LAND USE AND LAND COVER CHANGES AND THE WATER QUALITY OF THE ORANGE RIVER AT AUSSENKEHR, NAMIBIA

A THESIS SUBMITTED IN FULFILMENT

OF THE REQUIREMENTS FOR THE DEGREE OF

MASTER OF SCIENCE (GEO-INFORMATION SCIENCE)

OF

THE UNIVERSITY OF NAMIBIA

BY

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201203840

April 2021

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Abstract

River systems are essential to the human populations and aquatic organisms. However, they are greatly influenced by land use activities. It is therefore important to understand the effects of land use activities on river systems for environmental protection and resources planning. This study assessed the land use and land cover (LULC) changes and the water quality of the Orange River in the Aussenkehr area where agricultural activities and human settlements have increased over the last three decades. Water quality was tested at three sampling locations situated 26 km upstream, next to, and 3 km downstream of the Aussenkehr farms. Water quality measurements were carried out during the wet and dry seasons to allow for spatial and temporal comparison. Parameters examined included water pH, electrical conductivity (EC), and dissolved oxygen (DO), using handheld equipment. A total of 54 measurements were taken for each parameter. Changes in LULC were quantified using Landsat images for the years 1990, 2000, 2010 and 2019. The analysis showed that EC next to and downstream of the farms was much higher than at the upstream point of the farms. The high values recorded for EC and pH exceeded the category of excellent water quality based on the guidelines set by the Namibian Ministry of Agriculture, Water and Forestry (MAWF). Analysis of LULC revealed that agriculture (vineyards) and human settlements are the main land use in this area. Therefore, the lower water quality at and downstream of the farms could be attributed to fertilisers from irrigation, and the lack of waste management and proper sanitation in informal settlements. With more than 30% of the households in Aussenkehr consuming untreated water from the river, many people may be at risk of waterborne diseases from this low water quality. There is thus a need at Aussenkehr for urgent intervention measures in farm management, settlement development and the provision of essential services. Further research is also needed to investigate how farmers along the Orange River manage the application of fertilisers.

Keywords: drinking water; land use activities; random forest classification; satellite images; settlement; vineyard

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List of Abbreviations

A**NN** - Artificial Neural Networks

ANOVA - Analysis of Variance

BI - Brightness Index

CA - Cluster Analysis

DEM - Digital Elevation Model

Df - Degree of Freedom

DO - Dissolved Oxygen

DWAF - Department of Water Affairs and Forestry

EC - Electrical Conductivity

ESRI - Environmental Systems Research Institute

E-*coli* - *Escherichia Coliform*

FA - Factor Analysis

GIS - Geographical Information System

GPS - Global Positioning System

ha - Hectares

ISRIC - International Soil Reference and Information Centre

LULC - Land Use and Land Cover

MAWF - Ministry of Agriculture, Water and Forestry

NamWater - Namibia Water Corporation

NDVI - Normalised Differential Vegetation Index

NDWI - Normalised Differential Water Index

MME - Ministry of Mines and Energy

NIR - Near Infrared

NSA - Namibia Statistics Agency

PCA - Principal Component Analysis

RF - Random Forest

RS - Remote sensing

SRTM - Shuttle Radar Topography Mission

SVM - Support Vector Machine

SWIR – Short-Wave Infrared

TDS - Total Dissolved Solids

UNAM - University of Namibia

U**SGS** – United States Geological Survey

UV - Ultraviolet

WHO - World Health Organisation

Acknowledgements

I express my sincere appreciation and deep gratitude to my supervisors, Dr. Martin Hipondoka and Dr. Eliakim Hamunyela. Thank you for your invaluable patience, guidance, enthusiastic encouragement, time, support, and constant supervision of this research.

Many thanks to the Carl Schlettwein Foundation for funding my study and allowing me to complete my Master's degree. This study would not have been possible without the support of the Space in Time Project and all its members. I would like to acknowledge the support provided by Ms. Hilma Nghiyalwa, for taking time from her busy schedule to drive me in the field and assist me with data collection. Thanks, are also due to Gloria for being my field assistant.

I would like to thank staffs of the Karasburg NamWater offices for their help in providing historical water quality data. Many thanks go to the community members and the management of the farms at Aussenkehr for their support and help during field data collection.

I thank my special friends from M-block at University of Namibia (UNAM) for welcoming me, for pushing me to do my best, and providing an empowering atmosphere in which to complete my thesis. I also thank my sisters, friends and family for motivation and contributions toward my studies, and everyone that has helped me directly or indirectly. Thank you for your support.

Dedication

I dedicate my work to my mother. Thank you very much for being patient with me, despite all the challenges life brought. Thank you for making me into the woman I am today. It is with your constant support and unconditional love that I finished this work.

Declarations

I, Justina Tuulikefo Nangolo, hereby declare that this study is my own work and is a true reflection of my research, and that this work, or any part thereof, has not been submitted for a degree at any other institution.

Justina Tuulikefo Nangolo 09 March 2021

1. Introduction

1.1 Background of the study

River systems are vital to the environment and to human populations. These systems play a central role in protecting aquatic ecosystems and providing water for agriculture and human consumption (Lange, Mungatana & Hassan, 2007). However, rivers are dynamic and sensitive to change (Fryirs & Brierley, 2012); therefore, they need to be managed and monitored to track their fluctuations. Land use dynamics is one of the drivers that continues to impact river catchments and create negative consequences for the overall health of rivers (Ayivor & Gordon, 2012).

Previous studies focused on understanding how changes in Land Use and Land Cover (LULC) affect water quality (e.g. Munyika, Kongo & Kimwaga, 2014; Petersen, Jovanovic, Le Maitre & Grenfell, 2017). The term ‘land use’ in this study refers to specific activities for which the land is being utilised, such as agriculture and settlements; ‘land cover’ refers to the physical coverage of the land, such as vegetation or water. Water quality is defined as the process of determining the chemical, physical, and biological characteristics of water bodies, and identifying the sources of any possible pollution or contamination (Usali & Ismail, 2010).

The water quality of water bodies is significantly influenced by anthropogenic activities such as agriculture and informal settlements (Khatri & Tyagi, 2015; Mathebula, 2016; Mupedziswa, 2016). The health of hundreds of millions of people in Latin America, Asia, and Africa may be at risk when they come into contact with water polluted as a result of the low level coverage of improved sanitation and treatment (United Nations Environmental Program [UNEP], 2016). Meanwhile, across Europe an increase in anthropogenic activities has increased nitrogen enrichment in water resources, posing a threat to aquatic ecosystems and endangering good water quality (Grizzetti et al., 2011; Wendland et al., 2020). Findings by Ding et al. (2015) indicated that urban and forest land use, rather than agriculture land use, strongly affected water quality of the Dongjiang River Basin in China.

In Africa, land use changes of cultivated land along Lake Tana, Ethiopia, caused a decline in aquatic resources, led to land degradation, and the loss of biodiversity and forest cover, which in turn, led to environmental degradation and poverty (Wubie, Assen & Nicolau, 2016). In South Africa, sewage effluent from urban areas, settlement, and return flows from agriculture have been reported to modify river flows and cause the loss of indigenous fauna and flora, and of riparian and floodplain vegetation of the Upper Kuils River (Mwangi, 2014).

Diederichs et al. (2005) revealed that a decline in the water quality of the Orange River has caused fish mortality, which resulted in its status as a Ramsar site being rescinded. However, studies on the Orange River water quality mainly covered the upstream section or were limited in scope (e.g. Department of Water Affairs and Forestry [DWAF], 2014; Diederichs et al., 2005; Munyika et al., 2014; Pululu, Lobina & Tabukeli, 2015). Amongst others, linkages between land use activities and water quality, especially in the lower part of the Orange River where Aussenkehr is situated, received scant attention. Aussenkehr has the largest irrigation schemes on the Namibian side of the Orange River, and the schemes uses water drawn from the Orange River. As Munyika et al. (2014) posited, the return flows and effluent from Aussenkehr irrigation schemes may infiltrate the ground, either significantly or insignificantly, to cause major changes in the water quality of the river. It is against this background that this study explored the potential effects of the irrigation farms at Aussenkehr on the water quality of the adjacent stream.

Change in LULC is rarely documented in quantitative terms despite its importance in the formulation of floodplain and watershed management plans (Hazarika, Das & Borah, 2015).

Understanding river systems is critical in developing plans and strategies for environmental management, as well as for guiding decision-making processes for health and environmental issues (Fryirs & Brierley, 2012). Moreover, LULC changes are important in order to understand the human causes and environmental consequences of such changes.

1.2 Statement of the problem

From its establishment in the early 1990s as a small vineyard on the bank of the Orange River, the farms at Aussenkehr increased gradually to about 2000 hectares (ha) at present. The vineyards are under an irrigation system which relies on water sourced from the adjacent Orange River (Munyika et al., 2014).

This conversion of an area characterised by desert climate into vineyards has the potential to directly impact the ecology of the region (DWAF, 2009). Pottinger (1996) explains that river systems are ecologically linked and warned that the Orange River might be impacted by different land uses along the river, especially the construction of dams. This explanation hints that land use activities might act differently on the river systems. Currently, there is insufficient knowledge and understanding about what effects this transformation has on the river water quality and its functioning. The recent effort by Munyika et al. (2014) to address the link between land use and water quality of the lower Orange River was confronted by a lack of site-specific, historical water quality data and other hydrometric measurements.

The effects of LULC on the functioning of the river are known to be site-specific (Baker, 2006; Shukla et al., 2018). Volschenk, Fey and Zietsman (2005) monitored the water quality in the lower Orange, but they did not assess water quality at Aussenkehr specifically. Pululu et al. (2015), in their study of the upper Orange River, encouraged the applications of remote sensing (RS) and geographical information systems (GIS) techniques in guiding site-specific and best irrigation practices along the riparian zones. A combination of RS and in situ water quality measurements supplemented with historical water quality data from the nearest stations, was thus harnessed for this study as an attempt to fill the gap at Aussenkehr.

1.3 Aims and objectives

The aim of the study is to assess and analyse LULC change of the Aussenkehr settlement on the banks of the Orange River, and the water quality of the adjacent Orange River. To that end, the study formulated the following objectives:

- Employ medium resolution satellite images to quantify LULC change of Aussenkehr since its gradual transition from a desert landscape in 1990 to present day (2019) vineyard.
- Determine the spatial and temporal variation of Electrical Conductivity (EC), pH, Dissolved Oxygen (DO) and *Escherichia coliforms* (*E-coli*) in the Orange River around Aussenkehr.
- Based on results obtained in the first two objectives, relate the LULC changes to the water quality in the study area.

1.4 Significance of the study

Water of the Orange River is used for grape irrigation at Aussenkehr which contributes to the Namibian economy and increases employment opportunities in the country. The Orange River also supports a variety of biodiversity such as at the Ramsar site at the Orange River mouth. This study provides information on how water quality changes due to intensified human land use activities along river systems. This information can be used to target problematic land use and establish mitigation measures. Insight from this study is thus imperative for future planning of similar economic development activities along the Orange River.

1.5 Limitations of the study

We experienced difficulty in distinguishing classes with similar spectral signatures, particularly for settlement and bare soil, and natural vegetation and vineyards; therefore, they were combined into two classes. Subsequently, it was not possible to compare pixel-by-pixel changes between settlement and bare soil, and natural vegetation and vineyards.

The lack of historical water quality indicators for the study area necessitated field data collection. However, the collected data only represented the rising limb during the wet and recession limb during the dry seasons. To mitigate this lack of data, historical data were obtained from the nearest stations to complement the field data.

1.6 Delimitation of the study

The study was carried out in the Aussenkehr sub-catchment and therefore the results cannot be used to generalise or conclude behaviours for other sub-catchments of the Orange River, or river systems elsewhere. However, the results may be applicable to areas that have a similar set of socio-environmental conditions.

1.7 Thesis outline

This thesis consists of six chapters. Chapter One provides the background and purpose of the study. It includes the problem statement, the importance or relevance of the problem and the research objectives. Chapter Two covers the literature review, focusing on LULC, water quality and the relationship between the LULC change and water quality. The third chapter presents the research instruments and methods used for data collection and analysis, and Chapter Four provides the results of the study. Discussion, interpretation, and an evaluation of the research findings are the subject of Chapter Five. Chapter Six synthesises the implications of the study and makes recommendation for future action.

2.0 Literature review

This chapter profiles the effects of LULC changes on water quality; it also discusses techniques and approaches used in assessing LULC changes and how they apply to the current study. The water quality parameters used in the study are discussed, along with relevant water quality guidelines and standards used in Namibia for safe drinking water.

2.1 Land use and land cover change, water quality and remote sensing

It is generally understood that land use influences water quality positively or negatively (Khatri & Tyagi, 2015), but these influences have been poorly investigated, although several studies that assessed land use change have shown a connection between land use activities and surface water quality (Aher, Bairagi, Deshmukh & Gaikwad, 2012; Hazarika et al., 2015; Munyika et al., 2014; Ncube & Taigbenu, 2008; Ogden, 2013; Petersen et al. 2017; Trewby, 2003). Population growth and increased land use activities along river systems are regarded as the major drivers for the state of surface water quality. Human population growth and activities result in agricultural run-off, urban discharges, and sewage discharges, among other effects (Huang, Zhan, Yan, Wu & Deng, 2013). In New Zealand, for example, water quality degradation as a result of land use activities is seen as the most threatening environmental issue that the country faces (Ahiadu, 2019). In Malaysia, water quality deterioration is mainly a result of urban development, agricultural activities, and forest degradation (Camara, Jamil & Abdullah, 2019). Similarly, agricultural activities have been identified as the source of water quality pollutants in the Songhua River, China (Cheng et al., 2018).

In Africa, Ncube and Taigbenu (2008) concluded that an increase in land cover change in a South African river catchment resulted in stream flow reduction, and found a strong relationship between land use types where human activities prevail, and poor water quality in the Eerste River, South Africa (Matshakeni, 2016). Kambwiri, Changadeya, Chimphamba, and Tandwe (2014) have recorded the effect that land use in southern Malawi has on the water quality of the Ruo River, and that changes in seasons are a significant factor in the variability of water quality parameters. These views are exemplified by Mupedziswa (2016), who has suggested that water in the Muzvezve Sub-Catchment in Zimbabwe is not safe for drinking. An exception was recorded in the Okavango River, where Vushe, Haimene, and Mashauri (2014) concluded that land use activities in its catchment have limited impacts on water quality.

Aguilera, Marcé and Sabater (2015) have acknowledged the challenges associated with attributing changes in river water quality to specific factors because of the multiple factors that act at different temporal and spatial scales. These authors have therefore underlined the importance of examining long-term continuous data for drawing sound conclusions. Afed Ullah, Jiang and Wang (2018) have also noted that some land uses contribute more pollutants than others, and that pollutants may vary from season to season. Therefore, it is recommended that relevant data from the wet and dry seasons are analysed separately. Shukla et al. (2018) add that water quality might differ for different regions, based on topography, land use, land cover and climatic factors. This suggests that LULC effects are site-specific and vary in space and time.

Understanding these impacts requires a comprehensive understanding of hydrological systems of catchment areas (Ncube & Taigbenu, 2008). To better recognise these impacts, many studies have used GIS, RS and statistical approaches in hydrological environments. Usali and Ismail (2010) have demonstrated that GIS and RS can be especially useful as tools in monitoring and evaluating factors related to water quality.

A study in China on the impacts of land use on the water quality of the Chauho Lake Basin indicated that there is a positive correlation between some land use types (built-up) and water quality parameters (DO and NH_3) (Huang et al., 2013). These authors suggest that land use types with a negative correlation with water quality should be increased to reduce the effects of other land use effects. Ogden (2013) used GIS and RS to study the impacts of land use on water quality. Results suggested that an increase in human activities worsens water quality. Ogden (2013) has also showed that GIS and RS can be used successfully as a tool to classify land cover changes over time. Chen and Lu (2014) revealed that spatial variations in water quality are related to various anthropogenic and natural factors and used statistical measures to indicate these. Aragon (2009), too, revealed that high coliforms and nitrogen in the Alafia River were associated with agriculture and urban development.

Applications of GIS and RS have been used in many studies in southern Africa to monitor and evaluate LULC effects on water quality (e.g. Munyika et al., 2014; Trewby, 2003). Various techniques of RS and GIS have been employed to study LULC changes, which involve analysing satellite images and aerial photographs. This approach allows for efficient planning and management of resources in a timely manner (Babykalpana & ThanushKodi, 2010).

The use of GIS and RS technologies to identify, assess, evaluate and monitor changes in ecosystems have increased over the years (Babykalpana & ThanushKodi, 2010; Owojori & Xie, 2005); both systems are considered powerful and effective tools for documenting spatio-temporal changes in an area for conservation and management of natural habits (Raj & Azeez, 2010). Reis, Plangg, Tundishi, and Quevedo (2015) also affirm that RS and geoprocessing are essential tools for obtaining and maintaining records of human actions in space over the course of time. This effectiveness is evident in many applications of GIS and RS where they prove useful tools in detecting LULC change (Babykalpana & ThanushKodi, 2010; Darvishzadeh, 2000; Kamwi, Chirwa, Manda, Graz & Kätsch, 2015; Owojori & Xie, 2005).

The most important and widely used application of RS is generating LULC maps through image classification which is the process of assigning pixels to classes (Campbell & Wynne, 2011). However, classifying RS imageries to obtain reliable and accurate LULC information still remains a challenge (Manandhar, Odeh & Ancev, 2009). Classification accuracy depends on the RS data selected, image processing, classification method, the analyst's experience, and available reference data (Lu & Weng, as cited in Lu, Li, Moran & Hetrick, 2013; Manandhar et al., 2009).

When carrying out classification, it is best to identify the need for the satellite data, because the quality of satellite images continues to improve rapidly. Various satellite images can be used in LULC change, which include high-resolution images, and low- and moderate-resolution images.

High-resolution images provide a high level of details. However, they are regarded as expensive, and they cover a small area. Because of their relatively high cost, high-resolution images were not used in this study. Although low- and moderate-resolution images provide a low to moderate level of detail, they are mostly free of charge and provide historical images suitable for time series analysis. Therefore, Landsat images, which are freely available and provide historical images, were used for this study.

The classification accuracy can be enhanced by increasing the number of images used in the classification (Nitze, Schulthess & Asche, 2012). Image classification is most successful when the analyst selects different band combinations and create vegetation indices to highlight features of interest in the study. Such techniques are done through the process of class separability (Espach, 2006). Class/signature separability is a statistical measure of distance calculated between different combinations of bands used in image classification (Kamwi et al., 2015). By the same token, vegetation indices have proved useful in enhancing classification accuracy. However, they need to be chosen carefully, considering their limitations and specific uses (Xue & Su, 2017). In this study, a Normalised Differential Vegetation Index (NDVI), Normalised Differential Water Index (NDWI) and Brightness Index (BI) were used because of their specific use in highlighting vegetation and water, and reducing the effects of soil brightness, respectively.

Image classification can be organised into two broad categories: supervised and unsupervised classification. Unsupervised classification is the identification of natural groups within multispectral data (Campbell & Wynne, 2011); it mainly uses clustering algorithms to classify an image data (Richard as cited in Liu, 2005) and does not require humans to have foreknowledge of the classes, thus minimising human error. Unsupervised classification is easy to apply and does not need an analyst to specify training data (Largees, Chesire & Hunaes, as cited in Aldoski, Mansor & Shafri, 2013). In fact, the classification will be repeated if new information about classes appears (Campbell & Wynne, 2011). However, the utility of unsupervised classification is less effective, and supervised classification produces better results (Kafi, Shafri & Shariff, 2014).

Supervised classification occurs when the analyst controls and selects information/categories tailored to a specific purpose and geographic region (Campbell & Wynne, 2011). A maximum likelihood supervised classifier has been identified as the most widely used supervised algorithm (Liu, 2005), and assumes that a multivariate normal distribution can describe each spectral class. Shaker, Yan, and El-Ashmawy (2012) compared maximum likelihood, contextual class, and a minimum distance algorithm for flood hazard mapping and showed that the maximum likelihood classifier yields the best result. Nevertheless, Manandhar et al. (2009) insist that maximum likelihood cannot perform satisfactorily in delivering accurate and reliable classification of built-up and vineyard LULC categories, despite it being widely used. In addition, it is believed that these traditional pixel-based classification techniques can yield incorrect and incomplete results (Nkonyana, 2016). Examples of pixel-based image classification include maximum likelihood (supervised) and k-means classification (unsupervised).

Recently, object-based image classifications have gained more attention using satellite images to produce accurate image classification over pixel-based classification (Paul, 2013). Object-based image classification classifies an image based on the individual object that is identified on the image using its shape and size. With limited ancillary information available, machine learning algorithms provide a solution to determine LULC classes without ground information measurements for the entire study area (Tavares, Beltrão, Guimarães, & Teodoro, 2019).

Recent studies revealed that the use of machine learning algorithms during image classification have increased because they are inexpensive and broad (Kulkarni & Lowe, 2016). Machine learning algorithms include Random Forest (RF), Support Vector Machine (SVM), Artificial Neural Networks (ANN) and K-nearest neighbour (k-NN). Although ANN performs better than other algorithms, its disadvantages include low calculation robustness, complex architecture, and vast training time (Dixon & Candade, 2008; Nitze et al., 2012). In previous studies, RF classifier has proved to be an effective, accurate and widely used classification technique in RS applications (Kulkarni & Lowe, 2016; Maxwell, Warner & Fang, 2018; Nelson, 2017; Nguyen, Doan & Radeloff, 2018; Tokar, Vovk, Kolyasa, Havryliuk, & Korol, 2018). Although RF decreases the classification accuracy when only one image is used, it was found to be easy to use (Nitze et al., 2012). It also has an additional advantage in that it uses various decision trees to decide the class to be assigned to a pixel (Maxwell et al., 2018). However, many studies have noted the inferiority of maximum likelihood to machine learning classifiers such as RF in crop mapping (Dixon &

Candade, 2008; Maxwell et al., 2018; Nitze et al., 2012). Nevertheless, RF was recommended over other machine learning algorithms (Maxwell et al., 2018). Against this background, this study made use of RF in classifying and quantifying of LULC changes.

2.2 Water quality

The quality of water is an important factor to consider because water is used for domestic, irrigation, and industrial purposes. Although safe water is crucial to public health because it contributes to economic growth and poverty reduction, the crisis of water quality remains a global concern, especially in sub-Saharan Africa, the Middle East and Central Asia. This concern persists, despite legislation of water management and monitoring programmes set up at different scales (Diamantopoulou, Antonopoulos & Papamichail, 2007; UNEP, 2009). Approximately 10% of the global population does not have access to clean water (Oki & Quiocho, 2020; World Health Organisation [WHO], 2019).

