UNIVERSITY of the WESTERN CAPE

# Multispectral remote sensing of the impacts of drought and climate variability on water resources in semi-arid regions of the Western Cape, South Africa

by

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# ABSTRACT

The occurrence of droughts is a threat to global water resources and natural ecosystems, with the impact being more profound in semi-arid environments. The frequency of droughts is likely to increase because of climate change, and this poses a huge threat to the available water resources, to livelihoods and to ecosystems. Routine drought monitoring is fundamental for developing an early warning system and an area-specific drought mitigation and adaptation framework. Surface waterbodies, especially those in arid and semi-arid environments, are vulnerable to the impacts of drought. The development of moderate-resolution sensors, such as the Landsat 8 Operational Land Imager (OLI) and the Sentinel-2 Multispectral Instrument (MSI), allow new opportunities to monitor droughts and their impact on surface waterbodies. This work, therefore, assesses the extent to which remote sensing datasets can be used to monitor the impacts of drought on the surface water resources in the Western Cape, South Africa, over a period of five years (2016-2020). To achieve this, two multispectral datasets, namely Landsat-8 OLI and Sentinel-2, were tested to assess their ability to monitor the impacts of drought on the water resources. Specifically, multispectral indices, namely the Normalised Difference Vegetation Index (NDVI), Vegetation Condition Index (VCI), the Normalised Difference Water Index (NDWI), the Modified Normalised Difference Water Index (MNDWI) and the Land Surface Water Index (LSWI+5), as well as drought indices (e.g. namely the Standardised Precipitation Index (SPI) and the Water Requirement Satisfaction Index (WRSI)), were evaluated to determine the most suitable method for detecting surface waterbodies and for monitoring droughts. These indices were correlated with the available evapotranspiration (ET) products and in-situ climate data to provide a holistic approach for monitoring a drought and its impacts on the surface waterbodies. Furthermore, the study sought to assess the impacts of the ET rates in selected sub-catchments in the study area, by using ET products and in-situ data. Comparatively, Sentinel-2 MSI outperformed Landsat-8 OLI in the mapping of surface waterbodies, with an Overall Accuracy (OA) of 77% and 71%, respectively. This observation was further confirmed by the Analysis of Variance (ANOVA), which showed significant differences ($\alpha$ = 0.04) between the performance of the two sensors. In addition, the study demonstrated that the surface size of waterbodies was extremely small during the drought period, and that high ET rates and low precipitation rates were recorded during the same period, which highlighted the drought conditions. However, during the 2018 wet season, the rate of precipitation increased and the ET rates decreased; this trend continued in 2019 and 2020, resulting in an increase in the surface water resources. It can thus be concluded that new-

generation multispectral sensors provide new opportunities for drought detection and surface water monitoring, which was previously a challenge, due to the limited spectral, spatial and temporal resolutions.

**Keywords:** Climate change; drought; evapotranspiration; multispectral indices; satellite data; surface waterbodies.

# PREFACE

This research study was conducted in the Department of Earth Sciences, in the Faculty of Natural Sciences, at the University of the Western Cape in South Africa, from February 2020 to October 2021, under the supervision of Professor Timothy Dube.

**Full name:** Trisha Deevia Bhaga **Signature:** **Date:** 24/11/2021

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

**Full name:** Prof. Timothy Dube **Signature:** …………… **Date:** 24/11/2021 ………………..

**Full name:** Dr Munyaradzi Davis Shekede **Signature:** **Date:** 24/11/2021 ………………..

# DECLARATION

I declare that this thesis, entitled **"Multispectral remote sensing of the impacts of drought and climate variability on water resources in semi-arid regions of the Western Cape, South Africa"** is my own work, that it has not been submitted before, for any degree or examination, at any other university, and that all the sources that I have used, or quoted, have been indicated and acknowledged by means of complete references.

Full name: Trisha Deevia Bhaga

Signed: Date: 24/11/2021

## PUBLICATIONS AND MANUSCRIPTS

The following manuscripts have been submitted and published in international peer-reviewed journals and presented in a local conference. The co-authors played a role in reviewing and improving the manuscript, with my contribution being the largest:

1. **Bhaga, T.D.,** Dube, T., Shekede, M.D. and Shoko, C. (2020). Impacts of Climate Variability and Drought on Surface Water Resources in sub-Saharan Africa, using Remote Sensing: A Review. *Remote Sensing*, 12(4184) doi:https://doi.org/10.3390/rs12244184.

2. **Bhaga, T.D.,** Dube, T. and Shoko, C. (2020). Satellite monitoring of surface water variability in the drought-prone Western Cape, South Africa. *Physics and Chemistry of the Earth*. In press. doi:https://doi.org/10.1016/j.pce.2020.102914.

3. **Bhaga, T.D.,** Dube, T. and Shekede, M.D. 2021. Assessing the utility of Landsat-8 OLI and Sentinel-2 MSI satellite data to monitor the impacts of drought on surface water resources in the Western Cape Province, South Africa. *GIScience & Remote Sensing*. [Under review]

The research was presented at the following online conference:

1. The Geo-Information Society of South Africa WC AGM on the 6th of October 2021, South Africa

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# DEDICATION

This dissertation is dedicated to my:

Mother, Mrs S. Bhaga,
Father, Mr A. Bhaga,
Sisters, Meenal and Rekha Bhaga,
as well as the
Bhaga, Dana and Govender families.

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# ABBREVIATIONS

| | |
|---|---|
| ANOVA | Analysis of Variance |
| AVHRR | Advanced Very High Resolution Radiometer |
| $AWEI_{nsh}$ | Automated Water Extraction Index for non-shadowed regions |
| $AWEI_{sh}$ | Automated Water Extraction Index for shadowed regions |
| DEM | Digital Elevation Model |
| ET | Evapotranspiration |
| ETM | Enhanced Thematic Mapper |
| EVI | Enhanced Vegetation Index |
| LSWI+5 | Modified Land Surface Water Index |
| MNDWI | Modified Normalised Difference Water Index |
| MODIS | Moderate Resolution Imaging Spectrometer |
| MSI | Multi-spectral Imager |
| NDVI | Normalised Difference Vegetation Index |
| NDWI | Normalised Difference Water Index |
| NIR | Near Infrared |
| OA | Overall Accuracy |
| OLI | Operational Land Imager |
| PA | Producers' Accuracy |
| RMSE | Root Mean Square Error |
| SAR | Synthetic Aperture Radar |
| SPI | Standardised Precipitation Index |
| SPOT | Satellite Pour l'Observation de la Terre |
| SWIR | Shortwave Infrared |
| TOA | Top of Atmosphere |
| UA | User's Accuracy |
| USGS | United States Geological Survey |
| VCI | Vegetation Condition Index |
| WRSI | Water Requirement Satisfaction Index |

# CHAPTER 1

# INRODUCTION

## 1.1 Introduction

Droughts are a creeping natural hazard that affect agriculture, water resources, environmental flows and livelihoods (Sheffield *et al.*, 2012). Climate change and global warming have increased the frequency and severity of droughts by increasing the evapotranspiration (ET) rate and the land surface temperatures, which both have a negative influence on precipitation (Varghese *et al*., 2021). Africa's climate is highly variable, with an inter-annual rainfall variability in southern Africa of >40% in the drier western areas (Mason & Tyson, 2000). Therefore, droughts have a severe impact on rainfall-dependent sectors across the continent (Gommes & Petrassi, 1996; Masih *et al*., 2014). These impacts are further worsened by the high rate of poverty and the dependence on rain-fed agriculture, which affect people, animals, the environment and the economy (Masih *et al*., 2014).

A review of literature shows that droughts are a recurring phenomenon on the African continent. For example, Burkina Faso, where more than 80% of the population is dependent on subsistence farming, experienced severe drought episodes from 2015 to 2019, which led to water shortages, malnutrition and food insecurity (Bhaga *et al*., 2020). In 2019, 2.3 million people in Zimbabwe required food aid, due to food shortages caused by the drought (WFP, 2019). During 2019, the drought conditions in Zambia led to food shortages and a disruption in hydropower generation (Mwenda, 2019). The Western Cape Province in South Africa experienced below-average rainfall over the period from 2015-2017, which led to the worst drought and water shortages since 1904 (Friederike *et al*., 2018). The lack of rainfall is a key driver of the droughts that are experienced in the Western Cape.

The Western Cape water supply systems depend mostly on rainfall and are thus vulnerable to climate variability and change. The water supply reservoirs that rely on runoff from the source catchments, which, in turn, rely on wet season precipitation, were heavily impacted during the drought experienced from the end of 2015 through to mid-2018. This led to a water shortage and the inability to meet the demand for water by approximately 3.7 million people in Cape Town and the agricultural sector in the Western Cape. The low runoff rates led to a hydrological drought and affected the reservoir storage, due to higher-than-normal temperatures, a lower relative humidity and a higher evapotranspiration rate (Botai *et al*., 2017). Consequently, there was a 31.7% decrease in the harvest, from 1 098 200 tons to 749 800 tons, from 2016 to 2017 (The Western Cape Government: Department of Agriculture, 2017), as the waterbodies could not meet the water demand in the province. The agricultural sector also suffered severe losses, with R525 million and at least 50 000 jobs being lost in wine production (Evans, 2017). The deciduous fruit crop decreased by 20% and less than 50% of onions were planted in Ceres, which resulted in a loss of approximately R40 million in wages of agricultural workers. Therefore, droughts affect the local and national South African economy and lead to increased unemployment and production losses, an increase in food prices, as well as many other socio-economic impacts (Botai *et al*., 2017).

Droughts are traditionally monitored by using paleoclimatology and climatological data (d'Andrimont & Defourny, 2018). Paleoclimatolgy uses the past climatic conditions to understand the past climates by using historical data records of ice sheets, tree rings, sediments, rocks, diatoms and corals, to predict the future climatic conditions (Bhaga *et al*., 2020). Climatological data, such as rainfall, river flow, soil moisture and ET rates, are recorded and used as a means of validating drought conditions, by comparing the historic values and the climatic conditions experienced at the time that they were recorded. However, the use of paleoclimatology is time-consuming; thus the use of remotely sensed data is a promising method for the detection and monitoring of droughts in a time-efficient manner.



The physically-based techniques that are used to monitor surface water resources include the manual measurement of water levels, by using floats, sensors, buoy systems and pressure type equipment, as well as ultrasonic and radar techniques (Chapuis, 1998; Janke *et al*., 2006). However, these methods are costly, time-consuming and prone to human error; in addition, the equipment is prone to theft and damage and it may be problematic to install in remote or mountainous areas (Li *et al*., 2013). The use of remotely sensed data has recently been on the rise, as it provides a viable alternative for the monitoring of water resources, in terms of quantity and quality (Li *et al*., 2013). For example, the literature shows that remote sensing is more advantageous than the traditional methods for surface water monitoring, because of its ability to make high-frequency and repeatable observations at a low cost (Li *et al*., 2013). With the development of freely available, medium-resolution satellites, such as the Landsat series and Sentinel-2, the potential for monitoring droughts and surface water resources is high, due to the higher spatial, spectral and temporal resolution. The use of remotely sensed data, specifically spectral water indices derived from multispectral sensors, is a promising approach, because it has multi-band features, it has a wide coverage, it offers repeatable observations and it can be applied at various spatial scales, in both data-rich and data-poor areas (Masocha *et al*., 2018; Palmer *et al*., 2015). This means that droughts can be predicted in time to set up coping measures, to prevent water restrictions and to prevent an increase in water tariffs. The use of satellite data is cost-effective, and the results that are produced will be easier for decision-makers to interpret.

The monitoring of surface water availability is important for water resources management because it can help to predict droughts, flooding and water availability conditions (Jacobs *et al*., 2016). Since the drought in the Western Cape from 2015 to 2019, the monitoring of surface water levels has become vital for determining how much water is available for use. Using remotely sensed images for the monitoring of water quantity is common; however, it remains rudimentary, and this has affected water resource allocation and planning. The hydrological drought that struck the Western Cape had an impact on the water resources, on agricultural activities, on the economy and on daily lives; therefore, a study that investigates the impacts of drought on water resources will help to predict droughts and their effect on the province.

A study that investigates water availability in response to climatological data, such as rainfall and evapotranspiration, will help to predict drought conditions in a timely, reliable and cost-effective manner, which is vital for drought mitigation and adaptation strategies, as well as for water resource allocation. A study that combines remotely sensed data with climatological data will allow results that are far more accurate and will serve as a means of correlating the different data sets, which will assist researchers and decision-makers in monitoring the availability of surface water and drought detection. This is crucial, as droughts are becoming more frequent (Liu *et al*., 2020).

## 1.2 Aims and Objectives

### 1.2.1 Aim

The aim of this study is to assess the extent to which remote sensing datasets can be used to monitor the impacts of drought on water resources in the Western Cape, South Africa.

### 1.2.2 Objectives

The specific objectives of this study are:

a) To develop a model for the retrieval and tracking of changes and the impacts of drought and climate variability on surface waterbodies from the multispectral archival data; and

b) To assess the impacts of drought and climate variability or evapotranspiration rates in selected sub-catchments, using the available ET products and in-situ data.

### 1.3 Research Questions

The following research questions will be addressed:

a) How accurate are remote sensing datasets for monitoring and detecting surface water resources in the semi-arid regions of the Western Cape, South Africa? and
b) To what degree can the spatial and temporal changes of sub-catchments be described?

### 1.4 Conceptual Framework

This study uses Geographic Information Systems (GIS) and remote sensing techniques to detect and map the occurrence of a drought and its impact on the surface waterbodies in the Western Cape, South Africa. Figure 1.1 shows the conceptual framework for the detection and mapping of droughts and surface waterbodies. The outputs of this study are likely to be informative for drought management in the semi-arid regions of the Western Cape, South Africa.

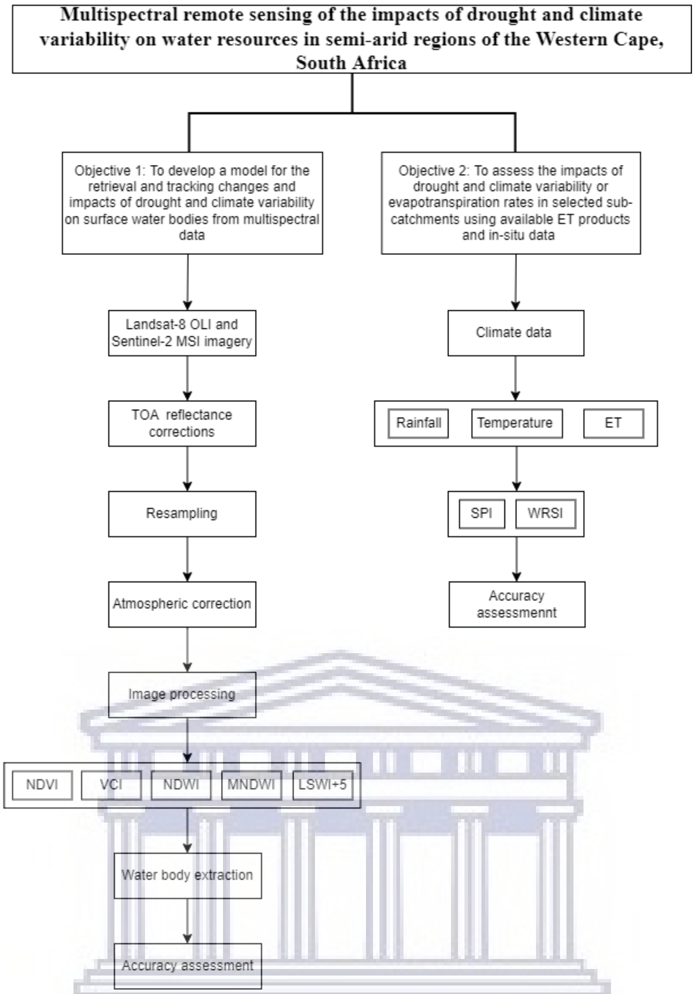


Figure 1.1 Conceptual framework of the study



## 1.5 Description of Study Area

The Western Cape Province of South Africa has a Mediterranean climate, which is characterized by hot, dry summers (November to March) and cold, wet winters (May to August), due to the orographic effects created by the presence of mountains (Midgley *et al*., 2003; Mkunyana *et al*., 2018). The temperatures range from 23°C in the summer to 13°C in the winter (Mkunyana *et al*., 2018), and it receives an annual rainfall of approximately 500 mm/year (Midgley *et al*., 2003). The main land cover types in the area are predominantly croplands, grasslands, fruit trees, winelands, built-up areas and roads. The surface waterbodies situated in the Cape Metro, Cape Winelands, Overberg and Garden Route regions were considered for this study (Figure 1.2). These waterbodies are important for sustaining the domestic and commercial water services, including agriculture, electricity generation and hydrological ecosystems. This region was hit by a severe drought from 2016 to 2018, which led to water restrictions that reached Level 6b on 1st February 2018 (Muller, 2018). This means that water consumption was limited to 50 litres, or less, per person per day, and the use of boreholes was discouraged, in order to preserve the groundwater resources (City of Cape Town, 2018). This emphasises the importance of monitoring the availability and variability of surface water in this region.

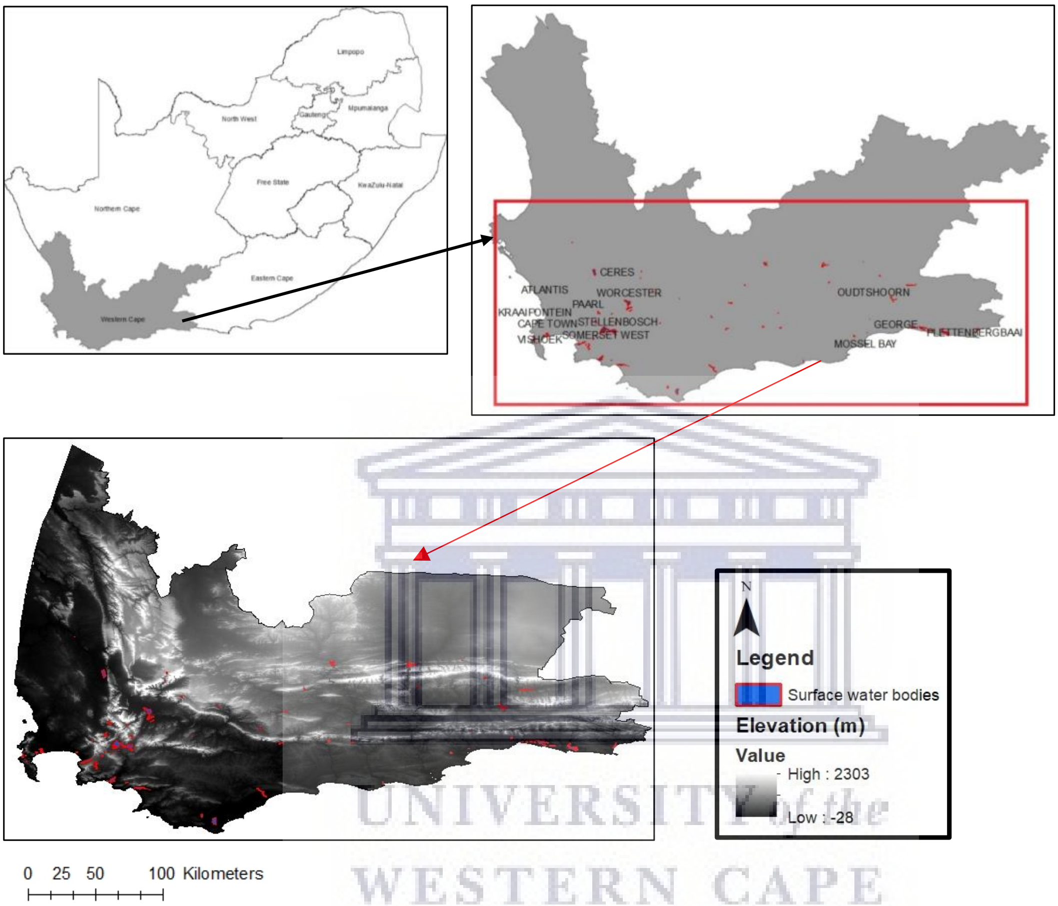


Figure 1.2 Locational map of the study area

## 1.6 Thesis Outline

This thesis consists of four chapters that are aimed at understanding the use of remote sensing in the detection of droughts and the monitoring of water resources. This study contains one paper that has been published in an international peer-reviewed journal, while the other paper is under review. Each chapter consists of stand-alone Introduction, Materials and Methods, Results and Discussion sections. Although attempts were made to conform to a general style in this dissertation, there may be overlapping and repetition in some of the sections.

Chapter One introduces the general background of the study and highlights the importance of drought monitoring, which is followed by the research problem, the research questions, as well as the aim and objectives

Chapter Two reviews the application and challenges in the detection and monitoring of the impacts of climate variability and drought on surface water resources in sub-Saharan Africa, using remote sensing.

Chapter Three assesses the accuracy of detecting and monitoring the impacts of climate variability and droughts on surface water resources, using Landsat 8 OLI and Sentinel 2 MSI data. This chapter also focuses on ET data, which is correlated to the seasonal and annual variations in the surface waterbodies. This chapter presents the data collection and data analysis methods, followed by the results and a discussion of the major findings.

Chapter Four presents a detailed synthesis of the main findings of the study. It also answers the research questions and provides recommendations for future studies, based on the limitations that are pointed out.

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# CHAPTER 2

# IMPACTS OF CLIMATE VARIABILITY AND DROUGHT ON SURFACE WATER RESOURCES IN SUB-SAHARAN AFRICA, USING REMOTE SENSING: A REVIEW


## Abstract

Climate variability and recurrent droughts have caused a remarkable strain on the water resources in most regions across the globe, with the arid and semi-arid areas being the hardest hit. The impacts have been most notable on the surface water resources, which are already under threat from massive abstractions, due to the increased demand, poor conservation and unsustainable land management practices. Drought and climate variability, as well as their associated impacts on the water resources, have gained increased attention in recent decades, as nations seek to enhance mitigation and adaptation mechanisms. Although the use of satellite technologies has, of late, gained prominence in generating timely and spatially explicit information on the impacts of drought and climate variability across different regions, they are somewhat hampered by the difficulty of detecting the evolution of droughts, due to their complex nature, their varying scales, the magnitude of their occurrence and the inherent data gaps. Several recent studies have been conducted to monitor and assess the impacts of climate variability and droughts on the water resources in sub-Saharan Africa, using different remotely sensed and in-situ datasets. This study provides a detailed overview of the progress that has been made in tracking droughts by using remote sensing, including its relevance in the monitoring of climate variability and the impact of hydrological droughts on the surface water resources in sub-Saharan Africa. This study also discusses the traditional and remote sensing methods for monitoring climate variability, hydrological droughts and water resources, and it tracks their application and key challenges, with a particular emphasis on sub-Saharan Africa. In addition, the characteristics and limitations of various remote sensors and their importance in the monitoring of climate variability and drought are discusses. The application of drought and surface water indices, namely the Standardized Precipitation Index (SPI), the Palmer Drought Severity Index (PDSI), the Normalized Difference Vegetation (NDVI), the Vegetation Condition Index (VCI), the Water Requirement Satisfaction Index (WRSI), the Normalized Difference Water Index (NDWI), the Modified Normalized Difference Water Index (MNDWI), the Land Surface Water Index (LSWI+5), the Modified Normalized Difference Water Index (MNDWI+5), the Automated Water Extraction Index (shadow) ($AWEI_{sh}$) and the

Automated Water Extraction Index (non-shadow) ($AWEI_{nsh}$) are also discussed. The key scientific research strides are also highlighted, as well as the knowledge gaps that require further investigation. While progress has been made in advancing the application of remote sensing with regard to water resources, this review indicates the need for further studies to be conducted, in order to assess the impacts of drought and climate variability on the water resources, especially in the context of climate change and the increased water demand. The results of this study suggest that Landsat-8 and Sentinel-2 satellite data are likely to be the best-suited for monitoring climate variability, hydrological drought and surface waterbodies, due to their availability at a relatively low cost, as well as their impressive spectral, spatial and temporal characteristics. The most effective drought and water indices are SPI, PDSI, NDVI, VCI, NDWI, MNDWI, MNDWI+5, AWEIsh and AWEInsh. Overall, the findings of this study emphasize the increasing role and potential of remote sensing in generating spatially explicit information regarding the impact of droughts and climate variability on surface water resources. However, future studies should also consider spatial data integration techniques, radar data, precipitation, cloud computing and machine learning or Artificial Intelligence (AI) techniques, in order to improve the understanding of the impacts of climate and drought on water resources across various scales.

