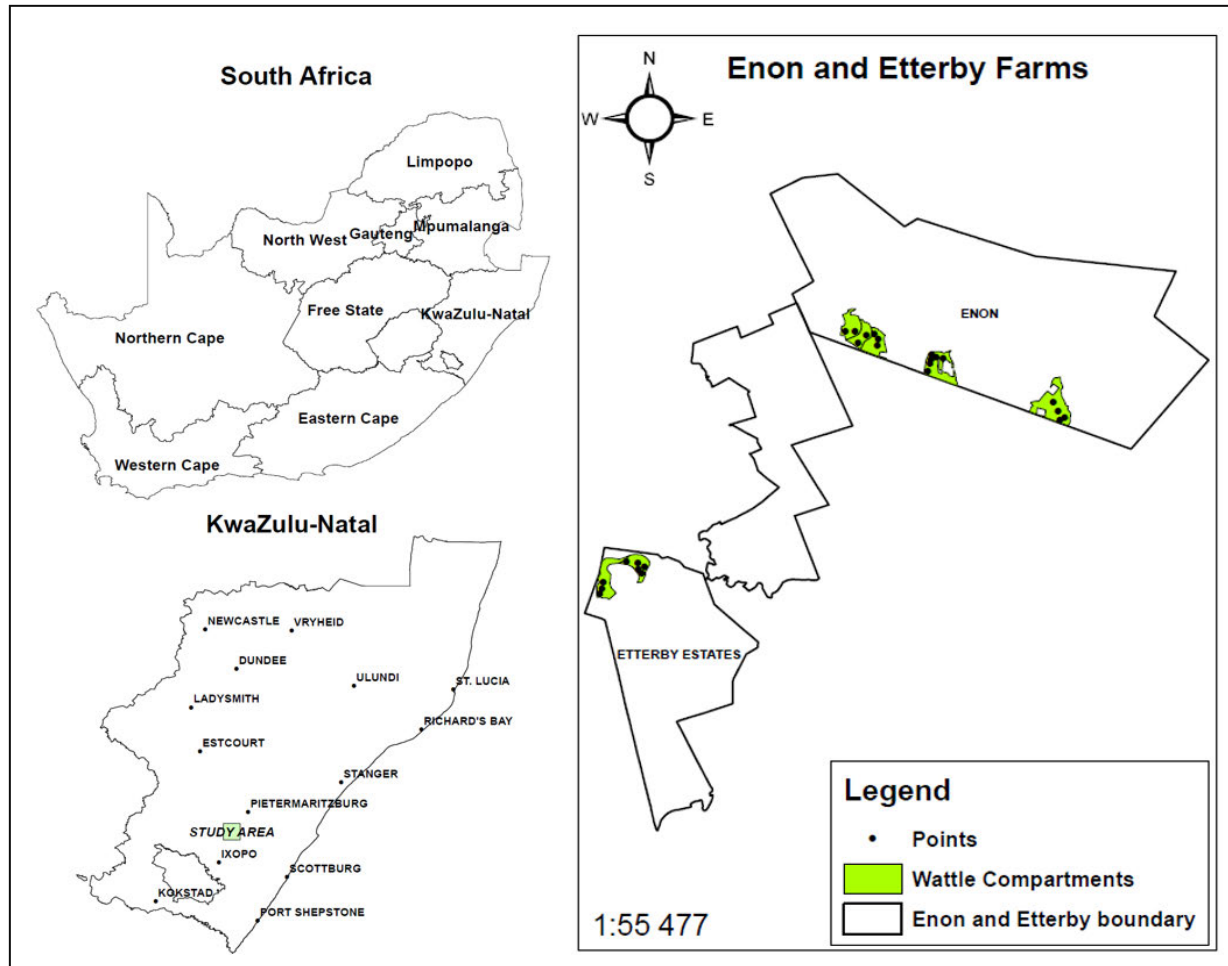


Figure 2. Location of the study area with the boundary of Enon and Etterby forest plantations.

2.3.2 Landsat 8

One scene of Landsat 8 multispectral data was acquired from the United States Geological Survey website (www.usgs.com) on 29th March 2015. Landsat 8 has narrower spectral bands compared to its immediate predecessor, Landsat 7. The near infrared in Landsat 8 (850 nm - 880 nm) and red (640 nm - 670 nm) improves on Landsat 7 near infrared (1550 nm - 1750 nm) and red (770 nm - 900 nm). The narrower bands will be better at distinguishing subtle changes in surface reflectance. Landsat 8 imagery has a scene size of 170 km north-south by 180 km east-west. The imagery consists of seven spectral bands at 30 meters resolution (Table 1) and is atmospherically and geometrically corrected by the data providers. Among the seven bands, the red and near-infrared were used to calculate the NDVI values owing to its success in

previous studies to detect forest defoliation (Oumar and Mutanga, 2013). 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 software 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 1	1570 - 1650	30
Band 7 - SWIR 2	2110 - 2290	30

2.3.3 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 7 ha (approximately 9 pixels) to avoid spectral noise from adjacent land cover. The field work was done between 19th March and 25th March 2015. 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 had a rectangular plot of 30 m x 30 m consisting of 100 trees planted at a spacing of 3 m x 3 m. A differentially corrected handheld GPS 60 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.

2.4. Statistical Analysis

2.4.1 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 VIP_k is the importance of the k th waveband based on a model with α components. W_{ak} is the corresponding loading weight of the k th waveband in the α th PLS-DA component. T_a , W_{ak} and Q_a are the α 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).

2.4.2 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 the KHAT statistic. This is calculated by adding the number of correctly classified values and dividing it by the total number of values in the confusion matrix. KHAT values range from -1 to +1, where +1 represents highest accuracy between training and test datasets. The user and producer accuracy was also calculated in the confusion matrix. The user accuracy is calculated by taking the number of correct classifications in each class and dividing it by the row total.

The producer accuracy is calculated by taking the number of correct classifications in each class and dividing it by the column total. (Congalton and Green, 1999).

2.5. Results

2.5.1 Mean reflectance of healthy and damaged trees

The mean reflectance of healthy and damaged wattle trees are 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. The healthy and damaged trees exhibited similar reflectance patterns, however the healthy trees had stronger reflectance in the red and near infrared owing to the higher levels of chlorophyll present.

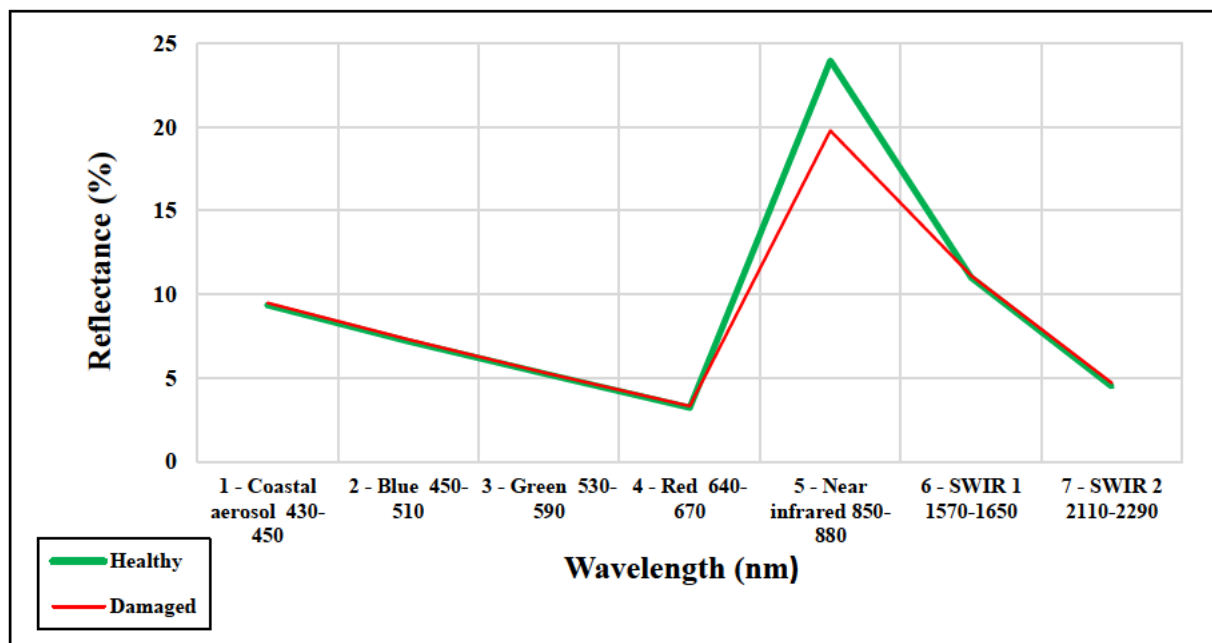


Figure 3. Spectral reflectance of healthy wattle trees versus trees damaged by *Uromycladium acaciae* from Landsat 8 bands ($n=7$).

