# ASSESSING THE SUCCESS OF ASBESTOS MINE REHABILITATION USING HIGH RESOLUTION SATELLITE IMAGES:

# THE CASE STUDY OF ASBESTOS MINES IN WHITEBANK, NORTHERN CAPE PROVINCE

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A research report submitted to the Faculty of Science, University of the Witwatersrand, Johannesburg, in partial fulfilment of the requirements for the Degree of Master of Science (Geographical Information Systems and Remote Sensing), School of Geography, Archaeology and Environmental Studies

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# DECLARATION

I declare that this research report is my own, original work, except where otherwise acknowledged. It is being submitted for the degree of Master of Science at the University of the Witwatersrand, Johannesburg. It has not submitted before for any degree or examination at any other University.

**Wongama Singalone Tengela** **Date**

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When asked about the speed of sound Albert Einstein replied: 'I do not carry such information in my mind since it is readily available in books. The value of college education is not the learning of many facts but the training of the mind to think.'

# DEDICATION

To the Heavenly Father; it is not an accident that I had to wait for 5 years to access higher education due to financial disabilities. I was depressed and dejected but not hopeless and you came at the right time, for right reasons and converted me from a mere bricklayer to a Remote Sensing Technologist, working at the South African National Space Agency.

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**ABSTRACT**

In 2012, Mintek was contracted to undertake the rehabilitation of the asbestos mines in the Whitebank area in Kuruman, Northern Cape Province. This was achieved by revegetating the abandoned asbestos mining sites. The aim of this study was to investigate whether remote sensing data and vegetation cover can be effectively used to assess the success of asbestos mine rehabilitation. The spatio-temporal changes of vegetation cover on and around the rehabilitated mine sites were identified and analysed using object-based classification. SPOT-5 and -6 images were used to map rehabilitated areas and to track vegetation cover change, at two-year intervals, between 2008 and 2016. NDVIs were computed from SPOT data to detect the vegetation recovery and density in the rehabilitated mine sites. RapidEye image data was also used to classify the flora in the study area using the Random Forest (RF) classifier to understand the species composition on the rehabilitated sites and surrounding areas. Between 2008 and 2010, the land surrounding the mine was left degraded and without any vegetation. The area experienced slow vegetation growth in 2012 (6 months after rehabilitation), but between 2014 and 2016, there was an increase in vegetation cover. Of the plant species identified, *Grewia flava* was the dominant species with a total of 390.0416 hectares classified. Four other predominant species were identified: *Tarchonanthus camphoratus* (637.945 hectares), *Eragrostis lehmanniana* (458.0825 hectares), *Acacia mellifera* (12.1075 hectares) and *Themeda triandra* (558.0875 hectares). Regarding the mean decrease in the Gini index, the most predominant band was the Near Infrared (Band 5), which was located around 760-880 nm. The Blue (Band 1: 440-510 nm) and the Green bands (Band 2: 520-590 nm) also significantly contributed to the classification of these species. The Red band (Band 3: 630-685 nm) did not play a major role in the species separability. The study showed the potential of remote sensing technology as a plausible tool for assessing mine site rehabilitation progress using high-resolution satellite imagery.

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## LIST OF ACRONYMS

AOI - area of interest

CGS - Council for Geoscience

D&O - derelict and ownerless

DEM - digital elevation model

DME – Department of Minerals and Energy

DMR - Department of Mineral Resources

DN - digital numbers

EFA – ecological function analysis

ETM+ - Enhanced Thematic Mapper Plus

GCP - ground control point

GIS - geographic information system

HRVIR - High-Resolution Visible and Infrared

KNN - K-Nearest Neighbors

LFA - landscape function analysis

LULC - Land Use and Land Cover

MPRDA - Mineral and Petroleum Resources Development Act

MS - multispectral

NDVI - Normalized Difference Vegetation Index

NIR - Near-Infrared

OOB - out-of-bag

RF - Random Forest

SANSA - South Africa National Space Agency

SPOT - *Satellite Pour I’Observation de la Terre*

SWIR - short-wave infrared

TM - Thematic Mapper

UTM - Universal Transverse Mercator

## DEFINITION OF TERMS

**Change -** In this context, refers to the general direction in which the vegetation classes tend to move or change towards.

**Rehabilitation -** In this context, refers to the cleansing of the degraded land or areas by revegetation.

**Vegetation -** In this context, refers to the plant life, that is, the ground cover provided by plants regardless of species or life forms.

**Derelict and ownerless -** In this context, can be defined as mines whose owners or mining rights or lease holders have abandoned and are not operating nor maintaining to mitigate and manage their associated safety, health and environmental impacts and can no longer be traced. These would comprise of mines that were operational during the period when environmental management at the mining sites was not well regulated.

**Dense grassland** – grassland that has a high density of grasses.

**Open grassland** – grassland that has a low density of grasses (a mixture of grasses and bare soil).

# 1. INTRODUCTION

## 1.1 Background

Owing to the growing demands of an ever-increasing human population, all ecosystems on the planet are now under anthropogenic pressures (Vitousek et al., 1997). Habitat degradation, driven by land clearing for agriculture, urbanisation, logging and mining, is recognised as a leading cause of biodiversity loss worldwide (Dobson et al, 1997). As a result, the restoration of degraded land has become a conservation priority (McMahon and Hall, 2001).

While mining may not have the largest physical footprint in comparison to other anthropogenic disturbances (<0.1% in Australia for instance; (Bell et al., 2001), it is recognized to have a significant and growing environmental impact (Levin et al., 2001).

A critical part of mine closure is ensuring that mined sites are rehabilitated in accordance with the public interest (Wilson, 1999). Mine rehabilitation is aimed at improving the conditions of sites degraded due to mining and broadly involves the reconstruction of stable landforms and the establishment of sustainable vegetation. To assess the success of mining rehabilitation, it is important to establish performance standards and to monitor the progress of rehabilitated habitats against such standards (Smyth and Dearden, 1998). The measures of physical factors (air quality, acid mine drainage, mine tailings, water quality, land topography) and fauna and flora (plant density and richness) are most commonly used as the basis for monitoring standards. Many studies have demonstrated that restoring flora leads to restoring fauna (Majer, 1990) (Clewell et al., 2000). Therefore, plant density and richness is the most important indicator for mine rehabilitation assessment.

There are a plethora of protocols to assess the plant density and richness of rehabilitated areas. Plant density refers to the quantity of the flora per unit measure (length, area or volume). In natural resource measurements, density is usually used to refer to the number of items per unit area (plant/m$^2$). On the other hand, species richness refers to the number of different species represented in an ecological community, landscape or region (Bonham, 2013). The Simpson diversity index, Shannon-Wiener diversity index and Pielou's evenness index are indices used to measure species richness. These fieldwork methods are limited by the fact that they are expensive and time-consuming (Bonham, 2013).

Satellite remote sensing can be helpful, as it is a cost- and time-effective tool to assess mine rehabilitation. Its capability for repetitive digital multispectral (MS) imaging of large areas is an important advantage over other methods. Thus, remote sensing often becomes the only alternative to field observations in cases where a historical record is needed for studying mining and reclamation activities (Fraser et al., 2005).

The common remote sensing methodology for monitoring and evaluating the status of the vegetation areas surrounding mining areas involves the use of different spectral derivatives including band ratios and vegetation indices. Hyperspectral remote sensing imagery from the Compact Airborne Spectrographic Imager and Probe 1 has been used effectively for monitoring the revegetation of mine tailings (Lévesque et al. (2008). However, the use of hyperspectral data is restricted due to its sparse availability, limited coverage (Lefsky et al. (2001), higher cost and complex processing (Watanachaturaporn et al., 2004). MS Landsat images are also capable of providing useful information for the assessment of mine restoration progress (Soverini et al., 2003); (Bonifazi and Serranti, 2007); (Petropoulos et al., 2012) and Straker et al. (2004) used QuickBird satellite images for reclamation assessment at the Bullmoose mine site in British Columbia. Erener (2011) used multitemporal Landsat images to evaluate the health of vegetation in the vicinity of a coal mine in Turkey. (Bao et al., 2012) used images from SPOT satellites to investigate seasonal changes in the percentage of vegetation cover of rehabilitation areas for a gold mine in Queensland, Australia. Recent advances in satellite remote sensing provide access to much higher spatial and spectral resolution data than was previously available. (Raval and Ramanathan, 1989) tested the performance of WorldView-2 imagery in monitoring rehabilitated mines at the Ulan Coal Mines Limited in Australia. RapidEye seems to be promising for area-wide in-depth analysis of mines, as it offers high resolution (6.5m pixel size), a swath width of 77 km and a maximum acquisition capacity of 1500 km per orbit. The sensor supplies five bands from visible to near-infrared (NIR), including additional spectral information from the Red-Edge in the wavelength range of 690-730 nm. There are no known studies testing the capability of RapidEye to monitor mine rehabilitation. In this respect, this study utilised RapidEye images to map species communities within and around rehabilitated mines in the Whitebank area in Kuruman, Northern Cape province, South Africa. In addition, SPOT data time series images were used to quantify changes that have been made before and after mine activities.

## 1.2 Problem statement

Asbestos is considered to be one of the oldest and most widely explored minerals and was mined extensively in South Africa from the early 1900s. In spite of its many advantages, asbestos exploitation and use has serious negative implications for the environment and to the health of people. As a consequence it was eventually banned in a number of countries, including South Africa in 2008. A number of asbestos mines were abandoned, and are collectedly termed ‘derelict and ownerless’. To counter the problems associated with derelict and ownerless mines (D&O), the Department of Mineral Resources (DMR) developed a strategy to rehabilitate them. This included developing a database recording all D&O mines. The cost implications for the implementation of rehabilitation programs were determined and approved; rehabilitation was in progress. This database recorded about 6152 mining sites (a portion of which were asbestos) and permitted the problem to be confronted in an organised manner. The mining sites needed to be evaluated regarding their purposeful use. Imperative recovery was to be done while keeping in mind the conscious end use that could include tourism, recreation or conservation. Rehabilitation has been continuing since 1994, and about 48 asbestos areas and 108 trenches and shafts have been rehabilitated. By 1999, it was reported that 1 of 12 asbestos mines in Mpumalanga, 29 of 41 asbestos mines in Limpopo and North West provinces and 25 of 68 asbestos mines in Northern Cape province had been rehabilitated (Castleman, 2005). Government budgets for rehabilitation make minimal provision for monitoring and follow-up, a vital component of the rehabilitation process. However, remote sensing and mapping may present a cost effective solution to evaluate the progress and effectiveness of rehabilitation.

### 1.3 Aim and objectives

**i.Aim**

This study aimed to investigate the effectiveness of the use of satellite remote sensing data for assessing the success of asbestos mine rehabilitation.

**ii.Objectives**

The objectives of this study were:

- To identify and analyse the Spatio-temporal changes of vegetation cover on and around the rehabilitated mine sites using object-based classification.
- To quantify the changes in the vegetation cover of rehabilitated mine sites using NDVI and time series analysis.
- To map the grass communities on and around the rehabilitated sites using Random Forest (RF) classifier.

# 2. LITERATURE REVIEW

## 2.1 Introduction

The following is a review of mine rehabilitation, with particular focus on asbestos mine sites in South Africa, and illustrates that traditional methods of mine rehabilitation are limited. The use of remote sensing to address mine rehabilitation challenges is assessed.

## 2.2 Mine rehabilitation

Mining is an environmentally destructive activity that involves the removal of vegetation, the excavation of soil and rock containing the ore, the generation of overburden and tailings, and the establishment of infrastructure to support the mining activity. It is expected and is legislated in many jurisdictions that at closure a mine site is cleaned up, the surface rehabilitated and alternative sustainable land use is implemented. This land use may include agriculture or conservation (Wiegleb and Felinks, 2001).

Rehabilitation resembles a form of primary succession (Glenn-Lewin, Peet et al; 1992); that is, a disturbed and barren area such as a waste rock dump or a tailings storage facility is covered with soil and vegetated over time to the point where a stable ecosystem is established (Wiegleb et al; 2001). Succession is the orderly development of plant communities through a series of seral stages where a seral stage refers to an intermediate stage in ecosystem development (Clements et al., 1929); Gibbons at al; 2006). (Walker and Del Moral, 2003) describe primary succession as the process of ecosystem development of surfaces that have been ripped of biological activity. It includes the development of complex ecological systems from simple biotic and abiotic components that is initiated when plants, animals and microbes colonise the disturbed surfaces. (Gogtay et al., 2004) reported that in Western Australia there were no mandated standards for assessing rehabilitation success for the mining industry. They argue that the primary objective for rehabilitation programmes should be the creation of near-natural, self-sustaining and functional ecosystems that can be assessed by monitoring flora and fauna. At the time, none of the existing mines used the same monitoring strategy, and across the board the monitoring was outsourced.

