Applying High-Resolution Remote Sensing to Quantify Baboon Damage at a Sub-compartment Level in Pine Stands in the Mpumalanga Escarpment Region of South Africa

by

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TITLE OF PROJECT: Applying High-Resolution Remote Sensing to Quantify Baboon Damage at a Sub-compartment level in Pine Stands in the Mpumalanga Escarpment Region of South Africa.

DECLARATION:

Under Rule G5.6.3, I hereby declare that the above-mentioned thesis is my work and that it has not previously been submitted for assessment to another University or for another qualification.

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Disclaimer

The research objectives achieved in this thesis was through a two-part study of baboon damage research (Chapter 2 and Chapter 3). Both of these chapters are being submitted as journal articles for publication at the time of review. These papers are written separately with regards to the methods and data acquisition but are linked with the overall objective of the study, which is to map different degrees of baboon damage using remote sensing as a forest health monitoring tool. The papers utilise the field data collected using similar protocols on selected baboon damage monitoring sites during different times. The major difference between the two papers are that Chapter 2 utilizes Sentinel-2 (443 – 2190 nm) at 10 m x 10 m resolution image data, coupled with the Extreme Gradient Boosting (XGboost) machine learning algorithm and various vegetation indices for a damage assessment at a compartment level. This dataset has a larger sample size and spatial coverage due to an industry collaboration with the Baboon Working Group. Chapter 3 utilizes high temporal PlanetScope (455 – 860 nm) 3 m x 3 m resolution image data and a deep learning Artificial Neural Network (ANN) approach. PlanetScope normalised difference vegetation index (NDVI) was also tested for damage distinction for developing a methodology for a tree level analysis. These two papers can be read independently from one another and share different results, thus overlapping of information is insignificant. The thesis consists of four chapters in total.

Executive Summary

Managing risk in intensively managed monoculture plantation forests is an essential task to ensure sustainable yield and a continuous flow of forest products. However, since risks can be either biotic or abiotic, not all of them have a predictable pattern of spread, which can cause severe losses if management does not have the chance to implement mitigation action. Monitoring the change in forest health is vital as this provides the opportunity for preventative management and quantifies the amount of damage that management has to deal with. To provide this window of opportunity for appropriate action, constant monitoring is required. Until recently, forest health was measured through field surveys which provided adequate data. This procedure, however, is time consuming. Remote sensing has become very popular as a monitoring tool, due to its ability to provide assessment data in a fraction of the time. In this study, baboon damage in plantations along the Mpumalanga escarpment area of South Africa was monitored using remote sensing methods.

While there are many methods of forest health monitoring using remote sensing, some approaches are less suitable as they either monitor damage caused at a plantation level, use lower spatial resolution (>10m) datasets or map damage using one available time period. The purpose of this study was first to establish the impact of baboon damage through time, using Sentinel-2 satellite imagery with all vegetation indices available, and the Extreme Gradient Boosting (XGboost) algorithm. The second part focused on analysing the damage at a tree level using PlanetScope imagery using a deep Learning approach. Overall, the study found that the use of Sentinel-2 data and PlanetScope data could accurately distinguish between the varying severity of baboon damage, achieving an accuracy of 95% and 82%. The processing time of the deep learning Artificial Neural Network (ANN) was greatly affected by the number of hidden layers and neurons used. Implementation of techniques used in this study has the potential to improve the accuracy of forest health monitoring in compartment forestry in South Africa.

THESIS OVERVIEW

Applying High-Resolution Remote Sensing to Quantify Baboon Damage at a Sub-compartment level in Pine Compartments in the Mpumalanga Escarpment Region of South Africa

Chapter 1

General introduction to South African forestry and risk monitoring using remote sensing.

Chapter 2

Objective:

A Spatio-temporal analysis of Baboon Damage using Sentinel-2 imagery and Extreme Gradient Boosting

Method:

Extreme Gradient Boosting algorithm with 10 m Sentinel-2 imagery, analysing 27 research plots.

Main Results:

XGboost proved very successful in the detection of damage with an overall accuracy of 95%.

Chapter 3

Objective:

A tree level analysis of baboon damage in commercial forests stands using deep learning techniques.

Method:

Deep learning ANN algorithm with 3 m PlanetScope imagery, analysing 8 research plots.

Main Results:

ANN succeeded in distinguishing between damage with an overall accuracy of 82%

Chapter 4

Summary of findings and overall conclusion

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CHAPTER 1

General Introduction to South African Forestry and Risk Monitoring using Remote Sensing

The South African forest industry occupies approximately 1% of the total land area (approx. 1 220 726 ha) and contributes an estimated R9 billion to the annual Gross Domestic Product (GDP) of the country's economy (FSA 2016). The plantation area consists mainly of species of pine (50%), eucalypts (47%) and wattle (0.4%), which are grown for various products such as sawtimber, pulpwood and mining timber (FSA 2018). In the Mpumalanga escarpment area, 62% of commercial forestry plantations are pine, producing both sawtimber and pulpwood (DAFF 2014). Globally there is growing pressure on forest resources due to a rapidly increasing population and competition for land use. Solid wood from forests is used to construct new commercial buildings as well as to improve and aid in the upkeep of existing structures (Mckeever and Howard 2009). There exists a growing demand for sawtimber and pulpwood to meet the needs of construction and paper products. It is essential to intensively manage monoculture forest plantations, as they curb degradation and deforestation of natural forests. (Elias and Boucher 2014). South Africa is no exception to this phenomenon (D'Annunzio *et al*. 2015; MacDicken *et al*. 2015)**.**

In South Africa, the majority of commercial forest plantations adheres to sustainable management with the need to mitigate any risks that threaten sustainability. Forest certification is a mechanism that subjects forestry to a set of principles that promotes sustainable practices and risk mitigation methods. Compliance with these sustainable practices allows companies to gain access to global markets that support the cause (Ham 2004; Auld *et al*. 2008). Such methods assist in meeting long term goals and implement cost-effective management decisions (Lindenmayer *et al*. 2000; Franklin 2001; Ham 2004; Auld *et al*. 2008; Louw 2012). All risks need to be managed to promote not just a high return but also compliance with certification, which encourages investments in plantation forestry (Louw 2012).

Various abiotic and biotic risks may impact a forest stand, which requires observation and monitoring of the compartment in an attempt to develop a feedback system, which will aid in management practices (Lindenmayer *et al*. 2000; Franklin 2001; Louw 2012). South Africa's forest plantations are affected by both biotic and abiotic risk such as fungal pathogens, insect pests and drought (FSA 2017). These risks cause stress in the environmental and the physical condition of plantation trees resulting in poor re-establishment, stand variability, low stocking and as a result lower timber yield (Carter 1989). A very prominent threat currently affecting commercially planted pine in the Mpumalanga escarpment area is damage caused by baboons (*Papio ursinus*). This was first detected in South Africa in the 1970s (Bigalke and van Hensbergen 1990). Damage has escalated continuously throughout the years, with as much as 28% of compartments in Mpumalanga currently showing some form of baboon damage in Mpumalanga. However, this damage may be much greater. Monitoring biotic and abiotic risks is important to acquire feedback and information for proactive intervention and to develop management practices to reduce their impact (Franklin 2001; Chornesky *et al*. 2005; Huang and Asner 2009).

Traditional ground surveys are demanding in terms of manpower and can be very costly, which has promoted the search for alternate methods of sampling (Kampouri *et al*. 2018). In South Africa, the majority of manual labour tasks are outsourced to contractors to reduce the communication line from company to contractor to negate having to manage large groups of people (Louw 2012; Haggstrom *et al*. 2013). Manual field risk surveys include impact assessment and surveillance of forest health measured by contractor teams and are recorded in-field. The use of manual labour for field surveys is very dependent on accessibility, which is influenced by weather conditions and topography, which may cause inconsistency in data capturing with regards to time schedules and varying sampling efforts, with less accessible areas not being regularly surveyed. It is imperative to do regular and prompt surveillance to respond to forest threats as soon as they occur for proper management intervention to take place (Franklin 2001; Carnegie *et al*. 2018). Remote sensing has greatly advanced in technology over the years and is more economically viable than before for forest health monitoring. (Franklin 2001; Joshi *et al*. 2004; Asner and Vitousek 2005; Chornesky *et al*. 2005; Huang and Asner 2009). However, this does not come without some challenges, such as accurately identifying the risk and establishing an information database, which can also be costly (Chornesky *et al*. 2005; Huang and Asner 2009).

The use of spatial technology to analyse biotic risks in forestry compartments has broad application value (Huang and Asner 2009; Germishuizen *et al*. 2017).

Monitoring biotic risks may prove more challenging than that of abiotic risks due to a higher level of complexity related to spatial-temporal variation (Chornesky *et al*. 2005; Huang and Asner 2009). Many studies have shown the benefits of mapping and monitoring damaging agents in plantation forestry using high resolution imagery. A study by Ismail *et al*. (2008) tested the optimum resolution of remote sensing data from Land Resources International (LRI), using vegetation Indices such as NDVI, to monitor *Sirex noctilio* in pine plantations within South Africa, which has caused the industry severe damage in the past. They found that damage was more accurately identified between resolutions of 1,75 m – 2,30 m and that resolution either above or below this range may yield inaccurate results (Ismail *et al*. 2008). A subsequent study by Ismail *et al*. (2010), attempted to model the distribution of pine plantations that are susceptible to *Sirex noctilio* damage (Ismail *et al*. 2010).

A study conducted by Germishuizen *et al.*, (2017) utilised bioclimatic (Hijmans *et al*. 2005) and environmental variables to quantify and evaluate the potential risk of baboon damage in pine compartments in the forestry sector that proved to be successful, identifying areas that have higher risk of baboon damage and allowed them to produce damage risk maps (Germishuizen *et al*. 2017). A subsequent study by Peerbhay *et al.* (2019) tested the utility of remote sensing to detect baboon damage in pine plantations. In-field data in the form of ground truthing was obtained in an attempt to determine the intensity of baboon damage. The Random Forest algorithm was incorporated into the study as it is one of the most successful tree-based ensemble methods. The final dataset yielded 5900 stands with more than 50% damage present and 7400 undamaged stands. This study also proved successful in detecting stand damage with monthly image data sets being more accurate than yearly image data sets (Peerbhay *et al.*, 2019). The industry currently lacks the knowledge necessary to develop an informed, science-based integrated strategy to mitigate the threat posed by baboons (Germishuizen *et al*. 2017). The damage consists mainly of bark-stripping resulting in tree deformity, wood deterioration and often causes mortality, as pines struggle to regenerate after the loss of apical dominance (Bigalke and van Hensbergen 1990). A study conducted in Zimbabwe that aimed at monitoring baboon damage showed that due to the extent of damage caused to trees, the economic profitability of the plantations was compromised. The lack of a sound strategy to mitigate baboon damage is likely to result in unsustainable economic losses in the future (Katsvanga *et al*. 2009). However, these studies do not quantify the damage at a tree level but rather at a farm and landscape level. Moreover, Landsat-derived damage detection may be related to biotic and abiotic causes other than bark stripping by baboons. The need arises for a more direct approach to mapping baboon damage.

