Spatial and temporal dynamics of flows and pools along non-perennial rivers in arid and semi-arid areas, South Africa

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Abstract

This study aimed to assess the use of multi-source remotely sensed data for monitoring the spatial distribution and dynamics of pools in two distinct sites (Touws and Molototsi) in South Africa. Various water extraction indices, including NDWI, Modified NDWI, and NDVI, were employed, along with a random forest classifier and Sentinel-1 SAR data, to map pools and their dynamics in both locations. The remote sensing methods effectively detected and mapped pools with satisfactory accuracy, except for small pools below 400 square meters. The study identified flow occurrences and rainfall as significant factors influencing changes in pool sizes. However, the interaction between pools and groundwater required further investigation and showed no conclusive evidence in this study. To evaluate the water fluxes affecting pool dynamics in the Touws River, a water balance approach was utilized. The analysis revealed that evaporation was the primary mechanism of water loss from the pools. The interaction between the main pool (Wolverfontein 2) and groundwater depended on water levels, with the pool losing water to the subsurface up to a specific depth before gaining water. When Wolverfontein 2 pool was full, it could retain water for approximately 258 days without any surface water inflow. A water balance model was developed, demonstrating a high correlation coefficient of 0.9 in simulating water levels. However, the model performed less accurately for the downstream pool compared to the upstream pool. When remote sensing-derived rainfall and evaporation data were incorporated into the model, the simulated water levels exhibited a slightly lower correlation coefficient of 0.7 with the observed water levels. Overall, the monthly flux estimates derived from remote sensing did not provide the detailed pool information necessary for a comprehensive water balance analysis. Errors or uncertainties could have originated from any of the three remotely sensed parameters: surface area, rainfall, or evaporation. Nevertheless, remote sensing offered valuable baseline data on pool dynamics despite its limitations in providing detailed information. The study also explored the spatiotemporal dynamics of non-perennial river systems and identified major runoff contributing areas in the Touws and Molototsi rivers. Sentinel-1 and Sentinel-2 satellite data sources were employed. The MNDWI was applied to Sentinel-2 images to extract water surface areas along the rivers, enabling the determination of hydrological states over a 32-month period from 2019 to 2022. The rivers were classified into flowing, containing pools, or dry states based on water presence. Sentinel-1 data assisted in detecting flow events that might have been missed by Sentinel-2 due to cloud cover and temporal resolution limitations. The results demonstrated that remote sensing could determine the hydrological state of the river with an overall accuracy of approximately 90%. However, there was a 30% chance of missing a flow event using Sentinel-2 due to clouds and temporal resolution issues. Sentinel-1 SAR data helped mitigate some of these limitations, as observed in the Molototsi River. The upper catchment contributed the majority of flows in the Molototsi catchment, while in the Touws River, the south-western part of the catchment was identified as the major contributing area for observed flows, primarily driven by rainfall. In summary, this study provided valuable hydrological information and simple approaches for monitoring hydrological states and pool dynamics. These findings contribute to a better understanding and management of non-perennial rivers (NPRs) and catchments.

Keywords: Dryland pools; dryland areas; ephemeral streams; hydrology; pool dynamics; Water resource management

19 May 2023

Declarations

"I declare that the thesis entitled" *Spatial and temporal dynamics of flows and pools along non-perennial rivers in arid and semi-arid areas, South Africa.*" is my own work, that it has not been submitted before for any degree or examination in any other university, and that all the sources I have used or quoted have been indicated and acknowledged by through of complete references."

Sagwati Eugene Maswanganye

Signed:...

Publications

Published papers and the manuscript were prepared by Maswanganye S.E, who also data collected and analyses the data. Timothy Dube, Dominic Mazvimavi, Nebo Jovanovic and Evison Kapangaziwiri reviewed and supervised the work. Below is the list of published work and a manuscript.:

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Dedication

I would like to dedicate this thesis to my parents Zamazisa and Nkhensani this is a product of your prayers. *Ninga rivali vamakwevo Khanyisa, Bumani, Migingiriko, Khutso na Nhlalala, na nkhensa vana ka hina.*

Abbreviations

ARC	Agricultural Research Council
CHIRPS	Climate Hazards Group InfraRed Precipitation with Stations
CSIR	Council of Science Industrial Research of South Africa
DEM	Digital Elevation Model
MODIS	Moderate Resolution Imaging Spectroradiometer
MNDWI	Modified Normalised Difference Water Index
NASA/ASF	National Aeronautics and Space Administration Alaska Satellite Facility
NPRs	Non-Perennial Rivers
NDWI	Normalised Difference Water Index
NDVI	Normalised Difference Vegetation Index
Ppt	Precipitation
RADAR	RAdio Detection And Ranging
SAR	Synthetic Aperture Radar
SAWS	South African Weather Service
SDG	Sustainable Development Goal(s)
SNAP	Sentinel Application Platform
USA	United States of America
USGS	United States Geological Survey
USDA	United States Department of Agriculture
WR2012	Water Resource 2012 Study, South Africa
WL	Water Level
WB	Water Balance
WMO	World Meteorological Organisation
WAD	World Atlas of Desertification

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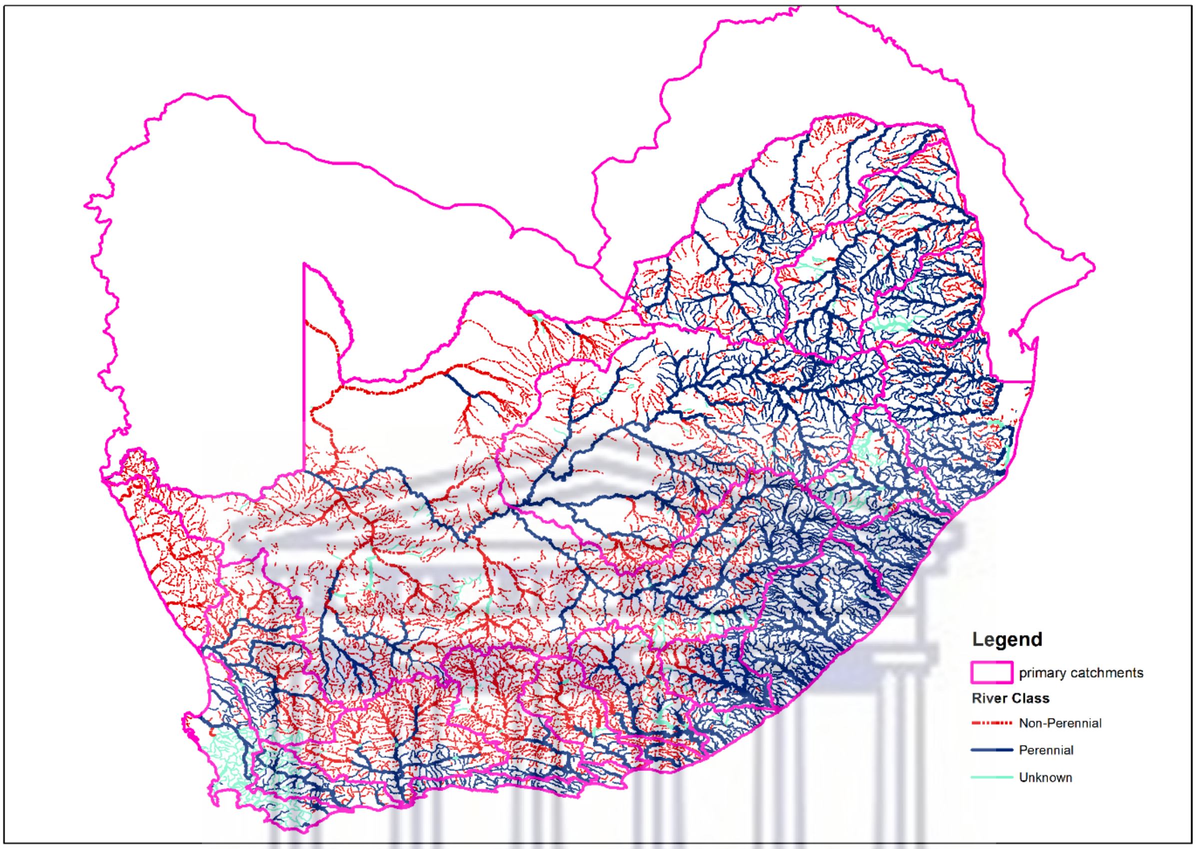
Chapter 1: General Introduction



1.1 Background and Problem Statement

Knowledge of the spatial and temporal dynamics of pools and river flows is important for water resource management, such as water allocation. The spatial and temporal dynamics have been well studied in perennial rivers due to the priority placed by society as they are perceived to be a reliable water source (Rodríguez-Lozano et al., 2020). This is not the case for non-perennial rivers, which remain understudied. Non-perennial rivers make up more than 50% of the total length of the global river network (Skoulikidis et al., 2018), and in South Africa, over 60% of the rivers are non-perennial (Seaman et al., 2006). In the next century, the number and length of non-perennial rivers will increase due to climate and land-cover change and increasing water demand for drinking, irrigation and other economic uses (Datry et al., 2014). Non-perennial rivers arguably have more complex flow regimes than perennial systems (Datry et al., 2018; Larned et al., 2010). Although non-perennial rivers are important water sources, and provide essential ecological services, they are still overlooked in terms of research and management, to the extent that there is an ongoing debate as to whether non-perennial rivers and streams should be considered as water bodies and be protected by water laws and policies (Messager et al., 2021; Skoulikidis et al., 2017; Acuna et al., 2014). According to the European Union, non-perennial rivers and streams may or may not be considered as water bodies by law, depending on the classification used (Acuña et al., 2014).

One of the characteristics of non-perennial rivers is that flow ceases for a period of time. The cessation of flow is caused by one or more of the following processes: transmission losses, evapotranspiration, a decline of groundwater tables, hillslope runoff recession and freeze-up (Larned et al., 2010; Zimmer et al., 2020). These processes are affected by physical factors, such as geology and slope. Price et al. (2021) assessed the drying regime of NPRs and concluded that land cover/use was more important to how the river dries than climate and physical characteristics. The hydrological connectivity of the flow controls meta-community and meta-ecosystem dynamics (Larned et al., 2010). There are also anthropogenic causes, such as the over-extraction of water and the construction of dams. The cessation of flow due to both natural and anthropogenic activities have hydrological and biogeochemical implications. The hydrological implications include the formation of pools.

Pools are one of the most distinguishing characteristics of non-perennial rivers when the flow has ceased (Datry et al., 2018; Hughes, 2005). These pools are important water sources in rural areas. They often provide water for vegetable gardening, livestock and wildlife, and therefore support the tourism sector and people's livelihoods (Amede et al., 2011; Mworia et al., 2008; Zamxaka et al., 2004). Pools also act as habitat, feeding, and spawning ground for various aquatic species (Makwinja et al., 2014). Taylor, (1997) states that there is a significant species-volume relationship for pools. The species richness also depends on the physical-chemical properties of the pools. Many studies have shown that pools are sources of water during drought to the surrounding communities, while some studies show that pools attenuate floods (Liu and Zhang, 2017) as they store flood water (Datry et al., 2017). Pools are also areas of groundwater and surface water interactions (discharge and recharge zones) (Hayashi and Rosenberry, 2002) as most pools in arid and semi-arid areas are groundwater-dependent (Bestland et al., 2017).

Despite the importance of these rivers, the spatial and temporal dynamics of flows and pools along non-perennial rivers are poorly understood. The occurrence and size of pools have been generally studied from a channel (slope, bed material) perspective by geomorphologists and mostly at reach scale (Booker et al., 2001; Buffington et al., 2002; MacWilliams et al., 2006).

These studies also show that the occurrence and sizes of pools vary from one landscape to another. Less work has been done from the hydrological perspective (Bonada et al., 2020; Shanafield et al., 2021) in terms of understanding the spatial distribution, the frequency of occurrence, and the persistence and storage of the pools in catchments. Gaining good knowledge of the spatial and temporal distribution of the pools will be useful for assessing water availability in a particular catchment, which is required for water allocation and setting the ecological reserve (Seaman et al., 2016).

Flow measurements at a point do not account for the river's hydrological phases (flow, pools, dry riverbed). The expansion and contraction in the length of wetted reaches can cause variations in water quality, the composition of aquatic and riparian communities, and meta-population dynamics, hence ecological studies of spatially variable streams need to identify and account for these hydrological phases (Turner and Richter, 2011). Gallart et al. (2016) state that knowing the distribution of hydrological phases is important for the selection of the correct periods and methods to determine the ecological status. Turner and Richter (2011) and Gallart et al. (2016) used citizen science, interviews and aerial photographs to assess the hydrological phases (flowing, pools, and dry riverbeds). The assessment of hydrological phases provided different insights, such as explaining the variations in water quality, and the composition and movement of aquatic communities, which cannot be obtained by conventional flow measurements.

According to Snelder et al. (2013), effective management of non-perennial rivers is hindered by the scarcity of information about their abundance, distribution patterns, flow variability and environmental conditions that produce these patterns. Avenant, (2012) and Seaman et al. (2013) outlined the challenges and constraints of establishing an ecological reserve for non-perennial rivers, and concluded that methods developed for perennial rivers should not be directly applied to non-perennial rivers as they are more complex, more dynamic, and highly variable compared to perennial rivers. Datry et al. (2018) and Leigh et al. (2016) affirm that conceptual models and insights from the perennial river system guide the current management of non-perennial rivers. There is a need to develop new methods for non-perennial rivers. However, there is a need first to develop an understanding of these systems. The required information includes seasonality, frequency of occurrence, duration, persistency and magnitude/volume stored of flows and pools, which is poorly understood (Seaman et al., 2016). Surface water connectivity including the rainfall threshold required for flow to occur, which then allows movements of nutrients and organisms, is also poorly understood, which affects the prediction capability of the occurrence of organisms under various scenarios. Extrapolation of data from data-rich to data-poor areas is problematic for non-perennial rivers due to the high variability of these rivers. For instance, each pool in the same river reach may function differently; as a result, the extrapolation of data may be very inaccurate, hence not recommended for non-perennial rivers (Seaman et al., 2013). Therefore, understanding is mostly limited to individual sites.

Remote sensing is continuously improving in spatial and temporal resolution and in how the obtained information is processed and analysed (algorithms) to overcome some weaknesses. However, the use of remote sensing has been limited to large (width of more than 400 m) wetlands and perennial rivers (Chawla et al., 2020), wetlands are hereby defined according to the South African National Water Act (36 of 1998). There are few studies focusing on the spatial and temporal dynamics of pools and flows in non-perennial rivers. Also, the potential of using remote sensing to obtain information about the spatial and temporal dynamics of flow and pools has not been thoroughly investigated in non-perennial rivers. If such a potential exists, this will contribute towards understanding spatial and temporal dynamics of non-perennial rivers and supporting the management of these rivers, especially in data-scarce regions like South Africa and the rest of Africa. In this study, the potential for remote sensing to obtain this useful hydrological information is tested while improving knowledge about the spatial and temporal of non-perennial pools and flows.

1.2 Aim:

To improve knowledge about the spatial and temporal dynamics of river flows and pools along non-perennial rivers, using remote sensing and in-situ measurements.

1.3 Objectives:

i) To review the strengths and limitations of the methods used to monitor non-perennial rivers from a hydrological perspective as well as provide an overview of the potential of using satellite remote sensing to monitor these rivers.

ii) To examine the nature of the spatial and temporal distribution of pools along non-perennial rivers.

iii) To establish factors and processes accounting for the water dynamics of selected and representative pools.

iv) To assess the spatial and temporal dynamics of the hydrological (flow) states as well as determine possible contributing areas.

1.4 Research questions

i) What is the spatiotemporal nature of the pools and the factors accounting for their distribution?

ii) At a reach scale, which water fluxes affect individual pools (filling and emptying rate) and how are they partitioned?

iii) What are the spatial and temporal dynamics of hydrological states?

iv) What is the rainfall threshold for the river to start flowing and where are the major flow-contributing areas of catchment?

v) To what extent can remote sensing be used to answer the above questions?

1.5 Study Area Description

The study was conducted in two non-perennial rivers (NPRs) found in two different catchments in South Africa. The two NPRs included the Touws and Molototsi River systems, located in the Western Cape and the Limpopo Provinces in South Africa, respectively (Figure 1.1). These study catchments were selected based on their varied properties (Land use& Land cover, Soil types, Catchment size, and Climate). This allowed the study to explore the effect of these properties on the hydrological dynamics of pools and flows.

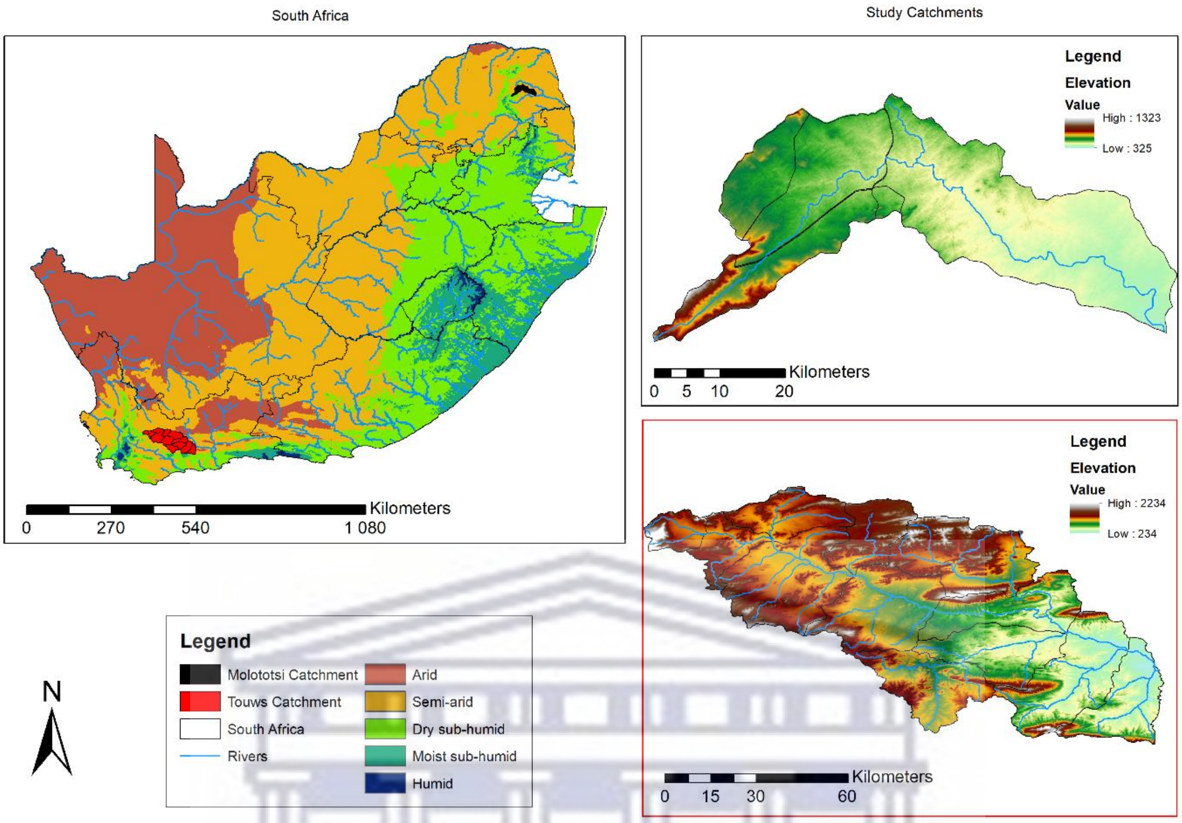


Figure 1.1: Location of the Molototsi (Black) and Touws (Red) River catchments in respective of South Africa on a map delineating provinces, river network and climatic regions(left). Topographic map of Molototsi (top right) and Touws River (bottom right) with river network and delineation of quaternary catchments.

The Touws River catchment covers an area of 6280 km^2 and 12 quaternary catchments (J12A – J12M). Ladismith and Montagu are some of the closest major towns to the area. The Touws River is the main river in the catchment. The catchment has a low gradient with an altitude ranging from 213 to approximately 2241 meters above sea level on the mountainous side (Figure 1.1). The Touws River is one of the main tributaries of the Groot River, rising at the western limit of the Great Karoo and draining in an east-south easterly direction to the confluence with the Groot River. The catchment has two major dams: Bellair and Prinsrivier.

The Touws River is sandy gravel above the Adolpaspoot shale formation. The catchment is mainly covered with natural vegetation, predominantly shrubland and fynbos, with some parts of the riparian zone used for agriculture purposes (Figure 1.2). The catchment has a mean annual rainfall of 244 mm/year (Grenfell et al., 2021). The catchment received 112, 91 and 182 mm/year in 2018, 2019 and 2020 respectively, without a seasonal pattern (Figure 1.3). Most rainy days received less than 5 mm/d of rainfall. Only four events exceeded 30 mm/day during the study period (Figure 1.3). These major rainfall events produced localised flows, with some of the flows not reaching the flow station at the catchment outlet (Department of Water and Sanitation Station J1H018). According to Petersen et al. (2017), the catchment has a mean annual runoff (MAR) of 16.32 Mm^3/year (1980-2013).

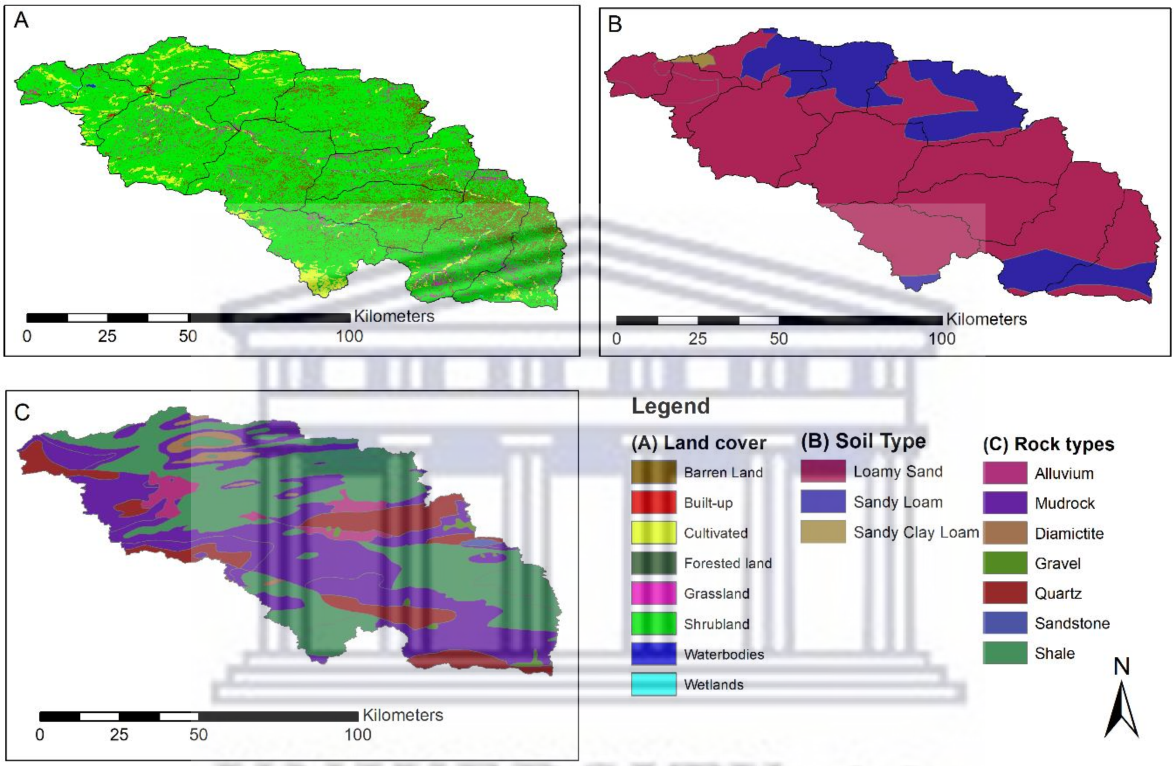


Figure 1.2: Land cover (A), Soil types (B) and Geology (C) of the Touws catchment. Data Sources: 2020 South African National Land Cover; Department of Environmental Affairs, WRC-WR2012 (Soil data), South African Council for Geoscience (Geology data).

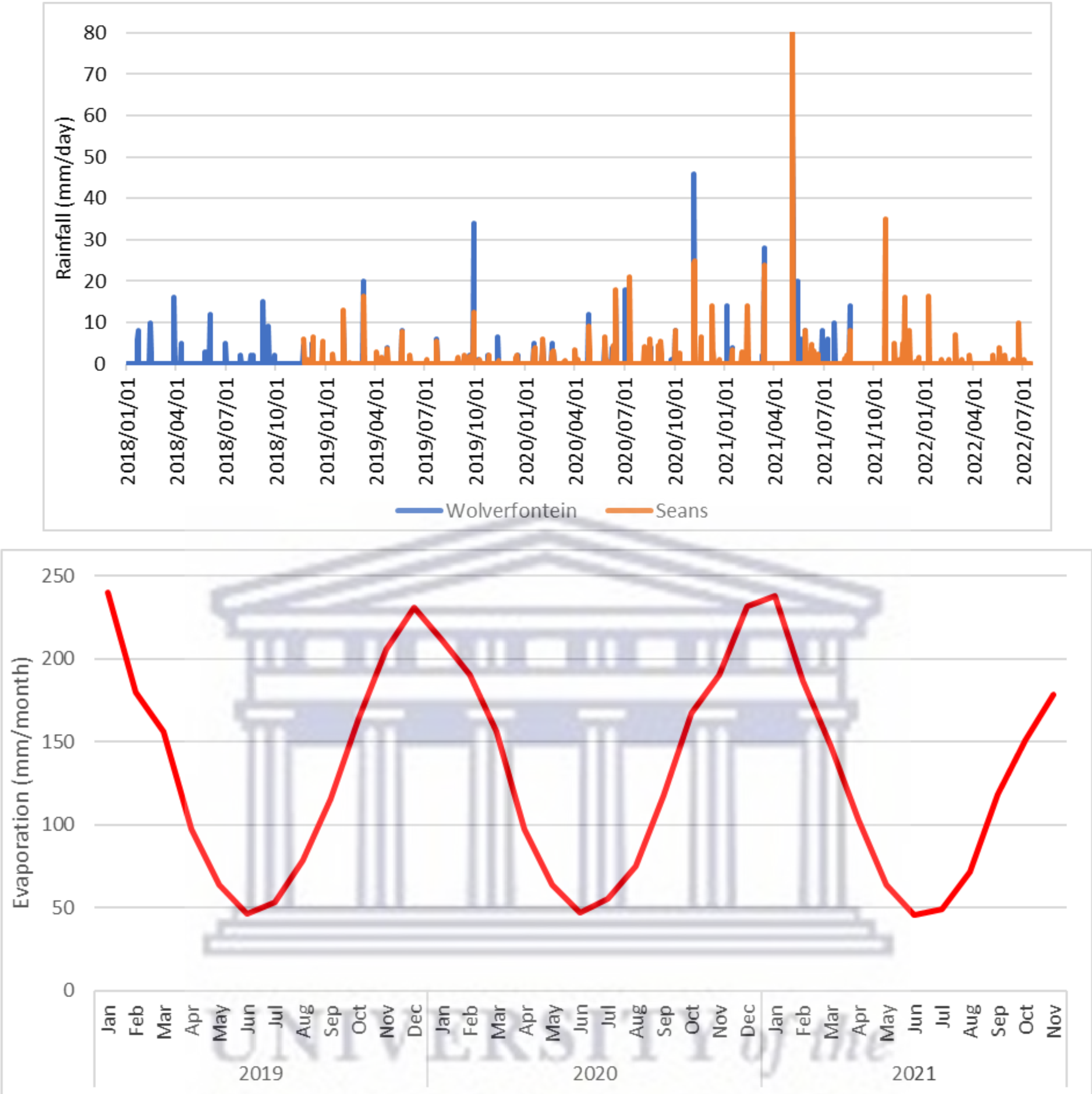


Figure 1.3: Rainfall (A), and Evaporation (B) of the Touws catchment. The rainfall data were collected through the citizen science programme, evaporation rates were estimated using the Penman method.

The Molototsi catchment is in the Greater Letaba primary catchment, which lies within the Mopani District, Limpopo. The Molototsi catchment is 1170 km^2 and covers quaternary catchments B81G and B81H. The closest towns include Giyani and Tzaneen. Molototsi River has a sandy riverbed and is approximately 120 km long and 50 m wide, and it is one of the tributaries to the Great Letaba River. The Molototsi River only has one major tributary called Metsemola. The Modjadji dam (8.4Mm^3 capacity) which was built in 1997 is the only major impoundment in the river, located in the upper part of the catchment (Figure 1.4). The dam has a catchment area of about 70 km^2. The dam supplies drinking water for the Great Letaba municipality area.

The geology of the Molototsi study catchment (Figure 1.4C) is predominantly characterized by the Letaba Gneiss lithostratigraphic unit, although the upper part of the catchment includes Duiwelskloof Leucogranite. The substrate of the river is sandy, while loamy sand is the dominant soil type (Figure 1.4B). The river is surrounded by communities (human settlements), with agriculture taking place in the riparian zone along the river (Figure 1.4A). The upper catchment has a mean annual rainfall of 1219 mm/year (1998-2017) measured close to the Modjadji dam (Walker et al., 2018). However, the flood plain receives between 300-400 mm per year (Lebea et al., 2021). The catchment receives rainfall mainly during the southern hemisphere summer season between December and March (Figure 1.5). The climate of the area is classified as semi-arid. The river has no flow monitoring station; however, locals expect river flows during the summer (November to February) in accordance with the rainy season (Figure 1.5A). It is estimated that the upper quaternary catchment (B81G) and lower quaternary catchment (B81H) have a mean annual runoff of 31.5 and 10.7 Mm3/year (1969-2010), respectively (Department of Water and Sanitation, 2011). Evaporation rates are the highest in January and December of each year (~180 mm/month), whereas the lowest evaporation rate occurred in June (~75 mm/month) (Figure 1.6B).

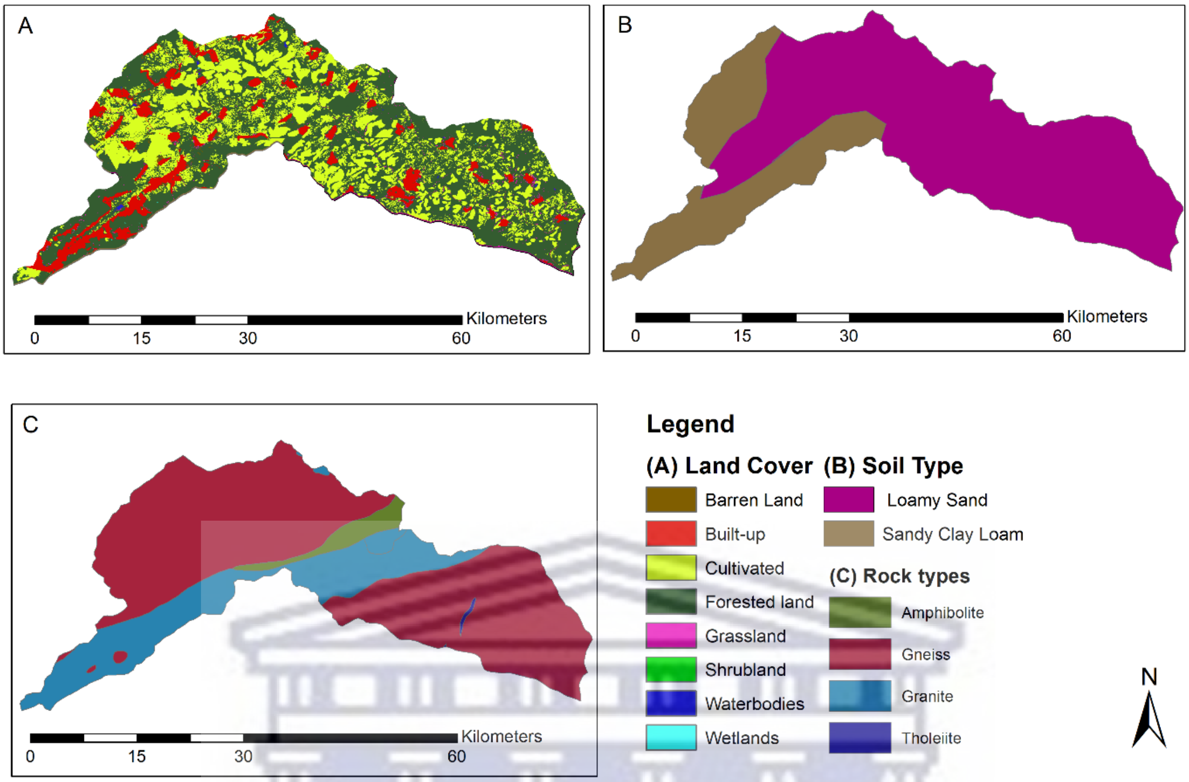
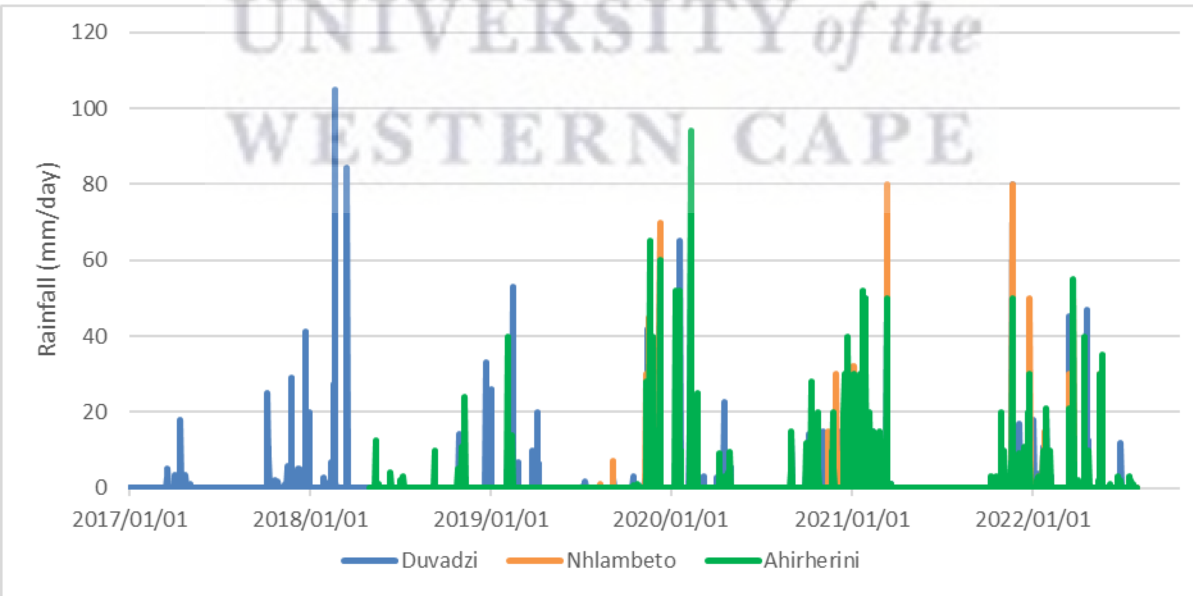


Figure 1.4: Land cover (A), Soil types (B) and Geology (C) of the Molototsi catchment. Data Sources: 2020 South African National Land Cover; Department of Environmental Affairs, WRC-WR2012 (Soil data), South African Council for Geoscience (Geology data).



