Use of remotely sensed data and spatial modelling techniques to assess impacts of different land management practices on surface water quality.

By

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ABSTRACT

The study uses remote sensing and statistical techniques in assessing land use land cover impacts on surface water quality in the Heuningnes Catchment, Cape Agulhas, South Africa. Firstly, a review of the advancements made in extracting water quality information because of land use land cover impacts, specifically the advancements of modelling techniques that consider spatiotemporal variations across water quality parameters was conducted. The review results show that advancements made across small-scale waterbodies and developing countries such as sub-Saharan Africa are impaired by resource and data constraints. The land cover classification findings showed that the Support Vector Machine (SVM) successfully categorized LULC in the catchment, with good overall accuracy (55% and 75%) and kappa coefficients (0.43 and 0.69), for July 2017 and July 2018. The Heuningnes catchment has recorded high concentrations of total phosphorus (TP) and total nitrogen (TN), 20mg/l and 18.9 mg/l, for March and July 2018 respectively, indicating a predominantly agricultural region. Water Ratio Index (WRI) performed the best overall accuracies, ranging between 75% and 81%. Band ratio regression techniques presented a significant positive relationship (0.4 and 1.88), in extracting water quality parameters, between July 2017 and July 2018. This research confirms the significant impacts of land management practices on surface water quality. Furthermore, Sentinel-2 has a high spatial resolution in accurately extracting water features, gathering timely data for dynamic changes in land cover that constantly occur; and is useful in assessing non-optical factors like TP and TN.

Keywords: Land use land cover; Remotely sensed data; Sentinel-2; Surface water quality; Water-based indices; Geographically Weighted Regression; Water resource management.

PREFACE

This research study was conducted in the Department of Earth Sciences, Faculty of Natural Sciences, University of the Western Cape in South Africa from February 2020 to December 2022 under the supervision of Professor Timothy Dube.

Full name: Danielle Cloete Signature: ………….. Date: June 2023

As the candidate's supervisors, I certify the aforementioned statement and have approved this thesis for submission.

Full name: Prof. Timothy Dube Signature: ………….. Date: June 2023

Full name: Dr. Sumaya Clarke Signature: ………….. Date: June 2023

DECLARATION

I declare that the thesis entitled "The use of remotely sensed data and spatial modelling techniques to assess the impacts of different land management practices on surface water quality for the Heuningnes Catchment, Cape Agulhas, South Africa." is my work, that has not been submitted before, for any degree or examination, at any other university, and that all the sources I have used or quoted have been indicated and acknowledged using complete references.

Full name: Danielle Cloete

Signed…………………… Date: June 2023

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I am honoured to have been granted an opportunity to complete my Masters's degree at the University of the Western Cape. Grateful to have gone through this journey where I learned a lot more about myself. I have the National Research Foundation (NRF) to thank for having made this all possible and providing me with financial support throughout this journey.

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DEDICATION

I dedicate this work to my parents, Helen and Russell Cloete, your love and support have been abundant.

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ABBREVIATIONS

AWEI	Automated Water Extraction Index
CA	Cluster Analysis
CLS	Constrained Least Square
CPI	Contamination Potential Index
DA	Discriminate Analysis
DEM	Digital Elevation Model
DOS1	Dark Object Subtraction
ESA	European Space Agency
EU	European Union
EVI	Enhanced Vegetation Index
FA	Factor Analysis
GIS	Geographical Information Systems
GOFC-GOLD	Global Observation of Forest and Land Cover Dynamics
GWR	Geographically Weighted Regression
IWS	Institute of Water Studies
LULC	Land Use Land Cover
MAE	Mean Absolute Error
MERIS	Medium-Resolution Imaging Spectrometer
ML	Maximum Likelihood
MLR	Multiple Linear Regression
MNDWI	Modified Normalized Difference Index
MSI	Multispectral Instrument
NDBI	Normalized difference built-up index
NDVI	Normalized Difference Vegetation Index
NDWI	Normalized Difference Water Index
NIR	Near-Infrared
OLS	Ordinary Least Squares
PCA	Principal Component Analysis
PLS-SEM	Partial Least Squares Structural Equation Modelling
R2	Coefficient of Determination
RDA	Redundancy Analysis
RF	Random Forest
RMSE	Root Mean Square Error
SANPSRKS	South African National Parks
SVM	Support Vector Machine
SWIR	Shortwave Infrared
TM	Thematic Mapper
TN	Total Nitrogen
TP	Total Phosphorus
VNIR	Visible Near-Infrared
WHO	World Health Organization
WQI	Water Quality Index
WRI	Water Ratio Index

CHAPTER ONE

1.1. Introduction

Surface water bodies and water resources, which serves as a supply to activities across different sectors, are under threat, because of anthropogenic activities, therefore resulting in the deterioration of water resources (Kondraju & Rajan, 2019). The leading factors affecting water quality is the growth of global population as it serves as the umbrella for which other additional factors contribute to the impacts on water quality. With population growth there is a greater magnitude of demands to be met, and greater strain is placed on environmental resources (He et al., 2008). Failure to monitor and assess water quality changes, climate change and other environmental changes will result in ecological, health, and socio-economic effects as water is a vital resource. Additionally, the understanding and assessment of historical and present impacts of land use and land cover (LULC) management and practices is necessary for effective water resource management. Water resources therefore requires routine monitoring by assessing, planning and managing water quality (He et al., 2008).

An increase in population increases food demand and therefore exerting pressure on land resources to supply food, which involves the extensive use of fertilizers. Reduced quality of soil and surface water bodies occurs through the increased application of fertilizers resulting in increased waste concentrations downstream (Mattikalli & Richards, 1996). Additional factors contributing to the way in which the transport of contaminants is affected, is vegetation cover, soil properties, the degree to which land is exploited and the spatial distribution of settlements, agricultural activities, and industrialized buildings within a catchment. Severe impacts can occur when changes in surface water is neglected and not monitored such as water shortages, flooding and waterborne disease outbreaks (Feyisa et al., 2014).

It is critical to assess water quality, as different water users require different water chemistry namely agricultural, industrial, and domestic use, through applying various physical, chemical, and biological parameters. Therefore, in understanding the origin of contaminants there is a probability of managing problems that arise from water contaminants, and understanding the degree to which it affects uses and users and research ways to alleviate threats it may pose (Ritchie et al., 2003). The source of contaminants vary depending on the main activity practiced in the particular region, this provides framework for efficient research purposes. In understanding changes of water quality, appropriate water treatment techniques can be applied to the various and frequent water uses to maintain resource quality and availability (Raman Bai et al., 2009).

In addition to agricultural activities, urbanization results in the development of impervious structures which increases runoff (Wicke et al., 2012). Along with excess nutrients discharged from agricultural activities, the occurrence of soil erosion and the resulting suspended sediment contributes to surface water quality degradation. Additionally, anthropogenic impacts aggravates degradation through water abstraction, dam construction and water pollution (Aguilera et al., 2012; Mattikalli & Richards, 1996). Specifically, dam construction poses adverse impacts such as inundation, flow manipulation and fragmentation where inundation is directly related to the degradation of surface water quality through the release of greenhouse gas (Nilsson et al., 2005). Burning natural vegetation within a catchment is practiced for the management and protection of native plant species, studies where the seasonal burning of vegetation of different ages presented different results such as 23 year old fynbos increased rainfall by 200 mm and 12 year old fynbos slightly influenced streamflow dynamics, as it is related to the percent vegetation canopy cover (Van Wilgen, 1994). As water quality deteriorates, terrestrial and aquatic ecosystems suffer and increased suspended sediments concentrations increases turbidity and therefore limiting sunlight penetration required for photosynthesis (Giri, 2013). With increased degradation of water quality comes increased cost for purification techniques, to ensure safe water quality standards (Tsegaye et al., 2006).

The motive behind remote sensing techniques for assessing the change in water quality patterns is driven by the time-consuming task of in situ water quality measurements, although accurate it can become an expensive technique. Remote sensing techniques is therefore extensively researched to uncover most efficient methods to achieve a spatial and temporal variation in water quality. This study therefore assesses the accuracy of water quality estimates obtained from remote sensing in comparison to in situ measurements. It was noted that a few studies such as Bonansea et al., (2015) which has displayed accurate results, however, no inclusion of the effects of environmental factors is discussed. Remote sensing techniques has the ability to provide spatial and temporal information on suspended matter present in surface water bodies, through estimating and mapping suspended sediment concentrations (Usali & Ismail, 2010). Remote sensing provides spatially variable results over a short temporal scale, allowing for a greater dataset to be continuously analysed (Somvanshi.S et al., 2012).

1.2. Aims and objectives.

1.2.1. Aim

The aim of the study is to assess the water quality in the Heuningnes Catchment, Cape Agulhas using remote sensing and statistical techniques, to determine the land use practices of significant influence on water quality. This study can be used for effective water resource management, specifically in inaccessible areas.

1.2.2. Objectives

The specific objectives are to:

a) identify and determine the impacts of land cover and land use on water quality.

b) assess the use of remote sensing to predict surface water quality with remotely sensed data

1.3. Thesis outline

Chapter one: A comprehensive summary of the background of the relevant research is given in this chapter. This section includes research main aim and objectives of the study.

Chapter two: This chapter provides a detailed review of remote sensing techniques and spatial modelling to evaluate the effects of land management activities on surface water quality, South Africa. Furthermore, discusses the impacts of land use land cover on surface water resources; and modelling techniques for determining the relationship between land use land cover and surface water quality. Remote sensing application to land use land cover monitoring and water quality monitoring is addressed. Traditional techniques for identifying LULC impacts on surface water quality is reviewed and advancements made in Remote sensing technology in land use land cover and water quality monitoring. Challenges with remote sensing for monitoring LULC and extracting water quality data has also been addressed.

Chapter three: This chapter highlights methodology to achieve land use land cover classification and a brief description of the selected study area: the Heuningnes Catchment, Cape Agulhas, South Africa.

Chapter four: This chapter highlights methodology of remotely sensed data and the statistical analysis for the prediction of surface water quality for the Heuningnes Catchment, Cape Agulhas, South Africa.

Chapter five: This chapter provides a synthesis of major research results. Major recommendations and significant findings, along with limitations of the study are also included in this chapter.

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CHAPTER TWO

Remote sensing techniques and spatial modelling to evaluate the effects of land management activities on surface water quality, South Africa.

2.1 ABSTRACT

This chapter reviews satellite image classification techniques which effectively monitors and classifies LULC. An emphasis is placed on the development of image classification techniques to determine LULC change. The research highlights the various techniques applied for optimal surface water body extractions, and advancements in water-based indices, therefore focussing on Modified Normalized Difference Water Index (MNDWI), Water Ratio Index (WRI) and Automated Weighted Extraction Index (AWEI). Thus, this research highlights various remote sensing techniques to assess the impacts of LULC on surface water quality and predicting surface water quality. Furthermore, this thesis highlights the importance and the benefits of remote sensing techniques in developing countries.

Keywords: land use/land cover; surface water bodies; Sentinel-2; automated water extraction index.

2.2 Introduction

Surface water bodies, providing water for natural and anthropogenic activities, are under threat and therefore resulting in the deterioration of water resources. Leading factors affecting water quality is the growth of global population as it serves as the umbrella for which other additional factors contribute to the impacts on water quality. With population growth there is a greater magnitude of demands to be met, and greater strain is placed on environmental resources (He et al., 2008). Failure to monitor and assess water quality changes, climate change and other environmental changes will result in ecological, health, social and economic effects as water is a vital resource. Additionally, the understanding and assessment of historical and present impacts of LULC management and practices is necessary for effective water resource management. Water resources therefore requires routine monitoring, assessing, planning, and managing water quality (He et al., 2008). An increasing population increases food demand and therefore exerting pressure on land resources to supply food, which involves the extensive use of fertilizers. Severe impacts can occur when changes in surface water is neglected and not monitored such as water shortages, flooding, and waterborne disease outbreaks (Feyisa et al., 2014). The quality of water provides information pertaining to land use activities in the surrounding area, as well as the land cover of the area. Through tracking the compounds present in surface water quality provides a direct link to the source of contamination, and representation of the area of interest. The relationship between LULC and water quality is not largely known and understood (Namugize et al., 2018a). To understand the impacts of land use and land cover it is necessary to firstly define this interconnected concept. Land cover is defined as land and topographic characteristics such as the spatial distribution of vegetation type and their species as well as surface water distribution, groundwater, soil and other natural landforms and physical man-made structures, structures such as roads, railways, and built-up areas. The motive behind remote sensing techniques for assessing the change in water quality patterns is driven by the time-consuming task of in situ water quality measurements, although accurate it can become an expensive method (Chingombe, 2012). Remote sensing techniques are therefore extensively researched to uncover most efficient methods to achieve a spatial and temporal variation in water quality. This study will therefore assess the accuracy of water quality estimates obtained from remote sensing in comparison to in situ measurements. It is observed that a few studies such as Bonansea et al., (2015), which has displayed accurate results however no inclusion of the effects of environmental factors are discussed. Remote sensing techniques has the ability to provide spatial and temporal information on suspended matter present in surface water bodies, through estimating and mapping suspended sediment concentrations (Usali & Ismail, 2010). Remote sensing provides spatially variable results over a short temporal scale, allowing for a greater dataset to be analysed, continually (Somvanshi. et al., 2012). Therefore, this thesis aims to further discuss and analyse 1) the relationship between land use land cover and water quality 2) the impacts of LULC on water quality, and 3) assessing the use of remote sensing to predict surface water quality with remotely sensed data. Furthermore, limitations and recommendations regarding materials and methods is discussed. This thesis aims to highlight and present the advancements and challenges in remote sensing approaches in assessing the impacts of LULC on surface water quality.