The studies mentioned above used the Random Forest (RF) algorithm. Random Forest is a popular machine learning algorithm used for forestry research and is often used in satellite and aerial image classification (Pal, 2005; Horning, 2010; Rodriguez-Galiano *et al*. 2011; Belgiu and Dragut, 2016). It works by producing multiple decision trees and uses random variables and a subset of training samples. It requires a few manually input parameters to run the algorithm and is capable of working with unbalanced and categorical data. Random Forest also achieves good accuracy, when compared with other machine learning algorithms and is not greatly influenced by overfitting (Pal, 2005; Horning, 2010; Rodriguez-Galiano *et al*. 2011; Belgiu and Dragut, 2016). Although machine learning succeeds in the detection of stress in forest plantations, deep learning techniques may be required to identify damage at a tree level. A study by Guan *et al*. (2015) used deep learning to classify trees with mobile waveform LiDAR data. They succeeded in detecting individual trees, achieving an accuracy of 86,1% with a kappa of 0,8 (Guan *et al*. 2015).

A definite need exists to use the newer generation, higher resolution sensors to achieve sub-compartment or tree level surveillance. Popular sensors such as Landsat 8 (443 – 1390 nm) and Sentinel-2 (443 – 2190 nm) have revisit cycles of 10 – 15 days, with spatial resolution ranging between 10 m – 30 m and are not ideal when regular feedback information is required at high resolution (Maselli 2004; Yu *et al*. 2011; Peerbhay *et al*. 2016). For instance, Hais *et al*. (2016) used Landsat Thematic Mapper 5 (30 m x 30 m pixel resolution) to detect the risk of bark beetle that causes severe damage to commercial and natural forests. They were successful in detecting stress in forests that may be caused by various climate factors such as heat and water stress that promote the presence of bark beetle infestations (Hais *et al*. 2016). Researchers have subsequently utilised high temporal and spatial resolution sensors such as Worldview-2 and GeoEye1. In a study by Dennison *et al*. (2010), GeoEye1 (450 – 920 nm), at a spatial resolution of 0,5 m, was used to measure the occurrence and stages of severe canopy damage caused by an outbreak of the mountain pine beetle

(*Dendroctonus ponderosae*). They proved successful in identifying the stages, although the grey class may have contained trees that died of other causes. They also suggested using a higher spatial resolution to acquire more detailed information on the outbreaks (Dennison *et al*. 2010). In a study by Immitzer *et al*. (2012), 8 band Worldview-2 (400 – 1040 nm) was used to distinguish between 10 different species in Austria, using the Random Forest algorithm, achieving an overall accuracy of 82%. A study by Lottering *et al*. (2018), mapped damage caused by *Gonipterus scutellatus* using various vegetation indices. The pest caused severe damage to *Eucalyptus* stands through defoliation leading to loss of productivity. Through the use of remote sensing, the degrees of damage caused by *G*. *scutellatus* were successfully mapped, allowing management action to be taken (Lottering *et al*. 2018). Oumar and Mutanga (2013) tested the prediction of damage caused by *Thaumastocoris peregrinus* in plantation forestry using WorldView-2, 0.5 m resolution panchromatic imagery and 2 m resolution multispectral imagery. They were successful in the detection, with an R^2 value of 0,65 using a Variable Importance in Projection (VIP) score, selecting the best variables such as red-edge and near-infrared. Although the accuracy results were low, the study's main purpose was to evaluate the potential of WorldView-2, which can be used as a guideline for future studies (Oumar and Mutanga 2013).

The spatial, spectral and temporal resolution of satellite sensors will affect the accuracy and quantification of baboon damage. Studies mentioned previously have relied on monitoring damage at a compartment level giving good results in the detection of damage but may not be able to provide an accurate framework for tree level or sub-compartment levels of baboon damage. This study will look at the use of cost-effective Sentinel-2 imagery (10 m) and higher resolution PlanetScope data (3 m) in an attempt to identify varying levels of tree damage caused by baboons, at a sub-compartment level in commercial forestry, within the Mpumalanga escarpment area of South Africa.

CHAPTER 2

A Spatio-temporal analysis of Baboon Damage using Sentinel-2 imagery and Extreme Gradient Boosting

Abstract

The use of remote sensing for forest health monitoring has increased in popularity over the years, with improved quality in spatial and spectral resolutions. However, satellite revisit times are generally too low to detect real-time changes at a pace fast enough to aid in early management actions. There exists a need to employ higher resolution monitoring to quantify the damage caused by biotic risks that are more difficult to detect, because of the different degrees and types of damage over time. Sentinel-2 MSI (Multispectral Instrument) data have a spatial resolution varying from 10 - 60 m, and a spectral range of 443 - 2190 nm. Using the appropriate bands and derived vegetation indices, this study achieved an overall accuracy of 89,34% with a Kappa of 0,85 using Extreme Gradient Boosting (XGboost). The following results were found: (1) Sentinel-2 was able to successfully identify baboon damage with high accuracy when compared to field measured data and (2) different severities of damage could be distinguished. Of the various indices calculated it was found that the soil adjusted vegetation index (SAVI) and structure insensitive pigment index (SIPI) were the most useful due to good discrimination of structural variations in the canopy. The proposed method provides an accurate and repeatable framework for rapid baboon damage mapping at a sub-compartment scale.

Keywords: baboon damage, Sentinel-2 MSI, XGboost, forest management

2.1 Introduction

Monitoring biotic and abiotic risk factors is an important aspect in forestry to acquire information for management practices that reduce their impact (Franklin 2001; Chornesky *et al*. 2005; Huang and Asner 2009). In recent years, advances in remote sensing have made this technology more accessible and economically viable for forest health monitoring at the landscape scale (Franklin 2001; Joshi *et al*. 2004; Asner and Vitousek 2005; Chornesky *et al*. 2005; Huang and Asner 2009). Accurate identification of the threat is the main challenge in detection and monitoring, which is affected by the resolution used in remote sensing (Chornesky *et al*. 2005, Xulu *et al*. 2018). Vegetation growth and development varies greatly from year to year, which requires constant monitoring to detect changes in stress levels of compartments. However, such datasets are usually only available and acquired by low-to-medium resolution systems (30 m – 250 m), which may not detect real-time changes fast enough to enable management to intervene. Landsat 8 is a new generation cost-effective passive sensor with a cycle time of 15 days. However, this delay may be too great if regular feedback is needed (Maselli 2003; Yu *et al*. 2011; Peerbhay *et al*. 2016). This lack of higher temporal resolution has encouraged methods of advancing spatial imagery and detection by improving the spatial resolution of images.

High temporal resolution imagery is very valuable as it reduces real-time detection delays of changes occurring in a compartment. The inability to acquire data daily prevents immediate action and or quantification of the damage occurrence (Tucker *et al*. 2005). When using passive sensors, the Landsat series is often used as it has a ground resolution of 30 m x 30 m and the largest archive of data (Zhao *et al*. 2018). However, it has a variable cycle time, which together with unpredictable cloud cover that may prevent images being obtained. In a study by Maselli (2004), Landsat (5) TM (Thematic mapper, 30 m x 30 m) acquired information from six spectral bands with a spectral range of 450 - 2350 nm and a revisit cycle of 16 days, was used to monitor the forest health conditions in a protected area in the Mediterranean. This study proved successful in determining the health of vegetation in the forested area that was monitored. Peerbhay *et al*. (2019) also used Landsat (8) at a 30 m x 30 m resolution with a 16-day cycle and they were successful in identifying baboon damage caused at a compartment level. However, it is not certain that damage caused to the compartment was primarily by baboons, which necessitated the need for higher spatial resolution images from cost-effective multispectral remote sensing platforms, such as Sentinel-2, to quantify damages. High spatial resolution images are becoming more readily available, with Sentinel-2 and Landsat 8 being the most popular (Chornesky *et al*. 2005; Huang and Asner 2009; Forkuor *et al*. 2017). There are a few advantages of using Sentinel-2 over other earth observation systems (Hawryło *et al*. 2018). Landsat 8 lacks the red-edge spectral band, which renders Sentinel-2 of increasing importance for vegetation analysis (Forkuor *et al*. 2017, Hawryło *et al*. 2018, Kampouri *et al*. 2018).

A comparative study was done by Labib and Harris (2018) using Sentinel-2 and Landsat 8 to determine Green Infrastructure (GI) in urban areas. This study showed that Sentinel-2 performed better than Landsat 8 for calculating GI in terms of accuracy, regardless of a few errors in classification caused by significant shadows due to the higher resolution of Sentinel-2. Landsat 8 was less susceptible to noise from shadows but yielded results with lower accuracy (Labib and Harris 2018). When taking the cost and availability of Sentinel-2 and other earth observation methods into consideration, Sentinel-2 was suitable for the study and would be more so if improvements were made to image classification methods (Labib and Harris 2018). In another study by Forkuor *et al*. (2017), Sentinel-2 and Landsat 8 were used to map land use and land cover, specifically focusing on Sentinel-2's red-edge bands. The study also compared Random Forest (RF), stochastic gradient boosting (SGB) and support vector machine (SVM) algorithms. It was found that Sentinel-2 performed better with a 4% - 5% increase in accuracy, with red-edge bands proving superior (Forkuor *et al*. 2017). These results suggest that the added value of Sentinel-2's red-edge in comparison to Landsat 8, may give it an advantage in vegetation analysis.

In summary, the lack of spatial resolution and low frequency of return has limited the ability to quantify baboon damage at a compartment level. Moreover, previous studies that have used Landsat for damage detection may be inaccurate because of biotic and abiotic factors other than bark stripping by baboons. There is a need for a more direct approach to mapping baboon damage. The main research questions in the present study were defined as follows (1) To what extent can Sentinel-2 detect baboon damage in commercial forest pine compartments? (2) To what extent can Sentinel-2 technology be used to distinguish between different levels of damage? and (3) How efficient are Sentinel-2 derived indices for modelling baboon damage?

2.2 Material and Methodology

2.2.1 Study area

The study was conducted in commercial pine plantations in the escarpment area of the Mpumalanga Province of South Africa (Figure 1). The compartments mainly consist of 6 – 19-year-old *Pinus elliottii*, *P. elliottii x Pinus caribaea*, *Pinus patula* and *Pinus taeda*. Of the trees planted, *P. patula* and *P. taeda* are more susceptible to bark stripping. Due to their excellent growth patterns in the area, these species have been widely planted for commercial forestry (Germishuizen *et al*. 2017). The plantations are owned by some of the companies that form part of the Baboon Damage Working Group, such as Sappi, SAFCOL, York Timber and a few private growers. The plots used, cover an area with significant ecological variation in terms of precipitation, temperature, altitude and geological and soil substrates (Mean annual precipitation (MAP): 900 – 1000 mm; mean annual temperature (MAT): 13ºC - 21ºC; altitude: 1000 – 1900 m) and are found in often complex landscapes with pronounced topographical features (Peerbhay *et al*. 2019). The area is mostly covered by Mesic Highveld grasslands, with fragments of Northern mist belt forest (Peerbhay *et al*. 2019).