In addition to the anthropogenic factors discussed in Section 2.1, changes in the water quality of rivers are believed to be influenced by the physical, biological, and chemical composition of the surrounding ecosystems. Natural factors that influence the quality of water in rivers include the geological, topographical, hydrological, and biological settings surrounding the water body. Water quality of rivers can be influenced by the bedrock and soil through water-rock interaction, and so affect the composition of the water (Lintern et al., 2018). Hydrological factors, such as excessive rainfall leading to floods, or drought, might change the water quality through dilution or concentration of the water content in river systems (Khatri & Tyagi, 2015). Precipitation was identified as the most important variable to be considered in hydrological factors that affect water quality (Xia et al., 2017). Surface run-off was found to be predominant on steep slopes (Tarlé, Mazzer, Luna, Galbiatti, & Borges, 2008). The topographical characteristics of the watershed which determine the content of the run-off have a profound influence on the water quality of a river.

Water scarcity and quality concerns are thus diverse, and they affect water quality differently. Consequently, there is a growing concern about water pollution, deteriorating water quality, ecosystem health, and the uncertain effects of climate change and land use activities on water resources (Lange et al., 2007). It is also feared that there are very few studies that focus on effects of agricultural land use on run-off and water quality in sub-Saharan Africa (Ngwenya, 2006; Ogden, 2013; Trewby, 2003; Uwimana, Dam, Gettel, Bigirimana & Irvine, 2017).

To determine the water quality of a water body, various water quality parameters are assessed against guidelines developed by water management bodies. The variables described below are regarded as effective proxy for rapid water quality assessments (e.g. Auer, 1997; Riddell, Killian, Versfeld & Kosoana, 2016), and subsequently adopted for this study.

2.2.1 Electrical conductivity

The ability of a water body to conduct or transfer electric current is referred to as EC (United Nations Environmental Protection Agency [UNEPA], 2001), and depends on the number of positive and negative ions dissolved in water (Matshakeni, 2016): the higher the EC, the more negative (–) and positive (+) ions dissolved in water. Minerals dissolved in water separate into charged particles (ions) that conduct electricity. Therefore, EC can be used as indirect measurement of Total Dissolved Solids (TDS). Higher concentrations of TDS in water bodies can be extremely toxic, making EC a very good indicator of water pollution. The higher the EC, the less water is available to plants because plants can transpire only pure water (Colorado State

University, n.d.). Agricultural activities influence EC. For instance, using pesticides in irrigation contaminates water and increases EC (Khatri & Tyagi, 2015) which may affect human health when people consume contaminated fish.

2.2.2 pH

The pH measurement indicates the acidity and alkalinity of water and ranges from 0 (very acid) to 14 (very alkaline). These pH ranges determination is due to the effect of hydrogen ions (H+) and hydroxyl ions (OH-) in water (Khatoon, Altaf, Khan, Rehman & Pathak, 2013). The higher the H+ concentration, the lower the pH, and the higher the OH- concentration, the higher the pH. Based on the Ministry of Agriculture, Water and Forestry (MAWF) guidelines, a high pH (8.6 and higher) indicates alkalinity, while a low pH (5.9 and lower) indicates acidic water; water that is suitable for human consumption should have a neutral pH value, somewhere between 6.0 and 8.5 (MAWF, 2012). Pollution can change the pH of water, which in turn, can harm animals and plants living in the water (United States Geological Survey [USGS], n.d.). That said, each organism adapts to a specific range of pH, so an extreme change in pH may threaten organism survival (Faiilagi, 2015). Fish and other aquatic animals prefer a pH between 6.5 and 8.5 and fish mortality occurs as the water pH varies from this value (UNEPA, 2001). Extreme pH can also negatively influence water's palatability and has a corrosive effect (Haydar, Arshad & Aziz, 2016; Napacho & Manyeke, 2010). Corrosion of water pipes releases metals into the water which can be toxic and causes health problems (Mupedziswa, 2016).

2.2.3 Dissolved oxygen

The quantity of oxygen particles dissolved in water bodies is DO, and it is crucial for the respiration of aquatic life, such as fish. Oxygen enters the water as a product of photosynthesis by aquatic plants or by diffusion from the atmosphere. If the water is good for fish, it is likely to meet all other beneficial requirements (Kumar & Puri, 2012). The main cause of low DO is organic pollution, which can lead to fish mortality (UNEPA, 2001). Organic pollution involves pollutants from sewage discharge, urban run-off and agricultural run-off. The organisms in water tries to break down the organic substances into smaller particles, however, they use up most oxygen during the process and therefore causing oxygen deficiency. Low DO concentration may lead to an increase in the toxicity of poisons (Lloyd, 1964; Mwangi, 2014); thus, a high DO concentration is preferable. Toxic pollutants in water ranges from being acute to lethal to aquatic organisms.

Other factors, such as agricultural run-off from fertilisers and pesticides washed into rivers, can also cause eutrophication in the river (Khatri & Tyagi, 2015) which is the process in which excess inorganic nutrients in the water stimulate the growth of algae and macrophyte (Mwangi, 2014). Eutrophication reduces oxygen levels in the water, threatening aquatic life, and significantly affecting recreational fisheries (Breen, Curtis & Hynes, 2018; EPA, 2001). In addition, decaying algal matter formed during eutrophication can develop slime and produce harmful odours, making the river less suitable for recreational purposes and increasing the cost of water treatment for human consumption (Breen et al., 2018).

2.2.4 *Escherichia coli*

Escherichia coli is a bacterium that indicates water is contaminated with human and/or animal waste (Haydar et al., 2016); it is considered to be the best bacterium indicator for faecal contamination in water bodies (Odonkor & Ampofo, 2013). *E-coli* can live naturally in the human body without causing illness; however, once the bacterium reaches the delicate organs such as the kidneys or livers, it can cause illness (Rock & Rivera, 2014). Many international studies that assessed the relation between water quality and diseases identified nausea, vomiting, and diarrhoea as the common symptoms of waterborne diseases caused by *E-coli* (Nicholson, Neumann, Dowling & Sharma, 2017; Price & Wildeboer, 2017; Rock & Rivera, 2014). The lifespan of *E-coli* is short; therefore, its presence indicates recent ongoing contamination (Odonkor & Ampofo, 2013). Against this background, constant monitoring and testing for *E-coli* is necessary to ensure the safety of drinking water.

2.3 Water quality standards

The composition of water bodies depends on their sources. At a local scale, water quality varies considerably (Mendelsohn, Jarvis, Roberts & Robertson, 2002), and also varies according to the specific use and the standards set up to assess the quality (Khatri & Tyagi, 2015). To determine the quality, water quality parameters are measured and compared against a set of standards and criteria established by individual countries or international bodies. The standards differ depending on the end user's context and the suitability of water for industrial, agriculture or human use (UNEPA, 2001). The standards differ owing to different environmental conditions, ecosystem, land use activities and human uses. In the current extent, the standards are aimed to know if the river systems meet the requirements for human health protection and the aquatic ecosystem.

In Namibia, regulations and policies exist to manage and disseminate water resources, such as the Water Act 54 of 1956 (Republic of Namibia, 2016); Namibia Water Corporation Act 12 of 1997 (Republic of Namibia, 2004), and the Water Resources Management Act 11 of 2013, which makes provision for management, protection, development, use and conservation of water resources through regulating and monitoring water services (Republic of Namibia, 2013). The MAWF and Namibia Water Corporation (NamWater) developed the Namibian water quality standards based on these policies and regulations for different water uses. MAWF is responsible for rural water supply, while NamWater is responsible for urban water supply (Ndokosho, Hoko & Makurira, 2007).

Table 1 shows the water quality standards for water quality assessments as established by MAWF guidelines. Although Namibia also uses the WHO guidelines and the NamWater standards, these two guidelines do not include some variables such as DO. For that reason, the MAWF guidelines were used for analysis in this thesis. The WHO develops the standards to help water regulators, policy makers and their advisers to create national policies on water safety and management (WHO, 2011).

Table 1: MAWF water quality guidelines for parameters covered in this study (MAWF, 2012)

Parameter	Units	Ideal guideline	Acceptable standard
pH	pH	6.0 - 8.5	6 - 9
EC	µS/cm	<800	<3000
DO	Mg/l	>6	>5

2.4 Statistical analysis of water quality

The application of statistical tests in water quality monitoring used for drawing meaningful conclusions from water quality data has been increasing over the past decades. To select the appropriate analysis procedure for water quality, it is recommended to use the characteristics of the data to discover whether the data will require a parametric or non-parametric test (Fu & Wang, 2012; Helsel & Hirsch, 2002). Parametric tests are applied when the sample data follow a normal distribution, have equal variance and an equal number of samples. Non-parametric tests are applied when the sample data do not follow normal distribution and have an uneven number of samples in categories (Fu & Wang, 2012).

Studies found non-parametric tests more robust than parametric tests when the data are not normal, skewed, or have outliers (Albek, 2003; Helsel & Hirsch, 2002). The datasets used in this study have an unequal number of observations, therefore non-parametric tests have been used.

However, normality tests, which assume that the data are normally distributed, are also carried out to determine if a parametric or non-parametric test can be employed using the data (Ngwenya, 2006). The most commonly used normality tests include the Shapiro-Wilk test, Chi-square test, Kolmogorov test and the Anderson-Darling test (Das & Imon, 2016). Several studies have preferred the Shapiro-Wilk test over other normality tests (Das & Imon, 2016; Helsel & Hirsch, 2002). Therefore, Shapiro-Wilk test is the test of choice in this research.

Different statistical methods of quantifying and assessing water quality have been introduced and studied intensively (Afed Ullah et al., 2018; Blanco, Alarilla, Dimalibot, Bonga & Paringit, 2014; Liu, Zheng, Liang, Liu & Rosenblum, 2016; Oke, Sangodoyin, Ogedengbe & Omodele, 2013). They are useful in informing decision-making processes related to water resources management. The use of multivariate techniques has been suggested in studies that involve more than two variables because these techniques give simpler and more easily interpreted results for evaluating observed water quality data (Mazlum, Özer, & Mazlum, 1999).

The Analysis of Variance (ANOVA) is a widely used method that compares river water quality and variation between variables (Chen & Lu, 2014). Priya, Das and Vareethiah (2016) found it useful in analysing the temporal and spatial variation of the Tambaraparani River water quality and in identifying the variation in water quality parameters at different stations. In addition, Al-Badaii, Shuhaimi-Othman & Gasim (2013) report the effectiveness of ANOVA, Factor Analysis (FA) and Cluster Analysis (CA) in analysing and relating the relationships of the physiochemical and biological parameters of the Semenyih River and seasonal changes to land use activities. These methods were successful in determining the association between deteriorating water quality, and industrial and agricultural activities.

Testing for variation between variables uses a null hypothesis, assuming that there is no statistical significance variation between variables. ANOVA, Principal Component Analysis (PCA) and CA are suggested as useful tools for water quality and management of water resources (Fan, Cui, Zhao, Zhang & Zhang, 2010). The application of ANOVA, PCA, CA, R2, and T-test have proved to be effective tools for studying and analysing spatio-temporal water quality classification (Chen & Lu, 2014). One major drawback of ANOVA, however, is that it assumes normality and equal variance between the variables.

Besides ANOVA, variation between variables can be analysed using the Kruskal-Wallis test which is a non-parametric test that compares the differences between medians of groups without assuming normal distribution of the data (Ding et al., 2015). When using asymmetrical populations, the non-parametric Kruskal-Wallis test is known to achieve better results than parametric ANOVA tests (Hecke, 2012). Finally, non-parametric tests are preferred in order to avoid normality problems (Helsel & Hirsch, 2002).

Post - hoc tests are applied to the datasets where a significant difference is found between variables, and to identify which specific variables are significantly different by applying the test to each pair of groups. The Dunn test is a post-hoc test used to test for multiple comparisons between variables for further analysis (Dinno, 2015).

Water quality trends have been investigated in studies using trend analysis of time series data (Ngwenya, 2006). Trend analysis determines whether the probability distribution from which the data arise has changed over time, with a null hypothesis stating that there is no trend (Antonopoulos, Papamichail & Mitsiou, 2001; Fu & Wang, 2012). Trend analysis methods are many, and selecting the appropriate tool depends on whether the data analysis follows a parametric, non-parametric or mixed method. The Mann-Kendall test is a non-parametric trend test for testing monotonic trends within datasets that can have missing values and censored datasets (Ground Water Monitoring and Assessment Programme, 1999).

In South Africa, the Seasonal Mann-Kendall test, an extension of Mann-Kendall, tests for seasonality, performed well in discerning temporal trends of water quality in the Eerste River (Ngwenya, 2006). The Theil test for slope is applied after the Mann-Kendall to test for linear dependence among parameters (Ground Water Monitoring and Assessment Programme, 1999). The Theil slope test is a promising strategy in terms of robustness and power (Moses & Klockars, 2008) because the test is not affected by non-normality and residual variance in the data.

The literature illustrates many statistical measures used to analyse the water quality of river systems. In this study, the following tests have been integrated to evaluate the water quality of the Orange River because of their capability and wide acceptability in the literature: Shapiro-Wilk, Kruskal-Wallis, Dunn test post-hoc, Mann-Kendall trend test, and slope test. These tests are also useful for testing data that do not follow normal distribution and are therefore compatible with data used in this study.

2.5 Conclusion

The literature review indicates that GIS and RS applications are useful in water resources management, and for quantifying LULC changes surrounding river systems. The literature shows that several factors need to be considered when quantifying LULC, including satellite images, image processing algorithms, image classification methods, and the reason for creating LULC theme maps. Using multiple images and vegetation indices in the RF classification method was found to yield the most promising results in crop mapping. In addition, water quality is assessed using various methods, depending on the nature of data collected and the kind of information one seeks to derive.

3. Research methods

3.1 Study area

The Orange River (Figure 1) is the longest river in southern Africa and forms Namibia's southern border with South Africa. The river is a key water resource in Namibia, South Africa, Botswana and Lesotho (Lange et al., 2007). The water of the Orange River is used for many sectors in these countries, with agriculture being the primary activity and accountings for over 60% of water demands (Pululu et al., 2015).

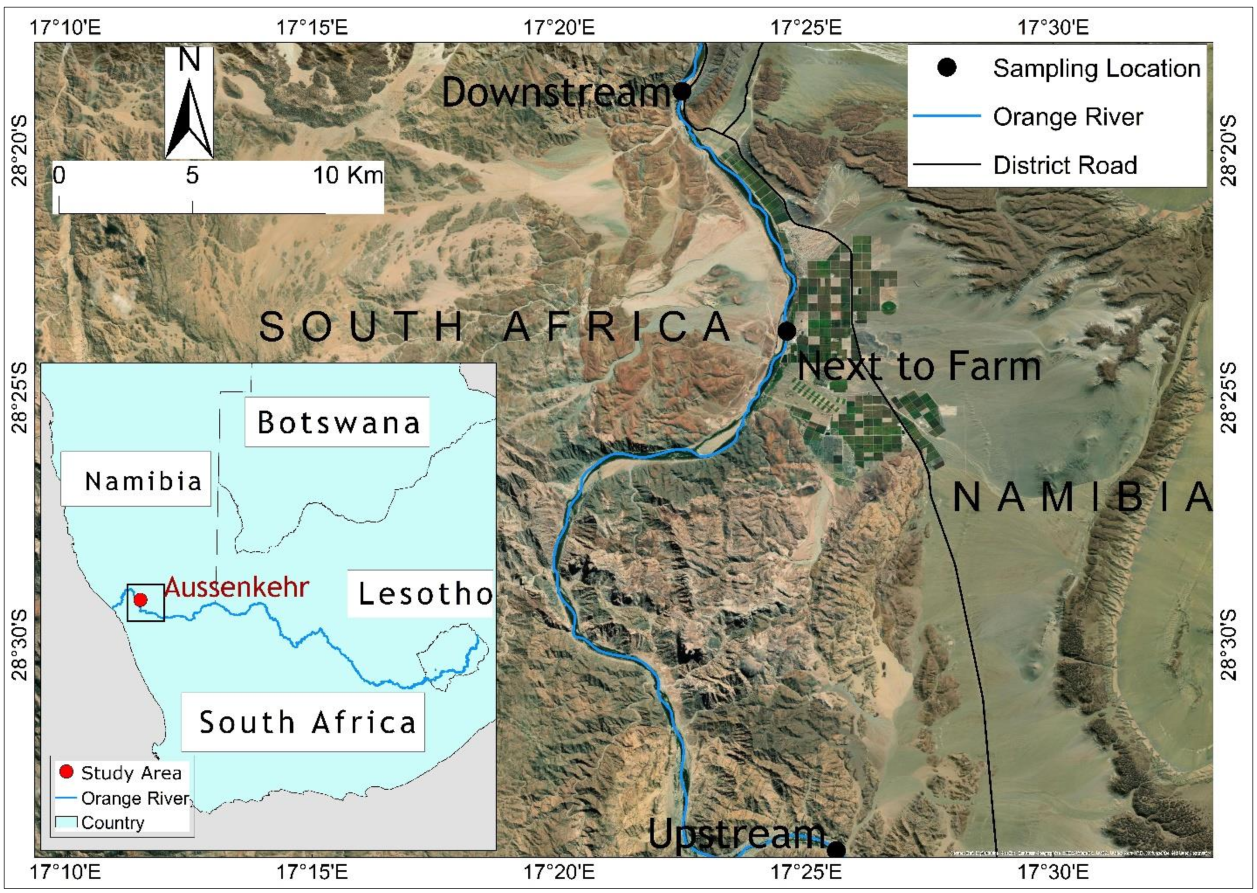

Figure 1: Location of the study area. Satellite image acquired from Environmental Systems Research Institute (ESRI) Satellite Image 2017; river, roads, settlement and Namibian boundary acquired from Namibia Statistics Agency (NSA) digital portal.

The Aussenkehr sub-catchment constitutes various land use / land cover, of which grape farms are the most prominent. The vineyard farms in the sub-catchment are situated downstream of Noordoewer, on the bank of the Orange River. The area surrounding Aussenkehr and downstream of the river is of strategic biodiversity to both Namibia and South Africa (Geo Pollution Technologies, 2016). For this study, the area surrounding the Orange River in Aussenkehr is the focal point.

3.1.1 Climate and topography

Aussenkehr is characterised by extremely hot and dry summers (Geo Pollution Technologies, 2016), and is located in an area with an average rainfall of less than 50 mm per annum (Diederichs et al., 2005; Mendelsohn et al., 2002). It experiences extremely high evaporation rates which results in losses up to 97% of rainfall (Scott et al., 2018). The area is characterised by hot, arid desert conditions which are suitable for growing grapes (Mcgregor, 2016). By contrast, Lesotho, where the Orange River originates, receives an annual rainfall of 1800 - 2000 mm annually. Most of the rainfall (85%) received in the Orange River falls from October to April (Diederichs et al., 2005).

Aussenkehr farms are surrounded by rocky mountain areas close to the Orange River, and water surface run-off in the area flows toward the Orange River (Geo Pollution Technologies, 2016). Figure 2 shows that the area is characterised by a high slope class, especially downstream and upstream of the farms. The area surrounding the sampling location next to the farms is characterised by flat slopes of 0 - 7 degrees.

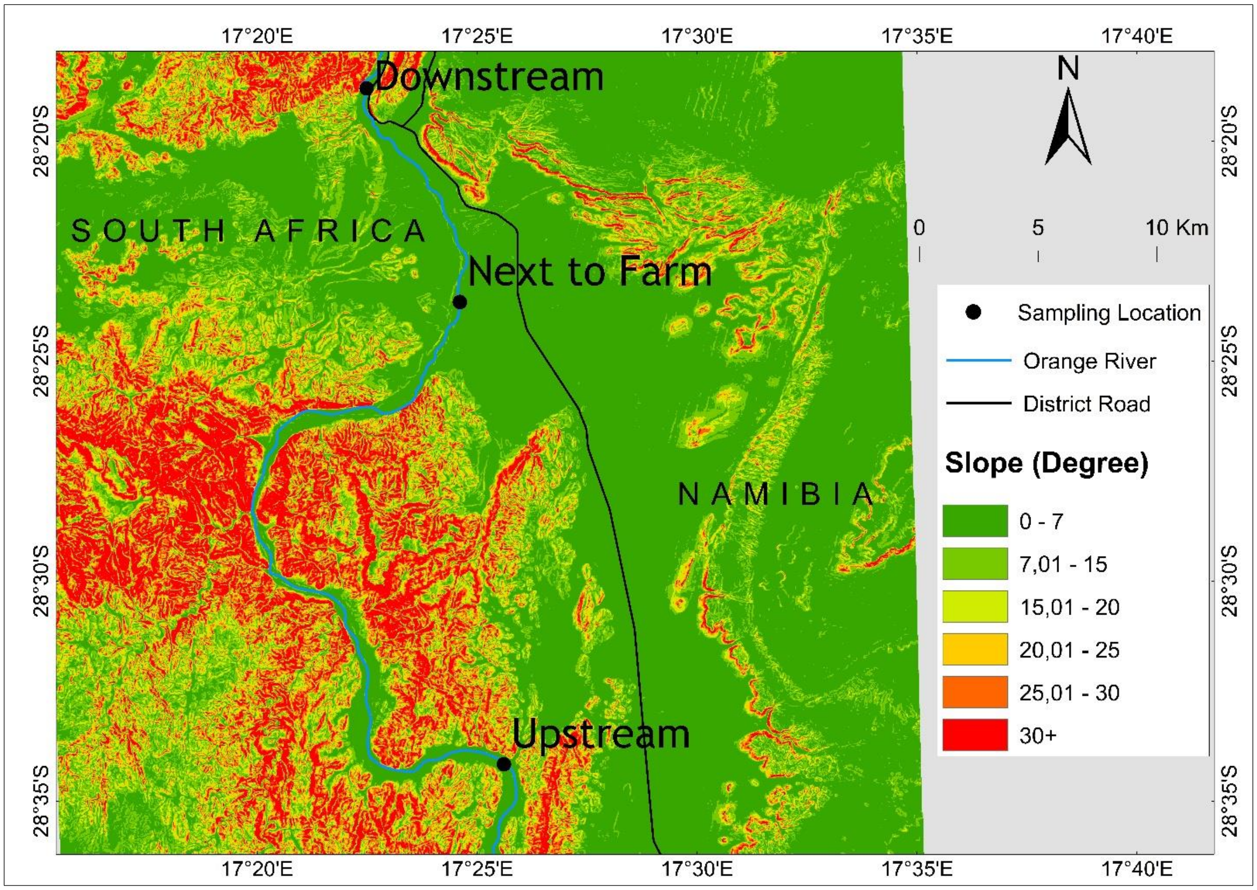

Figure 2: Slope classes in the study area. (Digital Elevation Model (DEM) acquired from USGS; road and river were acquired from NSA digital portal.)