Keywords: aridity; climate change; drought assessment; satellite-derived metrics; satellite data; sub-Saharan Africa; water quantity



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## 2.1 Introduction

Droughts are complex and naturally-occurring hazards that result from climate variability and climate change and that leads to a change in the water balance, due to drastic decrease in precipitation over an extended period (Du *et al*., 2013; Keshavarz *et al*., 2014; Huang *et al*., 2017). Droughts occur in all climatic zones, irrespective of the normal precipitation rates and trends of a region (Slette *et al*., 2019), and their onset and cessation are difficult to detect, which renders them highly unpredictable, unlike other natural disasters (Park *et al.,* 2017). Characterizing the impact of droughts is difficult, because they differ spatially and temporally (Wilhite *et al.*, 2007). Atmospheric climatic events, such as the El Nino Southern Oscillation (ENSO), may cause an increase in the frequency and intensity of droughts (Verner *et al*., 2018). The lack of precipitation, the high evapotranspiration rate and the over-exploitation of water resources can lead to droughts (Bhuiyan, 2004). The impacts of droughts are diverse and can be either direct or indirect. For example, they result in crop and biodiversity losses, the loss of livestock/wildlife, disruptions in hydropower generation, food losses, malnutrition, famines and even death. In 2011, poor rains in Mauritania led to drought conditions that caused poor harvests, the loss of livestock and an increase in food prices (World Health Organization, 2013). In 2015, a drought impacted farming in Mali, which led to starvation and 300 000 people suffering from food insecurity (Giannini *et al*., 2017). In Cote d'Ivoire, a drought in 2018 led to 70% of the dams that supply the cities running dry (The New Humanitarian, 2019). In 2018, approximately 3.7 million people in South Africa were affected by a drought, which was caused by below-average precipitation rates (Otto *et al*., 2018). At the end of 2019, more than 2.6 million in Madagascar were affected by a drought, which resulted in severe food shortages and led to a famine (Haile *et al*., 2019). In Lesotho, approximately 500 000 people were threatened with hunger in 2020, and it is estimated that more than 30% of the population will experience acute food insecurity due to the ongoing drought conditions (Moyo, 2020). Therefore, in order to reduce and mitigate these impacts, there is a need for droughts and climate variability to be monitored more effectively. Surface water resources are the major source of freshwater for the agricultural, drinking, sanitation and energy requirements of many countries in sub-Saharan Africa (Sheffield *et al*., 2018). However, previous studies by Wilhite *et al*. (2007), Sheffield *et al*. (2018), Huang *et al*. (2018) and Zhou *et al*. (2017) have demonstrated that surface waterbodies are vulnerable to climate change and that surface water resources need to be monitored more accurately, for the following reasons: (i) to determine their condition, (ii) to assess the influence of drought conditions and climate variability on the availability of water, and (iii) to ensure their sustainable utilization. This paper therefore seeks to provide a detailed overview of the progress of remote sensing applications in monitoring the impact of climate variability and droughts on surface water resources in sub-Saharan Africa. It first highlights the importance of monitoring the impact of climate variability and drought on the water resources in the region, which is followed by the details of how the relevant literature was searched and consulted, before highlighting the key advances in scientific research, as well as the knowledge gaps that require further investigation.

## 2.2 The Importance of Monitoring the Impact of Climate Variability and Droughts on the Water Resources in Sub-Saharan Africa

During the first two decades of the 21st century, 79 big global cities, including some cities in sub-Saharan Africa, experienced severe drought conditions (Zhang *et al*., 2019). It is projected that the occurrence of drought events is likely to increase and become more intense in the future, due to climate change and climate variability, and that this will pose an additional strain on the water supply (Sheffield *et al*., 2012; West *et al*., 2019). Droughts affect both the quantity and quality of water. In terms of water quality, a reduced flow results in a decrease in organic matter, nutrients and sediment pathways in the surface water streams (Sorensen, 2017). The reduced flows can, in turn, affect the stability of the wetlands and their ability to provide a habitat for wildlife and aquatic species. Droughts can also cause an intrusion of saline water into the groundwater system, a decrease in the groundwater level, as well as water supply problems, which result in limited water being available to support and sustain the various social, environmental and economic services. In this regard, reducing the environmental and socio-economic impacts of droughts and climate variability, as well as to work towards creating drought resilient societies remains a global priority (Hagenlocher *et al*., 2019). Monitoring climate variability and droughts is essential for the planning and management of water resources for various social, environmental and economic services, including public supply and sanitation, ecosystems, hydro-electricity, mining and agriculture (Huang *et al*., 2018). Understanding the different dimensions of droughts, such as historical droughts in the region, their impacts and their occurrence, is also a crucial step towards developing effective models to predict and investigate the different types of drought (Panu & Sharma, 2002). The prediction of drought occurrence permits drought preparedness (Abiodun *et al*., 2019) and necessitates the development of drought-specific contingency plans, such as water restrictions and the use of alternative water sources (Botai *et al*., 2017).

Waterbodies are vulnerable to climate change, and therefore, they need accurate, timely and routine monitoring (Du *et al*., 2014). This will help to determine the onset of drought conditions, in order to come up with mitigation and adaptation strategies and to avoid the loss of lives and crops, as well as famines (Masocha *et al*., 2018). On the other hand, monitoring the size and dynamics of waterbodies are also vital for water resource management, to determine how much water is available for maintaining the ecological state of the surrounding ecosystems (Sorensen, 2017). In addition, monitoring the number of water resources can be used to predict droughts, which is useful in arid and semi-arid areas, particularly in sub-Saharan Africa.

Thus far, much scientific research work has been conducted on the monitoring of droughts and the associated impacts of climate variability (AghaKouchak *et al*., 2015; Mishra & Singh 2010); however, the advancements in remote sensing applications and data processing techniques, particularly in sub-Saharan Africa, remain poorly documented. In the past, droughts have been monitored by using paleoclimatology, satellite data, physically-based techniques, e.g. floats, sensors, buoy systems, pressure type equipment, as well as ultrasonic and radar techniques and the inferences from climate variability modelling studies. Therefore, to achieve the objective of this work, this chapter will describe the methods used in reviewing and synthesizing the relevant literature before identifying the key research advancements, as well as the knowledge gaps that warrant further investigation.



## 2.3 Materials and Methods

*Literature Search*

In order to gather and determine the most relevant literature for this particular study, different search strategies were adopted. The literature search consisted of English peer-reviewed articles and relevant reports on droughts in sub-Saharan Africa that were published between 1900 and 2020. The relevant articles were identified by using targeted searches in Google Scholar, Scopus and the Web of Science. The criteria for the selection included the following: (i) the use of remote sensing in the monitoring of droughts, climate variability and surface water; (ii) the geographical location and year of occurrence; and (iii) the publication of this information in a scientific journal. This review omitted research that did not use geospatial technologies. Each article was assessed according to the accuracy of the results and the year of publication. The articles were then grouped into three main categories, namely: (i) drought monitoring, using remote sensing, (ii) surface water monitoring, using remote sensing, and (iii) the impacts of drought/or climate variability (Figure 2.1). In the drought monitoring category, it was interesting to observe that the use of remote sensing constituted more than half of the review material and consisted mostly of remote sensing data. Much of this work focused on drought risk assessments and drought severity mapping, using various indices. The third and final category, namely the impact of droughts, consisted of articles analysing the effects of droughts on various sectors in different countries in sub-Saharan Africa.

Various online reports and articles were also consulted, in order to tabulate the occurrence of droughts in the region from 1900 to 2020 (Table 2.1).

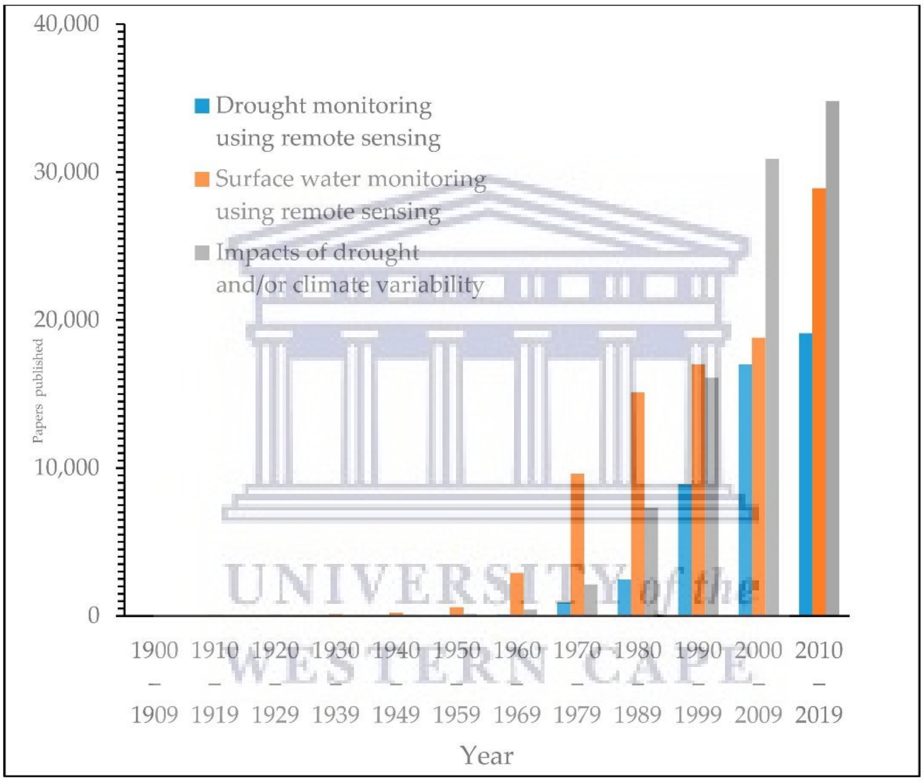


Figure 2.1 The number of journal article publications on drought monitoring, using remote sensing, on surface water monitoring, using remote sensing, and the impacts of droughts and/or climate variability

Overall, the literature showed that the use of remote sensing for the monitoring of droughts and surface waterbodies has increased significantly in recent years. However, remote sensing applications have not diversified, as there are still many gaps in the research, which suggests that its applicability has not been fully tested or exploited for monitoring purposes. Furthermore, not enough studies have been conducted by using remote sensing for the monitoring of droughts and surface waterbodies, with only approximately 18 000 articles on the use of remote sensing in drought monitoring being published from 2010 to 2019 (Figure

2.1). This observation implies that remote sensing has to be harnessed, to advance its scientific contribution to, and application in, various areas. These areas include, but are not limited to, drought monitoring, surface waterbody monitoring and climate variability, especially in Africa.

### 2.4 Definitions, the Occurrence and Impacts of Droughts and Climate Variability

To date, several definitions of a drought have been proposed, depending on the perspective from which it is being assessed (Wilhite *et al*., 2007). For instance, the Food and Agriculture Organization (1983) defines a drought as "the percentage of years with a poor crop yield, due to the lack of soil moisture", whereas the World Meteorological Organization (1986) describes it as "a sustained, extended deficiency in precipitation". On the other hand, the UN Secretariat (1994) defines it as "a naturally-occurring phenomenon that exists when precipitation is significantly below the normal recorded levels, causing serious hydrological imbalances that adversely affect land resource production systems". Thus, it is important to note that the definitions of drought vary significantly across different fields, depending on the variables, such as the concepts, the observational parameters and the measurement procedures used to describe this phenomenon, which lead to different categorizations (Bhuiyan, 2004). Droughts are usually classified into four different categories (Wilhite *et al*., 2007; Mishra & Singh, 2010; Guo *et al*., 2020), namely, meteorological, hydrological, agricultural and socio-economic droughts (Michaelides *et al*., 2009). Recently, a groundwater drought was proposed as the fifth category by Mishra & Singh (2010). However, few studies have been conducted on groundwater droughts.



A meteorological drought occurs when there is a lack of precipitation over an extended period of time (Park *et al*., 2017; Botai *et al*., 2017; Park *et al*., 2016). Prolonged meteorological droughts lead to a decrease in the soil moisture content, which can result in agricultural droughts (Park *et al*., 2017). When the streamflow, groundwater or the total water storage is below the long-term mean, a hydrological drought occurs (Jiao *et al*., 2019), resulting in low stream flows and reservoir levels (Park *et al*., 2017). This means that a given water source cannot supply the amount of water that is required for its intended use, which leads to a limited water supply (Huang *et al*., 2017). In contrast, an agricultural drought occurs when there is a deficit in the soil moisture (Du *et al*., 2013). A lack of water in the soil and subsoil that is caused by insufficient precipitation affects the crop growth, thereby causing a decrease in crop yields (Du *et al*., 2013; Botai *et al*., 2017; Jiao *et al*., 2019). Soil moisture is dependent upon several factors, such as the actual evapotranspiration and the potential evapotranspiration, as well as the physical and biological properties of soil and the biological characteristics of specific plants (Urban *et al*., 2018). A socio-economic drought occurs when the drought process affects production, because the water resources cannot meet the demand for water, which leads to a shortage of certain economic goods (Du *et al*., 2013). In this regard, the demand for economic goods is greater than the supply, due to a shortage in the water supply (Mishra & Singh, 2010). Thus, a socio-economic drought is driven by the previous three drought categories (Park *et al*., 2017). For a groundwater drought, the lack of precipitation and the high evapotranspiration rate result in low soil moisture, which leads to a low groundwater recharge (Eltahir & Yeh, 1999; Yeh *et al*., 2006). A low groundwater recharge, in turn, causes low groundwater levels, thereby reducing the groundwater discharge (Mishra & Singh, 2010). As the total amount of available groundwater is difficult to determine, this drought category is usually defined by a decrease in the groundwater level, groundwater storage and groundwater recharge or discharge (Marsh *et al*., 1994).

Drought-related impacts are complex, as they have an effect on various water-dependent sectors, such as recreation and tourism, energy and transportation, as well as the environment (Wilhite *et al*., 2007). The impacts of drought are classified as direct or indirect. For example, a reduction in crops, land degradation, deforestation, an increase in the fire hazard, reduced energy production, a decline in the water levels, increased mortality rates of fauna, and damage to wildlife and aquatic ecosystems, are all examples of the direct impacts (Wilhite *et al*., 2007; Haile *et al*., 2019). A decrease in the water level can lead to water shortages, and therefore, the water supply will be disturbed. Many countries experience drought-induced crop failures and water shortages during drought periods (Park *et al*., 2016). The indirect impacts are the consequences of the abovementioned direct impacts. Decreases in the crop, rangeland and forest productivity can lead to farmers and agricultural businesses running at a loss, thereby causing a decrease in food and timber, unemployment and an increase in the crime rate (Wilhite *et al*., 2007). Indirect losses often exceed the direct losses, since these can cascade to other critical socio-economic sectors.

Moreover, droughts and climate variability have severe consequences on the environment, on the economy and on human wellbeing (Frischen *et al*., 2020), and the impacts are linked through couplings in the land-atmosphere processes (Park *et al*., 2016). Groundwater resources become stressed when the region experiences an extended period with a decreased rate in precipitation and high temperatures, which, in turn, affect the groundwater recharge (Bhuiyan, 2004). For example, droughts across the globe, particularly in sub-Saharan Africa (Haile *et al*., 2019), affect the surface water and groundwater resources, which lead to a lack of water supply, a reduction in the water quality, crop failure and a change in the riparian habitats (Slette *et al*., 2019). When droughts occur in developed countries that have adequate coping mechanisms, the economic losses can be alleviated by means of contingency funds or insurance schemes. However, in poor countries, like those in Africa and South America, droughts can lead to food shortages and famines (Frischen *et al*., 2020).

The frequency of droughts in East Africa (EA) has doubled since 2005, from once every six years to once every three years (Haile *et al*., 2019); and between 2008 and 2010, droughts affected over 13 million people in EA (Muller, 2014). Djibouti, Eritrea, Ethiopia and Somalia, also known as the Horn of Africa (HOA), experienced a severe drought from 2010–2011, which caused food insecurity, famine and malnutrition, and this affected approximately 20 million people and led to a significant loss of life (Qu *et al*., 2019). The droughts in Somalia, Kenya and Ethiopia led to socio-economic instability, with Somalia alone recording 250 000 deaths during the same period (Haile *et al*., 2019; Qu *et al*., 2019) (Table 2.1).

Droughts have been recurring in sub-Saharan Africa over the past 30 years (Muller, 2014). During the 1991/1992 drought, agricultural production in Zimbabwe was reduced by 45% and the Gross Domestic Product (GDP) decreased by 11% (Du *et al*., 2013; Maphosa, 1994), which led to severe food insecurity and famine, due to its dependence on rain-fed agriculture (Frischen *et al*., 2020). The Western Cape of South Africa experienced a severe drought from 2015–2018 (Du *et al*., 2013; Zhou *et al*., 2017; Sousa *et al*., 2018) and dam levels dropped to approximately 20%, which affected ±3.7 million people (Abiodun *et al*., 2019). Water restrictions reached Level 6b, which means that the consumption of water was limited to 50 L, or less, per person per day, and the use of boreholes was discouraged, to preserve groundwater resources, while the use of non-potable water was encouraged to water fields and gardens (City of Cape Town, 2018; Muller, 2018). A detailed summary of the occurrence and impacts of the major recorded droughts in sub-Saharan Africa is provided in Table 2.1. Overall, West Africa has experienced the highest number of droughts, followed by East Africa, whereas Central Africa has experienced the least number of droughts. As for the individual countries, Tanzania in East Africa recorded the highest number of droughts. Figure 2.2 also indicates the global risk of drought occurrence, based on the Global Precipitation Climatology Centre (GPCC) Drought Index. It can be observed that the majority of countries in sub-Saharan Africa are high-risk areas for the occurrence of droughts. This further emphasizes the need for the continuous monitoring of droughts in the region.

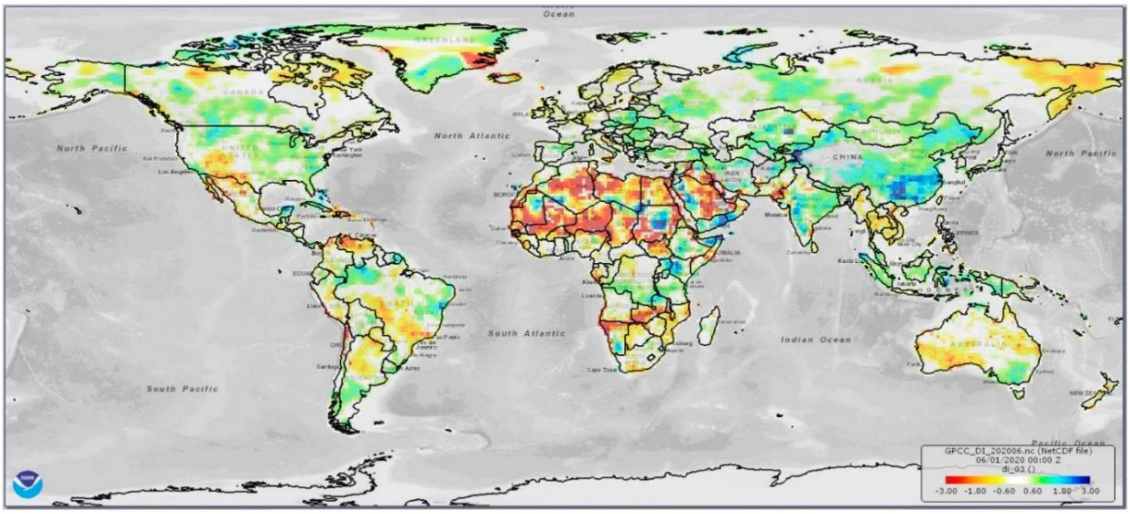


Figure 2.2 Global drought map, calculated by using the Global Precipitation Climatology Centre (GPCC) Drought Index, indicates the risk of drought occurrence globally, with the red zones showing high risk areas and the blue zones indicating low risk areas (Source: National Integrated Drought Information System (NIDIS)

Moreover, the occurrence of droughts affects several Sustainable Development Goals (SDGs) envisaged in the United Nations 2030 agenda (Zhang *et al.*, 2019), namely, Goal 1: "No poverty", Goal 2: "Zero hunger", Goal 6: "Clean water and Sanitation", Goal 11: "Sustainable cities and communities", Goal 12: "Responsible production and consumption", Goal 13: Climate action" and Goal 15: "Life on land" (Nilsson *et al.*, 2016; Zhang *et al.*, 2019).

Table 2.1 Occurrence and impacts of major recorded droughts in Africa from the 1900s. No data available for Equatorial Guinea, Gabon and Sierra Leone

| **Region/Country** | **Drought Years** | **Number of Events** | **Droughts Effects** |
|---|---|---|---|
| North Africa | | 32 | |
| Algeria | 1910–1920; 1945–1947; 1973–1980; 1981–1983; 1999–2002 | 5 | 90% loss of livestock in 1945; decrease in groundwater levels, shallow wells, dry springs, wildfires, crop loss and production loss, causing a famine in 1966. |
| Egypt | 1972–1973; 1978–1987; 1990–2002; 2010–2011 | 4 | Unemployment rates increased, as 55% of the population were employed by the agricultural sector and riparian vegetation was severely affected. |
| Libya | 1945; 1950s; 1960s | 3 | The 1945 drought led to the loss of cattle. The details are not available, due to political issues and poor record-keeping |
| Morocco | 1917–1920; 1930–1935; 1945–1950; 1981–1984; 1991–1995; 1999–2003; 2015–2016; 2018 | 8 | Disruptions in the water supply, agricultural sector and cereal production. In 1999, approximately 275 000 people were affected, and the economic damage was $900 million. |
| Sudan | 1967–1973; 1980–1984; 1985–1993; 2008–2009; 2011–2012; 2017–2019 | 6 | Approximately 7 million people suffered from severe food insecurity in 2019, and approximately 21 000 people are experiencing famine conditions. In 2016, Sudan experienced agricultural losses of over 2 million dinars ($900 million). |
| Tunisia | 1961–1969; 1987–1988; 1993–1995; 1999–2002; 2000–2008; 2015–2016 | 6 | Disruption in water supply, increase in salinity in water retention and decreased production of grains and forages. |
| Central Africa | | 22 | |

**Table 2.1.** *Cont.*

| Region/Country | Drought Years | Number of Events | Droughts Effects |
|---|---|---|---|
| Angola | 1981–1985; 2004–2006; 2012–2013; 2019 | 4 | Approximately 1.8 million people and 2.3 million people were affected by the drought in 2012 and 2019, respectively, leading to food insecurity and malnourishment. |
| Cameroon | 1971; 1990; 2001; 2005; 2011–2015 | 5 | Cereal production fell by 30 000 tons in 2011, when compared to 2010, leading to inflation. In 2015, 2.7 million people suffered from food insecurity. |
| Central African Republic | 1963; 1983 | 2 | 75% of Central African people rely on agriculture for their livelihoods, while 1.9 million people experienced severe food insecurity. |
| Chad | 1966–1967; 1969; 1993–1997; 2001–2005; 2012–2013; 2017–2018 | 6 | Droughts and food insecurity affected approximately 3.4 million people, leading to high unemployment rates, as most people were employed in the agricultural sector and are dependent upon subsistence farming. |
| Democratic Republic (DR) of Congo | 1978; 1983; 2017–2020 | 3 | The 2017 drought period affected hydro-electric power generation and left 13.1 million people severely food insecure. |
| Sao Tome and Principe | 1947; 1983 | 2 | Droughts led to food insecurity and severe famine and affected about 93 000 people. |
| West Africa | | 83 | |
| Benin | 1977; 1984; 1992; 2010–2013; 2017–2019 | 5 | In 2017, approximately 80% of the population that was dependent on the agricultural sector was unemployed. |

**Table 2.1.** *Cont.*

| | | | |
|---|---|---|---|
| Burkina Faso | 1968–1974; 1976; 1995; 1998; 2001; 2011; 2015–2019 | 7 | The drought in 2016 led to water shortages and affected 2 million people, as over 80% of the population relied on subsistence farming, which led to malnutrition and food insecurity. |
| Republic of Cabo Verde | 1941–1943; 1947–1948; 1969; 1977; 1998; 2002; 2015–2019 | 7 | The drought in the 1940s killed approximately 45 000 people due to starvation, and Santiago lost 65% of its population. In 2017, most farmers lost most of their production, which caused severe food insecurity in 2018. |
| Cote d'Ivoire | 1970–1974; 1976–1993; 2000–2005; 2006–2010; 2015–2019 | 5 | The drought in 2005 caused disruptions in the agricultural sector, reducing the harvests, per capita incomes and water supply. In 2018, the dams that supply 70% of cities ran dry. |
| Gambia | 1968–1974; 2012; 2016–2019 | 3 | The 2012 drought led to 70% of crop failure, triggering food insecurity and high unemployment rates, as 78% of the population is employed by the agricultural sector. |
| Ghana | 1980–1984; 1997–1998; 2006–2007; 2010–2012 | 4 | Approximately 35% of total food production was destroyed in the 1980s, leading to food shortages, and in 2006 there was a disruption of hydropower. |
| Guinea | 1980; 1998; 2015–2016; 2018–2019 | 4 | Droughts led to the disruption of income, interruptions in the agricultural sector, and disturbed river regimes, and 2.5 million people were affected in 2016 and suffered severe food shortages. |
| Guinea Bissau | 1910; 1940; 1969; 1980; 2002; 2004–2006 | 6 | In 2002, a drought affected 100 000 people, and 32 000 people in 2004 suffered from food security through disruptions in the production of agriculture and livestock. |
| Liberia | 1972–1973; 1983–1984; 1991–1992; 2019 | 4 | In 2019, 360 000 children under the age of five suffered from acute malnutrition due to extreme food shortages, which led to famine and death. |