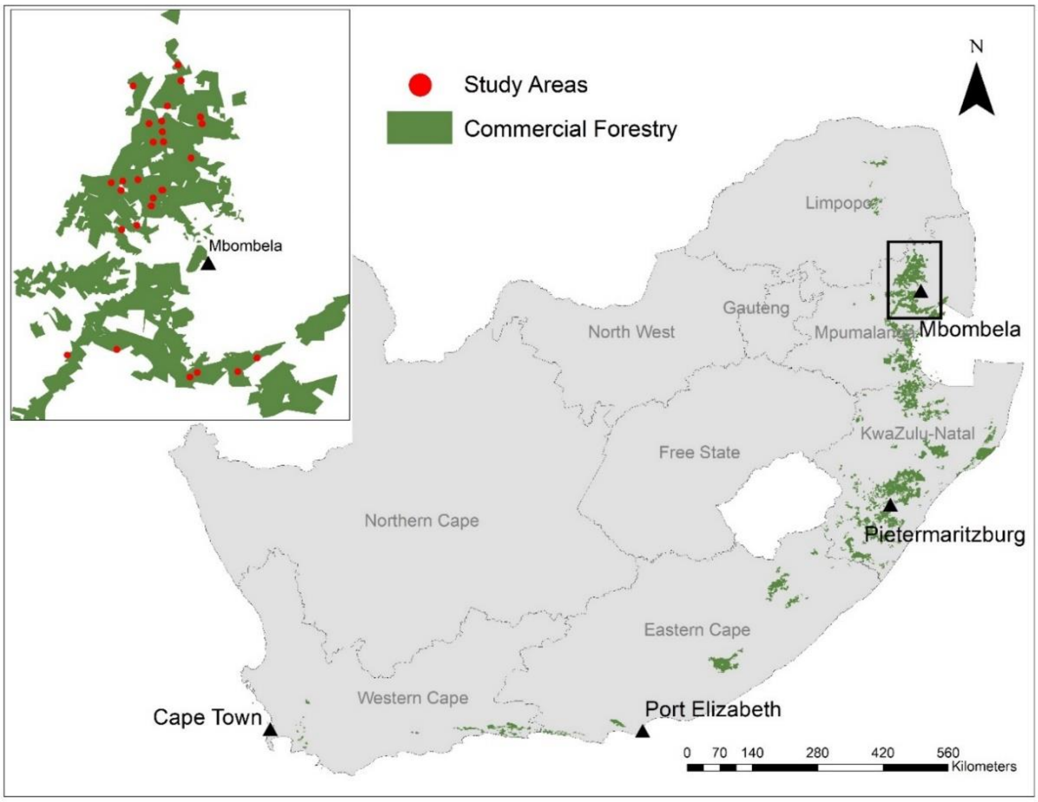

Figure 1: Location of the study area in the Mpumalanga region of South Africa

2.2.2 Field data

Field data on baboon damage and severity were collected in three phases. A total of 27 monitoring areas (approximately one-hectare in size) were set up across the plantations. Each monitoring area comprised of 16, 8 x 8 m plots. Data collected for the year 2016 yielded 144 plots, for 2017, 592 plots and 2018, 472 plots. The reduction in samples during certain years was due to compartments being felled for operational purposes or being burnt. The samples were collected over a period of time to observe how baboon damage evolved. The observations of damage occurrence were captured during scheduled annual field surveys by a team of trained individuals. Apart from data related to damage, additional tree physiological data were collected including diameter at breast height (DBH), measured with an electronic caliper of each tree within the plot and height measurements for a minimum of four trees per plot using a Vertex. A handheld GPS was used to mark the corners of the 16 plots within their respective monitoring area. Each one of the 16 plots were evaluated for damage on a tree basis. Plots were firstly measured for whether damage was present or absent and whether that damage was caused by baboons. If baboon damage was present, the intensity of that damage was scored according to severity in terms of girdling on a scale of 1 – 4 (Table 1), where:

1. A severity of 1 represents a scar affecting up to 25% of the tree's circumference
2. A scar affecting up to 50% of the tree’s circumference
3. A scar affecting up to 75% of the tree’s circumference
4. Complete ringbarking of the tree

The damage was recorded based on the intensity of bark removal, size and number of lesions, and display of a brown canopy. Additional comments regarding damage were also included in the surveys such as the position on the trees i.e. whether the damage was recorded at the base (classified at under the first branch cluster), the middle of the tree or the apex. Each plot was used to develop spectral datasets over the three years and used to create training and test samples for image analysis. For each plot, Sentinel-2’s spectral bands were extracted and used for statistical analysis.

Table 1: Classification of the severity of baboon damage used in this study.

Damage Class		Description
None		Severity score 1: Trees are scarred at the surface (<25%) and do show signs of a healthy recovery.
Low		Severity score 2: Half or more of the tree bark (>50%) has been removed causing severe damage and tree deformity.
Medium		Severity score 3: Trees are badly damaged (>75%) resulting in stunted growth and some mortality.
High		Severity score 4, trees are completely ringbarked (100%) or scarred to such an extent that they don’t recover.

2.2.3 Remote sensing imagery and data pre-processing

In this study, relevant Sentinel-2A MSI imagery that contained less than 10% cloud cover, covering the study region, were downloaded from the United States Geological Survey on 19 February 2019 (USGS, https://earthexplorer.usgs.gov/). Table 2 presents the sensor band characteristics of the images. Three Sentinel-2 image tiles were downloaded to cover the entire study area. Sen2Cor (Sentinel-2 atmospheric-, terrain and cirrus correction) was used to create a surface reflectance image from the raw radiance values, to reduce the impact of the atmosphere on the image reflectance values. Then, using the Sentinel Application Platform (SNAP), a mosaic was created to cover the entire study area so that data analysis of these images could be done as a whole. Each band value for each image year, throughout the study, was collected and used to calculate the various indices. Indices used for the detection of damage are as follows; normalized difference vegetation index (NDVI), enhanced vegetation index (EVI), enhanced vegetation index 2 (EVI2), moisture stress index (MSI), structure insensitive pigment index (SIPI), normalized difference water index (NDWI), modified chlorophyll absorption in reflectance index (MCARI), green normalized difference vegetation index (GNDVI), pigment specific simple ratio (PSSR), soil adjusted vegetation index (SAVI), normalized difference infrared index (NDII) and atmospherically resistant vegetation index (ARVI). The imagery was geo-referenced using Sentinel-2's ground control points.

Table 2: Sentinel-2A Satellite sensor characteristics

Sentinel-2 Bands	Central Wavelength (µm)	Resolution (m)
Band 1 - Coastal aerosol	0,443	60
Band 2 - Blue	0,490	10
Band 3 - Green	0,560	10
Band 4 - Red	0,665	10
Band 5 - Vegetation Red-edge	0,705	20
Band 6 - Vegetation Red-edge	0,740	20
Band 7 - Vegetation Red-edge	0,783	20
Band 8 - NIR	0,842	10
Band 8A - Vegetation Red-edge	0,865	20
Band 9 - Water vapor	0,945	60
Band 10 - SWIR - Cirrus	1,375	60
Band 11 - SWIR	1,610	20
Band 12 - SWIR	2,190	20

2.2.4 Extreme Gradient Boosting (XGboost)

The spectral dataset was processed in R studio (version 1.3) using the XGboost package (Chen and Guestrin, 2016; Rstudio 2020). XGboost is a machine learning method that uses the gradient tree boosting technique, which creates decision trees to gather results on classifications. It is very popular due to its fast processing speed and superb performances rivalling other models such as Random Forests (RF), Support Vector Machines (SVM) and K-nearest Neighbour (KNN) (Sandino *et al*. 2018; Zhang *et al*. 2019). It is especially advantageous when dealing with limited and uneven data and helps prevent overfitting by providing better control (Chen and Guestrin, 2016; Joharestani *et al*. 2019; Zhang *et al*. 2019). Boosting algorithms, like XGboost, uses weak learning, which builds numerous weak trees that are quite inaccurate on their own but are better than random guessing. The weak learners are used to produce strong learners that reduce error, improving accuracy (Freund and Schapire, 1996, Moller *et al*. 2016). XGboost's additive learning is expressed in the formulae below. The final model prediction is obtained from the summary of the predictions of the learners (Chen and Guestrin, 2016). The prediction at step *t* is presented in the following equation:

$$f_i^{(t)} = \sum_{k=1}^{t} f_k\,(x_i) = \ f_i^{(t-1)} + f_t(x_i) \qquad (1)$$

Where:

$f_t(x_i)$ is the learner at step *t*

$f_i^{(t)}$ and $f_i^{(t-1)}$ are predictions at step *t*

t-1 and x_i are the input variables

XGboost evaluates the model without overfitting using the following equation (Chen and Guestrin, 2016):

$$Obj^{(t)} = \sum_{k=1}^{n} l(\bar{y}_i, y_i) + \sum_{k=1}^{t} \Omega(f_i) \qquad (2)$$

Where:

l is the loss function

n is the number of observations

Ω the regulation term

More detailed information on the XGboost algorithm can be found from the author (Chen and Guestrin, 2016). To prevent bias in the estimation of important contributing factors, the study used XGboost's variable importance, which is calculated by dividing one of the input variables at each of the nodes at t, into two subregions (Hastie *et al*. 2008). Within those two subregions, a separate constant is fixed to response values. The specifically chosen variable is one that provides a maximum estimated improvement in squared error risk, over continuous fit of the entire region (Hastie *et al*. 2008).

2.2.5 Accuracy Assessment

The total number of baboon damaged plots for each year was divided into two sets randomly where 70% of the plots were used as training data and 30% as test data. This process was run 100 times to avoid any bias when splitting the dataset. The number of K-fold cross-validation was set at default (i.e. 10) and the number of decision trees was set to default (i.e. 500). Kappa analysis (KHAT statistics) was used for the performance evaluation of the model. Within the error matrix, it describes the agreement of the remote sensing data and the reference data. A perfect agreement is assumed when the KHAT value is equal to 1. KHAT is calculated with the following equation (Congalton and Green, 2008):

$$\widehat{K} = \frac{P_O - P_C}{1 - P_C} \qquad (3)$$

Where:

P_o is the actual agreement

P_c is the expected agreement

P_c also includes a degree of the actual agreement (Congalton and Green, 2008). The thematic accuracy of the remote sensing data was assessed using an error matrix, where the columns refer to the reference data and the rows refer to the remote sensing classification data (Congalton and Green, 2008; García-Balboa *et al*. 2018). The map accuracy was assessed through the producer's and user's accuracy. Producer accuracy ensures the correct classification of pixels where user accuracy ensures that pixels on the map correctly express to what they represent on the ground surface (Liu *et al*. 2006).