3.1.2 Soil and vegetation

Aussenkehr lies in a low fertility region (Mendelsohn et al., 2002) made up of leptosols soils which are typically found in actively eroding landscapes, in hilly or undulating areas (Mendelsohn et al., 2002). Leptosols soil is limited in depth owing to the underlying material, such as hard rock or highly calcareous materials, and has no diagnostic horizons apart from *mollic, ochric, umbric, yermic or vertic* horizons (Nachtergaele, 2010). The soils of the area support dwarf shrub grassland of the Succulent Karoo biome.

3.1.3 Geology

The geology of the study area consists of sedimentary rocks and patches of igneous rocks (Miller & Becker, 2008). The main lithologies consist of shale, granite, sandstone, diorite, siltstone, dolerite, grano-diorite and quartzite (Christelis & Struckmeier, 2001; Figure 3). As mentioned in Section 2.2, the water quality of a river is influenced by the surrounding lithology because all soil types dissolve in water, and in the process, add salts, hardness and alkaline (Hoch, 2008). The rock types in the study area vary in chemical composition, permeability, solubility and porosity, which determines the amount of water yielded (Hoch, 2008). Granites and sandstones are the most resistant to weathering and therefore they dissolve slowly in water (Hoch, 2008), whereas shales can attain very high levels of dissolved solids.

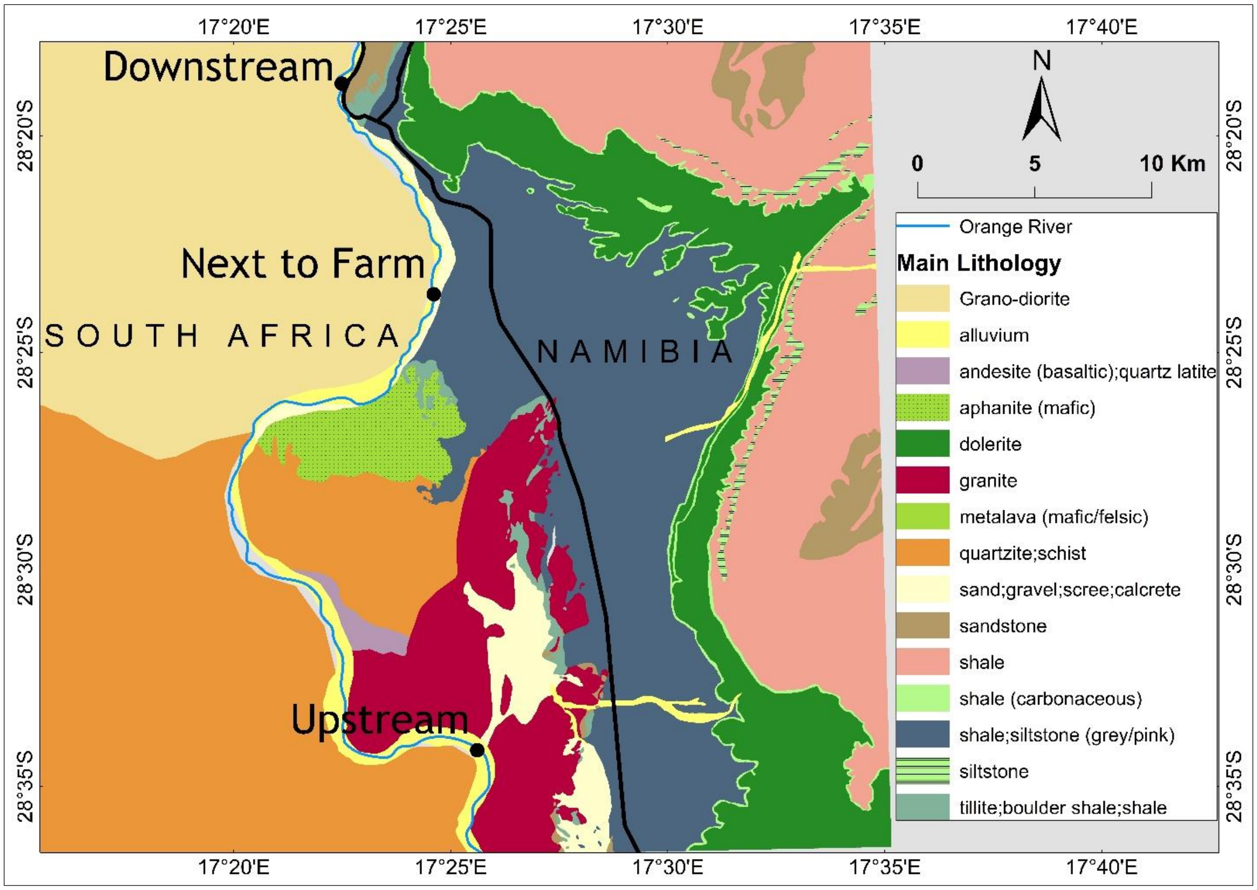

Figure 3: Lithology types in the study area. (Lithology data acquired from the Ministry of Mines and Energy; roads and river shapefiles acquired from the NSA digital portal).

3.2.4 Population and social-economic status

Aussenkehr is a rural community dependent on irrigation farming. According to a 2011 National Census, the population and households in Aussenkehr numbered approximately 4500 and 1500, respectively (NSA, 2011). In 2019, the population of the village was estimated at approximately 10 000 permanent residents. During the harvest, the arrival of seasonal migrant workers doubles the population (Geo Pollution Technologies, 2016; Lugman, 2019).

The settlement has inadequate housing facilities and infrastructure, such as a sewage system. Approximately 30% of the population obtains water directly from the river (Figure 4), which also receives the effluent from informal settlements (Lugman, 2011).

Agricultural production has now become an important part of Aussenkehr. Labour-intensive activities attract a large number of seasonal workers from as far as northern Namibia to the settlement (Lugman, 2011) to take part in pruning and harvesting, and applying different types of fertilisers (Table 2), some of which are nitrates (S10).

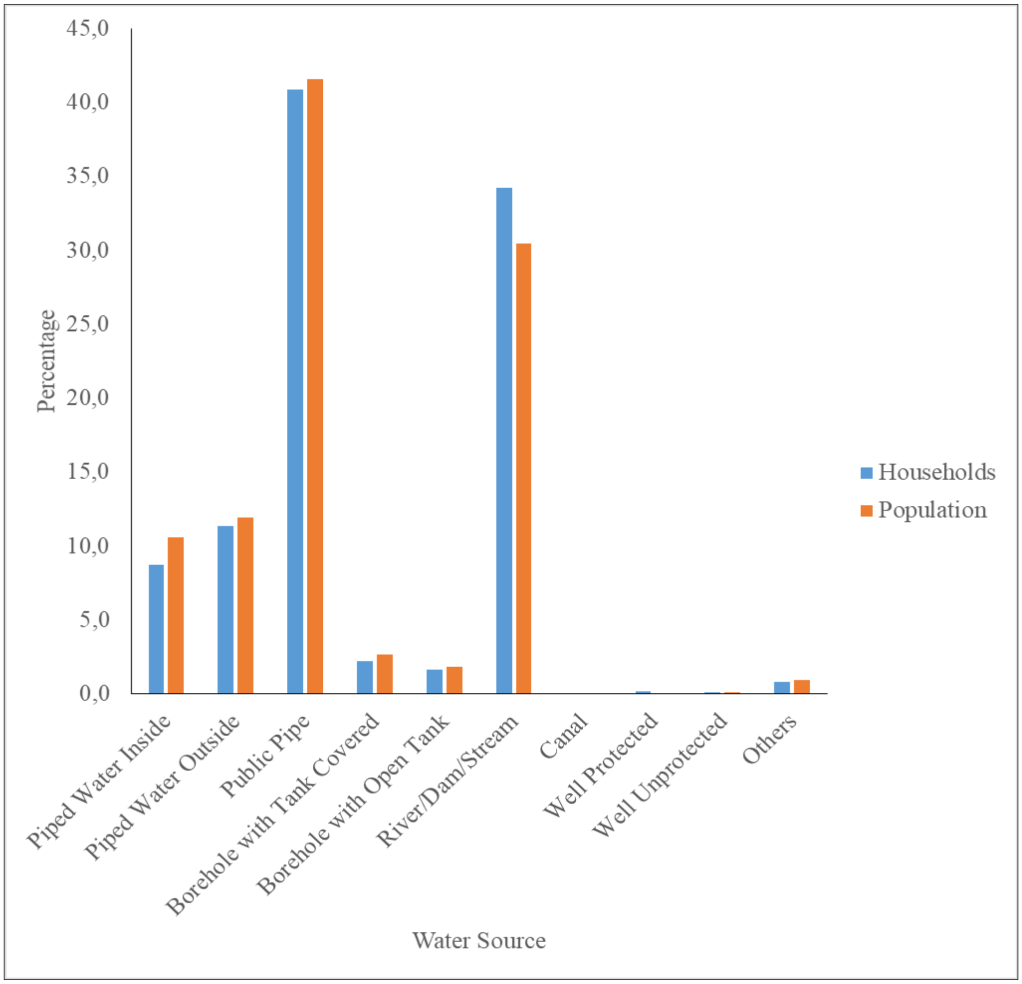

Figure 4: Households and population by main source of water in Aussenkehr in 2011. (Data acquired from NSA 2011 census).

Table 2: Vineyard growing and management cycle. Information obtained from farmers at Aussenkehr.

Period	**Activities**
January	After-harvest fertiliser and agro-chemical programme
February	Administration of organic materials and chicken manure Weed shovelling
March	Pest control Irrigation management, monitoring and treatment of plant infestations and disease.
April - May	Replacement of irrigation lines and trellising poles in plantation for replanting Preparation for replanting
June	Administration (hiring and trainings)
July	Commence with pruning Commence with agro-chemical programme after pruning is done Commence with irrigation programme
August-September	Agro-chemical spraying programme running Weeding Replanting
October	Agro-chemical spraying programme continues Prepare for harvesting
November - December	Harvest grapes and send to fruit processing, packaging, and refrigeration facilities

3.2 Research design

The study adopted a quantitative research approach to assess LULC changes and water quality of the Orange River at Aussenkehr. Satellite images were used to detect changes to the LULC. Assessing water quality involved collecting field data; historical data were also exploited. The overall approach followed is shown in Figure 5, while details for each approach are discussed in subsequent sections.

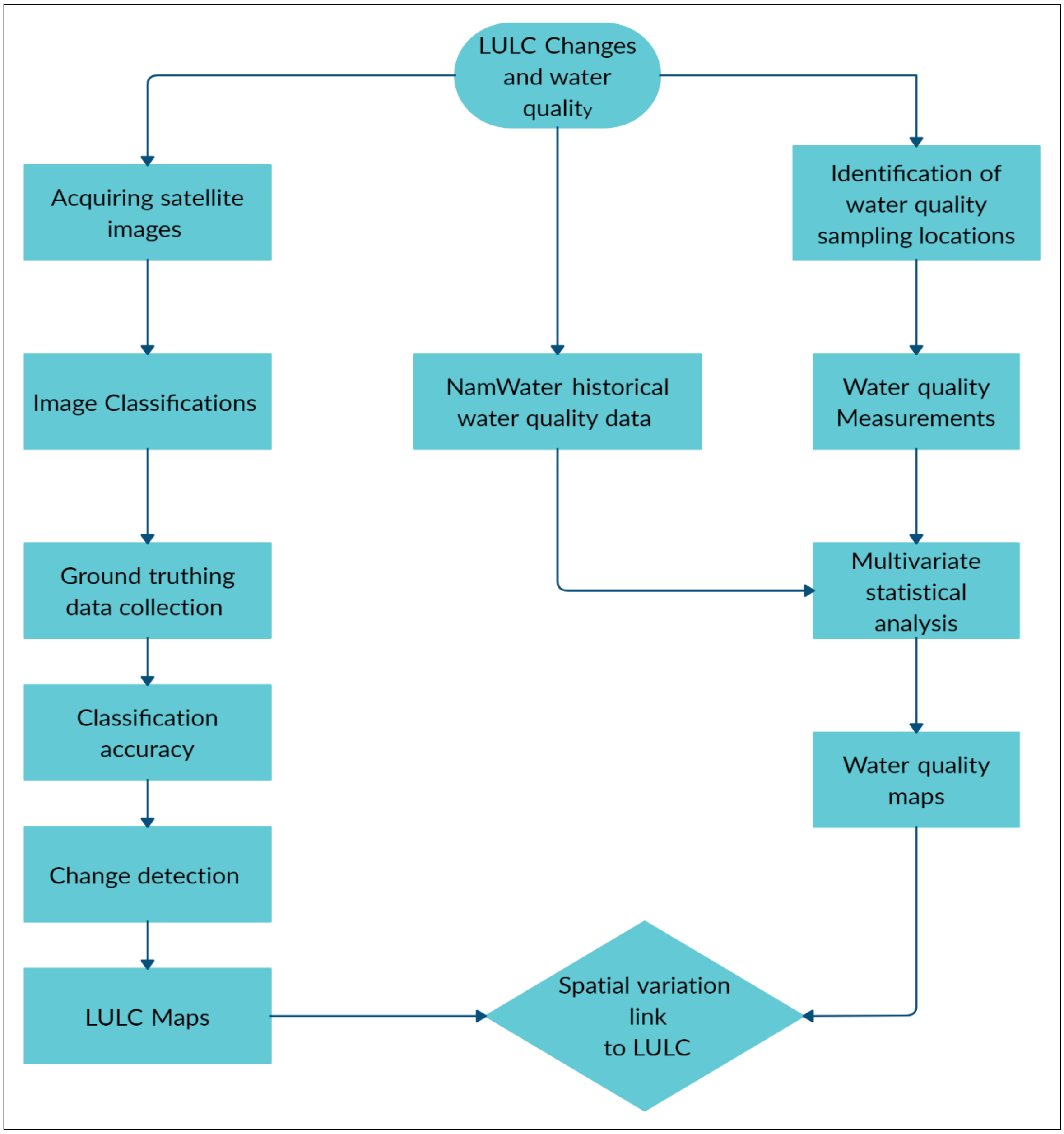

Figure 5: Research design flow chart

3.3 Research instrument

The spatial data were processed and analysed using ArcMap version 10.3, which is an ArcGIS interface that allows for visualisation, manipulation and analysis of spatial and non-spatial information. Water quality indicators were measured using portable instruments at three sampling locations (upstream, next to, and downstream of the farms; Figure 1) specifically for the following parameters: pH, EC, and DO using Hach field portable instruments (HQ40d Multimeter and HQ 14d conductivity meter). *E-coli* was sampled with Colilert test bottles. Water quality data were analysed using R-studio software, a programming language and software for statistical computing and graphics.

3.4 Procedure

3.4.1 Land use and land cover classification

3.4.1.1 Data acquisition and pre-processing

To characterise the LULC change, the study employed Landsat time series images acquired in 1990, 2000, 2010 and 2019. Landsat satellite images were selected for their relatively long historical record. The acquisition dates and the level of the cloud cover of images utilised are presented in Table 3**.**

Atmospherically and geometrically corrected images were downloaded from USGS Earth Explorer, an online database that provides data browsing, ordering, display and downloading for earth science applications. Pixel quality assurance (Pixel_qa), a file that comes with the ordered Landsat images, provides information imperative for clouds and shadows detection in an image. Pixel_qa was used to mask clouds and cloud shadows in the images.

Table 3: Satellite images for LULC analysis in 1990, 2000, 2010 and 2019

Reference ear	**Satellite and sensor**	**Path and row**	% Cloud Cover	**Acquisition date**
1990	Landsat_5_Thematic_Mapper	177_080	3.00	990_03_04
	Landsat_5_Thematic_Mapper	177_080	0.00	1990_06_08
	Landsat_5_Thematic_Mapper	177_080	40.00	1990_07_26
	Landsat_5_Thematic_Mapper	177_080	0.00	1990_11_15
2000	Landsat_5_Thematic_Mapper	177_080	43.00	2000_04_16
	Landsat_5_Thematic_Mapper	177_080	6.00	2000_10_09
	Landsat_7_Enhanced_Thematic_Mapper	177_080	18.00	2000_05_26
	Landsat_7_Enhanced_Thematic_Mapper	177_080	0.00	2000_06_27
	Landsat_7_Enhanced_Thematic_Mapper	177_080	6.00	2000_08_30
	Landsat_7_Enhanced_Thematic_Mapper	177_080	0.00	2000_12_04
2010	Landsat_5_Thematic_Mapper	177_080	0.00	2010_02_07
	Landsat_5_Thematic_Mapper	177_080	4.00	2010_03_27
	Landsat_5_Thematic_Mapper	177_080	21.00	2010_04_12
	Landsat_5_Thematic_Mapper	177_080	13.00	2010_04_28
2019	Landsat_8_OLI/TIRS	177_080	0.02	2018_10_27
	Landsat_8_OLI/TIRS	177_080	0.14	2018_12_14
	Landsat_8_OLI/TIRS	177_080	4.69	2019_01_31
	Landsat_8_OLI/TIRS	177_080	39.89	2019_02_16
	Landsat_8_OLI/TIRS	177_080	19.81	2019_03_04
	Landsat_8_OLI/TIRS	177_080	32.50	2019_03_20
	Landsat_8_OLI/TIRS	177_080	15.29	2019_08_11
	Landsat_8_OLI/TIRS	177_080	3.36	2019_08_27
NB: Most of the images do not have clouds present in the study area				

Geometric distortions and errors are caused by earth’s curvature and rotation, and by sensors used in capturing the image. Therefore, geometric correction of satellite images is required whenever the image is to be compared with other images or existing maps (Dave, Joshi & Srivastava, 2015). Mas (as cited in Kebebew, 2005) concurs that images acquired on different dates, need to be radiometrically corrected in order to be useful for time series analysis. However, in this study, no further processing was required because the images used in the study were Landsat level 2 Tier 1 images which are atmospherically and geometrically corrected. The only pre-processing that was done to the images was clipping downloaded images to the extent of the study area.

3.4.1.2 Ground truthing process

The study area was stratified, and the ground truthing points were selected from the identified classes. A total of 200 ground points was selected from the initial classification. These points were of different LULC classes such as agriculture, settlement, water, and bare soil. To confirm and validate information corrected from satellite images, a Global Positioning System (GPS) was used to navigate to ground points stratified from the LULC. Limited time and poor accessibility meant that points that were in the river, on top of mountains, or out of reach (far from the road) were not verified. Eighty six points were successfully reached and verified.

3.4.1.3 Image classification and change detection

In this study, ‘classification’ refers to the process of assigning pixels to groups (categories) to create a thematic map of LULC. The downloaded images were used to create three indices, namely NDVI, BI, and NDWI. The indices allow visual discrimination of land cover, such as vegetation and water, which helps to increase classification accuracy.

The following equations were used to obtain the indices (Gao, 1996; Schell & Deering, 1973; Schmidt & Karnieli, 2001):

Equation 1: $NDVI = \frac{NIR-Red}{NIR+Red}$

Where for the Landsat 4-7, Near Infrared (NIR) is Band 4 and Red is Band 3; and for the Landsat 8, NIR is Band 5 and Red is Band 4.

Equation 2: $NDWI = \frac{NIR - SWIR}{(NIR + SWIR)}$

Where for the Landsat 4-7, NIR is Band 4 and Short-Wave Infrared (SWIR) is Band 5; and for the Landsat 8, NIR is Band 5 and SWIR is Band 6.

Equation 3: $BI = (Green^2 + Red^2 \ + NIR^2)^{\frac{1}{2}}$

Where for the Landsat 4-7 Green is Band 2, NIR is Band 4 and Red is Band 3; and for the Landsat 8, Green is Band 3, NIR is Band 5 and Red is Band 4.

Multiple images were used in the classification to account for seasonal variations and increase classification accuracy. The process of RF supervised classification requires training samples, and these were created in ArcGIS for all land cover classes, with the help of high-resolution Google Earth images.

Before carrying out the classification, signature separability was carried out. Using ArcMap, spectral signatures for all classes were assessed to evaluate the quality of the training samples. The two methods used in assessing the training samples involved visual interpretation of the brightness of the training areas using histograms and visual analysis of training area locations in the n-dimension with scatterplots. These steps helped in identifying different band combinations that were useful for separating classes in image classification. After signature separability, some classes, such as bare soil and settlements, and vineyards and natural vegetation were combined because they yielded similar spectral signatures.

Training statistics for pixels of all years were analysed to ensure a clear distinction between different LULC classes. A composite of the near infrared, short-wave infrared and one band from the visible spectrum provided a clear distinction between water and agriculture, while an obvious distinction between bare soil and agriculture was provided by the combination of all visible bands.

The training samples were then exported to R-studio, where the algorithm for classification was run. Training samples for all years were divided into training and testing datasets during image classification. During classification, RF classifier first trains the model based on training data, then it uses the model to predict and classify the image into different LULC classes.

A post- classification change detection algorithm was also applied to the classified images to show the nature, extent, and area of change between different years. The post-classification change detection technique shows the from-to-changes between classified images.

The rate of change for each year's LULC class was calculated using the following formula (Kebebew, 2005):

Equation 4: $annual\ rate\ of\ change = \frac{(A-B)}{C}$

Where, A = Recent Year area (ha);

B = Previous Year area (ha); and

C = time interval between A and B (years)

The study had a special interest in the vineyards; therefore, to accurately quantify the changes in LULC in Aussenkehr, on-screen digitising of some land use and cover was carried out. The classes that were digitised included settlement, which was included in the bare soil during classification, and vineyards included in agriculture with natural vegetation. Owing to the limited availability of high-resolution images of the study area on Google Earth, the earliest image that was digitised was acquired in 2010, and the latest in 2018.

3.4.1.4 Accuracy assessment

Every classification algorithm needs to be evaluated to assess its accuracy. Lu and Weng (2007) assert that no classification algorithm can satisfy all the requirements; therefore, to assess accuracy, an error matrix which compares the classification results to ground truthing information was used. Accuracy assessment for 2019 classification was carried out from independent ground truthing data collected during May - June 2019 fieldwork. The ground truthing points were randomly selected from stratified sampling in the study area, but owing to difficulty in accessing the points, only 86 points were successfully collected and used to create a confusion matrix to assess the classification accuracy. A confusion (error) matrix describes the accuracy of the classification by providing a detailed assessment of how the classification performed compared to the reference data and produces information of the sources of the errors (Kim, 2016). An error matrix indicates both the user’s and producer’s accuracy. The producer’s accuracy refers to the probability that an area on the ground is classified as it is on the map, while the user’s accuracy refers to the probability that the pixels classified on the map are a real reflection of what is on the ground (Kim, 2016).

