ASSESSING THE IMPACT OF OPEN PIT GOLD MINING ON THE LAND USE LAND COVER CHANGE USING GIS & REMOTE SENSING: CASE STUDY IN YATELA GOLD MINE, MALI (1999-2015)

BY

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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) AT THE SCHOOL OF GEOGRAPHY, ARCHAEOLOGY & ENVIRONMENTAL STUDIES.

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23 MARCH 2017 IN JOHANNESBURG

DECLARATION

I, Vuledzani Hector Munyai, declare that this research report is my own unaided work. It is being submitted to the Degree of Master of Science in Geographical Information Systems and Remote Sensing to the University of the Witwatersrand, Johannesburg. It has not been submitted before for any degree or examination at any other University.

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Signature of candidate

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ABSTRACT

The main purpose of this research was to investigate the impact of open pit mining on the Land Use Land Cover Change (LULCC) of the Yatela region in Mali.

The methodology used to assess the open pit mining operations were remote sensing vegetation indices (NDVI) and LULC maps at a four year interval from 1999 to 2015. The Support Vector Machine (SVM) classification was used to create the LULC maps. Assessment of the quality from SVM classification outputs were analyzed using the confusion matrix technique. Three satellites (Landsat 5, 7 and 8) were used to analyze the images that were extracted from scene path 202 row 050. The NDVI results were able to detect the development and expenditure of the open pit mine in the Yatela region from 1999 to 2015. The roads and open pit mine area were easily detected from the 1999 NDVI results. Over the years the vegetation cover varied in the Yatela region, good vegetation cover was present before mine operations (1999) and after the mine closure (2015).

The average overall accuracy for the five classified images was 84.31%. The change detection statistics showed that there were significant changes in each of the five classes over the 16 year period. Anthropogenic factors are assumed to be the major contributing factor to the Land Use Land Cover Change in the Yatela region. Nonetheless, this should not mean that climate factors can be neglected as contributing factors to LULCC in the region. Due to data limitation this research was unable to test any climatic influences.

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ABBREVIATIONS AND ACRONYMS

IRS 1A	Indian Remote Sensing Satellite
KKI	Kedougou-Kenieba Inlier
LAI	Leaf Area Index
LULCC	Land Use Land Cover Change
NDVI	Normalized Difference Vegetation Index
ROI	Region of Interest
SAM	Spectral Angle Mapper
SPOT	Satellite Pour l'Observation de la Terre
SVM	Support Vector Machine

CHAPTER 1

INTRODUCTION

1.1 INTRODUCTION

The environment has dynamic external forces that contribute to equilibrium and change on the earth's surface through different feedback cycles (Bowman *et al*., 2015). Land cover changes can be influenced by natural earth cycles (seasonality and climate) or by anthropogenic factors (Georgescu *et al.,* 2008). The human population has been growing at an exponential rate to current estimates of seven billion worldwide (Ezeh *et al.,* 2012). This enormous growth of human population can put a lot of strain on the earth's resources such as minerals. Humans only occupy inland and coastal regions because they were not created to survive in water environments like oceans. Large parts of land need to be allocated for housing and farming processes, in order to accommodate human life. With the advancement of technology across the globe, the demand for natural resources has increased. The increase of resource demands, leads to the increase of mineral exploration and mine operations (Wellington and Mason, 2014).

There has been an increase of mining activities in West Africa due to new mineral discoveries. Every mining activity comes with advantages and disadvantages for the local economy (Al Rawashdeh *et al.,* 2016). The advantages would be job creation, skills development, housing and road infrastructures (Al Rawashdeh *et al.,* 2016). The disadvantages are environmental degradation (e.g. deforestation and water contamination), the other issue would be relocation of indigenous tribes from one location to another (Al Rawashdeh *et al.,* 2016). The assessment of land cover change and environmental monitoring has been receiving scientific attention recently due to the advancement of remote sensing. Ever since the launch of Landsat 1 in 1972 which has good temporal data of the earth surface (Wulder *et al.,* 2016). This data can be used for spatio-temporal analysis of any specific area on the earth. There are approximately 5,532,454 images in the USGS archive collected by Landsat satellites (Wulder *et al.*, 2016).

Mine rehabilitation monitoring remains a very important stage in mine planning, because every mine has a life span and when the time comes for closure, there should be systems in place that will be able to minimize environmental impacts (Rixen and Blangy, 2016). Anthropogenic and climatic factors can influence the spread of vegetation species across a landscape (Liu and Menzel, 2016). The most common error, mining companies make in the mine rehabilitation planning processes is that little or no spatial and temporal change analysis is done before or during the mine operations. Temporal change analysis is vital because planting a specific vegetation type that was indigenous in that area before the mine operation does not mean that it will grow again in that area after the mine operations close down. This research will investigate the spatial and temporal change of land use land cover in the Yatela mine area using GIS and Remote Sensing.

1.2 Problem statement

Open pit Mining activities have a lot of environmental impacts that are local such as removal of vegetation, increase of soil erosion, channel flow interruptions and contamination of water resources. The impacts from mining activities can be enhanced by the imbalance between economic growth and the environment. Many developing countries like Mali are forced to sacrifice the environment for economic growth because of high levels of poverty.

Open pit mine operations remove large quantities of topsoil and debris; this can have negative impacts on groundwater contamination and biodiversity species communities. Stock piles created from open pit mines prevent vegetation growth. Most mine company managers struggle to operate mines in a manner that will have minimal environmental impact after mine closure. The environmental impacts from the mine are a major area of concern that needs to be investigated.

1.3 AIM

The aim of this project is to investigate the impact of open pit gold mining on land cover in the Yatela region Mali (1999-2015) using quantitative analysis on Landsat Images.

1.4 OBJECTIVES

- To map the vegetation cover around a mined area by using vegetation indices and land cover change detection.
- Identify any land cover changes that occurred in the Yatela region.

1.5 RESEARCH QUESTIONS

- What impact does gold mining have on vegetation?
- How much Land Use and Land Cover Change transpired during the 16 year period (1999-2015)?
- Can support vector machine algorithm and NDVI be used to detect mine operations and quantify the LULCC caused by open pit mining?

CHAPTER 2:

LITERATURE REVIEW

2.1 OPEN PIT MINING

The aim of mining operations is to extract mineral resources from the earth through multiple processes: underground mining, surface mining, solution mining, dredge mining and undersea mining. The mining of minerals is solely for making profits and increasing buying power, (Espinoza *et al.,* 2013) state that mines have five stages:

- Prospecting or discovering mineral deposits
- Exploration/determining value of deposits
- Development
- Exploitation
- Reclamation

Open pit mining requires the removal of overburden/waste. This waste is then transported by vehicles to a surrounding area for dumping as stock piles. Extraction of minerals can only begin after the process of overburden removal is complete. Some of the open pit mines have characteristics such as bench height, ramp, crater, face and ore (Espinoza *et al*., 2013), refer to **figure 1** below.

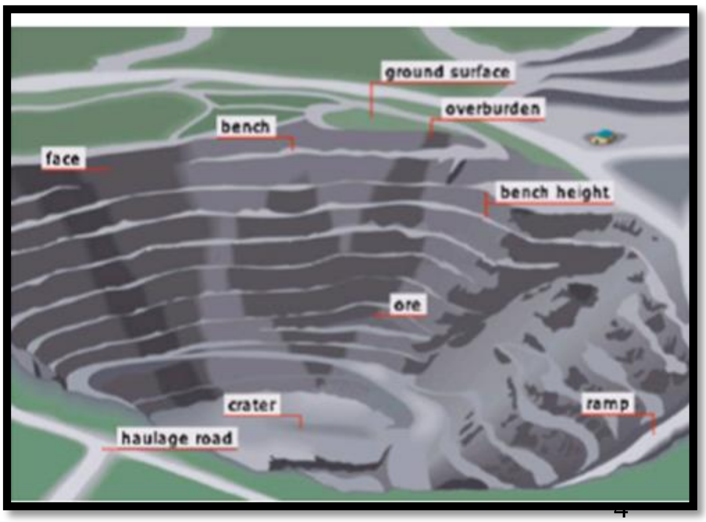


Figure 1: Open pit mine diagram (Espinoza *et al*, 2013)

Most open pit operations require blasting in order to reach ore mineral extractions. The blasting causes rock deformation and this process requires explosives. Any project that makes use of explosives would have a negative impact on the surrounding area. Approximately 20 to 30% of the explosive energy is used for rock deformation/fragmentation. So what happens to the rest of the 70 to 80% of energy left? Most of it is dissipated into ground vibrations, over break, fly rock, air blast and back break (Espinoza *et al.*, 2013). The ground vibrations were tested using two monitors white mini-scis and instant eliminate plus model for statistical analysis, the results indicated that ground vibration caused approximately 50% of damages to surrounding areas (Kahriman *et al.*, 2006).

2.2 Mining in Mali

An Economical Financial Report (2010) stated that Mali is the third largest producer of gold in Sub-Saharan Africa with an increase of 85% in production growth between 1991 to 2008 (Drakenberg, 2010). The majority of mines in Mali are not owned by locals but rather by foreign companies. Approximately 90% of the labour sources in the mines are Malians. Even though 90% of mine workers are Mali locals, there is approximately 100 000 to 200 000 people involved in artisanal mining. Artisanal mining is a growing informal industry whereby people work for themselves rather than working for mine companies (Fisher, 2007).

Artisanal mine workers include women and children in Mali fields. There are similarities between large and small scale mining on the social development impact. Both mine industries have high rates of HIV/AIDS, substance abuse, crime and prostitution. The main difference between the two sectors is that artisanal mining discourages children from attending school; while the high paying jobs in the formal mine industry attracts children to further their studies (Fisher, 2007).

There are many economic benefits from mining industries, but there is always resettlement involved in major development projects. Three villages had to be relocated in order to accommodate the Sadiola and Yatela gold mine in Mali (Maslen *et al*., 1999). The process of resettlement took place between 1998 and 2000. The Mali government has no guidelines for resettlement, but rather uses the World Bank involuntary resettlement directive. Approximately 2,135 people were relocated from Sadiola Hill by AngloGold mining company and the government. The cost of relocating the villagers cost US$ 5.5 million. In the case of Yatela village, approximately 162 people were relocated and this cost about US$ 750 000. The implementation responsibility fell to the working groups, SEMOS development foundation, mine and executive committee (Mackenzie *et al*., 2003)

2.3 Historical overview of Remote sensing

The growth of Land Use Land Cover Change analysis in research can be attributed to the improvement of remote sensing field. There are multiple definitions of remote sensing one of which states that "remote sensing is the science of acquiring, processing and interpreting images that record the interaction between electromagnetic energy and matter," (Kerle *et al.*, 2004, p293).

The development of Landsat 1 in 1972 gave rise to spatio-temporal data of the earth surface. Over the years, new sensors have been developed with improvements on the spatial, spectral and temporal resolutions. There are commercial and non-commercial satellite images that are available.

Table 1: Commercial satellites (USGS- United States Geological Survey)

Commercial Satellite	Background Information
GeoEye-1	Launched on 6 September 2008 1.65m resolution
IKONOS	Launched on September 1999 4m resolution
Quick bird	Launched on October 2001 2.62m resolution
Worldview 1,23	Launched in 2001,2007 and 2009 Approx. Resolution 0f 2m
Spot 7	Launched on June 2014 1.5m resolution

Source: Satellite Imaging Corporation (2017)

Table 2: Non-commercial satellites (USGS)

Non-commercial Satellite	Background Information
IRS 1A	Launched march 1988 36.25m resolution
Landsat	Landsat 1 was Launched in 1972 The current Landsat 8 was launched in February 2013 30m Resolution
Sentinel 2A	Launched in June 2015 10m resolution

Source: Satellite Imaging Corporation (2017)

There are several analyses that could be processed on satellite images such as unsupervised classification (ISODATA and K-means etc.), supervised classification (maximum likelihood, minimum distance, parallelepiped, SVM etc.). Remote sensing tools can be used for Land Use Land Cover Change maps, to depict any change that has occurred over a specific region. The benefits of using remote sensing are that there is no need for direct contact between the researcher and area of interest. There are many challenges that can affect the efficiency of field work data collection, such as no access to the area, travelling costs, civil wars in a country or under staffing for field work.