2.3 Results

2.3.1 Error Matrix analysis of baboon damage (2016-2018)

The error matrices for the years 2016 - 2018 are presented by Tables 3, Table 4 and Table 5, respectively. The classification of most of the featured samples by 2017, was successful with fewer misclassifications among high, medium, low and no damage classes respectively.

Table 3: Error Matrix displaying levels of baboon damage for the year 2016

2016	**High**	**Medium**	**Low**	**None**	**Row total**	**User's accuracy (%)**
High	**400**	0	100	0	500	80
Medium	60	**350**	200	100	710	49
Low	50	50	**1500**	100	1700	88
None	0	50	200	**1100**	1350	81
Column total	510	450	2000	1300	4260	
Producer's accuracy (%)	78	78	75	85		

The results for 2016 presented in Table 3, show a good classification of high damage with few misclassifications, with a producer's accuracy of 78% and a user's accuracy of 80%. Medium damage had the highest misclassifications, with a producer's accuracy of 78% and a poor user's accuracy of 49%, while Low damage had the lowest misclassifications with a producer's accuracy of 75% and a user's accuracy of 88%. No damage also showed satisfactory misclassifications in comparison to High damage and Medium damage, with a producer's accuracy of 85% and a user's accuracy of 81%.

Table 4: Error Matrix displaying levels of baboon damage for the year 2017

2017	**High**	**Medium**	**Low**	**None**	**Row total**	**User's accuracy (%)**
High	**1200**	0	300	80	1580	76
Medium	150	**1800**	340	200	2490	72
Low	50	200	**5500**	200	5950	92
None	40	400	100	**3600**	4140	87
Column total	1440	2400	6240	4080	14160	
Producer's accuracy (%)	83	75	88	88		

Table 4 illustrates a reasonable misclassification for High damage, with a producer's accuracy of 83% and a user's accuracy of 76%. Medium damage had the most but still reasonable misclassifications with a producer's accuracy of 75% and a user's accuracy of 72%. Low damage had few misclassifications, with a producer's accuracy of 88% and user's accuracy of 92%. No damage also had a few misclassifications with a producer's accuracy of 88% and a user's accuracy of 87%.

Table 5: Error matrix displaying levels of baboon damage for the year 2018

2018	**High**	**Medium**	**Low**	**None**	**Row total**	**User's accuracy (%)**
High	**1250**	0	200	0	1450	86
Medium	190	**1950**	290	200	2630	74
Low	0	150	**5650**	80	5880	96
None	0	300	100	**3800**	4200	90
Column total	1440	2400	6240	4080	14160	
Producer's accuracy (%)	87	81	91	93		

Table 5 shows a reasonable number of misclassifications for High damage, with a producer's accuracy of 87% and a user's accuracy of 86%. Medium damage had the most misclassifications with a producer's accuracy of 81% and a user's accuracy of 74%. Low damage had the least number of misclassifications with a satisfactory producer's accuracy of 91% and a user's accuracy of 90%. No damage also had a few misclassifications with a producer's accuracy of 93% and a user's accuracy of 90%.

The mapping accuracies are compared between the three years (2016, 2017,2018) of this study and is presented in Table 6. Noticeable is the improvement in the accuracy of the map produced and the user accuracy, due to an increase in the sample size in subsequent years of this research (i.e. 2017 and 2018). The produced map accuracies related to ground features for 2016 were between 75% and 85%, for 2017 between 75% and 88% and 2018 between 81% and 93%. User accuracy of those ground features for 2016 was between 49% and 88%, for 2017 between 72% and 92% and 2018 between 74% and 96%. Overall, the classification accuracy for 2016 was 78,64%, with a kappa value of 0,69 and an error rate of 21,36%. The year 2017 had a classification accuracy of 85,45%%, a kappa value of 0,79 and error rate of 14,55%. Finally, the year 2018 had an overall accuracy of 89,34%, a kappa value of 0,85 and an error rate of 10,66%.

Table 6: Overall accuracy for mapping baboon damage plots over three years

Year	**2016**	**2017**	**2018**
Overall Accuracy (%)	78,64	85,45	89,34

2.3.2 Variable importance

The variables that displayed the most importance in the best baboon damage model are presented in Figure 2. The variables are presented in descending order of importance. The most important variables in the modelling were found to be DBH and tree height, which had a ranking importance value of 1,000 and 0,905 respectively. It was found that Sentinal-2’s Band 5, Vegetation Red-edge was the highest ranked band variable with 0,469, followed by Band 11, SWIR (0,434) and Band 12, SWIR (0,398). Band 4 Red (0,287) and Band 3 Green (0,285) ranked the lowest. Of the indices, SAVI ranked highest with 0,492 followed by SIPI (0,452) and EVI (0,389), these indices were found to be most important. The lowest ranking indices were NDVI (0,293) and PSSR (0,279). Overall, the indices performed better than the individual bands except for Sentinal-2's Band 5 which contributed the most. Figure 2 shows that tree DBH and height, indicate that larger, more mature trees are favoured by baboons and are damaged to a greater extent. *P. patula* and *P. taeda* were damaged more by baboons than other pine species (Germishuizen *et al*. 2017).

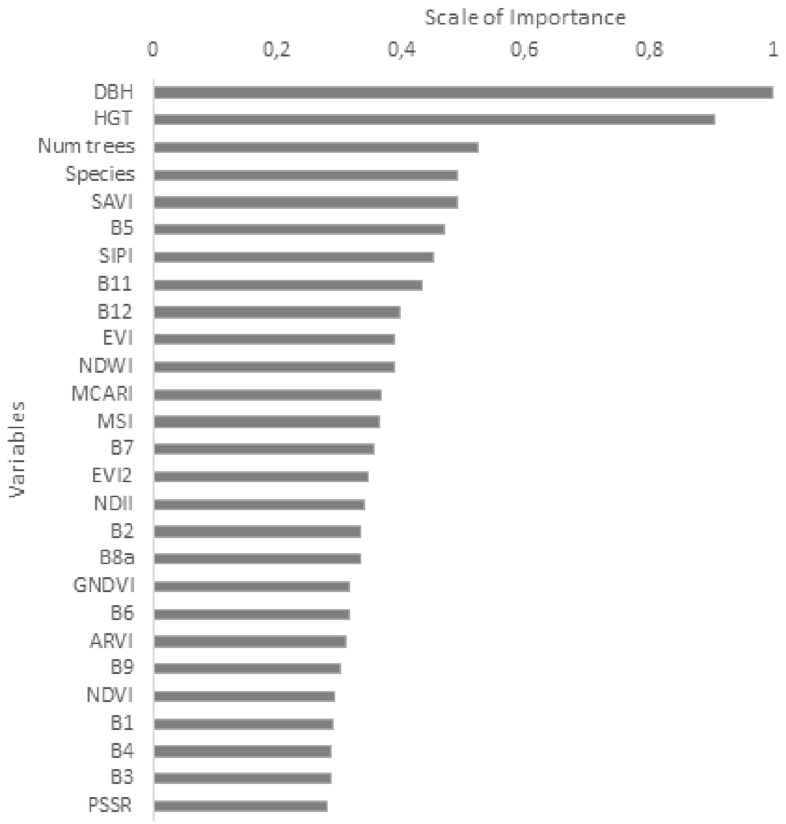

Figure 2: Variables that contributed to the detection of baboon damage and their importance scale, ranked from most to least important

The progression of baboon damage detected for the years 2016 – 2018 is illustrated in figure 3 using selected field sample plots. The advancement of damage is shown for the same plot as it progressively worsened through time. Certain plots displaying medium damage in 2016, showed a portion of the plot with high damage in 2017 and then, in 2018 severe damage across most sections of the plot. Other plots displayed no damage in 2016, low to medium damage in 2017 and then high damage in 2018.

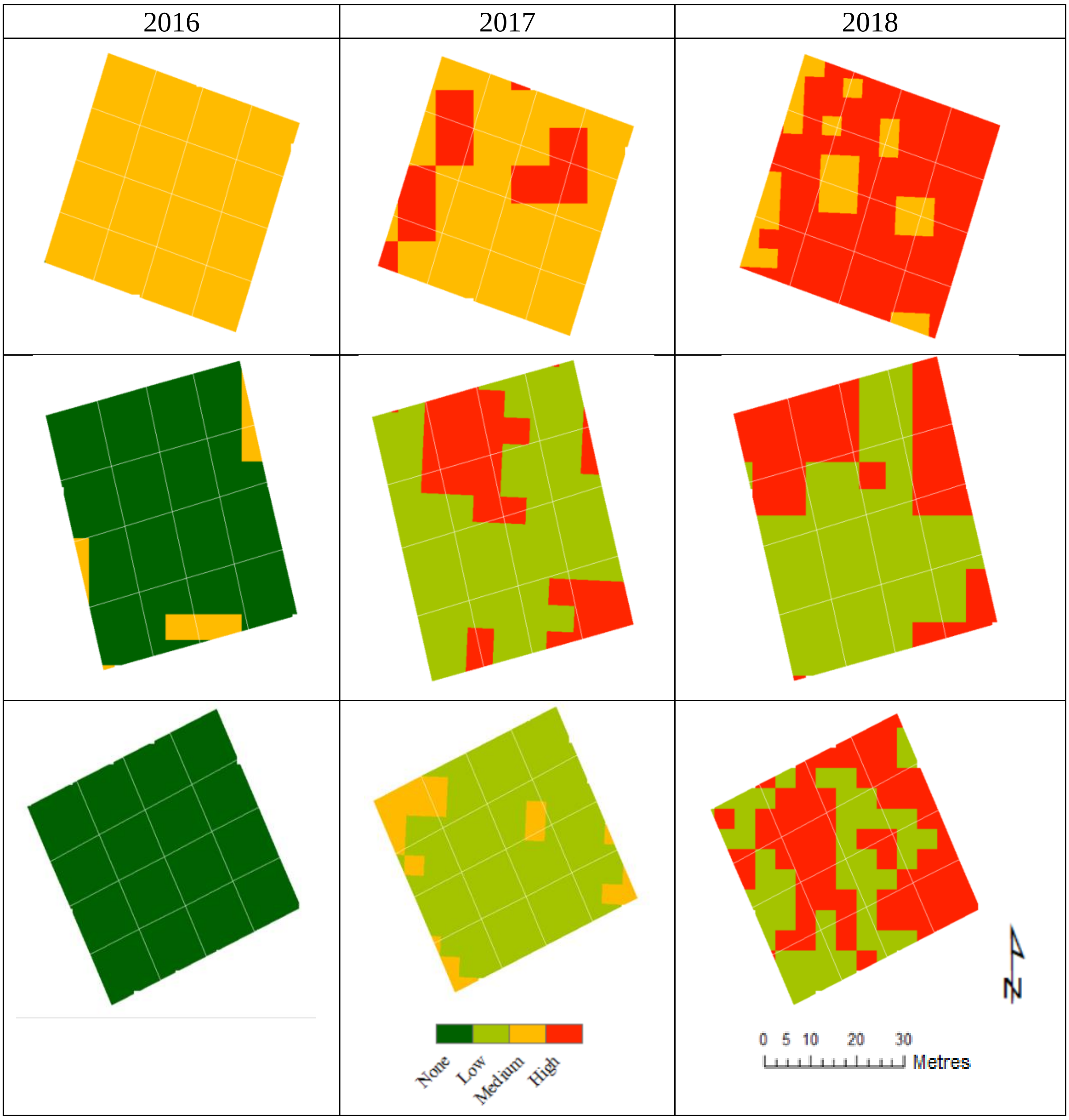

Figure 3: Progression of baboon damage from 2016 to 2018 showing an increase of damage severity