Ecological function analysis (EFA) (Dowo et al., 2013) is an effective but labour-intensive and time-consuming method of assessing rehabilitation success, which incorporates landscape organisation indices and soil surface indices. The core component of EFA is landscape function analysis (LFA), which includes the analysis of vegetation and structure composition and habitat complexity. (Dowo et al., 2013), describe the LFA process as a 'monitoring procedure that uses rapidly acquired field-assessed indicators to assess the biogeochemical functioning of landscapes at the hillslope scale'. This method is useful to standardise rehabilitation monitoring methods, but it remains labour-intensive and needs to be done on the site. Gibbons and Freudenberger (2006) state that there are numerous other approaches also employed for the rapid, *in-situ* assessments of vegetation condition. These methods only look at vegetation factors and not at the associated changes in soil condition. Remote sensing offers a distinct advantage in this regard as soil can be distinguished from tailings due to their spectral differences. The main question is: How can remote sensing be used to address the mine rehabilitation problem?

## 2.3 Rehabilitation monitoring options using remote sensing

Various processing tools are available to convert remotely sensed images to thematic maps. (O'Sullivan, 2005)demonstrated the potential of supervised classification of QuickBird images combined with an existing ground-based vegetation sampling programme for its use in rehabilitation assessment and as documented proof for the fulfilment of regulatory objectives. (Al-Ruzouq and Al Rawashdeh, 2014)) used remote sensing and supervised classification to highlight landscape characterisation needed for mine rehabilitation.

Change detection using remotely sensed images is a way to quantify the success of rehabilitation efforts. Several studies have monitored changes in vegetation status using various broadband MS satellite images. Li et al. (2004) investigated the change from barren land to grassland and cropland, in the Yulin prefecture of China, using Landsat Thematic Mapper (TM) data. Whereas (Röder et al., 2008) analysed a time series of remote sensing data spanning 1984 to 2000 for a retrospective assessment of rangeland processes in a test area of northern Greece using Landsat 5 TM and Landsat 7 Enhanced Thematic Mapper Plus (ETM+) imagery. They then interpreted the data in the light of land-use practices and previous management interventions. Another example is (Pan et al., 2008)who used SPOT-4

High-Resolution Visible and Infrared (HRVIR) and Landsat 5 TM imagery to evaluate vegetation health.

Mehner et al. (2004) examined the improvement of vegetation classification from low-resolution imagery (Landsat TM and SPOT HRVIR) to high-resolution imagery (IKONOS) by applying traditional remote sensing classification techniques. Simple radiometric corrections were carried out, and the data was geometrically corrected and referenced to the British National Grid by using ground control points (GCPs). They needed a ground resolution of 10 m or better and MS imagery with coverage in the NIR wavelengths to maximise spectral discrimination between vegetation types. This was achieved through IKONOS data with 4 m spatial resolution and a NIR band (Band 4). Unfortunately, the short-wave infrared (SWIR) information, which would have been provided by Landsat TM Band 5, was not available from the IKONOS data. They also found that winter and summer images maximised the discrimination between vegetation types as some plants are spectrally more distinct in winter. The Normalised Difference Vegetation Index (NDVI) was calculated to enhance discrimination between different vegetation types and to aid vegetation classification. Shadows were mainly used as a result of the steep relief of the study area. Switching from a hard or rigid to a soft classification approach improved the identification of mixed vegetation types. However, problems related to snow and shaded areas on the winter image were experienced.

(Turner et al., 2003) and (Walsh et al., 2008) concluded that imagery with high spatial resolutions, such as those provided by IKONOS and QuickBird, showed the greatest potential for the identification of vegetation types up to species level. Species differences in phenology (onset of greenness, fruiting and senescence) allow accurate identification of species type but require sensors with high temporal resolution. However, costs escalate when an area has to be scanned repeatedly (Gross et al., 2009). Therefore, instead of having to perform actual species-level flora identification, vegetation indices offer a measure to evaluate the state of vegetation. Data continuity can also be ensured by a multi-sensor detection procedure (Wulder et al., 2007).

Vegetation indices are dimensionless, radiometric measures that indicate relative abundance and activity of green vegetation (Bernard et al., 2007). Various indices have been developed for vegetation monitoring with NDVI being the most commonly used. (Leblon et al., 2002) maintains that an ideal vegetation index should be sensitive to the vegetation and not to the underlying soil. The author further explains that most ratio-based vegetation indices use the red and NIR bands, which contain the most information on vegetation characteristics and where the contrast between vegetation and soil is maximal. (Shank, 2008)showed that revegetation of mine sites can be successfully evaluated using NDVI and high-resolution QuickBird MS imagery. Zhang and Guo (2008) successfully compared 13 different vegetation indices calculated from SPOT-4 and Landsat-5 TM imagery for evaluating the prairie ecosystem that is characterised by an abundance of dead material along with soil and green vegetation classes. The NDVI’s limitations relate to the saturation effects for dense vegetation canopies, and a negative influence on soil background especially for bright soils and sparse vegetation canopies.

These studies were done over relatively large areas, but given that satellite sensor technology is becoming more advanced and high-resolution imagery from IKONOS (Menher et al., 2004) and QuickBird (Shank, 2008; Wulder et al., 2008; Hester et al., 2011) show promising results, more accurate change detection over smaller areas like mine sites has become feasible. Furthermore, image fusion or pansharpening can be implemented to increase the spatial resolution of MS data, but care needs to be taken to employ the methods that preserve spectral fidelity (Ŝvab and Oŝtir, 2006).

Short-term assessment of change detection was done by (Philippon et al., 2007), (Antwi et al., 2008)and (Koruyan et al., 2012), whereas Wulder et al. (2008) studied multitemporal cross-sensor change detection with medium-resolution images from Landsat, ASTER and SPOT and highlighted the importance of data continuity for long-term monitoring programmes. A long-term reclamation assessment of mine rehabilitation using NDVI derived from red and NIR bands of multitemporal airborne MS imagery has been done for the period 2001 to 2011 for the Highland Valley Copper Mine reclamation project (Richards et al., 2003); (Richards et al., 2004). This assessment was one of the first published, long-term remote monitoring programmes of mine rehabilitation. Repeatability of image scans is crucial to ensure continuous monitoring. Pre-ordered collections of higher-resolution images are possible, but sensor characteristics still need to correspond to historical collections regarding spectral band response function, solar zenith angle and sunobject sensor orientation to ensure accurate assessments. The timing of the imagery acquisition is critical to eliminate any effects caused by changes in soil moisture (Shank, 2008) and precipitation patterns must be studied before placing orders.

The validation of classes can be done either by comparing the spectral classes to an extensive available database of spectral reflectance measurements of typical soils, rocks and plant types (Röder et al., 2008) or by visually identifying features from the images and obtaining their spectral curves (Zhang and Guo 2008). Object-based image analysis is often the preferred as a more accurate method for the classification of medium to high spatial resolution images in land-use and land cover studies (Walsh et al., 2008; (Castillejo-González et al., 2009); (Myint et al., 2011); (Whiteside et al., 2011); and (Vavilapalli et al., 2013). Imaging spectroscopy and hyperspectral data also play important roles in accurately describing mine rehabilitation regarding the unique pH levels related to acid mine drainage (AMD) as well as land-use and land cover changes (Long et al., 2012).

### 2.4 Derelict and ownerless mines in South Africa

Mining is and has been for many years, a vital component of the development of South Africa. At the same time, mining has resulted in major impacts, both environmental and social, that have not been fully recognised or dealt with. South Africa, like many other mining jurisdictions, is faced with a legacy of the negative environmental and human impacts resulting from mining operations. The Department of Mineral Resources (DMR), through extensive research, has recorded about 6000 D&O mining sites including mine dumps that are impacting negatively on public health, safety and the environment. From the research conducted to date, it is clear that there is a need for a systematic approach to address this enormous challenge. D&O mines can be defined as mines whose owners or leaseholders have abandoned and are not operating nor mitigating or managing their associated safety, health and environmental impacts and can no longer be traced. These would comprise of mines that were operational during the period when environmental management at the mining sites was not well regulated (Zhang and Guo 2008).

The high number of D&O mines is as a consequence of limited legislation requiring rehabilitation at closure. For example, the Mines and Works Act 27 of 1956 had a minimum requirement of the fencing of sites and the safety of dangerous openings, although in terms of the Water Act some remediation with regards to contaminated water was required. Similarly, the Mining Rights Act 20 of 1967 did not have requirements for environmental management on mining sites. The Minerals Act 50 of 1991 was the first legislation to prescribe more comprehensive environmental management and rehabilitation that included providing financially for rehabilitation at the commissioning stage of mining. This was followed by the Mineral and Petroleum Resources Development Act (MPRDA). The government is now tasked with addressing the legacy of mining and funding the rehabilitation of D&O mines. In recent years, the government has developed and implemented a national strategy to address this issue that includes legislation to prevent mines from being abandoned. The Council for Geoscience (CGS) was contracted in 2006 by the then Department of Minerals and Energy (DME) to develop a national strategy on D&O mines, which was finalised in 2009. Mintek was appointed as the project manager for D&O asbestos mine rehabilitation.

An outcome of the National Asbestos Summit, held in November 1998, was the development of the 'Standard protocol and guidelines for the rehabilitation of derelict and/or ownerless asbestos mine residue deposits in South Africa'. According to the standard protocol and guidelines, the goals of rehabilitation are two-fold. The primary goal is to 'permanently eliminate the dispersion of asbestos fibres into the environment by wind and water' and that this 'must result in a self-sustaining, cost-effective solution to the problem that requires no or very little human after care'. Secondary to this is to return the disturbed area to an ecologically stable state. The rehabilitation of asbestos mines involves two main components. The first is the encapsulation of the pollution source through the reshaping of the dumps and subsequent covering of these with topsoil. Following this, the area is revegetated with indigenous vegetation. Activities associated with this may include building access roads, establishing equipment on site and the installation of erosion prevention measures.

Monitoring of the effectiveness and feedback from this is important to allow for improvements to the system. Monitoring, although included in the strategy, is limited and requires physical visits to the site that entails time and financial resources. Such resources are not always available. There is thus an opportunity to use remote sensing and geographic information system (GIS) to remotely monitor the effectiveness of rehabilitation.

# 3. METHODOLOGY

## 3.1 Methodological approach

A case study method was adopted due to its appropriateness for field investigation-type studies. Field investigations analyse situations as they arise and in the absence of any significant involvement by the investigators. This kind of method tries to answer certain research questions, as well as to emerge as a complete rationale of the incident under research, whilst simultaneously developing more common conceptual assertions about regularities in the observed situation (Hayes, 2000).

## 3.2 The case study of the Whitebank mine area in the Northern Cape Province

Asbestos is a generic name for six naturally occurring asbestiform or fibrous minerals from the amphibole and serpentine group of rock-forming minerals. South Africa was a significant global asbestos producer. Since the early 1900s, the county has been mining three types of asbestos (chrysotile, crocidolite and amosite). The asbestos mines were mostly located in, what is today known as, the Northern Cape Province, Limpopo and Mpumalanga. The mining methods depended on the type of ore body that was mined, but were generally crude with the fibre being separated from the ore by hand. The health impacts of asbestos were already known by the 1960s, but it was not until the 1980s that the medical profession in South Africa focused on the strong evidence of the negative effects of asbestosis. Due to health concerns global demand for asbestos decreased, and some of the mines closed or were abandoned. By 1981, foreign companies had withdrawn from active asbestos mining in South Africa. The last asbestos mine in South Africa closed in 2001.

One such mine is the Whitebank, located 27°24'0" S and 23°21'0" E, to the north of Kuruman a small town in the Northern Cape Province (Figure 1). The site usually gets most of its annual rainfall late in the summer rainfall season (between January and February), and the rainfall can be episodic in nature with massive 24-hour rainfall events. The mine is at an altitude of approximately 1380 metres above mean sea level. The area is sparsely populated with eight people per square kilometre. The closest town, Kuruman, is slightly bigger and more populous with about 50,000 occupants.