2.5.2 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 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 the 6th component at 4.09%. The model thereafter stabilised on the 7th and 8th components. Using the 6th component, the PLS-DA model was then developed with all 7 bands including the NDVI.

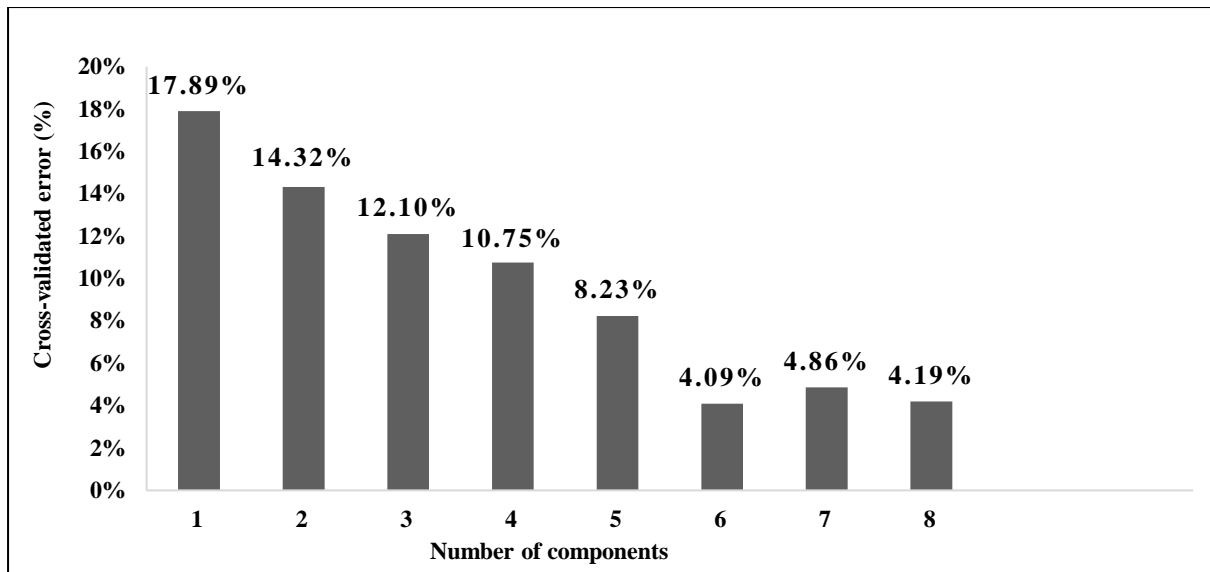


Figure 4. Testing PLS-DA components to determine the lowest CV error with 7 bands and NDVI using tenfold cross-validation.

2.5.3 PLS-DA classification

The confusion matrix in Table 2 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. The producer accuracy for absence of damage is 75 and for presence of damage is 100. The user accuracy for absence of damage is 100 and for presence of damage is 82.

Table 2. Confusion matrix using 7 Landsat 8 bands.

	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

KHAT	0.76		Absence of damage	Presence of damage
Overall Accuracy	88.24%			
	11.76%	Producer Accuracy	75	100
Error rate		User Accuracy	100	82

2.5.4 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 hierarchical scoring system which lists wavebands which are most relevant in the model. Band 5 near infrared (1.23) had the highest significance followed by coastal aerosol (1.05) and red (1.03). The NDVI had a value of (1.14) which represents greater significance than any of the bands and illustrates the significance of this variable in determining vegetation health.

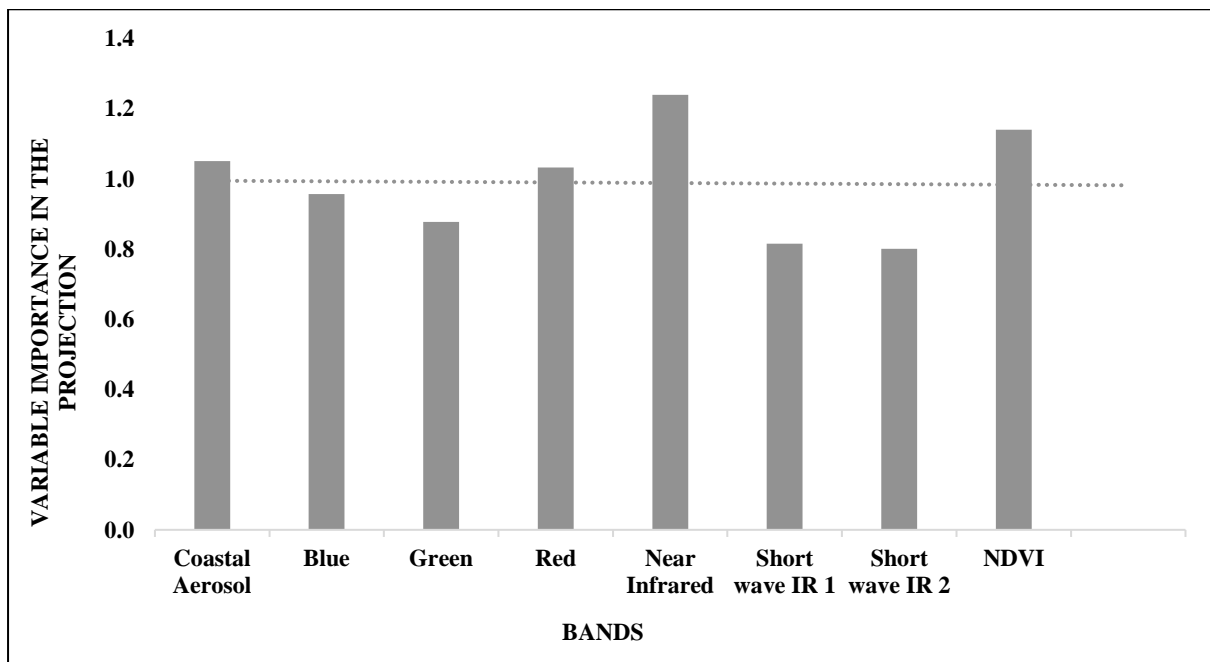


Figure 5. Waveband importance as determined by the VIP method. The important wavebands are those with VIP values greater than one.

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.

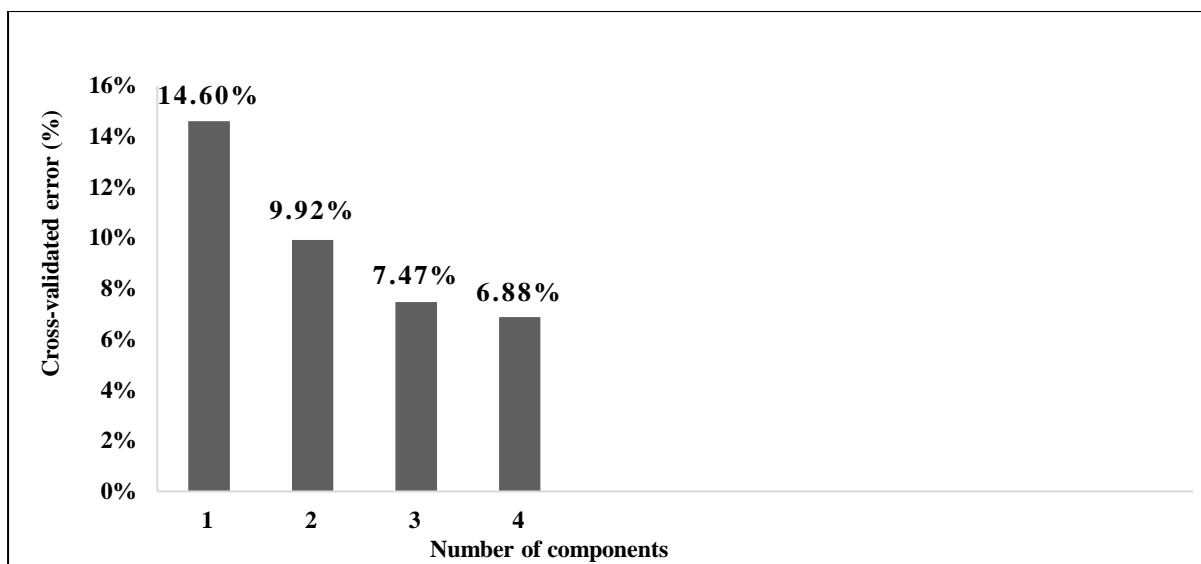


Figure 6. Testing PLS-DA components to determine the lowest CV error using the four VIP bands and NDVI.