2.4 Discussion

The monitoring of baboon damage using remote sensing is an accurate technique for detecting variations in tree reflectance at the plot level, to the extent where different degrees of damage can be identified. This study has demonstrated the importance of cost-effective multispectral remote sensing imagery to quantify the extent of baboon damage. This allows frequent monitoring and provides the necessary information to enable informed management of the plantations. Early detection of damage in compartments offers the advantage of reducing the cost of preventative measures, by reducing the total impact and thereby ensuring that the maximum obtainable yield of the compartment is achieved when harvested.

2.4.1 Temporal mapping of baboon damage using Sentinel-2

Using the 2016 Sentinel-2 dataset with derived indices, an overall accuracy of 89,34%, kappa value of 0,85 and user's (74% - 90%) and producer's accuracies (81% - 93%) show that this technique can be used to successfully map baboon damage. Using the 2017 dataset the overall accuracy was 85,45% % with a kappa of 0,79 and reasonable user's (72% - 92%%) and producer's accuracies (75% - 88%). In this dataset, the total number of sample plots was greater due to more sites being made available through collaboration with other companies, hence the algorithm may have provided better accuracies with more samples of each representative class for classification. The 2018 dataset produced the best accuracy (89,34%), user's (74% - 96%) and producer's (81% - 93%) accuracies and a kappa value of 0,85. These results are directly comparable to Peerbhay *et al*. (2019), who also monitored baboon damage, and offer improved overall accuracy for mapping baboon damage using remote sensing imagery. XGboost proved capable of separating the different damage classes, achieving higher accuracy compared to that obtained by Peerbhay *et al*. (2019).

2.4.2 Variables of importance for assessing damaged trees

The results show that the red-edge (band 5) was the most important in the damage classification and confirms its advantage in detecting variations in leaf area (Ramoelo *et al*. 2015). A study by Kumbula *et al*. (2019) used Sentinel-2 with the Maxent algorithm to detect the occurrence of *Coryphodema tristis* (Cossid moth) in *Eucalyptus* in Mpumalanga, South-Africa. They found that the Sentinel-2 red-edge played a very important role in detecting insect damage. Of the vegetation indices used in the present study, SAVI, SIPI and EVI performed slightly better than the rest. Enhanced vegetation index (EVI), surprisingly outperformed the popular normalised difference vegetation index (NDVI). This was due to the improved sensitivity of the index in areas with dense leaf mass and because of the algorithm, it reduced the atmospheric influence. Both SAVI and EVI have a better response to structural variations in the canopy, such as leaf area index (LAI) and canopy types and thus were more beneficial to detect damage (Matsushita *et al*. 2007).

Overall, the XGboost algorithm performed well, with the majority of the classes successfully classified with high accuracy. The pixel size and placement within the boundaries of the research plots, due to resolution restrictions, may also play a role in some of the misclassifications. This error can be reduced by using higher resolution (< 10 m) remote sensing and by processing the data at a tree level using high resolution digital imagery acquired using unmanned aerial vehicles (UAV's) or light detection and ranging (LiDAR). These closer approach sensors may be of value when detecting damage caused by baboons, which have similarities to other pests and disease. A disadvantage to the Sentinel-2's imagery is that it has a variable cycle time of 10-15 days. Forest compartments exhibit variability annually and seasonally, when there are possibilities of heavy insect infestations or damage. Any delay in monitoring may compromise early detection efforts and long-term forest protection strategies. With the advent of commercially available higher resolution satellites such as PlanetScope (3 m) or SkySat (< 1 m) constellations that image the earth daily at sub-metre pixel resolution, may overcome the challenge of obtaining high spatial and temporal resolution, cloud free imagery to enable rapid response to changes in plantation forest health, such as damage caused by bark stripping baboons.

2.5 Conclusion

This study has demonstrated the effective use of Sentinel-2 imagery for the detection of baboon damage at sub-compartment scale to contribute towards forest health monitoring and protection. The damage was measured over the course of three years (2016, 2017, 2018) in an attempt to track the changes in forest health over time. It was found that the damage severity in compartments had increased over time and that some compartments were damaged to the point of having to be cut down before rotation end to mitigate losses. Sentinal-2 imagery coupled with the XGboost algorithm was also able to map the different degrees of damage caused by baboons. Of the indices tested, SAVI and SIPI were most useful due to their sensitivity in detecting tree canopy variations, with the red-edge band having the advantage to detect variations in the leaf area. The future of remote sensing for forest health monitoring lies in higher temporal and spatial resolution imagery being able to monitor individual trees. Although passive sensors may be outdone in this regard by high resolution cameras on a UAV platform.

CHAPTER 3

A Tree Level Analysis of Baboon Damage in Commercial Forests Stands Using Deep Learning Techniques

Abstract

Commercial forest plantations in South Africa are homogeneous monoculture stands grown to deliver timber products of the best possible quality. However, due to their spatial distribution, breeding and similar genetics, these stands are susceptible to adverse effects with regards to pest and disease. Therefore, intense management is required to mitigate these risks. There is a need to implement a sustainable forest monitoring system, that can detect real-time change in the physical state of commercial forestry plantations, allowing management to act timeously to prevent loss. The use of Machine Learning algorithms is popular with remote sensing with acceptable levels of success. However, deep learning Neural Networks should also be explored to determine if they can produce comparable or even better results. Using PlanetScope (590 – 860 nm) imagery, which is a constellation of small Dove satellites, with a high temporal resolution (daily) and at 3 m spatial resolution, the study achieved an overall accuracy of 81,54%, with a Kappa of 0,69, using an Artificial Neural Network (ANN). The study successfully mapped different levels of baboon damage, within commercial forests. The results from this study aims to promote the use of higher resolution imagery, such as PlanetScope, to map damage severity from baboon influence and to provide a repeatable methodology for daily monitoring initiatives.

Keywords: PlanetScope, Deep Learning, Baboon damage, Forest monitoring system

3.1 Introduction

Commercial forestry stands contain monocultures of trees that have been bred to provide a product of optimal growth and quality. However, their small range of genetic variability may subject these compartments to a greater risk of damage by biotic and abiotic factors such as insects, mammals, fire, and drought requiring careful management to prevent the failure of the plantation. Mitigation measures must be taken to ensure sustainable forestry while guaranteeing profitability (Gardiner and Quine 2000; Huang and Asner 2009; Wu 2018). However, the information required to make informed management decisions to deal with a particular risk is not always readily available and requires constant monitoring of plantations to make management aware of the possible risk (Franklin 2001; Jactel *et al*. 2009; Yang *et al*. 2019). Of the instances of risk in the forestry sector in South Africa, baboon damage caused by bark stripping has escalated significantly in recent times in certain areas, to a point where as much as 28% of forest compartments show some form of damage (Germishuizen *et al*. 2017).

Baboons cause stress in the physical condition of plantation trees resulting in poor re-establishment of stands, high stand variability, low stocking and as a result lower timber yields (Gardiner and Quine 2000; Louw 2012). Some of the damage involves complete removal of the tree bark near the base of the tree, in a ring-like pattern causing the tree's imminent death. The bark at the apex of the tree is also removed causing a loss of apical dominance (Germishuizen *et al*. 2017). Few studies have succeeded in detecting the damage caused by baboons using spatial mapping techniques. For example, Peerbhay *et al*. (2019) used Landsat 8 (30 m), imagery to map baboon damage that was caused at a compartment level. Although the study was successful in identifying damage, it is uncertain whether the damage was caused by baboons alone (Peerbhay *et al*. 2019). A study by Germishuizen *et al*. (2017) evaluated the risk of baboon damage in South Africa using environmental variables such as climate, topography, and compartment factors. They found that the most important influences on excessive tree damage were tree age, species, site index and altitude of a given compartment (Germishuizen *et al*. 2017). In a similar application in Europe relating to mammalian damage to trees, Ruba and Miezite (2014) used geographic information systems (GIS), to assess damage in mixed stands of Norway spruce caused by local animals (moose and red deer), which reduced tree growth and recovery. These stands were subsequently affected by the Snow Blight Fungus and the Eastern Spruce Gall. This damage resulted in some economic losses due to a lack of timely intervention.

Near real-time detection is, therefore, an important consideration with regards to forest health monitoring to assist management to implement protection strategies early to mitigate the risk effectively. With the continuous development of remote sensing technologies, these methods of surveillance are becoming more proactive and reliable. Landsat 8 (30 m) and Sentinel-2 (10 m) are continuously being improved in terms of resolution and cycle times, thus their contribution to future management planning to aid in managing damage better will increase. However, the information acquired is only suitable for compartment level analysis. To better understand the condition and severity of damage by specific agents such as baboons, higher resolution sensors must be used to develop a spectral based framework that can be used for efficient monitoring at a tree level. The objectives of this study are, therefore: (1) To investigate the use of high temporal resolution (available daily) daily for near real-time detection of baboon damaged trees and (2) To assess the robustness of a deep learning approach for dealing with high resolution datasets and accurately mapping tree damage in complex commercial forestry environments.

3.2 Material and methodology

3.2.1 Study area

The area used for spatial analysis is in the commercial forestry plantations within the Mpumalanga escarpment area of South-Africa (Figure 4). The compartments mainly consisted of 7-20-year-old *Pinus elliottii*, *P. elliottii x Pinus caribaea*, *Pinus patula* and *Pinus taeda*. A study by Germishuizen *et al*. (2017) found that of the planted trees *P. patula* and *P. taeda* were more susceptible to bark stripping. Trees of these species are also more widely planted for commercial forestry in the area due to their excellent growth rates (Germishuizen *et al*. 2017). The area has a climate that ranges from cooler-temperate to sub-tropical, with a mean annual temperature range of 13 to 21°C. For the areas sampled in this study, the mean annual precipitation (MAP) varies from 900 to 1000 mm per year. The dominant vegetation covering the area is mesic grasslands, with an elevation range of 1000 to 1900 m above sea level (Peerbhay *et al.* 2019).