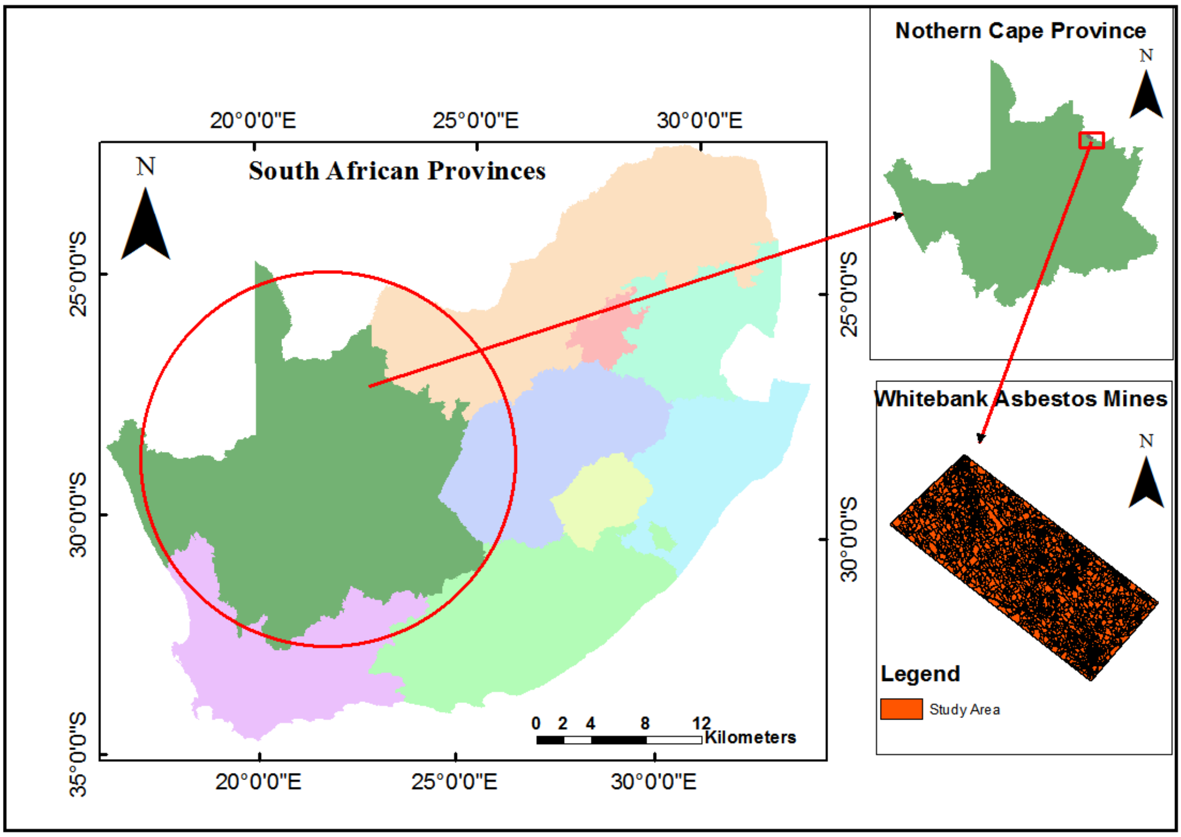


**Figure 1: Locality map and image showing the study area in the Northern Cape Province.**

### 3.3 Vegetation

The province of the Northern Cape has approximately 5 400 plant species with all of them classified in six large biomes; Fynbos Biome, Grassland Biome, Nama Karoo Biome, Savanna Biome, Succulent Karoo Biome and Desert Biome. It is recorded that the province has over 30 per cent endemic plants and the majority of them exist along the West Coast border and fall under the Succulent Karoo Biome. The majority of these plants are scarce with a restricted distribution. Invasive plant species are presenting a risk to the indigenous flora of the area (Ward et al., 1998). The province experiences bush encroachment leading to the extinction of grazing land, decreased species diversity and habitats that are no longer in their crude state (Ward et al., 1998).

Although there is a small quantity of winter rain in the western coastal area, which is influenced by succulent shrubs, the landscape is distinguished by widespread dry, arid lowlands with irregular rocky outcrops. The inland part of the area has a combination of grasses and short shrub (Hoffman and Todd, 2000). Sheet and wind erosion is immense (Zhang and Guo 2008) with salinisation disturbing a major part of the area (Hoffman and Todd, 2000). This soil salinisation originates from irrigated agriculture and is very prevalent in the arid regions. The water used for irrigation carries trace quantities of salt resulting in salt being left behind following evaporation from the soil surface. In addition, there is a naturally high salt content of the soil. Bush encroachment and alterations in species arrangements are the major causes of the devastation of the area (Hoffman and Todd, 2000). Alien plant invasion is also common throughout the province. A practical example is the *Prosopsis* species that uses approximately 200 million cubic metres of water annually (Hoffman and Todd, 2000). These species are significantly decreasing the quantity of groundwater accessible for farmers as well as for the rural surroundings.

### 3.4 Field data collection

A field survey was conducted to identify the distribution of *Acacia mellifera*, *Eragrostis lehmanniana*, *Grewia flava*, *Tarchonanthus camphoratus* and *Themeda tiandra*. Before going to the field, sample points were generated using ArcGIS 10.4 to avoid mixed pixel problems. Each plot was comprised of at least 90 per cent of the identified canopy cover of the target species. A total of 316 plots were delineated (Figure 2) for the five identified tree species and grass communities (Table 1).

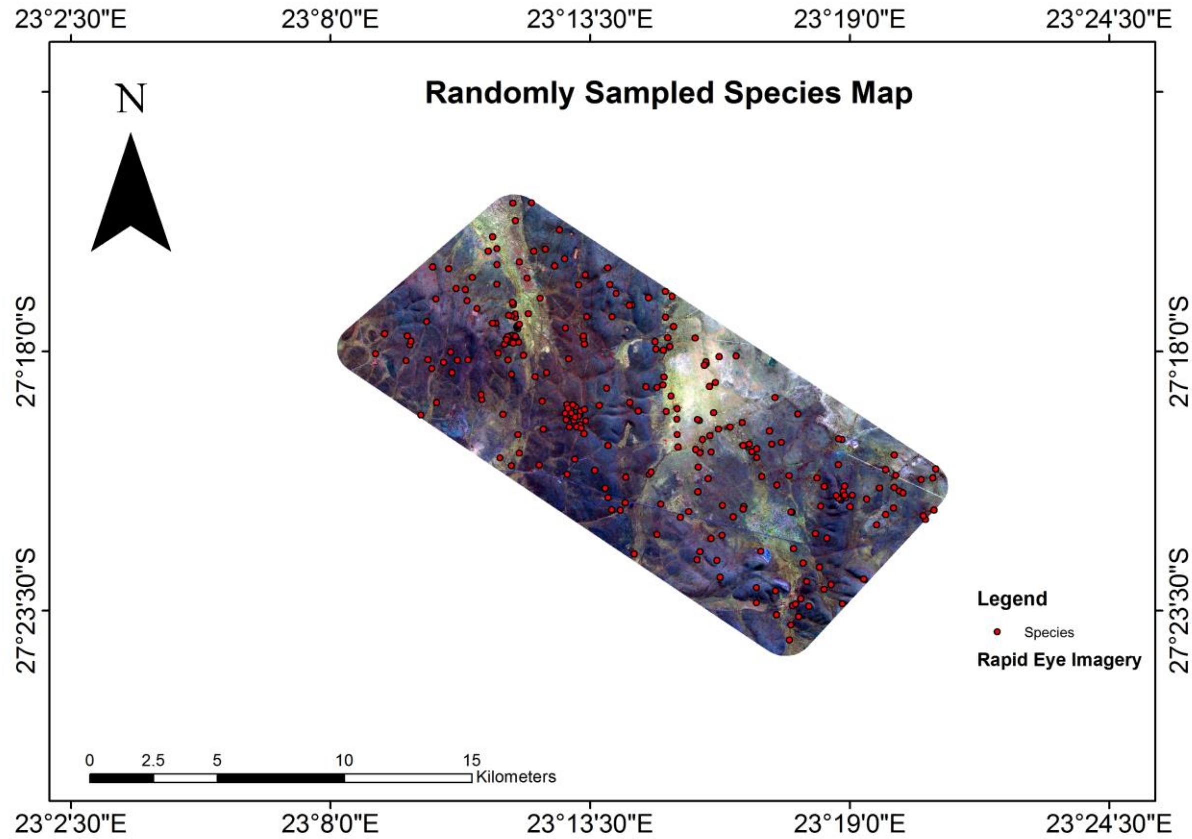


**Figure 2: Random sample selection for species mapping.**

**Table 1: Number of plots and number of training and validation datasets for each plant species.**

| **Species** | **Number of plots** | **Number of training datasets** | **Number of validation datasets** |
|---|---|---|---|
| *Acacia mellifera (tree)* | 58 | 41 | 17 |
| *Eragrostis lehmanniana (tree)* | 62 | 44 | 18 |
| *Grewia flava (shrub)* | 78 | 55 | 23 |
| *Tarchonanthus camphoratus (shrub)* | 68 | 48 | 20 |
| *Themeda tiandra. (grass)* | 50 | 35 | 15 |

### 3.5 Remote sensing data

Two satellite products were used in this study, SPOT and RapidEye. SPOT images were used to map the rehabilitation areas and to track vegetation cover change over time. SPOT images for the years 2008, 2010, 2012, 2014 and 2016 were used (Table 2). The images used in this study differed in their sensor and spectral range as illustrated in Table 3. The images for 2008, 2010 and 2012 were from SPOT-5; and those from 2014 and 2016 were from SPOT-7, and were obtained from the South Africa National Space Agency (SANSA). The images were acquired on different dates for each year but during the same summer season months to maintain the comparability integrity of the results. The images from two-year intervals were analysed to effectively evaluate the progress of the vegetation at each rehabilitated site.

**Table 2: SPOT imagery with acquisition dates.**

| **Imagery** | **Date of Acquisition** |
|---|---|
| SPOT-5 - 2008 | 13 November 2008 |
| SPOT-5 -2010 | 28 December 2010 |
| SPOT-5 - 2012 | 05 November 2012 |
| SPOT-6 - 2014 | 15 January 2014 |
| SPOT-6 - 2016 | 17 December 2016 |

**Table 3: SPOT-5 and SPOT-7 characteristics.**

| **SPOT-5** | | | | **SPOT-7** | | | |
|---|---|---|---|---|---|---|---|
| **Spectral bands** | **Wavelength (nm)** | **Spatial resolution (m) at nadir** | **Revisit time (days)** | **Spectral bands** | **Wavelength (nm)** | **Spatial resolution (m)** | **Revisit time (hours)** |
| PAN | 480 - 710 | 5 | 2-3 | PAN | Undefined | 1.5 | 24 |
| GREEN | 500 - 590 | 5 | 2-3 | GREEN | 530 - 590 | 6 | 24 |
| RED | 610 - 680 | 5 | 2-3 | RED | 760 - 890 | 6 | 24 |
| NIR | 780 - 890 | 5 | 2-3 | NIR | 625 - 695 | 6 | 24 |
| SWIR | 1580 - 1750 | 5 | 2-3 | | | | |

RapidEye images were purchased from Southern Mapping Company for the acquisition date 15 December 2015. The high resolution images were utilised to map the plant species of the study areas. Due to its potential to deliver orthorectified images at 5 meter resolution in five spectral bands (including a Red-Edge Band) makes it the preferred data source for observation purposes in the sectors of agriculture, forestry, and environment. RapidEye has five satellites, which orbit the earth at an altitude of 630 km in a sun-synchronous orbit. It contains numerous spectral push broom imagers, which have the potential of capturing the bands shown in Table 4.

**Table 4: RapidEye characteristics.**

| **Spectral bands** | **Wavelength (nm)** | **Pixel size (m)** |
|---|---|---|
| BLUE | 440 - 510 | 5 |
| GREEN | 520 - 590 | 5 |
| RED | 630 - 685 | 5 |
| RED EDGE | 690 - 730 | 5 |
| NIR | 760 - 850 | 5 |

### 3.6 Image pre-processing

The steps discussed below include image pre-processing, the acquisition of reference data, image classification and accuracy assessment and change detection.

