Assessing the Extent of Water Overflows and Vegetation Dieback along Ok Tedi Mine Affected River Systems (Ok Tedi and Fly Rivers, Papua New Guinea)

Willie W. Kurie

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School of the Environment, Faculty of Science and Engineering,
Flinders University of South Australia

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Declaration

I certify that this thesis does not incorporate without acknowledgment of any material previously submitted for a degree or diploma in any university; and that to the best of my knowledge and belief, it does not contain any material previously published or written by another person except where due reference is made in the text.

Willie Wilton Kurie

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Enjoy reading!

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List of Acronyms

AGHAM- Samahan ng Nagtataguyod ng Agham at Teknolohiya Para sa Sambayanan (in Filipino). It means ‘Advocates of Science and Technology for the People’, and it’s a non-governmental science organization based in Philipines.

AOI- Area of Interest

ASTER- Advanced Spaceborne Thermal Emission and Reflection Radiometer

AWEI- Automated Water Extraction Index

CSIRO- Commonwealth Scientific and Industrial Research Organization

CRISP- Centre for Remote Imaging, Sensing and Processing

DENR- Environment and Natural Resources

DFAT- Department of Foreign Affairs and Trade

DN- Digital Numbers

DOS- Dark Object Subtraction

EOS- Observing System

ERTS- Earth Resources Technology Satellite

EU- European Union

EVI- Enhanced Vegetation Index

GGCP- Geometric Ground Control Points

GIS- Geographic Information Science

GoPNG- Government of Papua New Guinea

IBON- A research, education and information development institute based in Philippines that has programs in research, education and advocacy.

ISODATA- Iterative Self-Organizing Data Analysis Technique

ISSU- International Student Services

LAI- Leage Area Index

MCDA- Multi Criteria Decision Analysis

MDWI-PC- Principal Components of multi-temporal Normalized Difference Water Index

METI- Ministry of Economy, Trade and Industry

MIR- Mid Infrared

MNDWI- Modified Normalized Difference Water Index

MODIS- Moderate Resolution Imaging Spectroradiometer

NIR- Near Infrared

MSS- Multi Spectral Scanner (MSS)

Mt- Million Tonnes

NASA- National Aeronautics and Space Administration

NDVI- Normalized Difference Vegetation Index

NDWI- Normalized Difference Water Index

OLI- Operational Land Imager

OTML- OK Tedi Mining Limited

EIS- Environmental Impact Studies

PCA- Principal Component Analysis

PMC- Philex Mining Corporation

PNE- People's Network for the Environment

PNG- Papua New Guinea

SEB- Significant Environmental Benefit

SPOT- Système Pour l'Observation de la Terre

SRL- Sedimentation Level Restriction

TRDRSS- The Tracking and Data Relay Satellite System

TIRS- Thermal Infrared Sensor

TM- Thematic Mapper

USA- United States of America

USGS- United States Geological Surveys

UTM- Universal Transverse Mercator

WGS- World Geodetic System

WRI- Water Ratio Index

Abstract

Mining has been one of humankind's most impactful activities, affecting human well-being and transforming the natural environment and landscapes. Its high waste-to-product ratio necessitates assessments of mining wastes and monitoring of the environmental health for damage mitigation and management. Environmental monitoring and assessment requires up-to-date data, and approaches or techniques applicable for detecting changes across a range of time spans, especially between two or more dates. Satellite imagery, GIS, and remote sensing techniques facilitate the detection of environmental changes. This is particularly important for large catchments that are remote, and/or hindered by climate and geography.

This study uses Landsat Imagery from three sensors: Multi Spectral Scanner (MSS), Thematic Mapper (TM) and Operational Land Imager (OLI), to provide datasets to assess changes in the vegetation, hydrology, and sedimentation along the Ok Tedi and Fly River floodplains of Western Province, Papua New Guinea. Images of the same location taken in 1984, 1988, 1996, 2004, and 2015 were processed for analysis with Image Classification (Unsupervised Classification), Normalized Difference Vegetation Index (NDVI), Normalized Difference Water Index (NDWI), Modified Normalized Difference Water Index (MNDWI), and Image Differencing. Feature types were grouped and quantified using the classification technique. Vegetation health and structure were assessed using NDVI, and NDWI/MNDWI were used to study the water bodies and sediments/built-ups. Image differencing was used to detect the changes that occurred during the span of years from1984-1988, 1988-1996, 1996-2004, and 2004-2015.

Analysis of the results of Unsupervised Classification, NDVI, NDWI/MNDWI, and Image Differencing indicates that there were changes in the features on each image set; changes of one feature type to another, changes in brightness values, and increase or decrease in quantity of each feature type. The results of the NDVI and NDWI/MNDWI show drastic changes in the brightness values in the floodplains of Ok Tedi and Fly Rivers where mine wastes have been deposited, when compared with a control. These features along the Ok Tedi and Fly River floodplains have reacted to the mining wastes. This study also confirms the past studies that showed reduced vegetation health and dieback, and sedimentation. The latest changes, which are the stabilization and declining of sedimentation and vegetation dieback, show reaction to the mitigation processes already put in place by Ok Tedi Mining Limited and the government of Papua New Guinea. These findings can be improved with a non-optical based satellite imagery such as SPOT -5/6 that reduces the impact of the cloud and shadow cover for accuracy and precision. Furthermore, other image classification techniques, such as Object-based classification, and ground-truthing, could better classify and quantify each feature class or types accurately.

Key Words

Change Detection, Environment, Landsat Imagery, MNDWI, NDVI, NDWI, Mining Wastes, Remote Sensing

Chapter 1. Introduction

1.1 Background of the Study

Natural events, such as landslips, volcanic eruptions and floods, together with human-induced activities, including mining, forestry, agriculture, and urbanization, have been major influencers of the health and well-being of human societies (Karr, 1987). Karr considered minimizing negative impacts to be the most important failure of the twentieth century. Of all these activities, mining has been one of the most damaging to human well-being and that of the natural environment and landscapes (Miller, 1997, Manu et al., 2004, Akiwumi and Butler, 2008, Paull et al., 2006, Tiwary, 2001, Townsend and Townsend, 2004).

Ok Tedi Mining Limited (OTML) started production in 1984 in the Western Province of Papua New Guinea. In the process of making revenue for themselves and their investors, the company has also helped in the development of the Province and the country. Apart from paying taxes, OTML established two townships (Tabubil and Kiunga), set up a hospital, and has supported in building schools and medical clinics, which have improved the living standards of the local communities. Despite these benefits, environmental destruction caused, especially along the riverine systems, is evident. The increased volume of sedimentation deposited along the river systems has been the major impact of the mining at Ok Tedi causing significant aggradation in the river channels (Akiwumi and Butler, 2008). OTML (2000, cited in Townsend & Townsend, 2004, p. 14) confirmed that in 1998, a total of 884 million tonnes (Mt) of wastes produced by the mine had entered the watershed, which Townsend and Townsend (2004) found to exceed the levels predicted in the Environmental Impact Studies (EIS). Since the beginning of mining in 1984, many control measures, such as the sediment restriction level (1989), dredging trials (1998), and mine waste tailings at Bige (2006), have been put in place to reduce its footprint on the Ok Tedi and Fly River system. However, James (1999, cited in Akiwumi & Butler, 2008, p. 310) anticipated that natural causes and equilibrium described by Miller (1997) cannot take effect immediately as the aggradations and other mine impacts may persist for a much longer period.

Therefore, assessing the impacts of mining wastes on the environment requires knowledge of the status and health of the surrounding landscape, especially of forests and vegetation, for better environmental mitigation and management (Ferretti, 1997). Assessment requires up-to-date data, software, and techniques applicable for detecting change over time (Giri et al., 2005). Dewan and Yamaguchi (2009) considered that GIS and remote sensing techniques had proven fit for land cover mapping and change detection for particular areas at different time lenghts. These techniques are needed to deal with data that have larger spatial and time scales (Aspinall and Pearson, 2000). Remotely sensed data, especially Landsat Images, have been very useful for change detection, quantifying temporal, spectral and spatial patterns, mapping and monitoring features, and assessing and monitoring environmental status (Akiwumi and Butler, 2008, Aspinall and Pearson, 2000, Ceccato et al., 2005, Manu et al., 2004, Shalaby and Tateishi, 2007, Townsend et al., 2009, Theler and Reynard, 2008).

1.2 Problem Statement

This research is directed at the Ok Tedi and Fly Rivers and their floodplains in the Western Province of Papua New Guinea (PNG) where OTML operations have impacted the surrounding environment. OTML's tailings dam collapsed six months before production began (Kay, 1995) and OTML's studies found that it was financially difficult to construct another tailings dam. Therefore, OTML negotiated an alternative method of disposing mine wastes, which led to the Government of Papua New Guinea (GoPNG) granting them permission to use river dumping (Kirsch, 2002, Townsend and Townsend, 2004, Hyndman, 2001, Baker, 1999, Kay, 1995). When the company started producing from its copper-gold porphyry mine in 1984, it was scheduled that approximately 1400 Mt of rocks were to be dumped directly into the river systems in the period 1984−2007 (Salomons and Eagle, 1990). However, the wastes have risen to an estimated two billion tonnes when the mining capacity was increased from 16 to 30 Mt per year (Townsend and Townsend, 2004). OTML's own report in 2002 (OTML, 2002, cited in Townsend & Townsend, 2004, p. 14) also confirmed that 884Mt of wastes had entered the watershed in the period from exploration and drilling (1981) through to 1998.

GoPNG allowed the mine to dispose of waste rocks and fine tailings directly into the river-streams assuming that the environmental damage would be minimal, but the studies have shown that it is significantly greater than earlier believed (*OK Tedi past, present & future, Ok Tedi Mining Limited*, 1999). Since then, teams of scientists and researchers together with the company's own environment team have conducted impact assessments and studies including water quality and biodiversity, and have concluded that the biggest impacts are to the main river channels of Ok Tedi and Fly Rivers. The studies (Day et al., 2008, Townsend and Townsend, 2004, Cui and Parker, 1999, Swales et al., 1999, Swales et al., 2000, Hettler et al., 1997, Salomons and Eagle, 1990) confirm that there is an observable increase in the turbidity (suspended solids), river bed aggradation causing an increase in sediment volume, changes in water chemistry (copper and metals), change in fish population and diversity, and high water and backwaters causing overbank flooding that blankets forests and gardens with mud which is smothering vegetation and contributing to forest dieback. From these studies, it is evident that the mine wastes have great impact on the riverine systems, vegetation, biology, environment, and the livelihoods of the people of Ok Tedi and Fly Rivers. Despite these earlier findings, later studies by Pickup (2003) , Townsend & Townsend (2004), and others, together with the company's (OTML's) own latest annual review (Ok Tedi Mining Limited, 2014), have shown that there appears to be some progress in controlling the mining wastes impacts as a result of the environmental damage mitigation processes in place. The greatest improvement is seen in the decline of sedimentation quantities.

Most of the studies undertaken by scientists and researchers along the Ok Tedi and Fly River plains as cited above have used soils, sediments, water sampling, coring techniques, pressure gauges, general observations, and ground-truthing. Samples were tested in laboratories for chemical contents, and radiocarbon dated to determine the ages of the sediments, or analysed for temporal and spatial patterns of the samples. Some writers have used satellite images, however, it was only used for digitizing of the flood and river-bank lines, as did Pickup (2007). These analyses indicated significant changes in sediment deposition in floodplains. However, difficulties in reaching swampy, vegetated floodplain sites in remote heavily vegetated areas limited the sampling of sediment cores and water to accessible areas only (Hettler et al. 1997, p. 281).

Due to the remoteness of the location, its rainy climate, and its geography spanning swampy lowlands and rugged headwaters (*OK Tedi past, present & future, Ok Tedi Mining Limited*, 1999), the presence of crocodiles, snakes and malaria carrying mosquitoes, and the 76,000 km^2 scale of Ok Tedi and Fly catchments, coverage of the studies of the vegetation, fish, water, sedimentations, floodplains or mangrove forests was difficult (Townsend and Townsend, 2004). Even the mangrove forest studies conducted at the Fly delta were done by aerial survey using a helicopter, and later took many months by foot for ground surveys (Robertson et al., 1990).

This study assesses the effects of the mining wastes on the river system and surrounding environment along Ok Tedi and Fly River floodplains using GIS and remote sensing approaches. Many researchers, geoscientists, environmentalists, and engineering professionals have found these decision making support tools useful because they produce current and accurate results at minimal cost and timeframe (Chica-Olmo et al., 2002, Giri et al., 2005). This study uses freely available Landsat images to map the hydrology and vegetation affected by mining. Satellites and aircraft record the interactions between matter and electromagnetic energy (Sabins, 1997). Spaceborne multispectral systems such as Landsat's

Multi Spectral Scanner (MSS) and Thematic Mapper (TM), the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER)[1], and the Système Pour l'Observation de la Terre (SPOT) have made it a simple matter to detect and define different land cover types by measuring differences in spectral reflectance signatures (Aspinall & Pearson, 2000, p. 305).

This study specifically uses a number of Landsat images to assess changes. A 1984 image, acquired before the mine began productions is used to identify the natural hydrology and vegetation, whereas the stages of environmental decline as marked by the hydrology and vegetation dieback since the mining operation began in 1984 are assessed using a further five images from 1988, 1996, 2004, and 2015.

1.3 Research Aim and Objectives

The aim of this research is to use Landsat images acquired from United States Geological Surveys (USGS) to assess and understand the effects of sediment deposition and water overflows in the floodplains of the Ok Tedi and Fly rivers, which have been affected by the Ok Tedi Mine operations beginning from the mine production date, 1984. To achieve this, spectral signatures from the Landsat Images will be used to capture the extents of the floods, map the temporal and spatial distribution of the sediment deposition, and determine and quantify the vegetation health and dieback.

1.4 Research Question

This study addresses the following questions:

[1] The Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) is an imaging instrument on board Terra, the flagship satellite of NASA's Earth Observing System (EOS) launched in December 1999. ASTER is a cooperative effort between NASA, Japan's Ministry of Economy, Trade and Industry (METI), and Japan Space Systems (J-spacesystems).

1. What is the extent of flood waters and sediment deposition on the floodplains affected by the Ok Tedi mine?
2. How much has mining affected vegetation health and caused dieback?
3. Are there any changes, especially improvements in the riverine sediments and vegetation dieback along the affected rivers, as a result of mitigations imposed by the company?
4. How useful are satellite images (Landsat) and GIS and remote sensing applications for assessing the effects of the mining wastes on environmental sediments, water, vegetation, and biodiversity of the mining affected river systems?

1.5 Scope of the Study and Anticipated Outcomes

Ok Tedi mine wastes that were dumped into the river systems forced water to overflow into the floodplains, built up sediments, and caused vegetation dieback. Therefore, this study uses Landsat images and rainfall information to examine and quantify the flood affected areas, sediment deposition, and the changes in health and structure of the vegetation caused by the effects of Ok Tedi mining wastes. It is hoped that the results and/or the information from the study can be used in identifying areas for further mitigation and improved environmental management. Furthermore, the government of Papua New Guinea can utilise similar techniques used in this study to assess and monitor environments in other mining operation regions in the country.

1.6 Study Area

The Ok Tedi Mine affected floodplains of Ok Tedi and Fly Rivers are located in the Western Province of Papua New Guinea (Figure 1). The 307,763.24 ha area covers the lower Ok Tedi and the upper Fly

Rivers, and includes Kiunga River, which is not directly affected by the mine as it is located in a separate tributary.

Ok Tedi River springs from the Star mountains, on 2,094 m high Mount Fubilan where Ok Tedi copper mine sits. It flows 900 kilometres through numerous villages and communities inhabited by approximately 50,000 people through D'Albertis Junction and into the Fly River. The Fly River meanders to the West Irian border and forms the international border between Papua New Guinea and Indonesia before it eventually joins with the Strickland River and ends in the Gulf of Papua (Hettler et al., 1997, Kay, 1995, Cui and Parker, 1999, Hyndman, 2001).

The region is wet all year round, however, the elevation and rainfall drops rapidly from the upper catchments to the coast. The rainfall is within 8,000−10,000 mm per annum in the upper catchment and approximately 4,600−3,000 mm per annum in the lower parts, while the elevation ranges from 2,094 metres in the Star mountains to 20 metres above sea level at the convergence of the Ok Tedi and Fly Rivers (Swales et al., 1998, Kay, 1995). The upper catchment is rugged limestone mountains covered with thick undergrowth of mosses and ferns, and provides a range of flora and fauna. In the lower catchment, the Fly River discharges an estimated mean of 6000 m^3/s (Townsend and Townsend, 2004). The floodplains along this tropical river are swampy, covered by grasslands, savannah woodlands, and patches of monsoon forests. Rivers and their tributaries are surrounded mostly by sago palms and host a diverse fish fauna of around 100 species representing 32 families (Swales et al., 1998) on which people depend for food sources.

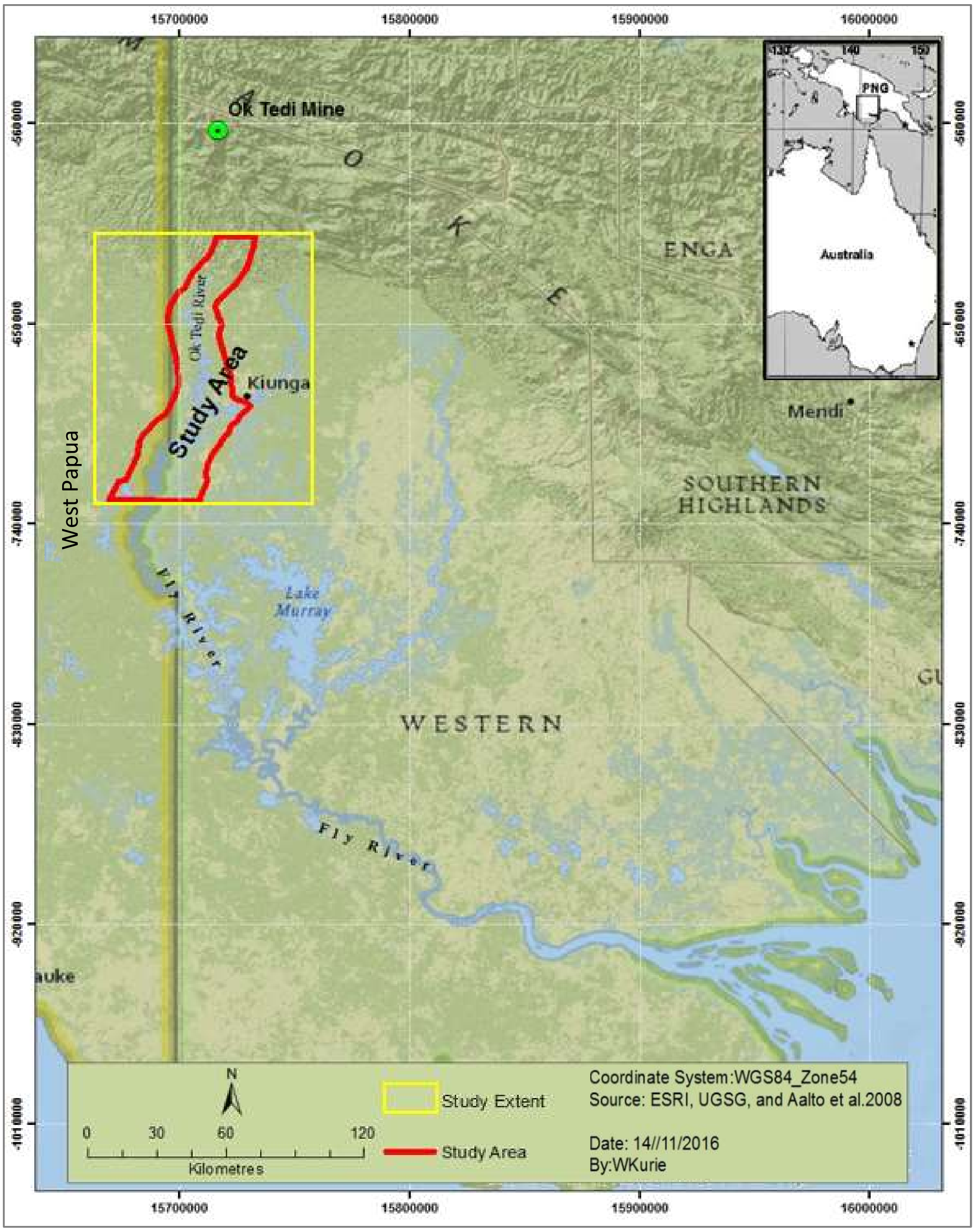


Figure 1. Study Area, Western Province of Papua New Guinea

1.7 Thesis Structure

The thesis contains five chapters. Chapter 2 reviews the literature on the use of GIS and remote sensing to detect, assess, and monitor environmental changes. Furthermore, it defines mining, discusses types of mining, and indicates benefits and negative impacts of mining with case studies. It goes on to detail the methods of preparing, accessing, and using remotely sensed data available in Landsat. Finally, it identifies remote sensing techniques used, especially the Normalized Difference Vegetation Index (NDVI), Normalized Difference Water Index (NDWI), and Enhanced Vegetation Index (EVI).

Chapter 3 describes the methods used in this research. It emphasizes the data sources and their preparation and processing. It details how the research models the extent of the floods, sedimentation, and vegetation health and structures.

Chapter 4 presents and discusses the results. The results derived along the Ok Tedi and Fly River floodplains are compared against the results from a control, which is an area unaffected by the mining wastes, to assess the effects of the natural causes and the mine wastes impacts.

Finally, Chapter 5 concludes the thesis by summarizing the findings, outcomes, limitations and recommendations.

Chapter 2. Literature Review

2.1 Assessing and Monitoring Environments

The health and well-being of humans and the rest of the biosphere have frequently been influenced by the natural and human-induced events (Karr, 1987). Natural events can be catastrophic at times and cannot be controlled, whereas the human-induced events as well as their effects on people and the environment can be controlled if assessed and monitored well. It has been recognized for some time that the process of assessing and monitoring the environment involves a team examining a problem, analysing the possible consequences of specific actions, and presenting reports for further decision-making and management (Holling, 1978, p. 38).

Stevens (1994, cited in Ferretti, 1997, p. 50) defined such monitoring as an act of 'tracking a particular environmental entity through time, and observing its conditions and the change of its conditions in response to a well-defined stimulus'. Environmental assessing, by contrast, is the estimation or measurement of the status of a given environmental entity at a given time (Ferretti, 1997, p. 49). In environmental assessment and monitoring, researchers and scientists are observing and measuring the conditions, health, and progress of an environmental entity over a period of time. Ferretti saw the process as a lead-up to development of environmental policies and strategies for managing resources.

The analysis of changes in vegetation, hydrology, biodiversity, and ecology in a given environment often reflects human activities and impacts (Lopez et al. 2001, cited in Dewan & Yamaguchi, 2009, p. 237). Dewan and Yamaguchi stressed that local and regional land use/cover and vegetation changes may lead to global environmental effects. Mitigation and management strategies are more effective when generated from quantified temporal and spatial patterns, and examinations of trends and rates of environmental changes (Dewan and Yamaguchi, 2009, Shalaby and Tateishi, 2007, Townsend et al., 2009).

The environment should encompass biological, chemical, and physical assessments and monitoring (Karr, 1987). Karr and Dudley (1981, cited in Karr, 1987, p. 249) described biomonitoring as a process of 'evaluating the health of biological systems to assess degradation from any of a variety of impacts of human society'. Karr emphasized that biomonitoring should include the attributes of individuals (health), population (structure and dynamics), communities (structure), and ecosystems (function) for a better understanding of the changes. Although biological and chemical assessments and monitoring are important in environmental studies, this research focuses only on physical assessment and monitoring.

Watershed/hydrology is one of many areas of the environment that require assessing and monitoring (Xiao and Ji, 2007). Turner et al., (2001, cited in Xiao & Ji, 2007, p. 111) assumed that water quality is related to landscape characteristics and composition types. Xiao and Ji (2007) point out that variations in landscape characteristics can also affect the ecological and hydrological conditions of a given environment.

Land use/cover is another element that has been studied extensively by various researchers (Dewan & Yasushi, 2009; Shalaby and Tateishi, 2007). Analysing the changes and quantifying the patterns of land use/cover has aided in devising environment management systems or has led to solving or minimizing environmental problems. Many researchers (Xiao and Ji, 2007, Townsend et al., 2009, Mars and Crowley, 2003, Manu et al., 2004, Miller, 1997, Akiwumi and Butler, 2008, Dewan and Yamaguchi, 2009, Ferretti, 1997) have attributed the effects of environmental change and degradation to agricultural developments, deforestation, urbanization, tourism, and mining. Of all these, mining has been one of the most devastating human-induced activities, affecting human well-being, undermining ecosystems and transforming landscapes (Akiwumi and Butler, 2008, Manu et al., 2004, Miller, 1997, Paull et al., 2006, Tiwary, 2001, Townsend and Townsend, 2004).