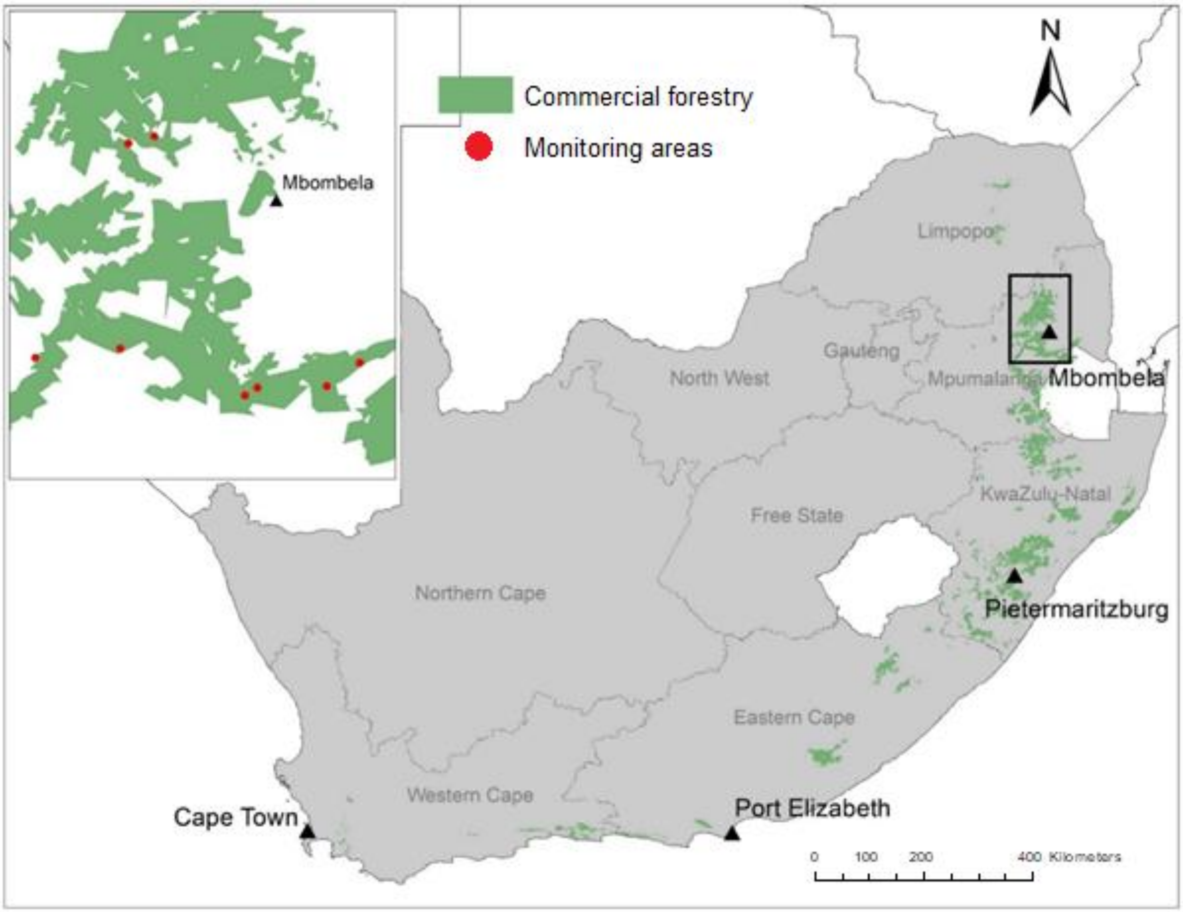

Figure 4: Study area of Mbombela located within Mpumalanga, South Africa

3.2.2 Field data acquisition

Eight field damage assessment areas, consisting of 128 plots, for monitoring baboon damage, were set up during 2019 in the study area and across plantations with high baboon activity zones. The plots were approximately 1 hectare in size and were further divided into 16 equal sub plots each consisting of 8 x 8 trees with a spacing of 2 x 3 m. During the field surveys, a handheld GPS was used to mark the corners of the 16 sub plots. Trees were measured individually for DBH (in centimetres), while height was measured (in meters) for a minimum of four trees per plot. Growth measurements were taken using a calliper and vertex (accurate to mm) respectively and recorded on a sheet containing the information for each tree. Damage was recorded for each tree and indicated as baboon or other. Damage involved extensive removal of the tree bark. Damage assessment was then allocated to a position on the tree either the apex, middle or base. A severity score based on percentage girdling was assigned on a scale of 1 – 4, where 1 represented a severity of 25% in area of the scar damage, 2 represented a severity of 50%, 3 represented a severity of 75% and 4 is the result of a tree being completely ring-barked, or severe damage to the apex that would not allow recovery. Additional comments were also given to each tree as necessary, such as whether it had a green crown or dead.

3.2.3 PlanetScope imagery and pre-processing

The PlanetScope dataset was acquired through a vendor called Geoswift in August 2019. PlanetScope data has a variable revisit time of 1 day and a swath width of 24.6 km x 16.4 km at a reference altitude of 475 km. Table 7 illustrates the spectral ranges of the data bands. This image data was subsequently clipped in ArcGis (version 10.4), where pixel values for each band was extracted and used to calculate the derived possible indices. Each pixel was then used to extract spectra to create datasets for training and test samples for statistical analysis. Of the indices available, the normalized difference vegetation index (NDVI) was calculated using the appropriate bands and analysed for its ability to distinguish of damage caused by baboons (Planet 2016).

Table 7: PlanetScope sensor band characteristics, spectral range and resolution

PlanetScope Bands	Wavelength range (nm)	Resolution (m)
Blue	455 – 515	3.0
Green	500 – 590	3.0
Red	590 – 670	3.0
NIR	780 – 860	3.0

3.2.4 Deep Learning Artificial Neural Networks

Generally, Artificial Neural Networks (ANN) have nodes that are interconnected with one another containing mathematical functions, known as neurons. These neurons are processing elements that react to the input weight form the node before it (Atkinson and Tatnall, 1997; Ingram *et al*. 2005). A network can have several node layers, the first layer type is for input features such as bands or indices, where the nodes represent the various bands or indices of the layer. The second layer type is known as the “hidden” layer, it does not contain output units. Increasing the number of hidden layers allows more complex problems to be learned by the network at the cost of generalization and increase training time (Atkinson and Tatnall, 1997). Any activation function can be used for the hidden layer such as sigmoids, rectified linear units, or hyperbolic tangents (Berg and Nystrom, 2018). The third layer type is the output layer that provides the output data (Atkinson and Tatnall, 1997; Mutanga and Skidmore, 2004; Ingram *et al*. 2005). For this study, to increase the depth of the ANN for a deep learning approach, the parameters were set to a greater number with many neurons and hidden layers. The number of neurons was set to 200, with 4 hidden layers.

Figure 5 represents the structure of a Deep ANN, where Layer 0 represents the input layer which is made up of vegetation indices and Layer L represents the Output layer. The layers $0 < l < L$ represent the hidden layers, there are 2 hidden layers represented as per the figure, where this study used 4 (Berg and Nystrom, 2018).

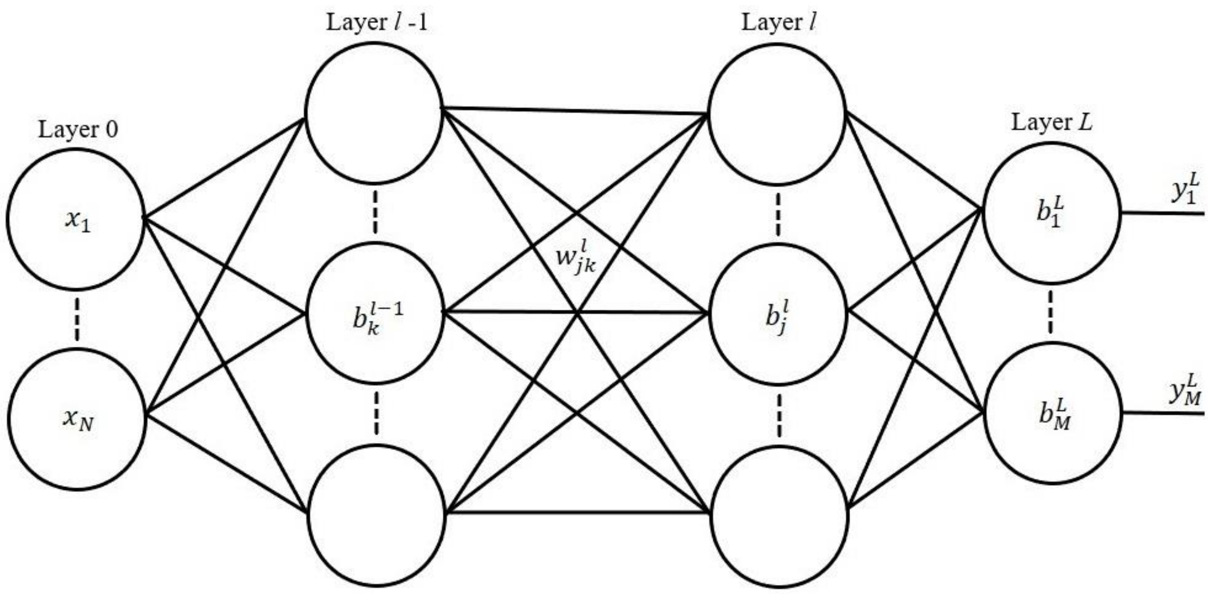

Figure 5: A Feedforward Artificial Neural Network, which is fully connected, taken from (Berg and Nystrom, 2018)

According to Mutanga and Skidmore, 2004, the algorithm of an ANN can be split into two phases namely the feedforward phase and the back-propagation phase. In the feed-forward phase, the input values are presented to an input node of the neural network where it is multiplied with a weighted factor (Mutanga and Skidmore, 2004). The weighted input is defined as follows (Berg and Nystrom, 2018):

$$z_j^l = \sum_k w_{jk}^l \sigma_{l-1}(z_k^{l-1}) + b_j^l \tag{4}$$

Where the sum of all inputs is taken to the neuron *j* in Layer l, which is the number of neurons. The vectorial form of this equation is as follows (Berg and Nystrom, 2018):

$$z^l = w^{l^{\sigma_{l-1}}}(z^{l-1}) + b^l = w^l y^l + b^l \tag{5}$$

Where the elements in the z^l and y^l vectors are provided by z_j^l and y_j^l and the activation function is then applied elementwise (Berg and Nystrom, 2018). The elements of the matrix w^l are provided by $w_{jk}^l = w_{jk}^l$. With these provided definitions, the output y^l given input x is calculated as follows (Berg and Nystrom, 2018):

$$\begin{aligned}
y^L &= \sigma_L(z^L) \\
Z^L &= w^L \sigma_L(z^{L-1}) + b^L \\
z^{L-1} &= w^{L-1}\sigma_{L-2}(z^{L-2}) + b^{L-1} \\
&\vdots \\
z^2 &= w^2\sigma_1(z^1) + b^2 \\
z^1 &= w^1 x + b^1.
\end{aligned} \tag{6}$$

The back-propagation phase occurs when the predicted and measured root mean square error variation, is sent back into the network to minimize the error. This step is repeated multiple times until this error is minimal (Mutanga and Skidmore, 2004; Lottering and Mutanga 2012). The algorithm works through the entire training data set 30 times, which is the number of epochs required for a deep learning approach.

