University of Zimbabwe

Faculty of Engineering

Department of Civil Engineering

Effects of Land use changes on water quality in Eerste River, South Africa

Zine Matshakeni

Msc Thesis in IWRM

Harare , July 2016

FACULTY OF ENGINEERING

DEPARTMENT OF CIVIL ENGINEERING

In collaboration with

EFFECTS OF LAND USE CHANGES ON WATER QUALITY IN EERSTE RIVER, SOUTH AFRICA.

By

Zine Matshakeni

Supervisors

Eng. Zvikomborero Hoko

Mr. Webster Gumindoga

A thesis submitted in partial fulfillment of the requirements for the Master of Science Degree in Integrated Water Resources Management at the University of Zimbabwe

JULY 2016

DECLARATION

I, **Zine Matshakeni**, declare that this research report is my own work. It is being submitted for the Master of Science Degree in Integrated Water Resources Management (IWRM) at the University of Zimbabwe. It has not been submitted for examination before for any degree at any other University.

Date: ____________________

Signature: _____________________

CONTENTS

DECLARATION i
CONTENTS ii
LIST OF FIGURES v
DEDICATIONS viii
ABBREVIATIONS ix
ABSTRACT x
CHAPTER ONE: INTRODUCTION 1
1.1 Background 1
1.2 Problem statement 2
1.3 Justification 2
1.4 Hypothesis 3
1.5. Objectives 3
1.5.1. Main objective 3
1.5.2 Specific Objectives 3
CHAPTER TWO: LITERATURE REVIEW 4
2.2 Water quality parameters 4
2.2.1 pH 4
2.2.2 Electric Conductivity 5
2.2.3 Nitrates 5
2.2.4 Ammonia 5
2.2.5 Phosphate 6
2.2.6 Chemical Oxygen Demand 6
2.2.7 Faecal coliforms 6
2.2.8 Dissolved Oxygen 7
2.3 Assessment of water quality trends 8
2.3.1 Water quality variation 8
2.4 Water quality monitoring system 9
2.5 Effective water monitoring system 9
2.6 Land use effects on water quality 10
2.7 Land use characterisation 11
2.8 Landuse/landcover classification techniques 11

2.9 Satellites for landuse/cover characterisation 12
2.10 The relationship between landuse change and water quality 14
CHAPTER THREE: METHOD AND MATERIAL 17
3.1 General Description of Eerste River 17
3.2 Climate 18
3.3 Soils and geology 18
3.4 Water resources 18
3.5 Vegetation 19
3.6 Land use activities 19
CHAPTER FOUR: STUDY DESIGN 21
4.1 Selection of study site 21
4.2 Sample sites description 21
4.3 Selection of parameters 22
4.4 Data collection methods 23
4.4.1 Primary water quality data collection 23
4.4.2 Obtaining Satellite data 24
4.4.3 Ground control point for accuracy assessment 25
4.4.4 Historical water quality data 25
4.4 Methods data analysis 25
4.4.1 Trend analysis 26
4.4.2 Classification of similar sites 27
4.4.3 Determination of important parameters that affect water quality 27
4.4.4 LULC analysis 27
CHAPTER FIVE: RESULTS AND DISCUSSION 29
5.1 Normality test for Eerste River 29
5.2 Water quality variations 30
5.2 Water quality data collected from February to April 2016 39
5.3 Cluster analysis 41
5.3.1 Classification of similar sampling sites 41
5.4 Principal component analysis 42
5.4.1 Scree plot showing eigenvalues 42
5.5 The spatial and temporal variation of land use/land cover 44
5.5.1 Accuracy assessment 47
5.6 Relationship between land use changes and water quality 47

. CHAPTER SIX: CONCLUSIONS AND RECOMMENDATIONS 50
6.1 CONCLUSIONS...50
6.2 RECOMMENDATIONS 50
REFERENCES 51
APPENDICES 57
Appendix 1: Questionnaire 57

LIST OF FIGURES

Figure 1: Location of the study area 17

Figure 2: Land use map..20

Figure 3: Sampling points in Eerste River 22

Figure 4: Monthly variation of chemical oxygen demand in Eerste River 2009-2016 32

Figure 5: Monthly variation of ammonia in Eerste River 2009-2016 32

Figure 6: Monthly variation of Electric conductivity in Eerste River 2009-2016...................33

Figure 7: Monthly variation of Nitrate in Eerste River 2009-2016 33

Figure 8: Monthly variation of Suspended solids in Eerste River 2009-2016.........................35

Figure 9: Monthly variation of Total Phosphorus in Eerste River in 2009-2016 37

Figure 10: Monthly variation of *Escherichia Coli* in Eerste River 2009-2016 38

Figure 11: Average nitrate concentration in Eerste River Feb-April 2016.............................39

Figure 12: Average turbidity concentration in Eerste River Feb-May 2016 40

Figure 13: Average Nitrogen, Ammonia concentration in Eerste River Feb-May 2016.........40

Figure 14: Dendrogram showing similar samping sites 42

Figure 15: Scree plot with three factors having high contribution 43

Figure 16: Landuse/land cover maps for year 1985-2015 for Eerste River.............................45

Figure 17: Area coverage for land cover classes 45

LIST OF TABLES

Table 1: Stations monitored by city of Cape of Cape Town..21

Table 2: Description of Eerste River sampling points...22

Table 3: Field and laboratory measurements...24

Table 4: Landsat images data...25

Table 5 Testing for normality...29

Table 6: Wilcoxon signed- rank test and t-test for Eerste River..30

Table 7:Trends between 2009 -2016 in Eerste River...31

Table 8: South African water guidelines..39

Table 9: Factors loading of historical data water quality...42

Table 10: water quality comprising of three loading factors...43

Table 11: Contribution of water quality variables (%)...44

Table 12: Area of Landuse/Landcover changes...46

Table 13: Confusion matrix..47

Table 14: Spearman'rho correlations between land use and water quality indicators.............48

ACKNOWLEDGEMENTS

Firstly, I would like to thank God for this opportunity to study IWRM. I would also like to thank Waternet for the sponsoring me. My gratitude goes to my supervisor Eng. Hoko, thank you for your guidance. I would also like to thank my other supervisor Mr. Gumindonga for helping with GIS techniques. I would like to thank Professor Mazvimavi for assisting me during data collection. I would like to thank the following institutions for helping me when I was collecting data and providing historical data: Cape Nature particularly Patrick Shone, and Jonkerhoek Nature Reserve Manager for granting me access to collect water samples. I would like to thank Mr. Humbulani Munzhelele from the City of Cape for completing the questionnaire. I also would like to thank Mr. Wana for helping with the editing of the document. I would like to thank my friends from the University of the Western Cape for supporting me while I was collecting data and my friends from the University of Zimbabwe. Lastly, I would like to thank my family for the love and support.

DEDICATIONS

This study is dedicated to family and friends.

ABBREVIATIONS

ASTER	Advanced Spaceborne Thermal Emission and Reflection Radiometer
CA	Cluster Analysis
COD	Chemical Oxygen Demand
CSIR	Council for Scientific and Industrial Research
DA	Discriminant Analysis
DO	Dissolved Oxygen
EC	Electric Conductivity
GIS	Geographic Information Systems
GDP	Gross Domestic Product
LULC	Land Use/Land Cover
MODIS	Moderate Resolution Imaging Spectroradiameter
NEPAD	New Partnership for Africa's Development
PCA	Principal Component Analysis
SADC	Southern Africa Development Community
SDG	Sustainable Development Goals
SPOT	Satellite Pour l'Observation de la Terra
TM	Thematic Mapper
USGS	U.S. Geological Survey
WWTW	Wastewater Treatment Works

ABSTRACT

Landuse/land cover change is the key factor causing water quality changes worldwide. Stellenbosch town in the Western Cape, South Africa depends on Eerste River water for drinking and irrigation. The water quality of Eerste River downstream of Stellenbosch has been reported to be deteriorating. The main objective of this study was to assess the spatial and temporal variation of water quality due to land use changes in Eerste River. Water samples were collected from 8 selected sampling points on the river during the period 12 February to 1 April 2016. To assess the variation of water quality, temperature, DO, EC, TDS, total phosphorus, nitrogen ammonia, turbidity, salinity, oxidation reduction potential, and chemical oxygen demand were analysed using standard methods. The Principal Component Analysis (PCA) was used to extract the most important factors and physico-chemical parameters affecting water quality while Cluster Analysis (CA) was used to group similar sampling sites. PCA results for historical data, Factor 1 describes 31.4 % total variance with a strong significant loading of ammonia, orthophosphate and total phosphorus CA identified 3 classes from 8 sampling points. Site 1, 2, 3 and 4 formed Group 1; at these sample sites the water is relatively clean and Site 1 and 2 fall within in a protected area. Site 5 and 6 are classified in the same group situated after industries and wineries and site 7 and 8 form group 3 located before and after the wastewater treatment plant. The status of water quality indicates that turbidity, nitrates and nitrogen, ammonia exceed the South African Water Targets from sampling sites. It can be concluded that water quality variation is mainly driven by and nitrates. As such the City of Cape Town which monitors water quality downstream of Stellenbosch should decrease the number of monitoring sites from four to three sampling points. For the year 1985 to 2015, the forest cover has been decreasing from about 15 % to about 10 % and from 2010 to 2015 decline was about 8% to about 2% while there is an increase of settlements from 1985 to 2015 about 38% to 55%. Bareland has been decreasing from 8% to 3%. There is a strong significant correlation ($p<0.05$) between water quality and land use changes.

Keywords*:* Cluster Analysis, Land uses, Principal Component Analysis, Water Quality

CHAPTER ONE: INTRODUCTION

1.1 Background

Approximately 99 % of world waters are described as unfit or unavailable for human consumption (Dabrowski and De Klerk, 2013). The remaining 1 % mostly consists of groundwater and only 0.0067 % of the total fresh water is surface water (Dabrowski and De Klerk, 2013). The water quality is affected by natural and anthropogenic activities globally despite the available usable water. Studies show that natural and human activities affect Landuse and land cover (LULC) changes, resulting in compromise of ecosystem services in rivers (Chu *et al*., 2013). The land use within a watershed has a great impact on the water quality of rivers. Point sources that affect the quality of water include wastewater treatment facilities while non- point sources include runoff from urban areas and farming activities (Chu *et al*., 2013) . Polluting substances that lead to deterioration of water quality affect most freshwater and estuarine ecosystems (Massoud, 2012).

Unsustainable human activities are becoming a key environmental concern as they deteriorate the quality of water in the rivers (Ding *et al*., 2015). Understanding the relationship between landuse and water quality helps in identifying threats to water quality. The relationships are important for effective water quality management such as relevant measures to minimize pollutant loadings (Ding *et al*., 2015). The rate of water quality deterioration is increasing in different regions of the world as a function of rapid demographic growth and socio-economic development (Zeilhofer *et al*., 2006).

Based on the study conducted in Denmark, agriculture was found to be responsible for 65 % to 83 % of yearly riverine total nitrogen transport on the basis of results from monitoring 130 stations (NEPAD, 2006). In Africa, the deterioration of the quality of water resources due to land use changes has been increasing, leading to serious health risks to both humans and the ecosystem (Pullanikkatil *et al*., 2015). A study conducted in Malawi's Likanga River revealed that total coliforms increased by 176 % and *Escherichia coli* (E.coli) counts increased by 157 % downstream of urban areas, these levels being above the permitted local and international standards (Pullanikkatil *et al*., 2015). South African rivers are constantly being degraded by industrial and sewage work effluents, storm water discharges and agricultural runoff (Fourie, 2005). The main water quality problems is salinization and an increase in total dissolved salts (Ogden, 2013). South Africa's natural waters average phosphorous is 0.73 mg/l, whereas the average concentration of chemical oxygen demand is 4.74 mg/l (Oberholster and Ashton, 2008). The values show that South African water resources are enriched considering the water to be moderate to highly eutrophic Plankenburg River which is a tributary of Eerste River flows through Stellenbosch industrial area which includes clothing, cheese and spray paint factory and Khayamandi informal settlements. The study conducted indicated that faecal coliform and E. coli count was about 9.2 x 10^6 (Paulse *et al*., 2009).

1.2 Problem statement

In the Western Cape, approximately 50 % of the rivers have been urbanised and are being affected by effluents (Nel *et al*., 2013)**.** About 42 % of rivers in Cape Town have poor to bad water quality mainly because of urbanisation (Nel *et al*., 2013). Eerste River is mostly urban in character and harbours various activities such as business, administrative, industrial and agricultural activities (Chingombe, 2012). The river currently supplements bulk water supply and water for irrigation to the town of Stellenbosch which is situated in the Western Cape Province, South Africa. Therefore, the quality of its water requires a high degree of protection. Eerste river consists of different land uses indicated to increasingly impact negatively on the quality of its water (Ogden, 2013). Previous studies (Fourie, 2005, Ngwenya, 2006) only assessed the spatial and temporal trends in water quality without explaining the contribution of land use activities to the variation of water quality parameters. This is despite the fact that there has been deterioration of water quality parameters that could be linked to land use activities downstream.

1.3 Justification

Insights gained from the study will be useful for the protection of the Eerste River. The river provides water to Stellenbosch town for domestic and agriculture water use (Ngwenya, 2006). The Stellenbosch Wine Route is situated in the wine-growing region of Stellenbosch (as demarcated by the Wine of Origin Scheme) and comprises 85 % of the vineyards in the region (Kirkman *et al*., 2013). The wine industry contributed R26.2 billion or 2.2 % to the Gross Domestic Product (GDP) in 2008,which confirmed the importance of the wine industry as a creator of employment and generator of household income (Kirkman *et al*., 2013). Also, poor quality water used for urban farming activities may severely compromise food production (Nel *et al*., 2013). Therefore, protection of the water resource will help in boost the economy of the country.

It is important to assess the potential impacts on water quality due to significant land use changes. The major causes and consequences of pollution on water quality in South Africa affect aquatic biota, human health and socio-economic impacts (Mwangi, 2014). Sustainable Development Goals (SDGs) are underpinned by environmental considerations to achieve sustainable development such as environmentally sound waste and chemical management, pollution control, clean technology and environmental education (DEA, 2014). One of the objectives of the South African National Water Act 36 of 1998 is to reduce, and prevent pollution and improving the quality of water needed to protect aquatic ecosystems (Kidd, 2011).

1.4 Hypothesis

Land use changes are significantly related to the deterioration of water quality in Eerste River Catchment.

1.5. Objectives

1.5.1. Main objective

The main objective of this study is to assess the spatial and temporal variation of water quality due to land use changes in Eerste River Catchment to improve management.

1.5.2 Specific Objectives

The specific objectives of the study were:

i. To determine the spatial and temporal variations in water quality parameters
ii. To evaluate the effectiveness of water quality monitoring system in Eerste river.
iii. To determine current land use changes and how they impact on water quality parameters.

CHAPTER TWO: LITERATURE REVIEW

2.1 Global water quality situation

Water quality is becoming a global concern as a result of the important role it plays economically and socially (Du Plessis et al., 2014). Deteriorating water quality has become a global issue of concern as human population grows, industrial and agricultural activities expand, and climate change threatens to cause major alterations to the hydrological cycle (UN-Water, 2011). Water quality issues are complex and diverse and deserving of urgent global attention and action (UN-Water, 2011). Developing countries often have less capacity to improve water quality and depend on lower-quality water for a variety of uses, including drinking water (Zimmerman *et al*., 2008). The water-intensive industrial sectors in China cause abundant water withdrawals and generate large amounts of wastewater at the same time, which potentially contaminate drinking water source (Grady *et al*., 2014). In Malawi, water downstream of industrial practices was shown to be potentially harmful for human consumption (Grady *et al*., 2014). In South Africa, it has been established that freshwater quality of the available sources has declined due to increased pollution caused by industry, urbanisation, mining, and agriculture activities (Musingafi and Tom, 2014).

2.2 Water quality parameters

The selection of water quality assessment parameters depends on the needs and objectives of the assessment (Patil et al., 2012). Primary parameters such as temperature, pH and dissolved oxygen are essential as they influence reactions in water and the later important for sustaining aquatic life (Dladla, 2012). This study considers the following parameters:

2.2.1 pH

The potential of hydrogen (pH) value can be defined as a measure of activity or concentration of the hydrogen ion in the water sample of the solution and is a measure of alkalinity or acidity of the water sample or solution in question. The pH scale ranges from 0 to 14 (Du Plessis 2014). The purity of pure water when it contains no solutes at a temperature of 24^0C is 7.0 (Dallas and Day, 2004). If the measurement is less 7.0 the solution is described as acidic and possesses a high concentration of positive ions. If the value is greater than 7.0 the solution described as alkaline or basic and is characterised by a high concentration of negative hydroxide ions.

Most fresh water in South Africa has a pH value ranging between 6 and 8 (Du Plessis 2014). The pH is considered to be an important water quality parameter as it influences biological and chemical processes within the water body itself and also processes involved in the water treatment and supply. The pH could have human health implication by affecting the taste and through its corrosive effects and chlorination efficiency as well as the solubility of the associated metal ions. Water has a sour taste when the pH is low and a soapy taste when the pH is high.

2.2.2 Electric Conductivity

Electric Conductivity (EC) and Total dissolved solids are used to pinpoint temporal changes in water quality and in variations in TDS namely the number of major ions dissolved in water as well as their effects on taste and freshness of the water (Jakhrani et al., 2012). EC is sensitive to variations that may occur in dissolved solids mostly minerals (Elbag, 2006). The degree to which these dissolved solids dissociate into ions, the amount of electric charge on each ion, ion mobility as well as the temperature of the water body all have an influence on the EC (Hubert and Wolkersdorfer, 2015).

2.2.3 Nitrates

It is considered to be inorganic intermediate product resulting from Oxidation of Ammonia and organic of nitrogen (Du Plessis *et al*., 2014). The natural sources that contribute to nitrates in the water body include the product resulting from oxidation of plants and animals debris, and fragmentation of igneous rocks and surface drainage. A nitrate is described as an essential nutrient for aquatic plant growth and decay. The sources of nitrate causing the contamination of surface water include fertilisers (Du Plessis *et al*., 2014). In order to limit nitrate concentration, good farming management practices need to be in place as well as good methods for applying fertilisers. Many consequences resulting from nitrates deposits in aquatic ecosystems are nutrients enrichment or organic pollution of the water body which stimulates the growth of algae. It is important to constantly measure and monitor the nitrate concentration.