2.2 Definitions of Mining and Mining Wastes

2.2.1 Mining

Although the styles and processes of mining have changed significantly over the years, it is still a science, technique, and business of mineral discovery and exploitation, which involves a process of extracting valuable minerals in the form of ores or associated rocks from the earth's crust (Thrush, 1968) . Practically, it involves opencast work, quarrying, alluvial dredging, and combined operations, including surface works, underground excavations, and ore treatments (Thrush, 1968, Dhillon, 2010, Hartman and Mutmansky, 2002). The ores are special types of rocks that contain large amounts of a particular mineral that are usually extracted from the surrounding rocks in the process of mining (McKinnon, 2002). These rocks containing precious or useful metals are extracted from the earth's crust and are refined through a smelting process to extract the valuable minerals. The minerals should occur in sufficient quantity, grade and chemical combination for the extraction to be economically profitable (Fay, 1947).

The kernel of mining is the excavation of the mineral deposits to the surface (Hartman and Mutmansky, 2002). Thus, apart from administration and fulfilling legal obligations, there are five steps involved in the life of a mine: prospecting, exploration, development, exploitation, and reclamation (Marjoribanks, 2010).

According to Majoribanks (2010), and Bell and Donnelly (2006), prospecting is done by geologists or explorers using hand tools to collect small samples after having undertaken literature search. These samples undergo chemical analysis to prove mineral contents. Exploration works begin with non-ground disturbing exploration followed by the drilling phase where the environment is disturbed when small holes of <100 mm and larger holes of =>140 mm are drilled through the soils and loose rocks using a hammer, a blade bit, or an industrial diamond impregnated bit. The small holes are used to confirm the presence or absence of minerals, while the larger holes are to quantify the minerals present. Once these steps are complete; the development and exploitation phases start with the miner or developer going ahead to build the mine and start exploiting the minerals. Exploitation requires blasting to loosen rocks prior to excavation or removing rocks using bulldozers. Ores and waste rocks are taken to primary crushers and stockpiles at the processing plants. Ores are of economic value, but the disposal of the waste rocks and other wastes associated with treating the ores become a challenge to the environment and human well-being. Finally, reclamation is the final stage of the mine in which the exhausted mine site is rehabilitated to approximate its natural setting. It can therefore be seen that mining boosts the economy, creates employment, earns foreign exchange, and increases investments, but at the same time creates negative environmental, human and financial impacts (Sinding, 1999, Hilson and Nayee, 2002, Bell and Donnelly, 2006, Denison and Michael, 2012).

2.2.2 Mining Wastes

Mining wastes are generally made up of barren rocks, and low grade, uneconomic ore deposits in a mine (Thrush, 1968). Mostly, they are valueless materials dug, hauled and dumped in the process of mineral excavation and quarrying to extract valuable ores/minerals underground (Lewis, 1933). According to Lewis, the mining wastes can be both the materials that do not enter into the dressing and beneficiating process[2], and the wastes generated from the process of separating the minerals from ores and other materials extracted during the mining and quarrying activities.

In a mine, overburdens are the materials (rocks, soils, ecosystems) that overlie a deposit of useful materials/ore-bodies that are mined from the surface by an open cut. These are uncontaminated materials removed during surface mining which can be used to rehabilitate the exhausted mine site after

[2] 'Mineral dressing is an initial process of ore extraction in a mine that includes preparation, milling and ore dressing or ore benefaction. Ore dressing is a mechanical process for separating grains of ore minerals from the gangie minerals to produce concentrate containing most of the ore minerals and tailings' (Lewis, 1933).

operations are completed. Tailings are the contaminated waste rocks and other materials generated in the process of separating the valuable fraction from the uneconomic fractions of ores (Bell and Donnelly, 2006). The extraction of minerals from ores is done using water and gravity to concentrate the valuable minerals (a method called placer mining), or by crushing and grinding the ore bearing rocks into fine particles and extracting the minerals in a chemical reaction process (hard rock mining). These processes, especially hard rock mining, incur a slurry of fine particles of varying sizes. Overall, mine wastes constitute 75−95% of the original ores (Swedish Environmental Protection Agency, 1993, cited in Ledin & Pedersen, 1996, p. 68). This makes waste the major product of mining in the modern open-pit system; a very high waste-to-product ratio (Coumans, 2002, p. 1).

Thrush (1968) pointed out that the materials derived by mechanical and chemical weathering that move down sloping surfaces or are carried by streams to the sea are also mine wastes. In this case, the mining waste rocks and materials dumped at the mining stockpiles, together with overburden and tailings, are exposed to mechanical and chemical weathering and washed down the streams (Ledin and Pedersen, 1996). There are instances where these wastes, in the form of suspended sediments, travel in large quantities that exceed the natural load capacities of the local rivers and streams (Townsend & Townsend, 2004). These excessive loads deter the natural flow and alter the paths of the watercourses, hence affecting the environment and biodiversity.

2.3 Types of Mining

Minerals are mined using two techniques: surface mining and underground mining (Okubo and Yamatomi, 2009, Bell and Donnelly, 2006, Hartman and Mutmansky, 2002, Shahriar et al., 2007). Shahriar, Oraee and Bakhtavar (2007), and Carli and Lemos (2015) emphasize that the choice of method depends on the characteristics of the minerals, especially in relation to the depth, geometrical properties of the deposits, their position, and economic feasibility. The method is chosen based on technical, economic, environment, and social factors but most importantly after comparing the economic efficiencies of extracting the minerals (Okubo and Yamatomi, 2009). Alternatively, a method combining surface and underground mining techniques is preferred if the features, especially the characteristics of the ore body, are present in both methods (Carli and Lemos, 2015).

2.3.1 Surface Mining

Surface mining is an open-air mining operation technique used for excavating minerals located less than 200 metres below the surface (Shahriar et al., 2007, Kennedy, 1990, Thrush, 1968). According to Okubo and Yamatomi (2009), modern surface mining operations are carried out by personnel operating on the surface without provision of manned underground operations. The minerals are mined downward in benches or steps sloping in towards the centre of the pit. This process usually involves explosives to loosen the ores for scoping and then materials are taken to crushers for further processing (Kennedy, 1990).

Okubo and Yamatomi class the processing technique into two groups according to extraction methods: mechanical and aqueous. They stress that the mechanical process is employed in a dry environment and has four sub-methods. The first and second are known as open pit and open cast mining. They involve the conventional mining cycle of mineral extraction operations (drilling and blasting of consolidated materials, excavating unconsolidated materials, and handling and transporting of materials). The third is the quarrying of dimension stones which is similar to open pit mining except that it does not involve blasting of rocks and consolidated materials to cut tabular slabs. Okubo and Yamatomi point out that this sub-method is labour intensive and, therefore, expensive. The final sub-method is highwall or auger mining. It is usually employed in coal mining where the outcrops are recovered by mechanical excavation without removing the overburden. The operators and crews remotely control the auger or cutting heads operating underground from the surface. Kennedy (1990) attributed this technique to the then recent development and use of increasingly sohisticated onboard electronics and microcomputer systems for mining equipment.

In contrast to the mechanical extraction, aqueous extraction uses water or liquid solvents to flush the minerals from the underground deposits by hydraulic disintegration or by physicochemical dissolution.[3] Okubo and Yamatomi stress that this method uses placer mining, a method for recovering heavy minerals from the alluvial or placer deposits using water to excavate, transport, and concentrate the minerals. This method is used when the metals of interest are associated with sediments in a stream bed or floodplain that require bulldozers, dredges, or hydraulic jets of water to extract the ores (Bell and Donnelly, 2006). Bell and Donnelly (2006, p. 5) point out that this method is environmentally destructive due to the large quantities of sediments released, which may affect surface water some distance downstream. Okubo and Yamatomi also noted another aqueous extraction method called solution mining. This method is employed for extracting soluble or fusible minerals using water or a lixiviant[4].

2.3.2 Underground Mining

Underground mining is mineral extraction conducted beneath the earth's surface (Okubo and Yamatomi, 2009, Bell and Donnelly, 2006, Shahriar et al., 2007, Hartman and Mutmansky, 2002). This method is chosen when the mineralization or ores are found deep beneath the surface, and when the waste-to-ore ratio would be much greater if the mineral were mined using surface mining methods

[3] An act of disintegrating the ore bodies/materials using chemical and physical processes.

[4] It is a non-toxic liquid medium (replacement of cyanide) used in gold/mineral leaching. It is used in hydrometallurgy to selectively extract the desired mineral or metal from the ore or mineral contexts (Gos & Rubo 2001).

(Okubo & Yamatomi, 2009, p. 171). Okubo and Yamatomi emphasize that the choice of whether to use underground mining is based on the geographical or spatial setting of the deposits.

When minerals are located deep beneath the earth’s surface, minimal amounts of overburdens are removed and access to the ore deposits is gained by vertical shafts or sloping tunnels. Bell and Donnelly (2006) note that, underground mining causes less environmental destruction to gain access to ore deposits; however, it is costly and entails greater safety risks. They further state that, although most large-scale mining projects prefer open-pit mining, many large underground mines are in operation throughout the world.

Underground mining poses a greater risk to personnel; however, the risks can be mitigated by ground support for operations. Okubo and Yamatomi (2009, p. 172) categorize these supports into three classes based on their requirements. The unsupported method does not use an artificial system of support as it relies on the natural competence of the walls of the opening pillars (Hartman and Mutmansky, 2002). On the other hand, Hartman and Mutmansky (2002) and Okubo and Yamatomi (2009) define supported methods as requiring artificial structures to maintain stability in exploitation openings as well as systematic ground controls throughout the mine. Okubo and Yamatomi emphasize that supported methods are used when production openings are not sufficiently stable to remain open during operation. Caving methods are those associated with induced, controlled, massive dug-out of the ore body, the overlying rocks, or both, where the exploitation openings are intentionally destroyed in the process of mining. The exploitation works in these methods are designed to collapse, with intentional caving of the ore and host rocks. Okubo and Yamatomi (2009) describe three major caving methods; longwall mining, sublevel caving, and block caving. Each has its own strengths and weaknesses, but longwall mining has been an effective way of mining coal (minerals) underground. It is used in horizontal, tabular deposits while the other two methods have applications in inclined or vertical massive deposits.

2.3.3 Combined Method Mining

Some mines are operated using both the surface and underground mining methods. In an instance where the mineral deposits are of modest depth, that is they are not shallow or so deep to warrant surface or underground mining, a combined method is preferred (Shahriar et al., 2007, Okubo and Yamatomi, 2009). Shahriar, Oraee and Bakhtavar (2007, p. 2) explain that this method involves beginning the mine as a surface mine and then continuing as an underground mine. Okubo and Yamatomi (2009) classify this as a hybrid method where the minerals are initially extracted using surface/open-pit mining followed by underground methods.

2.4 Benefits of Mining

Mining, alongside agriculture, has been at the forefront of human and societal development and civilization (Bell and Donnelly, 2006). Bell and Donnelly (2006, p. 1) claim that the oldest known mine is Lion Cave in Swaziland, which dates back 43,000 years. Manning (1995) notes that even early humans used minerals for pigmentation and stone tools for grinding and cutting. He further stresses that since then, the uses as well as their (minerals) exploitation has risen significantly. Aided by increased civilization, many different types of minerals have been discovered and mined throughout the world. The technological innovations and increased political developments require minerals for producing new products and materials in the manufacturing industries to cater for modern society (Manning, 1995).

There are nearly 5,000 known mineral species in the world, of which, 371 were named and/or given abbreviations (Whitney and Evans, 2010). Of these minerals, silver was one of the first five metals (others: gold, copper, lead, and iron) discovered and used by humans dating back to 4,000 BC in Greece. Unlike agriculture which has a choice of where it can be established, mining developments are operated based on mineral spatiality, that is, they are mined exactly on or at the spot where the mineralization is located (Bell and Donnelly, 2006, Sengupta, 1993). Most of these minerals are identified or spotted in relatively unspoiled nature, or very isolated areas.

Apart from making revenue for themselves, investors and shareholders; mines have been the backbones behind governments in establishing townships in mining centres to serve local communities. Sengupta (1993) notes that mines also create opportunities for other economic activities including forestry, recreation, and tourism because of the nature and their locations.

Generally, mining boosts the economy, creates employment, earns foreign exchange and creates revenue, and increases investments. The revenue generated from the mining activities can be used for building schools, hospitals, and other social amenities. Local communities can be paid compensation and royalties for the use of their land. Even their living standards can be (or have been) improved due to provision of proper health and educational services through schools and hospitals.

2.5 Negative Impacts of Mining on Environment and Humans

Throughout history, mining industries have contributed enormously to economic development; however, at the same time have added to environmental pollution and deterioration (Townsend and Townsend, 2004, Paull et al., 2006, Tiwary, 2001). The wastes produced from extraction and processing of mineral resources are the topsoil, overburden and waste rocks, as well as tailings after minerals have been extracted (European Commission, 2016). The European Commission notes that, these types of wastes have been the largest waste streams in the European Union (EU).

Sengupta (1993) notes that the types of wastes and the damage the mines can cause to the environment, ecosystems, hydrology, and humans depend on the type of mining and the method used in mining or extracting the minerals. Sengupta (1993, p. 1) listed the possible environmental impacts: destruction of landscapes, degradation of visual environments, disturbance of watercourses, destruction of agriculture and forest lands, damage to recreational lands, noise pollution, dusts, truck traffic, sedimentation and erosion, land subsidence, and vibrations from blasting and air blasts. In the process of mining (blasting, tailings preparation and disposal, crushing of the ores, stockpiling of ore and waste materials), a significant amount of land utilized is affected (Paul and Campbell, 2011). Sengupta (1993), and Paul and Campbell (2011) stress that the chemicals (cyanide and mercury) used in mining pose a health hazard to plants, animals, and humans. Mining also triggers erosion and landslides that cause deaths and destroy surrounding environments, such as farms and rivers or other water bodies.

According to the Massachusetts Institute of Technology (2016), unregulated mining has a greater potential to release harmful substances into the soil, air, and water. Improved technologies and better environmental regulations could reduce environmental damage. However, the mining impacts already created on the environments can take a longer term to recover (Townsend and Townsend, 2004).

2.6 Case Studies

Mining and related activities pose a potential for environmental degradation due to the greater ratio of wastes-to-ores production (Coumans, 2002). According to Mining, Minerals and Sustainable Development (2002, cited in Bravante & Holden, 2009, p. 526), much of the wastes produced are in the form of tailings and finely grained waste particles left over from mineral processing, which are stored in tailing ponds or dams, and the water in these ponds or dams is extremely toxic. Therefore, to illustrate the results of negative mining influences on the environment and surrounding communities, four case studies, including Ok Tedi Mining, are discussed in this research.

2.6.1 Baganuur Open-pit and Nalaikh Closed-pit Coal Mines, Mongolia

Mongolia is a country located between Russia and China in the northern part of central Asia. Since 1998, mining production has contributed around 50% of Mongolia's gross industrial products (Lkhasuren et al., 2007). The growing number of mines, especially gold and coal, contributed significantly to the country's economy; however, the economic benefits have been obtained at the expense of the environment and occupational health and safety of the people.

In reviewing the environmental and social policies and practices in Mongolia, Ruhrmann and Becker (2003) note that mining related environmental issues are far more overreaching than the benefits. From the many issues noted, topographical changes particularly associated with open cast mining and dredging were obvious. Dredging of the river sediments, and discharging of mining residuals into the surface water bodies have caused much surface water turbidity. The surface water levels and ground water tables together with the aquatic eco-systems were affected by the augmented abstraction[5] of the waters. This occurs due to the increased and constant use of water for washing the placer minerals. While conducting her studies on the permafrost of the region, Sharkhuu (2003) noted that it (permafrosts) thawed completely. She attributed the cause to pumping underground water at Baganuur open-pit coal mine, which also caused the nearby springs and the swamps to drain and dry out. Sharkhuu also explained that the thawing of the permafrosts was associated with the increased temperatures generated by the Nalaikh closed-pit coal mine.

Ruhrmann and Becker (2003) further stress that mining (especially the intensive traffic of trucks used at the mining site) causes air pollution that affects the employees/workers and the livestock grazing within the vicinity of the mines. Lung diseases, especially the dust induced chronic bronchitis and pneumoconiosis, were found to be very high in Mongolia (Lkhasuren et al., 2007). Other environmental

[5] The process of withdrawing or taking water from any sources temporarily or permanently using artificial means.

impacts include erosion and pollution. Ruhrmann and Becker discovered that the waste rock piles from the mines were unstable and prone to erosion when rainfall washed the gravels and soils downhill destroying grazing lands and polluting watercourses.

2.6.2 Philex Padcal Mine (Silver/gold/copper), Philippines

Padcal underground mine in Benguet Province of the Philippines, which is planned to close in 2020, has been operated by Philex Mining Corporation since 1958 (Alyansa ng mga Grupong Haligi ng Agham at Teknolohiya para sa Mamamayan, 2013). Originally, the mine was operated using the open-pit mining technique until 1963 when it changed to the block caving method, which according to Thrush (1968) is a mining technique that creates caves and extracts large volumes of rocks. The project produces copper concentrates containing copper, gold, and silver. In 2002, a total of 278.9 million tonnes of concentrates were mined and processed.

The technical report by the Philippine environmental NGO, *Alyansa ng mga Grupong Haligi ng Agham at Teknolohiya para sa Mamamayan* (AGHAM 2013) noted that, as in the 1980s and 1990s where there were tailings dam failures resulting in toxic tailings discharges, 1st August 2012 was a fatal day for Philex Mining Corporation. There was a failure in the tailings pond when the dam breached or overflowed resulting in a voluminous (80 million metric tons) discharge of toxic tailings into the Balog and Agno Rivers, and eventually into the San Rogue Dam. The observations and studies undertaken by AGHAM (2013) showed that there was significant damage done to the environment and the livelihoods of local people by these mining waste spill-overs.

Some of the characteristics of the damage from this event were the turbidity and the distinct dark greyish colouring of the rivers, the strong odour of the sediment, which smelled like stale fish, and the oily surfaces. The spill-overs also filled the river beds/banks with silted materials, and there were no macroinvertebrates found in the area during the time of study. A press release on 28th November 2012 addressing the Department of Environment and Natural Resources (DENR) described the scene as being filled with the stench of rotting fish indicating that the fish were killed by the mine tailings spill-overs (Kalikasan PNE 2012) . AGHAM further noted that the receiving rivers (Balog and Agno) were polluted by a high quantity of the mine tailings causing the waters to smell, change colour from dark brown to black, and they were covered with thick mud that clung to the plants and emitted strong odours. This also affected the livelihoods of the communities that depend on the rivers when the tailings were deposited on the farmlands and water systems. IBON (2006, cited in Bravante & Holden, 2009, p. 527) confirmed that mining in the Philippines has caused environmental impacts including deforestation, slope destabilisation, soil erosion, water sources degradation, crop damage, siltation, air pollution, increased water turbidity, and alteration of the sea-bottom topography. They also witnessed siltation of irrigation canals and paddy fields in the lowlands by the mine waters that were discharged through the process of mining.

2.6.3 Grasberg Gold Mine, PT Freeport Indonesia, Papua, Indonesia

Grasberg gold and copper mine is located on the highest mountain (4,300m) in West Papua Province, Indonesia (Abrash & Kennedy 2002; Banks 2002; Paull et al. 2006). The project is situated in an area that has an average rainfall of 5,000mm/annum in the highlands and 3000mm/annum in the lowland areas. It is owned and operated by Freeport-McMoRan using open pit and underground mining techniques since the project began in 1990. The project has four concentrators on site for crushing the cores before they are delivered to the mill complex for further crushing, grinding and floatation. It supplies nearly 10% of the world's copper each year through its annual output of 900,000 tonnes of copper and 2,750,000 oz. of gold (Martinez-Alier, 2001). In 2003, it was the largest gold producer in the world (Paull et al., 2006). Unfortunately, the tailings and the overburdens from the mine operation have been dumped into the rivers.

With this enormous scale of operations, Martinez-Alier (2001) has reported that the ecology of the province is sensitive to the mining operation and that the major environmental complaints are the water pollution and acid drainage in its river (Ajkwa). Abrash and Kennedy (1999) mentioned that, in 1999, there was a massive rockslide in the Wanagon stockpile that entered Wanagon Lake generating a pulse of water which flowed downstream similar in effect to tidal waves into the populated valley. According to the authors, the forest downstream is dead and forest dieback caused by suffocation and poisoning of the trees by the mining wastes is evident. Banks (2002) also confirmed that the area (120 km^2) labelled as Aikwa Deposition Area in the lowlands is primarily covered by dead trees and thick tailings sludge.

2.6.4 Ok Tedi Mining Limited, Papua New Guinea

Ok Tedi Mining Limited (OTML) is a gold and copper project located in the Star mountains of Western Province, Papua New Guinea; and is the focus of this study. It was formerly operated by BHP but has now been taken over by the government of Papua New Guinea (GoPNG). The project is situated at the headwaters of Ok Tedi River that flows 1,000 kilometres downstream into the Fly River through numerous villages and communities inhabited by approximately 50,000 people (Hettler et al., 1997). Just six months before gold production commenced, the $70 million tailings dam collapsed due to a landslide (Kay, 1995). OTML's studies found that it was financially difficult to construct another tailings dam, hence, they negotiated for an alternate method of disposing of mine wastes. This led to GoPNG granting permission to use river dumping (Kay, 1995, Townsend and Townsend, 2004, Cui and Parker, 1999, Baker, 1999, Hyndman, 2001)

Since the operation, OTML (2000, cited in Townsend & Townsend, 2004, p. 14) confirmed that 884 Mt of wastes produced by the company had entered the watershed in the period 1981 through to 1998. With these amounts of untreated mining wastes entering the river systems, a number of studies (Day et al., 2008, Hettler et al., 1997, Cui and Parker, 1999, Townsend and Townsend, 2004, Swales et al., 1999, Swales et al., 1998, Hyndman, 2001) have confirmed that there are observable increases in the turbidity (suspended solids), river bed aggradation causing increase in sediment volume, changes in water chemistry (copper and metals), high water causing overbank flooding that blankets forests and gardens with mud, which has smothered vegetation and contributed to forest dieback. OTML reported in 2002 that 1,461 km^2 of vegetation had been impacted, and studies by Storey and Marshall in 2003 found that riparian environments were altered, and there was a massive loss of fish habitat and decline in number and diversity of fish (Swales et al., 1998). Despite these, current reviews (Ok Tedi Mining Limited, 2014) indicate that the mining wastes are being controlled in response to the mitigation processes in place. The mitigation processes have been the sedimentation level restriction imposed in 1989, the dredging trials in 1998, and the creation of a mine waste tailings dam in 2006. These initiatives were to minimize the increasing sedimentation that is affecting the biodiversity and ecosystems along the Ok Tedi and Fly River catchments.

2.7 Significant Environmental Benefit

Significant Environmental Benefit (SEB) is the measure taken to compensate for the clearance of native vegetation which outweighs the value of retaining the vegetation (Dobrzinski, 2004). It is stated in the Australian government's 2005 Guidelines for a Native Vegetation Significant Environmental Benefit Policy for the clearance of native vegetation associated with the minerals and petroleum industries (Department of Water, Land and Biodiversity Conservation 2005) that the logic behind SEB is that once a landscape is cleared, the native vegetation[6] will lose its habitat, biodiversity and environmental values. Therefore, its intent is to replace the lost environmental values, and to introduce ways to improve the

[6] 'Native vegetation is a plant or plants of a species indigenous to a location including a plant or plants growing in or under waters of the sea' (*Native Vegetation Act 1991*).

conditions of the environment and the biodiversity of the region or location. The guidelines proposed that the SEB could be achieved at the site of operation, or within the same region of operation in the state or province.

From the case studies cited above, it is evident that most of the environmental impacts of mining were avoidable, were supposed to be minimal, and the operator can be held responsible for the damage done if proper and applicable systems had been used. The systems, processes, procedures, guidelines, and the types of government and politics used at the time of mining project initiation can also determine the outcomes. Most often, the details of how a mining company would operate within the vicinity and along its operational corridors are outlined in the environmental impact studies (EIS). The policies and acts in each country vary; however, in Australia there are some provisions in the Mining and Petroleum Acts (Mining Act 1971 and Petroleum Act 2000) that allow some exploration activities to clear the natural vegetation without incurring SEB. These exemptions are taken as long as the clearance is undertaken with acceptable industry environmental management practises, and only when there are no other practicable alternatives that can prevent the harm to the native vegetation (Dobrzinski, 2004). However, other programs that require increased intensities for clearing native vegetation or those that result in long-term impacts may require SEB on a case-by-case basis.

The Australian Department of Water, Land and Biodiversity Conservation (2005) demonstrated in its guidelines that all new mining operations that require clearing of native vegetation should provide a native vegetation management plan to demonstrate that the proponent is providing the required level of SEB applicable to the particular circumstance. Though SEB is currently practised only in South Australia, it is similar to the EIS documents in use by other agencies, except that the SEB provides an environmental gain over the impacts of an approved clearance, which involves management, and protection of an area (Government of South Australia, 2014). The Government of South Australia

(2014) thinks that SEBs operate in a similar way to offsets required under the Commonwealth's *Environmental Protection and Biodiversity Conservation Act 1999*.