3.4.2 Water quality

3.4.2.1 Sampling

Three sampling locations were chosen for measuring water quality because they were easy to access and because of their location in relation to the farms. The upstream sampling location was located 26 km from the farms; the topography of the area prevented selection of an upstream sampling point closer than 26 km. The sampling point adjacent to the farms was aligned with the middle of the farms and was accessible through a lodge. The downstream sampling location was 3 km from the farms. The location (latitude and longitude) for each sampling location was recorded using a GPS. As mentioned in Section 3.3, water was tested for pH, EC (µS/cm) and DO (mg/l). *E-coli* samples were taken in situ and the readings were done with an Ultraviolet (UV) light after 24 hours.

Fieldwork was carried out between 1 and 3 December 2018 for the wet season (S4) and between 25 and 28 May 2019 for the dry season (S5). The measurements were taken at all sampling locations three times a day: in the morning, afternoon, and evening. The total number of measurements for both the wet and dry season was 54 for each parameter (table 4).

Table 4: Total number of measurements (n) taken during the wet season (December 2018) and dry season (June 2019). Time constraints resulted in a lower number of observations for some stations.

Season	**Wet season**	**Dry season**	**Total**
Upstream	9	11	20
Next to farms	5	11	16
Downstream	8	10	18
Total	22	32	54

Although there were no historical data for water quality taken for Aussenkehr, the study made use of historical data collected by NamWater in the Orange River for the water purification plants at Noordoewer (upstream) and Roshpinah (downstream) (S6 & S7). Noordoewer is located 50 km upstream of Aussenkehr while Roshpinah is located 140 km downstream of Aussenkehr. The main land use activity occurring between Noordoewer and Roshpinah is agriculture on the farms in Aussenkehr.

The Fish River enters the Orange River after Aussenkehr and before the sampling location for Roshpinah. The data was measured on different days and at different times. The data were averaged to the months of observations in Aussenkehr to allow for comparative analysis. The months used were November and December for the wet season, and May and June for the dry season. Because data were missing for the months of November and December 2018, the average of the two closest readings taken in October and January were used to represent the wet season for that year.

3.4.2.2 Water quality data analysis

Data were subjected to the Shapiro-Wilk normality test to see if they followed a normal distribution, after which a decision was made about which test to follow in testing for differences. The Kruskal-Wallis test was used to test for significant differences between the seasons and differences between sampling locations. After testing for differences between sampling locations and differences between seasons, the Dunn test was applied to those pairs that showed a significant difference to compare the locations and seasons.

The Mann-Kendall trend test, a non-parametric test, was applied to detect monotonic trends in water quality time series data, while the Theil (Sen) slope test was used to provide an estimation of the slope or trend in the data. Trend analysis determines whether there is an increasing or decreasing trend, and the Sen slope was only applied after a linear trend had been found by Mann-Kendall. Data management and analyses for water quality data were performed using R-studio.

3.4.2.3 Land use and land cover, and water quality

The assessment of water quality as it relates to LULC was deciphered at two different levels. The first level was based on the water quality parameters at three sampling locations, located at and immediately before and after the farms. This level had the advantage of spatial coverage because the data were collected in close proximity to the farms. To address the limitation of temporal scale inherent in the data employed in the first level, the time series of water quality trend mentioned in Section 3.4.2.1 was used at the second level.

3. 5 Research ethics

The researcher applied for an ethical clearance certificate research from the University of Namibia (UNAM) Ethics committee prior to conducting this research (S1). Permission to use soil, historical water quality data, and water flow data was granted by International Soil Reference and Information Centre (ISRIC), NamWater, Ministry of Mines and Energy (MME), and DWAF, respectively. Satellite images and DEM data were freely available and were downloaded from USGS Earth Explorer. Data quality was preserved to avoid misleading data presentation. No data collected were confidential, therefore they are stored in the archives of the University's Geography, History and Environmental Studies Department with other freely available and non-confidential data at the University.

4. Results

This section presents the results of the LULC changes at Aussenkehr. It also focuses on the spatial and temporal aspects of water quality parameters as represented by the samples measured at the three sampling locations along the Orange River at Aussenkehr during the wet and dry season in 2018 and 2019, respectively, and how those parameters vary with the LULC. This section also presents the historical, average time series measured at Noordoewer and Roshpinah for the months of November to December, and May to June, representing the wet and dry seasons, respectively.

4.1 Land use and land cover classification and change detection

Training sample analysis revealed that, except for a noticeable overlap between settlement and bare soil, water and agriculture were distinct in the scatter plot and histogram.

Overall classification accuracy for the 2019 image was 81.4%, with a Kappa coefficient of 74.0%. Both agriculture and settlement had high producer accuracy of 90.7% and 90%, respectively. Water had the lowest producer accuracy of 36.4%; settlement had the highest user accuracy of 100%, while bare soil had the lowest user accuracy of 62% (S11).

From 1990 to 2019, bare soil was consistently the dominant class, occupying over 80% of the study area (Figures 6 and 7). In 1990, the agriculture class occupied 2.2% (586 ha) of the study area (Figures 6 and 7). This class doubled to 4.7% (1256 ha) in 2000, and then increased steadily to 6.3% (1678 ha) in 2010. In 2019, the class of agriculture nearly doubled again to 10.1% (2699 ha). This change was the highest recorded in the study area, translating to an increase of 113.3 ha per year over a nine-year period (S12).

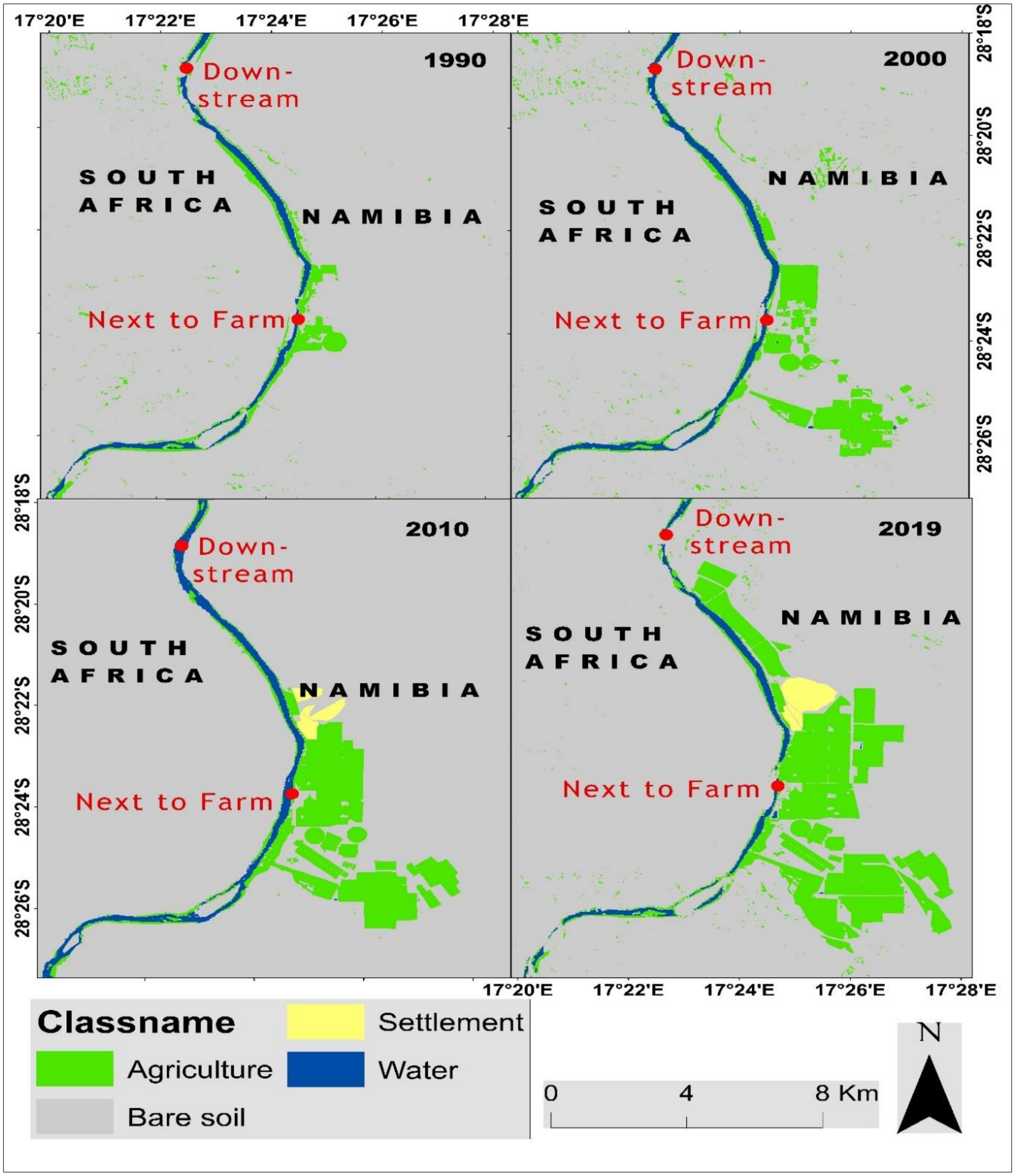

Figure 6: LULC classification of 1990, 2000, 2010 and 2019. Note that owing to coarse spatial resolution of the 1990 and 2000 images, settlement was merged with bare soil during that period. The upstream sampling point is located 26 km away and could not be shown in the current map.

Settlement was the other class in the study area that increased, albeit marginally, from 122 hectares in 2010 to 179 hectares in 2019, which amounts to approximately 6 ha per annum. These figures were obtained from high satellite images, which were not available for 1990 and 2000. The increase of the agriculture and settlement classes were recorded only on the Namibian side of the river (Figure 6).

Bare soil was the only class that had a consistently downward trend. It decreased from 96.5% (25 916 ha) in 1990 to 88.2% (23 670 ha) in 2019 (Figure 7). The water class was relatively stable (around 330 ha) during the study period, with the exception of 2019, when it decreased slightly to 295 ha.

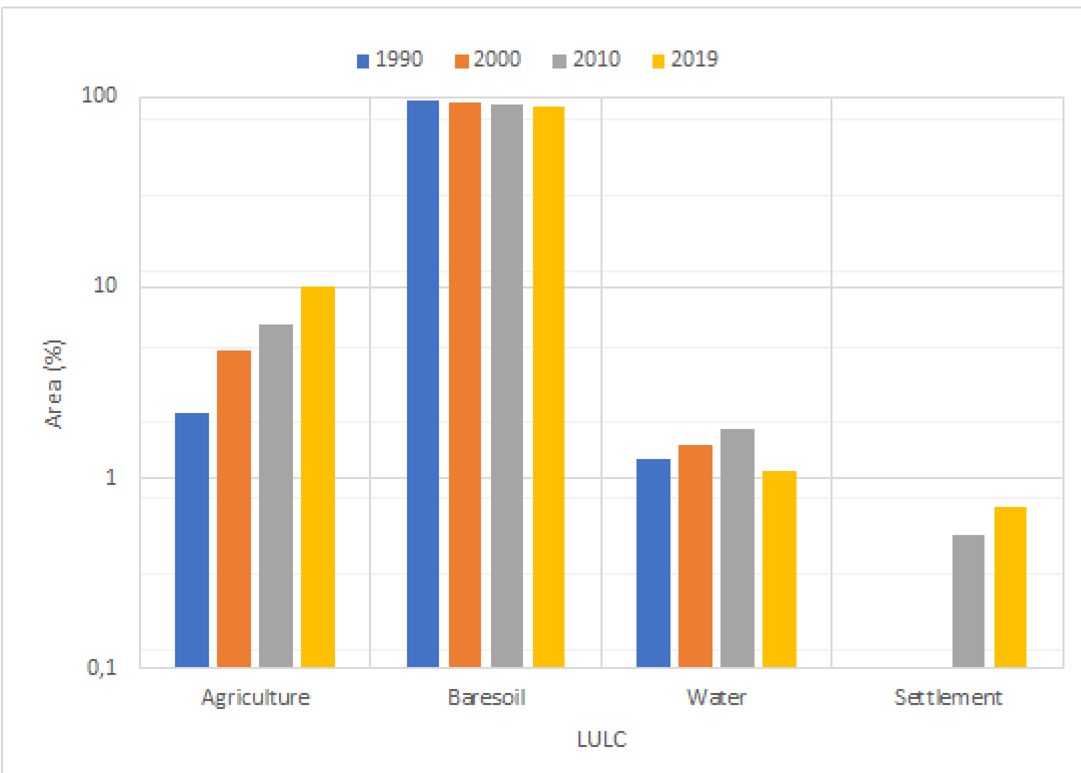

Figure 7: LULC classes and area coverage (1990 to 2019). Note that due to coarse spatial resolution of the 1990 and 2000 images, settlement was merged with bare soil during that period.

Change detection showed that during the period of 1990 and 2019, 53.6%, 90.2% and 79.6% of land area under agriculture, bare soil and water, respectively, remained in the same LULC class, whereas the area classified as agriculture in 1990 was converted to bare soil (44%), water (1.8%), and settlement (0.2%) by 2019. In addition, 9.1%, 0.1%, and 0.7% areas of bare soil in 1990 were converted by 2019 to agriculture, water, and settlement. In 2019, each of the agriculture and bare soil classes occupied approximately 10% of the area, 7.8% and 12.6% of which was classified as water in 1990.

4.2 Water quality

4.2.1 Electrical conductivity

Overall, EC values were lower (average below 550 μS/cm) upstream of the farms (Figure 8). However, EC values increased by more than a third (as much as 300 μS/cm) next to the farms. The highest value of 833 μS/cm, which exceeds the maximum threshold for the ideal guideline class water quality, was recorded next to the farms at the onset of the wet season. The downstream location recorded intermediate results in both seasons, ranging between 650 μS/cm during the onset of the dry season and 750 μS/cm during the onset of the wet season.

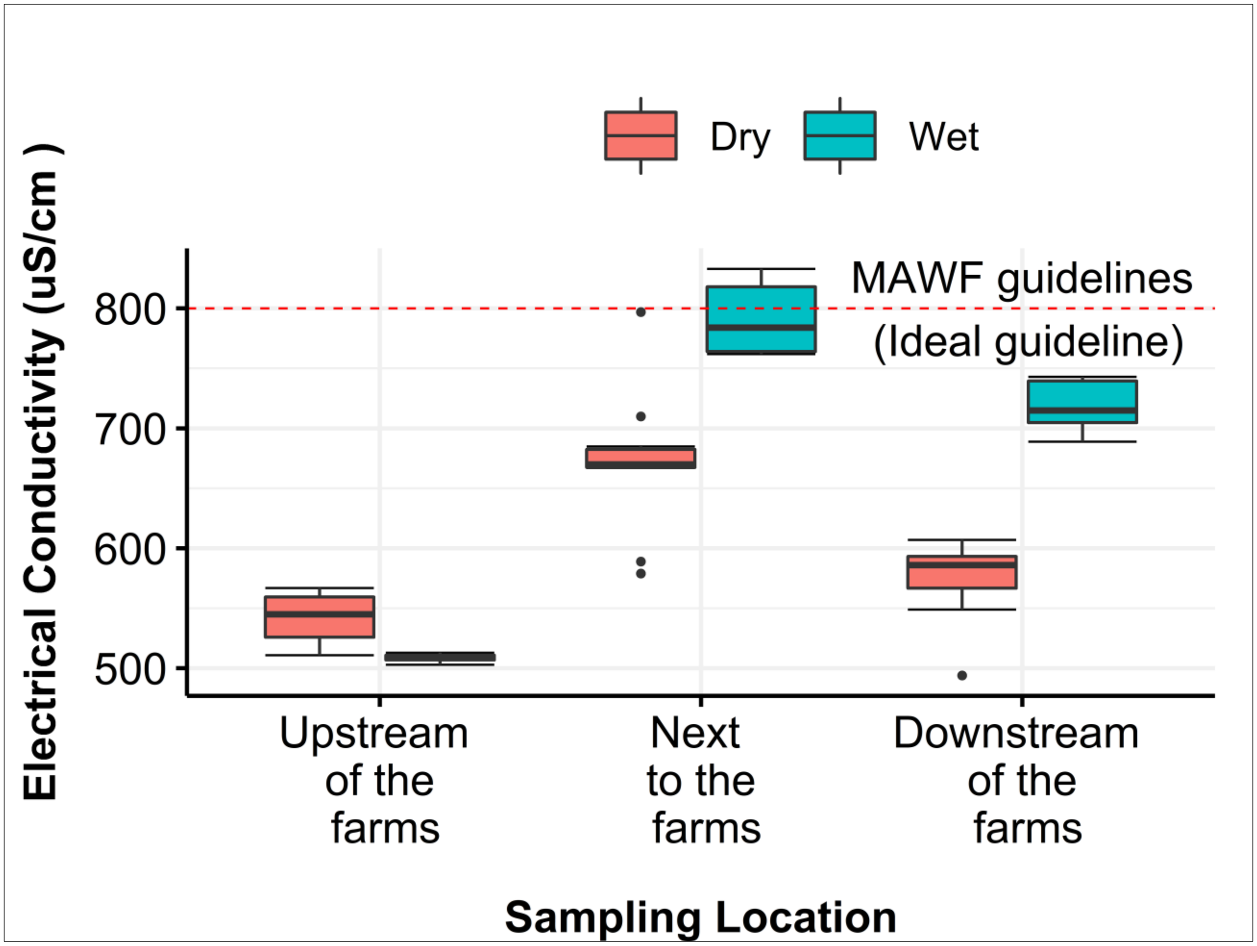

Figure 8: Box plot of EC measured in the Orange River in and around Aussenkehr at the beginning of the dry and wet seasons in the study area

Results of a Kruskal-Wallis test indicated that there was no significant difference between seasons (df=1) for EC (x^2=1.2499, p-value=0.2636; S13). However, a Kruskal-Wallis test showed that there was a statistically significant difference between sampling locations (df=2), EC (x^2=23.607, p-value =5.039e-08).

The Kruskal-Wallis test only indicates that there is a difference between variables without indicating the specific variable, so the Dunn post-hoc test was used to assess the differences between the groups. Dinno (2015) recommends the use of the Dunn test when Kruskal-Wallis' hypothesis test is rejected. The Dunn test results showed that EC differed significantly at all sampling locations (S14).

To place the results obtained during fieldwork in a wider temporal context, they were averaged and plotted against the time series from the nearby permanent stations at Noordoewer (upstream) and Roshpinah (downstream). Data of the time series were averaged for the months of November - December (wet season) and May - June (dry season) to align them with the fieldwork periods. The average EC measurements taken during fieldwork at the locations adjacent to and downstream of the farms were significantly higher in both seasons (Figure 9). In particular, field measurement from the site adjacent to the farms exceeded the average measurements from Noordoewer (upstream) by more than 250 µS/cm during the wet, and 80 µS/cm during the dry seasons. In contrast, field measurements from the upstream location were comparable to historical data from Noordoewer, with their error bars overlapping in the wet season. The field sampling location at the upstream had EC values averaging below 550 µS/cm and recorded the lowest variability between the two seasons.

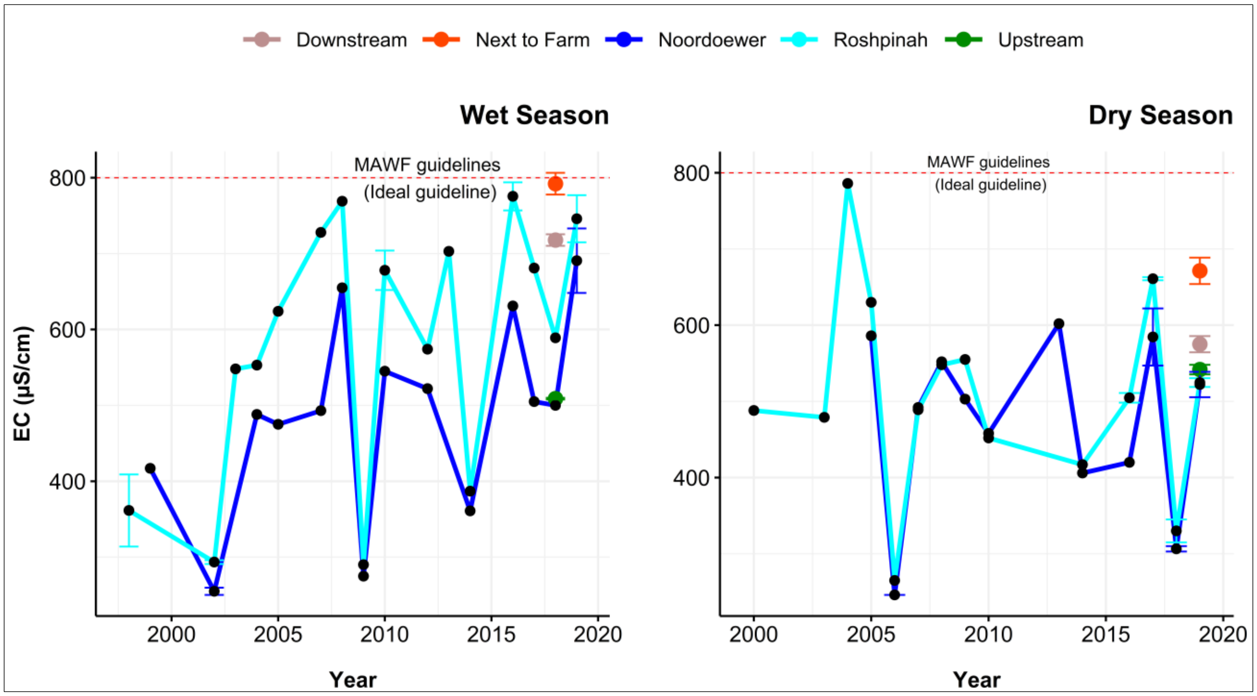

Figure 9: Average time series of EC for the months of November to December, and May to June, representing the wet and dry seasons, respectively, along with field measurements taken during the same months for this study. Owing to missing data for the months of November and December in 2018, the average of the two closest readings taken in October and January were used. (Time series data acquired from NamWater).

The Mann-Kendall test was applied to the time series of the EC data collected at Noordoewer (upstream) and Roshpinah (downstream). Results showed an increasing trend for EC in the downstream, with a rising Mann-Kendall tau of 0.291 and Sen's slope EC of 2.451. The trend upstream of the farms was up to a third lower than downstream, standing at EC Mann-Kendall tau of 0.242 (17% lower) and Sen's slope EC of 1.66 (32% lower) (S19).

