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Monitoring the impact of coal mining on vegetation cover changes over the last four decades in the coalfields region of Ermelo using Landsat earth observation data

Dudumashe, Noluvuyo

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Monitoring the impact of coal mining on vegetation cover changes over the last four decades in the coalfields region of Ermelo using Landsat earth observation data

Noluvuyo Dudumashe (1779167)

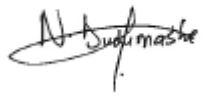
A research report submitted to the Faculty of Science, University of the Witwatersrand, Johannesburg, in partial fulfilment of the requirements for the degree of Master of Science (Geographical Information Systems and Remote Sensing) at the School of Geography, Archaeology & Environmental Studies

Supervisor: Dr Elhadi Adam

2020

Declaration

By submitting this thesis, I Noluvuyo Dudumashe (1779167) declare that the entirety of the work contained therein is my own, original work and that I have not previously in its entirety or part submitted it for obtaining any other University qualification.



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Abstract

Mining poses a major threat to grass communities and environmental systems. Hence, it is necessary to determine the state of vegetation cover around mines. This study compared three sensors (WorldView-2, Sentinel 2 and Landsat 8) to map grass cover within a mining landscape. The study established that the WorldView-2 image, with 88.5% accuracy, was superior in classifying grass communities. Results also established that *Erogrostic gummiflua, Monocymbium ceressiiformer, Seriphium plumosum* and Mixed-grass communities were most dominant within the study area. The study also sought to determine the value of Worldview 2 bands and Normalized Difference Vegetation Index on Landsat data to determine grass communities and other land use and covers. The results established reliable accuracies in mapping grass communities and other land use/ land covers. The results demonstrate the value of the above-mentioned data set in detecting grass community changes in a mining area.

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Abbreviation and acronyms

ETM+	Enhanced Thematic Mapper Plus
GPS	Global Positioning System
MLC	Maximum Likelihood Classifier
NDVI	Normalized Difference Vegetation Index
SVM	Support Vector Machine
AMD	Acid Mine Drainage
WV-2	WorldView-2

CHAPTER 1
GENERAL INTRODUCTION

1.1 General background

South Africa is endowed with an abundance of mineral resources, accounting for a notable amount of world production and reserves, specifically gold mining, which has helped in the growth of the country (McCarthy, 2011). SACRM (2010) state that in South Africa, coal is primarily used by Eskom to produce electricity and Sasol to produce liquid fuels and chemicals. The Mining Industry has been an important component as it contributes to the economy of South Africa (Swart, 2003; Tanner and Möhr-Swart, 2007). McCarthy (2011) further stated that the environmental effects of mining particularly mining from coal would be massive globally and includes issues of acid mine drainage (AMD). Coal industry threatens the ecosystem of the coal mining areas (Fan *et al*., 2003). According to McCarthy (2011), mining activities create negative effects on the environment during mining operations period and beyond closure.

Globally, vegetation is important and most valuable biosphere for various purposes such as habitat, soil stability and floods control (FAO, 2003). According to Carlier *et al.* (2009), the grass communities are the most presiding cover, roughly 52.5 million km^2 (40.5%) of the global coverage. Matsika (2007) stated that the grass communities in South Africa are the second of the largest biome, 16.5% of the country's coverage. Once a vegetation system is degraded, it is often costly and technically challenging to restore, and can be practically impossible to remediate in some instances (Thirumalaivasan *et al*., 2003). Many of these effects may affect and distress the growth of the environment directly or indirectly. Vegetation cover is an important and most useful aspect for evaluation of environmental conditions. Changes in the patterns of vegetation may also change the structure and functions of the landscapes causing the disturbance in ecological processes (Wang *et al.,* 2015). Heavy rainfall that results in flooding of the surface may lead to vegetation cover destruction, which is a negative impact, since vegetation cover may prevent soil erosion, landslides, surface roughness and sediments transportation into the river.

Grassland degradation strongly overwhelms characteristics of soil negatively such as soil stability, chemistry and texture, which influence the vegetation to grow (Dunn, 1989). Changes in the pattern of vegetation growth may also change the structure of the landscape and disrupts the ecosystem. Mpumalanga Province comprises grass biome that has the highest biodiversity in South Africa after the Fynbos biome (Driver *et al*., 2004). With the absence of trees, geophytes are often dominant except in a few localised habitats (Low and Rebelo, 1996). According to UNESCO (1996), in South Africa, approximate 40% of the grassland is irreversibly changed and 60% of grassland, remaining is threatened and about 3% is under formal protection. Mining in

Mpumalanga Province is growing extensively. It drastically transforms the relief, removing a large volume of soil, changing the soil stability and coverage of vegetation of the mined areas. The growth of vegetation around mining is slowly due to mines.

Remote sensing techniques are capable of mapping vegetation cover and other land use/land cover change and have a broad spatial cover. Many researchers have successfully used remote sensing in classifying grass communities. However, the use of multispectral satellite imagery particularly Landsat data, in classifying grass communities can be challenging. Remote sensing, as defined by most scholars, is the science of obtaining information about objects or areas on the Earth's surface without direct contact to that specific object (Aggarwal, 2004). The information is acquired through satellite images. Satellite images have been successfully employed to monitor and quantify water and vegetation cover changes (Makinde and Salami, 2013; Ahmad, 2012; Nemani *et al.*, 1996). WV-2 is distinguished by the highest and finer resolution. Over the decade, multispectral data have been used for many years in classifying landscape. Although the results have been good, it remains that classifying vegetation communities in the complex landscape using multispectral data is a challenge. Classifying grass communities demand information that is accurate about their spatial distribution. In this study, the use of the advance and robust RF classification using three imagery in classifying grass communities of Ermelo region will be conducted. Furthermore, the state of grass communities using the commonly used NDVI technique on the Landsat imagery will be done.

1.2 Problem statement

According to Erener (2011), opencast mining disturbs large areas of land including the grassland and could bring more environmental challenges in future. Some of the challenges brought up by the mining industry include pollution, which is a serious problem. Coal mining in some of the areas has recently become a concern (McCarthy and Pretorious, 2009). Bell *et al*. (2001) stated that the environment seems to be degrading more than before. The grassland biome of South Africa is critically at risk (Olsen and Dinerstein, 1998; Reyers *et al*., 2001) and demand conservation attention (Rebelo, 1997).

Grass biome provides important roles in the environment (Boval *et al*., 2002). Bell *et al.* (2001) noted that distortion in the natural balance of the vegetation cover is of serious concern within the mining environment. According to SANBI (2013), about 40% of the grassland biome has been changed and affects their important capacity. SANBI (2013) released a list of the vulnerable biodiversity across South Africa, with Mpumalanga Province grass communities being classified as the most threatened.

1.3 Aim and Objectives

1.3.1 Aim

The study aims to establish how historical activities of mining between 1978 - 2018 affected the grass communities cover in the coalfields and determine the extent of common grass communities growing in the area, using remotely sensed data and classification.

1.3.2 Objectives

- To assess the use of WorldView-2, Sentinel 2 and Landsat 8 images along with the random forest classifier in the detection of grass communities in the Ermelo coalfield.
- To determine changes of the grass communities health due to mining using multi-temporal remotely sensed data (Landsat Imagery) and change detection techniques.
- To establish the connection of the spatial distribution of vegetation condition with mining activities.

1.4 Research report outline

This dissertation comprises five chapters. The chapters covered are background and introduction, literature review, methodology, results, discussion and conclusions. The chapters are outlined as follows:

1.4.1 Chapter 1: General background

This chapter focuses on the background of the study area, research aim, and objectives, problem statement, research methodology and further outlines the rest of the chapters.

1.4.2 Chapter 2: Literature study

The review of papers on how remote sensing has been used in mapping the grass communities is outlined in this chapter. The concept of mining impact is explained in detail according to the findings of the studies that were conducted. The impacts of coal mining on vegetation according to past studies are also documented in detail. The methods that were utilised in these studies are also briefly explained. The advantages and disadvantages of using these methods are also reviewed. Relevant literature on remote sensing as the main part of the study is also explained in

detail as well as the past papers that used remote sensing techniques for water extent and vegetation mapping.

1.4.3 Chapter 3: Methodology

Chapter 3 discusses the methods used to process and analyse remote imagery and field data to achieve the aims and objectives of the project.

1.4.4 Chapter 4: Results

The results chapter includes the results of the data analysis.

1.4.5 Chapter 5: Discussion and Conclusion

This will focus on the discussion of the results of this study. It covers the conclusions that are made based on the findings. Recommendations of the study are also documented.

CHAPTER 2
LITERATURE STUDY

2.1 Mining and the natural environment

Mining poses a serious threat to the environment, with some of the notable primary effects (Bell *et al*., 2001). UNESCO (1996) noted that minerals from the mine have posed a serious risk to the environment such as abrasion of soil at a massive scale, water and land and reduction in biodiversity. The mining, particularly coal, seriously threatens the ecosystem and soil stability (Fan *et al*., 2003). Bell *et al*. (2001) stated that acid mine drainage is an accountable issue for the last decade through the generation of mine drainage. This harm water quality, as well as a notable effect on the aquatic environment and surrounding native vegetation. These have a detrimental effect on water quality, as well as a notable impact on the aquatic environment and surrounding vegetation. Additional effects of dust are struggling to quantify, but probably do have some effect on biodiversity, particularly during the dry season and for the duration of mine activity. After mine closure, the impacts remain critical for significant periods. Various diversity and system function may start to return after a few decades, but the information is limited. Acid mine drainage has become an environmental problem for lifelong of the country's freshwater supply and vegetation. This environmental problem may cause some areas to be devoid of vegetation (McCarthy and Humphries, 2013).

2.2 Coal mining effects on vegetation

Over a decade, researchers pose concentration on the consequences of open-cast mining on dispersing toxic chemical metals. These studies showed a high level of heavy metal in mining and soils affected by the oxidation of pyritic material (Pérez and Calvo, 1992; Taylor *et al*., 1992; Taylor *et a*l., 1993; Monterroso *et al*., 1999; Clark *et al*., 2001). Toxic metals can be leached to the soil and their toxicity controls on factors such as concentration, speciation and bioavailability. This results in a slowing of the rate of biomass growth, which is caused by fading of vegetation. The problems can exist in soils polluted by toxic metals related to mining activities if the contaminants reach the level, which prevents the growth of a protective layer of vegetation. This causes the soil to be eroded and spreading pollutants to surface and water (Ristic *et al*., 2001). The water seepage acidity and high concentration of total dissolved solids adversely affected vegetation locally. Mining, and in particular coal mining, is one of the main driving forces of land degradation in some regions of the globe (Gisladottir and Stocking, 2005; Lechner *et al.*, 2016). Vegetation cover change is a very significant indication of the ecological environment change (Sun *et al.,* 2008). Quantification of the important drivers of vegetation change is vital for the informed management of vulnerable habits (Rose *et al.,* 2016 and Liu *et al.,* 2016). A number of

studies in recent years have been interested in the examination of widespread vegetation changes (Chen *et al.,* 2014; Elliott *et al.,* 1998). Many of these authors noted that changes in temperature, soil moisture and water in the area could alter the vegetation cover characteristics (Stow *et al.,* 2004).

2.3 Grass quantity and quality mapping using remote sensing data

According to Ustin *et al.* (2009), there is a growing awareness among environmental scientists that remote sensing can and must play a role in providing the data needed to assess ecosystem conditions and to monitor change at all spatial scales. In the past few years, different vegetation types and ecosystems have been successfully mapped using multispectral data. Using integrated LIDAR data in combination with multispectral images to classify vegetation in Canada, Bork and Su (2007) reported an overall accuracy of 91%. In Finland, Toivonen and Luoto (2003) used Landsat imagery in mapping grasslands and achieved high accuracy results of 89%. Baldi *et al*. (2006) differentiated grass communities of South America with accuracies of 90% and 95%; (Masocha and Skidmore, 2011) achieved an overall accuracy of 80% in their study when they discriminated different season grasslands in the USA. Remote sensing and modelling approaches allow for large scale monitoring, quantification and prediction (Gao, 2006) of different phenomena occurring on the surface of the earth at varying spatial and temporal resolutions (Nordberg and Evertson, 2003).

The assessment of grassland use and monitoring of changes over time has been done in a number of studies. In Peru, object-based classification of Landsat image between 1987 and 2007 was used to investigate changes in a grassland ecosystem, yearly decrease in the spatial size on grassland ecosystem was observed and overall accuracy of 80.3% was achieved. Price *et al*. (2001) investigated the potential of Landsat and Synthetic Aperture Radar (SAR) imagery together with the dataset to discriminate among three commonly used grass in areas with high cool and warm-season grasses in the USA. An accuracy value of 91% was achieved using Landsat data and 73.2% using the SAR data. Masocha and Skidmore (2011) implemented a hybrid classification method in southern Zimbabwe to map invasive species. This study noted that it is often difficult to identify necessary pure endmembers in an image, especially on sparsely vegetated surfaces.

2.4 Impact of the degradation of the grassland communities

Vegetation plays a vital role during extreme events like floods, such as dissipating flows and stabilising banks by preventing erosive forces of overland flowing (Hickey and Salas, 1995). However, in most cases, vegetation cannot withstand the forces of these overflows. Latham *et al*.

(2014) stated that one of the most extensive vegetation types is grass biome. According to Derner and Schuman (2007), the grasslands are the largest terrestrial carbon sink after forests. Grass provides a lowest-cost feed source for animals and contributes to controlling natural disasters such as floods (FAO, 2003). Human activities, coupled with unfavourable conditions of environment causes changes in the grass communities.

Grasslands are among the ecosystems with the highest species richness in the world (Wilson *et al*., 2012), and they provide a wide range of ecosystem services. Grasslands play an important role within the global carbon cycle, as 90% of their biomass is below ground, accumulation rates are high, and decomposition of organic material slow (Gibson, 2009). As the main forage resource for livestock, grasslands are important for human well-being in many regions. They facilitate infiltration of water into the soil and thus to the maintenance of hydrological cycles. Finally, grasslands contribute to the landscape beauty of many regions.

2.5 South Africa grassland biomes

According to SANBI (2007), the grassland communities is the second largest biome in South Africa and occurring in eight provinces. SANBI (2007) stated that approximately 30% of the grass biomes has been transformed beyond repair and only 2% formally conserved. Grass biome in South Africa is critically vulnerable and threatened (Olsen and Dinerstein, 1998; Reyers *et al*., 2001). Grasses provide a wide range of ecosystem services that facilitated human settlement in the area in the past (O'Connor and Bredenkamp, 1997; Reyers *et a*l., 2001). These include energy supply, provision of food through current agricultural activities and forage for livestock (Reyers *et al*., 2001). At least 29.2% of its entire area has been transformed by human land use (Fairbanks *et al*., 2000; Neke and du Plessis, 2004) and it is the most threatened biome across South Africa. The loss of habitat through LULC changes are anticipated to be the main threat to biodiversity (Sala *et al.,* 2000) and more information about this phenomenon is needed. The processes behind the ecological results of land cover change should be a conservation planning priority for the biome (Rouget *et al*., 2003; Williams, 2007).