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. The producer accuracy for absence of damage is 100 and for presence of damage is 70. The user accuracy for absence of damage is 70 and for presence of damage is 100.

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

	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

KHAT	0.66		Absence of damage	Presence of damage
Overall Accuracy	82.35%			
	17.65%	Producer Accuracy	100	70
Error rate		User Accuracy	70	100

2.6. Discussion

This chapter 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.

2.6.1 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). 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 is improved.

2.6.2 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 (430 nm - 450 nm), red (640 nm – 670 nm) and NIR (850 nm – 880 nm) bands. 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 sensors such as Sentinel-2, 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*.

2.7. Summary

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 damage. The near infrared (1.23) coastal aerosol (1.05) and red (1.03) were

ranked as the most significant. The NDVI had a value of (1.14) which represents greater significance than any of the bands and illustrates the significance of this variable in determining vegetation health. 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. The next chapter in this study investigates estimating areas at risk of *Uromycladium acaciae* occurrence using the maximum entropy species distribution model and bioclimatic variables.

Chapter 3

Assessing the geographic suitability of wattle rust occurrence in South African black wattle timber forestry areas using indirect mapping approaches

3.1 Abstract

Wattle rust (*Uromycladium acaciae*) is a fast spreading rust fungus that has infected planted black wattle (*Acacia mearnsii*) forests in South Africa. This study illustrates the effectiveness of the maximum entropy species distribution model and bioclimatic variables sourced from WorldClim for assessing the potential geographic vulnerability of black wattle to *U. acaciae* under current and future climate conditions. Presence data was collected at various forest plantation farms in KwaZulu-Natal and Mpumalanga provinces of South Africa. The MaxEnt model produced an area under the curve (AUC) value of 0.97. The variable permutation metric identified the minimum temperature of coldest month (Bio6), precipitation of wettest month (Bio13), annual mean temperature (Bio1) and precipitation seasonality (Bio15) as the climatic variables which have the highest correlation with *Uromycladium acaciae* occurrence. The results emphasized the usefulness of species distribution models for forest management and highlights how climate change can influence the distribution of the pathogen due to the expansion and contraction of suitable climatic ranges.

3.2. Introduction

Industrial plantations in South Africa occupy an area of approximately 1.27 million hectares, of which 80% is found in the provinces of Mpumalanga and KwaZulu-Natal (DAFF, 2020). These plantations are dominated by three exotic genera: *Pinus* (50%), *Eucalyptus* (43%) and *Wattle* (7%) (FSA, 2020). Wattle constitutes a relatively smaller portion of the commercial plantations; however, it makes up for 66% of South African hardwood chip export and it is the preferred species by medium and small growers due to the diversified end products for local and export markets (Chan *et al.*, 2015). Nearly all these forest plantations consist of highly managed planted blocks of even-aged, single species trees that are commercially profitable. Commercial forest products contribute approximately 1% to the gross domestic product (GDP) of the country and the forestry sector provides employment to over 165000 individuals mostly in rural areas where opportunities for employment are limited (DAFF, 2020).

Wattle plantations are most commonly grown in KwaZulu-Natal (71 166 ha) and Mpumalanga (11 964 ha) (FSA, 2020). The uses of wattle extend to pulp and paper, wood chips, tannins, adhesives and charcoal (Chan *et al.*, 2015). Due to the variety of products derived from wattle trees, wattle plantations are one of the most profitable tree species per hectare.

The increasing number of pests and pathogens poses the most serious threats to plantation forests in South Africa (Wingfield *et al.*, 2008). In 2013, a severe outbreak of a rust fungus appeared on black wattle trees (*Acacia mearnsii*) in the KwaZulu-Natal Midlands. The fungus, then identified as *Uromycladium acaciae*, was first observed in South Africa in 1988 (McTaggart *et al.*, 2015). Symptoms of the fungus include gummosis of the bark, leaf curling, stunted growth of young trees and the appearance of brown slime on leaves and stems (McTaggart *et al.*, 2015). In severe instances, the rust fungus causes leaf defoliation and leaf drop with dark coloured pustules appearing on the underside of the leaf. Since the initial outbreak in KwaZulu-Natal, the rust has spread to most wattle plantations and woodlots in South Africa. All *A. mearnsii* plantations are at risk with no tolerant genotypes available to date.

In an effort to reduce the impact of the rust, an industry-wide working group was formed in partnership with research and academic institutions to support research projects in the development of a wattle rust integrated management strategy. Insect pests and pathogens often spread quickly across the landscape where suitable hosts are available; hence, monitoring is a key component of an effective strategy to manage these pests and pathogens, by providing the data required to evaluate the extent and intensity of the damage that they cause (Ismail *et al.* 2007; Oumar *et al.* 2016; Lottering *et al.* 2016). Our previous study on detecting canopy damage caused directly by wattle rust on commercial wattle in KwaZulu-Natal utilizing Landsat 8 imagery (430 nm - 2290 nm) achieved an accuracy of 88.24% using seven Landsat 8 bands and the partial least squares discriminant analysis algorithm (Oumar *et al.*, 2019). This work was limited to the detection of damage caused by the wattle rust and did not explore the environmental factors associated with the presence and severity of the disease. Understanding the relationship between environmental factors, particularly climate variability and rust occurrence is needed to evaluate the susceptibility of wattle plantations to the rust in different climatic areas of South Africa and to evaluate the potential distribution of the rust under future climate scenarios.

The life cycle of *U. acaciae* and the manifestation of the disease it causes are strongly climate driven. Fraser *et al.* 2017 investigated the optimal climatic conditions associated with key phases of the life cycle of *U. acaciae* in a climate-controlled environment. The development of teliospores, basidiospores and urediniospores was assessed at various temperatures and leaf wetness duration periods. It was found that the phases of the life cycle of the rust fungus and spore germination are strongly climate driven. The optimal conditions for *U. acaciae* infection on *A. mearnsii* is a 48-hour period of leaf wetness at an ambient temperature between 15°C and 20°C (Fraser *et al.*, 2017).

Guava rust (*Puccinia psidii*) is another rust species recently detected in South Africa and potentially affecting productive eucalypt plantations (Roux *et al.*, 2015). This rust was first observed in 2013 in KwaZulu-Natal and has since spread to most areas in South Africa where climatic conditions are favourable and susceptible hosts are present. Many species belonging to the Myrtaceae family, including commercially important *Eucalyptus* tree species as well as some indigenous species, are susceptible to infection by *P. psidii*. Risk maps based on climatic thresholds were developed to identify areas in South Africa that are climatically suitable for the establishment of a viable *P. psidii* population. Areas that experience seasonally a relative humidity greater than 80%, together with average temperatures between 18°C and 22°C were highlighted as potentially suitable for *P. psidii*. Most of the areas meeting these climatic requirements are located on the eastern seaboard of the country in areas that are currently utilised for commercial wood production (Roux *et al.*, 2015).

In this regard, plantation forests are strongly affected by changes in temperature and the resulting increase in biotic and abiotic risk. In South Africa, average temperatures have increased by at least 1°C over the past five decades, which is 1.5 times the observed global average, and rainfall patterns are becoming less predictable, with extreme rainfall events occurring more frequently (Ziervogel *et al.*, 2014). Such climatic changes can trigger existing and new rust occurrences (Berg *et al.* 2006; Jepsen *et al.* 2008) and could lead to the expansion of their geographic range. Climate-induced physiological stress has been associated with higher vulnerability of trees to pests and pathogens (Anderegg *et al.*, 2015) by lowering a tree's natural defence mechanism (Madden, 1968). The impact of climate change on forestry can be grouped into abiotic stressors such as temperature and moisture and biotic stressors such as diseases and pathogens (Boland *et al.*, 2004). Abiotic stressors have an influence on forests susceptibility to infections and additionally also influence the growth and reproduction of biotic diseases and

pathogens. Interactions between abiotic and biotic stressors are likely to be the key factors in forest disease outbreaks (Sturrock *et al.*, 2011).

For instance, Desprez-Loustau *et al.* (2007) investigated the influence of climate on two common Poplar leaf rusts *Melampsora medusae* and *Melampsora allii-populina*. Using simulated climatic environments, the research found that the highest occurrence of rusts was in summer months with higher than average mean temperature and with lower than average mean precipitation. This could possibly indicate that drought-stressed trees and warmer environments are two important variables for *M. medusae* and *M. allii-populina* outbreaks (Desprez-Loustau *et al.*, 2007).