2.8 The Use of GIS and Remote Sensing in Environment Assessment and Monitoring

The knowledge of the status and health of the environment (especially forests, vegetation, hydrology and ecology) is required for assessing and monitoring any changes. Once the status is known, better environmental mitigation and management strategies can be developed (Ferretti, 1997). Lu et al. (2004) stresses that, for better mitigation and managerial decision making, the understanding of the relationship between human and natural phenomena is necessary. This requires up-to-date data, software, and approaches or techniques applicable for detecting changes across a range of time spans especially between two or more dates (Giri et al., 2005). Dewan and Yamaguchi (2009) note that GIS and remote sensing techniques have proven suitable for land cover and change detection for longer and varying time spans (years). Aspinall and Pearson (2000) also affirm that data with larger spatial and time scales are better dealt with by GIS and remote sensing approaches (apart from meteorological and geographical approaches). GIS and remote sensing approaches, coupled with remotely sensed data, have been very useful for change detection, quantifying temporal, spectral and spatial patterns, mapping and monitoring features, and assessing and monitoring environmental status (Akiwumi and Butler, 2008, Aspinall and Pearson, 2000, Ceccato et al., 2005, Manu et al., 2004, Shalaby and Tateishi, 2007, Townsend et al., 2009, Theler and Reynard, 2008).

Remote Sensing technologies and their applications continue to provide up-to-date and recurring observations of the earth's features at local and global scales. Kennedy et al. (2009, cited in Ma & Xu, 2010, p. 228) stresses that remote sensing data has been the best data source due to the continual developments of the technologies and the improved spatiotemporal and spectral resolutions of the sensors. These data are being processed and analysed by many disciplines to help in decision making and solving problems (Lu et al., 2004). Ma and Xu (2010) emphasize that remote sensing and GIS technologies have used both local and global remotely sensed data in analysing, assessing, and monitoring environmental changes.

2.8.1 Geographic Information Systems (GIS)

The definitions of GIS vary across industrial and intellectual landscapes due to the wide ranging applications (Tomlinson, 2007). Tomlinson describes functional GIS as 'a process that involves a human operator analyzing the data (database), and converting them into useful/needed information products'. If it is dealing with data, a system, a process, and the products, then, it is a computer system for capturing, storing, checking, and displaying data related to positions on the earth's surface (Alibrandi, 2003, Tomlinson, 2007). Because the information processed has spatial connection to features on the earth's surface, it enables people to more easily see, analyse, and understand patterns and relationships. The National Geographic Society (2016) confirmed that GIS technology has given people the flexibility of comparing locations and analysing their relationships to other phenomena. They stressed that the locational component in the GIS technology has been an advantage for use of any spatial information. From the many uses of GIS, Alibrandi (2003) notes that it can be engaged in urban planning, weather reporting, and geological and demographic studies. GIS technologies are also useful for generating information about the land and environment such as the hydrology, different kinds of vegetation, soils, and other related characteristics (National Geographic Society, 2016).

Many times, both remotely sensed images (and information generated from them) and other datasets have been used in GIS to assess and monitor environments (Blaschke, 2010). Information produced from the process provides knowledge about the conditions or status of the environment, which is paramount for resources and actions associated with management and planning. Furthermore, Lu et al. (2004) asserts that better decisions can be made if the changes of the features on the earth's surface are detected accurately and within a minimal timeframe; only then can we understand the relationships and interactions between human and natural phenomena.

Numerous studies have been undertaken using GIS approaches (Lu et al. 2004, provides a full listing) to assess and monitor environments, most of which include detecting changes in the land use and land cover (Shalaby and Tateishi, 2007, Dewan and Yamaguchi, 2009). Others have assessed the impacts of surface mining (Manu et al., 2004), monitored malaria risks (Ceccato et al., 2005), mapped sediment transfers (Theler and Reynard, 2008), assessed environmental conditions in water catchments (Aspinall and Pearson, 2000) and produced land use suitability maps (Joerin et al., 2001), for example. In these studies, some have used GIS to produce models to assist in decision making. However, at times, GIS approaches do not act alone. Apart from producing suitability models, mapping changes, and localization maps, GIS is used together with other models and computing sciences, such as Multi Criteria Decision Analysis (MCDA) and remote sensing (and products of remote sensing) to produce useful information products for decision making and planning.

2.8.2 Remote Sensing

According to Campbell and Wynne (2011, p. 6), remote sensing has numerous definitions. Despite the varying definitions, the common concept is: the gathering of information at a distance. Therefore, in its simplest term, remote sensing is an activity of observing and recording the reflectance or emittance of electromagnetic energies of the earth's land and water surfaces from a far distance. The Centre for Remote Imaging, Sensing and Processing CRISP (2001) explains that,'it is a science and technology of obtaining information about the earth's surface and atmosphere with sensors onboard airborne (aircraft, balloons) or spaceborne (satellites, space shuttles) that are not in direct contact with the objects being observed'. The outputs are usually images representing the scenes being observed, which are analysed and interpreted to extract useful information.

The evolution of remote sensing dates back to the 1800s (Campbell & Wynne, 2011, p. 7). Though Galileo used optical enhancements to survey celestrial bodies back in the 1600s, the first real land surveys were made in 1859 by a French balloonist and photographer, Gaspard Felix Tournachon, using photos taken from tethered balloons. Union forces used similar technology four years later during the American Civil War of 1861-65. Since then, many developments and advancements have emerged. The term 'remote sensing' started taking prominence in 1960-1970, but it was first used in the United States in the 1950s by Ms. Evelyn Pruitt of the U.S. Office of Naval Research (Graham, 1999). Eventually, Landsat1 (formerly known as Earth Resources Technology Satellite ERTS-1) was launched in 1972, and the most recent, Landsat 8, was launched in April 2013. Apart from Landsats, there are many other remote sensing devices such as: Frances' Systeme Probatorie de la Observation de la Terre series (SPOT) launched in 1986, European Radar Satellite (1991), IKONOS which is a privately owned satellite (1991), OrbView-2 Satellite (1997), and other U.S. Space shuttles providing useful data sources for geospatial and remote sensing applications.

Analysing and extracting useful information from the images captured from the sensors is a very important part of remote sensing. This information can then be interpreted to help in planning and decision making, which requires assessing and monitoring the environments. The process involves the researchers and scientists using remote sensing technology to study the status and conditions of the environment. In doing so, they are either detecting changes (Akiwumi and Butler, 2008, Dewan and Yamaguchi, 2009, Ma and Xu, 2010, Shalaby and Tateishi, 2007, Townsend et al., 2009), remotely mapping the impacts of natural and/or human induced events (Lam et al., 1998, Manu et al., 2004, Mars and Crowley, 2003), or modelling and characterizing images (Giri et al., 2005) of the environment.

Images captured through remote sensors have spectral, spatial, radiometric, and temporal resolutions that determine their quality. Spectral resolution is the ability of the sensor to class the wavelengths or bands in an image into intervals or separate components (Natural Resources Canada, 2015). Spectral resolution determines the coarseness or fineness of the pixel on an image depending on which portion of the electromagic spectrum it is in. Generally, narrower wavelengths in each spectral band produces finer spectral resolutions, thus giving better quality spectral resolution images. However, these depend on the application involved and what information is desired for the tasks or experiments. Spatial resolution refers to the size and scale of the pixels in an image; the smallest possible feature detected and visible on the image components (Natural Resources Canada, 2015). The size and number of pixels depend on the spatial resolution, that is, the higher the spatial resolution (very small pixels), the clearer the small objects are, and vice versa. Temporal resolution refers to the precision of a measurement with respect to time, and radiometric resolution is the information contained in an image's components (Natural Resources Canada, 2015). It (radiometric resolution) is another charateristic of individul sensors. Natural Resources Canana (2015) states that radiometric resolutions describe the ability to discriminate slight differences in energy; the finer radiometric resolutions, the more sensitive the sensor to detecting small differences in reflected and emitted energy.

Depending on the application involved, and information intended for extraction from the exercise, correct resolution type can be determined, and spectral signatures of each pixels representing the reflected or emitted electromagnetic energy of each object/phenomena type can be studied (Teillet et al., 1997). The signatures in each band corresponds to each signature range and type, hence, the condition of vegetation and water resources can be analysed and interpreted using different remote sensing techniques to identify the changes. The study of the changes in the water bodies and vegetation have been useful in assessing and monitoring the environments, especially in the land cover and land use (Al-doski et al., 2013).

2.9 Change Detection

Change detection is a process of identifying differences in the state of an object or phenomena being observed at different times (especially two or more times) (Al-doski et al., 2013, Lu et al., 2004). Lu et al. stresses that the understanding of the differences can be used to draw relationships and interactions between humans and the environment for better management and use of resources. There are steps and procedures to follow as outlined by Jensen (2005) in achieving change detection results. Jensen outlined the processes as identifying the nature of the change detection problem, selecting the data (remotely sensed image/data), pre-processing the image, doing a classification on the image, selecting change detection algorithm, and evaluating the change detection results. Similarly, Théau and Duguay (2004, p. 872) had their change detection procedures to selecting images, registration of the images, applying radiometric and atmospheric corrections, doing multi-temporal analysis, and finally doing the change detection.

After explaining the processes of pre-processing, and post-processing/classification techniques in their research, Al-doski, Mansor and Shafri (2013, p. 39-41) claim that pre-processing techniques are more accurate due to their effectiveness in identifying and locating changes. They also claim that pre-processing techniques are more user-friendly, and easy to implement. Post-classification has also shown strengths in change detection analysis with its capability to minimize sensor, atmospheric and environmental differences, and it provides a complex matrix of land cover changes when using multiple images (Al-doski, Mansor & Shafri, 2013, p. 42).

The selection of images requires the researcher to choose an image that generally covers the whole study or research area. Because there are radiometric distortions in the images due to broad-scale spatial coverage (repeated coverage, radiometric inconsistencies between separate images due to atmospheric conditions, solar illumination angles, and sensor calibration trends), Du, Teillet & Cihlar (2002) advise that the images be pre-processed for land cover or land use detection. Among other techniques, Coppin and Bauer's methods of multi-temporal image registration, and radiometric calibration are outstanding (Coppin & Bauer, 1996, cited in Du, Teillet & Cihlar. 2002, p. 123).

Generally, the satellite images need to be geometrically and radiometrically corrected for better processing and land cover change detection. Geometric correction is the process of using the standard geographic coordinate system to match the image projection to precisely coordinate with a surface or shape projection (Du et al., 2002). This process involves identifying the geometric ground control points (GGCP) on the satellite image and tying them to the geographic coordinate system, which defines the geometric relationship between the image and the ground. Radiometric correction is the process of accounting for the sun's azimuth and elevation, atmospheric conditions, topography, and sensor's response which influence the radiometric distortions of the satellite images (Du et al., 2002, Chen et al., 2005).

There are two radiometric correction methods: absolute and relative. According to Du, Teillet and Cihlar (2002), absolute radiometric correction coverts the correct radiance or reflectance by using the sensor calibration data, the sun's angle and view angle, atmospheric models, and the ground truth data. On the other hand, relative radiometric correction can reduce the need to employ complicated atmospheric models when exact measurements of the atmospheric conditions are difficult to make or are unavailable (Chen et al., 2005, Du et al., 2002). It simply normalizes the multi-temporal data taken at different dates to a selected reference data at specific time. Once these corrections are performed on the multi-temporal images to reduce the influences mentioned above to increase sensitivity to landscape changes (as well as increase accuracy of classification), it is possible to apply change detection techniques on each feature type to determine the changes (Chen et al., 2005, Du et al., 2002, Meyer et al., 1993). Fortunately, with the increase and advancement of remote sensing and their techniques, spectral channels for improved atmospheric and cloud characterisation are included on some airborne and spaceborne (satellites, space shuttles) to remove atmospheric effects on surface observations (Justice et al., 1998) which does not require manual calculations by the operator.

NASA's Moderate Resolution Imaging Spectroradiometer (MODIS) (Justice et al., 1998), and Landsat4-5 TM, Landsat7 ETM, and Landsat8 OLI/TIR have surface reflectance products available (Masel et al. 2006; USGS, 2016) for direct use and change detection processing.

2.9.1 Vegetation

With remotely sensed images becoming freely available as data sources, the spectral signatures of the vegetation can be processed, detected, and interpreted to understand their status, health, and conditions (Rouse et al., 1974). There are numerous remote sensing methods used in studying vegetation but Gao (1996), and Teillet, Staenz & William (1997) state that Normalized Difference Vegetation Index (NDVI), and Enhanced Vegetation Index (EVI) are the most common and widely used.

2.9.1.1 Normalized Difference Vegetation Index (NDVI)

NDVI is a remote sensing technique used to determine the presence and absence of green vegetation (Rouse et al., 1974). Rouse et al. assert that its usage has helped in estimating crop yields, pasture performance, and rangeland carrying capacities among others. They also claim that NDVI does not act independently but has relationships with other ground parameters, such as percentage of ground cover, photosynthesis activity of the plants, surface water, leaf area index, and other biomass. According to Crippen (1990), NDVI is a standard form of a normalized band ratio for vegetation studies, utilizing near infrared (NIR) and Red bands of the spectrum. It is calculated by taking the ratio of the difference of NIR and Red, and the sum of NIR and Red channels (Formula 1) (Crippen, 1990, Carlson and Ripley, 1997, Rouse et al., 1974).

$$\text{NDVI} = \frac{\text{NIR} - \text{Red}}{\text{NIR} + \text{Red}} \quad (1)$$

This technique calculates the density of greenness of the vegetation at each pixel ranging from -1mm to +1mm. The pixels having (or are close to) +1 (0.8-0.9) have the highest possible density of greenness, and those sitting on (or close to) -1 have least greenness, whereas zero means no vegetation at all (Rouse et al., 1974).

Crippen (1990) assumes that if Red radiance is omitted in the ratio numerator to have only the NIR and divide it by the sum of NIR and Red (Formula 2), it functionally and linearly is equivalent to NDVI. However, it avoids negative values and only has an index ranging from 0 to 1, unlike NDVI.

$$\frac{\text{NIR}}{\text{NIR} + \text{Red}} \quad (2)$$

2.9.1.2 Enhanced Vegetation Index (EVI)

EVI is a modified version of NDVI that enhances vegetation signals with a much more improved sensitivity in high biomass regions and improves vegetation monitoring capability through a de-coupling of the canopy background signal and a reduction in atmospheric influences (Matsushita et al., 2007). The difference is that NDVI is chlorophyll sensitive, while EVI is responsible for the canopy structure variations, leaf area index (LAI), canopy type, plant physiognomy, and canopy structure (Liu and Huete, 1995, Matsushita et al., 2007). Because of its capabilities, it is being adapted by the MODIS Land Discipline Group as a second global based vegetation index to monitor the earth's terrestrial photosynthetic vegetation activity. Though it is gaining researchers' attention because of its ability to reduce adverse effects of environmental factors such as atmospheric conditions and soil background, it does not take into consideration the topographic effect (Matsushita et al., 2007).

Liu and Huete (1995), and Huete, Justice and Van Leeuween (1999) used NIR, Red, Blue and Green channels together with canopy adjustments and the coefficients of aerosol resistance terms to calculate EVI (Formula 3).

$$EVI = G \times \frac{(NIR - RED)}{(NIR + C1 \times RED - C2 \times Blue + L)} \qquad (3)$$

Where NIR, Red, and Blue are the spectral bands of the electromagnetic spectrum, L is the canopy background adjustment that addresses non-linear, differential NIR and Red radiant transfer through a canopy, C1 and C2 are the coefficients of the aerosol resistance term, which uses the Blue band to correct for aerosol influences in the Red band. The coefficients and parameter values suggested by Huete et al. (1997) are; L=1, C1 = 6, C2 = 7.5, and G (gain factor) = 2.5.

2.9.2 Water Bodies

According to Ridd and Liu (1998, cited in Rokni et al. 2014), human survival and social development depend very much on surface water. Lu, Wu, et al. (2011)express the view that water is an irreplaceable resource, which is essential for humans, crops, and whole ecosystems. Rokni et al. (2014, p. 4174) summarized their findings that the knowledge of the spatial distribution of water is vital for many applications, such as assessment of present and past water resources, building climate models, agriculture suitability, river dynamics, wetland inventories, watershed analysis, surface water survey and management, flood mapping, and environmental assessment and monitoring.

Remote sensing images are increasingly becoming the data source for analysis of the spatial distribution of water (Li et al., 2007). In a remotely sensed image, there are different spatial, spectral, and temporal resolutions that provide a large amount of data that needs to be processed and specific information detected and extracted. There are several remotely sensed image processing techniques used in extracting water information. Xu (2006) states that the process is divided into two methods according to the number of bands used: single band, and multi-band. According to Runquist et al. (1987, cited in Xu, 2006, p. 3025), the single band method requires the operator to extract open water information from a single band from the multispectral image. The multi-band method is done either by using different spectral bands to delineate water from other features by using an 'if-then-else' logic tree, or by the band-ratio approach which requires dividing one multispectral band by the other, usually from the near infrared (Xu, 2002, Xu, 2006). Xu (2006) concluded that both methods enhance the presence of water while suppressing non-water features in the images. Depending on the purpose, and geography of the study, this can be achieved using any of the procedures listed by Rokni et al. (2014, p. 4178). They include Normalized Difference Water Index (NDWI), Modified Normalized Difference Water Index (MNDWI), Principal Components of multi-temporal Normalized Difference Water Index (NDWI-PCs), Normalized Difference Moisture Index (NDMI), Water Ratio Index (WRI), Normalized Difference Vegetation Index (NDVI), and Automated Water Extraction Index (AWEI). However, in this thesis, only the first three procedures are covered.

2.9.2.1 Normalized Difference Water Index (NDWI)

NDWI is a remote sensing based method used to estimate plant water content and the spongy mesophyll structure in vegetation canopy (McFeeters, 1996, Gao, 1996). Though Gao and McFeeters have similar views, they have their own expression of the method. According to Gao (1996), NDWI is sensitive to changes in liquid water content of vegetation and, therefore, it is used for remote sensing of the vegetation liquid from space. He claims that NDWI is an independent vegetation index, which uses narrow or visible wavelengths, while NDVI employs longer wavelength bands. Unlike NDVI that uses NIR and Red bands, Gao utilizes two NIR channels (i.e. NIR [0.86μm] and MIR [1.24μm]) to express

NDWI which takes the ratio of the difference between NIR and MIR, and the sum of NIR and MIR channels (Formula 4).

$$NDWI_{GAO} = \frac{NIR - MIR}{NIR + MIR} \qquad (4)$$

McFeeters' (1996) NDWI is centred around the use of the reflected radiation NIR and Green bands to enhance the presence of water features while eliminating the presence of soil and terrestrial vegetation features. He calculates his NDWI by taking the ratio of the difference between Green and NIR, and the sum of Green and NIR channels (Formula 5). Apart from delineating open water features, McFeeters assumes that this method could also produce turbidity estimations of water bodies.

$$NDWI = \frac{Green - NIR}{Green + NIR} \qquad (5)$$

2.9.2.2 Modified Normalized Difference Water Index (MNDWI)

MNDWI is a modified version of McFeeters' (1996) NDWI substituting infrared (NIR) band for middle infrared band (MIR) (Xu, 2006). According to Xu, this remote sensing water information extraction method is more suitable for areas and regions very much covered or dominated by debris built-up areas because of its ability to reduce and even remove noises (built-up land noise, vegetation, and even soil noise). He argues that the NIR band of NDWI enhances water presence and does not consider the built-up noises, whereas the MIR band does. When comparing signatures of land water, built-up area, and vegetation, he discovered that all the digital numbers (DN) of MIR radiations were much higher than the NIR radiations and, therefore, he assumes that MIR can give negative values for the built-up land. Xu (2006) expresses it as follows:

$$MNDWI = \frac{Green - MIR}{Green + MIR} \qquad (6)$$

2.9.2.3 Principal Components of Multi-temporal Normalized Difference Water Index (NDWI-PCs)

NDWI-PCs is a twofold change detection method that blends NDWI and Principal Component Analysis (PCA) techniques (Rokni et al., 2014). The NDWI process is as presented in section 2.9.2.1, while PCA is a statistical procedure that uses mathematical principles to transform correlated variables into a set of values of linearly uncorrelated variables called principal components (Richardson, 2009). Richardson (p. 2) claims that PCA reduces large datasets using a vector space transformation. The process involves taking a large set of data and identifying a new set of bases to re-express the data. Richardson explains that this is done by finding the maximal variance of the data called the principal component (PC1). The data can be interpreted, but if the interpretation does not make sense or is not clear, a similar process is applied to PC1 to obtain PC2, which is the next best suit (re-expression) for approximating the original data. The process can iterate further to find more approximations of the original data, but the variance depreciates as principal components increase. That is to say, PC1 has the largest variance, while PC2 has the second largest, and so forth.

Rokni et al. described the NDWI-PCs process as first by calculating the NDWI from the multi-temporal remotely sensed images (using Formula 5). The method ends with individual NDWI images being stacked into one composite file. Finally, the PCA technique is applied to the composite image to transform it into a new PCA space/image. The transformed image (NDWI-PCs) can then be classified, and analysed to detect changes in the surface water bodies. Rokni et al. states that thresholding technique can be applied to classify the transformed image before detecting the changes.

2.10 Image Classification

Image classification is a technique of extracting information classes from the multispectral (as well as hyperspectral) images, where the pixels in the image are categorised into one of several land cover classes/themes (Lu et al., 2011a, Lillesand and Kiefer, 1994). Lillesand and Kiefer (1994) explain that the purpose of image classification is to identify and portray the features actually present on the ground as a unique grey level (or colour) on the images. This information can be extracted from the remotely sensed data by recognizing the statistical patterns (Jensen, 2005). Dengsheng Lu et al. (2011) also show that this is done by understanding the way in which the objects of interest on earth's surface absorb, reflect, and emit radiation in the electromagnetic spectrum.

There are a number of different image classification approaches, the two basic ones being supervised, and unsupervised (Lu et al., 2011a). Supervised approach involves the operator to specify the land-cover classes of interests, with the advantage of a priori knowledge of the area. On the other hand, unsupervised classification is a system generated technique based on spectral signatures of each pixel, that is, the software generates the classes of the features without the user providing sample training classes.

This thesis assumes the unsupervised classification approach as the most suitable for the research because the technique can be designed based on the user's need, the spatial resolution of the data, compatibility with previous work, and available image-processing and classification algorithm (Lu et al., 2011a). There was also the consideration of time constraints and other limitations in conducting the research.

2.11 Conclusion

In conclusion, though mining boosts economic growth, societal development, and civilization (Bell & Donnelly 2006), it is also one of the most damaging human activities to health and well-being of humans and the environment (Karr, 1987). The quantity and extent of wastes, land and seascape effects, and impacts on the environment, including people, are determined by the geography, and the methods used in extracting the minerals from beneath the earth's surface. The case studies described here demonstrate that mining has contributed in various ways to environmental pollution and degradation. Therefore, despite the development and use of environmental management policies and guidelines such as Significant Environmental Benefit or Environmental Impact Studies, the impacts of mining wastes on the environment should be assessed and monitored for control and measure, as well as for management and planning purposes.

Assessing and monitoring the environment (excluding humans) requires the study of the health, status, and condition of the plants or vegetation and hydrology. This requires up-to-date data, software, and approaches applicable, for which GIS and remote sensing techniques have proven fit, providing data and techniques, as well as having the capability to process land cover and change detection for longer and varying time spans.

This study uses remotely sensed data from Landsat4 MSS, Landsat5 TM, and Landsat8 OLI to detect the changes in the vegetation and surface water bodies. Though there are a number of remote sensing based change detection methods, this study uses NDVI to assess the changes in the vegetation health and dieback, and uses McFeeters' (1996) NDWI and Gao's (1996) MNDWI to study the hydrology and sedimentation. The research also uses Image Classification, and Image Differencing techniques to further detect and confirm the changes depicted in the NDVI and NDWI/MNDWI processes.

Chapter 3. Research Methods

3.1 Study Area and Method

Ok Tedi and Fly Rivers of Western Province, Papua New Guinea (Figure 1) were impacted by Ok Tedi mining wastes (Hettler et al., 1997). However, the full studies, assessments, and monitoring of the two river systems have been impeded by the large scale of their catchments, their remoteness, climate, and geography (*OK Tedi past, present & future, Ok Tedi Mining Limited*, 1999). To overcome these impediments to studying the impacts along the affected riverine systems, information about the status, conditions, and health of the plants and vegetation, and hydrology needs to be extracted remotely. The process requires detecting the changes (change detection) between two or more dates using remotely sensed data/images, and processing them using GIS and remote sensing techniques (Ma and Xu, 2010, Al-doski et al., 2013, Lu et al., 2004). It is expected that the model, techniques and processes applied on Ok Tedi Mine affected rivers in this research can be used on other study locations where there are similar obstacles to conventional field research methods.

3.2 Data Sources

Remote sensing data have been the best data sources for assessing, monitoring, and studying changes used in decision making (Ma and Xu, 2010, Chander et al., 2009). The satellite images captured by Landsat 4 Multispectral Scanner (MSS), Landsat 5 Thematic Mapper (TM), and Landsat 8 Operational Land Imager (OLI) have been the primary sources of data utilized for this research. The images from these satellite sensors provide a suitably high spatial resolution, along with the required spectral wavelengths and temporal characteristics, while also providing spatial coverage suitable for this study. These earth observing satellite missions (Landsat) are jointly managed by the National Aeronautics and Space Administration (NASA) and the U.S. Geological Survey (USGS), and have been the longest space-based programs capturing earth's information on a regular basis since 1972. The vital information they gather is being made freely available for civil uses (NASA, 2016, USGS, 2016).