#### i.Pre-processing

Before analysis the SPOT and RapidEye images were pre-processed. Mapping processes for historical data and species identification require images that have high-level geometric precision, radiometric and atmospheric correctness (Lu et al., 2004). This is done due to several factors, which include earth-sun distance, the angle of the zenith and view, the topography, conditions of the atmosphere and the temporal evolution of target characteristics that affect satellite images (Georgakilas et al., 2012). These irregularities affect the mapping results for land use and land cover (LULC) mapping and species detection if they are not corrected.

Radiometric standardisation for SPOT and RapidEye images were assigned to a group of images using sensor calibration guidelines to maintain constancy in different date images for investigation. According to (Almeida-Filho and Shimabukuro, 2002), the impact of the sensor characteristics influencing satellite images is moderately reduced by applying different date images obtained by the sensor. Additionally, they indicate that to reduce dissimilarities in the spectral response of the earth targets, cloudless images must be utilised, and images must also coincide to the dry period to ensure that vegetation cover is imaged under the same phenological conditions. To counteract for dissimilarities in sensor radiometric reactions over time as well for differences in the natural state of solar irradiance and solar angles, digital numbers (DN) were transformed to reflectance values by DN to reflectance conversion. Throughout this procedure, image pixels were changed to units of total radiance by applying 32 bit floating-point computations. Pixel values were then scaled to byte values before media output. This equation was applied to transform DN to radiance in a model run in ERDAS® IMAGINE 2018 utilising calibration guidelines acquired from the header folders of the unprocessed images.

Under normal circumstances, there is distortion of the electromagnetic energy passing through the atmosphere as a condition of its wavelength. This ordinarily captures a state of scattering, fluorescence, absorption and reflection. Scattering contains the major impact and is conditioned on fluctuating gas collections. Different methods are utilised for atmospheric rectification. The guidelines are a group to ATCOR 3 below the elevation data sub window and sensor type to SPOT and RapidEye with the given pixel size and also putting the pertinent date, combined with the calibration folder comprised at sensor information. Atmospheric explanation region is exerted to rural input with the constraint and thermal atmospheric explanation of the region. Correction guidelines that involve angles of the sun as well as radiance to temperature transformation elements are also executed. The correction is then applied to extract outcomes.

### 3.7 Land use and land cover mapping with SPOT

The LULC map was compiled to achieve the first objective of this study: to identify and analyse the spatio-temporal changes of vegetation cover on and around the rehabilitated sites. Individual LULC were mapped for the five SPOT images using object -based image classification. In total, five classes were discriminated: urban areas, open grassland, dense grassland, active mines and rehabilitated mines. Because of their large variation in spectral information, grasslands were divided into two sub-classes: open grassland that is classified as having a low density of grasses and a mixture of grasses and bare soil, and dense grassland that is classified as having a high density of grasses. This differentiation was important for classification purposes. The object-based approach was favoured over the pixel-based that has difficulty in distinguishing between classes as similar pixel values, such as urban areas and open grasslands, dense grasslands and rehabilitated mines. Additional information such as spectral similarities, shape, colour, texture, geometry and location was necessary to improve the LULC map.

Following atmospheric correction, the images were segmented applying an algorithm known as multiresolution segmentation using eCognition Developer 9.0 (Juel et al., 2015). This algorithm has three user-explanatory segmentation guidelines: a scale guideline (range 0 - ∞) that regulates the maximum diversity of image segments, a shape guideline (range 0 - 1) that regulates the weights of spectral and spatial information in the segmentation procedure, and a compactness guideline (range 0 - 1) that regulates the compactness of image segments (Peña et al., 2013). All of the bands for segmentation were utilised. Image segmentation was applied at four scale levels by changing the scale guideline of 30, which provided the best result. Because the trees were not consistent in shape, the shape guideline was applied to a low level (0.1) for all segmentations, which enhanced for spectral information to have a very high weight. The compactness parameter was set to 0.5 so that neither the compact nor the non-compact segments had a preference. These shape and compactness settings are representative for MS images since, in major scenarios spectral information is competent for designing significant segments (Peña et al., 2013).

The K-Nearest Neighbours (KNN) classifier was used for categorisation. As experienced in this study, the parametric categorisation patterns, such as the commonly applied Maximum Likelihood classifier, are not easily applicable to various data sources as well as compact object representatives. This is attributed to their dissimilar state (Foody, 1996). KNN is known as a non-parametric classifier, which lacks statistical speculation of data dissemination, and designates an unclassified phenomenon of interest according to its nearest neighbouring training object(s) in an attribute space. Generally, it is not commonly utilised for pixel-based classification, because of its tedious and slow rate of performance (Hardin and Thomson, 1992). Contrary to the Maximum Likelihood classifier, where training data are statistically concentrated into covariance matrices and mean vectors, the KNN classifier demands that the definite training vectors engage in all classification. Although, for the object-based method utilised in this research, the segments are least classification portions, i.e. classification primitives, instead of individual pixels. The quantity of classification primitives is hugely decreased via the segmentation procedure. Consequently, the application speed is not a challenge.

To classify a phenomenon of interest, KNN locates the k-neighbours closer to the fresh representative from the training space established on an acceptable distance metric. The diversity class between the nearest neighbours is the class label of the fresh representative. Similarity was calculated by the Euclidian distance in characteristic space. In terms of this investigation, standard deviation and band mean within each segment were utilised as features. KNN was associated with the rule-based classification methods established on skilled comprehension to clearly discriminate open grasslands to urban areas (Zhou et al., 2009).

### 3.8 Species mapping with RapidEye and Radom Forest

Species mapping was done to attain the third objective of the study: to map the current tree species on and around the rehabilitated sites using high-resolution satellite imagery (RapidEye). The Random Forest (RF) classifier was used to map these species. In many years the RF algorithm has been explored to present fresh ways of classifying Multi Spectral (MS) as well as hyperspectral remote sensing data for various thematic studies. RF is a unit of decision trees, evolved by Breiman in the sphere of machine learning, to enhance the Classification and Regression Trees (CART). This algorithm merges bootstrap sampling to assemble a sizeable group of decision trees established on model aggregation schemes. The two origins of randomness involve random characteristics as well as random inputs. The RF algorithm essentially profits from two influential methods, known as random subspace and bagging.

The first step of RF assembles various binary decision trees (*ntree*) to intensify the variety of the categorisation of trees, by utilising many bootstrap representatives with substitutions that are extracted from the original considerations (Johnson et al; 2013). Every individual decision tree donates, with one vote, for the allocation of the most constant class to the input data. The verifiable classification is resolved in compliance with the supreme integer of selections from the gathering of trees. These representatives that are not in the bootstrap representation are known as the out-of-bag (OOB) representation. The representation of OOB, which is approximately 30 per cent of the overall data, may be utilised to predict the mis-categorisation error as well as variable significance (Huang et al., 2006). In the second step occurring at every node, a specific integer of input variables (*mtry*) is unsystematically selected from a random subset of the characteristics. However, to fortify a lower resemblance like diversity into the single trees, as well as and consequently a small bias, every individual tree is developed without decreasing the actual bootstrap representation. To enhance the classification precision, RF guidelines *mtry* and *ntree* have to be perfected. In normal circumstances the standard number of trees (*ntree*) is 500, whilst the default rate for the integer of variables (*mtry*) is P, where P is equivalent to the integer of predictor variables inside a dataset. For this research, a grid-search method found on the OOB predictor of error was utilised to locate the best synergy for both of the guidelines (Johnson et al., 2013).The grid search value for *mtry* was mixed from two to five with an individual value period, and the extent of the grid search value for the *ntree* guideline was mixed from 500 to 8500 with an interval of 2000. Furthermore, RF presents an internal rate of variable importance utilising three distinct approaches; the number of periods every variable is nominated, the Gini Importance, and the permutation precision importance estimate. The Gini Importance measure was modified in this study.

The estimation power of every variable is aggregated through a rating (Gini Contrast or Gini Importance) based on the importance it obtained throughout all of the trees in the RF. The ensemble does this by using the Gini index (Johnson et al; 2013). Variables associated with the OOB sample are randomly permuted, and classification trees are grown on the modified dataset. In this study, the permuted characteristic is utilised to estimate the reaction as well as to gain the precision. Assuming that the wavelength is initially necessary for the final estimation, the precision will fall to the extremes after the permutation. Therefore, this variation in estimation accuracy with and without permuting the characteristic (wavelength) was utilised in this study to determine the importance of the characteristic. A useful benefit of the RF variable importance is that it not only considers with the effect of every variable separately, but it also examines multivariate interactions with other variables (Johnson, 2013). Many methods have assembled on the above assessment to discern the relevant group of characteristics. Nevertheless, they are either computationally costly or do not discover a non-redundant group of characteristics. In the current study, EnMap software was used for mapping and R statistical software was used for training the RF model. It should be noted that the research data were randomly divided into two datasets, namely the training dataset and the validation dataset. The training dataset accounts for 70 per cent of the whole dataset distributed as follows: 41 *Acacia mellifera*, 44 *Eragrostis lehmanniana*, 55 *Grewia flava*, 48 *Tarchonanthus camphoratus* and 35 *Themeda tiandra*. The remaining (30 per cent) are assigned to the testing dataset: 17 *Acacia mellifera*, 18 *Eragrostis lehmanniana*, 23 *Grewia flava*, 20 *Tarchonanthus camphoratus* and 15 *Themeda tiandra*

### 3.9 Accuracy assessment

A precision assessment was computed for SPOT and RapidEye imagery using object-based and pixel-based approaches respectively. The quality of each classified SPOT image was assessed for post-classification analysis that is meaningful (Lu et al., 2004). The main intention was to quantitatively determine whether the pixels were grouped effectively into their appropriate feature classes in each area of study. To examine the precision of LULC maps extracted from SPOT, a number of stratified random pixels were developed from each map. The confusion matrix using ground truth regions of interest was built to compute the kappa statistic, the overall accuracy, and the producer and user accuracies (Cohen 1960; Congalton and Green, 2008; Dube, et al, 2017). The overall accuracy is a percentage, which provides the probability that a randomly selected point is correctly classified on the LULC maps (Charrier and Li, 2012).

### 3.10 Normalised Difference Vegetation Index

Normalized Difference Vegetation Index (NDVI) is a technique that has been applied to examine the state of the vegetation in the rehabilitated area (Wang et al., 2004). SPOT images from alternate years for the period of 2008 to 2016 were obtained. For the purposes of the current study, it was decided that two-year intervals between each image would be sufficient to efficiently track the progress of vegetation cover. The NDVI values were obtained for each exploratory region to scrutinise the tendency as well as the variation on the mine rehabilitated site. This NDVI technique gives values ranging between - 1 and 1, where increasing positive values represent an increase in green vegetation and negative values represent non-vegetated surface characteristics such as clouds, snow, barren land, and ice.

To examine the computed NDVI outcomes to byte data range, the NDVI computed value is scaled to the range of 0 to 255, where computed -1 equals 0, computed 0 equals 100, and computed 1 equals 255. Therefore, NDVI values smaller than 100 indicate non-vegetated surfaces, whilst values equal to or greater than 100 indicate vegetated exteriors. This technique is applied from the red and NIR light that is reflected by the vegetation. Healthy vegetation assimilates more of the visible light that strikes it and reflects a great part of the NIR light. Spare or unhealthy vegetation reflects less NIR light and more red lights (Justice et al., 1985; Upper Midwest Aerospace Consortium, 2002). The difference between the area under vegetation and the non-vegetated areas was quantified using the histogram operation in TNT Mips software (Micro Images, Inc.) to find the number of pixels.

# 4. RESULTS

## 4.1 Land use and land cover mapping

In 2008 there were 3 per cent active and no rehabilitated mines in the Whitebank area (figure 4). This is consistent with the prior knowledge that, in 2008, no asbestos mines were active and all previously used mine sites had been left as degraded land. There was no active rehabilitation of mine sites at this time. Similarly, there were no active and rehabilitated mines in the years 2010, 2014, and 2016 (Figure 3). The LULC maps of the Whitebank area (Figure 3) and the percentage area of coverage (Figure 4) show dense grass covering of 63 to 82 per cent of the area between 2008 and 2016. There was a notable increase of 10 per cent in dense grass cover in 2012 compared to 2008, and this increase in rate was maintained through to 2016. Grass was planted on the degraded sites in 2012 and continued to grow and propagate through the years. The distribution of the open grass varies between 10 and 15 per cent; however, there was a decrease in open grass coverage during this time period.

