Assessing whether Soil Moisture Content (SMC) can be estimated for wetlands in the grassland biome of South Africa using freely available space-borne sensors

By

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For a full Master's thesis:

A thesis submitted in partial fulfilment of the requirements for the degree of *Master Scientiae* in the Faculty of Science, University of Witwatersrand

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May 2019

ABSTRACT

Soil moisture content (SMC) takes on an important role in the hydrological functioning of wetlands. Temperature increases associated with climate change is expected to impact the hydrological regime of wetlands. Therefore, regional monitoring of SMC is essential for improved understanding of potential changes to the hydrological regime of wetlands while supporting decision making and interventions. Conventional methods of measuring SMC are costly and have a limited view of processes occurring at regional to global scales. In contrast, remote sensing can potentially offer a regular, regional overview of the hydrological function of wetlands and is therefore more cost-affordable compared to conventional methods. In the past, estimations of SMC with remote sensing lacked a sufficient spatial resolution for palustrine inland wetland ecosystem types, particularly in semi-arid countries. However, the use of recently launched and freely available high spatial resolution sensors, such as the Sentinel series, may overcome these limitations. In this study, the use of European Space Agency's Sentinel-1A and 1B (S1A, S1B; Synthetic Aperture Radar) and Sentinel-2A and 2B (S2A, S2B; optical) sensors were evaluated for their ability to predict SMC for wetlands and drylands in the grassland biome of South Africa. The percentage Volumetric Water Content (%VWC) for 200 points was measured in the Colbyn Nature Valley which is dominated by a palustrine wetland. The %VWC in the wetlands and terrestrial area of the study area were measured using a hand-held SMT-100 soil moisture and temperature meter at a 5 cm soil depth during March and May 2018 (the peak of the hydroperiod) and regressed against the Synthetic Aperture Radar (SAR) and optical data using a parametric and non-parametric models. The results showed that Sentinel images can predict the percentage SMC, with both the S1B and S2B images achieving the highest coefficient of determinations ($R^2 > 0.8$; $R^2 > 0.9$) and relatively low Root Mean Square Errors (RMSE = 10 %; 12 %) respectively. Predicted maps showed significantly lower ranges of SMC below 50 % ($p \leq 0.05$) in the terrestrial area compared to the higher ranges of SMC (≥ 50 %) in wetlands for both sensors. Although the SAR C-band is limited to the upper 5 cm of the soil depth, it shows potential to measure ranges of SMC for palustrine wetlands and terrestrial areas in the grassland biome of South Africa which will be beneficial for wetland inventorying.

Key words: Sentinel-1; Sentinel-2; soil moisture content; volumetric water content; palustrine wetlands; hydroperiod; Random Forest regression; machine learning regression

DECLARATION

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ACKNOWLEDGEMENTS

Firstly, I want to thank the Almighty for giving me the strength and courage to complete this journey.

To my supervisor, Dr. Heidi van Deventer, how can I ever possibly thank you for the unconditional support you have given me ever since I met you and without you this project wouldn’t have been possible. You introduced me to remote sensing and guided me through scientific research. Through you, I learned the dedication of a researcher, persistence and earnestness. For all my life, I will never forget what you have done for me!

To my co-supervisor, Dr. Laven Naidoo, your expertise in remote sensing, visionary thoughts and working style has made a deep impression on me. I want to thank you for always being available when I needed advice, your suggestions and valuable feedback improved this project greatly. You acted as a pillar of strength and always encouraged me to do my best.

Dr. Elhadi Adam, for contributing to the development of this work.

To my mom, dad and siblings, for all the support and encouraging words throughout the duration of this research.

In particular, thanks to Heidi Van Deventer, Laven Naidoo, Razeen Gangat, Mohamed Gangat, Taskeen Gangat, Zahra Varachia, Salman Mia, Yonwaba Atyosi and Jason Le Roux who helped me in acquiring *in situ* measurements, especially in the worst conditions. A special thanks to Tamsyn Sherwill for including me in all of Colbyn Nature Valley Reserve projects and conservation initiatives.

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Chapter 1 : GENERAL INTRODUCTION

1.1. The Importance of estimating and monitoring soil moisture content of wetlands

Soil moisture is an important attribute in wetland extent and dynamics. The National Wetland Maps showed that wetlands occupy only a small portion of South Africa's surface area (Van Deventer *et al.,* 2018b). Despite their small extent, they offer various ecological and economical functions which include improving water quality, flood and drought regulation, groundwater recharge, habitation for animals and plants, agricultural production and assist in managing limited water resources in the country and support commercial activities (McLaughlin *et al.,* 2013). Different definitions of the term 'wetlands' have been used across the world (e.g., Burton and Tiner*,* 2009). Wetlands are areas of soil saturated or inundated with water within 50 cm from the soil surface, which occurs during water periods or long enough throughout the growing season to become anoxic (Burton and Tiner*,* 2009; Ollis *et al.,* 2013:1).

South Africa has a variable climate resulting in the formation of a variety of wetland types. The *Classification System for Wetlands and other Aquatic Ecosystems* (Ollis *et al*., 2013) in South Africa distinguished three types of wetlands such as marine, estuarine and inland systems. Unlike marine and estuarine systems, inland systems are not connected to large bodies of water like the sea (Ollis *et al.,* 2013). Inland aquatic ecosystems are systems that are found in different locations and natural settings, and hold a wide range of unique properties and functions.

Wetlands continue to decline on a global scale, in extent and quality, to such severe standards, placing these ecosystems under pressure as well as the services they provide such as supplying water or providing habitation for wildlife (Gardner *et al.,* 2015). Wetlands have been and are subjected to various stress induced modifications like polluted runoff, hydrological modifications, eutrophication and, more recently a major concern is the impact from global climate change (Levin *et al.,* 2001). Global changes are a major contribution to the degradation and loss of wetlands, these include: a higher demand for water supply due to an increasing population, urbanisation, infrastructure and development, agricultural activities such as overgrazing and increased water abstraction for irrigation purposes (Russi *et al.,* 2013). In addition to global changes, climate change poses as a huge threat to the ecological condition of wetlands due to increasing temperatures and evapotranspiration. Over the last few years, an unequivocal increase in temperature of 1.5 °C have been observed while, it had been predicted that by 2050 the temperature is likely to exceed 2 °C (IPCC, 2014). In addition, a general decrease in precipitation in lower latitudes is expected to occur (Day *et al.,* 2005). Examples of impacts that occur from climate change include, alterations in the base flow, changes in hydrology (for example changes in wet and dry periods due increasing temperatures), increased weather events such as floods and droughts and a decrease in water quantity, to name a few (STRP, 2002).

To overcome these challenges, regular monitoring of the spatial extent of inland wetlands is required to identify how much and where losses are occurring. However, inland wetlands are highly variable in spatial extent because the inundated and saturated areas change periodically, and often seasonally (Hess *et al.,* 2015; Li *et al.,* 2015). While inundation have been monitored well across the globe for larger wetlands (e.g. Pekel *et al.,* 2016), monitoring of palustrine (vegetated) wetlands are deficient. Monitoring of Soil Moisture Content (SMC) can serve as a possible indicator of wetland functionality in palustrine wetlands and could be valuable for wetland inventorying too. SMC acts as an important component in the hydrological processes in wetlands leading to the understanding of land-surface interactions and has a predominant influence on an ecosystem's response to the physical environment (Wei, 1995; Martinez *et al.,* 2014). Because of the spatial variability that characterise the earth surface in terms of soil (e.g. slope and texture), as well as other processes that influence the water fluxes of near surface soil moisture (e.g. precipitation and evapotranspiration), soil moisture is variable in both space and time. Near surface soil moisture is considered to correspond to the upper layer (~5 cm) in the top soil (Bousbih *et al.,* 2018).

Assessing soil moisture levels is particularly useful for determining the seasonal patterns of water levels in a wetland, otherwise known as 'hydroperiod' or 'hydrological regime' (Erwin, 2008). These seasonal variations describe the hydrological characteristics of a wetland, for example, whether it is inundated and for how long (permanent, seasonal, intermittent); and is used as a criterion to determine wetland types (Mitsch and Gosselink, 2007). A number of factors influence a wetland's hydroperiod, such as overgrazing from agricultural use or climate change. Therefore, monitoring the hydrodynamics of a wetland provides an understanding of a wetland's response to the changes in their hydrology (Dixon, 2002; Voldseth *et al.,* 2007). More so, having insight to the hydrodynamics of a wetland is useful to quantify the extent of a wetland and therefore a valuable asset to wetland inventorying, especially in semi-arid countries (Conway and Dixon, 2000).

South Africa is a semi-arid country and experiences a mean annual rainfall (MAR) of 497 mm which falls below the global MAR of 860 mm (Bailey and Pitman, 2016). In semi-arid regions, the amount of rainfall varies significantly within and between seasons; as such, surface water availability can easily fluctuate (Klemas *et al.,* 2015). The scarcity of rainfall is compounded by the highly variable and uneven distribution of rainfall in South Africa, where the western regions experiences less run-off as compared to the eastern regions that receive a higher rainfall run-off (Lumsden *et al.,* 2009). The flow regime in wetlands is linked to rainfall events which impacts the spatial and temporal distribution of soil moisture in inland aquatic wetlands (Whitfield and Matlala*,* 2011). These effects are noticeable in the changes of the hydrological period which may lead to the onset of increased evapotranspiration and a reduction in the availability of soil moisture (Bullock and Acreman*,* 2003; Dallas and Rivers-Moore, 2014; Brocca *et al.,* 2017). This in turn could accelerate the transformation and degradation of natural intact wetland ecosystems and their associated ecosystem services. Due to the limited coverage of wetlands in South Africa, their loss and degradation will result in severe consequences as compared to a country with a larger extent of wetlands, especially taking into consideration that South Africa is a semi-arid country (Kotze *et al.,* 1996).

To compound monitoring efforts, in 2011, the South African National Biodiversity Assessment reported that inland wetlands are poorly mapped, highly threatened and poorly protected (Nel and Driver, 2012). Therefore, frequent monitoring, under global and climate change conditions, is required to inform the status of the hydroperiod and cycle in a non-destructive manner. There is a need for automated inventorying of wetlands, particularly, palustrine wetlands which are poorly represented in the National Wetland Map (NWM). Monitoring changes to SMC across the hydrological cycle, at a regional scale, is important not only for addressing this shortcoming of the

NWM, but also future conservation strategies, decision making and intervention bringing in great economic and societal benefits in South Africa.

1.2. Regional monitoring of the variation and changes in the soil moisture content of wetlands

In recent decades, various methods have been developed to measure SMC at different scales (Bittelli, 2011). There are several ways of measuring SMC. Firstly, traditional *in situ* soil moisture measurements provide reliable point-scale data. However, soil moisture is highly variable both spatially and temporally, therefore direct measurements are not able to represent the spatial distribution of soil moisture and is rendered inadequate to carry out regional to global scale monitoring (Engman, 1991; Wood *et al.,* 1992). Three other disadvantages of direct measurements of SMC are that it is labour intensive, time consuming and costly (Santi *et al.,* 2013). Obtaining accurate soil moisture *in situ* measurements in wetlands is also difficult due to their dynamic hydrological characteristics, extensive areas which are difficult to access and remote locations. In the past, surface hydrology models have been developed to address the shortcomings of estimating SMC at a regional scale (Crow and Yilmaz*,* 2014; Tebbs *et al.,* 2016). The spatial scale of these applied models, however, remains too fine scale (~10 km - ~100 km) for accurate soil surface measurements of wetlands (Bloschl and Sivapalan*,* 1995; McDonnell *et al.,* 2007; Riley, 2014). Higher spatial resolution modelling is needed to produce more accurate predictions in the terrestrial environment (Wood *et al.,* 2011), particularly inland wetlands of semi-arid to arid environments. Also, the large range of temporal scales in hydrological modelling is limited because of a lack of up-to-date datasets for modelling purposes, for example a time series of saturation or inundation levels and water level discharge rates (Gentine *et al.,* 2012).

Remote sensing technologies, both Synthetic Aperture Radar (SAR) and optical, provides alternative tools for monitoring SMC of inland wetlands and to overcome the limitations of small scale *in situ* measurements and coarse spatial resolution of modelling SMC. International research has shown that space-borne sensors are able to estimate SMC in the top layer (5 cm to 10 cm) of the soil surface and are capable of producing regional estimates, with frequent temporal overpasses, and at a spatial resolution ranging tens of kilometres (Wang and Qu, 2009). The capability of these sensors remains to be assessed for South Africa's palustrine wetlands.