Landsat 4 MSS began operating on the 16th of July 1982, and ceased mission on the 15th of June 2001 (NASA, 2016). This satellite orbited the earth every 99 minutes, and repeated the cycle in 16 days (16 days' revisit cycle). It had a swath width of 185km, and crossed the equator at 9:45am +/- 15minutes. There were six detectors on board for each reflective band that provided six scan lines on each active scan. The images that were captured consisted of four spectral bands (refer Table 1) with 60 metres spatial resolution (Chander et al., 2009).

NASA designed and built Landsat 5 TM (launched 1st March, 1984) at the same time as Landsat 4 carrying the same payloads of MSS and TM instruments (Chander et al., 2009). Despite having issues in 1987 when its TDRSS[7] transmitter failed, which resulted in it being impossible to downlink data acquired outside U.S. data acquisition circle, Landsat 5 TM operated until November 2011 (NASA, 2016). It had a similar swath width, revisit cycle, and equatorial crossing time as that of Landsat 4. With the addition of mid-range infrared band, the images captured had seven bands in total (refer Table 1). All the bands of the images have 30m spatial resolutions, except band six (Thermal) which has 120m (Chander et al., 2009).

Landsat 8 was developed as a collaboration between NASA and USGS and launched on the 11th of February 2013 from Vandenberg Air Force Base, California (NASA, 2016, USGS, 2016). Design, construction, launching, and on-orbit calibration phases were led by NASA, while routine operations, such as post-launch calibration activities, satellite operations, data product generation, and data archiving, are taken care of by USGS. On board Landsat 8 are two instruments: Operational Land Imager (OLI), and Thermal Infrared Sensor (TIRS). They provide seasonal coverage of the global landmass, capturing 550 scenes per day in every 16 days (repeat/revisit cycle) at a spatial resolution of

[7] TRDRSS: The Tracking and Data Relay Satellite System

30 meters for all bands, except thermal which is 100m, and panchromatic at 15m (Table 1) (NASA, 2016).

OLI is an improved Landsat sensor using technical approaches used by NASA's experimental EO[8]-1 satellite. It has a push-broom sensor with a four-mirror telescope, and 12-bit quantization, which in addition to collecting data for visible and NIR bands, is responsible for the capture of the deep blue bands for coastal and aerosol studies, shortwave infrared band for cirrus detection, and a quality assessment band. The TIRS provides the thermal bands (NASA, 2016).

Table 1. Landsat 4 MSS, Landsat 5 TM, and Landsat 8 spectral band Information

Landsat 4 MSS		**Landsat 5 TM**		**Landsat 8 OLI**	
Bands	**Wavelengths (µm)**	**Bands**	**Wavelengths (µm)**	**Bands**	**Wavelengths (µm)**
1- Green	0.5-0.6	1- Blue	0.455-0.52	1- C/Aerosol	0.43 - 0.45
2- Red	0.6-0.7	2- Green	0.52-0.60	2- Blue	0.45 - 0.51
3- NIR	0.7-0.8	3- Red	0.63-0.69	3- Green	0.53 - 0.59
4- NIR	0.8-1.1	4- NIR	0.76-0.90	4- Red	0.64 - 0.67
		5- NIR	1.55-1.75	5- NIR	0.85 - 0.88
		6-Thermal	10.40-12.50	6- SWIR1	1.57 - 1.65
		7- MIR	2.08-2.35	7- SWIR2	2.11 - 2.29
				8- Panchromatic	0.50 - 0.68
				9- Cirrus	1.36 - 1.38
				10- TIR1	10.60 - 11.19
				11- TIR2	11.50 - 12.51

Source: NASA, 2016; USGS, 2016

Five Landsat images of Kiunga- Papua New Guinea; one Landsat 4 MSS, three Landsat 5 TM, and one Landsat 8 OLI were downloaded from the USGS website (http://earthexplorer.usgs.gov/). Refer Table 2 for the dates of which these images were captured. Though the cloud and shadow covers impacted on

[8] EO- Earth Observing

the selection, these images were chosen from the wetness months of PNG as per Papua New Guinea Weather Service, Australian Bureau of Meteorology, and Commonwealth Scientific and Industrial Research Organization (CSIRO) (2011) report. All the images and scenes were atmospherically corrected to contain surface reflectance, except the Landsat 4 images (USGS, 2016).

Table 2. Dates of which Landsat Images were captured

No	Sensor	Date
1	Landsat 4 MSS	12-Jan-84
2	Landsat 5 TM	29-Oct-88
3	Landsat 5 TM	8-Mar-96
4	Landsat 5 TM	12-Feb-04
5	Landsat 8 OLI	25-Jan-15

3.3 Data Preparation

The images (supplied by the USGS) were georeferenced to the UTM projection, Zone 54 using the WGS84 spheroid. Each image contained Digital Number (DN) values stored as unsigned 8-Bits for Landsat 4 MSS (1984 images), and 16-Bits for Landsat 5TM and Landsat 8 OLI images. When the data were downloaded, each layer or band came separately. As such, Erdas Imagine[9] was used to stack the individual layers together, that is, all the layers or bands were combined into a composite, multispectral images. They all have a 30m spatial resolution, except for Landsat 4 MSS which was gridded at a spatial resolution of 60m, although its intrinsic resolution is on the order of 80m.

3.3.1. Landsat4 MSS Data (1984 Image)

[9] A raster-based remote sensing software package designed specifically for extracting information from images.

Pursuant to the purpose of this research, Landsat4 MSS data (1984 images) needed to be radiometrically calibrated, and atmospheric effects minimized to contain surface reflectance in order to conform with the TM and OLI image data products, such that changes in vegetation indices across time will be meaningful. This was done using Dark Object Subtraction (DOS) or Chavez's COST model, which is simply the subtraction of dark objects less one percent (1%) to approximate the atmospheric path radiance, while the cosine of the solar zenith angle COS(TZ) was used to estimate the atmospheric transmittance in the illumination direction of the bands (Chavez, 1996). Chavez states that this method is purely an image-based solution for modelling atmospheric effects, which is an extension of radiometric calibration. Radiometric calibration involves converting the DN values to at-sensor radiance; then, it is converted to at-sensor planetary reflectance.

According to Song et al. (2001), COST or DOS2 model ignores the atmospheric transmittance in the sensor direction, and down-welling diffuse sky radiance in the general DN to at-surface reflectance. The image was generally converted from 'at-sensor planetary reflectance' to 'at-surface reflectance' by using the gain and offset values supplied with the image, the Earth-Sun distance (from Stellarium[10]), solar elevation (from http://landsat.usgs.gov/- Landsat4 MSS calibration parameter files), and the offset or starting haze values of each of the bands (from the histograms).

Because the images had a low spatial resolution (60m), it was resampled to 30m to match the TM and OLI images for further processing. Although low spatial resolution images are excellent for monitoring the general state of the phenomena (vegetation health, hydrology, and others) in large area coverage (such as the Moderate Resolution Imaging Spectrometer - MODIS), the study area for this research in

[10] A software that shows a realistic sky in 3D depending on the location and time. It calculates the positions of the sun, moon, planets and stars (http://www.stellarium.org).

PNG is on a smaller scale. Consequently, a high spatial resolution was favoured (Natural Resources Canada, 2015).

3.3.2. Subset Image

The images (1984, 1988, 1996, 2004 and 2015) covers the middle region of the Western Province of Papua New Guinea. As such, only a subset that covered the study region (Figure 2) is required for the research. Therefore, the area of interest was identified using an Inquire Box (Erdas Imagine tool) and the coordinates from it (Inquire Box) were used to subset or cut out the study area. The output images were all set to unsigned 16Bits or as the input data type.

Two areas were cut out or subset. The first is the study region with a total area of approximately 307,763 ha. The second is a Control, an area along Tobe River (also known as Waimeri River) within the vicinity of a settlement called Rumgina, which is unaffected by the Ok Tedi mining wastes. This region has a much smaller area of approximately 40,589 ha (Figure 2).

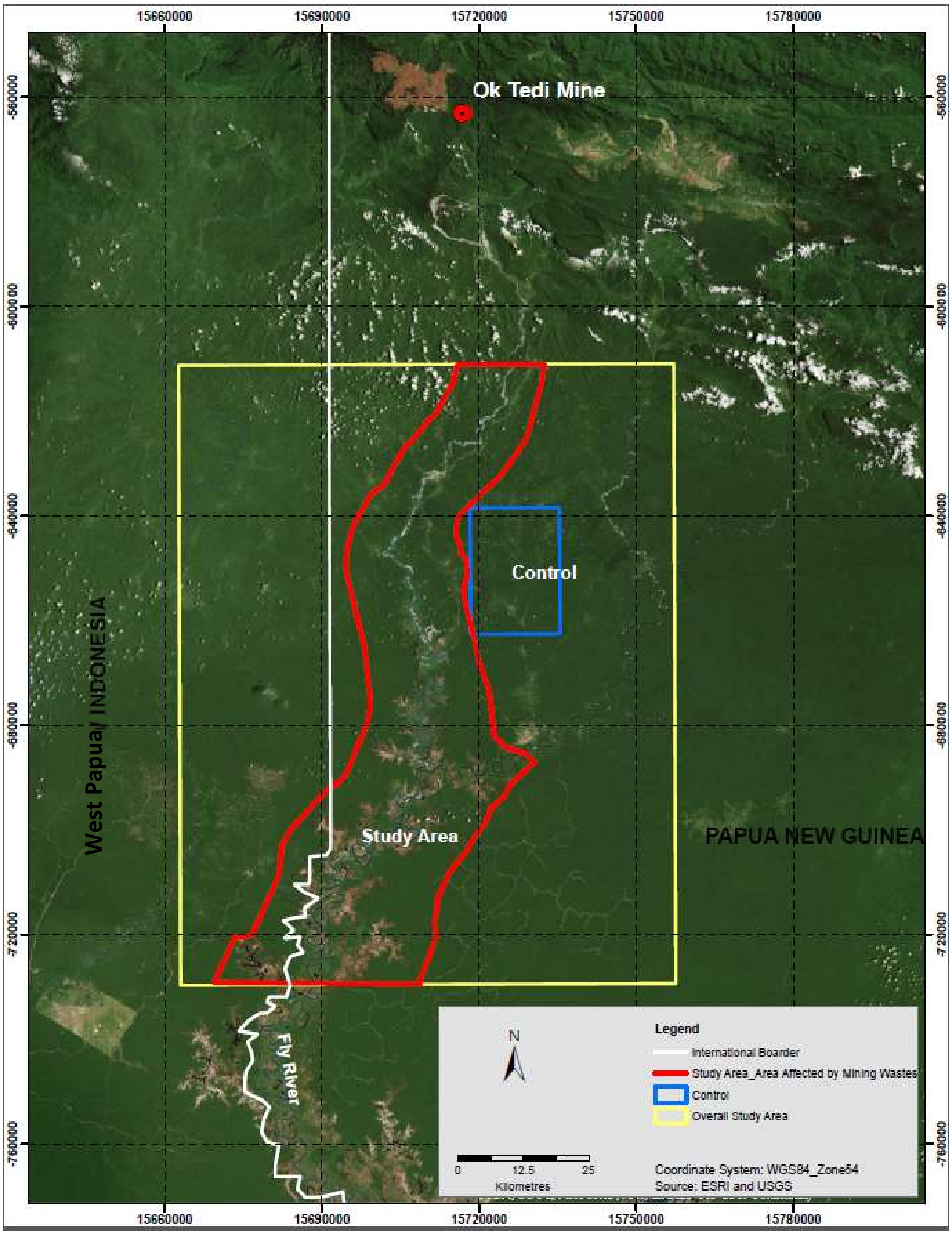


Figure 2. Subsets of the Study region and the Control Area.

3.3.3 Radiometric Correction of the Datasets Using Histogram Matching

The images were captured using different sensors (MSS, TM, and OLI) and at different times. Therefore, processing this multi-date image dataset for the purpose of detecting surface changes required similar radiometric characteristics to enable them to be compared with each other (Mas, 1999).

The entire process of radiometric compensation, which includes performing radiometric calibration and converting the entire dataset from DN values to ground reflectance values, and performing a relative radiometric divergence, have been done by the USGS. Therefore, instead of doing a complete radiometric compensation exercise, this research had all datasets (1984, 1988, 1996, and 2015) histogram-matched to 2004 TM image, which acted as the reference dataset.

This technique (Histogram Matching) transforms one image so that its histogram matches the histogram of the specified (reference) image (Shapira et al., 2013), and is considered suitable where change, significant or otherwise, between dates is a 'minor' component of the overall area of the scene. Each of the bands or layers in each image that corresponded to the reference (2004 image) was adjusted to have a histogram similar to that of the reference image. The adjusted bands or layers of each image were stacked together into a composite, multispectral image for processing.

The histogram matchings were carried out in two phases. First was done to the subset (study region), and the other done on the NDVI, NDWI, and MNDWI processed images. After transforming the histograms, the first phase involved stacking of the individual, transformed bands into multispectral image for processing the unsupervised classification and generation of NDVI, NDWI, and MNDWIs. However, the second phase only involved transformation of the histograms of NDVI, NDWI, and MNDWI processed images because they only had one band each.

3.3.4. Cloud Masking

The study region was heavily covered with clouds and shadows. Consequently, direct processing and mapping of the data would involve greater misclassification of the features, or they could be giving a false change information (Huang et al., 2010). Huang et al. (2010, p. 5449) describes the process of flagging or masking the clouds as, 'using clear view of the forest pixels as a reference to define cloud boundaries for separating clouds from clear view surfaces in a spectral-temperature space'. They stress that the cloud height estimates and sun illumination geometry can be used to predict the shadow locations, while their actual pixels can be identified by searching the darkest pixels surrounding the predicted locations. Hence, the clouds in the study region were masked out to allow the natural features only to be processed. The masked out areas have no pixel values, thus, when the images are processed, these areas remain unclassed or showed no information at all.

However, not all the datasets had their clouds and shadows masked out completely. This was due to the greater quantity of clouds and shadows covering the study region. To avoid obscuring the datasets, only a certain portion was masked out. Even if larger portions were to be masked out, similar features, such as the black water bodies were mistaken for shadows, and white features, such as sand, gravel and white surface built-ups, were mistaken for clouds. Therefore, to cater for the misclassification or misspecifications, the clouds and shadows were given a class in the classification process, or they were manually recoded using the AOI tool, as specified in section 3.4.

3.4 Unsupervised Image Classification

Each of the five images were initially classified using the ISODATA algorithm into twenty spectral classes, and then further regrouped into seven major classes, which are the most appropriate land cover groups. The images were run at ten maximum iterations with a convergence threshold[11] of 0.950. Having a convergence threshold of 0.950 means that, as soon as five percent or fewer of the pixels change clusters between iteration, the utility will stop processing (Lu et al., 2011a).

Each of the classes in the images were clumped together, and then any single or scattered pixels of two or less were eliminated. The elimination process automatically transferred the stand-alone pixel or

[11] Convergence threshold is the maximum percentage of pixels having cluster assignments that can go unchanged between the iterations (Dengsheng Lu, et al. 2011).

pixels to the neighbouring dominating class. Though all features were grouped into respective classes or themes, some of them have been misclassified. As such, the misclassified features were manually selected using AOI tools and recoded to their correct and respective classes.

3.5 Assessing Vegetation Health Using NDVI

NIR and Red bands of the electromagnetic spectrum were required to generate the presence and absences of green vegetation (Formula 1) (Rouse et al., 1974). Because the datasets came from different sensors, each dataset had different bands of NIRs and Reds (Refer Table 1). Therefore, bands 2 and 3 of the MSS dataset (1984 image) were used to generate the NDVI, bands 3 and 4 were used on TM datasets (1988, 1996, and 2004 images), while bands 4 and 5 were used for OLI dataset (2015 image).

The NDVI processed images had slightly different brightness values. Therefore, they were recoded to have their values stretched between -1 and +1. This stretching (contrast stretching) is simply an enhancement technique that improves the contrast of the image by stressing the range of intensity values it contains to span a desired range of values (Rouse et al., 1974). In this research, the intensity values were stretched between -1 and +1.

Finally, all the NDVI processed images were histogram-matched using the process outlined above (section 3.3.3). The 2004 NDVI processed image acted as the reference to which all the others were matched.

3.6 Assessing Water/Hydrology and Sedimentation/Built-ups using NDWI & MNDWI

NDWI and MNDWI utilizes Green and NIR, and Green and MIR bands respectively to generate the water features and enhance their presences (McFeeters, 1996, Gao, 1996). McFeeters' (1996) NDWI

(Formula 5) was used to enhance the presence of water features while eliminating the presences of soil and terrestrial vegetation features. The Ok Tedi and Fly River system has been subject to considerable sediment accumulation and subsequent shallowing, which has largely dispersed flood waters over a greater areas resulting in forest die-back and conversion to aquatic plants.

The use of Green and MIR bands in generating the MNDWI not only computes and enhances the water features, but also enhances any noise present in the images (Xu, 2006). This method (Formula 6) is chosen because of the nature of the study region, which has a high chance of having debris built-ups along the course of the riverine systems.

The computed NDWI and MNDWI images also had slightly different DN/brightness values just as with the NDVI images. So they were recoded to have their intensity values stretched between -1 and +1. Finally, all the NDWI and MNDWI processed images were histogram-matched to the reference image using the process outlined in section 3.3.3.

3.7 Change Detection using Image Differencing

The changes in the vegetation, hydrology, and built-up areas were identified by subtracting the pixels of the same images obtained from two different dates or times (Al-doski et al., 2013, Lu et al., 2004). This research had four change detection groups. The first was calculated by subtracting the pixels of 1984 from 1988 image; the second, from the differences of 1988 and 1996; the third, from 1996 and 2004; and the final group from 2004 and 2015. These changes were calculated using the NDVI, NDWI, and MNDWI processed images from sections 3.5 and 3.6. The change detections were set to indicate a fifteen or more percent increase or decrease in the change of the features to take into consideration natural seasonal variation between dates. Any features present on the former images but not present on the latest indicates a decrease, while the features present on the current images that are not present on the former indicates an increase on the change detection model or images.

Chapter 4. Results and Discussion

4.1 Data Preparation

There were two steps involved in data preparation that will be discussed in this chapter. First is the radiometric correction that involves transforming the histogram of one dataset to match the reference dataset. The 2004 image acted as the reference image to which all the other datasets of 1984, 1988, 1996, and 2015 images were matched to. The second step is the cloud masking, which involves cloaking out the clouds in the image. This process leaves the image cloud and shadow free for further processing.

4.1.1 Radiometric Correction of the Datasets using Histogram Matching

The transformed images are the images that were matched to 2004 image histogram. They showed much lower mean values, standard deviations, medians, and modes when compared to the originals. The values are much more similar to the reference image, making the interpretation and processing much more meaningful. Therefore, it is likely that the processing, especially the change detection processes, would produce much more precise results.

The three graphs in Figure 3 below show a sample of an original histogram of an untransformed image and a histogram of a histogram-matched 2015 NDVI image, while Figure 4 shows a sample of a grey scale histogram-matched image of 1988 that was matched to 2004 image.

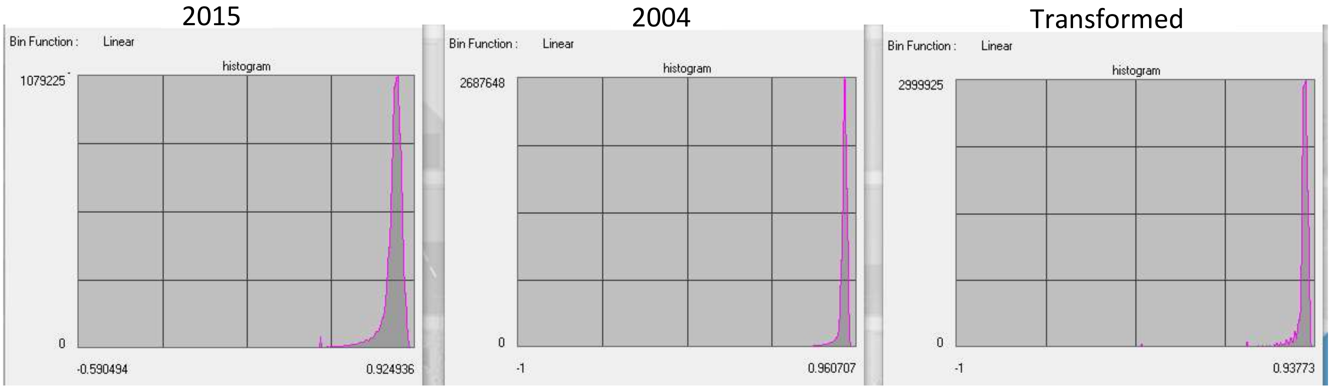


Figure 3. Histograms of the NDVI original images of 2015 and 2004, and transformed 2015 image

The transformed or histogram-matched image adjusted its histogram to match the histogram of the 2004, which is the reference image. It obtained similar mean, standard deviation, mode, and median of the reference image, and also stretched its DN values between -1 and +1 (0.94) from -0.59 and 0.92.

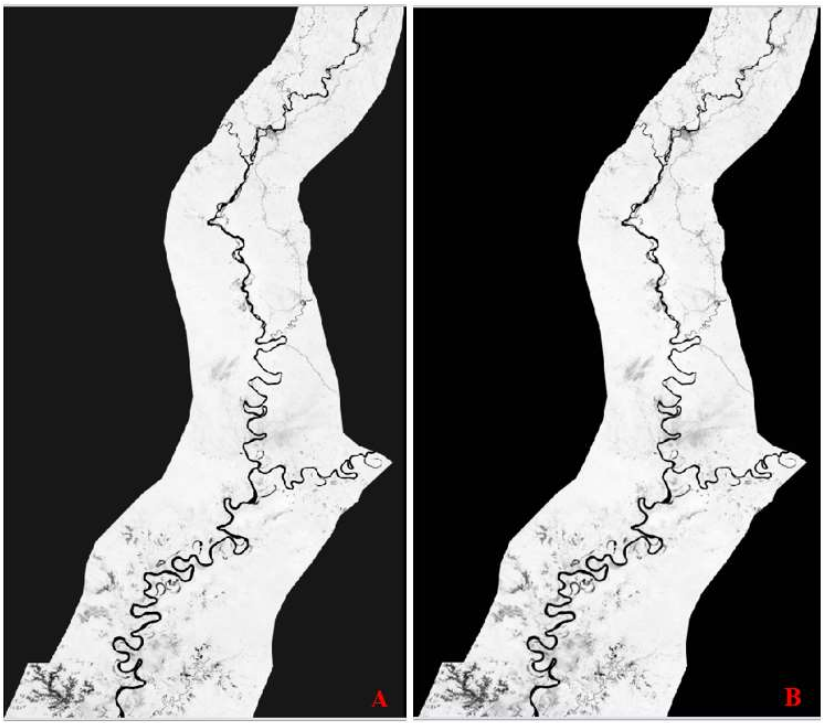


Figure 4. Original and Histogram-Matched NDVI Images of 1988 Image

The original 1988 NDVI processed image (Image A) transformed its mean, standard deviation, mode, and median figures to match those of the reference image (2004). This sets all the images into similar radiometry for subsequent processing.

4.1.2 Cloud Masking

Cloud masking is a process of eliminating clouds (Huang et al., 2010) so that any processing, whether it be image classification, image differencing, NDVI, NDWI, or MNDWI can be applied directly to the features on the earth's surface. The process masks out anything that is covered by the clouds and shadows and makes them a non-feature type. Once a feature is made a non-feature type, that spatial location automatically has no DN value. Therefore, when any process is run, the masked locations remain unaffected or unclassified. To illustrate this process, Figure 5 shows an original image (A) and a masked out image (B) of the 1988 image.