2.2.4 Ammonia

Ammonia is a chemical compound which occurs naturally in water bodies as a result of a breakdown in nitrogenous organic and inorganic matter that is present in soils and water and has its source in excretions by biota (Uriarte *et al*., 2011). Ammonia arises from the reduction of nitrogen gas in water body through microorganisms as well as a gas exchange in the atmosphere. Industrial processes such pulp and paper production increase ammonia concentration as well as municipal waste discharge. Unpolluted water usually has a concentration of less than 0.1 mg/l (Du Plessis 2014). High concentration of ammonia in water bodies are an indication of organic pollution resulting from domestic sewage, industrial waste, and fertiliser runoff from agricultural lands and from fertilisers applied to home lawns and golf courses.

2.2.5 Phosphate

Phosphorus is regarded as a key element in the growth of plants and animals. It occurs in numerous and inorganic forms. Elemental phosphorus does not occur in the natural environment. Phosphate or more specifically orthophosphate are formed from this element and produced through natural processes (Dallas and Day, 2004). They are generally found in sewage or wastewater and only forms soluble inorganic phosphorus and are directly used by aquatic biota. Phosphates have a relationship with soils and sediments and other particulate and are transported with these particles. High concentrations of phosphate accelerate the growth rate of algae, and it indicates pollution. It is important to be well informed about the levels of this water quality parameter in order to monitor algal growth.

2.2.6 Chemical Oxygen Demand

Chemical Oxygen Demand (COD) is the amount of oxygen required to oxidise all organic matter that is susceptible to oxidation by a strong chemical agent such as dichromate (Du Plessis 2014). The water quality parameter is used as an indicating and estimate of the presence of organic matter in the water body. Changes in the COD and colour are stated to be directly associated with inputs of organic matter and nutrients into the water quality. It is important to measure the oxygen demand of the organic compound or mixture. COD described as being non-specific does identify the oxidised material or differentiate between current organic and inorganic material in the water body. COD is stated to be useful variable as it is easily measured in the case of industrial waste (Du Plessis 2014). It is able to measure the susceptibility to oxidation both the organic and inorganic matter present in the water and also effluents form sewage and industrial works.

2.2.7 Faecal coliforms

Faecal coliform bacteria can be described as a collection of relatively harmless micro-organisms that live in large numbers in the intestines of human and other warm blooded animals (McQuaig et al., 2006, Du Plessis et al., 2014). Faecal coliforms are closely related to faecal or sewage pollution and thus are used for assessment of faecal pollution in wastewater and raw water sources (Du Plessis *et al*., 2014). E. coli is the most common member of this group and is used to indicate the presence of human faecal matter and other pathogens that are possibly associated with it. The presence of human faecal matter in water bodies poses significant health risks when the water is used for drinking.

The contamination of water by faecal coliform has its origin in both natural and anthropogenic sources (Du Plessis et al., 2014). When contaminated, water containing faecal coliforms is used for drinking, recreation and for shell fish harvesting adverse health effects can be expected (McQuaig et al., 2006). Non-point agricultural; pollution could contribute to the overall degradation of the water quality by releasing a large amount of faecal bacteria and nutrients which enter waterways (Du Plessis 2014). The presence of high level of faecal coliform is an indication that the water body has been significantly exposed to waste and high levels of various pathogens could be present in water (Paulse et al., 2009). Human waste is the major cause in SADC because it contains parasites and bacteria that could cause diseases (Du Plessis 2014). Faecal contamination is stated to be the primary water quality issues in water bodies especially in developing countries where human waste is not adequately treated.

2.2.8 Dissolved Oxygen

Dissolved Oxygen (DO) is the amount of gaseous oxygen dissolved in aqueous solution. Dissolved Oxygen can be an aqueous solution through atmospheric oxygen mixing into a stream in the turbulent area or through the release of oxygen form aquatic plants during photosynthesis (Dallas and Day, 2004). DO is influenced by natural as well as human factors. Natural factors include aquatic life, elevation, salinity, temperature, turbulence and vegetation (Du Plessis 2014). In the case of elevation, DO will decrease with increasing elevation furthermore water with high salinity content holds less oxygen than freshwater and decrease with rising temperature. Human factors include the clearing of the land as well as the destruction of the riparian area. Activities such as construction and logging are associated with the deposition of excess organic matter into the streams. The more organic waste in a stream the less DO will occur due to micro-organisms (Du Plessis 2014).

2.3 Assessment of water quality trends

Water quality assessment is the complete process of evaluation of the physical, chemical and biological nature of water based on human effects and intended uses (Mwangi, 2014). Water quality assessment includes monitoring trends and to provide the information permitting the establishment of cause-effect relationships (Organization, 2013, WMO, 2013). Moreover, It is stated that trends analysis of water quality data is an important environment diagnosis of the catchment (Zamani *et al.*, 2013). The presence of trends in water chemistry provides an indication of environmental changes and gives awareness of the contributing factors such as changes in land use and management (Zamani et al., 2013).

2.3.1 Water quality variation

Water quality varies in all three proportions that are physical, chemical and biological which are further changed by flow direction and discharge levels (Chang, 2008). Measuring water in one location may require a grid of network of sample site to understand the variations in the water body. Major trends in the water quality are more spatial than temporal (Ngwenya, 2006, Singh and Kumar, 2011).

In China, Xin'anjiang River, a study was conducted to assess temporal and spatial variations in water quality using multivariate statistical methods (Lei, 2013). Cluster Analysis (CA), Discriminant Analysis (DA), correlation analysis and Principal Component Analysis were employed. Based on the hierarchical CA results 12 months were classified into 3 clusters while DA identified three significant parameters (temperature, pH and E.coli) to distinguish temporal groups with close to 76 % correct assignment and Four Principal Component were identifies for the 3 groups identified in CA (Lei, 2013). The total variance of Group 1 was about 68.94 %, Group 2 was 67.48 % and Group 3 was 70.35 % of the total variance. It was concluded that the major sources influencing the river water quality in all three regions were physical parameters, soluble salts, domestic wastewater, agricultural land runoff, and a small amount of industrial waste (Lei, 2013). This study performed PCA and CA for the assessment of variations.

A study was carried out in KwaZulu-Natal, Bonsman Dam assessing effects of farming activities on seasonal variation of water quality (Shabalala *et al.*, 2013). The concentrations of elements such as total dissolved solids, pH and electrical conductivity values, did not exceed water quality targets for domestic, agricultural, livestock and aquatic ecosystem uses

(Shabalala et al., 2013). The inlet streams feeding the dam were established to be eutrophic during the wet season. In conclusion, it was found that analysis of nitrate in the water body of the study area indicated that agricultural applications of manure and fertilisers may be a potential source of nitrate contamination.

2.4 Water quality monitoring system

The aim of water quality monitoring is to acquire quantitative information on the physical, chemical, and biological characteristics of water through statistical sampling (EEA, 2008). The goals vary from revealing of drinking water standard violations to determination of the environmental state and analysis of temporal water quality trends (EEA, 2008). In the evaluation of water quality monitoring programmes, objectives should be clear to create a background for direct monitoring activities (EEA, 2008). For example, in the current study, the interview was conducted as shown in **Error! Reference source not found.** on Eerste River water quality monitoring system main objective of system looks at the "compliance, trend, impact and survey of the catchment condition/ river health against the potential pollutants that can come from runoff, agricultural."

The purpose of monitoring is generally guided by laws or other regulatory actions such as directives, water quality standards, action plans (Parka et al., 2006, EEA, 2008, Rasin and Abdullah, 2009). The regulatory actions set up water quality goals or standards for example 50 per cent reduction of nitrogen loading to surface waters and no pesticides in drinking water (EEA, 2008). It is important to understand that the purpose of monitoring is to supply data and information on the water quality in relation to regulatory actions. In many developing countries, most of the existing monitoring networks reveal deficiencies in terms of providing information required for integrated watershed management (Parka *et al*., 2006). Lack of consistent principles and diverse operations have created various challenges for the management of information on water quality parameters (Parka et al., 2006). Difficulties have also resulted from the vague methodology used in sitting monitoring stations in accordance with scientifically established planning objectives (Ouyang, 2005).

2.5 Effective water monitoring system

It is stated that the authorities still depend on experiential insights and subjective judgments in setting water quality monitoring stations, hence this study suggest the application of GIS for the management of water quality monitoring system (Parka *et al*., 2006). Web- based and GIS technologies can improve the access to and use of water quality data for the monitoring system (Parka et al., 2006). Modernized management of water resources requires a large amount of temporal and spatial information on variations in water quality to control pollution in water bodies (Rasin and Abdullah, 2009). Urbanization and industrialization have been increasing in the Eerste River catchment and water pollution is a threat in most areas. The evaluation of water monitoring system is important because it helps to improve the operations of the system. The results obtained can inform responsible personnel as well as policy makers.

A study was carried out to determine the effectiveness of water quality monitoring system (Ouyang, 2005). The study employed PCA and PFA techniques, the methods aim to reduce the number of variables while trying to preserve the relationships present in the original data (Ouyang, 2005). PCA technique is very valuable in reducing information from large data sets to select long-term monitoring which would greatly reduce the cost of the monitoring program. Forty-two water quality parameters from the 22 stations were examined in this study. The results showed that there was a potential for improving the efficiency and economy of the monitoring network by reducing the number of monitoring stations from 22 to 19 (Ouyang, 2005) and the reduction may result in significant cost savings without sacrificing important surface water quality data.

2.6 Land use effects on water quality

The effects of land use and land cover changes on water quality, associated with human activities and natural factors, are poorly identified because of the lack of information on the temporal and spatial extent of the land cover which affects the quality of water (Chu *et al*., 2013). However, fine resolution satellite images provide opportunities for land cover monitoring and assessment (Chu *et al*., 2013). Land use and land cover changes compromise many ecosystem services in rivers. The water quality of rivers may degrade due to changes in the land cover patterns within the watershed as human activities increase. Changes in the land cover and land management practices have been regarded as the key influencing factors behind the alteration of the hydrological system, which lead to the change in runoff as well as the water quality (Huang *et al*., 2013).

A study conducted on the impact of land use on river systems in Ghana aimed at investigating causes and impacts of land use change within the three river catchments and how these impacts could be reduced to protection river health and sustainable water supply (Ayivor and Gordon, 2012). One major finding was that most of the river basins have undergone a massive transformation over the last three decades as a result of various land use activities (Ayivo and Gordon, 2012). The dominating land use types in the basins include agriculture, urban development, grazing, residential and transportation and fishing. The study also discovered that mining, indiscriminate waste disposal, water extraction and deforestation for fuel wood and other domestic uses, excessive use of chemical fertilizers and land degradation due to improper agricultural practices are also major land use activities that impact negatively on the river systems (Ayivo and Gordon, 2012). It was concluded that there is a need to streamline land use activities, conserve vital ecosystems like watershed areas and maintain buffers along stream channels as a matter of policy to ensure adequate protection of aquatic fauna and to ensure sustainable water supply (Ayivo and Gordon, 2012).

Rizk and Rashed (2015) revealed that landuse/landcover (LULC) change has been reviewed from different perspectives in order to identify the causes of land use/land cover change, their process and consequences. Changes in LULC interact with anthropogenic and natural drivers to affect the water quality of rivers. This study will make use of Geographic Information System (GIS) in the classification of land use changes. Remote sensing technology and GIS provide efficient methods for analysis of land use issues and tools for land use planning and modelling. By understanding the driving forces of land use development in the past, managing the current situation with modern GIS tools, and modelling the future, one is able to develop plans for multiple uses of natural resources and nature conservation (Zamani et al., 2012).

2.7 Land use characterisation

Land use refers to man's activities on land which are directly related to the land use characterisation (Kiran, 2013b). Land use changes also involve the modification, either direct or indirect, of natural habitats and their impact on the ecology of the area. Understanding about existing land use and land cover and its trend of change is crucial for various reasons such as land use planning and management. Moreover, land use data are needed in the analysis of environmental processes and for the improvement of the current state (Kiran, 2013b) .

2.8 Landuse/landcover classification techniques

Remote sensing image classification methods can be divided into unsupervised and supervised (Hasmadi e*t al.,* 2009*).* The unsupervised classification does not need a prior knowledge of the area and while supervised classification needs prior knowledge of the area. In this study supervised classification method was employed because of prior knowledge of the area. Maximum likelihood algorithm was used based on the Bayes theorem making use of a discriminant function of assigning the pixel to the class with the highest likelihood (Ahmad, 2012). Supervised classification increase classification accuracy this is based on the study conducted and results of the study indicated that the overall accuracy for the supervised classification was 90.28 % where Kappa statistics was 0.86, while the unsupervised classification result was 80.56 % accurate with 0.73 Kappa statistics (Hasmadi *et al*., 2009).

2.9 Satellites for landuse/cover characterisation

Images from Google Earth only contain information from three visible bands, its band information is rather coarse and limited compared to the commonly used Landsat and satellite images (Jaafari and Nazarisamani, 2013). Moderate Resolution Imaging Spectroradiameter (MODIS) data is preferred for water analysis because of its daily images, it has all the visible bands in narrow spectral bands and various water parameters can be determined. However, MODIS is costly than other satellites. The aerial photographs image is usually subjected to ‘area’ computation, by utilising the inbuilt ‘polygon’ function to identify the distinct land cover patterns available in the aerial photographs. Polygon representation is vital in characterising land-cover (Jaafari and Nazarisamani, 2013).

Analysis of the images provides lesser efficiency and the results are subject to human error (Attua and Fisher, 2011). The Syste`me Pour l’Observation de la Terre (SPOT), Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER), QuickBird and IKONOS have the potential to improve classification of land-cover attributes (Herold et al., 2002, Houet et al., 2012). In this study, these satellites will not be used because of their relatively high cost.

A study was conducted in Santa Barbara, in California based on seven IKONOS images (Herold et al., 2002). IKONOS is the object-oriented image analysis approach in mapping urban LULC changes. In the study, image processing included geometric and atmospheric correction and image segmentation and classification using the spectral and spatial information to separate 9 land cover classes 79 % overall accuracy was achieved with this approach (Herold *et al*., 2002). The results showed the accurate information about the physical structure of urban areas and their relationship to urban land use and socioeconomic features (Herold *et al*., 2002).

A study was conducted in Turkey, Kahramanmaras in eastern Mediterranean regions (Yüksel *et al*., 2008).The study aimed at performing LULC classification of the study area in the Kahramanmaras province using ASTER sensor imagery. The results indicated that using surface reflectance data of ASTER sensor imagery can provide overall accuracy of 83.2 %. It was concluded that the method used can contribute to the generation of LULC maps for Mediterranean regions in Europe (Yüksel *et al*., 2008).

An additional study was carried out in Pakistan, Swily watershed using multispectral satellite data obtained from Landsat 5 and SPOT 5 for the years 1992 and 2012 respectively to detected LULC changes (Butt *et al*., 2015). The study applied supervised classification-maximum likelihood algorithm in ERDAS. Results indicated a significant shift from vegetation and water cover to agriculture, bare land/rock and settlements cover declined by 38.2 % and 74.3 % respectively. The attained overall accuracy classification was 95.32 % and 95.13 % and it was concluded that LULC practices in the study area have altered significantly in the 20 years (Butt et al., 2015).

The study carried out in South Africa, in Rustenburg City from 2007 to 2012 using temporal imagery acquired by Satellite Pour l'Observation de la Terra (SPOT) 5 satellite aimed at studying the urban spatial growth of Rustenburg City in South Africa (Mudau et al., 2014) . The SPOT 5 images used for the change detection were acquired on 17th April 2012, 27th May 2009 and 18th March 2007. For the purpose of the study, two classes, urban and non-urban were mapped (Mudau *et al*., 2014). Using a post-classification change detection technique, the study showed that there was a significant urban expansion of 11.1km² in Rustenburg which represented 25.5 % growth during a period of five years between 2007 and 2012. The study conducted in Limpopo applied a supervised Maximum Likelihood Classifier (MLC) to SPOT 5 image analysis in a remote savannah biome (Pretorius and Pretorius, 2015). A study by (Pretorius and Pretorius, 2015) found that use of an agricultural mask may be conducive to improved classification and It was concluded that probability thresholds may provide a measure of confidence in the absence of suitable reference data for accuracy assessment.

A study conducted in South Africa aimed at comparing imagery captured in winter and spring to determine which season was better suited for the image classification of bracken fern (Singh *et al*., 2013). Fuzzy classifications were employed to identify bracken fern infestations. The winter and spring classified images produced overall accuracies of 81.4 %

and 94.4 % with Kappa coefficients of 0.63 and 0.89 respectively (Singh *et al*., 2013). These results showed that high resolution satellite imagery in conjunction with fuzzy classification can be used to identify bracken fern and that spring is more suitable for monitoring of bracken fern as compared to winter.

2.10 The relationship between landuse change and water quality

A study was conducted in Taiwan, Tseng-Wen Reservoir aimed to assess the relationship between land cover and observed water quality. Multiple satellite images after typhoon events collected from 2001 to 2010 covering the area and land cover conditions were evaluated by Normalized Difference Vegetation Index (NDVI) (Chu *et al*., 2013). The results indicated that the long-term variations in water quality are explained by NDVI data in the reservoir buffer zones (Chu *et al*., 2013).

Moreover, suspended solid and nitrate concentrations are related to average NDVI values on multiple spatial scales and Annual NO_3-N concentrations are positively correlated with an average NDVI with a 1 km reservoir buffer area, and the SS after typhoon events associated with landslides are negatively correlated with the average NDVI in the entire watershed (Chu *et al*., 2013). It was concluded that landcover change had a significant influence on both suspended solid and nitrate-nitrogen loadings band satellite image data showed a general decline in the acreage of vegetation cover implying increased landslide and decreased forest pressure on the vegetation resources.

An additional study was carried out in Lake Victoria, Kenya comparing land cover changes with water quality (Sweta and Akwany, 2014). Mapping was done to provide the ability to identify turbid and clear water and analysis of Landsat and MERIS images. Vegetation health was analysed over the period selected for investigation 2002-2013. Based on the results chlorophyll concentration in Lake Victoria has increased over time from the year 2002 to the year 2013 (Sweta and Akwany, 2014). It has been confirmed that remote sensing is a useful technique in mapping spatial distribution parameters such as chlorophyll.

A study was carried out in Zimbabwe, Upper Manyame and aimed to assess the relationship between water quality parameters and changes in land use patterns (Kibena *et al*., 2014). Images were classified using supervised classification approach and water quality was assessed through analysis of historical concentration and pollution load (Kibena et al., 2014). Based on the results it was indicated that woodland/forest, grassland and bareland decreased between years 1984 to 2011 by 24.0 %, 22.6 % and 31.7 % respectively (Kibena *et al*., 2014).