In another study conducted in Wisconsin, United States, the occurrence of White Pine blister rust (*Cronartium ribicola*), a fungus which causes rusts in *Pinus* species, was evaluated to determine the ideal environmental conditions for the pathogen to spread (Van Arsdell *et al.*, 1956). The study found that the optimal conditions for rust infection were ambient temperatures between 0°C and 20°C and moisture saturated air for a period of 48 hours (Van Arsdell *et al.*, 1956).

Venier *et al.* (1998) assessed the historical distribution of Scleroderris canker in Ontario, Canada. This disease is caused by the *Gremmeniella abietina* fungus and affects *Pinus* species. Using a logistic regression model and the mean temperature and mean precipitation of the coldest quarter as predictors, a probability of occurrence map was produced with an accuracy of 84%. The most important climatic variables for Scleroderris outbreaks were cool, moist conditions (Venier *et al.*, 1998).

Recent studies have also used bioclimatic variables to model species distribution as tools for forest management. Barredo *et al.* (2015) utilized bioclimatic variables to model the present and future geographic distribution of large pine weevil (*Hylobius abietis* L) and horse-chestnut leaf miner (*Cameraria ohridella*) in Europe and showed the potential of applying species distribution models in forest management. Evangelista *et al.* (2011) assessed forests vulnerability and the potential distribution of three pine beetle species under the current and future climate in the interior west of the United States using bioclimatic variables as predictors of pine beetle presence. Climate models for 2020 and 2050 were created using data from WorldClim. The results revealed that suitable habitats for pine beetle will shift considerably. Host tree species will become more vulnerable in future in some areas whilst other areas will experience reduced risk of pine beetle attack.

Climate-based risk models (CBRM) therefore can be applied to predict current and future geographic distribution of pests and pathogens (Bosso *et al.*, 2017). With regard to the wattle rust and its management in South African black wattle commercial plantations, a risk map highlighting the projected geographic areas susceptible to *U. acaciae* infection is critical for an effective forest integrated management protection strategy (Germishuizen *et al.*, 2017). Moreover, *U. acaciae* threatens several endemic plant species that contribute to the rich and unique biodiversity of the southern African region, and a bioclimatic niche model may be applied also to evaluate the risk of severe infestation to these species for conservation purposes (Roux *et al.*, 2015). This present study seeks to find a relationship between climate and the occurrence and spread of *U. acaciae* by identifying the climatic niche associated with this fungus. The study aims to assist foresters to effectively manage this disease by proactively anticipating rust outbreaks and intervening accordingly. The work builds on previous research by Fraser *et al.* (2017) and Oumar *et al.* (2019) to develop a spatially relevant risk map based on the climatic niche of *U. acaciae*.

3.3. Methods and materials

3.3.1 Study area

The study was carried out in the KwaZulu-Natal and Mpumalanga provinces of South Africa. Enon and Etterby farms in KwaZulu-Natal are managed by NCT Forestry and were chosen as the study area due to intense outbreaks of wattle rust and the noticeable decline in tree health and productivity. Healthy black wattle data was collected from several privately owned farms in Mpumalanga which showed no symptoms of wattle rust. KwaZulu-Natal is characterized by a temperate to subtropical climate. Mean annual precipitation (MAP) ranges between 846 mm and 857 mm and the mean annual temperature (MAT) is 20°C in areas where *A. mearnsii* is grown. Timber and sugar cane farming are the primary activities planted across KwaZulu-Natal. Mpumalanga has a warm temperate in the north and a cool temperate in the south. Mean annual precipitation (MAP) ranges between 846 mm and 857 mm and the mean annual temperature (MAT) is 10.5°C in areas where *A. mearnsii* is grown. Agriculture in Mpumalanga largely consists of field crops such as maize, grain sorghum, wheat barley and soybeans with *A. mearnsii*, mainly planted in the south. *Acacia mearnsii*, *Eucalyptus dunnii* and *Eucalyptus grandis* and its hybrids are the dominant commercially planted tree species in both provinces. Commercial plantations are planted as single species and even age units (compartments) ranging in size from 1 ha to 100 ha and managed mainly for pulp, poles and sawtimber

production. Black wattle is predominantly grown for pulp production and tannin extraction from its bark.

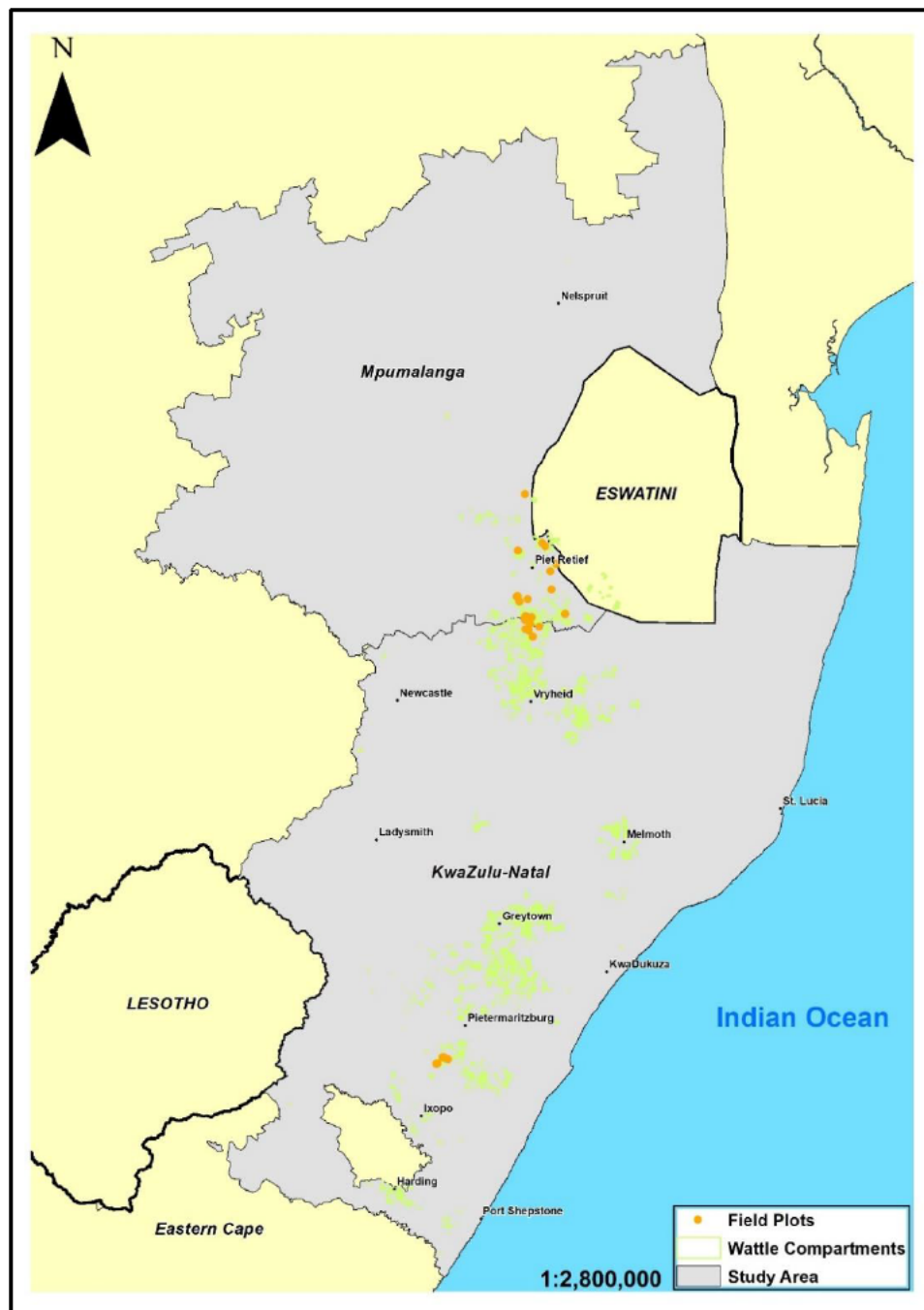


Figure 7. Location of study area in KwaZulu-Natal and Mpumalanga, South Africa

3.3.2 Data collection

Following the industry protocol developed in conjunction with the Tree Protection Co-operative Programme (TPCP), University of Pretoria and Forest Agricultural Biotechnology Institute (FABI), a total of 56 field plots were selected in wattle compartments between the

ages of 7 and 9 years and which were greater than 7 ha (approximately 9 pixels) to avoid spectral noise from adjacent land cover. The data was collected between 19th and 25th March 2015. Each field plot was laid in the middle of the compartment and consisted of a rectangular plot of 30 m x 30 m consisting of approximately 100 trees planted at a spacing of 3 m x 3 m where presence, level of infestation and impact of the rust on the forest canopy were assessed. Plot coordinates were recorded at the centre of each plot using a differentially corrected Garmin GPS 60 handheld Global Positioning System (GPS).