4.2.2 Dissolved oxygen

The minimum and maximum values measured for DO during the wet season were 6.74 mg/l and 10.93 mg/l, respectively. These values increased to 7.28 mg/l for the minimum and 15.25 mg/l for the maximum during the dry season (Figure 10). All the recorded values for DO were above the MAWF recommended minimum value of 6.0 mg/l. While there is no obvious trend during the wet season, DO measured during the dry season was slightly high in the upstream, dropped next to the farms, and then increased again at the downstream location.

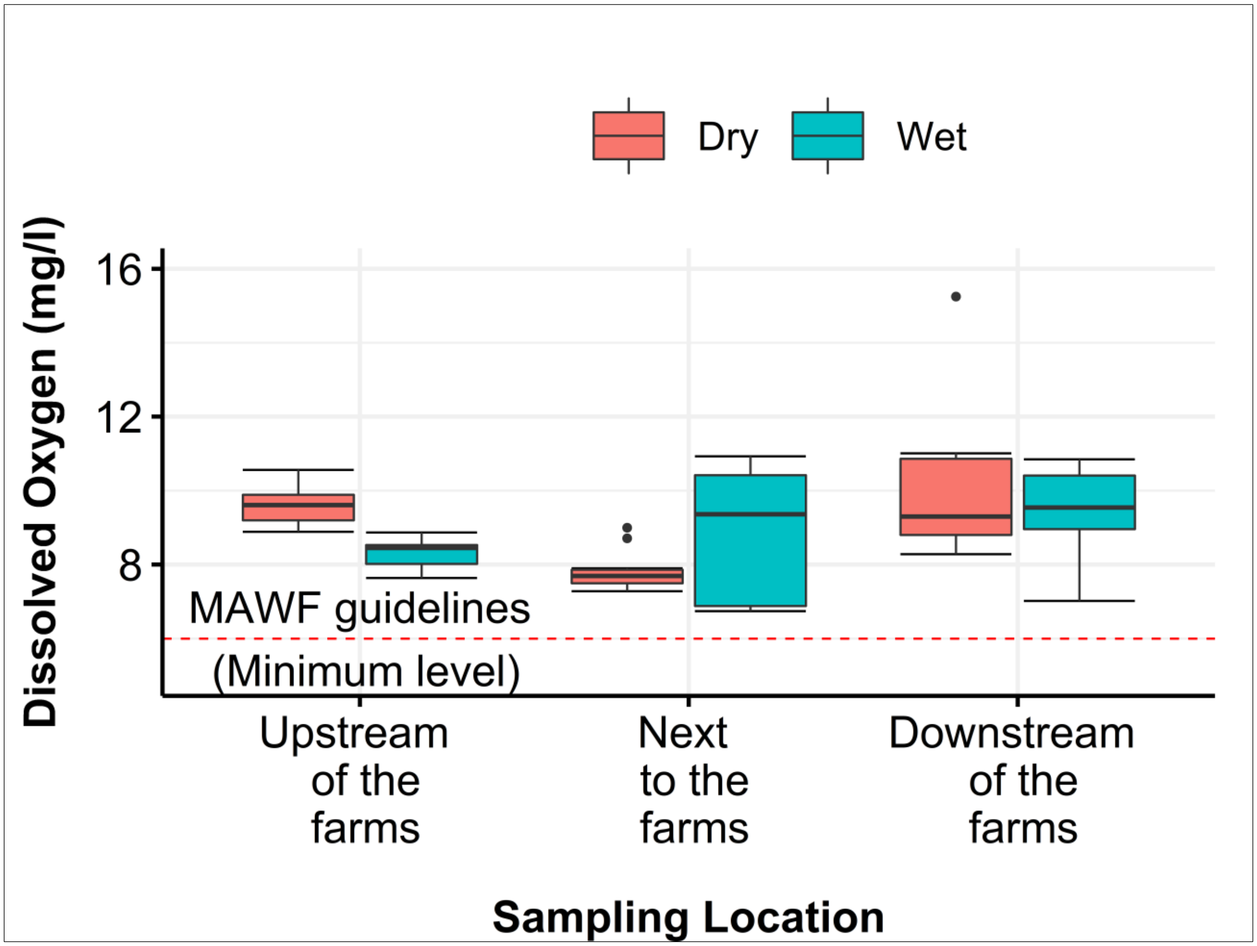

Figure 10: Box plot of DO measured in the Orange River at the beginning of the dry and wet seasons in the study area

Kruskal-Wallis results (S15) indicated that there was no significant difference in DO between seasons (df=1), DO (x^2=0.35825, p-value=0.5495). However, a Kruskal-Wallis test showed that there was a statistically significant difference between sampling locations (df=2) DO (x^2=12.379, p-value =0.002051).

Dunn test showed that DO upstream did not differ significantly from DO next to farms (0.054206563; S16). Similarly, there was no statistically significant difference (p=0.655617480) in DO measured upstream and downstream of the farms. However, a statistical difference (p=0.00155617480) was recorded between DO levels measured next to farms and downstream of the farms.

4.2.3 pH

The highest pH (8.87) in Aussenkehr was recorded at the downstream site during the wet season (Figure 11). The value is above the maximum threshold of the MAWF guidelines for drinking water (MAWF, 2012). At all sampling locations and during all seasons, the pH was found to be at the upper limit for good water quality, with few observations in the category of alkalinity next to and after the farms. An exception was an acidic outlier of a pH of 4.45, which was recorded during the wet season upstream of the farms.

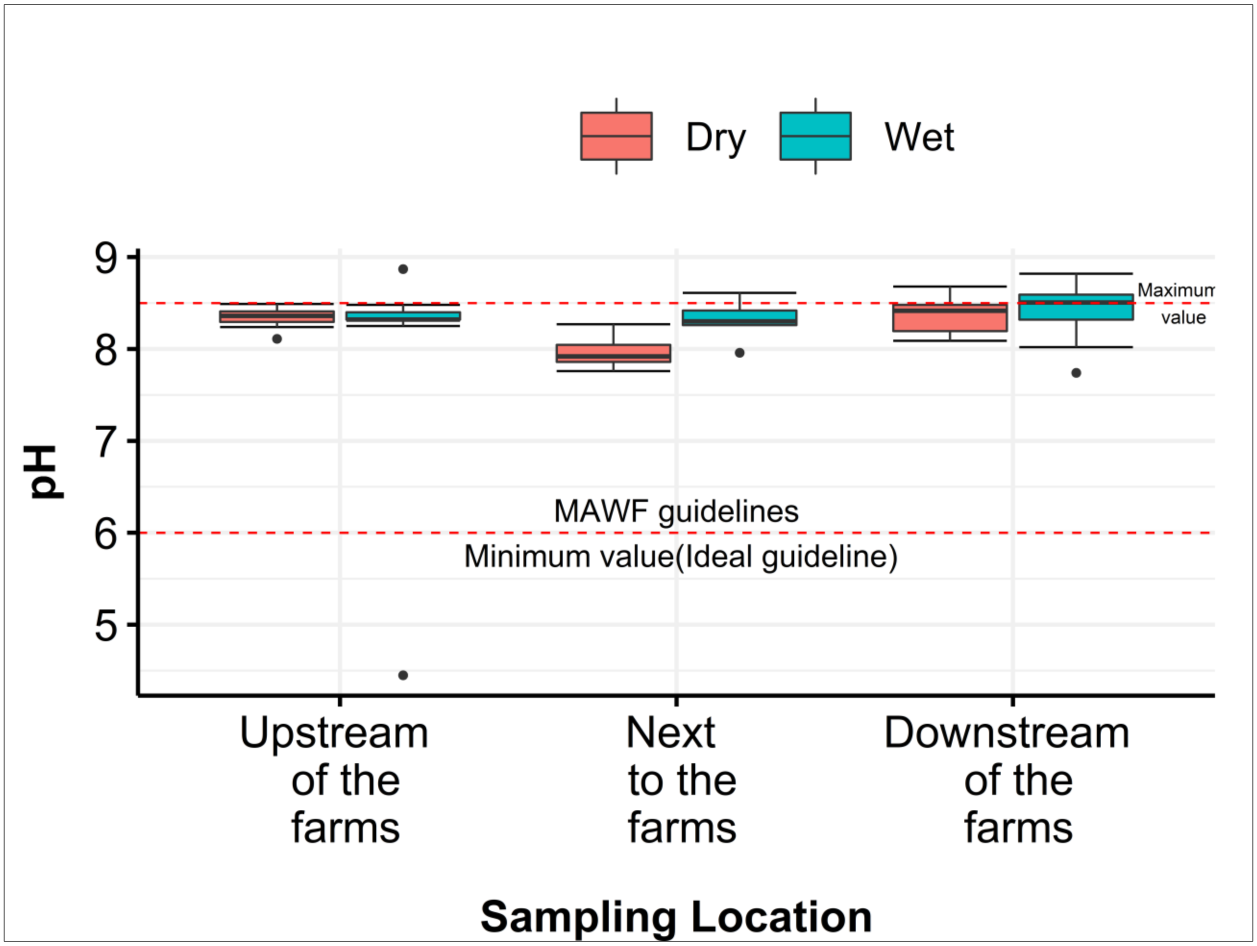

Figure 11: Box plot of pH measured in the Orange River at the beginning of the dry and wet seasons in the study area

The Kruskal-Wallis test indicated that there was no significant difference between seasons (df=1) for pH (x^2=3.4191, p-value=0.06445; S17). However, a statistically significant difference was found between sampling locations (df=2) for the measured pH (x^2= 13.128, p-value=0.001411).

Upstream pH measurements differed significantly from pH measured next to the farms (p=0.016627208), while pH measured upstream did not differ significantly from pH measured downstream (p=1.000000) and pH measured next to farms differed significantly from pH measured downstream of the farms (S18).

The plot of time series from Noordoewer (upstream) and Roshpinah (downstream), and those obtained during fieldwork over the same months show that field measurements taken immediately before and after the farms were comparable to results obtained from the corresponding stations upstream and downstream of the farms (Figure 12). pH averages obtained at all sampling locations at Aussenkehr in 2018 (wet season) were within limits for water with excellent water quality (ideal guideline), as opposed to averages at Noordoewer and Roshpinah, which were alkaline (Figure 12).

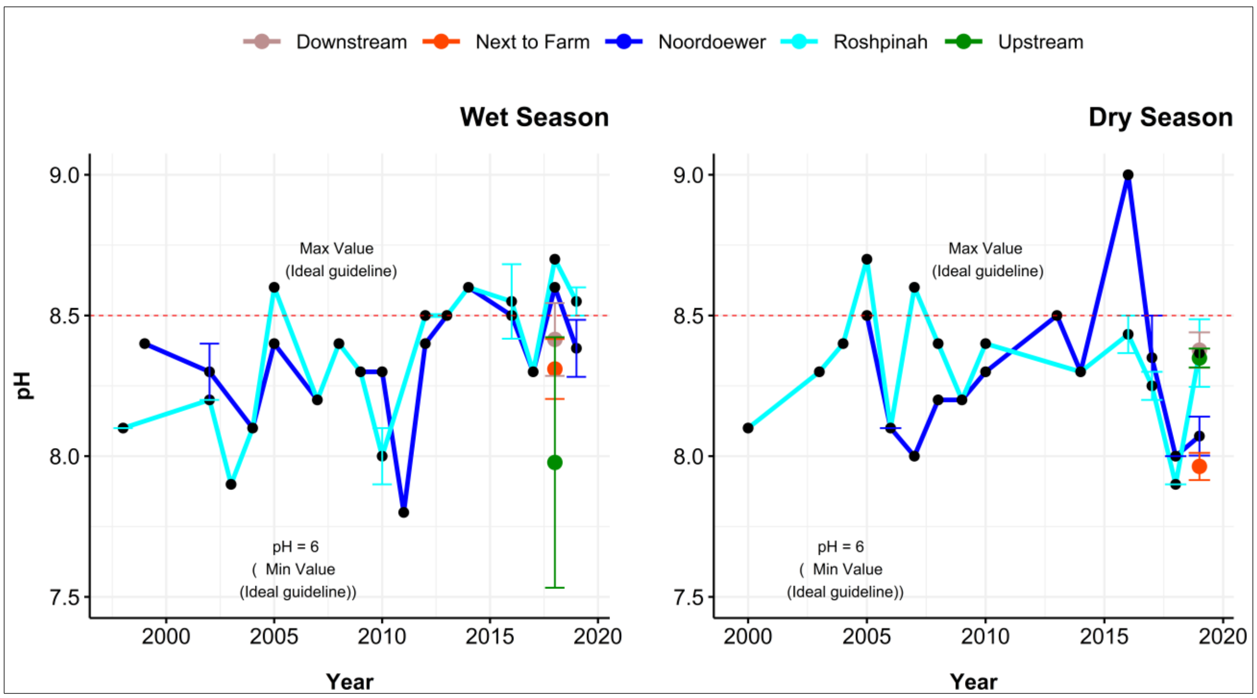

Figure 12: Average time series of pH for the months of November to December and May to June, representing the wet and dry seasons, respectively, along with field measurements taken during the same months for this study. Owing to missing data for the months of November and December in 2018, the average of the two closest readings taken in October and January were used. (Time series data acquired from NamWater, Namibia).

All averages at Noordoewer, Roshpinah and Aussenkehr in 2019 (dry season) were within the permissible water quality values as set by MAWF. The pH at the Noordoewer and Roshpinah fluctuates significantly; therefore, a clear trend was not observed in the measurements; neither did trend analysis show a trend for pH at Noordoewer, which resulted in a Mann-Kendall tau of 0.144 and Sen's slope of 0.000 (S21 & S22).

4.2.4 *E-coli*

All water samples taken during the wet season tested positive for *E-coli* (S23), which means that the water contained small organisms that are found in human and animal waste. Samples were only taken during the wet season upstream and downstream of the farms.

4.3 Land use and land cover changes and water quality

As reported in Section 4.1, agriculture and settlement were the only two classes in the study area that showed increased spatial extent during the study period. In Section 4.2, results showed that EC values were lower upstream of Aussenkehr and then increased by more than a third at the farms, before dropping to an intermediate level downstream of the farms. This section contextualises these spatial and temporal aspects of LULC changes in relation to the water quality at and around Aussenkehr. The EC, pH and DO measurements are used to exemplify the water quality variables.

Figure 13 shows the monthly averages of EC measured at Noordoewer (upstream) and Roshpinah (downstream), along with the timing of irrigation and the application of fertilisers at Aussenkehr. Three peaks above the A-class water limit were recorded for February, July and August. The highest peak in February is in excess of 900 µS/cm downstream of Aussenkehr. In July, a peak was recorded at both the upstream and downstream stations. The last peak in August was recorded at the downstream station.

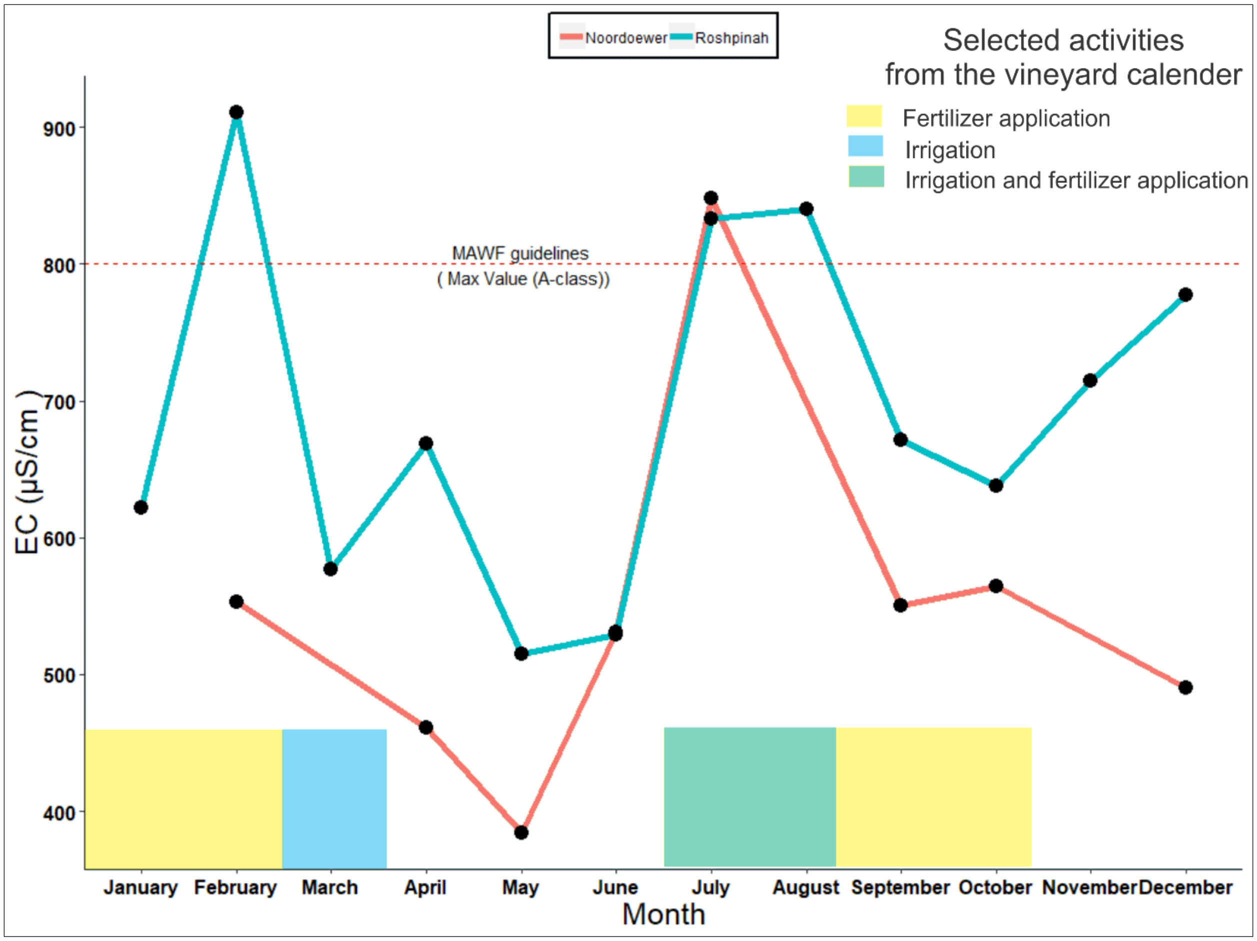

Figure 13: Monthly EC averaged at Noordoewer and Roshpinah in 2019 and selected land use activities practised at the farms in Aussenkehr during the corresponding months. (Time series data acquired from NamWater; land use activities obtained from farmers at Aussenkehr).

The peak in February coincides with the application of fertiliser that commences in January and lasts until February. The second and third peaks in July and August were synchronous with irrigation and the application of fertilisers.

Conversely, a noticeable drop in EC values was recorded in May at both stations, and in December at the upstream station. In general, the trend in EC values was similar throughout the year at both stations, with the exception of a divergence that occurred from October to December. During that period, EC values increased downstream, while a downward trend occurred at the upstream station. This divergence peaked in December, reaching a difference of more than 50% (approximately 300 µS/cm) between the two stations. The onset in October of the EC divergence between the two stations coincided with the end of the application of fertilisers that started in September.

Although there is no discernible pattern in the annual average of EC at the upstream and downstream stations (S19), overall, the EC values yielded a Sen's slope of 1.66 and 2.45 (S20), respectively, between 1997 and 2019. In other words, EC values increased gradually over time, with the downstream station rising by nearly 50% more than the upstream station. Coincidently, the area occupied by agriculture increased by 54% between 2000 and 2019.

Trend analysis of the time series data revealed that no trend was found in pH at either Noordoewer or Roshpinah. Despite that, it was clear from the averages calculated at Noordoewer and Roshpinah that the water quality had ranged from neutral to slightly alkaline over the years.

The DO at the upstream sampling location was found to be higher than next to the farms. As mentioned in section 4.1, the LULC revealed that the only difference between the three sampling locations was the dominance of agriculture and settlement found downstream and next to the farms.

5. Discussion

The aim of this study was to quantify and assess the LULC changes of the Aussenkehr area and the water quality of the nearby Orange River. Overall, the results indicate that the change in LULC was due to agricultural expansion, as expected. The results also show that the water quality of the Orange River measured in Aussenkehr varied with spatial location and time. The EC recorded during the onset of the wet season was higher compared to the beginning of the dry season. Higher EC results were also recorded next to the farms than at other stations during both seasons. These results are discussed further in the next sections.

5. 1 Land use and land cover classification and change detection

Change detection that was conducted for three different periods 1990 to 2000, 2000 to 2010, and 2010 to 2019 identified agriculture as the dominant driver of LULC change. This shift accords with the results found in the north-east of Namibia, where agriculture expansion was ranked as the most predominant driver of LULC change (Kamwi et al., 2015).

The expansion of agriculture of over 100 ha per year is not unique in the study area. Similar results were also found in Botswana (Matlhodi, Kenabatho, Parida & Maphanyane, 2019) and other countries where agricultural land has been increasing at the expense of bare soil and other LULC classes (Agaton, Setiawan & Effendi, 2016; Tsarouchi, Mijic, Moulds & Buytaert, 2014). This increase in agricultural land could be attributed to greater profits from commercial agriculture, as a result of market liberalisation, the abandonment of controls on currency exchange, and improved transportation links, as noted in Kenya (Campbell, Lusch, Smucker & Wangui, 2005).

A positive relationship was observed between agriculture and settlement LULC in 2019, possibly attributable to the need for more workers on the farms and, therefore, more houses needed to accommodate new workers. In that perspective, the conversion of LULC impacted the population by attracting more people because of increased employment opportunities on agricultural farms. Campbell et al., (2005) observed a similar trend in the South-East Kajiado district in Kenya. A similar trend was observed in New Zealand, where a positive relationship developed between agriculture and built-up areas (Dadson, 2016; Faiilagi, 2015).

An increase in agricultural land might pose environmental problems, as found in Little Kitten Creek watershed where increased agricultural activities along the water bodies increased contaminants in water supplies (Henderson, Mahoney, McClelland & Myers, 2014).

Despite the decline in bare soil in Aussenkehr, bare soil remained the major LULC class in the study area owing to the climatic conditions of the area, which is situated in an arid climatic zone. This finding corresponds with the results from the Heihe River Basin in China, where researchers found bare ground decreased, but remained the major LULC in the basin (Fu, Zhang & He, 2014).

A decrease in water for the final nine years of the analysis could be attributed to water evaporation during irrigation. Many studies have observed a decrease in water bodies due to anthropogenic activities and climate change (Bansal, Srivastav, Roy & Krishnamurthy, 2016; Chaudhuri, Singh & Rai, 2017; Malik, Tali & Nusrath, 2017; Tikader & Biswas, 2013). A decrease in water bodies could result in reduced water supply (Matlhodi et al., 2019), which in turn could result in decreased employment opportunities and income generated from agriculture due to reduced agricultural production.