There are passive and active sensors that can be used to collect data from the earth surface (Toth and Jozkow, 2016). An active sensor does not rely on the sun’s energy emission but rather it generates its own energy onto the earth, the advantages of these sensors are that they can operate during the day or night (Toth and Jozkow, 2016). Atmospheric influences like cloud cover can be avoided with active sensors. The passive sensor does not generate its own energy but rather depends on the sun's energy or the earth's energy to record the electromagnetic energy (Toth and Jozkow, 2016). Landsat satellites are passive and mostly rely on the sun's energy to collect data; since the data is collected during the day, Landsat imagery cannot be captured at night.

Everyday light interacts with the human eye, but only a small portion is detected by the naked eye, the rest is not detected. Sensors on the other hand can easily pick up different wavelengths of light (Toth and Jozkow, 2016). The electromagnetic spectrum is formed by gamma rays, microwaves, x-rays, visible light, infrared light and ultraviolet light (Oliveira and Santos, 2016). The visible light region covers a wavelength of approximately 0.4 millimetres to 0.7 millimetres. The longest wavelength in the visible region is red (0.620mm-0.7mm). The shortest wave length is violet (0.4mm-0.446mm). The visible region is where natural colours exist for example blue, green and red. The near infrared (NIR) region cannot be detected by the naked eye (Turner *et al.,* 2003). This region covers a wavelength of 0.7 millimetres to 100millimetres; the region can be divided into sub-groups of reflected IR and thermal IR (Turner *et al.,* 2003). The advantage of the thermal IR region is that it can detect heat radiation emitted from the earth surface. The microwave region covers one millimetre to one metre of the electromagnetic spectrum, this region is also important in the field of remote sensing (Turner *et al.,* 2003). The long wavelengths of the microwave region are used for radio broadcasting and the shorter wavelengths have similar properties as the thermal IR region (Turner *et al.,* 2003).

Light can interact with objects on the earth surface in different ways, depending on the nature object of interest. Some objects can absorb, transmit or reflect the light energy off a surface. These interactions can be detected by the sensors on satellites. The sensors do not see trees, water or built up areas like humans can but they only see digital numbers, depending on the clustering and number values a user can usually interpret the results as real features that represent the earth's surface (Toth and Jozkow, 2016).

2.4 Land Cover Mapping

Land cover mapping is a very important application to use in order to get an understanding of land features and land developments. Land cover mapping can show the link between humans and the natural environment (Otukei and Blaschke, 2010). Many undeveloped countries in Africa still lack the knowledge of how powerful the tools for land cover mapping can have on the growth and monitoring of their environment and resources (Otukei and Blaschke, 2010).

There are many classification algorithms that can be used for land cover mapping. The classifications algorithms are divided into two categories (common and advanced). The advanced categories includes algorithms such as support vector machine, artificial neural networks, object based classification and decision tree. The common classification algorithms are maximum likelihood classifier, K-means, minimum distance mean and ISODATA (Otukei and Blaschke, 2010).

In order to quantify the quality of the results from the different classification algorithms, an accuracy assessment should be processed on the algorithms. The most common accuracy assessment used is confusion matrix.

The term Land Use and Land Cover is used frequently together in the remote sensing profession. Thus a break-down of each term should be explained separately. Land use is a representation of current and future human induced activities and infrastructure on a specific area (Anderson 1976). The categories depend on the countries' scheme, but common schemes that are used globally are agriculture, industrial, forestry, commercial and residential (Rujoiu-Mare *et al*, 2016). Land cover is the representation of the earth surface (physical and biological) such as water bodies, forests, wetlands or agricultural areas (Anderson, 1976).

Land cover classes can be identified from field work or visual interpretation of orthophotos. With the development of technology remote sensing offers cheaper and quicker results compared to manual field work.

(Zhao *et al.*, 2016) say there are many gaps in land cover mapping around the globe, most of LULC maps on a provincial scale are missing while the national scale maps are inaccurate and too broad in class schemes. With the advancement of medium resolution images available, the task of creating good LULCC maps at a national and provincial level is possible now. Land Use Land Cover maps provide useful information that can be used for scientific earth studies, environmental monitoring and planning, assessment of natural and human-induced drivers of land use change (Clark and Kilham, 2016).

Land cover change can be due to human inducement or natural factors such as climate or hazards. Human induced factors can be assumed to occur at rapid rates compared to natural factors that take a longer time to cause significant change on a landscape (Melendez-Pastor *et al.*, 2014). The abandonment of agricultural live-stock areas can contribute to land cover change because invasive species can grow in these fields and occupy large portions of the area (Melendez-Pastor *et al.*, 2014). Mineral exploration and mining activities can influence the land cover change, particularly the type of mining that is taking place. The rate of land cover change is different for underground mining or surface mining. Underground mining causes slow change to the landscape (above surface) because it occupies less space and there is no removal of surface material, while surface mining activities generate huge environmental changes. The rapid rates attributed to surface mining are removal of soil, debris and rocks. The type of mineral been mined influences the type of pits constructed and quantities of waste debris deposited on the surface (Redondo-Vega *et al.,* 2017).

Another issue that arises from the mining sector is artisanal mining, which can contribute to land degradation and land cover change. Approximately over 13 million people are involved in artisanal mining across the globe, and the main reason is unemployment rates that force people into this business (Fisher, 2007). Most of the artisanal activities are not monitored by government or environmental officials, so their impacts on the environment are not well documented. These mining activities usually occur in patches across an area with different diameter sizes. The scale at which artisanal mining can change land cover is still not well researched and may vary for different areas depending on the type of mineral being mined.

Governments across the globe have implemented strategic laws to protect certain land cover areas. The effect is called conservation-induced resettlement, which is used to remove human population that occupies land that can be used to conserve natural resources e.g. national parks or wetlands (Platt *et al.,* 2016). Environmental laws can be compromised due to the economic status of a country, for example developing countries will properly continue with a project that has the potential to harm the environment, but brings in economic growth to the country.

2.5 Socio-economic environment of Yatela

The villages in the surrounding areas of Yatela mine project are headed by a chief with the assistance of an administrator. The responsibility of the chief is to handle issues that concern the village and its people. There is no clear boundary between the villages; most of the villages are cropping villages. The amount of livestock and water supply availability in an area will determine the growth of the area. Most of the villages in the area have similar crops such as maize, millet, peanuts and okra. Subsistence farming has less financial benefits compared to formal employment in town. That is the reason why most of the youth run away from subsistence farming practices (Maslen *et al*., 1999).

The common livestock found in villages around Yatela are goats, chickens, cattle, sheep and horses (Maslen *et al*., 1999). Water is a major contributing factor to the survival of livestock; most villagers have wells as a water source.

Artisanal gold mining is practiced in the area as a source of income for the village people. Due to low water flow in the tributaries, some villagers have abandoned gold panning practices (Maslen *et al.,* 1999). Cutting down of wood as a source of fuel is practiced in the area and it is considered a good business sector.

The level of education in the area is very low, because less than 1% of the population has completed four years of schooling while only 2.8% of the population has ever gone to school (Maslen *et al.,* 1999). Most of the villagers have agricultural and craft skills such as building, sewing, carving and weaving (Maslen *et al.,* 1999).

The Yatela mine covers an area of 450 hectares of land (163 hectares arable while 287 hectares is non-arable). The waste rock stockpile 1 and 2 impacts an area of 243 hectares. The mine villages constructed to accommodate the mine workers covers an area of nine hectares. The ore stockpiles cover an area of 10 hectares. The ponds constructed during the mine operation phase occupies an area of 75,565 square metres with a total volume of 271,500 cubic metres, vegetation and topsoil were removed to accommodate the pond construction (Maslen *et al*., 1999). Road networks were built around the open pit mine to the waste stockpiles (a one and a half kilometre road). The road to the ore stockpiles covers a distance of 0.6 kilometres; the total length of the road networks is approximately seven kilometres (Maslen *et al*., 1999)

Mine closure steps:

Return the land to its land use capability that existed before the mining operation, taking into consideration that structures such as the waste rock dumps, heap leach pad and open pit cannot be removed or backfilled.

Once the heap leach pad wash-down has been completed, the ponds will be decommissioned. As a result of the heap wash-down process it is anticipated that all solution in the ponds will also be reduced to 2% WAD cyanide (Maslen *et al*., 1999). If not, further dilution will continue. All pond solutions will be disposed of only when the cyanide concentration target has been met and disposal will be via the Detox Plant.

Where footprints are located on arable land, the topsoil that was initially removed will be returned. Some grass cover may be planted to counter dust generation, but no self-sustaining cover will be established, nor will any trees be planted as the arable land will be used for cropping (Maslen *et al*., 1999).

If the topsoil stockpiles are located on arable land, it is expected that the land will be used for farming after mine decommissioning and closure. There is therefore no need for establishing a self-sustaining vegetation cover, nor is there any point in planting trees (Maslen *et al*., 1999).

The ore stockpiles are located on arable land and it is expected that after mine decommissioning and closure, the land will be used for cropping. There is therefore no need for establishing a self-sustaining vegetation cover, nor is there any point in planting trees.

Once dewatering of the open pit ceases, the water table will re-establish, forming a lake of approximately 50 hectares and 175 metres deep. (These dimensions will obviously vary depending on the season and the rainfall history.)

The domestic landfill will be covered with soil from the landfill excavation and compacted. Any remaining void of the landfill excavation will be backfilled. The disturbed area will be rehabilitated by establishing self-sustaining vegetation.

Before any potentially useful buildings or other infrastructure are demolished, consultations will be held with the local community and regional authorities to determine what, if any, of the infrastructure should remain for their use. This includes plant buildings, mine village, power supply, water supply and treatment, sewage treatment and roads (Maslen et al., 1999).

Chapter 3

MATERIAL AND METHODS

3.1 STUDY AREA

The open pit mine in the Yatela region is approximately four kilometres in length and the study area for this research is 480 square kilometres (figure 2). The Yatela region contains the gold deposit in the Kedougou-Kenieba inlier (KKI). The different types of lithologies in the Yatela region are metamorphic and sedimentary rocks. South of the Yatela mine is the Sadiola gold mine.