3.4 Environmental variables

Bioclimatic variables obtained from the WorldClim dataset (Hijmans *et al.*, 2011) at 30 arc-second (1 km x 1 km) grid cell resolution was used as environmental predictors of wattle rust occurrence. The dataset consists of 19 bioclimatic surfaces derived from historical rainfall and temperature records from weather stations, and it is available at <http://www.worldclim.org> (accessed 01 November 2018). Bioclimatic variables are particularly suited for species niche modelling; they are ecologically meaningful, taking into account seasonality and extreme climatic events in addition to rainfall and temperature averages. The ecological niche model developed under current climate conditions was then applied to long-term future climate scenarios. Monthly rainfall, minimum temperature (tmin) and maximum temperature (tmax) surfaces were developed based on the medians of five global circulation models (GCMs) for long-term climate scenario (2080 - 2100) obtained from the WorldClim website (Table 5). The Representative Concentration Pathway (RCP) selected was the 4.5 emission scenario, which is based on moderate population and economic growth and emissions reduction from mid-century. From these surfaces, “future” bioclimatic variables were developed using the package Dismo (Hijmans *et al.*, 2011) in the R environment.

Table 4. Description of the 19 Bioclimatic variables (Hijmans *et al.*, 2011) used as predictors of the presence of the wattle rust

Bioclimatic Variables
BIO1: annual mean temperature
BIO2: mean diurnal range
BIO3: isothermally
BIO4: temperature seasonality
BIO5: maximum temperature of warmest month
BIO6: minimum temperature of coldest month
BIO7: temperature annual range
BIO8: mean temperature of wettest quarter
BIO9: mean temperature of driest quarter
BIO10: mean temperature of warmest quarter
BIO11: mean temperature of coldest quarter
BIO12: annual precipitation
BIO13: precipitation of wettest month
BIO14: precipitation of driest month
BIO15: precipitation seasonality
BIO16: precipitation of wettest quarter
BIO17: precipitation of driest quarter
BIO18: precipitation of warmest quarter
BIO19: precipitation of coldest quarter

Table 5. Global Circulation Models (GCMs) used for the development of monthly rainfall, tmin and tmax surfaces for long-term (2080-2100) climate change scenario.

Centre	Model	Variables	RCP
Centre National de Recherches Meteorologiques (France)	CCM3	rain, tmax, tmin	4.5
Canadian Center for Climate Modelling and Analysis (Canada)	GCCM	rain, tmax, tmin	4.5
The centre for Australian Weather and Climate Research (Australia)	CSIRI-MK	rain, tmax, tmin	4.5
Max-Planck-Institut for Meteorology (Germany)	ECHAM5	rain, tmax, tmin	4.5
Met Office Hadley Centre for Climate Change (UK)	HADGEM1	rain, tmax, tmin	4.5
Institut Pierre Simon Laplace (France)	IPSL	rain, tmax, tmin	4.5

3.5. Modelling approach

Spatially explicit ecological niche models (ENM) have become popular tools to gain an understanding of the potential distribution of insect pests and pathogens and resulting impact. In this study, the maximum entropy (MaxEnt) species distribution model algorithm (Phillips *et al.*, 2006) was used to assess the potential of the current and future occurrence of wattle rust in the commercial forestry areas in South Africa where the host tree species, black wattle, is present. MaxEnt is a general-purpose species distribution machine-learning algorithm that estimates the probability of species presence on a pixel basis using presence-only data, which eliminates the challenges associated with pseudo-absence (Elith *et al.*, 2011). For instance, a species may be absent from an environmentally suitable area due to a disturbance, a physical barrier to its expansion or absence of suitable host species; it could also be recorded as absent in areas where in fact it is present due to poor sampling effort (Elith *et al.*, 2011). The equation for the MaxEnt algorithm is:

$$\Pr(y = 1|z) = \frac{f1(z) \Pr(y=1)}{f(z)} \quad [2]$$

Where $\Pr(y=1|z)$ is the probability of presence of the species, $f(z)$ is the probability density of the environmental covariates (z) across the landscape of interest (f) and $f_1(z)$ is the probability density of the environmental covariates (z) across locations within f where the species is present (Elith *et al.*, 2011). Two criteria were used to evaluate the performance i.e. goodness-of-fit and predictive power of the model; the area under the receiver operating characteristic curve (AUC) and the true skill statistic (TSS) (Allouche *et al.*, 2006; Elith *et al.*, 2011). The AUC represents the probability that a randomly chosen presence point of the species will be ranked as more suitable than a randomly chosen absence point (Elith *et al.*, 2011). A model is considered as having a good fit when its AUC is close to one ($\text{AUC} \geq 0.75$) (Elith *et al.*, 2011). The TSS represents the capacity of the model to accurately detect true presences (sensitivity) and true absences (specificity). A model with $\text{TSS} \leq 0$ indicates a random prediction; while a model with a TSS close to 1 ($\text{TSS} > 0.5$) has a good predictive power (Allouche *et al.*, 2006).

The probability values provided by MaxEnt for present and future climate were converted to presence and absence information by applying the 0.5 Maximum Test Sensitivity and Specificity (MTS) threshold (Liu *et al.*, 2005).

3.5.1 Variable importance

One of the key aspects in this study is to understand which environmental variables are most important for the development of the wattle rust. To this end, both the variable importance and permutation metrics were calculated. Variable importance is calculated based on the gains of the model obtained when modifying the coefficient of a single feature; the gains are then assigned to the variables upon which the feature depends. It is a continuous process affected by the particular path used by MaxEnt to arrive to the optimal model; hence, variable rankings may vary in subsequent runs. Permutation importance is calculated based on the effect of random change of value of a given variable on the final model. This method of assessing variable contribution is independent from the path used by MaxEnt to develop the final model and it is not affected by correlativity of the environmental predictors, making it a preferred and more stable metric (Phillips., 2017).

3.6. Results

3.6.1 Current climate

MaxEnt identified 24703 ha within KwaZulu-Natal and Mpumalanga at high risk of wattle rust in the present climate. This represents 30% of the total wattle area in KwaZulu-Natal and Mpumalanga. The most suitable areas are southern KwaZulu-Natal and extend to southern Mpumalanga (Figure 8). This result coincides with wattle rust trends observed over the last five years. The AUC value was 0.97, suggesting excellent discriminatory power of the model.