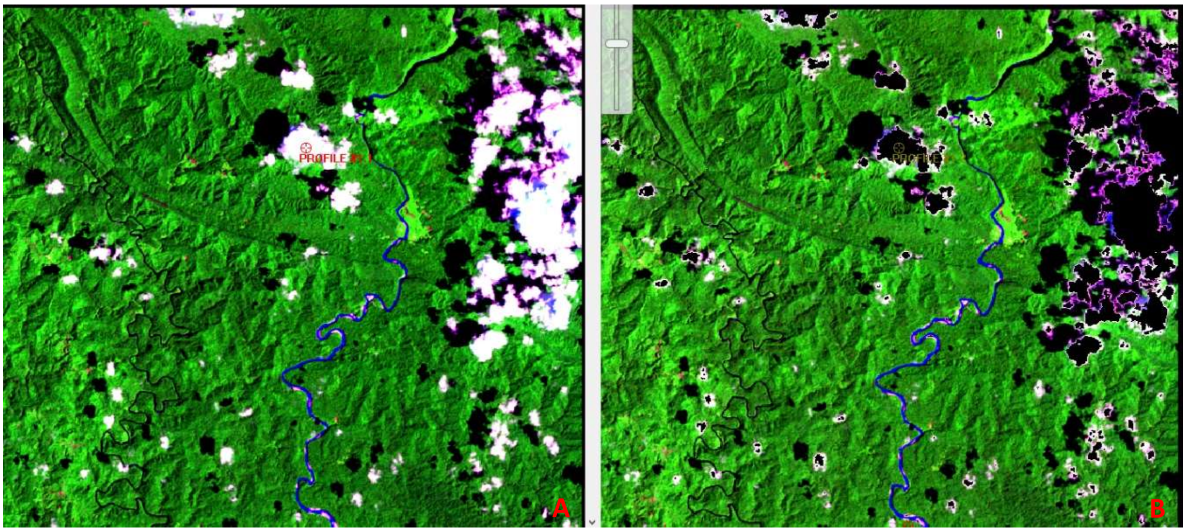


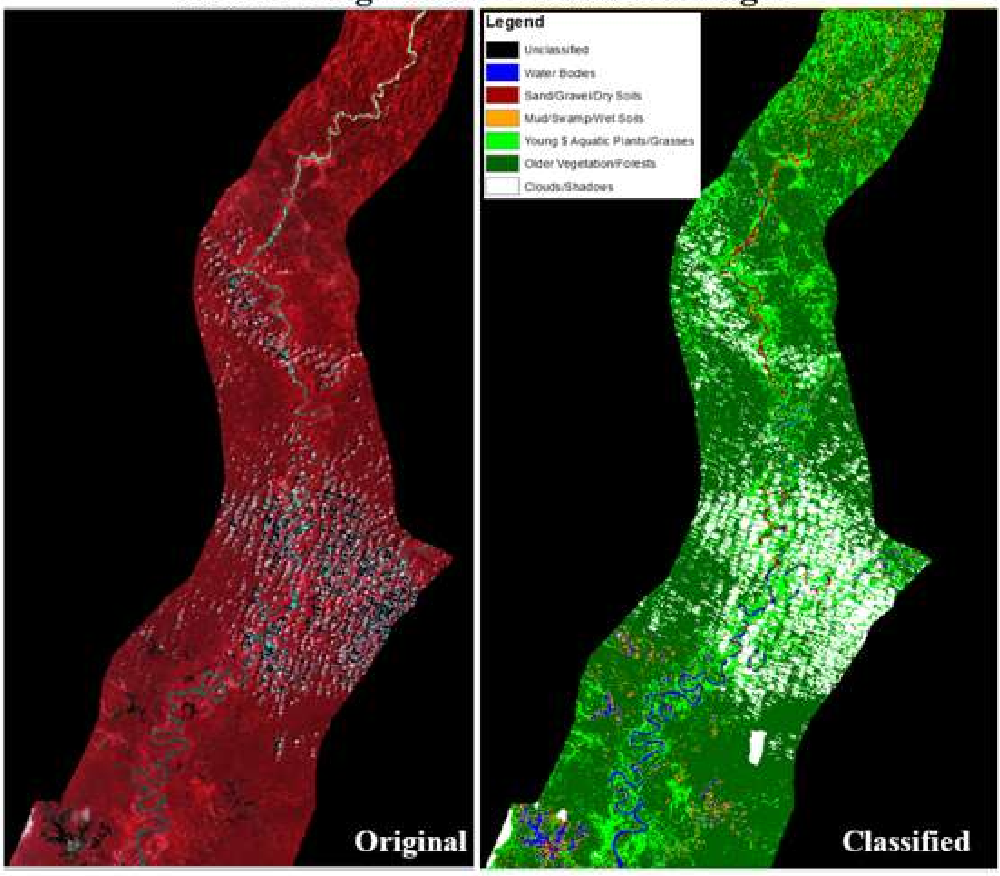
Figure 5. An Image, before and after cloud masking

Image A is the original and B is the masked image, a section in the top right corner of 1988 image.

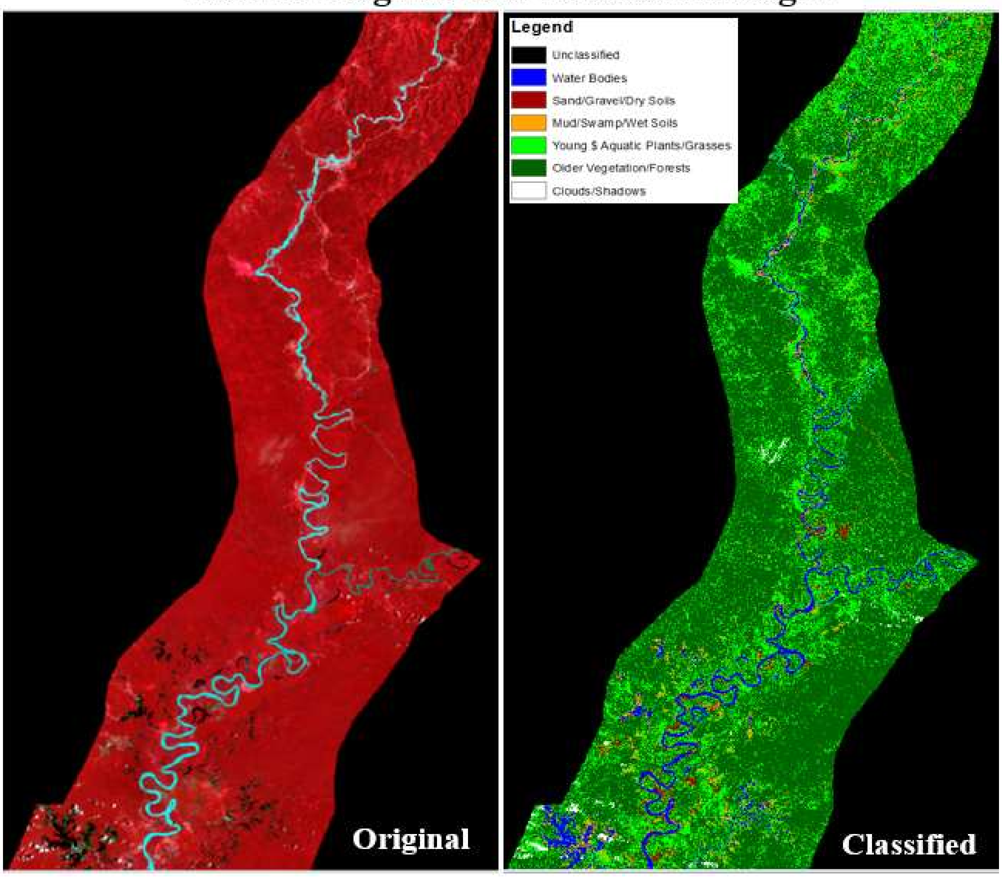
4.2 Unsupervised Image Classification

The five subset images (1984, 1988, 1996, 2004, and 2015) of the Kiunga region, especially the areas along the Ok Tedi and Fly Rivers, were coded into seven classes, including unclassified using ISODATA. Although the clouds and shadows obscured the images greatly, Figure 6 shows the original and classified images of each year. The areas of each feature types from the classified images were calculated for analysis and interpretations.

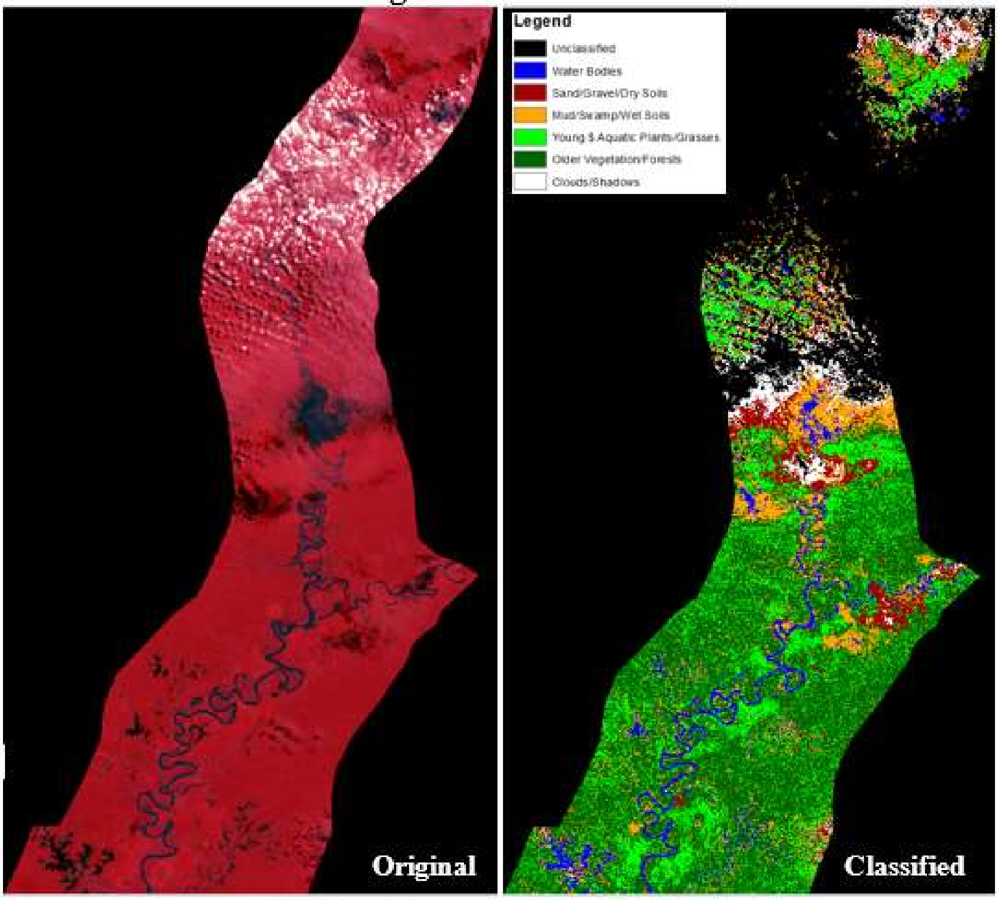
A:1984 Original and Classified Images



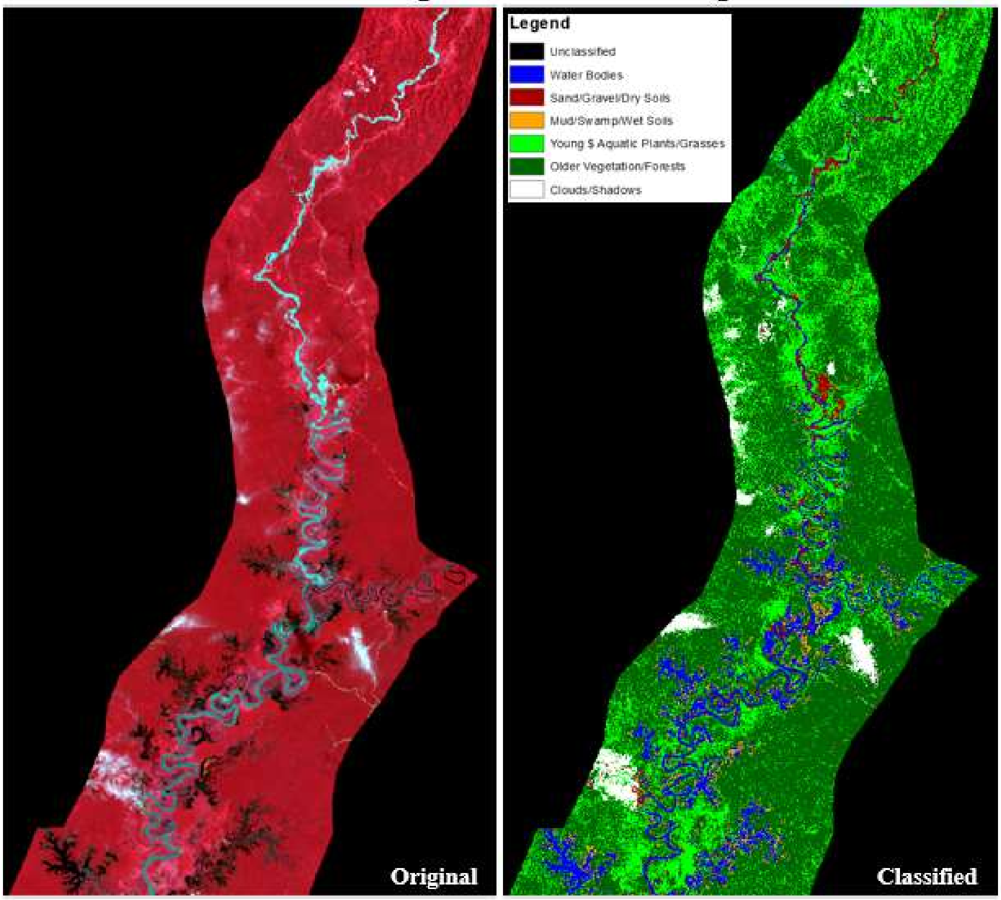
B:1988 Original and Classified Images



C:1996 Original and Classified



D: 2004 Original and Classified Images



E: 2015 Original and Classified Images

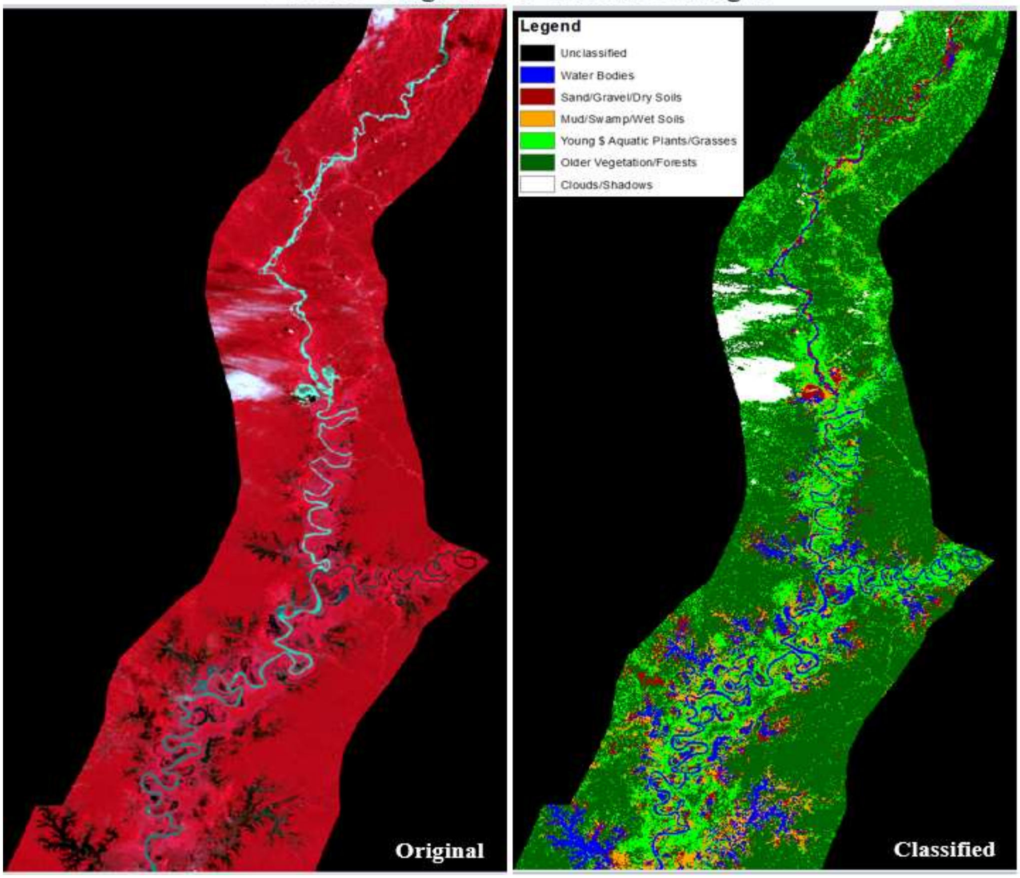


Figure 6. Original[12] and Classified Images of the study region in each year

A: The 1984 original and classified images of the region. It was very much a natural setting with a large cloud coverage in the central parts trending towards the south-east, and in the further south-western ends. **B:** Original and classified Images of 1988, a period through the mine production, and just before GoPNG placed a Sedimentation Level Restriction (SLR) on the company. **C:** Original and classified Images of 1996, a period after GoPNG has placed SLR, and just before dredging trials began. **D:** Original and classified Images of 2004, a period after the dredging trials were set and in operation. **E:** Original and classified Images of 2015, a period after the mine wastes tailings dam was set at Bige, approximately 100km downstream from the mine site.

[12] Original images where processed using the standard false colour composite; NIR as Red, Red as Green and Green as Blue.

The 1984 image (A) was taken just before the mine started producing; therefore, the features were relatively undisturbed and natural. However, all the other images after 1984 were exposed to mining wastes. The periods beyond the beginning of mine production year showed signs of changes in the natural riverine systems and biodiversity. The signs included the increases and decreases in quantity (meaning, there was a gain or a decline/loss in the volume or quantity of the feature type and class) and changes in the patterns and structure of sedimentation, mud, soil, and debris built-ups, and vegetation.

4.2.1 Hydrology and Sediment Changes

Figure 6B (1988 image) indicated a 17% increase in sand/gravel/dry soil quantities_from 1984. Unfortunately, there are no images before the 1984 image to understand the natural sedimentation rate, but the periods in between 1984 and 1988 had an increase in quantities of sedimentation (sand/gravel/dry soil) as displayed in the classification images (Figure 6A and 7B). Eventually, there was a significant increase in sedimentation of approximately 64%. This is the period after the mine had the Sedimentation Level Restriction (SLR) imposed in 1989 (Figure 6C). Despite the control measures (SLR), the quantities did not show any signs of regression until after 1996 as indicated in Figure 8, that is, there was a dramatic increase in sediment quantity in 1996 compared with other years. Beginning in 1996, the classifications indicated a gradual decline of 145% in sediments and soil/debris built-ups (the period between 1996−2004), and then regained 65% in between 2004 and 2015 (Table 3). These huge area (quantity) decline and increases can partly be attributed to the impacts of cloud and shadow covers. An approximate 72000ha of area was unclassified, in addition to ~14000ha of cloud and shadow covers (Table 4). These are same for the NDVI (sections 4.2.2 and 4.3) and Water Index thresholding classifications (section 4.4) too.

Table 3. Sedimentation and soil/debris built-ups and their percentage increase or decrease

Item	Years			
	1988-1984	1996-1988	2004-1996	2015-2004
Class Differences (Ha)	10,236	109,212	-10,036	130,697
Percentage Increase/Decrease (%)	17	64	-145	65

Table 4. Feature class and their areas in each year

Class No	Class Name	Quantity (ha)				
		1984	1985	1986	1987	1988
1	Water Bodies	7200.76	12061.35	13232.29	22142.13	24339.84
2	Sand/Gravel/Soil	4494.423	5415.553	15243.46	6212.138	17973.46
3	Mud/Swamp/Soil	8758.024	6974.887	29510.99	7142.357	16205.89
4	Young & Aquatic Plants/Grasses	57482.16	74855.4	49574.54	73812.51	65235.46
5	Older Vegetation/Forests	189130.1	207201.8	114701.5	189630.6	174097.1
6	Clouds/Shadows	40661.19	1217.735	13535.37	8787	9816.118
7	Unclassified	0	0	71928.59	0	59
		307,727	307,727	307,727	307,727	307,727

Clouds and shadows on the image had obscured and misclassified features to some extent. However, the sedimentation changes seemed to match expectations, if not immediately, then as the time went by, due to the control measures put in place by the GoPNG and the company (OTML). The increase in sand, gravel, and dry soil quantities in the earlier years (1984−1996) could be the result of the approximate 884Mt of wastes that entered the watershed since 1981 (OTML, 2002, cited in Townsend & Townsend, 2004). However, the models (Figure 6 and 7) indicate signs of quantity decline starting 1996; likely in reaction to the dredging (1998) and the mine's waste tailings dams (2006) that were put in place.

As previously discussed, the changes that happened in the period between 1984 and 1988 were more natural, whereas the real impacts of the mining wastes came into effect in 1996 with an increase of approximately 15,243 hectares of sediments from an average of 4,955 hectares; an increase of approximately 68%. The years, 1997−1998 (a period in between 1996 and 2004) were greatly affected by an El Nino drought. Therefore, its effects may have added to the dramatic changes in the natural riverine systems and biodiversity. This is because in 2004, the sedimentation appears to align with the quantities of 1988 and 1984, which is apparent after 2004, where the sedimentation returned to the normal mine waste affected flow.

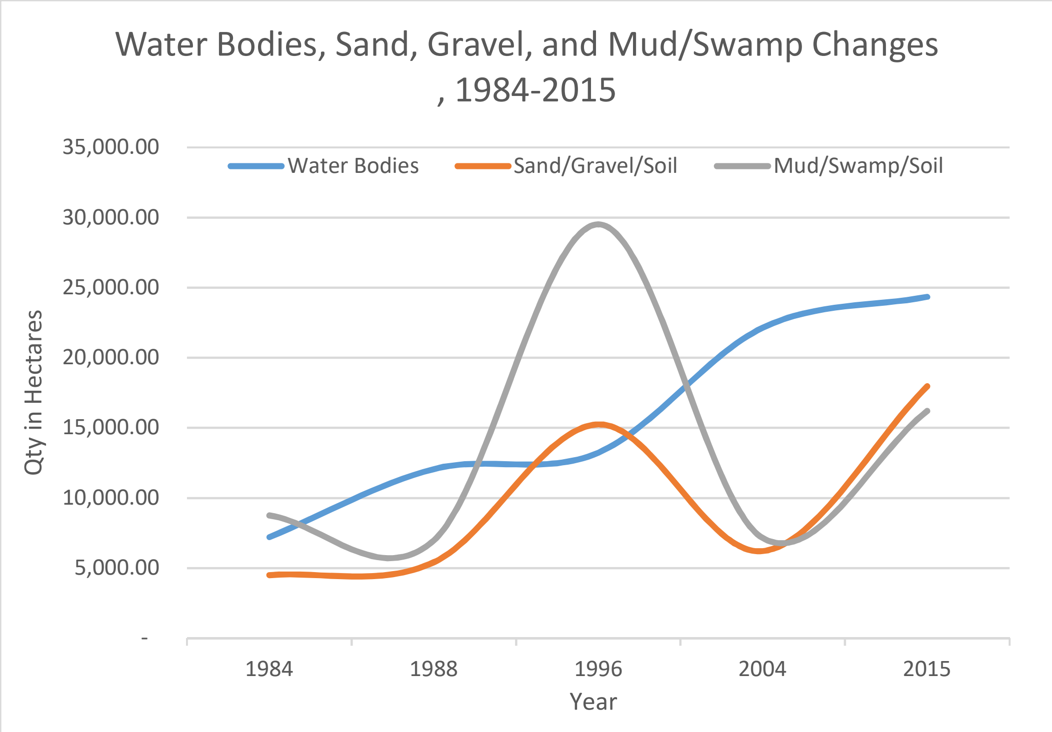


Figure 7. Quantities of water bodies, sand/gravel, mud/swamps and soils, 1984-2015

The quantities of the features or classes in 1984 were more natural than in other years. Sand/gravel/dry soils rose gently in between 1984−1996, then experienced a big decline in 2004, and increased in 2015. The water bodies maintained quantities despite minor gains and losses. While the mud/swamps/wet soils inflate greatly from 1988 to 1996, then had a big decline in 1996, but started gaining quantity rapidly since 2004.

The quantities of mud/swamps/wet soils showed similar changes to that of sediments (sand/gravel/dry soils), and opposite to changes in the water bodies (Figure 7). During the periods 1984-1988, and 1988-1996, there was a decrease of 26% and a gain of 76% respectively in the mud/swamps/wet soil quantities. Eventually, there was an incredible decrease of 313% in 1996−2004 (Figure 6C), but then regained 56% quantity in 2004−2015. On the contrary, the water bodies increased from approximately 8 hectares to 13.4 hectares in between 1984 and 1988; an increase of 40% (Figure 7). The quantities then further had a 9% increase between 1988 and 1996. Then there was another increase of 40% in 1996−2004, and again a 9% increase in 2004−2015. The water bodies seemed to have an increased rate of either 40 or 9 percent (average of 24.5%).

Again, the changes in between 1984 and 1988 were mainly natural, with slowly increasing effects of the mining wastes. As the mine was producing, the water bodies increased, forcing the amounts of mud/swamps/wet soils to decline, while the sand/gravel/dry soils rose at a slow pace. This was due to the sediment built-ups and rise of the Fly and Ok Tedi River beds that forced the water bodies to spread out, and blocked off small creeks and streams from flowing through their natural flow paths. These standing waters and over-flows had covered off the mud/swamps/wet soils, hence a decline in their quantity.

It is evident in the graph (Figure 7) that the water bodies did not gain much in the period 1988−1996, but the sand/gravel/dry soils, and mud/swamps/wet soils had large increases of 64% and 76% respectively. At this period, the overflow and trapped water bodies in the lower gradient areas seemed to have turned into mud/swamps/wet soils, and/or the water bodies have changed flow paths and courses that left the old flood beds opened and exposed as sand/gravel/dry soils, and/or mud/swamps/wet soils. There is also a possibility that the water bodies in the upper part of the Ok Tedi River were so muddy that they were identified as mud, swamps or wet soils.

Eventually, the mud/swamps/wet soils, and sand/gravel/dry soils declined in quantity, 313% and 145% respectively in the period 1996−2004, while the water bodies gained 40%. The effect of the El Nino drought was over, therefore, the increase in the water bodies had again overflowed and had blocked off streams and small creeks from following their natural flow paths and courses. This resulted in the mud/swamps/wet soils, and sand/gravel/dry soils being covered under water bodies. Thus, there was a reduction in their observed quantities. There was also a possibility that the vegetation had grown over the mud/swamps/wet soils, and sand/gravel/dry soils, thus, giving a rise in the vegetation quantities (Figure 9) and a decline in the mud/swamps/wet soils, and sand/gravel/dry soils quantities.