The built-up areas remained unchanged at 5 per cent of the area from 2008 to 2018. With the banning of asbestos mining, Whitebank no longer attracted investors and so further development was halted. Mine sites were abandoned and left to dilapidate. When comparing the results for 2008 and 2010, it can be seen that there is not much difference except the minimal active mines on the 2008 histogram.

Whitebank is an arid region and it is extremely difficult for vegetation to grow naturally. Figure 3 shows small yellow sites for the years 2012, 2014, and 2016. These yellow sites represent rehabilitated mine sites. Asbestos mine rehabilitation was executed in early March 2012 and the representation indicates that three mining sites were rehabilitated. In 2012, 2014 and 2016 dense grass covered between 80 to 90 per cent of the area.

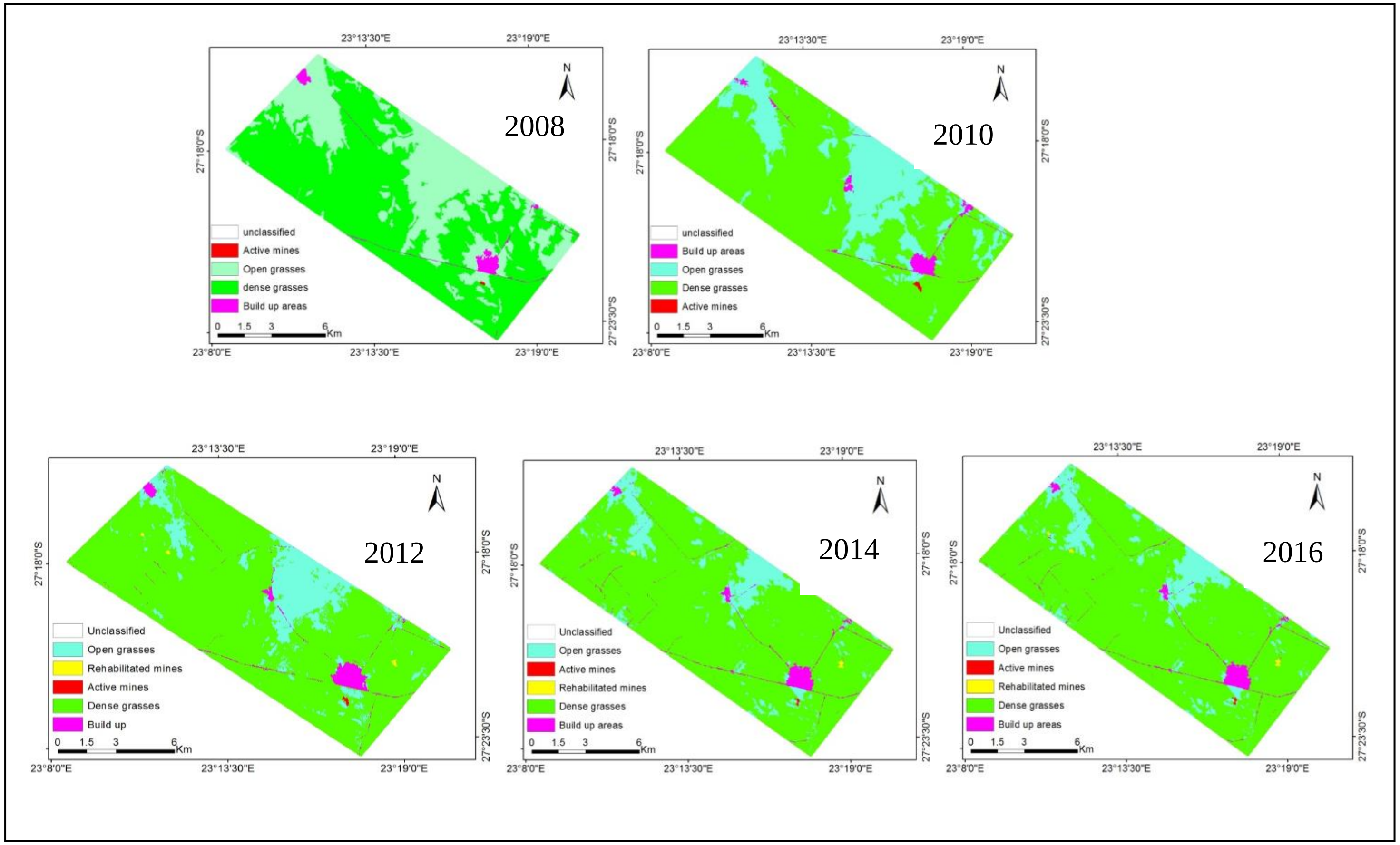


**Figure 3: LULC maps for the Whitebank area in 2008, 2010, 2012, 2014 and 2016.**

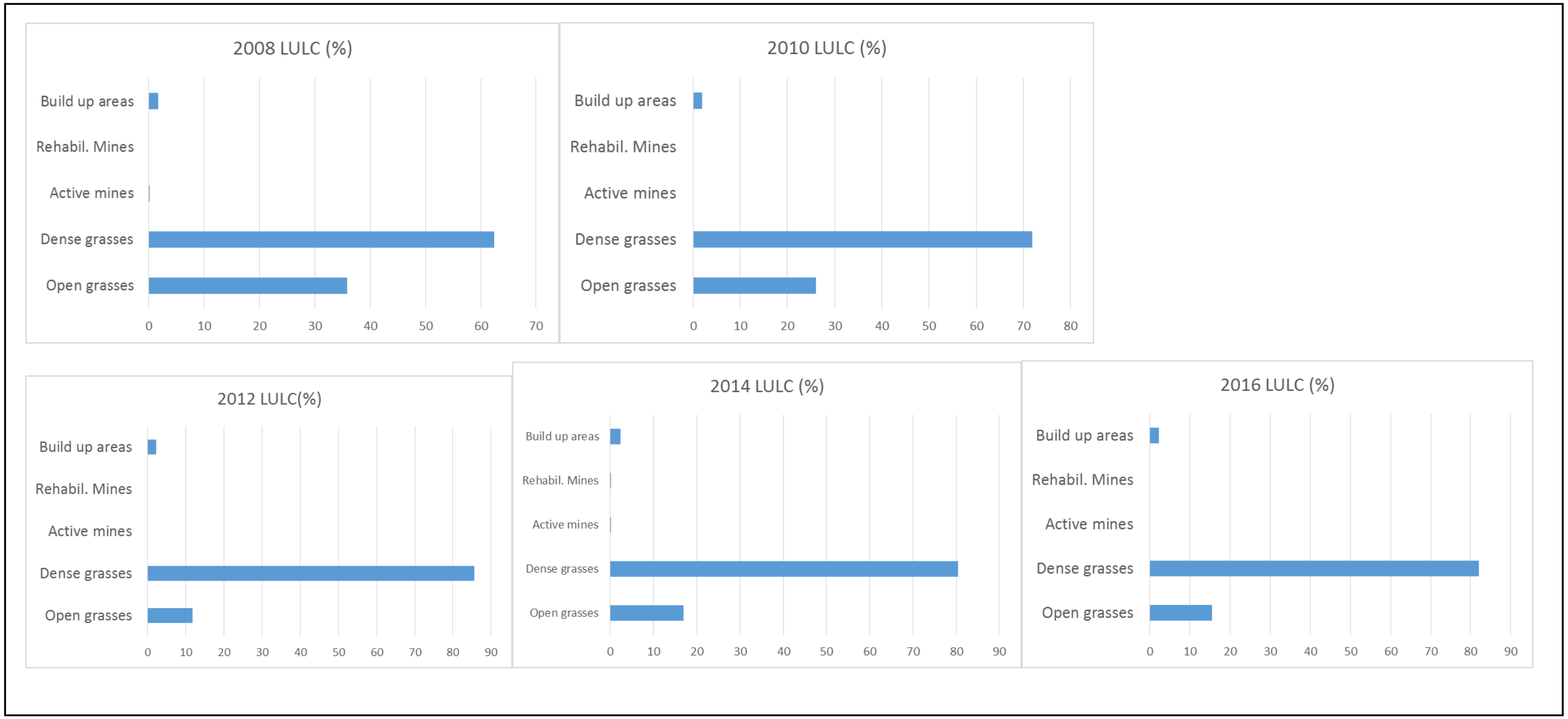


**Figure 4: Histograms of LULC coverage for 2008, 2010, 2012, 2014 and 2016.**

The LULC classes and their change statistics for the five years are summarised in both Table 5 and Table 6. No statistics is presented for rehabilitated mines in 2008 and 2010 as the rehabilitation of the mines only started in 2012.

**Table 5: Summary of LULC classes in the Whitebank area for 2008, 2010, 2012, 2014 and 2016.**

| LULC class | 2008 LULC (%) | 2008 LULC (ha) | 2010 LULC (%) | 2010 LULC (ha) | 2012 LULC (%) | 2012 LULC (ha) | 2014 LULC (%) | 2014 LULC (ha) | 2016 LULC (%) | 2016 LULC (ha) |
|---|---|---|---|---|---|---|---|---|---|---|
| **Open grasses** | 35.89 | 4867.1 | 26.075 | 3528 | 11.836 | 1458 | 16.95 | 2049 | 15.5 | 1873.8 |
| **Dense grasses** | 62.43 | 8467.1 | 71.933 | 9733 | 85.635 | 10551 | 80.49 | 9729 | 81.9 | 9906.7 |
| **Active mines** | 0.0298 | 4.05 | 0.0941 | 12.74 | 0.0445 | 5.45 | 0.039 | 4.754 | 0.059 | 7.1 |
| **Rehabilitated mines** | - | - | - | - | 0.1156 | 14.255 | 0.104 | 12.55 | 0.102 | 12.4 |
| **Build up areas** | 1.639 | 222.34 | 1.896 | 256.7 | 2.3678 | 291.75 | 2.404 | 290.55 | 2.365 | 285.9 |

Table 6 shows the precision of the LULC classification using an object-based approach. The overall accuracy for all of the five classified SPOT images ranged from 82.14 per cent to 93.8 per cent. The active mine class was classified at a producer's accuracy of 60 per cent in 2008, which is the lowest producer's accuracy (Table 6). The user's accuracy for active mines was the lowest in 2014 with a value of 36.36 per cent. The low figures could be attributed to the difficulty of successfully executing classification techniques in arid regions. This is as a result of compromised spectral reflectance caused by mixed pixels that results in the misclassification of some pixels and low producer and user accuracies. It is evident that there were no producer's or user's accuracy values generated for rehabilitated mines in 2008 and 2010 because rehabilitation only began in March of 2012. The classification accuracy assessment results in Table 6 met the recommended 85 per cent threshold value (Anderson, 1976).