Retrieving near surface soil moisture using various active and passive microwave remote sensing techniques with good spatio-temporal resolution have been conducted over primarily temperate and Mediterranean climates (Ulaby *et al.,* 1982; Su *et al.,* 1997; Kerr *et al.,* 2001; Njoku *et al*., 2002; Njoku *et al.,* 2003; Moran *et al.,* 2004; Wigneron *et al.* 2007; Baghdadi *et al.,* 2008; Parajka *et al.,* 2009; Sinclair and Pegram, 2010; Jackson *et al.,* 2016). To date, these studies have used both C and L-band sensors in their investigations, done for a wide variety of applications. Different applications require different spatial and temporal resolutions (Al-Yaari, 2017). For instance, L-band passive remote sensing products are suitable for acquiring SMC information at a global scale, ranging from tens of kilometres, such as the Soil Moisture and Ocean Salinity (SMOS) at 35 km spatial resolution and the Soil Moisture Active Passive (SMAP) satellite at 3 km spatial resolution with a temporal resolutions of two to three days for both satellites (Klinke *et al.,* 2018). However, the low spatial resolution of L-band products does not account for the high spatial and temporal variation of SMC which is unsuitable for monitoring of small spatial extent ecosystems such as palustrine wetlands. More recently, active remote sensing C-band SAR satellites have been employed in research studies due to its advantage to provide near surface SMC datasets at medium to high spatial resolution (from 10 m to 100 m) making it more suitable for detecting changes in wetlands, at a regional scale, such as the European Remote Sensing Satellite 1/2 (ERS-1/2), Environmental Satellite (ENVISAT) or RADARSAT-1/2 (Baghdad *et al.,* 2008; Doubkova *et al.,* 2009; Pathe *et al.,* 2009; Mladenova *et al.,* 2010; Widhalm *et al.,* 2015).

Two main features of microwave radiation are frequency and polarization. The depth to which a microwave signal can penetrate depends on the frequency (f) and wavelength of the satellite. Sensors with low frequency and longer wavelengths have the ability to penetrate deeper into the soil surface such as the L-band (f = 1-2 GHz, penetration depth = ~ 30 cm) as compared to higher frequency C-band (f = 4-8 GHz, penetration depth = ~ 5 cm), and X-band (f = 8-12 GHz, penetration depth = ~3 cm) sensors (Wagner *et al.,* 2006). Ideally L-band sensors would therefore be more suitable for monitoring wetlands, because of the ability to penetrate deeper in to the soil surface near the estimated depth of saturation for wetlands (50 cm), however owing to their coarse spatial resolution or low temporal resolution (e.g. ALOS sensor has a revisit time of 46 days), users are limited to sensors at 5 cm depth for features with smaller extents. In addition, estimating SMC becomes a challenge for high frequency remote sensing products when the study area is also densely vegetated and when there is high variability in the topography (e.g., surface roughness) (Ulaby *et al.,* 1979; Said *et al.,* 2012). Several studies made use of C-band data to retrieve SMC, however, the majority of these studies focused on the estimation of SMC in terrestrial ecosystems, usually where the cover was bare soil or very little to sparsely vegetated areas with correlation of determination (R) of > 0.5 and root square mean error (RMSE) of ≤ 40 % (Moran *et al.,* 2004; Carlson, 2007; Owe *et al.,* 2008; Verstraeten *et al.,* 2006; Wang and Qu, 2009). In the case of high frequency, C-band sensors, the wavelength (~ 5 cm) together with the polarization modes, improves the signal's ability to penetrate vegetation canopy cover and interact with the surface soil layer. In Hornacek *et al.* (2012), it was shown that vegetation ≤ 1 kg/m^2 had very little influence on the signal for terrestrial systems in a country. Other studies compensated for the influence of vegetation and texture through including these in the regressions (e.g. using sensors with different configurations such as different incident angles; testing during specific phenological periods where there is little to no vegetation activity or incorporating vegetation indices (Polascia *et al*., 2013).

SAR sensors uses two polarizations in regressions to features, including single polarization vertical-receive, vertical-transmit (VV) or horizontal-receive, horizontal-transmit (HH) vertical-receive and or cross-polarization such as vertical-receive, horizontal-transmit (VH). Different polarization modes have also been employed in several studies as a means of minimizing the effects of surface roughness or vegetation on radar return signal. For instance, different scattering mechanisms when dealing with agricultural lands result in direct backscatter from bare soils, direct backscatter from leaves, stem or fruit from plants, double-bounce backscatter from between the soil surface and vegetation canopy, and multiple scattering between ground-vegetation-ground interaction (Cable *et al.*, 2014). A research done by Dabrowska-Zielinska *et al.* (2018) tested the correlation between the C-band Sentinel-1 backscatter and the observed SMC measured and found that vertical-receive, horizontal-transmit (VH) had better accuracies (coefficient of determination, R^2 = 0.55) as compared to the VV (R^2 = < 0.5) in terrestrial and palustrine wetlands of Poland. Therefore, using sensors with dual-polarization modes allows a good compensation of wetland vegetation dynamics to retrieve SMC.

Optical remote sensing is an alternative tool for estimating near-surface SMC. The reflectance of SMC, together with vegetation and texture is detected across the visible/near infrared (VNIR: 400 nm–1200 nm) and the short wave infrared (SWIR: 1200 nm–2500 nm) spectrum, and SMC is particularly detected by the water absorption bands with a central wavelength of 970 nm, 1160 nm, 1440 nm and 1930 nm (Tian, 2016). A hyperspectral study done in the laboratory by Whiting *et al.* (2004) and Liu *et al.* (2002) found several bands in the SWIR (1200 nm – 2500 nm) were suitable for predicting SMC with RMSE 0.002–0.004 for both studies. Optical sensors, such as the Landsat series of multispectral scanner (MSS), thematic mapper (TM) and operational land imager (OLI) have been used to date to estimate SMC in palustrine wetlands as well as monitor wetland's hydrological regimes, by using vegetation type as a proxy (e.g. marshy, herbaceous or meadow) to determine the extent of wetlands and terrestrial areas, at various scales (e.g. Shalaby and Tateishi, 2007; Zhang *et al.,* 2009a; Tong, *et al.,* 2018). Other than the limitation in the spatial resolution of this sensor (30 m) being inadequate for small wetlands, frequent cloud coverage and heterogeneity vegetation cover could become a challenge when estimating SMC (Saalovara *et al.,* 2005). Other sensors such as the WorldView, IKONOS and RapidEye offer eligible accuracy with a sub-meter level spatial resolution imagery and an average revisit time of 1.1 days, for detecting the extent as well as other aspects of inland wetlands (Nouri *et al*., 2014). These sensors are ideal for monitoring wetlands as it overcomes the technical limitations previously mentioned, however, there are high costs associated with attaining the data from these commercial sensors, limiting its use in monitoring.

A number of studies have explored the use of remote sensing technologies in monitoring SMC in wetlands, however no literature has explored how this approach can be used to determine thresholding for determining the extent of a wetland, and using it subsequently in wetland mapping and inventorying. In general, several studies have shown *in situ* SMC measured in terrestrial systems to ranges from ±24 % to ±45 %, while in situ SMC in wetlands were generally above ±50 %. The aims of these studies were not directed at thresholding SMC for identifying the boundaries of wetlands.

Both SAR and optical sensors have been used successfully to date in estimating SMC at a regional to global scale, however the focus had been primarily in terrestrial and less so on palustrine wetlands. The coarse resolution of satellites used, limited testing across different environments and application of smaller features, such as palustrine wetlands in semi-arid countries remains to be assessed. Palustrine wetlands are considered crucial in the hydrological regime of the larger landscape, and have a valuable contribution to biodiversity (Biggs *et al.,* 2017). The recently launched European Space Agency's dual-polarimetric C-band SAR Sentinel-1 (launched in 2014) and optical sensor Sentinel-2 (launched in 2015), offer new opportunities to test the capabilities of these sensors in predicting SMC for small, palustrine wetlands. These sensors are able to provide relatively high spatial resolution (10 m) and high revisit time (5-6 days) imagery which is available to all users, at no cost (Sentinel Data Access Overview - Sentinel Online, 2018). Should these sensors be able to predict SMC in these small, palustrine wetlands, it has the potential to, on the one hand, contribute information on their varying extent for wetland inventorying and improved representation in the South African National Wetlands Map (NWM), and on the other hand, a means of monitoring their ecological condition under the pressures of climate change.

1.3. Motivation

It is estimated that since the 1900's, the world's wetlands have declined in extent from 71% to 64%, from the 20th century to the early 21st century (Davidson, 2014). In South Africa, a study by Begg (1988) showed that nearly 58% of the wetlands in the Umfolozi catchment have either undergone degradation or transformed to agricultural land. Many inland wetlands are located within the grassland biome of South Africa. The grassland biome is spread across six provinces of South Africa, covering approximately 350 000 km^2 of the country (O'Connor and Bredenkamp, 1997). Grasslands function as water production areas, this allows humans to benefit from its rich soil, for example, local communities use it for agriculture and livestock grazing and wildlife species, such as the blue crane, rely on dry grasslands for habitation. However, inland aquatic ecosystems in the grassland biome are facing major threats from mining plantation activities, urbanization and invasive alien plants (Neke, 1999; SANBI, 2013).

South Africa, like many other countries, requires an adequate monitoring system for inland wetlands. The intent is for the outcome of this study to contribute knowledge to South Africa's National Wetland Monitoring Programme (NWMP) (Wilkinson *et al.,* 2016), which is still to be implemented in South Africa. The methodologies considered in the NWMP includes an assessor to carry out rapid field-based assessments on prioritized wetlands (this information is based on existing datasets), intending to spend four to eight hours at each site. Such in-field assessments would be time-consuming and not cost-effective over the long run. Hence, if SMC can be predicted from the new and freely available Sentinel images, thresholds of SMC can be explored for the automated mapping and monitoring of palustrine wetlands in the grassland biome of South Africa across the hydroperiod.

Globally, SMC is considered as an 'Essential Climate Variable' by the Global Climate Observing System in the year 2010 (GCOS, 2010). Using remote sensing as a means of obtaining up-to-date information on SMC, can also contribute to the efforts carried out by Group on Earth Observations Biodiversity Network (GEOBON), in order to report and manage changes in the extent of different wetland types, and in this way inform ecosystem biodiversity. This would especially have a major positive impact on the conservation strategies for wetland biodiversity.

1.4. Study area

The study area chosen included a palustrine wetland in the grassland biome of South Africa. The study area is comprised of predominantly densely covered graminoid and sedge vegetation with a narrow channel to the western part of the study area. The study area provides an ideal opportunity for testing the capability of the Sentinel sensor's ability to estimate SMC, because of a gradual change in soil moisture from the drier terrestrial parts of the study area, to areas with increasing soil moisture up to the central part where a peat substrate occurs, where the wetland is fully saturated. The grassland biome of South Africa constitutes approximately a third of the surface extent of the country (Mucina and Rutherford, 2006), is considered ‘critically endangered’ and experiencing a high rate of land conversion for agricultural use and urban development. The boundary of the wetland has been previously mapped at a desktop level, using a single image date only (Van Deventer *et al*., 2018b). The full variation of the hydroperiod could therefore not be accounted for. It is expected that better representation of the full extent of the wetland can be determined based on better understanding of the SMC ranges in the study area. The study area therefore provides an opportunity to assess whether a threshold can be determined between the terrestrial and wetland ecosystems.

1.5 Aim and objectives

The aim of the study was to determine whether the Sentinel-1 and Sentinel-2 sensors are able to estimate soil moisture content (SMC) in palustrine wetlands in the grassland biome of South Africa, through:

1. Assessing the capabilities of the Sentinel sensors to estimate SMC in palustrine wetlands;
2. Assessing whether there are significant differences in SMC estimated for wetlands and terrestrial ecosystem types.

Two research questions have been formulated based on gaps identified in the literature, including:

1. Can the estimation of near surface SMC from the Sentinel series satellites improve the mapping and monitoring of palustrine wetlands?
2. Can the optical and radar remote sensing technology be used for distinguishing the ranges and differences in SMC between wetlands and terrestrial ecosystem types?