In the period 2004−2015, the water bodies were steady with only a small gain of 9%, while the mud/swamps/wet soils, and sand/gravel/dry soils had gains of 56% and 65% respectively. At this period, the flood beds were high due to increases in sediments. The water bodies were flowing in large volume but in small quantities[13] and in one direction, therefore creating visibility of mud/swamps/wet soils, and sand/gravel/dry soils. When the quantities of water bodies increased, the quantities of mud/swamps/wet soils, and sand/gravel/dry soils decreased, and vice versa.

Much of the change happened within the floodplains and along the riverine systems; however, human activities, including logging in the Indonesian side of the region, construction of road networks, development of new settlements, and other ground works, were also noted in this research. These other human activities may have added to the increase or decrease of sand, gravel, muds, and soils quantities in the study area.

4.2.2 Vegetation Interpretations

The whole region is highly vegetated and perennially green. Despite this, the vegetation changes seemed to be trending propositionally to each other when the older and newer vegetation were compared. That is, when the older vegetation area increases or decreases, the younger ones increases or decreases too, and vice versa. This research terms the mature trees and forests as ‘older vegetation’, and the ‘younger’ as much greener vegetation, aquatic plants, and grasses.

[13] The quantity in any feature type is the amount of space (area) covered by a feature type and not the volume.

Figure 9 shows that the mature vegetation had a 23% increase in quantity in the period 1984−1988, while the younger and aquatic plants increased by 9%. This period represents the natural growth, suggesting that, although the mining wastes were already being dumped into the river streams, the effect was not yet felt. The effects came to be evident in 1996 when the younger vegetation quantities had a significant decline of 51%, and the older vegetation at 81% in the period 1988−1996. This stage had both vegetation types reacting to the mining wastes. The water bodies that overflowed, and those that were prevented from flowing through natural flow paths, left behind sand, gravel, mud and soils after subduing and evaporating. These had engulfed and suffocated or had washed out both vegetation types (young and old) and causing them to die out, resulting in the decline in quantities. The region had a 27% cloud and shadow cover that may have decreased the visible vegetation quantities. However, if this 27% of the area is shared amongst other classes or feature types, the gain and loses on each will be somewhat similar.

There was a 40% increase in the mature vegetation area in the period between 1996−2004, while the younger vegetation also had a 33% increase. This is the period after the dredging had been introduced, and the period after the El Nino drought, hence the vegetation was transforming from one type to another. It is likely that the younger vegetation had matured and turned into older vegetation, which gave a rise in the older vegetation quantity, while the increase in the younger vegetation could be the dieback and regrowth and/or other plant species, especially the aquatic vegetation growth. The increase in the younger vegetation is the introduction of new spices, especially the aquatic plants germinating and slowly creeping in to replace the native vegetation (*OK Tedi past, present & future, Ok Tedi Mining Limited*, 1999).

The graphs (Figure 8) and classification images (Figure 6) show that, in the years between 2004 and 2015, there were slight declines in both vegetation types. The younger had a decrease of 13% and the older at 9%. This also is the period of vegetation dieback and transition where one vegetation type has matured or has transformed into another (*OK Tedi past, present & future, Ok Tedi Mining Limited*, 1999). Some of the younger vegetation noted in the period 1996–2004 had matured and, therefore, had decreased by 13% having transformed into matured vegetation. On the other hand, the quantities of matured vegetation declined due to die-out and aging, resulting in a 9% decrease.

Overall, the vegetation changes were responding oppositely to the mud/swamps/wet soils, and sand/gravel/dry soil quantities. That is, when the mud/swamps/wet soils and sand/gravel/dry soil quantities were high, the vegetation quantities were low. If vegetation quantity was high, then it was the opposite with the sediments. On the other hand, changes in the water bodies corresponded closely with the vegetation. Accordingly, the vegetation area increased or decreased parallel with the changes of the water bodies. This is the result of aquatic plants growing when the water is high and dying out when the water is low.

Again, though much of the mining wastes impacted changes happened along the riverine systems, other human activities, such as logging in the Indonesian side of the border, road networks, settlements, and other minor rubber plantation farming, were also noted in this research. These activities may have also caused minor increases or decreases in the quantities of vegetation too.

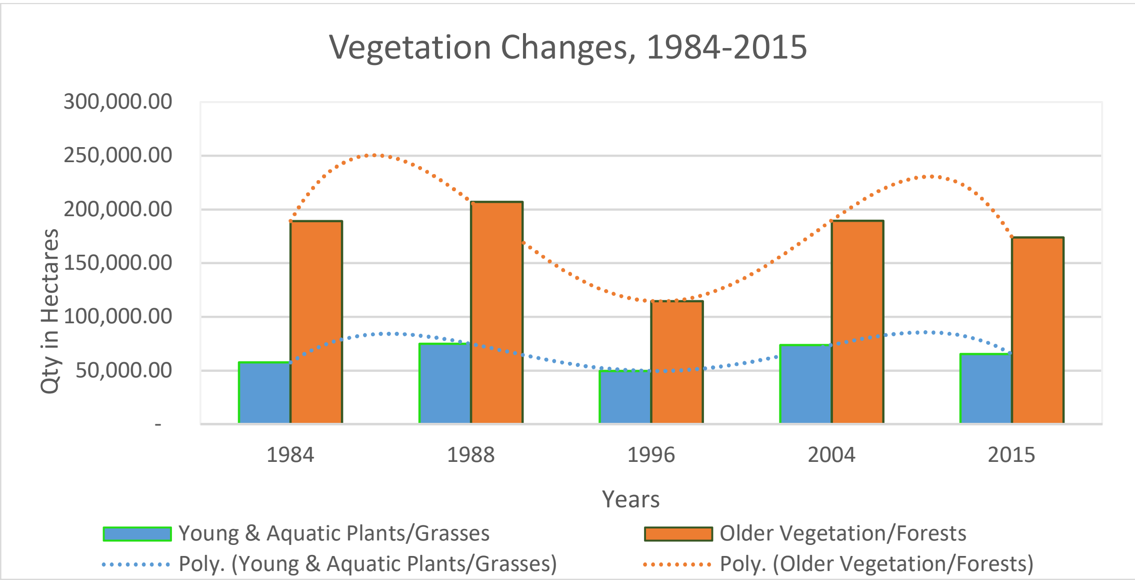


Figure 8. Vegetation Areas from 1984 to 2015

The graph indicates older and younger vegetation quantities between the years 1984 and 2015. Both vegetation types have similar reactions. They had an increase in area from 1984 to 1988, a decline in the period 1988−1996, then regained quantities in 2004, and finally a slight decline in 2015.

4.3 Assessing Vegetation/Plant Health using NDVI

NDVI calculates the greenness and the health of the features and ranges their DN/brightness values between -1.0 to +1.0, with negative numbers signifying water bodies and other non-photosynthetic features (Rouse et al., 1974). Figure 9 shows NDVI images of the region in the period from 1984 through to 2015.

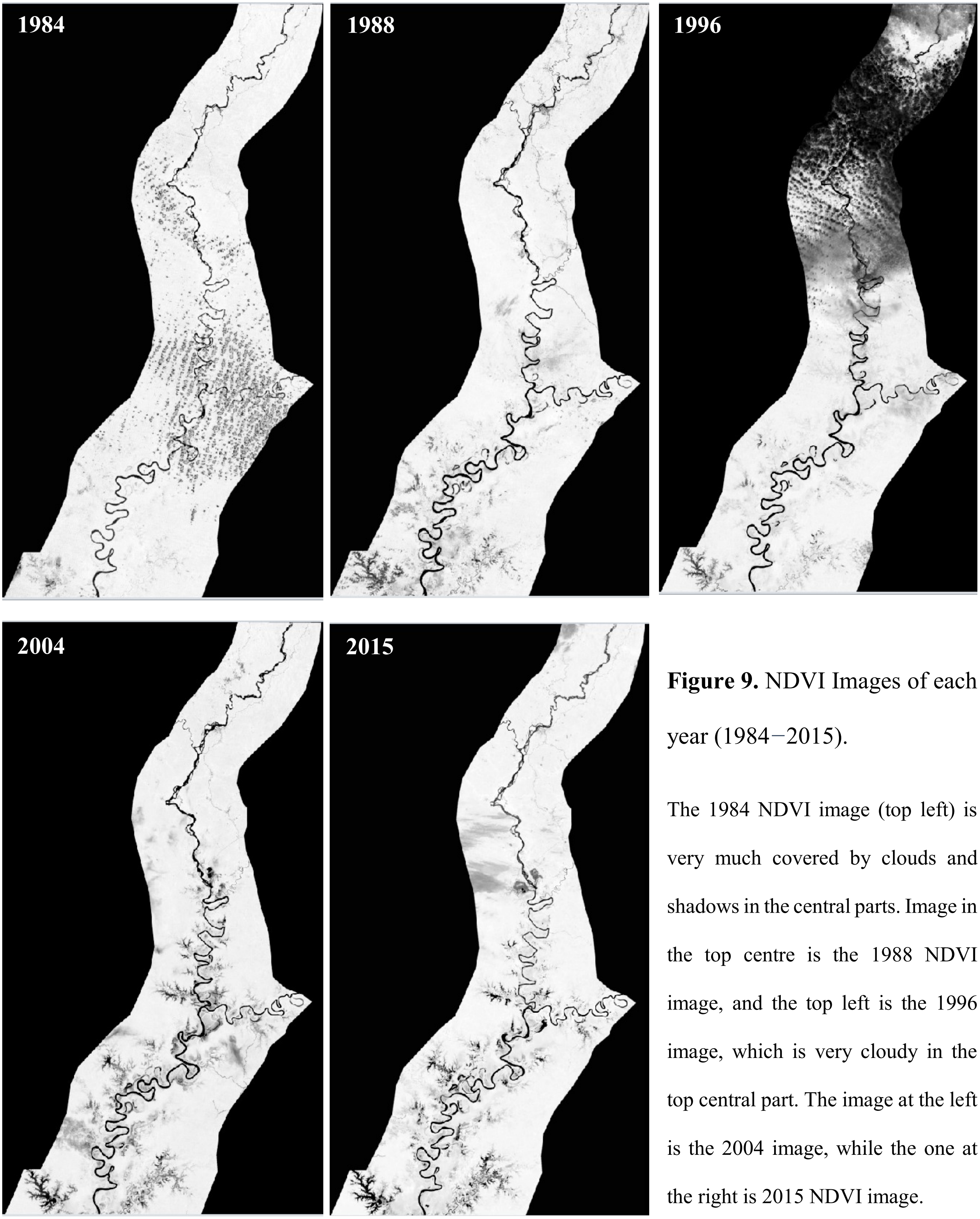


Figure 9. NDVI Images of each year (1984−2015).

The 1984 NDVI image (top left) is very much covered by clouds and shadows in the central parts. Image in the top centre is the 1988 NDVI image, and the top left is the 1996 image, which is very cloudy in the top central part. The image at the left is the 2004 image, while the one at the right is 2015 NDVI image.

The darker objects in the NDVI processed images indicate water bodies and non-photosynthetic features, such as clouds, shadows and/or built-ups. On the other hand, the lighter/whiter objects are the vegetation features; much lighter features indicate younger and aquatic vegetation, while the fading, greyish features represent the older vegetation/forests.

The NDVI images (Figure 9), and their density slices[14] show that the brightness values of each class type were spread between -1.0 and +1.0 (refer Table 5). The images (Figure 9 and 12) were processed after the histogram-matching step (Section 4.1.1) was applied. Therefore, the density sliced brightness values (Table 5, 6, 7 and 8) of these images do not affect the results, but only shows the enhanced information (range of brightness values) that were divided into intervals and colour-coded. The changes in the features on each image were detected by analysing the changes in the brightness values (Rouse et al., 1974). For instance, if the brightness value at time A is 0.845, and 0.800 in time B, then there is a transition of younger to older vegetation (sign of maturation). The same is applied to other features depending on the brightness values of the features.

Table 5. NDVI density sliced brightness values of each feature type.

No	Features	Brightness Values
1	Unclassified	-1.00 to -0.015
2	Water Bodies	-0.015 to 0.476
3	Mud/Swamps/Wet Soils/Clouds	0.476 to 0.690
4	Sand/Gravel/Dry Soils/Clouds	0.690 to 0.800
5	Older Vegetation	0.800 to 0.845
6	Younger Vegetation	0.845 to 0.903
7	Unclassified	0.903 to 1.00

Five sample locations (Figure 10) were randomly selected on the NDVI images of each year, and their

[14] Density slicing is a digital data interpretation method used to enhance the information by dividing the range of brightness values in a single band into intervals and assigning colours to each interval.

brightness values recorded (Table 6). It was noted that there were changes in the brightness values on each image, which indicated changes in the features. The brightness values of each year (Table 6) are compared against the density sliced values (Table 5) for analysis and interpretation.

The area in Location 1 (Table 6/Figure 10) was covered with sand/gravel/dry soils in 1984 but turned into water bodies in 1988. The features in this location shifted from sand/gravel/dry soils to water bodies, then to mud/swamps/wet soils, and lately (2015) back to water bodies. It was likely that the flooding and changing of watercourses had caused the water bodies to emerge and subside, thus changing land covers. Similarly, Location 2 was covered with young vegetation in 1984 but was converted into water bodies in 1988. After the area had been covered with water, there seemed to be a change between water bodies and sand/gravel/dry soils; sand/gravel/dry soils in 1996 and water bodies from 2004–2015. The impacts of the mining wastes had flooded and suffocated the younger vegetation and caused it to die out. Therefore, the area that was once covered with vegetation had changed cover into sand/gravel/dry soils, and eventually into water bodies. Viewing all the five locations, it appears that all the land cover types had changed from one feature to another in 1984 through to 2015.

Table 6. NDVI Brightness values at each location on the mining wastes affected region

	Location/Area		Brightness Values				
No	**Eastings**	**Northings**	**1984**	**1988**	**1996**	**2004**	**2015**
1	504366.31	-713497.33	0.762	0.469	0.706	0.557	0.399
2	509262.07	-669607.53	0.86	0.243	0.733	0.012	-0.195
3	513473.53	-681237.58	-0.006	0.006	0.652	0.757	0.811
4	508144.67	-696765.31	0.797	0.518	0.704	0.681	-0.111
5	495086.36	-704382.90	0.036	-0.216	-0.274	-0.151	-0.258

Comparing the brightness values of the features along the mining wastes affected rivers with an unaffected region (Table 7) showed that the features in the unaffected region (Figure 11) were steady with only minor changes in each year. For instance, Location 1 (Table 7/Figure 11) has been covered by vegetation since 1984. Though there were vegetation changes (young to old), this would be expected as the young ones would mature and lose vigour and strength. Similarly, in Location 5, the region was covered by water bodies throughout the years (1984−2015). Though there was some young vegetation cover noted in 1996, this reading is unreliable as the area was heavily clouded (27% cloud cover). Therefore, the area seemed to be unchanged and remained covered by water bodies throughout the years.

Table 7. Brightness values of each location at the Control (area unaffected by mining wastes).

	Location/Area		**Brightness Values**				
No	**Eastings**	**Northings**	**1984**	**1988**	**1996**	**2004**	**2015**
1	529526.33	-643592.77	0.875	0.86	0.817	0.875	0.883
2	530829.15	-641590.38	0.89	0.898	0.817	0.883	0.896
3	533176.11	-639361.22	0.868	0.875	0.795	0.875	0.886
4	530068.41	-651829.64	0.476	0.574	0.839	0.665	0.639
5	529708.68	-651115.18	0.665	-0.118	0.839	-0.043	0.416

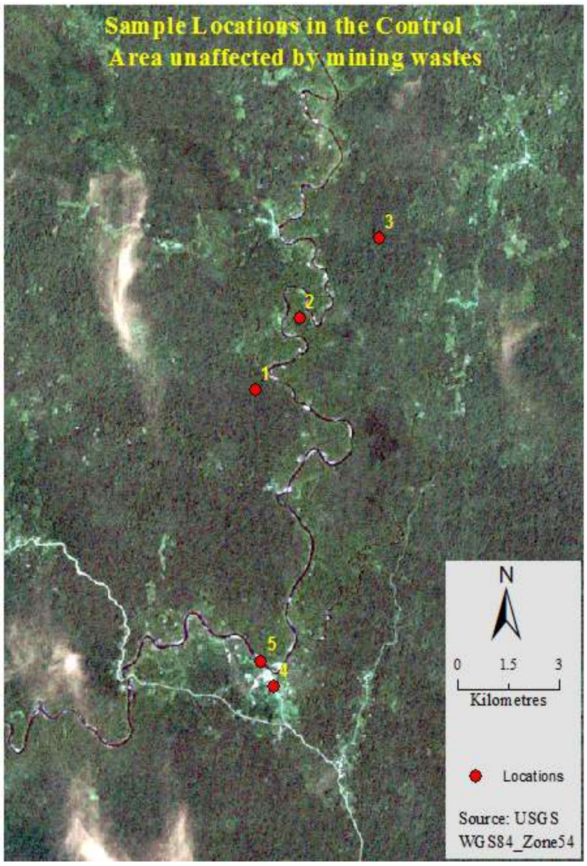
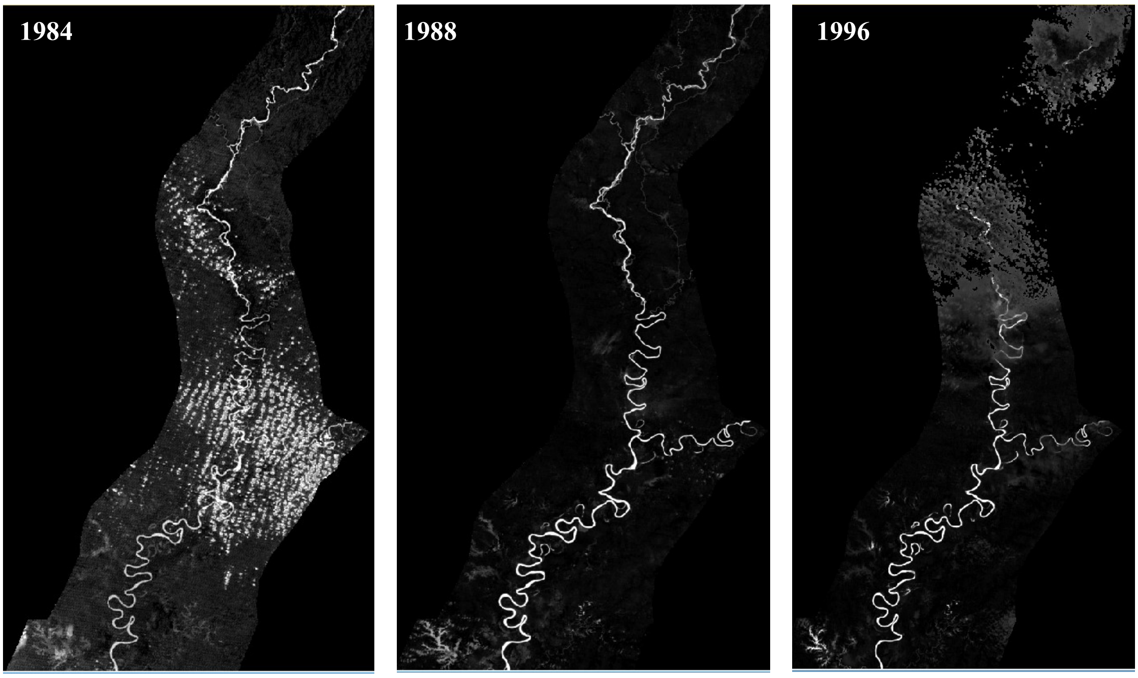


Figure 11. Sample location map of the Control (Area not affected by Ok Tedi Mine).

Figure 10. Sample location map of the along Ok Tedi and Fly Rivers

4.4 Assessing Water Bodies and Sedimentation/Built-ups using NDWI & MNDWI

Water bodies and sedimentation built-ups were assessed using NDWI and MNDWI. The 1984 image was processed using NDWI because the MSS scanner that captured 1984 image did not have the MIR band (Landsat, 2015), which was required for calculating MNDWIs, while the rest (1988, 1996, 2004 and 2015 images) were processed using MNDWI. The processed images were similar to NDVI images; however, unlike NDVIs, the water, built-up features, and clouds are lighter/whiter than the photosynthetic features (Refer Figure 12).



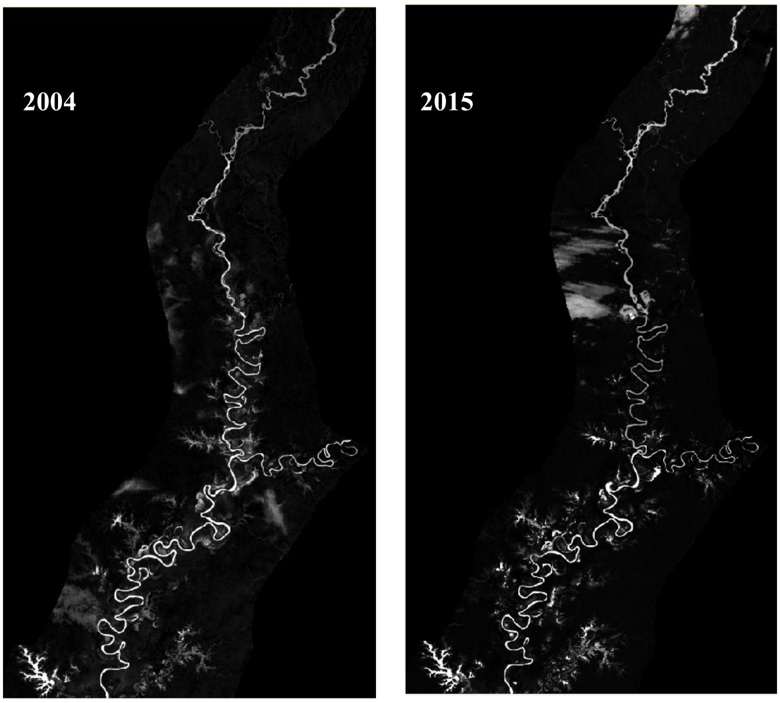


Figure 12. NDWI and MNDWI Images of each year- 1984-2015.

Top left is a 1984 NDWI image, while the rest (1988–2015) are MNDWI images. Water bodies, built-ups, and clouds were brighter than the other features. 1984 and 1996 images were cloudier than the others.

NDWI and MNDWI images were analysed (using density slicing) and it was noted that the brightness values closer to +1.0 were water bodies, and those closer to -1.0 were photosynthetic features, such as vegetation, especially the younger ones (refer Table 8). Values between +1.0 to -0.203 were water bodies and -0.529 to -1.0 were younger vegetation. The others vary between -0.203 and -0.529. Using these values, the changes were classed as dieback using similar processes described for NDVI analysis (section 4.3).

Table 8. NDWI and MNDWI density sliced brightness values of each feature type.

No.	Features	Brightness Values
1	Water Bodies	+1.0 to -0.203
2	Mud/Swamps/Wet Soils/Clouds	-0.203 to -0.370
3	Sand/Gravel/Dry Soils/Clouds	-0.370 to -0.436
4	Older Vegetation	-0.436 to -0.529
5	Younger Vegetation	-0.529 to -1.0

Table 9 shows the brightness values of five random positions (Figure 10) (same locations as used above in section 4.3) on each image of the mining wastes affected region, and Table 10 shows the values on the control (Figure 11). The brightness values in Table 8 were used as a reference to analyse and interpret the values of Tables 9 and 10

Table 9. NDWI/MNDWI Brightness values of each image of the mining wastes affected region

No.	**Location/Area**		**Brightness Values**				
	Eastings	**Northings**	**1984**	**1988**	**1996**	**2004**	**2015**
1	504366.3	-713497.3	-0.767	-0.09	-0.489	-0.182	-0.283
2	509262.1	-669607.5	-0.754	-0.576	-0.509	0.215	0.555
3	513473.5	-681237.6	-0.003	0.136	-0.529	-0.421	-0.443
4	508144.7	-696765.3	-0.716	-0.104	-0.483	-0.244	0.488
5	495086.4	-704382.9	-0.132	0.801	0.761	0.659	0.761

The NDWI/MNDWI analysis indicated that much of the features on the five locations (Figure 10) have changed from one type to another. For instance, Location 1 was initially covered by younger vegetation in 1984 and 1988, then they lost vigour and transformed to older vegetation in 1996, and finally, the area has turned into mud in 2004, and lately (2015), it has become a water body. Similarly, other locations, such as Location 3, were initially covered by water bodies (1984−1988), and then changed into some types of sand/gravel/dry soils and mud/swamp/wet soil mixtures, and eventually had vegetation growing. The second location had vegetation in 1984−1996, and then turned into mud/swamps/wet soils and water bodies in 2004−2015. Areas that were very much covered by vegetation in 1984 have changed into mud/swamps/wet soils, or even have turned into water bodies in the later years. Again, there were distinct changes in one vegetation type to another in all the sample locations.