Jeyaseelan (2003) noted that vegetation condition reflects the overall effect of rainfall, soil moisture, weather and agricultural practices. According to Lui *et al.* (2016) changes in vegetation directly or indirectly shapes the biosphere-atmosphere interactions including the hydrological cycle. Concerning vegetation growth, Lui *et al.* (2016) noted that the growth cools the local land surface temperature. This study has shown that increased vegetation coverage results in changes in water resources, which is a major element of the most ecological regions. This leads to a conclusion that vegetation may be good as well as bad for most of the delicate ecosystems (Lui *et al.,* 2016).

2.6 The use of Landsat 8, Sentinel 2 and Worldview-2 for grassland classification

Advances in sensor technology with improved image acquisition characteristics have greatly increased the ability to distinguish the structure, phenology and physiology of vegetation, providing new insights into the seasonal monitoring grassland. According to Adam *et al* (2010), in situ hyperspectral data is used as one of the most advanced remote sensing technology for discrimination of vegetation at the species level. Its measurements have been successfully acquired to extract and understand species spectral profiles (Adam *et al*., 2010). Several authors noted that the hyperspectral data acquires detailed spectral data using hundreds of narrow bands, ranging from the visible, near-infrared, to the shortwave-infrared portions of the spectrum (Adam *et al.*, 2012; Adelabu *et al.*, 2014; Liu and Cheng, 2011). This enables accurate and reliable seasonal spectral separability of C3 and C4 grasses. However, previous studies have noted that the high expenses required for the acquisition of hyperspectral data, as well as the high dimensionality, inherent multicollinearity associated with the data and technical difficulties (Adam *et al.*, 2012; Adjorlolo *et al.*, 2013; Peerbhay *et al.*, 2015).

The new generation of multispectral sensors that has emerged, which is characterised by strategically-positioned spectral bands, notably the Landsat 8 Operational Land Imager (OLI), Sentinel 2 Multispectral Instrument and Worldview 2 presents a valuable opportunity to monitor the seasonal variations of C3 and C4 species functional types (Shoko *et al.*, 2016). These sensors have enhanced image acquisition characteristics for detecting subtle spectral seasonal variations between C3 and C4 grasses, critical in their discrimination and monitoring. This study noted that the additional red edge bands (four bands for Sentinel-2 and 1 for WorldView-2) are perceived to have the capability of expanding the detection windows for the spectral separability of C3 and C4 grass species. Besides, red edge windows have been reported to be highly sensitive to vegetation species characteristics (Marshall *et al.*, 2012; Mutanga *et al.*, 2012; Rapinel *et al.*, 2014), which improve their ability to discriminate between species. Landsat 8 OLI has also been reported for vegetation monitoring, particularly species biomass quantification and mapping (Dube and Mutanga, 2015; El-Askary *et al.*, 2014; Hauglin and Ørka, 2016). These studies have revealed the potential of the sensor spectral configuration in increasing the monitoring of vegetation at large geographical coverage, in a cost effective manner.

2.7 Vegetation monitoring using remote sensing technique

Remote sensing tools can be used in vegetation monitoring. Satellite-based vegetation monitoring plays a significant role in defining the impacts and mining of their severity. Many types of research have identified the relationships of red and near-infrared (NIR) to the amount of vegetation

existing at a certain area on the ground (Jeyaseelan, 2003). The use of satellite imagery has enabled measurements in the changes in vegetation cover and its health. Zhang *et al*. (2003) noted that several techniques have been developed to determine the vegetation changes using different images of Normalised Difference Vegetation Index (NDVI).

2.7.1 Normalized Difference Vegetation Index

The NDVI is calculated by near-infrared and red reflectance values. Myneni and Asrar (1994) stated that generally, NDVI is less sensitive to differences in illumination and soil state than near-infrared to red reflectance ratio. According to Limpitlaw and Hoadley (2006), NDVI is used as vegetation cover indicator, especially existence and states of the vegetal communities. Detsch *et al*. (2016) also conducted a study on vegetation dynamics using time series analysis from 1982 to 2011. The study showed that the NDVI record that was used proved to be capable of capturing long-term and seasonal vegetation patterns.

Even though NDVI supply researchers with a way to monitor vegetation and tends to tactful reflectance of background (Rocha and Shaver, 2009). This factor is limiting when applied to areas with dense vegetation and various crops (Huete *et al*., 1997). Optical methods have been utilised in monitoring vegetation changes over large areas, but there are restrictions such as cloud cover, specifically in tropical regions (Engelbrecht *et al.,* 2013). According to Govaerts and Verhulst (2010), satellite-based NDVI is influenced by many factors that are not vegetation, and these are factors such as atmospheric conditions. Ryan (1997) noted that the measurements of NDVI are based on the proposition that growing plants absorb radiation in the visible region and strongly reflect radiation in the Near-Infrared region. The satellite-based NDVI is calculated using the formula,

$$\mathbf{NDVI = (NIR-Red)/ (NIR+Red)} \qquad \mathbf{(1)}$$

This formula yields the values that range from -1 to +1 usually representing water and the positive values representing the strongest vegetation cover. This formula also allows the understanding of the fact that two identical covers of vegetation could have different values. NDVI has a variety of applications in vegetation related studies as it can be used for estimation of crop yields, pasture performances and many other applications (Panda *et al*., 2010). Other ground parameters are mostly related to NDVI (Ceccato *et al.,* 2001). Numerous researchers have extensively employed the NDVI to analyse the various factors regarding vegetation cover (Lenney *et al*., 1996). With all the uses of NDVI, it becomes significant to utilize NDVI as a vegetation indicator and as a method for change detection calculations.

NDVI has also shown usefulness in measuring precipitation (Birtwistle *et al.,* 2016). Birtwistle *et al*. (2016) used the Normalized Difference Vegetation Index from Landsat imagery to estimate precipitation. The author used NDVI values for 26 years of before and after rainfall, season to determine the change. The study noted that the change in NDVI from pre to post-rainfall season image explained a high percentage of variance in annual monsoonal precipitation totals from a nearby rain-gauge. It was also noted that NDVISs are also useful in determining when and where the flow of events happen. With all the uses of NDVI, it becomes significant to utilize NDVI as a vegetation indicator and as a method for change detection calculations.

2.7.2 Image classification

According to Li *et al.* (2014), remote sensing imagery gives a unique opportunity in determining LULC change through the process of image interpretation and classification. Classification is the method of assigning pixels into different LULC depending on the reflectance of the object being classified. Image classification is a complex process that may be affected by many factors. Paradhan *et al.* (2010) stated that classifications are a statistical method. Ayhan and Kansu (2010) noted that major steps in image classification might include determining the most suitable classification methods, training samples, feature extraction, image processing and selection of suitable classification approaches as well as post-classification processing. How well a classification works may be determined by the accuracy assessment. Different classification algorithms have been successfully applied to gather vegetation information from multispectral and hyperspectral remotely sensed data (Omer *et al*., 2015; Dube and Mutanga, 2015; Adelabu *et al.,* 2014; Mutanga and Rugege, 2006). However, much recognition has been given to the advanced methods of image classification such as support vector machines (SVM), random forest (RF) and artificial neural networks (ANN) due to their greater effectiveness in image processing. The remote sensing technique of image classification is regarded as one of the significant methods.

Scientists and practitioners have made great efforts in developing advanced classification approaches and techniques for improving classification accuracy (Gong and Howarth, 1992; Kontoes *et al.*, 1993; Foody, 1996; San Miguel- Ayanz and Biging, 1997; Aplin *et al.,* 1999a; Stuckens *et al.*, 2000; Franklin *et al.,* 2002; Pal and Mather 2003; Gallego, 2004). However, classifying remotely sensed data into a thematic map remains a challenge because many factors such as the complexity of the landscape in a study area, selected remotely sensed data, and image- processing and classification approaches may affect the success of a classification. Although much previous research and some books are specifically concerned with image classification (Tso and Mather, 2001; Landgrebe, 2003), a comprehensive up- to- date review of classification approaches and techniques are not available.

2.8 Change Detection

Change detection in remote sensing can be defined as a measure of changes associated with land use as well as land cover (Lu *et al.,* 2004; Ramachandra and Kumar, 2004). Change detection is a method used in determining change from two or more dates. This method of identifying change is useful in various applications which include environmental changes. NDVI is being used widely for change detection. NDVI change detection technique uses the initial and final state image to produce a change detection difference map. Zhou *et al.* (2011) investigated two categories for land-cover change which were, categorical change using image classification and quantitative change using vegetation index. Both results of these change detection techniques worked out successfully. This technique is referred to as NDVI differencing is more like any other technique of change detection, however, this method minus the old NDVI image from the newest image. The subtraction is based on the pixel values. NDVI Differencing is formulated as:

$$\textbf{NDVI Differencing} = \textbf{NDVI}_{new} - \textbf{NDVI}_{Old} \qquad (2)$$

$NDVI_{new}$ refers to the NDVI results for the image acquired after the mining and $NDVI_{Old}$ refers to the NDVI results that were generated using the image acquired before mining. Gandhi *et al.* (2015) used the NDVI to present an improved change detection method for analysis. The authors used NDVI differencing as a method of analysis. The results showed that the Normalised Difference Vegetation Index is powerful in detecting changes within the features of an area. The study noted that the NDVI technique gives greater results for vegetation changing in quantity and for sparse vegetation using multi-spectral remote sensing.

2.9 Summary

This chapter comprises the detailed definition of the mining as well as their impacts on grassland cover. From the literature, it is evident that the methods presented are efficient in achieving the objectives that are mapped out for this study. This includes the use of indices, change detection and well as classification methods. Chapter 3 will include the detailed specific methods that will be used for the successful results of this study. The chapter includes the data used and the sources of the specific data as well as the methods of analysis for the acquired data and how each method was used to obtain the results.

CHAPTER 3
METHODOLOGY

3.1 Introduction

This case study highlights remote sensing techniques in monitoring vegetation. Over decades, remote sensing has increasingly been used in mapping vegetation species (Skidmore *et al.,* 2010b; Adelabu *et al*., 2014; Thenkabail *et al*., 2016; Vaglio Laurin *et al*., 2016a; Curran, 1989). Remote sensing has been reported to be timely, a cost-effective technique in providing accurate spatial information on grass species quality and quantity (Ramoelo *et al*., 2015).

3.2 The study area

The Ermelo coalfields are located in Mpumalanga covering an area of approximately 1 977 km^2. Location of the study area is, bestrides headwater region of the primary catchments as Upper Vaal, Olifants, Inkomati, Usutu and Thukela (Figure 3.1). In the west, the Ermelo Coalfield shares a boundary with the Witbank and Highveld Coalfields, and to the south with the Klip River and Utrecht Coalfields of KwaZulu-Natal (KZN) (Greenshields, 1986). Vegetation is mostly savannah grassland, with sparse bushveld where conditions are favourable. This area is covered by active coal mines which were abandoned and are nearby human settlements. The winter that is experienced around May to July is dry and cold, whilst the rainy season is experienced from December to February (Barnard, 2006).

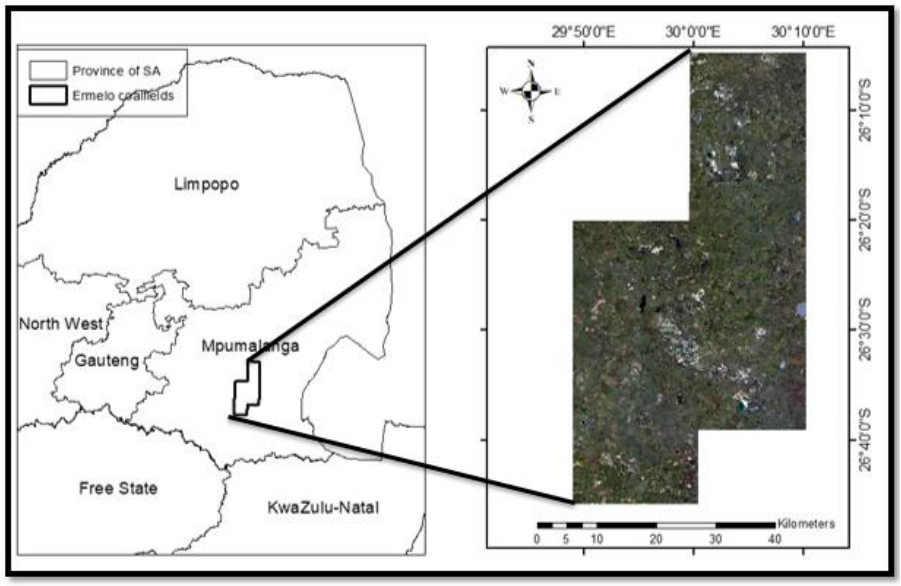


Figure 3.1: Map location for Ermelo Coalfields in South Africa

3.2.1 Vegetation and climate data

The Ermelo Coalfields area consists of different types of grass communities. The vegetation of the area is mostly short dense grassland. Table 4.1 shows pictures of common grass communities that were noticed during fieldwork. There is only one weather station within the area and other stations are surrounded by the study area. Ermelo receives approximately 625 mm of rain per year, with most rainfall occurring during summer (Figure 3.2).