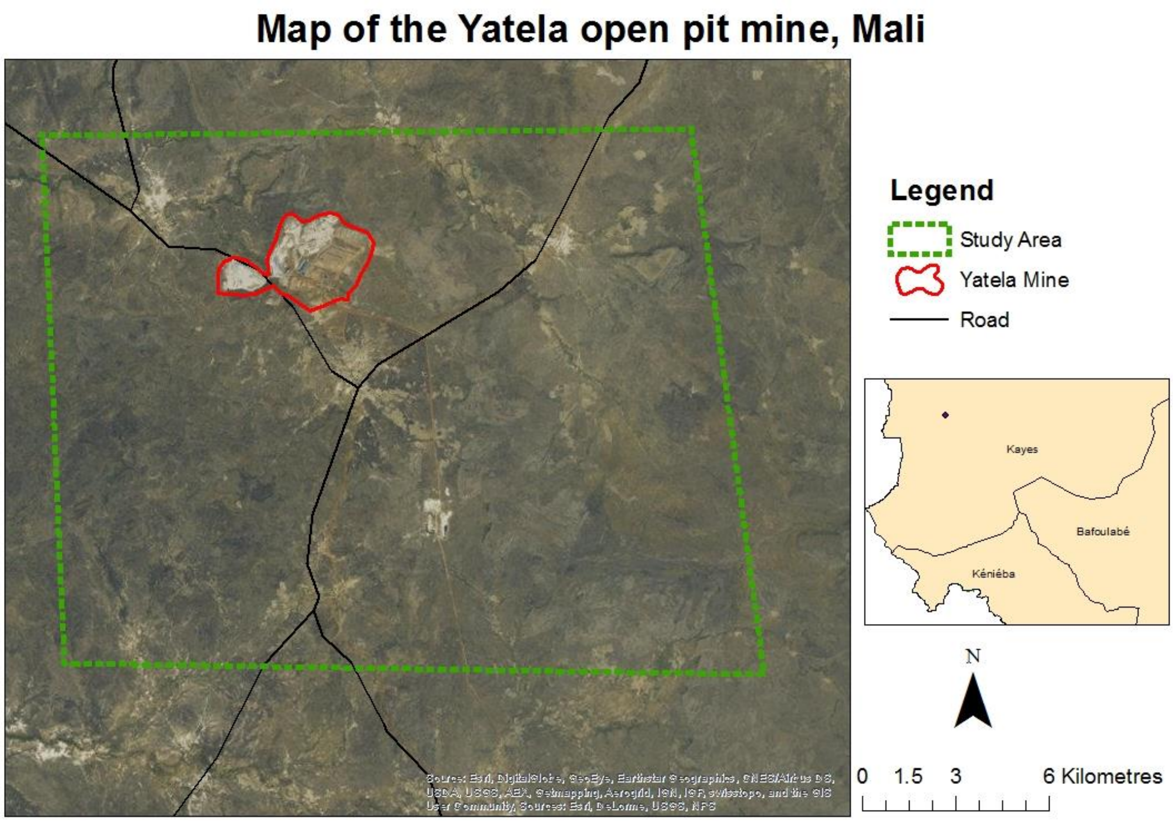


Figure 2: Yatela Region Location Map

The open pit mine operations in Yatela, Mali started in mid-2000. This was largely due to the growth of the mining sector which was evident from a report released in 2001 that Mali was ranked the third largest gold producer after South Africa and Ghana in the African rankings. There were multiple investors involved in starting the open pit Yatela mine; a total of approximately $75 million dollars was raised: 40% from AngloGold, 20% Mali government and 40% IAMGOLD. The mine was estimated to produce approx. 1.4 million ounces of gold (Szczesniak, 2003)

AngloGold Ashanti Mine Company started negotiations for annual wage and multiple meetings with two labour union bodies. Because AngloGold Ashanti (AGA) set out 7 main areas of focus in their mining operations such as: job security, accommodation and living conditions, human rights, employee safety and health, employee indebtedness, talent management and skills development . The production volumes of the Yatela Gold Mine have been steady since 2011-2014 with an annual average of 1.025Mt. The Association Subaahi Gumo (ASG) also reported electricity concerns in Mali that might have an impact on the mining operations in the country. Closure of the Yatela mine got underway in 2015 with 2019 projected as the year at which rehabilitation will be complete (Szczesniak, 2003).

3.2 Rainfall

The Yatela area has a dry season from November to early May. The rainfall season begins in June and lasts until October (World Meteorological Organization 2016)

There is a huge contrast between the dry season and wet season that can be observed from Landsat images with respect to vegetation cover. The preferred time interval for acquiring the images would be June to October, because higher vegetation cover will be present. The issue with the time interval mentioned earlier is cloud cover in the image. The solution to this issue was downloading images in October and November.

3.3 VEGETATION COMMUNITIES AND PLANT SPECIES

The Yatela region has seven different tree species that are listed in Table 3. The Acacia Albida can grow in different environments, such as savannah woodlands, along perennial streams or cultivated lands. The distribution of the Acacia Albida occurs across West Africa, East Africa, small portions in the coastal region benefit Angola, central and northern part of South Africa and Lesotho (Wickens, 1969).

Table 3: Types of Tree Species

Tree Species
Acacia albida
Bombaxcostatum
Borassus aethiopum
Butyrospemum parkii
Khaya senegalensis
Parkia biglobosa
Pterocarpus erinaceus

The Bombaxcostatum is a fire resisting tree, which is concentrated in West Africa. The Bombaxcostatum species grows well in stony soil conditions. Economic benefits of the tree are manufacturing of match-sticks and medicine for skin cancer.

The Borassus aethiopum can grow in low lying areas next to rivers, and any savannah type conditions. The timber can be used by the locals for roof materials and building bridges. The Butyrospemum parkii is also located in the West African region and parts of Sub-Saharan Africa. The main use of the species is to extract the vegetable oil for skin moisturizer (World Agro forestry Centre 2017).

Khaya senegalensis are evergreen trees that grow in areas that have savannah conditions and moderate to high rainfall. The benefits of Khaya senegalensis species is that it can be used as a fever remedy and making poison for hunting fish (World Agro forestry Centre 2017).

Parkia biglobosa can grow on rocky slopes, sandstone hills, savannah woodlands and anthropic communities. The timber can be used for furniture, firewood and food source for domestic livestock such as cattle (World Agroforestry Centre 2017).

Pterocarpus erinaceus is mostly located in open forest and savannah woodlands (West Africa). Some of the economic benefits of the species are the extraction of dye for cotton and the roots of the tree can be used as a cough remedy. The vegetation communities located in the Yatela region are Combretum dominated woodland communities, Sudanese gallery forest communities; open savannah community and sparse savannah woodland (World Agroforestry Centre 2017).

3.3 Remote sensed data

All the Landsat images were acquired from United States Geological Survey (USGS) earth explorer. The location of the tiles used were path 202 row 050. The 1999 and 2003 were Landsat 7 ETM images, while the 2003 and 2011 were Landsat 5 images. The chosen dates of acquisition were influenced by the construction and closure of the Yatela mine, which began in late 1999 and was closed down in 2013. The other contributing factor for selecting Landsat 5, 7 & 8 images were clear atmospheric conditions, summer seasonality and costs; Landsat images are freely available on the USGS website through Earth Explorer (table 4). The ideal season for acquiring the Landsat images was the summer season but due to high cloud cover during the raining season. This would make it difficult to do any analysis that would generate quality results due to the cloud cover. Most of the images were acquired from November (end of rain season), because the cloud cover was better. The reason for downloading the 2007 and 2011 Landsat 5 images was due to line stripping problems from Landsat 7. Line stripping is caused by malfunctioning sensors; they generate lines that cut across the raster datasets acquired by the sensor (Tsai and Chen, 2008). Line stripping can be removed by using different algorithms but requires two images that are consecutive with each other. Due to high cloud cover and non-availably of images for 2006 or 2008, Landsat 5 images were acquired to fix this problem of line stripping.

Table 4: Information on the Landsat Satellite images used in this projects

Satellite	**Spatial resolution**	**Spectral resolution**	**Band width**	**Date of acquisition**
Landsat.7 Enhanced Thematic Mapper (ETM)	30m	8 bands	Band 1 (0.45 - 0.52) Band 2 (0.52 - 0.60) Band 3 (0.63 - 0.69) Band 4(0.77 - 0.90) Band 5(1.55 - 1.75) Band 6(10.40 -12.50) Band 7 (2.09 - 2.35) Band 8 (0.52 - 0.90)	1999-11-12 2003-11-23
Landsat 5	30m	7 bands	Band 1 (0.45 - 0.52) Band 2 (0.52 - 0.60) Band 3 (0.63 - 0.69) Band 4 (0.77 - 0.90) Band 5 (1.55 - 1.75) Band 6 (10.40 - 12.50) Band 7 (2.09 - 2.35) Band 8 (0.52 - 0.90)	2007-10-25 2011-11-29
Landsat 8 Operational Land Imager (OLI)	30m	11 bands	Band 1 (0.43 - 0.45) Band 2 (0.45 - 0.51) Band 3 (0.53 - 0.59) Band 4 (0.64 - 0.67) Band 5 (0.85 - 0.88) Band 6 (1.57 - 1.65) Band 7 (2.11 - 2.29) Band 8 (0.50 - 0.68) Band 9(1.36 - 1.38) Band 10(10.60-11.19) Band 11(11.5 - 12.51)	2016-10-04

3.3.1 ANCILLARY DATA

Due to time and budget constraints of the project, reference data (topographic maps and aerial photographs) could not be obtained from the Mali government in time for the data analysis process. A substitution for this issue was using Google earth imagery as reference data.

3.4 PROCESSING

A summary of the overall workflow is presented in figure 3 below. Detailed descriptions of the operations follow.

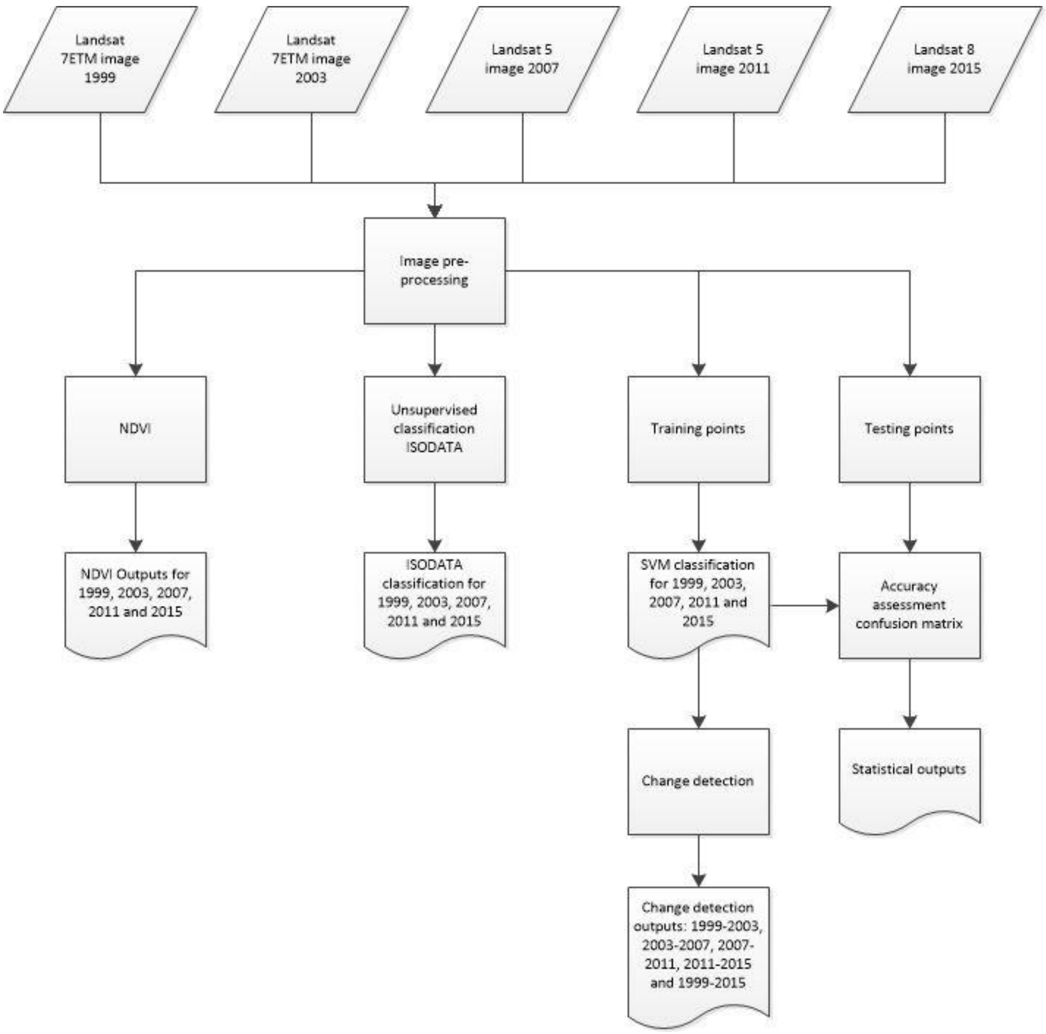


Figure 3: Work Flow Chart

3.4.1 Development of class scheme

The classification scheme: vegetation, water body, mine, settlements and bare land (refer to Table 5) were selected after running the ISODATA unsupervised classification and visual interpretation of the Yatela region on Google earth images.

Table 5: Land Use Land Cover Classification Scheme

Class	**Description**
Bare land	Land areas that have exposed rocks, sparse vegetation or no vegetation.
Vegetation	Land areas that contain trees and plant species.
Mine	Area that is used for mine operations.
Water	Water bodies like rivers, dams, lake and man-made ponds.
Settlement	Areas that contain houses.