2.3 Impacts of land use land cover on surface water resources

Impacts of land use land cover changes have been assessed and quantified over numerous decades. Studies have shown the influences of LULC on surface albedo and thus affecting the global climate (Lambin & Geist, 2006). The collective, global impacts of LULC can affect earth system functioning. Land use and land cover can influence the dynamics of a catchment, such as the hydrological response, geomorphology, and soil properties. The influence on catchment dynamics is associated with the varying distribution of precipitation into different components such as evapotranspiration, interception, infiltration, runoff, and the rate of groundwater recharge, within the hydrological cycle. The land coverage therefore has a major influence on water quality parameter concentrations (Aduah et al., 2015; Li et al., 2008; Namugize et al., 2018b). LULC affects the way in which compounds are filtered for their transport along a river, and before infiltration into groundwater. The spatial variations of vegetation affects hydrological processes, and regions occupied permanently by grasslands or forests experiences lower soil losses and sediment yields (Serpa et al., 2015). Wan et al., (2014) expresses the importance of understanding how the different catchment regions experiences varying impacts, where upstream reaches have fewer impacts as opposed to downstream reaches as well as steeper and flatter areas.

In areas dominated by agriculture, the degradation of surface water quality was found to be a result of the excess export of nutrients such as nitrogen, phosphorous and suspended sediments (Lambin & Geist, 2006). These parameters are found in fertilizers and used for crop production which leaches into the soil, and in turn results in run-off to water bodies causing eutrophication. Concentrations of these parameters are therefore analysed to portray the quality of the water bodies. Along with excess nutrients, the occurrence of soil erosion and the resulting suspended sediment contributes to surface water quality degradation (Issaka & Ashraf, 2017). Additionally, anthropogenic impacts aggravates degradation through water abstraction, dam construction and water pollution (Aguilera et al., 2012; Mattikalli & Richards, 1996). Specifically, dam construction poses adverse impacts such as inundation, flow manipulation and fragmentation where inundation is directly related to the degradation of surface water quality through the release of greenhouse gas, sedimentation, and an overabundance of nutrients (Nilsson, et al., 2005). Water quality is impacted according to the surrounding industries and activities, as run off from each industry or activity affects water quality to different degrees. Studies have shown the combined impacts of climate change and LULC change in degrading water quality, where regions with agricultural settings resulted in significant discharges of nitrates and phosphorous, into surface water bodies (Wu, et al., 2012; El-Khoury, et al., 2015; Mehdi, et al., 2015). This is evident in observing the average nitrogen levels present in waterways from the agricultural sector, which has had a 36% global increase since 1990 (Kanianska, 2016). Along with the impacts of various industries and human activities, comes along the increasing impact of climate change which exacerbates the impact of water quality. The vulnerability of water to being impacted is dependent on catchment conditions. With an increase in climate change, an already vulnerable waterbody with poor water quality could undergo worsened states as climate change results in lower flows within rivers (Mehdi, et al., 2015). The study by Nilsson & Renofalt (2008), evidence that when flows have been reduced, there is less volume for dilution and therefore an increase in the downstream concentrations of point discharges and resulting in toxic concentrations to ecosystems and human health. This motivates for the need to understand the connection between LULC and surface water interactions (Nilsson & Renofalt, 2008).

2.4 Modelling techniques for determining the relationship between land use land cover and surface water quality

Land use is referred to as the way in which humans, animals and other living organisms make use of ecosystem services within a holistic cycle. Ecosystem services such as prey and predator cycles within the Animalia Kingdom (Lambin & Geist, 2006). To determine the effect land use and land cover changes has on water quality, there is a need to determine the relationship between LULC and water quality, and their interactions. In addition to understanding the relationship, understanding importance of the riparian zone in maintaining water quality is as significant, in this way, methods for further protection of the riparian zone can be applied. The presence of the riparian zone is important for the way in which it regulates and controls the inflow of nitrates, phosphorous, and sediments into a stream however, where riparian zones has been removed, bank erosion occurs, and in turn leads back to the change and increase of nitrates, phosphorous and sediments. Therefore, analysing water quality from the riparian zone aids in the understanding and interpretation of water quality, as the riparian zone is a direct connection with terrestrial landscapes and streams (Mello et al., 2018, 2020; Gregory, et al., 1991).

Land use land cover and water quality have a complex relationship. The use of statistical modelling to quantify the relationship was found to be more popular due to its simplicity, as physical models require larger input data sets, together with calibration and validation of data sets (Giri & Qiu, 2016). Traditional methods have been applied namely: multiple linear regression (MLR), redundancy analysis (RDA), ordinary least square (OLS) and constrained least square (CLS) regression models. The above-mentioned models have been used for their simplicity and ability in approximating the effects of independent variables. However, the challenge experienced is the limitation to account for the spatial variation of the LULC and water quality relationship. Therefore, the current method in aid of determining the complex relationship between LULC and water quality, is known as the geographically weighted regression (GWR) regression model. The advantage of GWR allows for the integration of sample point coordinates into a regression equation to determine the relationship between LULC and water quality. This method has specifically been applied in North America, Europe, and Asia (Giri & Qiu, 2016). Previous, traditional statistical methods lack the importance of discovering and considering spatio-temporal characteristics of LULC and water quality interactions (Giri & Qiu, 2016). The Bayesian hierarchical framework has been applied in a study conducted in China by Wan, et al. (2014) in determining the effect of LULC on stream water quality. More specifically the Bayesian hierarchical model has the ability to compute missing data, allows for prediction and account for spatially varying regression parameters, successfully proven in studies conducted by (Blangiardo et al., 2011; Wan et al., 2014; Wikle & Anderson, 2003), indicative that this method can be applied broadly, ensuring adaptability. In Further understanding the relationship between LULC and water quality, it is important to understand how this relationship varies according to factors of seasonal variations, the intensity of land use, watershed characteristics, and the configuration and composition of the landscape (Mello et al., 2020).

Furthermore, to increase accuracy and reliability of determining the relationship between LULC and water quality using statistical models, Giri & Qiu (2016) has proven it necessary to use a combination of LULC indicators to eliminate flaws present within the indicator in use. The results show the inaccuracy of the sole use of the landscape development intensity (LDI) index, as it was not able to specify the exact location of the land use affecting water quality (Wan, et al., 2014) (Giri & Qiu, 2016). Therefore, Giri & Qiu (2016) proposed the incorporation of statistical models as a complementary sense, in accounting for various factors. Current multivariate statistical techniques include a cluster analysis (CA), principal component analysis (PCA), and factor analysis (FA) as well as discriminate analysis (DA). A study conducted by Barakat (2016) applied CA, PCA, FA and DA in order to assess the temporal and spatial variations of water quality, as well as to determine potential and significant contamination sources and to classify sampling sites according to water status. The results of the above mentioned multivariate statistical techniques presented the efficiency of these techniques as it produces reliable water quality information based on only a few monitoring sites and only requiring limited water quality parameters to be assessed. This may be especially relevant in studies where sufficient resources and technologies are inaccessible and unavailable. Furthermore, these techniques (FA) presented the parameters of concern, such as discharge and organic pollution, within the Indus River, Pakistan (Barakat, et al., 2016; Baluch & Hashmi, 2019).

Table 1: A summary of literature research on quantifying the relationship between land use/land cover and water quality, across a global scale.

Country	Methods	Research Findings	References
China	Multivariate regression model: Redundancy Analysis (RDA) and Partial Least Squares Structural Equation Modelling (PLS-SEM)	Water quality parameters displayed different results across different seasons. During the dry period, the watershed location was solely affected by urban cover. However, the rainy period was associated with organic and inorganic pollutants from agriculture and urban cover. The outcome displayed a negative correlation between urban and organic pollutants to water quality.	(Wang, et al., 2021)
North America, Europe, Asia	Geographically Weighted Regression (GWR)	Results presented a positive correlation between land use land cover and water quality, indicating the degradation of water quality with land use land cover change.	(Giri & Qiu, 2016)
Morocco	Multivariate statistics such as Pearson's correlation, principal component analysis (PCA) and CA.	Results presented by PCA indicated that the differences in water quality parameters stem from point source contamination, non-point source contamination as well as natural processes such as soil weathering. CA displayed the spatial and temporal variations that occur, affecting water quality, which is indicative of rainfall being a source of contamination.	(Barakat, et al., 2016)

2.5 Remote sensing application to land use land cover monitoring

Rawat & Kumar (2015) carried out a study whereby LULC classes are classified and thereafter, change is detected from the conversion of one kind of LULC class to another, over a significant period. Studies by Obeidat et al. (2019) and Rawat & Kumar (2015), indicate the use of the maximum likelihood classifier as a common classification method for land use land cover monitoring, in detecting different types of LULC classes such as built-up, agriculture and indigenous forests. To determine the amount of change that has occurred across land use and land cover, studies have presented the traditional method of detecting LULC change, which is the use of Normalized Difference Vegetation Index (NDVI), across remotely sensed images (Maselli, 2004; Lunetta, et al., 2006; Ramoelo, 2007). This vegetation index is applied to predict as well as assess the status of vegetation cover, as it expresses vegetation health, and is widely used for its ability to account for issues of sun elevation angle causing shadow variations and is not affected by topography (Obeidat, et al., 2019). The satellite imagery provides information on the location, type, and extent of LULC changes that have occurred, particularly according to its spatial and temporal characteristics (Obeidat, et al., 2019). Additionally, Obeidat et al. (2019) analyses high NDVI values, typically above 0.15 as dense vegetation, as opposed to zero NDVI values indicating no vegetation. This guidance allows for the observation of vegetation status of a specific period (Obeidat, et al., 2019).

Obeidat et al. (2019), presents a method for quantifying the amount and type of change that has occurred over a significant period, by presenting a compilation of various possible change outcomes, which is known as thematic change. Obeidat et al. (2019), presents a further method how image difference method is used to calculate how brightness values have changed with time, and the results of image difference directly displays LULC changes and displayed across a grayscale image. By observing the decrease in reflectance, image difference displays vegetated areas and areas which once were dry, and with time became saturated. Furthermore, the degradation of vegetation cover is observed by an increase in reflectance (Obeidat, et al., 2019). The above brings insight about the various LULC changes that have occurred across a given study area and period, by monitoring the changes of image brightness.

Table 2: A summary of literature research on land use/ land cover classification and change detection, across a global scale.

Country	Sensor	Methods	Research Findings	References

India	Multispectral Landsat Thematic Mapper	Supervised classification: Maximum Likelihood Classification. Change detection techniques: traditional post-classification cross tabulation, cross correlation analysis, neural networks, knowledge-based expert systems, image segmentation and object oriented classification. As well as the use of NDWI, MNDWI and normalized difference built-up index (NDBI)	Urban land increased from 23.7% in 1986 to 32.8% in 2002. Whereas agriculture, forest and wetland decreased from 69.6% to 60.5%	(Rawat & Kumar, 2015)
India	Landsat Thematic Mapper	Supervised classification method, maximum likelihood algorithm to perform land use land cover classification. Post-classification method for detecting land change, through pixel comparisons for change interpretation.	Classification results showed an overall accuracy of 90.29% in 1990 and 92.13% on 2010. Change detection results depict positive and negative LULC change patterns, in the class of vegetation, agriculture, barren, built-up and water body.	(Rawat & Kumar, 2015)

England	Landsat MSS and SPOT HRV	Unsupervised method of classification, specifically the K-means cluster. As well as obtaining land use land cover information through digital image processing. Land use change detection was achieved by the Boolean logic.	The method results in the grouping of pixels according to their spectral reflectance. Thereafter, producing various land cover classes, portrayed across land use land cover distribution maps. Land use change detection indicated an increase in the use of nitrogen and phosphorous fertilizers.	(Mattikalli & Richards, 1996)

2.6 Remote Sensing techniques for water quality monitoring

In the monitoring of water quality, Lambin & Geist (2006) presents evidence of the fact that water quantity and quality is dependent on the surface over which it flows as it encounters terrestrial characteristics. Examples of terrestrial contact includes forestation, changes in croplands, urbanization, and mineral extraction, and in turn affecting the hydrological cycle (Steffen, et al., 2004). Through the excess export of nutrients such as nitrogen and phosphorous, which is the product of fertilizers within the agricultural sector, eutrophication takes place. Eutrophication results in weed growth and an overall poor, indigestible water quality (Steffen, et al., 2004; Lambin & Geist, 2006). Furthermore, Tilman (1999) and Pimentel, et al (2004) studies states that 90% of diseases occur because of poor water quality, predominantly in third world countries. The above mentioned is evident that a relationship exists between land use land cover and water quality.

Studies have mentioned and presented the results of water indices applied in acquiring surface water information as opposed to inter-spectral relation methods, the way in which surface water has changed over a specific period (Zhai, et al., 2015; Wang, et al., 2020). Changes including channel width, volume of a river network, and the deterioration of water quality. With extracting surface water information, there is knowledge constraints posed by machine learning algorithms in training professionals, as opposed to traditional algorithms. With regards to machine learning algorithms, a study conducted by Li et al. (2013), stated the inability of machine learning algorithms to rapidly map surface water information across country and worldwide scales. Therefore, there has been a more common use within traditional methods for surface water extraction. More specifically, the common method used is the multi-band method, where a water index is used in combination with remote sensing indices. Specifically, the multi-band method as it performs better in producing higher water extraction accuracies and efficiency in surface water extraction across a larger scale (Li, et al., 2013; Feyisa, et al., 2014; Dong, et al., 2016; Fisher, et al., 2016; Tulbure, et al., 2016; Mohammadi, et al., 2017; Chen, et al., 2017; Wang, et al., 2018; Wang, et al., 2020).

The importance of utilising indices assessing vegetation conditions and the presence of vegetation, produces information pertaining to the way in which vegetation has changed as a result to land use land cover change, and the result of vegetation conditions due to the use of poor water quality through irrigation (Land and Water Development Division of FAO, 1997).. Rawat & Kumar (2015) presented the benefits of integrating the indices: MNDWI, EVI, and NDVI as a method to minimise flaws present in each above-mentioned indices, and therefore more accurately extracting surface water bodies and identifying water bodies against non-water bodies. This achieved by use of spectral combinations within the use of indices (Wang, et al., 2020). Thereafter, the change observed among surface water bodies can be the driver to further investigating cause of change (Rawat & Kumar, 2015).