**Table 2.1.** *Cont.*

| Region/Country | Drought Years | Number of Events | Droughts Effects |
| --- | --- | --- | --- |
| Mali | 1982–1984; 2001; 2005–2006; 2010–2011; 2017–2019 | 5 | The droughts impacted farming, leading to starvation. In 2015, 300 000 people suffered from food insecurity. Mali experienced severe food shortages, which led to famine in 2019. |
| Mauritania | 1910–1916; 1940s; 1968–1974; 1976–1978; 1993–1997; 2010–2012; 2017–2019 | 7 | In 2011, a drought led to poor harvests, the loss of livestock and an increase in food prices, and in 2012 approximately 700 000 people in southern regions were affected by food shortages, while in 2017 and 2018, 379 000 and 350 000 people, respectively, were food insecure. |
| Niger | 1966; 1980; 1988–1990; 1997; 2001; 2005–2007; 2009; 2010–2012 | 8 | Recurrent droughts led to food crises, the loss of livestock and desertification; in 2010, 8 million people needed food, due to the failure of crops. |
| Nigeria | 1911–1914; 1951–1954; 1972–1973; 1984–1985; 2007; 2011 | 6 | Crop and livestock production are a source of income for many people in Nigeria. In 2010, 65% of the population worked in the agricultural sector, and the drought caused an increase in the unemployment rate. |
| Senegal | 1979; 1980; 2002; 2011; 2014; 2017–2018 | 6 | In 2018, a drought left 245 000 people food insecure and 23 000 children suffering from severe acute malnutrition, due to crop failure and the loss of livestock. |
| Togo | 1942–1943; 1971; 1976–1977; 1980; 1982–1983; 1989 | 6 | Severe famine due to a decrease in agricultural yields, the death of livestock and a decrease in agricultural revenue. 71% of Togolese were vulnerable to food security. |
| East Africa | | 64 | |

**Table 2.1.** *Cont.*

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|---|---|---|---|
| Burundi | 1999; 2003–2005; 2008–2010 | 3 | In 2004, a drought affected 2 million Burundians and affected the agricultural sector, which is the main source of livelihood for 90% of the population. |
| Comoros | 1981; 2011–2012 | 2 | Droughts affected food security and led to food shortages. |
| Djibouti | 1980–1983; 1988; 1996–1999; 2005; 2008–2014 | 5 | In 2014, approximately 250 000 people were affected by more than four years of consecutive droughts, and 18% of the population suffered from malnutrition, due to crop and livestock losses. |
| Eritrea | 1993; 1998–1999; 2000–2004; 2008 | 4 | In 2004, 600 000 Eritreans were affected by drought, and 19% of the population suffered from acute malnutrition. |
| Ethiopia | 1973–1979; 1984–1985; 1997–1999; 2005; 2008–2009; 2015–2020 | 6 | Continuous droughts led to crop failure, which caused food insecurity and famine. In 1984, the drought led to famine, which killed approximately 1 million people. In 2017, 7.7 million Ethiopians experienced severe famine and needed emergency food aid. |
| Kenya | 1971–1975; 1994–1996; 1999–2000; 2004–2006; 2008–2012; 2016–2020 | 6 | Droughts have led to disruptions in hydropower generation, increasing unemployment rates and the loss of lives, crops and livestock. In 2010, 10 million people were at risk of being food insecure, due to failed harvests from the drought conditions. |
| **Region/Country** | **Drought Years** | **Number of Events** | **Droughts Effects** |
| Madagascar | 1981; 1988; 2000–2002; 2005–2007; 2010–2012; 2015–2020 | 6 | In 2016, 1.1 million Malagasy suffered from food insecurity due to crop failure, as agricultural production was 90–95% lower than usual. At the end of 2019, more than 2.6 million Malagasy were affected by drought. |

**Table 2.1.** *Cont.*

| | | | |
|---|---|---|---|
| Mozambique | 1991–1992; 2001–2003; 2005–2007; 2016–2019 | 4 | In 2010, 81% of Mozambicans relied on agriculture for food and employment, therefore increasing the unemployment rate and food shortages. By 2019, more than 60 000 Mozambicans were affected, and in some areas 60% of crops were lost. |
| Rwanda | 1976; 1984; 1989; 1996; 1999; 2003; 2016–2019 | 7 | More than 100 000 Rwandese were affected by drought in 2016 due to crop failure, which led to food shortages, and by 2017, 6.7 million Rwandese received food aid. |
| Somalia | 1964; 1999; 2004; 2005; 2008; 2010–2020 | 6 | The worst recorded drought after 60 years was experienced between 2010 and 2011, as more than 250 000 people died, and in 2017, 2.1 million Somalians were displaced by drought, and 6.7 million people suffered from food shortages. |
| Tanzania | 1996; 1999–2002; 2004–2006; 2011; 2016–2019 | 10 | In 2011, Tanzanians were affected by water and food shortages, and in 2017 the agricultural sector suffered a loss of approximately $200 million, causing food prices to increase by 12%. |
| Uganda | 1998–1999; 2005, 2008; 2010–2011; 2014–2019 | 5 | At least 200 000 Ugandans are affected every year due to drought conditions, and in 2010, the drought caused $1.2 billion of damage, which was equivalent to 7.5% of Uganda's GDP. |
| Southern Africa | | 53 | |
| Botswana | 1981–1984; 1990; 2005; 2012–2013; 2014–2020 | 5 | In 2015, some areas experienced decreased water pressure and the water supply was cut-off in some areas, and in 2019, 40 000 cattle died and it led to a 70% drop in land cultivation. |
| Lesotho | 1968; 1983; 1990; 2002; 2007; 2011; 2015–2020 | 7 | In 2019, approximately 71 000 people suffered from food insecurity, and in 2020 approximately 500 000 people were threatened with hunger; it is estimated that more than 30% of the population will experience acute food insecurity. |

**Table 2.1.** *Cont.*

| Region/Country | Drought Years | Number of Events | Droughts Effects |
|---|---|---|---|
| Malawi | 1987; 1991–1992; 2001–2002; 2005–2007; 2012; 2016–2017 | 6 | In 2016, maize production decreased by 12%, leading to food shortages. In 2017, 6.5 million Malawians were food insecure due to poor agricultural seasons. |
| Mauritius | 1999; 2011–2013 | 2 | The agricultural sector lost $160 million in 1999 due to crop failure, and in 2011, only 15–20% of the harvest was viable. |
| Namibia | 1981; 1990; 1995; 1998; 2001; 2002; 2013; 2015–2020 | 8 | In 2013, 463 581 people suffered from food insecurity, and in 2019. the Agricultural Bank of Namibia's employment opportunities from the agricultural sector decreased from 34% in 2012 to 23%. |
| Seychelles | 1998–1999; 2010–2011 | 2 | The 1998 drought led to the bleaching of 90% of the coral reefs. |
| South Africa | 1964; 1986; 1988; 1990; 1995; 2004; 2015–2019 | 7 | The worst drought experienced in 30 years occurred in 2015, and in 2018, approximately 3.7 million South Africans were affected by drought, leading to cut-offs of water supply in certain areas and to nation-wide water restrictions. |
| Swaziland | 1981; 1984; 1990; 2001; 2007; 2014–2020 | 5 | In 2016, 80 000 cattle died and maize production dropped by 67% between 2015 and 2016, while in 2017, 308 059 people suffered from food insecurity. |
| Zambia | 1981; 1983; 1990–1995; 1999–2002; 2004–2005; 2015–2020 | 6 | The drought in 1981 led to a disruption in maize production, which led to severe famine, and in 2019, 1.3 million people needed food aid, as maize production dropped from 2.4 million tons to 2 million tons, and there was a disruption in hydropower generation. |

**Table 2.1.** *Cont.*

| | | | |
|---|---|---|---|
| Zimbabwe | 1981–1983; 1986–1987; 1991–1992; 2010–2011; 2015–2020 | 5 | In 2019, 2.3 million Zimbabweans needed food aid; maize production dropped by more than 70%, compared to 2017/18, and the death of livestock affected 2.2 million people in cities and 5.5 million people in rural villages. |

Droughts and climate variability cannot be completely understood without understanding their impacts on the environment and on society (Bijeesh & Narasimhamurthy, 2020). It is important to monitor the trends and to profiling their impact on the surface water resources, as this helps to make informed decisions in order to address and mitigate the impacts (Abiy *et al*., 2019). Understanding the impacts of historical droughts can assist with future predictions or the development of possible adaptation and mitigation measures. Advancements in technology and using remotely sensed data has expanded our ability to monitor droughts and surface water resources. Thus, the use of remote sensing to monitor droughts and/or climate variability and surface water resources has been on the rise, which is promising for the future.

## 2.5 Advancements in Remote Sensing Systems and their Role in the Monitoring of Droughts, Climate Variability and Surface Water Resource in Sub-Saharan Africa

Before the launch of satellites, aerial photographs were taken on board low-orbiting aircraft to map the spatial distribution of land cover types. The first Landsat satellite was launched in 1972, and since then, remote sensing has been used to monitor changes in the land surface and to provide accurate information to ecologists, geologists, hydrologists, forest managers and soil scientists (Menarguez, 2015). Historically, aerial photography provided high-resolution spatial data, but with a low frequency, and the images were only updated every few years, with a limited spectral range. However, with the improvements in technology, aerial photography now provides high-resolution spatial data, with a high temporal frequency and a wide spectral range (Huang *et al.*, 2018).

Currently, various satellites are in orbit, which provide data at different resolutions; they can be used for the monitoring of water resources, as well as for assessing droughts and climate variability. The different sensors are provided in Table 2.2. For example, the Moderate Resolution Imaging Spectroradiometer (MODIS) has a swath width of 2 330 km, a revisit period of 1–2 days, and 36 spectral bands, with a spatial resolution of 250–1000 m (Table 2.2) (Huang *et al.,* 2018). Surface waterbodies are usually detected at 500 m by using the Green and Shortwave Infrared (SWIR) bands of MODIS, which have a spatial resolution of 500 m; therefore, the detection of surface waterbodies that are smaller than 4 km$^2$ is problematic (Che *et al*., 2015; Li *et al*., 2013). Since there are numerous surface waterbodies in Africa that are smaller than 4 km$^2$, they are likely to be poorly detected when using these data, thereby rendering MODIS unsuitable for such applications. Although the sensor has limitations for small waterbodies, MODIS can record the frequency and distribution of cloud cover, and it can measure other properties, such as the distribution and size of aerosols in the atmosphere, liquid water and ice clouds. MODIS also measures the photosynthetic activity of land and marine plants (phytoplankton), which makes this satellite suitable for monitoring lakes. A study conducted by Moser *et al*. (2014) monitored the surface waterbodies in Burkina Faso by using MODIS data to generate a time series from 2000 to 2012, with a temporal frequency of eight days. The results were validated by using Landsat imagery to create a water mask, and an accuracy of 75.7% was achieved. In a different study, d'Andrimont and Defourny (2018) used MODIS data to monitor surface waterbodies across the entire African continent, from 2004 to 2010, using daily observations. They used a surface water detection method to derive indicators that describe the location, temporal characteristics and inter-annual variations. The results were cross-validated with the existing maps and water products, and a commission error of less than 6% was associated with the findings. In addition, studies by Caccamo *et al*. (2011), Klisch and Atzberger (2016), Qu *et al*. (2019) and Henchiri *et al*. (2020) found that MODIS data were successfully used to monitor meteorological, hydrological and agricultural drought conditions in Australia, China, Kenya, North and West Africa and the Horn of Africa. Henchiri *et al.* (2020) conducted a study in North and West Africa to evaluate the performance of the MODIS data used to monitor meteorological and agricultural droughts from 2002–2018. The spatial correlation analysis indicated that the Drought Severity Index (DSI) was unreliable in the detection of meteorological droughts in North and West Africa; however, an association analysis between the Normalized Vegetation Supply Water Index (NVSWI) and the Normalized Difference Vegetation Index (NDVI), as well as the NVSWI and DSI, efficiently monitored the meteorological and hydrological droughts in that region. Qu *et al.* (2019) used MODIS data from the years 2000 to 2017 to monitor the meteorological and agricultural drought conditions in the Horn of Africa (HOA). The results of the study indicated that the croplands deteriorated due to the drought conditions, and there was therefore an urgent need for sustainable solutions to assist with the timely monitoring of droughts and to determine the severity of food security. Studies by Yan *et al.* (2010) and Berge-Nguyen and Cretaux (Berge-Nguyen & Cretaux, 2015) used MODIS data to detect floodplain inundation from 2001 to 2006 and from 2000 to 2013, respectively. A study by Berge-Nguyen and Cretaux (2015), monitored floodplain inundation over the Inner Niger Delta, using MODIS data from 2000–2013. They were able to describe inundations in the delta and to separate the flooded areas in the Inner Niger Delta into open water and the mixture of water and dry land. This study indicated that the MODIS data are able to detect surface waterbodies and to monitor the earth's surface efficiently, due to its short repeat time and wide coverage. However, its coarse spatial resolution causes a low accuracy, which may make it unsuitable for monitoring droughts and climate variability, as well as smaller surface waterbodies.

The Advanced Very High Resolution Radiometer on-board National Oceanic and Atmospheric Administration satellite (NOAA/AVHRR) has a coarse resolution, but has a high temporal resolution of 0.5 days and a relatively high spatial resolution of 1 100 m (Table 2.2) (Huang *et al.*, 2018). NOAA/AVHRR was designed to monitor the ocean and the atmosphere. Unganai and Kogan (1998) were able to monitor meteorological drought conditions in southern Africa by using NOAA/AVHRR data. However, heavy cloud contamination reduced the accuracy of the results. Anyamba and Tucker (2005) calculated the Normalized Difference Vegetation Index (NDVI) by using NOAA/AVHRR data in the Sahel, situated in Northern Africa, from 1981 to 2003, to improve the understanding of the persistence and spatial distribution of meteorological drought conditions. Rojas *et al.* (2011) used the NOAA/AVHRR-derived NDVI and the Vegetation Health Index (VHI) for Africa, to monitor agricultural droughts from 1981 to 2009 and to observe changes in the climate. The study demonstrated the use of these sensors to identify high risk areas for droughts, though the coarse resolution led to a low accuracy in small study areas. The NOAA/AVHRR data may therefore not perform optimally in monitoring drought and climate variability, due to their coarse resolution and susceptibility to cloud contamination. On the other hand, the Medium Resolution Imaging Spectrometer (MERIS) was designed to monitor ocean and land surfaces by using optical sensors to detect water or floods. It has a spectral resolution of 300 m, has 15 spectral bands and a temporal resolution of three days (Table 2.2). This satellite only has a 10-year data record, ranging from 2002 to 2012, and is therefore not recommended for the long-term monitoring of surface waterbodies (Huang *et al.,* 2018), due to its limited data records and its failure to provide near real-time data. MERIS data have been applied in water quality monitoring, especially in southern Africa. For instance, a study by Matthews *et al*. (2010) used MERIS data to monitor the water quality and cyanobacteria-dominated algal blooms in near-real-time in Zeekoevlei, a lake situated in Cape Town, South Africa. Chawira *et al*. (2013) efficiently monitored the water quality in two lakes in Zimbabwe, namely Chivero and Manyame, from 2011 to 2012, and found that MERIS is suitable for the near-real-time monitoring of water quality parameters, due to its ability to predict chlorophyll-a ($R^2 = 0.91$).

The Systeme Probatoire d'Observation dela Tarre (SPOT) has four to five spectral bands, with a relatively high spatial resolution ranging from 5.5 to 20 m and a temporal resolution of 26 days (Table 2.2) (Huang *et al*., 2018). However, the data is not freely available, thereby limiting its application in the detection of surface waterbodies and flood inundation. Haas *et al*. (2009) used SPOT data to monitor temporary waterbodies in sub-Saharan West Africa from January 1999 to September 2007. The data had an overall accuracy of 95.4% and produced satisfactory results. IKONOS, RapidEye and Quickbird are commercially available, high spatial resolution sensors, but due to their small scene coverage and low revisit time, only small surface waterbodies can be detected (Table 2.2). They are thus unable to detect large surface waterbodies, and their performance in urban and mountainous areas is weak, due to shadows, thus limiting their application in surface water monitoring on a large spatial scale (Huang *et al*., 2018).

As previously mentioned, the first Landsat mission was launched in 1972 and has since been supplying medium-resolution images (Bijeesh & Narasimhamurthy, 2020). Additional Landsat satellite missions were launched in the late 1970s and 1980s (USGS, 2020). The early Landsat satellites consisted of the Multispectral Scanner (MSS) sensors, followed by the Thematic Mapper (TM) on Landsat 4 and Landsat 5. Landsat 7 was launched in 1999 and was comprised of the Enhanced Thematic Plus (ETM+) (USGS, 2020). These Landsat missions were often used to detect surface waterbodies and changes on the earth's surface (Bijeesh & Narasimhamurthy, 2020). Landsat 8 was launched in February 2013 and consists of the Operational Land Imager (OLI) and the Thermal Infrared Sensor (TIRS). Landsat 8 has a spatial resolution of 30 m and a 15 m panchromatic band, which is a greyscale image that covers the red, green and blue portions of the electromagnetic spectrum (Forkour *et al*., 2018). It has a temporal resolution of 16 days and a swath width of 185 km, with nine reflective wavelength bands, and six of these bands are designed for land application (Table 2.2). It has a push-broom nature of scanning the earth's surface, which means that the satellite scans along the track design, therefore improving the sensitivity of critical surface features and reducing the problem of saturation. Although many studies have been conducted by using the Landsat OLI data to monitor and detect surface waterbodies, few of these have been conducted in Africa, and most of the studies have focused on monitoring the water quality. Zhou *et al*. (2017) and Masocha *et al*. (2018) successfully applied the OLI data to detect and monitor surface waterbodies, with a high accuracy. These results from various studies indicate that Landsat satellites have a relatively high spectral and spatial resolution, which is ideal for tracking land use and land cover change caused by climate change, droughts, wildfires, urbanization and other natural and human-caused changes. The use of these data for drought or climate variability monitoring remains rudimentary, particularly in sub-Saharan Africa, despite its potential to revolutionize and improve our understanding of the region.

The Sentinel-2 sensor, which was launched in June 2015, provides the required spatial data continuity for climate variability and drought monitoring, in addition to SPOT and Landsat missions, among others (Bijeesh & Narasimhamurthy, 2020). It consists of a Multispectral Instrument (MSI) and has 13 reflective wavelength bands, four 10 m visible and near-infrared (NIR) bands, six 20 m red edge, near infrared and shortwave infrared (SWIR) bands, and three 60 m bands (Bijeesh & Narasimhamurthy, 2020). Sentinel-2 has a temporal resolution of five days and has a swath of 290 km (Table 2.2). The data from the sensor have been used extensively in the monitoring of surface waterbodies (Yang *et al*., 2017; Zhou *et al*., 2017; Forkour *et al*., 2018). Forkour *et al*. (2018) used Sentinel-2 MSI data to map the Land Use and Land Cover (LULC), and to differentiate between waterbodies and non-waterbodies, in Burkina Faso, and it achieved an overall accuracy of 94.3%. In addition, different studies were conducted by Dotzler *et al*. (2015), Laurin *et al*. (2016), Urban *et al*. (2018) and Puletti *et al*. (2019) to monitor drought conditions, using Sentinel-2 data. For example, Dotzler *et al*. (2015) used the Sentinel-2-derived Photochemical Reflectance Index (PRI), Moisture Stress Index (MSI), Normalized Difference Water Index (NDWI) and Chlorophyll Index (CI) to analyse the response of deciduous trees to drought conditions in the Donnersberg region, in Germany. The results highlighted the benefits of the high spectral resolution of Sentinel-2 data for monitoring droughts and climate variability. A study by Urban *et al*. (2018) used Sentinel-1/-2 and Landsat 8 data from March 2015 to November 2017 to investigate the spatiotemporal dynamics of surface moisture and vegetation structure. The study found that it is vital to use land cover and vegetation information for analysing the dynamics of surface water and for understanding the effects of droughts on surface waterbodies, and it is therefore suited for monitoring droughts and climate variability, particularly in southern Africa. In another study, Laurin *et al.* (2016) used Sentinel-2 data to differentiate forest types, dominant tree species and the water used by plants in Ghana, by using various indices. The results were generated by using a Support Vector Machine and achieved an overall accuracy of 92.34%. These high accuracies indicate that this sensor is suitable for monitoring waterbodies, droughts and climate variability, due to its high spectral, spatial, and temporal resolution and therefore its use and application needs to be tested further in Africa; more particularly, in sub-Saharan Africa.

Table 2.2 Summary of remote sensors discussed

| Sensor | Swath Width (km) | Temporal Resolution (Days) | Number of Bands | Spatial Resolution (m) | Data Availability | Uses | Challenges |
|---|---|---|---|---|---|---|---|
| Moderate Resolution Imaging Spectroradiometer (MODIS) | 2330 | 1–2 | 36 | 250–1000 | 1999–present | Measures distribution and size of aerosols, liquid water and ice clouds, can also measure phytoplankton activity, floods, surface waterbodies and droughts. | Coarse spatial resolution, therefore, cannot detect waterbodies smaller than 4 $km^2$. |
| National Oceanic and Atmospheric Administration's Advanced Very High Resolution Radiometer (NOAA/AVHRR) | 2900 | 0.5 | 5 | 1100 | 1978–present | Able to monitor floods, surface waterbodies, clouds, sea surface temperature and vegetation greenness. | Coarse spatial resolution and susceptible to cloud contamination. |
| Medium Resolution Imaging Spectrometer (MERIS) | 1150 | 3 | 15 | 300 | 2002–2012 | Monitors ocean and land surfaces, water quality and occurrence of floods. | Has a 10-year data record and therefore cannot be used for long-term and near real-time monitoring. |
| Systeme Probatoire d'Observation dela Tarre (SPOT) | 60 | 26 | 4–5 | 20–5.5 | 1986–present | Used to detect surface waterbodies and flood inundation. | Data is not freely available and can only detect small waterbodies, due to small scene coverage. |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| IKONOS | 11 | 1.5–3 | 5 | 1–4 | 1999–present | Can map natural disasters, land cover changes and almost all aspects of environmental studies. | Data is not freely available and can only detect small waterbodies, due to small scene coverage. |
| RapidEye | 77 | 1–5.5 | 5 | 5 | 2008–present | Can be used in agriculture, forestry, mining and hydrological studies. | Data is not freely available and has limited application for monitoring large waterbodies, due to small scene coverage. |
| Quickbird | 16.8/18 | 1–3.5 | 5 | 0.61–2.24 | 2001–2015 | Used for environmental studies to monitor changes in land use, agriculture and forests. | Has a 14-year data record and data is not freely available. |

**Table 2.2.** *Cont.*

| Sensor | Swath Width (km) | Temporal Resolution (Days) | Number of Bands | Spatial Resolution (m) | Data Availability | Uses | Challenges |
|---|---|---|---|---|---|---|---|
| Landsat 1 | 185 | 18 | 4 | 60 | 1972–1978 | Designed to monitor the earth’s resources, such as water resources and agriculture. | Problem of cloud cover. |
| Landsat 2 | 185 | 18 | 4 | 80 | 1975–1982 | Used to monitor changes on land surfaces, seas and water resources. | Technical issues caused it to be decommissioned. |
| Landsat 3 | 185 | 18 | 4 | 80 | 1978–1983 | Designed to extend data acquisition of the earth’s resources by Landsat 1 and 2. | Became decommissioned. due to equipment failure. |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Landsat 4 | 185 | 16 | 7 | 30 | 1982–1993 | Designed to provide global satellite data on the earth's resources. | Banding affected data. |
| Landsat 5 | 185 | 16 | 7 | 30 | 1984–2013 | Used to observe and monitor earth's land and coastal areas. | Data loss occurred due to technical issues. |
| Landsat 6 | 185 | 16 | 8 | 15–30 | 1993 | Designed to continue the Landsat mission. | Failed to reach orbit. |
| Landsat 7 | 185 | 16 | 8 | 15–30 | 1999–present | Aimed to improve and extend medium-resolution data record of the earth's surfaces. | Issues of cloud cover affects data. |
| Landsat 8 | 185 | 16 | 9 | 15–30 | 2013–present | Designed to continue to provide medium-resolution data of the earth's surfaces and monitor land changes, due to climate change, urbanization, drought, wildfires and other natural and human-caused changes. | Clouds contaminate images. |
| Sentinel-1 | 400 | 6–12 | 1 | 5 | 2014–present | Developed to provide data continuity for the SPOT and Landsat missions and used to monitor changes on the earth's surface. | Satellite images may suffer from cloud contamination. |

**Table 2.2.** *Cont.*

| Sensor | Swath Width (km) | Temporal Resolution (Days) | Number of Bands | Spatial Resolution (m) | Data Availability | Uses | Challenges |
|---|---|---|---|---|---|---|---|
| Sentinel-2 | 290 | 5 | 13 | 10–60 | 2015–present | Used for land monitoring for mapping land cover and detecting land changes and to monitor vegetation and burned areas. | Cloud contamination affects images. |
| Sentinel-3 | 1270 | 1–27 | 21–11 | 300–1000 | 2016–present | Designed to measure sea surface topography, as well as sea and land surface temperature for environmental and climate monitoring. | Data missing due to anomalies. |
| Sentinel-4 | 8 | 0.1 | 3 | 0.5 nm–0.12 nm | 2019–present | Designed to monitor air quality trace gases and aerosols over Europe. | Only monitors Europe and does provide global data. |
| Sentinel-5 | 2670 | 16 | 7 | 5.5–7 | 2017–present | Aimed to monitor trace gas concentrations for atmospheric chemistry and climate changes. | Data anomalies due to issues onboard. |
| Sentinel-5P | 2600 | 1 | 7 | 8–50 | 2018–present | Designed to provide data delivery for atmospheric services between 2015–2020. | Data anomalies due to issues onboard. |

The above review shows that there has been an increase in the number of studies that are applying remote sensing data in the monitoring of the quantity and quality dynamics of surface water resources, as well as drought and climate variability. However, in resource-constrained regions such as Africa, most studies have taken advantage of the readily-available satellite data, such as NOAA/AVHRR, MODIS and Landsat, as well as the relatively long-term data record of some of the sensors e.g. Landsat (>40 years). Unlike the aforementioned sensors, IKONOS, SPOT and QuickBird have a coarse temporal resolution and are commercially available, thereby limiting their application in water-related studies in resource-constrained environments such as Africa. Deciding on which data set to use will depend on the type of study and the scale of monitoring. Therefore, there is a need to test the applicability of freely-available satellites for monitoring water resources, droughts and climate variability over large areas. With the technological advancements, sensors that have a higher temporal, spectral and spatial resolution need to be designed to integrate multi-datasets for monitoring water resources and to make remote sensing a more viable option.