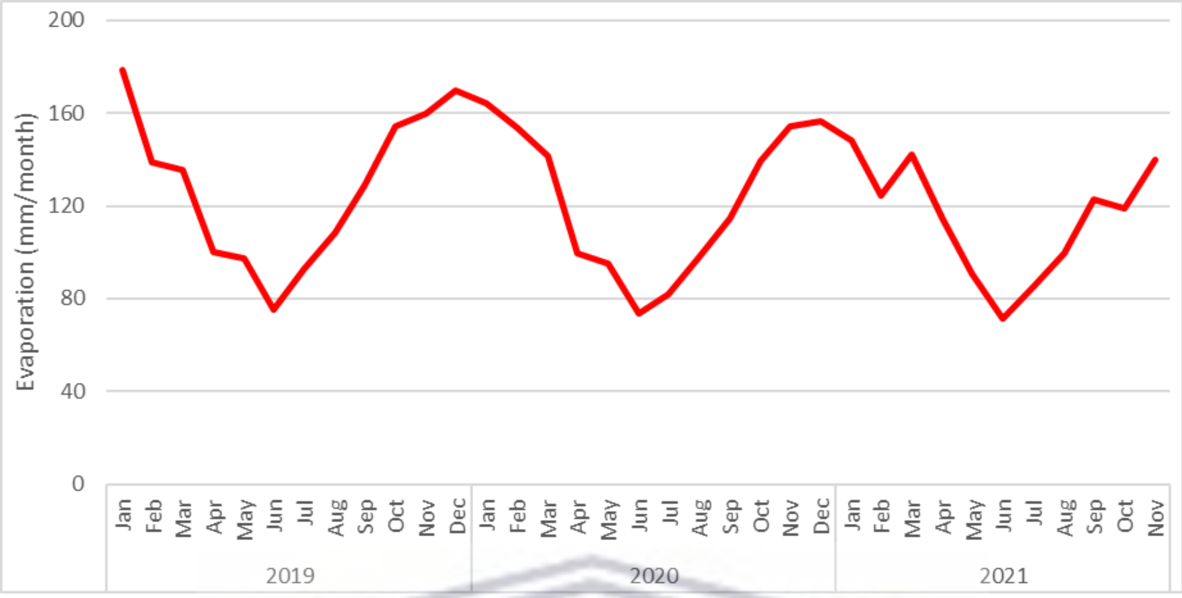


Figure 1.5: Rainfall (A) and Evaporation (B) for Molototsi the catchments. The rainfall data were collected through the citizen science programme, evaporation rates were estimated using Penman method.

****Each Chapter has a Specific Site Description due to the various components that they addressed****

1.6 Thesis Outline

Chapter 1 presents a background of the study, outlines the research problem and describes the aim and objectives of the study and furnishes an outline of the study. This chapter includes a general description of the study catchments.

Chapter 2 reviews the literature on the monitoring of non-perennial rivers, this chapter includes some of the monitoring and management challenges of non-perennial rivers, and lastly, the chapter outlines research gaps. **(Objective i)**

Chapter 3 presents the use of multi-source remotely sensed data in monitoring the spatial distribution of pools and pool dynamics along non-perennial rivers in semi-arid environments, South Africa. **(Objective ii)**

Chapter 4 uses a water balance approach to understand pool dynamics along non-perennial rivers in the semi-arid areas of South Africa. **(Objective iii)**

Chapter 5 presents an assessment of the spatiotemporal dynamics of the hydrological state of the non-perennial river systems and the identification of flow-contributing areas in South Africa. **(Objective iv)**

Chapter 6 concludes the study by providing answers to the research questions and furnishing a brief description of the limitations. Recommendations for further studies and government implementation are also made in this chapter.

Chapters 2 to 5 are standalone publications, each chapter has its abstract, introduction, methodology, discussion, and conclusion section. Some overlap and repetition in some sections/components may therefore occur.

Chapter 2:

Review on the monitoring of spatial and temporal dynamics of pools and flows along non-perennial rivers

The chapter is based on: **Maswanganye, S.E.**, Dube, T., Mazvimavi, D., and Jovanovic, N., 2021. Remotely sensed applications in monitoring the spatio-temporal dynamics of pools and flows along non-perennial rivers: a review. South African Geogr. J. 00, 1–19. https://doi.org/10.1080/03736245.2021.1967774

Abstract

Non-perennial rivers (NPRs) account for more than 50% of the world's river network and their occurrence is expanding. Some rivers that were previously classified as perennial have evolved to be non-perennial rivers in response to climate change and socio-economic uses. However, there is inadequate of understanding regarding the spatial and temporal dynamics of their pools and flows due to a lack of data, as priority of river monitoring has been placed on perennial rivers. The current understanding and methods used for monitoring NPRs are mostly derived from the perennial rivers' perspective. This review paper outlines the strengths and limitations of the methods used to monitor NPRs from a hydrological perspective. Furthermore, this paper provides an overview of the potential of using satellite remote sensing to monitor NPRs. Remote sensing methods are popular with wetlands and lakes monitoring, but little is known about their capabilities of monitoring pools along a river. It has also been successfully used to estimate the discharge of large perennial rivers, however, this has not been fully explored for NPRs. Remote sensing has the potential to extract more information that currently cannot be extracted using conventional in-situ measurement methods. With advancement, remote sensing technology could become useful for managing NPRs.

Keywords: Hydrology; Remote sensing; River discharge; Temporary rivers; Surface water inundation; Water storage

2.1 Introduction

Non-perennial rivers (NPRs) also referred to as temporary rivers or ephemeral rivers are streams and rivers that cease to flow for some time during the course of the year (Skoulikidis et al., 2017; Stubbington et al., 2017). These rivers and streams can either dry out completely or part of their length of the channel (Stubbington et al., 2017). The hydrology of NPRs differs from that of perennial rivers as they have high variable flows illustrated by a high coefficient of variance, as a result, the flows are difficult to predict (De Girolamo et al., 2015a; Larned et al., 2010). This is worsened by their spatial variability as information cannot be easily extrapolated from one river to another. The flow of these rivers are usually rainfall event-driven, but can be groundwater-dependent, especially during dry periods. During the zero flow periods, the storage and quality dynamics of static pools play a critical ecological and social role (Hughes, 2009). The term, definition and classification of NPRs vary from location to location (Delso et al., 2017), which can lead to confusion (Arthington et al., 2014; Busch et al., 2020). However, there is a global consensus about their characteristics which is the zero flow and high spatial and temporal variability.

Conventional river classification methods distinguish river types based on geographical, geological, climatic, or biotic boundaries (Rossouw, 2011). However, the most common way to classify non-perennial rivers is to use seasonal flow patterns and their flow characteristics. Hence, non-perennial rivers can be classified based on their flow permanence namely: intermittent, ephemeral and episodic (Buttle et al., 2012; Datry et al., 2017; Rossouw, 2011). There are, however, no fixed boundaries between the river classes (Datry et al., 2017). Intermittent rivers cease to flow on a seasonal basis for weeks to months. Ephemeral rivers flow for days to weeks in response to rainfall events. Episodic rivers flow for a short duration usually hours to days after heavy rainfall events (Skoulikidis et al., 2017; Datry et al., 2017). Given that flow permanence varies from one location to another, some studies further disaggregate flow permanence into percentages whereby intermittent (semi-permanent) have no flow between 1-25% of the time, ephemeral rivers have no flow between 26-75% of the time and episodic rivers have no flow for more than 76% of the time (Rossouw, 2011; Arthington et al., 2014; Seaman et al., 2016). This disaggregation made the classification of rivers more applicable in any region. Overall, the three types of river classification (intermittent, ephemeral, and episodic) are generally accepted, even though there is an overlap in their definition (Skoulikidis et al., 2017).

Non-perennial rivers occur worldwide, especially in arid and semi-arid areas (Aridity Index of 0 and 0.5). According to the World Atlas of Desertification (WAD) (2018), arid and semi-arid regions account for at least 40% of the world's terrestrial land area. At least 28 countries in Africa are mainly classified as semi-arid and arid (Cherlet et al., 2018), and twenty of these countries have 90% of their productive agricultural land in these areas (Turnbull, 2002). The WAD 2018 data show that 73% of South Africa is classified as semi-arid and arid, which may have evolved from the 60% estimated by Nomquphu et al. (2007). Despite the fact that that most NPRs are found in semi-arid and arid areas, Buttle et al. (2012) indicate that NPRs/ temporary rivers can also be found in humid and sub-humid areas, such as in Canada where precipitation significantly exceeds evapotranspiration.

Importance of non-perennial rivers

Despite the increase in the number of non-perennial rivers caused by climate change and anthropogenic activities such as water abstraction and land-use change (Skoulikidis et al., 2017), in some regions, NPRs are the only source of freshwater. Ecological research has revealed that they are very important in terms of supporting life on earth. NPRs may be more vital than perennial rivers, as they can support both aquatic and terrestrial species by alternating between dry and wet habitats (Snelder et al., 2013).

Pools are one of the most distinguishing characteristics of NPRs when the flow has ceased (Datry et al., 2017; Hughes, 2005). These pools are important water sources in rural areas as they often provide water for vegetable gardening, livestock, and wildlife, and therefore support the tourism sector and people's livelihoods (Amede et al., 2011; Naidoo et al., 2020; Zamxaka et al., 2004). Pools also act as habitat, feeding and spawning grounds for various aquatic species (Makwinja et al., 2014). There is a significant species-volume relationship in pools, as larger pools tend to have higher species richness and abundance (Bonada et al., 2020). Species richness also depends on the physical-chemical properties of the pools. Several studies have shown that pools are sources of water during drought to the surrounding communities, while some studies show that pools attenuate floods (Liu and Zhang, 2017) as they store floodwater (Datry et al., 2017). Pools are also zones of groundwater and surface water interactions (discharge and recharge zones) as most pools in arid and semi-arid areas are groundwater-dependent (Bestland et al., 2017).

Challenges of Non-Perennial Rivers

The spatial and temporal dynamics of flows and pools along non-perennial rivers are poorly understood due to limited studies aimed at understanding their spatial distribution, the frequency of occurrence, persistence and pool storage in catchments (Snelder et al., 2013). An inadequate understanding of pools results in difficulty in the prediction of consequences of the scenarios for land-use changes and result in difficulty in the prediction of movements of organisms and nutrients along the NPR system (Seaman et al., 2016). Research and management of NPRs have been lagging as compared to perennial rivers (Leigh et al., 2019; Skoulikidis et al., 2017). This is caused by a lack of data on the NPR system as monitoring has been prioritised for perennial rivers, as they are reckoned to be more important for water supply. The general public perceives NPRs to be less valuable compared to perennial rivers (Rodríguez-Lozano et al., 2020). This has resulted in a lack of political will to monitor or fund research on NPRs (Skoulikidis et al., 2017).

Monitoring various elements of non-perennial river systems is necessary to overcome knowledge gaps. However, monitoring of NPRs systems is a challenging task as compared to perennial rivers due to high variability and complex behaviour (Day et al., 2019). Extrapolation of data from data-rich to data-poor areas is problematic for NPRs due to the high variability of these rivers. For instance, a pool along the same river reach may function differently from a neighbouring one; as a result, the extrapolation of data may be very inaccurate and hence not recommended for NPRs (Seaman et al., 2016). Therefore, understanding is mostly limited to individual sites. Gaining valuable knowledge on the spatial and temporal distribution of the pools and flows at the catchment scale will be useful for assessing water availability in a particular catchment, which is required for water allocation and setting the ecological reserve (Seaman et al., 2016). Understanding the factors that influence or explain these patterns will be beneficial for the management of these rivers. This paper mainly discusses the methods used to monitor the spatial and temporal dynamics of flows and pools along non-perennial rivers, and further provides an overview of the potential of using satellite remote-sensing methods to monitor these river systems.

2.2 Monitoring of Non-Perennial Rivers

The importance of non-perennial rivers and the hydrological aspects that are important and need to be monitored are highlighted in the previous section. This section reviews the methods that are used to monitor the hydrological phases, and estimate the volume of pools along non-perennial rivers. Wetland and lake research is also included as pools can be monitored in the same way. Thereafter, monitoring of the spatial and temporal variation of flows in NPRs is reviewed. The section is concluded with general remarks on the use of remote sensing in monitoring both flows and pools along NPRs.

Monitoring the presence of surface water along non-perennial rivers

Flow measurements at a point do not account for the hydrological phase (wet and dry phases) of the river which is important for the non-perennial river system. Turner and Richter (2011) stated that the expansion and contraction in the length of wet reaches can cause variations in water quality, the composition of aquatic and riparian communities, and meta-population dynamics, hence ecological studies of spatially variable streams need to identify and account for these hydrological phases. Gallart et al. (2016) added that mapping wet and dry areas provide important information for the selection of correct sampling periods and the method to determine the ecological status. Mapping of the spatial distribution of flows provides information about the flow contributing areas. Such information will assist in explaining and predicting flows along non-perennial rivers.

The mapping of hydrological phases (flowing, pools, and dry riverbeds) provides different insights such as explaining the variations of water quality, the composition and movement of aquatic communities which cannot be obtained by conventional flow measurements (Turner and Richter, 2011; Gallart et al., 2016). Mapping of the hydrological phases is important as noted and gives first-order identification of flow-contributing areas. There are various methods used to determine the hydrological phases.

One of the most used methods for capturing the spatial and temporal variability of river flows involve establishing river flow gauging stations at several locations. There are various methods used to determine the hydrological phases (e.g. Sefton et al., 2019). This is rather expensive if the aim is to capture the variability along all important parts of the river. The involvement of communities residing alongside NPRs in collecting data through citizen science programmes provide an opportunity to overcome the constraints arising from reliance on data collected at river gauging stations with limited spatial coverage (e.g., Gallart et al., 2016; Walker et al., 2016). A major challenge in depending on local communities is the variable quality data collected (Walker et al., 2016; Weeser et al., 2018). These initiatives tend to be successful if members of the local community collecting and providing data perceive a benefit from improved understanding and management of their rivers including NPRs (Walker et al., 2016).

The most common method is to use sensors that collect data continuously, this includes water level, temperature, and conductivity sensors. The hydrological phases are thereafter derived through analyses of this data. However, this is laborious and costly to install and maintain, hence there is a decline in the number of operating flow stations worldwide (Samboko et al., 2020). Zimmer et al. (2020) also argue that the zero on these data can be misinterpreted due to frozen surface water, flow reversals, instrumental errors, and naturally driven source losses or bypass flow. Furthermore, monitoring takes place at small set geographic points at frequent time intervals require extensive interpolation to characterise catchment scale conditions, which may also not effectively communicate the essential spatial details of the complex hydrological system.

Assendelft and Ilja van Meerveld, (2019) used low-cost multiple sensors (electrical resistance, temperature, flow sensor, float switch sensor), and the combination of these was able to distinguish and time hydrological phases accurately (<10% error). However, like flow gauges these sensors can only be placed at points, limiting their spatial coverage. Furthermore, exposed to vandalism and may not be suitable for larger NPRs. Of recent, time-lapse imagery is also being used to monitor hydrological phases but suffers from the same limitations as sensors and gauges, in addition, the quality of the images can be affected by the surrounding environment such as fog and sunlight (Kaplan et al., 2019). Fritz et al. (2020) propose that physical and biological indicators can be used to predict the hydrological phases. For instance, the reduction in the extent and variety of aquatic habitat available indicates contraction of surface connected habitats to isolated pools to drying river beds and subsurface.

Hydrological modelling can also be used to derive hydrological phases, but often does not include assessing the presence of pools, making no separation between dry rivers and isolated pools. For instance, Jaeger et al. (2019) used the probability of streamflow permanence model (PROSPER) to determine wet-dry parts of the river, but the model was limited by the spatial extent of gauges. Yu et al. (2018) also simulated the spatial and temporal dynamics of dry/wet segments of a river using statistical predictive models. Models are mainly used in estimating the magnitude of flows and they require training data.

The hydrological phases can be derived through the use of remote sensing. Remote sensing has the ability to determine different land cover types including water. Hence, it can be used to detect the three hydrological phases. Walker et al. (2019) were able to determine the presence of flow in sandy NPRs by applying NDWI to Sentinel-2 images. The study concluded that knowing the presence/absence flow can assist the surrounding communities that rely on the sandy aquifer for water as this can provide information about the recharge occurrence and therefore provide information about the water available in the sand. Allen et al. (2020) also found that there was no significant difference between flow frequency distribution from multiple gauges and flow frequency obtained from Landsat images. Seaton et al. (2020)

mapped pools in non-perennial rivers and, Gallart et al. (2016) could also able to successfully determine river hydrological phases using aerial photography.

The combination of these approaches indicates that the hydrological phases along a river or reach can be determined using remote sensing with more ease as compared to other methods. Remote sensing, like any method, does have its limitation such as narrow rivers, and cloud cover for optical remote sensing which some are discussed in the next sections. It is noteworthy, that remote sensing is improving to overcome these challenges. For instance, SAR data is being used to overcome the cloud cover and images from some commercial satellites have very fine resolution with sub-meter spatial resolution and a 3-days revisit time such as Worldview 1-4, GeoEye-1 and Quickbird (Niroumand-Jadidi and Vitti, 2017). Chawla et al. (2020) provides a general overview of available remote sensing data for mapping water bodies.

Estimation of Surface Water Storage (Volume) in Pools along NPRs

Lakes, wetlands and other water bodies are important in the terrestrial water system. Information on the inundated area and water volume is essential for the effective management of competing functions and uses such as flood control, drought mitigation, agricultural irrigation, etc. (Cai et al., 2016). Estimating the volume of water in a water body is challenging as it often does not have a well-defined shape making it difficult to determine the area. Various approaches have been developed to estimate the volume of water bodies. Generally, water volume is expressed as a product of the water-occupied area and the height of the water from the bottom of the water body, the differences in the methods are mainly in the way the area is derived.

In situ methods require shore topography and bathymetry data, which are often difficult to acquire due to the high cost of labour and equipment (Lu et al., 2013). The alternative is to use remote sensing techniques, since they are capable of determining the different land cover types including water. Water strongly absorbs the near-infrared, thus the boundary between land-water can easily be defined. Remote sensing data is commonly used to estimate the inundation of water bodies, thereafter the volume is then inferred (e.g., Lu et al., 2013; Cai et al., 2016). There are limited studies done on estimating pool volume along NPRs. Seaton et al. (2020) successfully mapped the surface area of selected pools along NPRs using remote sensing, however, did not compute the volume. Hence, some of the studies used here are derived from wetland and lake research as pool volume can be estimated the same way.

One of the approaches to estimate volume is to use the combination of satellite-derived data and field-observed measurements. For instance, Lu et al. (2013) used field-observed water levels and satellite-derived surface area at an annual scale for 40 years. The underwater geometry was constructed using a triangulated irregular network (TIN) volume model. NDVI and MNDWI were applied to Landsat MSS/TM/ETM+ and HJ-1A/B to derive the inundated surface area. The volume of water was calculated using a 3-D analyst tool. The estimated volume was consistent with the one derived from the fitted equation of the lake which is 366 km^2 in size.

The Moderate Resolution Imaging Spectroradiometer (MODIS) imagery was used to determine the storage of 128 lakes and 108 reservoirs between 2000 and 2014 in the Yangtze River Basin, China (Cai et al., 2016). The MODIS-derived surface area was validated using Landsat 8 Operational Land Imager (30 m). Storage capacity is highly correlated with a surface area at a regional and global scale, thus storage was calculated as:

$$S = a * A^b \qquad (2.1)$$

Where S is the storage, A is the area, and a and b are constants which were calculated using maximum capacity pairs from the lakes and reservoirs. Cai et al. (2016) highlighted few sources of error including the issue of mixed pixels which can either be classified as water or non-water, the presence of clouds reducing the number of observations, etc. However, Smith and Pavelsky, (2008) demonstrated that assuming a linear relationship between the surface area and the water level is reasonable for many water bodies, and also concluded that the use of both water level and surface area can yield better results compared to estimates from surface area only.

Radio Detection and Ranging (RADAR) has also been successfully used for flood extent mapping. RADAR can be a solution for weather-vegetation induced errors, as it can penetrate clouds and able to operate day and night (Huang et al., 2018; Ritchie and Das, 2015; Smith, 1997). RADAR provides information often unavailable from the optical sensors, limitation of cloud and vegetation. Synthetic Aperture Radar (SAR) is able to monitor water under vegetation as long as it is not dense. Huang et al. (2018) have shown the potential of RADAR using Sentinel-1 SAR data. Besides having these advantages, SAR data have not been employed as much as optical sensors, due to the limited availability of the data.

Another approach is to derive a rating curve between satellite altimetry data and field observed storage (e.g Zhang et al., 2006). The use of altimetry has also been limited to large water bodies due to the narrow swath, low spatial resolution, small footprint size and complex terrain around some of the small water bodies (Alsdorf et al., 2007; Gao et al., 2012; Magome et al., 2003). Alsdorf et al. (2007) and Politi et al., (2016) further argued that altimetry is not very useful as too many inland water bodies are missed. In addition, the temporal resolution of altimetry is generally poor (10 days to 35 days) (Hirpa et al., 2013). As indicated, the errors are due to i) poor detection of surface area due to sensors and/or ii) the classification methods (water identification). Furthermore, Smith and Pavelsky, (2008) suggested that volume can be estimated by combining satellite-derived surface area, altimetry and in situ measured water levels (e.g., Gao et al., 2012; Getirana et al., 2018). However, with this approach, Gao et al. (2012) highlighted that errors can be emitted from altimetry data, surface area, the relationship and the reported configuration.

Some approaches are fully remote sensing-based with no required field measured inputs. Avisse et al. (2017) used Landsat imagery and DEM to obtain information about water storage. Whereby Landsat imagery is used to estimate surface area and DEM is used to derive underwater topography of the water body. The obtained storage was compared to observed storage from a close-by lake, there was a good agreement (R=0.84). However, this method also has DEM-induced errors such as determining the elevation/geometry in reservoirs that were significantly covered with water when the data used to derive the DEM was captured.

The combination of remote sensing derived from inundated surface area and water level from satellite altrimetry can be used in estimating water body storage. For instance, Busker et al. (2019) used water surface area obtained from the JSC global surface water dataset which is derived from L1T Landsat 5, 7 and 8. The satellite-derived altimetry was obtained from the Database for Hydrological Time Series over Inland Waters (DAHITI) which combines altimeter data from different satellites. The improved threshold re-tracker method achieved better accuracy. The water levels were strongly related (R<0.8) to the surface area. However, there was a weak relationship for the smaller lakes and those that had nearly constant area and those that had no data on the JSC surface water dataset. Muala et al. (2014) and Getirana et al.

(2018) used the same approach and also found that there was a good relationship (~R^2=0.94) between estimated and observed volume. The use of both altimetry and surface area is excepted to be advanced by the launch of the SWOT mission in 2021 as both surface area and water level are obtained from one satellite.

A major application of remote sensing on water bodies has been in estimating the inundation area of large water bodies such as large lakes and wetlands and it is by far the most effective method (Huang et al., 2018). Some studies take it further by estimating volume and discharge. However, some studies, such as Sharma et al. (1989) and Avisse et al. (2017) used remote sensing for small water bodies. Avisse et al. (2017) were able to produce accurate results for reservoirs smaller than 0.5 km^2 using data from Sentinel-2 and Landsat 8. Sharma et al. (1989) were able to detect water bodies that are smaller than 0.9 ha using Landsat TM. Avisse et al. (2017) suggested that combining Sentinel-2 and Landsat 8 data could yield better results for small reservoirs as it would reduce the revisit time and could provide near real-time monitoring.

However, like any other methods, the remote-sensing derived water body storage methods have limitations and disadvantages. The use of inaccurate satellite-derived data can be carried to the estimated storage; the inaccuracies can be sensor or algorithm related. The nearly constant surface area can result in weak relationships used to estimate the volume or rating curves (A-V, H-V, H-A) e.g elevation-area relationship, surface area-storage elevation (Alsdorf et al., 2007; Magome et al., 2003). The water storage will be biased if the characteristics at capacity are not accurate. The storage capacity might have changed, due to sedimentation over time. However, it is rare for sedimentation to be the major cause of errors.

The launch of the Surface Water and Ocean Topography (SWOT) satellite which will have both altimetry and optical sensors for the surface area measurement will improve the accuracy of remote sensing, and further advance the application of remote sensing in water resource management (Getirana and Peters-Lidard, 2013). Fusing RADAR, in particular the Synthetic Aperture Radar, and the optical remote sensing data can be an advancement in the application of remote sensing. However, there are few SAR-based products at sub-hectare (100 m) surface extent products. Smith (1997) and Bioresita et al. (2018) argued that the interpretation of RADAR images is less straightforward than optical images; in addition, the wind-induced waves or emergent vegetation can roughen the surface of open water bodies, making it difficult to distinguish water from other land cover types. Therefore, the ideal situation will be smooth and open water bodies. There are also developments of using satellite gravimetry (e.g GRACE) to estimate water levels and storage changes (e.g Hwang et al., 2011) will also aid in improving the accuracy of remote sensing.

Monitoring spatial and temporal variation of flow in NPRs

The conventional methods of measuring flows that are used for perennial rivers are also used in non-perennial rivers whereby discharge is a product of average velocity and the cross-sectional area. Using continuous water level measurements from instruments such as pressure transducers, continuous discharge can be obtained from predetermined stage-discharge relationships. This relationship is described in the form of analytic formulae and/or graphs referred to as rating curves. This relationship is verified or calibrated periodically to determine whether the relationship has changed which is often caused by channel geometry and/or channel roughness. To avoid frequent changes in the geometry and channel roughness, weir or flumes are constructed to stabilize the cross-section. However, this still requires calibration occasionally. Dobriyal et al. (2017) state that weirs are suitable for the long-term monitoring of small hill streams. Other once-off or experimental methods include particle image velocity, float and dilution methods. However, in developing countries, the financial cost associated with the methods (installation, maintenance) becomes a constraint, consequently, a low-cost method is often used. Errors associated with conventional methods of measuring discharge, even when they are used in perennial rivers. However, the errors are often within the required accuracy for most of the applications. These errors include gauge reading, stage sensor, water surface to the sensor, hydraulic induced and recorders errors (World Meteorological Organization, 2010). The non-contact measurement methods, in particular, remote sensing poses the potential for providing the required information.

Remote sensing is widely applied in hydrology, however, it is still considered new in the estimation of river discharge (Kebede et al., 2020). The general principle is to use the information that can be derived from satellite imagery (width and depth) as a proxy to discharge. Some methods require field-measured variables; some methods do not, and thus solely based on remote sensing. The general trend is to move toward estimates that are solely based on remote sensing without any field-measured variables. However, the biggest challenge is that velocity can not be directly obtained through satellite remote sensing methods.

River discharge can be estimated using the relationship between ground-measured discharge and satellite-derived inundation area. This assumes that there is a relationship between discharge and inundated areas. This relationship is described using rating curves. These rating curves can thereafter be used to solely estimate discharge from remote sensing data. Like in estimating storage/volume, this is also affected by the determination of the inundated area. Smith (1997) states that it is difficult to extrapolate the relationship to other rivers, however, it can be used in ungauged catchments. However, Smith and Pavelsky, (2008) demonstrated that satellite-derived width-discharge rating curves and hydraulic geometry (b exponents) converge around the stable value (b=0.48) which indicates that the method is transferable to different locations. This approach is only successful when field-observed data is available for calibration as they fail to indicate the dynamic topography of the water surfaces (Alsdorf et al., 2007; Pan et al., 2016). Some studies show that this can be achieved by using a Digital Elevation Model (DEM) to derive topographic information such as slope (Pan et al., 2016). Other studies argue that DEM is limited as it can be too coarse, hence problematic for small water bodies. Secondly, DEMs can be inaccurate when the elevation was extracted when the water body had water.This can therefore be addressed by either using high-resolution DEM or in situ elevation measurements.

Orbital sensors, such as passive microwave sensors do not suffer from clouds and vegetation interference and allow the separation between non-water and water pixels, hence they can be used in the same way as optical remote sensing data. Brakenridge et al. (2007) used passive microwave data to estimate discharge in the United States. Advanced Microwave Scanning Radiometer (AMSR-E) at 36.5 GHz was resampled to produce daily estimates. The study concluded that AMSR-E can provide useful international measurements of daily river discharge even if only mean discharge data is available. Ahmad and Kim, (2019) used Sentinel-1 SAR data, and discharge was estimated accurately, but they were not able to estimate in smaller rivers with a channel width of less than 20 metres. Hirpa et al. (2013) also concluded that this method can be useful in data-scarce regions. The errors may be due to misclassifying and rating curve-related issues.

Another common approach is to use satellite altimetry data to estimate discharge (e.g. Bogning et al., 2018; Zakharova et al., 2006). Like the above approach, discharge is estimated from rating curves developed from satellite altimetry and field-measured discharge (Equation 2.2).

$$Q = a.(H-z)^b \quad (2.2)$$

Where Q is the discharge, a and b are coefficients, H is the height of the water and z is the zero flow height.

The errors are relatively small when applied to large water bodies such as the Amazon River, Ob River, Chari River, Lake Chad, and Ogooue River (Getirana and Peters-Lidard, 2013). There are few studies where this approach was applied to small water bodies and non-perennial rivers. As stated the measurements (satellite altimetry) mask many small water bodies. Therefore, it is not ideal to use it for non-perennial rivers as they are often small (<100 m). Several studies have attempted to estimate discharge using the water balance approach whereby water body storage, evaporation and precipitation are estimated using remotely-sensed data and water inflows from models. The results vary, for example, Muala et al. (2014) obtained acceptable results in Roseires reservoirs, Sudan, although they obtained high error for lakes in Egypt. Swenson and Wahr, (2009) also used the same approach for Lake Victoria and concluded that remote sensing data are unable to estimate the outflow of the lake with acceptable accuracy. The error may be induced by the number of inputs required for this approach (e.g rainfall, evaporation), these inputs have their own errors which are carried into the discharge estimates.

More recently, there have been attempts to measure discharge with no field-measured variables. This is achieved by combining remotely sensed stage and width. The combination of orbital/optical-sensed(e.g NIR) and altimetry data is used to improve the temporal or/and spatial information or even accuracy. Sichangi et al. (2016) used MODIS and altimetry data to optimize unknown parameters of the modified Manning's equation. Huang et al. (2018) and Bjerklie et al. (2018) also merged stage-discharge and width-discharge equations, and the results demonstrated that the use of both altimetry and infrared data improves discharge estimation. However, due to the spatial properties of altimetry data, both studies were done in large perennial rivers (channel width >100 m). Discharge can be also solely derived from remotely sensed data by including the channel geometry such as width and depth. This is done using the characteristics scaling law referred to as At-Many station Hydraulic Geometry (AMHG), which eliminates half of the parameters, required by traditional hydraulic geometry, and is able to estimate from only repeated surface widths (Gleason and Smith, 2014; Gleason and Wang, 2015). However, the uncertainty in this method is high and still requires prior knowledge about the river. The method has mostly been tested in large perennial rivers and performed poorly in a river with temporary flows due to the high variability of discharge (Gleason and Smith, 2014; Sichangi et al., 2018).

Every technique and sensor has its limitations and advantages. For the area-discharge methods, the main errors may be high when small changes of a few meters in river width are not easily detected from remote sensing, and they produce significant changes in discharge. Due to the high availability of optical remote sensing and advancement in ways to obtain the surface area of the water body, which makes it user-friendly, the area/width to discharge method has been commonly used and has shown to be more accurate compared to other methods. The stage-discharge method has also shown good accuracy but is not commonly used because satellite altimetry has poor temporal and spatial resolution, hence it has been mostly applied to large rivers, considered as not suitable for small rivers. However, the combination of data from different sensors can yield better estimates and further improves temporal resolution estimates.

General remarks on the use of remote sensing in monitoring NPRs

The use of remote sensing data for estimating hydrological information offers an opportunity to obtain information in areas with inadequate coverage by in-situ measurements (Bjerklie et al., 2005). It is possible to use remote sensing to map wet-dry parts of the river system. This implies remote sensing may provide information about the spatial and temporal distribution of the pools. Factors and processes can be explained using the physiographic characteristics of the catchment. Remote sensing also has the potential to estimate river flows. This implies that the amount of contribution by each stream into the river can be estimated, thereafter identifying the major source areas. Since NPRs have become more important in water resource management issues owing to the conversion of perennial rivers to NPRs, there is a need to monitor these temporary rivers. The identification of source areas may assist in determining the streams that need to be monitored for hydro-modifications impacts (Beck et al., 2017). Furthermore, this will inform monitoring programs in identifying the best methods and tools for the task. Turner and Richter (2011) state that remote sensing may even be capable of providing information that cannot be directly feasible when using models and flow data such as the mapping of the hydrological phase (wet-dry mapping) of the river system. There are platforms that provide mapped surface water globally (e.g., https://global-surface-water.appspot.com/#features ; https://land.copernicus.eu/global/products/wb), and this could provide ready-made useful information about NPRs for any end-user.

Remote sensing is continuously improving in terms of spatial and temporal resolution, and in the ways the obtained information is processed and analysed (algorithms) to overcome some of the weaknesses. However, the use of remote sensing has been limited to large (width of more than 400 m) wetlands and perennial rivers. There are few studies focusing on pools and flows spatial and temporal dynamics (occurrence and changes in storage) in NPRs. Whereas, the potential of using remote sensing to obtain this information has not fully been investigated in NPRs. Given such potential, this will contribute towards understanding the spatial and temporal dynamics of NPRs and in supporting the management of these rivers especially in data-scarce regions like South Africa and the rest of Africa. There is a need to test the ability of remote sensing in obtaining this useful information in NPRs.

2.3 Strengths and Limitations of Monitoring Non-Perennial Rivers

The applicability of common methods used to monitor NPRs are summarised in Table 2.1. The following were considered: the ability to determine the hydrological phases; the ability to estimate flow magnitude and pool sizes; the spatial and temporal dynamic of these and the accuracy at which this can be monitored. The experimental/once-off methods such as were excluded as they are meant to measure flow and cannot be used to determine the occurrence of flow or volume of pools. Overall, in situ monitoring through gauging stations provides good accuracy but is constrained by financial, institutional, political, and spatial factors, remote sensing has the potential to fill the gap and provides more insights. Hydrological modelling has also been shown to have advancement in terms of modelling beyond the individual point (e.g., Jaeger et al. 2019) but the drawback is that it requires input data which may not be available for many non-perennial rivers (Table 2.1). However, it is worth noting that combining these methods can improve the results and provide greater insights.

Table 2.1: Summary of the strengths and weaknesses of commonly used methods

Method	Strengths	Limitation/weaknesses	Examples
In-situ river gauging	-Availability of continuous data capturing temporal variability of flows -Capable of producing data with high accuracy	-Limited spatial coverage -Costly to install and maintain -Exposed to vandalism -Presence/size of pools omitted	Delso et al. (2017); Tramblay et al. (2021) Zimmer et al. (2020)
Hydrological Modelling	- Improves understanding of the main hydrological processes -Can be used for predictive purposes	-Considerable uncertainty of parameter values -Input data requires to adequately represent spatial variability, mostly unavailable	De Girolamo et al., (2015b)); Jaeger et al. (2019) Daliakopoulos and Tsanis, (2016)
Unmanned Aerial Vehicles (UAVs)	-Appropriate spatial coverage -High-resolution imagery -Hydrological phases can be determined -Flow and pools can be estimated	-Flying Conditions need to be met -Costly to purchase and operate -Laborious (operator needs to be close to the site)	Allen et al. (2020); Samboko et al. (2020)
Optical remote sensing	-Appropriate spatial coverage -Hydrological phases can be determine	-Observation limited by Cloud cover, night-time condition	Walker et al. (2019); Kebede et al. (2020); Seaton et al. (2020);

	-Flow and pools volume can be estimated -Images available at no to low cost	-Flow and pool volume are inferred from the inundation of water	
Orbital-microwave remote sensing	-Appropriate spatial coverage -Hydrological phases can be determined -Flow and pools can be estimated -Images available at no to low cost -All-weather/all-time capabilities	-Flow and pool volume are inferred from the inundation of water -Images can be difficult to interpret as compared to optical remote sensing (Separation between water and non-water features)	Bioresita et al. (2018); Zhang et al., (2020) :Ahmad and Kim, (2019), Mengen et al. (2020)

2.4 Possible future research directions and recommendations

Much of what is known about the NPRs is based on studies done in Australia, the USA, Spain, Portugal, and France (Datry et al., 2017). Inadequate work has been done in Africa which is the continent where most NPRs occur and will further be the most impacted by the decrease in rainfall due to climate change (United Nations Environment Programme, 2020). This uneven distribution of knowledge can result in bias in understanding the NPRs systems. Much of the understanding of the pools and flows dynamics are also based on ecology perspectives and not often from hydrology and from multiple discipline perspectives. Currently, there is a need to develop ways of monitoring these systems. Based on the challenges of NPRs, some are highlighted in this review, the future research direction can be derived as follows: future research should seek to bring an understanding of these river systems which means innovative ways to monitor the river system with a great understanding of the information needed to effectively manage these rivers, for instance, the use of remote sensing techniques as highlighted by this study. The innovative ways need to be evaluated, and their strengths and weaknesses outlined. Beyond monitoring the changes in these rivers, it is imperative to establish the factors that affect the spatial and temporal dynamics of both flows and pools such as precipitation, evaporation, soil properties and geology.