1.6. Thesis outline

There are six chapters in total for this study**. Chapter one** is a general introduction, outlining the importance of wetlands, the threats they are facing and what measures can be put in place to monitor inland wetlands in South Africa. **Chapter two** is the literature review which provides an overview of wetlands and delineating a wetland, SMC and its relevance as well as methods of measuring SMC. **Chapter three** describes the study area and datasets used in the study and it also discusses the procedure and methods for analysing the data for objective one and two. **Chapter four** contains the results of the algorithms and methods used for analyses. **Chapter five** presents the discussion based on the results and compares previous literature and their results. **Chapter six** closes this thesis with a conclusion.

Chapter 2 : LITERATURE REVIEW

2.1 Wetlands

2.1.1 Definitions and concepts

The term ‘wetland’ has been defined on the basis for keeping a record of natural habitats, for carrying out various scientific studies, and in some countries, for regulating the usage of these sensitive ecosystems. Many technical definitions exist (Table 1) for the term ‘wetland’, however all these definitions have some shared elements. These include, wetlands may be permanently or temporarily saturated or inundated; the water in wetlands are either salty or freshwater; wetlands are either natural habitats or have been artificially created; these ecosystems are wet long enough to support, even if periodically, hydrophytic vegetation and aquatic life and; hydric soils exist in wetlands (Burton and Tiner, 2009).

Table 1: Types of definitions used for wetland inventories (Source: Adapted from Tiner *et al.*, 2015:7)

Definition of wetland	Country
‘Areas of marsh, fen, peatland, or water, whether natural or artificial, permanent or temporary, with water that is static or flowing, fresh, brackish, or salt, including areas of marine water, the depth of which at low tide does not exceed 6 m.’ (Ramsar Convention Bureau, 1998:7)	International
‘Areas of seasonally, intermittently, or permanently waterlogged soils or inundated land, whether natural or otherwise, fresh or saline.’ (Semeniuk and Semeniuk, 1995:104).	Australia
‘Land that is saturated with water long enough to promote wetland or aquatic processes as indicated by poorly drained soils, hydrophytic vegetation, and various kinds of biological activity which are adapted to a wet environment.’ (Warner and Rubec, 1997:1)	Canada
‘Includes permanently or intermittently wet areas, shallow water, or land water margins that support a natural ecosystem of plants and animals that are adapted to wet conditions.’ (Johnson and Gerbeaux, 2004:7)	New Zealand
‘Lands transitional between terrestrial and aquatic systems where the water table is usually at or near the surface or the land is covered by shallow water.’ (Cowardin *et al.,* 1979:3)	United States
‘An area of marsh, peatland or water, whether natural or artificial, permanent or temporary, with water that is static or flowing, fresh, brackish or salt, including areas of marine water the depth of which at low tide does not exceed ten metres’ (South African National Biodiversity Institute (SANBI), 2009:6) ‘Land which is transitional between terrestrial and aquatic systems where the water table is at or near the surface, or the land is periodically covered with shallow water, and which land in normal circumstances supports or would support vegetation typically adapted to life in saturated soils’ (Republic of South Africa, 1998:4; Ollis *et al.,* 2013:103)	South Africa

As a signatory of the Ramsar Convention, South Africa's broad definition of a wetland has adapted to the Ramsar definition for a proposed *National Wetland Classification System* (NWCS) (SANBI, 2009). The definition as per the NWCS includes all types of ecosystems that are either permanently or periodically wet, other than marine waters deeper than ten meters (Lombard *et al.,* 2005). In 2010, the South African National Biodiversity Institute (SANBI) collaborated with experts and stakeholders to develop a '*Classification System for Wetlands and other Aquatic Ecosystems in South Africa*' (hereafter called the Classification System) (Ollis *et al.,* 2013). The Classification System consists of a hierarchical classification process which distinguishes inland wetlands from estuaries and marine systems. A combination of the broad climatic regions at Level 2 and the hydrogeomorphic (HGM) units at Level 4A identifies wetland ecosystem types for South Africa (Figure 1). At Level 5, attributes distinguish palustrine (vegetated wetlands) from lacustrine (open waterbody) systems. The Classification System has adopted the definition of wetlands from South Africa's National Water Act (NWA), Act 36 of 1998 (RSA, 1998). In order for a wetland to meet the definition above, certain criteria are required such as, (a) the presence of a high water table causing saturation near the surface of the top soil layer, resulting in anaerobic conditions in the top 0.5 m of top soil; (b) hydromorphic soils, indicating long periods of saturation through, for example mottling and; (c) hydrophilic plants such as hydrophytes have to be present in that environment (DWAF, 2005).

Wetland/Aquatic Ecosystem Context	
LEVEL 2: REGIONAL SETTING	LEVEL 3: LANDSCAPE UNIT
DWA Level I Ecoregions OR NFEPA WetVeg Groups OR Other spatial framework	Valley Floor Slope Plain Bench (hillslope, saddle, shelf)
FUNCTIONAL UNIT	
LEVEL 4: HYDROGEOMORPHIC (HGM) UNIT	LEVEL 5: HYDROLOGICAL REGIME
River	Perenniality
Floodplain wetland	Period and depth of inundation Period of saturation
Channelled valley-bottom wetland	
Unchannelled valley-bottom wetland	
Depression	
Seep	
Wetland	
WETLAND/AQUATIC ECOSYSTEM CHARACTERISTICS	
LEVEL 6 : DESCRIPTORS	
Natural vs. Artificial Salinity pH Substratum type Vegetation cover type Geology	

Figure 1: Six -tiered hierarchical structure based on the characteristics of the South African Classification System for Wetlands and other Aquatic Ecosystems (Ollis *et al*., 2013:6). Soil moisture saturation regimes are attributed at Level 5.

Different climate conditions, soils, vegetation, hydrology and other factors are used to determine wetland types. According to the Ramsar Convention and the Classification System, wetland types are broadly categorised into coastal, estuarine and inland wetlands (Ollis *et al.*, 2013). Inland wetlands are interconnected systems which grade laterally in soil moisture saturation or inundation from terrestrial to wetland, as well as longitudinally from one wetland type to another through ecotones (transition zones) (Chamorro *et al.,* 2015). Inland wetlands are subdivided into lacustrine and palustrine systems, depending on whether they are inundated or vegetated. Lacustrine wetlands are permanently flooded areas (aquatic systems) that have little flow which include lakes and dams and are characterised by emergent plants. Palustrine wetlands are ecosystems that occur between the terrestrial and aquatic system, are vegetated and the soils vary in saturation (Noble and Hemmens, 1978).

Wetland hydrology is the key driver responsible for the formation of wetlands. The presence of water and its variations within an ecosystem and underlying soil is the 'hydrological regime' of a wetland (Collins, 2005; Ollis *et al.,* 2013). According to the Classification System, the hydrological regime can be further categorised based on its hydroperiod, which is whether the HGM units are inundated or saturated (Figure

2). Inundation occurs when the water can be seen on the surface for a minimum period of 3 months (intermittently), with seasonal systems inundated between 3 and 6 months and permanently inundated systems > 9 months per year (Ollis *et al*., 2013). Other systems which are not inundated, could be divided in similar categories, based on their soil saturation in the upper 0.5 m of the soil surface (this is the commonly accepted depth for wetland delineation) (Ollis *et al.,* 2013:98, 101). These saturation zones create an environment that supports hydric soils as well as the growth of wetland vegetation specifically adapted to these saturated conditions (Figure 2).

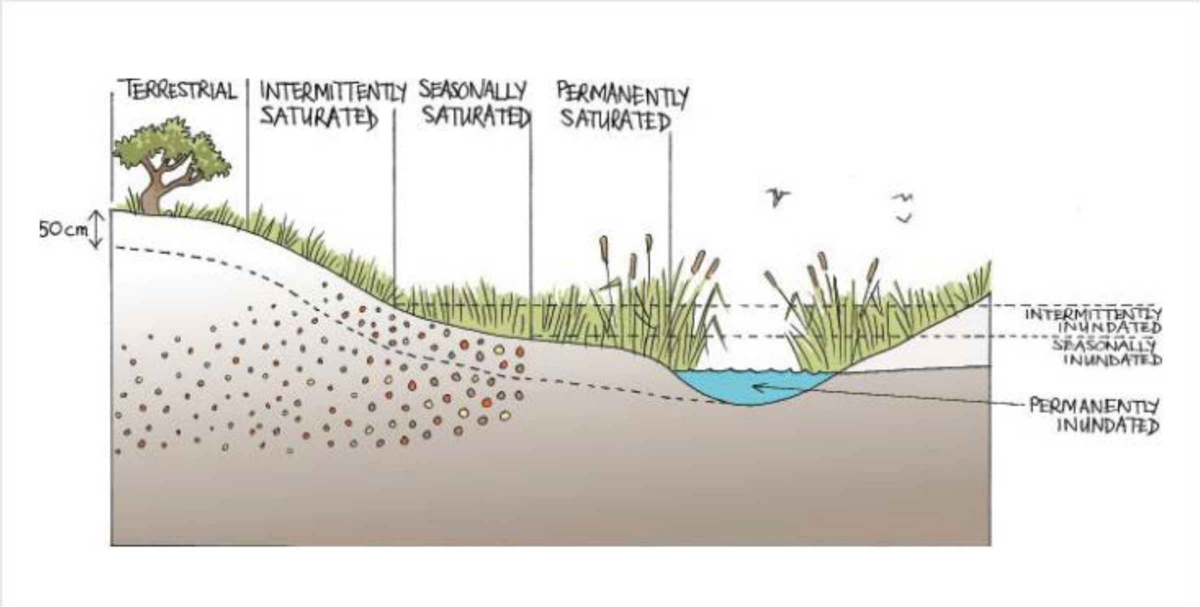

Figure 2: A diagram of a wetland representing the difference between the saturation and inundation zones (Source: Ollis *et al.,* 2013:41)

Variations in water depth, the level of inundation and duration of inundation influences the ecological function of wetlands and subsequently soil and vegetation characteristics (Collins, 2005). For example, permanently inundated zones of a wetland would host aquatic vegetation and gleyed soils, while seasonally inundated areas would host a mixture of wetland and terrestrial grasses. Delineation of wetlands through in-field assessment uses a combination of water, vegetation and soil characteristics to infer the long-term inundation or saturation zone of a wetland (DWAF, 2005).

2.1.2 Wetlands under pressure

Wetlands play a vital role in South Africa as they provide many ecosystem services (MEA, 2005; Kotze *et al.,* 2008; Working for Wetlands, 2008). They provide habitats for plant species, aquatic species and wildlife; they act as water storage systems and reduce peak runoff; they recharge groundwater and function as water filters; they provide nutrients and minerals and; they provide numerous recreational activities (Wu, 2018). However, in the face of global climate change, these ecosystems are highly threatened and evidently can be observed through alterations in the hydrological regime (Erwin, 2009).

Global climate change is a major concern in South Africa. The main drivers of climate change are temperature, precipitation and evapotranspiration (Dallas and Rivers-Moore*,* 2014). According to the 2014 South African Long Term Adaptation Scenarios and the Fifth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC, 2014), temperatures will increase by 3—6 ^{o}C by the year 2081 in the interior (Ziervogel *et al.,* 2014). These will impact the hydrological cycle and subsequently change the structure and functioning of wetlands and in turn the goods and services they offer. Water quantity, water quality, habitat with associated fauna and flora are likely to be affected by global climate change. For example, if there is an increase in water, it could destabilise the ecosystem because some fauna and flora cannot adapt to specific water temperatures and this could lead to a loss in plant and animal species (Poff *et al.,* 2002; Mitsch *et al.,* 2009).

The majority of wetland ecosystems have been degraded or lost through anthropogenic activities (Frenken, 2005). Water abstraction reduces the amount of water available for wetland ecosystems support and can lead to altering water flow direction (Davies *et al.,* 1998). Agricultural practices, such as the spraying of pesticides or overgrazing from cattle and water abstraction, cause disturbances and changes in the soils and vegetation conditions of wetlands. Also, due to water being used from wetlands for irrigation purposes, this leads to the disturbance of how precipitation is routed to wetland catchments and causes a change in the water budget or water cycle (Voldseth *et al.,* 2007). Mitigating the effects of anthropogenic activities will lead to increased resilience of wetlands in order to continue to provide essential ecosystem services under climate change (Kusler *et al.,* 1999; Ferrati *et al.,* 2005).