**Table 6: Confusion matrices for validation of 2008, 2010, 2012, 2014 and 2016 LULC maps.**

| Year | Overall accuracy | Kappa coefficient | Accuracy type | Rehabilitated mine | Active mine | Built-up | Open grasses | Dense grasses |
|---|---|---|---|---|---|---|---|---|
| **2008** | 82.14 | 72.6 | Producer | - | 60 | 82.35 | 96.5 | 90 |
| | | | User | - | 95.64 | 87.5 | 88.7 | 75 |
| **2010** | 95.8 | 92.9 | Producer | - | 97.3 | 80 | 96 | 94.6 |
| | | | User | - | 95.3 | 95 | 96 | 97.2 |
| **2012** | 86.4 | 80.52 | Producer | 70 | 77.77 | 82.08 | 80 | 96.4 |
| | | | User | 97.3 | 96.3 | 88.7 | 86.6 | 82.94 |
| **2014** | 92.9 | 88.27 | Producer | 75 | 36.36 | 91.8 | 89.1 | 98 |
| | | | User | 98 | 66.66 | 94.91 | 95.7 | 91.3 |
| **2016** | 93.8 | 90.2 | Producer | 71.4 | 75 | 73.9 | 97.8 | 97 |
| | | | User | 96 | 97 | 89.47 | 90 | 96.4 |

### 4.2 Normalised Difference Vegetation Index analysis for rehabilitated mine sites

Normalized Difference Vegetation Index (NDVI) is an indicator of vegetation growth and coverage and has been widely employed to describe the Spatio-temporal characteristics of land use land cover (LULC) as well as percent vegetation coverage. The visible and near infrared bands on the satellite multi spectral sensors allow monitoring of the greenness or vigour of vegetation. In another study a time-series high resolution SPOT images were used to create a NDVI profile of each pixel and classified them into 4 land class viz. bare soil, herbaceous crops, trees on bare soil and trees along with herbaceous crops (Charrier and Li, 2012). This was done to illustrate the application of Normalized Differential Vegetative Index to measure the vegetative vigour and assess land use/land cover. In this study in order to ascertain whether NDVI can be used to assess the effectiveness of rehabilitation, the NDVI was computed for each area of interest (AOI; Figure 9) using SPOT images (Figure 5). All the images were collected in the same season at 2-year intervals. The NDVIs obtained is consistent with the progress of grass propagation from planting in 2012 (Figure 6). In 2008 and 2010, the NDVI values were extremely low, which is consistent with the AOI being mainly degraded land with no grass (Figure 6). In 2012, there was a slight increase in NDVI values compared to the previous two years (Figure 6). This is attributed to the grass that was planted to rehabilitate the degraded site. In 2014, the NDVI value increased further and this is because the grass was steadily growing, whilst in 2016 the NDVI values showed a significant increase and that is attributed to the grass that is evidently growing in the AOI (Figure 6). The computations of NDVI thus allow for validation of vegetation conditions and exhibit the momentum of vegetation increase or change thus indicating whether rehabilitation is progressing well or not.

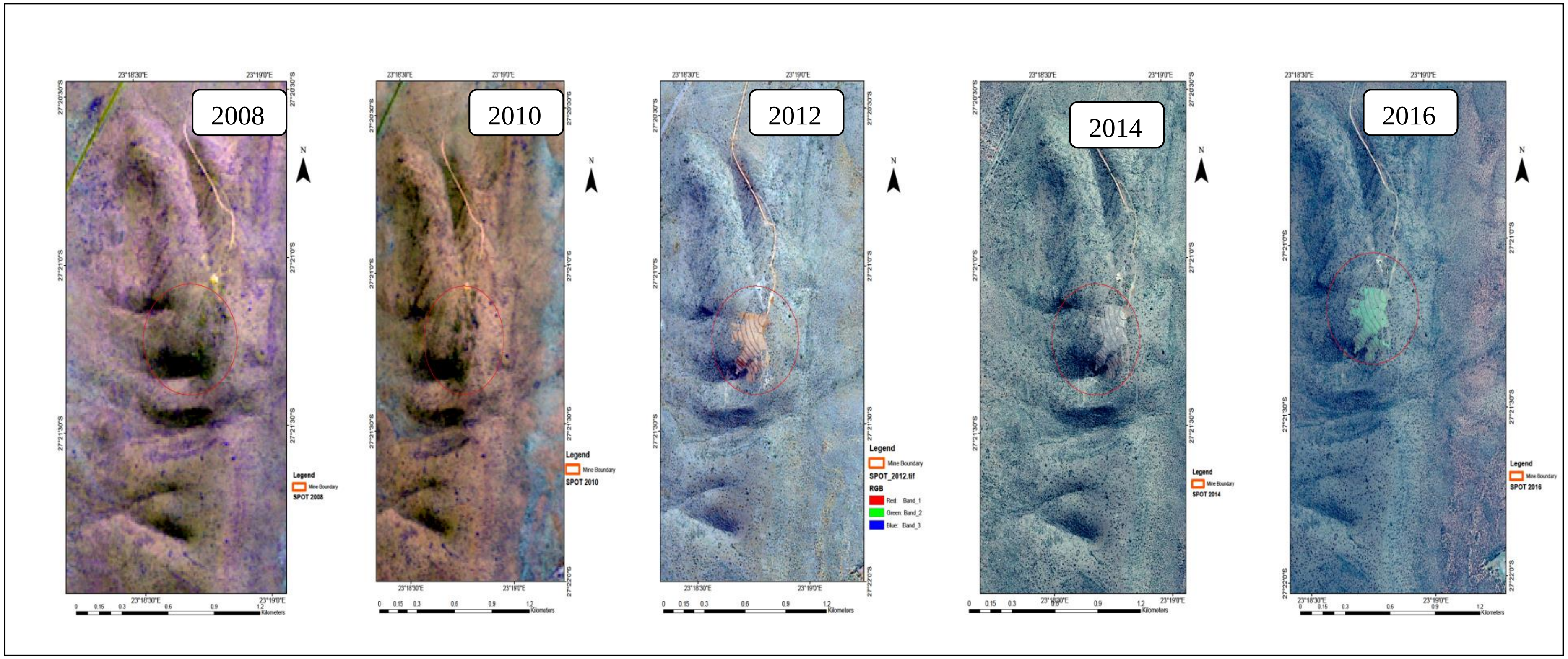


**Figure 5: SPOT images showing the rehabilitated site indicated by the mine boundary (circled in red).**

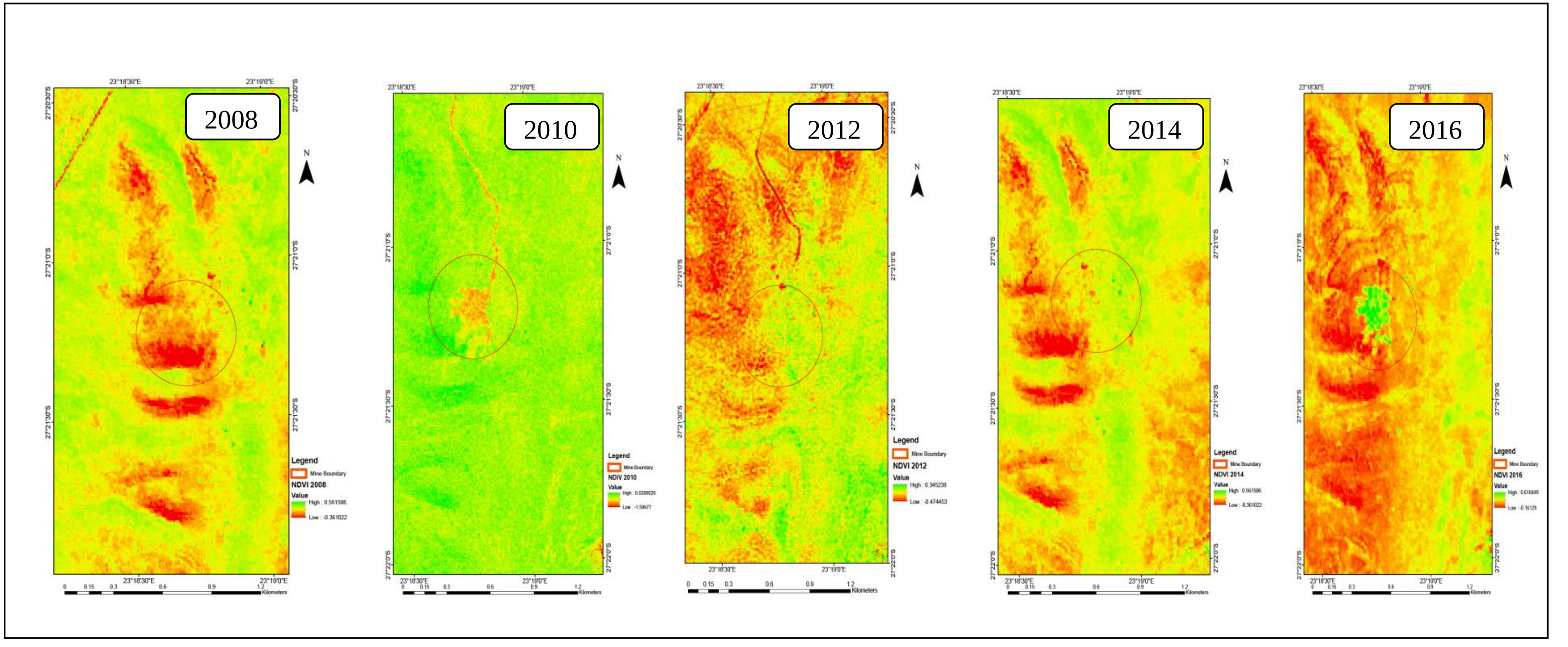


**Figure 6: NDVI maps showing the rehabilitated site (circled with red colour).**

### 4.3 Mapping tree species and grass communities

The flora species on and around the rehabilitated sites were mapped using RapidEye, and species were identified using RF classifier optimised using 10-fold cross validation. The distribution of *Tarchonanthus camphoratus*, *Themeda tiandra*, *Eragrostis lehmanniana*, *Acacia mellifera* and *Grewia flava* is plotted in Figure 7. 75008 pixels were classified as *Grewia flava*, 255178 as *Tarchonanthus camphoratus*, 183233 pixels as *Eragrostis lehmanniana,* 4843 pixels as *Acacia mellifera* and 223235 pixels as *Themeda tiandra*. *Grewia flava* is a gregarious species (Figure 7). This particular species is not regularly distributed over the study area but is, instead, clustered in a specific area whilst other species are regularly distributed over the study area.

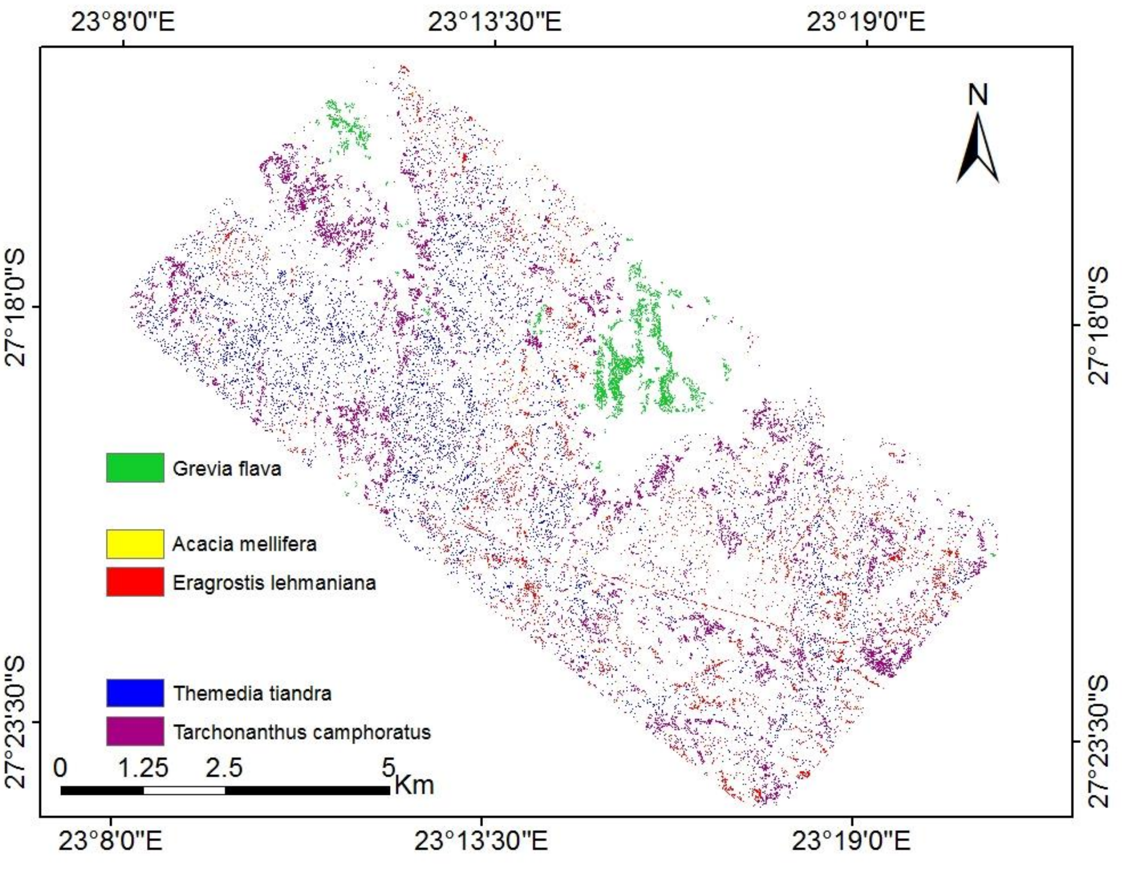


**Figure 7: The distribution of flora species on and around the rehabilitated sites.**

For RF model optimization, 20 combinations of *ntree* and *mtry* were performed (Figure 8). The model best combination was obtained with 5 *mtry* and 4500 *ntree* with an OOB rate of 0.72.