2.5 Conclusion

This study reviewed existing literature on the monitoring of flows and pools along non-perennial rivers. NPRs are becoming increasingly significant at both local and global scales as there are more NPRs than perennial rivers in the world. The extent and magnitude of NPRs are likely to increase at a high rate due to climate change and socio-economic uses. There is, therefore, a need to understand their spatial and temporal dynamics. This includes the comprehension of the effects of climatic conditions, topography, land use/cover type, underlying geology/bed material on the distribution of flows and pools which may not be well understood. The significance of each of the factors may differ from one location to another as NPRs are highly variable. The inadequate understanding of NPRs is caused by a lack of monitoring of these systems. The conventional monitoring methods are laborious, costly, and may not be adequate to derive some of the information that is important for NPRs. Therefore, a need for the development of tailor-made methods for NPRs. Satellite remote sensing has the potential of extracting some of the information that may not be feasible to obtain with the current methods; hence, the need to fully explore the potential of remote sensing. Remote sensing still has its shortcomings such as misclassification, and spatial resolution limitations, but these are being improved through the launching of new and advanced satellites with new and advanced technology, and the ways how the data are analysed are also advancing.

Chapter 3: Use of multi-source remotely sensed data in monitoring the spatial distribution of pools and pool dynamics along non-perennial rivers in semi-arid environments, South Africa

This chapter is based on**:**

Maswanganye, S.E., Dube, T., Jovanovic, N., Mazvimavi, D., 2022. Use of multi-source remotely sensed data in monitoring the spatial distribution of pools and pool dynamics along non-perennial rivers in semi-arid environments, South Africa. Geocarto Int. 0, 1–20. https://doi.org/10.1080/10106049.2022.2043453

Abstract

This study explored the use of multi-source remotely sensed data in monitoring the spatial distribution of pools and pool dynamics in two distinct semi-arid sites in South Africa. The factors that control the pool dynamics were also examined. Three water extraction indices were used, these included Normalised Difference Water Index (NDWI), Modified NDWI (MNDWI) and Normalised Difference Vegetation Index. In addition, random forest classifier and Sentinel-1 SAR data were used in mapping pools and pool dynamics for both sites. Overall, the remotely sensed methods detected and mapped pools with acceptable accuracy, except for small pools (<$400m^2$). The results suggest that flow occurrences and rainfall are key in controlling temporal changes in pools sizes, and there was no interaction between pools and groundwater. The study showed that remote sensing methods are essential for filling ground monitoring gaps in non-perennial rivers and determining hydrological processes and water availability from pools in semi-arid environments.

Keywords: Dryland pools, Ephemeral streams, Pool dynamics, Remote sensing, water resource management

3.1 Introduction

Non-perennial rivers (NPRs) are characterised by the lack of flows for varying periods during the year. Some of these rivers will also have permanent or temporary pools not connected by flows. These pools are one of the most distinguishing features of NPRs (Hughes, 2005; Datry et al., 2017), they are found worldwide and are expected to increase as NPRs expand (Grenfell et al., 2021; Pumo et al., 2016) due to climate change and increased socio-economic uses. Zacharias and Zamparas (2010) defined pools as shallow water bodies that vary in depth, shape, and size, and are usually flooded from time to time and last long enough to sustain/support life.

Pools along NPRs are important water sources as they often provide water for livestock and domestic purposes in rural areas (Zamxala et al. 2004; Amede et al. 2011; Naidoo et al. 2020). In addition, these resources provide ecohydrological services and indirectly support the tourism sector and livelihoods. Besides, they also act as habitats, feeding and spawning grounds for various aquatic species (Makwinja et al. 2014). There is a significant species-volume relationship in pools as species richness increases with the size of the pools (Bonada et al., 2020). Species richness also depends on the physical-chemical properties of the pools. Pools attenuate floods (Liu and Zhang, 2017) as they store floodwater (Datry et al. 2017) and are regarded as important zones of groundwater and surface water interactions (discharge and recharge zones).

Despite being important, pools along the NPRs are perceived to be of low value compared to perennial rivers (Rodríguez-Lozano et al. 2020), as they are considered an unreliable source of water. However, of late, pools along NPRs have received attention because of their ecological significance (Sheldon et al. 2010; Marshall et al. 2016; Ilhéu et al. 2020), hence also referred to as refugia or refuge, indicating their ecological importance as a habitat during the dry phase (Davis et al., 2013). Studies on the ecology of pools have suggested that they should be incorporated in river and water management. For instance, Groves et al. (2012) state that protecting these pools should be included in climate change adaptation plans. According to the definition of Wetlands, pools along NPRs are part of wetlands (Haas et al., 2009). Therefore, they could be protected as part of wetlands. The importance of these pools is also recognised in most environmental flow assessments of NPRs as minimum water discharge is often maintained to ensure the persistence of pools during the dry period (Theodoropoulos et al., 2019).

Although pools are being recognised for their ecological importance, there is still limited scientific research on pools' hydrological and geomorphological aspects (Bonada et al. 2020; Bourke et al. 2020; Shanafield et al. 2021) due to limited in-situ monitoring sites along NPRs. Hence, monitoring is an essential step in understanding and managing pools effectively. However, monitoring these pools using in-situ methods can be challenging as they can be sparsely distributed along the river (Maswanganye et al. 2021). The ability of remote sensing to distinguish between water and bare surfaces provides unique opportunities to monitor these pools both individually and at catchment scale. Seaton et al. (2020) demonstrated the potential of using multispectral remote sensing data (Sentinel-2 and Landsat 8) in monitoring the pool surface areas along NPRs with once-off validation. However, the study indicated that the number of observations was limited due to cloud cover over the study sites. Synthetic Aperture Radar (SAR) data such as Sentinel-1 can be used to overcome issues of cloudiness.

However, monitoring pools without understanding the factors influencing their distribution and occurrences remains inadequate for the sustainable management of these systems. So far, few studies have assessed controlling factors of pool storage dynamics across varying landscapes.

For instance, Hamilton et al. (2005) investigated the persistency of pools using stable isotopes and major ions. The results showed that evaporative losses explained the changes in the pool’s sizes between the flows, and there was no evidence of groundwater inputs into the pools. Using radon, (Lamontagne et al., 2021) found that most pools were perennial and groundwater-fed in South Austria. Bestland et al. (2017) also made a similar observation in South Austria, however they added that the interaction between pools and groundwater may be seasonal, not a continuous water supply from groundwater to pools.

This study aimed at determining the spatial and temporal distribution of pools in two contrasting non-perennial rivers located in semi-arid environments (Touws and Molototsi Rivers in South Africa). This was done through i) detection of pools along reaches of non-perennial rivers, ii) accuracy assessment of remotely-sensed pool’s surface area, and iii) determination of changes in pool sizes and factors that control these changes.

3.2 Material and Methods

3.2.1 Site Description

The study was conducted in two NPRs found in two different catchments in South Africa. The two NPRs included the Touws and Molototsi River systems, located in the Western Cape and in the Limpopo Provinces in South Africa, respectively. The Touws River (Figure 3.1) is sandy gravel above Adolpaspoot formation shale. The majority of the pools in this non-perennial river are associated with bedrock outcrops (Hattingh, 2020) (Figure 3.2). Grenfell et al. (2021) and Hattingh (2020) provided a geomorphological account of how the pools form.

The geology of the Molototsi study site (Figure 3.1) is predominantly characterized by the Letaba Gneiss lithostratigraphic unit, although the upper part of the catchment includes Duiwelskloof Leucogranite. The substrate of the river is sandy (Figure 3.2). The river is surrounded by communities (human settlements), with agriculture taking place in the riparian zone along the river.

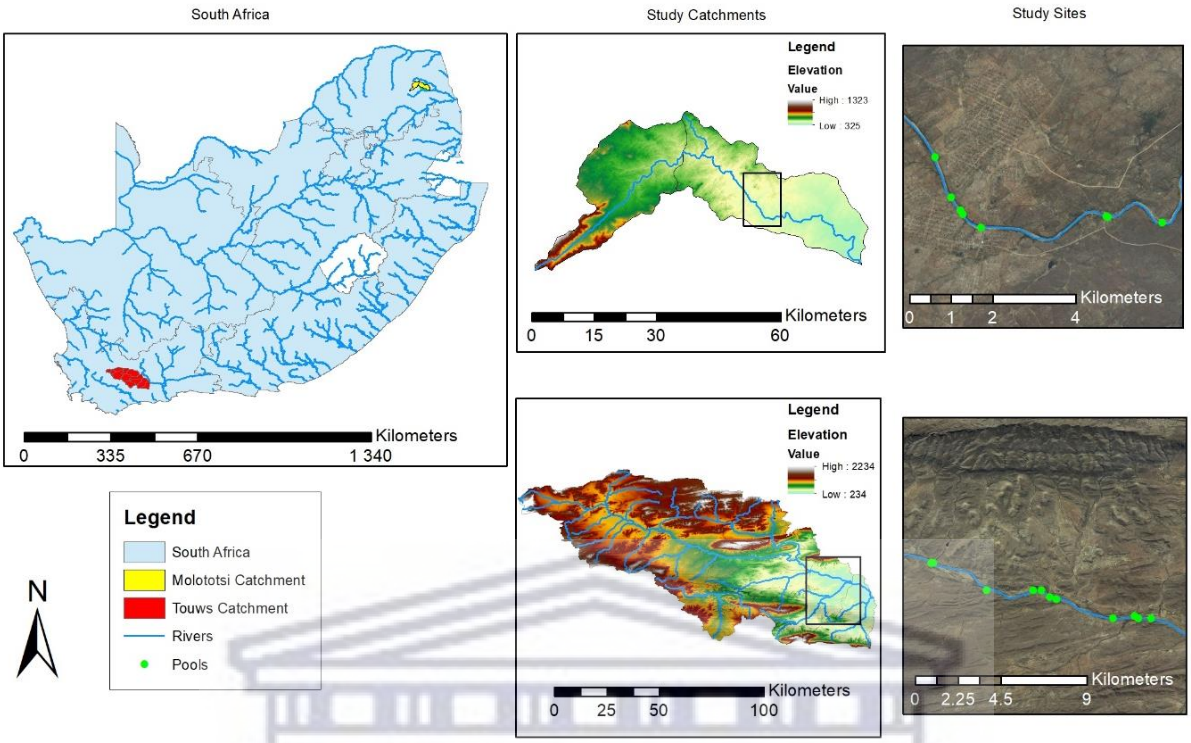


Figure 3.1: Location of the monitored pools along the Molototsi and Touws River catchments.

Figure 3.2: Field photographs showing typical pools along the Molototsi (top) and Touws River (bottom).

3.2.2 Remote Sensing Data Description and Collection

This study made use of open and freely available remote sensing data. The choice and selection of these data were informed by the lack of high-resolution spatial data in many developing countries that cannot afford commercial satellite data sets. Sentinel-2 images were therefore used. Sentinel-2 comprises twin polar-orbiting satellites in the same orbit, phased at 180° to each other. The combination of these satellites reduces the revisit time from 10 days for each satellite to 5 days at the equator and 2-3 days at mid-latitudes. Sentinel-2 has 13 spectral bands in total, four bands at 10, six at 20 m and three at 60 m spatial resolution. Sentinel-2 data are provided at different pre-processed levels (1B, 1C and 2A) products for users. The data were acquired from the USGS earth explorer (http://earthexplorer.usgs.gov/ accessed on 8 August 2020) and the Copernicus (https://scihub.copernicus.eu/ accessed on 8 August 2020) website. The level 1C data were downloaded from the USGS website throughout the study duration.

Further, this study included SAR data obtained by Sentinel-1 to overcome the cloud-induced challenges of optical remote sensing. Sentinel-1 has C-band imaging operating in 4 modes (strip map, interferometric-wide swath, extra-wide swath and wave modes). This band can reach down to 5 m and covers a swath of up to 400 km. Each satellite has a 12-day revisit time at the equator, the revisit time is bettered by the two satellites (Sentinel-1A and Sentinel-1B) orbiting in the same plane (~700 km above the earth), resulting in a revisit time of 6 days. For the Sentinel-1, SAR data under interferometric wide-swath (IW) mode were downloaded from the National Aeronautics and Space Administration Alaska Satellite Facility (NASA/ASF) (https://search.asf.alaska.edu/#/). In total, eight images with dates closest to the field surveys were used for accuracy assessment (Table 3.1). The use of Sentinel was informed by its performance in water resources and other related environmental applications (Kwang et al., 2017; Seaton et al., 2020). Literature has shown that Sentinel-2 performs better than Landsat 8 and has a better spatial and temporal resolution. For example, Seaton et al. (2020) highlighted that clouds are problematic for the extraction of water areas using Sentinel-2 (optical remote sensing), as they reduce the number of observations, hence the need to use Sentinel-1 data (Seaton and Dube, 2021).

3.2.3 Field Data Collection

During field visits, global positioning system (GPS) measurements were collected along the edges of the pools (boundary of water and non-water) in the study areas using a hand-held GPS with an error of margin of less than 3 m. The accuracy level was within five metres for all collected points and approximately three metres apart (Figure 3.3). To assess the factors that control the changes in pool sizes, additional hydrometeorological data were needed. A few datasets including rainfall and flow occurrence obtained from the local community were used. Weather station data were obtained from the Agricultural Research Council. Landcover data were obtained from the National Geographic Institute (NGI) of South Africa. Groundwater levels were continuously measured using dataloggers in the vicinity of the pools and river.

Figure 3.3: Example of the field-collected points using a GPS in the Touws River on a Google Earth map.

Table 3.1 Field visits and image acquisition dates

Site	Field Visit	Sentinel-1 Image	Sentinel-2 Image
Touws River	2019/07/31	2019/07/27	2019/08/01
	2020/12/14	2020/12/16	2020/12/12
	2021/03/30	2021/03/30	2021/03/28
Molototsi River	2020/01/08	*	*
	2021/06/30	2021/06/28	2021/06/30

*Indicates not used because of clouds on Sentinel-2

3.2.4 Pool Extraction from Satellite Data

Two methods were used to derive the spatial distribution of pools along NPRs. Field surveys and satellite images were used to identify and determine the locations of pools and pool sizes. Various remote sensing derivates were tested; these included the MNDWI, NDWI, NDVI and random forest classification derived from Sentinel-2 images and Sentinel-1 SAR data. To understand pools and pool dynamics, rainfall, flow occurrence, groundwater levels and evaporation rates were integrated. A detailed summary of the methods is summarised in Figure 3.4.

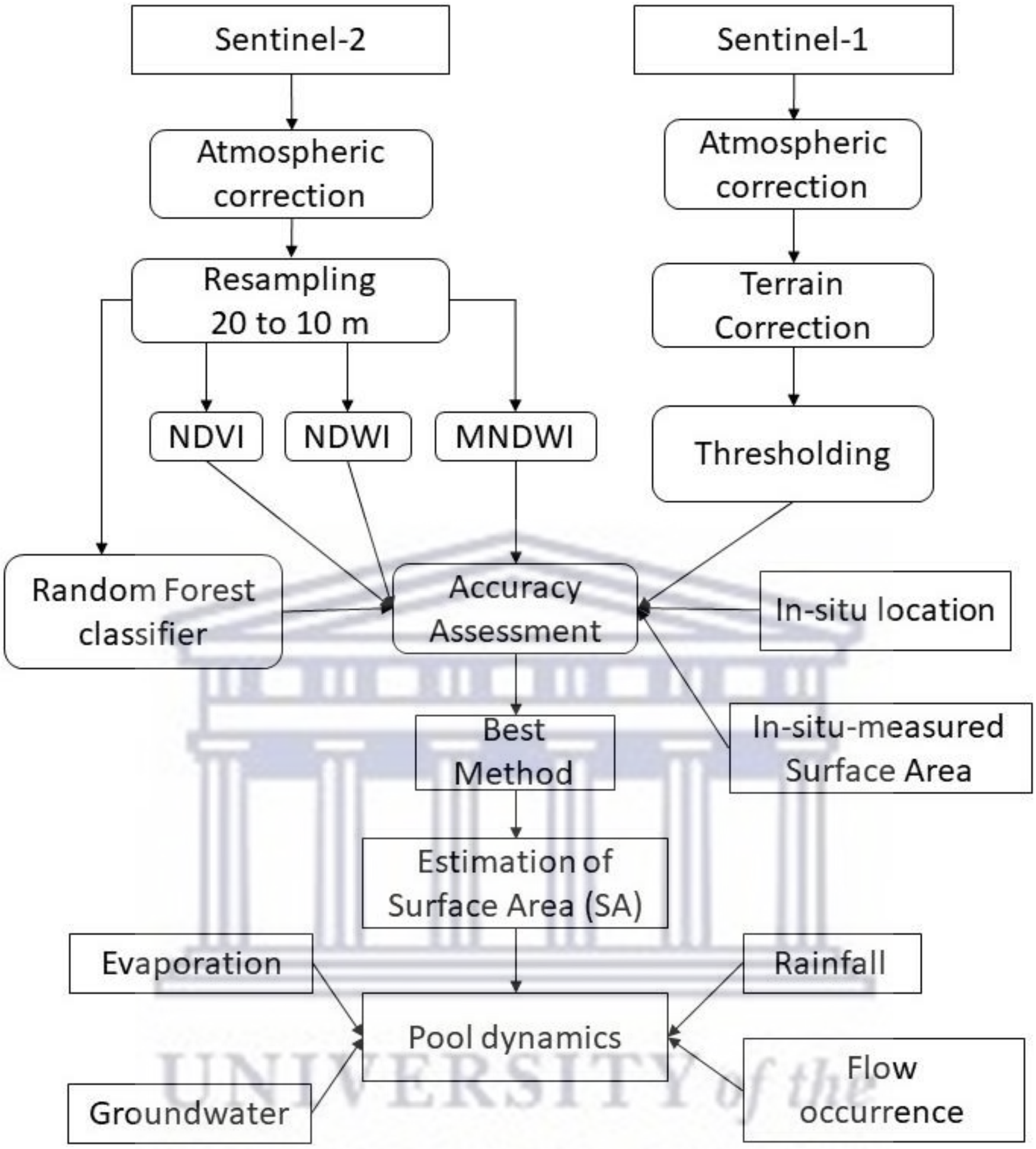


Figure 3.4: A flow diagram illustrating the methodological procedure used in this study.

Sentinel-2 Pre-processing and Analyses

Pre-processing and analysis of satellite images were conducted to detect water bodies/features. Seaton et al. (2020) compared atmospheric correction methods (Sen2Cor, DOS1, TOA), and concluded that the Top of the Atmosphere (TOA) reflectance images are the most suitable methods for Sentinel-2. A similar conclusion was made by Rumora et al. (2019). Seaton et al. (2020) further indicated that the incorporation of atmospheric correction can eliminate some of the significant water surface areas. Therefore, the TOA images were used for this study. The downloaded Sentinel-2 images were first resampled to 10 m using Sentinel Application

Platform (SNAP) with Band 3 as the reference band. Water indices were used to extract water areas from the images because the method is reliable, user-friendly, efficient, and with low computation cost (Du et al., 2016). The processing was done using SNAP and ESRI ArcGIS 10.3 software.

Water indices are used to distinguish between water and non-water features. This study used the most commonly used water indices, including Normalized Difference Water Index (NDWI) (McFeeters, 1996) (Equation 3.1), the Modified Normalized Difference Water Index (MNDWI) by Xu, (2006) (Equation 3.2), and the Normalised Differential Vegetation Index (NDVI) by (Tucker, 1979) (Equation 3.3).

$$NDWI = (Green - NIR) / (Green + NIR) \qquad (3.1)$$

where Green is the green band and NIR is the near-infrared band. Pixels of water have positive values.

$$MNDWI = (Green - SWIR2)/(Green - SWIR2) \qquad (3.2)$$

where Green is the green band and SWIR is the short-wave infrared band. Pixels of water have positive values.

$$NDVI = (NIR - Red)/(NIR - Red) \qquad (3.3)$$

where NIR is the Near-infrared band, Red is the red band. Pixels of the water body have negative values.

The random forest classification as proposed by Breiman, (2001), was also used as it is one of the commonly used methods and has been proven to produce higher accuracy in the extraction of water areas than other supervised classifiers (Acharya et al., 2018; Kalaivani et al., 2019; Ko et al., 2015). Random forest classification is an ensemble classification that produces multiple decision trees using a randomly selected subset of training images. In this case, the pools that were assessed were excluded from the training set, and all bands of Sentinel-2 were used in the classification.

Shadow removal

Mountain shadows can be easily confused with water areas as they have similar spectral signatures as noted by Xu (2006). The random forest was also used to classify the areas of shadows, and an outcome raster was used to clip out areas that the indices might have confused to improve the classification accuracies.

Sentinel-1 Pre-processing and Analyses

Sentinel Application Platform (SNAP) was used for pre-processing the Sentinel-1 images. Firstly, the images were calibrated to convert raw digital numbers to the RADAR backscatter coefficient. To reduce speckle noise, the lee filter was used with a 3×3 kernel width and height. The images were aligned and corrected for elevation interference using the STRM 3sec DEM which is auto-downloaded by the SNAP tool. Water surfaces act as mirrors and reflect almost all incoming radiation; they cause very low backscatter. Therefore, surface water detection using SAR data is often based on applying a threshold of the SAR backscatter coefficient, with low backscatter values attributed to surface water (Pham-Duc et al., 2017; Seaton and Dube, 2021) Therefore, a thresholding method was used to separate water and non-water features from Sentinel-1 data. A threshold was determined for each scene, as the accuracy of Sentinel-1 in distinguishing water from other features is affected by wind-induced roughness effects, poor image quality (speckle noise) and incidence angle variance (Bioresita et al. 2018). However, based on multiple trails, the threshold used for this study was ~-22 dB on the VH polarisation.

3.2.5 Accuracy Assessments

General classification accuracy at catchment scale

Accuracy assessment was done in two folds, the one to focus on the location of the pools along the rivers and the other focused on the pool size. Random points were created and labelled based on expert knowledge of the area and high-resolution images from Google Earth Pro to obtain reference points for accuracy assessment at the catchment level. The location of the field-observed pools were also added to the random points; this was done to avoid having the random points exclusively in one class (non-water), as water bodies cover a small portion of the catchment. Pixel values were then extracted for the created points. The extracted values were then compared to the field observations. User's accuracy, producer's accuracy and overall accuracy were computed, derived from Table 3.2. True Positive is the number of correctly extracted water pixels, False Negative is the number of undetected water pixels, False Positive is the number of incorrectly extracted water pixels, and True Negative is the number of correctly rejected non-water pixels derived.

Table 3.2: Confusion matrix used for accuracy assessment

		Reference Data	
		Water	Non-water
Classified Data	Water	*True Positive*	*False Positive*
	Non-water	*False Negative*	*True Negative*

Accuracy assessment of remotely-sensed pool's surface area

The accuracy of the detection of pools was examined to determine the method to be used for pool dynamics (time series). Two representative pools were selected at each of the study catchments. The pools were selected based on the feasibility to monitor using satellite images, determined by pre-inspection. The variation in the riverbed material (bedrock, sand, gravel) was taken into account in order to determine how the underlying material affects the pool's storage. Proximity to hydrometeorological monitoring stations was also considered in the selection of pools. Accessibility, in terms of roads and permission, was considered. The digitised field boundary of the pools was used as reference data. The buffer technique proposed by Brovelli et al. (2015) was applied to develop a confusion matrix (Table 3.2) for the accuracy assessments. All pixels within the boundaries of the surface water bodies digitised were known to be water pixels. All pixels within the area of the buffer were known to be non-water pixels.

Assessing the difference between the observed and remotely-sensed surface area of pools

The surface water areas of the selected pools were measured during the field visits. These were then compared to the sizes obtained from the remote sensing using the Differential Area Index (DAI) also referred to as the deviation. DAI is a dimensionless index used to compare true area and estimates (Acharya et al., 2018; Sawunyama et al., 2006). In this study, DAI was used to get standardised differences between the observed area and the estimated area of pools by remote sensing approaches (Equation 3.4). The DAI values range from -1 to 1, with 0 being the perfect score indicating total agreement and -1 and 1 being the worst scores, negative indicates underestimation and positive indicates overestimation (Acharya et al., 2018). In this study, we multiplied the DAI by 100 to obtain Percentage DAI, which allows for a standardised comparison.

$$DAI = (Ao - Ae)/Ao \times 100 \qquad (3.4)$$

Where Ao is the observed area, and Ae is the estimated area.

Changes in the sizes of the selected pools

Based on the performance of the methods, the most suitable method was used to estimate the changes in surface area of the pools from 2019 to 2021. A total of 27 images were used, these were selected to represent different phases, from when the pool is full to its driest state. Rainfall, flows occurrence, evaporation rates and groundwater levels were used to explain the factors that affected the changes in pools sizes.

3.3 Results

3.3.1 Detection of pools along Touws and Molototsi Rivers at catchment scale

Remote sensing methods were able to detect the pools along NPRs, although the accuracy of the results varied with methods and site. In the Touws River, when the MNDWI was applied on the Sentinel-2 image, 7 out of 11 pools were detected (Table 3.3). All pools that were not detected were relatively small (>400 m^2) in size. The NDWI detected 10 of the 11 pools, however, it detected most parts of the river as water (Figure 3.5). This is evident from the high producer's accuracy and the poor user's accuracy (Figure 3.5). NDVI was able to detect the five largest pools. Random forest classification and the Sentinel-1(S1) thresholding correctly detected four of the largest pools. Along the Molototsi River, the eight surveyed pools had an average size of 1033 m^2 and an average depth of 0.3 m. NDWI detected 3 out of 8 pools. MNDWI, NDVI and supervised classification (RF) detected 2 of the 8 pools, whereas the thresholded-Sentinel-1 did not detect any of the pools. The poor detection of pools in this study site can be attributed to the size of the pools, the majority of which were fairly small. The methods failed to detect the smaller pools, as it was the case for the Touws River. The estimates in the Molototsi study area did not show an overestimation (noise) of water surface areas (Figure 3.5).

Table 3.3: Detection of pools along the Touws (A) and Molototsi River (B)

<table>
<tr><th colspan="9">Touws River (A)</th></tr>
<tr><th>Pool name</th><th>Surface Area (m^2)</th><th>Depth (m)</th><th>MNDWI</th><th>NDWI</th><th>NDVI</th><th>RF</th><th>S1</th></tr>
<tr><td>Touwsberg Farm 1</td><td>237.8</td><td>0.41</td><td>UD</td><td>UD</td><td>UD</td><td>UD</td><td>UD</td></tr>
<tr><td>Touwsberg Farm 2</td><td>9694.5</td><td>0.94</td><td>Detected</td><td>Detected</td><td>Detected</td><td>Detected</td><td>Detected</td></tr>
<tr><td>Sean</td><td>697.2</td><td>0.3</td><td>Detected</td><td>Detected</td><td>UD</td><td>UD</td><td>UD</td></tr>
<tr><td>Wolverfontein 1 (WW1)</td><td>4403.5</td><td>0.76</td><td>Detected</td><td>Detected</td><td>Detected</td><td>Detected</td><td>Detected</td></tr>
<tr><td>Wolverfontein 2 (WW2)</td><td>7198</td><td>1.3</td><td>Detected</td><td rowspan="3">Detected as one</td><td>Detected</td><td>Detected</td><td>Detected</td></tr>
<tr><td>Touwsberg Office 1</td><td>158.4</td><td>0.4</td><td>UD</td><td>UD</td><td>UD</td><td>UD</td></tr>
<tr><td>Touwsberg Office 2</td><td>27500</td><td>0.9</td><td>Detected</td><td>Detected</td><td>Detected</td><td>Detected</td></tr>
<tr><td>R62Bridge</td><td>413</td><td>0.46</td><td>UD</td><td>Detected</td><td>Detected</td><td>UD</td><td>UD</td></tr>
<tr><td>JJ1</td><td>680</td><td>1.4</td><td>Detected</td><td>Detected</td><td>UD</td><td>UD</td><td>UD</td></tr>
<tr><td>JJ2</td><td>1640</td><td>0.75</td><td>Detected</td><td>Detected</td><td>UD</td><td>UD</td><td>UD</td></tr>
<tr><td>Die sand</td><td>166.4</td><td>0.17</td><td>UD</td><td>Detected</td><td>UD</td><td>UD</td><td>UD</td></tr>
<tr><th colspan="9">Molototsi River (B)</th></tr>
</table>

Pool name	Surface Area (m^2)	Depth (m)	MNDWI	NDWI	NDVI	RF	S1
Mol_pool 1	127	0.28	UD	UD	UD	UD	UD
Mol_pool 2	578	0.3	UD	UD	UD	UD	UD
Mol_pool 3	3448	0.46	Detected	Detected	Detected	Detected	UD
Mol_pool 4	2880	0.43	Detected	Detected	Detected	Detected	UD
Mol_pool 5	337	0.35	UD	UD	UD	UD	UD
Mol_pool 6	590	0.52	UD	Detected	UD	UD	UD
Mol_pool 7	111	0.29	UD	UD	UD	UD	UD
Mol_pool 8	190	0.28	UD	UD	UD	UD	UD

*UD= undetected

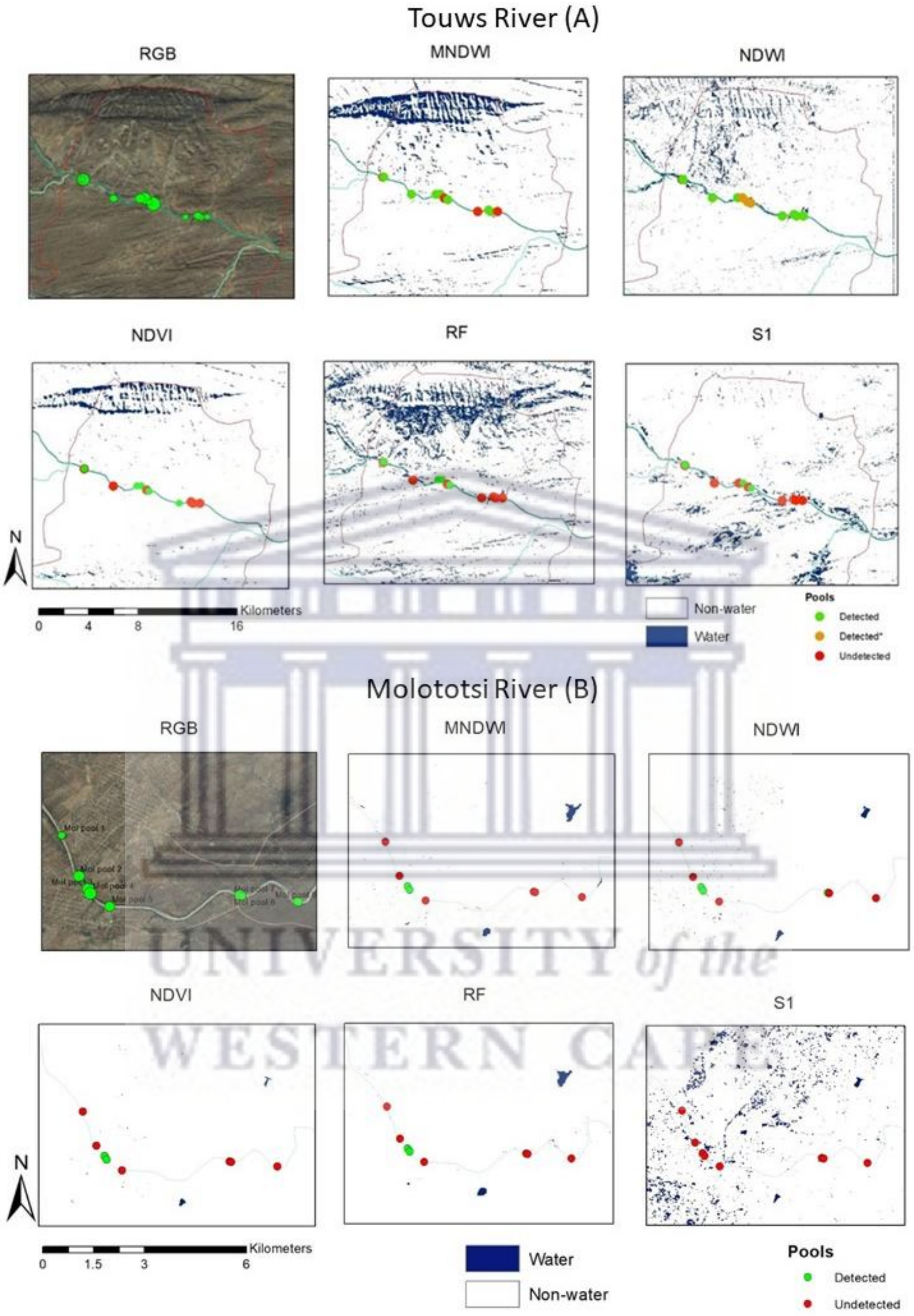


Figure 3.5: Performance of the methods in the detection of water surfaces along the Touws (A) and Molototsi river (B). Green dots indicate detected pools, red dots show undetected pools, and orange dots show two or more pools that were detected as one.

Overall, the adopted remote sensing methods were able to distinguish between water (pools) and non-water pixels (roads, buildings, mountainous shadows, vegetation, and bare land) for the two study sites. MNDWI outperformed other methods (Overall Accuracy= 89%), whereas NDWI had a high score for user's accuracy (Figure 3.6). The NDVI had the ability to distinguish between water and non-water pixels. The thresholded Sentinel-1 (S1) data had the worst performance with the user's and producer's accuracy of less than 30%. For pools in the Molototsi area, high user's and overall accuracy were obtained; this shows that water and non-water pixels could be mapped with high accuracy (Figure 3.6). However, the low producer's accuracy scores were recorded for all methods due to failure to detect the smaller pools, as these were predominant in this study area. The MNDWI and NDVI performed better than the other methods, and Sentinel-1 was the worst.

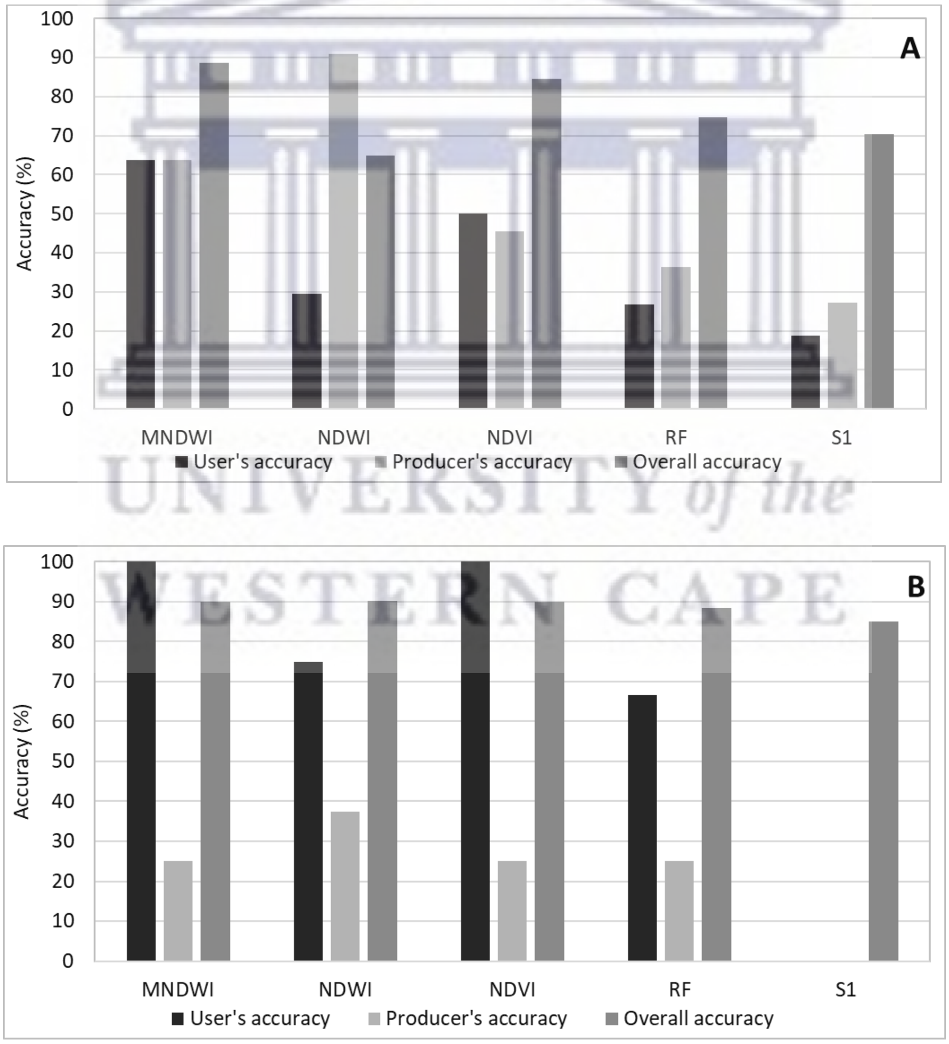


Figure 3.6: Accuracy of the methods in distinguishing water and non-water features at the catchment scale in the Touws (A) and Molototsi river (B)

3.3.2 Accuracy assessment of remotely sensed pools' surface areas in the Touws and Molototsi river

The surface areas obtained with MNDWI, NDWI, NDVI and RF applied to Sentinel-2 image and Sentinel-1 threshold (S1) were compared to the field obtained surface areas. Random forest classification and thresholding of Sentinel-1 had the highest user's accuracy (92%) for the WW1 and WW2 pools (described in Table 3.3), respectively. Overall, MNDWI outperformed the other methods as it had acceptable accuracies for all three accuracy measures for both pools, ranging from 74% to 80% (Figure 8). When comparing the scores from the two pools, the WW1 pool size was better estimated. Field survey was done from 30 June to 1 July 2021 along the Molototsi River. The MNDWI slightly outperformed the other methods for Pool 3 (Figure 3.7), whereas NDWI was the only method that detected Pool 6. S1 had the worst performance as it did not detect both pools. Comparing the extraction of the two pools, Pool 3 was better extracted when all methods are considered.