Despite the importance of wetlands, it has been estimated that 64% of the world's wetlands have disappeared since 1900 (Ramsar Convention, 2009). Roughly 50% of wetlands in the Umgeni catchments of South Africa have been lost (Begg, 1988). According to the 2011 National Biodiversity Assessment (NBA 2011), 65% of the country's wetland types are under threat (48% critically endangered, 12% endangered and 5% vulnerable) (Nel and Driver*,* 2012). In addition, the NBA 2011 found that only 11% of wetland ecosystem types were well protected, with 71% not protected at all. However, the extent of all wetlands, as well as the rate of loss, is unknown and it is estimated that the National Wetland Map (NWM) used for the NBA 2011, represented < 54% of wetlands mapped at a fine scale (Van Deventer *et al.,* 2016). Knowledge on the extent and type of wetlands is crucial for the management and protection of wetland resources, especially in a semi-arid country like South Africa where water is scarce. Therefore, developing a wetland inventory is essential for reasons of acquiring knowledge on the distribution and extent of wetlands and monitoring their hydrological characteristics.

2.1.3 Inventorying and monitoring of palustrine wetlands in South Africa

South Africa, as a signatory to the Ramsar Convention, has an obligation to manage and protect its wetland resources. The South African Department of Water and Sanitation developed a National Aquatic Ecosystem Health Monitoring Program in the 1990s, in which all inland aquatic ecosystems were to be maintained and monitored (DWAF, 2006). The extent of inland wetlands and estuaries are represented in the National Wetlands Map (NWM) and its updates, attempting to aim for the maximum extent of inundation. However, a lack of basic knowledge on the extent and distribution of inland wetlands still existed. Initial assessments of omission errors of the NWM identified those in the savannah or woodlands of the KwaZulu-Natal, Limpopo and Mpumalanga provinces (NLC2000 management committee, 2008), whereas more recent estimates are linked to various biomes, but more specific to palustrine wetlands (Van Deventer *et al*., 2018b). Full representation of the extent of wetlands is crucial for prioritising areas in a monitoring system for *in situ* measurements. South Africa's National Wetland Monitoring Programme (NWMP) was conceptualised in 2013 through a project funded by the Water Research Commission (WRC) developed a project titled, 'The Design of a National Wetland Monitoring Programme (NWMP) (Wilkinson *et al.,* 2016). Although the NWMP framework considered the use of hydrological parameters such as SMC to detect the extent of palustrine wetlands, remote sensing was not considered in any of the methods discussed (Wilkinson *et al.,* 2016). If remote sensing can detect and monitor the inter- and intra-annual variation in SMC of palustrine wetlands, it would contribute towards a better representation and understanding of the variability of the hydrological regime of inland wetlands in South Africa.

Various methods can be used to map palustrine wetlands. Field-based methods of measuring SMC are spatially the most accurate way of delineating acquired data, however, it is limited to a single snap-shot in time. Repeat visits are required to characterise the hydrological regime and other characteristics of the wetland rendering it as impractical, labour intensive and time-consuming when attempting a regional scale survey. Remote sensing, on the other hand, can provide a regional overview of the landscape and is a cost effective approach compared to field-based surveys and monitoring (Ozesmi and Bauer*,* 2002). For example, Henderson and Lewis (2008); Zhao *et al.* (2015) and Pekel *et al.* (2016) have compiled extensive reviews on studies in which contained reference to wetland detection focusing primarily on using medium spatial resolution (> 10 m) C-band SAR (e.g. ERS or SIR-C) and optical remote sensing (e.g. Satellite Pour l'Observation de la Terre (SPOT) or Landsat) and where soil moisture was used, vegetation type served as a proxy to infer soil saturation.

To date, the coarse spatial resolution of space-borne sensors, as well as limitations in the spectral bands, limited the detection and mapping of palustrine wetlands in South Africa. For instance, different inland wetland types such as lacustrine and palustrine, may display similar spectral or backscattering signatures in remote sensing imagery, due to similarities in their vegetation cover, such as reeds and grass sedges these wetlands hold (Amani *et al.,* 2017). In the grassland biome of South Africa, the boundary between palustrine wetlands and terrestrial areas are much more gradual and therefore becomes more challenging to use vegetation as means of delineating or determining a cut-off, as has been used in previous literature. Therefore, using remote sensing technology with medium to high spatial and temporal resolution coupled with a multi-temporal approach to monitor soil moisture would be able to provide much more information and insight to the hydrological regime of palustrine wetlands. Vegetation could be incorporated in the estimation of soil moisture (Haas, 2016).

2.2 Soil moisture content

2.2.1 The role of soil moisture content in wetlands

Soil moisture plays a major role in the climate system and was recognised as an Essential Climate Variable (ECV), defined by the Global Climate Observing System (GCOS) in 2010 (GCOS, 2010). It assumes the role of an important variable in hydrology, climatology and meteorology (Legates *et al.,* 2010). Precipitation and ground water percolates the soil and either goes deep into the soil layers or stays in the soil surface, depending on the substrates (Esch, 2018). In general, soil moisture content (SMC) is water that is contained in the spaces between soil particles, against gravity (Arnold *et al.,* 1999; Pitts, 2016). In the geosciences field, the surface of the soil is regarded as the top 2.5 cm to 10 cm deep (Bulfin and Gleeson, 1967; Shaver *et al.,* 2002). SMC is variable in both space and time even within a few meters (Buttafuoco *et al.,* 2005; Seneviratne *et al.,* 2010). The spatial variability of SMC often follows terrain and vegetation canopy cover which is linked to water-holding capacity. Other contributing factors such as precipitation and evapotranspiration influences the spatial and temporal distribution of SMC, especially in semi-arid countries where there is a fluctuation in precipitation and evapotranspiration (Mohanty and Skaggs, 2001; Lam *et al.,* 2007).

Soil moisture takes on an integral role in shaping the functioning of a wetland's ecology. It is a determining factor in the interaction between land surface and atmosphere through evaporation (Dente, 2016). It modulates plant transpiration and soil evapotranspiration and controls the division of precipitation into runoff and ground water storage. Furthermore, it supports vegetation species (Trasar-Cepede *et al.,* 2008). Monitoring SMC would assist in the detection of palustrine wetlands as well as general wetland health. Information on long term spatial distribution of SMC can aid in monitoring the impacts that climate and global change have on these ecosystems (Brekke *et al.,* 2009).

With the aim of improving the detection and characterisation of palustrine wetlands, a monitoring system which is as accurate as possible, reports as quick as possible and provides continuous time-series data of soil moisture, is required. Several methods exist to measure soil moisture content, ranging from tools to measure soil moisture in-field, to laboratory assessments and estimations derived from satellite images, taken by remote sensors. The following subsections discuss the different methods which can be used.

2.2.2 In situ soil moisture measurements

In situ SMC measurements can be acquired directly or indirectly. The standard gravimetric method is considered as a direct measurement and requires numerous samples to be taken across large areas in order to capture the variation in SMC. The samples are then taken to the laboratory for analysis. The Gravimetric method is the basic measurement of soil moisture of known weight or volume, on soil samples. Physical soil samples are extracted at a desired depth and location where the soil samples are taken to the laboratory for evaluation. They are weighed before being dried in an oven for 24 hours at 105 °C (Schmugge *et al.,* 1980). After the drying period, the samples are weighed again and the difference in weight is calculated as the amount of moisture in the soil. Soil moisture content based on weight is defined in Equation 1. Gravimetric soil moisture can be converted to volumetric soil moisture. Soil samples are collected with a tube auger or a core sampler where the volume of the samples is already known. The amount of water that is contained in the soil samples are estimated by drying it in an oven and calculating the moisture content. Soil moisture content based on weight is defined in Equation 2.

Equation 1: Gravimetric method equation (Black, 1965).

$$Moisture\ content\ (\%) = \frac{Wet\ weight - Dry\ weight}{Dry\ weight}\ x\ 100$$

Equation 2: Volumetric Water Content equation (Black, 1965).

$$Moisture\ content\ (\%) = moisture\ content\ (\%)\ by\ weight\ x\ bulk\ density\ (\%)\ by\ volume$$

Depending on the soil type and the number of point measurements to represent variability, other methods such as neutron scattering or tensiometers can be used to measure SMC in the field. Neutron probes make use of high energy neutrons which are lowered into the ground through a tube and measures the slow backscattered neutrons. A detector counts how many neutrons are slowed down by colliding with hydrogen particles present in the soil water. A relationship with volumetric soil water content is achieved when the slow neutrons are calibrated with gravimetric soil moisture samples and bulk densities (Vachaud *et al.,* 1977). Radioactive scattering takes place across a spherical shaped tube, therefore, the neutron probe will measure a volume sized sample instead of a point. The depth resolution of the neutron probe influences the large volume sampled, making it prone to errors due to adjoining air also being sampled (Dorigo *et al.,* 2010). The neutron probe requires repeated calibration which makes it time consuming, it is also considered a health hazard due to the radioactive material used in the probes (Puri, 2009). The principle of a tensiometer instrument is based on measuring the tension of water trapped in the soil. The tension to hold water particles in the soil is less in saturated conditions, and as the water gets depleted the tension increases as the soil particles hold on to the water. The instrument consists of a liquid-filled ceramic cup that is attached to a vacuum gauge. When the cup is submerged into the soil it fills up with liquid until the pressure from the liquid reaches equilibrium with the pressure from the cup. The readings it gives range from a unit of zero for saturated soil and drier soils are recorded at approximately 85 units.

In contrast to direct methods of measuring SMC, indirect methods require an instrument to be placed in the ground to measure soil properties that are related to soil moisture. Dielectric properties of the soil help to obtain soil moisture content measurement due to the large differences between the relative dielectric properties of liquid water (roughly 80) and dry soil (2 to 5) (Schmugge, 1985; Engman and Chauhan, 2016). When an element is inserted into a condenser's electrical field, it influences the electrical forces within that field and is expressed as the ratio between the force in the element and the force which would exist in the space. This ratio is known as the 'dielectric constant (ε)' and accounts for approximately 20 times more water than the average dry soil, due to the fact that water molecules retain permanent dipole moments. Because of the dielectric properties water can be compared to those of dry soil, the Volumetric Water Content (VWC) can be measured from the dielectric characteristics. This is a reliable and non-destructive method because it preserves the soil water structure. Indirect methods can determine the volumetric soil water content without the need for determining the soil density (Zhang and Zhou, 2016).

Common indirect methods that are used to estimate SMC in the field are acquired from time-domain reflectometry or capacitance frequency-domain reflectometry (TDR). Time-domain reflectometry measures the dielectric permittivity of a medium (in this case, soil) by calculating how long an electromagnetic wave will take to travel along a probe which is surrounded by the soil. The time period measured is then translated and related to the electrical conductivity of the soil (Puri, 2009). Basically, TDR is based on the principle where the bulk electrical permittivity (εb) of the soil is measured and determined as a function of electrical wave velocity. The VWC is derived from the length of the electromagnetic waves travelling through the probes (Topp *et al.,* 1980). The relation volumetric water content (ε) is measured for different soil types, referred to as the *Topp equation* (Equation 3).

Equation 3: Topp's equation for measuring soil water content (Topp *et al.,* 1980).

$$\theta = -5.3\ x\ \ 10^{-2} + 2.92\ x\ 10^{-2}\ \varepsilon b - 5.5\ x\ 10\ ^{-4} \varepsilon b^2 + 4.3\ x\ 10^{-6} \varepsilon b^3$$

Where: $\theta = dialectric\ content\ or\ water\ content$; $\varepsilon b =\ permettivity$

Frequency-domain reflectometry is a sensor that measures the dielectric constant of SMC. This instrument is comprised of an open-ended coaxial cable and a single reflectometer, situated at the probe tip, of which the dielectric constant is measured at a particular frequency. Soil measurements are referenced to air, and are usually calibrated with dielectric liquids of known dielectric properties. An advantage of using liquids for calibration is that it is possible to maintain a perfect electrical contact between the tip of the probe and the material (Jackson, 1980). However, only a small volume of soil is estimated at a time, due to a single small probe tip that is used, and therefore soil contact is essential.

Frequency-domain reflectometry sensors measure the dielectric constant from an open-ended coaxial cable and from a single reflectometer at the tip of a specified frequency. Soil measurements are referenced to air and are usually calibrated with known dielectric properties dielectric liquids. An advantage of using liquids for calibration is that the electrical contact is perfect.