Giri & Qiu (2016) conducted a study displaying the use of water quality indices such as the Water quality index (WQI) mentioned above, as well as the Contamination potential index. However, the challenge of CPI is the inability of the index to be applied only to non-point source pollution due to its complex nature and therefore making it more challenging to accurately estimate flow rate and area of contamination, especially since flow rate and contaminated area is vital for quantifying waste material. Therefore, a study conducted by Sapna et al. (2018) made use of the Water Quality Index (WQI) which aids in resolving water quality data in order to be simply interpreted by the public and to avoid complexities. WQI presents water quality data over a particular area and time, as a single value, and therefore provides an overall description of the water quality of concerning parameters. WQI quantified by the following overall mathematical equation:

$$WQI = \frac{\square \text{ Wi Pi}}{\square \text{ Pi}} \quad \text{eq. 1}$$

Equation 1, first assigns a range of 1-6 to water quality parameters of concern, representing the degree to which water quality affects human health, which is known as the parameter's weight in affecting human health. The equation above may also be applied to analyse water quality for general use (Lion, et al., 2004; Sapkal & Valunjkar, 2013). WQI is correlated with water quality parameters and analysed to determine either a negative or positive correlation. Concerning parameters are determined by the following factors: its effect on human health; the concentration of the parameter in comparison to insignificant parameters; and the possibility of treatment or removal. The study evidences the suitability of WQI in determining the state of water quality for drinking purposes as well as general use (Sapkal & Valunjkar, 2013). WQI moreover describes the impacts of certain water quality parameters in relation to World Health Organization (WHO) standards. The Water Quality Index (WQI) is commonly used which aids in resolving water quality data to be simply interpreted by the public and to avoid complexities. WQI presents water quality data over a particular area and time, as a single value, and therefore provides an overall description of the water quality of concerning parameters.

Table 3: A summary of literature research on water body delineation and water quality extraction, across a global scale.

Country	Sensor	Methods	Research Findings	References
India	Landsat Thematic Mapper (TM)	Remote sensing indices, normalized difference water index (NDWI) and modified normalized difference water index (MNDWI) to detect changes of water bodies (El-Asmar, et al., 2013)	The accuracy assessment of the classification indicates an overall accuracy of 90.29% for 1990 and 92.13% for 2010. In 1990, 0.90% was classified under water body and in 2010, there is a deduction in water body of 0.82%	(Rawat & Kumar, 2015)

China	Landsat TM, Landsat ETM+, Landsat OLI and Sentinel-2 Multispectral Instruments (MSI)	Water extraction algorithms: Modified Normalized Difference Water index (MNDWI), Enhanced Vegetation Index (EVI) and Normalized Difference Vegetation Index (NDVI) to map surface water bodies.	The results display accurate classification and dynamic monitoring of surface water bodies, with overall accuracy being 95.9%, the producer accuracy at 93.24% and the kappa coefficient 0.91. Furthermore, the results displayed a decreasing trend in seasonal waterbodies across the Hetao Plain whereas more permanent waterbodies displayed an increasing trend as a result of annual precipitation.	(Wang, et al., 2020)
Denmark	Landsat 5 TM	Comparison of different classification methods namely: MNDWI and Maximum Likelihood (ML). As well as the improved	AWEI produced a higher accuracy in extracting water bodies as opposed to MNDWI and ML, as it is especially applicable in mountainous regions, and effective for omitting cloud and hill shade limitations. Kappa coefficient showed a 0.93 classification	(Feyisa, et al., 2014)

		classification method developed, Automated Water Extraction Index (AWEI).	accuracy, with AWEI.	

2.7 Traditional techniques for identifying LULC impacts on surface water quality

Remote sensing is used to determine the physico-chemical and biological characteristics of waterbodies, as well as by identifying possible pollution or contamination sources. This information found in waterbodies is related to remote sensing reflectance. To understand remote sensing techniques for monitoring water quality parameters, it is imperative that individual parameters are identified and thoroughly understood to determine whether a relationship exists between water quality parameters and radiance data and therefore relate water quality parameters to spectral reflectance values and determine which section of the electromagnetic spectrum water radiates to.

To get to the source of water quality changes, it is necessary to firstly identify and apply methods which help identify additional influences on water quality. These factors are LULC impacts, climatic factors, and hydrologic conditions. In this way there is the ability to eliminate factors which cause insignificant changes and place emphasis on factors of concern (Spooner, et al., 2014). Furthermore, Giri & Qiu (2016) have proposed various methods to determine these water quality variables such as riparian zone approach, hydrologic sensitive areas, nonspatial land use matrix and critical source areas, to describe factors that have additional impacts on water quality status. However, the limitation found with this approach is the inability to accurately delineate a riparian zone as well as it lacks the representation of any hydrological variations present (Giri & Qiu, 2016). Because of riparian zone approach limitations, hydrologic sensitive area functions as a contributing area towards runoff, and therefore supports and accounts for limitations experienced with the riparian zone approach. Automatically, this method is related to the effects of land use land cover change on water quality due to the active runoff serving as a vehicle of potentially polluting factors. The application of non-spatial land use metrics presented results from a study by Schueler (1994), where it indicated the direct deterioration of stream water quality is the result of a 10 percent conversion to impervious surfaces. These methods mentioned above as water quality behaviour indicators, are analysed to determine the way in which water quality behaves, which can therefore be related to the status of water quality for an area under investigation. Collectively, explanatory variables utilise the percentage of land use land cover change, such as the conversion of land to urban impervious areas, to determine the impacts of that specific change on water quality (Giri & Qiu, 2016).

The study conducted by Dewidar & Khedr (2001) has determined the relationship between the following water quality parameters: potassium (K+) and sodium (Na+), total phosphorous., total nitrogen, dissolved oxygen, pH, and salinity, through the use of regression models for the various water quality parameters namely: salinity, sodium and potassium model and related in accordance with radiance values, and the results displayed a significant positive correlation between salinity, sodium and potassium (Dewidar & Khedr, 2001). Somvanshi.S et al. (2012) suggests the STATISTICA 6.0 software to relate water quality parameters to spectral reflectance using a multiple linear regression to produce multiple correlation coefficients (R^2). The result of this method is to test which independent variable is more favourable with the dependent variables, to produce an effective regression model to estimate water quality parameters. A previous study conducted by Ritchie & Charles (1996) and Usali & Ismail (2010) developed an empirical equation relating remote sensing measurement of radiance and water quality parameters of concern, determined by spectral reflectance values of a parameter. The above study proposed the following equation:

$$Y = A + BX \text{ or } Y = AB^X \quad \text{eq. 2}$$

A parameter of importance that commonly occurs in surface water is suspended matter, as it relates to the primary production and fluxes of heavy metals as well as this parameter provides awareness to micro-pollutants that are present within the water resource and acts as an important function of water quality management. Therefore, the above-mentioned equation was developed to estimate suspended sediments. The variables present the following: Y refers to the remote sensing measurement, either radiance, reflectance or energy. Water quality parameters of concern is represented by the variable X. Variables A and B presents the value obtained from the statistical relationship between spectral reflectance, of water quality parameters, and measured in situ water quality parameters. In this study it is revealed that suspended matter is found to increase reflection of surface water in the visible and near infrared range of the electromagnetic spectrum, between the wavelengths 705 nm and 865 nm. The surface water reflection within these ranges is influenced by the texture, colour, and water depth of sediments as well as sun angles. A more specific range of water quality parameter estimation is between 400 and 850nm (Ritchie & Schiebe, 1976; Dekker, et al., 2002; Usali & Ismail, 2010).

Remote sensing produces a spectral radiance known as $L_{(\square)}$, and is observed against the interaction of incident solar radiation with surface water constituents, the result of this interaction is indicative of a positive empirical relationship between suspended sediments and $L_{(\square)}$. The empirical relationship between SS and $L_{(\square)}$ is applied to estimate suspended sediment concentrations. To increase effectiveness of this method, understand environmental factors affecting these variables such as suspended sediment concentration, the grain size of the sediment, sensing geometry, and water depth and water components. The following conditions is ensured for the correction of influential environmental factors: cloudless skies; a wind speed of 10 knots; and at midday where the solar zenith angles falls between 30□ and 60□ (Atkins et al., 2016; Novo et al., 1989; Ritchie et al., 1976).

Turbidity is measured by the rate light is scattered from suspended solids therefore, the greater the amount of scattered light the higher the turbidity concentration present in water. Campbell et al. (2011) discussed the extraction of water quality data based on remote sensing spectral data, through the way a parameter such as turbidity absorbs and scatters light, these interactions are modelled using a semi-analytical approach. This refers to the way in which spectral data is analysed and processed in relation to water quality parameters. Parameters present in surface water bodies contains information, which is extracted by remote sensing, providing deductions about that specific parameter. Furthermore, this approach is especially important for requiring minimal field data and accounting for numerous time scales, as opposed to the empirical and analytical method. Campbell et al. (2011) developed linear equation models for identifying the optical properties of water and the way in which water quality parameters behave, in terms of absorption; scattering and backscattering; and volume scattering. Therefore, it can be deduced that the absorption of a water quality parameter is relative to the total concentration of the water quality parameter present of a particular waterbody. This approach aims to provide accurate estimations of water quality parameters (Rijkeboer & Dekker, 1997; Campbell, et al., 2011).
The effectiveness of applying image classification techniques is based on the environment and the purpose of investigation. To gain optimal results of land change detection, methods are required to produce classification maps to display categorical land cover changes and address future land changes (Aduah et al., 2015). To quantify the relationship of the two variables, LULC is determined and classified along with delineating surface water bodies. Namugize et al. (2018b) avoided the over estimation of sub-catchment areas by combing the use of

automated hydrology and arc hydro tools of ArcGIS 10.1. The extraction of surface water bodies is compromised by low accuracy when using Landsat imagery therefore, Feyisa et al. (2014) proposed various water classification methods such as thematic classification, linear unmixing, single-band thresholding and two-band spectral water indices to be assessed. The above study has proposed that with a combination of the above-mentioned classification methods, accurate results is obtained in comparison to the individual application of each classification method. This will allow for minimal accuracy problems where discrepancies can be made between water and hill shade or cloud shadows, and low albedo urban surfaces. However, Feyisa et al. (2014) proposed the Automated Water Extraction Index (AWEI) method which is a multiple-band index, to resolve challenges. The use of this method is supported by the high accuracies obtained, when compared to Modified Normalized Difference Water Index (MNDWI) and Maximum Likelihood (ML) classifiers, as AWEI ensured that 50% of errors is omitted, specifically when applied to water bodies (Feyisa et al., 2014). This method is especially suitable as it has been applied in a range of climates, particularly South Africa with its mountain ranges, which is the region of interest within the study. Feyisa et al. (2014) has formulated and redeveloped AWEI, a multiple-band index, where shadow impacts usually effect the accuracy of extracting water bodies, and therefore more specifically developed the AWEIsh (Automated Water Extraction Index Shadow) most importantly for separating water from non-water pixels and further, to eliminate classification errors. AWEIsh (Eq.1) is more commonly used in areas with a predominant presence of snow, ice, and high albedo however without significant built-up area present. AWEInsh (Eq.2) is applied in regions where shadow effects don’t pose major impacts on water surface extractions and classifications, however, is applied where there is a combination of high albedo and shadow regions are present. Specific environmental conditions in testing the effectivity of the AWEI, is the application of the index in a range of environmental conditions, such as humid temperate, sub-tropical and tropical dry regions, as well as a range of land cover types (Feyisa et al., 2014). Land cover types range from mountainous regions, built-up areas and deep hill-shade areas in Denmark, Switzerland, Ethiopia, South Africa, and New Zealand. The AWEI equations is expressed as follows:

$$AWEIsh = 4 \times (\square band2 - \square band5) – (0.25 \times \square band4 + 2.75 \times \square band7) \quad (1)$$

$$AWEInsh = \square band + 2.5 \times \square band – 1.5 \times (\square band4 + \square band5) – 0.25 \times \square band7$$
(2)

□ displays the spectral reflectance values of Landsat 5 TM bands where: band 1(blue), band 2(green), band 4(NIR), band 5(SWIR) and band 7(SWIR). Large negative results are associated with vegetation, soil and built-up areas which has high reflectance values within near infrared and shortwave infrared bands, whereas low reflectance bands are associated with shadow surfaces. The formulation of the two above mentioned equations is in aid of accounting for limitations where, in applying only one of the AWEI equations, and AWEInsh is unable to classify shadowed areas and low albedo surfaces from water surfaces (Feyisa, et al., 2014).

2.8 Advancements made in remote sensing technology in land use land cover and water quality monitoring

The contamination of water has become a worldwide issue impacting many countries and communities. Water quality is monitored to ensure corrective measures are taken place. The aim is to examine the various traditional and advanced water quality monitoring techniques to assess their suitability. The study conducted by Griffith (2002) is used to depict the advancements of remote sensing and GIS in monitoring and assessing water quality status. About 20 years ago, traditional methods are seen as time consuming and expensive, particularly over large-scale areas. Certainly, different satellites are used and applied according to the specific scenario in question, to optimise results. A global application of remote sensing technology is evident, seen in use as early as 1984, where applied in India specifically for hydrological applications and water resource management (Bhavsar, 1984). With the advancement of remote sensing technology, initially with the development of Landsat 1 in 1972, Landsat Thematic Mapper (LTM) has been largely used and applied to inland water quality monitoring studies. Lambin & Geist (2006) expresses the project responsible for the tracing of land use land cover change of historical and modern-day information obtained during the past 300 years, using census data, tax records and land surveys, globally, between 1981 and 2001. The project expressed in the above-mentioned study is known as the Global Observation of Forest and Land Cover Dynamics (GOFC- GOLD).