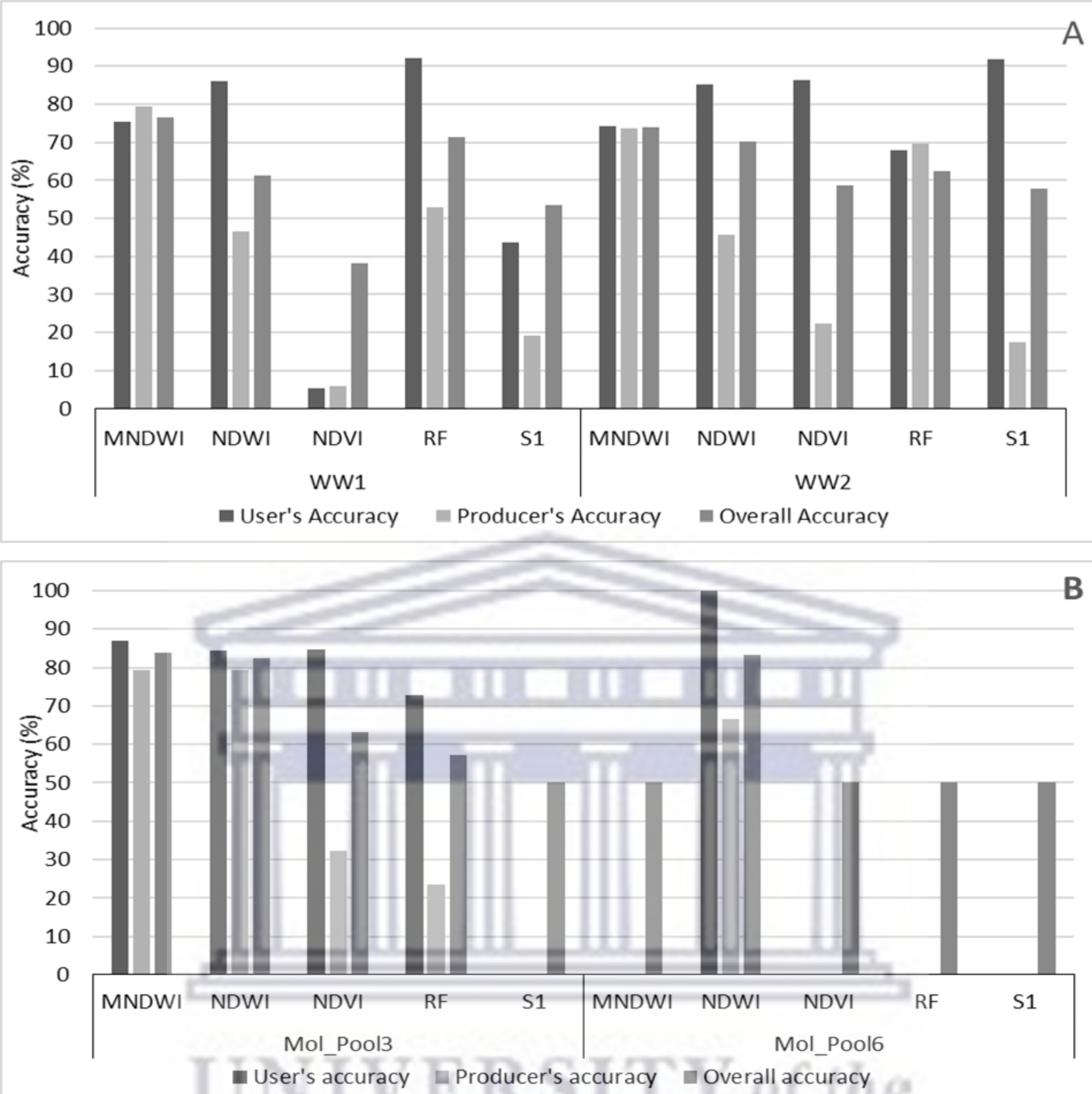


Figure 3.7: Performance by MNDWI, NDWI, NDVI, RF and S1 in the classification of pools in Touws (A, WW1 and WW2-Wolverfontein 1 and 2 pool) and Molototsi River (B, Pool 3 and 6).

The difference in observed and estimated surface areas of pools

The pool areas estimated with remote sensing tended to be overestimated for both pools (Table 3.4). Further, the MNDWI showed lower errors when estimating the surface water area of pools, as it outperformed all other methods, in one instance, the difference was 1.5%. The thresholded Sentinel-1 data and NDVI showed high differences/errors ranging from 43% to 100%, although NDVI had the best estimate for the WW1 pool on one occasion (PDAI= -8.6%). When comparing the estimates for the two Touws pools, the WW1 pool was better estimated. For the Molototsi pools, NDWI showed lower errors when estimating the surface water area of pools, as it outperformed all other methods, with PDAI of 5.9% and 33.3% for Pool 3 and Pool 6, respectively. The thresholded Sentinel-1 data had the highest errors of 100% for both pools, indicating that pools were not detected. When comparing the estimates for the two Molototsi pools, Pool 3 was better estimated.

Table 3.4: Percent Differential Area Index for three surveys in Touws (A, pools WW1 and WW2) and one survey Molototsi (B, pool 3 and 6)

Touws River (A)				
WW1 pool				
MNDWI	**NDWI**	**NDVI**	**RF**	**S1**
-25.7	-71.4	-8.6	-31.4	85.7
6.1	78.8	100.0	53.0	43.4
1.5	81.8	100.0	87.9	77.5
WW2 pool				
MNDWI	**NDWI**	**NDVI**	**RF**	**S1**
-28.9	58.5	65.5	-31.7	96.2
26.2	74.6	93.1	50.0	71.0
-11.3	27.4	68.9	22.6	70.2
Molototsi River (B)				
Mol_Pool 3				
MNDWI	**NDWI**	**NDVI**	**RF**	**S1**
8.8	5.9	61.8	67.6	100.0
Mol_Pool 6				
MNDWI	**NDWI**	**NDVI**	**RF**	**S1**
100.0	-33.3	100.0	100.0	100.0

3.3.3 Changes in pool sizes and factors that control the changes in Touws and Molototsi Rivers

There were four major flow events in Touws River from 2019 to May 2021. The maximum surface water area estimated was 12000 m^2 and 20800 m^2 for WW1 and WW2 pools, respectively (Figure 3.8). The maximum surface area was stable for WW1 but fluctuated for the WW2 pool, possibly due to errors of WW2 detection. During the study period (2019-2021), the pools were at the driest level in January 2019 with surface areas of 1600 and 400 m^2 for WW1 and WW2, respectively. This was after two years of no river flows. This was followed by October 2020 when the pools had surface water areas of 3700 and 5200 m^2 for WW1 and WW2, respectively. This was after six months without significant inflows. Compared to Touws, Molototsi had two major flow events during the summer season of each year. The pools were present at the end of flow events in February/March and dried out in June/July of each year (Figure 3.9). The maximum surface water area was estimated to be 2900 m^2 and 1300 m^2 in Pools 3 and 6, respectively. Pool 3 was completely dry in 2020 and did not exist in 2019. Pool 6 dried up in June 2020, and it was almost completely dry in June 2021 with a surface water area of 100 m^2.

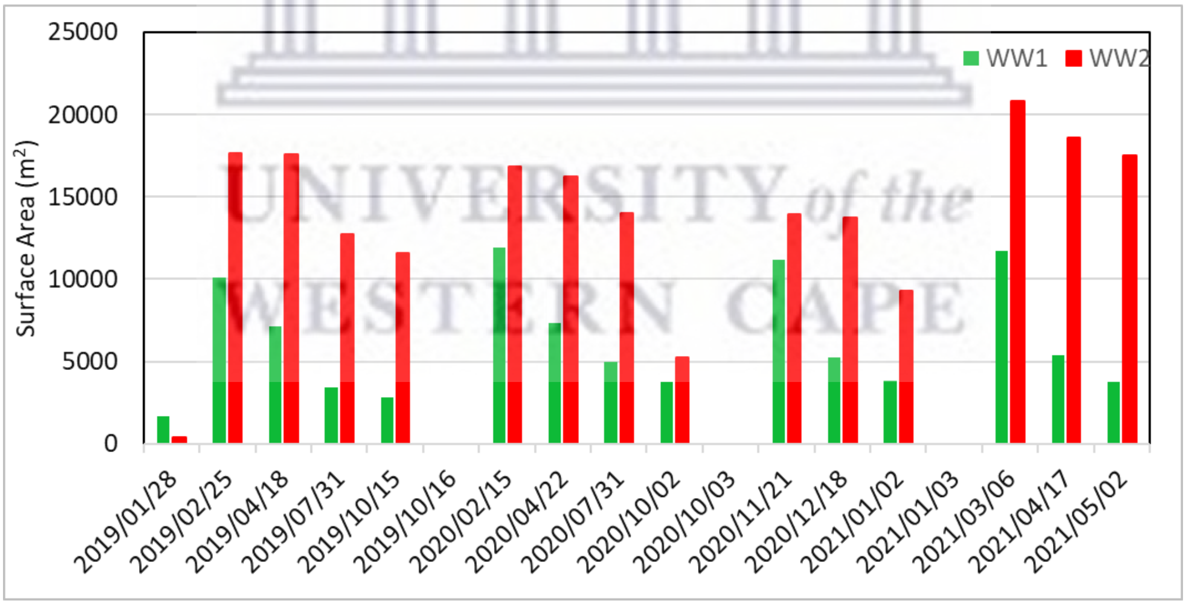


Figure 3.8: Changes of the surface water area of WW1(green bars) and WW2 (red bars) in the Touws River when full, at intermediate and dry stage

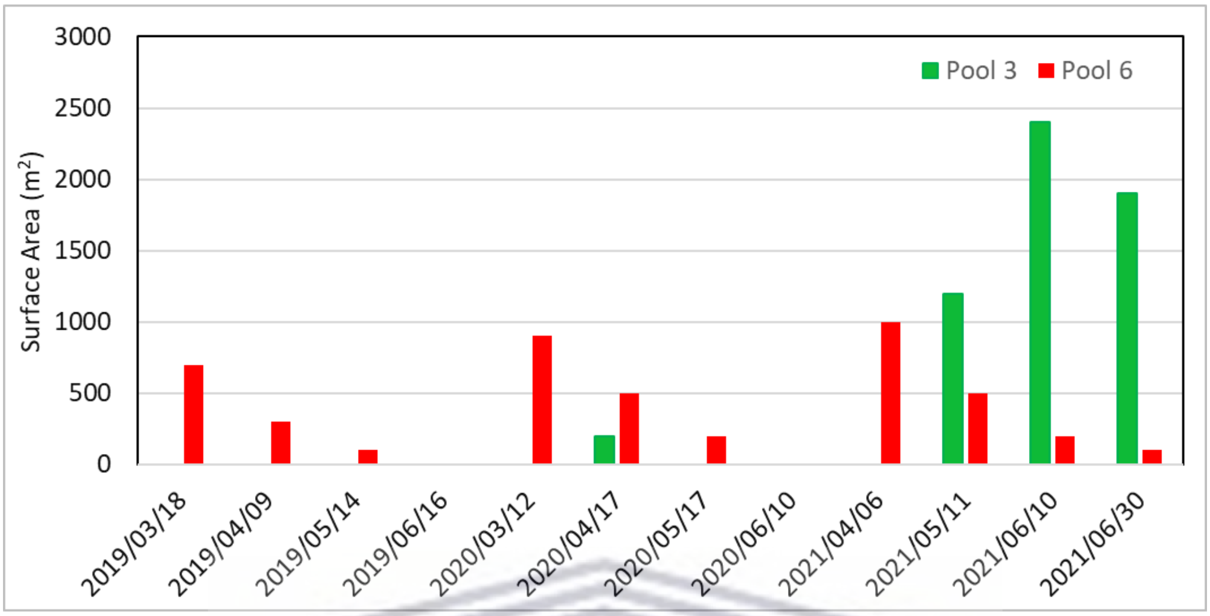


Figure 3.9: Changes of the surface water area of Pool 3 (green bars) and Pool 6 (red bars) in the Molototsi River when full, at the intermediate and dry stage

The remotely sensed estimates of surface water area correlate well with rainfall and flow occurrence for the Touws River (Figure 3.10). After flow events, the surface area of the pools increased to maximum size. The flow event marked with red occurred downstream of the WW1 pool, therefore, it did not affect the size of the WW1 pool. Rainfall adds water that maintains the pools, delaying the drying up of pools. The surface area of pools decreased after the major inflow; this means some losses occurred. Both shallow and deep groundwater levels did not show any notable changes in relation to the surface area of the pools, rainfall and the occurrence of flow. This suggests that there might be no vertical interaction between the pools and the groundwater system. This indicates that water is lost to the atmosphere through evaporation and to the unsaturated zone. Potential evaporation at the site was 94 and 82% higher than rainfall in 2019 and 2020, respectively. Evaporation, therefore, plays a significant role in water losses. These patterns were observed for the two pools, although the maximum size of the

WW2 pool fluctuated and should have been affected by the event that occurred in October 2019, however, there was no increase in the size of the pool (Figure 3.9).

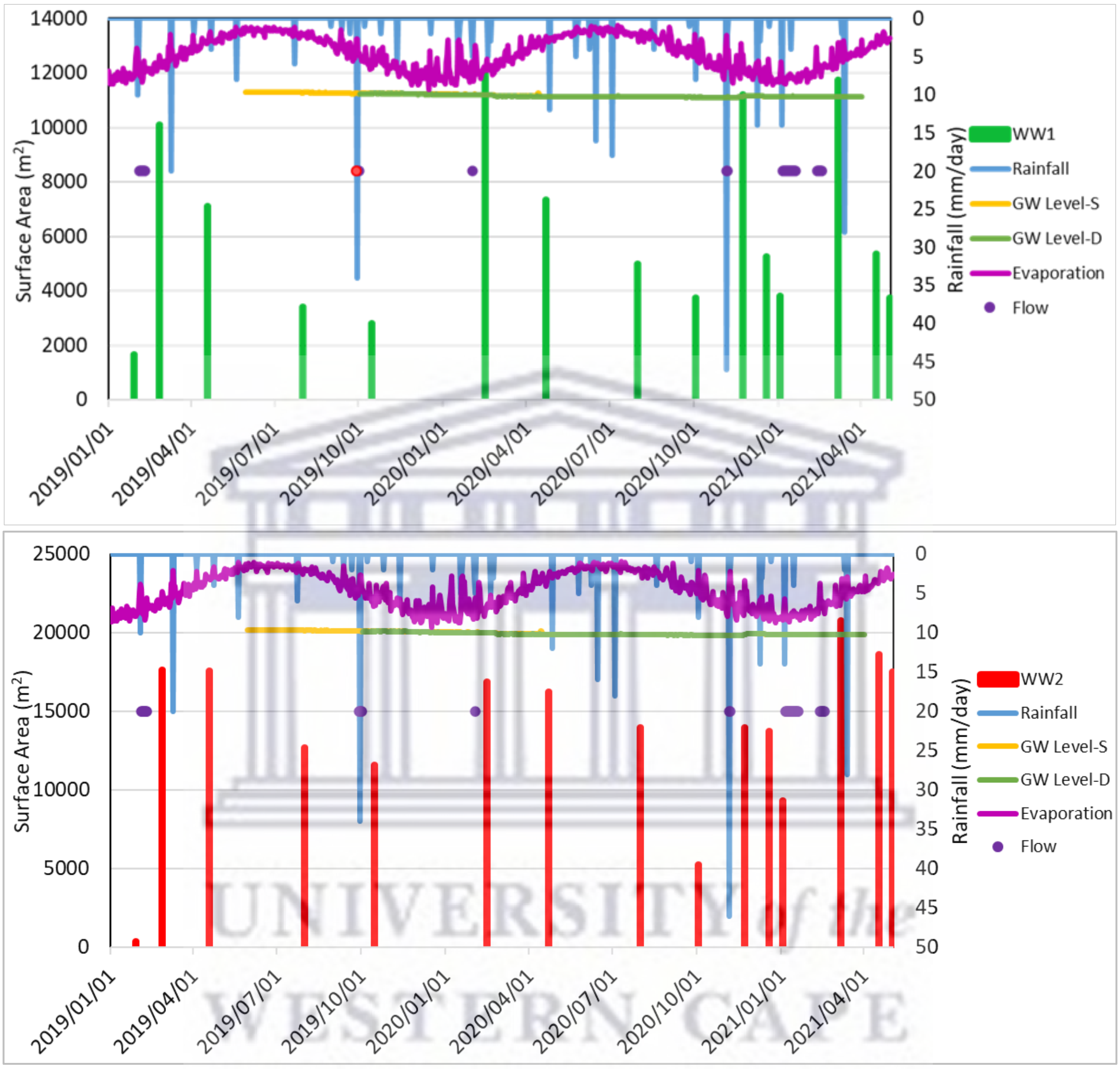


Figure 3.10: Changes of the surface water area of WW1 (green bars), WW2 pool (red bars), with daily rainfall (blue line), the occurrence of flow (purple dot), shallow (orange line) and deep (green line) groundwater levels, evaporation (purple line).

In the Molototsi site, remotely sensed estimates of the surface water area correlated well with rainfall and the occurrence of flow for Pool 6 (Figure 3.11). Rainfall added to the water that maintained the pool, delaying the drying up of the pool. The surface area of pools decreased after the major inflow; this means some losses occurred. Groundwater levels did not show any notable changes in relation to the surface area of the pools, rainfall, and flow occurrence, suggesting that there might not be vertical interaction between the pools and the groundwater system. This suggests that water is lost to the atmosphere through evaporation and to the unsaturated zone. In this area, potential evaporation was 77 and 75% more than rainfall received in 2019 and 2020, respectively. There was no evident relation between rainfall and Pool 3. Other factors such as river sand mining and water withdrawals from the river might have influenced its size.

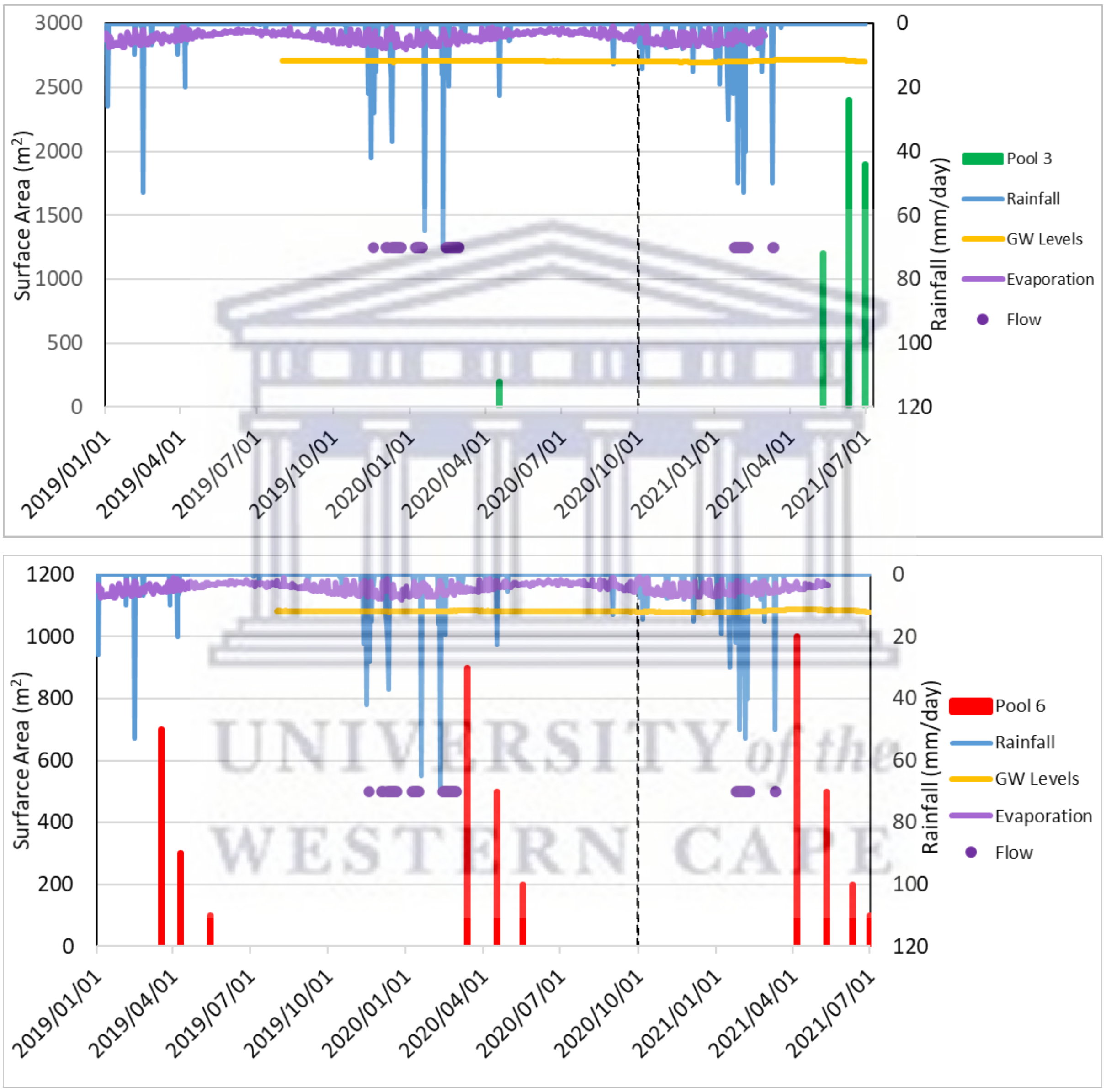


Figure 3.11: Changes in the surface water area of Pool 3 (green bars) and Pool 6 (red bars), with daily rainfall (blue line), the occurrence of flow (purple dot) and groundwater levels (orange line). The black dashed line indicates the start of groundwater pumping on the site.

3.4. Discussion

This study explored the use of remote sensing in monitoring the spatial distribution of pools and pool dynamics along non-perennial rivers in two distinct areas. The results showed that the pools in the Touws River were bigger than the pools in the Molototsi River. This might be due to the Molototsi River having sandy bed material with high hydraulic conductivity draining water after flash floods (Walker et al. 2018). In contrast, the Touws River has bedrock that is not far from the riverbed, hence it is classified as a mixed alluvial and bedrock river (Grenfell et al. 2021). Furthermore, Molototsi has a clear dry and wet season, whereas the Touws River receives rainfall and flows at any time of year. However, the use of remotely sensed data demonstrated the capability to detect pools at both river and pool scales.

In both rivers, pools with shallow water (depth of approx. 0.3 m) were detected, but those that were small in surface area were not detected. The failure to detect pools with small surface areas may be due to the satellite image resolution, where pixels including small pools are detected as non-water. The MNDWI and NDWI detected pools better than other methods in both Touws and Molototsi Rivers, respectively. However, the MNDWI did not detect pools that were smaller than 400 m^2. This is due to the short-wave infrared band of Sentinel-2 having a slightly coarser spatial resolution (20 m). Resampling it to 10 m did not make a difference, whereas the NDWI uses bands that have a 10 m spatial resolution and it was able to detect some pools that are less than 400 m^2. Li et al. (2021) made the same observation when mapping a small river. The NDWI is known to have challenges in separating shallows and built-up areas (Bangira et al., 2019). This might explain why the index did not outperform MNDWI on the mountainous Touws River site as compared to the relatively flat Molototsi site. All this also suggests that the small pools require better resolution imagery in order to be detected.

The random forest classification detected the pools with acceptable accuracy, however it did not meet expectations at both the catchment and pool scale. This might be because pools tend to have different characteristics that affect the training of the classifier, such as the presence of algae, vegetation, sediments in the pools, and the size and shape of the pool. Even parts of pools can have different spectral signatures. All these might have limited the detection of pools by the random forest classifier as there are usually few water bodies that can be used to train the classifier in these dry areas. As a result, the training might not be diverse enough to capture the differences found in pools. Bangira et al. (2019) state that this is the disadvantage of machine learning classifiers. Sentinel-1 did not perform well compared to results obtained from Sentinel-2. This is similar to the results obtained by Bangira et al. (2019). Although Sentinel-1 had been applied to mapping floods over large areas, it was not suitable for detecting pools at both study sites. For an index that was produced to detect vegetation, NDVI performed well in both catchments.

When comparing the accuracy at the pool's size scale in Touws River, the WW1 pool was estimated better than the WW2 pool. All methods had difficulty in classifying the pixels around the WW2 pool due to the shadow in the morning, the time of day when Sentinel-2 captures images. To reduce this misclassification, the random forest classifier was trained for the hill shadows, thereafter, some misclassified pixels were removed. Pool 3, which was the largest pool in the Molototsi River, was also detected better than Pool 6. However, only the NDWI was able to detect Pool 6.

In both catchments, the surface area of the pools generally correlated well with the occurrence of flows and rainfall except for one flow event that did not match the change in surface area of the WW2 pool. The results showed no notable responses of groundwater levels to the surface water area of the pools, nor to rainfall and river flows. This can be attributed to the nature of the underlying geology of the study sites, shale for Touws and gneiss rock for Molototsi. This suggests that the pools are not losing water to the groundwater system. These findings differ from many studies that have indicated that groundwater sustains the pools (Bestland et al. 2017; Lamontagne et al. 2021). However, Walker et al. (2018) made the same finding in the Molototsi catchment using water levels and geochemical analyses. Hamilton et al. (2005) reported similar findings for pools in Australia, adding that clay found at the bottom of pools can also contribute to reducing the interaction between groundwater and pools.

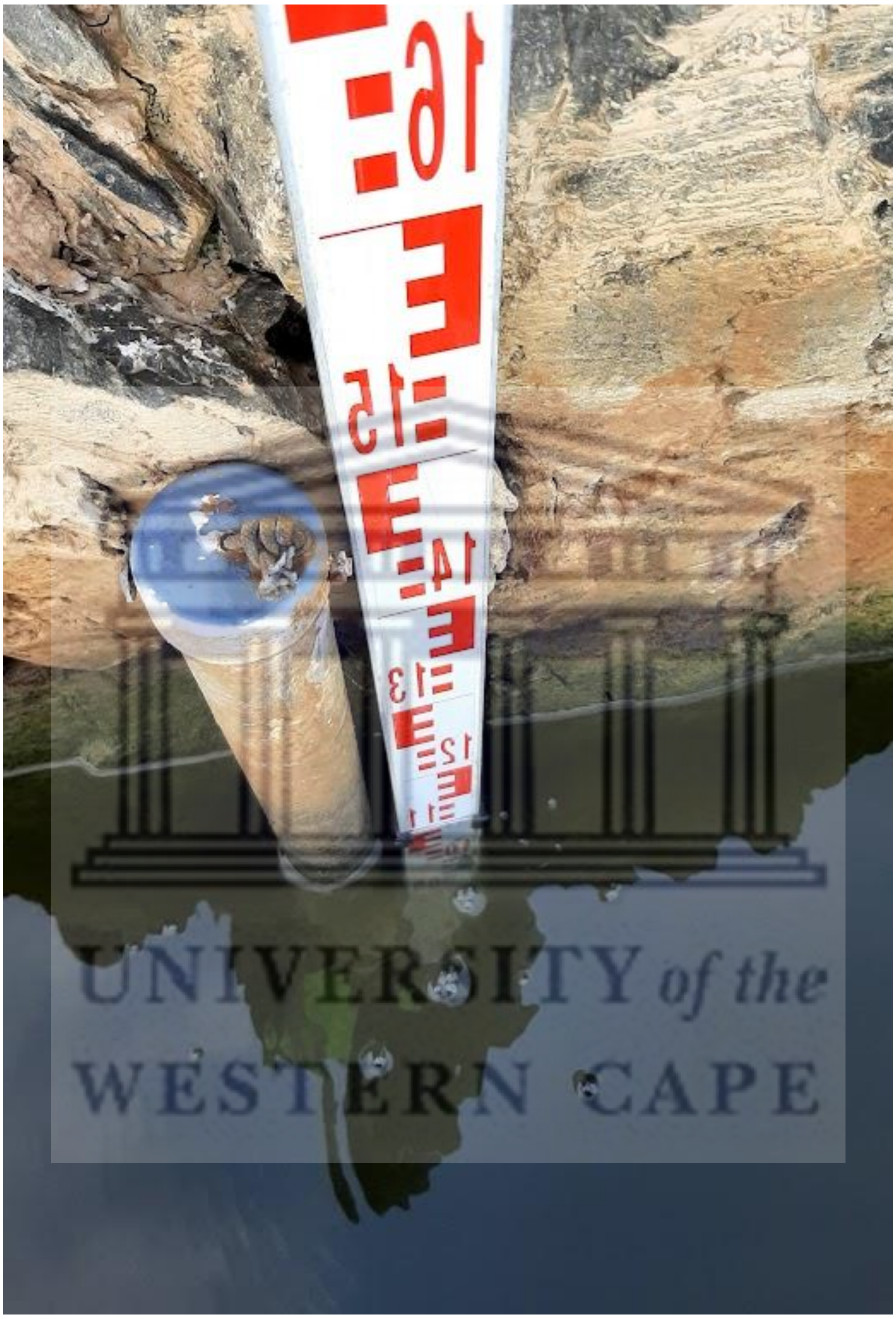
The results imply that altering the flow regime will significantly affect the spatial distribution of pools and pool dynamics. The pools are not only important water sources for the surrounding communities, but they also provide habitat and maintain the aquatic life of the river (Bonada et al. 2020). Further, they improve food security in the surrounding communities (Sustainable Development Goal 2) as complete drying of pools may result in total loss of aquatic life, including fish (Marshall et al. 2016). The results also showed that pools at the study sites might not be sensitive to groundwater abstraction.

3.5 Conclusion

The study demonstrated the potential of using remote sensing methods to determine the spatial distribution and dynamics of pools in two contrasting non-perennial rivers, the one characterized by a sandy-gravel bed with pools associated with bedrock outcrops (Touws River) and the other exhibiting a sandy alluvium with pools migrating following flow events (Molototsi River). Remote-sensing methods detected pools with acceptable accuracy in both rivers, except for small pools (<400 m^2). Overall, MNDWI performed better than other methods in the mountainous Touws River, whereas NDWI performed better in the relatively flat Molototsi floodplain. The pools in the Touws River showed a perennial pattern, whereas pools in the Molototsi River showed ephemeral behaviour persisting only for a few months after flows. Rainfall and flow occurrences are key in controlling temporal changes in pools sizes, and there was no evidence of interaction between pools and groundwater in both rivers. Water balance analysis, however, may be able to clarify, to a greater extent, how these fluxes are responsible for the changes over time in pools.

Remote sensing proved to be a useful approach to record water occurrence and availability in poorly monitored non-perennial rivers. It is suggested that this approach could be used to fill ground monitoring gaps in non-perennial rivers, and it could be incorporated into national hydrological monitoring networks. Water available in non-perennial river pools can be considered an important water resource in semi-arid environments. If properly managed, this additional water resource could serve to provide water for livestock and domestic purposes in rural communities. It also provides ecohydrological services such as flood attenuation and storage of floodwaters, as well as habitats, feeding and spawning ground for various aquatic species, thereby indirectly supporting the tourism sector and livelihoods.

Chapter 4: Using the water balance approach to understand pool dynamics along non-perennial rivers in the semi-arid areas of South Africa



This chapter is based on**:**

Maswanganye, S.E., Dube, T., Jovanovic, N., Kapangaziwiri, E., Mazvimavi, D., 2022. Using the water balance approach to understand pool dynamics along non-perennial rivers in the semi-arid areas of South Africa. J. Hydrol. Reg. Stud. 44, 101244. https://doi.org/10.1016/j.ejrh.2022.101244

Abstract

Study Focus: This study sought to improve the understanding of pool dynamics (Wolverfontein 1 and 2) along non-perennial rivers (NPRs) by utilising the water balance approach to assess the water fluxes that influence pool dynamics in the Touws River. The water balance model made use of various in-situ and satellite-derived data.

New Hydrological Insights: The analysis of the water losses from the pool showed that most of the water was lost through evaporation. The interaction between the pool and groundwater is dependent on the water levels, as the pool loses water to the subsurface up to a certain depth then it starts gaining. When the Wolverfontein 2 pool is full, it can retain water for approximately 258 days without having a surface water inflow. A water balance model was established, and it simulated the water levels with a high correlation of 0.9. This model was also evaluated in the neighbouring pools, and while it simulated the water levels of the upstream pool well, this was not the case for the downstream pool. When remote sensing-derived rainfall and evaporation data were used in the model, the simulated water levels had a slightly lower correlation of 0.7 with the observed water levels. Overall, the remotely sensing-based monthly fluxes estimates could not provide the detailed pool information that was required for the water balance. Errors may have arisen, or they may have been inherited, from any of the three remotely sensed parameters, namely, the surface area, the rainfall or the evaporation. Although remote sensing did not provide detailed information, it is worth noting that it provides baseline information on the pool dynamics. Overall, this work underscores the relevance of multisource data and the water balance, it helps to better understand the pool dynamics and it will help with the better management of NPRs.

Keywords: Dryland areas; Pool hydrodynamics; Hydrological water balance; River ponds; Temporary Rivers; Water budget

4.1 Introduction

Non-perennial rivers (NPRs) comprise all rivers that cease to flow for certain periods of the year. These occur globally and across all climatic zones and biomes (Messager et al., 2021), and their occurrence is increasing due to climate change, social-economic uses, and land-use effects. For some NPRs, when flows cease, water occurs in pools along these rivers. These pools are of importance for aquatic life as refugia and surrounding communities as a source of water for livestock, garden watering and domestic use (Maswanganye et al., 2022a). Pools occurring along NPRs have been recognised for their ecological importance (Ilhéu et al., 2020; Marshall et al., 2016; Sheldon et al., 2010). There is a relationship between the ecological state of pools and their hydrology. For example, Bonada et al. (2020) found that larger pools tend to have a higher species richness and abundance. Because of this, pools are often considered when determining environmental flows. There is, however, limited information about the nature and causes of spatiotemporal variations of water storage in pools (Bonada et al., 2020; Bourke et al., 2020; Shanafield et al., 2021). This knowledge gap constrains the formulation of appropriate management measures. Consequently, management decisions are made by extrapolating knowledge based on the spatiotemporal variations of water storage in lakes (Bonada et al., 2020; Maswanganye et al., 2021). Shanafield et al. (2021) recommended the need to improve the understanding of the persistence of pools and how they are impacted by climatic shifts and groundwater abstractions. Furthermore, the communities that utilise these pools need information for allocation and planning purposes; for example, how long will it take for them to dry up (Ali et al., 2015).