The ThetaProbe works in a similar way in the sense that it measures the VWC using a well-established method in which changes in the dielectric constant is detected (Ventrella *et al.,* 2008). The pins on a ThetaProbe detect these changes, which are converted into a direct current (DC) voltage, in the same manner as a radio frequency is transmitted, and is reflected by the soil (Ventrella *et al.,* 2008). The handheld device displays the percentage VWC readings.

Direct and indirect methods are considered the best way to measure SMC due to its ability to acquire accurate and detailed information about soil characteristics and to estimate SMC at different depths (e.g. 5, 10, 20 or 50 cm) (Majone *et al*., 2013). Direct methods, unlike indirect methods, are relatively inexpensive, however, due to its sampling procedure, it is rendered as a destructive method and potential errors can arise from sample transporting and constant weighing. The biggest limitation of in-field approaches to measuring SMC is carrying out repetitive measurements at a regional scale which is time consuming and impractical, especially when sampling in areas that are difficult to access, such as palustrine wetlands.

Ranges of the percentage of VWC (%VWC) have been recorded in various studies for terrestrial and wetland areas. For instance, in Paloscia's *et al.* (2013) study, mean *in situ* soil moisture measurements ranged between 35 %VWC to 40 %VWC, measured during the peak growth period, over a terrestrial area covered by dense grasses, in Northern Italy. Holtgrave *et al*. (2018) also recorded %VWC for their study area in Germany, over a grassland covered floodplain of which > 50 % VWC was measured during summer (growth period). Similar trends were found in Lang *et al.* (2007) in which mean %VWC of 59 % and 24 % were recorded for wetland and terrestrial areas, respectively, in a coastal plain of the United States of America. Based on these studies, there appears to be a possible trend in %VWC being > 50% for palustrine wetlands, irrespective of climatic regions and terrains.

2.3 Remote sensing approaches for estimating near surface soil moisture content

Remote sensing is a method of obtaining information on the nature, properties or state of an object by not having direct physical contact with the object (Lillesand *et al.,* 2008). Imaging radar sensors are divided into airborne and space-borne sensors based on which platforms are used. Airborne sensors are carried by platforms within the Earth's atmosphere (e.g. aircraft), whereas space-borne sensors use platforms that exist outside the earth and are carried on-board a spacecraft or space-shuttle. Airborne sensors are extremely flexible in terms of spatial resolution, spectral range and temporal coverage, however, extensive planning is required for airborne surveys and acquiring an image is very costly. Space-borne sensors offer medium to high spatial and temporal images which is useful for time-series research, and acquiring imagery is less complicated (Haji Gholizadeh *et al.,* 2016).

The main advantage of remote sensing over conventional methods of measuring SMC, is that remote sensing can provide regional estimates of soil moisture at regular temporal intervals. Continuous coverages further make it possible to generate global maps of SMC which could provide information on the effects of climate and global change on wetlands (Seneviratne *et al.,* 2010). To date, a number of studies have shown that soil moisture can be retrieved through different technologies of remote sensing such as optical, thermal infrared and microwave (MW) remote sensing (e.g. Mattia *et al.,* 2009; Jagdhuber *et al.,* 2013; Zhang *et al.,* 2016; Peng *et al.,* 2017). The primary difference between these technologies include the wavelength of the electromagnetic spectrum that is used, the source of the electromagnetic energy and how the signal of the sensor responds to the soil moisture content (Wang and Qu, 2009). Table 2 is a summary of the merits of each type of remote sensing sensor. Available sensors of different platforms offer different spatio-temporal, radiometric and spectral resolutions making SMC retrieval at a regional to global scale possible (Barret *et al.,* 2009; Barret *et al.,* 2012). Even though remote sensing has proven its potential to estimate SMC, *in situ* soil moisture measurements are needed for calibration and validation for satellite-based SMC retrieval.

Table 2: Summary of the advantages and disadvantages of each different remote sensing technologies method to in retrieving soil moisture content (Adapted from Barret *et al.,* 2012:87).

	Property observed	**Advantages**	**Limitations**
Optical	- Albedo (soil reflection)	- High to medium spatial resolution (1.1 m - 30 m)	- Susceptible to cloud coverage and atmospheric effects - Cannot penetrate deeper than 5 cm of soil surface - Cannot penetrate vegetation cover
Thermal infrared	- Surface temperature	- Medium spatial resolution (> 10 m) - Large swath coverage - Frequency physics well understood	- Meteorological conditions - Topography - Vegetation cover (density)
Passive remote sensing	- Brightness temperature - Dielectric properties - Soil temperature	- Low atmospheric noise - Moderate vegetation penetration	- Roughness - Vegetation cover - Temperature - Low resolution
Active remote sensing	- Backscatter coefficient - Dielectric properties	- Low atmospheric noise - High spatial resolution	- Roughness - Surface slope - Vegetation cover

Several studies showed that remote sensing can be used in the estimation of SMC (e.g. Wagner *et al.,* 2008; Pathe *et al.,* 2009; Su *et al.,* 2013,). Sensors that operate in the visible light region of the electromagnetic spectrum (Wavelength (λ) = 0.3—0.7 µm) measures the soil surface albedo. Reflected radiation of the sun from the earth's surface (albedo), allows visible or optical remote sensing to measure soil moisture, by knowing the relationship between reflected and incoming solar radiation. The increase of SMC results in a decrease of albedo. The reflected radiation is easily affected by the organic matter, soil texture, surface roughness, incidence angle and density of vegetation cover. Reflectance values represent the top few millimetres of the soil surface, furthermore, the reflected values are attenuated by atmospheric elements (Engman, 1991; Walker, 1999). Filion *et al*., (2016) investigated the potential of Landsat Thematic Mapper 5 (with a spatial resolution of 30 m) to generate reliable soil moisture maps. The research took place over non-irrigated arable lands in a semi-arid region of Italy. They tested the linear relation between measured soil moisture and estimated soil moisture using a cross validation method. The results demonstrated the potential of Landsat Thematic Mapper 5 to estimate surface soil moisture with a correlation coefficient (R^2) of 0.54 and Root Mean Square Error (RMSE) of 5 %. Their research also showed the reflectance to be most dominant in the near infrared (NIR) and red bands. In another study conducted by Muller and Decamps (2001), SPOT 1, 2 and 3 were used to acquire soil moisture reflectance values over arable soils (at the time when the crops were sewn) in Garonne valley, France. They obtained satisfactory results for each band with R^2 = 0.59; RMSE = 6 % for band 1 (green); R^2 = 0.57; RMSE = 6.1 % for band 2 (red) and; R^2 = 0.5; RMSE = 6.6 % for band 3 (NIR).

Thermal infrared sensors indirectly measure soil moisture content (SMC) through the soil surface temperature at wavelengths between 3.5 and 14 µm (Curran, 1985). It assumes areas with high levels of SMC emit less thermal radiation compared to areas that contain low SMC levels. Vegetation canopy cover (density) influences the sensitivity of the signal to SMC and the SMC data is representative of the top few millimetres of soil surface (Walker, 1999). A number of studies reported strong relations between SMC and thermal infrared estimations (Verstraeten *et al.*, 2006, 2008; Minacapilli *et al.,* 2009; Lu *et al.,* 2009). Up to the 1990s, studies using thermal infrared were conducted over bare and dry lands so as to avoid interferences of vegetation and evapotranspiration patterns (Price, 1985), however, recent studies demonstrated that thermal infrared could be used to estimate SMC over partially vegetated covered (Maltese *et al.,* 2003). Gao *et al*. (2013) used Landsat Thematic Mapper (TM) and Enhanced Thematic Mapper (ETM+) to determine a direct relation between soil moisture and soil reflectance from the red and NIR bands, for wheat crop fields in northeast Beijing, China. The results for this experiment gave good results for both bands, including the red (R^2 = 0.87) and NIR (R^2 = 0.85).

The abovementioned approaches display a potential for estimating near surface SMC under conditions where the area is sparsely vegetated to bare soil lands in order to minimise the influences of reflectance from vegetation on soil moisture estimates. A commonly used method to overcome the limitations of vegetation cover, is applying vegetation indices, to detect water or saturation levels beneath canopy cover. The Normalised Difference Vegetation Index (NDVI) was used in a number of studies in which all obtained satisfactory results of R^2 = 0.6 and RMSE of > 40 % (for example, Moreau *et al*., 2003; Takeuchi *et al*., 2003; Zoffoli *et al*., 2008). In the same study above, Gao *et al.* (2013) obtained a R^2 of 0.8 between ground measurements and SMC measurements estimated from ETM+ on Walnut creek, America using NDVI. The vegetation in their study area mainly comprised of corn and soybean and the remainder was made up of grass, alfalfa and trees. Most of these studies were conducted over large scale areas (> 30 m) suggesting the suitability of using optical and thermal remote sensing technologies for large scale studies. Moreover, the studies above detected or measured SMC using only single bands implying the use of band combinations is unnecessary.

MW remote sensing operates in the radiowave part of the electromagnetic radiation spectrum (λ = 1 m–1 mm) corresponding to frequencies between 0.3 GHz and 300 GHz. MW remote sensing is categorised into passive and active sensors depending on the source of electromagnetic radiation. Passive MW remote sensors require no external energy; they detect the natural emitted radiation from all physical objects that emit a temperature of 0 K. Active MW remote sensing, on the other hand, provides its own electromagnetic energy to measure the intensity of radiation that is reflected back from the earth's surface (Scott *et al.,* 2003). Microwave remote sensing has several advantages over optical sensors operating in the visible and thermal infrared portions of the electromagnetic system, particularly when estimating SMC in vegetated ecosystems (Smith, 1997). MW energy has a relatively low attenuation by vegetation canopy making it more sensitive to hydrological parameters (e.g. SMC, flooding) below, for example, a deciduous forest canopy cover (Hall, 1996; Kasischke *et al.,* 1997). The longer wavelengths of these instruments allow data to be collected independently of cloud cover, during night and daytime (Barret *et al.,* 2012).

The principle behind active and passive MW sensing of soil moisture is formulated on the large difference of dielectric properties between water (ε ≈ 80) and dry soil (ε ≈ 4). The large contrast in the dielectric constant in the soil varies and will cause the electromagnetic field to also vary when it passes through soil particles, air and water in the soil (Walker, 1999). By measuring the strength of the signal in the MW sensor, an amount of water content contained in the soil can be determined through the soil's dielectric properties (Schmugge, 1985; Engman and Chauhan, 1995). However, it becomes a challenge when distinguishing whether the MW signal is derived from the soil surface or from the actual soil water content itself. This is because of the influence on the signal from the sensor (wavelength and polarization), vegetation cover and surface roughness (Barret *et al.,* 2012). For example, the effects of vegetation cover on an active sensor's backscatter signal decreases with increasing wavelength (Figure 3). MW sensors used to retrieve SMC are acquired in different wavelengths that range from X-band (λ = ~3 cm), C-band (λ = ~5 cm) and L-band (λ = ~30 cm) (Moghaddam *et al.,* 2000). Sensors with a short wavelength (X-band = ~3 cm) are only able to penetrate into the top layer of the soil surface unlike longer wavelength sensors (L-band = ~30 cm) which are able to penetrate deeper into the soil surface (Wagner *et al.,* 2006).