A significant development can be seen through the study conducted by Munyati & Ratshibvumo (2011) where Landsat TM/ Enhanced Thematic Mapper Plus (ETM+), was used for linking water quality to vegetation cover, where it has been discovered that waterbodies high in turbidity levels are found close to bare land where runoff is high, and therefore assists in monitoring water quality of degraded areas (Munyati & Ratshibvumo, 2010). Advancements made in remote sensing industry stems from experiencing various challenges, such as the influences of cloud and vegetation in the veiling of optical sensors. Among many others, the introduction of Digital Elevation Models (DEM) aids in omitting shadow effects presented by clouds, vegetation, and mountain shadows, with the earliest use of elevation data implemented in 1986 with the use of the SPOT 1 satellite (Balasubramanian, 2017). Recently, advancements have resulted in the ability to obtain surface water information solely through remote sensing optical imagery, such as the measurement of river discharge, and along with other environmental applications (Huang, et al., 2018). These advancements altogether aid in meeting demands with regards to surface water applications, at global and regional scales and small-scale waterbodies specifically in Sub-Saharan Africa (Dube, et al., 2015; Huang, et al., 2018). Sentinel-2 satellites were produced by the European Space Agency (ESA) and the European Union (EU) in 2015, succeeding the initial Sentinel-1A satellite produced in 2014. The suitability and accuracy of Sentinel-2 has been tested in the study conducted by Phiri et al. (2020), which has presented many advantages of the use of Sentinel-2 images. Senitnel-2 has been developed with multispectral scanners, allowing for higher spatial resolution, temporal resolution and furthermore for its various applications. Sentinel-2 Multispectral Instrument (MSI) contains spectral bands: RGB and Near-Infra-Red (NIR) and Short-Wavelength InfraRed (SWIR) with resolutions of 10m and 20m respectively. These bands are specifically relevant for obtaining surface water information (Yang, et al., 2017).

2.9 Challenges with remote sensing for monitoring LULC and extracting water quality data

There are various limitations of remote sensing, especially experienced when remote sensing is used to extract water quality data from smaller waterbodies, as well as the availability of insitu measurements required to validate remote sensing obtained measurements (Dube, et al., 2015). Challenges experienced is that of incident energy affecting remote sensing reflectance and significantly altering the outcome, and therefore requiring thorough atmospheric correction of data (Lavery, et al., 1993). More specifically, challenges related to sensors where multispectral sensors are preferred over hyperspectral sensors, especially for use in subSaharan Africa where there are certain financial constraints, as well as the limited access to hyperspectral data. Overall, there is a specific degradation of surface water quality within developing countries, namely sub-Saharan Africa, therefore requiring the frequent and thorough monitoring of surface water quality (Chawira, et al., 2013). Although, hyperspectral sensors have been proven more accurate in remote sensing of water quality as opposed to broadband multispectral sensors, this is not necessarily the case in developing countries where financial resources and skilled individuals are limited. (Dube et al., 2015), presented the need to develop advanced techniques, specifically the advancement of medium to fine-resolution multispectral data to achieve the water quality monitoring specifically of small-scale waterbodies, as there have been limitations of resolutions of certain sensors such as coarse resolutions obtained from MERIS data.

2.10 Conclusion

Due to the ever-changing society and exponential growth of the human population, human needs and demands have too increased. To account for this growth, there is a need to convert the land cover to the appropriate land cover required, such as urban development, commonly resulting in a change from pristine natural land to polluted urban areas. In addition to the above, there is a need for the conversion of land cover to agricultural land to meet food security. However, waste and pollution accumulated from either of the mentioned land cover classes has vastly affected water sources. The impacts coupled with these land use land cover changes will continue to affect surrounding environments, vital water resources as well as human health and livelihood. Therefore, many studies have determined the suitability, performance, and effectiveness of remote sensing to predict, monitor and assess these changes and impacts, and ways in which to solve for this and reduce major impacts. Literature has presented advanced methods of accurately classifying LULC classes, and indices to extract surface waterbodies such as the development of more advanced algorithms allows for the utilisation of medium to fine-resolution multispectral data to achieve the water quality monitoring of small-scale waterbodies. Furthermore, in addition to these advancements, the development of models for relating LULC and water quality parameters to determine LULC classes with significant effect on surface waterbodies. Most importantly, there is a need in applying the above-mentioned methods specifically to developing countries with a history of poor financial resources, in countries such as Sub-saharan Africa. This is especially necessary as developing areas are more vulnerable to polluted waterbodies, and advancements are to be applied to obtain water quality parameters effectively and accurately with remote sensing techniques, and in so providing better spatial coverage of polluted waterbodies to plan and make timely decisions.

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CHAPTER THREE

The use of remotely sensed data for land use land cover classification for the Heuningnes Catchment, Cape Agulhas, South Africa.

3.1 Abstract

The study aimed to assess the performance of machine-learning techniques for the classification of land use land cover classes, and its impacts on the Heuningnes Catchment, Cape Agulhas, South Africa. Urban and agricultural land use land cover practices have a major influence on the quality of surface water bodies. Diverse forms of land cover have different effects on hydrological features, such as flow rate, runoff, and overland flow. Sentinel-2 images were used to compute image classification using the machine-learning technique, Support Vector Machine (SVM), for July 2017, October 2017, March 2018, and July 2018, representing the dry and wet periods of the Heuningnes Catchment. Classification results indicates a steady increase of bare rock and soil, increasing from October 2017 to July 2018 with 18%, which is directly linked to changes in surface water quality. The wet season, July 2017, and July 2018, displays the highest classification percent of vegetation cover. The overall accuracy ranged between 55% and 75%, specifically the wet season presented greater overall accuracies of 75%. The performance of SVM is expressed as a moderate to substantial level agreement, with kappa statistics of 0.43 to 0.69. For mapping land cover and estimating forest parameters, particularly with the red-edge band, Sentinel-2 provides timely, high-resolution data which accounts for dynamic environmental changes across a large area.

Keywords: Machine-learning algorithms; Land use land cover; Remotely sensed data.

3.2 Introduction

Managed water resources are important for the benefits they provide to the economy, social institutions, and infrastructure (Horne et al., 2017). Among the benefits is access to safe and healthy drinking water; ecosystem services such as drought, disease, and food control; recreational facilities and aesthetic features (Kim, 2021). There is a positive correlation between LULC impacts and water quality degradation. Various land cover types result in different effects on hydrological characteristics, such as changes in flow rate, runoff, and overland flow. These changes occur due to urbanization where there is an increased development of impervious surfaces, such as buildings, roads, and concrete surfaces. The development of such impervious surfaces directly impacts the water quality, as various harmful materials become incorporated with water, as runoff occurs. Poor water quality has a direct impact on the following factors, such as water temperature, sediment arrangement, fluvial geomorphology, aquatic ecosystems, and ecological biodiversity. Therefore, resulting in water quality degradation. Furthermore, majorly affected surface water quality is related to regions dominated by agricultural activities due to the extensive use of fertilizers and chemicals, therefore being the dominant pollutant, along with nitrogen and phosphorus. However, regions dominated by forested and woodland areas displays a positive impact on surface water quality. This is a result of their nutrient absorption function, and being able to intercept pollutants, from polluting waterbodies (Cheng et al., 2022). Early identification of pollution sources allows for timely action to be taken. It is therefore crucial to monitor land use land cover change to manage the impacts of these changes. This is especially important, in protecting developing countries as it is significantly impacted by LULC types and changes, due to poor infrastructure and lack of financial resources available and may therefore easily succumb to flood and drought damage, and may experience health issues such as diarrhoea, vomiting, cardiovascular disease and hypertension. The impacts of LULC have been researched for decades due to its impact on surface water quality (Cheng et al., 2022; Ighalo et al., 2021; Park & Lee, 2020).

The application of remote sensing, together with geographic information system (GIS) techniques, for land use land cover monitoring and change detection, results in extracting highresolution, multispectral information, and data which covers large inaccessible areas, on a realtime basis. Providing data which is more cost and time effective. These techniques allow for the mapping of land cover changes, and understanding urbanization, a factor responsible for the degradation of water quality (Butt et al., 2015). Furthermore, this information is used to ensure strategies necessary for spatial planning, utilization, and conservation of vital land resources, to sustain the exponential growth of human populations, and to make provision for increasing land degradation. Traditional use of remote sensing application presented limitations of time consuming, expensive and lacks updated information of continuously changing land use patterns. The advancement of remote sensing technologies, specifically Landsat 1 in 1972, has brought about achieving applications for natural resource monitoring and ecosystem processes. Additionally, the launch of Sentinel-2 in 2015, has majorly impacted the specific monitoring of land use land cover, due to its multispectral, and high spatial and temporal resolution capabilities and the availability of timely and free access data over large scale areas (Phiri, et al., 2020).

For identifying land use land cover types, image classification is applied to achieve accuracy and precision in determining various land use land cover types. (Phiri, et al., 2020) has found that Sentinel-2 classifications of land use land cover is dominated by machine-learning techniques namely, as random forests (RF) and support vector machine (SVM) and is great in improving accuracies for land use land cover classifications. Additionally, classification algorithms is categorized into two groups namely, supervised, and unsupervised classification, each yielding different results, which is dependent on spatiotemporal resolutions and system processes (Talukdar et al., 2020). Supervised classification focuses on user inputs, and predominantly used method due to the continuous advancements made with classification algorithms, and therefore yielding more accurate results. For supervised classification, land cover classes are trained by the user, based on pixels of similar characteristics, and individual land cover types is determined by these training classes selected by the user (Phiri, et al., 2020; Rwanga & Ndambuki, 2017). Unsupervised classification is a clustering technique, which does not require the creation of training samples by the user, as classes are automatically generated without regarding thematic characteristics of land cover types, however this technique has many limitations.

This study aims to assess the use of remote sensing and geographic information system (GIS) techniques for mapping and change-detection of land use land cover within the Heuningnes catchment, South Africa. The techniques involve the image classifications and accuracy assessments, and to determine various land use land cover types with significant impact on the quality of surface water quality.

3.3 Materials and methods

3.3.1 Selected study area

The study was conducted in The Heuningnes catchment, the Overberg District in the Western Cape Province, South Africa (34.4874° S, 20.0450° E). The catchment covers an area of 1 401 km^2 which includes towns such as Bredasdorp, Napier, and Elim. The Droe, Kars, Poort and the Nuwejaars river, form part of the sub-catchments within the Heuningnes catchment (Clark et al., 2015). The Nuwejaars River then feeds the Soetendalsvlei, with a width of 3km and length of 8km, and is the (Mkunyana, et al., 2019) (Figure 1). The Heuningnes River feeds an estuary, called the Heuningnes River estuary, it extends over 19 km with 1475 ha of open water, at the South Coast (Estuarine & Plan, 2019). The river estuary is joined by two tributaries, the Kars River and the Nuwejaars River. The topography is described as mountainous within the upper reaches of the catchment, and gradually becoming flattered towards the lower-lying areas alongside the coast. More specifically, the topography of the sub catchments within the Heuningnes catchment, is categorized as steep, flat, and undulating Land cover types and uses are categorized as agricultural, industrial, irrigation and recreational activities. These activities are contributing factors to water quality within the Heuningnes catchment, specifically runoff of pesticides and fertilizers and wastewater from treatment plants. Recreational activities which involve fishing and the introduction of alien invasive species, which majorly affect water availability in the area, as they consume larger quantities of water compared to indigenous vegetation.

The geology of the region is classified by shales and sandstones of the Table Mountain Group, where the shale deposits are found downstream due to slow moving water, and the porous sandstone allows for water percolation and storage of significant amounts of water. Soil characteristics of this region is classified as shallow, medium, and moderate sandy clay loams (Clark et al., 2015). Weather stations are located at the following locations: Moddervlei, Napier, Spanjaardskloof, Tiersfontein, Tussenberg, and Visserdrift. These weather stations record minimum and maximum temperatures and relative humidity, wind speed, wind direction, pressure, solar radiation, and rainfall, which is obtained from the database of the Institute of Water Studies (IWS). The catchment experiences a Mediterranean w and receives about 450 mm of rain per year along the coast and 650 mm inland along foothills. Maximum temperatures are experienced in January at 27 °C and minimum temperatures in July and August at 8 °C. Agricultural activities are dominant within this region, and more specifically the Heuningnes river estuary (Estuarine & Plan, 2019). Fynbos accounts for 41% of the land cover types. Vegetation in the area, as different vegetation may also contribute to certain water qualities, as well as geology, as phosphates and nitrogen may be present in water quality due to certain rock types.

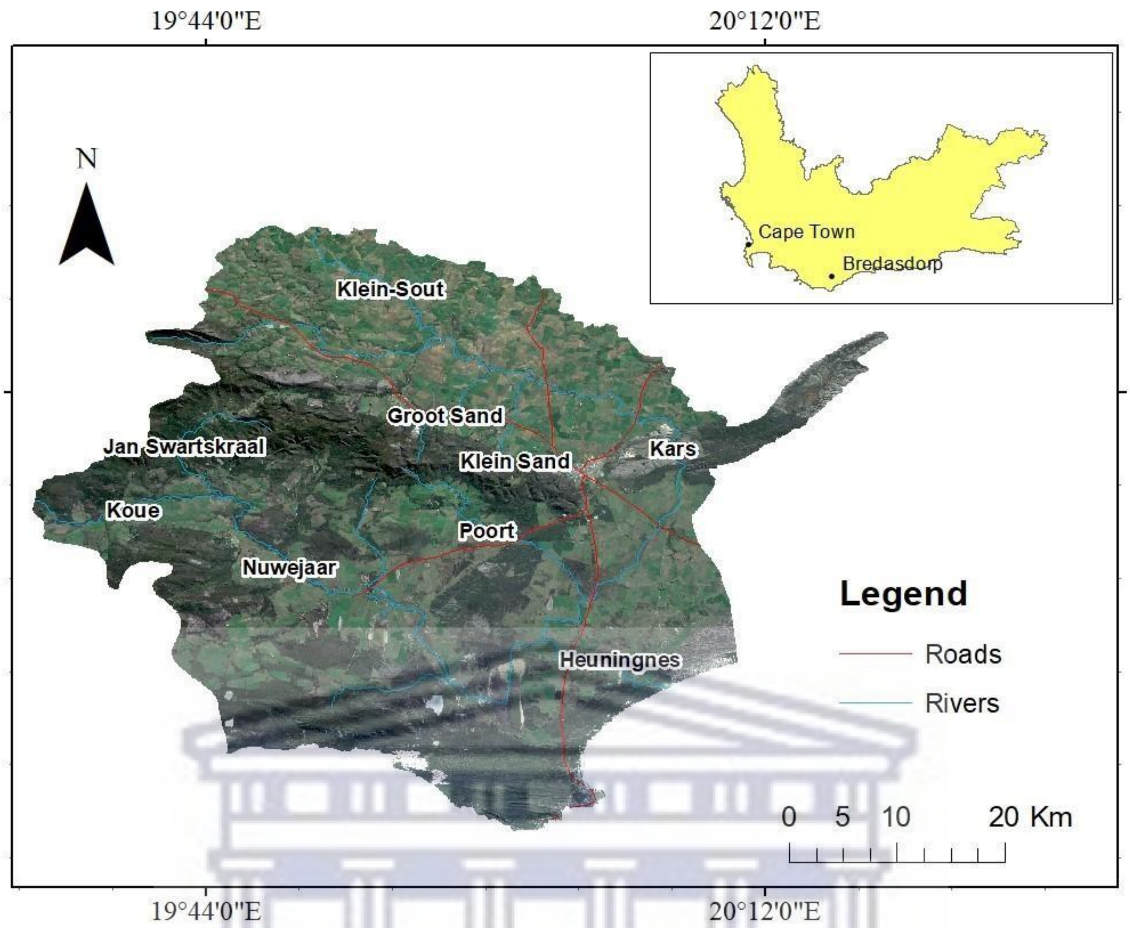

Figure 3. 1. The Heuningnes Catchment, Cape Agulhas, South Africa.