It was established that settlements and agricultural areas mainly affect the water quality in Upper Manyame River.

Satellites in water quality monitoring Satellites and sensors for monitoring water quality include Terra and Aqua MODIS with 9, MODIS level 1 and 2 data and level 3 data with 9 km and 4 km spatial resolution. National Polar Partnership (NPP) has a spatial resolution of 375 while Landsat has a resolution of 30-60 m. The satellites measure different parameters for example spectral reflectance, chlorophyll-a concentration, temperature, Colored Dissolved Oxygen Matter (CODM), Turbidity and euphotic depth. Application of remote sensing in water quality indicated to be valuable prospect mostly in Sub Saharan Africa. However, there are limitations that hinder the development of the studies using remote sensing (Dlamini et al., 2016) . The aspects include lack of technical expertise, limited financial resources and lack of accessibility of appropriate remote sensing dataset required for accurate water quality monitoring (Dlamini et al., 2016).

Spatial resolution is based on the geometric properties of the imaging system while spectral resolution refers to the dimension and number of specific wavelength intervals in the electromagnetic spectrum to which a sensor is sensitive (Al-Wassai and Kalyankar, 2013). The radiometric resolution of a remote sensing system is defined as a measure of how many gray levels are measured between pure black and pure white while the temporal resolution refers to the length of time it takes for a satellite to complete one entire orbit cycle (Erener and Düzgün, 2009, Al-Wassai and Kalyankar, 2013).

Higher spectral resolution decreases the SNR of the sensor output. The signal is the information content of the data received from the sensor, while the noise is the unwanted variation that added to the signal. Therefore, a compromise is required between the two in requirements of narrow band (high spectral resolution) and a low SNR (Erener and Düzgün, 2009).

Moreover, a low-quality instrument with a high noise level has a lower radiometric resolution compared with a high-quality, high signal-to-noise-ratio instrument. Also higher radiometric resolution may conflict with data storage and transmission rate (Setiawan and Yoshino, 2012).

The increase in spatial resolution indications an exponential increase in data quantity (which becomes particularly important when multispectral data should be collected (Al-Wassai and

Kalyankar, 2013). Since the amount of data collected by a sensor has to be balanced against the state capacity in transmission rates, archiving and processing capabilities, this leads to the dilemma of limited data volumes. An increase in spatial resolution must, therefore, be compensated by a decrease in other data sensitive parameters, e.g. swath width, spectral and radiometric resolution, observation and data transmission duration (Setiawan and Yoshino, 2012).

CHAPTER THREE: METHOD AND MATERIAL

3.1 General Description of Eerste River

The Eerste River is located in the Western Province of South Africa. The river originates at the Jonkershoek Forest Reserve. It flows in a north westerly direction to Stellenbosch, then south to where it discharges into False Bay at Macassar (Meek *et al*., 2013). In its middle reaches it flows through mainly agricultural land and the town of Stellenbosch towards the confluence with the Kuils River (Ngwenya, 2006, Chingombe, 2012).The Eerste River is approximately 40 km long with a catchment of 420 km² (Chingombe, 2012). The river comprises of a mountain stream zone (Jonkershoek) known as the upper zone which is about 7 km long. The middle zone is from Jonkershoek valley to the confluence with Plankenburg River in Stellenbosch; and the lower zone stretches from Stellenbosch to the estuary at False Bay (Meek et al., 2013). In its lower zone, the Eerste River is joined by the Veldwagters, Blouklip, and Kuils River. The study area map is shown in Figure 1: Location of the study area.

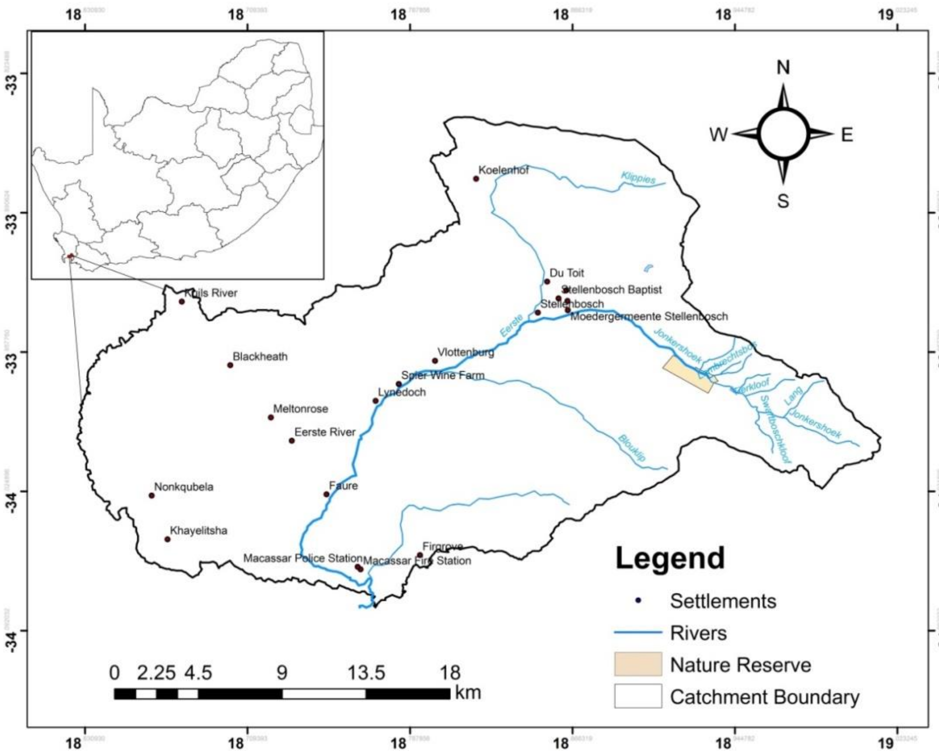

Figure 1: Location of the study area

3.2 Climate

The winter season from June to August in the Western Cape is the rainfall season as is typical of the Mediterranean climate that characterises this province. This results in high flow in the winter season and low flows in the summer season. The south Atlantic anti-cyclones generally influence climate as the catchment falls in the south easterly wind regime (Chingombe, 2012). The summers are dry, warm to very hot with strong south-easterly winds prevailing with daily temperatures reaching 40^{o}C. Winters are wet and cold, often with gale-force north-westerly winds that bring temperatures to as low as 0^{o}C often leaving the high peak valleys inundated with snow (Chingombe, 2012).

Orographic rainfall is the predominant form of precipitation typically due to the mountainous topography (Roe, 2005). About 85 % of the rainfall occurs within six months of the winter period, this is from April to September (Chingombe, 2012). The highest mean monthly precipitation occurs in June as a consequence of cold fronts linked with the tropical cyclones, which traverse the Cape from the Atlantic Ocean. The mean annual rainfall in the Jonkershoek area of the catchment ranges from 1100 mm to 1400 mm, of which most occurs during the winter months (Ngwenya, 2006).

3.3 Soils and geology

The Eerste River Catchment area consists of undulating hills with fertile soils overlying Cape Granite and Malmelsbury shale (Heydorn and Grindley, 1982). The lower reaches of the river lie in the low-lying coastal plain on aeolian sands (Meek *et al*., 2013). While scattered deposits of gravel, sandstones and conglomerates together with the irregular development of silicrete and calcrete occur throughout the area (Heydorn and Grindley, 1982). Catchment geology is known to influence water chemistry in a stream hence it is important to understand the geology of the catchment.

3.4 Water resources

The Kleinplaas Dam which is on the Jonkerhoek tributary regulates the Eerste River flow (Meek et al., 2013). The dam also serves as a balancing and diversion dam in a tunnel transfer system between Theewaterskloof Dam and the Stellenbosch berg tunnel outlet (Meek et al., 2013). During summer months, a municipal weir above Theewaterskloof dam diverts the river's flow to the Ida's Valley Dam, which supplies drinking water and water for domestic use to the town of Stellenbosch (Meek *et al.*, 2013). At the inflow into the dam, water is abstracted and then stored in the two municipal dams in Stellenbosch for the town's water supply. The dam system supplies water to irrigation farmers as well as the City of Cape Town's water treatment works at Blackheath and Faure.

3.5 Vegetation

The upper river reaches are surrounded by natural vegetation within the Hottentots Holland and Jonkershoek Nature Reserves and is relatively unaffected by human influence (Meek et al., 2013). Although forestry plantations of *Pinus radiata* known as pine occur in portions of the landscape in the Jonkershoek Nature Reserve, natural fynbos vegetation has been preserved between the river and plantation areas (Meek *et al*., 2013). Vegetation has an effect on water, particularly when it is being cleared because it makes the soils prone to transportation to the water resources.

3.6 Land use activities

Eerste River consists various land uses in the form of agriculture (vineyards, orchards, crops and pasturing of cattle, sheep and goats), commercial forestry, and communal grazing, as well as domestic use in highly urbanized residential areas. Stellenbosch is the main urban area in the catchment, with additional urban development present in Macassar (Meek *et al*., 2013). Treated municipal effluent from the Stellenbosch Waste Water Treatment Works enters the river through the Veldwagters tributary. There are wineries after the Stellenbosch town which have an effect on the water quality of the river. Agricultural land occupies significant sections of the catchment and all activities related to agriculture are likely to affect water quality. The greater part of the catchment consists of agriculture land.

The river consists of two major towns, Stellenbosch and 'Macassar, along the river with low population density settlements. The sources of pollution have been predominantly from domestic areas resulting from ablution facilities, sanitation, and laundry and dumping on open spaces (Chingombe, 2012). There are also formal settlements with the proper drainage system. Eerste River receives treated municipal effluent (8.4 million cubic metres/ annum) from the Stellenbosch Waste Water Treatment Works through the Veldwagters tributary (Ngwenya, 2006). The treated effluent contributes not only to the changes in water chemistry but also to changes in flow regime in the summer season. Further downstream at Macassar estuary further Eerste river receives treated effluent (13.3 million cubic metres / annum) from the Macassar Waste Water Treatment Works before discharging into False Bay (Ngwenya, 2006). The land use map is shown in Figure 2

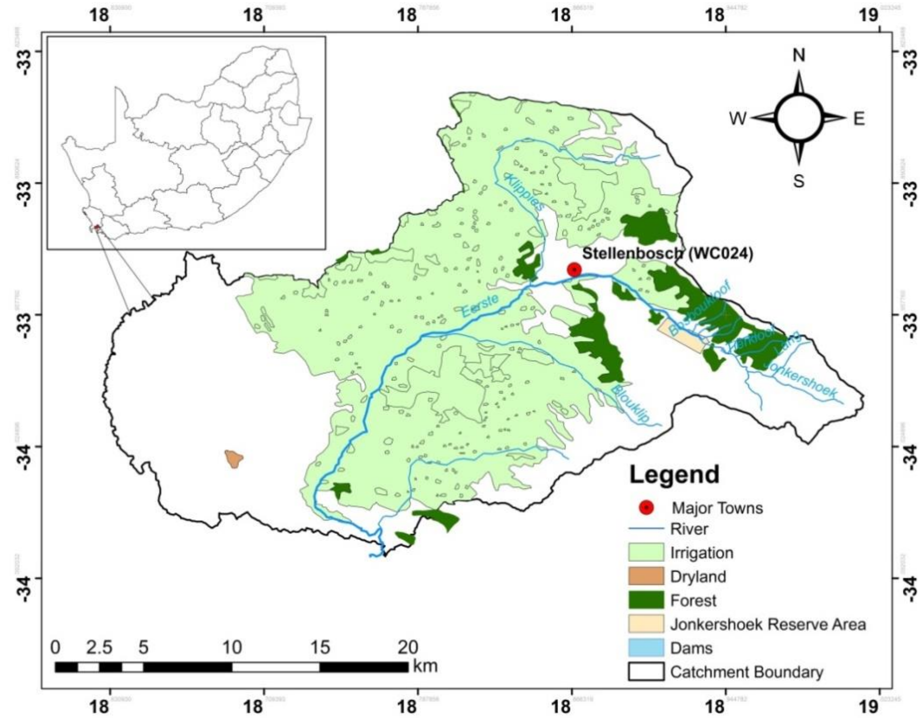

Figure 2: Land use map

CHAPTER FOUR: STUDY DESIGN

The study employed quantitative data collection method.

4.1 Selection of study site

Eerste River Catchment was selected for the study because there is limited information on land uses which might have an effect on water quality. The river supply Stellenbosch Town with drinking water and for irrigation which contributes to the economy of the country (Ngwenya, 2006). The river consists of different land uses that are indicated to progressively impact negatively on the quality of water (Chingombe, 2012).There is a need for an understanding of the effects of land use so as to enhance/strengthen monitoring water resource of the study site.

4.2 Sample sites description

Sampling sites were selected on the basis of different land use patterns and selection was further based on accessibility, safety and nature of the water source of the sampling points. To assess the effects of land uses of water quality, systematic random sampling was applied to the selection of 8 sampling points shown in

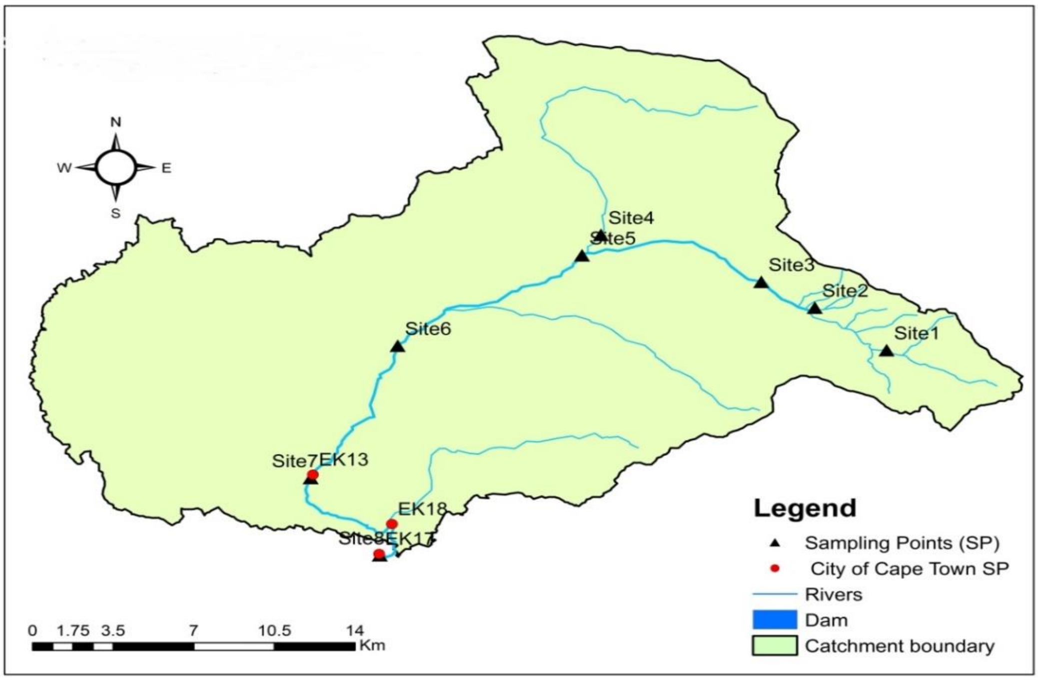

Figure 3.This selection was based on the background knowledge of the study area. For historical data, the study used the sampling sites that are monitored by the City of Cape Town as shown in Table 1.The description of the 8 sampling sites is shown in Table 2.

Table 1: Stations monitored by city of Cape of Cape Town

NAME	DESCRIPTION	LATITUDE	LONGITUDE
EK13	Eerste River on N2 Freeway, upstream of Kuils confluence	-34.043493°	18.737857°
EK15	Kleinvlei canal	34.04405°	18.43463°
EK17	Eerste River estuary downstream of Macassar WWTW	-34.079437°	18.763773°
EK18	Moddergatspruit – (d/s of Macassar Rd)	-34.065917°	18.768758°

Table 2: Description of Eerste River sampling points

Site	Description	Latitude (S)	Longitude (E)
1	Langrivier (wier)	-33.984°	18.967°
2	Bridge After the Dam	-33.967°	18.933°
3	Before Stellenbosch (CBD)	-33.952°	18.917°
4	After Stellenbosch (CBD)	-33.934°	18.85°
5	After Industries and Settlement	-33.934°	18.83°
6	Wineries	-33.983°	18.767°
7	Before Treatment Plant	-34.0434°	18.737°
8	After Macassar WWTW	-34.0794°	18.7637°

Figure 3: Sampling points in Eerste River show sampling points in Eerste River

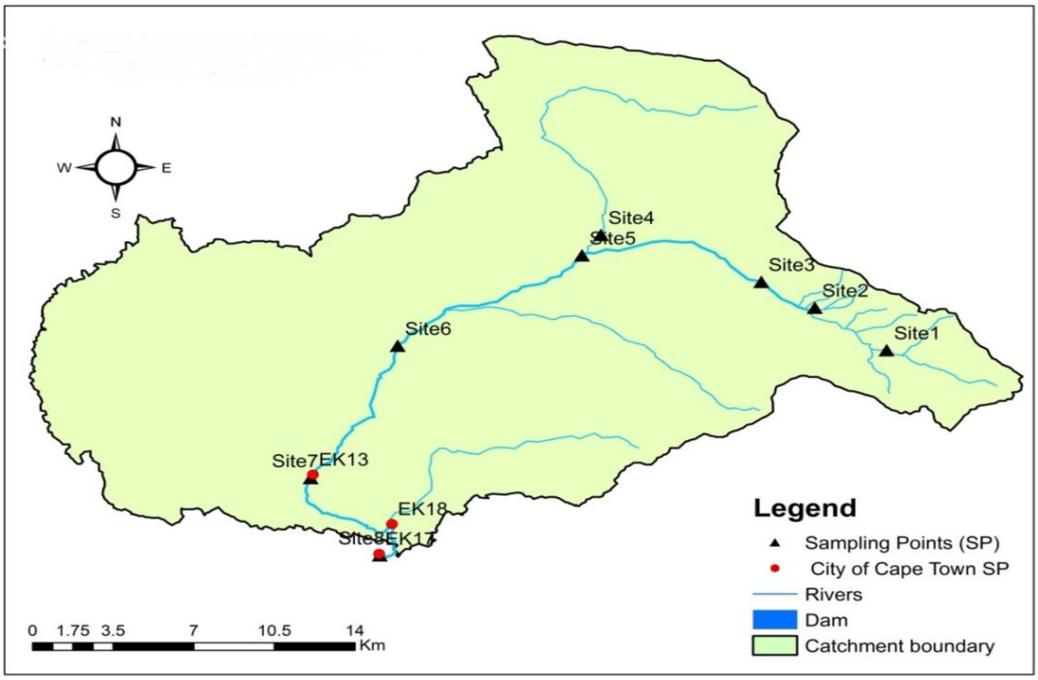

Figure 3: Sampling points in Eerste River

4.3 Selection of parameters

The following physical and chemical parameters were measured from the eight sampling sites namely: pH, temperature, DO, EC, TDS, salinity, nitrates, nitrogen ammonia, turbidity, chemical oxygen demand, suspended solids and total phosphorus. Characteristics of these parameters give either a direct or an indirect indication of the type and occurrence of pollution in water which in turn highlights possible sources of pollution (Kibena, 2012). The parameters also provide an overall view of the health of a river (Fourie, 2005).