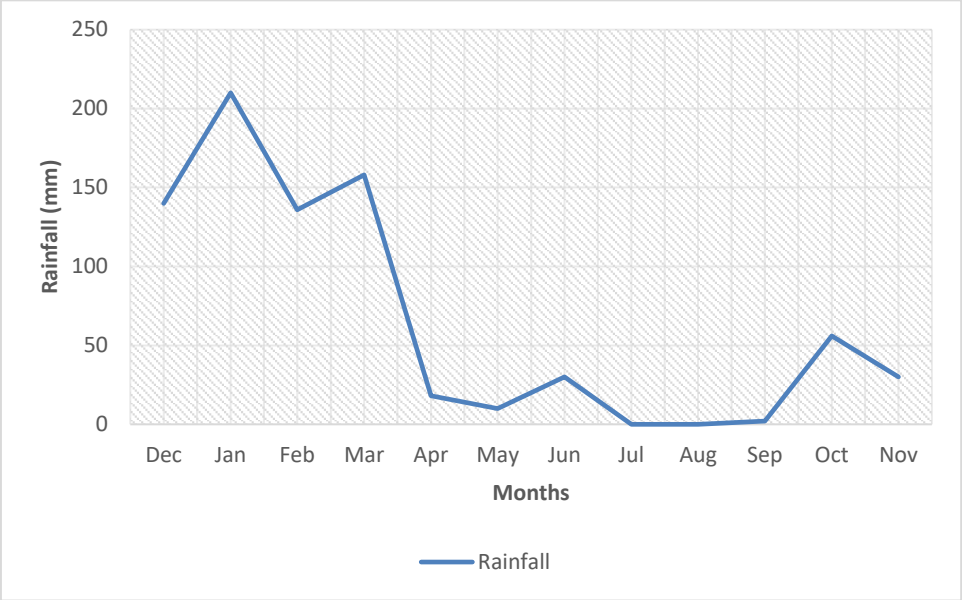


Figure 3.2: Climatic data from Ermelo station showing the temperature and rainfall distribution throughout the year

3.2.2 Geology and mining

Ermelo Coalfields are composed of many seam deposits with the expansion of up to five major coal seam horizons. Coal is hosted in the Ecca Group of the Karoo Supergroup, which dates back to the Permian period between 280 and 250 Ma (Hancox and Götz, 2014) (Figure 3.3). Grodner and Cairncross (2003) stated that the Ecca Group is composed of sandstone, siltstone, mudstone and shales (Grodner and Cairncross, 2003). Coal is mined by opencast methods because the resources are shallow, largely unfaulted and slightly inclined (Chamber of Mines of South Africa, 2017). More geological background and coal seam details of Witbank, Highveld and Ermelo Coalfields can be found in Sakala *et al.* (2018).

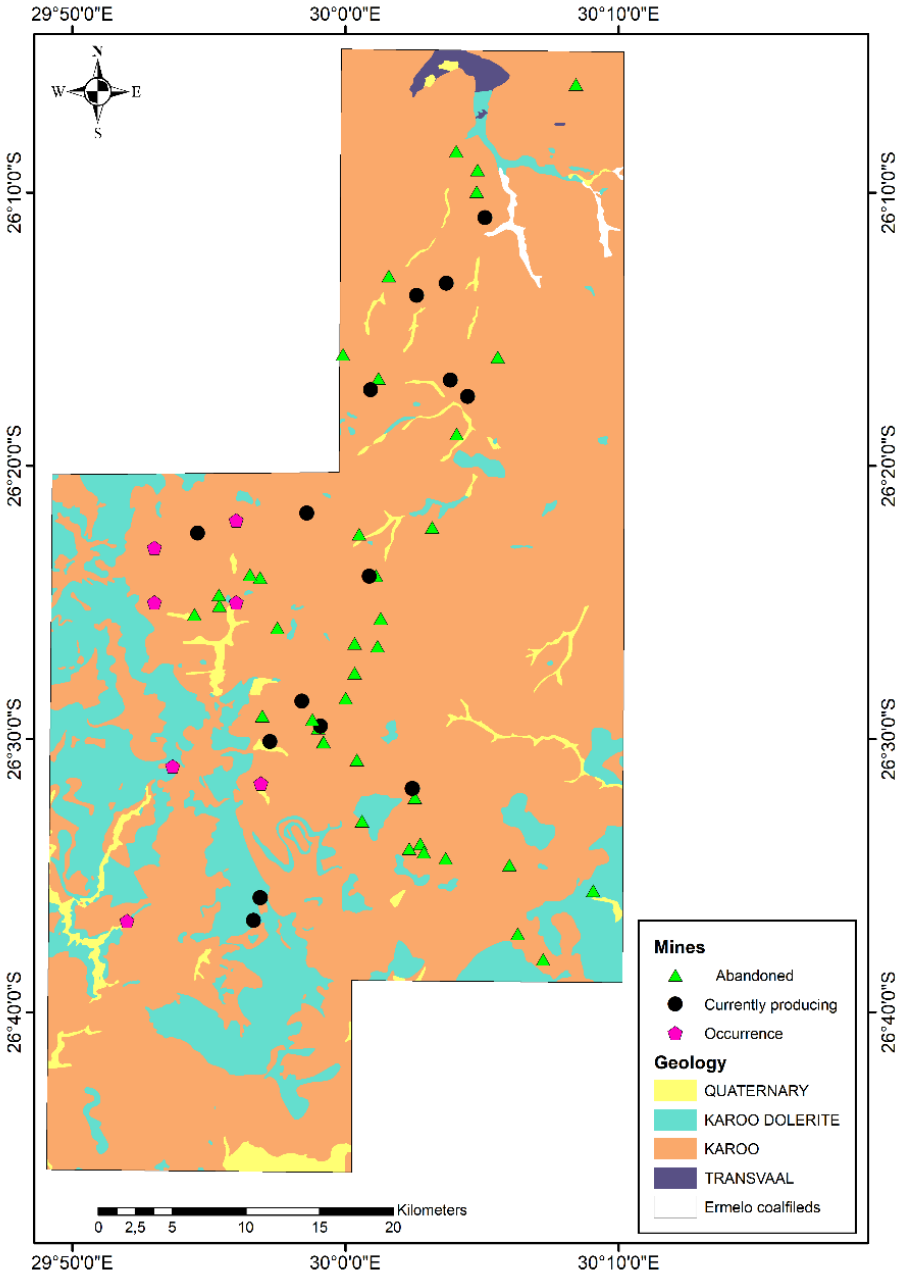


Figure 3.3: Geology of the area with abandoned and active mines

3.2.3 Hydrology

The area falls within the Quaternary drainage region C11B, part of the Upper Vaal water management area. The affected stream is the Humanspruit, which flows in a southeasterly direction to join the Witpuntspruit, and eventually the Vaal River. The Vaal River in this area feeds the Grootdraai Dam, which is situated east of Standerton.

3.3 Material

3.3.1 Satellite data acquisition

Remote sensing satellite data has become an important cost-effective technique in monitoring and evaluating land cover changes (Rawat and Kumar, 2015). To attain the main aim of the study remotely sensed imageries were obtained from different providers. For performance comparison classification, a WorldView-2 (WV-2), Sentinel 2, Landsat 8 as well as five different Landsat images were used for NDVI calculations.

3.3.2 Remote sensing data for classifying the current dissemination of the vegetation cover.

Satellite imagery was used to map the common grass communities distribution pattern in the study area. For the performance of comparison, the three images were used WV-2, Sentinel 2 and Landsat 8. The reason these three data were compared was to collate the execution of the WV-2, Sentinel 2 as well as Landsat 8 images in classifying the grass communities in the coal mining area.

WorldView-2 (WV-2)

WorldView-2 imagery was used for this study to map the common vegetation communities in the study area. WV-2 was launched in 2009 and has very high resolution with the panchromatic resolution at 50 cm as well as the multispectral resolution of 2 m. It was used for this study for the reason that it has a remarkably improved resolution, which for this study can be used for better vegetation species identification. The WV-2 that was utilised was acquired on March 3, 2019, and was provided by the digital globe of no charge. Table 3.1 shows generally designated bands for this satellite imagery. Digital Globe stated that the WV-2 spectral bands are used and matched with recent remote sensing use in classifying the LULC.

Table 3.1: WorldView-2 designated bands

Spectral Bands	**Wavelength min-max (µm)**
Panchromatic	450 - 800
Coastal blue	400 - 450
Blue	450 - 510
Green	510 - 580
Yellow	585 - 625
Red	630 - 690
Red edge	705 - 745
Red edge	705 - 745

NIR 1	770 - 895
NIR 2	860 - 1040

Sentinel 2 data

The Sentinel 2 consists of two satellites produced to help vegetation, LULC and environmental monitoring. This image was launched on 23 June 2015 and provides a high range of multispectral bands with the lack of panchromatic band which disables the production of a set of fine-resolution bands. The image that was acquired in the summer season and it was provided by USGS at no cost. For performance comparison, a Sentinel 2 imagery acquired on 22 February 2019 was used for this study.

Table 3.2: Sentinel 2 designated bands

Spectral 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	20
Band 5- Vegetation Red Edge	0.705	20
Band 6- Vegetation Red Edge	0.740	20
Band 7- Vegetation Red Edge	0.783	10
Band 8- NIR	0.820	10
Band 8A- Vegetation Red Edge	0.865	20
Band 9- Water vapour	0.945	60
Band 10- SWIR- Cirrus	1.375	60
Band 11- SWIR	1.610	20
Band 12- SWIR	2.190	20

Landsat 8 data

For performance comparison, a Landsat 8 imagery acquired on the 22 of January 2019 was used. USGS website earth explorer provided this image at no cost. Landsat 8 was launched on February 11, 2013, in California on an Atlas-V rocket. It has very high resolution with the panchromatic resolution at 30 cm. Landsat 8 was utilised to map grass communities that were identified on the field. Table 3.3 shows the Landsat 8 designated bands.

Table 3.3: Landsat 8 designated bands

Spectral bands	Central wavelength (µm)	Resolution (m)
Band 1- Coastal aerosol	0.43 – 0.45	30
Band 2- Blue	0.45 – 0.51	30
Band 3- Green	0.53 – 0.59	30
Band 4- Red	0.64 – 0.67	30
Band 5- NIR	0.85 – 0.88	30
Band 6- SWIR 1	1.57 – 1.65	30
Band 7- SWIR 2	2.11 – 2.29	30

3.3.3 Landsat data for vegetation cover change

To map vegetation change, multitemporal Landsat images were used. These images were downloaded from the USGS website (https://earthexplorer.usgs.gov/) at no cost. Landsat 3, 4, 5 and 8, were used for the change detection using NDVI time series. Due to the unavailability of the same time scenes, the researcher downloaded another scene one month before or after the image during the summer season. The images were atmospherically corrected using FLAASH plugin in ENVI software. The five images used for monitoring vegetation cover are 16 March 1978 (MSS), 02 February 1988 (TM), 14 February 1998 (ETM+), 29 February 2008 (ETM+) and 20 January 2018 (OLI).

3.4 Reference data for image classification

Ground truthing field data were gathered during the summer season where the remotely sensed data were also downloaded. Ground truth data include grass communities identification and acquiring ground-truthing points using GPS coordinates. The fieldwork was carried out from the 04 to 15 February 2019. In the field survey, eight dominant grass communities were identified. Field data was then used with gathered and digitised points to produced the map displayed as Figure 3.4. Table 4.1 points were then overlaid on WV-2, Sentinel 2 as well as Landsat 8 data to extract the spectral signature of training (70%) and test (30%) data to gather image spectral signature of all classes.

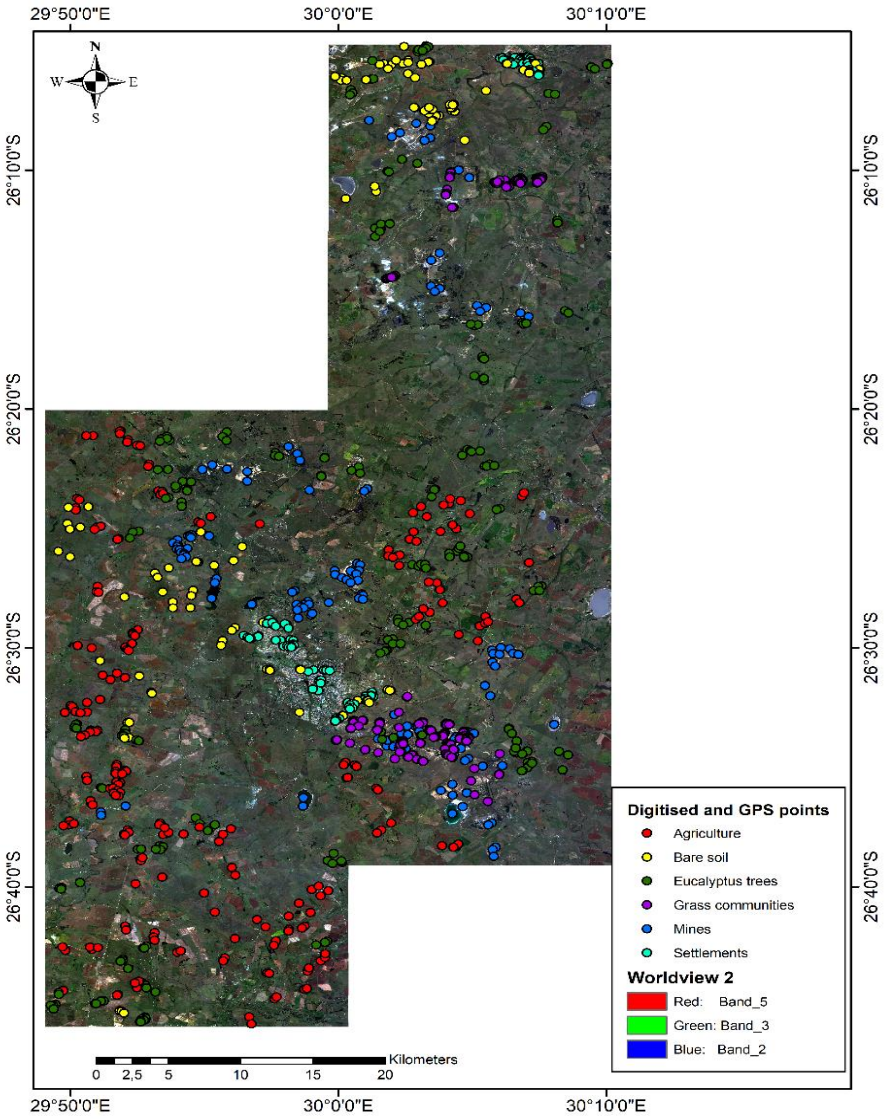
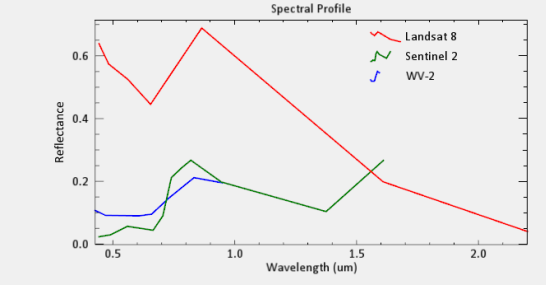
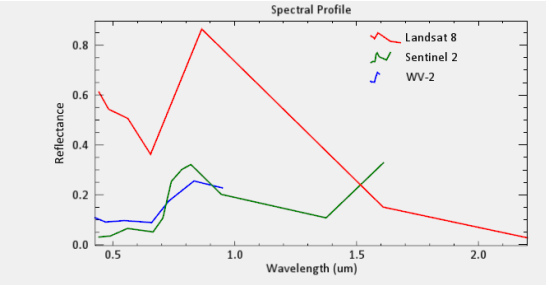
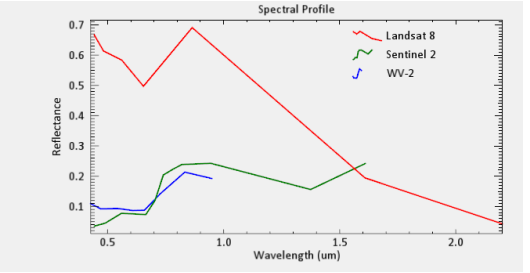
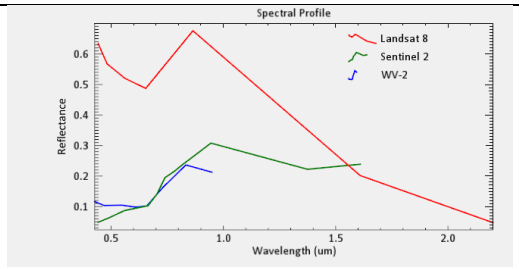
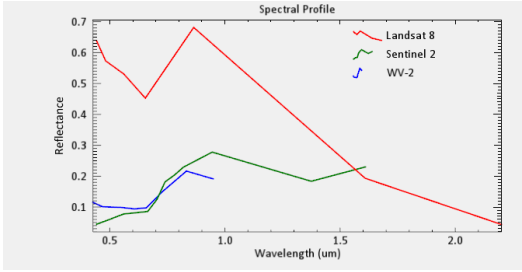
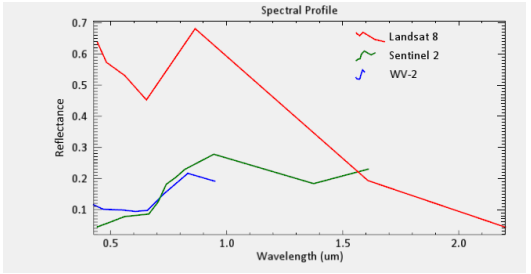
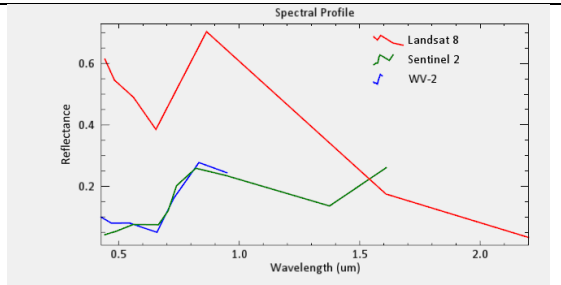
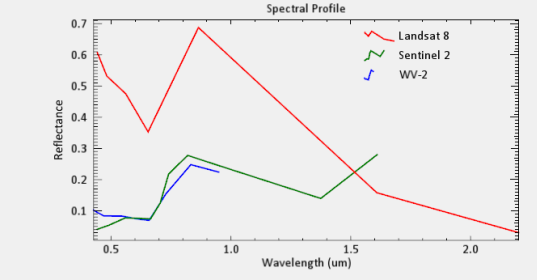
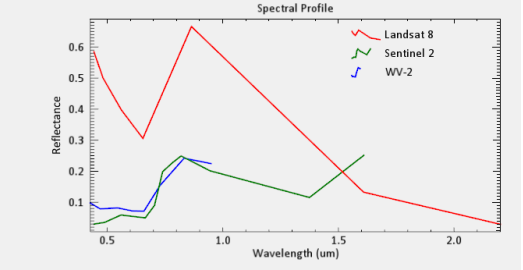
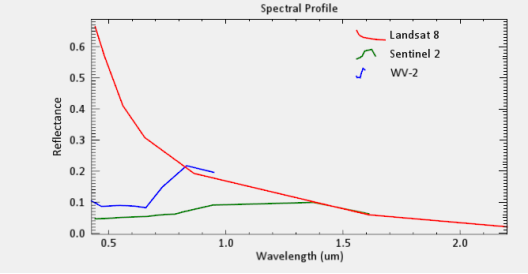