Table 10. NDWI/MNDWI Brightness values of each image of the Control

No	Location/Area		Brightness Values				
	Eastings	**Northings**	**1984**	**1988**	**1996**	**2004**	**2015**
1	529526.3	-643592.8	-0.806	-0.546	-0.511	-0.566	-0.528
2	530829.2	-641590.4	-0.813	-0.593	-0.471	-0.532	-0.545
3	533176.1	-639361.2	-0.798	-0.593	-0.471	-0.579	-0.563
4	530068.4	-651829.6	-0.589	-0.593	-0.531	-0.573	-0.599
5	529708.7	-651115.2	-0.618	-0.006	-0.537	-0.262	-0.289

Similar to NDVI analysis, the brightness values of the features at each location on the control indicated little to no change at all. The transition of younger to older vegetation is expected because, as plants and vegetation mature, they lose vigour and chlorophyll, and consequently there is less reflection in the NIR band. All the locations appear to be covered by vegetation all year, and the locations on the water bodies seem to be water bodies throughout the years also. The change from younger vegetation on location 5 of 1984 to water bodies in 1988−2015 could be that the area was originally a waterway. The river shifted and was replaced by younger vegetation covers. Later (1988), the river returned to its original flow path. Therefore, the location was covered by water body throughout the years (1988−2015).

4.5 Change Detection using Image Differencing

The change detected images were calculated based on pixel by pixel analysis, that is, the pixels of the former image were subtracted from the later of the same region (Al-doski et al., 2013, Lu et al., 2004). The vegetation and the water bodies including the debris built-ups were calculated by subtracting one from the other. Figure 13 shows changes in water bodies in each of the periods, with a sample of the change detected images. They also have their original images attached for comparison. Table 11 shows quantities in hectares of the areas changed, that is, there were either 15 % increases or decreases of water, vegetation, and built-ups on the images in each period.

Table 11. Changes detected by image differencing

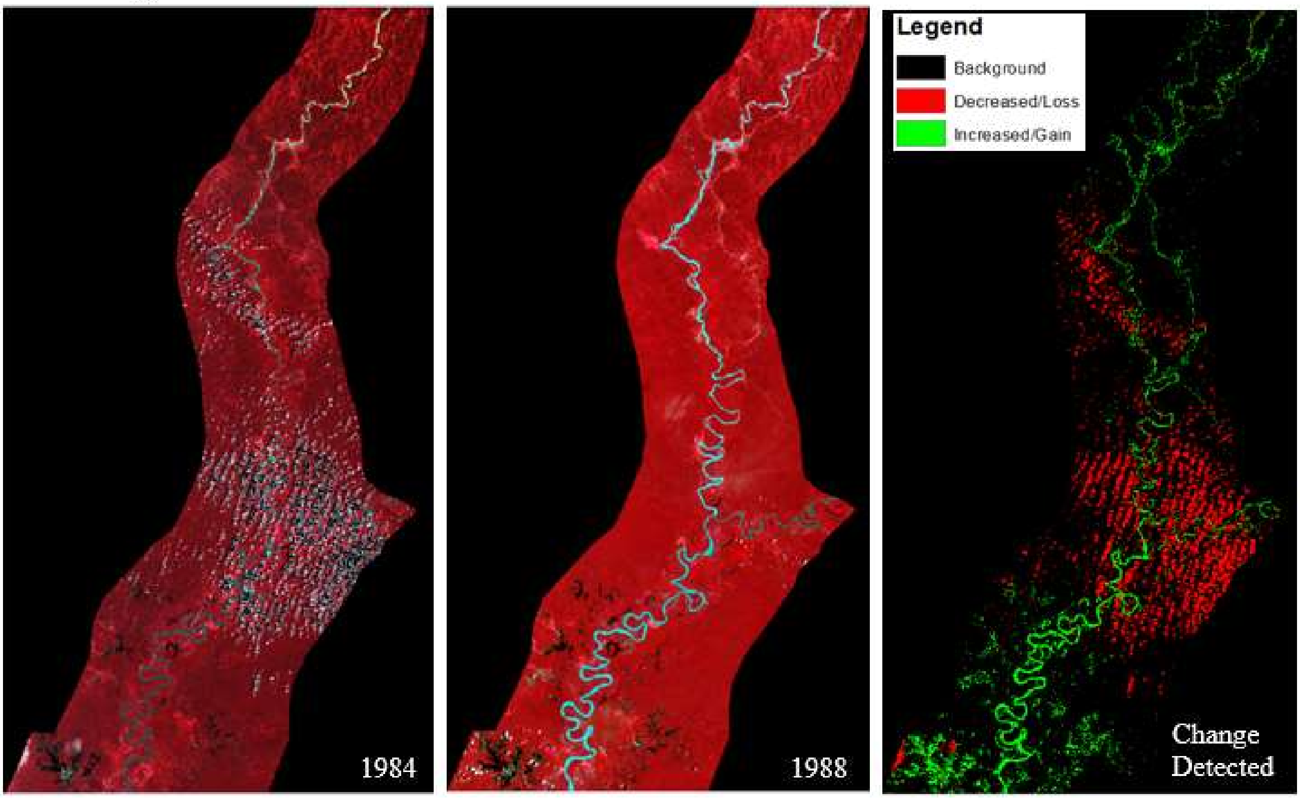
Period	Vegetation (ha)		Water Bodies/Built-Ups (ha)	
	Increased	Decreased	Increased	Decreased
1984-1988	22.5504	17.0917	18.3639	27.4333
1988-1996	12.8618	16.1488	12.0275	11.7055
1996-2004	14.3333	11.3741	14.8168	13.844
2004-2015	9.6804	9.6642	10.3883	8.6168

The cloud covers and shadows on the images have contributed immensely to the major quantity increases or decreases in the change-detected images. However, in general, most of the changes have happened along the riverine corridors, and much further downstream from the mine site.

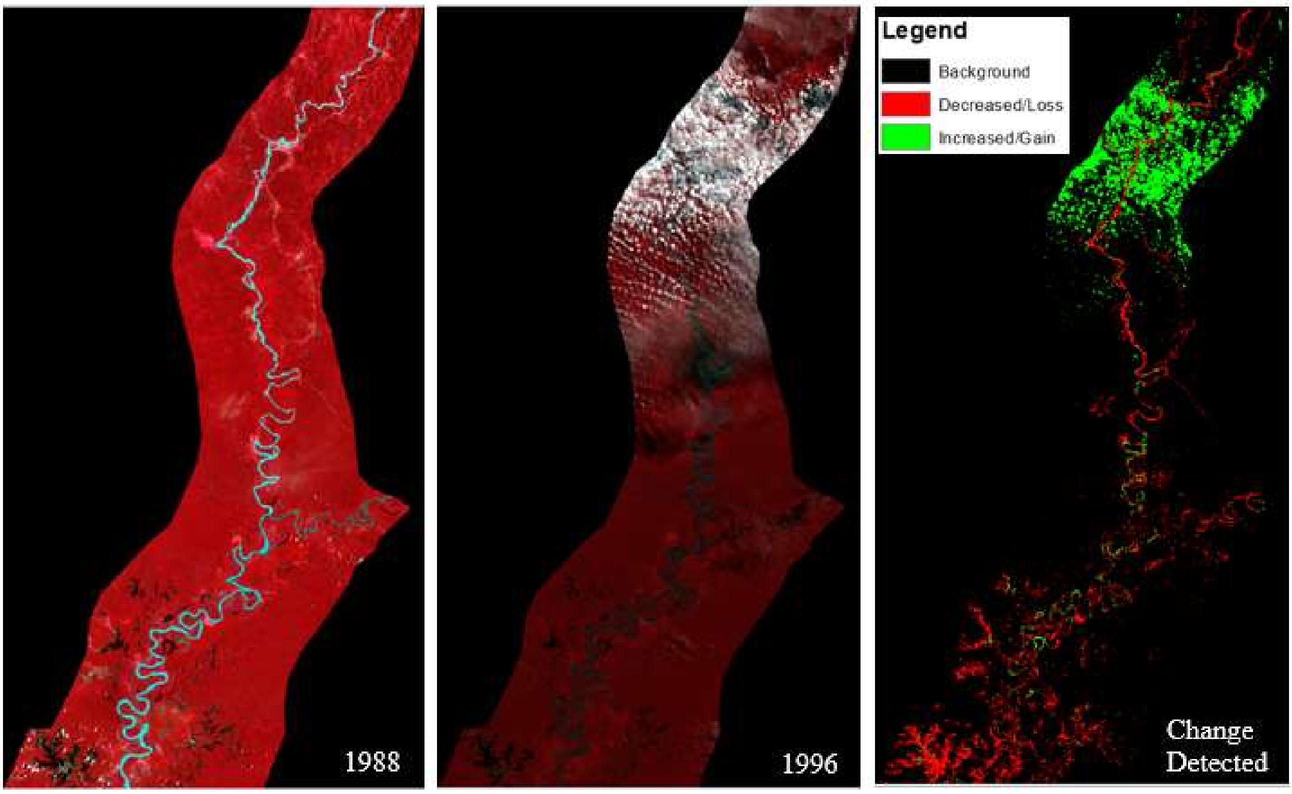
The features present in time one that were not found in time two of the same location registered a decrease in value, or were marked as a decrease on the processed images, while the features on time two that were not present in time one received an increase (refer Table 11 and Figure 13). These changes, whether they be a decrease or increase, could also indicate the transition or change of one feature type to another.

There were apparent gains in water bodies and built-ups throughout the years with a much higher gain in 1984 to 1988. However, throughout the year, the changes seemed to have declined (refer Table 11). Similarly, the vegetation gained considerably in 1984−1988. However, this high gain has been attributed to high cloud cover. Generally, the decreases in vegetation have substantially reduced over the time

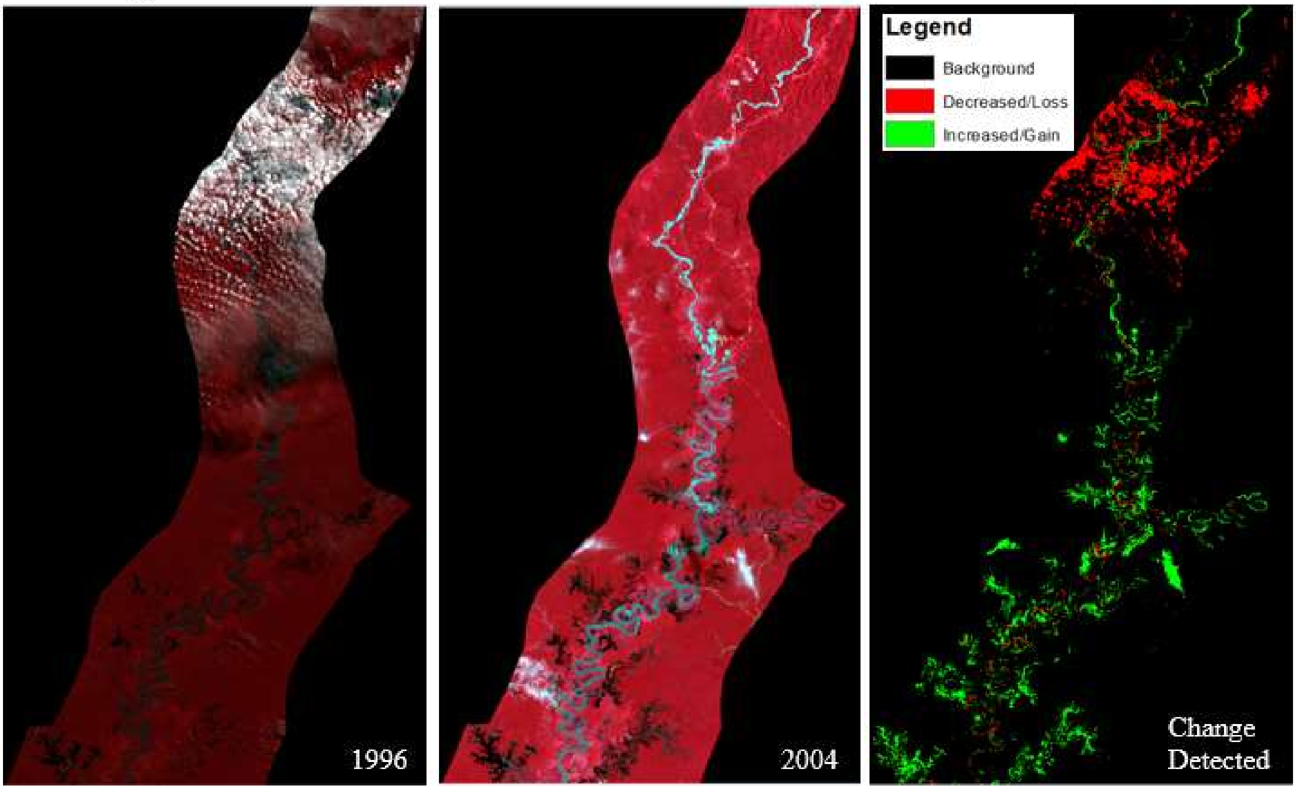
A. Changes detected between 1984 and 1988



B. Changes detected between 1988 and 1996



C. Changes detected between 1996 and 2004



D. Changes detected between 2004 and 2015

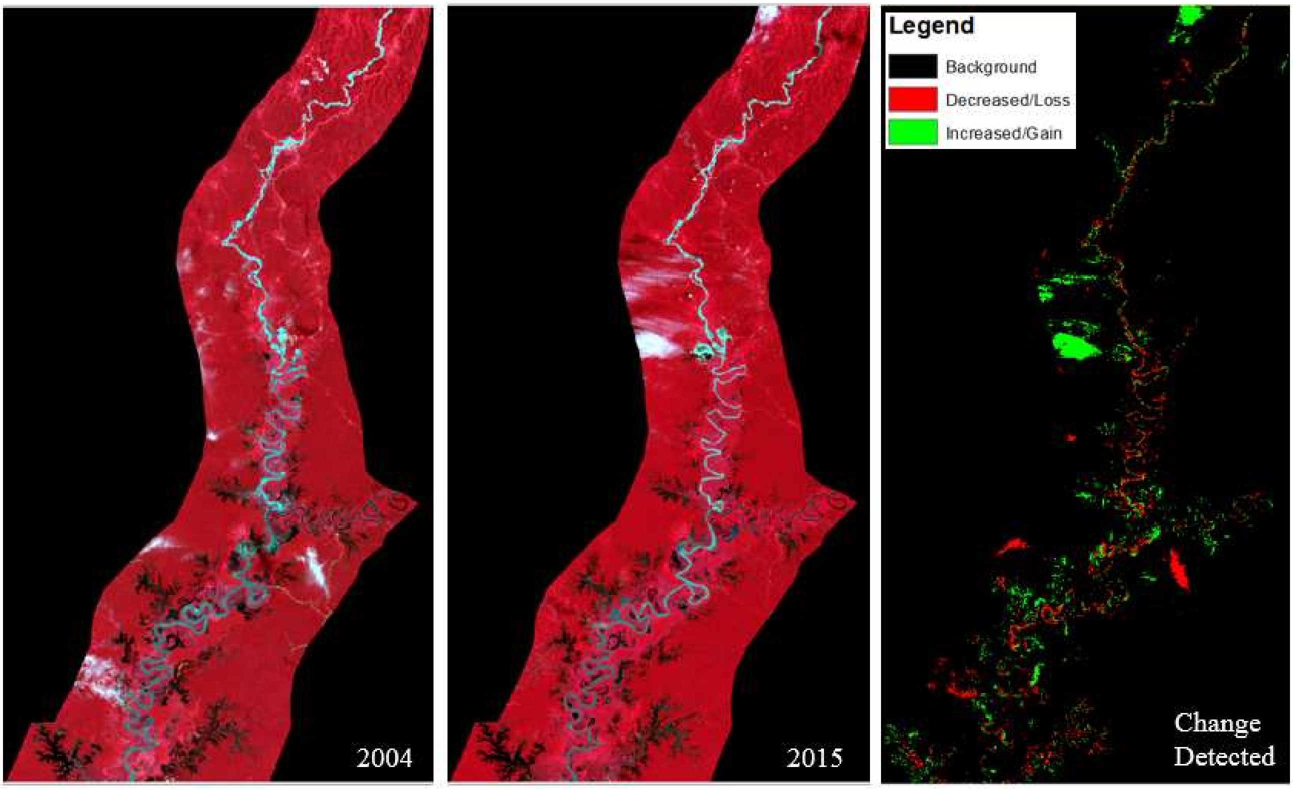


Figure 13. Change detected Images, changes in water bodies in each period

This method (image differencing) does not accurately indicate or identify what types of features were changed (increases or decreased), or were converted from what feature type to another apart from indicating the quantities. Therefore, the results of the change-detected methods are best used together with NDVI and NDWI/MNDWI images for analysis and interpretation.

There are some areas that visually appear to have a certain feature type, but their spectral signatures have changed, therefore indicating changes in the processed images. This may be caused by the area being covered by vegetation on both images (time one and two), however, it is indicated as a gain and/or loss in the change-detected image. In this case, it is likely that the vegetation has lost vigour. Similarly, if there is a change detected in areas appearing to be water bodies on both images, then it is likely that the water body areas have changed to mud/swamps/wet soils, which the human eye cannot decipher from a distance.

Chapter 5. Conclusion

5.1 Research Findings

This research has used Landsat Images to detect the changes in water bodies, sedimentation/built-ups, and vegetation health along the Ok Tedi and Fly Rivers since the commencement of Ok Tedi mine operations in 1984. Four methods/techniques/models (classification, NDVI, NDWI/MNDWI, and Image differencing) were used to investigate the impact of Ok Tedi mining wastes on the riverine systems and biodiversity. Whilst previous studies of the riverine systems, vegetation, and biodiversity studies in the region have used coring techniques and pressure gauges, visual observations, and ground-truthing[15] (also known as face-to-face) methods, (Day et al., 2008, Cui and Parker, 1999, Swales et al., 1999, Swales et al., 2000, Hettler et al., 1997, Salomons and Eagle, 1990), this study demonstrates the capability of conducting studies of the environment using remotely sensed image (Landsat datasets) analysis. Further, it has shown the value of this method in studying areas where field access is constrained by remoteness, climate and geography, and the large scale of sites, such as the Ok Tedi and Fly River catchments. Therefore, it is expected that the methods used in this study can be applied in similar environments elsewhere.

The analysis using the four techniques/models (classification, NDVI, NDWI/MNDWI, and Image differencing) indicated that there were greater changes over the years (1984−2015) in the vegetation health and structures, water bodies, and sedimentation/built-ups along the mining wastes affected rivers compared with the results of a Control. Although the cloud covers and shadows had influenced the results of the analysis, all four techniques, despite slight differences, have indicated significant changes in the land cover of all images. These remotely sensed results have also confirmed past ‘face-to-face’ studies (Townsend and Townsend, 2004, Cui and Parker, 1999, Kay, 1995) that indicated

[15] Information collected and/or provided by direct observation as opposed to information provided by inference. Usually the researcher goes into the field to observe and collect spatial and descriptive data.

increases in sedimentation and water bodies, and the dry soils at water edges being water logged due to water rises that consequently smothered the vegetation causing dieback.

OTML's own report (2002, cited in Townsend & Townsend, 2004, p. 15) noted that in 2002 146,100 ha of vegetation in the entire river catchment were impacted. However, this research conducted on a 307,763.24 ha land area in the catchment indicates an approximate 132% (51% young and 81% older) decrease and an approximate 104% increase in vegetation cover from 1984 through to 2004. These decreases could be the transformation of vegetated areas into water bodies, mud/swamps/wet soils, and/or sand/gravel/dry soils, while the increases could be the vegetation dieback and regrowth of the aquatic vegetation, as noted in the studies of OTML (*OK Tedi past, present & future, Ok Tedi Mining Limited*, 1999).

The study also notes that, although it is acceptable to analyse and interpret each processed image (classification, NDVI, NDWI/MNDWI, and Image Differencing) independently, it is also wise to cross-reference two or more images for confidence and confirmation of the interpretation and analysis, especially when the area of study is not familiar to the researcher or when no ground-truthing has been done. In this research, all four (classification, NDVI, NDWI/MNDWI, and Image differencing) images were used for interpretation and analysis as a means of ensuring consistency and accuracy of conclusions drawn from the study.

5.2 Outcomes

Analysis of the processes of change of the water bodies, sand/gravel/dry soils, mud/swamps/wet soils, and vegetation over the period of this study indicates that they have reacted to the mining wastes. Though there were no initial data sighted to determine the changes attributed to natural systems, drastic and sudden changes (increases and decreases) in the quantities of each feature type/class (Table 11) are an indication of features reacting to an unnatural force that defies natural cycle and ecosystem.

Although the whole intent of this research was to remotely examine the extent of flooding and sediment deposition, and vegetation health and dieback on and along the floodplains of the Ok Tedi mine affected rivers, it does not rule out the usage of 'face-to face' studies. This research has otherwise confirmed the results of the past 'face-to-face' studies, and has shown that remote sensing/GIS and their techniques are useful for assessing and monitoring environments, especially the sediments, water bodies, and biodiversity. Arguably, combinations of 'face-to-face' methods, especially the ground-truthing, and the use of remote sensing techniques/models (classification, NDVI, NDWI/MNDWI, and Image differencing) can give confidence, clearer meaning, and better understanding of the interpretation and analysis of land cover research results.

Despite the limitations (section 5.3), the techniques, models and datasets used in this study and the results may:

- ✓ Inform the stakeholders especially the government of Papua New Guinea and the company (OTML) that remote sensing techniques and models (classification, NDVI, NDWI/MNDWI, and Image differencing) are available for use in assessing and monitoring environments. It may also advertise that the Landsat datasets (and others) are freely available for use.
- ✓ Be used by the Department of Mining, and the Environment and Conservation of Papua New Guinea to identify the areas of the Ok Tedi catchment needing mitigation and environmental management. One of the mitigation strategies recommended is to introduce the principals of significant environmental benefit (SEB) into the mining regulation and to incorporate environmental impact studies (EIS) to avoid future similar instances in the country.
- ✓ Be used by the government of Papua New Guinea to assess and monitor the environment along the mining operation corridors. This technique can act as a watch dog that assesses and

monitors the environment to ensure the company is operating within the EIS and SEB specifications.

- ✓ Be used by the company, government of Papua New Guinea, and the local communities for environmental damage compensation charges if there are any. The quantified features, such as the vegetation, can be used for evidence if an environmental damage compensation claim is lodged by the local communities. The local communities can also claim the exact compensation values without over or under charging the company or the government.

5.3 Limitations

5.3.1 Cloud and Shadow Covers

Landsat and other satellite images is fast becoming a reliable data source for geospatial analysis (Kennedy et al. 2009, cited in Ma & Xu, 2010, p. 228). Whilst the information generated using remote sensing and GIS approaches has been very useful in decision-making, problem solving and management, satellite images is quite problematic for tropical regions especially the areas where heavy rainfall, thick and continuous cloud and haze cover occurs, and shadows are unavoidable.

The clouds and shadow cover over the study region has influenced the datasets/images for this research. However, dataset images used in this study were relatively cloud free when compared to others in the same years and periods. Despite careful selection, almost all images contained at least some cloud and shadow covers. Furthermore, although cloud-masking technique was applied on each image to eliminate as much as possible the cloud and shadows, the technique happened to also select other features that have similar spectral characteristics. For instance, water bodies were mistaken for shadows, and sand/gravel/dry soils for clouds. As such, not all clouds and shadows were masked out in the image before processing. Therefore, these may have affected the results in minor ways, especially on the locations that were heavily clouded and shadowed.

5.3.2 Interpretation and Analysis

The researcher had difficulties in identifying features on the images, especially the classification and image differencing products, and also difficulty in linking a DN (brightness) value to a class type or a feature in the NDVI or NDWI/MNDWI analysis. As mentioned above, although it is acceptable to analyse the remotely processed results independently, it is also beneficial to have a first-person knowledge of the study region to confirm the features and their brightness values on the images. An approach using ground-truth data and the first-person spatial and temporal data of the study region would give the researcher the benefit of confirming features on the images for better understanding, interpretation and analysis. This research lacks the first-hand knowledge of the study region, and also does not incorporate any ground-truth data for comparison, thus making interpretation and analysis of the results somewhat troublesome and still able to be improved upon in a later study.

5.3.3 Landsat Images as the Datasets

Although the timelines of each mitigation process in relation to how the Ok Tedi mining company controlled the mining wastes and sedimentation levels helped in determining which datasets to use, datasets were primarily limited by the cloud and shadow covers, and the availability of the images. As a result, this study was somewhat restricted in having its earliest dataset starting in 1984. A selection of satellite images taken in the years before the mine production date would have enabled a better understanding of the environmental conditions existing prior to the development of the Ok Tedi mine and would have helped to calculate the natural changes in the features. However, there were no data available from before the 1984 image. Even though MSS 1-5 started operating and making data available from 1972 through to 1987, the region had no Landsat images (datasets) available as per USGS where this study acquired its data.

Much higher spatial resolution images from various sensors on-board EOS are suitable for mapping, assessing and monitoring the extent of the floods and the inundated areas, and even detecting changes. For example, SPOT provides multispectral images with very high (6m) spatial resolution and it can give precise views of the changes of the earth surface features. Therefore, high spatial resolution images would have been beneficial for this study to more accurately identify and analyse the changes. However, very high spatial resolution images, such as from SPOT, is not free and not suitable for large-scale areas. As a result, this research resorted to using Landsat images as they freely available and able to cover large-scale areas. If economics is not a major consideration, Ok Tedi Mining and GoPNG could purchase high spatial resolution images for better and more accurate mapping, assessing and monitoring of the environment, which would enable improved management practices.