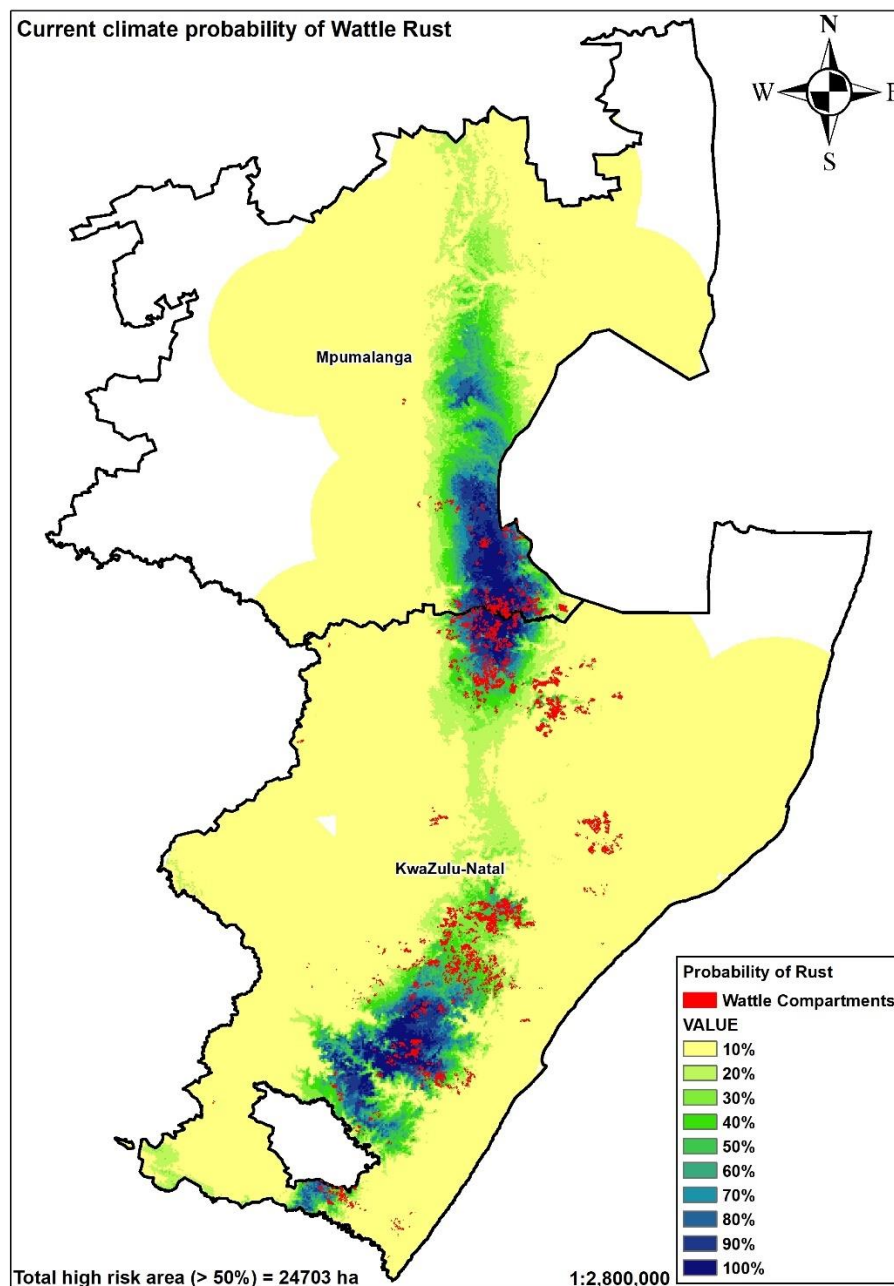


Figure 8. The distribution of wattle rust based on current climatic data

3.6.2 Future climate

When the model was applied to the future bioclimatic variables (2080 and 2100) the potential geographic distribution of the rust changed substantially. The climatically suitable area decreased in extent under the future climate scenario, with the total high-risk area shrinking to 7316 ha as opposed to the 24703 ha identified under the current climate. This represents 8.9% of the total wattle area in KwaZulu-Natal and Mpumalanga. The suitable area moved further south of KwaZulu-Natal (Figure 9). Overall, climatic conditions appeared to be less favourable for the occurrence of wattle rust with the climate tending to be generally drier and warmer.

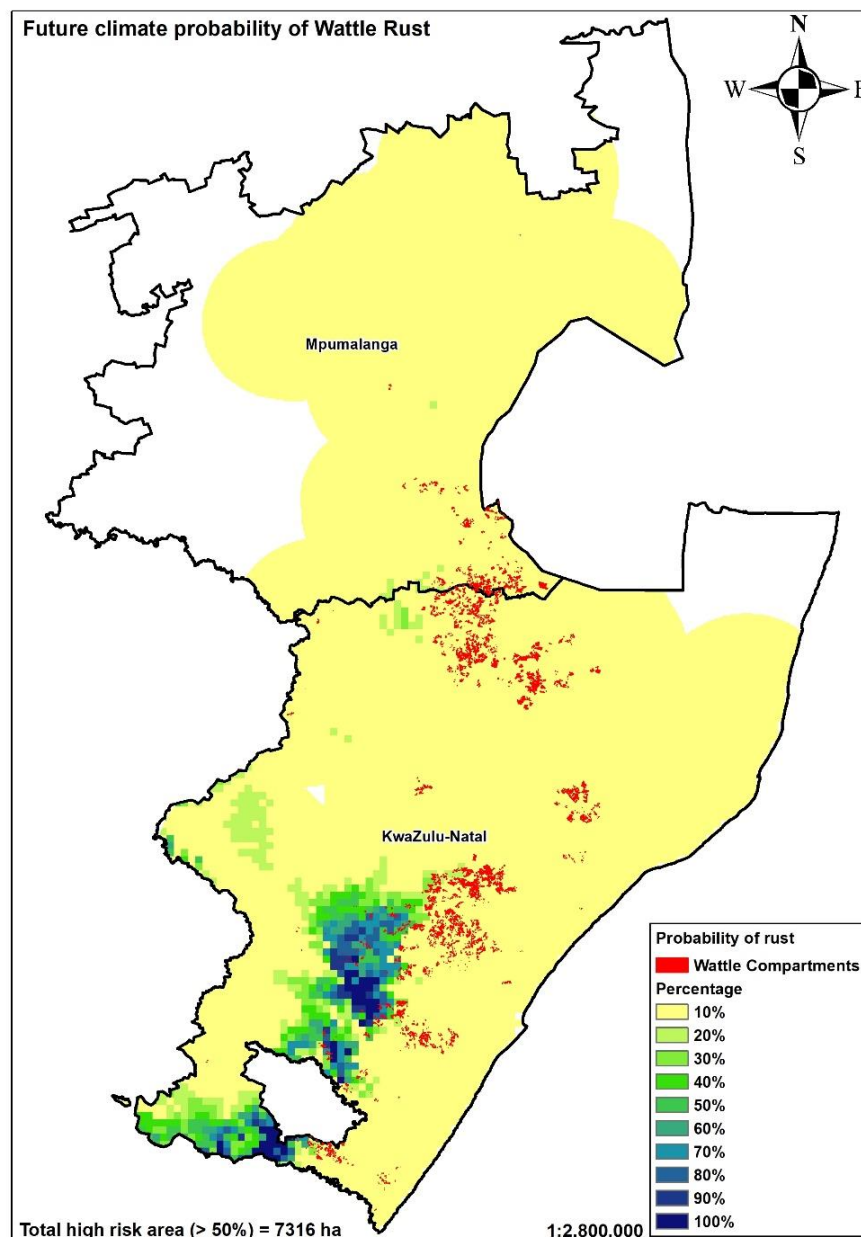


Figure 9. The distribution of wattle rust based on future climatic data

3.6.3 Variable importance results

The bioclimatic variables that contributed at least 5% to the model's accuracy were considered important determinants of the occurrence of the wattle rust (Figure 10). Minimum temperature of coldest month (Bio6) and precipitation of wettest month (Bio13) were overall the most important variables, accounting together for 70% of the model accuracy. Annual mean temperature (Bio1), precipitation seasonality (Bio15) and precipitation for the driest month (Bio14) were also important determinants of the probability of occurrence of the wattle rust. Minimum temperature of coldest month (Bio6) was scored as the most important variable in both the permutation and percentage importance methods. These results are consistent with the findings of Fraser *et al.* (2017) which identified wet conditions and mean temperature between 15°C and 20°C as optimal for the development of rust.

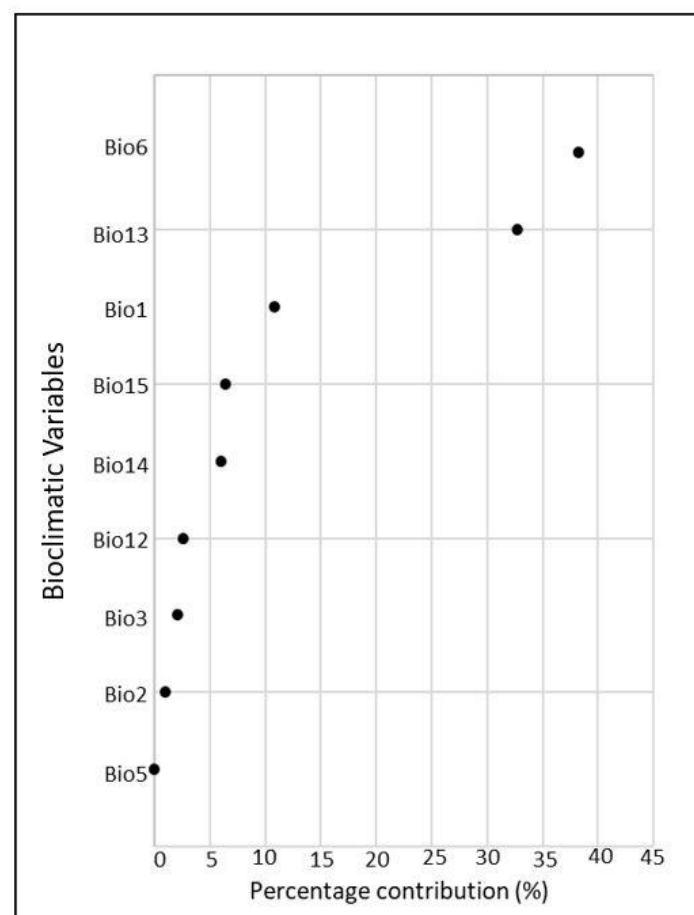


Figure 10. Percentage contribution of bioclimatic variables to the wattle rust distribution model determined using the variable permutation metric.