Physical parameters often relate to chemical parameters and pH can be affected by chemicals in water. Aquatic species adapts to a specific range of pH and significant change in pH may threaten organism survival (Lei, 2013). The temperature may affect both chemical and biological water features and rate of biological and chemical processes differ with temperature. Dissolved Oxygen is also inversely associated with the temperature of the water (Lei, 2013). High conductivity is a result of high inorganic dissolved solids which can be affected by both natural and anthropogenic factors in the catchment. The high rate of organic matter by biological processes can affect the conductivity of water (Dallas and Day, 2004). Area of high impervious surfaces such as urban areas can yield runoff containing oils that lower the conductivity of nearby surface water. Agriculture and residential areas may raise the conductivity of surface water. The presence of phosphates and nitrates can raise conductivity in the water (Elbag, 2006).

4.4 Data collection methods

4.4.1 Primary water quality data collection

Grab sampling was employed in this study because the catchment is relatively small and there is rapid mixing in the flowing water. Sampling at one depth is generally a representative of the water quality in the sample site. At each site, a water sample was collected in the middle of the river considering the depth and how fast water is flowing, in the middle it is unlikely to disturb the sediments using a sterile white plastic jar of 250 ml (Elbag, 2006). Chemical reactivity varies widely within the same group of materials, depending on the chemical, the physical configuration, and the manufacturing process. The plastic bottle was used for sampling because it is cheaper and it does not change the chemical composition of the sample when preserved.

Before sampling, the container was rinsed three times with the water to be sampled. And then, the container was plunged into the stream and filled up with water. Once filled, the container was tightly closed to prevent air from entering. The samples were transported to the laboratory and kept in the refrigerator at 4°C before analysis because chemical characteristics of the water start to change after sampling from the source; preservation keeps the quality of water sample stable. The samples were collected in February, March and April. This averaged the water quality for the dry and beginning of the wet season in the catchment.

It is more accurate to measure pH, conductivity, DO and EC in-situ other than analysis in the lab. However, the temperature has to be measured in-situ as it changes with time of sampling. To evaluate nutrient (nitrate, nitrogen ammonia) concentrations, water samples were analyzed at the laboratory using DR6000 Benchtop spectrophotometer. It is an instrument that can pass light of a single wavelength through a solution and measure the amount that passes through. The nutrients can be visible through the use of the instrument based on the wavelength. Turbidity was measured using Hach 2100Q turbidity meter. Total phosphorus, Chemical Oxygen demand, Suspended solids were analysed at Council for Scientific and Industrial Research (CSIR) using standard methods. Summary of the field and laboratory measurements are shown in Table 3.

Table 3: Field and laboratory measurements

Parameters	**Units**	**Instrument/Method of determination**
pH		Hach Multi-meter (HQ40d)
Electric Conductivity	µS/cm	Hach Multi-meter (HQ40d)

Turbidity	NTU	Hach 2100Q Turbidity meter (Nephelometric method)
Total Suspended Solids	mg/l	APHA 2540 D, Gravimetric method
Nitrate	mg/l	Cadmium reduction: DR6000 Benchtop spectrophotometer
Ammonia as Nitrogen	mg/l	Nessler method: DR6000 Benchtop spectrophotometer
Total phosphate as Phosphorus	mg/l	DR6000 Benchtop spectrophotometer
Salinity	PPT	YSI 550A
Temperature	^{0}C	Hach Multi-meter (HQ40d)
Dissolved Oxygen (DO)	mg/l	Hach Multi-meter (HQ40d)
Chemical Oxygen Demand (COD)	mg/l	ASS13 Hach method

4.4.2 Obtaining Satellite data

The land use data was obtained from Landsat images because Landsat TM is appropriate for the purpose of this research due to the fact that it is free online and can be downloaded easily. Images covering the study area were acquired from the USGS website http://glovis.usgs.gov. The information about obtaining images is shown in Table 4. Landsat images were used because of their relatively high spatial resolution (30 m) and their wide application for land cover classification across the world (Kibena *et al*. 2014).

Table 4: Landsat images data

Reference year	**Sensor**	**Resolution**	**Date of Acquisition**
1985	Landsat TM	30 m	9 April 1985
1995	Landsat TM	30 m	21 April 1995
2005	Landsat TM	30 m	11 Feb 2005
2010	Landsat TM	30 m	26 April 2011
2011	Landsat TM	30 m	17 April 2011
2013	Landsat TM	30 m	11 April 2013

2015	Landsat 8	30 m	4 April 2016

4.4.3 Ground control point for accuracy assessment

The hand-held Global Positioning system (GPS) was used to validate satellite data. Locations of points for accuracy assessment are determined through the device (Attua and Fisher, 2011, Jaafari and Nazarisamani, 2013, Gopinath et al., 2014). The advantage of GPS is that it gives accuracy in real time or 1 to 3 meter post processing. At times no consistent pattern between the various surfaces can be directly detected due to the complex nature of ground cover, hence the application of Hand held GPS (Gopinath et al., 2014).

4.4.4 Historical water quality data

Water quality data was obtained monthly from the City of Cape Town for the period 2009 - 2016 and this was based on the data available.

4.4 Methods data analysis

The water quality dataset was tested for normality using Shapiro-Wilk test through Statistical package for Social Science (SPSS) and confirmed with XLSTAT 2016 version and gave the similar results. The normality tests are supplementary to the graphical assessment of normality. The main tests for the assessment of normality are Kolmogorov-Smirnov (K-S) test, Lilliefors corrected K-S test, Shapiro-Wilk test, Anderson-Darling test, Cramer-von Mises test, D’Agostino skewness test, Anscombe-Glynn kurtosis test , D’Agostino-Pearson omnibus test, and the Jarque-Bera test (Ghasemi and Zahediasl, 2012).

Among these, K-S is a mostly used test and Shapiro-Wilk tests. The Shapiro-Wilk test is based on the correlation between the data and the corresponding normal scores and provides better power than the K-S test even after the Lilliefors correction (Ghasemi and Zahediasl, 2012). Power is the most frequent measure of the value of a test for normality the ability to detect whether a sample comes from a non-normal distribution. Some researchers recommend the Shapiro-Wilk test as the best choice for testing the normality of data (Ghasemi and Zahediasl, 2012).

Tests such as the coefficient of skewness; the Shapiro-Wilk test (test statistic, W) and the Kolmogorov-Smirnov (test statistic D) are among many that can be used to investigate the probability distribution of the data and thus aid the selection of appropriate trend detection methods, that is, parametric versus non-parametric (Ngwenya, 2006). The sample t-test was performed. It is a technique to compare two or more monitoring sites including one or more water quality parameters (Singh and Kumar, 2011).

The two-tailed Wilcoxon rank sum test was used to determine if the distribution of water quality data was significantly different site types. With statistically testing such as Wilcoxon rank-sum test, differences in water quality data between categories can be statistically significant but not environmentally significant.

Wilcoxon rank test was performed using SPSS version 23. The analysis was carried to determine the significant differences between sampling sites. Moreover, Cluster Analysis (CA) was performed by means of Eclidean distances of wards method to sort variables of sampling points and water quality indicators through XLstat 2016 version. Additionally, Principal Component Analysis (PCA) was executed to identify pollution factors influencing water quality using XLstat 2016. PCA and CA are applied for assessment of water quality (Razmkhah et al., 2010) and evaluation of effectiveness of water quality monitoring system.

4.4.1 Trend analysis

A trend in water quality data is defined as a monotonic change in a particular constituent with time, the causes of which may or may not be known (Ngwenya, 2006). The purpose of trend testing is to investigate whether the measured values of a water quality constituent are increasing or decreasing over time in statistically significant terms (Ngwenya, 2006). To perform a trend analysis, Mann- Kendall test was applied through the use of XLSTAT 2016 version. Quantitative analyses of changes with time or trends were used with the dataset from 2009-2016 at ($p<0.05$). Determination of significant difference in water quality between different sites along Eerste River Statistical analysis was performed for historical data. When data are collected from more than one sampling site within the same area or the same hydrological basin, it is worthwhile to evaluate these trends using non-parametric tests (Shelton, 2013). A general assessment about the presence or absence of trends can be meaningful if trends show precise direction, upward or downward the importance of determining trends assist in cases where there is a need to alter monitoring programme.

4.4.2 Classification of similar sites

Cluster Analysis (CA) is useful in solving classification problems because it groups them such that the degree of association is strong between members of the same cluster (Zhao and Cui, 2009). CA assist in understanding the data and indicates the spatial and temporal patterns (Eneji *et al.,* 2012*)*. In hierarchical clustering, clusters are formed successively by starting with the most similar pair of objects and forming higher clusters step by step (Wang *et al*., 2012) CA was performed on the transformed water quality data sets by means of the Ward's Method using squared Euclidean distance as a measure of similarity (Gibrilla *et al*., 2011). Based on the results, it was possible to design or improve an optimal sampling strategy, which would reduce the number of sampling stations, the frequency of sampling, the number of samples collected and associate costs and also help to understand complex nature of water quality issues and determine priorities to improve water quality.

4.4.3 Determination of important parameters that affect water quality

PCA was carried out to extract the most important factors and physicochemical parameters affecting the water quality and to evaluate the effectiveness of the water quality monitoring system (Lei, 2013). Principal Component Analysis extract the information to some extent and explain the structure of the data in detail, on temporal characteristics by clustering the samples, but it could also describe their different characteristics and help to clarify the relationship between different variables by the variable lines (Vaghefi *et al*., 2012).

4.4.4 LULC analysis

To determine land covers of Eerste River Catchment, Landsat images were used and the supervised classification method was adopted in this research, which is the procedure most frequently used for quantitative analysis of remote sensing data (Kibena, 2012) . Maximum likelihood algorithm was employed to detect the land cover types. Maximum likelihood algorithm was considered because it is most suitable for minimization of classification error (Ahmad, 2012). ArcGIS software was used in the classification of different land uses. Based on the priori knowledge of the study area and additional information from previous research in Eerste River catchment, a classification system concerned with land classes was established for this study area, including forest, cultivation ,irrigation settlement, bareland and the water bodies the description of these land cover classes.

.

CHAPTER FIVE: RESULTS AND DISCUSSION

5.1 Normality test for Eerste River

Table 5 show results for normality test. According to the available literature, assessing the normality assumption should be taken into account for using parametric statistical tests (Ghasemi and Zahediasl, 2012) . It is preferable that normality be assessed both visually and through normality tests, of which the Shapiro-Wilk test, provided by the SPSS software, is highly recommended (Ghasemi and Zahediasl, 2012).

Table 5 Testing for normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Ammonia	.269	242	.000	.668	242	.000
Un-Ionised ammonia	.334	242	.000	.456	242	.000
COD as O	.189	242	.000	.719	242	.000
Conductivity	.364	242	.000	.442	242	.000
Dissolved Oxygen	.157	242	.000	.887	242	.000
Nitrate	.176	242	.000	.815	242	.000
Ortho Phosphate	.229	242	.000	.768	242	.000
Oxygen Saturation	.176	242	.000	.848	242	.000
pH	.501	242	.000	.049	242	.000
Temperature	.098	242	.000	.969	242	.000
Total Phosphorus	.458	242	.000	.056	242	.000
Total Oxidised Nitrogen	.166	242	.000	.798	242	.000
Suspended solids	.352	242	.000	.308	242	.000

Table 5 show results for normality test. According to the available literature, assessing the normality assumption should be taken into account for using parametric statistical tests (Ghasemi and Zahediasl, 2012) . It is preferable that normality be assessed both visually and through normality tests, of which the Shapiro-Wilk test, provided by the SPSS software, is highly recommended (Ghasemi and Zahediasl, 2012).

Table 5, it can be deducted that the dataset is normally distributed because all the water quality parameters have a statistical significance of ($p<0.05$).

Table 6 shows the results for Wilcoxon signed rank test and t-test. The two statistical analysis methods were applied. The t-test is the most widely used statistical test for comparing the means of two independent groups (Kitchen, 2009). This parametric test assumes that the data are distributed normally, that samples from different groups are independent and that the variances between the groups are equal (Kitchen, 2009).

Table 6: Wilcoxon signed- rank test and t-test for Eerste River

Parameter	**Wilcoxon rank test**	**Significance**	**t-test**	**Significance**
Ammonia	0.000	Yes	0.000	Yes
Un-ionised ammonia	0.000	Yes	0.000	Yes
COD as O	0.000	Yes	0.000	Yes
EC	0.000	Yes	0.000	Yes
Dissolved Oxygen	0.000	Yes	0.000	Yes
Nitrate	0.000	Yes	0.000	Yes
Ortho phosphate	0.000	Yes	0.000	Yes
Oxygen Saturation	0.000	Yes	0.000	Yes
pH	0.000	Yes	0.000	Yes
Temperature	0.000	Yes	0.000	Yes
Total Phosphorus	0.000	Yes	0.004	Yes
Total Oxidised Nitrogen	0.000	Yes	0.000	Yes
Suspended solids	0.000	Yes	0.000	Yes

The test shows that for Eerste River, all the water quality parameters are statistically significant ($p < 0.05$). Similarly for the t-test the results indicate statistical significance .In a study conducted by Sharma et al. (2015), the water quality analysis indicated a statistical significance for all the 18 parameters except BOD and pH while t-test about 11 parameters which include pH, BOD, turbidity etc. indicated a statistical insignificance ($p<0.05$).

5.2 Water quality variations

This chapter presents historical data from four monitored stations which comprise of 20 parameters monitored montly over five years (2009-2016). However for the purpose of this study, 9 physical and chemical parameters were selected and 2 microbiological parameters. Data was obtained from City of Cape Town (2009-2016). River flow data was obtained from Department of Water and Sanitation. The primary data was collected from Feb-April 2016 from Eight different sites. Table 7 show Trend analysis with p values from 2009-2016 in Eerste River

In order to detect trend in the water quality data, the following trend hypothesis were stated;

The null hypothesis H0 : There in no trend of a water quality variable with time and in space.

The alternative hypothesis H1: There is significant trend of a water quality with time and in space.

Table 7: Trends between 2009 -2016 in Eerste River.

Sites	NH_4	COD	EC	NH_3	OrthoPhosphate	DO	pH	Temp	TP	SS	DO %	Nitrate
EK 13	0.84	0.00	0.27	0.00	0.16	0.04	0.15	0.24	0.24	0.52	0.00	0.93
EK 15	0.84	0.87	0.59	0.13	0.22	0.20	0.00	0.00	0.78	0.00	0.04	0.21
EK 17	0.00	0.67	0.66	0.33	0.61	0.10	0.00	0.27	0.19	0.35	0.05	0.10
EK 18	0.23	0.96	0.43	0.79	0.20	0.43	0.38	0.50	0.11	0.71	0.50	0.89

Figure 4 indicates chemical oxygen demand concerntration from four different sites in Eerste River for the year 2009-2016. However the important information is based on trend analysis because there can be variations that are not significant.

The Chemical Oxygen Demand (COD) observed range from 0- 200 (mg/L) Kleinvlei Canal (EK 15) has high COD in May of 2009 followed by the river estuary downstream of Macassar WWTW (EK 17) 2010 where the Macassar Wastewater Treatment Plant discharges. Even after 2010, the concentration is higher than the rest of the sampling points mostly in wet seasons. Other sampling points show consistence in the dry and wet seasons throughout the five year period. The trend analysis results indicated that the p value is less than ($p<0.05$) and that means COD at EK 13 is statistically significant.