3.3.2 Satellite data acquisition

Sentinel-2 images were used to assess the land use land cover activities on surface water quality, in the Heuningnes catchment, Cape Agulhas, South Africa. Images were obtained from the USGS earth explorer website (https://www.usgs.gov), and represented the period between July 2017 and July 2018, containing wet and dry periods, October 2017 and March 2018, to observe how land use land cover may have changed, as well as how surface water bodies and streams may have changed. Typically to observe whether surface water quality has further deteriorated or rehabilitated. This specific period selected was based on water quality sampling, which took place. Images were selected with a 10% less cloud coverage however, images containing a percentage of cloud cover, underwent atmospheric correction.

3.3.3 Image pre-processing and classification

These images were pre-processed in Quantum GIS, for atmospheric correction by applying the dark object subtraction (DOS1) correction tool, which considers and corrects shaded objects, and is an essential step in obtaining true colour of inland water bodies (Bi et al., 2018) (Rumora et al., 2020). Atmospheric correction is vital as it ensures accuracy in classification results. Additionally, image segmentation was applied as pre-processing step for the preparation of the image classification. The segment mean shift algorithm groups pixels of a similar spectral and spatial characteristic, to reduce noise effects, because of overlapping pixels causing inaccuracies within the final classification result. Typically, where pixels of waterbodies and certain vegetation types group together and identifies as the same or similar objects. Furthermore, segmentation is the process of using similar smaller units together to produce larger regions, where different land cover classes can be discerned. Further processing was done in a GIS environment, where bands 5, 6, 7, 8a, 11 and 12 were resampled from a 20m and 60m resolution respectively to a 10m resolution. Once the bands were resampled, Sentinel-2 images were mosaicked resulting in a single complete image of the study area, an integration of the extracted bands 8, 4, 3 and 2, and resulting in a complete study area image. See table 3.1 displaying Sentinel-2 band number, description, wavelength unit and resolution.

For image classifications, five different land use classes were observed namely: surface waterbodies and streams; vegetation collective including indigenous, grasslands, invasive plants, and agricultural land; bare rock and soil; urban and other, which includes hill shade. Classifications was achieved by applying the supervised classification method, Support Vector Machine (SVM). As stated by (Rudrapal, 2015), SVM can function regardless of having a small training dataset, it is less prone to noise and continues to produce accurate results. For preparation of SVM, training samples were prepared by creating polygon signatures where a class is assigned to pixels representing the various land use land cover classes.

Table 3. 1. Spatial and spectral properties of Sentinel – 2 satellite data.

Band number	Band description	Wavelength unit	Resolution
2	Blue	490 nm	10 m
3	Green	560 nm	10 m
4	Red	665 nm	10 m
5	Visible and Near Infrared (VNIR)	705 nm	20 m
6	Visible and Near Infrared (VNIR)	740 nm	20 m
7	Visible and Near Infrared (VNIR)	783 nm	20 m
8	Visible and Near Infrared (VNIR)	842 nm	10 m
8a	Visible and Near Infrared (VNIR)	865 nm	20 m
11	Short Wave Infrared	1610 nm	20 m

	(SWIR)		
12	Short Wave Infrared (SWIR)	2190 nm	20 m

3.3.4 Accuracy Assessments

Accuracy assessments performed was to evaluate the accuracy of image classifications. A total of 350 points were created to determine the image classification accuracy, the 350 is a collection of 70 points per class, for a total of 5 classes namely: surface waterbodies and streams; vegetation collective including indigenous, grasslands, invasive plants, and agricultural land; bare rock and soil; urban and other, which includes hill shade. To evaluate the accuracy and performance of the image classification and to identify errors pertaining to the image classification technique, an error matrix is created, to demonstrate the classified pixels to the reference pixels. Evenly distributed reference points are created based on visual observations made on the image, of the different classes being classified. These reference points are then compared to the classified image to see whether there is correspondence between them. The results of the accuracy assessment will determine whether the classification algorithm used, provides acceptable results or not. The accuracy assessments measurements in use are the overall accuracy, user's accuracy, and producer's accuracy. The producer accuracy refers to the correctly classified pixels for each class, in relation to the total reference points created for each class and indicates how well the Support Vector Machine will classify a new dataset of classes; and whereas user accuracy represents the correctly classified pixels proportionate to validated points for each class. The overall accuracy refers to the number of correctly classified pixels proportionate to the incorrectly classified pixels, and where the kappa statistic represents the agreement of the classification technique (Olofsson et al., 2013; Rwanga & Ndambuki, 2017; Zhen et al., 2013).

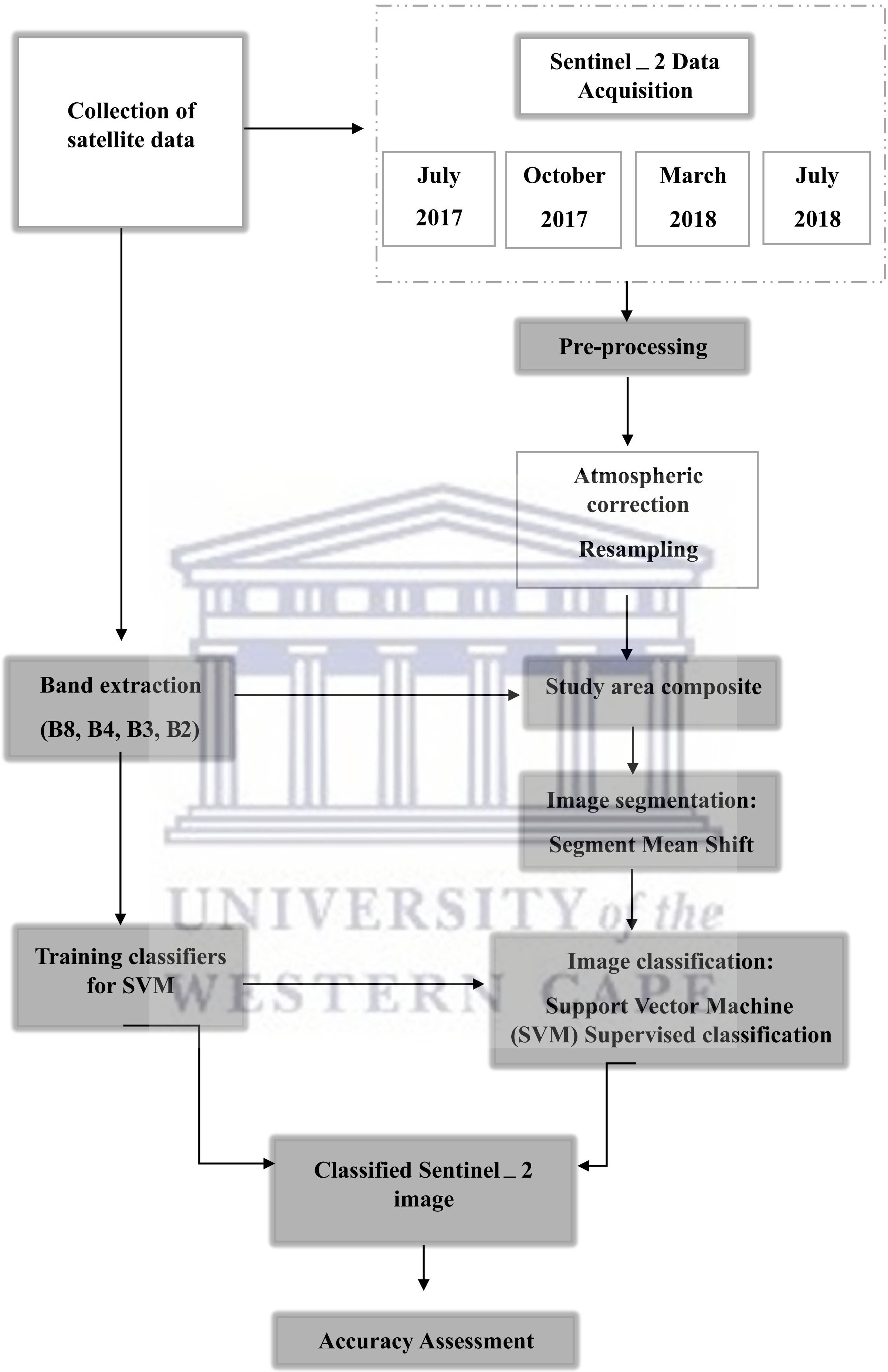

Figure 3. 2. Flow chart illustrating the process for image classification of a Sentinel – 2 image.

3.4 Results

3.4.1 Climate Data

Climate data received from the Institute of Water Studies (IWS) to observe rainfall and temperature variation across the Heuningnes catchment, see figure 2. The highest average rainfall was recorded as 10.43mm within Tierfontein in 2017, and the lowest average rainfall was recorded as 4.46mm within Napier in 2018. In 2018, Spanjaardskloof recorded the highest maximum temperature of 24.42 °C and in 2017, Moddervlei recorded the lowest minimum temperature of 9.98 °C.

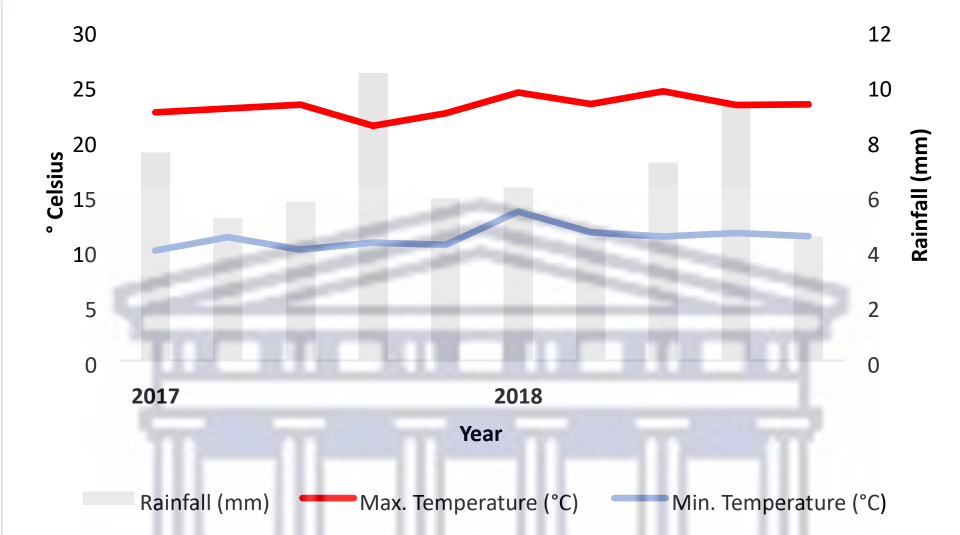

Figure 3. 3. Displaying the climate data for 2017 and 2018 of Moddervlei, Napier, Spanjaardskloof, Tiersfontein and Vissersdrift.

3.4.2 Classification accuracies

Table 3.2 displays accuracy assessment results of Support Vector Machine image classification, for Sentinel -2, using kappa statistics, producer and user accuracy, and overall accuracy for July 2017 to July 2018, as well as determining omission and commission error. Omission error is the percentage of reference pixels that has been excluded from the classification, which should have been classed as a specific land cover class. The SVM algorithm error of omission, for July 2017 was 54% for urban areas; 100% for vegetation for October 2017; 67% for vegetation for March 2018; and 51% for bare rock and soil for July 2018. Specifically for October 2017, the high omission error percentage indicated that none of the pixels were classified as vegetation. Commission error is the percent that the reference pixels were incorrectly classified as a class. The commission error for July 2017 was 43% for urban area; 100% for vegetation for October 2017; 60% for urban area for March 2018; and 48% for urban area for July 2018. The high commission errors can be seen as the over classification of a certain class.

For the wet seasons, July 2017 and July 2018, the overall accuracy is 75%, with a kappa coefficient of 0.69. According to (Rwanga & Ndambuki, 2017), this kappa value indicates a substantial level of agreement, within the SVM classification algorithm used. The five land cover classes had a producer accuracy, ranging between 46% and 97% and user accuracies ranging between 52% and 96%, for the wet season. For the dry seasons, October 2017 and March 2018, the overall accuracy ranges between 55% and 66%, with kappa coefficients of 0.43 and 0.58 respectively, indicating moderate level agreement (Rwanga & Ndambuki, 2017). The five land cover classes had a producer accuracy, ranging between 0% to 100% and user accuracies ranging between 40% and 96%, for the dry season.

Table 3. 2. Sentinel – 2 image classification accuracies, with support vector machine (SVM), for the Heuningnes Catchment for the wet season, July 2017 and July 2018, and the dry season, October 2017, and March 2018.