5.2 Land use and land cover changes and water quality

5.2.1 Electrical conductivity

Numerous studies warn that water quality is affected by both natural and human influences (e.g. Bartram & Balance, 1996; Nguyen, Helm, Hettiarachchi, Caucci, & Krebs, 2019) which means that there could be many possible explanations for high EC next to the farms in our study area. However, the current results suggest that fertilisers from irrigation may leak into the river, causing high EC next to the farms; the fertiliser residue remains in the river, as recorded further downstream. This is in line with studies by DWAF (2009, 2014), which found high levels of dissolved solids in the lower Orange River.

High EC results next to the farms coincide with related LULC activities at the sampling location next to the farms, attributing such results to the dominance of agriculture next to and downstream of the farms, but not upstream of the farms, where EC levels were lower. These results are consistent with findings from the Muzvezve catchment in Zimbabwe, where high dissolved solids were due to the presence of agriculture on the banks of the river (Mupedziswa, 2016).

This study corroborates observations that EC decreases as one moves away from the source of pollution (Mwangi, 2014). A study in the Upper Kuils River showed that lower levels of dissolved solids were found downstream of the river (Mwangi, 2014), a finding that is consistent with the current findings where EC is relatively lower downstream of the farms, as opposed to next to the farms.

Results of this study further suggest that high EC next to the farms is associated with LULC activities occurring at Aussenkehr. High EC occurring during the wet season (November and December) coincides with activities such as the application of agro-chemicals and irrigation programmes which are carried out in Aussenkehr until October. This concurs with the work done in the Okavango River, where high levels of dissolved solids were observed in December (Trewby, 2003). In addition, Auer (1997) confirms that high EC is found in Etosha before the start of the rainy season. Considering the climate of Aussenkehr, which receives less rainfall than Etosha, activities such as agro-chemical and irrigation spraying programmes require drawing more water from the river. Diederichs et al. (2005) warn that the high rate of evaporation increases the levels of EC in the water.

High EC next to the farms might be ascribed to the use of nitrate fertilisers in the vineyards. A similar study found that agricultural run-off increases EC from the nitrates and phosphate fertilisers applied in agriculture (Healey, 2014).

Time series results further support the view that agricultural run-off increases EC, as water quality found at Roshpinah (downstream) is poorer than at Noordoewer (upstream), and the Aussenkehr farms are the main activity occurring between the two towns. It is possible that high EC found at Roshpinah could be attributed to the Fish River that flows into the Orange River before the Roshpinah sampling station. However, this is highly unlikely because the Fish River is a non-perennial river which flows only during the rainy season, and high EC was recorded in Roshpinah during both wet and dry seasons.

High EC recorded at Roshpinah during July to August could be attributed to irrigation activities occurring in Aussenkehr during these months. A spike in EC recorded in February at Roshpinah could be attributed to the application of the after-harvest fertilisers and chicken manure carried out in Aussenkehr during January and February. The study found much lower EC downstream of the farms and at Roshpinah compared with the high EC found next to the farms. This finding might be ascribed to the effect of dilution, where EC decreases with increasing distance from the source of contamination. These findings are consistent with findings by Ogden (2013).

EC is primarily affected by the geology of the streams it runs through (UNEPA, n.d.). Aussenkehr is characterised by many different geological structures with different chemical compositions which may affect the water quality differently. With respect to the lithology of the river and its water quality, the area under study is mainly composed of granite, gneiss and old volcanic lithologies (Christelis & Struckmeier, 2001). Other rock types found on-site include granodiorite, slate, dolerite, and quartzite. Felsic rocks, including granite, slate and granite gneiss are known to be associated with low dissolved solids and low hardness (Feth, Roberson & Polzer, 1964; Legrand, 1958). This means that poor water quality in the river could not be attributed to either of the mentioned lithologies.

Dolerite rocks, formed from basic igneous groups that are rich in iron and magnesium, and low in silica, are also found in the study area (Van Engelen & Wen, 1991). Dolerite is characterised by high pH and dissolved solids (Legrand, 1958). Pal et al. (2015) agree that nutrients contained in the soil could enter the river via rainfall and therefore increase EC in the water. In this study, dolerite rocks are situated far from the river and farms and cannot contribute to high EC found next to and downstream of the farms, except after high rainfall.

Although the study area comprises shales, alluvium and sandstone which can attain high levels of dissolved solids from underground water, close to the river, and be a source of poor water quality (Hoch, 2008), the monthly analysis of EC at Roshpinah ruled out the that possibility. High EC in Roshpinah only coincides with the activities practised in Aussenkehr at the time, which rules out a distinct influence from the lithology.

5.2.2 pH

Values higher than the MAWF guidelines were recorded at all stations during the wet seasons, and downstream during the dry season. Similar results of a pH close to alkalinity have been recorded previously in the lower Orange River (Munyika et al., 2014).

Low pH found next to the farms during the wet season could be attributed to high EC found in the water during the same time. Napacho and Manyeke (2010) found that high levels of dissolved minerals in the water reduces the pH. This means that low pH found next to the farms might be attributed to agricultural activities occurring there. The study also recorded an outlier in pH at the sampling location upstream of the farms, which could not be attributed to any of the factors within the scope of the current study. Therefore, further investigation is needed into the matter because most fish die at a pH below 4, and fish production is chiefly affected by a pH below 5 (Coche, Muir & Laughlin, 1996).

pH is an important parameter in measuring water quality. It affects various biological and chemical processes. Extremely low or high pH can make the water unsuitable for human consumption, hostile to aquatic organisms, and might cause fish mortality (Faiilagi, 2015; Gandaseca, Rosli, Pazi & Arianto, 2014). In addition, water with high pH may cause problems by encrusting irrigation pipes and clogging drip irrigation systems (DWAF, 2014).

5.2.3 Dissolved oxygen

Results of DO revealed that water quality in the Orange River at Aussenkehr is suitable for aquatic life, which needs a minimum of 6 mg/l. This finding matches previous studies done in the lower Orange River, which found that DO was within the normal category (DWAF, 2009; Munyika et al., 2014). The observed lack of temporal variation in DO between the wet and dry season corresponds with findings by Fritsch and Troy (2006), who obtained similar results at the mouth of the Orange River. In this study, a decrease in DO observed next to the farms was highly likely to have been the result of agricultural run-off, as also noted by Faiilagi (2015). Measuring DO in water bodies is a means of assessing the water quality in relation to sustaining aquatic organisms.

5.2.4 *E-coli*

The results suggest that the water quality in the Orange River at Aussenkehr might be contaminated with human and animal waste. This means that they are not bacteriologically safe for human consumption without treatment (Healey, 2014).

The presence of *E-coli* in the study area can be ascribed to anthropogenic activities such as livestock grazing and defecation, swimming, and disposal of waste along the river. Similar findings were observed in studies done elsewhere (Dedzo et al., 2017; Hayman, 2000; Mensah, 2011; Santo Domingo & Edge, 2010; Wagner, Redmon, Gentry & Harmel, 2012). These are all activities that are practised over most of the lower Orange River, including Aussenkehr (DWAF, 2007). *E-coli* is the prime cause of most diarrheal diseases, meningitis, and septicaemia in children, worldwide (Makvana & Krilov, 2015).

6. Conclusion and Recommendation

Agricultural expansion has been identified as the main driver for LULC transformation in Aussenkehr since 1990. Based on the field observations and time series data of water quality parameters measured at Noordoewer and Roshpinah, results suggest that the river water is influenced by the LULC activities occurring at Aussenkehr. This is supported by high EC recorded next to the farms as opposed to upstream of the farms. Time series data also show higher EC at Roshpinah than at Noordoewer, which corresponds with agricultural activities practised in Aussenkehr.

The expansion of agricultural activities accompanied by population growth in informal settlements, lack of sanitation, and continued use of untreated water in the study area have the potential to impact both human and river health. Therefore, this study suggests that there is a need for urgent and critical measures at Aussenkehr to improve the management of fertilisers, settlement development and the provision of essential services, such as potable water and sewage disposal, to avoid further deterioration of water quality in the river. In addition, constant monitoring of the river is needed to ensure that good water quality standards are met and to create a temporal and spatial database on water quality. Another possible area for further research will be an investigation into how farmers along the Orange River manage the application of fertilisers. Future studies may expand on the methods of analysing the relationship between water quality and land use activities using other statistical methods such as regression and taking in account other factors such as climate, rainfall, and discharge. Future work may as well focus on other water quality parameters such as nitrates, a by-product of unused nitrogen, which is a primary component of fertilizers. Increase sampling interval is also imperative to allow full representation of the status of the water quality in relation to possible source(s) of pollutants.

References

Aher, S. P., Bairagi, S. I., Deshmukh, P. P., & Gaikwad, R. D. (2012). River change detection and bank erosion identification using topographical and remote sensing data. *International Journal of Applied Information Systems*,*2*, 1–7. doi:10.5120/ijais12-450283

Ahiadu, H. O. (2019*). Land use and climate change impacts on water quality and quantity in the Waipara River catchment North Canterbury, New Zealand* (Doctoral dissertation, Lincoln University, Lincoln, New Zealand). Retrieved from https://researcharchive.lincoln.ac.nz/handle/10182/11073

Afed Ullah, K., Jiang, J., & Wang, P. (2018). Land use impacts on surface water quality by statistical approaches. *Global Journal of Environmental Science and Management*,*4*(2), 231–250. doi:10.22034/GJESM.2018.04.02.010

Agaton, M., Setiawan, Y., & Effendi, H. (2016). Land use/land cover change detection in an urban watershed: a case study of upper Citarum Watershed, West Java Province, Indonesia. *Procedia Environmental Sciences*, *33,* 654–660. doi: 10.1016/j.proenv.2016.03.120

Aguilera, R., Marcé, R., & Sabater, S. (2015). Detection and attribution of global change effects on river nutrient dynamics in a large Mediterranean basin. *Biogeosciences*, *12*(13*)*, 4085–4098. doi:10.5194/bg-12-4085-2015

Albek, E. (2003). Estimation of point and diffuse contaminant loads to streams by non-parametric regression analysis of monitoring data. *Water, Air, and Soil Pollution*, *147*(1–4), 229-243.

Aldoski, J., Mansor, S. B., & Shafri, H. Z. M. (2013). Image Classification in Remote Sensing. *Journal of Environment & Earth Science*, 3 (10), 141–147. doi:10.1007/3-540-29711-1_11

Al-Badaii, F., Shuhaimi-Othman, M., & Gasim, M. B. (2013). Water quality assessment of the Semenyih river, Selangor, Malaysia. *Journal of Chemistry, 2013.* Retrieved from https://doi.org/10.1155/2013/871056

Antonopoulos, V. Z., Papamichail, D. M., & Mitsiou, K. A. (2001). Statistical and trend analysis of water quality and quantity data for the Strymon River in Greece. *Hydrology and Earth System Sciences, 5*(4), 679–691.

Aragon, J. M. (2009). *Spatial and temporal trends in water quality in the Alafia River watershed* [Master's thesis]. Retrieved from https://scholarcommons.usf.edu/cgi/viewcontent.cgi?article=2834&context=etd/

Auer, C. (1997). Chemical quality of water at waterholes in the Etosha National Park. *Madoqua*, *1997*(1), 121–128.

Ayivor, J. S., & Gordon, C. (2012). Impact of land use on river systems in Ghana. *West African Journal of Applied Ecology*, *20*(3), 83–95. doi:10.4314/WAJAE.V20I3

Babykalpana, Y., & ThanushKodi, K. (2010). Classification of LULC Change Detection using Remotely Sensed Data for Coimbatore City, Tamilnadu, India. *Journal of Computing, 2(5)*. doi:arXiv:1005.4216v1

Baker, A. (2006). Land use and water quality. In M. Anderson (Ed.), *Encyclopedia of hydrological sciences*. John Wiley & Sons.

Bansal, S., Srivastav, S. K., Roy, P. S., & Krishnamurthy, Y. V. N. (2016). An analysis of land use and land cover dynamics and causative drivers in a thickly populated Yamuna River Basin of India.

Applied Ecology and Environmental Research, 14(3), 773–779. doi: http://dx.doi.org/10.15666/aeer/1403_773792

Bartram, J., & Ballance, R. (Eds.). (1996). *Water quality monitoring: a practical guide to the design and implementation of freshwater quality studies and monitoring programmes* (1st ed.). London, England: CRC Press.

Blanco, A., Alarilla, A., Dimalibot, R., Bonga, M., & Paringit, E. C. (2014). Assessment of water quality variations in San Juan River using GIS and multivariate statistical techniques. *ASEAN Engineering Journal Part C, 2*(2), 24. Retrieved from http://www.aseanengineering.net/aej/

Breen, B., Curtis, J., & Hynes, S. (2018). Water quality and recreational use of public waterways. *Journal of Environmental Economics and Policy, 7*(1), 1–15. doi:10.1080/21606544.2017.1335241

Camara, M., Jamil, N. R., & Abdullah, A. F. B. (2019). Impact of land uses on water quality in Malaysia: a review. *Ecological Processes, 8*(1). doi:10.1186/s13717-019-0164-x

Campbell, D. J., Lusch, D. P., Smucker, T. A., & Wangui, E. E. (2005). Multiple methods in the study of driving forces of land use and land cover change: a case study of SE Kajiado District, Kenya. *Human Ecology, 33*(6), 763–794. doi: 10.1007/s10745-005-8210-y

Campbell, J. B., & Wynne, R. H. (2011). *Introduction to remote sensing*. New York, USA: Guilford Press.

Chaudhuri, A. S., Singh, P., & Rai, S. C. (2017). Assessment of impervious surface growth in urban environment through remote sensing estimates. *Environmental Earth Sciences, 76*(15), 541. doi:10.1007/s12665-017-6877-1

Chen, J., & Lu, J. (2014). Effects of land use, topography and socio-economic factors on river water quality in a mountainous watershed with intensive agricultural production in East China. *PLoS One*, *9*(8), e102714. doi:10.1371/journal.pone.0102714

Cheng, P., Meng, F., Wang, Y., Zhang, L., Yang, Q., & Jiang, M. (2018). The impacts of land use patterns on water quality in a trans-boundary river basin in northeast China based on eco-functional regionalization. *International Journal of Environmental Research and Public Health*, *15*(9), 1872. doi: 10.3390/ijerph15091872

Christelis, G., & Struckmeier, W. (2001). *Groundwater in Namibia-An explanation to the Hydrogeological Map of Namibia*. Windhoek: Department of Water Affairs, Ministry of Agriculture, Water and Rural Development.

Coche, A. G., Muir, J. F., & Laughlin, T. (1996). *Simple methods for aquaculture: management for freshwater fish culture ponds and water practices*. Rome: Food and Agriculture Organization.

Colorado State University (n.d). Irrigation Water quality criteria. Retrieved from https://water.usgs.gov/edu/dissolvedoxygen.html

Dadson, I. Y. (2016). Land Use and Land Cover Change Analysis along the Coastal Regions of Cape Coast and Sekondi. *Ghana Journal of Geography*, *8*(2), 108–126.

Darvishzadeh, R. (2000). Change detection for urban spatial databases using remote sensing and GIS. *In Proceeding of International Archives of Photogrammetry and Remote Sensing*, *320*. Retrieved from https://pdfs.semanticscholar.org/a6bd/32fd3dd790c8a17870c52126594b675c4bc5.pdf

Das, K. R., & Imon, A. H. M. R. (2016). A brief review of tests for normality. *American Journal of Theoretical and Applied Statistics*, *5*(1), 5–12. doi:10.11648/j.ajtas.20160501.12

Dave, C. P., Joshi, R., & Srivastava, S. S. (2015). A survey on geometric correction of satellite imagery. *International Journal of Computer Applications*, *116*(12). doi:10.5120/20389-2655

Dedzo, M. G., Tsozué, D., Mimba, M. E., Teddy, F., Nembungwe, R. M., & Linida, S. (2017). Importance of rocks and their weathering products on groundwater quality in Central-East Cameroon. *Hydrology*, *4*(2). doi:10.3390/hydrology4020023

Department of Water Affairs and Forestry. (2007). Water quality in the Orange River. Retrieved from http://www.the-eis.com/data/literature/Water%20Quality%20ORASECOM.pdf

Department of Water Affairs and Forestry. (2009). Orange River: Assessment of water quality data requirements for water quality planning purposes. Retrieved from http://www.dwa.gov.za/Dir_WQM/docs/WQMonitoringandStatusQuoReport3.pdf

Department of Water Affairs and Forestry. (2014). Development of Reconciliation strategies for large bulk water supply Systems Orange River: water quality and effluent re-use. Retrieved from http://www6.dwa.gov.za/Orange%20Recon/Docs/final/8%20Water%20Quality.pdf

Diamantopoulou, M. J., Antonopoulos, V. Z., & Papamichail, D. M. (2007). Cascade correlation artificial neural networks for estimating missing monthly values of water quality parameters in rivers. *Water resources management*, *21*(3), 649–662. doi:10.1007/s11269-006-9036-0

Diederichs, N., O'Regan, D., Sullivan, C., Fry, M., Mander, M., Haines, C., & McKenzie, M. (2005). *Orange River Basin Baseline Assessment report*. Netwater.

Ding, J., Jiang, Y., 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. *Water, 7*(8), 4427–4445. doi:10.3390/w7084427

Dinno, A. (2015). Nonparametric pairwise multiple comparisons in independent groups using Dunn's test. *The Stata Journal*, *15*(1), 292–300. doi:10.1177/1536867X1501500117

Dixon, B., & Candade, N. (2008). Multispectral landuse classification using neural networks and support vector machines: one or the other, or both? *International Journal of Remote Sensing*, *29*(4), 1185–1206. doi:0.1080/01431160701294661

Espach, C. (2006). Rangeland productivity modelling: Developing and customising methodologies for land cover mapping in Namibia. *Agricola*, *16*, 20–27. Retrieved from https://agricola.nal.usda.gov/

Faiilagi, S. A. (2015). *Assessing the impacts of land use patterns on river water quality at catchment level: a case study of Fuluasou River Catchment in Samoa* (Doctoral dissertation, Massey University, Palmerston North, New Zealand). Retrieved from https://mro.massey.ac.nz/handle/10179/7548

Fan, X., Cui, B., Zhao, H., Zhang, Z., & Zhang, H. (2010). Assessment of river water quality in Pearl River Delta using multivariate statistical techniques. *Procedia environmental sciences, 2,* 1220–1234. doi:10.1016/j.proenv.2010.10.133

Feth, J. H. F., Robertson, C. E., & Polzer, W. L. (1964). *Sources of mineral constituents in water from granitic rocks, Sierra Nevada, California and Nevada*. Washington: United States Government Printing Office.

Fritsch, J.M., & Troy, B. (2006). *Hydro-environmental assessment of the Orange River mouth*. Johannesburg, South Africa: Institut de Recherche pour le Développement.

Fryirs, K. A., & Brierley, G. J. (2012). *Geomorphic analysis of river systems: an approach to reading the landscape.* Oxford, UK: John Wiley & Sons.

Fu, L., Zhang, L., & He, C. (2014). Analysis of agricultural land use change in the middle reach of the Heihe River Basin, Northwest China. *International Journal of environmental research and public health*, *11*(3), 2698–2712. doi:10.3390/ijerph110302698

Fu, L., & Wang, Y. G. (2012). Statistical tools for analyzing water quality data. In K, Voudouris & D, Voutsa, (Eds.), *Water quality monitoring and assessment*. Retrieved from https://www.intechopen.com/books/water-quality-monitoring-and-assessment/statistical-tools-for-analyzing-water-quality-data

Gandaseca, S., Rosli, N., Pazi, A. M. M., & Arianto, C. I. (2014). Effects of land use on river water quality of Awat-Awat Lawas Mangrove Forest Limbang Sarawak Malaysia. *International Journal of Physical Sciences*, *9*(17), 386–396. doi:10.5897/JPS2014.4179

Gao, B. C. (1996). NDWI—A normalized difference water index for remote sensing of vegetation liquid water from space. *Remote sensing of Environment*, *58*(3), 257–266. doi:10.1016/S0034-4257(96)00067-3

Geo Pollution Technologies (2016). Environmental assessment for the silverlands agricultural project in Aussenkehr, Namibia: Scoping report. Retrieved from https://www.miga.org/sites/default/files/archive/Documents/Silverlands%20Scoping%20Report%20%20for%20DEA%20Submission%20-%20Final.pdf

Grizzetti, B., Bouraoui, F., Billen, G., van Grinsven, H., Cardoso, A. C., Thieu, V., … & Johnes, P. (2011). Nitrogen as a threat to European water quality. In M. A. Sutton, C. M. Howard, J. W. Erisman, G Billen, A. Bleeker, P. Grennfelt,... & B. Grizzetti (Eds.), *The European nitrogen assessment: sources, effects and policy perspectives.* Cambridge University Press.

Haydar, S., Arshad, M., & Aziz, J. A. (2016). Evaluation of drinking water quality in urban areas of Pakistan: A case study of Southern Lahore. *Pakistan Journal of Engineering and Applied Sciences*, *5*, 16 – 23. doi:10.1155/2017/7908183

Hayman, A. A. (2000). *The effects of land use practices on water quality and quantity in the Hope River watershed, Jamaica* (Doctoral dissertation, University of British Columbia, Vancouver, British Colombia). Retrieved from https://open.library.ubc.ca/cIRcle/collections/ubctheses/831/items/1.0089551

Hazarika, N., Das, A. K., & Borah, S. B. (2015). Assessing land-use changes driven by river dynamics in chronically flood affected Upper Brahmaputra plains, India, using RS-GIS techniques. *The Egyptian Journal of Remote Sensing and Space Science*, *18*(1), 107–118. doi:10.1016/j.ejrs.2015.02.001

Healey, M.N. (2014). *A Baseline Assessment of Water Quality in the Gambia River and the Potential for Community-Based Monitoring in The Gambia, West Africa* (Master's thesis, Saint Mary's University, Halifax, Nova Scotia). Retrieved from http://library2.smu.ca/handle/01/26226#.Xzjf0egzbIU

Hecke, T. V. (2012). Power study of anova versus Kruskal-Wallis test. *Journal of Statistics and Management Systems, 15*(2-3), 241–247. doi:10.1080/09720510.2012.10701623

Helsel, D. R., & Hirsch, R. M. (2002*). Statistical methods in water resources,23.* Reston, VA: United States Geological Survey.