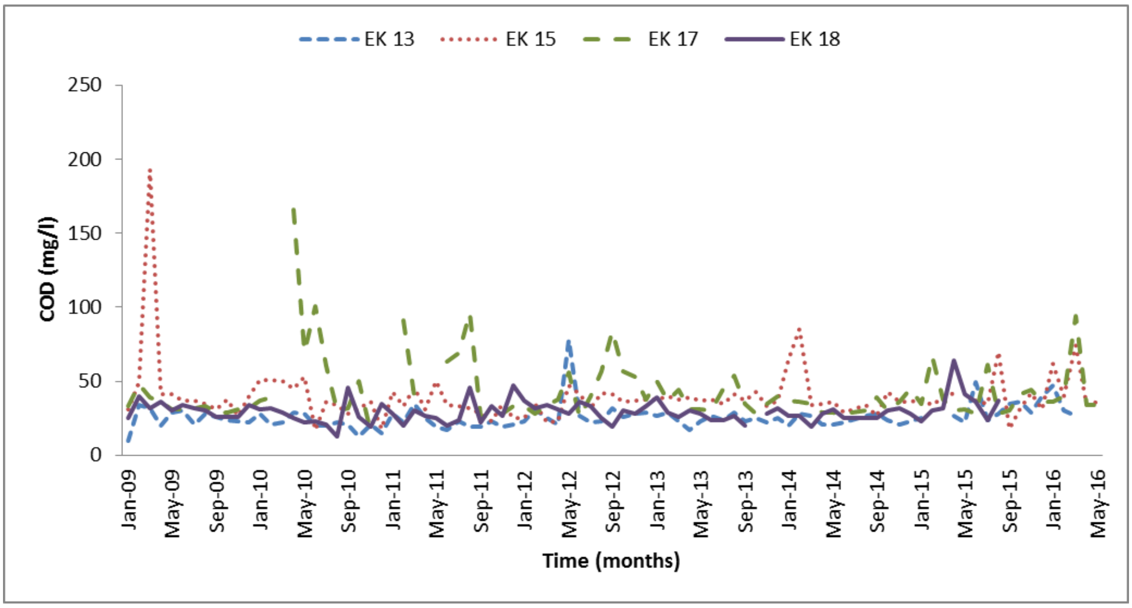

Figure 4: Monthly variation of chemical oxygen demand in Eerste River 2009-2016

Figure 5 indicate ammonia concerntration from four different sites in Eerste River for the year 2009-2016

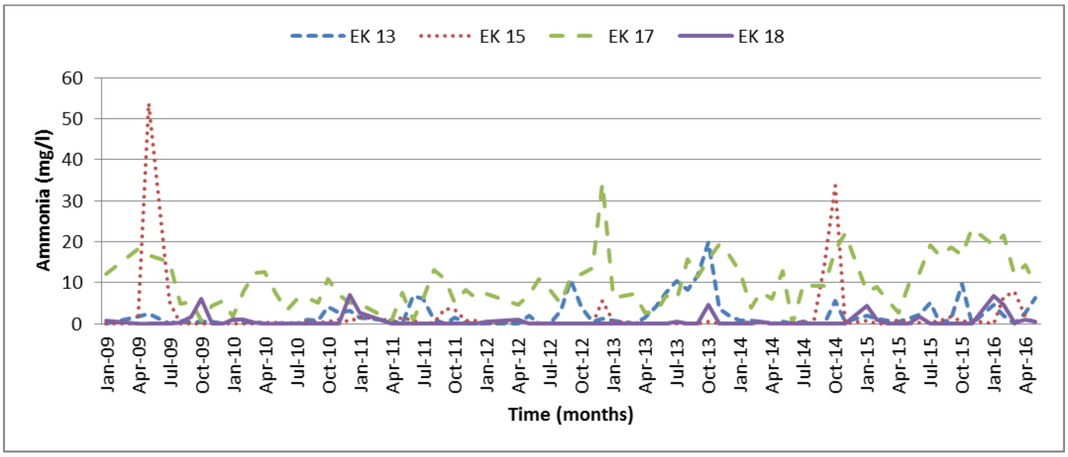

Figure 5: Monthly variation of ammonia in Eerste River 2009-2016

Ammonia concentration observed range from 0-55 (mg/l) and Klein Canal show an abrupt increase during the dry period in 2009 while River estuary downstream of Macassar WWTW shows a consistent variation from the 2009-2013. Eerste River on N2 Freeway, upstream of Kuils confluence (EK 13) and Moddergatspruit – d/s of Macassar (EK 18). Ammonia is a common pollutant generally associated with sewage and industrial effluents and occurs in either free, un-ionized form or as ammonium ions. It has been established that the toxicity of ammonia is directly related to the concentration of the un-ionized form and that the ammonium ion has little or no toxicity (Dallas and Day, 2004). At low to medium pH values, the ammonium ion dominates but as pH increases ammonia is formed, the latter being toxic to aquatic organisms. Ammonia toxicity is also affected by the concentration of dissolved oxygen, carbon dioxide and total dissolved solids. It has been established that ammonia have a significant trend with the p value of 0.0001 in EK 17.

Figure 6 indicates electric conductivity concerntration from four different sites in Eerste River for the year 2009-2016.

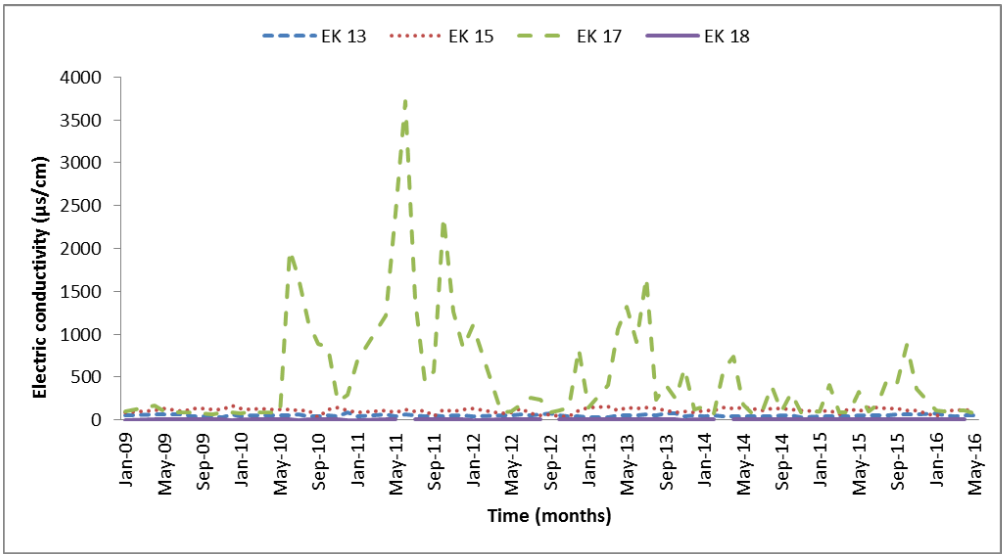

Figure 6: Monthly variation of Electric conductivity in Eerste River 2009-2016

Electric conductivity range from 0-4000 (µs/cm) showing higher variation estuary downstream of Macassar WWTW (EK 17) in the wet period between the year 2010, 2012 and 2013 while other sampling points show constant variation. However, there is no significant trend ($P<0.05$) for EC in any of the sampling points between the year 2009-2016.**Figure 7** show nitrate concerntration from four different sites in Eerste River for the year 2009-2016.

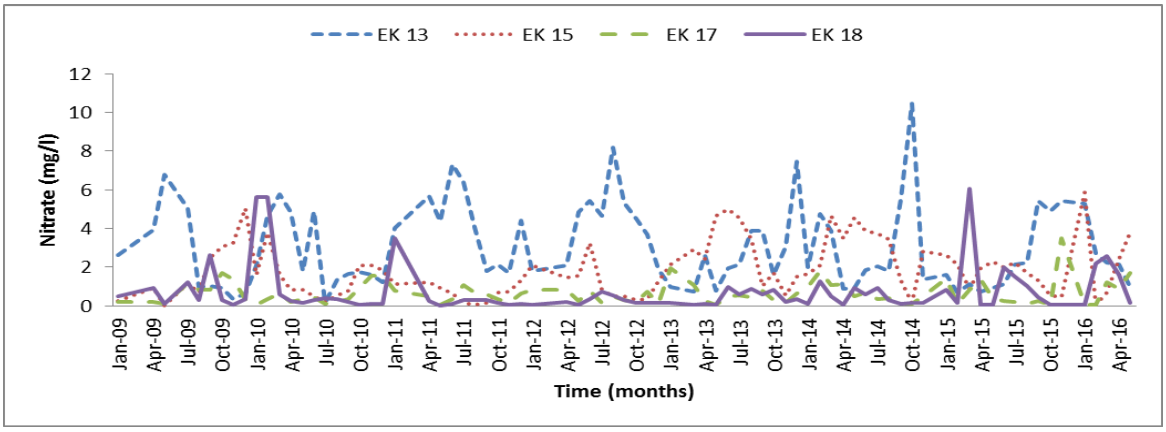

Figure 7: Monthly variation of Nitrate in Eerste River 2009-2016

Nitrate + Nitrate concentration range from 0-9 (mg/L) is highest in Eerste River on N2 Freeway, upstream of Kuils confluence (EK 13) in dry and wet season. Moreover, EK 15 show increased variation between Feb- April of 2010 and 2011. EK 15 show increasing variation in dry period from 2009-2013. Nitrates are the end products of the aerobic stabilization of organic nitrogen and may enter water through the application of fertilizers that are washed into the water bodies. Nitrates are seldom in natural surface waters and are not normally toxic but high concentration can be toxic. Nitrite is naturally occurring anion in fresh and fresh saline water. Anthropogenic activities that increase nitrite concentrations in aquatic environments include the industrial production of metals, dyes and celluloids, sewage effluents and a certain type of aquaculture (Dallas and Day, 2004).

Toxic effects of nitrite are modified by water chemistry particularly chloride concentration. Nitrite toxicity increases as chloride concentration decrease. EK 13 shows a high variation of Nitrate in a dry and wet period. This may be due to agricultural activities that occur in the area which has an impact on the quality of water in the catchment**.** Nutrients are particularly important in surface water, where they are the main contributors to eutrophication, which is the excessive nutrient enrichment of water (Dallas and Day, 2004). Nitrate (NO_3) occurs in the environment from a variety of anthropogenic and natural sources. High nitrate-n values in agricultural areas are expected and are the result of the application of nitrogen fertilizer. It occurs naturally in the environment most often as the result of the oxidation of organic forms of phosphorus; it is found in animal waste and in detergents. Phosphorus contributes to the eutrophication of surface water. Nevertheless, there is no significant trend ($p<0.05$) of nitrate from all the sampling points.

Figure **8** show suspended solids from four different sites in Eerste River for the year 2009-2016.

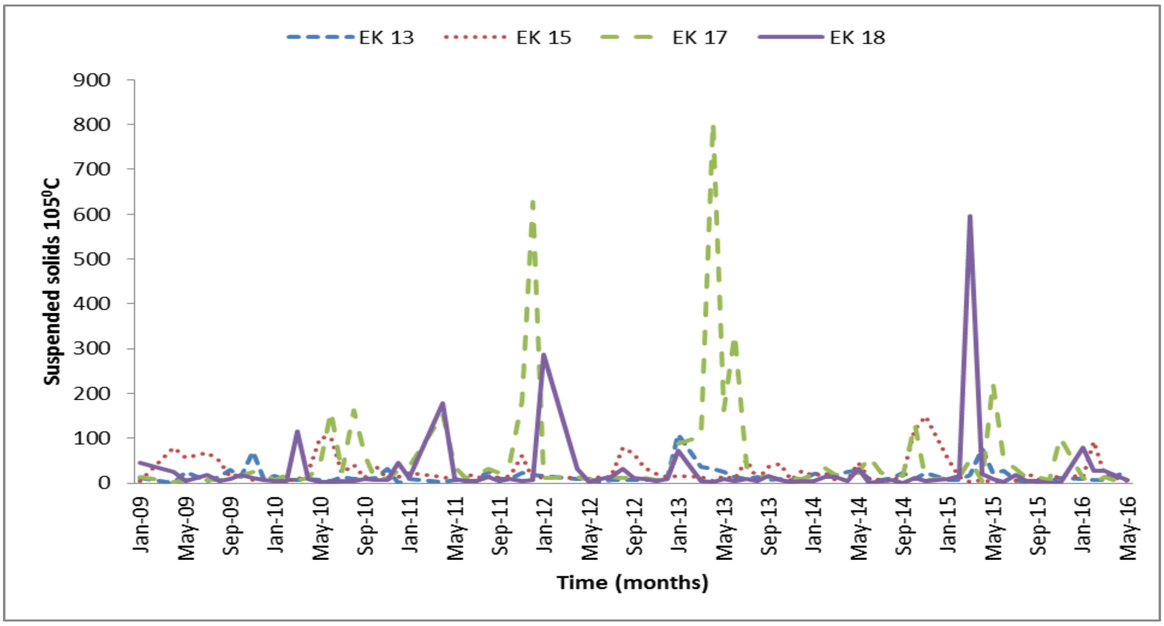

Figure 8: Monthly variation of Suspended solids in Eerste River 2009-2016

Suspended solids at 105^0C range from 0-900 (mg/L), EK 17 has highest Suspended Solids in the dry period between Oct-Dec in 2011 and 2013, while EK 18 show increased Suspended Solids between Feb-April 2011 ,2012 and 2015. There is a high concentration of suspended solids in a dry period in EK 17 and yearly average there is a gradual increase from 2009-2012 and abrupt change decline in 2013. Based on the trend analysis results suspend solids show a significant trend at EK 17. High Total Suspended Solids (TSS) affects the taste and odour of water and in general, levels above 300 mg/L become noticeable to consumers. Total Suspended Solids (TSS), also known as non-filterable residue, are those solids (minerals and organic material) that remain trapped on a 1.2 μm filter. Suspended solids can enter water body through runoff from industrial, urban or agricultural areas (Dallas and Day, 2004). Elevated TSS reduces water clarity, degrade habitats, clog fish gills, decrease photosynthetic activity and cause an increase in water temperatures.

Total Dissolved Solids (TDS) represent the total quantity of dissolved material, organic and organic and ionized and un-ionized in a water sample (Dallas and Day, 2004). Natural TDS in rivers is determined by geological or atmospheric conditions. Anthropogenic activities such as industrial effluents, irrigation, and water re-use lead to increases TDS. There is a high concentration of suspended solids in a dry period in EK 17 and yearly average there is a gradual increase from 2009-2012 and abrupt change decline in 2013.Total Dissolved Solids measures the solids remaining in a water sample filtered through a 1.2 μm Filter. High TDS affects the taste and odour of water and in general, levels above 300 mg/L become noticeable to consumers (Dallas and Day, 2004).TDS increases, the water becomes increasingly unacceptable. Total Suspended Solids (TSS), also known as non-filterable residue, are those solids (minerals and organic material) that remain trapped on a 1.2 μm filter. Suspended solids can enter water body through runoff from industrial, urban or agricultural areas. Elevated TSS reduces water clarity, degrade habitats, clog fish gills, decrease photosynthetic activity and cause an increase in water temperatures.

Total phosphorus range from 0-8 (mg/L) EK 15 and EK 17 showing the highest concentration in dry period Feb-April of 2009. EK 18 show increasing variation in the dry period Feb-April of 2012. Higher concentration of phosphorus likely to occur in waters that receive sewage and leaching or runoff from cultivated land (Dallas and Day, 2004). EK 15 and EK 17 show the highest concentration in dry period Feb-April of 2009. EK 18 shows increased variation in the dry period Feb-April of 2012. Moreover the trend analysis results indicate that there is no significant trend in total phosphorus from all the sampling sites from the year 2009-2016.Total phosphorus is the sum of organic and inorganic forms of phosphorus.

Agricultural and urban areas showed only slightly greater levels, indicating possible non-point source impacts from animal waste in agricultural areas and human waste and phosphatic detergents from sanitary sewer leaks, as well as the application of lawn fertilizer, in urban areas. Total phosphorus range from 0-8 (mg/L) EK 15 and EK 17 showing the highest concentration in dry period Feb-April of 2009. EK 18 show increasing variation in the dry period Feb-April of 2012. Higher concentration of phosphorus likely to occur in waters that receive sewage and leaching or runoff from cultivated land (Dallas and Day, 2004). EK 15 and EK 17 show the highest concentration in dry period Feb-April of 2009. EK 18 shows increased variation in the dry period Feb-April of 2012.

Moreover the trend analysis results indicate that there is no significant trend in total phosphorus from all the sampling sites from the year 2009-2016.Total phosphorus is the sum of organic and inorganic forms of phosphorus. Agricultural and urban areas showed only slightly greater levels, indicating possible non-point source impacts from animal waste in agricultural areas and human waste and phosphatic detergents from sanitary sewer leaks, as well as the application of lawn fertilizer, in urban areas.

Figure 8 show total phosphorus concentration from four different sites in Eerste River for the year 2009-2016.

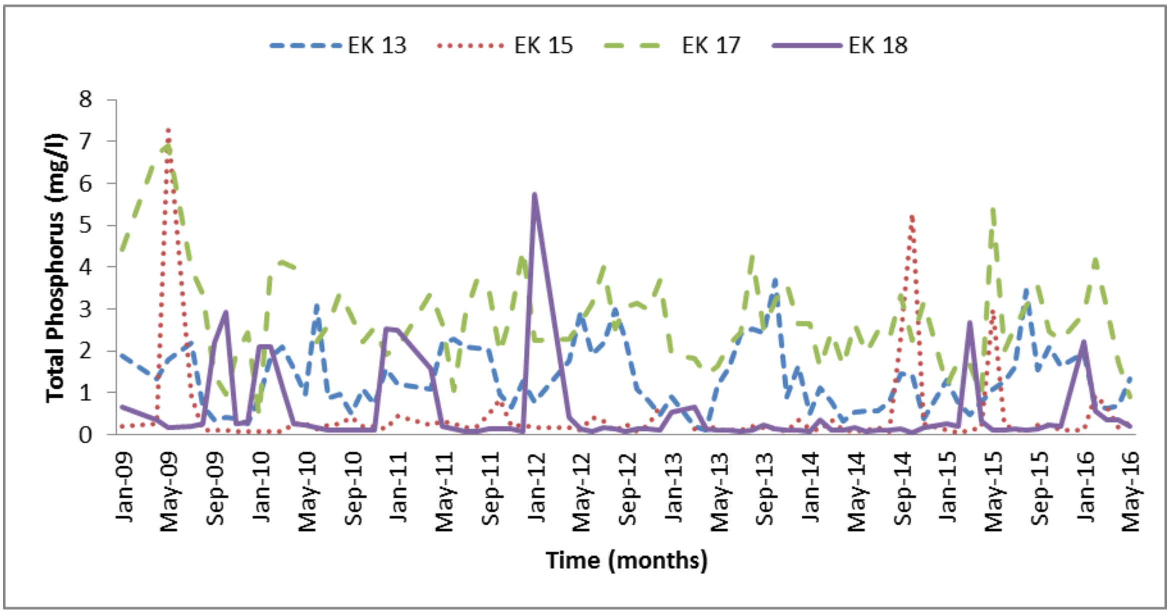

Figure 9: Monthly variation of Total Phosphorus in Eerste River in 2009-2016

Total phosphorus range from 0-8 (mg/L) EK 15 and EK 17 showing the highest concentration in dry period Feb-April of 2009. EK 18 show increasing variation in the dry period Feb-April of 2012. Higher concentration of phosphorus likely to occur in waters that receive sewage and leaching or runoff from cultivated land (Dallas and Day, 2004). EK 15 and EK 17 show the highest concentration in dry period Feb-April of 2009. EK 18 shows increased variation in the dry period Feb-April of 2012. Moreover the trend analysis results indicate that there is no significant trend in total phosphorus from all the sampling sites from the year 2009-2016.Total phosphorus is the sum of organic and inorganic forms of phosphorus. Agricultural and urban areas showed only slightly greater levels, indicating possible non-point source impacts from animal waste in agricultural areas and human waste and phosphatic detergents from sanitary sewer leaks, as well as the application of lawn fertilizer, in urban areas.

According to the study by Li et al. (2009), it is stated that nutrients in a river mostly originate from industrial and municipal wastewater, runoff from urban and agricultural areas, mining practices, septic tanks and atmospheric deposition via rainfall. Natural factors, such as weathering of the rock and natural runoff of the drainage basin, endorse indication of spatial variation nutrients in streams (Li et al., 2009). Moreover anthropogenic influences such agricultural runoff, urban domestics and industrial effluents also contribute to nutrient loading in the water (Li et al., 2009). A spatial variation of nutrients is influenced land use practices and urban development, higher nitrogen and phosphorus concentrations usually occur in areas of urban and agricultural activities (Li *et al*., 2009).