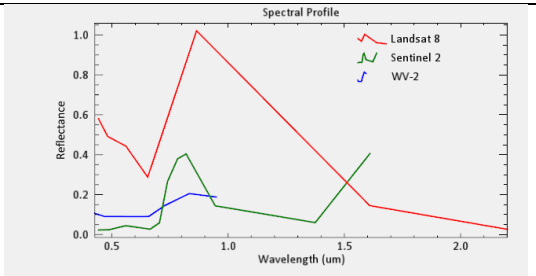
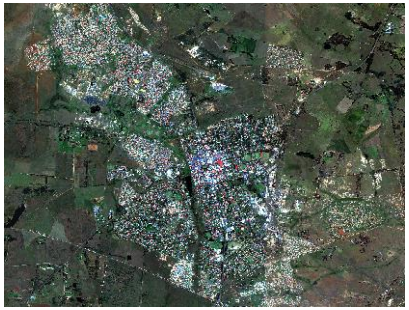
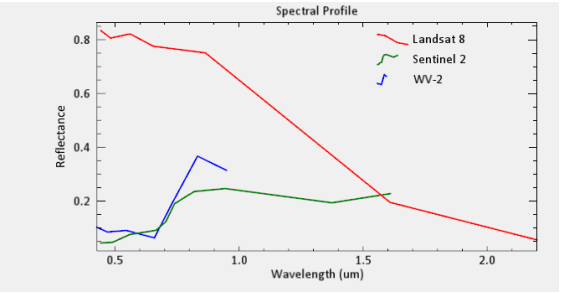
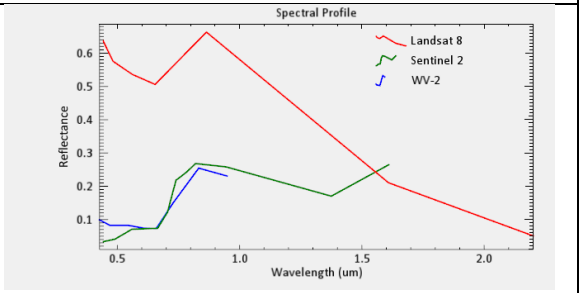
Figure 3.4: Location of GPS points gathered in the field combined with digitised points

Table 3.4: Training and test set for grass communities with the spectral signature in different classes, with the blue line representing WorldView-2, green the Sentinel 2 and red line for Landsat 8.

Land cover Classes	Training	Test	Total	Photo	Spectral signatures
Eragrostis plana	42	18	60		
Panicuum ecklonii	30	13	43		
Monocymbium ceressiiformer	30	13	43		
Sorghum halepen	30	13	43		

					
Erogrostic gummiflua	45	19	64		
Mixed grassland	46	20	65		
Cladoraphis cyeroides	43	19	62		

Seriphium plumosum	40	17	57		
Eucalypts trees	125	53	178		
Mines	97	41	138		
Agriculture	100	43	143		

					
Settlements	104	44	148		
Bare soil	77	35	117		

3.5 Remote sensing data pre-processing

Pre-processing of the data was carried out for the correction of any possible distortions within the imagery data as well as for the preparation of the image analysis. The images for before and after the mining started were all subset to give the study a specific focus on the confluence area as well as the small portion of the surrounding areas. Atmospheric correction carried out using the ENVI FLAASH were performed in Landsat images as well as WV-2 and Sen2Cor for sentinel 2. Berk *et al*. (2002) stated that FLAASH is an atmospheric correction method that modifies the wavelengths. Sen2Cor is a processor for Sentinel 2 Level 2A product generation and formatting (ESA SP-1322/2 March 2012). Re-sampling of the image was done using 10 m, 20 m and 60 m based on the resolution of different spectral bands as shown in Table 3.2.

3.6 Image classification

To discriminate the grass communities with other LULC classes, the powerful and advanced random forest (RF) classification described in section 3.6.1 was used to classify WV-2, Sentinel 2 and Landsat 8 imagery.

3.6.1 Random Forest classification

Random forest classifier is a machine learning technique created by Breiman (2001). The technique produces multiple bootstrap samples from the main training data set with a replacement to create many classification trees (ntree) and uses the entire forest as a complex composite classifier. Approximately 33% of the main data is left out from each bootstrapped sample, known as out-of-bag (OOB) data (Breiman, 2001; Liaw and Wiener, 2002; Archer and Kimes, 2008). Each tree is independently grown to maximum size without any pruning in RF. Classification technique uses randomness by selecting a random subset of candidate features (mtry) to establish the best break at each node for each tree in RF (Breiman, 2001). The majority on the correct classification then votes classification trees in the ensemble. RF classification supplies three independent variable significance measures. The accuracy importance measure is considered as the best by-product in RF because of its capacity to compute the variable importance which depends on mean decreases in accuracy as calculated using OOB samples (Breiman, 2001). The measure of the importance of the variables is produced by OOB error by comparing how much the OOB error of estimate increases when a variable is arranged and the other variables are left unchanged (Archer and Kimes, 2008). In this study, the importance of each WV-2, Sentinel 2 and Landsat 8 spectral bands in classifying grass communities were determined using OOB estimates of classification error. The dissimilarities in misclassification rate for the predicted and original OOB sample observations over all trees were averaged to measure the importance of the variables. Ranking index using mean was then used for determining the most suitable variables for classifying grass. RF classification can be found among others Breiman (2001) and Touw *et al*. (2012) for a more

detailed description. The R software library for statistical analysis was used to do the classification algorithm (Liaw and Wiener, 2002). The ground control points were used to produce all spectral reflectance for classes using WV-2, Sentinel 2 and Landsat 8 data.

3.6.2 Mapping the current distribution of the grass communities using different images

In mapping grass communities, Landsat 8, Sentinel 2 and WV-2 image were classified using the random forest classification. Ten years ago, the RF classification was largely used for classification. Detailed information of classification can be obtained from Pal (2005) and Adam *et al.* (2012) studies. Breiman (2001) developed a group of learning methods to refine the classification and regression trees method by combining a large set of decision trees. One tree gives one vote for the assignment to the input data of the most useful class. Random forest classifier was used for the Landsat 8, Sentinel 2 and WV-2 imagery to classify the image into thirteen classes that include mines, bare soil, agriculture land and settlement as well as grassland types observed. The training and the test sites were created for all classification as well as the accuracy assessment as shown in Table 4.2. NDVI was also used to monitor change in grass communities before and after mining continuation.

3.6.3 Measurement of variable importance

The importance of variables is computed in a random forest, which measures the strength of each spectral band variable in the classified map. Variable importance is the measurement of how much classification accuracy would decrease if any of spectral band could be removed while other bands remain the same (Verikas *et al.,* 2011). RF variable significance is an important output for getting insight on which set of variables apply to the final map. The classification accuracy measurement is based on estimation called the OOB error computed from the foresee of the data that are not used in increasing the trees of classification.

3.7 Monitoring the vegetation cover changes

3.7.1 Normalized Difference Vegetation Index (NDVI)

NDVI was used in this study to monitor vegetation cover change using the above-mentioned Landsat data that was downloaded. The mapping of vegetation is an important task as vegetation plays a significant role in defining most of the Landscape (Ahmad, 2012). Forkel *et al.* (2013) define NDVI as a remote sensing method to measure the greenness of vegetation and associated with the structural properties of vegetation. NDVI can detect the areas where the grass communities are not healthy and can further analyse a variety of vegetation changes (Forkel *et al.,* 2013). The NDVI uses the visible and the Near-Infrared bands on the electromagnetic spectrum. Its values are calculated by the formula:

NDVI= (NIR-RED/NIR+RED)

The related mining impact on the vegetation index will be shown by the low value of vegetation indices where there is vegetation. The reflectance of grass community, which represent low, intermediate and high levels of soil contamination, shows that the decrease of reflectance in near-infrared between 800 nm and 1300 nm is due to soil contamination.

3.7.2 NDVI Differencing Method

To measure the grass communities, the NDVI differencing (DNDVI) was performed. Several authors stated that DNDVI values compare between images of two different dates. Differencing in NDVI map applied when a single map for NDVI produced on a scale of -1 to +1 (Sellers *et al.,* 1990). The resulting NDVI images were subtracted to determine the positive as well as the negative change (Cakir *et al.,* 2006). The NDVI new image minus to the old NDVI map like provided by the following equation for the study:

$$\mathbf{NDDVI = NDVI}_{new} \mathbf{- NDVI}_{Old}$$

In identifying the changed areas in a different date image, a threshold technique based on differencing image histogram was selected. According to Singh (1989), the important changes are found in the tails of the histogram distribution while pixels showing no significant change tended to be clumped around the means.

3.8 Accuracy Assessment

The classifier computes accuracy assessment to collate the correct pixel given in a map. The assessment was done after classifying the grass communities using the test data from the field. The utilised test dataset is displayed in Table 4.1 together with the training set. Accuracy assessment is reviewed as a level of proximity to obtaining the accurate results (Zăvoianu *et al.*, 2004). Accuracy assessment for the final map results is important in classification. The quality of a produced map is determined by its correctness (Forkuo and Frimpong, 2012). Error matrix of the outcomes can be described by procedures and user's assessment. Procedures assessment are features that are correctly classified by the classifier and user's accuracy report the possibility that the feature will be correct when corresponding with the landscape. Accuracy assessment was done from the outcomes RF classification for three images (WV-2, Sentinel 2 and Landsat 8). This was done to see the standard of the classifications and identify the error from the final maps.

3.9 Change detection

Xu *et al.* (2009) stated that change detection is an important application of remote sensing technology for understanding the relationships and interactions of humans and natural phenomenon for decision-making. Coppin and Bauer (1996) noted that choosing the appropriate methods is of significance. Lu *et al*. (2004) stated that all change detection techniques despite factors affecting the selection of the change detection techniques are the most commonly used. Landsat imagery has also been considerably used for detection techniques. In this study, Change Detection Statistics method was used. This was done to detect the condition of grass communities coverage within Ermelo coalfields region before and after mining. The main purpose for this was to determine areas where there has been an increase in vegetation (positive change), decrease (negative change) as well as the areas of no change. The results were presented in a map that is shown within the results chapter. The classified images for WV-2, Sentinel 2 and Landsat 8 were used.

3.9.1 Change detection statistics

Change detection statistics is a post-classification statistical technique that is done using images of different times to determining changes in classes within the two images. Kafi *et al.* (2014) stated that detection of changes is executed by detecting changes within the classes and to determine the cause and extent of those changes. Change detection statistics method was performed as a post-classification process to determine changes within the area under study. By using the change detection statistics method, the matrix table showing the NDVI differencing initial state to the final state change was obtained. Change detection statistics tool used was performed on the ENVI software. The results are shown in chapter 4 and are presented on the matrix table in percentages.