Routine monitoring of water storage in pools along NPRs has not been included in most national hydrological monitoring systems, partly because these systems are often considered to have low value (Rodríguez-Lozano et al., 2020) and due to the absence of adequate financial resources. There are also physical limitations, as some of these pools are not easily accessible, and some may disappear after flow events, depending on riverbed material (Hattingh, 2020; Maswanganye et al., 2022a). However, very few studies have shown that remote sensing can provide useful information about these pools, including their spatial distribution and size (Maswanganye et al., 2021; Seaton et al., 2020). Maswanganye et al. (2022a) found that river flows are the major controlling factor of pool dynamics and suggested that rainfall is important for delaying the drying out of pools in the semi-arid and arid environments of South Africa. However, the study also expressed that there is a need to assess pools in detail, in order to gain a better understanding of their hydrodynamics.

Several methods can be applied for assessing the pool water fluxes. These methods include direct measurements (LaBaugh et al., 2016), as well as linear and multiple regression (Stasik et al., 2020). Although direct measurements are accurate, the limited availability of data on some components remains challenging, due to the complexity associated with field measurements and monitoring. For instance, it is challenging to quantify the interaction between groundwater and pools. The linear and multiple regression methods also require data and are easy to use, but difficulties are experienced with non-linear and non-stationary systems (Li et al., 2016; Seo et al., 2015). To overcome this issue, more complex process-based models are used, such as deterministic and stochastic models, while Artificial Intelligence (AI) and machine learning have also been used to assist with the complexity of the water systems (Seo et al., 2015). These models may have difficulty estimating beyond the data ranges that are used for training and they may be difficult to interpret, due to hidden processes (layers) (Talebizadeh and Moridnejad, 2011). While environmental tracers can also be used to qualify the water sources in a pool (as in Hamilton et al., 2020), in some cases, water types cannot be separated by a hydrochemical analysis (Bourke et al., 2020).

The water balance approach has been widely used to represent and predict changes in water storage of water bodies (Ali et al., 2015). This approach is based on the law of conservation and has been used to understand water fluxes that influence water body dynamics and simulate the water availability in hydrological systems, such as lakes and wetlands (Gronewold et al., 2020; Mbanguka et al., 2016). The water balance, like other methods, requires data or estimates of each of the hydrological components (evaporation, precipitation, surface water in- and outflows and groundwater in- and outflows). However, the advantage of the water balance is that it can be used to estimate an unknown component of the water balance equation. This component is usually the groundwater in- and outflows, which are difficult to measure directly (e.g., Xiao et al., 2018). For instance, Parsons and Vermeulen (2017) found that ~16.9 and 83.1% of the water lost by the Groenvlei Lake were due to groundwater outflows and evaporation, respectively. In addition, the water balance method can be used to predict the responses of pools to changes in inputs or outflows. This information can also be used to predict how development, for example, building a dam, will alter the hydrology of a water body.

Although the water balance has been applied to understand the dynamics of water bodies across the globe, it has not been used to understand pools along NPRs. Maswanganye et al. (2022a) and Bourke et al. (2020) suggest that the water balance approach can assist in improving the understanding of pool dynamics, which could be useful in the management of NPRs and their contributing catchments. Therefore, this study aims to improve the understanding of pool dynamics or water storage changes in pools along non-perennial rivers (NPRs) in the semi-arid environments of the Karoo region of South Africa. The study uses the water balance method to assess water fluxes that influence the pool dynamics. In addition, because most areas with these pools may not have the required data for the water balance approach, this study also explores the potential of using open access, remotely sensed data in the water balance model.

4.2 Material and Methods

4.2.1 Site and Pool Description

The study was conducted in the pools occurring along the Touws River, which is in the Karoo region in South Africa (Figure 4.1). Although the catchment is 6 280 km^2, but this study is confined to a site where the catchment area is ~5750 km$^{2.}$ The study investigated three pools located along a 1.2 km stretch of the Touws River in the Plathuis area at Wolverfontein (Figure 4.1). The pool on the upstream end referred to as Wolverfontein 1 (WW1) is located at 33.641726° S and 20.965985° E and had a maximum area of 10,045 m^2. The second pool, Wolverfontein 2 (WW2) is 700 m downstream of WW1, located at 33.639076° S and 20.975719° E, and with a maximum area of 17,742 m^2. The third pool is 450 m downstream of WW2 at 33.642918° S and 20.982405° E and is referred to as Touwsberg (TWB). This third pool had a maximum area of 15,722 m^2. The study focuses mainly on Wolverfontein 2 (WW2) pool which is situated along the left bank that is hilly with exposed bedrock while the right bank has a sparsely vegetated floodplain (Figures 1C and D). According to Hattingh (2020), the WW2 pool has a substrate of predominantly fine sand. This pool has a maximum depth of 1.7 m. The WW2 pool nearly dried up during the 2016-2019 drought. During flow events, these pools connect, they are accessible and they persist for long enough to sustain some form of life (aquatic vegetation and animal community), as described in Zacharias and Zamparas, (2010). Furthermore, these pools are located close to the flow occurrence, rainfall, and groundwater level observation points.

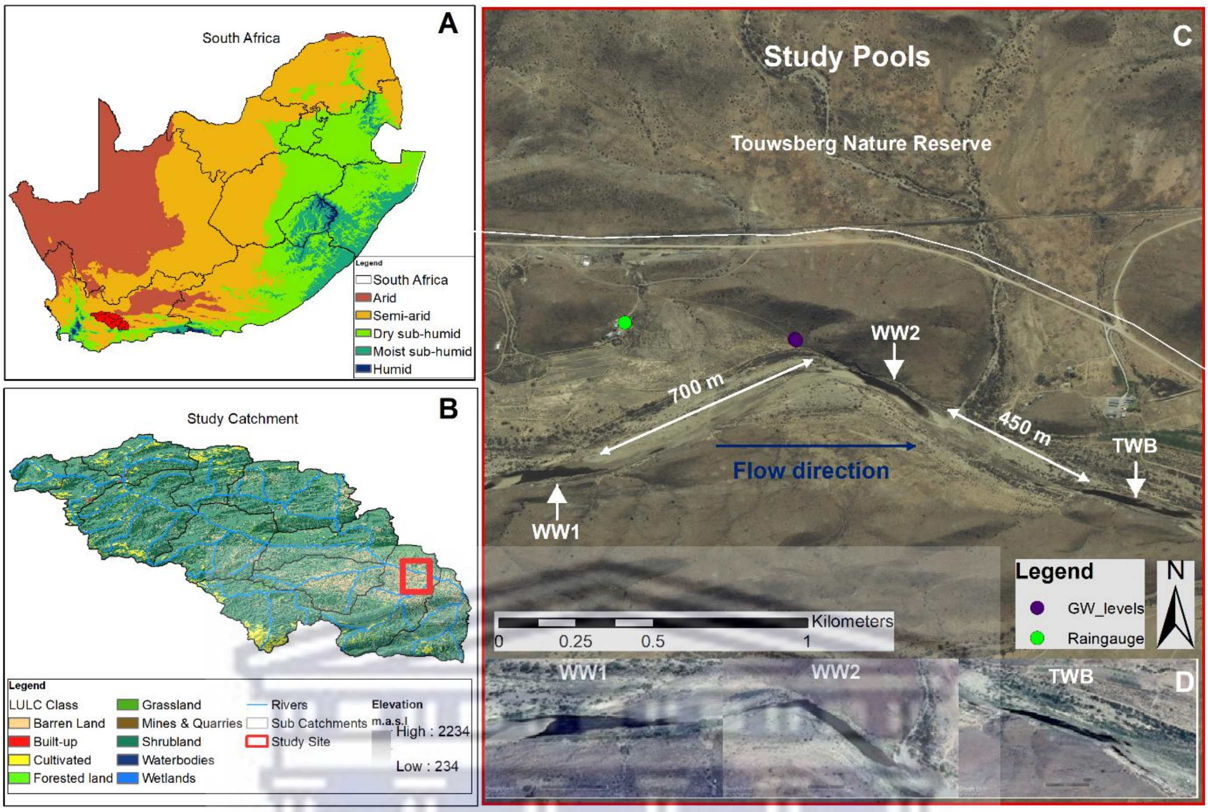


Figure 4.1: Location of the study catchment (red) within South Africa (a), the location of the study pools in the study catchment (b), the location of the three pools along the river [National Geo-Spatial Information, South Africa] (c), while the bottom images provide a closer view of the three pools [Google Earth Satellite Imagery] (d).

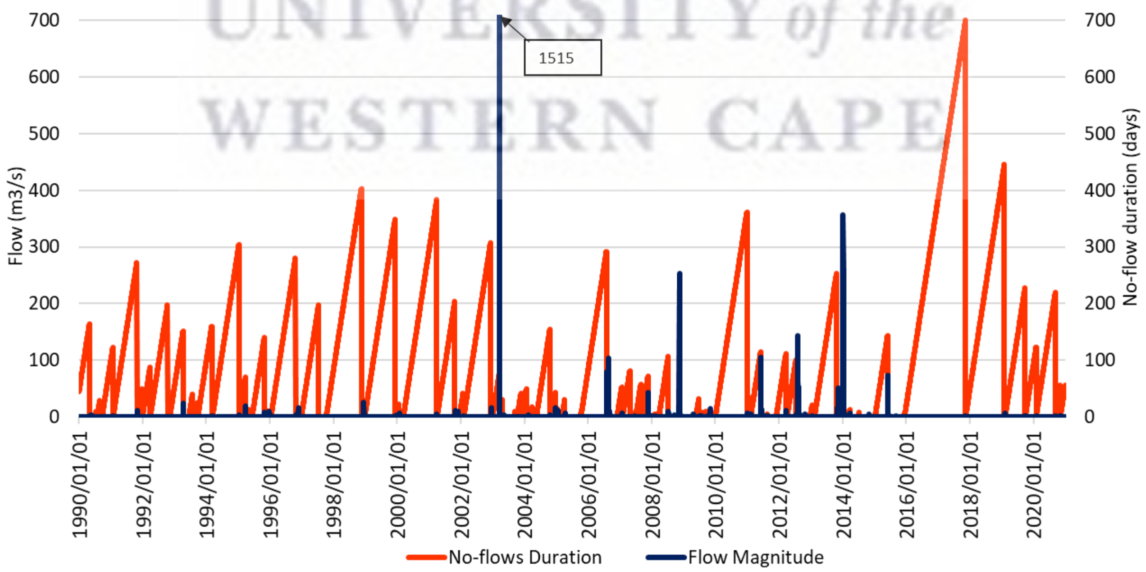


Figure 4.2: Flow data (dark blue line) and the number of no-flow days (red line) of the Touws River [Department of Water and Sanitation, Station J1H018]

4.2.2 Data collection and analyses

In-situ data

A water balance analysis of water storage in pools requires data on rainfall, evaporation rates, pool storage, and inflows and outflows of both river water and groundwater. The surface area data were obtained from the Global Positioning System (GPS) measurements collected along the edges of the pools, using a hand-held GPS, and a staff gauge was used to measure the water levels during the field visits (Table 4.1). A Solinst water level logger (M3001, M5, and logging at hourly intervals) was installed in each pool to measure water levels. Water levels in WW2 were measured for two years (2019-2021), while this was done for a year (2020-2021) in WW1 and TWB pools. Data from this rain gauge were used for water balance analysis. Two boreholes for monitoring changes in the depth to the water table were drilled on the left bank, 200 m upstream of WW2. This site was the closest to WW2 that a drilling rig could access because of the hilly terrain adjacent to WW2. The two boreholes had depths of 25 m and 60 m. A water level data logger (logging at hourly intervals) was installed in each borehole. Weather data were required for estimating evaporation rates using the Penman method. Data from the closest weather station owned by the Agricultural Research Council were used. This station is located 27 km southeast of the study pools. Rainfall and flow occurrences were obtained from the Citizen Science monitoring programme, whereby farmers neighbouring the pools collected these data. The rainfall data were collected using non-recording rain gauges (manual), notes on flow occurrence (absence and presence) were recorded by event. One farmer is located within the study site, 600 meters from the WW2 pool (Figure 4.1), and the other is located one km upstream of the study site.

Table 4.1: Size of the three pools (WW1, WW2 and TWB) during the site visits

	WW1 Pool		**WW2 Pool**		**TWB Pool**	
Date	**Surface Area (m^2)**	**Water Level (m)**	**Surface Area (m^2)**	**Water Level (m)**	**Surface Area (m^2)**	**Water Level (m)**
2019/07/31			13242	1.2		
2019/10/01			16742	1.7		
2020/12/14	6821	0.5	10836	1.1	16557	0.8

2021/03/30	6538	0.5	12891	1.1	15722	0.76
2021/08/10	10045	0.7	15339	1.4	25789	1
2021/12/01	3500	0.4	8913	0.75		

*Blank spaces indicate no observation.

The relationship (rating curves) between the surface area, depth and volume were determined, in order to be able to convert between these measurements. The volume of the pool was estimated based on the following equations, which were derived using 3D analyst on ArcGIS and by using the Differential Global Positioning System (DGPS) points and continuous water level measurements (Equations 4.1 and 4.2). The following relationships were specifically derived and used for the WW2 pool.

$$H=0.00009A; \quad R=0.99 \qquad (4.1)$$

$$V= 0.00005A^2+0.1415A+18.83; \quad R=0.99 \qquad (4.2)$$

Where H is the depth of water in a pool in metres, V is the volume of water stored in m^3 and A is the area of the pool in m^2.

Remote sensing data

Since in-situ data on water balance components of non-perennial pools are often unavailable, the study explored the use of readily- and freely available remotely sensed data for water balance analysis of water storage in pools along Touws River. Evaporation data were obtained from the Moderate Resolution Imaging Spectroradiometer (MODIS) 16 PET product, as described by Mu et al. (2011, 2007). The data were downloaded from the AppEARS website (https://lpdaacsvc.cr.usgs.gov/appeears/). MODIS 16 evapotranspiration data are widely and commonly used, and Jovanovic et al. (2015) found that MODIS 16 evapotranspiration and potential evapotranspiration estimates over South Africa’s landscape were satisfactory; however, they cautioned that the spatial resolution can limit its potential for small-scale use. Some studies have argued that MODIS 16-derived PET is suited for small-scale applications (Astuti et al., 2022). Bugan et al. (2020) utilised the MODIS 16 dataset in a hydrological model at a catchment level and concluded that the dataset has the potential to be used in data-scarce regions. Based on the findings of these previous studies, the study explored the use of this, it was assumed that MODIS 16 PET would provide the closest satellite-derived and freely accessible estimates. Satellite derived rainfall estimates were obtained from the Climate Hazards InfraRed Precipitation with Stations (CHIRPS) product, as described by Funk et al. (2015), which was downloaded from the climate engine website (https://app.climateengine.com/climateEngine#). Many studies, such as those of Maswanganye (2018), Plessis and Kibii (2021) and Pitman and Bailey (2021), have suggested that CHIRPS can be used in the absence of in-situ data.

To obtain the surface area of the pool from remote sensing data, Sentinel-2 images were downloaded, and the Modified Normalized Difference Water Index (MNDWI) was computed to distinguish the water areas (pixels) from the non-water areas. Shadows in the imagery were classified using the Random Forest technique and were used to mask out their effect on the derived MNDWI water pixels (Maswanganye et al., 2022a). Twenty-four-monthly Sentinel-2 images close to the end of each month, from August 2019 to August 2021 were used. The relationship between the surface area and the water depth obtained from the bathymetric survey (presented in the in-situ data analysis section) was used to convert the remotely-sensing-derived surface area to water depth, and then compared with the observed water levels.

Pool Dynamics Data Analyses

This study first examined the water depths of the focal pool (WW2) in relation to the water fluxes, to gain an insight into the water gains and losses. The time to empty, and the probability of the pool drying out, were then determined. The water balance model was established by using in-situ data, which will be explained in the next section. The water balance model calibrated using WW2 data was evaluated on the other two pools, WW1 and TWB. Satellite-derived rainfall and evaporation estimates were incorporated into the model by substituting the observed rainfall and evaporation, which resulted in an in-situ and remote sensing hybrid water balance; this model does not consider the groundwater in and outflows (Figure 4.3). The fully remote sensing-based analysis used the changes from the surface area that were obtained from the Sentinel-2 images and the satellite-derived rainfall and evaporation. The performance of all the models was evaluated by using the actual water levels measured in the pools. Figure 4.3 illustrates the methodological flow of the analyses.

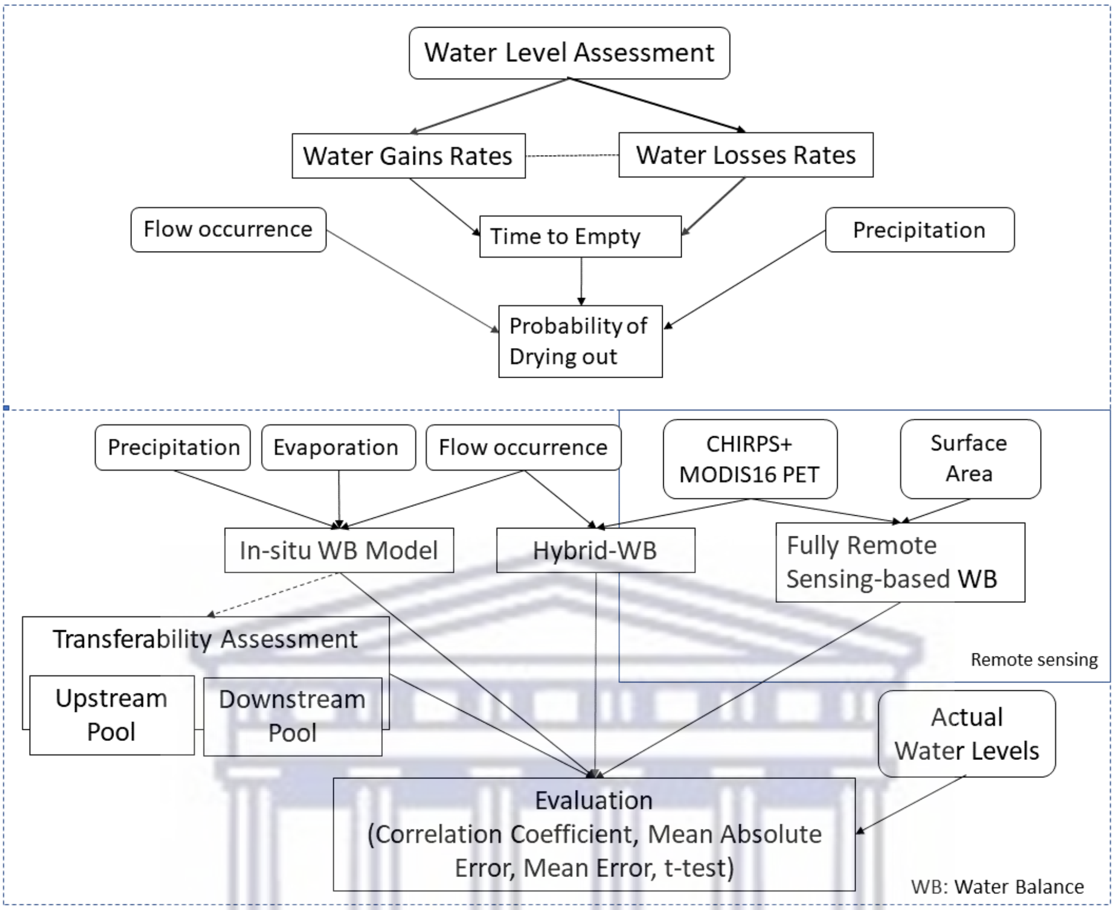


Figure 4.3: A flow chart illustrating the methodological procedure that was followed in this study.

In this study, the Time to Empty (TE) was defined as the time it takes for a pool to completely drain out the water, from being full. This is based on the water loss rate of the pool and assumes that there are no surface water inflows into the pool.

$$TE = \frac{S_{max}}{L_{wl}} \qquad (4.1)$$

Where S_{max} is the maximum water level in meters and L_{wl} is the average water loss per day in meters, which is obtained from assessing the observed water levels. The probability of the pool drying out is the chance of finding the pool dry, which is calculated based on the dry period (no streamflow duration) exceeding the time to empty, while considering that the rainfall over the pool can reduce the number of days that the pool will be dry. In this study, this was calculated by using the 30-year flow occurrence and rainfall data, because there is no long-term data on the other water balance components.

Water balance analysis

Water storage in the pool is described by the following water balance equation (4.2) and illustration (4):

$$S_{(t)} = S_{(t-1)}+P_{(t)}-E_{(t)} +Q_{in(t)}-Q_{out(t)}+ G_{in(t)}-G_{out(t)} \quad (4.2)$$

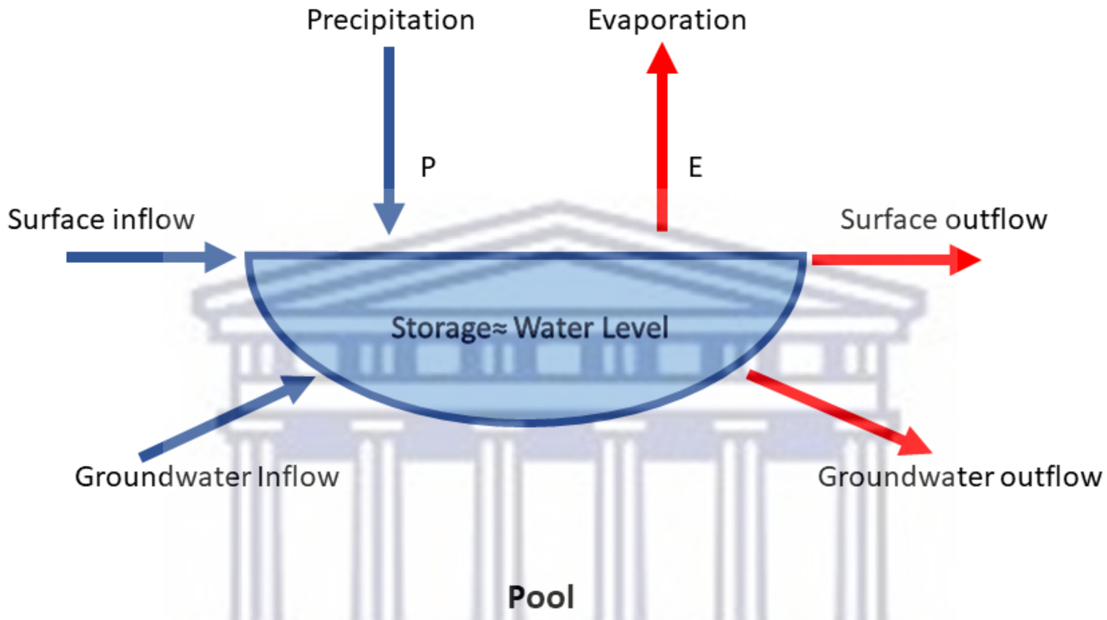


Figure 4.4: Concept of the water balance model, with the blue arrows showing the water gains (precipitation, surface and groundwater inflows) and the red arrows showing the water losses (evaporation, surface and groundwater outflows) from the pool.

Where $S_{(t)}$ is storage at the end of time period t, t being a daily interval, $P_{(t)}$ is a volume of rainfall over the pool, E(t) is a volume of water evaporated from the pool during the day t, $Q_{in(t)}$ is river inflows into the pool, $Q_{out(t)}$ is the surface outflow from the pool, $G_{in(t)}$ is groundwater discharge into the pool, $G_{out(t)}$ is groundwater recharge from the pool.

Daily rainfall p(t)) data obtained from the nearby homestead was used to estimate the volume of rainfall over the pool using the following relation

$$P(t) = p(t)A(t) \quad (4.3)$$

Where A(t) is the surface area of the pool obtained using the relationship between surface area and water storage. Evaporation from the pool (E(t)) was estimated similarly to P(t) with evaporation rates derived using the Penman (1948) method, based on weather station data, as it is a commonly-used method for estimating open water evaporation (Mbanguka et al., 2016; Yihdego and Webb, 2018).

Based on empirical observations, the study assumed that when river inflows are occurring continuously, then the pool fills and during that period inflows will equal outflows from the pool, thus, $Q_{in(t)} = Q_{out(t)}$. During this period, although the pool remains full, some of the inflowing water will contribute to subsurface water around and beneath the pool. The influence of the pool recharging subsurface water will materialise when no surface inflows occur. After the inflows have ceased, the amount of water flowing from the pool into the subsurface material will depend on the area of the pool, or the volume of water in storage. Thus $G_{out(t)}$ was assumed to be described by the following relationship

$$G_{out(t)} = a(S_{(t)} - S_1)^b \quad (4.4)$$

Where S_1 is the volume of water in the pool below which there will be no positive hydraulic gradient into the subsurface material. The volume of water in the pool can also be represented by the depth of water in the pool. We assumed that $G_{out(t)}$ will be a function of the depth of water in the pool

$$G_{in(t)} = cH \ (4.5)$$

Where c is a coefficient

The model was built specifically for the WW2 pool by using the above water balance approach, and its equation and assumptions were transferred to the WW1 and TWB pools. Only two adjustments were made: the initial water level (starting point) and the maximum water level, as these pools were not of equal size. These pools are close to the WW2 pool; therefore, it was assumed that they have the same hydroclimatic conditions.

4.2.3 Statistical analysis

In order to evaluate the performance of the water balance analysis the following statistics were used; the mean error (ME), the mean absolute error (MAE), the correlation coefficient (R) and the paired T-test were used. The Mean Error (ME), which is also called bias, measures the average of the estimation error; this considers the direction of the errors (Equation 4.6). The

ME ranges from negative infinity to positive infinity and has a perfect score of 0. A positive score indicates that the model is over-estimating, while a negative score indicates that it is under-estimating, on average. However, with the ME, a perfect score can be achieved when the over- and under-estimation compensate for each other. Hence, the Mean Absolute Error (MAE) was used to provide a true estimation error (Equation 4.7), and the ME was used to derive the direction of the error.

$$ME = \frac{1}{n}\sum_{i=1}^{n}\left(H_{obs,i} - H_{sim,i}\right) \qquad (4.6)$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|H_{obs,i} - H_{sim,i}\right| \qquad (4.7)$$

Where $H_{obs,i}$ is the observed water level, $H_{sim,i}$ is the simulated water level, and n is the total number of data points.

A t-test (Equation 4.8) was used to determine whether there is a significant difference between the means of the observed and simulated water levels

$$t = \frac{\sum \mathrm{x-y}}{\sqrt{\frac{\mathrm{n}(\sum \mathrm{x}^2 - \mathrm{y}^2) - (\sum \mathrm{x-y})^2}{\mathrm{n-1}}}} \qquad (4.8)$$

where t is the t-statistic, x is the observed water level mean, y is the modelled water level, and n is the total number of data points. A paired t-test assumes that the data sets are continuous, that they follow a normal distribution, that the mean is a good measure of the central tendency and that the two samples are paired (Helsel et al., 2020).

To assess the relationship between the simulated and observed water levels at different time steps (daily, monthly), a correlation coefficient (Equation 4.9) was used. The correlation ranges from -1 to +1, with ±1 being a perfect relationship, and 0 meaning that there is no relationship between the observed and the simulated values.

$$r = \frac{n\,(\sum OE) - (\sum O)(\sum E)}{\sqrt{[n\sum O^2 - \sum O)^2 - [n\sum E^2 - (\sum E)^2}} \qquad (4.9)$$

where O is the observed water level measured by a logger, E is the simulated water level, and n is the number of score pairs of scores.

The mean error, mean absolute error, t-test and correlation coefficient were also used to assess the transferability of the model to a pool that is upstream and downstream of WW2.

4.3 Results

4.3.1 Water level assessment

The water balance analysis shows that the major gains in water level were due to river flow occurrences, and that the minor gains were due to the rainfall received over the pool (Figure 4.5). High losses always followed the high gain episodes, which suggests that water losses might be a function of the water level. The depth to water of the shallow and deep boreholes shows no significant changes in relation to the pool water levels, nor to the occurrence of flows. However, the water level data between 2020/02/07 to 2020/07/31 was missing, due to a stolen logger during the COVID-19 hard lockdown period.

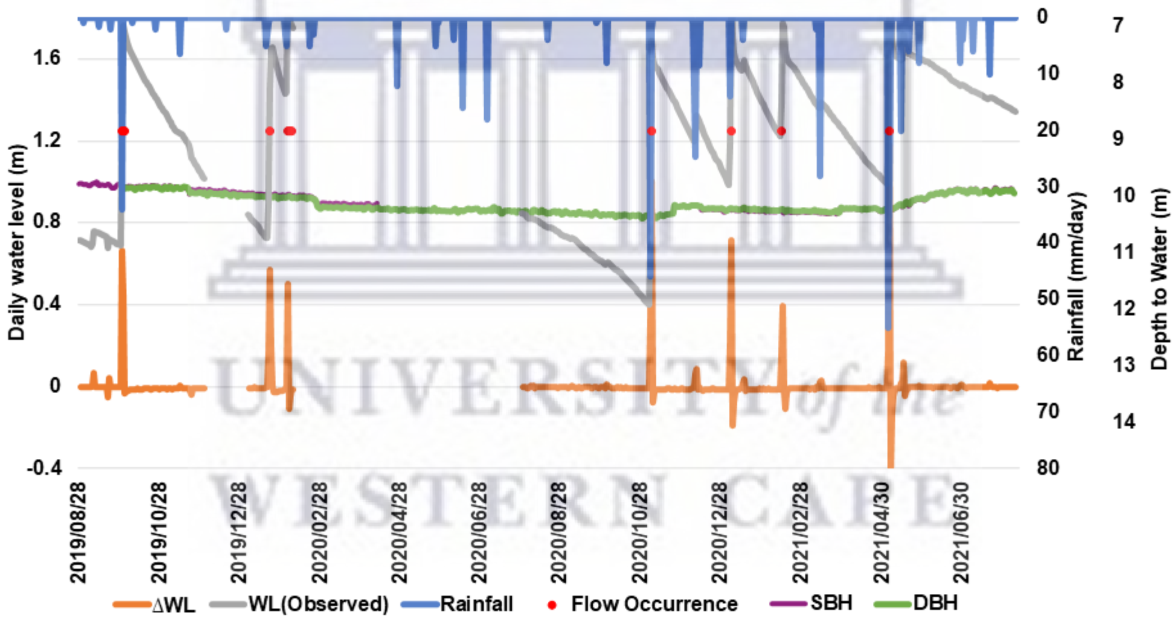


Figure 4.5: Changes in water levels of the pool, with negative and positive values indicating the losing and gaining pools, respectively (orange line), the actual water level (grey line), the rainfall over the pool (blue line), and the flow occurrence (red dots), with the depth to water of the shallow pool (purple line) and deep borehole (green line).

Assessment of the water losses from the pool

The observed pool water level data from August 2019 to August 2021, suggests that the pool loses approximately 0.2 m per month or 2.4 m per year. The losses are high during the southern hemisphere summer (~0.29 m/month) and low during the winter months (~0.09 m/month) (Figure 4.6). This indicates that when the pool is full, it can last, on average, for ~258 days (8.5 months) without any inflows. This pool loses 0.7 m/year more than the estimated Penman evaporation rates. The difference may be attributed to water lost through seepage into the subsurface material. When the volume of water in storage or the water surface area of the pool is large, evaporation losses will be large. Similarly with a large pool bed covered with water, and if the underlying subsurface material is unsaturated, seepage will also be large. Since the water depth increases with the volume of water in storage or pool surface area, water losses from the pool will increase with water depth.

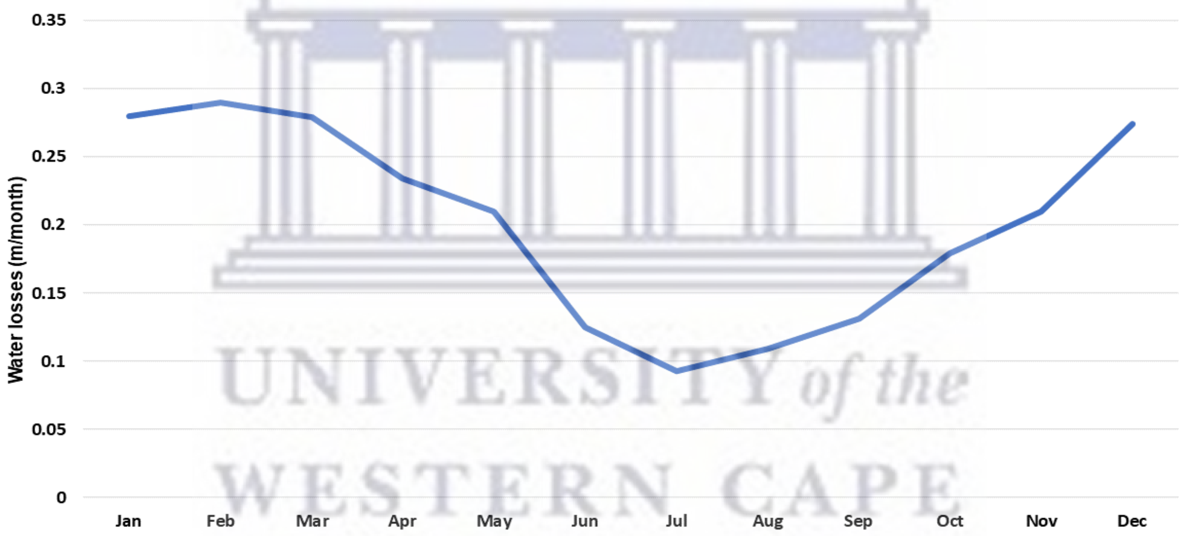


Figure 4.6: Average monthly water losses from the WW2 pool for the study period.

Probability of the pool drying out

Based on the observed losses and time to empty, the river flow and rainfall data from 1990 to 2020 were used to establish the chances of the pool drying out. There is only a 10% chance of finding the pool dry, as the pool was likely to have dried out 11 times in 30 years, or it could have potentially dried out for 1115 days out of 11322 days (30 years) (Table 4.2). This is based on the no-flow and no-rain days exceeding 258 days. Rainfall reduces the number of potential pool dry days; for instance, 52 mm during the no-flow period can delay the drying of the pool by eight days. These estimates suggest that the most prolonged period with no water was 411 days during the 2015-2017 drought, assuming that it did not receive any water from the groundwater.

Table 4.2: Drying out of the pool based on the estimated time to empty, using data from 1990-2020

Start of no flow	End of no flow	No. of days the pool could be dry (excluding rainfall)	Rainfall (mm)	No. of days the pool could be dry (including rainfall)
1991/01/29	1991/10/29	15.0	54.0	6.8
1994/03/14	1995/01/12	46.0	52.0	38.1
1996/01/15	1996/10/22	23.0	34.0	17.9
1997/10/11	1998/11/18	145.0	89.0	131.6
1998/12/26	1999/12/09	90.0	79.0	78.1
2000/03/14	2001/04/01	125.0	80.0	112.9
2002/02/05	2002/12/10	50.0	110.0	33.4
2005/10/12	2006/07/31	34.0	187.0	5.7
2010/01/03	2010/12/31	104.0	97.0	89.3
2015/12/14	2017/11/13	442.0	203.0	411.3
2017/11/14	2019/02/02	187.0	111.5	170.2
Total		**1283.0**	**1096.5**	**1115.3**
Probability		**0.113**		**0.099**

4.3.2 The Water Balance Model

Based on the understanding of the pool, the water balance approach was used to simulate its water levels. The water balance satisfactorily predicted the water levels (ME=-0.03 m;

MAE=0.05 m; r =0.96) and there was no significant difference between the means (t=-4.5) over the assessed period (2019/08/25 to 2021/08/10) (Figure 4.7). Besides the inputs (rainfall and evaporation), the model was supplied with a maximum water level of 1.7 m (which is also the cease-to-flow level) and the initial water level. Moreover, the model was able to predict the water levels during the period when no observed data were available (February-July 2020). The model shows that when the pool has more water, the water is rapidly lost via seepage into the subsurface strata or aquifer, and that the seepage ranged from 0 to 0.005 m/day and was defined as 0.003 of the water level of the pool. Rainfall delays the drying of the pool. The pool is sensitive to the flow occurrence, and the assumption that every flow will fill the pool to capacity is correct and drives the model. After the river flow has ceased, evaporation dominates the water losses. The model suggests that seepage into the subsurface material occurs when the water depth exceeds ~1.1 m. Seepage out of the pool does not occur below this water depth. Instead, groundwater discharge into the pool occurs when the water depth is less than 1.1 m. This proposed behavior could be that the water level in the pool will be greater than the local water table around the pool when the water depth exceeds 1.1 m. Hence, groundwater recharge occurs from the pool. With a water depth below 1.1m, the local water table will be above the pool water level, hence groundwater discharges into the pool. Figure A1 in the appendices shows the model that does not consider the above behavior.