5.4 Recommendation for Future Research

This research has identified drastic changes in the environment along the Ok Tedi and Fly River floodplains, which were confirmed as resulting from the effects of the mining wastes. Furthermore, it found that the significant increases and decreases of areas in each of the land surface feature types of water, sedimentation and vegetation are the effect of the mining wastes. However, the cloud cover has greatly influenced the results and analysis. Therefore, it is advisable to conduct a further research using non-optical based satellite images such as SPOT -5/6 that can reduce the impacts of the clouds and shadow covers, hence giving high accuracy and precision in the results. Furthermore, the images can be classified using other image classification methods, such as Object-based classification that can better class and quantify each feature type accurately. It is also recommended that the difficulty in identifying corresponding signatures and image features to real world features can be overcome in the future research if processing the satellite images is followed by field work on location to conduct a ground-truth. This method would allow supervised classification to determine accuracy and minimise errors in the classifications of the remote sensing data.

References

Abrash, A & Kennedy, D 2006, ‘Repressive Mining in West Papua’, In: Evans, GR, Goodman, J & Lansbury (eds), *Moving Mountains: Communities Confront Mining and Globalization*. London: Zed Books, pp. 59-76.

Aalto, R, Lauer, J & Dietrich, WE 2008, 'Spatial and temporal dynamics of sediment accumulation and exchange along Strickland River floodplains (Papua New Guinea) over decadal-to-centennial timescales', *Journal of Geophysical Research: Earth Surface*, vol. 113, no. F1.

Akiwumi, FA & Butler, DR 2008, 'Mining and environmental change in Sierra Leone, West Africa: a remote sensing and hydrogeomorphological study', *Environmental monitoring and assessment*, vol. 142, no. 1-3, pp. 309-18.

Al-doski, J, Mansor, SB & Shafri, HZM 2013, 'Change Detection Process and Techniques', *Change*, vol. 3, no. 10.

Alibrandi, M 2003, *GIS in the Classroom: Using Geographic Information Systems in Social Studies and Environmental Science.[with CD-ROM]*, ERIC.

Alyansa ng mga Grupong Haligi ng Agham at Teknolohiya para sa Mamamayan 2013, 'Environmental Investigation Mission on the Impacts of the Philex Mining Corporation (PMC) Mine Tailings Pond 3 Failure', *TECHNICAL REPORT*.

Aspinall, R & Pearson, D 2000, 'Integrated geographical assessment of environmental condition in water catchments: Linking landscape ecology, environmental modelling and GIS', *Journal of Environmental Management*, vol. 59, no. 4, pp. 299-319.

Baker, EK 1999, 'Sedimentology and the impact of mining in a tidally dominated delta: Fly River, Papua New Guinea', *PhD Thesis*.

Banks, G 2002, 'Mining and the environment in Melanesia: contemporary debates reviewed', *The Contemporary Pacific*, pp. 39-67.

Bell, FG & Donnelly, LJ 2006, *Mining and its Impact on the Environment*, CRC Press.

Blaschke, T 2010, 'Object based image analysis for remote sensing', *ISPRS journal of photogrammetry and remote sensing*, vol. 65, no. 1, pp. 2-16.

Bravante, MA & Holden, WN 2009, 'Going through the motions: the environmental impact assessment of nonferrous metals mining projects in the Philippines', *The Pacific Review*, vol. 22, no. 4, pp. 523-47.

Campbell, JB & Wynne, RH 2011, *Introduction to Remote Sensing*, Guilford Press.

Carli, CD & Lemos, PRd 2015, 'Project optimization', *Rem: Revista Escola de Minas*, vol. 68, no. 1, pp. 97-102.

Carlson, TN & Ripley, DA 1997, 'On the relation between NDVI, fractional vegetation cover, and leaf area index', *Remote Sensing of Environment*, vol. 62, no. 3, pp. 241-52.

Ceccato, P, Connor, S, Jeanne, I & Thomson, M 2005, 'Application of geographical information systems and remote sensing technologies for assessing and monitoring malaria risk', *Parassitologia*, vol. 47, no. 1, pp. 81-96.

Chander, G, Markham, BL & Helder, DL 2009, 'Summary of current radiometric calibration coefficients for Landsat MSS, TM, ETM+, and EO-1 ALI sensors', *Remote Sensing of Environment*, vol. 113, no. 5, pp. 893-903.

Chavez, PS 1996, 'Image-based atmospheric corrections-revisited and improved', *Photogrammetric engineering and remote sensing*, vol. 62, no. 9, pp. 1025-35.

Chen, X, Vierling, L & Deering, D 2005, 'A simple and effective radiometric correction method to improve landscape change detection across sensors and across time', *Remote Sensing of Environment*, vol. 98, no. 1, pp. 63-79.

Chica-Olmo, M, Abarca, F & Rigol, J 2002, 'Development of a decision support system based on remote sensing and GIS techniques for gold-rich area identification in SE Spain', *International Journal of Remote Sensing*, vol. 23, no. 22, pp. 4801-14.

Coumans, C 2002, *Submarine tailings disposal toolkit. Mining Watch Canada & Project Underground*.

Crippen, RE 1990, 'Calculating the vegetation index faster', *Remote Sensing of Environment*, vol. 34, no. 1, pp. 71-3.

CRISP 2001, *What is Remote Sensing?*, viewed 27 August 2016, <http://www.crisp.nus.edu.sg/~research/tutorial/intro.htm>.

Cui, Y & Parker, G 1999, *Sediment transport and deposition in the Ok Tedi-Fly River system, Papua New Guinea: the modeling of 1998-1999*, University of Minnesota, St. Anthony Falls Laboratory.

Day, G, Dietrich, WE, Rowland, JC & Marshall, A 2008, 'The depositional web on the floodplain of the Fly River, Papua New Guinea', *Journal of Geophysical Research: Earth Surface*, vol. 113, no. F1.

Denison, M & Michael, JB 2012, *Environmental Management for Extractives*, EPS-PEAK, UK, viewed 22 November 2016, <https://assets.publishing.service.gov.uk/media/57a08a63e5274a27b2000593/Environmental_management_for_extractives.pdf>.

Department of Water Land and Biodiversity Conservation 2005, *Guidelines for a Native Vegetation Significant Environmental Benefit Policy for the clearance of native vegetation associated with the minerals and petroleum industry, South Australia.*, viewed 12 September 2016, <https://www.environment.sa.gov.au/files/sharedassets/public/native_veg/con-nv-guideline-sebmining.pdf.>.

Dewan, AM & Yamaguchi, Y 2009, 'Using remote sensing and GIS to detect and monitor land use and land cover change in Dhaka Metropolitan of Bangladesh during 1960–2005', *Environmental monitoring and assessment*, vol. 150, no. 1-4, pp. 237-49.

Dhillon, BS 2010, *Mine safety: a modern approach*, Springer Science & Business Media.

Dobrzinski, I 2004, 'Requirements for mineral exploration and mining activities under Native Vegetation Act and Regulations - a summary', *MESA Journal*, vol. 34.

Du, Y, Teillet, PM & Cihlar, J 2002, 'Radiometric normalization of multitemporal high-resolution satellite images with quality control for land cover change detection', *Remote Sensing of Environment*, vol. 82, no. 1, pp. 123-34.

European Commission 2016, *Environment: Mining Wastes*, viewed 10 August 2016, <http://ec.europa.eu/environment/waste/mining/>.

Fay, AH 1947, *A glossary of the mining and mineral industry*, US Government Printing Office.

Ferretti, M 1997, 'Forest health assessment and monitoring–issues for consideration', *Environmental monitoring and assessment*, vol. 48, no. 1, pp. 45-72.

Gao, B-C 1996, 'NDWI—A normalized difference water index for remote sensing of vegetation liquid water from space', *Remote Sensing of Environment*, vol. 58, no. 3, pp. 257-66.

Giri, C, Zhu, Z & Reed, B 2005, 'A comparative analysis of the Global Land Cover 2000 and MODIS land cover data sets', *Remote Sensing of Environment*, vol. 94, no. 1, pp. 123-32.

Gos, S & Rubo, A 2001, 'The relevance of alternative lixiviants with regard to technical aspects, Work safety and environmental safety', *Cyplus. Degussa AG, Hanau, Germany*.

Government of South Australia 2014, *Significant Environmental Benefit (SEB) reforms*, viewed 21 August 2016, <http://www.environment.sa.gov.au/managing-natural-resources/native-vegetation/reforms-under-way/seb-reforms>.

Graham, S 1999, Remote Sensing. *Retrieved from NASA website: http://earthobservatory. nasa. gov/Features/RemoteSensing/remote_08. php*.

Hartman, HL & Mutmansky, JM 2002, *Introductory mining engineering*, John Wiley & Sons.

Hettler, J, Irion, G & Lehmann, B 1997, 'Environmental impact of mining waste disposal on a tropical lowland river system: a case study on the Ok Tedi Mine, Papua New Guinea', *Mineralium Deposita*, vol. 32, no. 3, pp. 280-91.

Hilson, G & Nayee, V 2002, 'Environmental management system implementation in the mining industry: a key to achieving cleaner production', *International journal of mineral processing*, vol. 64, no. 1, pp. 19-41.

Holling, CS 1978, 'Adaptive environmental assessment and management', *Chester, USA, Wiley*.

Huang, C, Thomas, N, Goward, SN, Masek, JG, Zhu, Z, Townshend, JR & Vogelmann, JE 2010, 'Automated masking of cloud and cloud shadow for forest change analysis using Landsat images', *International Journal of Remote Sensing*, vol. 31, no. 20, pp. 5449-64.

Huete, A, Justice, C & Van Leeuwen, W 1999, 'MODIS vegetation index (MOD13)', *Algorithm theoretical basis document*, vol. 3, pp. 213.

Huetet, A, Liu, H, Batchily, KV & Van Leeuwen, W 1999, 'A comparison of vegetation indices over a global set of TM images for EOS-MODIS'. *Remote sensing of environment,* vol. 59, no. 3, pp. 440-451.

Hyndman, D 2001, 'Academic responsibilities and representation of the Ok Tedi crisis in postcolonial Papua New Guinea', *The Contemporary Pacific*, vol. 13, no. 1, pp. 33-54.

Jensen, JR 2005, 'Introductory digital image processing 3rd edition', in *Upper saddle river: Prentice hall*.

Joerin, F, Thériault, M & Musy, A 2001, 'Using GIS and outranking multicriteria analysis for land-use suitability assessment', *International Journal of Geographical information science*, vol. 15, no. 2, pp. 153-74.

Justice, CO, Vermote, E, Townshend, JR, Defries, R, Roy, DP, Hall, DK, Salomonson, VV, Privette, JL, Riggs, G & Strahler, A 1998, 'The Moderate Resolution Imaging Spectroradiometer (MODIS): Land remote sensing for global change research', *IEEE Transactions on Geoscience and Remote Sensing*, vol. 36, no. 4, pp. 1228-49.

Kalikasan PNE 2012, *Walk the talk on punishment of Philex min disaster, DENR told*, viewed 19 August 2016, <http://www.kalikasan.net/press-release/2012/11/28/walk-talk-punishment-philex-mine-disaster-denr-told>.

Karr, JR 1987, 'Biological monitoring and environmental assessment: a conceptual framework', *Environmental Management*, vol. 11, no. 2, pp. 249-56.

Kay, PJ 1995, *PNG's Ok Tedi, Development and Environment*, Department of the Parliamentary Library.

Kennedy, BA 1990, *Surface mining*, SME.

Kirsch, S 2002, 'Anthropology and Advocacy A Case Study of the Campaign against the Ok Tedi Mine', *Critique of Anthropology*, vol. 22, no. 2, pp. 175-200.

Lam, NSn, Quattrochi, D, Qiu, Hl & Zhao, W 1998, 'Environmental assessment and monitoring with image characterization and modeling system using multiscale remote sensing data', *Applied Geographic Studies*, vol. 2, no. 2, pp. 77-93.

Ledin, M & Pedersen, K 1996, 'The environmental impact of mine wastes—roles of microorganisms and their significance in treatment of mine wastes', *Earth-Science Reviews*, vol. 41, no. 1, pp. 67-108.

Lewis, RS 1933, *Elements of mining*, J. Wiley & sons, Incorporated.

Lillesand, TM & Kiefer, RW 1994, 'Remote sensing and photo interpretation', *John Wiley and Sons: New York*, p. 750.

Liu, HQ & Huete, A 1995, 'A feedback based modification of the NDVI to minimize canopy background and atmospheric noise', *IEEE Transactions on Geoscience and Remote Sensing*, vol. 33, no. 2, pp. 457-65.

Lkhasuren, O, Takahashi, K & Dash-Onolt, L 2007, 'Occupational lung diseases and the mining industry in Mongolia', *International journal of occupational and environmental health*, vol. 13, no. 2, pp. 195-201.

Lu, D, Mausel, P, Brondizio, E & Moran, E 2004, 'Change detection techniques', *International Journal of Remote Sensing*, vol. 25, no. 12, pp. 2365-401.

Lu, D, Weng, Q, Moran, E, Li, G & Hetrick, S 2011, *Remote sensing image classification*, CRC Press/Taylor and Francis: Boca Raton, FL, USA.

Lu, S, Wu, B, Yan, N & Wang, H 2011, 'Water body mapping method with HJ-1A/B satellite imagery', *International Journal of Applied Earth Observation and Geoinformation*, vol. 13, no. 3, pp. 428-34.

Ma, Y & Xu, R 2010, 'Remote sensing monitoring and driving force analysis of urban expansion in Guangzhou City, China', *Habitat International*, vol. 34, no. 2, pp. 228-35.

Manning, D 1995, 'Introduction', in *Introduction to Industrial Minerals*, Springer, pp. 1-16.

Manu, A, Twumasi, YA & Coleman, TL 2004, 'Application of remote sensing and GIS technologies to assess the impact of surface mining at Tarkwa, Ghana', in *Geoscience and Remote Sensing Symposium, 2004. IGARSS'04. Proceedings. 2004 IEEE International*, vol. 1.

Marjoribanks, R 2010, *Geological methods in mineral exploration and mining*, Springer Science & Business Media.

Mars, JC & Crowley, JK 2003, 'Mapping mine wastes and analyzing areas affected by selenium-rich water runoff in southeast Idaho using AVIRIS imagery and digital elevation data', *Remote Sensing of Environment*, vol. 84, no. 3, pp. 422-36.

Martinez-Alier, J 2001, 'Mining conflicts, environmental justice, and valuation', *Journal of Hazardous Materials*, vol. 86, no. 1, pp. 153-70.

Mas, J-F 1999, 'Monitoring land-cover changes: a comparison of change detection techniques', *International Journal of Remote Sensing*, vol. 20, no. 1, pp. 139-52.

Masek, JG, Vermote, EF, Saleous, NE, Wolfe, R, Hall, FG, Huemmrich, KF, Gao, F, Kutler, J & Lim, T-K 2006, 'A Landsat surface reflectance dataset for North America, 1990-2000', *IEEE Geoscience and Remote Sensing Letters*, vol. 3, no. 1, pp. 68-72.

Massachusetts Institute of Technology 2016, *Environmental Risks of Mining, viewed* 18 August 2016, <http://web.mit.edu/12.000/www/m2016/finalwebsite/problems/mining.html>.

Matsushita, B, Yang, W, Chen, J, Onda, Y & Qiu, G 2007, 'Sensitivity of the enhanced vegetation index (EVI) and normalized difference vegetation index (NDVI) to topographic effects: a case study in high-density cypress forest', *Sensors*, vol. 7, no. 11, pp. 2636-51.

McFeeters, SK 1996, 'The use of the Normalized Difference Water Index (NDWI) in the delineation of open water features', *International Journal of Remote Sensing*, vol. 17, no. 7, pp. 1425-32.

McKinnon, E 2002, 'The environmental effects of mining waste disposal at Lihir Gold Mine, Papua New Guinea', *Journal of Rural and Remote Environmental Health*, vol. 1, no. 2, pp. 40-50.

Meyer, P, Itten, KI, Kellenberger, T, Sandmeier, S & Sandmeier, R 1993, 'Radiometric corrections of topographically induced effects on Landsat TM data in an alpine environment', *ISPRS journal of photogrammetry and remote sensing*, vol. 48, no. 4, pp. 17-28.

Miller, JR 1997, 'The role of fluvial geomorphic processes in the dispersal of heavy metals from mine sites', *Journal of Geochemical Exploration*, vol. 58, no. 2, pp. 101-18.

NASA 2016, *The Landsat Program*, viewed 20 September 2016, <http://landsat.gsfc.nasa.gov/>.

National Geographic Society 2016, *GIS (geographic information system)*, viewed 27 August 2016, <http://nationalgeographic.org/encyclopedia/geographic-information-system-gis/>.

Natural Resources Canada 2015, *Spatial Resolution, Pixel Size, and Scale*, viewed 24 October 2016, <http://www.nrcan.gc.ca/earth-sciences/geomatics/satellite-imagery-air-photos/satellite-imagery-products/educational-resources/9407>.

Ok Tedi Mining Limited 2014, *Ok Tedi Mining Limited Annual Review 2014*, viewed 15 November 2016, <http://www.oktedi.com/media-items/publications/annual-review/373-2014-annual-review/file>.

OK Tedi past, present & future, Ok Tedi Mining Limited 1999, DVD, Global Vision [distributor], Papua New Guinea.

Okubo, S & Yamatomi, J 2009, 'Underground MINING Methods and Equipment', *Civil Engineering-Volume II*, vol. 2, p. 170.

Paul, J & Campbell, G 2011, 'Investigating rare earth element mine development in EPA region 8 and potential environmental impacts', *A National Service Center for Environmental Publications*.

Paull, D, Banks, G, Ballard, C & Gillieson, D 2006, 'Monitoring the environmental impact of mining in remote locations through remotely sensed data', *Geocarto International*, vol. 21, no. 1, pp. 33-42.

Pickup, G 2003, *Effects of Mine Life Extensions and Rates of Dredging on the Ok Tedi and Fly River. Uncertainty Analysis for the Null Scenario*, viewed 15 November 2016, <http://www.oktedi.com/media-items/reports/environmental/sedimentation/168-uncertainty-analysis-for-the-null-scenario-2003-sediment-transport-modelling>.

—— 2007, *Investigation of Changes in the South Fly from Satellite Imagery and Design of a Sediment Sampling Program*, viewed 15 November 2016, <http://www.oktedi.com/media-items/reports/environmental/sedimentation/169-sedimentation-in-the-fly-river-delta>.

PNG Weather Service, Australian Bureau of Meteorology, & Commonweath Scientific and Industrial Research Organization, 2011. *Current and future climate of Papua New Guinea,* viewed 15/06/2017*,* <http://www.pacificclimatechangescience.org/wp-content/uploads/2013/06/14_PCCSP_PNG_8pp.pdf>.

Richardson, M 2009, 'Principal component analysis', *URL: http://people. maths. ox. ac. uk/richardsonm/SignalProcPCA. pdf (last access: 3.5. 2013). Aleš Hladnik Dr., Ass. Prof., Chair of Information and Graphic Arts Technology, Faculty of Natural Sciences and Engineering, University of Ljubljana, Slovenia ales. hladnik@ ntf. uni-lj. si*.

Robertson, A, Alongi, D, Christoffersen, P, Daniel, P, Dixon, P & Tirendi, F 1990, 'The influence of freshwater and detrital export from the Fly River system on adjacent pelagic and benthic systems', *Australian Institute of Marine Science*.

Rokni, K, Ahmad, A, Selamat, A & Hazini, S 2014, 'Water feature extraction and change detection using multitemporal Landsat imagery', *Remote Sensing*, vol. 6, no. 5, pp. 4173-89.

Rouse, JW, Haas, R, Schell, J & Deering, D 1974, 'Monitoring vegetation systems in the Great Plains with ERTS', *NASA special publication*, vol. 351, p. 309.

Ruhrmann, G & Becker, J 2003, 'Review of the environmental and social policies and practices for mining in Mongolia', *Final report for The World Bank. Rheinbraun Engineering und Wasser GmbH, Cologne, Germany*.

Sabins, FF 1997, 'Remote Sensing — Principles and Interpretation', *W.H. Freeman, New York, NY,* 3rd edn., p. 494.

Salomons, W & Eagle, A 1990, 'Hydrology, sedimentology and the fate and distribution of copper in mine-related discharges in the Fly River system, Papua New Guinea', *Science of the Total Environment*, vol. 97, pp. 315-34.

Sengupta, M 1993, *Environmental impacts of mining monitoring, restoration, and control*, CRC Press.

Shahriar, K, Oraee, K & Bakhtavar, E 2007, 'Effective factors investigation in choice between surface and underground mining', in *VII-th International Scientific Conference SGEM2007*, pp. 04-27.

Shalaby, A & Tateishi, R 2007, 'Remote sensing and GIS for mapping and monitoring land cover and land-use changes in the Northwestern coastal zone of Egypt', *Applied Geography*, vol. 27, no. 1, pp. 28-41.

Shapira, D, Avidan, S & Hel-Or, Y 2013, 'Multiple histogram matching', in *ICIP*, pp. 2269-73.

Sharkhuu, N 2003, 'Recent changes in the permafrost of Mongolia', in *Proceedings of the 8th International Conference on Permafrost, 21-25 July 2003, Zurich, Switzerland*, pp. 1029-34.

Sinding, K 1999, 'Environmental impact assessment and management in the mining industry', in *Natural Resources Forum*, vol. 23, pp. 57-63.

Song, C, Woodcock, CE, Seto, KC, Lenney, MP & Macomber, SA 2001, 'Classification and change detection using Landsat TM data: when and how to correct atmospheric effects?', *Remote Sensing of Environment*, vol. 75, no. 2, pp. 230-44.

Swales, Storey, A, Roderick, I, Figa, B, Bakowa, K & Tenakanai, C 1998, 'Biological monitoring of the impacts of the Ok Tedi copper mine on fish populations in the Fly River system, Papua New Guinea', *Science of the Total Environment*, vol. 214, no. 1, pp. 99-111.

Swales, S, Storey, AW & Bakowa, KA 2000, 'Temporal and spatial variations in fish catches in the Fly River system in Papua New Guinea and the possible effects of the Ok Tedi copper mine', *Environmental Biology of Fishes*, vol. 57, no. 1, pp. 75-95.

Swales, S, Storey, AW, Roderick, ID & Figa, BS 1999, 'Fishes of floodplain habitats of the Fly River system, Papua New Guinea, and changes associated with El Nino droughts and algal blooms', *Environmental Biology of Fishes*, vol. 54, no. 4, pp. 389-404.

Teillet, P, Staenz, K & William, D 1997, 'Effects of spectral, spatial, and radiometric characteristics on remote sensing vegetation indices of forested regions', *Remote Sensing of Environment*, vol. 61, no. 1, pp. 139-49.

Théau, J & Duguay, C 2004, 'Lichen mapping in the summer range of the George River caribou herd using Landsat TM imagery', *Canadian Journal of Remote Sensing*, vol. 30, no. 6, pp. 867-81.

Theler, D & Reynard, E 2008, 'Mapping sediment transfer processes using GIS applications', in *Proceedings of the 6th ICA Mountain Cartography Workshop, Lenk, Switzerland*.

Thrush, PW 1968, 'A Dictionary of Mining, Mineral and Related Terms', *Bureau of Mines (Dept. of Interior), Washington, DC*.

Tiwary, R 2001, 'Environmental impact of coal mining on water regime and its management', *Water, Air, and Soil Pollution*, vol. 132, no. 1-2, pp. 185-99.

Tomlinson, RF 2007, *Thinking about GIS: geographic information system planning for managers*, ESRI, Inc.

Townsend, PA, Helmers, DP, Kingdon, CC, McNeil, BE, de Beurs, KM & Eshleman, KN 2009, 'Changes in the extent of surface mining and reclamation in the Central Appalachians detected using a 1976–2006 Landsat time series', *Remote Sensing of Environment*, vol. 113, no. 1, pp. 62-72.

Townsend, PK & Townsend, WH 2004, 'Assessing an Assessment: The Ok Tedi Mine', *Bridging Scales and Epistemologies: Linking Local Knowledge and Global Science in Multi-Scale Assessments, Alexandria, Egypt*, pp. 17-20.

USGS 2016, *Landsat Processing Details*, viewed 01 September 2016, <https://landsat.usgs.gov/Landsat_Processing_Details.php>.

Whitney, DL & Evans, BW 2010, 'Abbreviations for names of rock-forming minerals', *American mineralogist*, vol. 95, no. 1, p. 185.

Xiao, H & Ji, W 2007, 'Relating landscape characteristics to non-point source pollution in mine waste-located watersheds using geospatial techniques', *Journal of Environmental Management*, vol. 82, no. 1, pp. 111-9.

Xu, H 2002, 'Spatial expansion of urban/town in Fuqing and its driving force analysis', *Remote Sensing Technology and Application*, vol. 17, no. 2, pp. 86-92.

—— 2006, 'Modification of normalised difference water index (NDWI) to enhance open water features in remotely sensed imagery', *International Journal of Remote Sensing*, vol. 27, no. 14, pp. 3025-33.