CHAPTER 4
RESULTS

4.1 Grass communities classification

The grass communities in the study area were classified using the Landsat 8, Sentinel 2 and WV-2 image and the field data. The results for the classification using the random forest are shown in Figure 4.1, whilst the confusion matrix results determining accuracy are displayed in Table 4.2, Table 4.4 and Table 4.6. Figure 4.1 presents the RF maps of three data sets. Because of the extent of the maps, the visibility of difference between classes to the three maps in the WV-2, Sentinel 2 as well as Landsat 8 spectral bands is not clear. However, the grass communities were confused with agriculture when Sentinel 2 and Landsat 8 images were used in Figure 4.1(A, B and C).

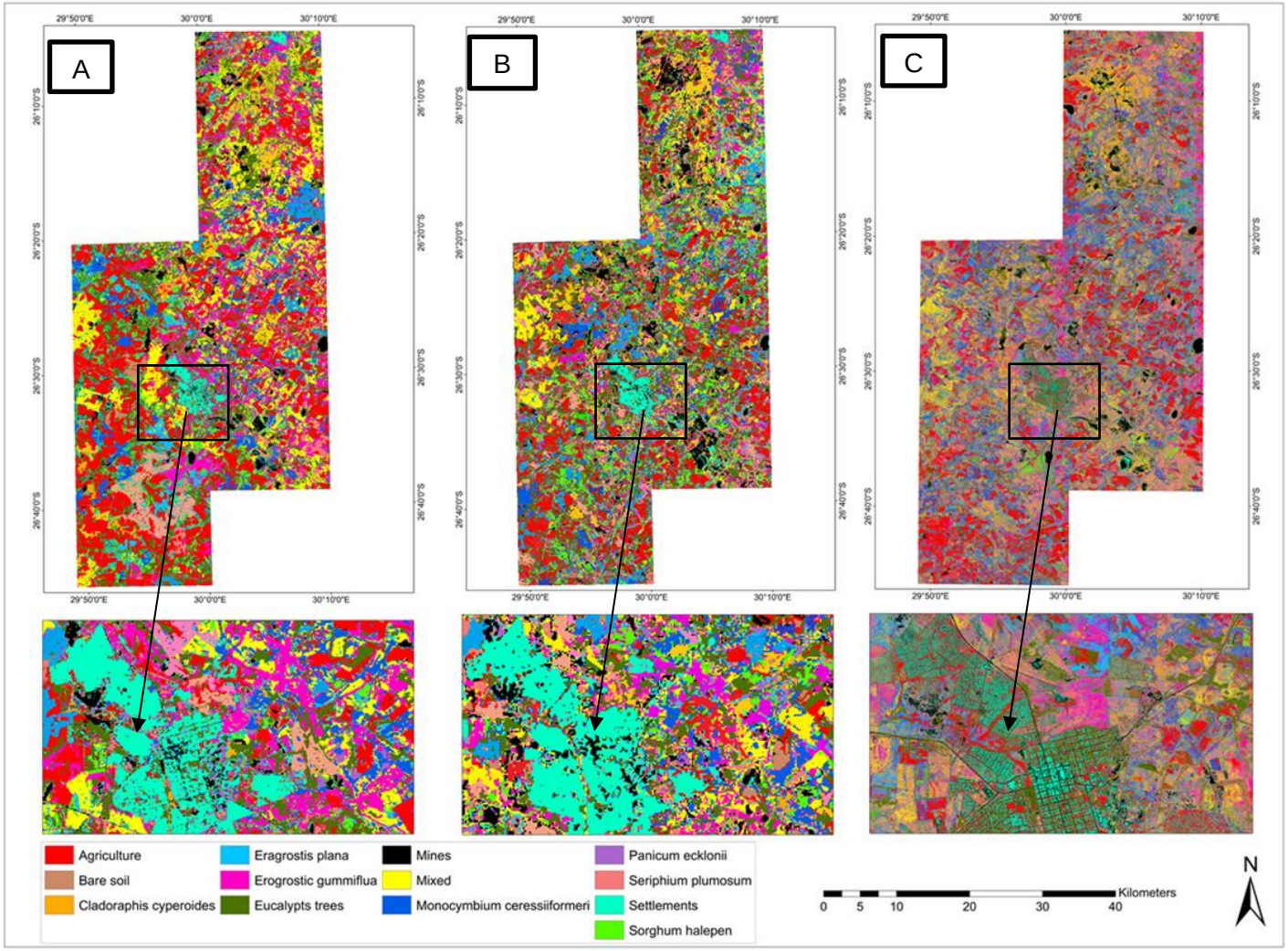


Figure 4.1: Maps of classes for (A) Landsat, (B) Sentinel 2 and (C) WorldView -2 using the random forest algorithm

Identification of grass communities was done during the field visit and notes of the other vegetation types present in the area (trees, agriculture etc.) were taken. The classification was based on the expected eight grass communities plus a general settlement, mines, bare soil, trees and agriculture. The results show that the most dominant communities in this area include *Monocymbium ceressiiformer, Erogrostic plana, Erogrostic gummiflua, Seriphium plumosum, Cladoraphis cyeroides* and Mixed-grass, along with the mines. The results also show a clear distribution of the mines. The distribution of *Monocymbium ceressiiforme, Seriphium plumosum* and mixed communities are mostly found in the study area; however, these types occur on the northern side of the Ermelo. The agriculture and *Erogrostic plana* grass are also widely distributed in the classification.

4.2 Confusion matrix assessment

The RF classification used an independent data set (30%) which was tested for each image Landsat 8, Sentinel 2 and WV-2. Classification results show the performance of random forest algorithm in distinguishing different communities as shown in Table 4.2, Table 4.4and Table 4.6. The assessment of accuracy revealed Landsat 8 sensor with 66.67% and exceeded by WV-2 (88.50%) and Sentinel 2 (76.15%). Table 4.7 displays the final accuracy of the three maps.

Table 4.1: Confusion Matrix for verification of the grass communities classification

Classes	AG	BS	CC	EP	EG	ET	MN	MX	MC	PE	SP	ST	SH	Total
AG	29	5	1	0	2	7	5	5	1	0	5	5	2	67
BS	1	25	0	0	1	6	4	0	1	0	0	3	0	41
CC	0	0	14	0	0	1	0	0	0	0	0	0	0	15
EP	3	1	1	14	1	0	1	1	1	1	1	0	0	25
EG	1	1	0	0	15	1	0	0	1	0	0	0	1	20
ET	3	0	1	2	0	31	0	2	0	1	1	1	1	43
MN	1	2	0	0	0	0	28	0	0	1	0	0	0	32
MX	0	0	0	0	0	3	0	10	2	1	1	0	0	17
MC	1	0	2	0	0	3	0	1	7	0	0	0	0	14
PE	0	0	0	0	0	0	0	1	0	9	1	0	1	12
SP	0	1	0	2	0	0	1	0	0	0	7	0	0	11
ST	0	0	0	0	0	1	2	0	0	0	0	35	0	38
SH	4	0	0	0	0	0	0	0	0	0	1	0	8	13
Total	43	35	19	18	19	53	41	20	13	13	17	44	13	348

Note: MX=Mixed grass, SH= *Sorghum halepen*, EP=*Eragrostis plana*, PE=*Panicuum ecklonii*, MC=*Monocymbium ceressiiformer*, EG=*Erogrostic gummiflua*, CC=*Cladoraphis cyeroides*, SP= *Seriphium plumosum*, MN=Mines, ST=Settlements, AG= Agriculture, BS = Bare soil, ET= *Eucalypts* trees.

Table 4.2 displays the Landsat 8 sensor error matrix (confusion matrix) for each class. This classification obtained 66.67% final accuracy with a kappa coefficient of 0.63%. Variations of correctly or incorrectly

classification of single communities are depicted in Table 4.3. The accuracy in Table 4.2 shows the number of the sampled pixel for each class, as well as the number of the pixels that were correctly classified and misclassified. The highest accuracy is seen on Eucalypts trees as well as the settlement classes (Table 4.2). Most of the classified grass communities show misclassification to bare soil, as well as other types of vegetation classes. The other vegetation types are misclassified, which may have similar spectral signatures as the identified tree communities.

Table 4.2: Landsat 8 producer's and user's accuracies for each class obtained

Classes	**Producers (%)**	**Users (%)**
AG	67.44	43.28
BS	71.43	60.98
CC	73.68	93.33
EP	77.78	56.00
EG	78.95	75.00
ET	58.49	72.09
MN	68.29	87.50
MX	50.00	58.82
MC	53.85	50.00
PE	69.23	75.00
SP	41.18	63.64
ST	79.55	92.11
SH	61.54	61.54

The accuracy achieved for most grass communities in Landsat 8 (AG, BS, CC, EP, EG, ET, MN, MC, PE, ST, and SH) was high (Table 4.3). ST class had the highest producers 79.55% and the lowest accuracy achieved was 41.18% (SP). The SP class was miscalculated to the final classification map.

The classes correctly classified were higher in BS, EG, PE, CC, ET, MN, ST and SH. However, AG only achieved the lowest user's accuracy of 43.28% meaning that some pixels were misclassified whereas CC class had the highest users 93.33%. The accuracy assessment for classification using the Sentinel 2 image was used to compare results. In the mapping of grass communities with more high-resolution data, Sentinel 2 gave better results as compared to Landsat 8. The classification for Landsat 8 misclassified other grass communities to agriculture.

Table 4.3: Confusion Matrix for validation of the grass communities classification

Classes	**AG**	**BS**	**CC**	**EP**	**EG**	**ET**	**MN**	**MX**	**MC**	**PE**	**SP**	**ST**	**SH**	**Total**
AG	39	3	0	0	0	0	0	0	0	0	0	0	0	42
BS	0	22	0	0	0	6	2	0	1	0	0	0	0	31
CC	0	0	15	0	0	0	0	0	0	0	0	0	0	15
EP	1	0	0	15	1	2	3	1	0	0	1	0	0	23

EG	0	3	0	1	17	2	1	1	0	1	1	0	3	29
ET	0	1	0	0	1	36	2	0	0	0	0	2	0	43
MN	0	1	0	0	0	1	26	0	1	0	0	1	0	30
MX	2	0	2	0	0	0	1	15	0	0	0	1	0	21
MC	1	1	1	0	0	2	2	1	10	1	1	0	0	20
PE	0	0	0	1	0	1	1	1	0	9	2	0	1	16
SP	0	2	1	0	0	3	0	2	0	0	12	0	0	20
ST	0	0	0	0	0	0	3	0	1	1	0	40	0	45
SH	0	2	0	1	0	0	0	1	0	1	0	0	9	13
Total	43	35	19	18	19	53	41	20	13	13	17	44	13	348

Note: MX=Mixed grass, SH= *Sorghum halepen,* EP=*Eragrostis plana,* PE=*Panicuum ecklonii,* MC=*Monocymbium ceressiiformer,* EG=*Erogrostic gummiflua,* CC=*Cladoraphis cyeroides,* SP= *Seriphium plumosum,* MN=Mines, ST=Settlements, AG= Agriculture, BS = Bare soil, *ET= Eucalypts* trees.

The accuracy of the classified Sentinel 2 image is shown in Table 4.4. The overall accuracy obtained using the test data set is 76.15% with the Kappa Coefficient of 0.73%. The accuracy Table 4.4 shows the number of the sampled pixel that were correctly and incorrectly classified. The classes that have the highest accuracy are agriculture, settlements as well as the mine classes. The number of pixels that are incorrectly classified is mostly the classes that represent bare soil and trees as bare soil.

Table 4.4: Sentinel 2 producer's and user's accuracies for each class obtained

Classes	**Producers (%)**	**Users (%)**
AG	90.70	92.86
BS	62.86	70.97
CC	78.95	100.00
EP	83.33	65.22
EG	89.47	58.62
ET	67.92	83.73
MN	63.41	86.67
MX	75.00	71.43
MC	76.92	50.00
PE	69.23	56,25
SP	70.59	60.00
ST	90.91	88.89
SH	69.23	69.23

The accuracy achieved for Sentinel 2 (AG, BS, CC, EP, EG, MX, MC, SP and ST) was high (Table 4.5). AG and ST class had the highest producer's 90.70% and 90.91% and the lowest accuracy achieved was 62.85% (BS). The BS class was underestimated in the classified image. CC class had the highest user's of 100% (CC) and the lowest accuracy achieved was 50.00% (MC). The MC class was

miscalculated in the classified image. The pixels reliability that correctly classified were higher in BS, AG, CC, ET, MN, ST and SH.

The grass communities in the study area were further classified using the WV-2 image and the field data to compare the results. In the mapping of grass communities with more high-resolution data, WV-2 image was also classified to contrast with the results of two other imagery. Table 4.5 shows the accuracy of the classification.

Table 4.5: Confusion Matrix for validation of the grass communities' classification

Classes	AG	BS	CC	EP	EG	ET	MN	MX	MC	PE	SP	ST	SH	Total
AG	40	5	1	1	0	0	0	1	2	2	0	0	0	52
BS	0	27	1	0	2	0	0	1	0	0	0	2	0	33
CC	0	0	16	1	0	0	0	0	1	0	0	0	0	18
EP	1	0	0	15	0	0	0	0	0	1	0	0	1	18
EG	0	1	0	0	17	0	0	0	0	0	0	0	1	19
ET	0	0	1	0	0	53	0	0	0	0	0	0	0	54
MN	0	1	0	0	0	0	40	0	0	0	0	0	0	41
MX	1	0	0	0	0	0	0	15	2	0	0	0	1	19
MC	0	1	0	0	0	0	0	0	8	0	0	0	0	9
PE	0	0	0	1	0	0	0	1	0	10	1	0	1	14
SP	0	0	0	0	0	0	0	1	0	0	16	0	0	17
ST	0	0	0	0	0	0	1	0	0	0	0	42	0	43
SH	1	0	0	0	0	0	0	1	0	0	0	0	9	11
Total	43	35	19	18	19	53	41	20	13	13	17	44	13	348

Note: MX=Mixed grass, SH= *Sorghum halepen*, EP=*Eragrostis plana*, PE=*Panicuum ecklonii*, MC=*Monocymbium ceressiiformer*, EG=*Erogrostic gummiflua*, CC=*Cladoraphis cyeroides*, SP= *Seriphium plumosum*, MN=Mines, ST=Settlements, AG= Agriculture, BS = Bare soil, ET= *Eucalypts* trees.