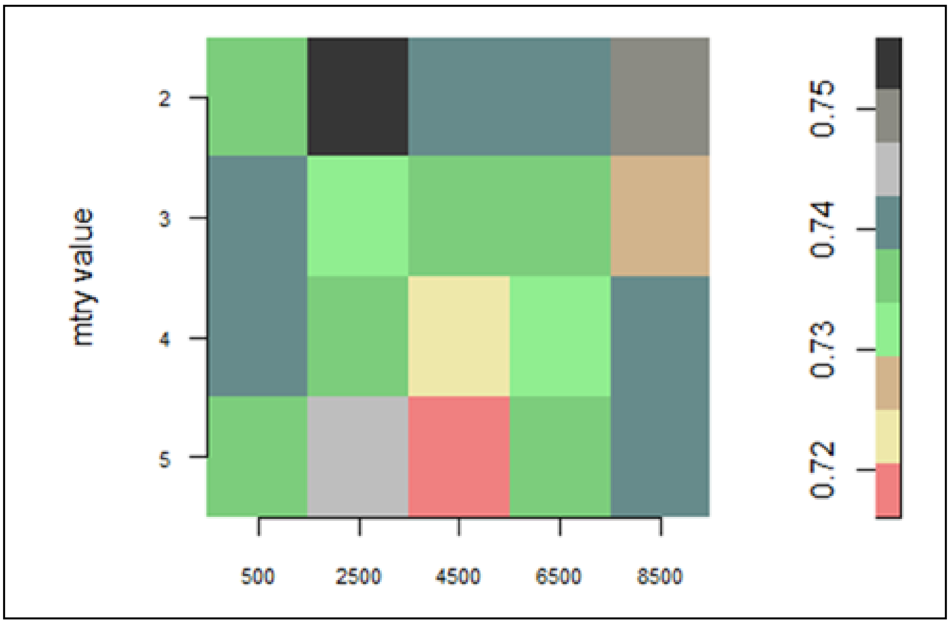


**Figure 8: Results of grid-based Random Forest classifier optimisation.**

The distribution of *Tarchonanthus camphoratus*, *Themeda tiandra*, *Eragrostis lehmanniana*, *Acacia mellifera* and *Grewia flava* within the study area was mapped (Figure 9). Each species is distributed evenly throughout the AOI except *Acacia mellifera* that is sporadic (Figure 9). *Tarchonanthus camphoratus* is distributed throughout the study area (Figure 9), which is attributed to this species being more suited to grow in the soil conditions of the area compared to the other species.

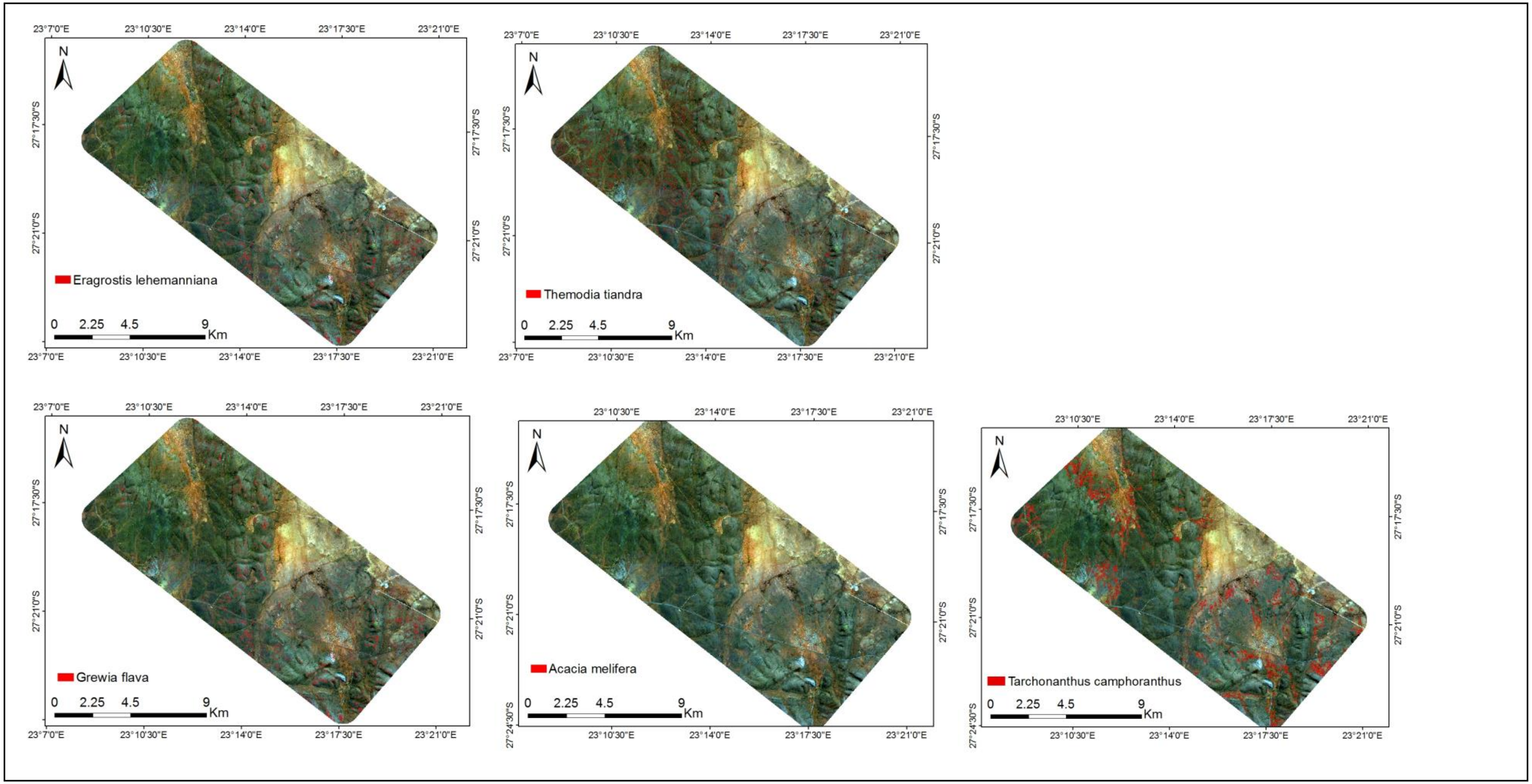


**Figure: 9. The distribution of five dominant plant species within the study area.**

RapidEye and the RF algorithm cannot successfully discriminate these five species because the overall accuracy and kappa statistic are weak, at 40 per cent and 0.251 respectively. However, *Grewia flava* could be correctly discriminated from the other species because of the highest producer and user accuracies, at 73 per cent and 53 per cent respectively (Table 7; OOB and test dataset).

**Table 7: Confusion matrix for the differentiation of five vegetation species.**

| | *Acacia mellifera* | *Eragrostis lehmanniana* | *Grewia flava* | *Tarchonanthus camphoratus* | *Themeda tiandra* | ***Total*** | ***User accuracy*** |
|---|---|---|---|---|---|---|---|
| *Acacia mellifera* | **-** | 2 | 0 | 5 | 1 | 14 | 42% |
| *Eragrostis lehmanniana* | 3 | **5** | 2 | 3 | 4 | 17 | 29% |
| *Grewia flava* | 5 | 5 | **17** | 1 | 4 | 32 | 53% |
| *Tarchonanthus camphoratus* | 0 | 5 | 3 | **7** | 3 | 18 | 38% |
| *Themeda tiandra* | 3 | 1 | 1 | 4 | **3** | 12 | 25% |
| ***Total*** | 17 | 18 | 23 | 20 | 15 | 93 | - |
| ***Producer accuracy*** | 35 % | 27% | 73% | 35% | 20% | - | - |
| **-Overall accuracy: 0.4086, CI (0.3077, 0.5154)**<br>**-Kappa statistic: 0.251**<br>**-McNnemar t-test p value is 0.059** | | | | | | - | - |

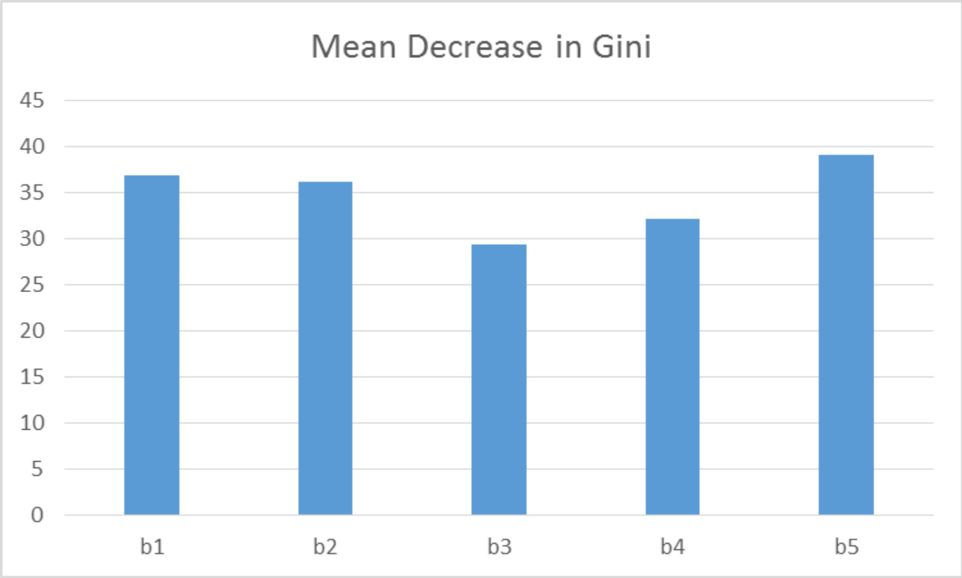


**Figure 10: The importance of wavelengths as measured by the traditional RF using the mean decrease in the Gini index.**

Figure 10 shows the importance of each wavelength band in discriminating between the five species, namely *Tarchonanthus camphoratus, Themeda tiandra, Eragrostis lehmanniana, Acacia mellifera* and *Grewia flava*. Based on the mean decrease in the Gini index, the most important band was the Near Infrared (Band 5) that is located around 760-880 nm. In addition, the Blue (Band 1: 440-510 nm) and the Green bands (Band 2: 520-590 nm) significantly contributed to the discrimination of these species. The Red band (Band 3: 630-685 nm) did not contribute very much to the species separability. The most important variables are those with the highest mean index.

## 5. DISCUSSION

The majority of the data used for this research was of good quality. The supplied SPOT imagery was clean and could be used immediately after being othorectified. The aim of this study was to investigate the effectiveness of the use of satellite remote sensing data for assessing the success of asbestos mine rehabilitation. Three methodologies were employed in this study to answer the following objectives:

### 5.1 To identify and analyse the Spatio-temporal changes of vegetation cover on and around the rehabilitated mine sites using object-based classification

Change detection analysis conducted on five SPOT images shows minimal changes over time. The results indicate that the overall accuracy for all the five classified SPOT images ranged from 82.14 per cent to 93.8 per cent. The active mine class was classified at the lowest producer's accuracy value of 60 per cent in 2008. The user's accuracy for active mines was the lowest in 2014 at 36.36 per cent. The low figures are attributed to the difficulty of conducting successful classification algorithms over arid regions as a result of compromised spectral reflectance in these areas. There were no producer's or user's accuracies generated for rehabilitated mines in 2008 and 2010, which is consistent with the rehabilitation of the site only beginning in March 2012.

Geerken and Ilaiwi (2004) advocated Landsat TM and SPOT remotely-sensed datasets for assessing surface mining programs in an efficient, rapid and affordable manner. Luque (2000) emphasised the significance of periodic classification as well as assessing the aerial range and position of land degradation associated with mining, for use in formulating strategies for land reclamation once mining has ceased. The literature brought forward an argument that revegetation gives support and structure to mine soil growth, generates a beautiful and aesthetically pleasing landscape, and promotes post-mining land use.