## 2.6 Remote Sensing Products for the Monitoring of Droughts and Climate Variability

With the advancements in technology, there has been an increased use of satellite images for various water-related studies (Bijeesh & Narasimhamurthy, 2020). For instance, advancements in the development of water indices, in analysis or integration techniques, and in the availability of multi-temporal and multi-spectral images, mean that it is easier to detect changes in surface waterbodies (Du *et al*., 2014). It also enables the monitoring of various aspects of hydrology, such as precipitation, evapotranspiration, soil moisture, groundwater, water quality and surface water variability. Although rain gauges are the main source of rainfall data, the networks are inadequate in many sub-Saharan African countries, due to their sparse distribution. The limited networks are therefore unable to provide reliable data and to produce detailed rainfall information over a large spatial scale. On the other hand, rainfall can be estimated by using satellite data, which provide information in near real-time and give more spatially distributed estimates (Michaelides *et al*., 2009). The most common satellites used to estimate precipitation are the Climate Hazards Group Infra-Red Precipitation with Stations (CHIRPS), the Tropical Rainfall Measuring Mission (TRMM), the Meteosat-8, Geostationary Operational Environmental Satellite (GOES), the Tropical Applications of Meteorology using Satellite data and ground-based observations (TAMSAT) and the Special

Sensor Microwave Imager (SSM/I) (Jin *et al*., 2013). Dinku *et al*. (2018) compared the performance of the CHIRPS data, the African Rainfall Climatology Version 2 (ARC2) and the TAMSAT data over Ethiopia, Kenya, Somalia, Uganda, Rwanda and Tanzania, and the results indicated that CHIRPS had the highest accuracy, although it often overestimated the precipitation. In addition, a study by Seyama *et al*. (2019) evaluated TAMSAT data in southern Africa to accurately estimate the precipitation and found that the algorithm needs improvement in the accurate detection of high precipitation events. Measuring evapotranspiration is important for modelling hydrological processes and climate change and for estimating evapotranspiration by using physically-based methods (Chappell *et al*., 2013). Using remote sensing techniques to estimate evapotranspiration has been done by using various sensors, such as the AVHRR, MODIS and Landsat (Chappell *et al*., 2013). A study by Kiptala *et al*. (2013) used MODIS data and the Surface Energy Balance Algorithm of Land (SEBAL) model to estimate the actual evapotranspiration for 16 land use types from 2008 to 2010 in the Upper Pangani River Basin, which is shared by Kenya and Tanzania. The study indicated that there was a good agreement of the different validations and it achieved a correlation coefficient of 0.74. On the other hand, Alemayehu *et al*. (2017) used daily MODIS data and Global Land Data Assimilation System (GLDAS) to effectively estimate the evapotranspiration in the Mara River Basin, which is shared by Kenya and Tanzania.

Soil moisture is vital for understanding and predicting the variations in surface temperature, droughts, floods, the impacts of climate change and weather forecasting (Roback *et al*., 2000). Soil moisture controls the rate and amount of precipitation infiltrating into the soil and recharging into aquifers (Muller, 2014). Remote sensing techniques are preferred over ground-based methods for monitoring soil moisture, as they have a wider spatial scale (Muller, 2014). In this regard, the Normalized Difference Vegetation Index (NDVI) and Land Surface Temperature (LST) are the most common parameters used to remotely estimate soil moisture, with MODIS, Landsat and Soil Moisture Active Passive (SMAP) being the most popular satellites (Fontanet *et al*., 2018). For example, Xulu *et al.* (2018) used the MODIS-derived Normalized Difference Vegetation Index (NDVI) and precipitation data for KwaMbonambi, northern Zululand, from 2002 to 2016, to understand the effects of droughts on the forest resources, by using remote sensing techniques. The results were validated by using multiple linear regression and Mann–Kendall tests, which proved to be reliable indicators for temporal drought conditions and which efficiently characterized the plantations and their response to climate variability. A study by Ugbaje and Bishop (2020) used remote sensing observations of soil moisture and ancillary climatological data to assess the impact of hydrological controls on the vegetation greenness dynamics over Africa, from 2003 to 2015. To do this, the study used daily soil moisture data from the European Space Agency Climate Change Initiative data portal, which was resampled to co-register with the MODIS EVI data. The accuracy was assessed by comparing the out-of-bag prediction of EVI against the observed values, and it was found that it is one of the robust ways of assessing the importance of hydrological variables.

Groundwater is a vital component of the hydrological cycle, as it contributes significantly to the water resources, as well as to agriculture and to the health of ecosystems (Yeh *et al*., 2006). Despite the increasing use of remote sensing-based methods for monitoring groundwater, such as the Gravity Recovery and Climate Experiment (GRACE) and Thermal Airborne Spectrographic Imager (TASI), traditional methods are still popular for studying the groundwater–surface water interactions (Agutu *et al*., 2019). Munch & Conrad (2007) combined remote sensing and GIS techniques to create a GDE (Groundwater Dependent Ecosystem) probability rating map for the Sandveld region in South Africa, by using Landsat TM imagery. The results provided useful information and it proved to be a cost-effective solution; however, the imagery was unsuitable for the detailed mapping of GDE features. Nanteza *et al*. (2016) integrated the GRACE and Lake altimetry data within a soil moisture model to compare GRACE-derived groundwater storage changes to in-situ groundwater observations in East Africa, from 2003 to 2011. The results proved that GRACE data are efficient in monitoring groundwater resources in data-scarce and hydrologically-complex regions. The results indicated a 0.6 correlation between GRACE-derived data and in-situ data, which suggests that the results are fairly accurate, despite the overestimation of groundwater by GRACE. A similar study by Bonsor *et al.* (2018) found that changes in groundwater storage of 12 sedimentary aquifers in Africa could be monitored by using GRACE data, combined with the physical datasets derived from Land Surface Models (LSMs). In another study, Agutu *et al.* (2019) found a strong link between GRACE-derived groundwater changes and climate variability in the Greater Horn of Africa, based on a 10-year dataset. Specifically, GRACE-derived groundwater changes correlated well ($R^2 = 0.7$) with the results from the WaterGap Hydrological Model (WGHM), which further indicates the potential of GRACE in groundwater monitoring. Using the GRACE data from 2003 to

2016, Frappart (2020) characterized the dynamics in groundwater storage that occurred in the major North African transboundary aquifers. In the study, a moderate correlation ($R^2 = 0.5$) was observed between GRACE and the Tindouf Aquifer System (TAS), with the correlation being attributed to the small size of the system. This implies that the coarse spatial resolution of GRACE is problematic for monitoring the groundwater resources of small areas. A recent study by Skaskevych *et al*. (2020) assessed the feasibility of the GRACE-based estimation of groundwater storage changes in the Ngadda Catchment in the Lake Chad Basin and demonstrated that GRACE-based modelling is a cost-effective method for monitoring groundwater changes. While important insights have been gained from using this sensor, its coarse resolution limits its application over finer spatial scales. There is therefore a need to improve the spectral, spatial and temporal resolutions of this sensor, in order to overcome some of its shortfalls and to enable its use in the monitoring of water resources, drought and climate variability in near real-time. In fact, the potential of high-resolution images, i.e. Landsat-8 and MODIS, in the monitoring of groundwater is promising, as demonstrated by Nhamo *et al*. (2020) in a study that quantified groundwater use by crops in the Venda-Gazankulu region of the Limpopo Province, South Africa.

## 2.7 Current Remote Sensing-based Approaches for Monitoring Drought and Surface Water Resources

Droughts and surface waterbodies can be monitored by using traditional physically-based methods and/or remote sensing methods. Physically-based methods for the monitoring of droughts include paleoclimatology and recording meteorological data, such as rainfall, river flow and soil moisture (d'Andrimont & Defourny, 2018). Paleoclimatology takes advantage of the past climatic conditions by using data records from ice sheets, tree rings, sediments, rocks, diatoms and corals to understand the past climates and to predict future climate conditions (Bruckner, 2020). However, the most common paleoclimatic datasets used for drought monitoring are tree rings and peat lands. Physically-based methods of surface water monitoring are in-situ measurements, which include the manual measurement of water levels using equipment such as floats, sensors, buoy systems, pressure type equipment and ultrasonic and radar techniques (Chapuis, 1998; Janke *et al*., 2006; Donald *et al*., 2008). Remote sensing uses cameras on satellites and airplanes, as well as sonar systems on ships, to obtain remotely sensed images, by measuring their reflected and emitted radiation at a distance to detect and monitor the physical characteristics (USGS, 2020). Computer models use paleoclimate data as a framework on which to base these models (Bruckner, 2020). However, physically-based methods are costly, time-consuming and the equipment cannot be installed in remote or mountainous areas, thus the use of satellite data for monitoring surface waterbodies is increasing, due to its ability to make high-frequency and repeatable observations at a low cost (Li *et al*., 2013).

### 2.7.1 Traditional drought and surface waterbody monitoring techniques

Dendroclimatology is the study of determining past climates from tree rings. The use of tree ring data is widely used in the highland and lowland environments of the Mediterranean Basin, the Middle East and Asia. Although it is often used as a means to validate remote sensing data in other countries (Bradley, 2011), this method is not often used for drought studies in sub-Saharan Africa, because there are still many methodological problems pertaining to its use (Wils *et al*., 2011). Measuring and recording the surface water levels can be done by using various types of recording sensors, which are often used across Africa, such as bubblers, pressure transducers and ultrasonic sensors; the results from these sensors can be recorded directly into a data logger, or into a specialized flow meter (Donald *et al*., 2008). Bubblers are sensors in which air, or an inert gas, is forced through a small bubble line that is submerged in a river channel, and they measure the water level by determining the pressure needed to force air bubbles out of the line (West *et al*., 2019). Pressure transducers use a probe that is fixed to the bottom of the channel and that senses the pressure of the overlying water (Donald *et al*., 2008). Ultrasonic sensors, or ground-based weather radar, are placed above the flow stream and transmits a sound pulse that is reflected by the surface of the flow, and the time it takes between sending the pulse and receiving an echo determines the water level (Donald *et al*., 2008). The ground-based weather radar has been used to detect precipitation by sending out pulses of microwave energy in narrow beams that scan in a circular motion, and when these pulses encounter precipitation particles, the energy is scattered in all directions, and some of this energy is sent back to the radar (World Bank Group, 2020). The energy that is measured is then used to estimate the intensity, altitude, type of precipitation and motion. These different types of recording sensors provide the measurements of dam levels and other surface waterbody levels, such as rivers and lakes. These measurements indicate changes in the water levels, and if there is a drastic drop in the water levels associated with low levels of precipitation, it could mean that there is an onset of drought conditions. Rain gauges are the most common physically-based method for measuring the amount of precipitation received (World Bank Group, 2020). Rain gauge measurements are point-based and measure the amount of precipitation received at a specific location. They can be classified into non-recording rain gauges and recording rain gauges. Non-recording rain gauges collect precipitation, but do not record the amount of precipitation, while recording rain gauges automatically record the amount of precipitation on graph paper and note the duration of rainfall events. However, manual measurements are not effective, due to human error and point-based measurements that might not be representative of the entire area, as precipitation might fall more, or less, intensely at the location of the gauge (Alsdorf *et al*., 2007). Physically-based readings are often difficult to record during drought periods as the accuracy of the readings decreases; however, if the water levels are high, they are easier to record (Huang *et al*., 2018). Damage to equipment may also induce measurement errors. As the measuring equipment is in direct contact with the water, its life span is limited, due to the chemical and physical properties of water, such as corrosion, underwater pressure and the composition of the water. This causes physically-based techniques to be costly and time-consuming (Nirupam *et al*., 2015).

### 2.7.2 Remote sensing techniques for drought monitoring

Due to its wide coverage, repeatable observations, multi-band features, as well as its applicability on a local and global scale, both in data-rich and data-poor areas, the use of remotely sensed data and, more specifically, the spectral water indices derived from multispectral sensors, is a promising approach for the monitoring of droughts (Xulu *et al*., 2018; Palmer *et al*., 2015). Remote sensing is an important tool that provides consistent and continuous data (Rhee *et al*., 2010; Jiao *et al*., 2019). Radar altimetry has been used for more than 10 years to monitor the elevation changes in surface waterbodies, such as inland seas, lakes, rivers and wetland zones (Crétaux & Birkett, 2006). Altimetry data can be used to monitor changes in the surface water storage (Khaki & Awange, 2020). The surface water is measured with a repeatability that varies from 10 to 35 days, depending on the satellite (Crétaux & Birkett, 2006). Weather conditions do not affect the data collection; however, altimetry does not have a global view and has several limitations. Varying topography and complex terrains reduce the accuracy of the elevation data, and the target size and surface roughness affect the accuracy of altimetry-derived data, which therefore limits global surveying (Crétaux & Birkett, 2006). The use of altimetry data is limited to the monitoring of rivers that are wider than 1 km, due to its low temporal and spatial resolution, and thus the accurate monitoring of smaller waterbodies is challenging (Sulistioadi *et al*., 2015). Recent studies have focused on developing indices for the reliable detection of droughts and for identifying surface waterbodies by using satellite data (Huang *et al*., 2017). These indices are applied in the early detection of the onset, intensity, cessation, duration and spatial extent of droughts, as well as in mapping the surface waterbodies (Huang *et al*., 2017). A suite of indices exists, and each has its own advantages and weaknesses (Jiao *et al*., 2019). In this study, a number of indices were selected, based on their performance, as reported in literature (Tables 2.3 and 2.4).

Advances in remote sensing and its associated indices (algorithms) provide an alternative source of data. These indices are obtained from satellite-based infrared (IR), passive microwave (PMW) or spaceborne precipitation radar (PR) data. Drought conditions can be identified by using a drought index, which assesses the effects of a drought, as well as its intensity, duration, severity and spatial extent (Abiy *et al.*, 2019). These drought indices use meteorological data, such as precipitation, temperature and soil moisture data (Henchiri *et al*., 2020). Meteorological droughts have been detected by using the Standardized Precipitation Index (SPI), the Palmer Drought Severity Index (PDSI), the Standardized Precipitation Evapotranspiration Index (SPEI) and the Enhanced Vegetation Index (EVI) (Zhang *et al*., 2019). The indices used to detect hydrological droughts include the Palmer Drought Severity Index (PDSI), the Normalized Difference Vegetation Index (NDVI), the Anomaly Vegetation Index (AVI), the Normalized Difference Water Index (NDWI), Normalized Difference Drought Index (NDDI) and the Temperature Condition Index (TCI) [102]. Agricultural droughts can be detected by using the Palmer Drought Severity Index (PDSI), the Drought Severity Index (DSI), the Evapotranspiration Deficit Index (ETDI), the Vegetation Condition Index (VCI) and the Standardized Precipitation and Evaporation Index (SPEI) (Su *et al.*, 2016). Many indices have been developed for drought monitoring; however, the indices considered in this study are SPI, PDSI, NDVI, VCI and WRSI, which is based on their widespread use (Table 2.3).

The Standardized Precipitation Index (SPI) was developed by McKee *et al*. (1993) to monitor the status of droughts in Colorado and has since been used to monitor dry and wet conditions over various time scales (Wu *et al*., 2001). It is based on the long-term precipitation records for the study period and is then fitted to a probability distribution to ensure that the mean SPI is zero for the study period and location (McKee *et al*., 1993). Palmer (1965) developed the Palmer Drought Severity Index (PDSI) to quantify and compare the spatial and temporal drought characteristics across various regions (Jacobi *et al*., 2013). It uses precipitation and temperature data to estimate the moisture supply and demand within two soil layers. The Normalized Difference Vegetation Index (NDVI) measures the photosynthetic ability and productivity of plants, which is the difference between the near-infrared and red bands (Xulu *et al*., 2018). It has been widely used to evaluate drought conditions across the globe (Dong *et al*., 2014; Qu *et al*., 2019; Henchiri *et al*., 2020). The Vegetation Condition Index (VCI) was developed by Kogan (1995) to detect and track droughts by focusing on their impact on the vegetation. It records changes in the vigour of the vegetation by using the visible band and near-infrared bands, and compares it with the historical data. The VCI provides information on prolonged and short-term droughts. The Water Requirement Satisfaction Index (WRSI) was developed by the Food and Agriculture Organization (Bijeesh & Narasimhamurthy, 2020). The WRSI is the ratio of the actual evapotranspiration to the potential evapotranspiration and indicates the performance of crops, based on the water availability during the growing season (Legesse & Suryabhagavan, 2014; Suryabhagavan, 2017). It is used to monitor crop production in regions that suffer from famines.



Surface waterbodies can be identified by using optical sensors or microwave sensors. Optical sensors are used to calculate the differences between the spectral bands, and microwave sensors are dependent upon the reflection of water surfaces, relative to surrounding land surfaces; however, the return signals can be reduced by the waves on the water's surface (Huang *et al*., 2018). There are many methods of extracting surface waterbodies from remote sensing imagery, based on the principle of comparing the low reflectance of water, to land cover types with a higher reflectance in infrared channels. Water indices can be used to extract surface waterbodies, which are calculated from two or more bands, to distinguishing between waterbodies and non-waterbodies (Li *et al*., 2013; Zhou *et al*., 2017; Xulu *et al*., 2018). Many indices have been developed; however, only the following seven indices will be considered for this study, based on their performance in previous studies: the Normalized Difference Water Index (NDWI), the Modified Normalized Difference Water Index (MNDWI), the Land Surface Water Index VI (LSWI+5), the Modified Normalized

Difference Water Index VI (MNDWI+5), the Automated Water Extraction Index shadow ($AWEI_{sh}$), and the Automated Water Extraction Index non-shadow ($AWEI_{nsh}$) (Table 2.4).

The NDWI was introduced by McFeeters (1996) and it extracts waterbodies from the satellite data. Waterbodies have positive values and non-waterbodies have zero or negative values, and they are enhanced and suppressed, respectively (Sarp & Ozcelik, 2017). The MNDWI was proposed by Xu in 2006 [113] to improve the accuracy of the NDWI in built-up areas (Huang *et al*., 2018). The Near Infrared (NIR) band in the NDWI was replaced with the Shortwave Infrared (SWIR) band, because it reflects the subtle characteristics of water better (McFeeters, 1996), and it is less sensitive to the sediment concentrations in water than the NIR band (Sarp & Ozcelik, 2017). The LSWI+5 was introduced by Menarguez (2015) and is derived from the LSWI; it uses the NIR and SWIR portions of the electromagnetic spectrum. It was developed to identify flooding and waterbodies. MNDWI+5 was also introduced by Menarguez (2015) and uses the NIR and red bands to map flooding or clear water (Zhou *et al*., 2017). The AWEI, which can detect waterbodies, was introduced by Feyisa *et al*. in 2014. It includes two indices: the $AWEI_{nsh}$, is applied when there are no shadows, and the $AWEI_{sh}$ is applied to distinguish between the water pixels and shadow pixels.

However, the results of these indices are region-specific, and therefore certain indices will yield low accuracies due to cloud cover, pixel mixing and shadows in mountainous or built-up areas. Some indices also need to be used in conjunction with other indices and/or meteorological data, as they cannot account for factors such as evapotranspiration, runoff and infiltration. Therefore, the indices need to be improved, in order to improve the monitoring conditions, which will be useful for detecting the onset, duration and end of droughts.