The overall accuracy obtained using the test data set of WV-2 is 88.50% which is part of positive results in terms of accuracy assessment. The accuracy Table 4.6 shows the number of the sampled pixel for each class as well as the pixel number that was correct and misclassified. The classes that have the highest accuracy are agriculture as well as the mine classes. The numbers of pixels that are misclassified the most are those of the classes that represent bare soil and agriculture as bare soil. Some of the classified grass communities show misclassification to agriculture, as well as other types of grass communities. The class settlement is represented as mines because the mine dumps have similar spectral signatures as the identified settlement hence the misclassification of mine dumps to this class.

Table 4.6: WV-2 producer's and user's of each class obtained

Classes	Producers (%)	Users (%)
AG	93.02	76.92
BS	77.14	81.81
CC	84.21	88.89
EP	83.33	83.33
EG	89.47	89.47
ET	100.00	98.15
MN	97.56	97.56
MX	75.00	78.75
MC	61.54	88.89
PE	76.92	71.43
SP	94.12	94.12
ST	95.45	97.67
SH	69.23	81.81

The accuracy achieved for all the grass communities with other classes (AG, BS, CC, EP, EG, ET, MN, PE, SP, ST and SH) was high. The highest producer's accuracy for ET class is 100% and the lowest accuracy achieved was 61.54% (MC). The reliability of pixels that were correctly classified was higher in BS, AG, CC, ET, MN, ST and SH. However, MX only achieved the lowest user's accuracy of 71.43% meaning that some pixels were misclassified.

The results presented in Table 4.7 shows the overall accuracy from 66% to 88%, the average user's from 68% to 84%, and the average producer's from 68% to 86%. There was also an improvement in the average user's accuracy (68% to 84%) and average producer's accuracy (65% to 86%). However, the best performance in terms of the accuracy assessment was recorded by the WV-2 image which produced the highest accuracy.

Table 4.7: Overall, Kappa coefficient, Error rate, Producer's accuracy (Percentage) and user's accuracy (percentage) of thirteen classes

Accuracy	Landsat 8 (%)	Sentinel 2 (%)	Worldview 2 (%)
Overall accuracy	66.66	76.15	88.50
Producer's accuracy	65.49	76.04	86.85
User's accuracy	68.40	73.37	84.39
Kappa coefficient	0.63	0.73	0.87
Error rate	0.30	0.20	0.10

The achieved Kappa was 0.87% and the error rate of 0.10% was achieved in this study in WV-2 (Table 4.7). The low error rate achieved by the classifier demonstrates the high performance of the classifier

incorrectly classifying the different grass species. WV-2 got a lower error rate than both Sentinel 2 and Landsat 8.

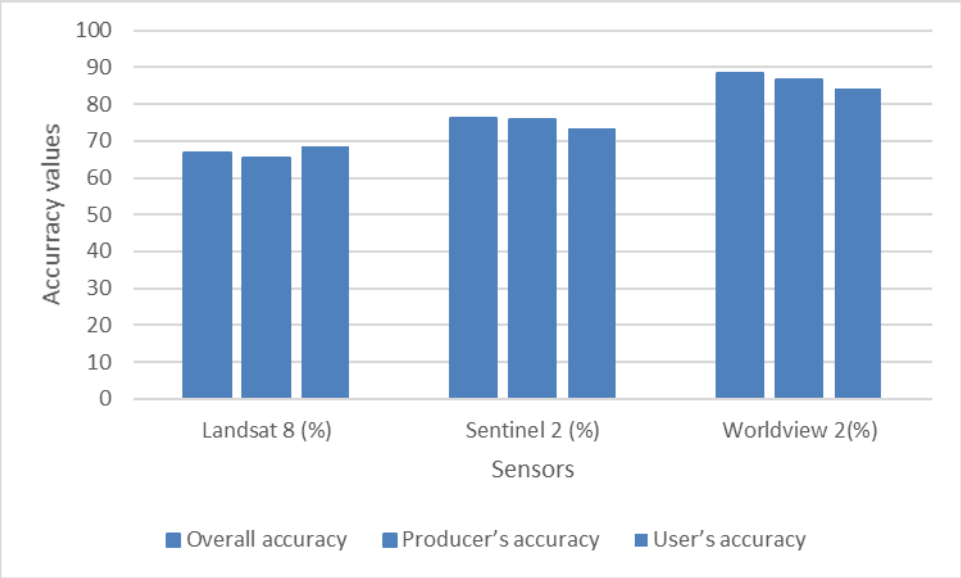


Figure 4.2: Overall, user's and producer's accuracies for three satellite sensor

The results presented in Table 4.7 shows the overall accuracy from 66% to 88%, the average user's from 68% to 84%, and the average producer's from 68% to 86%. There was also an improvement in the average user's accuracy (68% to 84%) and average producer's accuracy (65% to 86%). However, the best performance in terms of the accuracy assessment was recorded by the WV-2 image, which produced the highest accuracy values (Figure 4.2).

4.3 Random forest variable important bands

The RF model demonstrated the ability to measure and rank the importance of each band that is effective in the three classified images. Figure 4.3 shows the variable importance in bands based on the random forest classification increase, which demonstrates the weakness of the prediction model when each variable is calculated.

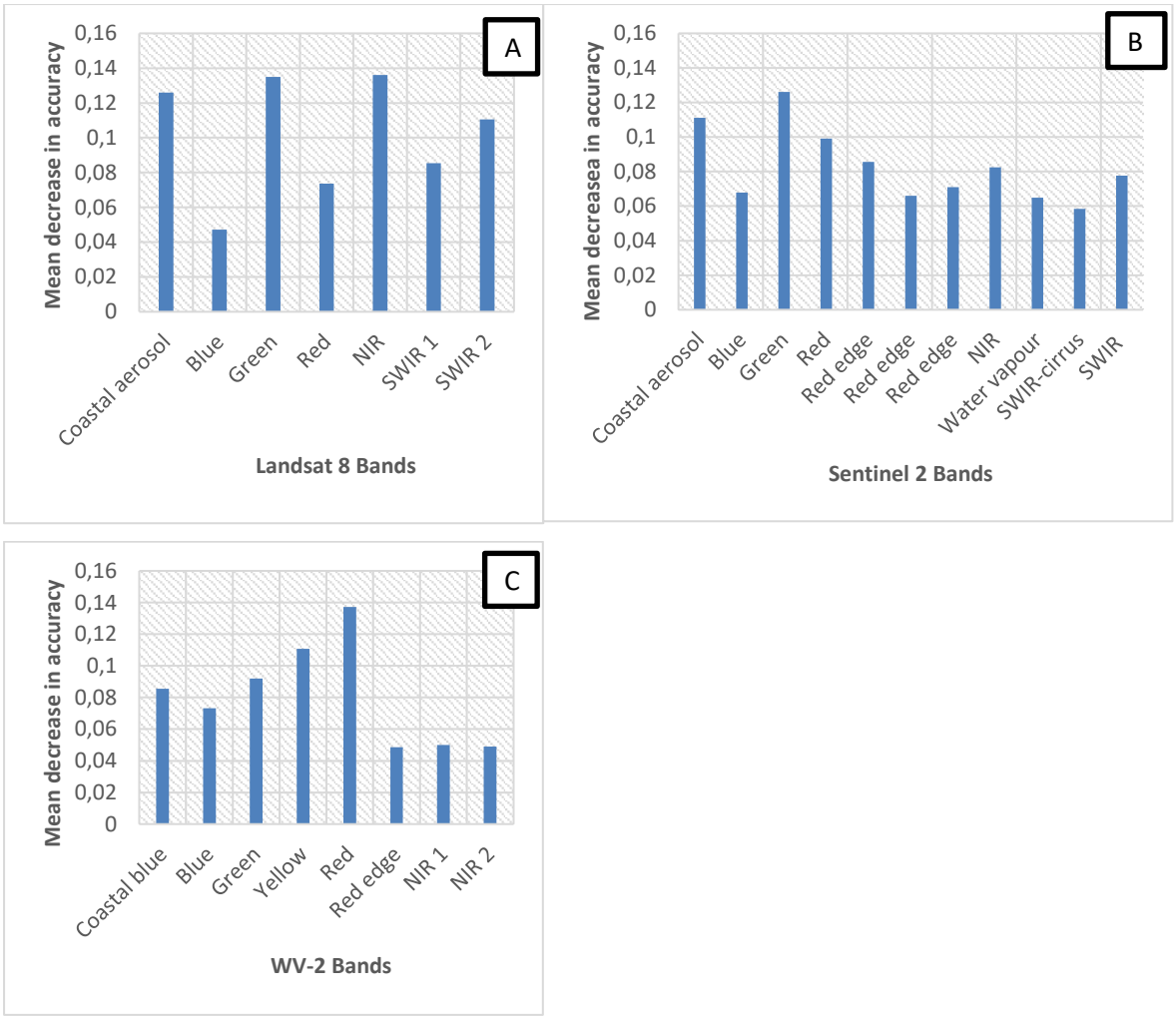


Figure 4.3: The variable importance of WV-2 (C), Sentinel 2 (B) and Landsat 8 (A) spectral bands in classifying grass communities and LULC classes as measured by random forest classifier

The mean decrease in accuracy measures the significance of each of the WV-2 eight spectral bands, eleven for Sentinel 2 including seven for Landsat 8 for classifying thirteen LULC. The importance of each variable spectral bands as established by the RF classification is shown in Figure 4.3 for each image. The important variables for Sentinel 2 spectral bands were coastal blue, green, SWIR cirrus and water vapour, while the coastal were green, red edge and the coastal blue, green, NIR and SWIR2 for Landsat 8. In WV-2 the (0.51 - 0.58 nm yellow), (0.40 - 0.45 nm coastal blue -), (0.45 - 0.51 nm green), and (630 - 690 nm red). The WV-2 spectral band's performance of yellow was among top importance variable bands, which work well in grass communities than the traditional bands.

4.4 Vegetation cover changes

Vegetation change results are presented in this section. To determine the changes in grass communities from past to current, and the effect of mining on grass community conditions in the area, the NDVI calculations were obtained for all the five different Landsat images. The NDVI differencing

technique is also presented as a technique for change detection for the NDVI results. The results are indicated using NDVI maps in Figure 4.4 and Figure 4.5. The lowest negative NDVI values from the results represent bare soil, built up, water bodies as well as dry or unhealthy vegetation. Figure 4.4 and Figure 4.5 are results of NDVI calculations, which shows the variation in NDVI values for each image.

4.4.1 NDVI for the five images

The use of NDVIs developed from Landsat data spectral bands were able to delineate the condition of common grass communities in the area with other LULC, such as agriculture as well as *Eucalypts* trees. The NDVI was calculated from the combination of red and NIR. Results showed that fluctuations in vegetation NDVI is a response to changes in vegetation. Vegetation disturbance caused by coal mining may lead to loss of biomass in the area.

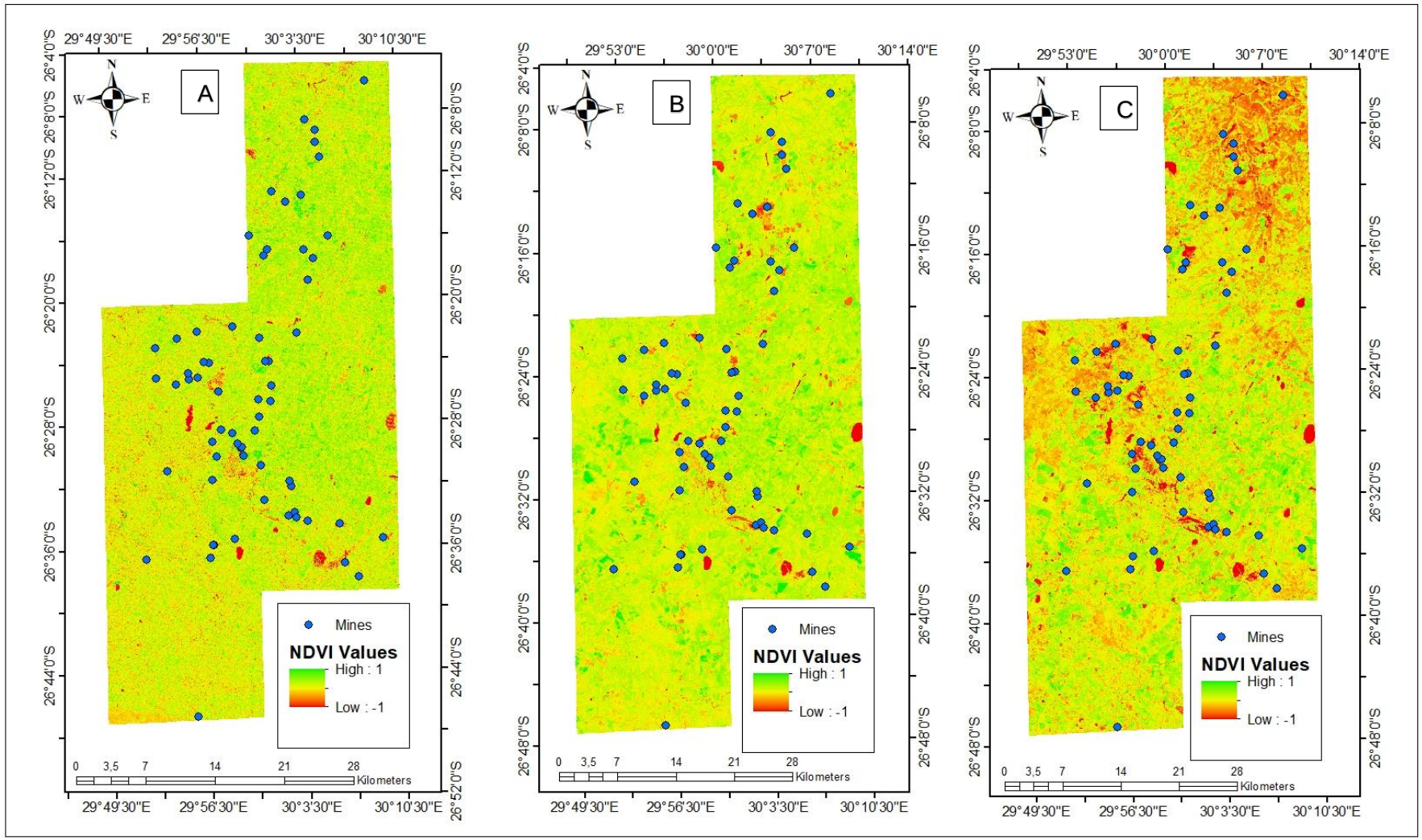


Figure 4.4: Map showing NDVI results for the year 1978 (A), the year 1988 (B) and year 1998 (C**)**