Source: Ruelland et al., (2010)

3.4.2 Image pre processing

All the images were pre-processed to reduce any atmospheric effects or sensor distortions. For any remote sensing image analysis process, the images should have minimum distortions or cloud cover in order to produce sufficient results that can be used for environmental monitoring analysis.

There are multiple types of calibration to use like Fast Line of sight Atmospheric Analysis of Spectral Hypercubes (FLAASH) or dark subtraction etc. For this analysis FLAASH was chosen because of its popular choice in research papers as (Feyisa *et al* 2014, Li *et al* 2013 and Nazeer *et al* 2014) mention. FLAASH combines different types of aerosol and atmosphere MODTRAN with the MODTRAN 4 radiative code to generate a scaled radiance reflectance (Kutser *et al.*, 2005).

The equation used for calculating the spectral radiance is:

$$L^* = A\rho/(1-\rho_e S) + B\rho_e/(1-\rho_e S) + L^*_a$$

L^*_a is the radiance backscattered by the atmosphere, A and B are coefficients that depend on atmospheric and geometric conditions, ρ e is an average surface reflectance for the pixel and the surrounding region, ρ is the pixel surface reflectance and S is the spherical albedo of the atmosphere (Adler-Golden *et al.,* 1999).

The ideal environment for researchers to analyse radiance values would be recording the radiance value directly from the earth surface to the sensor without any external disturbance, but due to the dynamic atmosphere of the earth this ideal environment is unrealistic. The atmosphere is not homogenous but rather a heterogeneous body that is layered and dense with gases: carbon dioxide, nitrogen, oxygen, argon and water vapour. These gases will interfere will the signals being transmitted from the satellite to the earth's surface. There are multiple factors that can influence the quality of the image such as the position of the sun relative to the satellite during image acquisition (Kerle *et al* 2004, pp293).

Pan-sharpening was conducted on the Landsat 5 and 7 images to improve the spatial resolution of the images. The pan-sharpening tool in ENVI 5.2 requires a panchromatic band from the image bands to increase the spatial resolution of the multispectral image. Most satellites have multispectral images that lack quality spectral resolutions, while the panchromatic images have poor spectral resolutions, combining the two would generate better results (Rahmani *et al.,* 2010).

Table 6 shows the number of training points used for the SVM classification. The training points were split into 70% training and 30% testing for the accuracy assessment. In total each class had 100 points allocated for training and testing. The training and testing points were randomly selected from each image. 30 testing points and 70 training points were extracted randomly for each class per image.

Table 6: Summary of the Training and Testing Points

Classification image year	**Number of classes**	**Training points**	**Testing points**
1999	3	210	90
2003	5	350	150
2007	5	350	150
2011	5	350	150
2015	5	350	150

3.4.3 SUPPORT VECTOR MACHINE

"In its simplest form, SVMs are linear binary classifiers that assign a given test sample a class from one of the two possible labels. An instance of a data sample to be labelled in the case of remote sensing classification is normally the individual pixel derived from the multi-spectral or hyper spectral image" (Yu et al., 2012). Such a pixel is represented as a pattern vector, and for each image band, it consists of a set of numerical measurements. Elements of the feature vector may also include other discriminative variable measurements based on pixel spatial relationships such as texture. An important generalization aspect of SVMs is that frequently not all the available training examples are used in the description and specification of the separating hyperplane. The subsets of points that lie on the margin (called support vectors) are the only ones that define the hyperplane of maximum margin (Yu *et al*., 2012).

The performance of an SVM is controlled by the value of the penalty term (denoted as ‘‘c’’) and the parameter(s) of the kernel function, for example, width (presented as ‘‘gamma’’) in the case of the radial basis function. As discussed above, very high penalty values entail very low slack variable values, which, in turn, allow very few outliers. As a result, the SVM will have poor generalization capability, even if it shows high classification accuracy for the training data. The parameter(s) of the kernel function similarly influence the generalization capability of an SVM. For example, very large basis widths for radial basis kernels might lead to over fitting such that the resultant boundary between the classes is specific to the examples used in the training dataset (Yu *et al*., 2012).

The support vector machine learning algorithm was used to detect change over a 25 year time period in Axios and Aliakmonas rivers in Greece (Petropoulos *et al*., 2015). The detection was focused on erosion and deposition change over time. Some advantages of the SVM over other classification algorithms are that SVMs can handle large dimensionality datasets. Secondly, the implementing process is user friendly and does not require high levels of experience in order to run the classification, because few parametres are changed by the user and the accuracy of the SVM has yielded better results compared to other algorithms (Petropoulos *et al.,* 2015).

SVMs produce higher accuracy results compared to other classification algorithms (Jakob *et al.,* 2015) as mentioned by (Petropoulos *et al*., 2015). Other supervised classification algorithms used in a geological mapping study by Jakob et al (2015) were maximum likelihood, minimum distance, Spectral Angle Mapper (SAM) and neural net. Out of the five supervised classification algorithms used, the Support Vector Machine produced an overall accuracy of 99.81%, while neural net produced 84.43%, SAM 54.86%, minimum distance 57.29% and the maximum likelihood 47.16%. (Jakob *et al.,* 2015).

Five machine learning algorithms were used for geological mapping of the Broken Hill area in Western New South Wales by Cracknell and Reading (2014). The results of these supervised classifications confirmed the good performance of SVM, which produced an accuracy of 87%. Random forest machine learning algorithm outperformed SVM(91.4%).

Although Random Forest algorithm outperforms SVM, Random Forest algorithm is too advanced for the scope of work in the Mali project, because broad classes will be used in the analysis.

The benefit of using Google earth temporal images is that they are a combination of different spatial resolution satellite images of 15 metres and higher (Clarke *et al.,* 2010). Considering that Landsat images have a spatial resolution of 30 metres, this will not be sufficient enough to identify features in the Yatela region. With the aid of Google earth images, the task of identifying land features is made easier because five land classes were identified from visual interpretation. The results from visual interpretation could be sufficient enough to begin creating ROI for SVM classification. The use of ISODATA unsupervised classification will help in allocating the number of classes for the supervised classification. “The ISODATA unsupervised classification is a statistical clustering method that creates a well-defined classification of data points in which each data point is assigned to a particular class” (Irvin *et al.*,1997, p141).

Three steps were used to generate the SVM classification outputs; the first step was creating the five class scheme: vegetation, bare land, mine, water body and settlement. The second step was to assign image pixels to the different class schemes as training and testing data. As mentioned earlier the training and testing data were split into a ratio of 70 / 30 for each class scheme per image. Two different ROI files were created for each image; 70 points were allocated as training data for each class while 30 points were allocated as testing data for each class scheme per image. The total number of training and testing points will depend on the number of classes per image. Google earth images were used as a guide for allocating the correct pixels to the class scheme. The reason for using the Google earth images is the high spatial resolution. The third step was computing the ROI file and image into the SVM classification tool.

3.4.4 Accuracy assessment

The final process after completing the classification is accuracy assessment. Validation of the results is an important stage in any scientific research, for example this research used satellite images for LULCC. Comparison of pixels between the training and testing data will show the performance results of an algorithm in terms of whether pixels were classified correctly or incorrectly. The validation process consists of four parametres of interest: producer accuracy, user accuracy, kappa coefficient and overall accuracy.

Producers' accuracy assesses the probability of the extracted pixels from the image being classified correctly. Depending on the number of classes used in the classification, each class will be compared to other classes to estimate how many pixels were assigned to a particular classification correctly (Congalton, 1991).

User accuracy assesses the performance of the user (person that assigned the pixel to each class). The person selecting which pixels should be assigned to a particular class scheme is neither good nor bad, will be reflected by the results (Congalton, 1991).

Overall accuracy is the assessment of the total sum ratio of all the classes divided by the total number of classes (Congalton, 1991).

Kappa coefficient assesses the relationship ratio between the classes based on statistical agreement or no agreement. The results will lie between zero and one; depending on the outcome any value that is closer to one will represent a good agreement between the training pixels and classification output. Any value that is closer to zero will represent no agreement/poor agreement between the classification output and the training pixels (Congalton, 1991).

3.5 CHANGE DETECTION

Change detection determines the change of a selected feature or class over a time interval (Haque and Basak, 2017). Change detection is a very useful tool to use in remote sensing because it generates useful information in quantitative form about the change that has occurred to a specific feature (Haque and Basak, 2017). There are many methods used for change detection such as principal component analysis, spectral feature variance method, and image subtraction, method of change detection after classification and image ratio method (Szczesniak, 2003).

The method that is relevant to this project is the change detection after classification. This analysis technique is very common and less complicated; the whole aim is to compare two different classification images together (Xu *et al.*, 2009). The important steps to take during change detection are discussed by Szczesniak, (2003) who states that the first step is image pre-processing followed by selection of a suited technique for the area studied and finally accuracy assessment. Land cover change can be influenced by nature or by anthropogenic factors. Some examples of natural influences to land cover change could be climate change, soil erosion and vegetation.

Current activities in the Yatela mine area are mostly agriculture, livestock farming, artisanal mining, fire wood collection and open pit mining.

Monitoring analysis of the environment is a crucial component in the research community and private sector businesses. Quantifying the change is also crucial in order to understand how dynamic the area of interest is and the contributing factors (Haque and Basak, 2017).

Time is a major factor to consider before any change detection analysis can be done, because having one year period is not sufficient enough to run the change detection (Haque and Basak, 2017). Satellite images and topographic maps can be used for the change detection analysis, but they first need to be classified into class scheme. For example, shape files created from topographic maps will first need to be converted into a raster format. The raster image can then be classified to any supervised classification algorithm.

It is very rare for the environment to remain static, considering the many internal and external forces that act on the earth. There are four changes that can occur in a region: gradual change, abrupt change, ephemeral change and seasonal change (Vogelmann *et al*., 2016).

Gradual changes are changes that occur within a state (a specific land cover type). For example in a vegetation cover region gradual changes can occur due to plant disease or insects, drought, vegetation growth, ground water levels etc. Abrupt changes are major alterations to a land cover due to wildfires and urban development etc. Ephemeral changes are temporary interruptions that occur in a region due to flooding, wind storms and droughts. Seasonal changes occur due to seasonality changes such as winter, summer, spring and autumn. This change is mostly evident on plant species (Vogelmann *et al*., 2016).

To analyse the changes that have occurred from 1999 to 2015 in the Yatela region located in Mali, a post-classification was applied on the five classified images. The change detection algorithm in ENVI 5.2 was applied on the classified images: 1999, 2003, 2007, 2011 and 2015. In total five change detection statistics were generated, the interval used were 1999-2003, 2003-2007, 2007-2011, 2011-2015 and 1999-2015. Change detection analysis is a common approach used to quantify any change that has occurred in an area. The statistical analysis compares similar classes together (initial and final difference) as a percentage, area or pixel counts. The success of the change detection analysis is dependent on the classified images.

The post-classification comparison analysis was applied on the SVM classification images. The comparison is a statistical analysis that requires two classified images (initial and final) at a time to run the analysis (Radke *et al.,* 2005). The purpose of running the change detection statistics was to quantify the amount of change that occurred in the Yatela region and identify the areas within the study region which experienced any change. The accuracy of the results depends on the quality of the classified images used in the comparison analysis.

3.6 VEGETATION INDICES

"The normalized different vegetation index (NDVI) is defined as where amr and a.+ represent surface reflectance's averaged over ranges of wavelengths in the visible (1-0.6 Pm, "red") and near infrared, IR (2-0.8 Pm) regions of the spectrum, respectively. It is clear from its definition that the NDVI (like most other remotely sensed vegetation indices) is not an intrinsic physical quantity, although it is indeed correlated with certain physical properties of the vegetation canopy: Leaf Area Index (LAI), fractional vegetation cover, vegetation condition, and biomass" (Carlson and Ripley, 1997 p242).