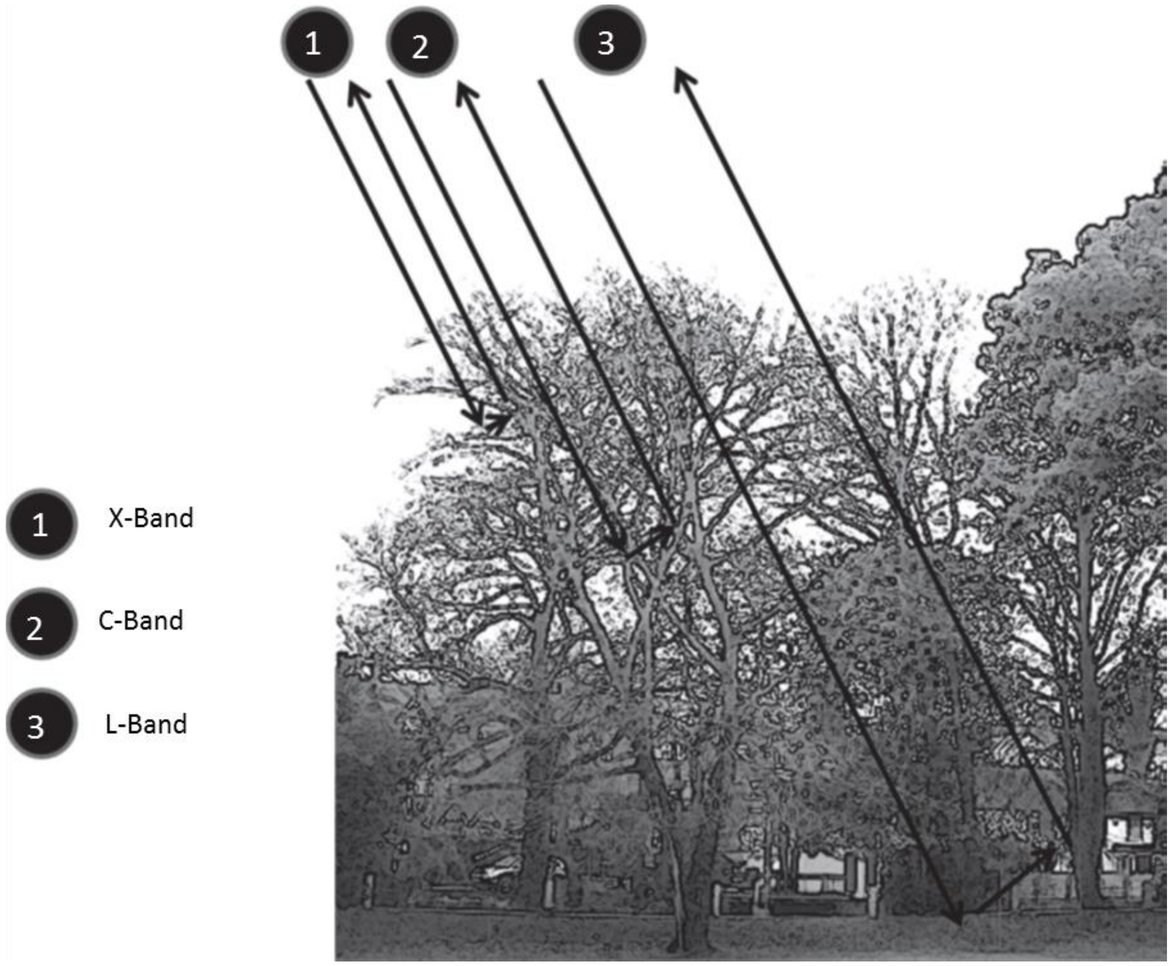

Figure 3:The shorter microwave wavelength (X-band, 3cm) interacts mostly with the top of the canopy cover, sensors with longer wavelengths (L-band, 24 cm) are able to further penetrate into the canopy and interact with the soil surface (adapted from Barrett and Petropoulos, 2012: 91)

Specific to retrieving SMC under vegetated areas, passive L-band MW sensors have displayed the potential to be more robust compared to active C-band MW sensors (Narvekar *et al.,* 2015). This is due to the scattering and attenuation from vegetation cover and surface roughness having very little influence on the lower frequency backscatter (L-band) as compared to higher frequencies (C-band) backscatter signal (Oveisgharan *et al.,* 2018). Currently, two space missions such as European Space Agency's Soil Moisture and Ocean Salinity (SMOS) and National Aeronautical and Space Administration's (NASA) Soil Moisture Active Passive (SMAP) offer 40 km to 50 km spatial resolution imagery with a short two to three days revisit time (Wagner *et al.,* 2006). Various research studies relating L-band radar data to soil moisture have been conducted, however, to date, most studies have focused on forests and occasionally agricultural areas. For example, a recent study by Al-Yaari *et al*. (2014), showed that L-band SMOS and C-band AMSR-E (spatial resolution of 25 km) were able to capture the variability of SMC in different biomes, climatic regions and soil conditions, spatially and temporally, although SMOS had better correlation values in densely vegetated biomes (e.g. tropical and temperate humid) compared to AMSR-E ($R = 0.64$ and $R = 0.15$, respectively). In a research study, Sanli *et al*. (2008) regressed RADARSAT-1, ASAR and PALSAR estimated backscatter against *in situ* soil moisture over Turkey. The results showed good accuracies of $R^2 = 0.76$, 0.81 and 0.86, respectively. From these studies, it is evident that the L-band sensors are most appropriate to estimate soil moisture under vegetated areas due to their advantage of wavelength and penetration depth. However, L-band passive MW sensors are characterised by broad spatial coverage, and course spatial resolutions (from tens of kilometres) (Barret *et al.,* 2012). Whilst this resolution is practical for global terrestrial application, it is not sufficient for estimating small features in the landscape and heterogeneous ecosystems, such as the palustrine wetlands in semi-arid regions (Entekhabi *et al.,* 1999; Crow *et al.,* 2000; Piles *et al.,* 2011). Palustrine wetlands in South Africa are small in extent and require high spatio-temporal resolution imagery in order to detect changes in SMC (Haas, 2016).

C-band data has been in operation since 1991 such as the European Remote Sensing Satellites (ERS) (Lang and Kasischke*,* 2008). C-band backscatter coefficient is mainly influenced by the scattering caused by canopy cover. This is due to the length of the MW wavelength in relation to the size, orientation and density of canopy that determines how deep the MW is able to penetrate (Lang and Kasischke*,* 2008). This coupled with the sensor's characteristics affects the MW transmission in dense vegetation cover (Lang and Kasischke*,* 2008). For instance, vertically transmitted and received (VV) MW energy is not able to readily penetrate through forests as compared to horizontally transmitted and received (HH) MW energy. This is because structures that are vertically orientated would interact more with the VV polarization mode and attenuate the penetration. Therefore, the HH polarization mode would be able to transmit through the vertically orientated structures and reach the surface where hydrological parameters such as inundation or SMC can be detected, particularly for biomass ≤ 1 kg/m^2 (Hess *et al.,* 1995; Wang *et al.,* 1995; Lang and Kasischke, 2008; Hornacek *et al.,* 2018).

Once the polarization energy is transmitted through the canopy it is able to interact with the surface, then the soil moisture can either increase double-bounce scattering, volumetric scattering or eliminate surface scattering (Figure 4) (Wang *et al.,* 1995; Kasischke *et al.,* 2003). Various studies investigated the response of backscatter to soil moisture. For example, Dabrowska-Zielinska *et al.* (2016) showed that VH obtained a better accuracy in estimating SMC with R^2 = 0.72 compared to VV with R^2 = 0.63 over an area comprised of grasses and sedges, using Sentinel-1 sensor. The results from another study done by Dabrowska-Zielinska *et al.* (2018) investigated the response of single polarization modes and cross-polarization modes, using Sentinel-1, at depths of 5, 10 and 20 cm over two types of vegetation (marshland and grassland) in the Biebrza wetlands, Europe. The results show that for the marshland area, the VH polarization mode achieved a Pearson's correlation (R) of 0.56; 0.46 and 0.59 and for the VV polarization mode, R = 0.55; 0.39 and 0.52. For the grassland area the VH polarization mode achieved an R = 0.55; 0.53 and 0.47, while for the VV polarization mode R^2 = 0.72; 0.69 and 0.55. In conclusion, using cross-polarization modes such as VH in general present higher coefficients of determination for grassland type vegetation in wetlands due to its ability penetrate the vegetation structure and interact with the soil surface.

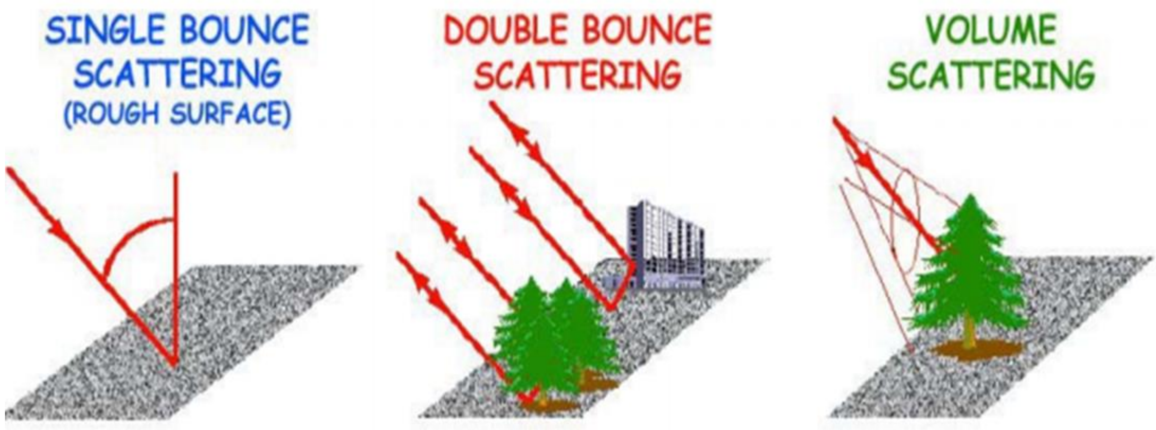

Figure 4: Three types of scattering (transmit and receive signals) depending on target (Source: adapted and modified from: Bai *et al*. (2017a:186).

In summary, L-band sensors have the advantage of detecting soil moisture in highly densely vegetated areas due to their longer wavelength and deeper penetration properties. However, L-band sensors are limited by their coarse resolution for certain sensors, for example SMOS; the revisit time, for example ALOS has a revisit time of 46 days; and the cost associated with acquiring the images, when it comes to estimating SMC in features with small extents, such as palustrine wetlands of semi-arid regions. The most common active remote sensor that has been tested to date, for estimating SMC in grasslands is the C-band Synthetic Aperture Radar (SAR) system (Wulf *et al.,* 2015). This is likely linked to the fact that the Sentinel sensors can provide imagery at a high spatial resolution of 10 m, making them more suited to quantify and map SMC for smaller features (Zhang *et al.,* 2017a). In order to monitor the hydrological regime in palustrine wetlands, especially in a semi-arid country, relatively high spatial resolution imagery is required at frequent revisit times. Since S1 has proven success in other grasslands and palustrine wetlands, as per the Dabrowska-Zielinska *et al.* (2018) and other studies, can it be used in South Africa for improving the detection and monitoring of palustrine wetlands in the grassland biome?

Sentinel-1A (S1A) which was launched on 3 April 2014 and Sentinel-1B (S1B) which was launched on 25 April 2016, uses two C-band SAR satellites that operate in Interferometric Wide Swath (IWS) mode with a high spatial resolution of 5 m x 20 m which images a wide swath in dual polarization. This includes VV and VH polarimetric modes. A few requirements for operational users include a high temporal sampling rate, near-real-time data availability and free and easy access. The temporal revisit time for S1 satellites is every five days, making it suitable for detecting changes in the hydrological period. Sentinel-2A (S2A) was launched on the 23 June 2015 and is an optical space-borne sensor. Multispectral Instrument (MSI) images are obtained in 13 spectral bands that range from visible, NIR to Short-wave Infrared (SWIR). The first four bands (at 10 m spatial resolution) traditionally provide information required for land cover classification; the next six bands (20 m spatial resolution) meet the basic requirements for vegetation studies while the last three bands (60 m spatial resolution) are used to measure atmospheric conditions (Drusch *et al.,* 2012). The advent of Sentinel-2B (S2B) on the 1 March 2017 implied an even shorter revisit time to five days. This means that from all the mainstream freely available satellites, to date, the Sentinel-2 series have the shortest revisit time.

In conclusion, a small number of studies have investigated the use of the Sentinel sensors to estimate SMC for grasslands and palustrine wetlands. To my knowledge, these include Dabrowska-Zielinska *et al.* (2016; 2018) in Europe; Bai *et al.* (2017b) over the Tibetan Plateau; El-Hajj *et al*. (2017) in France; Holtgrave *et al*. (2018) in Germany; and Möller (2014) in central region of Western Cape of South Africa. No studies have been undertaken in the grassland biome of South Africa, there has been no investigation of the use of Sentinel 1 and Sentinel 2 in palustrine wetlands in the grassland biome of South Africa.

Chapter 3 : MATERIALS AND METHODS

3.1 Study area

3.1.1 Description of study area

The study area is situated primarily within and around the Colbyn Valley Nature Reserve (CVNR) (25°44’30” S; 28°15’49” E), a municipal protected area of approximately 20.8 Ha, located within the City of Tshwane Metropolitan Municipality and the Gauteng Province of South Africa (Figure 5). The location of the CVNR is positioned within the grassland biome of South Africa and more locally within a residential urban area. The Hartebeesspruit River drains the catchment from the head of the watershed and flows in a northerly direction up to a dolerite dyke. The dolerite dyke forms a barrier on the northern side of the study area, and even though it has been breached by the River, water backs up south of the dyke, resulting in the formation of a channelled valley-bottom wetland. The restricted flow through the breach and the seeps from the adjacent hillsides contribute interflow from the sides contributing to the wetland (Grundling, 2015).