Table 2.3 Drought indices used and their performance in previous studies

| Drought Index | Reference of Study | Key Findings | Limitations of Index |
|---|---|---|---|
| Standardized Precipitation Index (SPI) | Tirivarombo and Hughes (2011) | Rainfall data from 1960 to 2002 was used to calculate SPI for selected parts of the Zambezi River Basin, in Africa, for a comparative analysis of the relationship between agricultural droughts and food security. | Needs to be used with other indices, because it does not account for the deficits caused by evapotranspiration, infiltration and runoff. |
| | Chisadza *et al*. (2015) | SPI calculated for the Mzingwane Catchment, in the Limpopo River Basin, situated in southern Africa, by using rainfall data from 1999 to 2013 to determine the severity of droughts. | Achieved poor results over short study periods and achieved highly accurate results over longer study periods. |
| | Khezazna *et al*. (2017) | SPI indices calculated for 13 rainfall stations in the Seybouse Basin, Algeria, to differentiate between dry, normal and wet periods to analyse variations in the annual rainfall over the basin. | Required historical rainfall data. |
| | Tirivarombo *et al*. (2018) | SPI was able to detect temporal variations of droughts in the Kafue Basin, in northern Zambia. | SPI to be used with caution to characterize droughts, as it only uses rainfall data and not temperature data, and temperature data is important for characterizing droughts. |
| | Lawal *et al*. (2019) | Used SPI to quantify the severity of droughts in southern Africa. | Low accuracy achieved in regions where precipitation was low and over short time periods. |
| | Kalisa *et al*. (2020) | Calculated SPI over East Africa from 1920 to 2015. Adequately estimated dryness or wetness, and the study that proved it can be | Results highly variable for shorter time scales; however, for longer time scales, |

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| | | used to assess drought intensity, especially in drought-prone regions. | results were more accurate, therefore should be used for long-term studies. |
| Palmer Drought Severity Index (PDSI) | Mehta *et al*. (2014) | PDSI was correlated with the PDSI forecast by the MIROC5 Earth System Model (ESM) from 1961 to 2019–2020, to assess the accuracy of predictability across southern Africa. This method achieved efficient results. | Higher accuracies over longer study periods. Decadal results were more accurate. |
| | Zeleke *et al*. (2017) | PDSI obtained from station- and satellite-based observation data sets from the Ethiopian National Meteorological Agency (EMA) for drought monitoring in Ethiopia from 1979 to 2014. Accurate data indicated the drought periods. | Only accounted for drought impacts, based on temperature and precipitation data. |
| | Asfaw *et al*. (2018) | PDSI data collected from Climate explorer: KNMI Climate Change Atlas and used to analyse extent of meteorological drought from 1951–2013. Detected increase in drought years since the 2000s, in the Woleka sub-basin, situated in Ethiopia. | Short-term application is problematic, due to lower accuracies, compared to long-term application. |
| | Orimoloye *et al*. (2019) | PDSI used to identify the susceptibility of Cape Town, South Africa, to drought. | Less accurate in areas with extremely dry vegetation. |
| | Ogunrinde *et al*. (2020) | PDSI detected a hydrological drought approximately 12 months before the low flow occurred in the River Niger in Nigeria. | More effective in long-term monitoring of meteorological drought impacts than short-term monitoring. |

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| | Gelassie (2012) | Analysed NDVI to monitor the development of biomass in Amhara, Ethiopia, and found that NDVI can be used to estimate crop yields. | Noise presence due to cloud cover and shadows, which decreased the NDVI values. |
| | Tonini *et al*. (2012) | NDVI data collected by using SPOT 4 and SPOT 5 satellites from 1998 to 2009, and accurately identified which areas are more prone to drought in the Tigray region, Ethiopia. | Accuracies affected by the atmosphere, aerosol scattering, snow and cloud cover. |
| | Chisadza *et al*. (2015) | Evaluated vegetation condition and tracked drought severity and occurrence by using the GEONETCast ten-day composite, SPOT VEGETATION, NDVI (S10 NDVI) over the Beitbridge, Esighodini, Mangwe and Mwenezi districts in Zimbabwe, from 1998 to 2013. | Background brightness led to lower accuracies. |
| Normalized Difference Vegetation Index (NDVI) | Klisch & Atzberger (2016) | NDVI was calculated in Mandera and Garissa, Kenya, using MODIS data and successfully monitored vegetation. | High noise interference due to cloud cover. |
| | Lawal *et al*. (2019) | NDVI used to understand impacts of droughts on southern African vegetation and achieved efficient results. | Errors in seasonal NDVI data due to different algorithms used to translate measured wavelengths. |
| | Qu *et al*. (2019) | NDVI data derived from MODIS was used to investigate drought conditions in the Horn of Africa (Djibouti, Eritrea, Ethiopia and Somalia) from 2000 to 2017. | Mainly sensitive to vegetation greenness, therefore limited in monitoring drought directly. |

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| Vegetation Condition Index (VCI) | Unganai & Kogan (1998) | AVHRR/NOAA data was successfully able to monitor the temporal and spatial characteristics of drought conditions in southern Africa. | Cloud cover affected the drought signal. |
| | Gelassie (2012) | Examined spatial drought by using the VCI and found that drought can be detected and mapped in the Amhara region, Ethiopia, from 1999 to 2009. | Drought conditions can be monitored during the growing season. |
| | Ghoneim *et al*. (2017) | Used MODIS data to calculate the VCI and to assess spatial and temporal distribution of drought occurrence in Tunisia from 2000–2013 and accurately identified drought periods. | Problematic with the occurrence of excessive rain. |
| | Qu *et al*. (2019) | Investigated agricultural drought by calculating the NDVI from the MODIS data from 2000 to 2017 in the Horn of Africa (Djibouti, Eritrea, Ethiopia and Somalia) and achieved a 95% accuracy. | Cloud contamination affected accuracy. |
| | Frischen *et al*. (2020) | The VCI used to assess vegetation health and drought conditions in Zimbabwe, from 1989 to 2019 and found it detects the drought dynamics | Not suited for analysing one single season. |
| Water Requirement | Gelassie (2012) | The spatial distribution of droughts was examined by using the WRSI in Amhara, Ethiopia. | Ground truthing for crops and detailed crop calendar is essential, as well as a water balance calculation. |

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| Satisfaction Index (WRSI) | Moeletsi & Walker (2012) | The WRSI was used to quantify droughts in the Free State Province, South Africa, which affect rain-fed maize production. | The WRSI values in semi-arid areas are locality-dependent. |
| | Jayanthi *et al*. (2014) | The WRSI was used to monitor crop productivity in Southern Africa. | Limited hazard and exposure data; therefore, a long-term synthetic rainfall record had to be generated. |
| | Legesse & Suryabhagavan (2014) | The WRSI was used to assess the spatio-temporal variation in agricultural drought patterns in the East Shewa Zone, Ethiopia, and found to be a good indicator of agricultural drought. | Showed good results for agricultural drought, but further investigation is required for other types of droughts. |

Table 2.4 Surface waterbody indices used and their performance in previous studies

| **Surface Waterbody Index** | **Reference of Study** | **Key Findings** | **Limitations of Index** |
|---|---|---|---|
| Normalized Difference Water Index (NDWI) | El-Asmar *et al*. (2013) | Used MSS, TM, ETM+ and SPOT images to obtain the NDWI data to quantify change in the Burullus Lagoon in Egypt between 1973 and 2011, and accurately noted changes in size. | Had to apply radiometric normalization to adjust solar angles. |
| | Masocha *et al.* (2018) | Had an overall accuracy of 77% when extracting surface waterbodies from Landsat-8 | Cannot suppress the signal from built-up features efficiently. |

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| | | OLI data in the Mutiriki Catchment, Zimbabwe. | |
| | Orimoloye *et al.* (2019) | Used Landsat 8 data to derive the NDWI to assess drought occurrence in Cape Town, South Africa, from 2014 to 2018, and mapped changes in waterbodies. Results agreed with dam levels recorded by the City of Cape Town. | Does not consider soil type, geographic location and climate zone. |
| | Asfaw *et al.* (2020) | NDWI used to note changes in Lake Ziway, Ethiopia, from 2009 to 2018, using Landsat ETM+/OLI data and obtained an overall accuracy of 91%. | Problematic in urban areas with a higher reflectance. |
| | Fujihara *et al.* (2020) | Calculated the NDWI by using Landsat-8 data to classify land cover types in the Gash River, Sudan, and achieved a Kappa coefficient of 0.960, which is reasonably good. | Problematic in built-up areas, water features often confused with built up areas. |
| Modified Normalized Difference Water Index (MNDWI) | El-Asmar *et al.* (2013) | MNDWI data obtained from MSS, TM, ETM+, and SPOT images to quantify change in the Burullus Lagoon in Egypt between 1973 and 2011, and accurately noted changes in size. | Radiometric normalization applied to adjust solar angles. |
| | Malahlela (2016) | Landsat-8 data was used to calculate the MNDWI to extract waterbodies in South Africa, the Republic of Congo and | Classified shadows as waterbodies. |

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| | | Madagascar from 2013 to 2015, and achieved an overall accuracy of 78.4%. | |
| | Masocha *et al*. (2018) | Landsat-8 OLI data was used to map surface waterbodies in the Mutirikwi Catchment, Zimbabwe; it achieved an overall accuracy of 84.3%. | Higher performance in areas with vegetation, compared to other land covered surfaces. |
| | Asfaw *et al*. (2020) | Used the MNDWI to note changes in Lake Ziway, Ethiopia, from 2009 to 2018, using Landsat ETM+/OLI data, and obtained 99% overall accuracy. | Misclassified shadows as waterbodies. |
| | Ndehedehe *et al*. (2020) | Used Sentinel-2 data to calculate the MNDWI to detect changes in the Lake Chad Basin from 2015 to 2019, and achieved an overall accuracy of 97.4%. | Sensitive to water content in soil and vegetation. |
| | Slagter *et al.* (2020) | Used the MNDWI for wetland mapping and surface water dynamics in St Lucia wetlands, South Africa, using Sentinel-1 and Sentinel-2 data from 2016 to 2018, and achieved an overall accuracy of 87.1%. | Highly-vegetated areas led to lower accuracies. |
| Land Surface Water Index (LSWI+5) | Jin *et al.* (2013) | Used the MODIS data in southern Africa to monitor vegetation phenology from 1999 to 2009, and results agreed with in-situ data. | Problematic in built-up areas. |
| | Benefoh *et al*. (2018) | Used TM, ETM and OLI data to get a comprehensive understanding of the | Lower accuracies in dry regions. |

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| | | landscape in Ghana from 1986 to 2015. Results were correlated with in-situ data and achieved an overall accuracy of 82.6%. | |
| | Masocha *et al.* (2018) | Had an overall accuracy of 86% when mapping surface waterbodies in the Mutirikwi Catchment, Zimbabwe, and outperformed the other indices when applied to map surface waterbodies in subtropical catchments. | Further investigation required for performance in various climatic zones. |
| | Ali *et al.* (2020) | Used LSWI+5 to analyse plant and soil water content in various watersheds in Ethiopia from 2006 to 2016 from Landsat-7 data. | Cloud contamination affected results. |
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| Modified Normalized Difference Water Index (MNDWI+5) | Masocha *et al.* (2018) | Used to map surface waterbodies in the Mutirikwi Catchment, Zimbabwe, and had an overall accuracy of 79.3%. | Performed best in vegetated areas. |
| Automated Water Extraction Index (shadow) ($AWEI_{sh}$) and Automated Water Extraction Index | Feyisa *et al.* (2014) | Used Landsat-5 data to map waterbodies in South Africa, Ethiopia, Denmark, Switzerland and New Zealand, and achieved a Kappa coefficient of 0.98 and 0.97 in South Africa and Ethiopia, respectively. | Variables that were not tested and could affect accuracies, due to variations in the angle of the sun, atmospheric composition, and biophysical and chemical changes in waterbodies. |
| | Malahlela (2016) | Landsat-8 data was used to extract waterbodies in South Africa, Republic of Congo and | Classified shadows as water in built-up areas. |

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| (non-shadow) ($AWEI_{nsh}$) | | Madagascar from 2013 to 2015, and achieved an overall accuracy of 83.8%. | |
| | Masocha *et al*. (2018) | $AWEI_{sh}$ and $AWEI_{nsh}$ had an overall accuracy of 81.6% and 50.3%, respectively, when mapping surface waterbodies in the Mutirikwi Catchment, Zimbabwe. | $AWEI_{nsh}$ problematic due to background noise and unable to differentiate between waterbodies and built-up areas. |
| | Asfaw *et al*. (2020) | Used Landsat ETM+/OLI data to note changes in Lake Ziway, Ethiopia, from 2009 to 2018, and obtained an overall accuracy of 99.2%. | Problematic in urban areas due to high reflectance. |
| | Danladi *et al*. (2020) | Used Landsat imagery to delineate coastal erosion and accumulation in Nigeria from 1973 to 2017. | Problematic in built-up areas. |
| | Herndon *et al*. (2020) | Achieved an overall accuracy of 98% when using Landsat-8 data to identify waterbodies in the Nigerian Sahel. | Background noise led to misclassification. |

## 2.8 Challenges of Remote Sensing in the Monitoring of Droughts, Climate Variability and Surface Water Resources and Possible Future Research Directions

The vulnerability of Africa to droughts is high, due to poverty and the dependence on rainfed agriculture, and therefore, there is a need to monitor droughts in an efficient and timely manner. The use of satellite data could significantly improve the monitoring techniques, as well as the drought planning and mitigation strategies. Remote sensing is a useful tool for the monitoring of droughts and surface water, especially in large areas where there is a limited ability to conduct in-situ monitoring, as this approach is cost-effective and repeatable. The use of remote sensing, especially in Africa, will provide information on the past, current and future conditions of droughts and it will help to understand the need for sustainable monitoring solutions. Early drought detection is vital for decision-making and preparedness, and there are many satellites that provide meteorological data, such as near-surface air relative humidity and vapor pressure deficits, which can improve the early detection of drought and provide vital information (AghaKouchak *et al.*, 2015). A major limitation in the use of remote sensing for drought and surface water monitoring is the continuity of the data (AghaKouchak *et al.*, 2015). Many of the currently-available satellite datasets, such as GRACE, do not have long historical records and only provide approximately 10–15 years of data, which might not be enough for drought studies, from a climatological perspective; however, these records can be used for impact studies (AghaKouchak *et al.*, 2015). The satellites with sufficient records are Landsat, GOES and AVHRR-MODIS-VIIRS. A major challenge of satellite data is the background noise, which negatively influences the classification of the land use zones. Another challenge of using remote sensing data are the sensor uncertainties, which is why models and indicators were developed for the uncertainty assessment of satellite-based data. However, with the continuous development of algorithms and free access to satellite data, it is a promising approach for monitoring the impacts and onset of droughts and various other climatological changes (Xulu *et al.*, 2018).

## 2.9 Future Research Directions and Recommendations

This review has shown that remote sensing technology has improved the monitoring of drought and water resources, as well as climate variability. However, if the data from earth observations are to make a significant impact in resource-poor regions, such as those in sub-Saharan Africa, there are still grey areas that require further research. For instance, most of the aforementioned drought monitoring and water detection indices were developed for specific satellite data; therefore, with the development of new satellites, new indices need to be developed and tested across diverse environments to enhance their use (Huang *et al.,* 2018). There is also a need for more studies to be conducted in sub-Saharan Africa, in order to test the remote sensing applications and data processing techniques, as well as to improve the drought detection, mitigation and monitoring of water resources. Future studies need to be conducted to determine which datasets are best-suited for monitoring groundwater resources, as researchers are currently struggling with the coarse resolution provided by GRACE, which reduces the accuracy of the results over small areas (Frappart, 2020). More studies need to be conducted using the Landsat, GOES or AVHRR-MODIS-VIIRS data, as these satellites have historical data, which will assist in impact studies, in characterizing patterns and in the future predictions of drought models (Bijeesh & Narasimhamurthy, 2020). Indices and satellites also need to be developed to reduce the inaccuracies caused by background noise, cloud cover, pixel mixing and shadows in mountainous or built-up areas, as mountains and clouds are often classified as waterbodies due to their reflectance. Further studies need to also investigate the applicability and feasibility of blending remote sensing methods with rain gauge estimates and/or climate models and precipitation models, to test whether, and in what way, the blending of these datasets reduces the estimation variance. Similarly, the fusion of different remote sensing datasets (e.g. active and passive remotely sensed data) with various earth imaging characteristics is promising for the improved detection and spatial characterization of droughts and water resources. Furthermore, more studies need to be conducted using rain gauge estimates integrated with radar data, as radar data is useful for estimating precipitation (Chappell *et al*., 2013). Machine Learning (ML) is another promising field that needs to be explored for use in the monitoring of droughts (Bijeesh & Narasimhamurthy, 2020). The commonly-used ML algorithms are Artificial Neural Network (ANN), Support Vector Machine (SVM), minimum distance classification, maximum likelihood classification, regression tree-based algorithms, ISODATA and K-means clustering; however, these methods have yet to be tested in sub-Saharan Africa. The use of panchromatic images with a higher resolution has been theoretically studied in surface water detection and monitoring, but it still needs to be implemented and tested (Bijeesh & Narasimhamurthy, 2020). Future studies could also test the effectiveness of integrating Digital Elevation Models (DEMs) with multi-spectral data in cloud removal, to enhance water detection and delineation (Chappell *et al*., 2013).

## 2.10 Conclusions

Droughts are characterized by various climatological and hydrological parameters, and in order to reduce the impacts of droughts and climate variability, these parameters need to be understood and monitored in a timely and efficient manner. The occurrence of droughts is likely to increase, due to climate change; this means that their impacts need to be analysed, based on historical, present and future scenarios, especially in Africa, which is a data-scarce continent. The use of remote sensing for the monitoring of droughts and surface water resources has become popular, since the launch of satellites with improved spatial, spectral and temporal resolutions, which were designed to monitor and detect changes on the earth's surface. However, remote sensing is not being utilized to its full potential, especially in data-poor areas. Advancements in indices and techniques, and the availability of multi-temporal and multi-spectral images, have led to the improvement of the monitoring and detection of droughts and surface water resources; however, there is still a need to improve the indices, in order to remedy cloud contamination and the problem of shadows in mountainous and built-up areas. Remotely sensed data have the potential to be used in data-scarce areas, such as Africa, where there are a limited number of physical monitoring stations, due to the high costs involved and the location. With these advancements available, there is an urgent need for future studies to test the applicability of these satellites and indices, in order to improve early drought warning systems and preparedness and to assist with proactive decision-making. This approach will allow for fast drought identification, which is essential for drought-prone regions like Africa, for water resource planning purposes and for helping decision-makers to set appropriate measures to alleviate future drought events.



## 2.11 References

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# CHAPTER 3

# ASSESSING THE EXTENT TO WHICH LANDSAT-8 OLI AND SENTINEL-2 MSI SATELLITE DATA CAN BE USED TO MONITOR THE IMPACTS OF DROUGHT ON WATER RESOURCES IN THE WESTERN CAPE PROVINCE OF SOUTH AFRICA


**Abstract**

Drought is a devastating phenomenon that is increasing in frequency and magnitude. Surface waterbodies are highly vulnerable to the impact of droughts, especially those in arid and semi-arid environments. The availability of moderate-resolution satellite data provides a unique opportunity for monitoring surface waterbodies and the impact of droughts on surface water resources. In this study, we assessed the extent to which Landsat-8 OLI and Sentinel-2 MSI satellite data can be used to track the impact of droughts on the water resources in the Western Cape, South Africa. Multispectral indices (the Normalised Difference Vegetation Index (NDVI), the Vegetation Condition Index (VCI), the Normalised Difference Water Index (NDWI), the Modified Normalised Difference Water Index (MNDWI) and the Land Surface Water Index (LSWI+5)), and drought indices (the Standardised Precipitation Index (SPI) and Water Requirement Satisfaction Index (WRSI)) were computed to establish the most satisfactory method for detecting surface waterbodies and monitoring droughts. These indices were used along with climate data, to provide a holistic method for monitoring the impact of droughts on surface waterbodies and to successfully detect and map the surface water variability from 2016 to 2020. The Sentinel-2-derived NDVI performed the best when mapping surface waterbodies, with an overall accuracy of 77.27%; however, LSWI+5 performed poorly, due to the misclassification of built-up areas and mountainous areas as surface waterbodies. The SPI, VCI and WRSI accurately detected the drought period and had a positive correlation with the climate data, which indicated that low rainfall and high evapotranspiration rates were experienced during the drought period from 2016 to 2018. These results are key in explaining the surface water variability, as well as the impact that droughts have on surface waterbodies in the study area. This study indicates the usefulness of using moderate-resolution datasets to assess the impact of droughts on surface water resources, which can assist in the management of water resources and in the improvement of drought identification and preparedness.

**Keywords:** climate change, drought detection, multispectral indices, multi-date monitoring, satellite data, semi-arid environments.

## 3.1 Introduction

Droughts are a creeping phenomenon and a natural hazard that affect various sectors, such as agriculture, hydropower generation, industry and water availability, as well as different aspects of the environment (Sheffield *et al*., 2012; Jang, 2018; Bhaga *et al*., 2020). It is said that the occurrence and intensity of droughts will increase in the future, due to the changing climate and the erratic rainfall and that this will lead to a decreasing rainfall rate and an increasing evapotranspiration (ET) rate (Panu & Sharma, 2002; Sheffield *et al*., 2012; Hagenlocher *et al*., 2019). Recently, droughts have become more frequent and have expanded over several areas, especially over semi-arid regions (Liu *et al*., 2020). For example, subtropical eastern Australia experienced a drought from 2017 to 2019, which affected agricultural practices and the water supply (Nguyen *et al*., 2021). In Senegal, 245 000 people suffered from hunger due to low crop yields, as a result of a drought in 2018 (Action Against Hunger, 2018). In 2019, a drought led to a decline of more than 70% in maize production in Zimbabwe (Ndlovu & Mjimba, 2021). In the past, drought events have wrought havoc across the globe and have remained a recurrent phenomenon in sub-Saharan Africa, where 53 severe droughts have been recorded (Mishra & Singh, 2010). Seven of these drought episodes occurred in South Africa in 1964, 1986, 1988, 1990, 1995, 2002-2004 and 2015-2019 (Mishra & Singh, 2010; Bhaga *et al*., 2020). Furthermore, the occurrence of droughts affected a number of Sustainable Development Goals (SDGs) between 2015 and 2030 (Zhang *et al*., 2019), namely, No. 1 (no poverty), No. 2 (zero hunger), No. 6 (clean water and Sanitation) No. 11 (sustainable cities and communities), No. 12 (responsible production and consumption), No. 13 (climate action), No. 15 (life on land) and No. 16 (peace and justice) (Nilsson *et al*., 2016; Zhang *et al*., 2019; Bhaga *et al*., 2020). Surface waterbodies are often used as a water supply and are vital for humans, animals and vegetation (Masocha *et al*., 2018); however, they are currently vulnerable to climate change and variability, as well as to droughts (Zhou *et al*., 2017; Sheffield *et al*., 2018). The poor management of surface waterbodies and the low precipitation rate can lead to severe water shortages, which can be compounded further by the increased susceptibility of the resource to climate change, climate variability and droughts (Sheffield *et al*., 2012; Feyisa *et al*., 2014). Therefore, it is necessary to continuously monitor the waterbodies, in order to detect the onset of drought conditions, to determine the availability of water and to ensure its sustainable use.

Previously, drought monitoring included the use of paleoclimatology and climatological data, such as the precipitation, river flow, soil moisture and evapotranspiration (ET) rates (d'Andrimont & Defourny, 2018). Paleoclimatology predicts future climatic conditions by analysing and understanding the past climatic conditions (Bhaga *et al*., 2020). The previous methods of monitoring surface waterbodies made use of in-situ measurements by using sensors, floats, buoy systems, pressure-type equipment and ultrasonic and radar techniques (Chapuis, 1998; Janke *et al*., 2006). However, these methods are costly and time-consuming. The equipment is also prone to theft and damage, or it may be problematic to install in inaccessible areas (Li *et al*., 2013). Therefore, the utilization of remotely sensed datasets for monitoring droughts and surface waterbodies has the potential to provide repeatable observations (Li *et al*., 2013; Bhaga *et al*., 2020).

Using remotely sensed data and multispectral indices allows for the development of spatially-explicit methods to monitor surface waterbodies and to determine the effect of droughts on the water resources. Although numerous studies have investigated the applicability of remotely sensed data for surface waterbody monitoring, most of these studies have centred around mapping the size of waterbodies (Feyisa *et al*., 2014; Sarp & Ozcelik, 2017; Masocha *et al*., 2018), while not many have been conducted on the monitoring and mapping of surface waterbodies in semi-arid environments. This can be attributed to the sparse network of in-situ monitoring instruments or the absence of high-resolution spatial data. In addition, the type of study being conducted will determine which satellite dataset will be the best one to use, based on the temporal, spatial and spectral characteristics of the satellite. The Moderate Resolution Imaging Spectroradiometer (MODIS) and the Advanced Very High-Resolution Radiometer (AVHRR) are sensors with a coarse spatial resolution of 1 km and might not be suitable for surface water monitoring, due to their inability to detect small surface waterbodies. The Landsat series and Sentinel 2 have a medium resolution and the data is freely available; therefore, they have potential for the monitoring of surface waterbodies as they have a relatively higher temporal resolution i.e. 5 to 15 days (Dube & Mutanga, 2015; Seaton *et al.*, 2020). The use of multispectral water indices seems to be a viable method for classifying surface waterbodies, as they are cost-effective, easy to apply and their accuracy is relatively high (Seaton *et al*., 2020).

Several drought and water indices have been developed and this study will use the following indices, based on the results achieved in previous studies: the Normalised Difference Water

Index (NDWI), the Modified Normalised Difference Water Index (MNDWI) and the Land Surface Water Index (LSWI+5), the Normalised Difference Vegetation Index (NDVI), the Vegetation Condition Index (VCI), the Standardised Precipitation Index (SPI) and the Water Requirement Satisfaction Index (WRSI). Seaton *et al*. (2020) used the NDWI, MNDWI and NDVI to map the variability of pools along the Breede, Nuwejaars, Tankwa and Touws Rivers that are situated in the Western Cape, South Africa, during the 2016–2017 period, by using Landsat-8 and Sentinel-2 data. The accuracies ranged from 60 to 86%, which suggests the feasibility of using these datasets, and the associated metrics, to detect any variations in the surface waterbodies. Benefoh *et al*. (2018) used LSWI+5 and NDVI to understand the landscape of Ghana by using TM, ETM and OLI data from 1986 to 2015, and an overall accuracy of 82.6% was achieved. In another study, Jiao *et al*. (2016) monitored a drought in the Continental United States of America by using VCI, NDVI and SPI, and the findings indicated that these indices have the potential to monitor drought. Legesse & Suryabhagavan (2014) assessed the drought patterns in the East Shewa Zone in Ethiopia by using the WRSI, and it was found to be a highly-accurate drought indicator. Similarly, Moeletsi & Walker (2012) used the WRSI to classify droughts in the Free State Province in South Africa, and the results indicated a high inter-seasonal variability and accurately detected extreme drought conditions. The results from these studies have demonstrated the potential of these indices to map the occurrence of droughts and surface water variability. A few of these studies have also integrated climatic factors, such as rainfall, temperature and ET, to detect the occurrence of droughts, and the integration of these multispectral indices with climate data provides a holistic approach to the monitoring of droughts and their impacts on the surface waterbodies. However, no studies have been conducted by using drought indices and surface water indices to assess the effects of a drought on the surface waterbodies in the Western Cape region. By determining which dataset is best and using a combination of the drought indices, surface water indices and climatic data, researchers and decision-makers will be able to monitor the availability of surface water and to improve drought detection. In spite of the improvements in satellite remotely sensed data, their ability to detect droughts and to monitor surface waterbodies remain unresolved. A study that investigates the consistency between Landsat-8 and Sentinel-2 will help data-scarce areas and contribute towards drought mitigation and water resource allocation. Therefore, this study tested the use of Landsat-8 OLI and Sentinel-2 MSI data for monitoring the impact of droughts on the water resources in the Western Cape Province, South Africa.