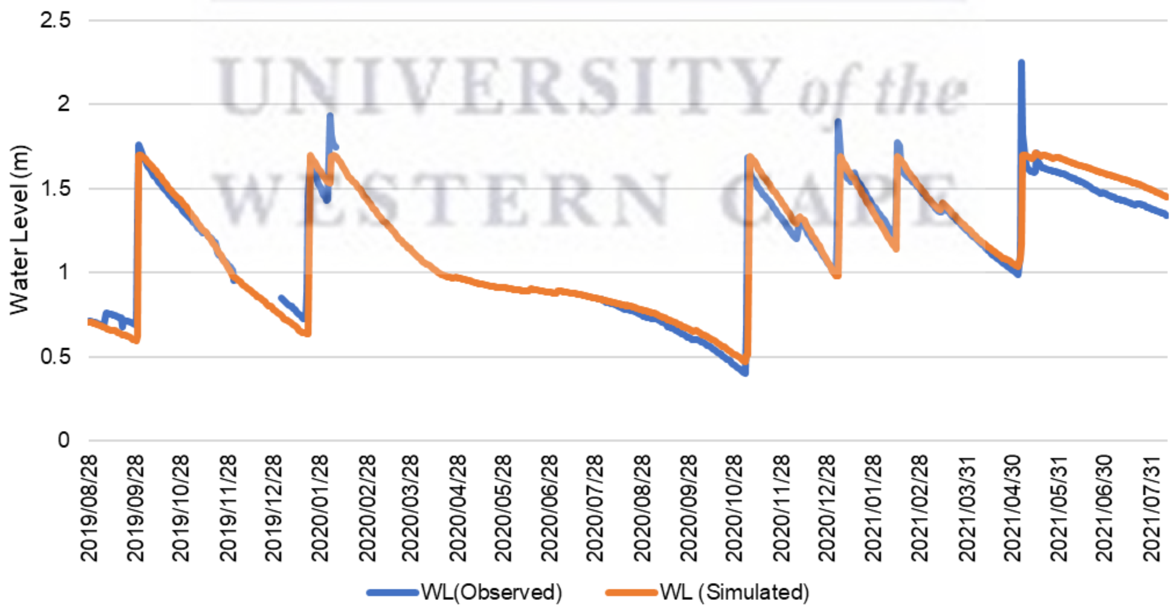


Figure 4.7: The water balance model of water levels of the WW2 pool in the Touws River. The blue line indicates the observed water level, and the orange line indicates the simulated water level, using in-situ inputs.

Transferability of the water balance to the surrounding pools

The simulated water levels of the WW1 pool were in good agreement with the observed water level (r=0.96; ME=-0.02 m; MAE=0.04 m) (Figure 4.8). The only changes made from the original water balance model from the WW2 pool was the maximum water level, which was adjusted, by trial and error, to be 0.95 m for the WW1 pool and the initial observed water level. Water lost to groundwater was estimated in the same way as for the WW2 pool (0.003 of the water depth). However, the model overestimated the water lost by the pool between December 2020 and November 2021, which resulted in the lowest predicted level of 0.2 m, compared to the observed level of 0.35 m. For the TWB pool, which is 450 m downstream of the WW2 pool, the model did not perform as well as the WW1 pool (r=0.86; ME=0.02 m; MAE=0.06 m), which suggests that the pool varies significantly from the focus pool (WW2). During a field visit, seepage into the pool was observed. The constant water level of the pool between June and August 2021 suggests that it probably receives substantial sub-surface inflows, in order to maintain such water levels.

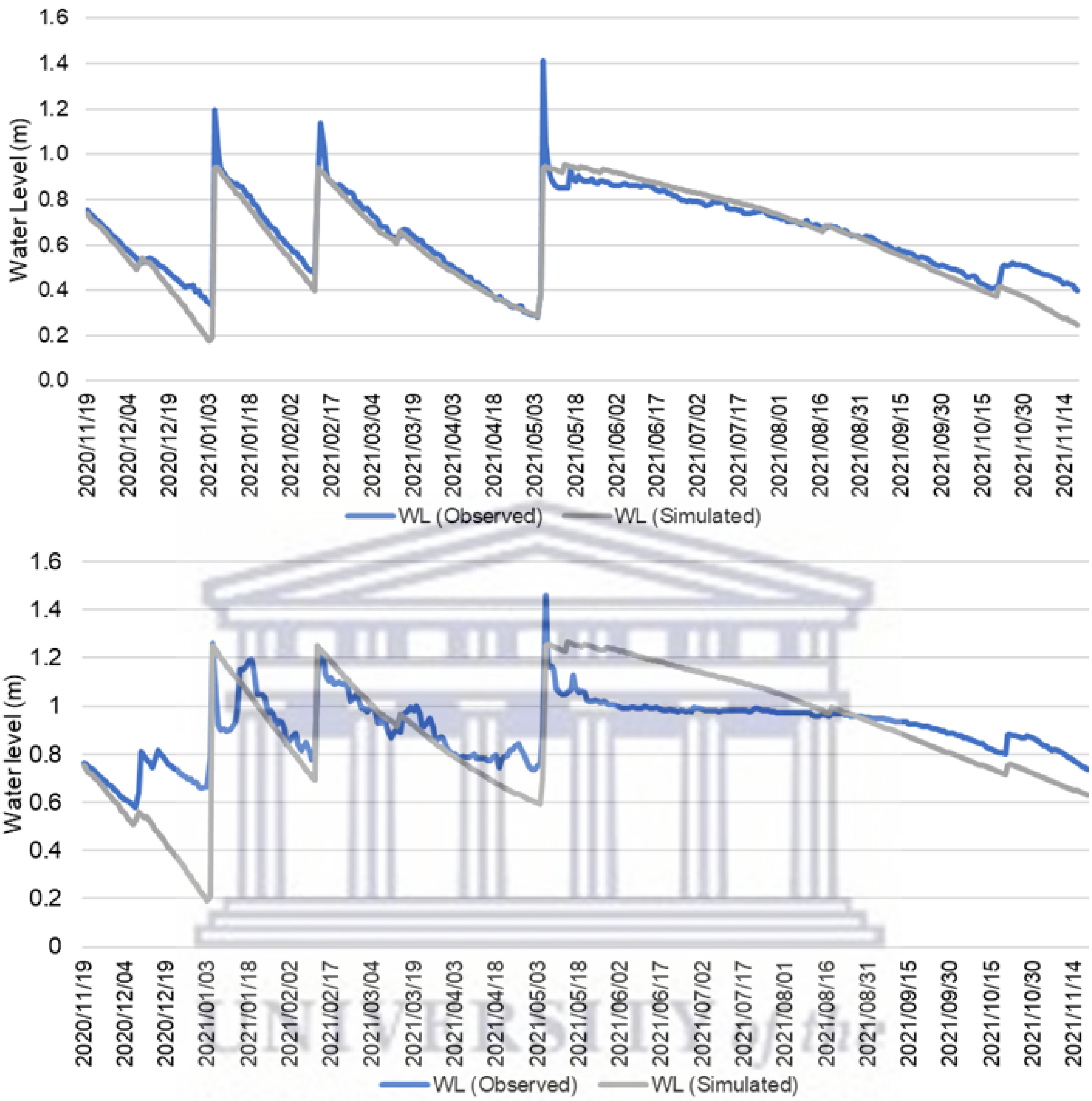


Figure 4.8: Observed (blue line) and simulated (grey line) water levels for the WW1 pool (top) and the TWB pool (bottom)

The paired *t*-test (t=8.3) showed that, at a 5% significance level, there is no significant difference between the observed daily mean water level (0.64 m) and the simulated mean (0.62 m) for the WW1 pool. There was, however, a significant difference (t=1.9) between the modelled mean water level (0.89 m) and the observed mean (0.91 m) of the TWB pool.

4.3.3 Water balance analysis using remote sensing data

Comparison of the remote sensing and observed inputs of the model

In terms of comparing the inputs, the CHIRPS rainfall estimates compared well with the observed rainfall data (r=0.6). However, it has errors during some periods, such as July to August 2020 (Figure 4.9). Although the remotely sensed evaporation rates from MODIS 16 PET are closely related to the observed evaporation rates that were derived by using the Penman equation (r=0.98), they overestimated the months with lower evaporation (April to Sept) (Figure 4.10). A general assessment of the climatic water balance shows that the remotely sensed climatic water balance is strongly associated with observed climatic water balance (r=0.87) (Figure 4.11), which suggests that a monthly-based water balance can have errors caused by rainfall and evaporation, but these are likely to be small. The negative climate water balance indicates that the catchment is potentially in a water deficit.

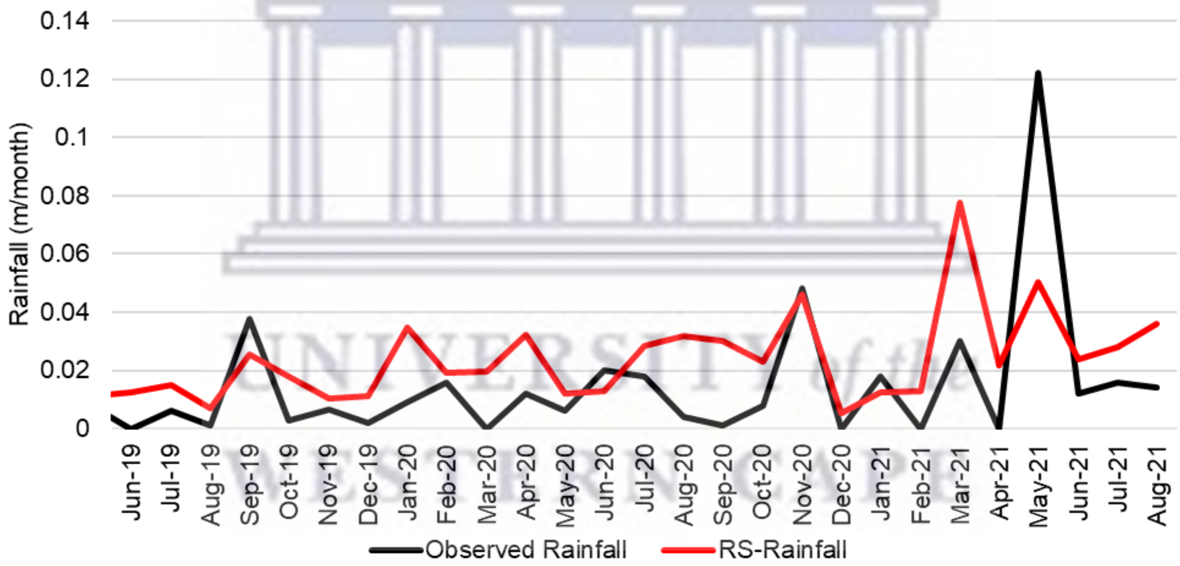


Figure 4.9: Comparison of observed (black line) and estimated (red line) rainfall by CHIRPS

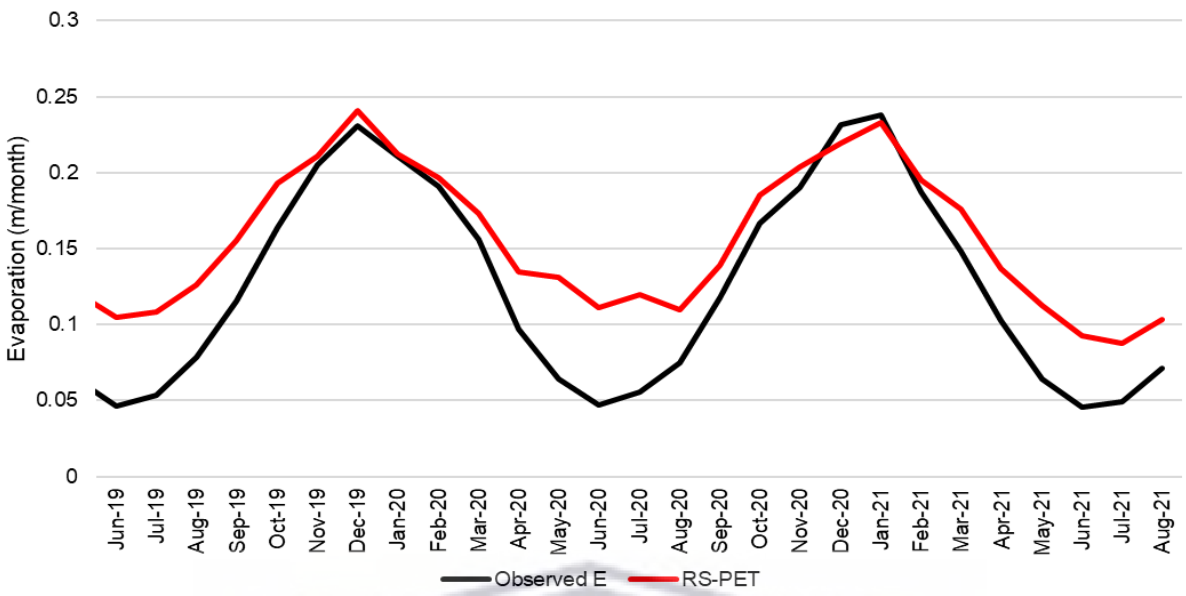


Figure 4.10: Comparison of observed evaporation (black line) and estimated potential evaporation (red line) by MODIS 16.

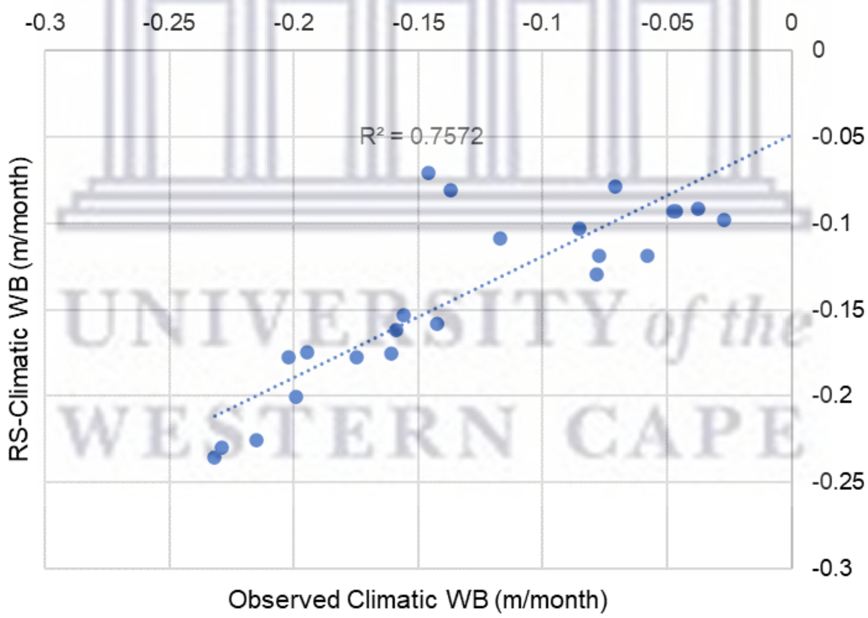


Figure 4.11: Correlation between the observed and estimated climate water balance (rainfall-potential evaporation)

The comparison between the observed water level and the remotely sensed surface area of the pool is in good agreement (r=0.72, ME= 0.04 m, MAE=0.2 m) (see Figure 4.12). There seem to be more discrepancies, but they are minor when the pool is almost full (water level>1.2 m). Overall, the remote sensing estimated surface water of the pool is promising.

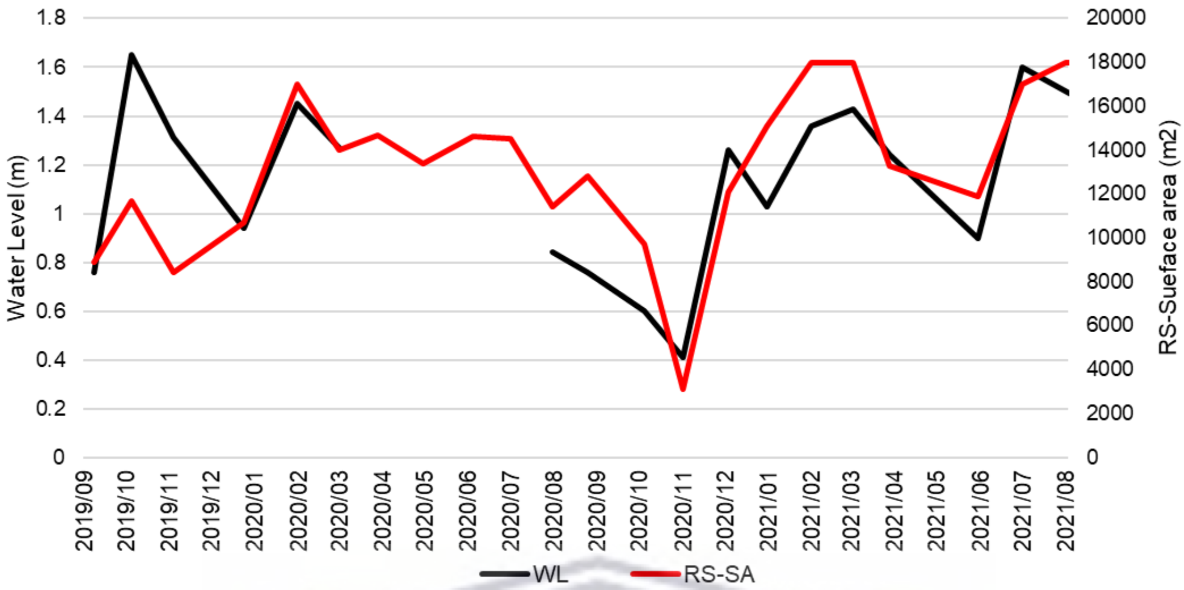


Figure 4.12: Comparison between the observed water levels (black line) and remote sensing derived surface area (red line).

Therefore, freely accessible remote-sensing data were incorporated into the water balance, particularly in the CHIRPS and MODIS16 PET data. The initial and maximum water level and flow occurrence were the only inputs used. This also assumes that no information exists about water losses due to subsurface/groundwater. The results show an underestimation of the water losses, as expected (Figure 4.13), as losses into the sub-surface are not incorporated.

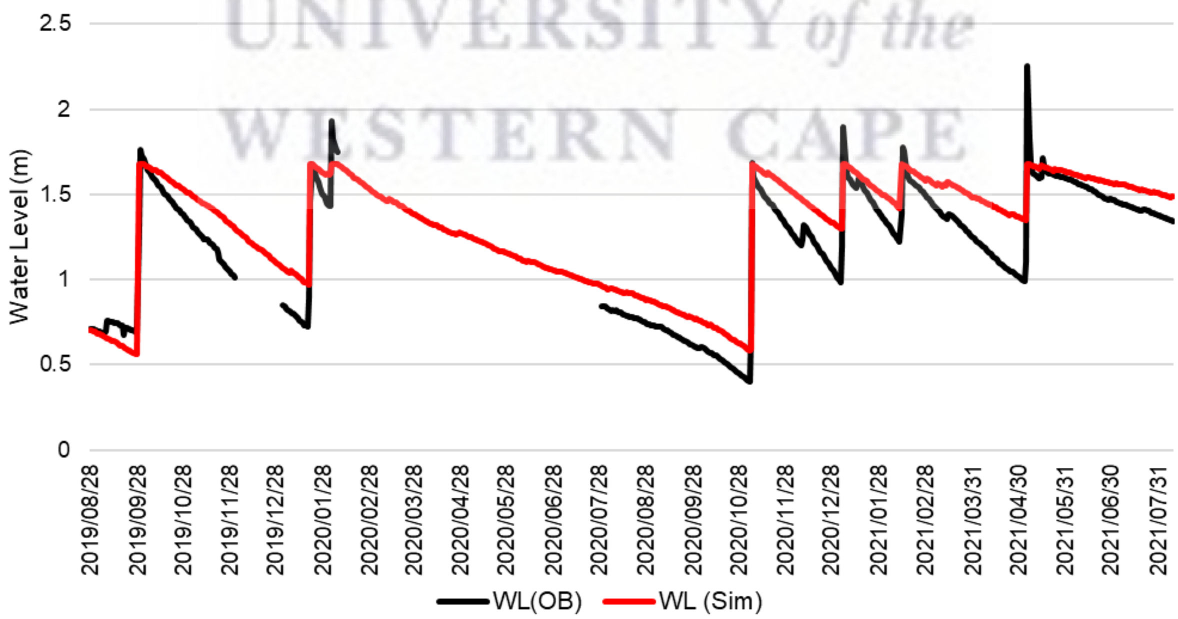


Figure 4.13: Observed water level (black line) and simulated water levels based on remotely sensed estimated climatic variables (rainfall and evaporation) (red line).

The surface area of the pool obtained from remote sensing was converted to the water level (Equation 12). The remote sensing-based estimation showed an increase in the water level, in response to the flow occurrence (Figure 4.14). The remote sensing-based water balance suggests that 65% of the water is lost through evaporation; therefore, 35% is lost to the sub-surface (negative residual), which is higher than the outcomes from the in-situ-based estimation.

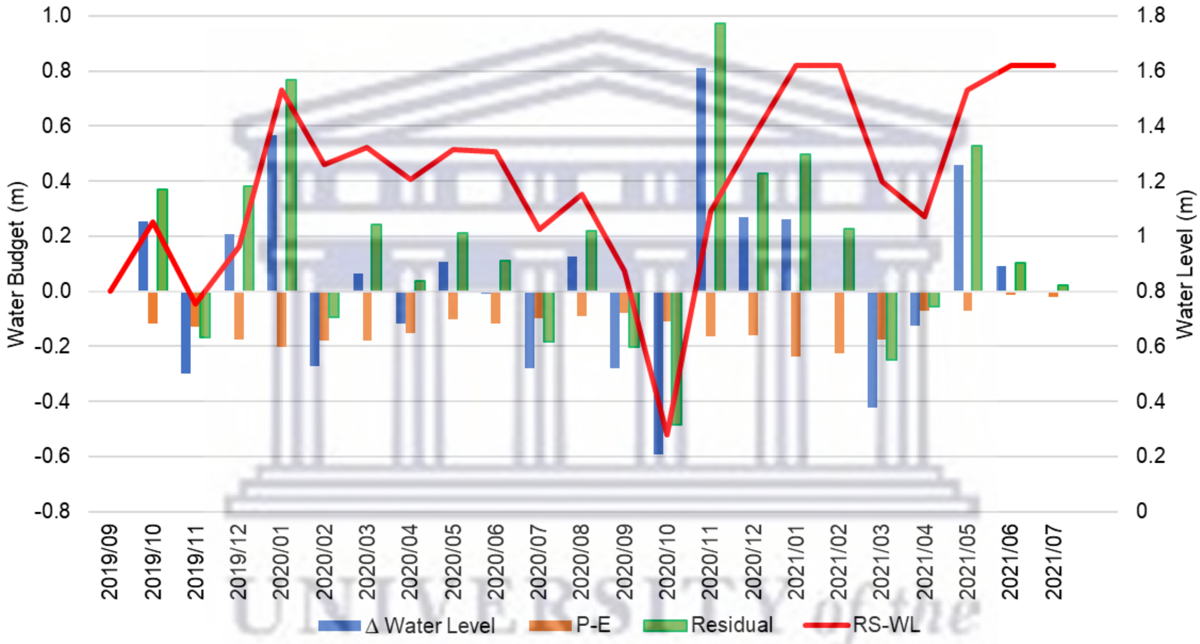


Figure 4.14: Remotely sensed water balance of the pool with the negative and positive values denoting the losing and gaining pools, respectively (blue bar), the estimated water level (red line), the difference between evaporation and rainfall over the pool (orange bar), as well as the residual of water level and the difference between precipitation and evaporation (green bars).

4.4 Discussion

The study focused on improving the understanding of pool dynamics along non-perennial rivers by assessing the water fluxes using the water balance approach. The results showed that one flow event can sustain the pool for 258 days without any inflows, although the probability of such a prolonged no-flow is low (10%). This suggests that the WW2 pool that was focused upon is semi-permanent to permanent. Pools in South Australia showed a similar persistency, i.e., 286 days for the pool, with a maximum water level of greater than 1.6 m (Marshall et al., 2016). The water balance model also supports the fact that the pool is very sensitive to the flow occurrence, as indicated by Maswanganye et al. (2022a). The persistence of the pool might change over time, as evaporation increases and as the rainfall declines over the region, due to climate change (Department of Environmental Affairs, 2018). These findings also suggest that if there is dam construction upstream, which reduces the frequency of the river flows, the pools will be impacted and this could lead to the drying out of the pools, which has further implications for the biodiversity found in these pools (Bonada et al., 2020; Larned et al., 2010). Therefore, this information should be considered when proposing any new development, such as the construction of a dam.

The water balance models indicate that there might be groundwater inflow into the pools that will occur during the period of low water depth, this might be seasonal, as observed by Bestland et al., (2017). In the case of the current study, this was observed when the pool reached a certain level, as it has been stated that the study catchment has no clear wet and dry season. Maswanganye et al. (2022a) found that surface flow and rainfall did not cause a fluctuation in the groundwater levels, hence it was suggested that the groundwater does not feed the pool. The water balance analyses revealed that water losses from the pool into the subsurface are insignificant to cause groundwater level fluctuations. The substrate and the underlying geology of the pool also suggest that there is limited, or has no interaction (low conductivity) (Hwang et al., 2017; Mohuba et al., 2020). The interaction might also depend on the gradient between the pool and the water table, as illustrated in Figure 16. This observation is further supported by the elevation plot, using DGPS measurements, which shows that groundwater usually fluctuates at around 1.1 m of the pool's water level (Figure 17). Bourke et al. (2020) referred to this kind of pool as a through-flow pool.

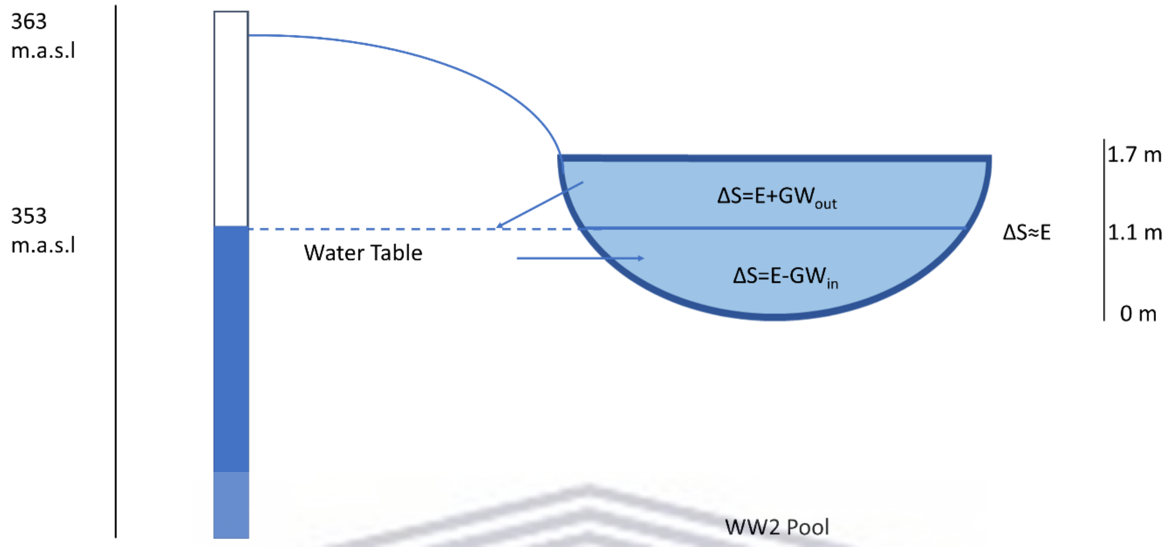


Figure 4.15: Conceptual model of the pool, based on water balance simulation

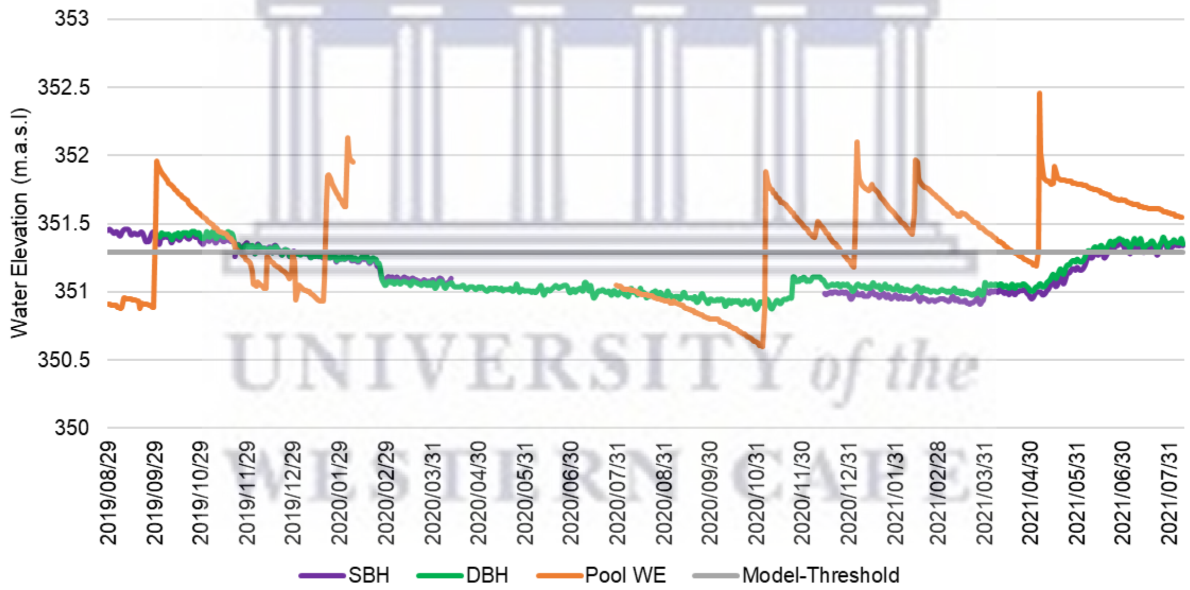


Figure 4.16: Water elevation of shallow (purple line) and deep (green line) boreholes, compared to the observed water elevation of the pool (orange line) and the threshold, whereby groundwater could be flowing into the pool, as estimated by using the model (grey line).

Although the water balance models performed well by using just the flow occurrence, having information about the discharge into and out of the pool could have provided more insight; for instance, how the relationship between the discharge and pool water level affects the water losses. Furthermore, to determine whether the pool water losses from upstream are detected downstream (interaction between the pools), some studies have suggested that pools can remain hydrologically connected through shallow groundwater paths while being disconnected on the surface (Larned et al., 2010).

The water balance model displayed robustness and transferability to the WW1 pool, albeit with minor adjustments to the maximum and initial water levels. However, it did not perform as well when evaluated at the TWB pool. This might be due to the pool having a strong subsurface flow impact, which influences the dynamics of the pool. It is also possible that the properties of the TWB pool may differ, for example, the presence of algae and shade over the water, which might significantly reduce evaporation (Trimmel et al., 2018). Furthermore, Seaman et al. (2016) indicated that neighbouring pools along the same reach can differ significantly. The WW1 pool (upstream) was shown to have the same pattern as the WW2 pool; however, it will dry out before the WW2 pool, because it is smaller in size. The TWB pool (downstream) showed a very distinct pattern in terms of losses, as it sustained its size or water level for longer periods, which suggests that this could be a permanent pool.

Remote sensing detects the pools and provides a general overview of the pool dynamics, as suggested by Maswanganye et al. (2022a), as it was able to detect major changes correctly; however, it does not provide detailed information or an understanding of the pool dynamics at the water balance level. This might be due to errors emanating from each of the model input variables. Furthermore, errors may also be caused by the resolution of the remote sensing data, when compared to the size and the temporal dynamics of the pool. When the water balance approach is applied in larger surface bodies, such as large dams and lakes, these errors might be negligible (Chen et al., 2022; Deus et al., 2013). The water balance can also provide a better insight when applied on a long-term basis. However, to improve the remote sensing-based water balance model, there is a need to acquire more information on the flow occurrence. This could be done by detecting flows from satellite images or it can be predicted through rainfall (a runoff-rainfall model). Furthermore, the groundwater information that is required for predicting pool water losses to subsurface stores is still a mystery in the remote sensing field. This could be predicted by using the climatic variable(s); for instance, in this study, groundwater losses could be expressed as a function of evaporation. This estimation should take into account the substrate and underlying geology of the area and the fact that the relationship is not linear, as it depends on the size of the pool and the season. Predicting the

GW_{in} flow will still be a challenge, as it was shown that it could be a function of the groundwater table. The GRACE satellite showed to be useful in larger water bodies (Deus et al., 2013). However, the incorporation of remote-sensing-based climatic variables was shown to be limited by the unknown groundwater-pool interaction. This suggests that remote sensing can be used to understand the pool dynamics of pools that are not influenced by groundwater processes.

Overall, the results provided a better understanding of the pool dynamics, and they imply that the water balance approach could be useful for understanding pools along non-perennial rivers. The information derived from the water balance should be incorporated into the water resource management of NPRs and catchments. Water resource managers can determine the water that is available in the pools, by knowing the last day of the flow.

4.5 Conclusion

There are limited studies on the hydrology of pools along non-perennial rivers. Using pools along the Touws River in the Karoo region of South Africa, this study assessed the pool dynamics by using the water balance approach. The study established that Wolverfontein 2 pool is a semi-permanent pool that has little chance of completely drying out. The water balance of the pools was established and modelled with limited data, and the simulated water levels showed satisfactory performance. The model was transferable to the neighbouring pools, although it required an adjustment of the maximum and initial water levels. The water balance approach that was applied to the pool provided a better insight into the pool dynamics.

The models suggest that there is groundwater-pool interaction at the assessed site. However, the magnitude of the losses are minor, when compared to the losses into the atmosphere via evaporation. The pool has a point where the rate of loss is less than the evaporation, which indicates that there is a potential gain from the groundwater. These gains and rainfall in the pools delay the drying out of the pools. We assume that the errors in the estimation of water levels are due to the uncertainty related to a full understanding of the pool-groundwater interactions. The use of remotely sensed climatic variables with a maximum water level can provide temporal dynamics for pools with no groundwater influence when the flow occurrence is known. If the size of the pool is known, remote sensing can provide an overview of the general behaviour of the pool, but it cannot provide the detailed information that an in-situ observation can provide. However, with all the rapid advancements in the remote sensing field, this gap will soon be closed. This study successfully used the water balance approach to understand the pool dynamics, and the information derived from the water balance models is of significant importance for the management of pools and pool dynamics in semi-arid environments.

Chapter 5: Assessment of the spatiotemporal dynamics of the hydrological state of the non-perennial river systems and identification of flow-contributing areas in South Africa.

This chapter is based on:

Maswanganye, S.E., Dube, T., Jovanovic, N., Kapangaziwiri, E., Mazvimavi, D., (Under review). Assessment of the spatiotemporal dynamics of the hydrological state of the non-perennial river systems and identification of flow-contributing areas in South Africa. (WaterSA).