	July 2017		October 2017		March 2018		July 2018	
Class	Producer	User	Producer	User	Producer	User	Producer	User
Water	79	96	76	96	76	88	77	93
Vegetation	96	69	0	69	33	64	96	78
Other	97	91	100	61	93	93	91	96
Bare rock & soil	57	62	19	62	53	71	49	61
Urban	46	57	79	45	76	40	61	52
Overall Accuracy	75%		55%		66%		75%	
Kappa Coefficient	69%		43%		58%		69%	

3.4.3 Mapping land use land cover and observing changes

Figure 3.3 illustrates LULC classification of surface waterbodies and streams, vegetation, bare rock, and soil, urban and other, with includes hill shade, for the wet seasons of July 2017 and July 2018 and for the dry seasons, October 2017, and March 2018. From the figure below (Figure 3.4) vegetation is the dominant land cover class for the Heuningnes catchment with a total of 77% coverage in July 2017. October 2017 holds the lowest vegetation cover percentage of 33%. For 2018, March had the highest water coverage percentage of 12%, and October 2017, the lowest water coverage with only 1%. It is evident that the wet season has the highest vegetation cover. Urban and other, has a 29% and 35% coverage respectively, and is recorded as the period with the highest urban and other land cover. These land cover types are predominantly along the Western part of the catchment, and along the coast, for October 2017 specifically. The other land cover type is predominantly present within the mountain range area, at the centre of the Heuningnes catchment, as most of the other land cover type consists of hill shade effects. In March 2018 and July 2018, bare rock and soil has increased from 2% in October 2017, to 17% in March 2018 and then a further increase to 18% in July 2018.

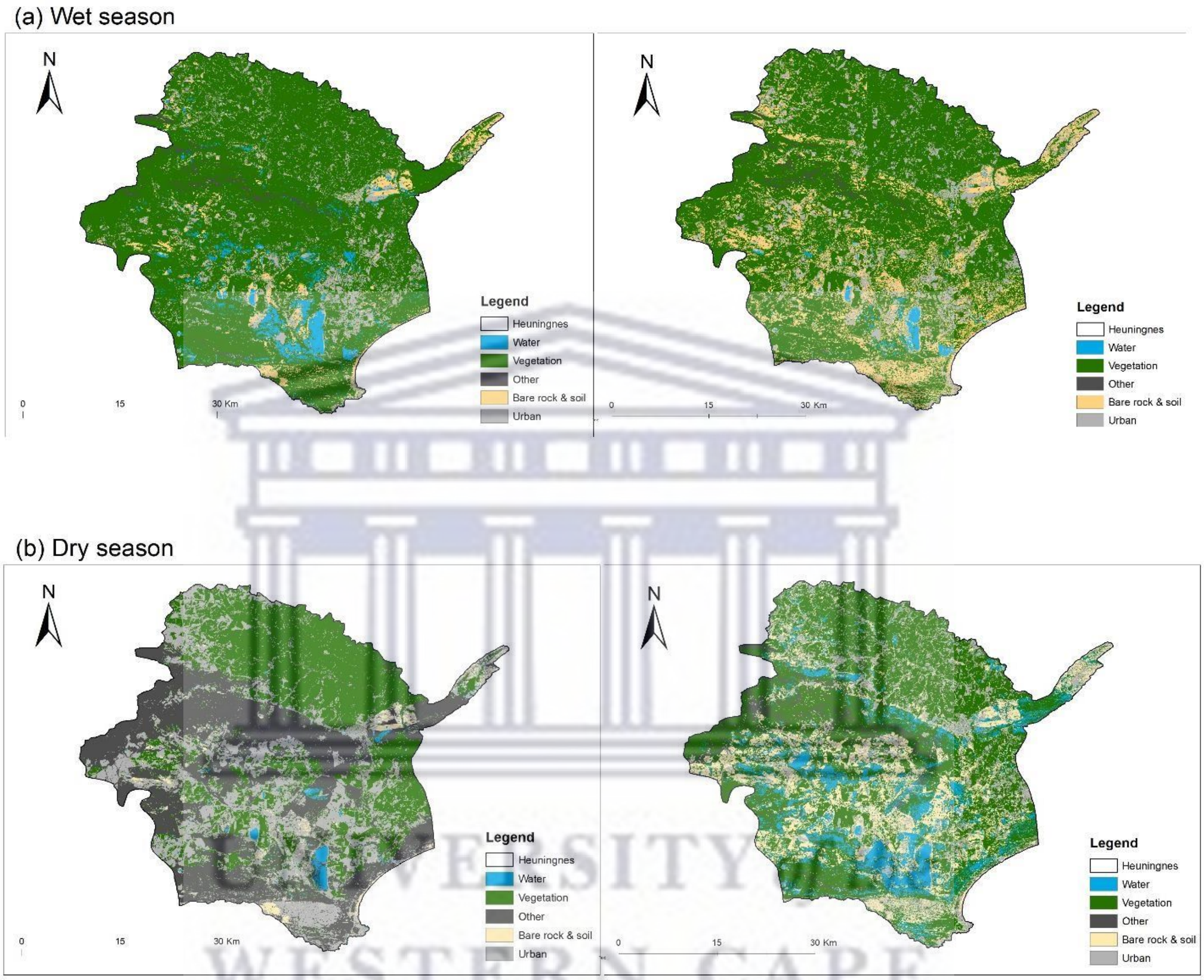

Figure 3. 4. Displaying the image classification with support vector machine (SVM), for the period between July 2017 and July 2018, covering the wet season and October 2017 and March 2018, the dry season, for the Heuningnes Catchment.

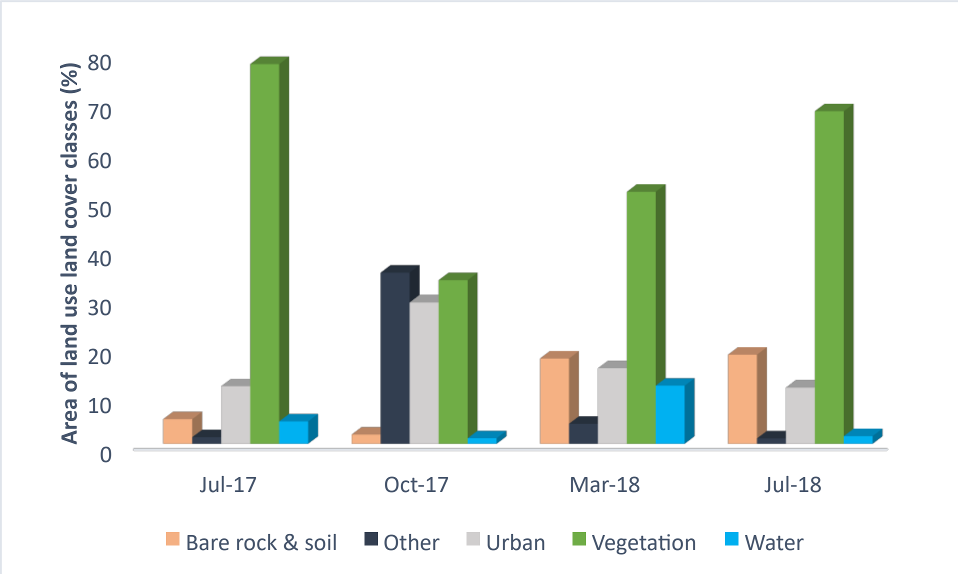

Figure 3. 5. Graph illustrating the area of land use land cover classes, and the changes between July 2017 and July 2018, for the Heuningnes Catchment.

3.5 Discussion

The study conducted was focused on ensuring the application of a suitable image classification algorithm for land use land cover analysis, within the Heuningnes Catchment, Cape Agulhas, South Africa, during the wet season of July 2017 and July 2018, and the dry season, October 2017, and March 2018. Results indicates that the wet seasons, July 2017, and July 2018, display the highest percentage of vegetation cover.

Image classification is vital to monitor environmental factors, as classification techniques evaluate each individual pixel, and assesses the spectral information of land cover for the creation of thematic maps, relevant for specific environmental applications such as monitoring land use land cover. However, classification algorithms experience several factors affecting the accuracy of classification results, such as the spatial resolution of the satellite used (Foody, 2008). Classification results show a common error of mixed pixels which occurred throughout the image analysis, predominantly between waterbodies and vegetation covers, predominantly due to the Voelvlei and Soetendalsvlei environment. In correcting the error of mixed pixels, an object-based classification technique was applied, such as image segmentation which is responsible for aggregating spectrally similar objects as a specific class (Y. Chen et al., 2018).

Classification results for October 2017 depicts an overestimation of urban areas and hill shade, with a 100% producers' accuracy, and none of the pixels were classified as vegetation, with a user's accuracy of 69%. For March 2018, waterbodies within this catchment appeared to be over classified. The use of SVM is best suited for land cover mapping as opposed to other classification algorithms such as maximum likelihood classification, as SVM doesn't assume that data is normally distributed and therefore including a wider range of values, allowing for representation. SVM does not require large training sets, however, still succeeds in achieving more accurate results (Kang et al., 2018). The results indicate SVM effective in classifying the various land cover types with an overall accuracy ranging between 55% and 75%, and kappa coefficients ranging between 43% and 69%, for the period July 2017 to July 2018. The over classification error could be a result of the image segmentation technique employed, as the algorithm may result in over segmentation of objects where low spatial resolution images are used, and high-resolution images may result in under segmentation (Y. Chen et al., 2018; Liu & Xia, 2010).

The specific use of Sentinel-2 for land cover mapping, is the accessibility of data, particularly economically beneficial for developing countries. For land cover mapping, especially with the presence of the red-edge band 5, for its ability for mapping and predicting forest parameters. Sentinel-2 ensures high resolution and timely data to account for dynamic environmental changes, across extensive areas (Astola et al., 2019; Phiri, Simwanda, Salekin, Nyirenda, et al., 2020).

3.6 Conclusion

The study focused on the use of Sentinel-2 data in image classification for land use land cover mapping, between July 2017 and July 2018, for the Heuningnes Catchment, Cape Agulhas, South Africa. Sentinel-2 was especially successful in mapping land use land cover, vegetation, hill shade, waterbodies and streams, and urban areas. A few limitations were experiencing mixed pixels between waterbodies and vegetation cover, as well as the over classification of hill shade and urban cover. However, the overall classification accuracies ranging between 55% and 75%, indicating high classification accuracies and kappa coefficients of 43% to 69%, indicating substantial level agreements of the support vector machine (SVM) algorithm. It is concluded that the application of Sentinel-2 for land cover mapping can be used to retrieve high resolution and timely information for the constant dynamic changes of land cover.

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CHAPTER FOUR

Remotely sensed data and the statistical analysis for the prediction of surface water quality for the Heuningnes Catchment, Cape Agulhas, South Africa.

4.1 Abstract

Information on water quality can be obtained in a timely and cost-effective manner, owing to remote sensing and machine learning techniques. The concentrations of the following surface water quality parameters namely: nitrates, phosphorus, total nitrogen and total phosphorous was assessed for July 2017 to July 2018. Due to the red-edge band group of bands 4, 5 and 6, as well as the satellite's spectral and spatial characteristics, Sentinel-2 is the most efficient satellite for extracting total phosphorus and total nitrogen. Sentinel-2 images were used to apply a linear regression model for the prediction of surface water parameters and was validated against in-situ field measurements collected. The performance of the regression model was assessed using coefficient of determination (R^2) and Root Mean Square Error (RMSE). The strength of the relationship between band ratios predicted water parameters and in-situ measurements presented R^2 between 0.4 and 1.88, representing significant positive relationships. March 2018 represents the highest total phosphorus concentration of 20 mg/l as a result of the Voelvlei outlet. July 2018 represents the highest total nitrogen concentration of 18.9 mg/l due to the Nuwejaars tributary location, a point of nutrient influx.

Keywords: Sentinel-2; Regression analysis; Water quality prediction; water resource management.

4.2 Introduction

The quantity of available water resources is vital for the sustenance of life, it is therefore much greater to ensure the quality of available water resources remains pure. To ensure safe water quality, pollution factors such as pollution sources and the degree of pollution, should be known and understood. This knowledge is vital for understanding how pollution factors can be mitigated, and for policy creation for water resource management. Water quality is defined by the physical, chemical, and biological composition of water. These compositions are measured according to human and ecosystem requirements, necessary for livelihood and sustainability, and therefore used as a standard of measurement for ensuring safe water quality overall. Furthermore, water pollution sources are categorised as being discharge to water bodies, either directly or indirectly, and is defined by point or non-point pollution sources. Point pollution sources are those linked to a specific source such as leakage from a sewage treatment plant or construction sites. Non-point pollution sources, however, cannot be linked to a specific source but is a collective of various pollution sources such as storm water runoff, which is a cumulation of runoff from agricultural and urban environments. These pollution sources may also be described as occurring either naturally or anthropogenically (Shah et al., 2021)

Remote sensing and machine learning approaches has introduced cost-effective and timely ways of obtaining water quality information. As water quality alters on a spatial and temporal basis, therefore requiring the collection of frequent data, which could pose financial implications, a time-consuming and labour-intensive task, due to sampling and laboratory analysis (Avdan et al., 2019). Field data collection is limited to providing spatial and temporal variation of water quality parameters, as it only provides a point reference, and certain topographic positions, such as mountainous regions limit accessibility of certain water bodies. Water quality parameters possess different chemical and physical structures, according to the various pollutants present within water bodies. Water quality parameters such as total phosphorus and total nitrogen is categorized as a non-optical parameter indicating a weak signal for remote sensing and therefore requiring the integration of remote sensing with multiple linear regression models. Sentinel-2 was found to be the effective satellite for extracting total phosphorus and total nitrogen, due to the red-edge band group of bands 4,5 and 6, and the spatial and spectral properties of Sentinel-2 (Hassan et al., 2020).

Additionally, these limitations has resulted in the advancements of remote sensing techniques and machine learning approaches with band ratio combinations, more so for the prediction of water quality parameters. The combination of band ratios with regression models, produces significant coefficient of determination values, for the prediction of water quality parameters (Avdan et al., 2019; Nouraki et al., 2021). The application of band ratio techniques allows for water quality prediction related to regions with insufficient in-situ data (Torbick et al., 2013). This study aims to compare the field collected water quality parameters to water quality parameters obtained from remotely sensed data and statistical analysis. With the specific observation and analysis of the following water quality parameters, nitrate, and phosphate, and the use of statistical analysis for water quality parameter prediction.