## 3.2 Methods and Materials

### 3.2.1 Description of the study area

This study was conducted in the Western Cape Province of South Africa (Figure 3.1) and focused particularly on the Cape Metro, Cape Winelands, Overberg and Garden Route regions. The Western Cape is situated along the southern-west coast of South Africa and has a Mediterranean climate, with warm, dry summers and cold, wet winters. The Western Cape has the highest rainfall variability in South Africa and temperatures vary from 23°C in the summer to 13°C in the winter. Spatially, rainfall varies from 60 mm/yr to 3345 mm/yr in the mountainous regions (Provincial Spatial Development Framework, 2005; Seaton *et al.*, 2020), due to the westerly winds and the moisture that is transported from the Indian Ocean onto the southern mountains and coastal plains in the Western Cape Region (Mtengwana *et al.*, 2021). The waterbodies in the study area are important for the supply of domestic and commercial water, as well as for agriculture, ecosystems and for hydro-electric power generation. The Western Cape experienced a severe drought from 2015 to 2018, which led to water restrictions reaching Level 6b on 1st February 2018 (Muller, 2018), which means that water consumption was limited to citizens using 50 litres, or less, per day and borehole water use was discouraged in order to protect the groundwater resources (City of Cape Town, 2018). This emphasises the importance of monitoring the occurrence of droughts, as well as the availability and variability of surface water in this region.

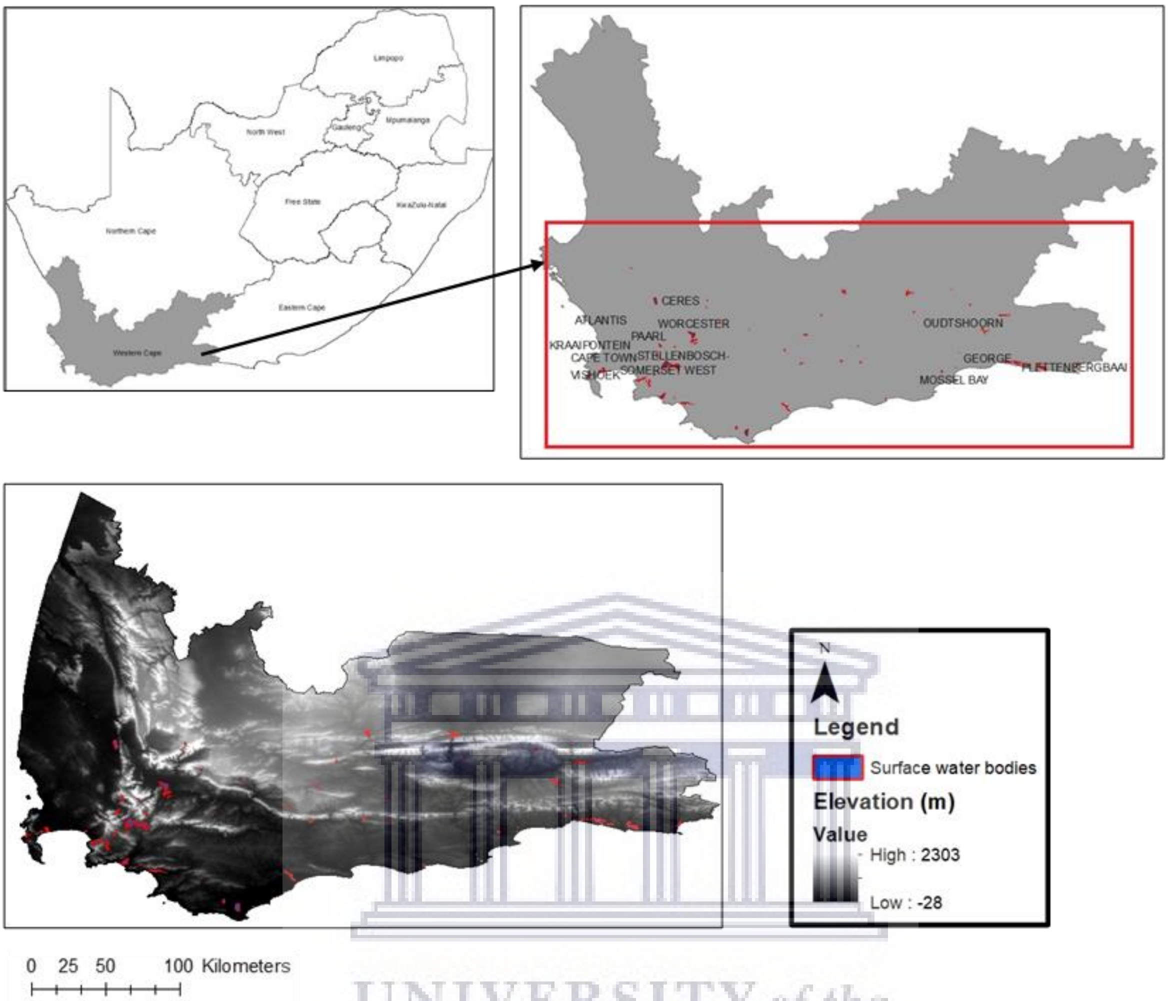



Figure 3.1 Map of the study area

### 3.2.2 Remote sensing data acquisition and image pre-processing

The Landsat-8 OLI and Sentinel-2 MSI datasets were acquired for the period between 2016 and 2020 to coincide with Sentinel-2 data that has been available since 2015. Therefore, drought conditions were monitored from 2016 to 2020, due to the limited availability of high-resolution data. Images were downloaded for both the wet and dry seasons. The cloudless images, covering the Cape Metro, Cape Winelands, Overberg and Garden Route regions in the Western Cape, South Africa, were acquired freely from the United States Geological Survey (USGS) (http://earthexplorer.usgs.gov), with 10 tiles of Landsat-8 OLI and 19 tiles of Sentinel-2 MSI covering the study area. The Landsat-8 OLI images were downloaded as Level-1, GEOTIFF images and these images were projected into the Universal Transverse Mercator System, while Sentinel-2 MSI images were downloaded as JPEG2000 images and projected into the Universal Transverse Mercator System. The satellite images underwent atmospheric correction, using the Dark Object Subtraction 1 (DOS1) (Masocha *et al*., 2018; Chen *et al*., 2019) tool in Quantum GIS (QGIS) Version 2.18.03. The Sentinel-2 images were corrected by using the Sen2Cor pre-processing tool in the Sentinel Application Platform (SNAP) (Thamanga & Dube, 2019; Seaton *et al*., 2020). The 20 m spectral bands of Sentinel-2 were resampled to 10 m by using the nearest neighbour resampling method, in order to achieve consistency. All tiles were then mosaicked in a GIS environment to form a single image scene. The corrected data were then used to compute spectral indices for detecting the surface waterbodies. Higher resolution datasets i.e. Google Earth images, were used to assess the mapped accuracy of the surface waterbodies from the Landsat-8 and Sentinel-2 data. Details of the spectral and spatial characteristics of these satellite images are presented in Table 3.1.

Table 3.1 Spectral and spatial characteristics of Landsat-8 OLI and Sentinel-2 MSI used for this study

| Band | Wavelength | Resolution |
|---|---|---|
| **Landsat-8** | | |
| Blue | 0.450-0.515 | 30 |
| Green | 0.525-0.600 | 30 |
| Red | 0.630-0.680 | 30 |
| Near Infrared (NIR) | 0.845-0.885 | 30 |
| Shortwave Infrared 1 (SWIR 1) | 1.560-1.660 | 30 |
| **Sentinel-2** | | |
| Blue | 0.439-0.535 | 10 |
| Green | 0.537-0.582 | 10 |
| Red | 0.646-0.685 | 10 |
| Near Infrared (NIR) | 0.767-0.908 | 10 |
| Shortwave Infrared 1 (SWIR1) | 1.539-1.681 | 20 |

### 3.2.3 Calculation of indices for detecting drought occurrence and surface waterbodies

Several indices have been developed to map droughts and surface waterbodies (Mishra & Singh, 2011; Huang *et al*., 2018; Masocha *et al*., 2018; Seaton *et al*., 2020) (Table 3.2). These indices were developed, based on the absorption and reflectance rates of the waterbodies, and they are compared to other materials. The indices are calculated by using several different spectral bands to differentiate the waterbodies from the non-waterbodies (Huang *et al*., 2018; Masocha *et al*., 2018). Two multiband methods, namely the Normalised Difference Vegetation Index (NDVI) and the Vegetation Condition Index (VCI), were used to detect and map the occurrence of a drought. Three multiband methods, namely the Normalised Difference Water Index (NDWI), the Modified Normalised Difference Water Index (MNDWI) and the Land Surface Water Index (LSWI+5), were used to detect and map the surface waterbodies. These methods were used to identify and map the occurrence of a drought and the surface waterbodies from the Landsat-8 and Sentinel-2 data.

The NDVI is a vegetation index, but it is also used to detect waterbodies and floods or droughts, as it deduces the existence of water by detecting the aboveground biomass (Huang *et al*., 2018; Seaton *et al*., 2020). The index is computed by using the Near-Infrared (NIR) and red bands (West *et al*., 2019). The VCI is used to detect and track a drought and is able to calculate its beginning, magnitude and duration, as well as the impact that it will have on the vegetation (Mishra & Singh, 2011; Frischen *et al*., 2020), by using the NDVI value of the year of interest and the minimum and maximum NDVI values of the study period. VCI classes are characterised by Kogan's aridity classification standards (Kogan, *et al*., 2004). The NDWI was introduced by McFeeters in 1996 (McFeeters, 1996) and delineates surface waterbodies by using the green and NIR bands (Feyisa *et al*., 2014). By using these bands, the land and vegetation are suppressed and the waterbodies are enhanced; however, it is known to misclassify the built-up areas as water (Asfaw *et al*., 2020; Seaton *et al*., 2020). In order to address this issue, Xu (2006) developed the Modified NDWI (MNDWI) and used the Shortwave Infrared (SWIR) band as an alternative for the NIR band, which further suppresses the built-up areas (Feyisa *et al*., 2014; Asfaw *et al*., 2020). The Land Surface Water Index (LSWI+5) was introduced by Menarguez (2015) by combining the Land Surface Water Index (LSWI) with the Enhanced Vegetation Index (EVI) and the NDVI (Menarguez, 2015; Bhaga *et al*., 2020). These indices have been used to assess climate variability, to recognise a drought and to assist in water resource management (Huang *et al*., 2018; Asfaw *et al*., 2020; Bhaga *et al*., 2020). Where $B_{NIR}$ indicates the Near-Infrared band, $B_{red}$ indicates the red band. $B_{green}$ indicates the green band, $B_{SWIR-1}$ indicates the first shortwave-infrared band and $NDVI_{min}$ and $NDVI_{max}$ indicates the minimum and maximum NDVI values for the study period (Table 3.2).

Table 3.2 Selected indices used to detect and map the occurrence of droughts and surface waterbodies from Landsat-8and Sentinel-2 datasets

| Index | Equation | Threshold | Reference |
|---|---|---|---|
| NDVI | NDVI = ($B_{NIR}$ - $B_{red}$) / ($B_{NIR}$ + $B_{red}$) | NDVI < 0 | (Rouse *et al.*, 1973) |
| VCI | VCI = (NDVI – $NDVI_{min}$) / ($NDVI_{max}$ - $NDVI_{min}$) * 100 | | (Kogan *et al.*, 2004) |
| NDWI | NDWI = ($B_{green}$ - $B_{NIR}$) / ($B_{green}$ + $B_{NIR}$) | NDWI>0 | (McFeeters, 1996) |
| MNDWI | MNDWI = ($B_{green}$ - $B_{SWIR-1}$) / ($B_{green}$ + $B_{SWIR-1}$) | MNDWI>0 | (Xu, 2006) |
| LSWI+5 | LSWI = ($B_{NIR}$ - $B_{SWIR-1}$) / ($B_{NIR}$ + $B_{SWIR-1}$) | EVI < 0.1 and (LSWI > NDVI or LSWI > EVI) | (Menarguez, 2015) |

## 3.3 Climate data acquisition

Spatial data on the rainfall, temperature, humidity, wind speed and sunshine hours were obtained from the online weather database (https://www.timeanddate.com/weather/south-africa/cape-town/climate) for the years 2016 to 2020, and the ET was derived by using the Penman-Monteith method (Trajkovic, 2007), with the formula:

$$\lambda ET = \frac{\Delta(R_n - G) + \rho_a c_p \frac{(e_s - e_a)}{r_a}}{\Delta + \gamma\left(1 + \frac{r_s}{r_a}\right)}$$

Whereby, $R_n$ is the net radiation, G is the soil heat flux, ($e_s$ - $e_a$) is the vapour pressure deficit of the air, $r_a$ represents the mean air density at constant pressure, $c_p$ is the specific heat of the air, D is the slope of the saturation vapour pressure temperature relationship, g represents the psychrometric constant, and $r_s$ and $r_a$ are the (bulk) surface and aerodynamic resistances. The rainfall data were obtained to determine the amount of rainfall variability in the area under study, the temperature data were obtained to determine the correlation between the temperature and rainfall rates and the evapotranspiration rates were estimated to account for the water loss in the area. The climate and ET data were correlated with the derived seasonal and annual remotely sensed surface waterbodies, by comparing the size of the surface waterbodies to the rainfall and the ET data. The climate and ET data were also used to calculate the drought occurrence indices, which were chosen based on their performance in previous studies (Moeletsi & Walker, 2012; Lawal *et al*., 2019; Bhaga *et al*., 2020; Kalisa *et al*., 2020). Two indices were used, namely the Standardised Precipitation Index (SPI) and the Water Requirement Satisfaction Index (WRSI). The SPI was introduced by McKee in 1993 (McKee *et al*., 1993), based on the notion that the reduced precipitation rate, compared to the normal precipitation rate, is the main cause of the drought conditions. These prolonged periods of below-average precipitation rates lead to a shortage of water for numerous natural and human needs (Jang, 2018). The SPI has been used to study many aspects of droughts, for example, drought prediction, their regularity, spatio-temporal occurrence and climate impact studies (Mishra & Singh, 2011). The SPI is based on the precipitation record for the desired study period and can be calculated for 3, 6, 9 or 12 months; however, for this study, it was calculated every three months, from January 2016 until October 2020, in RStudio by using the SPI package and climate data. The obtained SPI values were then classified to establish the degree of the drought conditions (Table 3.3) (Jang, 2018). The Food and Agriculture Organisation created the WRSI (Legesse & Suryabhagavan, 2014) and specifies the crop performance, based on the amount of water available during the growing season. The WRSI is the relationship between the actual ET and the potential ET. It was calculated in RStudio by using the climate data and the WRSI package for the years 2016 to 2020. The derived WRSI values were also classified to determine the extent of the drought conditions (Table 3.4). These indices were then correlated with the climate data to provide a holistic approach to drought monitoring and its impact on the surface waterbodies.

Table 3.3 SPI categories for drought classification

| SPI VALUES | CLASSIFICATION |
|---|---|
| 2.0+ | Extremely wet |
| 1.5 to 1.99 | Very wet |
| 1.0 to 1.49 | Moderately wet |
| -0.99 – 0.99 | Near normal |
| -1.0 to -1.49 | Moderately dry |
| -1.5 to -.199 | Severely dry |
| -2 and less | Extremely dry |

Table 3.4 WRSI drought severity classes

| WRSI (%) | Drought severity class |
|---|---|
| 80 - 100 | No drought |
| 70 - 79 | Slight drought |
| 60 – 69 | Moderate drought |
| 50 - 59 | Severe drought |
| <50 | Complete crop failure |

## 3.4 Accuracy Assessments

Accuracy assessments were conducted for each classified image for the study period, to verify the results of the derived classified surface waterbodies and non-waterbodies. Overlaying 800 randomly-created points (400 for the surface waterbodies and 400 for the non-waterbodies) determined the accuracy analysis of the results. The accuracies were assessed, using confusion matrices, namely, the user's accuracy (Equation 3.1), the producer's accuracy (Equation 3.2), the overall accuracy (Equation 3.3) and the Kappa coefficient (Equation 3.4). These accuracy metrics were selected based on their ability to indicate the degree of accuracy of the classified images (Congalton *et al.*, 1983; Seaton *et al.*, 2020; Dzurume *et al.*, 2021). Figure 3.2 provides a summary of the major steps that were used to identify and map the surface waterbodies. In order to test if there were substantial differences, the Analysis of Variance (ANOVA) was used in the mapping capability of the remotely sensed estimates. The formulae for each confusion matrix are as follows:

$$\text{User's accuracy} = \frac{n_{ii}}{n_{i+1}} \tag{3.1}$$

$$\text{Producer's accuracy} = \frac{n_{ii}}{n_{+1}} \tag{3.2}$$

$$\text{Overall accuracy} = \frac{\Sigma_{i=1}^{m} nii}{n} \times 100\% \tag{3.3}$$

$$\text{Kappa coefficient} = \frac{(\text{total accuracy} - \text{random accuracy})}{(1 - \text{random accuracy})} \tag{3.4}$$

Whereby $n$ is the total number of testing pixels, $m$ is the number of classes, $nii$ is the element in the $i$-th row and the $i$-th column, $ni+$ is the sum of the class row and $n+i$ is the sum of the class column.

The Root Mean Square Error (RMSE) was used to assess the accuracy of the VCI, SPI and WRSI from 2016 to 2020. The RMSE was calculated as:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(a_i - b_i)^2}{n}} \tag{3.5}$$

Where α is the observed value dataset, b is the estimated value dataset and $n$ is the number of samples.

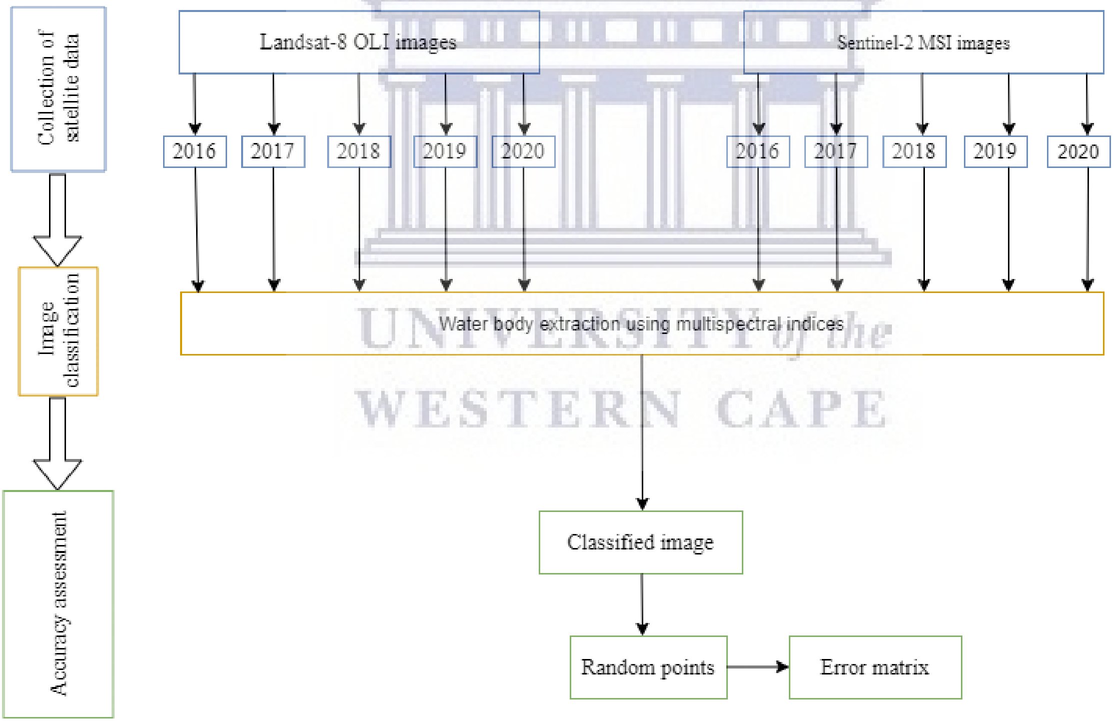



Figure 3.2 Workflow summary of Surface waterbody mapping and accuracy assessment

## 3.5 Results

### 3.5.1 Seasonal and spatial distribution of surface waterbodies

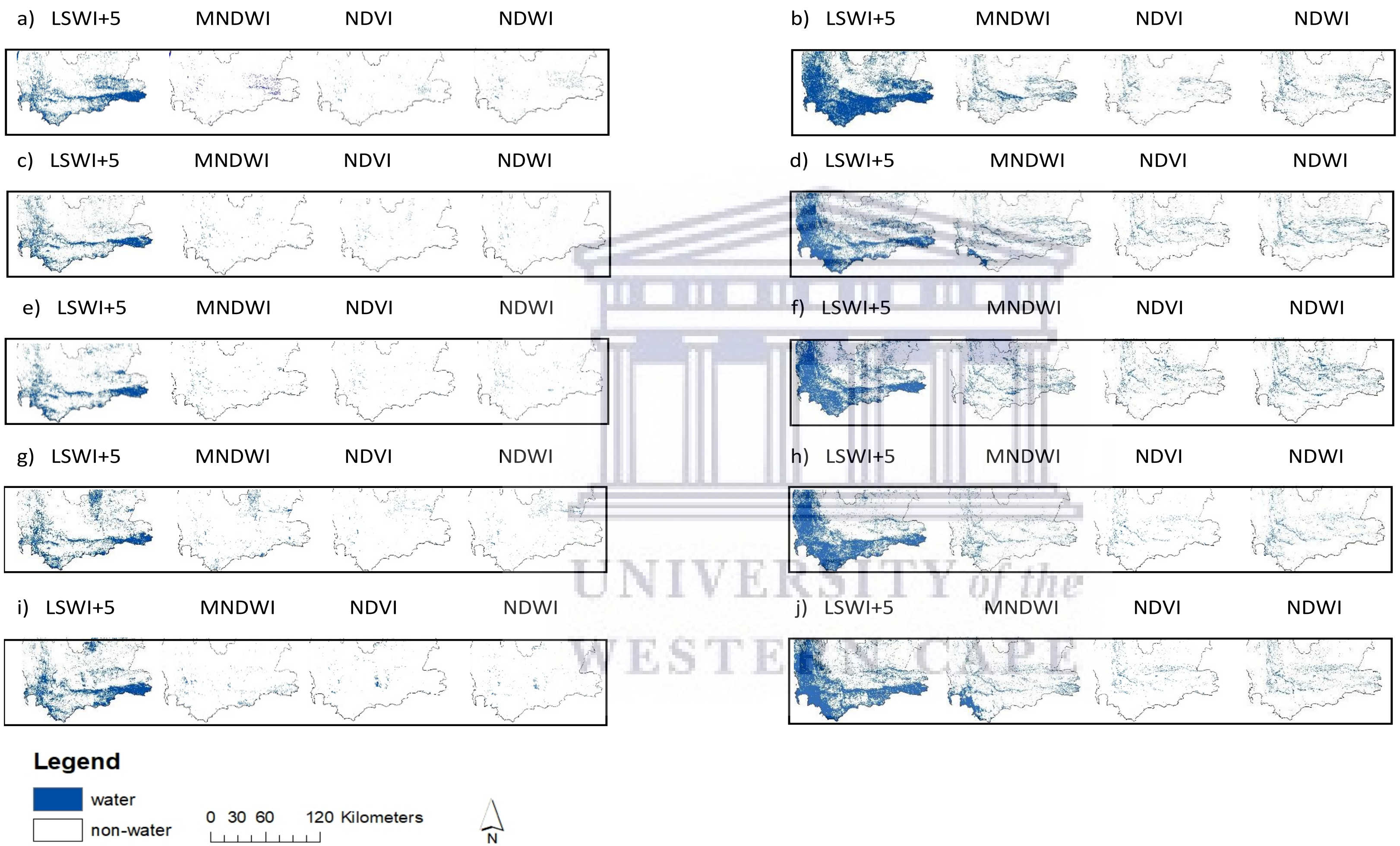
Figure 3.3 illustrates the spatial variations in surface waterbodies that were detected by using indices computed by using the Landsat-8 (i) and Sentinel-2 (ii) datasets from 2016 to 2020.