Henderson, L., Mahoney, C., McClelland, C., & Myers, A. (2014). The effect of land use and land cover on water quality in urban environments. Natural Resources and Environmental Sciences (NRES), Kansas State University. Retrieved from https://pdfs.semanticscholar.org/392d/abe6ab482742d78f72940cc18b73a854340d.pdf

Hoch, T. (2008). How geology affects your well water quality. *Barnyards & Backyards*, 19 – 21. Retrieved from http://www.uwyo.edu/barnbackyard/index.html

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*. doi: 10.1155/2013/329187

Kafi, K. M., Shafri, H. Z. M., & Shariff, A. B. M. (2014). An analysis of LULC change detection using remotely sensed data; A Case study of Bauchi City. *Earth and Environmental Science*, 20(1), 012056. doi:10.1088/1755-1315/20/1/012056

Kambwiri, A. M., Changadeya, W., Chimphamba, J., & Tandwe, T. (2014). Land use impacts on water quality of rivers draining from Mulanje Mountain: a case of Ruo River in the Southern Malawi. *Malawi Journal of Science and Technology*, *10*(1), 15–31. doi:10.4314/MJST.V10I1

Kamwi, J. M., Chirwa, P. W., Manda, S. O., Graz, P. F., & Kätsch, C. (2015). Livelihoods, land use and land cover change in the Zambezi Region, Namibia. *Population and Environment*, *37*(2), 207–230. doi:10.1007/s11111-015-0239-2

Kebebew, Z. (2005). *GIS and Remote Sensing in land use and Land cover change detection in Finchaa Valley Area* (Master's thesis, Addis Ababa University, Addis Ababa, Ethiopia). Retrieved from http://etd.aau.edu.et/handle/123456789/8166

Khatoon, N., Khan, A. H., Rehman, M., & Pathak, V. (2013). Correlation study for the assessment of water quality and its parameters of Ganga River, Kanpur, Uttar Pradesh, India. *International Organization of Scientific Research Journal of Applied Chemistry*, *5*(3), 80–90. doi:10.9790/5736-0538090

Khatri, N., & Tyagi, S. (2015). Influences of natural and anthropogenic factors on surface and groundwater quality in rural and urban areas. *Frontiers in Life Science*, *8*(1), 23–39. doi:10.1080/21553769.2014.933716

Kim, C. (2016). Land use classification and land use change analysis using satellite images in Lombok Island, Indonesia. *Forest Science and Technology*, *12*(4), 183–191. doi:10.1080/21580103.2016.1147498

Kulkarni, A. D., & Lowe, B. (2016). Random forest algorithm for land cover classification. *International Journal on Recent and Innovation Trends in Computing and Communication*, *4*(3), 58 – 63. Retrieved from https://ijritcc.org/index.php/ijritcc

Kumar, M., & Puri, A. (2012). A review of permissible limits of drinking water. *Indian Journal of Occupational and Environmental Medicine*, *16*(1), 40. doi:10.4103/0019-5278.99696

Lange, G. M., Mungatana, E., & Hassan, R. (2007). Water accounting for the Orange River Basin: An economic perspective on managing a transboundary resource. *Ecological Economics*, *61*(4), 660–670. doi:10.1016/j.ecolecon.2006.07.032

LeGrand, H. E. (1958). Chemical character of water in the igneous and metamorphic rocks of North Carolina. *Economic Geology, 53*(2), 178–189. doi:10.2113/gsecongeo.53.2.178

Lintern, A., Webb, J. A., Ryu, D., Liu, S., Bende-Michl, U., Waters, D.,... & Western, A. W. (2018). Key factors influencing differences in stream water quality across space. *Wiley Interdisciplinary Reviews: Water, 5*(1), e1260.doi:10.1002/wat2.1260

Lloyd, R. (1961). Effect of dissolved oxygen concentrations on the toxicity of several poisons to rainbow trout (Salmo gairdnerii Richardson). *Journal of Experimental Biology, 38*(2), 447–455. Retrieved from https://jeb.biologists.org/

Liu, X. (2005). Supervised Classification and Unsupervised Classification. Retrieved from https://pdfs.semanticscholar.org/9ca2/3399424a8ea60ec040cd2705224e776e1920.pdf

Liu, Y., Zheng, Y., Liang, Y., Liu, S., & Rosenblum, D. S. (2016). *Urban water quality prediction based on multi-task multi-view learning*. Proceedings of the 25th International Joint Conference on Artificial Intelligence. Retrieved from https://pdfs.semanticscholar.org/a259/c57646400bafab69fae79f7ef03c76743f79.pdf

Lu, D., Li, G., Moran, E., & Hetrick, S. (2013). Spatiotemporal analysis of land-use and land-cover change in the Brazilian Amazon. *International Journal of Remote Sensing*, *34*(16), 5953–5978. doi:10.1080/01431161.2013.802825

Lu, D., & Weng, Q. (2007). A survey of image classification methods and techniques for improving classification performance. *International Journal of Remote sensing*, *28*(5), 823–870. doi:10.1080/01431160600746456

Lugman, C. (2011, January 19). Aussenkehr residents use river for drinking water and as toilet. *The Namibian.* Retrieved from https://www.namibian.com.na/index.php?id=28&tx_ttnews%5Btt_news%5D=76926&no_cache=1

Lugman, C. (2019, February 19). Aussenkehr housing development in jeopardy. *The Namibian*, p 7.

Makvana, S., & Krilov, L. R. (2015). Escherichia coli infections. *Pediatrics in Review, 36*(4), 167–70. doi: 0.1542/pir.36-4-167

Malik, M. M., Tali, J. A., & Nusrath, A. (2017). Assessment of land use and land cover change in District Baramulla, Jammu & Kashmir. *Journal of Space Science & Technology, 6*(33), 2321 – 2837. doi:10.37591/.v6i3.92

Manandhar, R., Odeh, I., & Ancev, T. (2009). Improving the accuracy of land use and land cover classification of Landsat data using post-classification enhancement. *Remote Sensing*, *1*(3), 330–344. doi:10.3390/rs1030330

Mathebula, B. (2016). *Assessment of the surface water quality of the main rivers feeding at Katse Dam Lesotho* (Doctoral dissertation, University of Pretoria, Pretoria, South Africa). Retrieved from https://repository.up.ac.za/handle/2263/53521

Matlhodi, B., Kenabatho, P. K., Parida, B. P., & Maphanyane, J. G. (2019). Evaluating Land Use and Land Cover Change in the Gaborone Dam Catchment, Botswana, from 1984-2015 Using GIS and Remote Sensing. *Sustainability, 11*(19), 5174. doi:10.3390/su11195174

Matshakeni, Z. (2016). *Effects of land use changes on water quality in Eerste River, South Africa* (Master's thesis, University of Zimbabwe, Harare, Zimbabwe). Retrieved from http://ir.uz.ac.zw/handle/10646/3384

Maxwell, A. E., Warner, T. A., & Fang, F. (2018). Implementation of machine-learning classification in remote sensing: An applied review. *International Journal of Remote Sensing, 39*(9), 2784–2817. doi:10.1080/01431161.2018.1433343

Mazlum, N., Özer, A., & Mazlum, S. (1999). Interpretation of water quality data by principal components analysis. *Turkish Journal of Engineering and Environmental Sciences, 23*(1), 19–26

Mcgregor, N. (2016, December 8). Namibia: Grape grower's biggest challenge is heat and dust. *Fresh Praza.* Retrieved from https://www.freshplaza.com/article/2167966/namibia-grape-grower-s-biggest-challenge-is-heat-and-dust/

Mendelsohn, J., Jarvis, A., Roberts, C., & Robertson, T. (2002). *Atlas of Namibia: A Portrait of the Land and its People.* Cape Town, South Africa: David Philip.

Mensah, M.K. (2011). *Assessment of drinking water quality in Ehi Community in the Ketu-north District of the Volta region of Ghana* (Master's thesis, Kwame Nkrumah University of Science and Technology, Kumasi, Ghana). Retrieved from http://ir.knust.edu.gh/xmlui/handle/123456789/4103?show=full

Miller, R. M., & Becker, T. (2008). *The Geology of Namibia*. Windhoek, Namibia: Geological Survey of Namibia.

Ministry of Agriculture, Water and Forestry. (2012). *Regulations for drinking water quality and supply in terms of part x (water supply, abstraction and use) and part xi (water service providers) of the water resources management act, 2011.* Windhoek: Department of Water Affairs.

Moses, T., & Klockars, A. (2008). An evaluation of standard, alternative, and robust slope test strategies. *Journal of Modern Applied Statistical Methods, 7*(1), 7. doi:10.22237/jmasm/1209614760

Munyika, S., Kongo, V., & Kimwaga, R. (2014). River health assessment using macroinvertebrates and water quality parameters: a case of the Orange River in Namibia. *Physics and Chemistry of the Earth, Parts A/B/C, 76*, 140–148. doi:10.1016/j.pce.2015.01.001

Mupedziswa, F. (2016). *Impacts of land use and land cover changes on the water quality of surface water bodies: Muzvezve Sub-Catchment, Zimbabwe* (Master's thesis, University of Zimbabwe, Harare, Zimbabwe). Retrieved from http://ir.uz.ac.zw/handle/10646/3398

Mwangi, F. N. (2014). *Land use practices and their impact on the water quality of the Upper Kuils River (Western Cape Province, South Africa)* (Doctoral dissertation, University of Western Cape, Cape Town, South Africa). Retrieved from http://etd.uwc.ac.za/xmlui/handle/11394/3366

Nachtergaele, A. F. (2010, August 1 - 6). *The classification of Leptosols in the World Reference Base for Soil Resources.* Paper presented at the Nineteenth World Congress of Soil Science, Soil Solutions for a Changing World Conference, Brisbane, Australia. Retrieved from https://www.iuss.org/19th%20WCSS/Symposium/pdf/2302.pdf/

Namibia Statistics Agency. (2011). *Namibia 2011 population and housing results. Windhoek: Namibia Statistics of Agency*. Windhoek, Namibia.

Napacho, Z. A., & Manyele, S. V. (2010). Quality assessment of drinking water in Temeke District (part II): Characterization of chemical parameters. *African Journal of Environmental Science and Technology*, *4*(11), 775–789. doi:10.4314/AJEST.V4I11.71349

Ncube, M., & Taigbenu, A. E. (2008). Application of the SWAT model to assess the impact of land cover and land use on the hydrologic response in the Olifants Catchment. *Physics and Chemistry of the Earth, 33.* Retrieved from https://www.sciencedirect.com/journal/physics-and-chemistry-of-the-earth

Ndokosho, J., Hoko, Z., & Makurira, H. (2007). Assessment of management approaches in a public water utility: A case study of the Namibia water corporation (NAMWATER). *Physics and Chemistry of the Earth, Parts A/B/C*, *32*(15-18), 1300–1309. doi:10.1016/j.pce.2007.07.039

Nelson, M. (2017). *Evaluating Multitemporal Sentinel-2 data for Forest Mapping using Random Forest* (Master's thesis, Stockholm University, Stockholm, Sweden). Retrieved from http://www.diva-portal.org/smash/record.jsf?pid=diva2%3A1138282&dswid=6668

Nguyen, H. T. T., Doan, T. M., & Radeloff, V. (2018). Applying random forest classification to map land use/land cover using landsat 8 Oli. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, 363–367. doi:10.5194/ISPRS-ARCHIVES-XLII-3-W4-363-2018

Nguyen, T. H., Helm, B., Hettiarachchi, H., Caucci, S., & Krebs, P. (2019). The selection of design methods for river water quality monitoring networks: a review. *Environmental Earth Sciences,* *78*(3), 96. doi:0.1007/s12665-019-8110-x

Ngwenya, F. (2006). *Water Quality Trends in the Eerste River, Western Cape, 1990-2005* (Doctoral dissertation, University of the Western Cape, Cape Town, South Africa). Retrieved from https://etd.uwc.ac.za/handle/11394/2008?show=full

Nicholson, K. N., Neumann, K., Dowling, C., & Sharma, S. E. (2017). E. coli and coliform bacteria as indicators for drinking water quality and handling of drinking water in the Sagarmatha National Park, Nepal. *Environmental Management Sustainable Development*, *6*(2), 411–28. doi:10.5296/emsd.v6i2.11982

Nitze, I., Schulthess, U., & Asche, H. (2012, May 7-9,). *Comparison of machine learning algorithms random forest, artificial neural network and support vector machine to maximum likelihood for supervised crop type classification*. Proceedings of the GEOBIA, Rio de Janeiro, Brazil. Retrieved from https://www.researchgate.net/publication/275641579_COMPARISON_OF_MACHINE_LEARNING_ALGORITHMS_RANDOM_FOREST_ARTIFICIAL_NEURAL_NETWORK_AND_SUPPORT_VECTOR_MACHINE_TO_MAXIMUM_LIKELIHOOD_FOR_SUPERVISED_CROP_TYPE_CLASSIFICATION/

Nkonyana, T. N. (2016). *Image classification using machine learning techniques* (Doctoral dissertation, University of Johannesburg, Johannesburg, South Africa). Retrieved from https://ujcontent.uj.ac.za/vital/access/manager/Repository/uj:21061?site_name=GlobalView

Odonkor, S. T., & Ampofo, J. K. (2013). Escherichia coli as an indicator of bacteriological quality of water: an overview. *Microbiology Research*, *4*(1), e2–e2. doi:10.4081/mr.2013.e2

Ogden, M. (2013*). Land use impact on water quality in two river systems in South Africa* (Master's thesis, Lund University, Lund, Sweden). Retrieved from https://lup.lub.lu.se/student-papers/search/publication/3910312

Oke, A., Sangodoyin, A., Ogedengbe, K., & Omodele, T. (2013). Mapping of river waterquality using inverse distance weighted interpolation in Ogun-Osun river basin, Nigeria. *Acta Geographica Debrecina Landscape & Environment, 7*(2), 48–62.

Oki, T., & Quiocho, R. E. (2020). Economically challenged and water scarce: identification of global populations most vulnerable to water crises. *International Journal of Water Resources Development, 36 (*2-3*)* 416–428. doi:10.1080/07900627.2019.1698413

Owojori, A., & Xie, H. (2005, March). Landsat image based LULC changes of San Antonio, Texas using advanced atmospheric correction and object-oriented image analysis approaches. *International Symposium on Remote Sensing of Urban Areas, Tempe, AZ.* doi:10.1.1.221.9860

Paul, S. S. (2013). *Analysis of land use and land cover change in Kiskatinaw River watershed: A remote sensing, GIS & modelling approach* (Master's thesis, University of Northern British Columbia, Prince George, British Columbia). Retrieved from https://unbc.arcabc.ca/islandora/object/unbc%253A16875

Petersen, C. R., Jovanovic, N. Z., Le Maitre, D. C., & Grenfell, M. C. (2017). Effects of land use change on streamflow and stream water quality of a coastal catchment. *Water SA, 43*(1), 139–152. doi:10.4314/wsa.v43i1.16

Pottinger, L. (1996). Environmental Impacts of Large Dams: African Examples. *International Rivers, 1*. Retrieved from https://www.internationalrivers.org/

Price, R. G., & Wildeboer, D. (2017). E. coli as an indicator of contamination and health risk in environmental waters. In Escherichia coli-Recent Advances on Physiology, Pathogenesis and Biotechnological Applications. IntechOpen. doi:10.5772/67330

Priya, S., Das, S. S. M., & Vareethiah, K. (2016). Analysis of Water Quality in Selected Stations along River, Tambaraparani Kanyakumari District, Tamilnadu, India. *International Journal of Innovative Science, Engineering & Technology*, *3*(8). Retrieved from http://ijiset.com/articlesv3/articlesv3s8.html

Pululu, M. S., Lobina, P. G., & Tabukeli, R. M. (2015). The Upper Orange River water resources affected by human interventions and climate change. *Hydrology: Current Research*, *6*(3), 1. doi:10.4172/2157-7587.1000212

Raj, P. N., & Azeez, P. A. (2010). Land use and land cover changes in a tropical river basin: a case from Bharathapuzha River basin, southern India. *Journal of Geographic Information System*, *2*(04), 185. doi:10.4236/jgis.2010.24026

Reis, D. R., Plangg, R., Tundisi, J. G., & Quevedo, D. M. (2015). Physical characterization of a watershed through GIS: a study in the Schmidt stream, Brazil. *Brazilian Journal of Biology*, *75*(4), 16-29. doi:10.1590/1519-6984.01313suppl

Republic of Namibia. (1956). Namibia Water Act, Act 54. Government Gazette December 1997.

Republic of Namibia. (2003). Water Resources Management Act, Act 24. Government Gazette 19 December 2003.

Republic of Namibia. (2004). Namibia Water Corporation Act 12 of 1997. Government Gazette 31 May 2004.

Republic of Namibia. (2016). Water Act 54 of 1956. Republic of Namibia: Annotated statues.

Riddell, E. S., Kilian, W., Versfeld, W., & Kosoana, M. (2016). Groundwater stable isotope profile of the Etosha National Park, Namibia. *Koedoe, 58(1)*, 1–7. doi:10.4102/koedoe.v58i1.1329

Rock, C., & Rivera, B. (2014). Water quality, E.coli and your health. Retrieved from https://extension.arizona.edu/sites/extension.arizona.edu/files/pubs/az1624.pdf

Santo Domingo, J. W., & Edge, T. A. (2010). Identification of primary sources of faecal pollution. In G. Rees, K. Pond, D. Kay, J. Bartram & J. Santo Domingo. I (Eds.), *Safe Management of Shellfish and Harvest Waters (pp 51–90).* London, UK: IWA Publishing

Schell, J. A., & Deering, D. (1973). Monitoring vegetation systems in the Great Plains with ERTS. *NASA Special Publication*, *351*, 309. Retrieved from https://history.nasa.gov/publications.html

Schmidt, H., & Karnieli, A. (2001). Sensitivity of vegetation indices to substrate brightness in hyper-arid environment: the Makhtesh Ramon Crater (Israel) case study. *International journal of Remote Sensing, 22*(17), 3503–3520. doi: 10.1080/01431160110063779

Scott, D., Iipinge, K. N., Mfune, J. K., Muchadenyika, D., Makuti, O. V., & Ziervogel, G. (2018). The story of water in Windhoek: a narrative approach to interpreting a transdisciplinary process. *Water, 10*(10), 1366. doi:10.3390/W10101366

Shaker, A., Yan, W. Y., & El-Ashmawy, N. (2012). Panchromatic satellite image classification for flood hazard assessment. *Journal of Applied Research and Technology*, *10*(6), 902–911. doi: 10.22201/icat.16656423.2012.10.6.350

Shukla, A. K., Ojha, C. S. P., Mijic, A., Buytaert, W., Pathak, S., Garg, R. D., & Shukla, S. (2018). Population growth, land use and land cover transformations, and water quality nexus in the Upper Ganga River basin. *Hydrology and Earth System Sciences*, *22*(9), 4745–4770. doi:10.5194/hess-22-4745-2018

Tarlé, P. T. C., Mazzer, R. F., Luna, A. C., Galbiatti, J. A., & Borges, M. J. (2008). Topographical characteristics and evaluating water quality in watershed management. *Ingeniería e Investigación, 28*(3), 87–91.

Tavares, P. A., Beltrão, N. E. S., Guimarães, U. S., & Teodoro, A. C. (2019). Integration of sentinel-1 and sentinel-2 for classification and LULC mapping in the urban area of Belém, eastern Brazilian Amazon. *Sensors*, *19*(5), 1140. doi:10.3390/s19051140

Tikader, S., & Biswas, B. (2013). Impact of LULC changes on surface water resources: A spatial modelling approach. *International Journal of Geology, Earth & Environmental Sciences, 3*(3), 40–51.

Tokar, O., Vovk, O., Kolyasa, L., Havryliuk, S., & Korol, M. (2018, September). Using the Random Forest classification for land cover interpretation of Landsat images in the Prykarpattya region of Ukraine. *2018 International Scientific and Technical Conference on Computer Sciences and Information Technologies (CSIT), 1,* 241–244. doi:10.1109/STC-CSIT.2018.8526646

Trewby, F. (2003). *The effect of land use/land cover change on the water quality of the Okavango River, Namibia* (Master's thesis, University of Arkansas). Retrieved from http://jaesnet.com/journals/jaes/Vol_3_No_2_June_2014/15.pdf

Tsarouchi, G. M., Mijic, A., Moulds, S., & Buytaert, W. (2014). Historical and future land-cover changes in the Upper Ganges basin of India. *International Journal of Remote Sensing*, *35*(9), 3150-3176. doi:10.1080/01431161.2014.903352

Usali, N., & Ismail, M. H. (2010). Use of remote sensing and GIS in monitoring water quality. *Journal of Sustainable Development*, *3*(3), 228. doi:10.5539/jsd.v3n3p228

United Nation Environmental Program. (2009). *Annual report, seizing the green opportunity*. Retrieved from http://www.unep.org/PDF/UNEP_AR_2009_FINAL.pdf

United Nation Environmental Program. (2016). *Snapshot of the World's Water Quality: Towards a Global Assessment.* Nairobi. Nairobi, Kenya: United Nations Environment Programme.

United Nation Environmental Protection Agency. (n.d). Conductivity: what is conductivity and why is it important. Retrieved from https://archive.epa.gov/water/archive/web/html/vms59.html

United Nation Environmental Protection Agency. (2001). Parameters of water quality: Interpretation and standards. Retrieved from https://www.epa.ie/pubs/advice/water/quality/Water_Quality.pdf

United States Geological Survey. (n.d). Electrical conductivity and Water. Retrieved from: https://water.usgs.gov/edu/electrical-conductivity.html

Uwimana, A., Dam, A., Gettel, G., Bigirimana, B., & Irvine, K. (2017). Effects of river discharge and land use and land cover (LULC) on water quality dynamics in Migina catchment, Rwanda. *Environmental Management*, *60*(3), 496–512. doi:10.1007/s00267-017-0891-7

Van Engelen, V.W.P., & Wen, T.T. (Ed).(1991). *The SOTER Manual: Procedures for Small Scale Digital Map and Database Compilation of Soil and Terrain Conditions*, (4th ed). Wageningen: ISRIC.

Volschenk, T., Fey, M. V., & Zietsman, H. L. (2005). *Situation analysis of problems for water quality management in the lower Orange River region with special reference to the contribution of the foothills to salinization*. Pretoria: Water Research Commission.

Vushe, A., Haimene, E. P., & Mashauri, D. (2014). Namibian land use changes and nutrient water quality of the Okavango River. *Journal of Agriculture and Environmental Sciences*, *3*(2), 219–239.