3.2.5 Accuracy assessment

The pixels extracted from the baboon damage monitoring plots were randomly split into two sets of datasets: 60% training data (*n* = 5850) and 40% testing data (*n* = 3900). An error matrix was used to evaluate the thematic accuracy of the remote sensing data, where the reference data is represented by columns and the image data by rows (Congalton and Green, 2008; García-Balboa *et al*. 2018). To evaluate the model's performance, the kappa analysis (KHAT) was used. When the KHAT value is equal to 1, it is assumed that there is a perfect agreement between the remote sensing data and the sample data. To calculate KHAT the following formula used: (Congalton and Green, 2008)

$$\widehat{K} = \frac{P_o - P_c}{1 - P_c} \quad (7)$$

Where:

the actual agreement is represented by P_o

the expected agreement is represented by P_c.

A degree of the actual agreement is also included in P_c (Congalton and Green, 2008). The agreement between the remote sensing data and the reference data was also expressed by the error matrix as the overall accuracy. Producer and user accuracy were used to evaluate the accuracy of the maps produced. The correct classification of pixels on the map is represented by producer accuracy. The correct classification of pixels on the map concerning the geographic location they represent on the ground is expressed by the user accuracy (Liu *et al*. 2006).

3.3 Results

3.3.1 Deep learning model scoring history

The deep ANN model's scoring history is illustrated in Figure 6, which shows the comparison between the progression of the training and validation of 30 epochs using 4 hidden layers and 200 neurons. The classification error is presented on the y-axis. The number of epochs on the x-axis represents one cycle of the feed-forward phase and backward propagation phase to the network completed. The most "learning" occurred during the first ten epochs, thereafter the model moved in conjunction with the rest of the training sample reducing the error rate to around 0.12 by the 26th epoch. The error rate thereafter remained consistent.

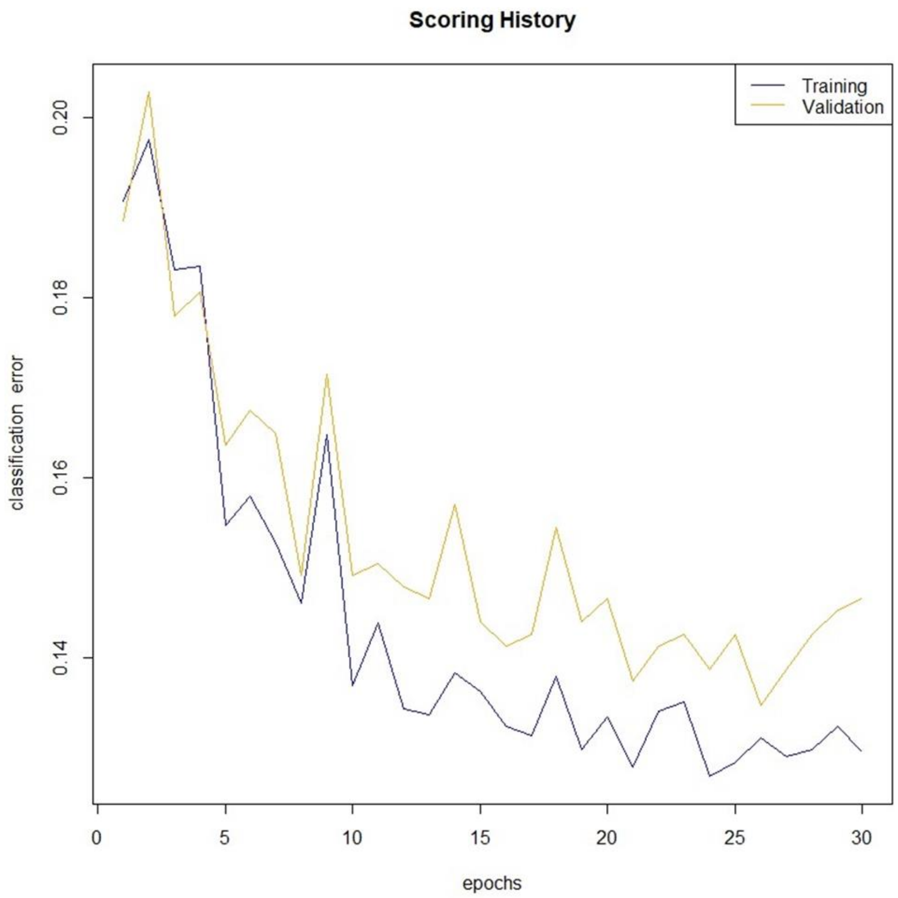

Figure 6: The scoring history of Deep Learning Artificial Neural Network, showing classification error at each epoch interval

3.3.2 Error matrix

The error matrix and accuracy assessment for the year 2019 is presented in Table 8 (*n* = 3900). The test results indicate that the high resolution PlanetScope pixels produced an overall accuracy of 81,54%, a Kappa value of 0,69 and an error rate of 18,46%. The producer's map accuracies ranged between 70% and 85% and the user's map accuracies between 56% and 90%. The classification procedure for trees with no damage and low damage worked well with few misclassifications, with a producer's and user’s accuracy of 80%. A producer's accuracy of 85% and user's accuracy of 90% were shown for trees with low damage with very few misclassifications. Medium damage trees revealed a reasonable producer's accuracy of 70% and a good user's accuracy of 80%. Pixels displaying high damage, on the other hand, had an acceptable producer's accuracy of 76%, but a low user's accuracy of 56% and had the greatest number of misclassified pixels.

Table 8: Error Matrix for the year 2019. The values in bold indicate the correctly classified pixels

2019	None	Low	Medium	High	Row total	User's Accuracy (%)
None	**400**	100	0	0	500	80
Low	100	**2050**	50	80	2280	90
Medium	0	50	**350**	40	440	80
High	0	200	100	**380**	680	56
Column total	500	2400	500	500	3900	
Producer's Accuracy (%)	80	85	70	76		

Figure 7 shows a visual representation of damage results of several one-hectare plots, taken from the sample plots of 2019. It is noted that there is a clear distinction between the high baboon damaged plots and low damage plots as illustrated, where some compartments were damaged so severely that the best option was to clear fell or salvage the timber and replant.

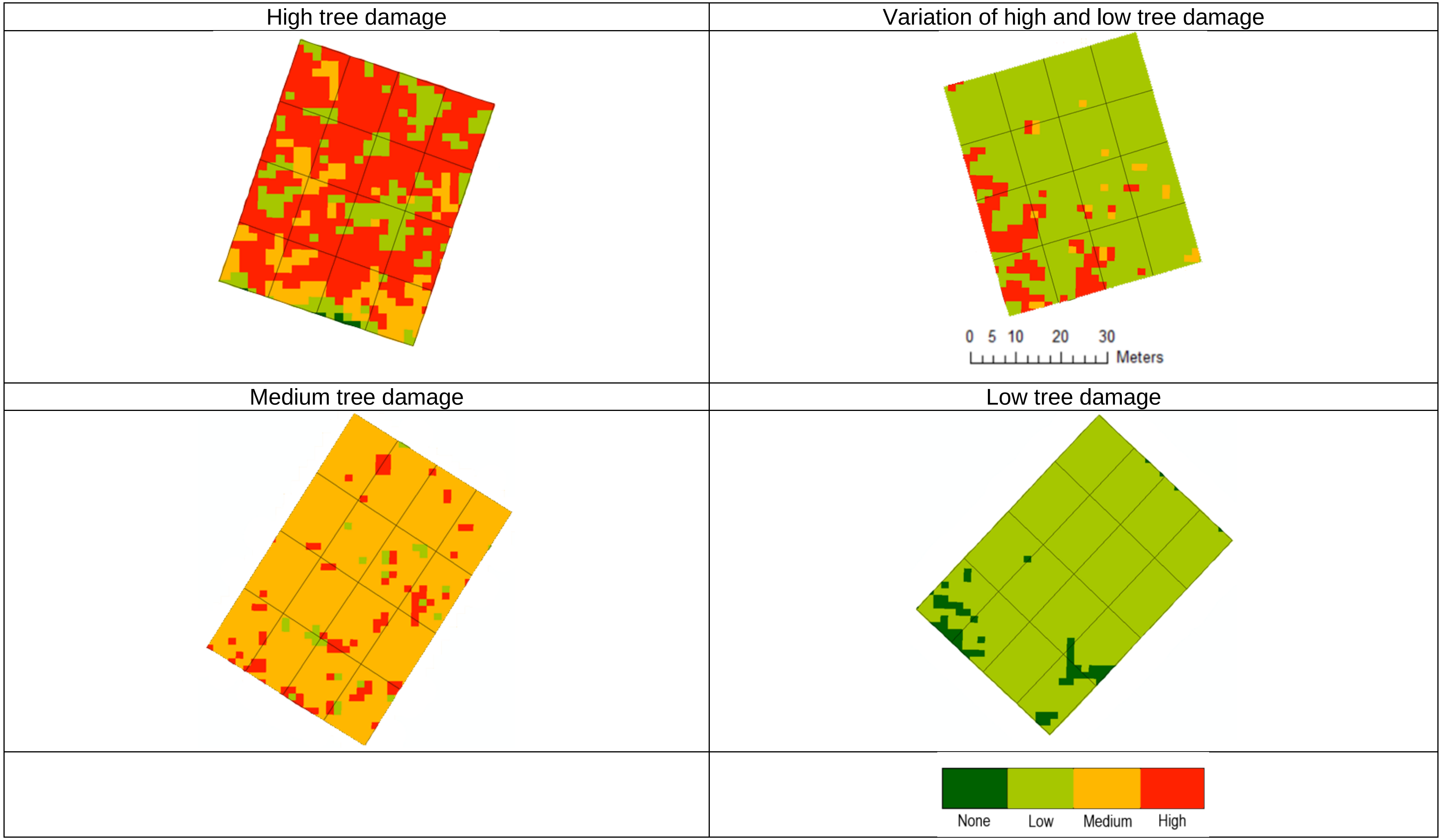

Figure 7: A representation of mapped baboon damage tree pixels using high resolution PlanetScope imagery for 2019.