These images were classified into water (blue) and non-water (white) classes. The four spectral water indices, namely the Normalised Difference Vegetation Index (NDVI), the Modified Normalised Difference Water Index (MNDWI), the Normalised Water Difference Index (NDWI) and the Modified Land Surface Water Index (LSWI+5), were applied to the study area to highlight variability of the surface water. Overall, the indices efficiently mapped and detected surface waterbodies in the study area by using both sensors. However, the Sentinel-2 MSI results surpassed the Landsat-8 OLI results. Observations show that both sensors detected a high concentration of waterbodies in the south-western parts of the region. As expected, both sensors detected more surface waterbodies during the wet season than in the dry season, and visually, all the results exhibited comparable patterns of waterbodies. Of the four surface waterbody detection indices, the Normalised Difference Vegetation Index (NDVI) showed the most promising results in mapping the surface waterbodies in the study area, as they were detected with minimal misclassification and, therefore, had the highest accuracy. The Modified Normalised Difference Water Index (MNDWI) and the Normalised Water Difference Index (NDWI) produced similar results to those of the NDVI. However, the Modified Land Surface Water Index (LSWI+5) exaggerated the occurrence of the surface waterbodies and therefore had the lowest accuracy, compared to the other indices. The results show that surface waterbodies can be discriminated successfully from non-waterbodies across the region of study over time, by using these multispectral indices.



Figure 3.4 shows the performance of the Vegetation Condition Index (VCI) for the years 2016 to 2020 by using Landsat-8 and Sentinel-2 imagery for the wet and dry seasons, with red representing extreme drought, orange is severe drought, yellow representing moderate drought and light green representing light drought and green and dark green representing no drought. The VCI was compared with the surface water indices and meteorological drought indices, namely, the Standardized Precipitation Index and the Water Requirement Satisfaction Index (WRSI). Both indices produced similar results for 2018; however, the results for the years 2016, 2017, 2019 and 2020 differed markedly. Water stress was evident across the study area from 2017 to 2018, but the conditions improved during the wet season of 2018, especially in the south-western area. The spatial variation in vegetation health is a result of the rainfall variability in the region, with the northern regions receiving less rainfall than the southern regions. Both satellite datasets detected that the vegetation was extremely impacted by the drought conditions during the 2017 and 2018 dry seasons. The Sentinel-2 results indicate the presence of a drought more accurately than those of Landsat-8.

(i)



a) LSWI+5
MNDWI
NDVI
NDWI
b) LSWI+5
MNDWI
NDVI
NDWI
c) LSWI+5
MNDWI
NDVI
NDWI
d) LSWI+5
MNDWI
NDVI
NDWI
e) LSWI+5
MNDWI
NDVI
NDWI
f) LSWI+5
MNDWI
NDVI
NDWI
g) LSWI+5
MNDWI
NDVI
NDWI
h) LSWI+5
MNDWI
NDVI
NDWI
i) LSWI+5
MNDWI
NDVI
NDWI
j) LSWI+5
MNDWI
NDVI
NDWI
Legend
water
non-water
0 30 60 120 Kilometers
N

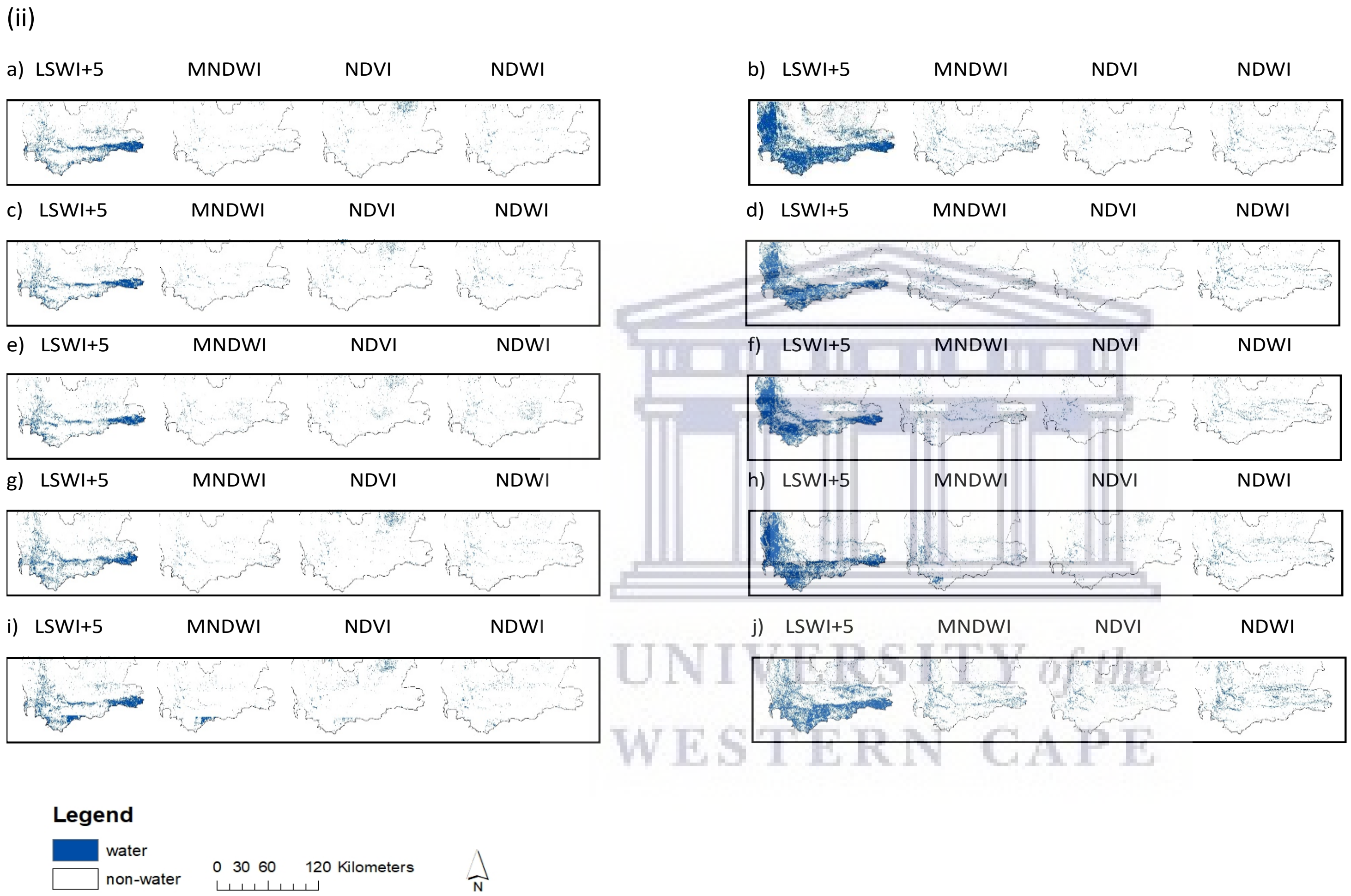



Figure 3.3 Performance of the four indices applied to different pre-processed images obtained by Landsat-8 (i) and Sentinel 2 (ii): a) 2016 dry season, b) 2016 wet season, c) 2017 dry season, d) 2017 wet season, e) 2018 dry season, f) 2018 wet season, g) 2019 dry season, h) 2019 wet season, i) 2020 dry season, and j) 2020 wet season

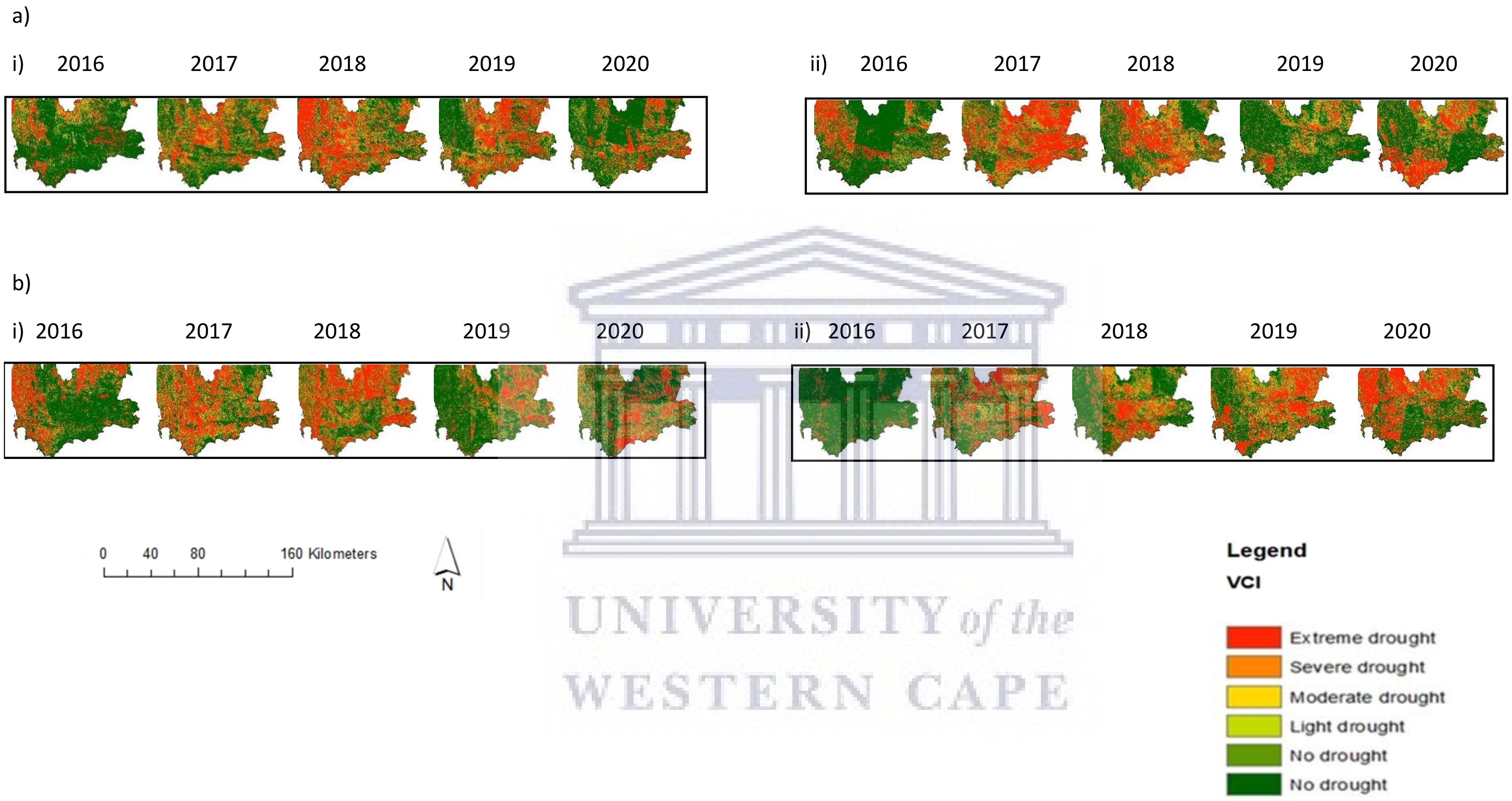



Figure 3.4 Performance of the VCI applied to different pre-processed images obtained by Landsat-8 (a) and Sentinel-2 (b) for the years 2016 to 2020 for the dry season (i) and wet season (ii)

### 3.5.2 Detection of drought occurrence

The monthly evapotranspiration (ET) rates increased from the years 2016 to 2018, before decreasing in 2019 and 2020, with the year 2018 having the highest ET rate, while 2020 experienced the lowest ET rate (Figure 3.5). The lowest rainfall was recorded in the year 2020, with the highest being recorded during 2018 (Figure 3.6). These observed trends could explain the derived multispectral results that detected and mapped the occurrence of a drought and the surface waterbodies.

Figure 3.7 shows the Standardised Precipitation Index (SPI) values for every three months, from the years 2016 to 2020. The SPI was applied to verify the drought conditions in the study area and it was related to other surface water indices and meteorological drought indices. The SPI values ranged between -0.99 to 0.99 and indicated almost normal conditions, with values lower than -0.99 indicating dry conditions and values higher than 0.99 that indicating wet conditions, respectively. January 2018 had the highest SPI value, which confirms the drought conditions experienced in early 2018. The year 2020 was classified as a very wet period, indicating the end of the drought in the area of study, which confirms the climatological and satellite-derived findings. These findings correlate well with the findings derived from the surface water indices and the VCI. The results of the Water Requirement Satisfaction Index (WRSI) illustrate a moisture deficit during the years 2016 and 2017, which further confirms that a drought was experienced during these years (Figure 3.8). The WRSI values increased from 2018 until 2020, which correlate with the climatological and multispectral results. When the WRSI results were correlated with surface water indices and drought indices, the overall results indicate that there was a drought from 2016 until the wet season of 2018.

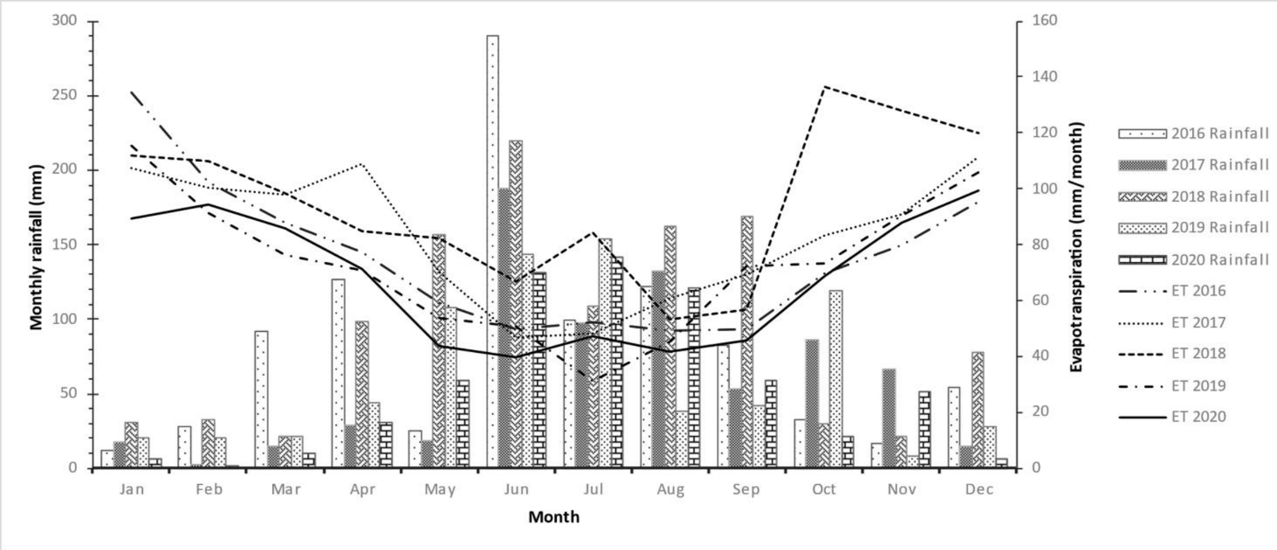



Figure 3.5 Monthly rainfall with the evapotranspiration rates for the Western Cape, South Africa

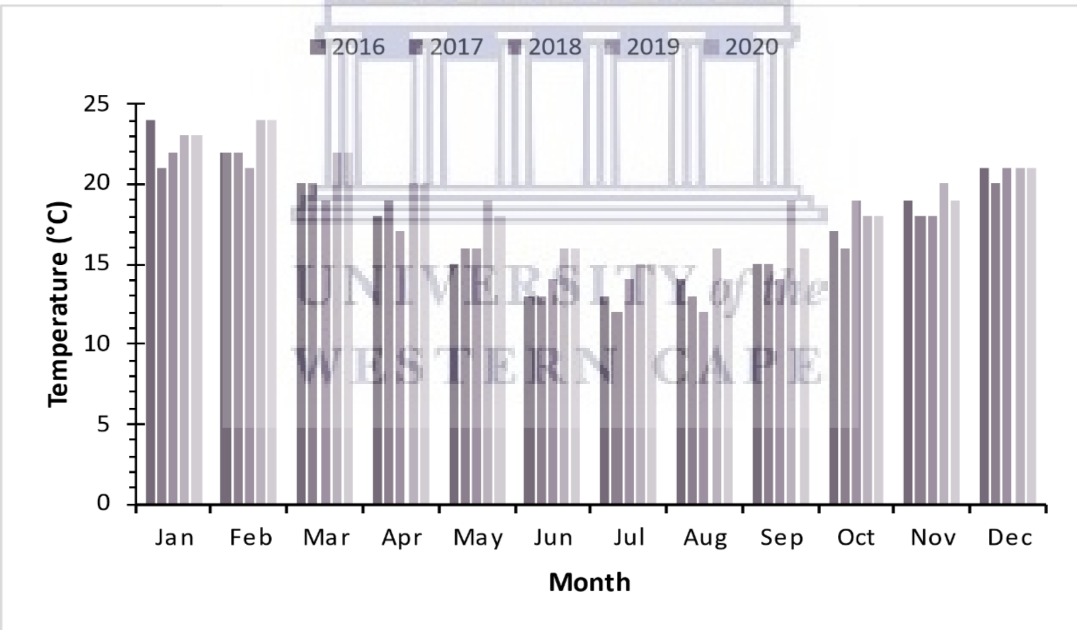



Figure 3.6 Monthly temperatures recorded in the Western Cape

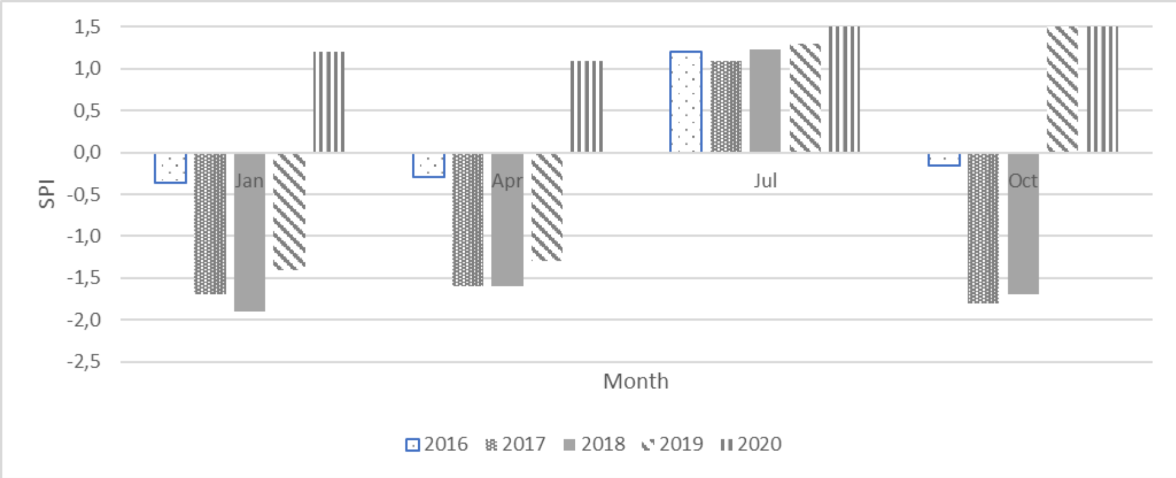



Figure 3.7 Standardised Precipitation Index values for the study area for the years 2016 to 2020

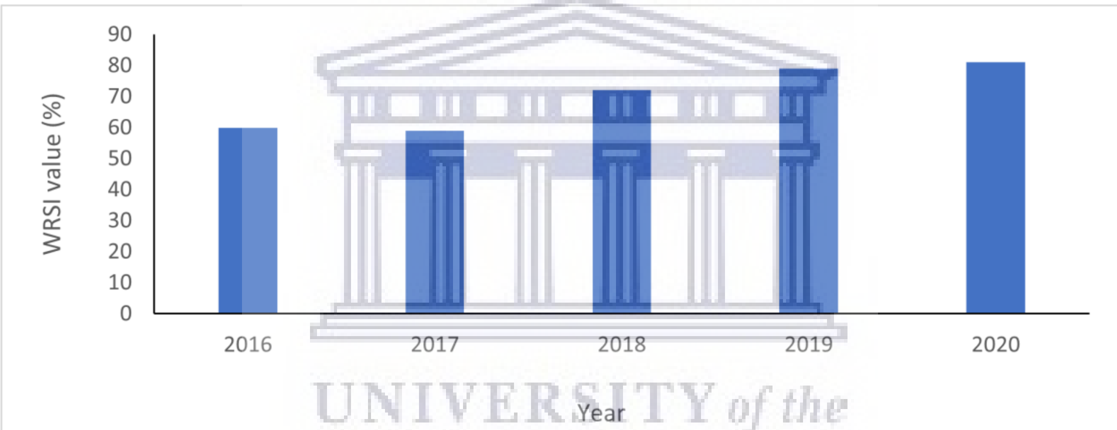



Figure 3.8 Water Requirement Satisfaction Index values for the study area for the years 2016 to 2020

## 3.6 Accuracy Assessment of the Satellite-derived Waterbodies and Drought Detection and Mapping Indices

Figure 3.9 shows the Producer's Accuracy (PA), the User's Accuracy (UA), the Overall Accuracy (OA) and the Kappa coefficient by using different multispectral indices to identify and map the occurrence of droughts and surface waterbodies. Sentinel-2-derived NDVI extracted the surface waterbodies with the highest accuracy during the wet and dry seasons. The NDVI-derived from Landsat-8 had the best performance for the wet season and the Landsat-8-derived MNDWI had the best performance for the dry season. During the dry season of 2016, Sentinel-2 data produced the highest accuracy when identifying the surface waterbodies. The indices that were used yielded comparable results, except for LSWI, which overestimated the presence of surface waterbodies for both satellite datasets and for both seasons. The Analysis of Variance (ANOVA) indicated a few differences (Fvalue= 3.40, df=399, $\alpha = 0.04$) when identifying and mapping the surface waterbodies by using multispectral indices, which shows that both satellite datasets could identify and map surface waterbodies.

Figure 3.10 illustrates the Root Mean Square Error (RMSE) for the Vegetation Condition Index (VCI), using the Landsat-8 and Sentinel-2 datasets. The Landsat-8-derived VCI outperformed the Sentinel-2-derived VCI for both seasons, with the Landsat-8-derived VCI based on the 2020 dry season having a RMSE value of 76 $m^2$. Furthermore, the RMSE for the Standardised Precipitation Index (SPI) calculated every three months, from January 2016 until October 2020, shows that July 2020 had the highest RMSE value, followed closely by October 2020 (Figure 3.11). July 2017 had the lowest RMSE value, which correlates with the SPI results. The SPI results for July 2017 do not correlate with the climatological data, as they do not indicate drought conditions. However, the climatological data indicate that the region experienced a severe drought during July 2017.