4.3 Materials and Methods

4.3.1 In-situ measurements of water quality parameters

Water quality samples were collected between July 2017 to July 2018, during the wet season and dry season of October 2017 and March 2018. Water sample data was collected with 250ml plastic bottles, along the course of various rivers within the Heuningnes catchment, with a total of 180 samples collected. There are many important water quality parameters to test for however, in this study the following parameters was collected and analysed, namely: nitrate, total nitrogen, phosphate and total phosphorous. The samples were collected across a variation of locations ranging from urban locations, tributaries, a dairy farm, hay fields and vlei locations.

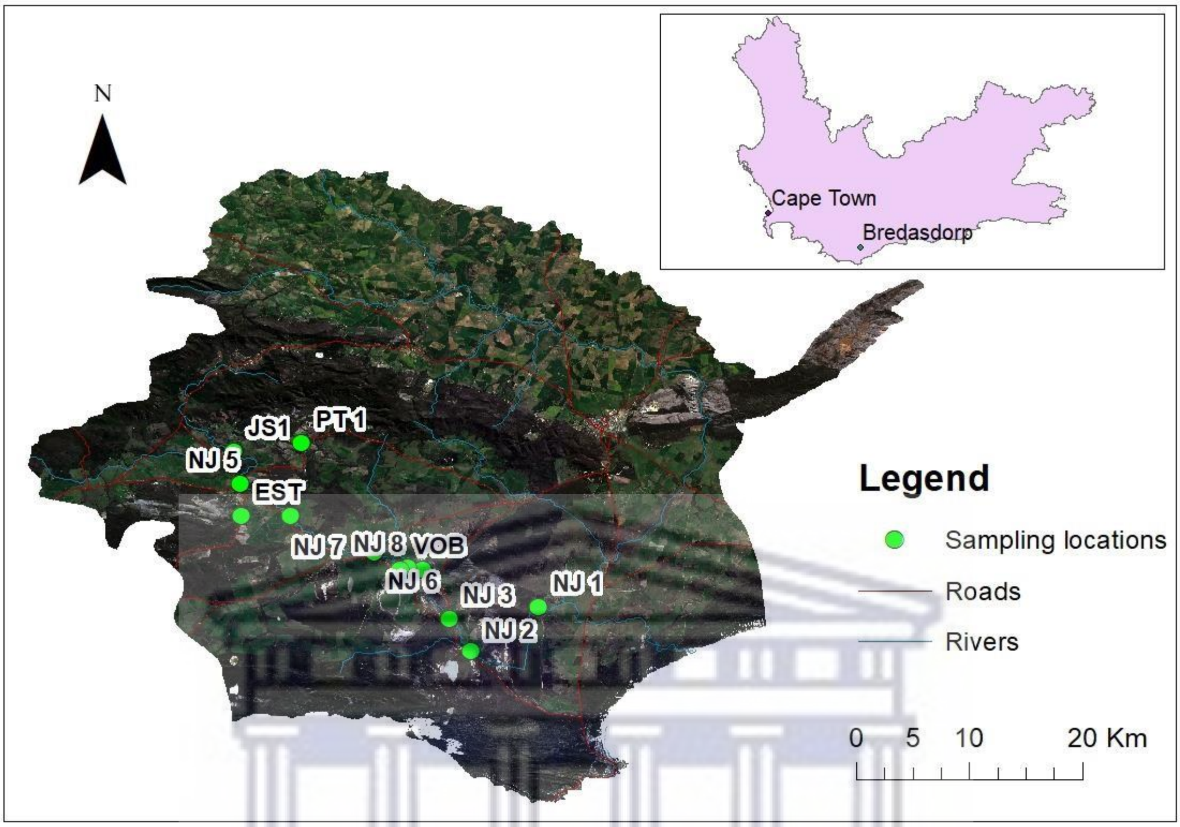


Figure 4. 1. Depicts the sampling locations across the Heuningnes Catchment. *NJ 1 = Soetendalsvlei outlet bridge; NJ 2 = SANParks Offices; NJ 3 = Dairy farm; NJ 4 = Hay field close to Elandsdrift farm; NJ 5 = A bridge in Elim; NJ 6 = Nuwejaars river bridge; NJ 7 = Moddervlei site; NJ 8 = Voelvlei outlet bridge; VOB = Voelvlei outlet; PT 1, JS 1 and ETS = Tributary to Nuwejaars.*

4.3.2 Spatial interpolation of water quality parameters

The kriging interpolation technique was used within the ArcGIS software, to determine the spatial distribution of water quality parameters, nitrates, phosphates, total nitrogen, and total phosphorus, across the Heuningnes Catchment. Kriging allows for the estimation of surface water quality distribution, and particularly in regions without in-situ measurements. Kriging is used as it yields accurate results by minimizing potential errors (Nagalakshmi et al., 2016; Weerasinghe & Handapangoda, 2019).

4.3.3 Statistical Analysis and band ratios for water quality parameter prediction

In-situ measurements of water quality parameters were correlated with water quality parameter estimation from remotely sensed data, by assessing satellite reflectance with the physicochemical properties of water. Specifically, various band ratio combinations were assessed to determine the combination yielding the most significant result. The various band ratio combinations for total phosphorus (TP) and nitrogen were between blue and shortwave infrared (B2/B11); shortwave infrared and blue (B12/B2); green and red (B3/B4), green and near-infrared (B3/B8); red and near-infrared (B4/B8); and near-infrared and red (B8/B4). The independent variable was the various band ratios, correlated against measured water quality parameters as the dependent variable. The significance of the regression relationship was measured by the coefficient of determination (R^2), and the predictive model determined by the root mean square error (RMSE) (El Saadi et al., 2014).

4.4 Results

4.4.1 Spatial distribution of water quality parameters

For in-site measurements, July 2018 recorded the highest total nitrogen concentration of 18.9 mg/l and the lowest total nitrogen concentration of 0.1 mg/l. In March 2018, the highest total phosphorus concentration was recorded, of 20 mg/l, with July 2017 recording the lowest total phosphorus concentration of 2.7 mg/l. The average total nitrogen between July 2017 and July 2018 ranged between 0.45 mg/l and 2.26 mg/l, and the average total phosphorus ranged between 1.95mg/l and 3.74 mg/l. Phosphate and total phosphorus has high standard deviations of 5.77 mg/l and 5.3 mg/l, in March 2018 and July 2018, respectively. Figure 4.2 (a-h) represents remotely sensed estimated spatial distribution of total nitrogen and total phosphorus between July 2017 and July 2018. For July 2017, higher total nitrogen concentrations, 1.99 mg/l, is distributed along the tributary point to the Nuwejaars river, and slightly lower TN concentrations to be predominant across the Heuningnes catchment, figure 4.2 (a). However, higher TP concentrations, 2.12 mg/l, can be seen predominantly present across the entire Heuningnes catchment, for July 2017, figure 4.2 (b). For October 2017, TN concentrations, 2.90 mg/l, are evenly distributed across the catchment, figure 4.2 (c). TP concentrations, 0.49 mg/l, are shown to be in various locations NJ1, NJ3, NJ5, NJ7, NJ8 and PT1, and lower TP concentrations, 0.32 mg/l, is evenly distributed across the catchment. In March 2018, TN and TP concentrations is located close to SANPark offices, 3.66 mg/l and 8.96 mg/l respectively. In July 2018, TN concentrations, 9.30 mg/l, is distributed close to a bridge and tributaries to the Nuwejaars River.

Table 4. 1. Descriptive statistics of measured water quality parameters within the Heuningnes Catchment, for July 2017 to July 2018.

July 2017				
Water quality parameter (mg/l)	Min.	Max.	Mean	Std. Dev.
Nitrate	0.1	0.7	0.23	0.18
Total Nitrogen	0.2	2	0.72	0.55
Phosphate	0.3	2.3	1.73	0.61
Total Phosphorus	0.7	2.7	2.11	0.57

October 2017				
Water quality parameter (mg/l)	Min.	Max.	Mean	Std. Dev.
Nitrate	0	0.3	0.11	0.12
Total Nitrogen	0.3	0.5	0.45	0.07
Phosphate	1.4	3.6	2.63	0.63
Total Phosphorus	1.9	3.8	2.9	0.58

March 2018				
Water quality parameter (mg/l)	Min.	Max.	Mean	Std. Dev.
Nitrate	0.1	0.6	0.3	0.15
Total Nitrogen	0.4	4.4	0.93	1.14
Phosphate	0.2	18.6	3.23	5.77
Total Phosphorus	0.5	20	3.74	6

July 2018				
Water quality parameter (mg/l)	Min.	Max.	Mean	Std. Dev.
Nitrate	0	4.2	0.51	1.18
Total Nitrogen	0.1	18.9	2.26	5.3
Phosphate	1	3.7	1.7	0.72

Total Phosphorus	1.3	3.9	1.95	0.73

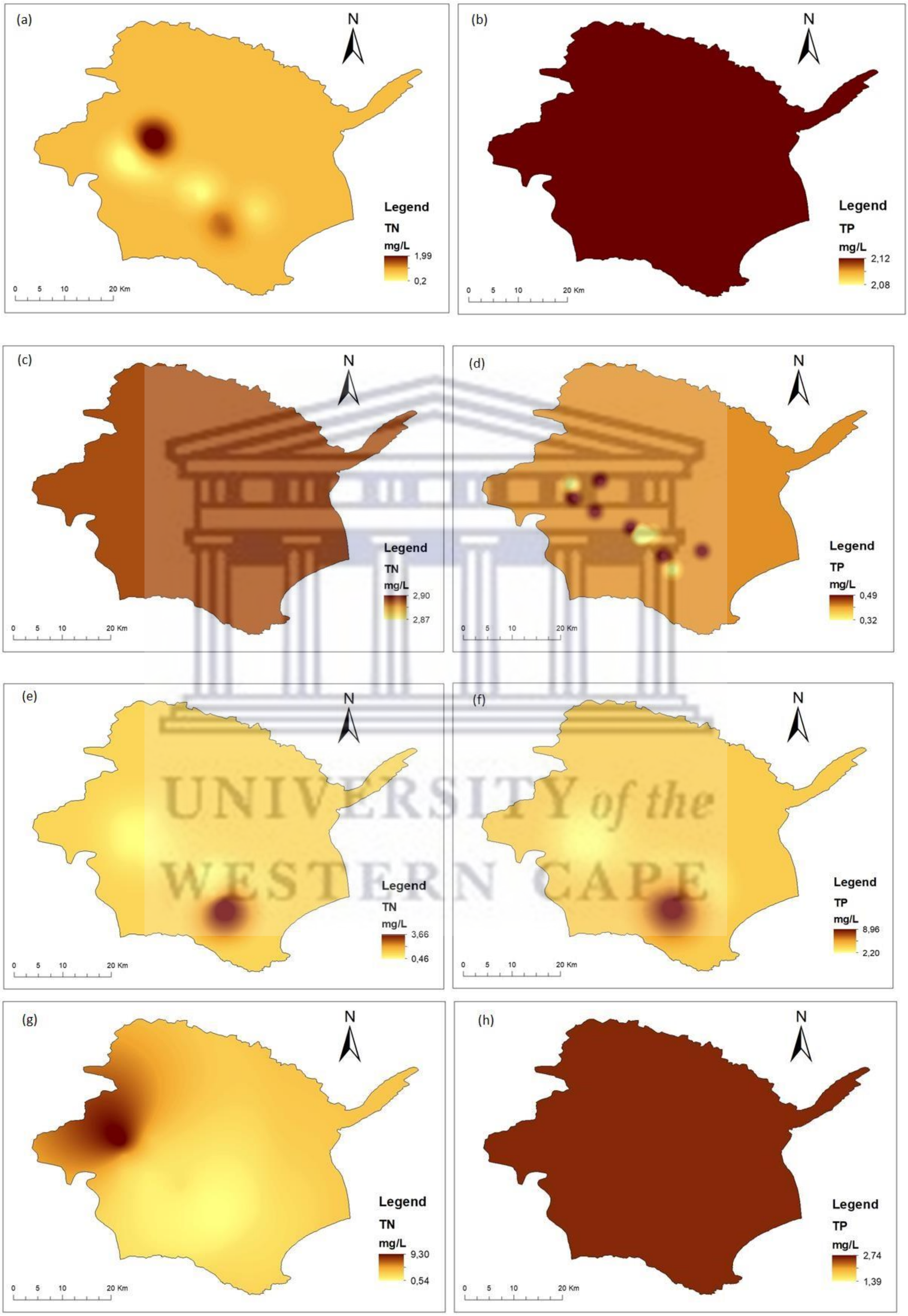


Figure 4. 2. (a-h) Depicts the spatial distribution of in-situ measurements of total nitrogen and total phosphorus, between July 2017 and July 2018, across the Heuningnes Catchment.

4.4.2 Regression analysis between measured and predicted water quality parameters

ANOVA test was performed to determine regression models to understand the relationship between measured water quality parameters and water quality parameters predicted with spectral band ratios. For July 2017, results show a significant positive relationship, $p<0$, between the dependent variable, total phosphorus, and the band ratio between green and red (B3/B4), with a R^2 of 0.56, and RMSE and MAE values of 0. Correlation between nitrogen and band ratio shortwave infra-red and blue (B12/B2), indicates a negative R^2 value of -0.06 however, low RMSE and MAE values of 0.02 and 0.01 respectively, $p<0.03$. For October 2017, the R^2 value of 1.83 indicates a significant positive relationship, $p<0.32$, between nitrogen and the band ratio between green and red (B3/B4), and RMSE and MAE values of 0.01 and 0 respectively. For total phosphorus, a significant relationship exists with a R^2 value of 0.4 for various band ratios namely, green, and red (B3/B4), green and near-infrared (B3/B8), and red and near-infrared (B4/B8). For March 2018, results show a significant positive relationship between nitrogen and band ratio shortwave infra-red and blue (B12/B2), with a R^2 value of 1.88, and RMSE and MAE values of 0.32 and 0.23 respectively. Total phosphorus also displays a significant positive relationship with band ratio shortwave infra-red and blue (B12/B2), with a R^2 value of 10.34, and RMSE and MAE values of 0.72 and 0.52. In July 2018 the regression between nitrogen and band ratio (B12/B2) displays an unusually high R^2 value of 268.3, and high RMSE and MAE values of 2.09 and 1.9 respectively. The result for total phosphorus displays a negative of R^2 value of -0.04 for band ratios (B2/B11), (B3/B4), and (B4/B8) however, low RMSE and MAE values of 0.