Abstract

This study sought to determine the spatiotemporal dynamics of the hydrological state of non-perennial rivers (NPRs that is the Touws river-karoo drylands and Molototsi river located in the semi-arid Limpopo) as well as identify major runoff contributing areas of the two river systems. Two satellite data sources were used, including Sentinel-1 and 2. Specifically, the modified normalised difference water index (MNDWI) was applied to Sentinel-2 images to extract water surface areas along the two rivers, and then the derivatives were then used to determine the hydrological states over a period of 32 months (2019-2022). Sentinel-1 was used to assist in detecting flow events that could have been missed by Sentinel-2. The river was classified as flowing, pools or dry state based on the water's presence. The results showed that remote sensing can be used to determine the hydrological state of the river with ~90% overall accuracy. However, there is about a 30% chance that a flow event can be missed using Sentinel-2 due to clouds and temporal resolution. Some of these gaps can be filled using Synthetic Aperture Radar (SAR) data (Sentinel-1) as the study demonstrated with the Molototsi River. In the Molototsi catchment, the upper catchment contributes the majority of flows. For the Touws River, the southwestern part of the catchment showed to be the major contributing area for the observed flows. This suggests that the chosen observation site might not be representative of upper catchment dynamics, therefore, require a site in the upper catchment. This study provided hydrological information and an approach that can be used to monitor the hydrological states for a better understanding and management of NPRs and catchments.

Keywords: Aquatic states; Hydrological phases; Hydrodynamics; Runoff; Temporary rivers hydrology.

5.1 Introduction

Non-perennial rivers (NPRs) are rivers that naturally cease to flow periodically. They account for more than 50% of the world's river network and are highly dynamic, switching between three hydrological states: flowing, pools and dry riverbeds. Many studies have summarised these hydrological states into the wet and dry states, with periods when the river has isolated pools considered as dry or wet (flow or no-flow), depending on the study's objective (Bonada et al., 2020). Pools tend to form immediately after flow cessation and begin to dry out. Some rivers or reaches can be without pools subsequently, which is the dry riverbed state. These hydrological states are also referred to as hydrological phases. It is noteworthy that some ecological studies define hydrological states as river health (De Girolamo et al., 2015a). In this study, hydrological state refers to the flow state or water presence along NPRs, which some ecological studies refer to as the aquatic state (Kaletova et al., 2021).

Each of the hydrological states has its function, importance, and implications for water resource management. For instance, a flowing river will be important in increasing water availability for socio-economic uses, directly or indirectly by recharging groundwater (Shanafield et al., 2021) and sand aquifer (Walker et al., 2019). Flowing rivers also allow the mixing and transporting/movements of biota, sediments, nutrients, etc., which are important for the ecosystem (Goodrich et al., 2018; Seaman et al., 2016). This state is also perceived to be the most valuable to society (Rodríguez-Lozano et al., 2020). When flow ceases, pools form along the river; these pools are important sources of water for communities along these rivers during the no-flow periods (Walker et al., 2019). They are also of ecological importance as they provide refuge and spawning zones for aquatic life (Makwinja et al., 2014). Although generally perceived to be less important when compared to the flowing state (Leigh et al., 2019; Rodríguez-Lozano et al., 2020), some studies suggest that this is the most important state of NPRs as it caters for both aquatic and terrestrial life (Eastman et al., 2021). Dry riverbeds are perceived to be the least valuable of all three hydrological states and are often overlooked. However, some aquatic species and riparian vegetation require a dry state to begin their life cycle (Nicolás Ruiz et al., 2021). Furthermore, some cultural activities, including spiritual rituals, can only occur on dry riverbeds (Steward et al., 2012). Dry rivers can also be sources of food and water in the form of sandbanks aquifers that support domestic use and irrigation. In Botswana, some communities dig the dry riverbed to harvest catfish (Steward et al., 2012). If climate change predictions of a decrease in rainfall for many parts of the world, including southern Africa (IPCC, 2022), are correct, the dry phase might become dominant for many rivers.

Knowledge of the hydrological states of NPRs is important as it informs the river and water management strategies. Furthermore, each state may require a different river and water management approach. The duration of these hydrological states which depends on the local hydrogeology and precipitation (Bonada et al., 2020), is also key for water resource management purposes. Besides, the duration of these phases may be more important than the magnitude of the flow for the communities along these rivers such as prolonged flows allowing water access for farmers for a longer period and likely to enhance recharge of the alluvial aquifers as compared to short duration flow with high magnitude. However, prolonged flows can also mean that there is no access to alluvial aquifers, which may have better quality than a flowing river (Saveca et al., 2022). In addition, Datry et al. (2017) indicate that the biodiversity of fauna and flora can be associated with the duration of the dry phases. These hydrological states or phases have implications for the water quality of the river (Shanafield et al., 2021). For example, flow can transport pollutants from upstream, which will in return, pollute persistent pools along the river.

There have been inadequate studies focusing on the identification of the hydrological states of NPRs, which might be a result of a lack of data, and the complexity that arises with monitoring and understanding. Tools to objectively determine the hydrological state are required (Gallart et al., 2016; Kaletova et al., 2021). Eastman et al. (2021) used a statistical model to simulate the hydrological states along the river. The Environmental Protection Agency of England has been monitoring the hydrological states of some rivers since 1997 using field surveys (Eastman et al., 2021; Sefton et al., 2019). France also started a similar programme called Onde in 2012 (Bonada et al., 2020). Other studies have proposed the use of multiple sensors (Assendelft and Ilja van Meerveld, 2019) and time-lapse imagery from game cameras. Maswanganye et al. (2021) highlighted some of the strengths and limitations of these methods. Generally, the hydrological states are often established from gauging data and often do not recognise the 'pool' state. Direct observations of these states are the most accurate, this can be done at several parts of the river using citizen science programmes (Gallart et al. 2016). Maswanganye et al. (2021) further suggest that hydrological states could be determined using satellite remote images, especially in ungauged areas that do not have a functional monitoring network. This study thus aimed at determining the spatiotemporal dynamics of the hydrological state of two NPRs as well as to identify major runoff contributing areas of the Touws and Molototsi river systems in South Africa. This was done by (i) assessing the accuracy of remote sensing to distinguish between the hydrological states, (ii) determining the changes in the hydrological states, and (iii) identifying the major flow contribution areas using readily available data.

5.2 Methodology

5.2.1 Study Site Description

The study was conducted along Touws and Molototsi Rivers, (Detail description in Section 1.6) which are distinct NPRs. The Touws River is in the southern part of South Africa in the Western Cape province (Figure 5.1). Touws River has a sandy-gravel riverbed and is approximately 140 km long with a width of 60-120 m in the mid-reaches. The area is generally classified as a winter rain region but the rainfall at this study site shows no pattern of wet/dry seasons (Maswanganye et al., 2022a). The Touws River Catchment is 6280 m^2 and can be divided into 12 sub-catchments based on the Water Resources 2012 (WR2012) study (Bailey and Pitman, 2016). Flows occur in response to heavy rainfall events of ~≥20 mm/day. The river flow data from the Department of Water and Sanitation indicated that flows have a short duration. The pools in the Touws River are semi-permanent. The Molototsi River is in the northern part of South Africa and receives most of its rainfall in summer. Molototsi River catchment is 1170 km^2 and has two sub-catchments (WR2012) (Figure 5.1). Although there is no flow gauging station in this river, flow events tend to occur during the summer period between October to February. Similar to the Touws River, the Molototsi River flows for weeks with multiple flow events between October and March. The pools in the Molototsi River tend to dry after winter (July). However, the river has been modified through sand mining, which may result in the formation of unnatural pools (Maswanganye et al., 2022a). The hydrological state monitoring sites are shown in red.

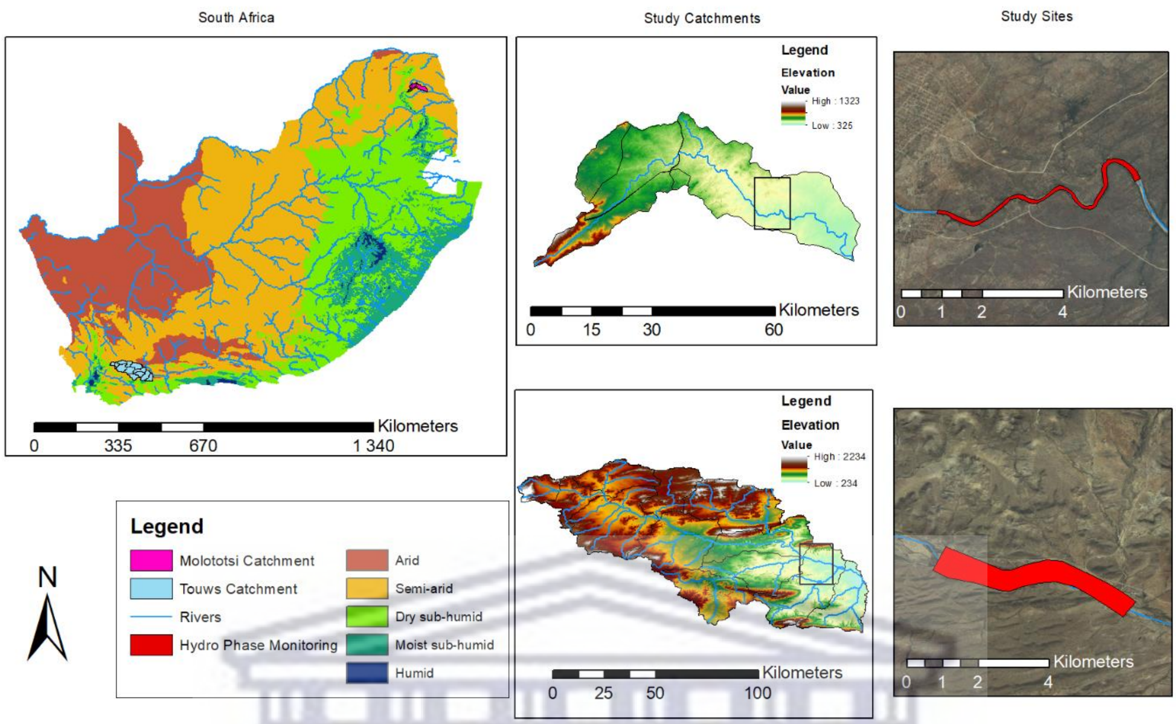


Figure 5.1: Location of the studied Touws (light blue) and Molototsi catchments (purple) on the climate (aridity) map, study catchments on the elevation map, and the location of monitored reaches within the catchments (red).

5.2.2 Data Collection and Analyses

In-situ monitoring of hydrological phases

Citizen science was adopted to monitor hydrological phases for both the Touws and Molototsi River systems. Citizen scientists were observing the changes in the river. The data used for the Touws River was also verified using water levels measured at pools and river discharge measured at the river's outlet. For the Molototsi River, water level loggers could not be installed due to the nature of the substrate and flow in the area. We (researchers), however, visited the sites quarterly, targeting to observe different seasons and hydrological states. Figure A2 in the supplementary material shows field pictures of the different hydrological states.

Remote Sensing data

Sentinel-2 images were used to determine the hydrological state of the rivers. About 100 images per site were used (July 2019 to March 2022). This was based on the availability of the images, as some of them were not useable due to cloud cover (Figure 5.2). Sentinel-1 was used to determine if it could detect some of the flow events that Sentinel-2 could have missed. Sentinel-1 is a Synthetic Aperture Radar (SAR) satellite, capable of penetrating through clouds. Sentinel-1 and 2 were selected as they are open, freely accessible, and have a relatively high temporal and spatial resolution (5 days, 10 m). Sentinel-2 images were downloaded from the USGS earth explorer (http://earthexplorer.usgs.gov/), and Sentinel-1 images were downloaded from the National Aeronautics and Space Administration Alaska Satellite Facility (NASA/ASF) (https://search.asf.alaska.edu/#/).

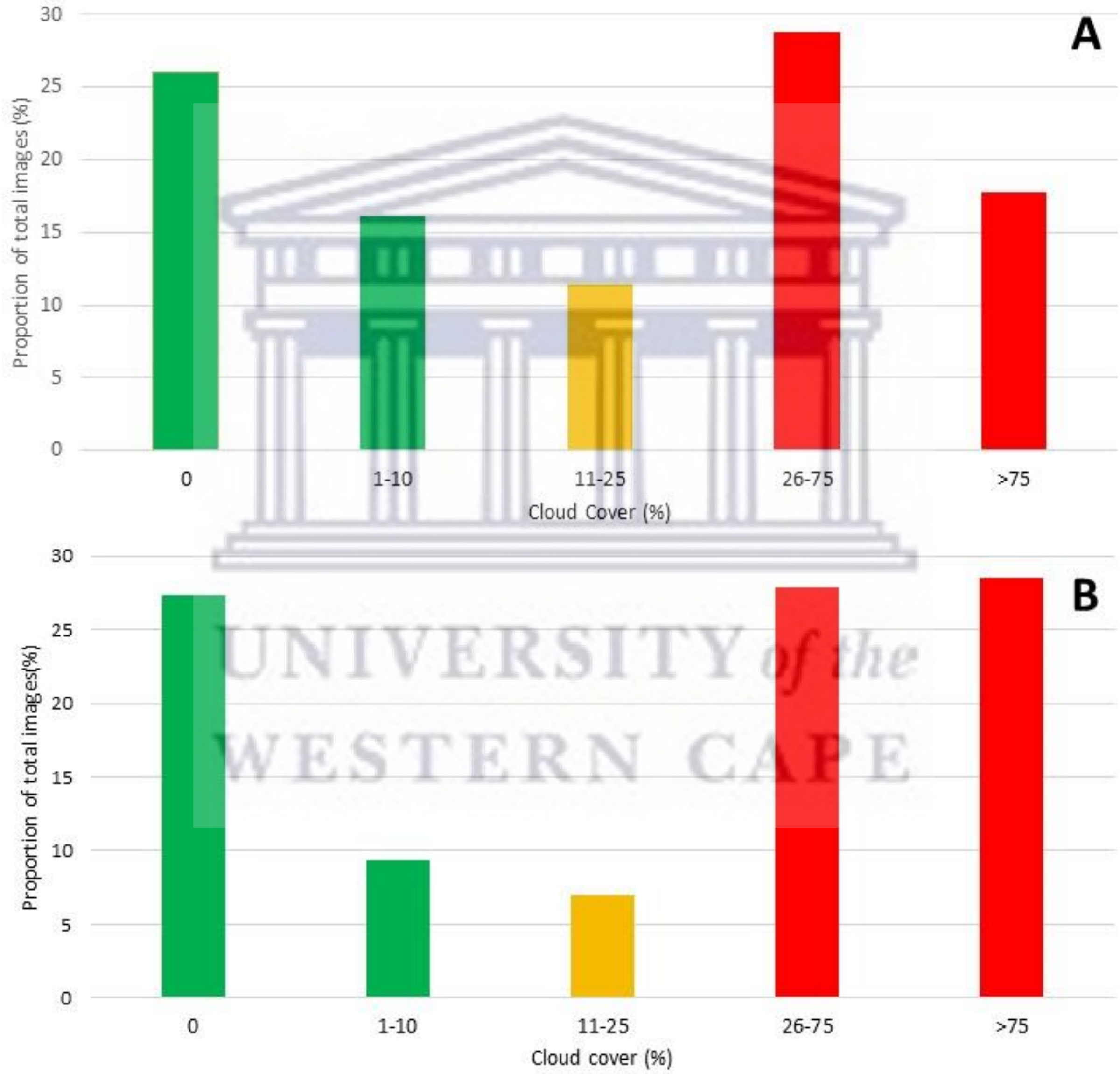


Figure 5.2: Useable Sentinel-2 satellite image availability for Touws (A) and Molototsi River (B) based on cloud cover percentage. Green bars indicate useable images, orange bar denotes selectively useable images, and red bars indicates images that could not be used.

Rainfall: CHIRPS data

The rainfall data collected through the citizen science programme was not adequately distributed to capture the spatial variation of rainfall over the catchment. Hence, Climate Hazards InfraRed Precipitation with Stations (CHIRPS) data as described by Funk et al. (2015) for spatial distribution was used to determine the rainfall for the catchments. The data was downloaded through the climate engine website (https://app.climateengine.com/climateEngine#) for the time series and at (https://data.chc.ucsb.edu/products/CHIRPS-2.0/africa_daily/tifs/p05/) for the raster files. Various studies have shown that CHIRPS data has adequate accuracy in South Africa (Maswanganye, 2018; Plessis and Kibii, 2021).

Detection of hydrological phases

The selection of the monitoring reach was representative of the river and had to be accessible. Hence, the selected sites are within the dominant geology and soil types of the catchment. These sites are also located within the average slope (2.6 m/km for the Molototsi River and 3.7 m/km for the Touws River) of the river. The study used the remote sensing technique to determine hydrological phases. These were monitored in a selected 5 km reach of the river. The Modified Normalised Difference Water Index (MNDWI) was used to extract water pixels from Sentinel-2 images, as Maswanganye et al., (2022a) showed that it was superior compared to other methods that were assessed. For Sentinel-1, the thresholding method was used to separate water from non-water pixels. Connected surface water meant that the river was flowing. However, because the rivers meander and can tend to be flowing in a small part of the channel, the detection can be compounded by the lack of cloud-free images during peak flow, a threshold of 50 % or 2.5 km of the 5 km reach was therefore used. This means that if the reach has 2.5 km or more with water, it was assumed that there was flow. Surface water presence of less than 2.5 km was labelled as pool and dry riverbed when no water pixel was detected. The length of water along the selected reach was determined using spatial analyst tools in a GIS environment. Figure 5.3 illustrates an example of the different hydrological states of the Touws and Molototsi Rivers, respectively.

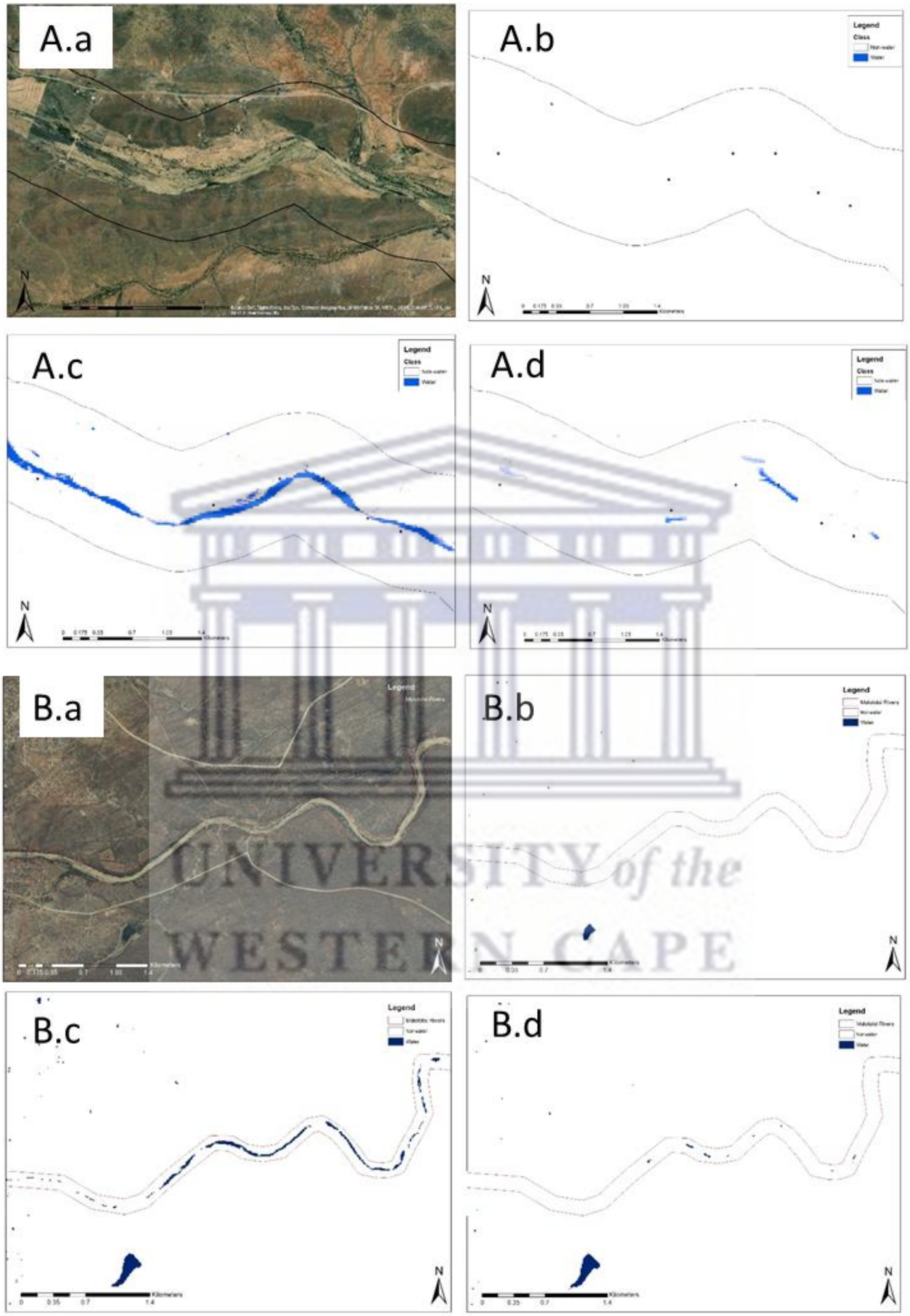


Figure 5.3: Three hydrological phases, dry (b), connected flow (c) and isolated pools (d) in a 5 km reach of the Touws (A) and Molototsi River (B).

Identification of flow-contribution areas

Usually, the identification of contributing areas is done using observed data from the tributaries outlet (Tena et al., 2021), however, rainfall and physical characteristics (soil type, slope and land use and cover) can be used in the absence of the flow data. Several methods can be used to determine the contributing area, mainly proxies such as the Soil Conservation Service (SCS) Curve Number method and the Runoff coefficients. In this study, remote sensing-derived rainfall was used to determine where rainfall occurred to produce observed flows (antecedent rainfall). The SCS curve number method was used to determine which parts of the catchment are likely to generate runoff based on the physical characteristics. The curve number (value) is allocated to each cell which is proxy to the amount of rainfall that will be required before a cell/pixel can generate overland runoff. The curve number ranges from 0 to 100, with zero indicating that no runoff can be generated by the cell and 100 indicates that a cell will generate maximum possible runoff. USDA (1986) provides the detailed description of the curve number method. This is the most popular method for estimating direct runoff (Gajbhiye, 2015) and uses data that can easily be obtained even in data-scarce areas. Soil types were obtained from the WRC website (https://waterresourceswr2012.co.za/) (Figure 5.4). The 2020 South African National Land Cover (SANLC) (https://egis.environment.gov.za/) was used for land cover and land use. For topography, Shuttle Radar Topography Mission (SRTM) 1 Arc-Second Global Digital Elevation Model (DEM) was used, available at the USGS website (https://earthexplorer.usgs.gov/).

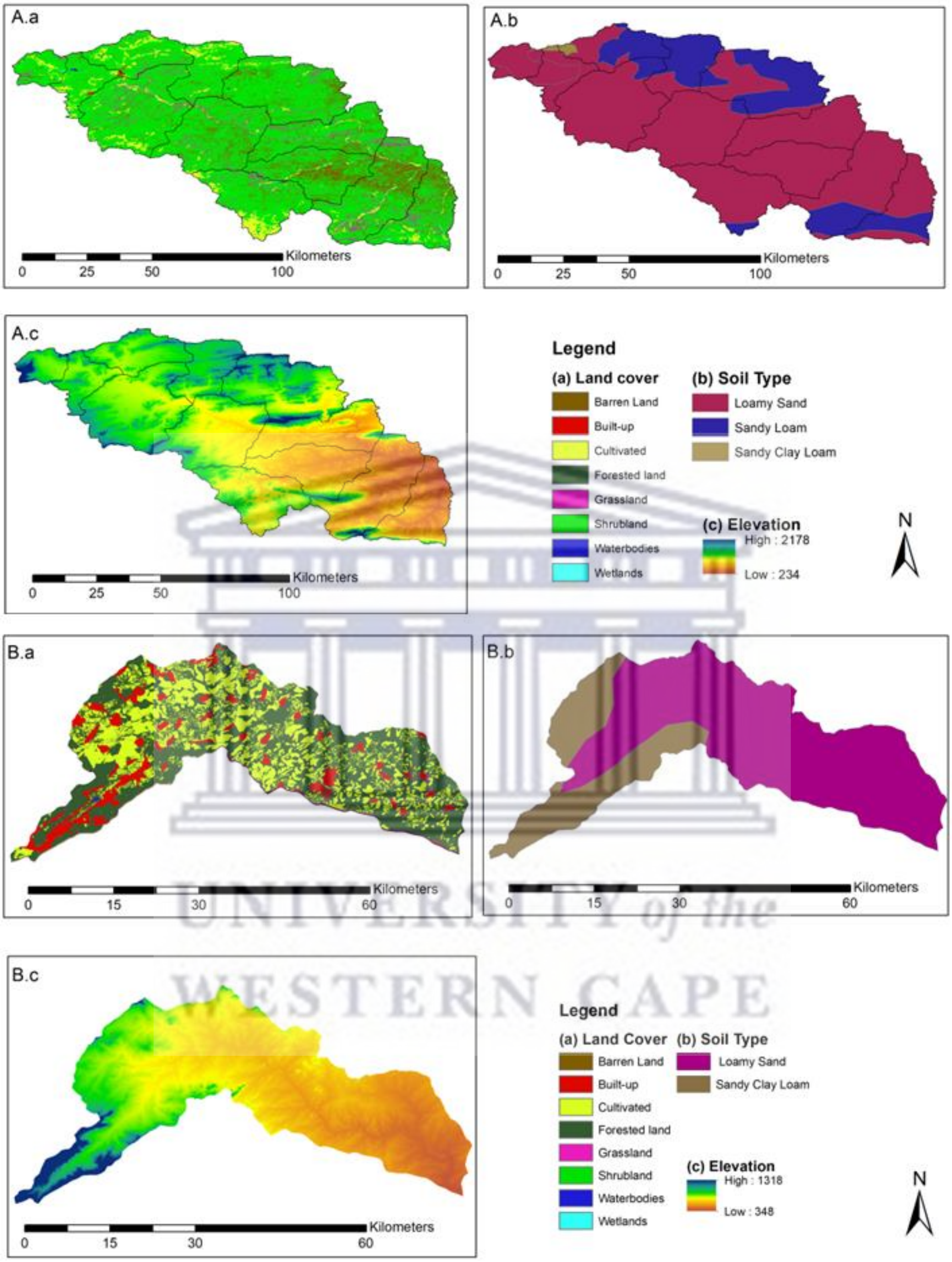


Figure 5.4: Data that were used to derive curve numbers in the Touws (A) and Molototsi Catchment (B).

Evaluation metrics

Overall, producers' and users' accuracy metrics were used to assess the ability of remote sensing to distinguish between the dry riverbeds, pools and flowing states of the rivers. Flow occurrence is of importance for NPRs, for instance, it is important to know how many flow events are likely to be missed by the satellite (Sentinel-2) observation. Hence this study calculates this chance:

$$Fdp = \left(\frac{no.\ of\ detected\ flow\ events}{Total\ no\ of\ events\ observed}\right) * 100 \qquad (5.1)$$

where *Fdp* is the flow occurrence detection power measured in percentage, with 0% being the worst score and 100% being the perfect score.

The study further investigated whether using Sentinel-1 improves the detection of flow events. Furthermore, the effect that the duration of flow events has on the ability of remote sensing to detect the flow events.

5.3 Results

5.3.1 Detection of the hydrological phases in the Touws and Molototsi River

Remote sensing methods were able to detect and distinguish the hydrological phases of the selected NPRs, the accuracy varied between the two sites. In the Touws River, only pools and flow phases were detected and observed, and the river did not dry up during the study period (Figure 5.4 A). In the Touws River, the presence of pools were better detected (User's and Producer's Accuracy= 99%) compared to flow (UA and PA=86%). High accuracies were also obtained in the Molototsi River (OA=90%), however, the dry phase had the lowest producer accuracy (78%), and the flow phase was better detected (Figure 5.4B). The Sentinel-2 data had 70% flow detection power (equation 1) in Molototsi River, suggesting that there is a 30% chance that a flow event can be missed due to cloud cover. The detection power was 65% for the Touws River. Overall, pools were the dominant phase for both rivers, the Touws Rivers pool did not dry out during the study period. Because of the two phases observed, the Touws River hydrological phases were detected better than the Molototsi River. Furthermore, the Molototsi River had a few pool phases that were misclassified and confused with the dry phases (Figure 5.5B). Only on one occasion flow occurrence was misclassified as the pool phase.

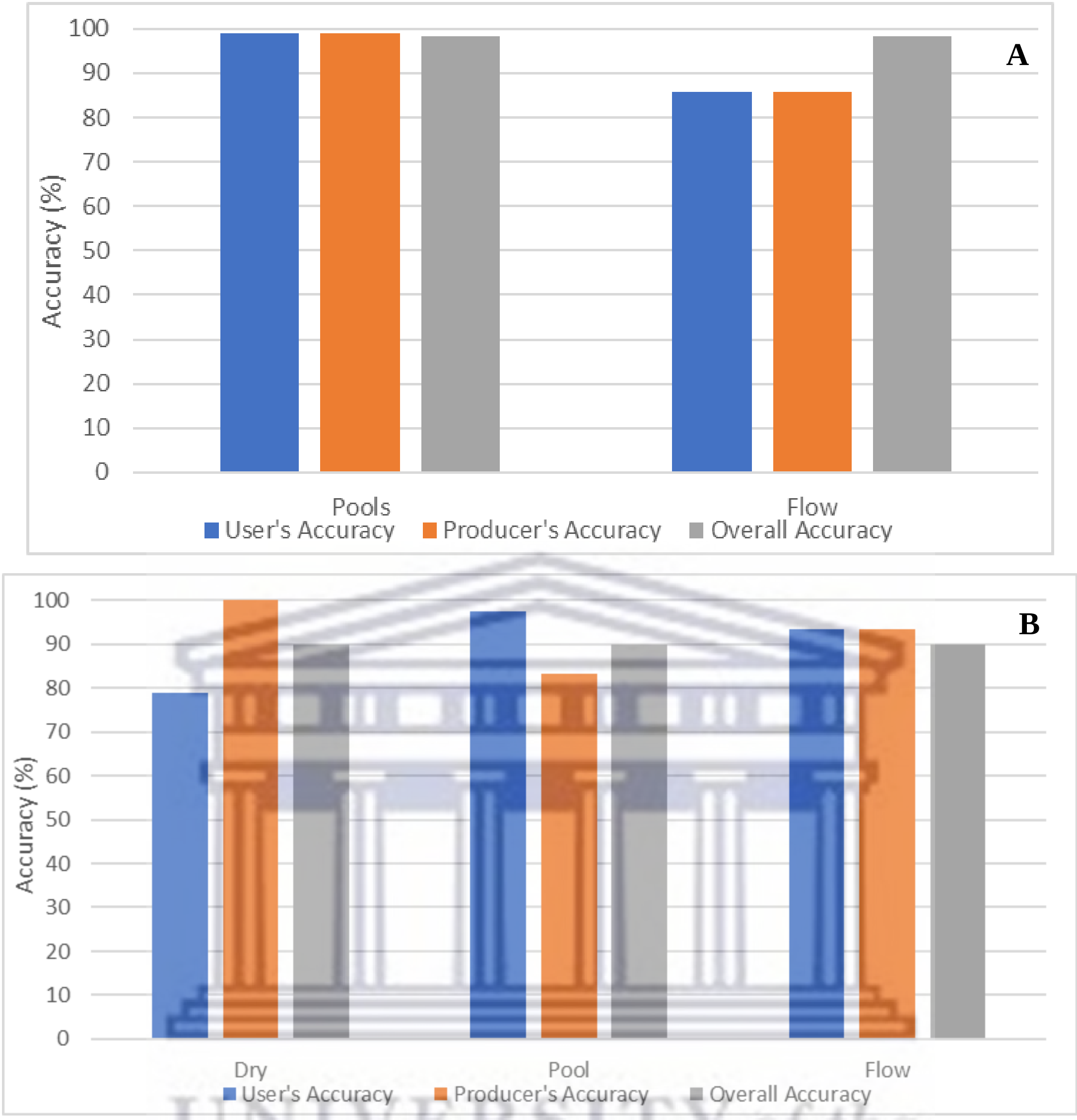


Figure 5.5: Accuracy of the Remote Sensing in distinguishing between hydrological phases in the Touws (A) and Molototsi River (B). The Touws River only had two states, whereas the Molototsi River had all three phases.

Sentinel-1 was able to detect two of the three events missed by Sentinel-2 in Molototsi River, improving the flow phase detection by 20% (Table 5.1). However, it was not able to detect any of the events missed in Touws River. It even failed to detect some of the flow events detected by Sentinel-2. Sentinel-1B faced challenges in 2021, resulting in the images being unavailable. The short-duration flow events tend to be difficult to detect using remote sensing as 83% of the missed events had a duration of less than five days (Table 5.1), which is problematic as most NPRs have a short flow duration (less than 5 days).

Table 5.1: Remote sensing's ability to detect flow events with various duration

Touws River					Molototsi River			
Duration (days)	Observed events	RS-detected events	Missed events		Duration (days)	Observed events	RS-detected events	Missed events
<5	6	2	4		<5	5	3(+1)	2
6-10	4	4	0		6-10	3	2(+1)	1
11-15	1	1	0		11-15	2	2	0

+1 indicates additional events detected using Sentinel-1

5.3.2 Temporal dynamics of the hydrological phases

NPRs are known to be highly dynamic, and flow events are difficult to predict. Touws River hydrological phases are less dynamic but showed no seasonal pattern (Figure 5.6A). Although Molototsi River is more dynamic in terms of changes between the phases, it is however seasonal. Flow usually occurs during the southern hemisphere summer (December to February), this is then followed by pools occurring from autumn into winter (March to August) then dry riverbed tends to be dominant from August to November (Figure 5.6B). The changes in hydrological phases can be associated well with the catchment rainfall patterns. The changes in hydrological phases did not correlate well with rainfall in the Touws catchment. There were events that could not be explained using mean rainfall patterns. The general cycle is usually dry to flow to pools, there is a rare pattern of the river being dry to pools to flows illustrated in Figure 7B and Touws River only had two phases (Figure 5.7C). Comparing the two catchments, Molototsi River flows are more frequent and tend to last longer than the Touws River.

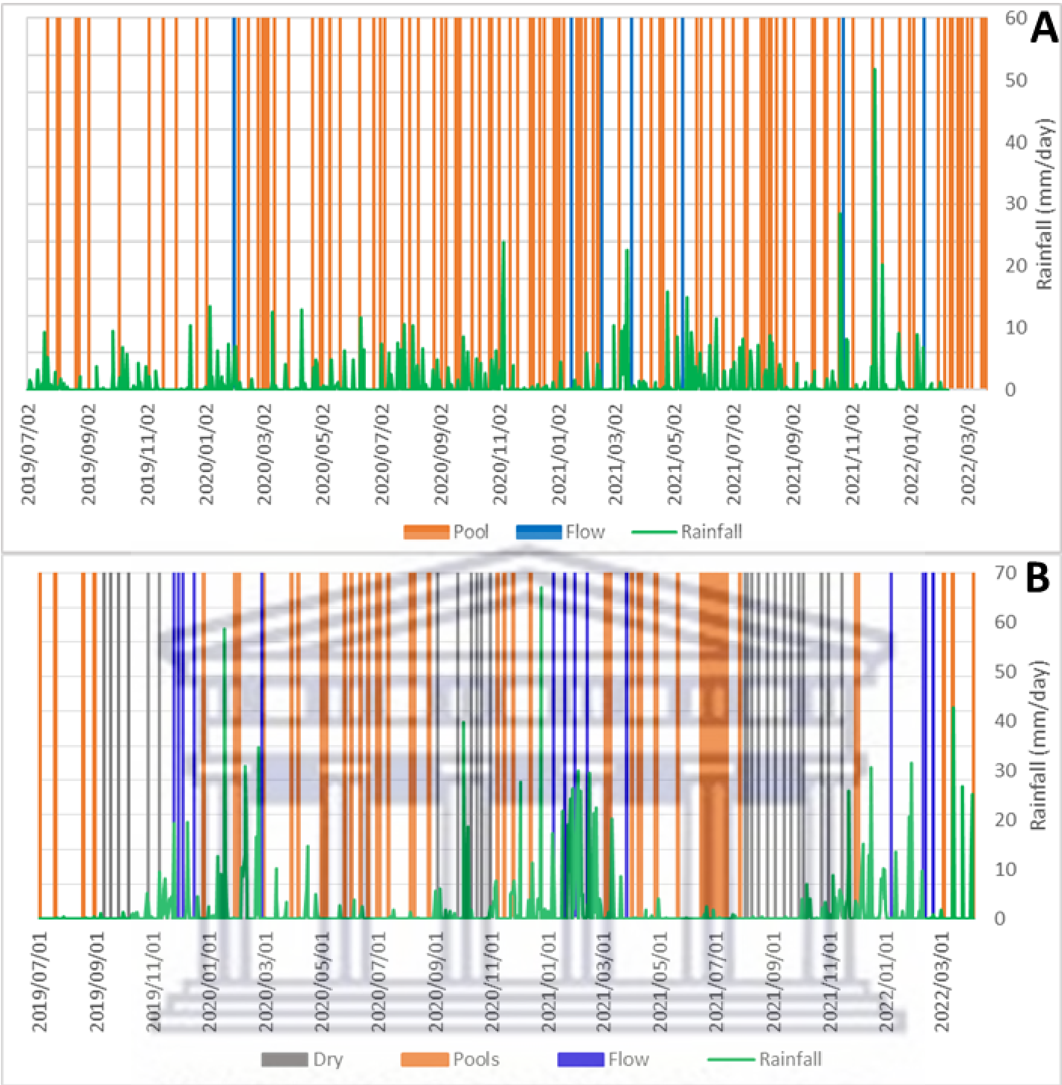


Figure 5.6: The temporal changes of hydrological phases in the Touws (A) and Molototsi River (B) detected through remote sensing. The grey bars indicate the dry phase, the orange bars indicate the pool phase, and the blue bars indicate the flowing phase. The remote sensing (CHIRPS) estimated mean catchment rainfall indicated with the green line.