Most of the wetland remains permanently saturated throughout the hydroperiod and coincide with the centre part of the wetland where peat have accumulated (extent estimated at 4.68 Ha) (Delport, 2016). The peat is made up of medium fibrous reeds and sedges and accounts for much of the water-holding properties. Highly organic soils can be found in the permanently wet areas which display wetness approximately 50 cm from the surface and show hydromorphic characteristics such as mottling and high clay content (Venter *et al.,* 2016).

The site is exposed to a number of pressures and impacts. Drainage has been disrupted by numerous roads resulting in high energy runoff leading to erosion of the wetland (Sherwill, 2015). Weirs have been built along the channel to alleviate the effects of erosion in order to prevent further degradation of the wetland near the Koedoespoort Railway line causing soil compaction which could induce flooding in some areas, as well as altered drainage which could lead to a loss of recharge (DEA, 2015). These affects have a consequence on the wetland’s soil moisture regimes and plant species (Sherwill, 2015).

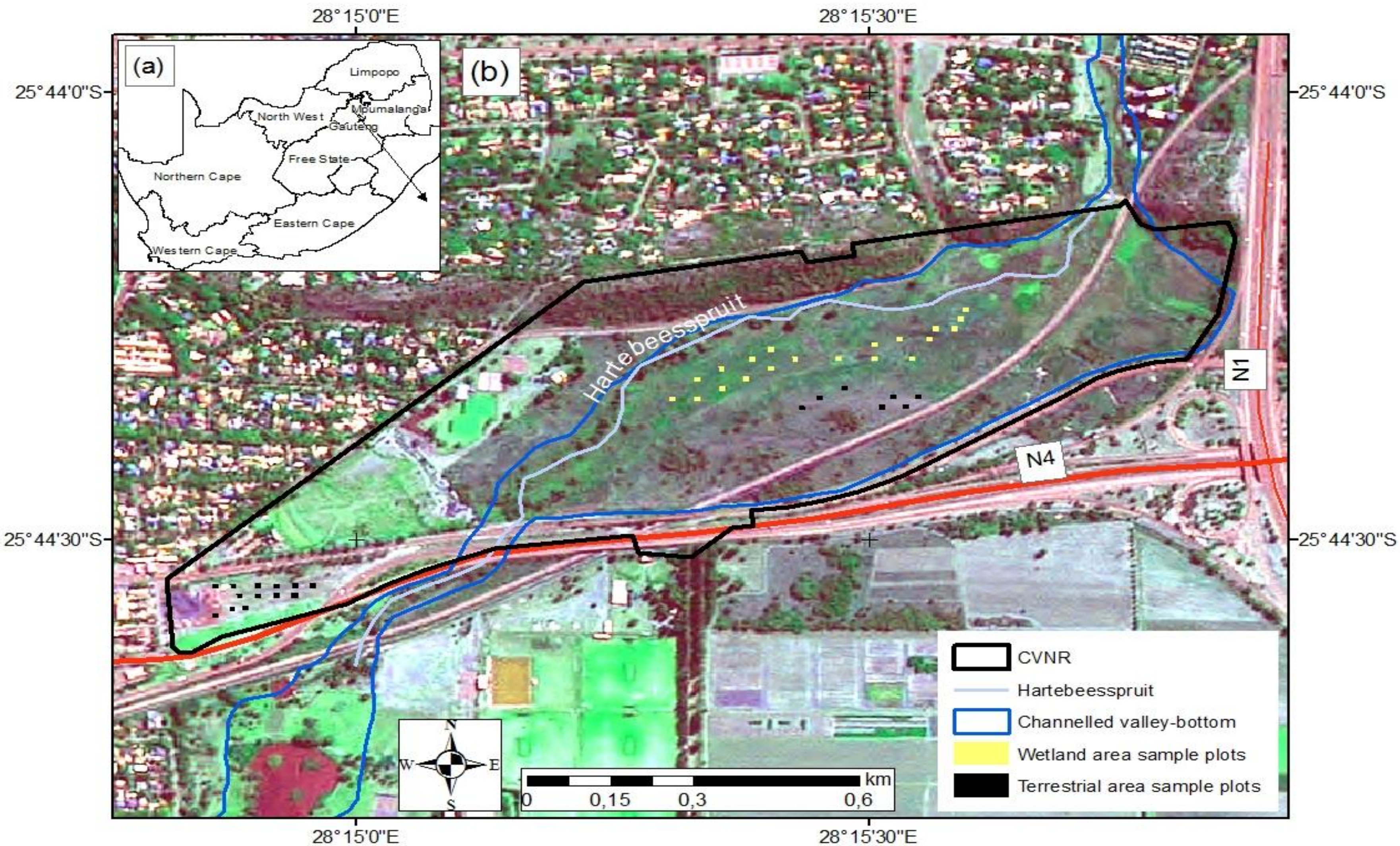

Figure 5: The location of the study area, the Colbyn Valley Nature Reserve (CVNR), is located within the Gauteng Province of South Africa (a). The CVNR hosts a channelled valley-bottom wetland (b) through which the Hartebeesspruit (River) runs. The location of sample plots is displayed in the wetland and terrestrial areas.

3.1.2 Climate

The study area is located within the Rocky Highveld region of the Grassland biome which encounters a mean annual temperature of 12-20 °C (Kleynhans *et al.,* 2005; Mucina and Rutherford, 2006). Geographically, the area is located on the Highveld Plateau between 1 335 m and 1 340 m above mean sea level and experiences a temperate climate with the rainfall season between September and March and the dry season between April and August. This ecoregion experiences an average summer rainfall between 650 and 750 mm per annum (Figure 6) and an evapotranspiration of 524 mm annually (ARC-ISCW, 2018).

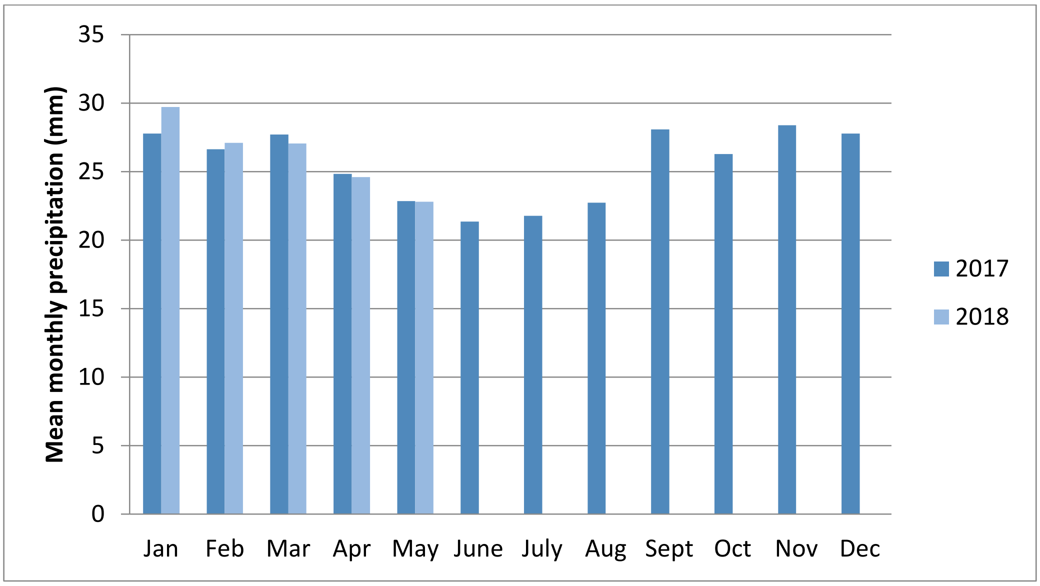

Figure 6: Mean monthly precipitation for 2017 and 2018 (especially during sampling periods) according to the Station 30687 situated in Pretoria, South Africa (ARC-ISCW, 2018).

3.1.3 Vegetation

The CVNR is considered a palustrine wetland type which is dominated by a variety of graminoids and sedges. The temporary saturated zones of the wetland are predominantly grass species such as *Imperata cylindrica,* which gradually flows into a sedge community under moister conditions, up to the permanently saturated zones with *Phragmites australis, Typha capensis* and *Carex acutiformis* (Venter *et al.*, 2016). The area along the river channel known as the riparian zone is marked by exotic riparian vegetation; most of which is in the form of trees (*Salix babylonica*) and the remainder of the study area is covered with vegetation throughout the year (Figure 7).

Figure 7: Vegetation found in the wetland area varying from *Typha capensis* to *Imperata cylindrica* during end of peak growing season (left and right, respectively).

3.2 Data collection

3.2.1 Image acquisition and pre-processing

Sentinel-1 SAR data acquisition and pre-processing

The Sentinel-1A (S1A) and Sentinel-1B (S1B) Synthetic Aperture Radar (SAR) C-band images were acquired in the Interferometric Wide (IW) swath mode, at 5 m by 20 m spatial resolution. The images were downloaded from the Copernicus website (https://scihub.copernicus.eu/dhus/#/home) (Table 3). The data were acquired in the vertical-transmit, vertical-receive (VV) and vertical-transmit, horizontal-receive (VH) polarization modes. S1A and S1B Ground Range Detected (GRD) data was pre-processed using ESA's Sentinel Application Platform software (SNAP) version 6.0 (2018) for radiometric calibration, multi-looking and terrain correction. Multi-looking was applied to each Sentinel-1 image to convert a 10 m spatial resolution image to 20 m spatial resolution image to reduce the speckle present in the images. Radiometric calibration of the Synthetic Aperture Radar (SAR) images converts the data from a digital number (DN) format to backscatter in *sigma naught* or *sigma dB*.

Errors associated with terrain, orientation and geo-referencing of the imagery were corrected with the Range Doppler Terrain Correction using the Shuttle Radar Topography Mission 3 (SRTM 3) arc-seconds 30 m Digital Elevation Model (USGS, 2004).

Table 3: Acquisition dates and times of the Sentinel 1A/1B and Sentinel 2A/2B images as well as the dates of ground measurements.

Sensor	Scene ID no.	Date (2018)	Time of overpass of sensor (GMT+ 2 hrs)	Hydroperiod
S1A	S1A_IW_GRDH_1SDV_20180326T164655_20180326T164720_021188_0246E	26 March	18:44	Peak
S1B	S1B_IW_GRDH_1SDV_20180328T033428_20180328T033453_010226_012958_A3E7	28 March	05:33	Peak
S2A	L1C_T35JPM_A014432_20180328T081650	28 March	09:45	Peak
S2B	L1C_T35JPM_A006024_20180502T081534	02 May	09:45	End

Sentinel-2 data acquisition and pre-processing

Sentinel-2 optical images were acquired as close as possible to the SAR images, though avoiding imagery with > 20% cloud coverage. The images were downloaded from the United States Geological Survey (USGS) Earth Explorer website (USGS, 2000) as ten individual spectral bands. Bands 2, 3, 4 and 8 are provided by ESA at a 10 m spatial resolution while bands 5, 6, 7, 8a, 11 and 12 are at 20 m spatial resolution (Table 4). Bands with a 60 m spatial resolution (bands 1, 9 and 10) are mainly used in atmospheric correction and cirrus-cloud screening and were not required for estimating the percentage Soil Moisture Content (%SMC). Three procedures were necessary for pre-processing the satellite images, (1) resampling the 20 m multispectral images to 10 m to maintain an image with the same spatial resolution and number of pixels. This higher spatial resolution image provides more detail for data extraction and modelling, required at the level of palustrine wetlands; (2) atmospheric correction, terrain and cirrus correction to Top-of-Atmosphere was applied to each image using the iCOR plugin in SNAP and; (3) a subset selection was applied to extract the study area.

Table 4: Spectral bands and associated wavelength ranges of the optical Sentinel 2A and 2B images (adapted from ESA Sentinel online, 2019).