Table 4. 2. Regression models for remotely sensed water quality parameter prediction, a using spectral band ratios.

July 2017

Water quality parameters	Band Ratio	Prediction model	RMSE	MAE	R_2
Nitrogen	B12/B2	y= -0,000x+0,2296	0,020	0,007	-0,063
Total Phosphorus	B3/B4	y=1,025x-0,05	0,000	0,000	0,556

October 2017

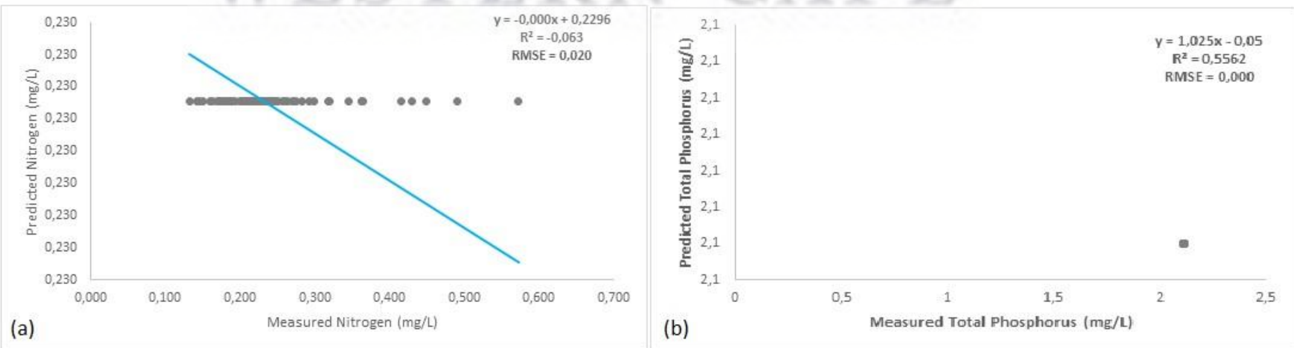
Water quality parameters	Band Ratio	Prediction model	RMSE	MAE	R_2
Nitrogen	B3/B4	y= -0,000x+0,4537	0,005	0,001	1,827
Total Phosphorus	B3/B4	y=1.1366x-0,3934	0,000	0,000	0,404
	B3/B8	y=1.1366x-0,3934	0,000	0,000	0,404
	B4/B8	y=1.1366x-0,3934	0,000	0,000	0,404

March 2018

Water quality parameters	Band Ratio	Prediction model	RMSE	MAE	R_2
Nitrogen	B12/B2	y=0,000x+1,1652	0,320	0,232	1,8753
Total Phosphorus	B12/B2	y=0,000x+4,1037	0,717	0,522	10,336

July 2018

Water quality parameters	Band Ratio	Prediction model	RMSE	MAE	R_2
Nitrogen	B12/B2	y= -0,000x+4,1476	2,092	1,891	268,3
Total Phosphorus	B2/B11	y=x+0,0121	0,000	0,000	-0,044
	B3/B4	y=x+0,0121	0,000	0,000	-0,044
	B3/B8	y=x+0,0121	0,000	0,000	-0,044
	B4/B8	y=x+0,0121	0,000	0,000	-0,044



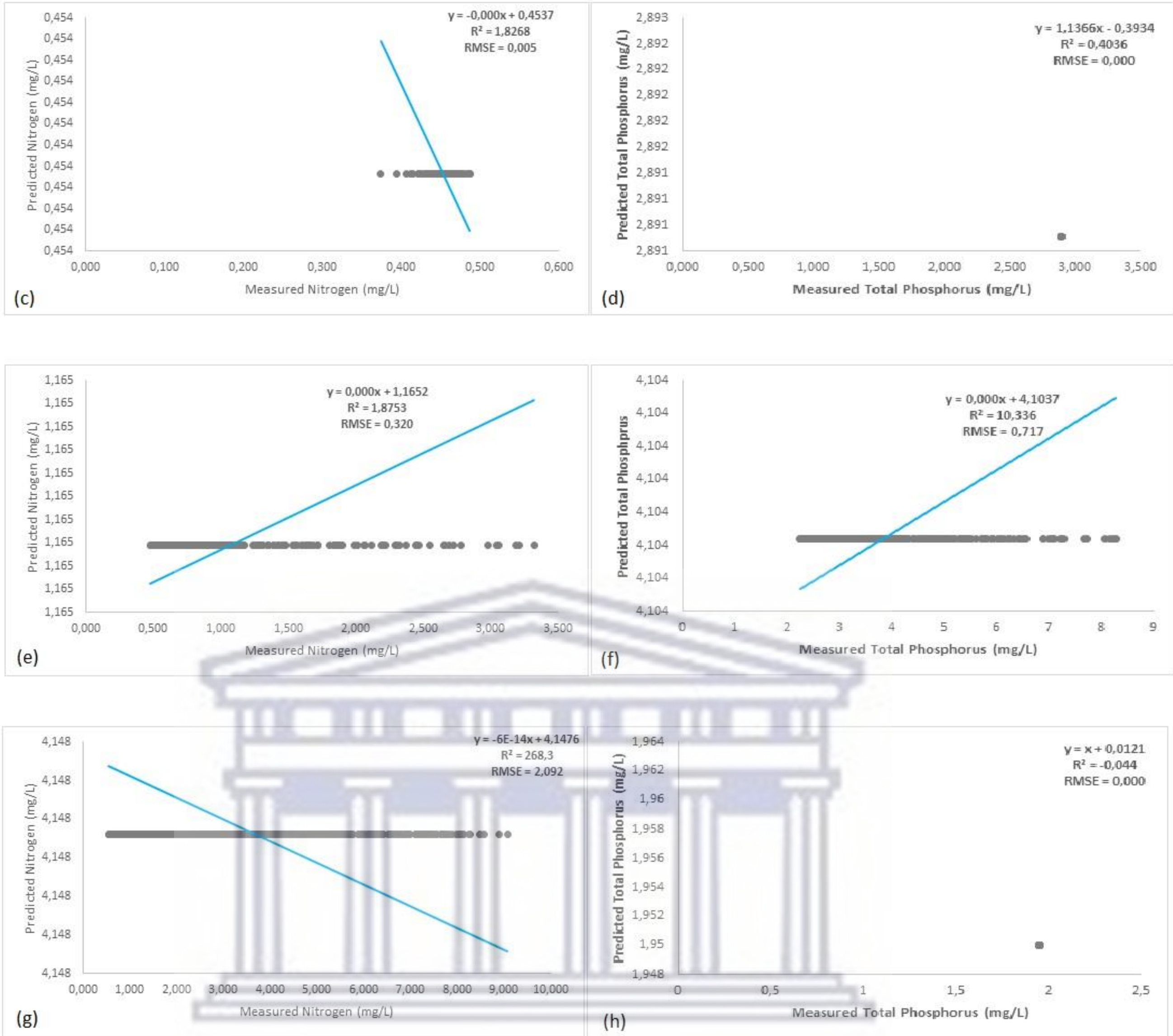


Figure 4. 3. Displaying predictive models to determine water quality parameters, displaying the relationship between predicted and measured TN and TP between July 2017 and July 2018.

4.5 Discussion

The study conducted was focused on extracting water quality parameter information with remotely sensed data, for the creation of prediction models for water quality parameters, specifically total phosphorus, and total nitrogen, within the Heuningnes Catchment, Cape Agulhas, South Africa. This particularly highlighted the significance of remote sensed data with regression models for advancing water resource management, by reducing financial challenges, ensuring time-efficiency, reduced labour intensity while increasing accuracy.

March 2018 represents the lowest measured total phosphorus (TP) value of 0.5 mg/l, with the highest measured TP value of 20 mg/l. The highest value could be representative of the sampling location being around the South African National Parks (SANPARKS) offices and the Voelvlei outlet. The Voelvlei environment is particularly responsible for the high TP concentrations as vleis is the natural habitat of waterbirds, and these species may have significant influence on nutrient cycling as a result of their consumption and excretion processes (Scherer et al., 1995). July 2018 represents the lowest measured total nitrogen (TN) value of 0.1 mg/l, with the highest measured TN value of 18.9 mg/l. The highest value could be representative of the sampling location being the tributary location of the Nuwejaars river, resulting in the influx of nutrients at this location. Overall, the high values of TP and TN is representative of the Heuningnes catchment being predominantly agricultural and farmland region. These water quality parameters are especially associated with these practices. Total phosphorus and total nitrogen is particularly difficult to measure due to it having non-optical properties, as certain satellite sensors are unable to extract information from those parameters. The analysis shows Sentinel-2 to be successful in monitoring non-optical parameters such as TP and TN, and especially useful when integrated with machine learning techniques. In July 2017 the low values of RMSE, MAE and R^2 indicates great accuracy of the resultant regression model for both total nitrogen and total phosphorus, with the band ratios shortwave infra-red and blue (B12/B2), and green and red (B3/B4) respectively. October 2017 displays low values for RMSE, MAE and R^2, for total nitrogen and total phosphorus when correlated with band ratio green and red (B3/B4). Between July 2017 and July 2018, the R^2 values indicate the relevance of band ratios in predicting total phosphorus and total nitrogen concentrations.

4.6 Conclusion

The study assessed the predictive mapping of water quality parameters for the Heuningnes Catchment, Cape Agulhas, South Africa, with the use of in-situ measurements collected. Band ratio regression techniques was successful in extracting spectral information from water quality parameters, total phosphorous (TP) and total nitrogen (TN). The significant coefficient of determination indicated the successful application of remote sensing and regression models for the prediction of water quality parameters, in comparison to in-site measured water quality parameters. Sentinel-2 satellite has been successful in measuring non-optical parameters such as total phosphorus and total nitrogen, because of its high spatial and temporal, and spectral properties, especially when Sentinel-2 is integrated with machine learning techniques. The land use land cover classes assessed is evident of the predicted water quality parameters. This analysis can be useful in predicting water quality parameters, to implement safe water quality standards and water use, and to undertake precautionary measures toward public health.

4.7 References

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CHAPTER FIVE

The use of remotely sensed data and spatial modelling techniques to assess the impacts of different land management practices on surface water quality for the Heuningnes Catchment, Cape Agulhas, South Africa: A synthesis

5.1 Introduction

Many surfaces water resources experience degradation because of land use activities and certain land cover types. It is vital to monitor surface water resources to mitigate further deterioration, and threat. Therefore, firstly understanding the nature of potential threats are important. Furthermore, land use and land cover affect GIS and remote sensing aids in the timely extraction of necessary earth surface information required. Sentinel-2 satellite has been proven favourable in the specific application to land management; together with the image classification technique Support Vector Machine (SVM) in categorizing various land use and land cover classes (Talukdar et al., 2020). Total phosphorous (TP) and total nitrogen (TN) were used as water quality indicators, and band ratio regression algorithms were successful in obtaining spectral information. When compared to on-site measured water quality metrics, the considerable coefficient of determination demonstrated the successful application of remote sensing and regression models for the prediction of water quality parameters (Avdan et al., 2019; Nouraki et al., 2021; Torbick et al., 2013). Therefore, the objectives of this work aimed to:

a) identify and determine the impacts of LULC on water quality.

b) assess the use of remote sensing to predict surface water quality with remotely sensed data.

5.2 Summary of findings

In determining the impact land use land cover classes has on surface water quality, Support Vector Machine (SVM) was used as the image classification technique to identify various land use land cover classes. The usage of SVM is better suited for mapping land cover since it does not assume that the data is normally distributed and consequently includes a wider range of values, allowing for representation. SVM still succeeds in producing more accurate results while not requiring extensive training data (Kang et al., 2018). The findings show that SVM is effective in categorizing the different types of land cover, with an overall accuracy of about 55%. Sentinel-2's excellent spatial resolution has helped in extracting water features with the highest degree of accuracy. One of the objectives aimed to extract water quality parameter information from remotely sensed data. This underlined the importance of using remote sensing data integrated with regression models to advance water resource management by lowering costs, ensuring efficiency, lowering labour intensity, and increasing accuracies. Total phosphorus (TP) and total nitrogen (TN) were used as water quality parameters, band ratio regression algorithms were successful in obtaining spectral information. The significant coefficient of determination demonstrated the effective use of regression models and remote sensing for the prediction of water quality parameters.

5.3 Conclusion

The main aim of the study was to assess the water quality in the Heuningnes Catchment, Cape Agulhas using remote sensing and statistical techniques, to determine land use practice of significant influence on water quality. This study can be used for effective water resource management, specifically in inaccessible areas, and countries with insufficient financial resources. Throughout this study there has been significant achievements with regards to identifying land use land cover activities with significant impact on surface water quality and remote sensing technique, band ratio regression, in effectively estimating surface water quality parameters.

- Sentinel-2 can be used to acquire timely, high-resolution data for land cover mapping, to account for dynamic changes in land cover.
- High concentrations of total phosphorous (TP) and total nitrogen (TN) are attributed to agricultural activities and the presence of Vleis which habitat's waterbirds.
- Machine learning techniques and Sentinel-2 has successfully measured non-optical parameters, total phosphorous (TP) and total nitrogen (TN), necessary for water quality parameter predictions.

5.4 Recommendations

Throughout conducting this research, below are a few recommendations to consider for advanced water resource monitoring and management:

- Local agricultural communities should be made aware of certain agricultural activities contributing to increases of total phosphorous (TP) and total nitrogen (TN) concentrations.
- Ensuring the representativeness of band-ratio regression models by applying the model to various locations and environmental conditions, and a data set across a larger period.

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