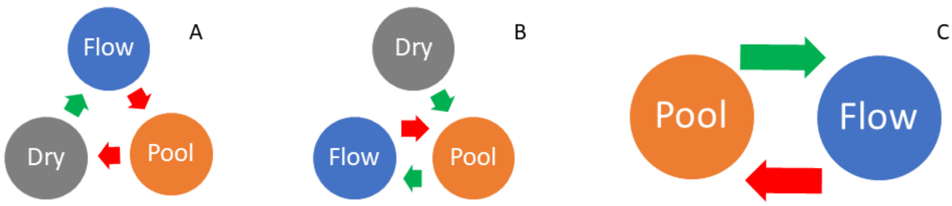


Figure 5.7: Summary of hydrological phases pattern observed in this study, A and B were observed in Molototsi and C was observed in Touws River. The green arrows denote water added to the river, and the red arrows indicate water loss by the river.

5.3.3 Flow contributing area in the Touws and Molototsi River

The spatial distribution of rainfall that results in flows in the Touws River suggests that the Southwestern part of the catchment (Quaternary catchment J12J) tends to receive more rainfall (Figure 5.8A). This further suggests that this area may be generating most of the runoff observed in the river. However, there are cases whereby rainfall was received elsewhere (shown using the red frame in Figure 5.8A). The rainfall distribution suggests that there are also flow events that may have occurred mid to lower parts of the catchment but did not occur upstream of the river. The highest 5-days antecedent rainfall (i.e., total rainfall preceding the flow event) observed was ~120 mm and the lowest was 20 mm.

In the Molototsi River, rainfall leading to most of the flow events tends to occur in the upper catchment (B81G) (Figure 5.8B). There were events whereby rainfall occurs in mid-catchment (shown using the red frame in Figure 5.8B). The locals suggest that the flows originating from the upper catchment (Modjadjiskloof) area tend to last for longer compared to other parts of the catchment. The highest antecedent rainfall observed for the Molototsi catchment was ~96 mm and the lowest was 24 mm. However, receiving the highest rainfall sometimes does not result in any runoff being generated and/or observed, the physical characteristics (soil type, slope, and land use and cover) of the catchment have a significant role to play in this regard.

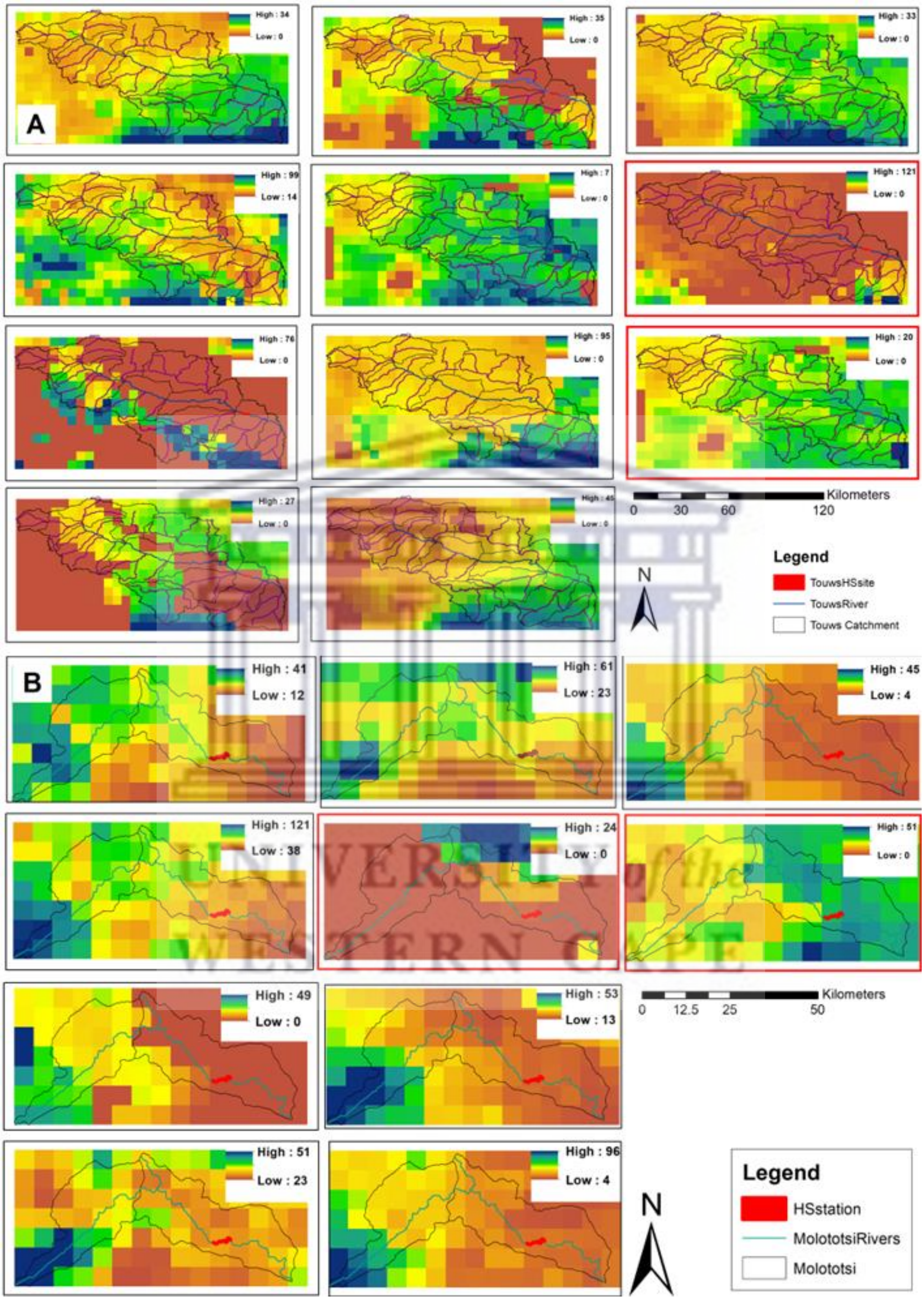


Figure 5.8: Spatial distribution of the antecedent rainfall for flow events that occurred between August 2019 to March 2022 in the Touws (A) and Molototsi River (B).

Curve number method

To consider the physical characteristics of the catchment, the SCS curve number (CN) was used to determine contribution areas. Due to the small variation in soil types and land cover in the Touws catchment, the curve numbers showed small variation, indicating that runoff produced in the catchment is mainly controlled by the spatial distribution of rainfall. The area where most of the antecedent rainfall occurs (Figure 5.8A) is also one of the areas with a high probability of producing runoff (CN>61) (Figure 5.9A). The upper parts of Molototsi Catchment have higher curve numbers (>78), implying that it is likely to produce more runoff than the lower parts (B81G) (Figure 5.9 B). The area also tends to receive more rainfall. Comparing the two catchments, the curve number method suggests that the Molototsi catchment has a greater probability of producing runoff (Figure 10), and generally receives more antecedent rainfall. The estimated initial abstraction derived through the curve number method is similar to the estimated antecedent rainfall (remotely sensed estimated) for the Molototsi Catchment, which indicates that some parts of the catchment can potentially start to generate runoff from receiving as little as 10-20 mm of rainfall (Figure 5.10). Whereas the Touws catchment can potentially generate runoff from 20-30 mm of rain.

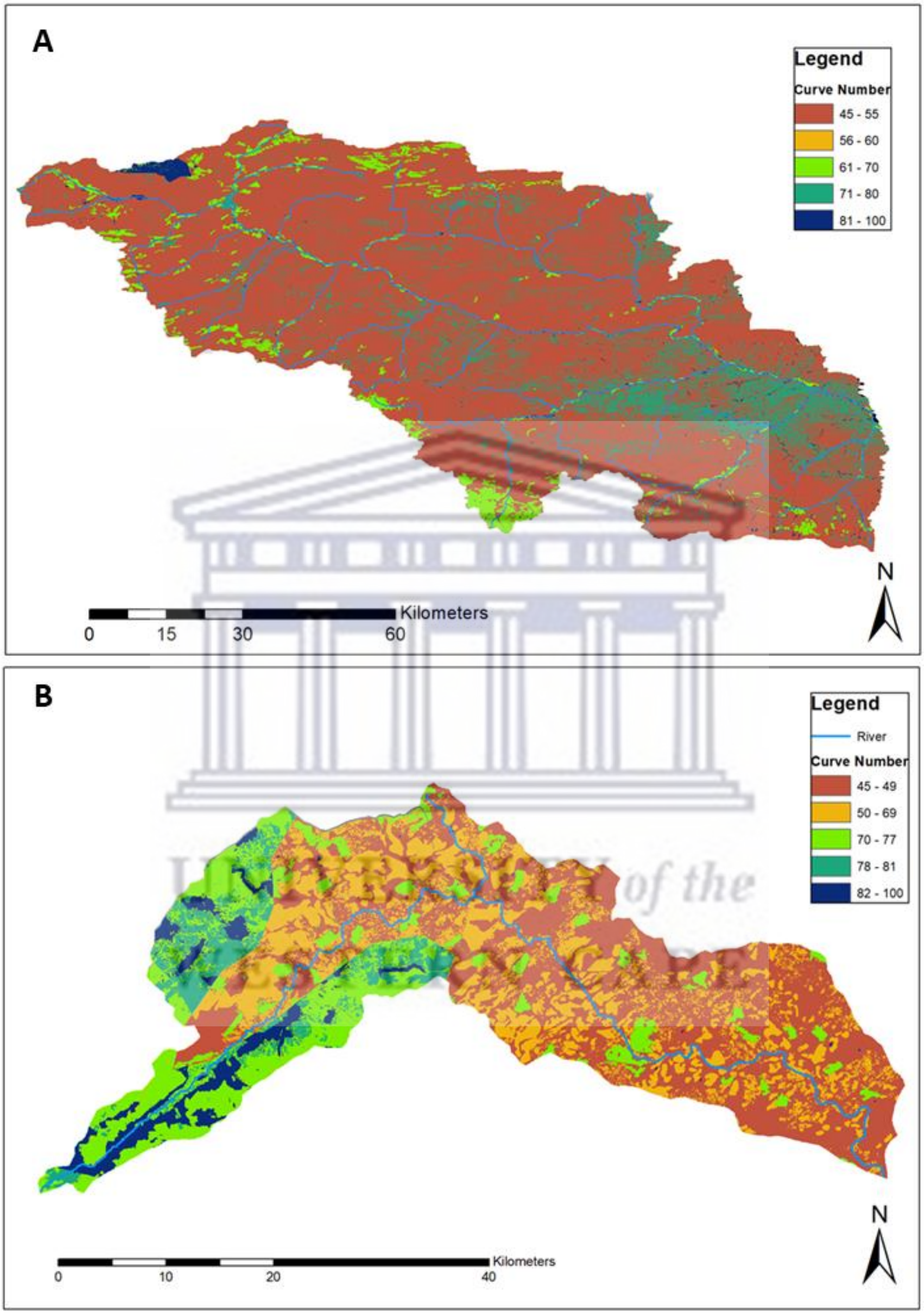


Figure 5.9: Runoff curve numbers of the Touws (A) and Molototsi (B) Catchment using AMC II.

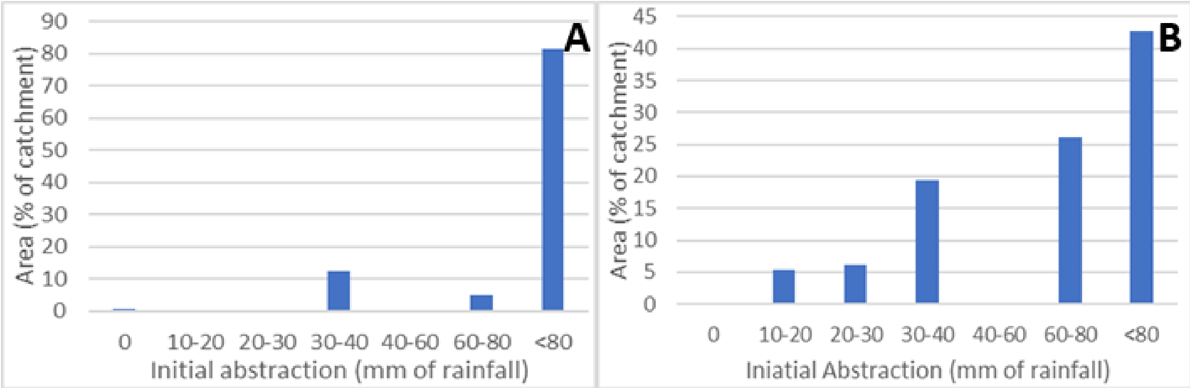


Figure 5.10: Initial abstraction of rainfall before runoff as a proportion of the Touws (A) and Molototsi catchment area (B).

5.4 Discussion

Non-perennial rivers are highly dynamic, switching between different hydrological phases. Remote sensing was used to detect these phases and the results showed that this approach has the ability to distinguish between the hydrological phases. Although, the detection of the transition between the phases, especially from pools to dry seems to be a slight challenge for remote sensing. This might be caused by the pools becoming very small to be detected at satellite spatial resolution as Maswanganye et al. (2022a) suggested that it is a challenge to detect pools of less than 400 m^2. The remote sensing performance was better in Touws River than in Molototsi River, this might be because i) the Touws River only had two phases ii) the pools in the Touws River tend to be bigger than those found in Molototsi River as observed by Maswanganye et al., (2022a) allowing for easier detection. This suggests that the method used might not be applicable in rivers with a small width (<40 m). Molototsi River phases were more dynamic. The findings of this study, in terms of the persistence of the pools in both catchments, are in line with the findings made by Maswanganye et al. (2022a) which suggested that the pools are permanent to semi-permanent in the Touws River and ephemeral in the Molototsi River.

The Touws River showed to have less clouds but they persisted when flows occurred, resulting in some flow events being missed, whereas the flow in Molototsi River tends to be more persistent allowing more time for the capturing of cloud-free images. The missed flow events by Sentinel-2 were of shorter duration (<5 days). This study used Sentinel-1 to try and overcome these issues. Although Sentinel-1 had poor detection of pools (Maswanganye et al., 2022a), it was able to detect two of three flow events missed due to cloudy images in the Molototsi River, however, it was unsuccessful in the Touws River. Seaton and Dube (2021) suggested that this is due to the flat and arid landscapes creating similar backscatter to water, resulting in difficulty in the separation of water and the surrounding areas. This study only used Sentinel-2 and 1, including other remote sensing data from various satellites that can improve the temporal resolution, hence giving it the potential to estimate the duration of the flow events.

In both catchments, the pool phase is dominant, this is permissible for arid and semi-arid rivers (Bonada et al., 2020), this means that people will have access to pools for recreational purposes and domestic use (i.e., swimming and doing laundry). The flow events showed no seasonality in the Touws River and generally had a shorter duration compared to the Molototsi River. This might be a result that Molototsi receives more rainfall and has a better probability of generating runoff based on the physical characteristics of the area (i.e., soil types, land cover, etc) according to the curve number method. These flows are important for communities living along the river as they might also recharge sand/alluvial aquifer, which provides water for domestic use (Walker et al., 2019, 2018). These flows are also a major control for pool occurrence along the river. For instance, Maswanganye et al. (2022b) estimated that it would take around 258 days for one of the pools along the Touws River to dry out if river flow does not occur.

The analysis of major contributing areas of flows for the Touws River suggests that the site or reach used in this study did not capture the hydrological states of the upper stream well as much of the runoff generated in the mid-catchment, therefore, there is a need to use multiply sites when determining the hydrological state to provide a good representation of the river. This can be located in between the major confluences of the main river. This can be easily done through remote sensing but might be timely and laborious for direct observation. The minimum antecedent rainfall was estimated to be 20 and 24 mm in the Touws and Molototsi catchments, respectively. However, the spatial coverage of the antecedent rainfall is also important. The Touws catchment is drier compared to the Molototsi catchment, as it receives less rainfall. The runoff curve numbers further suggest that the Molototsi catchment has a better probability of generating runoff than the Touws catchment.

5.5 Conclusion

There are limited studies on the dynamic of hydrological states of non-perennial rivers, hence this study sought to establish the spatial and temporal dynamics of hydrological states as well as to determine possible contributing areas. Remote sensing was able to distinguish between the three hydrological phases when the images were available and cloud-free. However, it had challenges in detecting rapid flows with short duration, as seen in Touws River and small pools as seen in Molototsi River. Besides these limitations of the temporal resolution resulting in missing some flow events, remote sensing showed great potential. Molototsi River showed a regular pattern between hydrological states (flow, pool, dry riverbed) associated with rainfall season patterns, whereas the Touws River had an unpredictable pattern associated with its irregular rainfall. The pool state is dominant for both rivers. Flow-contributing areas should be prioritised for water resource protection and maintaining the river's hydrological states and flow regimes. Remote sensing and GIS showed to be useful approaches in identifying these flow-contributing areas.

With the advancing and increasing availability of high-resolution satellites, remote sensing will be more useful in determining the hydrological states and providing hydrological information about non-perennial rivers that are otherwise challenging to get through in situ measurements. This information is critical for water resource availability as well as catchment management.

Chapter 6: Synthesis and Conclusion

6.1 Introduction

Non-perennial rivers are important and can be the only water source for many communities in semi-arid and arid areas. These rivers account for more than 50% of the world's river network and are expanding as result of climate change and social and economic uses. One of the main distinguishing features of NPRs is the pools that occur when flow ceases. The dry river state is also important. Due to these states, the hydrology of NPRs is highly variable as compared to perennial rivers. However, NPRs are not perceived as important as perennial rivers as they are not deemed a reliable water source (Rodríguez-Lozano et al., 2020). As a result, there is an inadequate understanding of the spatial and temporal dynamics of the pools and flow of these rivers. NPRs are rarely monitored, and when they are monitored, perennial river methods are used, which may not adequately capture the spatial and temporal dynamics of these rivers. Hence, this study aimed to improve the understanding and monitoring of non-perennial rivers using both in-situ and remote sensing data, which was achieved through the following objectives:

i) Reviewing the literature on monitoring of non-perennial rivers with a focus on the potential application of remote sensing.
ii) Assessing the spatial distribution of pools and pool dynamics along non-perennial rivers.
iii) Establishing factors and processes accounting for the occurrence of selected and representative pools.
iv) Assessing the spatiotemporal dynamics of the hydrological state of the non-perennial river systems and identification of flow-contributing areas.

6.2 Review on Monitoring of the Spatial and Temporal Dynamics of Non-Perennial Rivers

The chapter reviewed methods used in the monitoring of the spatial and temporal dynamics of flows and pools along non-perennial rivers, as well as the potential of using remote sensing as an alternative. Several studies have indicated that non-perennial rivers are increasing and are expected to increase in most regions of the world as rainfall declines due to climate change. Besides their importance for some communities and the role they play in the ecosystem, they are still poorly studied as compared to perennial rivers. Many studies suggest that this is caused by a lack of political will and research funding based on the perception that NPRs are not perceived as reliable for water supply. The chapter included some of the challenges, such as the lack of data and the complexity of monitoring these rivers. The flows and pools along non-perennial rivers are highly variable, making them rather challenging to model effectively, especially using current methods that are developed in/for perennial rivers. Most of the available work that has been done on pools and flow dynamics is from ecological perspective and not from hydrology. Much of the studies on NPRs are done in Australia, the United States of America, Spain, Portugal and France, and inadequate research has been conducted in Africa, where most such river systems occur in relative abundance.

To overcome the identified and known knowledge gaps, monitoring of various components of NPRs is a prerequisite. Currently, laborious and time-consuming conventional methods are used to monitor NPRs. These methods are derived from the perennial river's perspective and might not adequately capture the dynamics of non-perennial rivers. The review found that satellite remote sensing has been used to extract important and useful hydrological information, although this was mostly done in large perennial rivers and wetlands. The study concluded that remote sensing might have the potential to monitor the spatial and temporal dynamics of non-perennial rivers. However, this potential has not been explored. This potential is expected to improve as satellite technology and methodology become more advanced. This study, therefore, evaluated the use of remote sensing to extract useful hydrologically useful information of non-perennial rivers using in-situ data whilst addressing some of the knowledge gaps.

6.3 Monitoring of Spatial Distribution and Pool Dynamics along Non-Perennial Rivers

When non-perennial river flow ceases, pools often form. These pools are an important water source for livestock and domestic purposes in rural areas (Bonada et al., 2020; Makwinja et al., 2014). This chapter explored the use of remote sensing approaches to monitor the location and size of the pools along the Touws and Molototsi Rivers. Water areas were extracted using the thresholding method for Sentinel-1, and Normalised Difference Water Index (NDWI), Modified NDWI (MNDWI), Normalised Difference Vegetation Index, and Random Forest classifier were used forSentinel-2 imagery. Overall, the findings of the study showed that MNDWI applied to Sentinel-2 performed better than the other tested methods. Pools were detected with acceptable accuracy of 74 to 84% at both the pool and catchment scales. Pools in the Touws River showed a perennial nature, whereas the pools along the Molototsi River had a distinct ephemeral pattern. The changes in pool sizes in the two study sites correlated well with the occurrence of flows and rainfall. The study concluded that remote sensing can be used to extract significant hydrological information on pools. However, the water balance approach was recommended to better understand the water fluxes driving changes in the pools. The next chapter presented water balance.

6.4 Water Balance of Pools along Non-Perennial Rivers

Based on the limitations of the previous chapter, this chapter used water balance approach to provide a better understanding of pools in NPRs. The results of the study suggested that the focal pool (Wolverfontien 2) loses most of its water through evaporation. The pool also loses water to the subsurface to a certain water depth of about 1.1 m, beyond which groundwater starts to sustain the pool, reducing net water losses. The use of satellite-derived climatic variables of rainfall and evaporation in the model was promising as it yielded acceptable results. However, the attempt to solely use remote sensing data in the water balance was unsuccessful as result of the temporal and spatial resolution of satellite imagery and the lack of river flows information, which is the major driver of pool dynamics as observed from the- in-situ model. The water balance model developed and used for this study is simple and did not require river discharge measurements but uses flow occurrence as a proxy, hence it can potentially be applied to many pools. This study also recommended that remote sensing be used to detect the occurrence of river flow, this was done in the next section. Water resource management should consider the conservation of these pools in policy and decision-making so that the impact of an upstream and/or local activities is known and avoided or minimized.

6.5 Assessment of Spatial and Temporal Dynamics of Hydrological States of Non-Perennial Rivers

Non-perennial rivers are dynamic switching between the three distinct states, i.e., flow, pools, dry riverbed. Each state has its function, importance, and implications for water resource management This study focused on assessed the dynamics of these states on the two study sites aswell as identifying flow-contributing areas. The study demonstrated that remote sensing could distinguish the three states with acceptable accuracy of ~90%, although it struggled to capture short duration flow events of less than 5 days, mainly due to satellite imagery revisit time which is 5 days. Pools state was the most dominant for both study sites. Flow occurrence showed no seasonality in the Touws River, whereas in the Molototsi River the flows are predictable as they occur during a well-defined season. The flow contributing-areas were identified using freely available data, and these areas should be strategically protected to maintain the hydrological states. The analyses further revealed that the study catchments start the generation of runoff after receiving about 20 mm of rainfall with the Molototsi River exhibiting a higher probability of generating runoff compared to the Touws River. The approach used in this study can be adopted in other catchments to extract such useful information. Water resource practitioners and catchment management agencies are advised to consider monitoring and assessing hydrological states as well as identifying flow-contributing areas to make informed decisions.

6.6 Conclusion

The purpose of this study was to improve the understanding of the spatial and temporal dynamics of pools and flows along non-perennial rivers using in-situ and remote sensing data sources. The study made the following conclusions:

- The two studied areas (Touws and Molototsi Rivers) exhibit different flows and pool dynamics as a result of differences in physical characteristics such as riverbed material, landcover and land use.
- MNDWI applied to Sentinel-2 imagery provided better performance compared to the other tested methods (NDWI, NDVI, Random Forest, Sentinel-1 thresholding).
- Remote sensing can be used to monitor spatial and temporal dynamics of pools along non-perennial rivers as well as determine the hydrological state of a river with acceptable accuracy.
- The major limitation of remote sensing in extracting hydrological information was the temporal and spatial resolution of the satellite imagery, which will improve as satellite technology advances.
- A detailed understanding of pools can be derived using a water balance approach, which includes information about the persistence of pools. One of the pools in Touws River could retain water for 258 days without being refilled by river flows. The study also found that extrapolating understanding from one pool to another along the same river could be inaccurate.

- The flow-contributing areas can be identified using readily available data such as rainfall, soil types.

Overall, the study showed various ways by which hydrological information of non-perennial rivers can be extracted from freely available remote sensing data, while improving the understanding of spatial and temporal dynamics of flows and pools along non-perennial rivers in semi-arid and arid areas. The insights that are provided by this study are useful for better management of NPRs and their host catchments. The methods used in this study can be used by water resource managers for planning and decision-making, and by researchers for further investigations such as the ones suggested in the next section.

6.7 Overall Recommendations

This study contributed to knowledge on the better understanding and management of non-perennial river and their catchments. The study demonstrated the methods that can be used for the extraction of important hydrological information about non-perennial rivers from remote sensing. Now that the accuracy and the limitations of using remote sensing to monitor non-perennial rivers were established by this study, future studies could investigate:

- Upscaling the monitoring of the hydrological states to the catchment level.
- Focus on estimating river discharge using remote-sensing derived information considering the complexity of non-perennial rivers.
- The use of new and advanced satellites including the use of multi-satellites, to overcome the challenges of temporal resolution posed by using single satellite imagery.
- The use of advanced and rapid methods through platforms like Google Earth Engine to detect water areas along non-perennial rivers.
- The hydrological connection or flow of water in between the pools in the subsurface along the river when flow ceases to improve the understanding of pool dynamics.
- Impact of river sand harvesting on the formation and location pools along non-perennial rivers.
- The delineation of pool protection zone, the boundary where activities such as water abstraction are prohibited, is crucial for better management.
- The use of the citizen science programme was key in collecting data used in this study. I, therefore, do recommend that water authorities consider establishing such networks for ungauged catchments in line with SDG 6B.

- The incorporation of the hydrological information such as the hydrological states of each non-perennial river, the presence of pools and their persistency (temporal or permanent) by government authorities in their database. This information could also be included as part of the river description/properties.
- Land use planning (development and management) should seriously consider the effects that they will have on non-perennial river flows and pools.
- Given that the number (and possibly importance) of non-perennial rivers are believed to be largely underestimated, there is a need to review classification of national river system. For instance, the Molototsi River used in this study is well documented to be a non-perennial river, however, it appears as a perennial river in the Department of Water and Sanitation data (Appendix Figure A3). Remote sensing could help in the reclassification process of these rivers, especially in the ungauged systems.

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Appendices

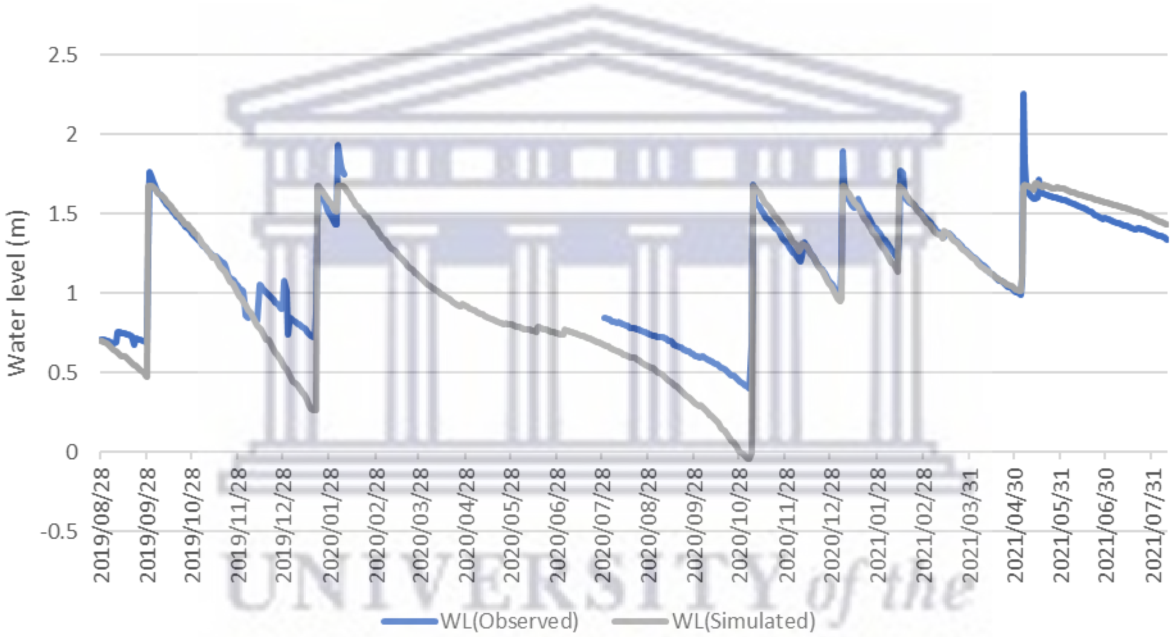

Figure A1: Initial model did not take into groundwater inflows. This model suggests losses to groundwater throughout and has no threshold.

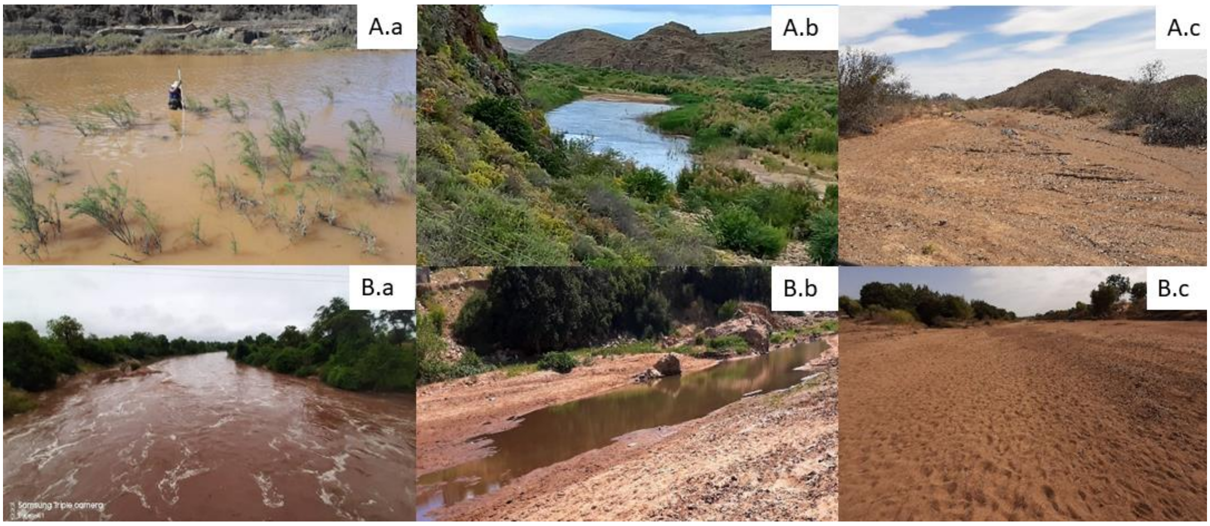

Figure A2: Photographs of Touws (A) and Molototsi (B) River in a flowing (a), pools (b), and dry riverbed state (c) NB: Touws River did not have a dry riverbed state during the study period.

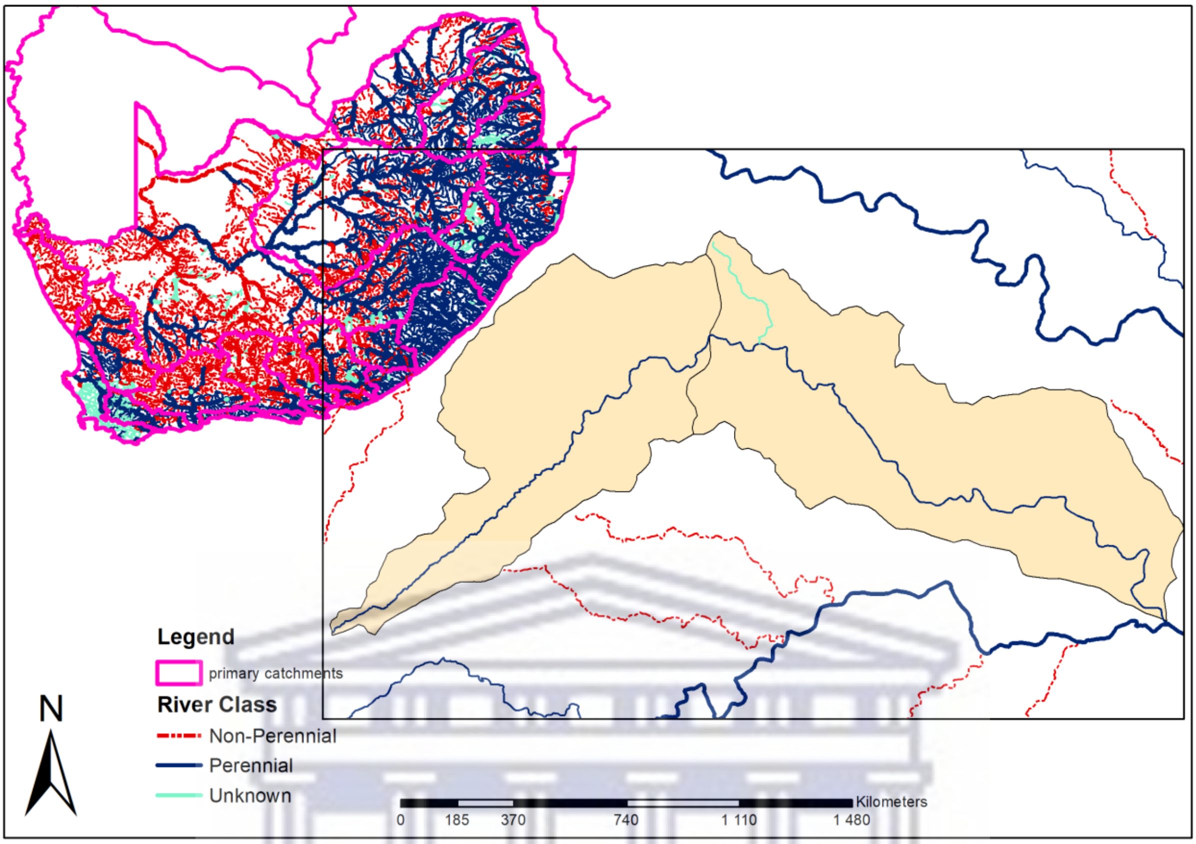

Figure A3: Classification of South African Rivers (top left), with Molototsi River misclassified as a Perennial River (bottom right).