The presence of large amounts of total coliform bacteria may indicate the presence of other bacteria species that are pathogenic (Christensen *et al*., 2001). The table below show E.coli from four sampling points for the year 2009-2016.

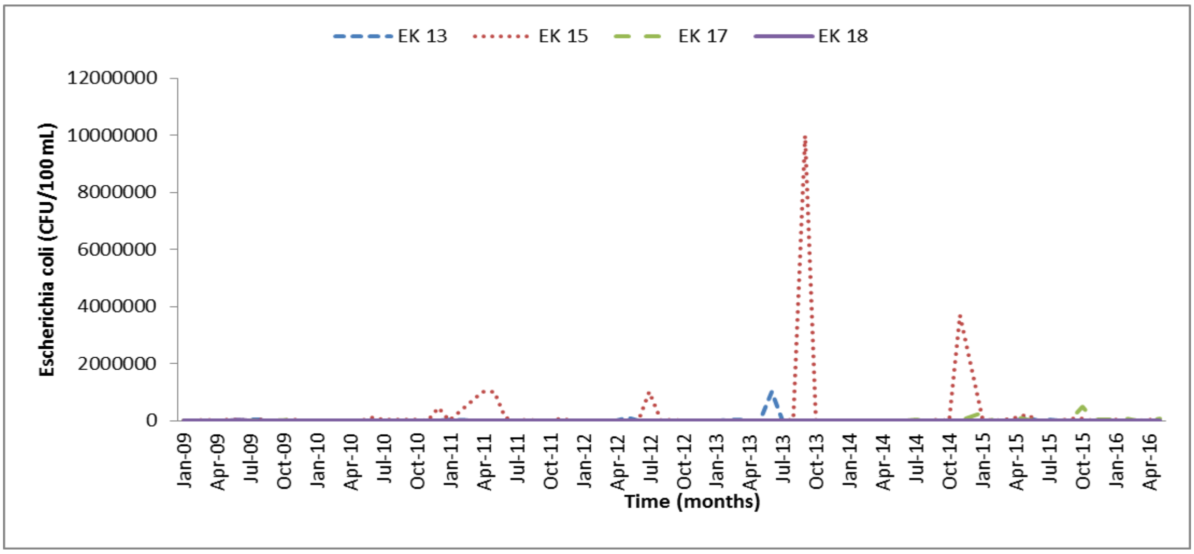

Figure 10: Monthly variation of *Escherichia Coli* in Eerste River 2009-2016

Escherichia Coli ranges from 100000-500000 (CFU/100 mL), EK 15 showing the highest variation between November to December in a dry period while the other sampling points show constant variation.

Table 8 consists of South African different water quality targets ranges for different water uses. In this particular study, the water quality targets were compared with primary data in 2016 in the Eerste River. It was observed that site 3 and site 6 exceeded water quality targets for agriculture and recreation. Site 2 exceeded turbidity guidelines for agriculture and recreation

Table 8: South African water guidelines

Sampling campaigns	Nitrate	Turbidity	pH	Nitrogen ammonia
1	0.98	-	6.5	0.51
2	0.66	12.8	7.7	1.77
3	0.78	24.8	7.6	5.1
4	0.18	8.9	7.6	0.65
SA Water Guidelines (Recreation and Agriculture)	0-0.5	50	6.5-8.4	5
Exceedance	100	0	0	20

5.2 Water quality data collected from February to April 2016

Figure 11 presents water quality data collected in 2016. The data was collected from February to April 2016 and the same months were used for plotting the graphs.

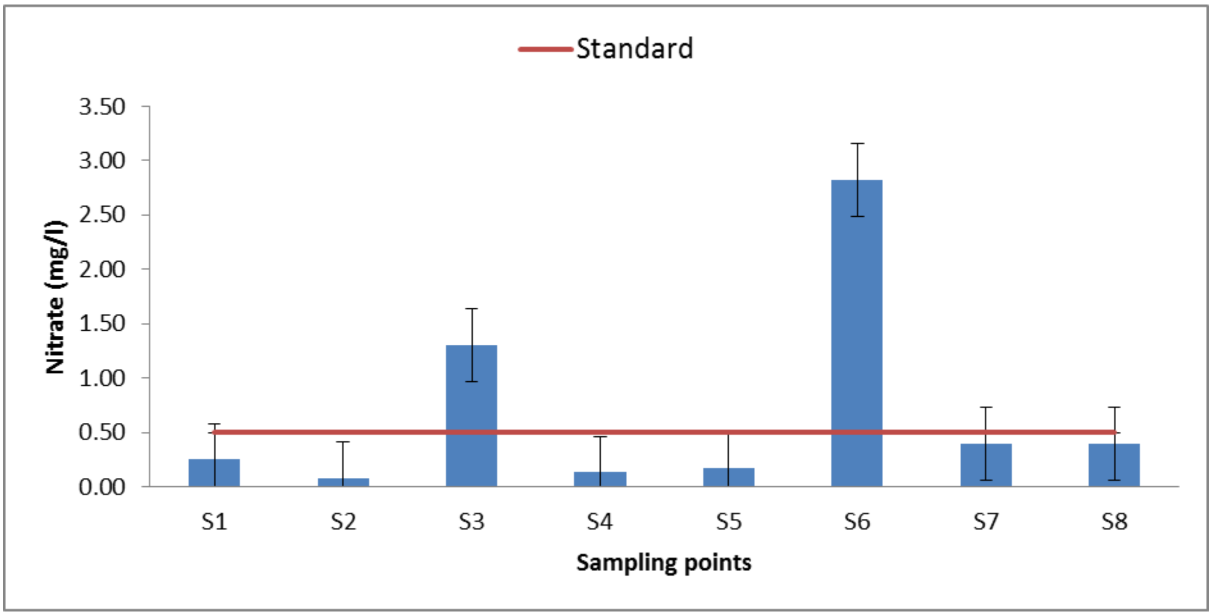

Figure 11: Average nitrate concentration in Eerste River Feb-April 2016

Figure 11 shows that the nitrate concentration within the sampling sites is below South African standards except for site 3 and site 6.

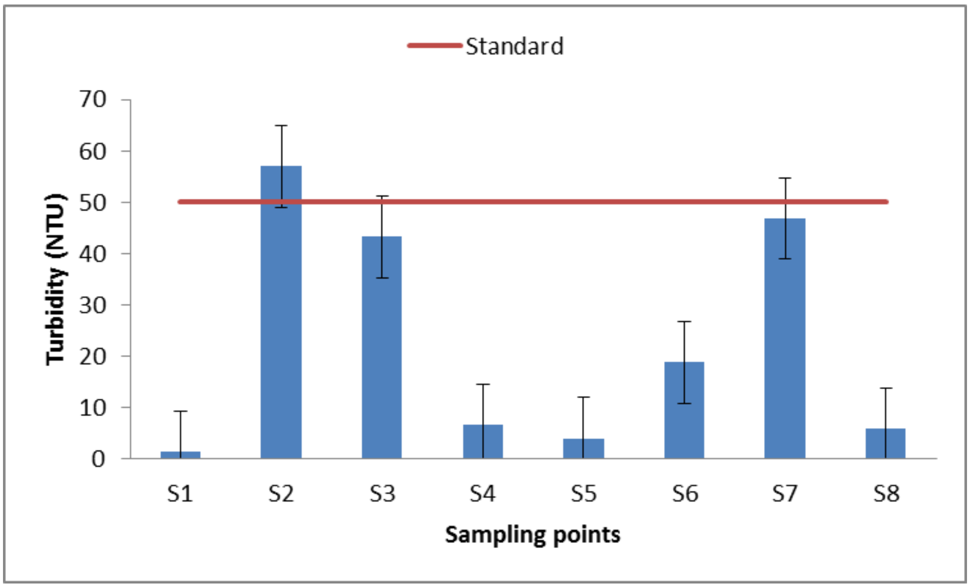

Figure 12: Average turbidity concentration in Eerste River Feb-May 2016

Figure 12 shows that the turbidity concentration within the sampling sites is high, particularly on site 2, Site 3 and Site 7. However, only site 6 exceeded the guidelines. The City of Cape could add a sampling point to monitor upstream.

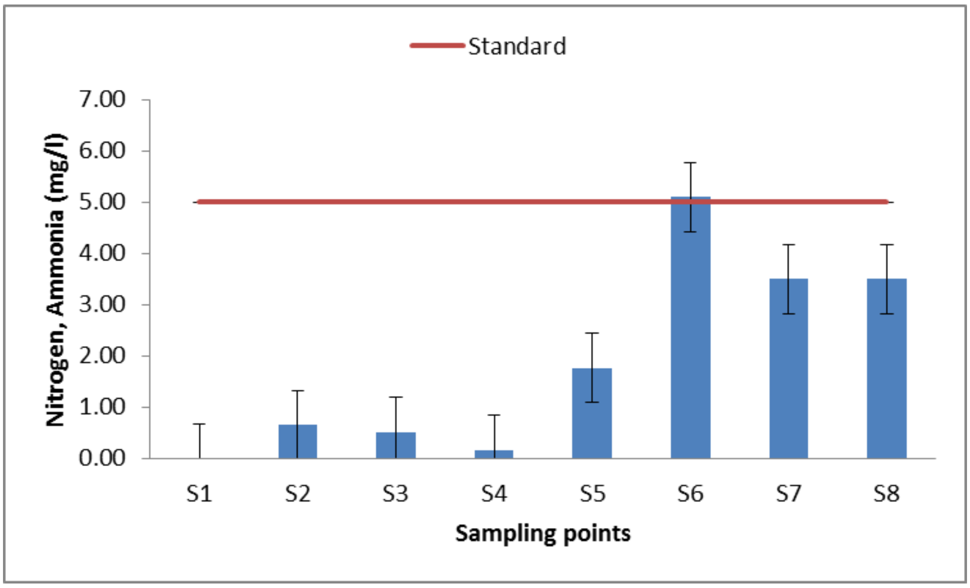

Figure 13: Average Nitrogen, Ammonia concentration in Eerste River Feb-May 2016

As illustrated on Figure 13, the nitrogen, ammonia is increasing from site 5. However, site 6 exceeded the South African guides. The site is situated in the wineries and it shows that fertilisers affect water quality.

5.3 Cluster analysis

5.3.1 Classification of similar sampling sites

In the study, CA showed strong spatial and temporal association on the basis of variations of principal pollution factors and indicated that the effects of human activities on water quality vary spatially as well as temporally. The dendrogram indicates pollution status as well as the effect of contamination at the sampling sites. It provides a visual summary of the clustering processes, presenting a picture of the groups and their proximity as shown in Figure 14. CA is an unsupervised pattern recognition technique that uncovers intrinsic structures in order to group objects into clusters, which once grouped, should exhibit internal (within cluster) homogeneity and external (between clusters) heterogeneity based on their proximity or similarity (Sayadi et al., 2014). Hierarchical agglomerative cluster analysis is the most common approach that naturally provides similar relationships between each sample and the entire data set (Al-Badaii et al., 2013). In this study, hierarchical agglomerative cluster analysis was performed on the standardized data set by Ward's Method, using squared Euclidean distances to measure similarity.

CA was used to detect similarities between the eight sampling sites in a dry period. CA generated a dendrogram, grouping the sampling sites on the basis of similarity of water quality parameters. CA produced a dendrogram, which grouped the eight sites into three clusters as shown in Figure 14. Sites affected by similar sources were classified into groups. Site 1, 2, 3 and 4 formed Group 1; form these sample sites the water is relatively clean and Site 1 and 2 fall within in a protected area. Site 5 and 6 are classified in the same group. The sites are situated around wineries, settlements and industries and are moderately polluted while site 7 and 8 form group 3 before and after the WWTW which is highly polluted.CA gives an overview of the problem and helps to classify and better explain PCA results (Al-Badaii et al., 2013, Razmkhah et al., 2010).

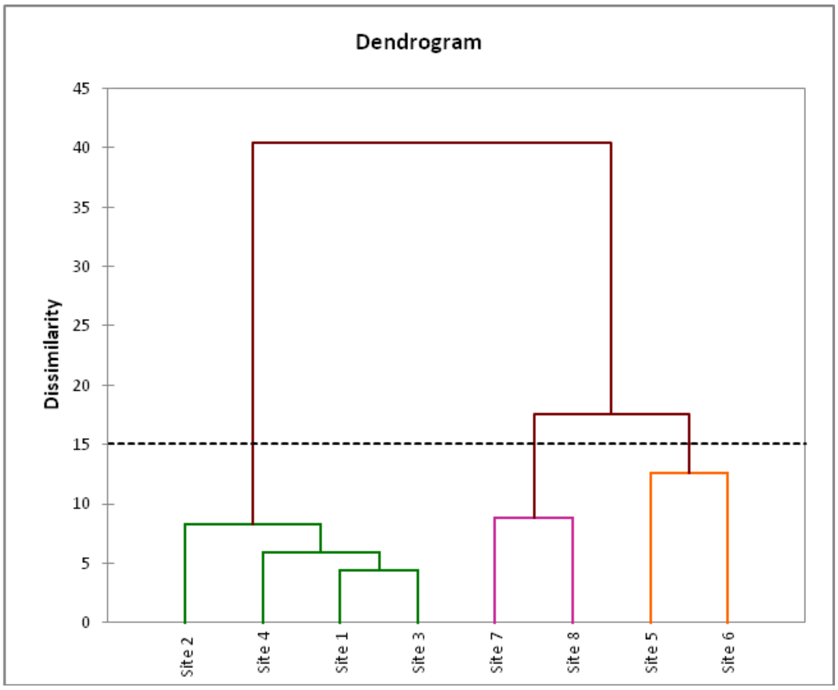

Figure 14: Dendrogram showing similar samping sites

5.4 Principal component analysis

PCA results include the (factor loadings, eigenvalue, and variance contribution rate of each PC and the cumulative variance contribution rate) scree plot, and bi-plot diagram are presented in Table 5.5 below. PCA was first performed in this study to identify the potential for reducing the number of monitored parameters. Table 9 shows factor loading for water quality parameters with eigenvalue variability and cumulative %.

Table 9: Factors loading of historical data water quality

	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12
Eigenvalue	3.778	2.934	1.520	0.984	0.729	0.680	0.512	0.341	0.267	0.186	0.062	0.006
Variability (%)	31.48	24.45	12.66	8.200	6.078	5.669	4.268	2.839	2.222	1.547	0.517	0.051
Cumulative %	31.48	55.93	68.60	76.80	82.88	88.55	92.82	95.66	97.88	99.43	99.94	100.0

5.4.1 Scree plot showing eigenvalues

The scree plot show factors that have high eigenvalues as show from Figure 15 there are three factors that have the eigenvalues greater than 1

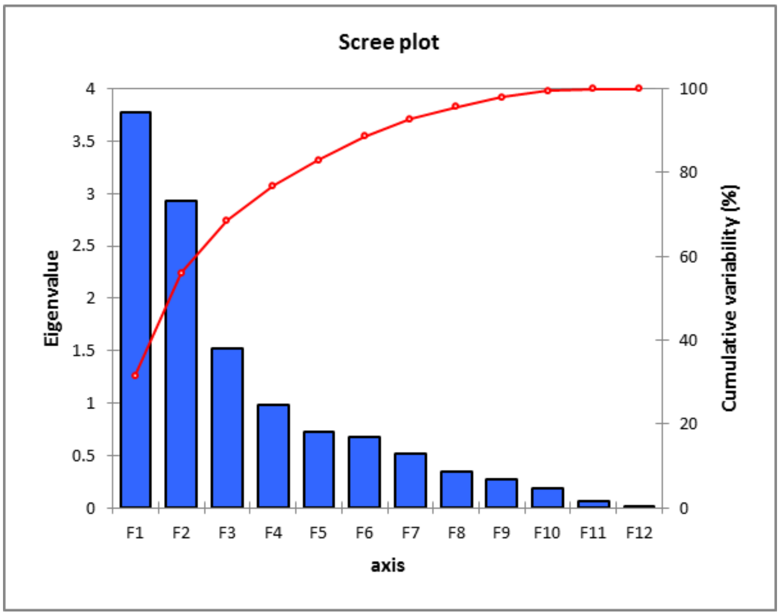

Figure 15: Scree plot with three factors having high contribution

The scree plot was used to identify the number of PCs in the monthly data collected from 2009-2016. Figure 15 shows a distinct change of slope after the 7th eigenvalue but explaining 4.7 % of the total variance of 68.35 %. Three factors were retained. The significance of factor is determined by the eigenvalue (Mustapha and Nabegu, 2011). The eigenvalues of 1.0 or larger are signification. Factor loadings were classified to strong, moderate and based on loading values of greater than 0.75, 0.75-0.50 and 0.50-0.30 (Al-Badaii et al., 2013). Table 10 indicate factor loading with eigenvalues that are greater than 1 and this also indicate correlation from three principal factors.

Table 10: water quality comprising of three loading factors

	F1	F2	F3
Ammonia	0.853	0.245	-0.170
Un-Ionised Ammonia	0.592	0.545	0.017
COD as O	0.481	0.532	0.335
Conductivity	0.299	0.336	0.497
Dissolved Oxygen	-0.592	0.691	-0.112
Nitrate+ Nitrite	-0.146	-0.223	-0.585
Ortho Phosphate	0.846	0.064	-0.363
Oxygen Saturation	-0.560	0.755	-0.155
pH	-0.373	0.796	-0.006
Temperature	0.069	0.648	-0.435
Total Phosphorus	0.896	0.096	-0.210
Suspended Solids	0.177	0.131	0.623

Contribution of variables in Table 11 illustrates the factors that have the highest contribution which can help in identifying parameters that can be reduced in a monitoring system.

Table 11: Contribution of water quality variables (%).

	F1	F2	F3
Ammonia	19.245	2.041	1.902
Un-Ionised Ammonia	9.281	10.109	0.019
COD as O	6.120	9.634	7.360
Conductivity	2.367	3.850	16.257
Dissolved Oxygen	9.263	16.290	0.823
Nitrate+ Nitrite	0.566	1.698	22.476
Ortho Phosphate	18.945	0.141	8.662
Oxygen Saturation	8.296	19.406	1.578
pH	3.688	21.602	0.002
Temperature	0.126	14.330	12.469
Total Phosphorus	21.271	0.316	2.900
Suspended Solids	0.830	0.583	25.551

Factor 1 describes 31.4 % total variance with a strong significant loading of ammonia, orthophosphate and total phosphorus. The variables mentioned are associated agricultural activities (Sayadi et al., 2014). Un-Ionised Ammonia has a moderate significant loading. This is because the sites are surrounded by agricultural area in the study site. Factor 2 explains 24.45 % pH and oxygen saturation have a strong significant loading while DO, Ammonia, COD and temperature have a moderate significant loading. Factor 3 explains 12.66 % has a moderate strong significant loading of suspended solid that would indicate agricultural activities (Sedibe et al., 2013).