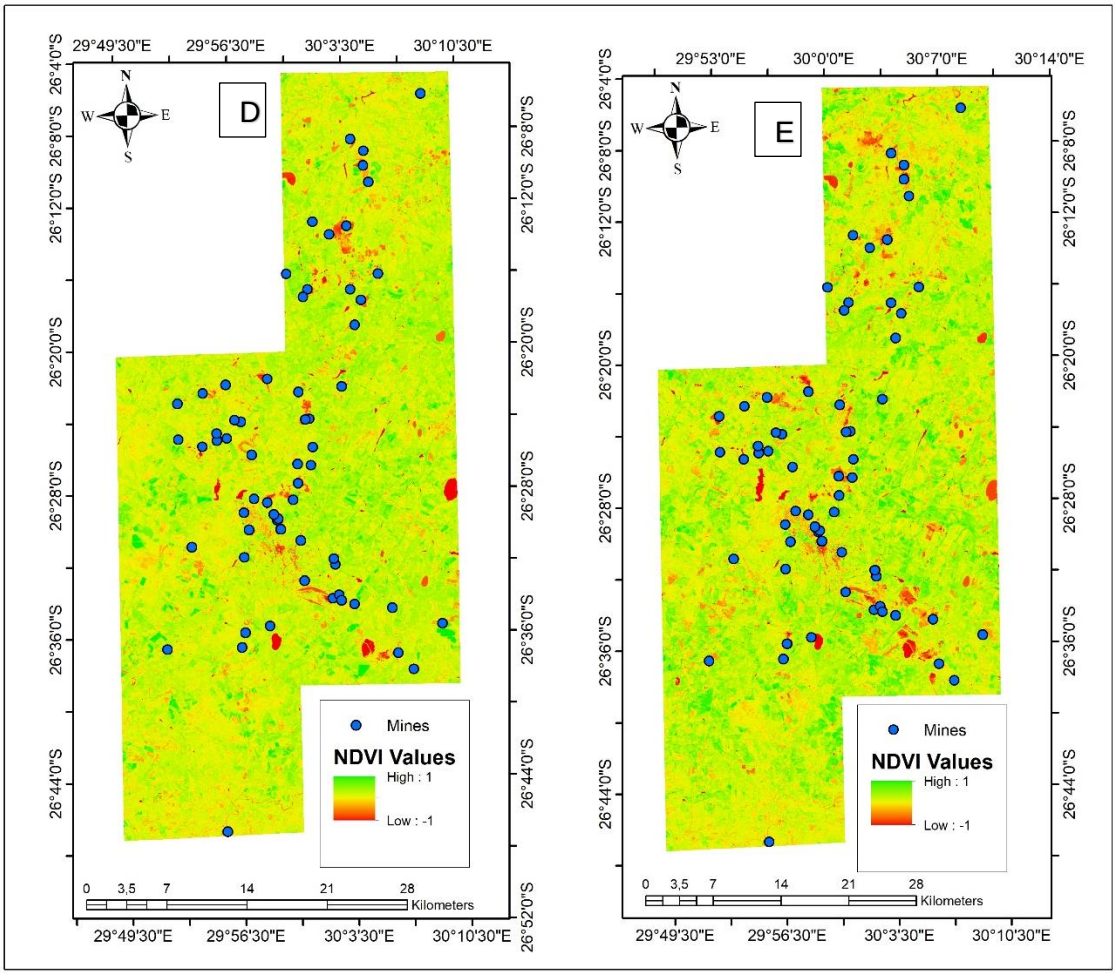


Figure 4.5: Maps showing NDVI results for the year 2008 (D) and year 2018 (E)

The NDVI values (from -1 to 1) stipulate the condition of vegetation in the pixel, where the NDVI values area shows more green vegetation. Vegetated areas will have higher values because of their higher near-infrared reflectance and low visible reflectance. The mining area changed rapidly from 1978 to 2018, and a significant spatial increment occurred within the area. Besides, an increment was observed in regions of high vegetation density (red-coloured areas). Because NDVI provides an adequate index that reflects the health status of vegetation (Pettorelli *et al.,* 2005), changes in NDVI over this period, were used to indicate the change of health status of the vegetation in the target Ermelo Coalfields area. A significant decline of NDVI was observed in 1998, which suggests that the vegetation is sensitive and vulnerable to contamination from mines.

Ermelo region is characterised by mining activities of the past and present with increasing agricultural practices than before. The results in Figure 4.4A showing the NDVI representation for 1978 healthier in more areas than in 1988. Values that are represented by NDVI starting from -0.7 are shown to be the representation of what may be dry or woody vegetation and the maximum is 1. NDVI values for the types of grass communities decreased more rapidly than the areas away from the coalmines, and agricultural areas also decreased. In the year 1988 (Figure 4.4B), the values decreased more than in

the year 1978. The minimum value for grassland NDVI is -0.85 and maximum is 0.77. It shows that the values have decreased in red to orange around the mining area. The mining operation increased within the area whilst the NDVI values for some grass communities decrease rapidly than the areas away from mines. The minimum is -0.55 which shows that the vegetation area is affected by the mining activity through toxic metals and contamination of the soil. The grass communities in the year 1998 were affected mostly; as indicated by the low NDVI values (Figure 4.4C). The lowest value for 1998 is -0.84 and highest is 0.90. The orange colour, which shows low NDVI values, is dominant in grass and agricultural land close to the mines. Mostly in all the areas close or around the mines the grass community and agricultural areas, the NDVI values are lower than the area far from mines as shown from the Figures.

Figure 4.5 shows the NDVI values for 2008 and 2018 within the area of grass communities which are not healthy in the areas close to mines than the ones far from mines. The grass communities recovered in 2008 because of the rainy season or adaptation to the environment. Figure 4.5D has identified that the grass communities decrease rapidly less than in 1998. There is an increase in NDVI values as compared to the 1998 state. The increase in NDVI values is a representation of grass communities regaining the healthy state. However, more of the areas that reflected red before now reflects yellowish/orange. The areas that are mostly showing a rapid decrease in the amount of green are the grass communities and agricultural areas. This, however, does not give a clear indication of the cause of the decrease within these areas. The degree of environmental damage in coal mining areas is high, resulting in significant ecological disturbance.

Figure 4.5E shows the results for 2018; the NDV values are between -0.2 and 0.6. Some of these areas are affected by the increment to the mining activity within the area. In some of the areas, the grass communities are yellowish because they have adapted to the mining environment though not in a healthy state. Figure 4.5E shows areas where the spatial distribution of grass communities have more yellow to red colour. The results show that grass communities at this time are not healthier as compared to the initial state. It has been recorded that when there is the contamination of soil, the green vegetation tends to decrease and the values of NDVI decreases as well. Several areas shown in yellow to orange close to the mine starts from 1998 than the areas far from mines. NDVI before and after using five images; then one-way analysis of variance was performed to test whether the average NDVI of these five images was equal. The results show that the average NDVI before and after mining was significantly different.

4.4.2 NDVI Differencing

The change detection results for 1978, 1988, 1998, 2008 and 2018 are presented in Figure 4.6 and Figure 4.7.

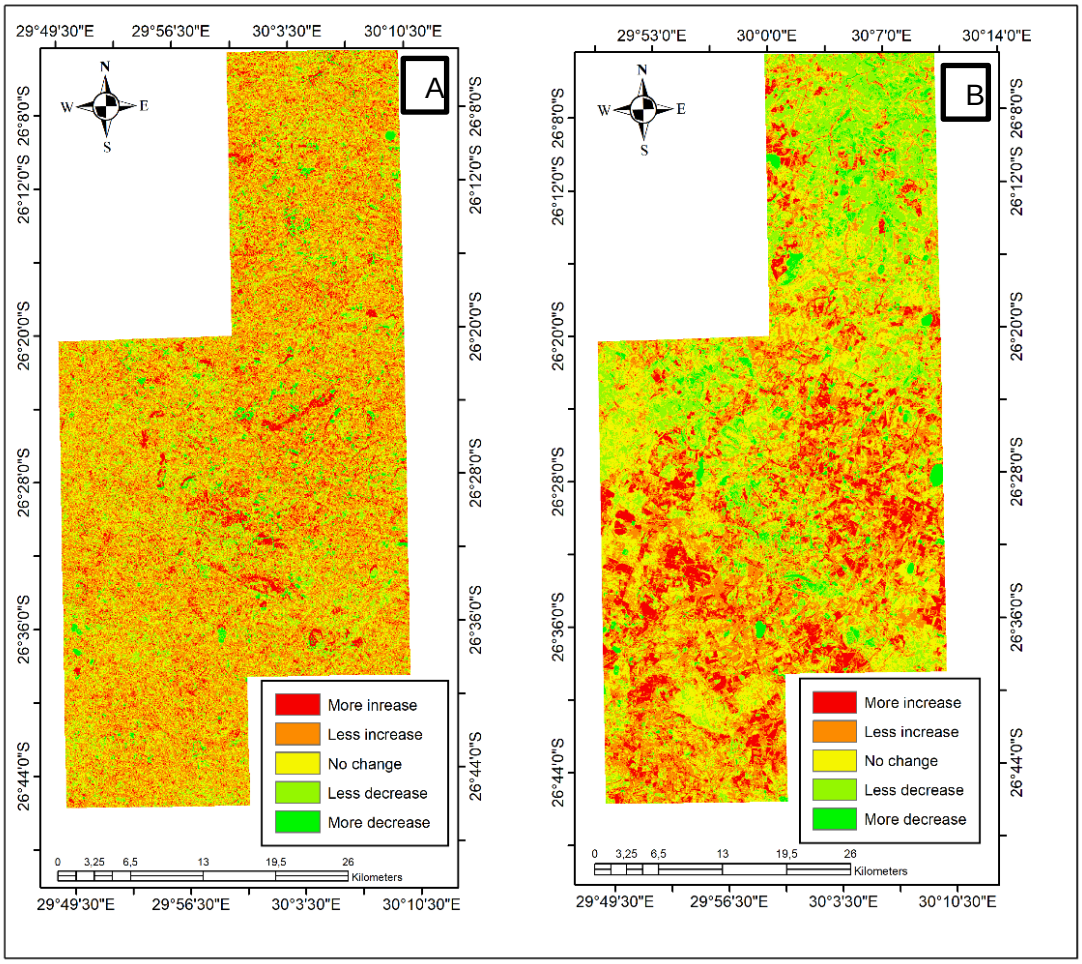


Figure 4.6: Maps showing NDVI differencing for 1978 and 1988 (A), 1988 and 1998 (B)

Figure 4.6 and Figure 4.7 shows the NDVI differencing results in the five images. The NDVI differencing results are represented using five classes, which are, more increase, less increase, no change, less decrease as well as more decrease. The results show that there are more areas with vegetation that have slightly increased. The findings show that during the period 1978 to 1988, the area has experienced less increase in vegetation as compared from 1988 to 1998. This described by the increase in agriculture in the area as before. From the year 1988 to 1998, the major differences in the area are found in areas where agriculture started developing. The areas with more increase correlate with areas where agriculture increased. Figure 4.6 A and B shows small areas with no change in the vegetation condition which is mostly areas away for mines with yellow colour. The results show that in most areas, the vegetation has slightly deteriorated as presented by the 'less decrease's class. The areas with more decrease, especially in vegetation are shown as grass communities.

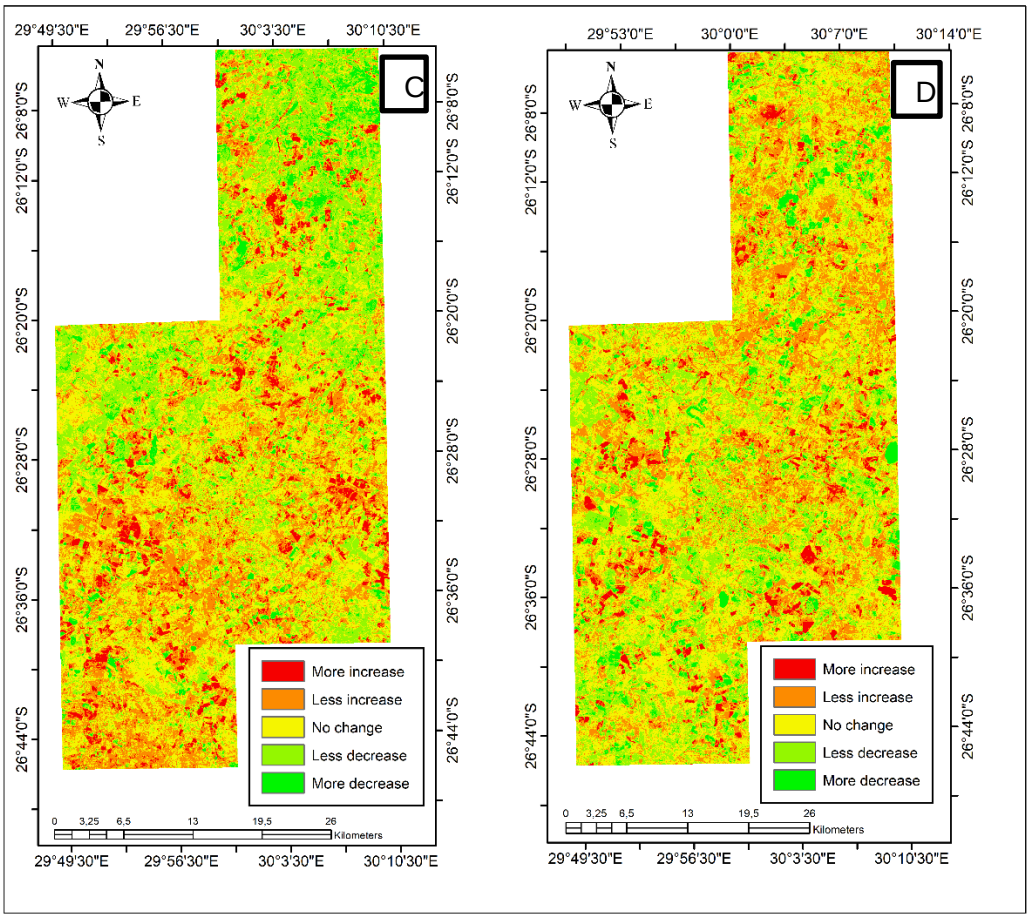


Figure 4.7: Maps showing NDVI differencing for 2008 and 1998 (C), 2018 and 2008 (D)

Less more increase is shown in Figure 4.7C than Figure 4.7D. Few areas show no change on the greenness of grass communities. The areas where there are less decrease and more decrease are between these years. Figure 4.7 shows more areas where a decrease in some areas with no change in yellow. The areas that are mostly affected are the grass communities close to the mining area. More decrease and less decrease in most areas around mines are in agriculture and grass communities close to the mines. The areas with more decrease in NDVI values shown as grass communities and agricultural areas can be seen in Figure 4.6. The results show a clear difference between the initial image and the final state image 'more increase' and class. These results show that there is a less positive and more negative change in vegetation as compared to the NDVI difference map for the year 1978 to 1988. The results also simply show some areas with no changes. This results in a slowing of the rate of biomass growth, which is caused by fading of vegetation.