Based on the results obtained from this study, it appears as if the process of mine rehabilitation is progressing well. There was, however, a fluctuation of vegetation growth rate on the rehabilitated sites during the time from 2012 to 2016. This fluctuation could have mainly been due to the landscape ecology and rainfall of the area. The majority of the province receives less than 400 mm of rainfall annually and the climatic conditions in the Northern Cape are mostly dry and very hot. The climate in the eastern parts of the Northern Cape is by far the hottest and most extreme in Southern Africa. The landscape is made up of vast arid flatlands with unsystematic rocky outcrops. The western coastal region, which receives small amounts of winter rain, is dominated by succulent shrubs.

The results confirm Prakash and Gupta's (1998) assertion that change observation utilising satellite information permits a convenient and unchanging prediction of change in the land activity tendency over large regions. Successful examination and restoration strategies are dependent on the timely observation of vegetated regions, so that plant development and strength may be routinely gauged and restorative action tackled if required (Rathore and Wright, 1993). The results of the current study indicate that SPOT-based change detection can provide information related to the assessment of mines under rehabilitation. This is consistent with the findings of several similar studies (Fraser et al., 2005); (Gillanders et al., 2008) (Huang et al., 2006) assessed the desertification processes using a time series of SPOT-Vegetation images. (Yadav, 2011) combined the use of Landsat imagery with physicochemical analysis of surface water samples of the post-mining lakes in central Germany to evaluate the environmental conditions and to develop a monitoring system for surface mining.

### 5.2 To quantify the changes in the vegetation cover of rehabilitated mine sites using NDVI and time series analysis?

This study explored the use of the NDVI to assess the change in vegetation on the rehabilitated mine site. The 2008 NDVI values ranged from 0.561 to -0.361, with the low values mainly located within the AOI where the land was severely degraded. The 2010 NDVI values were also low within the study area, ranging from 0.028 to -1.599, again indicating degraded land. The 2012 NDVI map shows a slight improvement within the mine boundary although the values are still low ranging from 0.345 to -0.474. This makes sense since the imagery was collected only a few weeks after the area was revegetated. A significant change was noted in the 2014 and 2016 NDVI values; 0.561 to -0.361 and 0.610 to -0.161 respectively. This indicates that the grass on the rehabilitation site was growing well.

The progress in vegetation growth as indicated by the NDVI values at the rehabilitation site confirms that revegetation is an effective and reliable method for rehabilitating mines. The difference between vegetated and non-vegetated areas was quantified using the histogram operation in TNT Mips software (Micro Images, Inc.). A 9 per cent increase in vegetation was observed in the AOI when comparing 2008 (before the implementation of rehabilitation) and 2016 imagery (four years after revegetation began).

The variation in the results from year to year can be attributed to the rainfall of the preceding rain season or the variability of the onset of the growing season. Rainfall is scarce in the Northern Cape Province, especially in the area of study, and has a major impact on vegetation growth and this leads to notable changes in NDVI from year to year. As a result, this makes it difficult to identify and monitor the trends. However, the research managed to grasp a 9 per cent increase in the vegetation of the rehabilitated mine site and means the rehabilitation process is progressing very well.

## 5.3 To map the grass communities on and around the rehabilitated sites using Random Forest (RF) classifier

Classification was done using RF classification to map out the flora species inside and around the rehabilitated mining areas. The distribution of *Tarchonanthus camphoratus*, *Themeda tiandra*, *Eragrostis lehmanniana*, *Acacia mellifera* and *Grewia flava* in the study area was shown. The species are not regularly distributed over the study area.

RapidEye and RF algorithms did not successfully discriminate these five species because the overall accuracy (40 per cent) and kappa statistic (0.251) were weak. This could be attributed to the landscape ecology, soil type and rainfall proportionality of the area. Generally, Whitebank has very unique landscape ecology, and as a result, only a few plant species survive the area. Most of the species that were identified are shrubs that naturally grow on hills and in mountainous regions. *Acacia mellifera* was mostly found and collected in clay soil conditions. Even during the data collection stage, the *Acacia mellifera* GCPs were acquired in a harmonized landscape where there were no hills and mountains. It is relevant that mostly *Acacia mellifera* was located and distributed near and around the mining sites.

The study area is scattered with rocks that make it challenging for some plant species, such as *Eragrostis lehmanniana*, to grow. The spatial distribution analysis concluded that *Tarchonanthus camphoratus* is evenly distributed throughout the study area compared to the other plant species. This species can survive and thrive under harsh environmental conditions that many other plants cannot tolerate. One other aspect could be that the data was acquired in November, which is the blooming season of the species.

Although the Northern Cape is a semi-arid region with minimal rainfall, the plant species identified in this study are able to withstand these harsh conditions and can grow successfully. *Tarchonanthus camphoratus*, being the most adapted to this environment, is the most widely dispersed species followed by *Grewia flava* and *Themeda tiandra*, which is mostly found on the northern side of the Whitebank where there are many hills. *Eragrostis lehmanniana* is also located near the mining sites and on the south-eastern side of Whitebank.

Another study conducted in the area (Mureriwa et al., 2016) examined the spectral separability of *Prosopis glandulosa* (mesquite) from co-existent species using field spectral measurements. Results from this study showed that mesquite can be discriminated accurately from other species in an arid environment of South Africa using hyperspectral data and machine learning algorithms. Using RF, they were able to classify four species, namely: *Prosopis glandulosa*, *Acacia karroo*, *Acacia mellifera* and *Ziziphus mucronata*. They were also able to generate 77 per cent kappa statistic and 80 per cent overall accuracy.

The regions in which the Mureriwa (2016) study and the current study were conducted are in different locations within the Northern Cape Province, with the former being in the northwest part. The landscape ecology of the two study sites is vastly different, with the rainfall proportionality being better in northwest part compared to Whitebank. This means that the plant vigour will be more affected in the Whitebank area, which can explain the misclassification experienced in the current study. However, it should be noted that using a spectrometer has a better chance of getting higher accuracy compared to using satellites that only take snapshots. The spectrometer takes advantage of the field frequency thus making it better.

## 5.4 The effectiveness of using remote sensing for assessing mine site rehabilitation success

This study aimed to investigate the effectiveness of the use of satellite remote sensing data for assessing the success of asbestos mine site rehabilitation. All the three methodologies that were employed to achieving the aim of the study produced favourable results. Following the LULC analysis; it became evident that remote sensing plays a significant role in monitoring the effectiveness of the mine site rehabilitation. The LULC showed that there was a marked improvement of grass in the rehabilitated area from 2008 to 2016 and was consistent in that no rehabilitated values were obtained for 2008 and 2010 before the revegetation was done. The NDVI values increase in the mine boundary in 2014 and 2016, and values for 2008 and 2010 are consistent with the timing of the rehabilitation of the site. Dominant plant species were classified using RF classifier *Tarchonanthus camphoratus* was the most widely distributed species followed by *Grewia flava* and *Themeda tiandra*, which is mostly found on the northern side of the Whitebank area where there are many hills. The results show that remote sensing can be used as an efficient and cost-effective tool to track the progress of mine site rehabilitation. Results of the statistical analysis were in agreement with the qualitative information provided by field observations and visual interpretation of the SPOT imagery. Remote sensing provided invaluable information to characterise and measure the effectiveness of the mine rehabilitation success, condition, and functioning. SPOT data and RapidEye imagery were used to delineate rehabilitated areas and provide information on dynamic rehabilitation extents.

## 5.5 Limitations

The results are favourable especially for LULC and NDVI maps. However, limitations were noted:

- The lack of socioeconomic data and difficulties encountered when accessing the whole study area presented some drawbacks to the study.
- The range of the study was limited due to the poor quality and extent of the satellite imagery available, especially for 2008.
- The satellite data available for the study area were all acquired for consecutive months (November, December and January). Although the temporal differences were not

large, some spatial variability in the land use changes, sun angle and altitude, cloud cover and shadows contributed to additional processing. Using radar imagery to overcome the cloud problem would be recommended because radar can penetrate cloud and shadow.

- Due to the spatial resolution difference for SPOT-5 and SPOT-7 images, a resampling was done during the pre-processing stage that may have compromised the extent of the images.

**5.6 Recommendations**

The use of RapidEye Imagery and RF classification did not yield positive results. According to Cuong-Nguyen, HaNam-Nguyen and Yong (2001), classification accuracy of RF classifier can be improved by using feature impurity and Bayesian probability. This is recommended as an improvement on the current study. Furthermore, the use of hyperspectral data and machine learning algorithms can yield more accurate results especially in semi-arid regions like the Northern Cape (Mureriwa et al; 2016)

**5.7 Conclusions**

The research has shown the necessity of utilising remotely sensed data to track the progress of mine site rehabilitation. For the purposes of this research, SPOT and RapidEye imagery was utilised satisfactorily for the detection of vegetation classes. This was done for SPOT imagery obtained in 2008, 2010, 2012, 2014 and 2016 where NDVIs were computed to generate values to track the vegetation cover of rehabilitated mine sites. Progress in vegetation was observed, especially for the year 2014 (2 years after rehabilitation had begun) and 2016 (4 years after rehabilitation had begun). The study showed the potential of remote sensing technology as a plausible tool for assessing mine site rehabilitation progress using high-resolution satellite imagery.

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# 7. APPENDICES

## Appendix 1- Plant Species

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***1.Acacia Mellifera***

***Family FABACEAE***

***Genus Acacia***

***Specie mellifera***

Acacia mellifera is very drought resistant, hardy, thickset, deciduous Acacia with vicious, hook thorns. The bark is purplish-black on the young stems and turns grey with age.

The leaflets are blue-green, round and quite large for an Acacia. It blooms profusely from September to November with scented, white, puffball flowers that are especially fragrant at night. These are followed by small, beige pods that are very nutritious. It makes a good screen and security fence as it can form impenetrable thickets. It is a small tree with character and a good bonsai subject.

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2.***Grewia Flava***

***Family MALVACEAE***

***Genus Grewia***

***Specie flava***

Grewia flava is a hardy, medium sized, drought resistant, deciduous shrub with blue green foliage with an asymmetrical base. It bears abundant, yellow, scented, star-shaped flowers from October to March. When this compact shrub is in full flower it is a sight to behold. The flowers are followed by 2 lobed, edible fruit that are irresistible to birds. Plant in a sunny spot in well-drained soil. It is a good fodder plant for cattle and game.

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|  | 3.***Tarchonanthus camphoratus***<br><br>***Genus Tarchonanthus***<br><br>***Specie camphoratus***<br><br>Tarchonanthus camphoratus is a hardy, large, decorative, evergreen shrub or small tree with attractive silver foliage that smells of camphor when crushed. Sprays of white, thistle like flowers covered in white woolly hairs are borne from March to November. All parts of the plant are aromatic and smell strongly of camphor. This useful plant makes an excellent screen and windbreak. It has a fibrous root system and can be used for binding the soil. It also makes a lovely shade tree for a small garden. This drought resistant shrub is heavily browsed on by game. Used extensively as a medicinal plant. The wood is beautiful and among other things has been used to make musical instruments. |
|  | 4.***Eragrostis lehmanniana***<br><br>Generally, Eragrostis lehmanniana propagates exceptionally between 1000-1500 m. It acclimatizes to semi-arid regions and is tolerant of drought. It thrives in areas of low rainfall of 300-500 mm and favours light to medium soils of pH 7.0-8.5. This tree species allows high pH which originates by calcium and magnesium preferably by sodium.The species is widely used to re-seed rangeland because it provides a quick soil cover (FAO, 2011). Eragrostis lehmanniana has been extensively utilised for stabilising the roadsides and range restoration many deserts in the United States (Uchytil, 1992). |
|  | 5. ***Themeda triandra***<br><br>**Family: *Poaceae* (grass family)**<br><br>It is common in South Africa, germinating in composed grasslands to savanna and in regions of normal to outrageous rainfall. While the grass propagates in any kind of soil, it favours soils with high organic content as well as clay soils. It is an everlasting or undying grass that is extremely changeable in development and magnitude, fluctuating from 0.3-1.5 m in altitude. In high altitude areas plant is prone to be dark purple and shorter in as much as at low altitude areas, plants are purple and always light coloured. Blooming time is usually October to July |