3.4 Discussion

This study aimed at mapping various levels of tree damage caused by baboons, to better quantify plantation damage as a whole. Damaged compartments are often cut down before rotation end as the losses are too severe to retain profitability at full rotation age. The use of remote sensing has become widely popular as a tool for monitoring damage, due to its ability to cover large areas and provide reliable results in comparison to field-collected data. The results of this study demonstrate the ability of high spatial and temporal resolution satellite imagery, combined with a deep learning ANN to detect and map the degree of baboon damaged trees in commercial forestry plantations of the Mpumalanga escarpment area. The framework performed well in achieving an accuracy of 81,54% in an attempt to distinguish between different degrees of baboon damage caused to individual trees. The PlanetScope data performed well in comparison with other studies using high resolution images to detect and monitor biotic pests. For instance, Oumar and Mutanga (2013) achieved an accuracy result of 65% in detecting damage caused by *Thaumastocoris peregrinus* using WorldView-2 (400 – 1040 nm at 2 m) data and Lottering *et al*. (2018) also succeeded in detecting damage caused by *Gonipterus scutellatus* using the same remote sensing sensor. Kumbula *et al*. 2019, succeeded in the detection of *Coryphodema tristis* in Eucalyptus plantations with a spectral band accuracy of 0,898 for test and 0,891 for training data using Sentinel-2 MSI. Abdel-Rahman *et al*. 2014 used ASIA Eagle (393,23 - 994,09 nm), hyperspectral imagery (2,4 m) to detect the final stages of *Sirex noctilio* and dead standing lightning struck trees and to distinguish between them. They achieved an accuracy of 74,5% for the Random Forest and 73,5% for Support Vector Machine algorithms (Abdel-Rahman *et al*. 2014). In comparison to these studies, the results of the present study are shown to be satisfactory.

This study improved on the results found by Peerbhay *et al*. (2019) by providing higher resolution information at a tree level, in comparison to their results provided at a compartment level. Their study was limited to six image tiles as the cloud cover was excessive on some images at the time of data acquisition. Shadows produced by cloud cover and background noise also affected some of the change detection in those images. By using PlanetScope with a daily revisit cycle, this issue could be resolved to allow a better seasonal analysis of baboon damage. The accuracy in this study is relatively good compared to the studies mentioned given the sample size of eight monitoring areas, each consisting of one-hectare blocks that were divided into 16 plots to manage individual tree measurements and assessments. The use of the deep learning ANN generally provided good results when classifying damage caused to individual trees, and effectively deals with a large number of pixels for each damage severity class. The short revisit time of one day by PlanetScope makes it a very attractive platform to use for future forest monitoring events. Although it could be confirmed that the damage detected in the intensively managed monitoring plots was caused by bark stripping by baboons, it is possible that damage caused may have been done by other stressors such as *Sirex noctilio* or *Fusarium circinatum*. Future mapping of damage caused by baboons will improve the detection rate, paired with more frequent monitoring provided by a high temporal resolution platform such as PlanetScope. As far as the use of deep learning algorithms such as ANN is concerned, a large sample size should be included to enable adequate training when building the model. The use of a high spatial resolution sensor had a great impact on the detection of damage severity and is possibly the reason for the success of using deep learning with a reasonable sample size.

3.5 Conclusion

The results of this study illustrate the ability to detect baboon damage in forestry compartments using PlanetScope imagery (3 m), NDVI and a deep learning Artificial Neural Network. Using NDVI determined from PlanetScope data at 3m x 3m resolution, it was possible to detect the presence and severity of baboon damage at an accuracy of 81,54% and an error rate of 18,46%. The study achieved improved results when compared to a previous study using Landsat 8 (30 m) for mapping damage at compartment scale (Peerbhay *et al*. 2019). The ability to detect damage at tree level using a deep learning approach advocates for high resolution monitoring of forests with high temporal image capability. This study was the first attempt to detect baboon damage in pine forest trees using PlanetScope 3 m data and a deep learning ANN. Future studies may benefit by combining high resolution imagery with light detection and ranging (LiDAR) datasets for an in-depth tree level assessment. If used in combination with new advances in UAV technology, it is possible to allow a faster, more targeted reaction to implement management decisions, reducing the risk of losses to an acceptable level.

CHAPTER 4

Synthesis and conclusion

4.1 Summary of major findings and recommendations

Forest health monitoring for efficient plantation forestry is critical to ensure sustainable management practices and to reduce losses. Biotic risks do not have a precise and predictable damage pattern and can be spread throughout the compartment making it difficult for management to detect and quantify damages. The implementation of a reliable and constant monitoring system is important to optimise decision making and preventative management. Traditional methods of collecting forest health information, namely field surveys, have become less used in favour of remote sensing, which has become increasingly viable for forest health monitoring. This is due to the gradual decrease in the cost of remote sensing products, quicker access to imagery, higher levels of accuracy and with diversity to the user. While there are various methods of capturing forest inventory with remote sensing, field data still has a use, as it allows a comparison of accuracy and infield indication as to the exact cause of the damage. It can be difficult to assign a spectral signature to some causes of damage as their symptoms can be very similar and it is difficult to distinguish between those symptoms with imagery alone. Also, the resolution available with the remote sensing imagery plays an important role to narrow down damage to either a tree or sub-compartment level. Lower resolution imagery is more useful when an overall estimation of potential damage in a compartment is required and higher resolution imagery more valuable to monitor a specific damage-causing agent. The challenge in this study was to determine whether it is possible to distinguish between various levels of damage to trees caused by bark stripping baboons, through time

To develop accurate and reliable frameworks, the potential of Sentinel-2 satellite imagery was assessed at a resolution of 10 m x 10 m and higher resolution PlanetScope imagery of 3 m x 3 m. Tree damage was divided into four severity classes as determined during scheduled field surveys and mapped using contemporary statistical modelling approaches.

This study had the following key questions and focus areas:

1. To what extent could the Sentinel-2 satellite imagery be used to map baboon damage in commercial forest plantations at a sub-compartment level?

2. To what extent could Sentinel-2 derived indices be able to distinguish between different severities of damage?
3. The effectiveness of utilising high temporal (available daily) and spatial resolution satellite monitoring for near real-time tree damage assessment.
4. The utility of a deep learning approach for dealing with high-resolution pixels to map baboon damaged trees in commercial forestry.

4.1.1 Sentinel-2 imagery and the mapping of sub-compartmental baboon damage

An analysis of damage caused in pine forestry compartments over the period 2016 - 2018 indicated that damage had become worse in the monitored plots. Baboons had returned to damage new trees and continued to damage trees that were previously damaged. This continued to a point where some of the monitored plots were clear-felled and re-planted. The Sentinel-2 imagery paired with the Extreme Gradient Boosting (XGboost) algorithm, worked well at monitoring and distinguishing between the various levels of damage. All of the available indices derived from Sentinel-2 imagery were used to establish their efficacy in the detection of baboon damage. It was found that the soil adjusted vegetation index (SAVI) and Structure Insensitive Pigment Index (SIPI) were the most effective, due to their sensitivity to changes in the forest canopy. The Red-edge band proved to be more important than the other bands because it is sensitive to changes in leaf area index. The approach achieved an overall accuracy of 89,34% and a Kappa statistic of 0,85.

4.1.2 PlanetScope imagery and the mapping of tree level baboon damage

The focus to detect and distinguish between the degrees of baboon damage in the monitoring areas was successful. The study sample size consisted of eight one-hectare plots of which each (3 x 3 m) pixel was extracted and used in the analysis using a deep learning ANN. This approach had a slightly lower accuracy than the analysis of the Sentinel-2 data and its derived indices. Since 2019 was the first year of measurement for the monitored plots in this study, compared to the three years (i.e. 2016, 2017,2018) of field data collected using the Sentinel-2 imagery, this may have had an impact on the final results due to the lower sample size and could only improve once more data is collected for modelling through annual field expeditions. The parameters set for ANN were 200 neurons and 4 hidden layers, which drastically increased the training time and completion of processing and should be taken into consideration for future research to address. Overall, the results of the study were satisfactory achieving an accuracy of 81,54% and a Kappa statistic of 0,69.

4.2 Limitations of the study, future research and concluding remarks

For a long time, field surveys have been a trusted method of gathering data. To reduce data acquisition times and increase data collection, several teams are often used to collect data from different areas simultaneously. However, this approach can be problematic due to bias and subjective judgement. To help mitigate this, a well-defined classification system and/or scoresheet is often used, to score all trees consistently. Remote sensing approaches can remove this type of bias from algorithms by analysing data more objectively. The results obtained in this study shows that baboon damage is a serious problem in commercial forestry in South Africa. With advances in technology used to obtain remotely sensed spatial data, a wide variety of options for forest monitoring exists. It is therefore important to test and evaluate the performance of these monitoring methods to find the most appropriate techniques for forest management and protection.

A variety of algorithms used in remote sensing can be considered for application in forest management. The focus of this study was on Extreme Gradient Boosting (XGboost) and Deep Learning Artificial Neural Networks (ANN). XGboost performed well with a few parameter changes and processed the data relatively quickly. The large sample (i.e. 27 one-hectare plots) described in Chapter 2 was beneficial to the weak learner method of gradient boosting. However, if the smaller sample (i.e. 9 one-hectare plots) described in Chapter 3 was used with XGboost, the results may have been less accurate. Nonetheless, the deep learning ANN approach used each pixel (3 x 3 m) in the analysis of tree level damage, generating enough samples for training and testing, and performed well given the smaller number of overall one-hectare sample plots. The parameters of the deep ANN, with 4 hidden layers and 200 neurons, as well as the higher resolution of the PlanetScope imagery, may have been the reason for the algorithm’s success, even with a smaller sample.

Results of this study indicate that higher resolution imagery is able to be used at a tree level and holds great potential for forest health monitoring. Passive sensors, such as Sentinel-2 and Landsat 8, have been a reliable method of identifying damage caused by pests and disease in forestry and have improved their spatial and temporal resolutions. Further improvements can be expected with the release of Landsat 9 near the end of 2020. However, these platforms remotely sense the damage at a plantation or compartment level, while the need often arises to detect damage at a sub-compartment level or tree level. Furthermore, they are multispectral platforms and focus on a broad spectrum of changes within compartments. To detect specific damage caused by different pests and diseases that forest scientists have to manage, it is necessary to use imagery and algorithms that are capable of detecting and distinguishing between various types and degrees of damage that these agents cause. The use of the high spatial and temporal resolution PlanetScope has successfully demonstrated the capability of mapping damage to trees with reliable results, with further research and development of techniques for automated monitoring prioritised. deep learning Neural Networks paired with high resolution hyperspectral imagery or LiDAR, therefore have the potential to greatly improve the efficiency and accuracy of forest health monitoring in commercial forests within southern Africa.

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