4.4.3 Change detection using NDVI differences

Figure 4.8 is a representation of the NDVI differencing results for the five images showing the changes. NDVI maps also showed that the increment of the agricultural areas around Ermelo area derived

distribution of change intensities and change trends. These values support the increase in agricultural density.

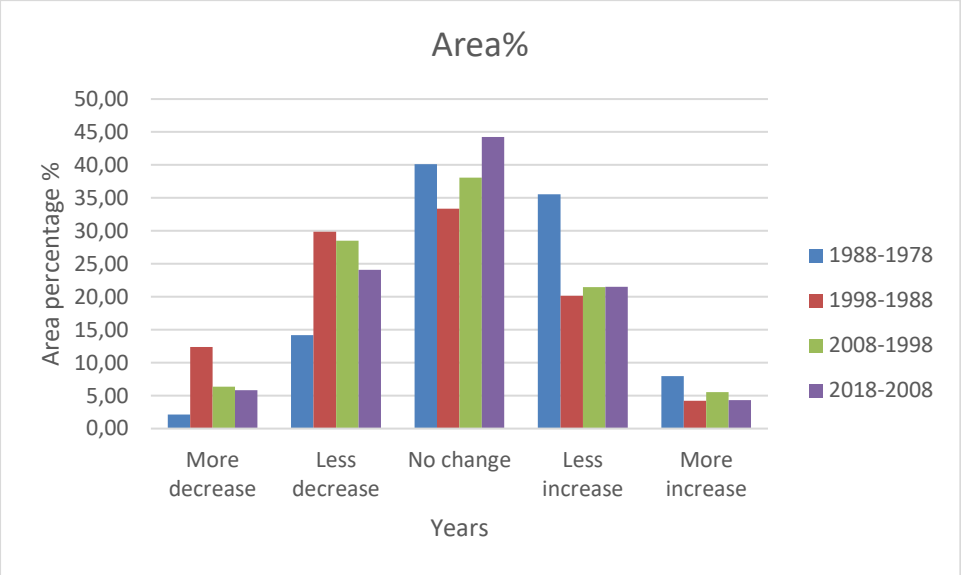


Figure 4.8: NDVI difference percentage plot

Figure 4.8 clearly shows that between 1978 and 2018, there was a decrease but 'Less decrease' than any other class. These results indicate that there is a less positive change in vegetation as compared to the NDVI difference in negative change. The results indicate that more areas have developed vegetation since the initial state. This is described by the extensive growth in agriculture in the area.

4.5 Time Series analysis

The time-series average mean results for 1978, 1988, 1998, 2008 and 2018 are presented in Figure 4.9.

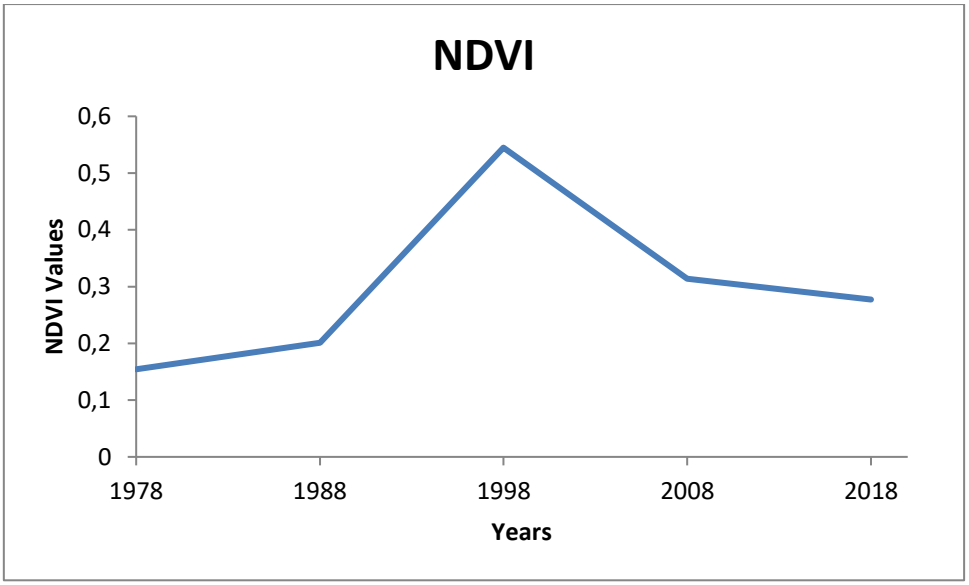


Figure 4.9: Changes in the NDVI in a historical series

Figure 4.9 analyzed the annual mean NDVI before and after using five images; then one-way analysis of variance was performed to test whether the average NDVI of these five images was equal. The mining in the area started between the 1970s as it is confirmed by the grass communities state than other years. The results show that the average NDVI at the beginning of mining in the area and later was significantly different. Figure 4.9 shows a decrease in average mean value from 2008 to 2018 means the time series analysis is seasonal and there is the trend. In 1998, the NDVI value was higher than between 1978 and 1988. Then from 2008 and 2018, the average means were decreased. This method was chosen for the evaluation of the NDVI temporal change on how the trend is estimated.

CHAPTER 5
DISCUSSION AND CONCLUSION

5.1 Discussion

Due to the complexity and much disruption of the grass communities in the mining area and the risk of biodiversity, grass communities mapping is required for better management. The advent of new-generation sensors, such as WV-2, with the enhanced spatial and spectral resolution, provides new opportunities for mapping areas in the grass communities. The enhanced fine resolution of recent remotely sensed data, like WV-2, advanced up with recent changes in delineating places where grass communities decrease. This finding is compatible with research by Omar (2010) who spotlight the capacity of the recent WV-2 with extra spectral bands in enhancing the accuracy of forest trees in a Malaysian forest. Using the RF classifier, the results from a Landsat 8 and Sentinel 2 with WV-2 images were compared by classifying the grass communities in an Ermelo coalfield. The WV-2 red-edge band and division of near-infrared recognised as important to enhance classification accuracy (Cochrane, 2000; Omar, 2010; Mutanga and Skidmore, 2007). The superiority of the WV-2 over Sentinel 2 and Landsat 8 images data can be attributed to its unique combination of high spatial and spectral resolutions. Contrasted with multispectral images, WV-2 show that the additional band (yellow - 585 - 625 nm) are essential in classifying grass communities. The effectiveness of the yellow band was established by assessing the significance of each spectral band WV-2 in the classification.

Results show that different sensors' spectral resolution has a different capacity in the insight of grass communities. The finding variable importance in this study for (SWIR 1) Landsat 8, (red) Sentinel 2 as well as (yellow) WV-2 bands is compatible with previous studies (Féret *et al.,* 2015; Marshall *et al.,* 2012). Findings also confirm that the yellow band (585 to 625 nm) on WV-2 needs to be included as one of the ideal bands in discriminating grass communities. The finding was compatible with the previous study by Féret *et al.* (2015) who showed that a yellow spectral band of the WV-2 is a middle band, which is helpful to the content of the chlorophyll, while compared to the green band enhancing classification. Results found that green spectral window in all three sensors was the least controlling band in classifying grass communities during summer. This shows that through the summer period, the green band was less powerful and may be assigned to the reality that as much as it was a period of high chlorophyll concentration, the spectral band was not as useful as the red (0.665 nm) in Sentinel 2 (Gitelson and Merzlyak, 1996 and Marshall *et al*., 2012). Marshall *et al.* (2012) stated that the traditional NIR band contributed the least in classifying buffel. An invasive C4 grass community in Australia reported the same finding. Furthermore, the grass condition was mapped using NDVI from Landsat 3, 4, 5, and 8 spectral bands to check the quality of the grass communities around the coal mining.

Grass communities monitoring, detection, and mapping using remote sensing have attracted scientific attention. Satellite images are timely reliable with cost-effective and relatively correct data (Lees and Ritman, 1991 and Ustin *et al.,* 2009) that provide helpful details in assessing grass deterioration.

Multispectral data are easily accessible and cost-effective whereas hyperspectral data are not. Recently, researchers have recommended the WV-2 image in classifying vegetation at the communities' level. The strategically located bands (yellow) of the recent sensors and with finer spatial resolution allow vegetation communities' classification accuracy elevated (Cho *et al.,* 2012). Mansour and Mutanga (2012) have used WV-2 data to classify grass communities and assess the grass deterioration in South Africa's ecosystem. Authors consider the WV-2 imagery for operational grass communities' classification costly. However, using free remotely sensed data grant adequate understanding of large-scale grassland degradation assessment.

Recently, many researchers identified RF as a powerful technique in classification (Adam *et al.,* 2012; Lawrence *et al.,* 2006; Ham *et al.,* 2005; Ismail and Mutanga, 2010). This study affirms RF's robustness remote sensing technique in classifying the grass communities. These results are compatible with previous research that revealed the RF importance in enhancing the discrimination between features (Adam *et al.,* 2012). Furthermore, Adam *et al.* (2012) noted the challenge of arranging bands in RF in terms of classification inaccuracy. This study shows the capability of WV-2 bands classifying the grass communities and NDVI for quality of grass communities. However, there is a need to determine spectral bands that cause the lowest misclassification error. Results show the success of RF performance in classification of the bands that discriminate the grass communities. Confusion matrix was calculated for checking the accuracy of the three images by comparing the true class with the class assigned by the classifier. Overall accuracy assessment shows the results to be 88.50%, 76.15% and 66.67% with kappa coefficient of 0.87%; 0.73%; 0.63% respectively. On the variable importance measurements in RF, the mean decrease in accuracy was applied to each of the WV2, Sentinel 2 with Landsat 8 classifying the thirteen LULC.

On the study, it was noted that images obtained during the summer seasonal are most useful for classifying the grass communities because the grass communities wilt, perish, and exhibit a typical red to brown colour during the winter season. It is common for grass communities in winter to perish and become red/brown because there is no rain. The NDVI results, as well as the NDVI difference results, shows that vegetation condition has decreased greatly before and after the mining commenced. The study finds that the grass communities areas far from the mines are good condition than the areas close to the mines. The results also show diminished vegetation in the area where vegetation was previously high before and after the mining commencement. In addition, the areas that are characterised by the *Sorgum halepen* and *Panicum ecklonii* shows decease in the condition after the mining lifespan. The changes with these grass communities may depend on their adaptation. NDVI values were calculated to see the condition of the grass communities and NDVI differencing of five images. The negative effect that includes a decrease in grass communities around mining areas of study is high, thus resulting in the likelihood of floods to occur. The results of this study have shown that *Monocymbium ceressiiformeri*, mixed grass and *Seriphium plumosum* communities thrive in mining. These grasses only show some minor changes.

NDVI was calculated using average mean-variance of the classes from image statistics which shows the temporal behaviour of the normalised vegetation index (Washington-Allen *et al.,* 2008). The approach was used to identify the grass communities state between 1978 to 2018, using the mean which shows vegetation in the surface. However, NDVI values that were higher are seen as healthy vegetation during the growing season. The reason for this could be the seasonality of the images or the grass communities, which are less tolerant of the mining environment. The mining in the area started between the 1970s as confirmed by the grass communities state than other years. During the year, the vegetal of the area started experiencing changes. In comparison, field surveys could provide more detailed information related to changes in vegetation. In the present study, the disturbance and recovery of the vegetation community were determined using NDVI. However, catastrophic and extensive changes in the vegetation environment pattern were observed. The surface vegetation shows a certain capacity to persist in its state when suffering from mining disturbance. This type of capacity is termed resilience, which refers to the ability of an ecosystem to tolerate disturbance and reorganize to retain essentially the same function, structure, and feedback and to have the same identity (Walker and Salt, 2012). The same results of this study were consistent with the above-mentioned study. The results show that the average NDVI at the beginning of mining in the area and later were significantly different. Ermelo coalfields in the mining area and other regions that have the same natural conditions and human activities were taken as the controls of vegetation NDVI variation. These controls allowed other factors affecting NDVI to be separated from coal mining to highlight the change in NDVI in the coalmine area owing to the disturbance of the vegetation by coal mining. This indicated that continuous coal mining could be problematic on the vegetation in the mining area. The response of vegetation NDVI values had greater fluctuations.

5.2 Conclusions

In this research, the grass communities, spatial distribution and health condition of grass communities were assessed. The study also pursued to assess and compare the capacity of the WV-2, with the Sentinel 2 and Landsat 8 images. The findings of WV-2 have shown its capacity in classifying grass communities. The NDVI calculated was found to be useful in checking the quality of the grass communities. However, future mining activities designed to extract coal resources below the current mine level could still expose the local ecosystem to degradation hazards. The level of accuracy needed with the extent of grass communities patches depends on the amount of information needed. The recent remote sensing imagery (WV-2) in the mapping of grass communities is recommended but the medium resolution imagery may be used.

However, the classification of Landsat 8 is likely to be less accurate, especially for a small area where types of grass communities exist. In those circumstances, the finer resolution WV-2 data is advised for better classification accuracy. Knowledge of land-cover and land-use change is necessary to model the earth system and its environments. However, monitoring of grass communities will have a significant ability to stop natural hazards that results in disasters. Therefore, observations and methods are needed

to quantitatively characterize historic and current grass communities dynamics in a way that influence climate change and extreme weather events. Some disasters such as flooding, landslides, and mudslides to name but a few, occur due to void of grasses from the surface. The characteristics and nature of these hazards are closely related to the terrain conditions, grass dynamics and changes in grass communities growth.

This study provides the method to determine the state of vegetation coverage to observe the progress of rehabilitation using NDVI. Comparing the results for 1978 with 2018, it was noted that some of the regions undergone degradation and/or the grass communities are not in good health condition. However, it requires monitoring because it could lead to the area to be void in grass communities. However, the results have highlighted the capacity of the bands of the WV-2 sensor on the classification of grass communities. Overall, these findings propose that medium resolution can successfully give a baseline for the distribution of grass communities and assessing grassland deterioration. Three images ability successfully classify the grass communities spectral differences. In this study, the peak of the summer season has been recognised as an acceptable time for effective classification of grass communities as this is a suitable season for their growth. It is recommended that, due to the surface occupied by mining activities, the medium resolution data could be used even though data remain a problem. It is further recommended that long-term ecological monitoring and resilience assessment should be conducted to gain a deeper understanding of changes to the surface vegetation shortly.

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