Equation:

$$NDVI = (NIR - VIS) / (NIR + VIS)$$

NDVI is the most common and easily obtainable vegetation index to detect live green plant canopies using multispectral remote sensing data based on spectral reflectance measurements acquired in the visible (red band) and near-infrared regions, respectively NDVI values range from minus one to zero; in general terms, very low values of NDVI (0.1 and below) correspond to barren areas of rock, sand, water or snow. Moderate values (0.2–0.3) represent shrubs and grassland, while high values (0.6–0.8) indicate temperate and tropical rainforest) (Gascon *et al*., 2016)

Over the past few years the normalized difference vegetation index has been used to monitor vegetation change and health (Fan and Liu, 2016). This index is mostly used by climate change scientists that want to monitor and predict vegetation changes due to anthropogenic impacts (Fan and Liu, 2016). Many other studies have shown that human interference with land use can be detected using NDVI. From the early 1980s NDVI datasets were available for use. NDVI can be used to measure precipitation in semi-arid environments by detecting the amount of vegetative growth (chlorophyll) under the assumption that the area of interest only depends on rainfall for biodiversity growth. A positive NDVI value in this case would indicate that plant growth was influenced by increased precipitation. Negative values would indicate that no precipitation occurred over the region. Zero value would mean that minimal rainfall occurred over the region (Birtwistle *et al*., 2016).

When working with NDVI analysis, the assumptions about possible influence to vegetation change should be clearly stated in the beginning because there are many factors that can play a role on vegetation change, such as anthropogenic and climatic factors. The assumptions for the Mali open pit mine operation project are that anthropogenic factors will play a major role in the fluctuations of the NDVI results. The first major anthropogenic factor is the construction of the open pit mine and growth of the operation size over time. The other factor is human practices such as livestock farming, small scale farming and artisanal mining. Performance of NDVI can be slightly different depending on the kind of sensors used (multispectral or hyper spectral) and different equipment functions. Any difference in spectral wavelength can have an approximate 10% difference on the NDVI results. The performance of NDVI between Landsat 7 ETM and Landsat 8 yielded results which showed that Landsat 8 produced better NDVI results compared to Landsat 7 ETM sensor, this was based on variability results in identifying water areas (Landsat 8 was able to detect more water areas) (Ke *et al*., 2015). The mean standard deviation of Landsat 8 OLI (Operational Land Imager) was higher than Landsat 7 ETM + on pattern analysis of crop and urban areas. These results were influenced by the different equipment installed on the satellites; Landsat 8 can detect more land surface characteristics due to thousand sensitive sensors compared to Landsat 7 ETM. The results from Ke *et al*., 2015 indicate that it is very important to do NDVI analysis on the same sensor images to eliminate high variation on NDVI results that can be falsely interpreted (with reference to the contribution factors).

The atmospheric corrected images were used to generate NDVI values by using the NDVI tool in ENVI 5.2 software (figure 3). The NDVI results are determined by the ratio difference of near-infrared (NIR) and Red band. The Red and NIR bands are the same for Landsat 5, 7 ETM band 3 (Red) and band 4 (NIR), while Landsat 8 will use different band numbers, band 5 (NIR) and band 4 (Red).

CHAPTER 4

RESULTS AND DISCUSSION

4.1UNSUPERVISED CLASSIFICATION

The ISODATA classification was used as the unsupervised classification for the five Landsat images: 1999, 2003, 2007, 2011 and 2015. Each image generated 8 classes for the ISODATA classification, some significant information was detected from the five ISODATA classifications. From visual interpretation of the Landsat image and ISODATA classification results, the open pit mine surface, bare land and road networks were detected by class 8 (refer to Figure 4). The water body in the Yatela mine area, which is present from 2007 is depicted by class 1. The vegetation cover could not be clearly distinguished amongst the different classes that were generated from the classification.

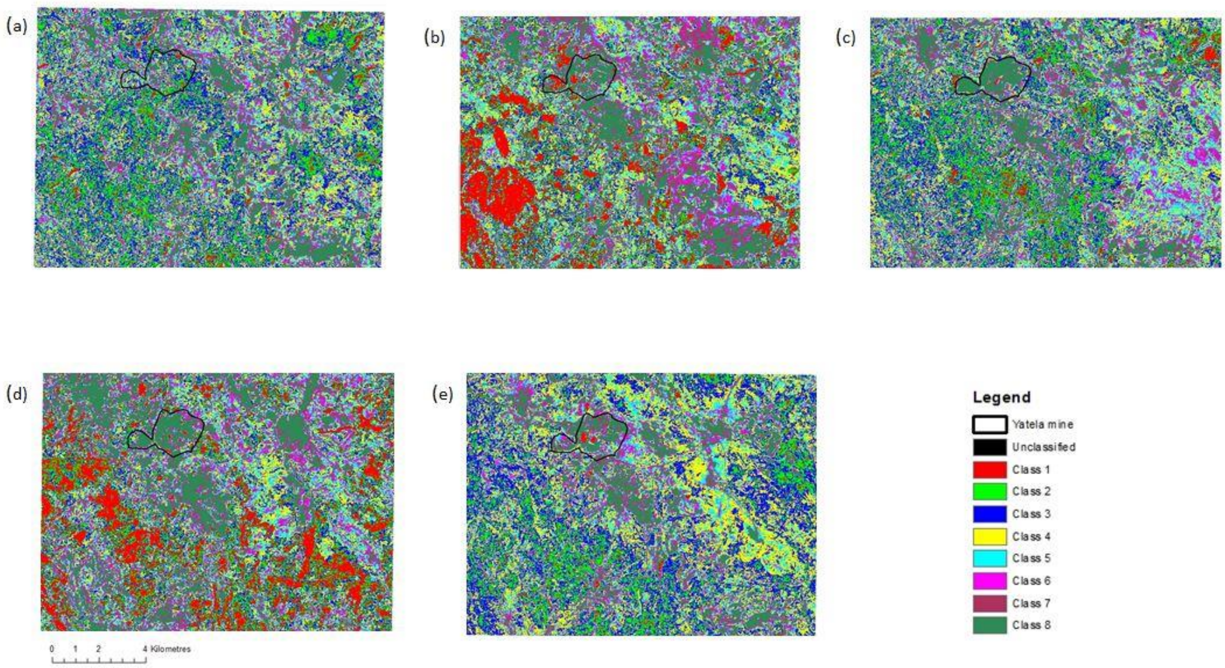


Figure 4. Unsupervised ISODATA Classification

4.2 LAND USE LAND COVER

The LULC results were derived from the SVM classification images. Figure 5 shows the histogram for 1999, which quantifies the results displayed by Figure 6. The LULC map for 1999 shown in Figure 6(a) generated three classes: bare land, vegetation and settlement. The results indicate that 68% is dominantly bare land, while vegetation accounts for 23% of the area and settlement is 9%.From 2003 LULC map shows the emergence of the mine in the area (refer to Figure 6(b)). The 2003 histogram indicates that 57% of the area is covered by bare land, 26% is vegetation followed by 14% of settlement and the mine is covering 2%. The duration from 1999 to 2003 shows a decrease of 11% in bare land from 68% in the year 1999 to 57% in year 2003. Vegetation showed an increase of 3% from year 1999 to 2003. Settlement also increased by 6% from 1999 to 2003.

The LULC map and histogram for 2007 were shown in Figure 5 and 6. In 2007 the area was dominantly covered by 80% of bare land followed by 12% of vegetation, 6% was settlement, 2% was the mine and a small fraction of 0.04% was covered by water body. The duration from 2003 to 2007 shows an increase of 23% for the bare land class, from 57% in year 2003 to 80% in year 2007. Vegetation cover decreased by 14% from 26% in year 2003 to 12% in year 2007. Settlement area decreased by 8% from 14% in year 2003 to 6% in year 2007. There was no change in mine coverage considering that it remained at 2% from the year 2003-2007 In year 2007 there was an emergence of water body which covers 0.04%. The water body was located in the central part of the mine area. This could be due to excavation in the area or construction of a water pond for mine operations.