Figure 3.12 shows the RMSE for the Water Requirement Satisfaction Index (WRSI) calculated yearly from 2016 until 2020. The year 2018 achieved the highest RMSE of 82.36 $m^2$, which correlates with the climatological data, as 2018 received significant rainfall during the wet season, which relieved the drought conditions.

a(i)

| Index | PA(%) | | | | | UA(%) | | | | | OA (%) | | | | | Kappa coefficient (%) | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **2016** | **2017** | **2018** | **2019** | **2020** | **2016** | **2017** | **2018** | **2019** | **2020** | **2016** | **2017** | **2018** | **2019** | **2020** | **2016** | **2017** | **2018** | **2019** | **2020** |
| **LSWI+5** | 62.1 | 53.1 | 62.7 | 55.6 | 57.7 | 36.5 | 36.5 | 37.0 | 28.5 | 30.0 | 57.1 | 52.1 | 57.5 | 52.9 | 54.0 | 14.3 | 4.3 | 15.0 | 5.8 | 8.0 |
| **MNDWI** | 67.9 | 83.5 | 66.0 | 68.0 | 75.4 | 66.3 | 75.8 | 70.5 | 67.5 | 75.0 | 67.5 | 80.4 | 67.1 | 67.9 | 75.3 | 35.0 | 60.8 | 34.3 | 35.8 | 50.5 |
| **NDVI** | 59.4 | 60.6 | 63.8 | 64.2 | 75.4 | 79.8 | 80.3 | 86.5 | 79.3 | 79.5 | 62.6 | 64.0 | 68.8 | 67.5 | 76.8 | 25.3 | 28.0 | 37.5 | 35.0 | 53.5 |
| **NDWI** | 58.2 | 75.0 | 59.5 | 60.3 | 67.4 | 64.8 | 89.3 | 72.8 | 73.0 | 80.3 | 59.1 | 79.8 | 61.6 | 62.5 | 70.8 | 18.3 | 59.5 | 23.3 | 25.0 | 41.5 |

b(i)

| Index | PA(%) | | | | | UA(%) | | | | | OA (%) | | | | | Kappa coefficient (%) | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **2016** | **2017** | **2018** | **2019** | **2020** | **2016** | **2017** | **2018** | **2019** | **2020** | **2016** | **2017** | **2018** | **2019** | **2020** | **2016** | **2017** | **2018** | **2019** | **2020** |
| **LSWI+5** | 70.9 | 59.7 | 67.2 | 74.4 | 66.0 | 34.8 | 33.0 | 40.0 | 30.5 | 31.0 | 60.3 | 55.4 | 60.3 | 60.0 | 57.5 | 20.5 | 10.8 | 20.5 | 20.0 | 15.0 |
| **MNDWI** | 71.4 | 62.1 | 49.3 | 73.7 | 75.6 | 39.3 | 52.0 | 41.3 | 47.8 | 38.8 | 61.8 | 60.1 | 49.4 | 65.4 | 63.1 | 23.5 | 20.3 | 1.3 | 30.8 | 26.3 |
| **NDVI** | 72.0 | 68.4 | 70.7 | 62.3 | 64.1 | 75.3 | 73.5 | 73.0 | 61.3 | 47.8 | 73.0 | 69.8 | 71.4 | 62.1 | 60.5 | 46.0 | 39.5 | 42.8 | 24.3 | 21.0 |
| **NDWI** | 73.3 | 65.1 | 66.9 | 67.9 | 66.2 | 63.0 | 66.3 | 58.5 | 57.8 | 54.8 | 70.0 | 65.4 | 64.8 | 65.3 | 62.8 | 40.0 | 30.8 | 29.5 | 30.5 | 25.5 |

a(ii)

| Index | PA(%) | | | | | UA(%) | | | | | OA (%) | | | | | Kappa coefficient (%) | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **2016** | **2017** | **2018** | **2019** | **2020** | **2016** | **2017** | **2018** | **2019** | **2020** | **2016** | **2017** | **2018** | **2019** | **2020** | **2016** | **2017** | **2018** | **2019** | **2020** |
| **LSWI+5** | 59.8 | 46.1 | 66.2 | 66.3 | 53.2 | 35.8 | 25.0 | 35.8 | 27.5 | 25.3 | 55.9 | 47.9 | 58.8 | 56.8 | 51.5 | 11.8 | 4.3 | 17.5 | 13.5 | 3.0 |
| **MNDWI** | 83.2 | 67.7 | 70.3 | 65.5 | 68.6 | 78.3 | 72.8 | 61.5 | 68.3 | 73.8 | 81.3 | 69.0 | 67.8 | 66.1 | 70.0 | 62.5 | 38.0 | 35.5 | 32.3 | 40.0 |
| **NDVI** | 79.2 | 76.6 | 76.0 | 70.4 | 66.9 | 87.8 | 80.3 | 83.8 | 84.3 | 81.8 | 82.4 | 77.9 | 78.6 | 74.4 | 70.6 | 64.8 | 55.8 | 57.3 | 48.8 | 41.3 |
| **NDWI** | 80.8 | 71.3 | 71.4 | 74.7 | 70.8 | 78.8 | 81.3 | 76.8 | 72.3 | 75.3 | 80.0 | 74.3 | 73.0 | 73.9 | 72.1 | 60.0 | 48.5 | 46.0 | 47.8 | 44.3 |

b(ii)

| Index | Producer's Accuracy (%) | | | | | User's Accuracy (%) | | | | | Overall Accuracy (%) | | | | | Kappa coefficient (%) | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **2016** | **2017** | **2018** | **2019** | **2020** | **2016** | **2017** | **2018** | **2019** | **2020** | **2016** | **2017** | **2018** | **2019** | **2020** | **2016** | **2017** | **2018** | **2019** | **2020** |
| **LSWI+5** | 86.3 | 46.4 | 64.2 | 64.7 | 58.2 | 28.3 | 26.0 | 26.5 | 27.5 | 27.5 | 61.9 | 48.0 | 55.9 | 56.3 | 53.9 | 23.8 | 4.0 | 11.8 | 12.5 | 7.8 |
| **MNDWI** | 91.1 | 60.0 | 75.7 | 74.6 | 71.2 | 46.3 | 43.5 | 46.0 | 52.3 | 43.3 | 70.9 | 57.3 | 65.6 | 67.3 | 62.9 | 41.8 | 14.5 | 31.3 | 34.5 | 25.8 |
| **NDVI** | 79.7 | 75.2 | 84.7 | 78.6 | 69.6 | 79.5 | 67.5 | 68.0 | 69.8 | 61.8 | 78.1 | 72.6 | 77.9 | 75.4 | 67.4 | 59.3 | 45.3 | 55.8 | 50.8 | 34.8 |
| **NDWI** | 87.9 | 78.2 | 77.6 | 75.1 | 77.1 | 65.3 | 60.3 | 62.3 | 58.0 | 50.5 | 78.1 | 71.8 | 72.1 | 69.4 | 67.8 | 56.3 | 43.5 | 44.3 | 38.8 | 35.5 |

Figure 3.9 Overall model classification performance for the dry season (a) and wet season (b), based on the Landsat-8 (i) and Sentinel-2 (ii) derived indices

| | 2016 | 2017 | 2018 | 2019 | 2020 |
|---|---|---|---|---|---|
| **L8 Dry** | 28 | 48 | 70 | 73 | 76 |
| **L8 Wet** | 32 | 71 | 66 | 72 | 21 |
| **S2 Dry** | 39 | 72 | 75 | 70 | 19 |
| **S2 Wet** | 15 | 63 | 65 | 21 | 19 |

Figure 3.10 RMSE ($m^2$) of the VCI applied to pre-processed Landsat-8 and Sentinel-2 data

| | 2016 | 2017 | 2018 | 2019 | 2020 |
|---|---|---|---|---|---|
| **January** | 68.02 | 48.34 | 73.25 | 70.16 | 79.64 |
| **April** | 69.63 | 47.54 | 72.76 | 73.57 | 82.91 |
| **July** | 52.32 | 29.34 | 36.92 | 82.34 | 84.38 |
| **October** | 43.87 | 70.34 | 68.26 | 83.35 | 84.26 |

Figure 3.11 RMSE ($m^2$) of SPI for the years 2016 to 2020

| | 2016 | 2017 | 2018 | 2019 | 2020 |
|---|---|---|---|---|---|
| **RMSE value** | 78.47 | 67.16 | 82.36 | 80.94 | 79.26 |

Figure 3.12 RMSE ($m^2$) of WRSI for years 2016 to 2020

### 3.7 Discussion

This study examined the use of various multispectral indices obtained from the Landsat-8 OLI and Sentinel-2 MSI data to monitor the impacts of the drought on the surface water resources in the Cape Metro, Cape Winelands, Overberg and Garden Route regions in the Western Cape, South Africa. The climate data and remotely sensed data were integrated to assist with the interpretation of the results. The results of the analysis indicated a high surface waterbody variability for the study period, which implies the potential of satellite data for monitoring the effects of a drought on the surface water resources. Numerous waterbodies were identified by Landsat-8 and Sentinel-2 during the wet season, which is expected, as the precipitation is higher during the wet season. Both sensors detected few surface waterbodies during the dry season in 2017 and early 2018, which indicates a restricted surface water availability across the study area and correlates with the recorded climatological data. Climatological reports by the Department of Water and Sanitation and the City of Cape Town indicated that this had been the worst drought experienced in the area since 2002 (Department of Water and Sanitation, 2016; City of Cape Town, 2018). Low rainfall rates were recorded from 2016 to mid-2018, and 2017 was characterized as a drought period, which led to water shortages in the Western Cape. High evapotranspiration rates were recorded between the year 2017 and 2018. Evapotranspiration is directly linked to temperature and they have a proportional relationship, when temperatures are high during the dry season, the ET rates are also high, due to more energy being available (Kosa, 2009; Marshall *et al.*, 2012). The availability of surface water was severely impacted during this drought period and this could be detected by both sensors; therefore, these findings emphasize the need to improve the monitoring of droughts and surface water resources.

Although the multispectral results show visually similar patterns of waterbodies from the indices applied to the Landsat-8 and Sentinel-2 images, the LSWI+5 was the exception and had the lowest accuracy. This index is centred on the link between vegetation greenness and the Enhanced Vegetation Index (EVI), and since most waterbodies are surrounded by vegetation and mountainous areas, it is possible that the LSWI+5 index misclassified these land types as waterbodies (Chandrasekar *et al.*, 2010; Huang *et al.*, 2018; Bhaga *et al.*, 2020). The LSWI+5 performed poorly during the wet season and this could be attributed to the index being more sensitive to the plant leaf water content and soil water content, which led to the overestimation of the surface waterbodies (Chandrasekar *et al*., 2010; Jin *et al*., 2013; Bhaga *et al*., 2020). The tendency of the index to overestimate the area of surface waterbodies has previously been documented in literature (Jin *et al*., 2013; Seaton *et al*., 2020; Bhaga *et al*., 2020); therefore, it may not be appropriate for mapping surface waterbodies in highly-vegetated environments, due to the confusion arising from its sensitivity to the leaf water content.

The results from the MNDWI, NDVI and NDWI had similar performances, although the Sentinel-2-derived NDVI had the highest accuracy, irrespective of the seasonal differences, with an overall accuracy of 71.9% for the dry season and 67.6% for the wet season. NDVI is sensitive to plant biomass and therefore indicates water stress, which leads to high accuracies in mapping surface waterbodies. The NDWI was able to delineate the vegetation and waterbodies, as the green band maximises the reflectance of the waterbodies and minimises the low reflectance of near-infrared (NIR) reflection of the waterbodies, while simultaneously using the high reflectance in the NIR of vegetation and soil. This enhances the surface waterbodies and restricts the vegetation and soil features; however, not all built-up features can be suppressed and small waterbodies may not be detected (Huang *et al*., 2018; Bhaga *et al*., 2020). The MNDWI was developed in order to identify waterbodies in built-up areas. The MNDWI uses the green band and shortwave-infrared (SWIR) band, because it is able to reflect the elusive properties of water, which reduces its sensitivity to the presence of sediments in the surface waterbodies (Huang *et al*., 2018), hence the higher accuracy during the dry season, as the water is not as turbulent (Li *et al*., 2013). However, mountainous areas are still misclassified as water, due to the low albedos and the effects of shadows from mountainous terrain (Sarp & Ozcelik, 2017; Seaton *et al*., 2020). The MNDWI, NDVI and NDWI had reasonable overall accuracies; the lowest accuracy was recorded for the year 2017, which was the year in which the lowest rainfall rates and highest ET rates were experienced. The results obtained from Sentinel-2 indicate that it outperformed Landsat-8 during both seasons. The complexities of mapping surface waterbodies were primarily caused by the mixed pixels at the edges of the waterbodies and shadows, due to the neighbouring landscape. These challenges were also experienced by Masocha *et al*. (2018) and Seaton *et al*. (2020).

The variations of the detected surface waterbodies were significant over the study period, as they decreased in size and dried up, due to the low precipitation rates and high ET. High ET rates are experienced, due to higher temperatures, which causes the surface waterbodies to dry up. Little rainfall is received throughout the dry season, due to the Mediterranean climate. This was shown by both satellite datasets and it correlates with the studies conducted by the Department of Water and Sanitation (2016), City of Cape Town (2018) and Department of Water and Sanitation (2018). The volume of surface waterbodies decreased due to the low amount of precipitation received in 2016, 2017 and the dry season of 2018, which emphasised the drought period experienced by the Western Cape Province (Department of Water and Sanitation, 2018; Muller, 2018). The study conducted by the Department of Water and Sanitation (2018) indicated that the main dams in the Western Cape, namely, the Theewaterskloof, Voëlvlei, Berg River, Wemmershoek, Steenbras Upper and Steenbras Lower Dams, all experienced low dam levels in November 2017. Theewaterskloof Dam, which is the city's main water supplier, was only 27.2% full, and the Voëlvlei Dam was 28.5% full. They also noted that the Theewaterskloof Dam had high ET rates in 2017 and early 2018, which emphasises the drought conditions and further confirms the results of this study. However, after the wet season in 2018, the Theewaterskloof Dam level was 57.9% full and the Voëlvlei Dam was 96.1% on the 31st October 2018. This corroborates the results of this study, as the rate of precipitation increased during the wet season of 2018, which caused the size of the surface waterbodies to increase and eased the drought conditions in the Western Cape. The high precipitation rates in 2019 and 2020 led to the increased size of the surface waterbodies.

The Vegetation Condition Index results by Landsat-8 and Sentinel-2 indicated the drought conditions experienced by crops in the region of study. The findings showed that a severe drought was experienced in 2017 and during the dry season of 2018, which supports the other satellite data findings and climatological data. The Landsat-8-derived VCI is more accurate than the Sentinel-2-derived VCI, as the Sentinel-2 results overestimated the drought conditions and did not relate to the other multispectral and climatological results. The application of the Standardized Precipitation Index (SPI) has gained importance as a potential drought indicator (Kalisa *et al.*, 2020). The SPI results were used to quantify the drought and these results supported the satellite data findings and the climatological data, which classified 2016 and 2017 as moderately and severely dry. The SPI also classified July (the wet season) as having near normal to wet conditions, which is expected, as the study area receives most of its precipitation during this month. The SPI results showed that from the wet season of 2018, conditions returned to being near normal to wet, due to an increase in precipitation. The Water Requirement Satisfaction Index (WRSI) is often applied to study the variations in a drought over space and time (Legesse & Suryabhagavan, 2014). Low WRSI values indicate drought conditions, and this was revealed during 2016 and 2017, with 2016 having a value of 60% and 2017 having a value of 59%, which indicate a moderate and a severe drought, respectively. The WRSI values started increasing yearly from 2018, which was confirmed by the climatological results, as well as the multispectral results, of this study. The performance of Landsat-8-derived VCI and the SPI and WRSI is relatively accurate and achieved acceptable RMSE values, which indicates that these indices can be used as drought indicators.

The findings of this study indicate that Sentinel-2 MSI imagery had a slightly higher accuracy in the mapping of the surface waterbodies, in comparison to Landsat-8 OLI imagery. This is due to the 10 m spatial resolution, which can detect small waterbodies. The push-broom characteristic of Sentinel-2 allows the sensor to scan along the track, which improves its ability to detect the surface features (Dube & Mutanga, 2015; Bhaga *et al.*, 2020). The results of this study prove that satellite data are suitable for monitoring the impacts of a drought on the water resources, with NDVI being the best index for extracting surface waterbodies. The Landsat-8-derived VCI detected drought conditions more accurately than the Sentinel-2, and the SPI and WRSI achieved high RMSE values, which means that they are suitable for detecting drought conditions. When combined, our results emphasise the importance of satellite data, not only for mapping surface waterbodies, but also for assessing the impacts of a drought on the surface water resources. Their ability to do this lays a strong foundation for sustainable water resource monitoring and management, as remotely sensed data are freely available at a moderate resolution. This is extremely important in drought-prone areas, where access to information is costly or scarce.

Other studies were able to show the considerable contribution made by vegetation indices; however, the findings of these were not often correlated with the climatological data. There is also inadequate documentation on the use of remote sensing for monitoring the impact of droughts on the water resources in the Western Cape and beyond. This study investigated the effects of a drought on the surface water resources in the Western Cape by using drought indices, surface water indices and climatological data. The results indicate that water availability responds to changes in the climatological variables, which will help to predict drought conditions in a timely, reliable and cost-effective manner. This is important for water resource management, as it is vital for determining how much water is available for use. This study was able to correlate the multispectral results of the surface waterbodies with the drought multispectral results and with the climatological data and to note a relationship between these datasets, as the climate impacts the surface water resources. When the precipitation rates were low, the size of the waterbodies shrunk, and when the size of the waterbodies was extremely small over a prolonged period, the region experienced drought conditions. Therefore, the climatological data was able to consolidate the remote sensing results. Overall, the outcomes of this study provide a new understanding of the application of multispectral indices, climatological data and the usefulness of sensors for monitoring the impacts of drought on the water resources. The results can be vital in decision-making and in the development of new policies. However, the results of the study were also limited, as a result of the misclassification of shadows from mountainous regions and built-up areas. In the future, more studies need to be conducted over larger areas, in order to test the suitability of using remotely sensed data, multispectral indices and climatological data to monitor the impacts of drought on water resources on a national level. There is also a need for future studies to improve the indices, so that they can differentiate between shadows from mountainous areas and surface waterbodies more accurately.

## 3.8 Conclusion

This study investigated the possible application of satellite imagery for monitoring the impacts of a drought on the water resources in the Cape Metro, Cape Winelands, Overberg and Garden Route regions of the Western Cape, South Africa. Three surface water multispectral indices and four drought detection indices were used to establish the most appropriate technique for surface water detection and drought monitoring. These indices were closely linked to climatological data, such as the evapotranspiration (ET) rate, the precipitation rate and the temperature. There appeared to be a relationship between the ET rate, precipitation and the detected surface waterbodies. When there was an increase in precipitation, the size of the surface waterbodies increased, and when there was an increase in ET, there was a decrease in the size of the surface waterbodies. The Sentinel-2-derived NDVI was the most appropriate method for identifying and mapping surface waterbodies, with an overall classification accuracy of 77.27%, and the Landsat-8-derived VCI was the most accurate method for detecting drought conditions. The results of this study show that Landsat-8 and Sentinel-2 produced similar results for the study region; however, Sentinel-2 generated higher accuracies. Most importantly, the outcomes of this study showed the reliability of using freely available satellite images for informing water resource management. It is therefore essential to monitor drought patterns and their effect on the water resources. Derived information helps to address and mitigate the impacts of a drought on a short- and long-term basis. The application of remote sensing provides for rapid drought detection and the near real-time monitoring of water resources, which is vital for the water resource management of drought-prone areas.

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# CHAPTER 4

# A SYNTHESIS: MULTISPECTRAL REMOTE SENSING OF THE IMPACTS OF DROUGHT AND CLIMATE VARIABILITY ON WATER RESOURCES

## 4.1 Introduction

Surface waterbodies are vulnerable to drought and need to be monitored in an efficient manner (AghaKouchak *et al*., 2015). Therefore, there is a need to determine the onset of drought conditions, especially in drought-prone regions. Drought prediction and the monitoring of surface waterbodies is vital for water resource management, as well as for mitigation and adaptation strategies. Although research has been conducted on the detection and mapping of droughts and surface waterbodies, many of these studies have not been conducted in sub-Saharan Africa, and more particularly, not in the Western Cape Province of South Africa. The traditional methods used for drought detection and surface waterbody monitoring have been challenging because they are time-consuming and costly. The use of MODIS and Landsat TM/ETM+ images have previously been used to detect droughts and to map surface waterbodies; however, their results are not very accurate in complex environments. With the advancements in remote sensing, Landsat-8 and Sentinel-2 have been developed with a high spectral, spatial and temporal resolution, and they have been used in recent studies to map surface waterbodies with reliable and highly accurate results (Sarp & Ozcelik, 2017; Masocha *et al*., 2018; Seaton *et al*., 2020; Bhaga *et al*., 2021). Remote sensing therefore provides new opportunities for the accurate detection, mapping and monitoring of droughts and surface waterbodies, as well as determining the impact of droughts on surface waterbodies (Varghese *et al*., 2021). Hence, the objectives of this study were:

a) to develop a model for the retrieval and tracking of the changes and impacts of drought and climate variability on surface waterbodies from the multispectral archival data; and

b) to assess the impacts of drought and climate variability, as well as the evapotranspiration rate, in selected sub-catchments, by using the available ET products and in-situ data.

## 4.2 Summary of Findings

Two multispectral remotely sensed data sources (Landsat-8 and Sentinel-2) were assessed for the detection and mapping of the impacts of drought on surface water resources, in order to provide reliable information on the variability of water resources. The results of this study have successfully demonstrated the capability of both satellite datasets to detect and map the occurrence of a drought and its impacts on the surface waterbodies. The results showed that both satellite datasets are able to adequately detect and map surface waterbodies. The Analysis of Variance (ANOVA) showed that there was a significant statistical difference between the two sensors in the discrimination of surface waterbodies from non-waterbodies ($\alpha = 0.04$). However, Sentinel-2 yielded better overall accuracy results, with an improved user's and producer's accuracy in detecting and mapping surface waterbodies, compared to Landsat-8. This could be due to the high spectral and spatial resolution of Sentinel-2. The Sentinel-2-derived Normalised Difference Vegetation Index (NDVI) produced the best overall accuracy results and was able to differentiate between the drought periods and normal conditions by the variability in surface water size and their occurrence. The Modified Land Surface Water Index (LSWI+5) produced the lowest overall accuracy results for both sensors and overestimated the occurrence of surface water resources; it was therefore unable to identify drought conditions. Overall, the results have demonstrated the improved capability of Sentinel-2 to detect and map surface waterbodies with less overestimation, which therefore makes it more accurate for the monitoring of surface water resources and for assisting in the detection of droughts.

Secondly, evapotranspiration (ET) data and climatological data were analysed together with the remote sensing data, in order to interpret the results more accurately and to note the variability in the surface waterbodies, to indicate either drought or normal conditions. Climatological data, namely the Vegetation Condition Index (VCI) and Standardized Precipitation Index (SPI), were also used to calculate drought indices, and the Water Requirement Satisfaction Index (WRSI) was used to classify the drought conditions. The changes in the variability of the surface waterbodies were significant over the study period. They decreased in size due to the lack of precipitation and the high ET rates. The volume of the surface waterbodies changed in response to the seasonal rainfall; however, due to the low precipitation rates in 2016 and 2017, there was no significant increase in the volume of the surface waterbodies, which indicated drought conditions. The size of the surface waterbodies was extremely small during the dry season of 2018, which emphasized the drought period in the Western Cape. The rate of precipitation increased during the wet season of 2018 and continued to increase in 2019 and 2020, which caused the size of the surface waterbodies to increase and indicated the end of the drought period.

Overall, the study demonstrated the use of integrating multispectral and climatological data in the detection of droughts and for assessing the impacts of a drought on the water resources. This capability provides reliable and vital information on drought conditions and the variability of water resources within the study area. Therefore, these results will provide the necessary information for the mapping and management of surface water resources and will help to provide drought preparedness and mitigation.

### 4.3 Conclusion

The main aim of this study was to assess the extent to which remote sensing datasets can be used to monitor the impacts of a drought on the water resources in the Western Cape, South Africa. The findings of this study highlighted the capabilities of multispectral remote sensing satellite imagery in the detection and mapping of surface waterbodies. Based on the objectives of the study, the following findings were obtained:

- Landsat-8 OLI and Sentinel-2 MSI have the great capability of mapping and detecting the occurrence of a drought and its impacts on the surface water resources. However, Sentinel-2 outperformed Landsat-8, due to its improved spectral and spatial resolution. As a result, it can aid in water resource management and decision-making.
- Remotely sensed multispectral indices demonstrated their capability to track the variability of surface water.
- The Sentinel-2-derived NDVI yielded the most accurate results.
- ET, in conjunction with other climatological data, can be used to monitor drought conditions and surface water variability.
- SPI and WRSI can accurately detect drought conditions in the study area.
- Drought conditions were detected from 2016 to the wet season of 2018, which correlates with the conditions experienced in the study area.

Overall, the results provide for the near real-time monitoring and effective management of surface water resources. Thus, this approach can help water resource managers with management and drought preparedness, especially in arid and semi-arid regions.

## 4.4 Recommendations

The results obtained in the present study provide an insight into the impacts of drought on water resources and their spatial variability. These results also provide new insights into the developments in remote sensing and their potential application in the detection and mapping of droughts and their impact on water resources. There is therefore a need to shift towards using freely- and readily available remote sensing datasets that have an improved spatial and spectral resolution. This study makes the following recommendations for future research:

- The results of this study suggest that Landsat-8 is not suitable for mapping the spatial variations in surface waterbodies; therefore, it is recommended that Sentinel-2 be the primary dataset.
- In the future, more studies need to be conducted over larger areas, to test the suitability of using remotely sensed data, multispectral indices and climatological data to monitor the impacts of droughts on water resources on a national level.
- There is a need for future studies to develop indices that improve the differentiation of mountainous areas and surface waterbodies, as satellite images are susceptible to shadows, built-up areas, cloud cover and pixel mixing.
- The remote sensing results need to be blended with climatological data to test if this will reduce the varying estimations.
- More studies need to be conducted in sub-Saharan Africa, especially in South Africa, to test the applicability of remote sensing for improving drought detection and water resource management.

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