Response plots were created for the most important variables to determine the climatic ranges associated with the highest predicted likelihood of wattle rust occurrence (Figure 11). Minimum temperature of the coldest month below 5°C, precipitation in the wettest month above 150 mm and above 20 mm in the driest month characterize the climate more conducive to wattle rust infestation. Precipitation seasonality saw a reduction in wattle rust occurrence when the coefficient of variation was greater than 75%. Therefore, extreme variances in seasonal rainfall reduce the likelihood of wattle rust.

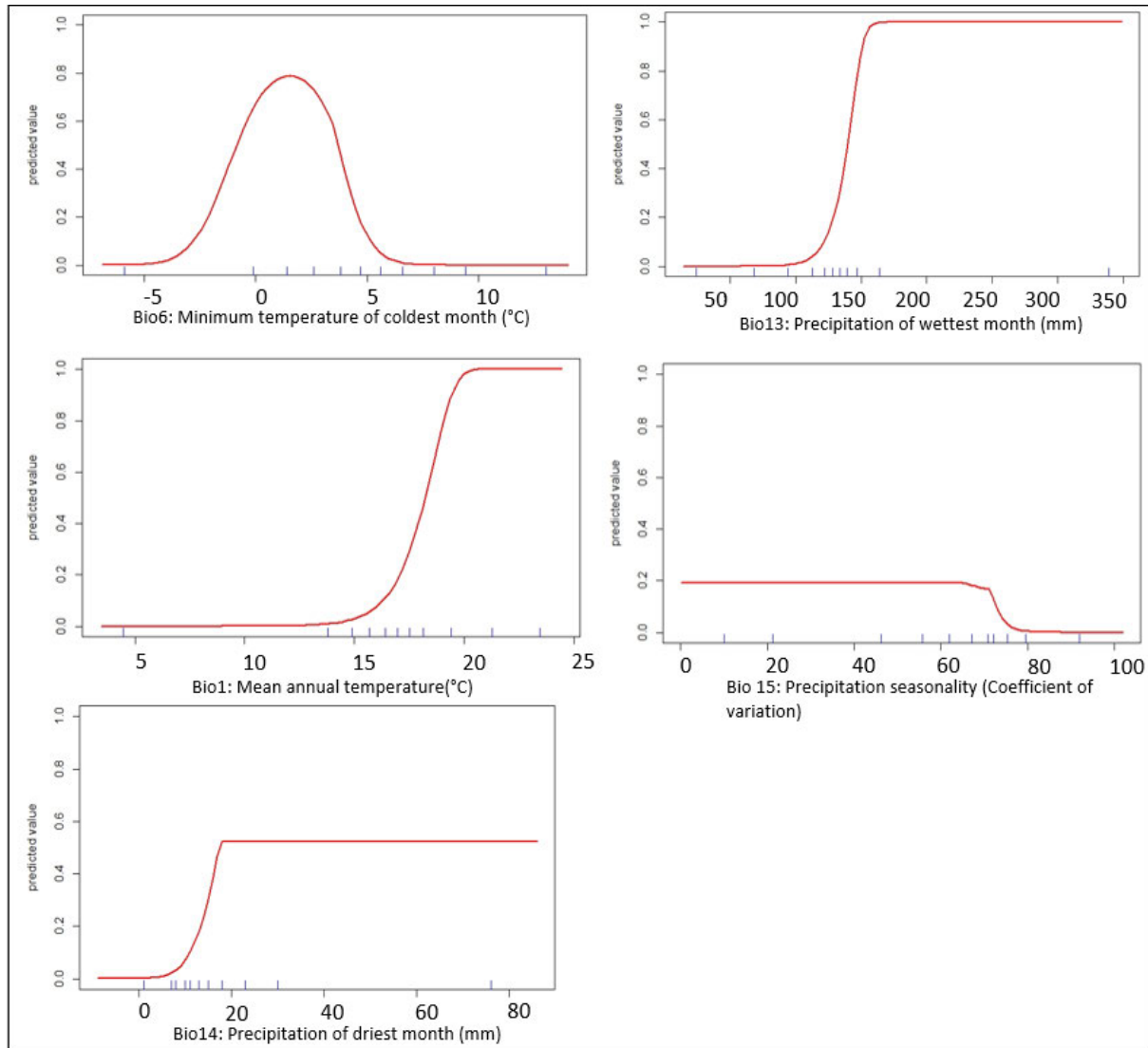


Figure 11. Response plots of the most important variables in the model.

3.7 Discussion

This study has developed a method of estimating the suitable geographic distribution of *U. acaciae* based on the climatic conditions conducive to the development of the wattle rust disease in commercial wattle plantations, South Africa. The results illustrate the potential

effects of climate change on the distribution of the disease and highlights the expansion and contraction of suitable climatic ranges. The MaxEnt algorithm combined with the bioclimatic variables successfully identified areas at higher risk of wattle rust outbreaks. The development of a niche model for *U. acaciae* contributes towards developing a routine monitoring system for the management of this pathogen. Moreover, this study builds on the remote sensing work done to detect damage caused by *U. acaciae* on black wattle (Oumar *et al.*, 2019) and now provides a successful working framework for assessing the potential risk of wattle rust outbreaks across a wide geographical extent using indirect mapping approaches.

3.7.1 Mapping the potential extent of *U. acaciae* across South African wattle plantations

The ability to estimate the risk of *U. acaciae* infection in prevailing climates enables a proactive approach to disease management and prevention based on risk assessment and monitoring. The *U. acaciae* distribution model can help with defining the climatic niche within which the pathogen is more likely to cause severe wattle rust infection. The study has shown that Mpumalanga and northern KwaZulu-Natal provinces are favourable locations for rust development in the current climate but become less favourable locations under the future climate scenario. Conversely, the Eastern Cape is at higher risk for rust outbreaks in the future than it is under current climate conditions. The results in this paper coincide with other research that predict changes in the geographic distribution of species as a result of climate change. For example, Barredo *et al.* (2015) observed a shift in geographic location of pine weevils under future climate conditions, whilst Evangelista *et al.* (2011) had similar results with Pine beetle in the interior West of the United States. The study also demonstrates the success of the MaxEnt algorithm combined with the bioclimatic variables to produce a species distribution model for *U. acaciae*, which can be used towards the development of a monitoring system for this pathogen as part of the integrated management strategy to curb the impact of wattle rust outbreaks based on economically and environmentally sound principles.

The MaxEnt model has the advantage of requiring presence-only data to predict species distribution. This makes sampling easier and mitigates the potential errors of pseudo-absence. The model produced an AUC value of 0.97. The accuracy obtained in this study is comparable to other studies using bioclimatic variables and the MaxEnt model (Bradie and Leung, 2017; Bosso *et al.*, 2017). For example, Bradie and Leung assessed a total of 1900 MaxEnt species distribution models. The study found precipitation and temperature to be the most important variables in species distribution modelling. The average discriminatory power of the MaxEnt

model was $AUC = 0.92$. Similarly, Bosso *et al.* (2017) used MaxEnt and climatic variables to predict the future disease outbreaks of *Diplodia sapinea* shoot blight in Italy. The most important contributors to the model were identified as land cover, mean temperature of wettest quarter, altitude and precipitation of wettest quarter. The overall predicted accuracy of the model was $AUC = 0.87$.

3.7.2 Variable permutation metric to determine the main climatic variables for *U. acaciae* appearance.

The variable permutation metric is a valuable tool to identify which climatic variables contributed most to the MaxEnt model. Five variables accounted for 94% of the model accuracy with minimum temperature of coldest month (Bio6) and precipitation of wettest month (Bio13) accounting for 71%. Annual mean temperature (Bio1), precipitation seasonality (Bio15) and precipitation of driest month (Bio14) also contributed to the predictive power of the model. The response plots of these variables highlight that optimum conditions for wattle rust outbreaks are associated with cool and moist climate in areas where seasonal variation is not extreme. The results in this study are comparable to the findings of Fraser *et al.* 2017 where the study found the optimal conditions for *U. acaciae* infection on *A. mearnsii* is a 48-hour period of leaf wetness at an ambient temperature between 15°C and 20°C. Van Arsdell *et al.* 1956 also observed a similar climatic range for White Pine Blister in the United States, where the optimal conditions for rust infection were ambient temperatures between 0°C and 20°C and moisture saturated air for a period of 48 hours.