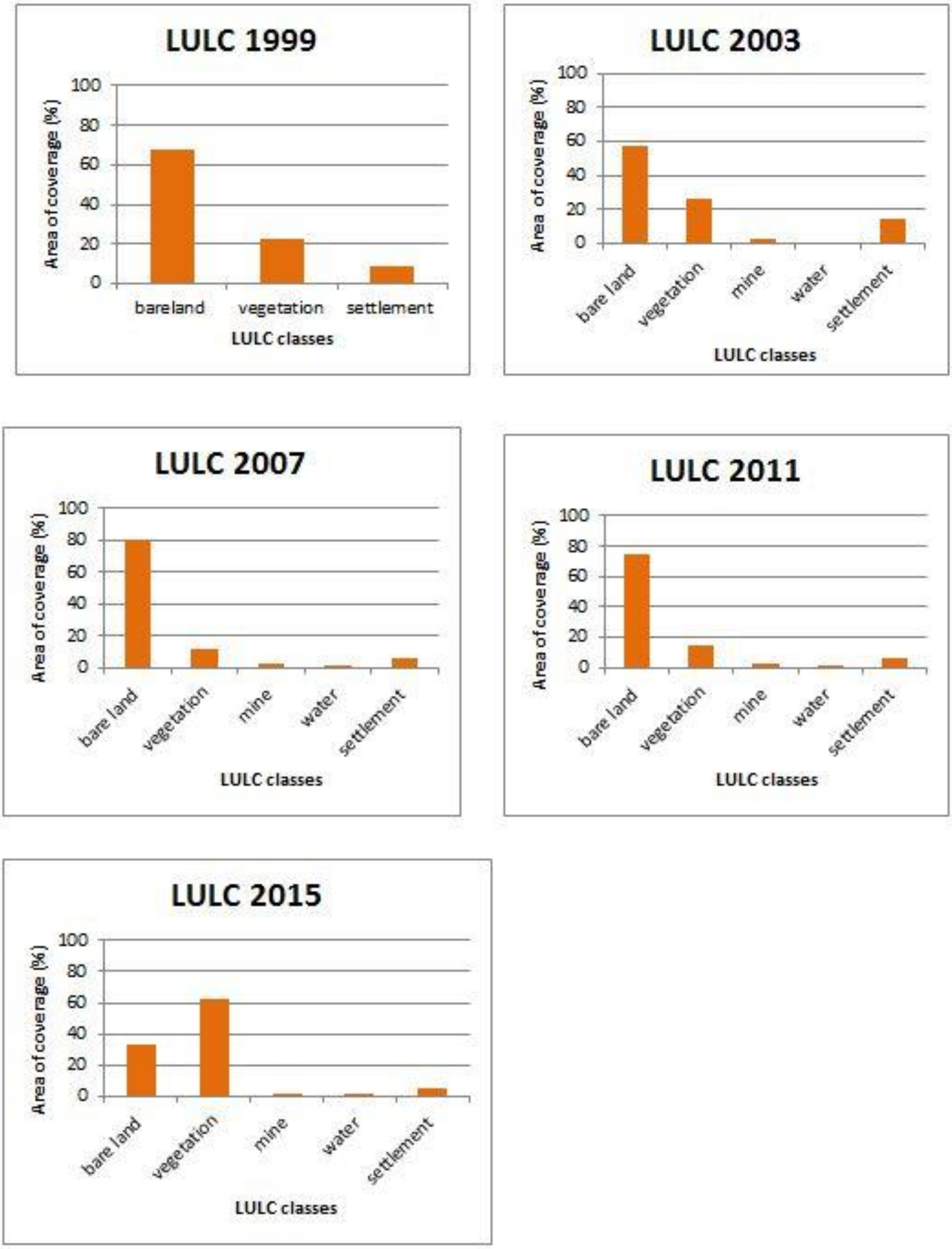


Figure 5. Histogram of LULC for the Yatela Region

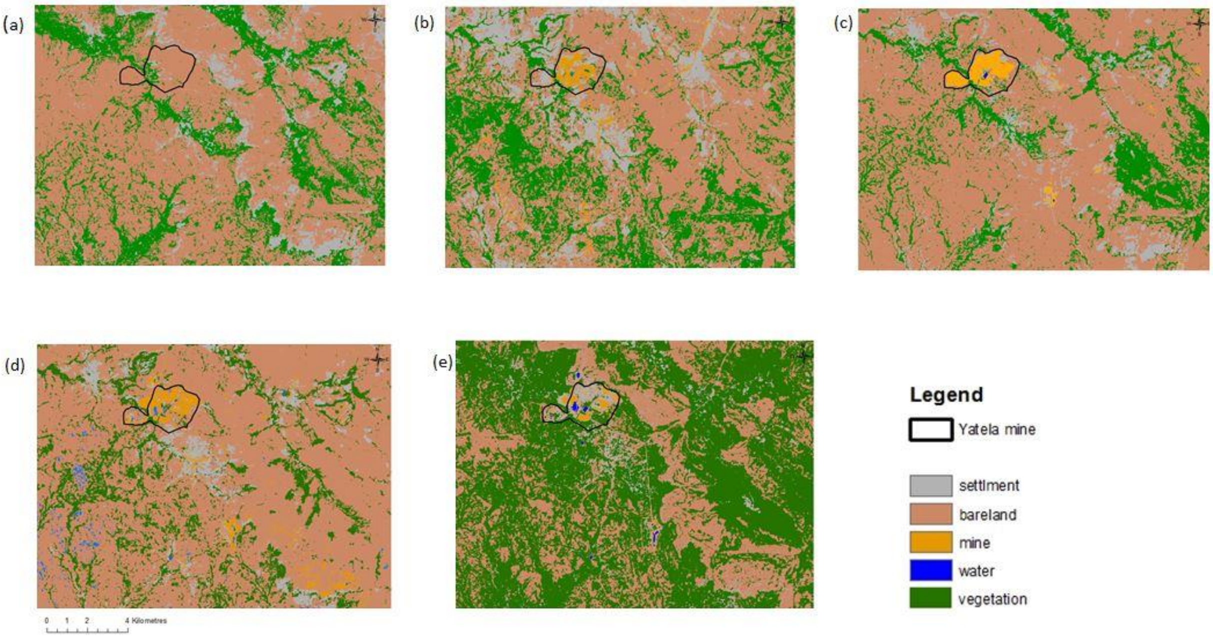


Figure 6. SVM Classification results for the year a) 1999, b) 2003, c) 2007, d) 2011 e) 2015

The LULC map and histogram for 2011 were shown in Figure 5 and 6(d). The area was dominantly covered by 75% of bare land, 15% was vegetation, 3% was mine, water body was 1% and settlement was 6%. The duration from 2007 to 2011 showed a decrease of 5% for bare land from 80% in year 2007 to 75% in year 2011. Vegetation increased by 3% from 12% in year 2007 to 15% in year 2011. The mine showed an increase of 1% from 2% in year 2007 to 3% in year 2011, the growth of the mine is mostly in the west direction. Water body also showed an increase of 0.94% from 0.04% in 2007 to 1% in 2011. Settlement had no change from 2007 to 2011.

The LULC map and histogram for 2015 were shown in Figure 5 and 6 (e). The area was covered by 33% of bare land, 62% was vegetation, mine was 1%, water body was 0.1% and the settlement is 4%. There was an enormous decrease of bare land from 75% in year 2011 to 33% in year 2015.Vegetation increased by 47% from 15% in year 2011 to 62% in year 2015. Water decreased by 0.9% from 1% in 2011 to 0.1% in 2015. The mine area also decreased by

2% from 3% in year 2011 to 1% in year 2015. This is due to the mine closure in 2013 where by operations of extracting minerals stopped. Settlement decreased by 2% from 6% in year 2011 to 4% in year 2015, this could be due to the closure of the mine forcing people to relocate to other areas in search of employment.

4.3 NDVI

The NDVI outputs (refer to figure 7) were derived from the same Landsat images and year interval that was used for the SVM classification. The results were generated using the NDVI tool in ENVI 5.2 software. The disturbance to vegetation cover is also detected by the NDVI values, the disturbances are similar to the SVM results with regards to the expansion of mining activities in the Yatela mine and vegetation cover.

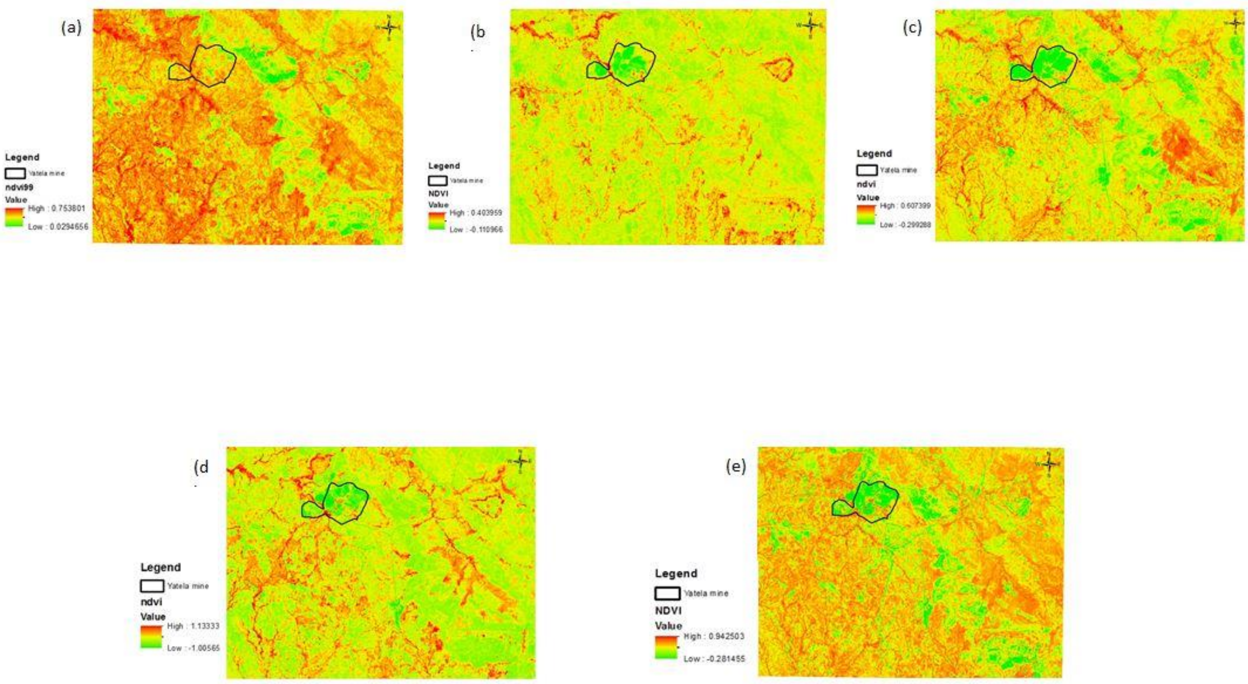


Figure 7: NDVI Results For Study Area of Yatela a) 1999, b) 2003, c) 2007, d) 2011 e) 2015

4.3.1. NDVI 1999

The Yatela mine area is dominantly covered by high NDVI values of 0.5 to 0.75, there are small patches of low NDVI values of 0.029. The high NDVI values show the presence of vegetation cover prior to the mine operations, the patches of low NDVI values in the mine could indicate that open pit mine construction phase 1 had already began. The surrounding area shows high presence of vegetation, the exposed rock ridge that runs parallel to Yatela Mine has low NDVI values that range from 0 to 0.029(refer to Figure 7(a)).

4.3.2. NDVI 2003

The whole area is dominantly covered by low NDVI values that range from 0 to -0.11. The Yatela mine area has a NDVI value of -0.11, which indicates lack of vegetation presence in the area. The absence of vegetation in Yatela can be due to the construction of the open pit mine in late 1999. There are sections of high NDVI values of 0.40 that cover the 480 km^2 area. There is a decrease of the NDVI max value of 0.75 in 1999 to 0.40 in 2003. The same applies to the minimum NDVI value which dropped from 0.029 to -0.11(refer to Figure 7(b)).

4.3.3. NDVI 2007

The Yatela mine is still covered by low NDVI values of -0.299, indicating low presence of vegetation cover. High NDVI values of 0.61 are concentrated in the south eastern and south western direction of the Yatela mine. The low NDVI values of -0.299 show infrastructure development in the area south of Yatela mine, there is evidence of road development detected by NDVI which is represented by the line features. Considering that relocation occurred in the area, some of the patches located in the northern and north western direction could indicate the new settlements region where people moved to. (refer to Figure 7(c)).

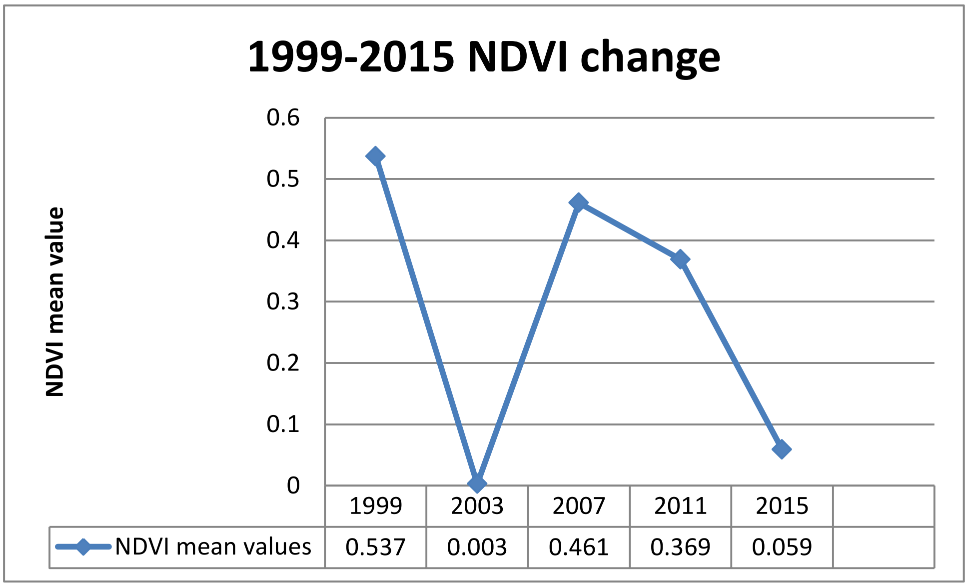
4.3.4. NDVI 2011

The Yatela mine area is dominantly covered by low NDVI values of -1, there are small patches of high NDVI values that range from 0 to 1. The low NDVI values show the absence of vegetation cover in the area. The surrounding area shows presence of road network development which is detected by the NDVI algorithm (low NDVI values), the exposed rock ridge that runs parallel to Yatela mine still shows low NDVI values that range from 0 to -1(refer to Figure 7(d)).

4.3.5 NDVI 2015

The study area of 480square kilometres is mostly covered by high a NDVI value of 0.94. The Yatela mine is still covered by low NDVI values of -0.28 even though mine operations stopped in 2013. The road network and rock ridge still have a low -0.28 NDVI value, (refer to Figure 7(e)).

Figure 8: NDVI mean values of the Yatela Region



The NDVI mean values for 1999, 2003, 2007, 2011 and 2015 are depicted in Figure 8. The highest NDVI mean value recorded was in 1999 before mine construction was at full phase. The lowest NDVI mean value occurred in 2003. The trend depicted from Figure 8 starts at a peak value of 0.537 in 1999, and then a decrease of the NDVI mean value is observed in 2003. Then in 2007 there is an increase of the NDVI mean value to 0.461 followed by a decrease trend from 2011 to 2015 (0.369 and 0.059).

NDVI RESULTS CONCLUSION

The NDVI results were able to detect the development that occurred in the Yatela region from 1999 to 2015. The roads and open pit mine area were easily detected from 1999. Over the years the vegetation cover varied in the Yatela region, good vegetation cover was present before mine operations (1999) and after the mine closure (2015). In the absence of climatic data for the study area, these results cannot be used conclusively to assume that vegetation cover decreased during mine operations and increased after mine closure in 2013.

4.4 ACCURACY ASSESSMENT

The confusion matrix was used to assess the accuracy of the SVM classification outputs for year 1999, 2003, 2007, 2011 and 2015 (refer to table 7). Testing points that amount to 30 were extracted randomly for each class per image. The 1999 SVM image had 3 classes, so 90 testing points were extracted from the Landsat image. There were 5 classes for the 2003, 2007, 2011 and 2015 SVM classification outputs. The overall accuracy ranged from 77% to 86.88% for the 5 images. The kappa coefficient had a range of 0.70 to 0.82.