Wagner, K. L., Redmon, L. A., Gentry, T. J., & Harmel, R. D. (2012). Assessment of cattle grazing effects on E. coli runoff. *Transactions of the ASABE*, *55*(6), 2111–2122. doi:10.13031/2013.42503

Wendland, F., Bergmann, S., Eisele, M., Gömann, H., Herrmann, F., Kreins, P., & Kunkel, R. (2020). Model-Based Analysis of Nitrate Concentration in the Leachate—The North Rhine-Westfalia Case Study, Germany. *Water*, *12*(2), 550. doi:10.3390/w12020550

World Health Organization. (2011). Guidelines for drinking-water quality. *WHO chronicle*, *38*(4), 104–8.

World Health Organization. (2019). Drinking Water. Retrieved from https://www.who.int/news-room/fact-sheets/detail/drinking-water

Wubie, M. A., Assen, M., & Nicolau, M. D. (2016). Patterns, causes and consequences of land use/cover dynamics in the Gumara watershed of lake Tana basin, Northwestern Ethiopia. *Environmental Systems Research*, *5*(1), 8. doi:10.1186/s40068-016-0058-1

Xia, J., Wang, L., Yu, J., Zhan, C., Zhang, Y., Qiao, Y., & Wang, Y. (2018). Impact of environmental factors on water quality at multiple spatial scales and its spatial variation in Huai River Basin, China. *Science China Earth Sciences, 61*(1), 82–92. doi:10.1007/s11430-017-9126-3

Xue, J., & Su, B. (2017). Significant remote sensing vegetation indices: A review of developments and applications. *Journal of Sensors, 2017*. Retrieved from https://doi.org/10.1155/2017/1353691

Appendices

S1 Ethical clearance letter

UNAM
UNIVERSITY OF NAMIBIA

ETHICAL CLEARANCE CERTIFICATE

Ethical Clearance Reference Number: EEREC/0005 **Date: 13th March 2020**

This Ethical Clearance Certificate is issued by the University of Namibia Research Ethics Committee (UREC) in accordance with the University of Namibia's Research Ethics Policy and Guidelines. Ethical approval is given in respect of undertakings contained in the Research Project outlined below. This Certificate is issued on the recommendations of the ethical evaluation done by the Environment and Engineering Research Ethics Committee (EEREC).

Title of Project: *Land Use and Land Cover Changes and The Dynamics of the Orange River in the Aussenkehr Area, Namibia*

Nature/Level of Project: *MSc*

Researcher: *Justina Tuulikafo NANGOLO*

Student Number: *201203840*

Faculty: *Humanities and Social Sciences*

Supervisors: *Prof Martin Hipondoka, (Main) UNAM*
Dr Eliakim Hamunyela (Co-) UNAM

Take note of the following:

(a) Any significant changes in the conditions or undertakings outlined in the approved Proposal must be communicated to the EEREC. An application to make amendments may be necessary.

(b) Any breaches of ethical undertakings or practices that have an impact on ethical conduct of the research must be reported to the EEREC.

(c) The Principal Researcher must report issues of ethical compliance to the EEREC (through the Chairperson of the Faculty/Centre/Campus Research & Publications Committee) at the end of the Project or as may be requested by EEREC.

(d) The EEREC retains the right to:
  i. Withdraw or amend this Ethical Clearance if any unethical practices (as outlined in the Research Ethics Policy) have been detected or suspected,
  ii. Request for an ethical compliance report at any point during the course of the research.

REC wishes you the best in your research.

Prof. O. T. Johnson: EEREC Chairperson

Signature

S2 Research instrument - Ground truthing

GROUND TRUTHING DATA COLLECTION SHEET	
I. Taken by: ______________________	**Date:** ______________
II. Site ID: _______________ **Instruments**: GPS **Photo Numbers:** ____	**Latitude:** _____________ **Longitude:** _____________

III. Site description (check (✓) appropriate)

land cover (✓): ( ) Built-up Area ( ) Agriculture ( ) Vegetation ( ) Bare soil ( ) Water ( )

If Agriculture, indicate(✓) :

1) Agriculture type Commercial ( ) Subsistence ( )
2) surface coverage (%) 0-19 % ( ) 20-39 % ( ) 40-59 % ( ) 60-79 % ( ) 80-100% ( )

If Water Bodies Indicate (✓):

3) Water depth Deep ( ) shallow ( )

If Built-up area, Indicate (✓):

4) Built up area Type Residential ( ) Transportation ( ) Industrial ( )

If Natural Vegetation, Indicate (✓):

5) Vegetation type Grass/ Herb ( ) Shrub ( ) Tree ( )
6) Vegetation coverage Dense ( ) Intermediate ( ) Sparse ( )

If Bare Soil, Indicate (✓):

7) Bare Soil Type Rocks ( ) Sand pits ( )

S3 Research instrument - Water quality

Research Instrument Checklist

Area: Orange River, Aussenkehr

Title: Land use and land cover changes and the dynamics of the Orange River in Aussenkehr Area, Namibia.

Date: _______________ By: _____________________

Site ID Lat/lon	
Photo Numbers	
Human Activities Water condition	
Soil type	
Weather	

Research Instruments	GPS, Total Dissolved solids meter, PH meter, Dissolved Oxygen (DO) meter, Electrical Conductivity Meter

Instructions:
Use the research instruments to measure the water quality of Orange River for Electrical conductivity, PH, dissolved oxygen, salinity and total dissolved solids at 2 sampling location in Aussenkehr. Use a GPS to get Geo-location of each sampling site.

Results:

Time HR: Min	Total dissolved oxygen (ppt)	Dissolved oxygen (mg/l)	PH (standard units)	Electrical Conductivity (µS/cm)	Temperature (degree Celsius)	Salinity (mg/l)

Comments:

**
X = latitude, Y= longitude, ppt = part per thousand, µS/cm = microsiemens per centimeter, mg/l = milligrams per liter , HR:Min = Hour: Minute

S4 Water quality data sampled at the beginning of the wet season in the study area (November to December 2018)

Year Sampled	DO	pH	EC	Site
2018	7,64	8,25	507	Upstream
2018	8	8,32	503	Upstream
2018	8,46	8,32	505	Upstream
2018	8,02	8,32	510	Upstream
2018	8,41	8,4	509	Upstream
2018	8,67	8,48	509	Upstream
2018	8,45	8,39	513	Upstream
2018	8,87	4,45	511	Upstream
2018	8,53	8,87	513	Upstream
2018	9,36	8,42	762	Next to Farms
2018	10,93	8,61	764	Next to Farms
2018	6,74	7,96	784	Next to Farms
2018	6,88	8,26	818	Next to Farms
2018	10,42	8,3	833	Next to Farms
2018	9,15	8,51	689	Downstream
2018	10,85	8,82	692	Downstream
2018	8,39	8,5	709	Downstream
2018	9,65	8,53	718	Downstream
2018	10,3	8,78	712	Downstream
2018	7,02	8,02	741	Downstream
2018	9,43	8,42	739	Downstream

2018	10,74	7,74	743	Downstream

S5 Water quality data sampled at the beginning of dry season the study area (May to June 2019)

Year Sampled	**DO**	**EC**	**Ph**	**Site**
2019	9,2	567	8,24	Upstream
2019	9,29	564	8,36	Upstream
2019	8,89	566	8,11	Upstream
2019	9,72	555	8,48	Upstream
2019	9,79	551	8,36	Upstream
2019	9,61	545	8,33	Upstream
2019	10,48	536	8,39	Upstream
2019	9,99	529	8,49	Upstream
2019	9,2	523	8,26	Upstream
2019	10,56	512	8,42	Upstream
2019	9,13	511	8,4	Upstream
2019	7,9	579	8,05	Next to Farms
2019	7,78	589	7,88	Next to Farms
2019	7,28	685	7,79	Next to Farms
2019	7,83	680	7,91	Next to Farms
2019	7,69	672	7,84	Next to Farms
2019	7,36	797	7,76	Next to Farms
2019	7,56	710	8,04	Next to Farms
2019	7,66	668	7,92	Next to Farms

2019	7,43	668	7,95	Next to Farms
2019	8,71	667	8,19	Next to Farms
2019	9	670	8,27	Next to Farms
2019	10,87	494	8,63	Downstream
2019	8,77	564	8,09	Downstream
2019	8,28	549	8,49	Downstream
2019	9,07	575	8,24	Downstream
2019	10,84	605	8,18	Downstream
2019	9,53	591	8,45	Downstream
2019	8,58	594	8,45	Downstream
2019	15,25	607	8,18	Downstream
2019	8,9	582	8,68	Downstream
2019	11,01	590	8,38	Downstream

S6 Roshpinah water quality data series (1998 to 2019)

Date sample taken	**Time taken**	**pH**	**Conductivity mS/m**
2019/03/25	-	8,5	57,7
2019/02/26	-	8	91,1
2019/01/21	-	8,7	62,2
2018/10/18	-	8,7	58,9
2018/09/25	-	8,3	61,4
2018/05/21	-	7,9	34,5
2018/05/16	17:00	7,9	31,5

2018/03/14	17:07	8,6	52,8
2018/01/24	14:55	8,5	52,1
2017/11/29	-	8,3	68,1
2017/09/06	-	8,6	69,7
2017/06/21	-	8,3	65,9
2017/05/08	-	8,2	66,3
2017/03/13	-	7,8	48,5
2017/02/01	-	8,3	63,5
2017/01/31	-	8,3	65,5
2017/01/17	-	8,4	110
2016/11/09	-	8,3	75,1
2016/11/15	-	8,4	75,4
2016/11/22	-	8,9	83
2016/11/01	-	8,6	76,7
2016/09/21	-	8,7	72,6
2016/08/01	-	8,5	66
2016/07/20	-	8,2	57,4
2016/07/18	-	8,4	60,9
2016/06/14	-	8,3	51,1
2016/05/18	-	8,5	49,2
2016/06/02	-	8,5	51,1
2016/04/26	-	8,6	49,5
2016/03/30	-	8,4	64
2016/03/09	-	8,3	51

2016/02/23	-	8,3	50,2
2016/01/25	-	8,1	34,5
2014/12/12	14:11	8,6	38,7
2014/06/13	-	8,3	41,7
2014/03/07	-	8,2	39,7
2013/11/22	17:34	8,5	70,3
2013/09/02	-	8,4	57,6
2012/11/30	-	8,5	57,4
2012/07/06	-	8,1	55,5
2011/08/15	-	8,6	51,2
2011/03/14	-	8,2	24,8
2011/03/01	-	8,2	24,5
2011/01/18	-	8,1	31,6
2010/11/24	-	7,9	70,4
2010/11/22	-	8,1	65,2
2010/10/18	-	8,3	67,3
2010/09/16	09:00	8,5	62,3
2010/09/07	-	8,6	57,8
2010/08/18	-	8,3	52,7
2010/06/07	-	8,4	45,2
2010/03/16	-	8,5	35,2
2009/11/30	-	8,3	29
2009/09/07	-	8,4	67,5
2009/06/08	-	8,2	55,5

2009/03/09	-	8	38,6
2008/12/01	-	8,4	76,9
2008/09/10	-	8,4	71,5
2008/06/20	-	8,4	54,8
2007/11/28	-	8,2	72,8
2007/09/10	-	8	77,7
2007/06/18	-	8,6	48,9
2007/04/04	-	8,3	50,4
2006/09/11	-	8	25,4
2006/06/02	-	8,1	26,5
2006/03/13	-	7,8	64,2
2005/11/28	-	8,6	62,4
2005/09/12	-	8,4	76,2
2005/06/10	-	8,7	63
2005/03/04	-	8,1	55,2
2004/11/29	-	8,1	55,3
2004/09/22	-	8,3	74,7
2004/06/16	-	8,4	78,6
2004/04/06	-	7,7	44,6
2004/03/07	-	8,1	57,9
2003/11/29	-	7,9	54,8
2003/09/14	-	8,4	61
2003/06/15	-	8,3	47,9
2003/03/09	-	8,5	50,5

2003/03/09	-	8,5	51,2
2003/01/20	07:30	8,6	38
2002/12/01	-	8,2	29,1
2002/12/01	-	8,2	29,6
2002/10/29	-	8,2	23,9
2002/10/03	-	7,1	28,3
2002/09/08	-	8	24,7
2002/09/08	-	8,1	26,5
2002/07/31	11:05	8,3	49,2
2002/04/04	10:00	8,1	33,4
2002/03/17	-	8,1	25,2
2002/03/17	-	8,2	24,5
2001/10/10	-	8,2	32,7
2001/10/10	-	8,2	30,9
2001/09/08	-	8,3	43,9
2001/09/08	-	8,6	44,2
2001/04/06	-	8,5	42,3
2001/04/06	-	8,5	66,4
2000/08/21	09:00	8,5	41,5
2000/05/17	-	8,1	48,8
1999/08/12	-	8,4	52,5
1999/02/11	-	7,9	56,4
1998/11/26	-	8,1	40,9
1998/11/06	-	8,1	31,4

1998/10/12	-	8	27,1

S7 Noordoewer water quality data series (1997 to 2019)

Date sample taken	Time taken	pH	Conductivity mS/m
2019/02/25	-	8,2	55,3
2018/10/29	14:22	8,6	50
2018/09/24	10:38	8,3	55,3
2018/08/28	11:25	8,5	49,7
2018/07/23	13:45	8,5	49,6
2018/07/02	12:00	8,3	45,5
2018/05/16	14:35	8	31
2018/05/14	14:17	8	30,3
2018/03/14	15:10	8,6	42,6
2018/01/24	13:05	8,4	38,9
2017/11/29	-	8,3	50,5
2017/10/16	12:38	8,3	57
2017/09/06	-	8,7	61,1
2017/07/31	14:00	8,4	65,8
2017/06/21	-	8,5	54,7
2017/05/02	14:30	8,2	62,2
2017/02/01	-	8,3	47,6
2016/11/09	-	8,5	63,1

2016/05/18	-	9	42
2016/03/09	-	8,4	37,7
2014/12/12	11:19	8,6	36,1
2014/06/13	-	8,3	40,6
2014/04/25	-	8,4	37
2014/03/07	-	8,5	33,8
2013/09/02	-	8,3	58,8
2013/06/24	10:00	8,5	60,2
2012/11/30	-	8,4	52,2
2012/07/06	-	8,4	65,9
2012/04/16	-	8,2	43,8
2012/02/16	-	8,3	41,8
2011/11/16	-	7,8	-
2011/04/19	-	8,4	27,1
2011/03/11	-	8,2	23,7
2010/11/19	-	8,3	54,5
2010/09/06	-	8,5	55,9
2010/08/10	-	8,3	45
2010/06/04	-	8,3	45,8
2010/03/15	-	8,2	36,5
2009/11/27	-	8,3	27,5
2009/09/04	-	8,4	59,7
2009/06/05	-	8,2	50,3
2009/03/06	-	8,1	33,7

2008/11/05	12:37	8,4	65,5
2008/09/09	-	8,3	68,4
2008/06/20	-	8,2	55,2
2008/03/18	-	8,3	43,3
2007/11/28	-	8,2	49,3
2007/09/07	-	8,3	64,7
2007/06/15	-	8	49,2
2007/04/03	-	8,2	40,6
2006/09/08	-	8,2	24,6
2006/06/02	-	8,1	24,6
2006/06/02	-	8,1	24,6
2006/03/11	-	8,1	62,9
2005/11/25	-	8,4	47,5
2005/09/09	-	8,5	65,7
2005/08/02	09:00	8,5	62,2
2005/06/10	-	8,5	58,6
2005/03/04	-	8,3	44,4
2004/11/24	-	8,1	48,8
2004/09/21	-	8,4	71,7
2004/03/29	-	7,5	47,5
2003/04/18	-	8,1	37,6
2003/04/18	-	8,4	36,2
2003/04/18	-	8,4	34
2003/04/18	-	8,5	35,3

2003/04/18	-	8,6	36,5
2003/04/18	-	8,2	33,5
2003/03/08	-	8,4	41,1
2002/11/20	-	8	26,1
2002/11/20	-	8,4	24,1
2002/11/20	-	8,4	25,7
2002/11/20	-	8,4	26,1
2002/09/07	-	8,3	27,1
2002/04/04	12:00	8,5	32,3
2002/04/04	09:00	8,1	28,4
2002/04/04	11:00	8,1	31,6
2002/04/04	11:00	8,1	31,5
2002/04/04	10:00	8,4	29,8
2002/04/04	09:00	8,4	29,7
2002/04/04	13:00	8,2	28,8
2002/04/04	09:00	8,4	29,7
2002/04/04	10:00	8,2	30,6
2002/03/16	-	8,2	23,4
2001/09/21	-	8,3	49
2001/09/21	-	8,3	45,6
2001/09/21	-	8,2	47,1
2001/09/21	-	8,1	23,9
2001/09/21	-	8,3	34,5
2001/09/21	-	8,3	44,2

2001/09/08	-	8,4	49,7
2001/04/06	-	8	40,5
1999/11/10	-	8,4	41,7
1999/08/12	-	8,4	53
1997/07/10	10:00	7,8	46,3
1997/01/21	12:45	8,2	36

S8 Sources of datasets used in the thesis

Datasets	**Source**
Space Shuttle Radar Topography Mission (SRTM) DEM	USGS Earth explorer
Vegetation	Food and Agriculture Organisation (FAO)
Landsat 5,7 and 8 Satellite Images	USGS Earth explorer and Google Earth
Soil & Landform	ISRIC, Soil and Terrain Database for Southern Africa (SOTERSAF)
Lithology	MME
Roads, settlements, and rivers	NSA digital
Time series water quality	NamWater, Karasburg Offices
Permission to use datasets that are not available freely was acquired from their respective suppliers	

S9 Description of LULC classes

LULC Class	**Description**
Agriculture	Areas with irrigated arable land and vineyards, and natural vegetation found along the river

Water	Areas that have water including rivers, canals and dams
Bare soil / Built-up area	Areas that include cliffs, rocks and mountains, and built-up areas. It also includes shadows. Shadows found on mountains during the capture of the images; they fall under bare soil

S10 Types of fertilisers in use in the study area

Mostly granular fertiliser pre-harvest combined with enriched composted chicken manure post-harvest
* Ammonium Sulphate Nitrate (Asn) * Lime Ammonium Nitrate (Lan) * Calcium Nitrate * Potassium Sulphate * Potassium Nitrate * Blends (TURBO K 14-6-14, 19:7:6 (32) 19:3:7 (31), 4:1:1 (31))

S11 Accuracy assessment confusion matrix

LULC class		**Ground truthing points**				
		Agriculture	**Bare soil**	**Settlement**	**Water**	**Total**
Classification Points	**Agriculture**	**39**	4	0	3	46
	Bare soil	3	**18**	1	4	26
	Settlement	0	0	**9**	0	9
	Water	1	0	0	**4**	5

	Total	43	22	10	11	**86**
Producer Accuracy (%)		90,7	81,8	90,0	36,4	
User Accuracy (%)		84,8	69,2	100,0	80,0	
Overall Accuracy (%)	**81,4**					
Kappa Accuracy (%)	**74,0**					

S12 Land use and land cover change rates calculated for each period of observation (1990 to 2000, 2000 to 2010, and 2010 to 2019)

Class Name	**1990 - 2000**	**2000 - 2010**	**2010 - 2019**
Agriculture	67.0	42.2	113.3
Bare soil	-73.4	-61.2	-100.1
Water	6.4	6.8	-19.6
Settlement	No data	No data	6.4

S13 Source of variation in EC generated by Kruskal-Wallis test; variation is considered significant when p-value is less than 0.05.

Water Parameter	**Source of Variation**	**Df**	**Chi-Squared (x^2)**	**p-value**
EC	Location	2	23.607	5.039e-08
	Season	1	1.2499	0.2636

S14 Dunn test (1964) multiple comparison of EC by location

Parameter	Comparison	P-values adjusted
EC	A – B A - C B – C	1.016677 e-07 1.206412 e-04 3.963331 e-01
NB: A=Upstream, B=Next to farms and C=Downstream of farms		

S15 Source of variation in DO generated by Kruskal-Wallis test; variation is considered significant when p-value is less than 0.05.

Parameter	Source of Variation	Df	Chi-Squared (x^2)	p-value
DO	Location	2	12.379	0.002051
	Season	1	0.35825	0.5495

S16 Dunn test (1964) multiple comparison of DO by location

Parameter	Comparison	P-values adjusted
DO	A – B A - C B – C	0.054206563 0.655617480 0.001553457
NB: A=Upstream, B=Next to farms and C=Downstream of farms		

S17 Source of variation in pH generated by Kruskal-Wallis test; variation is considered significant when p-value is less than 0.05.

Water Parameter	**Source of Variation**	**Df**	**Chi-Squared (x^2)**	**p-value**
pH	Location	2	13.128	0.001411
	Season	1	3.4191	0.06445

S18 Dunn test (1964) multiple comparison of pH by location

Parameter	**Comparison**	**P-values adjusted**
pH	A-B	0.016627208
	A-C	1.00000000
	B-C	0.001603841
NB: A=Upstream, B=Next to farms and C=Downstream of farms		

S19 Mann-Kendall trend analysis of EC at Noordoewer and Roshpinah from 1998 to 2019

Water Parameter	**Town**	**Mann-Kendall Tau**	**P-value**
EC	**Noordoewer**	0.242	0.0005281
EC	**Roshpinah**	0.291	1.2398e-05

S20 Sen's slope trend analysis of time series water quality at Noordoewer and Roshpinah from 1997 to 2019

Water parameter	Town	Sen's slope	Trend	Confidence limits at 0.05	Regression slope
EC	**Noordoewer**	1.66	Rising	Lower limit - 0.730 Upper limit - 2.630	1.643
EC	**Roshpinah**	2.451	Rising	Lower limit - 1.33 Upper limit - 3.47	2.417

S21 Mann-Kendall trend analysis of pH at Noordoewer and Roshpinah from 1998 to 2019

Water Parameter	Town	Mann-Kendall Tau	P-value
pH	**Noordoewer**	0.144	0.052544
pH	**Roshpinah**	0.191	0.0064182

S22 Sen's slope trend analysis for pH at Noordoewer and Roshpinah from 1997 to 2019

Water parameter	Town	Sen's slope	Trend	Confidence limits at 0.05	Regression slope
pH	**Noordoewer**	0.0000	No trend	Lower Limit - 0.000 Upper limit - 0.002	0.001
pH	**Roshpinah**	0.002	Rising	Lower limit - 0.000 Upper limit - 0.004	0.002

S23 *E-coli* results for the wet season at Aussenkehr

Date	Time	Upstream	Downstream
01/12 /2018	Morning Midday Late Afternoon	Positive Positive Positive	Highly positive Positive Positive
02/12/2018	Morning Midday Late Afternoon	Positive Positive Positive	Positive Positive Positive
NB: Owing to logistics, E-coli was not tested at the sampling location next to the farms			