3.7.3 Summary

The aim of this study was to define the climatic niche of *U. acaciae* and identify areas at risk of infection based on the prevailing climate. Using the current presence points of *U. acaciae* and the bioclimatic variables obtained from the WorldClim dataset, the MaxEnt model successfully determined areas which are vulnerable to *U. acaciae* infection under current and future climates. Cool, wet conditions were determined to be the key predictors of wattle rust outbreaks. The methodology developed in this study can be used to implement a monitoring system for wattle rust at landscape level to support the management of this important disease. This encourages assessing *U. acaciae* seasonally and at different lifecycles where smaller symptoms of the pathogen can be managed prior to the advent of cooler, wetter conditions.

Chapter 4

Conclusion

4.1 Introduction

The mapping of forest pests and diseases is an important aspect of forest management. Monitoring and surveillance are key to understanding the nature and distribution of pests and pathogens (Dyer *et al.*, 2010). Field surveys are accurate in determining forest health; however, the process of sampling trees manually is not always feasible when sampling of large geographic areas is required (Ismail *et al.*, 2007; Oumar *et al.*, 2016; Lottering *et al.*, 2016). Earth observation technologies such as remote sensing provide global coverage at regular intervals which can offer researchers a real-time synopsis of forest health. Additionally, climate-based risk models can help researchers identify trends and patterns in the distribution of pests and pathogens (Bosso *et al.*, 2017; Germishuizen *et al.*, 2017). The aim of this research was to assess the utility of GIS and Remote Sensing to monitor the wattle rust causing pathogen *U. acaciae*. The main objectives were (1) to assess the capability of multispectral satellite imagery to detect wattle rust damage using PLS-DA, (2) to test the effectiveness of partial least squares variable importance in the projection (VIP) to select the most influential wavebands to detect wattle rust damage, (3) to use bioclimatic variables and the MaxEnt model to identify geographic locations that may be susceptible to *U. acaciae*, (4) to use the variable permutation metric to identify the most important climatic variables for *U. acaciae* development, (5) to create a wattle rust risk map based on the current and future climate. The section below discusses each of these objectives.

4.2 Assessing the capability of Landsat 8 multispectral satellite imagery to detect wattle rust damage using PLS-DA

Results from the study showed that the PLS-DA model using all seven Landsat 8 wavebands produced a classification accuracy of 88.24% and a kappa value of 0.76. Overall, the Landsat 8 image data combined with PLS-DA successfully detected damage caused by the wattle rust on *A. mearnsii*. This is possible due to the sensors ability to discern between healthy and damaged tree canopies.

4.3 Testing the effectiveness of PLS-DA variable importance in the projection (VIP) to select the most influential wavebands to detect wattle rust damage

The VIP method is useful for determining the wavebands that are optimal for damage detection. The highest VIP scores were coastal aerosol (430 nm - 450 nm), red (640 nm - 670 nm) and near infrared (850 nm - 880 nm). The near infrared and calculated NDVI values were the most significant variables to detect wattle rust damage. The results correspond with other studies which have found the visible region of the electromagnetic spectrum to provide a good indication of forest health (Oumar, 2016; dos Santos *et al.*, 2017). The overall accuracy of the model using only the VIP selected variables was 82.35% and the kappa value was 0.66. This is a reduction in classification accuracy of 5.89%. The VIP results contrasted with the study by Peerbhay *et al.* (2013) which found the VIP analysis to improve classification accuracy. However, it can be concluded that the VIP method when used with the PLS-DA model can identify the most significant wavebands for classification.

4.4 Using bioclimatic variables and the MaxEnt model to identify geographic locations that may be susceptible to *U. acaciae*

The results from this study confirm the effectiveness of species distribution modelling to predict the potential spread of *U. acaciae* and the occurrence of the disease it causes. The MaxEnt model used the presence data of wattle rust disease and the WorldClim bioclimatic variables to produce an AUC value of 0.97. The results emphasised the model's ability to discern between suitable and unsuitable climates for *U. acaciae* development.

4.5 Using the variable permutation metric to identify the most important climatic variables for *U. acaciae* development

The variable permutation metric provides a useful framework to identify the climatic variables that most likely correlate with the occurrence of wattle rust. The highest scores were minimum temperature of coldest month (Bio6), precipitation of wettest month (Bio13), annual mean temperature (Bio1) and precipitation seasonality (Bio15). The results in this study are comparable to the findings of Fraser *et al.* (2017) which found cool and wet conditions ideal for *U. acaciae* development. It can be concluded that the variable permutation metric when used in conjunction with the MaxEnt model can provide insight into which climatic variables are needed for *U. acaciae* development.

4.6 Creating a wattle rust risk map based on the current and future climate

Two wattle rust risk maps were created using ArcMap 10.4. The bioclimatic values obtained from the MaxEnt model were overlaid onto the forestry areas in South Africa. The results from the current climate showed an area of 24703 ha as susceptible to rust infection, with the most high-risk areas being in KwaZulu-Natal and southern Mpumalanga. When applied to future bioclimatic surfaces, the MaxEnt model identified an area of 7316 ha as suitable for the growth and development of *U. acaciae*. The most high-risk areas under future climate conditions were southern KwaZulu-Natal and northern Eastern Cape. The maps illustrate two key observations 1) a dramatic reduction in suitable climatic area for *U. acaciae* development and 2) the suitable climatic area for *U. acaciae* will move further south. A possible reason for these observations is the projected climate obtained from the WorldClim dataset which estimates the future climate in South Africa to be warmer and drier. The northern part of the country will bear the brunt of warmer and drier conditions and therefore the rust will more likely appear further south where conditions will be more suitable for *U. acaciae* development.

4.7.1 Recommendations for future research in detecting wattle rust with satellite imagery

One of the disadvantages of broad band sensors is the discreet changes in spectral reflectance by stressed vegetation can be hidden by field geometry, lighting and the density of the canopy (Ismail *et al.*, 2007). Hence, the results of this study may be influenced by such factors and thus opens up the possibility of analysing the impacts of *U. 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 teliospores 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 also exists to investigate the Sentinel-2 sensor 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.

4.7.2 Recommendations for future research in modelling *U. acaciae* with species distribution models

One of the limitations of this study was the limited availability of current South African weather data from available weather stations. Long term climate surfaces were used instead, with the model being developed by associating sites where the disease was present to long-term climate averages rather than current weather records. The widespread nature of *U. acaciae* also makes collecting absence data difficult in forest plantations. Hence, the results of this study may be influenced by such factors and opens up the possibility of analysing *U. acaciae* using locally derived climate data together with topographic data and real-time high-resolution satellite imagery. Moreover, management interventions may alter the presence or severity of infestation in some areas, limiting opportunities for comprehensive surveys. Future studies could also explore opportunities to assess *U. acaciae* infection using more advanced techniques such as alternate one-class mapping approaches, such as one-class support vector machines (OCSVM), to classify presence-only datasets.

4.8 Conclusion

The aim of this research was to assess the utility of Landsat 8 imagery and the PLS-DA algorithm to monitor the infection caused by *U. acaciae* on black wattle. The research undertaken in this study showed it is possible to detect *U. acaciae* infection using remote sensing information. Additionally, risk maps were created which highlighted areas which may be susceptible to *U. acaciae* and where the risk of wattle rust is hence more prominent. The final conclusion is based on the following observations made in this dissertation:

1. Landsat 8 remotely sensed data is capable of detecting damage caused by wattle rust. The study produced an overall accuracy of 88.24% and a kappa value of 0.76 using all Landsat 8 bands ($n = 7$). However, using only the VIP selected wavebands coastal aerosol (430 nm - 450 nm), red (640 nm - 670 nm), near infrared (850 nm - 880 nm) and the NDVI resulted in a reduced accuracy of 82.35% and a kappa value of 0.66. However, the model still produced high accuracy results for excellent classification results.
2. The MaxEnt model is capable of estimating geographic areas that are susceptible to *U. acaciae* occurrence. Using the WorldClim bioclimatic variables and MaxEnt model, the study produced an AUC value of 0.97. The variable permutation metric identified minimum temperature of coldest month (Bio6), precipitation of wettest month (Bio13), annual mean

temperature (Bio1) and precipitation seasonality (Bio15) as the most significant climatic variables for *U. acaciae* appearance. *U. acaciae* appears to thrive in cool and wet conditions.

3. It is possible to create wattle rust risk maps in ArcMap using remote sensing imagery and the classification tools. The current climatic variables in the map highlighted KwaZulu-Natal and southern Mpumalanga as the most likely areas to display symptoms of *U. acaciae*. Using the simulated future climatic variables, the map highlighted a significant change in the distribution of *U. acaciae* and identified southern KwaZulu-Natal and northern Eastern Cape as the most likely hosts for *U. acaciae*.

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