Accuracy assessment (confusion matrix)

Table 7: Accuracy Assessment Results for SVM Classification Images in the Yatela region (1999-2015)

Year	Overall Accuracy (%)	Kappa Coefficient	Accuracy Type	Vegetation	Mine	Bare land	Settlement	Water
1999	77	0.70	Producers	81.6	-	81.2	68.2	-
			Users	86.7	-	78.1	83.3	-

2003	87.26	0.83	Producers	95.3	83.1	86.7	71.2	100
			Users	88.9	75.3	88.4	86.0	100
2007	86.74	0.84	Producers	94.2	80.1	87.2	72.2	100
			Users	97.2	74.3	91.8	66.3	95.3
2011	83.66	0.81	Producers	93.4	82.3	82.7	73.6	86.3
			Users	98.3	77.8	88.2	58.2	73.1
2015	86.88	0.82	Producers	91.2	87.6	86.4	69.2	100
			Users	90.2	71.6	84.7	63.8	85.2

The confusion matrix was used to test the accuracy assessment of the SVM classifications for the different Landsat images from 1999 to 2015 (refer to Table 7). The training and testing data were split into 70/30. The overall accuracy for the different time periods had a range of 77% to 87%.

Table 7 shows the results of the confusion matrix for the SVM classification. The producer accuracy for year 1999 generated 81.6% for vegetation, 0% for the mine, 81.2% for bare land, 68.2% for settlement and zero percent for water body. The reason for zero value for the mine and water body class is that these features were not present in the area during that time period. The user's accuracy for 1999 generated 86.7% for vegetation, 0% for mine, 78.1% for bare land, 83.3% for settlement and 0% for water body. The kappa coefficient was 0.70 and the overall classification was 78% for year 1999. The overall accuracy for 2003 was 87.26% and the kappa coefficient was 0.83. The producer accuracy for 2003 was 95.3% for vegetation, 83.1% for the mine, 86.7% for bare land, 71.2% for settlement and 100% for water body. The user accuracy results generated 88.9% for vegetation, 75.3% for the mine, 88.4% for bare land, 86% for settlement and 100% for water. The highest producer accuracy result was the water body class (100%) and the lowest was the settlement class (71.2%). The highest user's accuracy result was the water body class and the lowest was the mine class.

The overall accuracy for 2007 was 86.74% and the kappa coefficient was 0.84. The producer accuracy for 2007 was 94.2% for vegetation, 80.1% for the mine, 87.2% for bare land, 72.2% for settlement and 100% for water body. The user accuracy results generated 97.2% for vegetation, 74.3% for the mine, 91.8% for bare land, 66.3% for settlement and 95.3% for water. The highest producer accuracy result was the water body class (100%) and the lowest was the settlement class (72.2%). The highest user's accuracy result was the vegetation class (97.2%) and the lowest was the settlement class (66.3%).

The overall accuracy for 2011 was 83.66% and the kappa coefficient was 0.81. The producer accuracy for 2011 was 93.4% for vegetation, 82.3% for the mine, 82.7% for bare land, 73.6% for settlement and 86.3% for water body. The user accuracy results generated 98.3% for vegetation, 77.8% for the mine, 88.2% for bare land, 58.2% for settlement and 73.1% for water. The highest producer accuracy result was the vegetation class (93.4%) and the lowest was the settlement class (73.6%). The highest user's accuracy result was the vegetation class (98.3%) and the lowest was the settlement class (58.2%).

The overall accuracy for 2015 was 86.88% and the kappa coefficient was 0.82. The producer accuracy for 2015 was 91.2% for vegetation, 87.6% for the mine, 86.4% for bare land, 69.2% for settlement and 100% for water body. The user accuracy results generated 90.2% for vegetation, 71.6% for the mine, 84.7% for bare land, 63.8% for settlement and 85.2% for water. The highest producer accuracy result was the water body (100%) and the lowest was the settlement class (69.2%). The highest user's accuracy result was the vegetation class (90.2%) and the lowest was the settlement class (63.8%).

4.5 CHANGE DETECTIONS

The change detection statistics for 1999-2003, 2003-2007, 2007-2011, 2011-2015 and 1999-2015 were generated from the SVM classification images. The statistical results were represented in a table format. Change detection is the comparison of all the classes from a final and initial classified image. The values are represented as a percentage in the table 8. The class change is the representation of the amount of change that has occurred from one class to another class type.

Table 8: Change Detection Matrix Results for LULC in the Yatela Region (1999-2003) in Percentage (%).

	Initial State 1999			
Final State 2003		Bare land	Vegetation	Settlement
	Bare land	63.2	14	33.7
	Vegetation	5.3	43.2	9.5
	Settlement	31.5	42.8	56.8
	Class total	100	100	100
	Class changes	36.768	56.811	43.183

The initial state is the representation of the different classes in 1999 and the final state is the representation of the 2003 classes (refer to Table 8). Bare land had an initial class total of 100% in 1999, and then in 2003:63.2 % remained as bare land class while 5.3% changed to vegetation and 31.5% into settlement. The conversion of bare land to settlement was the biggest transformation that occurred to the bare land class from 1999 to 2003. Vegetation had an initial class total of 100% in 1999, and then in 2003 43.2% remained as vegetation while 14% changed to land and 42.8% to settlement. The conversion of vegetation to settlement was the biggest transformation that occurred to the vegetation class from 1999 to 2003. The total class change that occurred to the vegetation class was 56.8%. Settlement had an initial class total of 100% in 1999, and then in 2003: 56.8% remained as settlement while 33.7% changed to bare land and 9.5% to vegetation. The conversion of settlement to bare land was the biggest transformation that occurred to the settlement class from 1999 to 2003. The total class change that occurred to the settlement class was 43.2%.

Table 9: Change Detection Matrix Results For LULC in the Yatela Region (2003-2007) in Percentage (%).

	Initial State 2003					
Final State 2007		Bare land	Vegetation	Mine	Water body	Settlement
	Bare land	61.5	39.3	48.3	25.1	41.7
	Vegetation	26	44.9	3.6	21.4	3.7
	Mine	1.2	1	28.6	14	8.8
	Water body	0	0	0	14	0
	Settlement	11.3	14.8	19.5	25.5	45.8
	Class total	100	100	100	100	100
	Class changes	38.530	55.075	71.430	86.047	54.166

The initial state is the representation of the different classes in 2003 and the final state is the representation of the 2007 classes (refer to Table 9). The change that occurred in the bare land class resulted in 61.5% remaining as bare land while 26% changed to vegetation, 1.2% to mine, 0% to water body and 11.3% to settlement. The total class change that occurred to the bare land class was 38.5%. The conversion of bare land to vegetation was the biggest transformation that occurred to the bare land class from 2003 to 2007, while no transformation occurred to the bare land class from 2003 to 2007 between bare land and water body. The change that occurred to the vegetation class resulted in 44.9% remaining as vegetation while 39.3% changed to bare land, 1% to mine, 0% to water body and 14.8% to settlement. The total class change that occurred to the vegetation class was 55.1%. The conversion of vegetation to bare land was the biggest transformation that occurred to the vegetation class from 2003 to 2007, while no transformation occurred to the vegetation class from 2003 to 2007 between vegetation and water body. The change that occurred to the mine class resulted in 28.6% remaining as mine while 48.3% changed to bare land, 3.6% to vegetation, 0% to water body and 19.5% to settlement. The total class change that occurred to the mine class was 71.4%. The conversion of mine to bare land was the biggest transformation that occurred to the mine class from 2003 to 2007, while no transformation occurred to the mine class from 2003 to 2007 between settlement and water body. The change that occurred to the water body class resulted in 14% remaining as water body while 25.1% changed to bare land, 21.4% to vegetation, 14% to mine and 25.5% to settlement. The total class change that occurred to the mine class was 86%. The conversion of water body to settlement was the biggest transformation that occurred to the water body class from 2003 to 2007. The least transformation that occurred to the water body class from 2003 to 2007 was the conversion of water body to the mine class. The change that occurred to the settlement class resulted in 45.8% remaining as settlement while 41.7% changed to bare land, 3.7% to vegetation, 8.8% to mine and 0% to water body. The total class change that occurred to the settlement class was 54.2%. The conversion of settlement to bare land was the biggest transformation that occurred to the settlement class from 2003 to 2007, while no transformation occurred to the settlement class from 2003 to 2007 between settlement and water body.

Table 10: Change Detection Matrix Results For LULC in the Yatela Region (2007-2011) in Percentage (%).

	Initial State 2007					
Final State 2011		Bare land	Vegetation	Mine	Water body	Settlement
	Bare land	82	47.4	41.1	42.8	52
	Vegetation	12.6	42.7	0.2	0	4.4
	Mine	0.9	0.3	50.3	21.9	12.6
	Water body	0.7	0.2	2.1	34.8	0.4
	Settlement	3.8	9.4	6.3	0.5	30.6
	Class total	100	100	100	100	100
	Class changes	17.973	57.321	49.738	65.116	69.521

The initial state is the representation of the different classes in 2007 and the final state is the representation of the 2011 classes (refer to Table 10). The change that occurred in the bare land class resulted in 82% remaining as bare land while 12.6% changed to vegetation, 0.9% to mine, 0.7% to water body and 3.8% to settlement. The total class change that occurred to the bare land class was 18%. The conversion of bare land to vegetation was the biggest transformation that occurred to the bare land class from 2007 to 2011. The least transformation that occurred to the bare land class from 2007 to 2011 was the conversion of bare land to water body. The change that occurred to the vegetation class resulted in 42.7% remaining as vegetation while 47.4% changed to bare land, 0.3% to mine, 0.2% to water body and 9.4% to settlement. The total class change that occurred to the vegetation class was 57.3%. The conversion of vegetation to bare land was the biggest transformation that occurred to the vegetation class from 2007 to 2011. The least transformation that occurred to the vegetation class from 2007 to 2011 was the conversion of vegetation to water body.

The change that occurred to the mine class resulted in 50.3% remaining as mine while 41.1% changed to bare land, 0.2% to vegetation, 2.1% to water body and 6.3% to settlement. The total class change that occurred to the mine class was 49.7%. The conversion of mine to bare land was the biggest transformation that occurred to the mine class from 2007 to 2011. The least transformation that occurred to the mine class from 2007 to 2011 was the conversion of mine to vegetation. The change that occurred to the water body class resulted in 34.8% remaining as water body while 42.8% changed to bare land, 0% to vegetation, 21.9% to mine and 0.5% to settlement. The total class change that occurred to the water body class was 65.1%. The conversion of water body to bare land was the biggest transformation that occurred to the water body class from 2007 to 2011, while no transformation occurred to the water body class from 2003 to 2007 between water body and vegetation.

The change that occurred to the settlement class resulted in 30.6% remaining as settlement while 52% changed to bare land, 4.4% to vegetation, 12.6% to mine and 0.4% to water body. The total class change that occurred to the settlement class was 69.5%. The conversion of settlement to bare land was the biggest transformation that occurred to the settlement class from 2011 to 2015, the least transformation that occurred to the settlement class from 2007 to 2011 was the conversion of settlement to water body.

Table 11: Change Detection Matrix Results for LULC in the Yatela Region (2011-2015) in Percentage (%).

	Initial State 2011					
Final State 2015		Bare land	Vegetation	Mine	Water body	Settlement
	Bare land	40.2	6.7	34.6	43.8	13.7
	Vegetation	57.2	92.4	5.9	44.3	67.2
	Mine	0.1	0	16.6	0.7	0.3
	Water body	0.1	0.1	0.6	8.6	0
	Settlement	2.4	0.8	42.3	2.6	18.8

	Class total	100	100	100	100	100
	Class changes	59.851	7.634	83.354	91.378	81.160

The initial state is the representation of the different classes in 2011 and the final state is the representation of the 2015 classes (refer to Table 11). The change that occurred to the bare land class resulted in 40.2% remaining as bare land while 57.2% changed to vegetation, 0.1% to mine, 0.1% to water body and 2.4% to settlement. The total class change that occurred to the bare land class was 60%. The conversion of bare land to vegetation was the biggest transformation that occurred to the bare land class from 2011 to 2015. The least transformation that occurred to the bare land class from 2011 to 2015 was the conversion of bare land to mine and water body.