5.5 The spatial and temporal variation of land use/land cover

The images were classified under supervised classification for the following years: (1985, 1995, 2005, 2010 and 2015 for the months between Dec-March for the dry season and the months were selected based on primary data collection months and the download of the images was based on low cloud cover. Thematic maps are shown in Figure 16 with six Land cover classes namely settlements, cultivation, irrigation, bareland, forest and shrubs and water and marshy.

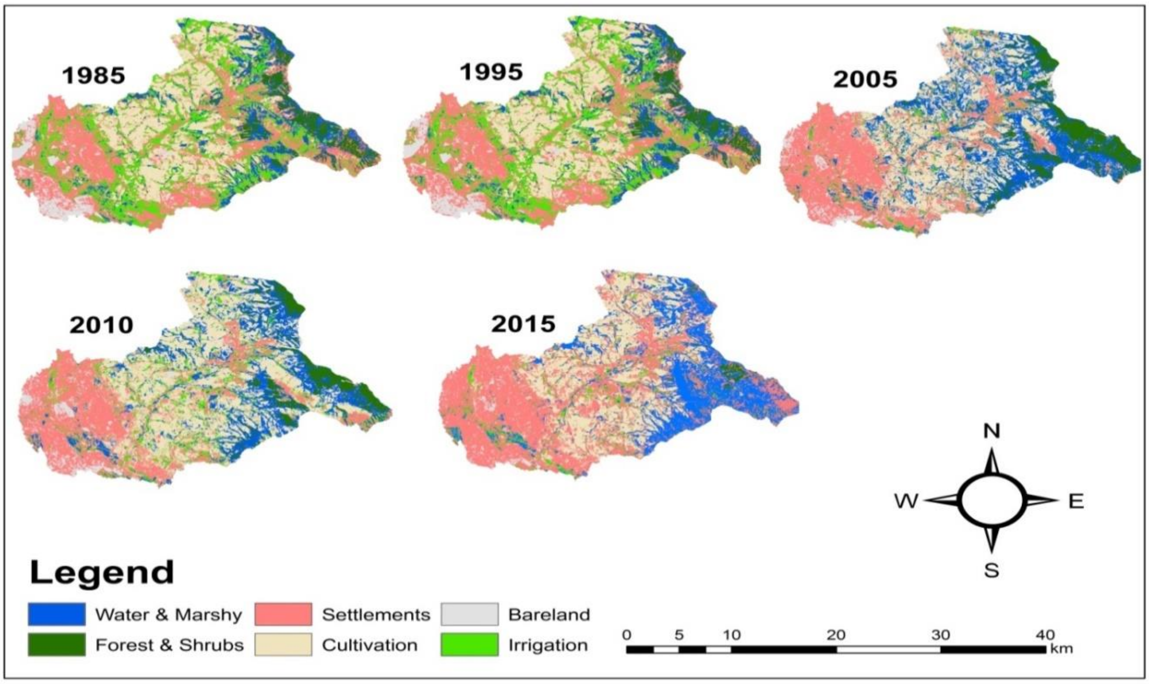

Figure 16: Landuse/land cover maps for year 1985-2015 for Eerste River

The Figure 17 represent area coverage (%) for different land use classes from the year 1985-2015.

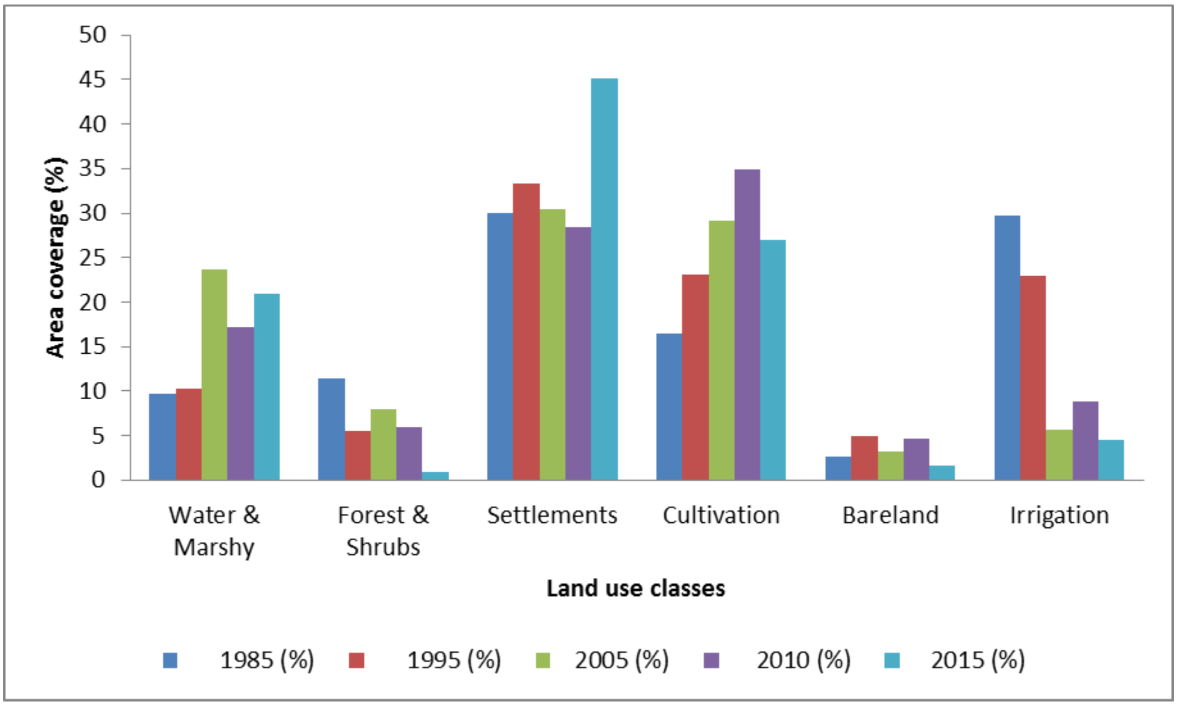

Figure 17: Area coverage for land cover classes

Table 12 shows % of the landuse/landcover changes from the year 1985 to 2015.

Table 12: Area of Landuse/Landcover changes

Class	1985 (%)	1995 (%)	2005 (%)	2010 (%)	2015 (%)
Water & Marshy	9.64	10.22	23.68	17.18	20.95
Forest & Shrubs	11.40	5.49	7.95	6.02	0.92
Settlements	30.04	33.31	30.37	28.45	45.09
Cultivation	16.53	23.06	29.16	34.92	27.00
Bareland	2.61	4.99	3.17	4.61	1.58
Irrigation	29.77	22.92	5.67	8.81	4.45

Based on Figure 17, it is shown that for the year 1985 to 1995 the forest cover has been decreasing over the years from 15 % to about 8 %. However, forest cover increased in 2005 to about 9.5 %. In a study conducted by Sewnet (2015) from the year 1973 to 2011, it was shown that there was an increase in the forest cover from 12.2 % in the year 1986 and declined to 5.1 % and 7.3 % for the years 1995 and 2011 respectively. This was related to the establishment of Bahir Dar City in Ethiopia as the regional capital increased demand of wood for construction and firewood. From 2010 to 2015 there was a decrease of the forest cover from 9 % to 2%. In another study conducted by Kiran (2013a), results revealed that area of forest cover decreased from 58% in 1990 to 33% in 2000 but increased to 39% in 2005.

There is an increase of settlements from 1985 to 2015 from about 38% to 55%. According to the study by Longa et al. (2007) results indicated a decrease of forest cover from about 8 % to 2.6 % for the years 1994 to 2000 and settlements increased from 47.1 % to 41 % . A study by Sewnet (2015) indicated an increase in settlements for the years 1986, 1995 and 2011 were 24.2%, 34.8% and 43.8% respectively. Bareland has been decreasing from 1985 to 2015. The main town in the study area is surrounded by vineyards because of the rich soil properties and good rainfall. The irrigation has been fluctuations with the years without following a trend. The outcome of the study carried out indicated that during the research period, land use pattern changes in the study area were categorized by the loss of large quantities of farmland and increase in water areas. The present study show similar trend with water and marshy the reason might be that even though it was a dry season it might have been raining that particular day when the image was taken. The dry season in Western Cape is between Jan-April, however sometimes in rains towards the end of April in some years.

5.5.1 Accuracy assessment

The user and producer accuracy are two widely used measures of class accuracy (Tilahun and Teferie, 2015). The producer's accuracy refers to the probability that a certain land-cover of an area on the ground is classified as such, while the user's accuracy refers to the probability that a pixel labelled as a certain land-cover class in the map is really this class (Tilahun and Teferie, 2015). The results of the accuracy assessment for the study are shown in Table 13. The user and producer accuracy for any given class typically are not the same.

The accuracy matrix was calculated for the year 2015 for all the classes and it is shown that settlements accuracy was about 83.3 %, Cultivation about 56.6 %, Irrigation about 61.10 %, while Bareland was about 95.5 %, Forest and Shrubs about 77.3 % and Water & Marshy 95 %. The study conducted by Tilahun and Teferie (2015) on classification of land cover changes for 2014 showed an accuracy of 77 % and it was stated that accuracy about 75 % is acceptable. The overall accuracy classification for the current study was about 79.2 % which is acceptable.

Table 13: Confusion matrix

	Water & Marshy	**Forest & Shrubs**	**Settlements**	**Cultivation**	**Bareland**	**Irrigation**	**Total**	**Producers accuracy**
Water & Marshy	**20**	0	0	0	0	0	**20**	100
Forest & Shrubs	0	17	0	0	0	0	**17**	100
Settlements	1	5	20	7	1	2	**36**	55.6
Cultivation	0	0	1	10	0	5	**16**	62.5
Bareland	0	0	0	1	21	0	**22**	95.5
Irrigation	0	0	3	0	0	11	**14**	78.6
Total	**21**	**22**	**24**	**18**	**22**	**18**	**125**	**82**
Users Accuracy	**95**	**77.3**	**83.3**	**55.6**	**95.5**	**61.1**	78	**79.2**

5.6 Relationship between land use changes and water quality

A correlation analysis was conducted to examine the relationships between water quality variables and land use changes. The dataset was tested for normality through Shapiro Wilk's test and it concluded that the dataset is not normally distributed. Based on the normality results, the Spearman correlation coefficient was employed showed in Table 14. The most commonly used techniques to determine the relationships between land uses in watersheds and water quality indicators are correlation or regression analyses (Hwang et al., 2016).

The Spearman's rho, also known as the Spearman's Partial Rank Correlation is a non-parametric coefficient of rank correlation between two variables (X, Y) used to determine whether or not an association exists between the two variables (Ngwenya, 2006).

Table 14: Spearman'rho correlations between land use and water quality indicators

Variables	**Water & Marshy**	**Forest & shrubs**	**Settlements**	**Bareland**	**Cultivation**	**Irrigation**
Ammonia	-0.429	0.029	0.429	-0.771	0.086	0.200
COD	-0.429	0.429	-0.771	-0.943	-0.086	-0.200
EC	-0.029	0.314	0.257	0.143	0.029	-0.714
Un-ionise ammonia	-0.486	0.771	-0.657	0.714	0.371	-0.257
DO	-0.314	0.429	0.829	-0.143	-0.429	-0.600
Ortho Phosphate	-0.143	0.088	0.143	-0.314	0.257	0.714
pH	-0.086	0.371	-0.257	0.049	0.086	-0.314
Temp	-0.600	0.771	0.371	-0.086	0.143	0.600
TP	-0.429	0.429	0.771	-0.086	0.943	-0.086
SS	0.657	-0.429	-0.371	0.314	0.143	-0.429
DO %	-0.314	0.429	0.829	-0.143	-0.429	-0.600
Nitrate	0.943	0.771	-0.200	0.429	-0.429	-0.086

The relationship between water quality and land use was tested at a significant level of p<0.01 and 0.05 which showed that ammonia has a strong negative correlation with bareland. The study conducted by Ogden (2013) showed that ammonia has a strong positive correlation with settlements (0.756), similarly EC showed a strong positive correlation with cultivation. Un-ionised ammonia has a strong positive correlation with forest and shrubs and cultivation. Moreover, there is a strong negative correlation between Un-ionised ammonia and settlements. The strong positive correlation between forest and shrubs with nitrate concentration is also shown in the study conducted in China on the evaluation of the impacts of land use on water quality in Chaohu lake basin (Huang et al., 2013). Similarly there is a strong correlation between water and marshy.

According to the study conducted by Ding et al. (2015), it was shown that there was a negative correlation between EC and forest and shrubs while the current study show a positive correlation. COD has a positive correlation with Forest and Shrubs. There is a strong positive correlation between total phosphorus and settlements. There is a weak correlation between total phosphorus, water and marshy (Zhang and Wang, 2012, Huang et al., 2013) According to the study by Huang et al. (2013) COD, water and marshy show a weak positive correlation. DO show a strong positive correlation with settlements, whereas there is a strong negative correlation between irrigation. DO showed a positive correlation with forest ($r > 0.57$, $p < 0.01$) in a study carried out which indicates the same results as the current study (Ding et al., 2015) There is a strong negative correlation between temperature and water and marshy and the strong positive correlation between temperatures and forest and marshy. Overall, the correlation analysis revealed close relationships between land use types with extensive human activities and poor water quality.

. CHAPTER SIX: CONCLUSIONS AND RECOMMENDATIONS

6.1 CONCLUSIONS

From the study the following conclusions where made:

1. Based on the water quality results, the majority of the water quality parameters are within the South African water quality target. However, some parameters that are not may lead to deterioration of the water quality in Eerste River.

2. Based on Cluster Analysis conducted, it is suggested that the council can reduce the number of monitored sites or change location as the water quality deteriorates after Stellenbosch Based on the PCA, City of Cape Town can reduce the number of parameters monitored.

3. Land cover and land use are impacting on the water quality of Eerste River. There was a strong significant relationship between some water quality parameters and LULC. The parameters that had strong relationship were 7 out 12 i.e unionised ammonia, dissolved oxygen, ortho phosphate, temperature, total phosphorus, oxygen saturation and nitrate.

6.2 RECOMMENDATIONS

The study made the following recommendations:

- To improve water resources, the country needs to improve management approaches such as strict regulations by the Department of Water and Sanitation on the industries discharging to the river.

- It is recommended that there should be a constant update on studies looking at land use changes as urbanisation is increasing in Cape Town.

REFERENCES

Ahmad, A. 2012. Analysis Of Maximum Likelihood Classification On Multispectral Data *Applied Mathematical Sciences,* 6, 6425 - 6436.

Al-Badaii, F., Shuhaimi-Othman, M. & Gasim, M. B. 2013. Water Quality Assessment Of The Semenyih River, Selangor, Malaysia. *Journal of chemistry***,** 1-10.

Al-Wassai, F. A. & Kalyankar, N. V. 2013. Major Limitations Of Satellite Images. *1307.2434*. Retrived from: https://arxiv.org/abs/1307.2434 [Accessed 20 June 2016]

Attua, E. M. & Fisher, J. B. 2011. Historical And Future Land-Cover Change In A Municipality Of Ghana. *Journal of Earth Interactions,* 15**,** 1-26.

Ayivo, J. S. & Gordon, C. 2012. Impact Of Land Use On River Systems In Ghana. *West African Journal Of Applied Ecology,* 20 (3), 84-94.

Butt, A., Shabbir, R., Ahmad, S. S. & Aziz, N. 2015. Land Use Change Mapping And Analysis Using Remote Sensing And Gis: A Case Study Of Simly Watershed, Islamabad, Pakistan. *The Egyptian Journal Of Remote Sensing And Space Science,* 18**,** 251-259.

Chang, H. 2008. Spatial Analysis Of Water Quality Trends In The Han River Basin, South Korea. *Water Research,* 42**,** 3285-3304.

Chingombe, W. 2012. *Effects Of Land-Cover-Land-Use On Water Quality Within The Kuils-Eerste River Catchment.* Unpublished: Philosophea Doctor (Phd) Full Thesis, Univeristy Of The Western Cape.Retrived from: http://etd.uwc.ac.za/xmlui/handle/11394/3309 [Accessed 18 April 2016]

Chu, H. J., Liu, C. & Wang, C. 2013. Identifying The Relationships Between Water Quality And Land Cover Changes In The Tseng-Wen Reservoir Watershed Of Taiwan. *International Journal Of Environmental Research And Public Health,* 10**,** 478-489.

Dabrowski, J. M. & De Klerk, L. P. 2013. An Assessment Of The Impact Of Different Land Use Activities On Water Quality In The Upper Olifants River Catchment. *Water Sa* 39**,** 231-241.

Dallas, H. F. & Day, J. A. 2004. The Effects Of Water Quality Variables Om Aquatic Ecosystems: A Review, . Cape Town: Macmillan.

Ding, J., Jiang, J., Fu, L., Liu, Q., Peng, Q. & Kang, M. 2015. Impacts Of Land Use On Surface Water Quality In A Subtropical River Basin: A Case Study Of The Dongjiang River Basin, Southeastern China. *Journal Of Water*, 7**,** 4427-4445.

Dladla, B. W. 2012. The Impact Of Sub-Catchment Activityon River Water Quality: A Case Study Of Mbabane River In The Ezulwini Valley,Swaziland. Unpublished:Master Of Science Degree In Integrated Water Resource Management University Of Zimbabwe. Retrived from: http://ir.uz.ac.zw/handle/10646/1030 [Accessed 14 July 2016].

Dlamini, S., Nhapi, I., Gumindoga, W., Nhiwatiwa, T. & Dube, T. 2016. Assessing The Feasibility Of Integrating Remote Sensing And In-Situ Measurements In Monitoring Water Quality Status Of Lake Chivero, Zimbabwe. *Physics And Chemistry Of The Earth, 93, 2-11*.

Du Plessis , A. 2014. Quantifying And Predicting Hydrological Responses On The Water Quality Associated With Land Cover Changes Within Upper Vaal River, South Africa. Unpublished:Doctor Of Philosophy In Geography, University Of Johannesburg.Retrived from: http://ujdigispace.uj.ac.za/handle/10210/13706 [Accessed 18 May 2016].