The change that occurred to the vegetation class resulted in 92.4% remaining as vegetation while 6.7% changed to bare land, 0% to mine, 0.1% to water body and 0.8% to settlement. The total class change that occurred to the vegetation class was 7.6%. The conversion of vegetation to bare land was the biggest transformation that occurred to the vegetation class from 2011 to 2015, while no transformation occurred to the vegetation class from 2011 to 2015 between vegetation and mine. The change that occurred to the mine class resulted in 16.6% remaining as mine while 34.6% changed to bare land, 5.9% to vegetation, 0.6% to water body and 42.3% to settlement. The total class change that occurred to the mine class was 83.4%. The conversion of mine to settlement was the biggest transformation that occurred to the mine class from 2011 to 2015. The least transformation that occurred to the mine class from 2011 to 2015 was the conversion of mine to mine and water body. The change that occurred to the water body class resulted in 8.6% remaining as water body while 43.8% changed to bare land, 44.3% to vegetation, 0.7% to mine and 2.6% to settlement. The total class change that occurred to the water body class was 91.4%. The conversion of water body to vegetation was the biggest transformation that occurred to the water body class from 2011 to 2015. The least transformation that occurred to the water body class from 2011 to 2015 was the conversion of water body to the mine class. The change that occurred to the settlement class resulted in 18.8% remaining as settlement while 13.7% changed to bare land, 67.2% to vegetation, 0.3% to mine and 0% to water body. The total class change that occurred to the settlement class was 81.2%. The conversion of settlement to vegetation was the biggest transformation that occurred to the settlement class from 2011 to 2015, while no transformation occurred to the settlement class from 2011 to 2015 between settlement and water body.

Table 12: Change Detection Matrix Results For LULC in the Yatela Region (1999-2015) in Percentage (%).

	Initial State 1999			
Final State 2015		Bare land	Vegetation	Settlement
	Bare land	82.1	61.7	50.2
	Vegetation	3.2	33.3	19.5
	Settlement	14.7	5	30.4
	Class total	100	100	100
	Class changes	17.923	66.712	69.626

The initial state is the representation of the different classes in 1999 and the final state is the representation of the 2015 classes (refer to Table 12). The change that occurred to the bare land class resulted in 82.1 % remaining as bare land class while 3.2% changed to vegetation and 14.7% into settlement. The conversion of bare land to settlement was the biggest transformation that occurred to the bare land class from 1999 to 2015. The change that occurred to the Vegetation class resulted in 33.3% remaining as vegetation while 61.7% changed to bare land and 5% to settlement. The conversion of vegetation to bare land was the biggest transformation that occurred to the vegetation class from 1999 to 2015. The total class change that occurred to the vegetation class was 66.7%.

The change that occurred to the Settlement class resulted in 30.4%% remaining as settlement while 50.2% changed to bare land and 19.5% to vegetation. The conversion of settlement to bare land was the biggest transformation that occurred to the settlement class from 1999 to 2015. The total class change that occurred to the settlement class was 69.6%.

Table 13: Summary of LULC in Yatela Region (1999-2015).

	1999	**2003**	**2007**	**2011**	**2015**
Bare land (%)	68	57	80	75	33
Vegetation (%)	23	26	12	15	62
Mine (%)	0	2	2	3%	1
Water (%)	0	0	0.04	1	0.1
Settlement (%)	9	14	6	6	4

The class for settlement increased from 1999 to 2003 by 5%. In 2007 there was a downward trend of 8% in settlements. Over a four year period the settlement cover remained constant at 6% but then in 2015 the numbers dropped to 4% (refer to table 13). The trends that can be observed between 1999 to 2003 is that settlements increased due the influx of people looking for employment in the Yatela region, some of the people were relocated due to the mine constructions. A state of equilibrium in the area can be observed between 2007 and 2011; this could be due to lack of job opportunities in the area since it can be assumed that all possible job opportunities have been filled up. The mine closure operations began around 2013; this is evident by the decrease in the numbers of settlement cover. Most of the people would have relocated to other areas in search of job opportunities, because the economic status of the Yatela region will not be able to sustain the people that moved to the area for a better life.

The villagers in the area have common livestock: sheep, horse, goats and cattle. The impacts of such livestock cannot be detected from the LULCC results because over a 16 year period (1999-2015) vegetation cover only decreased once in 2007 to 12%. More information would be required in order to consider livestock having any impact on the area. Basic information that will be required is the number of livestock in the area over the years, GPS location of where they are located and the trail paths they use to graze.

The magnitude of the open pit mine in Yatela having an impact on the surrounding environment can be assumed to be on a small scale. The only areas with significant change were due to the mine water pond and expansion of surface operations. This only covered approximately 1% of the study area during the 16 year period. In 1999 there was zero percent of mine cover but over the years it increased in 2003 to about 2% and remained constant in 2007. An increase occurred in 2011 to about 3% and a decrease occurred in 2015. The reason for the decrease in the mine area could be due to the mine closure operations that began in 2013. The surface area of the mine could have been covered by vegetation after the mine closure. The impact of the mine operation on a large scale could not be determined due to lack of ground data of the vegetation species in the area and the medium resolution satellite images. The only information that was available about the vegetation species is that there are four vegetation communities and seven tree species in the Yatela region but data about their spectral signature is missing. Information on the spectral signature would help create a vegetation species map of the Yatela area, the map could be helpful with regards to making analyses to see which tree species of vegetation communities were impacted before and after mine operations.

4.6 Discussion

The results from change detection statistics and NDVI results will be used for this section. The change detection statistics were generated from SVM classification images: 1999-2003, 2003-2007, 2007- 2011, 2011- 2015 and 1999-2015.

What impact does gold mining have on vegetation?

The LULCC results show that in 1999 there was 23% vegetation cover, after four years the vegetation cover increased by 3% (26%). In 2007 there was a huge decrease of vegetation cover from 26% to 12%. An increase occurred in 2011 to about 3% from the 2007, a 47% increase occurred from 2011 to 2015. The results from NDVI show variations of vegetation cover in the Yatela region over the years, high vegetation cover was present in 1999 and 2015, low to medium vegetation cover was present in 2003, 2007 and 2011. Keeping in mind that mine operations started late in 1999 and the mine operations were closed by 2015, it can be assumed that gold mining operations had an impact on the decrease of vegetation cover. The mine area and road developments were detected by the low to negative NDVI values. Redondo-Vega *et al* (2017) support the notion that mining has negative impacts on vegetation cover (decrease in the number of vegetation in an area).

How much land use and land cover change transpired during the 16 year period (1999-2015)?

	1999-2003	**2003-2007**	**2007-2011**	**2011-2015**
Bare land	-11	+23	-5	-42
vegetation	+3	-14	+3	+47
Mine	+2	0	+1	-2
Water	0	+0.04	+0.96	-0.9
Settlement	+5	-8	0	-2

The table above shows the LULCC that occurred in the Yatela region over 16 years (1999-2015). The most change occurred during 2011-2015, there was a decrease of 42% for bare land cover and an increase of 47% for vegetation cover. This can be assumed to be due to mine closure and the rehabilitation process which involved planting vegetation over stock piles and open surface areas. The least change occurred in the water class; 1999-2003 there was zero change to the water class. There were significant increases that occurred in 2003-2007 and 2007-2011, the increase was 0.04 and 0.96 respectively. The increases could be due to mine expansion from 2003 to 2011, the decrease that occurred in 2011-2015 by -0.9% could have been due to mine closure. The change that occurred in the vegetation class cannot be entirely assumed to be due to the mine operations because of the limitations from acquiring Land sat images. During the period of 1999-2003 settlement class increased by 5%. A decrease of 8% occurred in the settlement class from 2003-2007. There was no change in 2007-2011, a decreased in settlement class occurred again in 2011-2015.

Can Support Vector Machine algorithm and NDVI be used to detect mine operations and quantify the LULCC caused by open pit mining?

The SVM classification and NDVI results were produced from Land sat satellite images from 1999 to 2015 at a four year interval. The classification and NDVI were produced in ENVI 5.2 software. The outputs were displayed in a table and raster image form. Change detection statistics were generated for 1999-2003, 2003-2007, 2007-2011, 2011-2015 and 1999-2015. The SVM outputs were able to detect the mine operations and the road networks. The quantifying of LULCC by open pit mining was shown by the change detection statistics, which was generated from the SVM images. The five NDVI image results were able to detect the growth of the open pit mine operations and vegetation cover in the Yatela region. Karan *et al* (2016) supports the notion that SVM and NDVI can quantify LULCC caused by surface mining.

4.7 LIMITATIONS

- Some of the images were acquired towards the end of the rain season while some were acquired early in the rain season that occurs from June to October. This caused some variation of images with vegetation cover. The variation of image acquisition dates was due to the availability of cloud free satellite images.
- The lack of GPS coordinates of the initial area where tribe villagers stayed before they were moved to a new area.
- The absence of temperature and rainfall data from the Yatela region.
- The use of Landsat 5 images to avoid the line stripping problem of Landsat 7 images may have an impact on the NDVI results, this is supported by Ke *et al* (2015) who found out that using different satellite images has an influence on the NDVI results.
- The medium resolution images made it difficult to differentiate land cover classes such as settlement, bare land and mine (surface). The SVM algorithm most of the time mixed the classes together (settlement, bare land/mine surface). The ground truth images from Google earth did not have the exact image dates with the Landsat images. This made it difficult to assign particular raster cells to a Land cover class because visibility was poor and the reference images (Google earth) did not help much.
- The lack of socio-economic and livestock data to use for analysis was a problem.

CHAPTER 5

CONCLUSION AND RECOMMENDATIONS

5.1 CONCLUSION

The objectives for this research were to map the Land Use and Land Cover around a mine area by using vegetation indexes and land cover change detection. Secondly, it was to identify any relationship between mining operations and spatial distribution of vegetation in the Yatela region. The main reason was to contribute and advance knowledge in understanding the potential impacts of open pit mining on the environment using LULCC techniques. Results from NDVI outputs indicated a pattern of vegetation cover change before and after the mine operations. In 1999 and 2015, the vegetation cover was predominately good over the Yatela region. The vegetation cover decreased in-between the years.

The average overall accuracy for the five classified images was 84.31%. The change detection statistics showed that there was significant change in each of the five classes over the 16 year period. But the challenge was to pinpoint the main contributing factor to vegetation cover and bare land, because climatic factors cannot be ignored in this case.

The mine rehabilitation process is still ongoing at the Yatela mine and the main goal of the rehabilitation process is to get the land back to its land use capability that existed before the mining operation, taking into consideration that structures such as the waste rock dumps, heap leach pad and open pit cannot be removed or backfilled.

The SVM classification and NDVI results were able to detect mine developments and LULCC.

5.2 RECOMMENDATION AND FUTURE RESEARCH

This research used medium resolution Landsat images for LULCC, for future studies high resolution images from platforms like Quick bird, IKONOS or Worldview should be used.

Collection of socio-economic data in the Yatela region will help in understanding social and economic drivers. Information on how much livestock they own and the kind of plants they consume.

Spectral signature information for different vegetation species and tree species will help in creating species mapping for the region.

The use of temperature and rainfall data can be used to investigate if there is any relationship between the climatic variables and vegetation cover in the Yatela region.

Testing the accuracy of NDVI results was a tough task to do; because ENVI 5.2 and Arc Map do not have an assessment tool for NDVI results. Development of a testing method to assess the accuracy of NDVI results will be very beneficial to LULCC analysis.

The rehabilitation process being conducted at the Yatela mine cannot be assessed because it is not yet complete. Only after the rehabilitation programme has been completed, can there be an assessment which can be done for future research, such as to investigate how effective the rehabilitation process was and if there was any environmental disturbance that was caused through the process.

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