Du Plessis , A., Harmse, T. & Fethi Ahmed, F. 2014. Quantifying And Predicting The Water Quality Associated With Land Cover Change: A Case Study Of The Blesbok Spruit Catchment, South Africa.*Journal of Water* 6**,** 2946-2968.

Eea 2008. Surface Water Quality Monitoring. Denmark: European Union.
Elbag, M. A. 2006. *Impact Of Surrounding Land Uses On Surface Water Quality.* Unpublished:Master Of Science In Environmental Engineering, Worcester Polytechnic Institute. Retrived from: https://www.wpi.edu/Pubs/ETD/Available/etd-050306-155834/unrestricted/Thesis_Final_draft2.pdf [Accessed 20 December 2015].
Eneji, I. S., P., A., Onuche, A. P. & Sha'ato, R. 2012. Spatial And Temporal Variation In Water Quality Of River Benue, Nigeria. *Journal Of Environmental Protection,* 3**,** 915-921.
Erener, A. & Düzgün, H. Ş. 2009. A Methodology For Land Use Change Detection Of High Resolution Pan Images Based On Texture Analysis. *Italian Journal Of Remote Sensing,* 4, 47-59.
Fourie, S. 2005. *An Assessment Of Water Quality And Eerste/Kuils River Catchment System, Western Cape, South Africa.Unpublished:* Master Of Science, University Of Stellenbosch. Retrived from: http://scholar.sun.ac.za/handle/10019.1/20917 [Accessed 10 June 2016].
Ghasemi, A. & Zahediasl, S. 2012. Normality Tests For Statistical Analysis: A Guide For Non-Statisticians. *Internation Journal Of Endocrinology Metabolism,* 10**,** 486-489.
Gibrilla, A., Bam, E. K. P., Adomako, D., Ganyaglo, S., Osae, S., Akiti, T. T., Kebede, S., Achoribo, E., Ahialey, E., Ayanu, G. & Agyeman, E. K. 2011. Application Of Water Quality Index (Wqi) And Multivariate Analysis For Groundwater Quality Assessment Of The Birimian And Cape Coast Granitoid Complex: Densu River Basin Of Ghana. *Water Quality, Exposure And Health,* 3**,** 63-78.
Gopinath, R., Akella, V. & Bhanumurthy, P. R. 2014. Comparison Studies In Land-Cover Mapping Analysis. *International Association of Scientific Innovation and Research (IASIR)* 14, 499-503.
Grady, C. A., 2014. Global Potable Water: Current Status, Critical Problems, And Future Perspectives. In Weng, S., Ernest, R. & Blatchley Iii, E. R (ed). The Handbook of Environmental Chemistry.Switzeland:Springer International Publishing.
Hasmadi, M., Pakhriazad, H. Z. & Shahrin, M. 2009. Evaluating Supervised And Unsupervised Techniques For Land Cover Mapping Using Remote Sensing Data. *Malaysian Journal Of Society And Space,* 5 1- 10.
Hegazy, R. I. & Kaloop, R. M. 2015. Monitoring Urban Growth And Land Use Change Detection With Gis And Remote Sensing Techniques In Daqahlia Governorate Egypt. *International Journal Of Sustainable Built Environment,* 4**,** 117-124.
Heydorn, A. E. F. & Grindley, J. R. 1982. Estuaries Of The Cape. Synopses Of Available Information On Individual Systems. Council For Scientific And Industrial Research. Retrived from: http://researchspace.csir.co.za/dspace/handle/10204/3489 [Accessed 16 June 2016].
Huang, J., Zhan, J., Yan, H., Wu, F. & Deng, X. 2013. Evaluation Of The Impacts Of Land Use On Water Quality : A Case Study In The Chaohu Lake Basin. *The Scientific world Journal,* 2013**,** 1-7.
Hubert, E. & Wolkersdorfer, C. 2015. Establishing A Conversion Factor Between Electrical Conductivity And Total Dissolved Solids In South African Mine Waters. *Water Sa* 41**,** 490-500.
Hwang, S., Hwang, S., Park , S. & Lee , A. 2016. Examining The Relationships Between Watershed Urban Land Use And Stream Water Quality Using Linear And Generalized Additive Models. *Journal of Water, 8(4), 155; ,* 8**,** 155.
Jaafari, S. & Nazarisamani, A. 2013. Comparison Between Land Use/Land Cover Mapping Through Landsat And Google Earth Imagery. *American-Eurasian Journal. Agriculture. & Environment. Science.,* 13**,** 762-768.

Jakhrani, A. Q., Samo, S. R., Sobuz, H. R., Uddin, A., Ahsan, M. J. & Hasan, N. S. 2012. Assessment Of Dissolved Salts Concentration Of Seawater In The Vicinity Of Karachi. *International Journal Of Structural And Civil Engineering,* 1 61-69.
Kibena, J., Nhapi, I. & Gumindoga, W. 2014. Assessing The Relationship Between Water Quality Parameters And Changes In Landuse Patterns In The Upper Manyame River, Zimbabwe. *Physics And Chemistry Of The Earth, 93,* 153-163.
Kidd, M. 2011. *Environmental Law,* Cape Town: Juta & Company Ltd.
Kiran, V. S. 2013a. Change Detection In Landuse/Landcover Usingremote Sensing & G.I.S Techniques: A Case Study Of Mahananda Catchment, West Bengal. *International Journal Of Research In Management Studies,* 2**,** 68-72.
Kiran, V. S. S. 2013b. Change Detection In Landuse / Landcover Using Remote Sensing & G . I . S Techniques : A Case Study Of Mahananda Catchment , West Bengal. *International Journal Of Research In Management Studies,* 2**,** 68-72.
Kirkman, A., Strydom, J. W. & Van Zyl, C. 2013. Stellenbosch Wine Route Wineries: Management's Perspective On The Advantages And Key Success Factors Of Wine Tourism. *Southern African Business Review,* 17**,** 93-112.
Kitchen, C. M. R. 2009. Nonparametric Versus Parametric Tests Of Location In BiomedicalResearch. *Am J Ophthalmol,* 147**,** 571–572.
Lei, L. 2013. *Assessment Of Water Quality Using Multivariate Statistical Techniques In The Ying River Basin, China.Unpublished:* Master Of Science (Natural Resources And Environment), University Of Michigan. Retrived from: https://deepblue.lib.umich.edu/handle/2027.42/106539 [Accessed 16 June 2016]
Li , S., Liua, W., Gua, S., Chenga, X., Xu, Z. & Zhanga, Q. 2009. Spatio-Temporal Dynamics Of Nutrients In The Upper Han River Basin, China. *Journal Of Hazardous Materials* 162**,** 1340–1346.
Longa, H., Tang, G., Lia, X. & K. Heilig, G. K. 2007. Socio-Economic Driving Forces Of Land-Use Change In Kunshan, The Yangtze River Delta Economic Area Of China. *Journal Of Environmental Management,* 83 351–364.
Massoud, M. A. 2012. Assessment Of Water Quality Along A Recreational Section Of The Damour River In Lebanon Using The Water Quality Index. *Environmental Monitoring And Assessment,* 184**,** 4151-60.
Mcquaig, S. M., Scott, T. M., Harwood, V. J., Farrah, S. R. & Lukasik, J. O. 2006. Detection Of Human-Derived Fecal Pollution In Environmental Waters By Use Of A Pcr-Based Human Polyomavirus Assay. *Applied And Environmental Microbiology,* 72**,** 7567-7574.
Meek, C. S., Richardson, D. M. & Mucina, L. 2013. Plant Communities Along The Eerste River, Western Cape, South Africa: Community Descriptions And Implications For Restoration. 55**,** 14. Retrived from: http://dx.doi.org/10.4102/ koedoe.v55i1.1099 [Accessed 6 March 2016] .
Mudau, N., Mhangara, P. & Gebreslasie, M. 2014. Monitoring Urban Growth Around Rustenburg , South Africa , Using Spot 5. South African Journal of Geomatics 3(2)**,** 185-196.
Musingafi, M. C. C. & Tom, T. 2014. Fresh Water Sources Pollution: A Human Related Threat To Fresh Water Security In South Africa. *Journal Of Public Policy And Governance,* 1**,** 72-81.
Mustapha, A. & Nabegu, A. B. 2011. Surface Water Pollution Source Identification Using Principal Component And Factor Analysis In Getsi River, Kano, Nigeria. *Australian Journal Of Basic And Applied Sciences,* 5(12)**,** 1507-1512.
Mwangi, F. N. 2014. Land Use Practices And Their Impact On The Water Quality Of The Upper Kuils River (Western Cape Province, South Africa). Unpublished: Magister

Scientiae, University Of The Western Cape.Retrived from: http://etd.uwc.ac.za/xmlui/handle/11394/3366 [Accessed 29 January 2016].

Nel, N., Parker, P. & Silbernagl, P. 2013. Improving Water Quality In Stormwater & River Systems: An Approach For Determining Resources. *Journal Of The South African Institution Of Civil Engineering,* 55**,** 22–35.

Ngwenya, F. 2006. Water Quality Trends In The Eerste River, Western Cape, 1990-2005. Unpublished: Magister Scientiae, University Of The Western Cape. Retrived from: http://etd.uwc.ac.za/xmlui/handle/11394/2008 [Accessed 10 November 2015].

Ogden, M. B. 2013. *Land Use Impact On Water Quality In Two River Systems In South Africa.*Unpublished: Master Degree Thesis, Lund University. Retrived from: https://lup.lub.lu.se/student-papers/search/publication/3910312 [Accessed 7 May 2016].

Ouyang, Y. 2005. Evaluation Of River Water Quality Monitoring Stations By Principal Component Analysis. *Water Research,* 39**,** 2621-2635.

Parka, S., Choia, J. H., Wangb, S. & Park, S. S. 2006. Design Of A Water Quality Monitoring Network In A Large River System Using The Genetic Algorithm. *Ecological Modelling,* 199**,** 289–297.

Patil, P. N., Sawant, D. V. & Deshmukh, R. N. 2012. Physico-Chemical Parameters For Testing Of Water – A Review. *International Journal Of Environmental Sciences,* 3**,** 1994-1207.

Paulse, A. N., Jackson, V. A. & Khan, W. 2009. Comparison Of Microbial Contamination At Various Sites Along The Plankenburg- And Diep Rivers , Western Cape , South Africa. *Water SA,* 35**,** 469-478

.

Pretorius, E., & Pretorius, R. 2015. Improving the potential of pixel-based supervised classification in the absence of quality ground truth data. *South African Journal of Geomatics*, *4*(3), 250-263.

Pullanikkatil, D., Palamuleni, L. G. & Ruhiiga, T. M. 2015. Impact Of Land Use On Water Quality In The Likangala Catchment, Southern Malawi. *African Journal Of Aquatic Science,* 40**,** 277-286.

Rasin, Z. & Abdullah, M. R. 2009. Water Quality Monitoring System Using Zigbee Based Wireless Sensor Network. *International Journal Of Engineering & Technology Ijet,* 9**,** 24-28.

Razmkhah, H., Abrishamchib, A. & Torkia, A. 2010. Evaluation Of Spatial And Temporal Variation In Water Quality By Pattern Recognition Techniques: A Case Study On Jajrood River (Tehran, Iran). *Journal Of Environmental Management* 91**,** 852–860.

Sayadi, M. H., Rezaei, A., Rezaei, M. R. & Nourozi, K. 2014. Multivariate Statistical Analysis Of Surface Water Chemistry: A Case Study Of Gharasoo River, Iran *Proceedings Of The International Academy Of Ecology And Environmental Sciences,* 4**,** 114-122

Sedibe, M. M., Mgcoyi, W. B. & Combrink, N. 2013. Quality Assessment Of Agricultural Water Used For Fertigation In The Boland Region Of South Africa. *Life Science Journal* 10**,** 1319-1327.

Setiawan, A. Y. & Yoshino, K. 2012. Change Detection In Land-Use And Land-Cover Dynamics At A Regional Scale From Modis Time-Series Imagery. *Isprs Annals Of The Photogrammetry, Remote Sensing And Spatial Information Sciences,* 1(7)**,** 243-248.

Sewnet, A. 2015. Land Use/Cover Change At Infraz Watershed, Northwestren Ethiopia. *Journal Of Landscape Ecology* 8**,** 69-84.

Shabalala, A. N., Combrinck, L. & Mccrindle, R. 2013. Effect Of Farming Activities On Seasonal Variation Of Water Quality Of Bonsma Dam, Kwazulu-Natal. *South African Journal Of Science,* 109**,** 1-7.

Sharma, M., Kansal, A., Jain, S. & Sharma, P. 2015. Application Of Multivariate Statistical Techniques In Determining The Spatial Temporal Water Quality Variation Of Ganga And Yamuna Rivers Present In Uttarakhand State, India. *Journal of Water Quality Exposure and Health,* 7**,** 567–581.

Shelton, A. 2013. *The Accuracy Of Water Quality Monitoring Data: A Comparison Between Citizen Scientists And Professionals.* Unpublished: Degree Of Master Of Science In Applied Science, Saint Mary's University, Halifax, Nova Scotia. Retrieved from: http://curah2o.com/wp-content/uploads/shelton-msc-thesis-final.pdf [Accessed 10 July 2016]

Singh, K., Forbes, A. & Akombelwa, M. 2013. The Evaluation Of High Resolution Aerial Imagery For Monitoring Of Bracken Fern. *South African Journal of Geomatics,* 2 (4)**,** 296-308.

Singh, Y. & Kumar, M. 2011. Application Of Statistical Methods To Analyze Groundwater Quality. *Journal Of Earth Sciences And Geotechnical Engineering,* 1**,** 1-7.

Sweta, L. O. & Akwany, L. O. 2014. Monitoring Water Quality And Land Cover Changes In Lake Victoria & Wetland Ecosystems Using Earth Observation. *International Journal Of Science And Research (Ijsr),* 3**,** 1490-1497.

Tilahun, A. & Teferie, B. 2015. Accuracy Assessment Of Land Use Land Cover Classification Using Google Earth. *American Journal Of Environmental Protection,* 4**,** 193-198.

Uriarte, M., Yackulic, C. B., Lim, Y. & Arce-Nazario, J. A. 2011. Influence Of Land Use On Water Quality In A Tropical Landscape: A Multi-Scale Analysis. *Landscape Ecology* 26**,** 1151-1164.

Vaghefi, H. R. S., Hajiali, A. & Farzam, S. 2012. Water Quality Assessment Of Taleghan River. *Life Science Journal,* 9**,** 375-382.

Wang, X., Cai, Q., Ye, L. & Qu, X. 2012. Evaluation Of Spatial And Temporal Variation In Stream Water Quality By Multivariate Statistical Techniques: A Case Study Of The Xiangxi River Basin, China. *Quaternary International,* 282**,** 137-144.

Yüksel, A., Akay, A. E. & Gundogan, R. 2008. Using Aster Imagery In Land Use/Cover Classification Of Eastern Mediterranean Landscapes According To Corine Land Cover Project. *Journal of sensors,* 8**,** 1237-1251

Zamani, M., Sadoddin, A. & Garizi, A. Z. 2012. Assessing Land-Cover / Land-Use Change And Its Impacts On Surface Water Quality In The Ziarat Catchment, Golestan Province-Iran. *Hydrology Current Research,* 4 (3), 1-5

Zamani, M., Sadoddin, A. & Garizi, A. Z. 2013. Assessing Land Cover/ Land Use Change And Its Impacts On Surface Water Quality In The Ziarat Catchment, Golestan Province-Iran. *Journal Of Waste Water Treatment & Analysis,* 04**,** 5-5.

Zeilhofer, P., Lima, E. B. N. R. & Lima, G. A. R. 2006. Spatial Patterns Of Water Quality In The Cuiaba River Basin, Central Brazil. *Environmental Monitoring And Assessment,* 123**,** 41-62.

Zhang, Y. & Wang, Y. 2012. Assessment Of The Impact Of Land-Use Types On The Change Of Water Quality In Wenyu River Watershed (Beijing, China). *International Perspectives On Global Environmental Change***,** 275-294.

Zhao, Z. & Cui, F. 2009. Multivariate Statistical Analysis For The Surface Water Quality Of The Luan River, China. *Journal Of Science,* 10**,** 142-148

Zimmerman, J. B., Mihelcic, J. R. & Smith, J. 2008. Global Stressors On Water Quality And Quantity.*Journal of Environmental Science and Technology*, 42(12), 4247-4254.

APPENDICES

Appendix 1: Questionnaire

The study is conducted on the Land use changes and effects on water quality in Eerste River Catchment, South Africa.

By Zine Matshakeni

University of Zimbabwe

Interview Questions

Organisation :

Position :

Date :

Instructions: Fill in the answers electronically

A. Water quality monitoring system

1. Why do you have a water quality monitoring system?
2. What is the main objective of your water quality monitoring system?
3. When was the monitoring system established?
4. From the four categories which one is your monitoring system and why?
   A. Compliance monitoring, B. Trend monitoring, C. Impact assessment monitoring or D. Survey monitoring, E. Other?
5. What are the strengths of your monitoring system?
6. What are the weaknesses of your monitoring system?

B. Water use/ allocation/Quality

7. What are the common water, users?
8. How is the water allocated?
9. What is the water quality status of the river?

C. Institutional and legal framework

10. What are your coordination principles of monitoring system?
11. Which other institutions are involved in monitoring Eerste River and what are their responsibilities?
12. Which legal document informs the monitoring system?
13. Do you have guidelines/ targets/standards?
14. Are the guidelines/targets/standards met?
15. Which department is responsible for monitoring system?
16. How does the department relate to the rest of the organisation?
17. How do you report to the national office Department of Water and Sanitation and How often?
18. Do you issue penalties to the polluters?
19. If yes, what penalties do you issue out?

D. Data acquisition

20. Sampling points of Eerste River:
    a. How did you decide on the sampling site?
    b. Give details of the sampling sites?
21. What is your sampling frequency?
22. How did you decide on the sampling frequency?
23. Which sampling parameter are you monitoring?
24. How did you decide on the parameters to be measured?
25. Where are the water samples analysed?
26. Is the lab accredited, if yes which accreditation system?
27. What are the major challenges in data collection?
28. What are the data control measures that are applied?

E. Data utilisation

29. What is the data storage method and why?
30. How is the data obtained utilised?
31. How is the data analysed?
32. How is the information disseminated?
33. Do you inform the public about your findings?
34. Do you use the results to implement measures to improve the environmental state of the water body?