		S2A		S2B		
Spatial Resolution (m)	Band Number	Central Wavelength (nm)	Bandwidth (nm)	Central Wavelength (nm)	Bandwidth (nm)	Use
	2	442.7	21	442.2	21	Aerosol correction, Land measurement
	3	492.4	66	492.1	66	Land measurement
10	4	559.8	36	559.0	36	Land measurement
	8	664.6	31	664.9	31	Land measurement, water vapour correction
	5	704.1	15	703.8	16	Land measurement
	6	740.5	15	739.1	15	Land measurement
	7	782.8	20	779.7	20	Land measurement
20	8a	832.8	106	832.9	106	Land measurement, water vapour
	11	864.7	21	864.0	22	Land measurement
	12	945.1	20	943.2	21	
	1	1373.5	31	1376.9	30	Aerosol correction
60	9	1613.7	91	1610.4	94	Water vapour correction
	10	2202.4	175	2185.7	185	Cirrus detection

3.2.2 In situ soil moisture measurements

Prior to sampling, several field visits were made to plan sampling positions in the wetland and terrestrial areas. The wetland and terrestrial areas were identified by characterising the nature of the soil, extracted from the ground using a soil auger; vegetation type such as the *Typha capensis, Phragmities* and *Imperata Cylindrica;* as well as the National Wetlands Map 5 (NWM5). The duration of the sampling period was selected to coincide with the peak hydroperiod, which would help to detect the maximum level and extent of soil moisture in the wetland for wetland inventorying. A stratified random sampling method was chosen to collect *in situ,* percentage Volumetric Water Content (%VWC) measurements in the wetland and the terrestrial areas. The reason for the stratified random sampling was to ensure the point sample measurements are well distributed in order to represent the wetland and terrestrial sampling areas. Previously dated Sentinel images were downloaded and used to determine suitable positions for the sampling plots which were positioned to match both the Sentinel SAR and optical image. Therefore, a sampling plot the size of 10 m x 10 m was positioned within a 20 m x 20 m grid. There were forty sampling plots in total, 20 located in the wetland area and 20 located in the terrestrial area (Figure 5). For each sample plot, five replicate measurements of %VWC were recorded in order to capture the variation of the observed %SMC within the top layer of the soil surface (refer to Figure 8 for a representation of the sampling plots and *in situ* sampling measurements). This yielded a total of 200 readings for the terrestrial and wetland areas during each sampling campaign. The reason was to guarantee that a single field plot will have a corresponding S1 and S2 extracted data pixel.

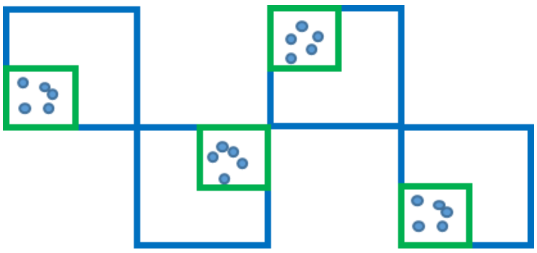

Figure 8: Diagram illustrating the planning of sampling according to the Sentinel 1 and 2 image pixels. The smalls (green) squares represent the in situ sampling measurements that were specifically located with both Sentinel 1 and Sentinel 2 pixels (blue outline) to ensure values could be extracted for both sensor's pixels.

Near-surface volumetric soil moisture content was acquired using a hand-held SMT-100 soil moisture and temperature probe (Sichuan Weinasa Technology Co., Ltd. 2017). The probe measures the %VWC at a depth of 5 cm. The centre and corners of each sample plot was mapped in ArcGIS version 10.5 (ESRI, 2016) and then uploaded to several e-Trex 30 Global Positioning Systems (GPSs) (GARMIN, 2011). The GPSs was then used to navigate to the same location for successive sampling campaigns. Previous studies recommended that ground measurements should be made within a two-hour window period around the sensor overpass time so as to minimise diurnal variation in soil moisture content and vegetation on radar backscatter (Möller, 2014; Baghdadi *et al.,* 2015;). Therefore, three probes were used by three teams, deployed to record the %VWC within a two-hour time period around the satellite overpass, including the hour before and after the time of overpass of each Sentinel sensor.

During the field campaigns, the vegetation height in various zones were randomly measured and recorded. The height of the vegetation in the terrestrial area, for example, comprised of short grasses with an average height of < 3 cm. The vegetation in the wetlands zone ranged from sedges and graminoids to macrophytes with an average height range between 1.5—2 m. The density and height of the vegetation in both zones varied little for the duration of %VWC data collection between March and May of 2018. The biomass of these grass and sedge communities where sampling took place considered to be ≤ 850 g/m^2 (Naidoo *et al*., 2019). According to Hornacek *et al.* (2018), vegetation and texture have very little impact on the %SMC modelling if grass vegetation is ≤ 1 kg/m^2. Consequently, no adjustments were made for vegetation or texture in the regression models used.

3.3 Data analysis

In order to assess the Sentinel sensor's capability to estimate the %SMC, backscatter from Sentinel-1A and 1B (S1A and S1B) and reflectance values for Sentinel-2A and 2B (S2A and S2B) were extracted from the respective images and regressed against the *in situ* %VWC measurements. The centre point recorded for each sample plot in shapefile format were used to extract backscatter values for VV, VH polarization modes as well as VV+VH as a modelling scenario, in ArcMap 10.5 (ESRI, 2016). Similarly, the spectral reflectance values of the optical sensors were extracted for all the bands, excluding bands 1, 9 and 10 (60 m resolution bands), individually as well as the combination of them, for the same points.

Factors such as precipitation, evapotranspiration, soil compaction and reflectance can influence the distribution of %SMC (Lu *et al.,* 2001). Therefore, the distributions of the *in situ %*VWC measurements were tested first for normality. By performing a normal-distribution graph in order to visualise the nature of the *in situ* data, one can determine whether parametric and non-parametric models are appropriate for assessing the senor's capability to estimate %SMC. The principle behind the parametric approach is that the model assumes normal distribution of the data, and therefore depends on mean and standard deviation statistics, whereas non-parametric analysis does not assume normal distribution. Spectral data is often found to be not normally distributed, and hence non-parametric approaches have previously been found to outperform the parametric approaches in remote sensing.

Parametric models repetitively selects features, randomly, which is then used in the regression, and the procedure is repeated with the remaining features in bootstrapping. This process continues until the combinations within the dataset are exhausted. The features are rejected and ranked accordingly and this will then provide the best results in terms of estimation accuracy (Ali *et al.,* 2015). Parametric models, such as simple linear regression, are simple and less complex in terms of tuning, but they use only a fixed number of input variables and thus can only be used if the data is assumed to be normally distributed.

Non-parametric analyses produce a model of multidimensional and non-linear relationships between the target (%SMC) and input variables (Attarzadeh *et al.,* 2018). Unlike parametric models, the number of input variables in non-parametric models is flexible and changes as it learns from the data and it makes fewer assumptions about the data (Ali *et al.,* 2015). This study could significantly gain from using non-parametric models due to its ability to undertake small training databases in order to perform a strong SMC retrieval. Ahmed *et al.* (2010) conducted a time series analysis from 1998-2005 using the Advanced Very High Resolution Radiometer (AVHRR). A Support Vector Machine (SVM) algorithm was employed to estimate %SMC on 10 sites comprised of low to dense vegetation, of which five years was used as the training dataset and the remaining three years was used to test the model. The correlation coefficients for the estimated %SMC ranged from 0.34 – 0.77 with an RMSE < 2% for all of the study sites, indicating the capability of the SVM model to capture the variability of measured %VWC. Several studies showed capabilities of both parametric and non-parametric approaches in estimating %SMC from both SAR and optical data with ranges of accuracies. In this study, both approaches were tested to assess whether any differences were noted in the results. The S1 backscatter values and S2 reflectance band values were regressed against the %VWC values (*in situ* measurements) using both parametric (Simple Linear Regression model or SLR) and non-parametric (SVM, Random Forest or RF) algorithms in the Waikato Environment for Knowledge Analysis (Weka) software version 3.8 (Eibe, 1999-2016). In another study, Srinivaso Rao *et al.* (2013) estimated %SMC using the modified Dubois Model (parametric model) over the agricultural lands in the region of India. The results were validated against *in situ* %VWC measurements. Their poorest fit was a correlation (R^2) of 0.46 over a densely vegetated area, $R^2 = 0.5$ was achieved over an area where the vegetation had reached the matured stage and the highest accuracy achieved was $R^2 = 0.77$ over an area with sparse vegetation with a mean height of 10 cm. Overall they obtained a RMSE of < 4.31 %. Their poorest fit was attributed to the intense vegetation coverage and heavy rainfall prior to sampling. Therefore, the differences in accuracies suggest that retrieving SMC if the data is normally distributed, i.e. no dense vegetation cover or heavy rainfall periods prior or during sampling periods, the use of parametric models would be appropriate.

A data split was used with 30 % data for the training dataset and 70 % for the validation dataset to test the best model for regressing the observed %VWC to the estimated %SMC. In addition to the data split approach, a cross-validation procedure was also performed to evaluate the best-fitting models. The purpose of including the cross-validation method is because it is appropriate for scenarios where the dataset may be too small. Individual polarizations and bands, as well as a combination of the polarizations and all bands have been evaluated for each sensor in predicting %SMC. The sensor, algorithm and variables which can predict %SMC with the highest coefficient of determination (R^2) and lowest the Root Mean Square Error (RMSE) were considered the best to use for producing a predicted %SMC map for each of the Sentinel (SAR and optical) sensors (Figure 9).

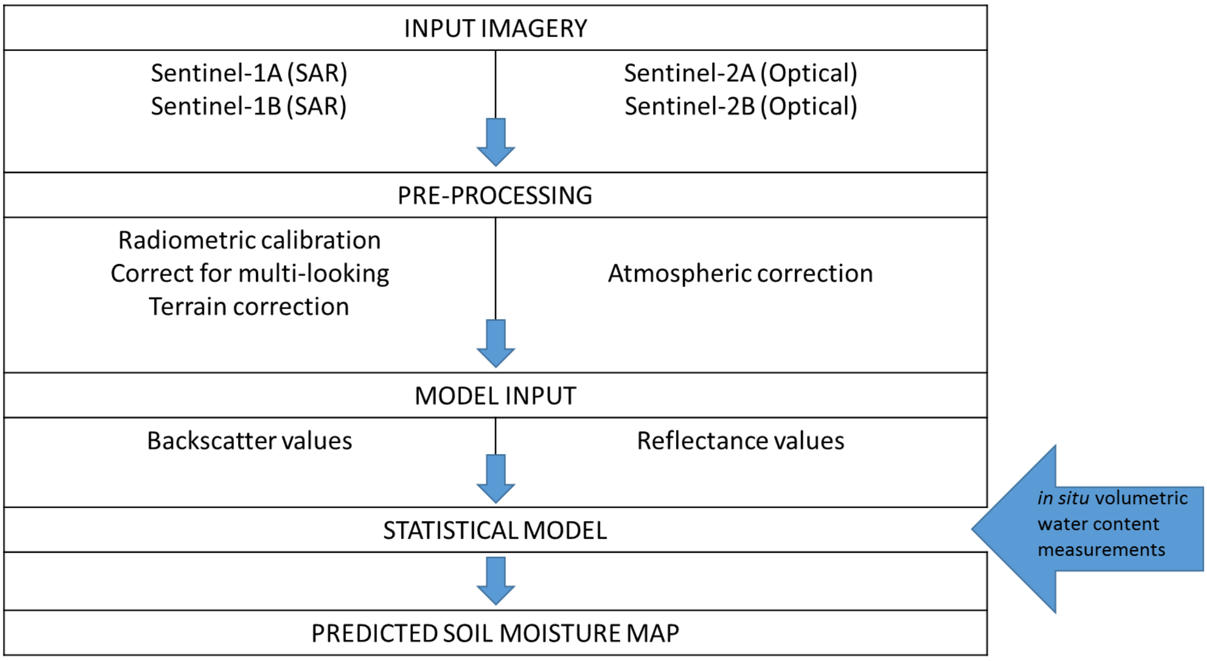

Figure 9: Flowchart illustrating the different stages of the overall procedure and methodology to generate the final outcome of a predicted percentage Soil Moisture Content (%SMC) maps.

Data from both the *in situ* %VWC measurements and predicted %SMC maps were used to assess the differences in SMC. The 200 points collected across wetland and terrestrial areas were used to test a significant difference by conducting a Welch two sampled t-test in RStudio version 1.1.456 (Rstudio, Inc., 2009-2018) at a 95% confidence interval. If significant differences between these plots were found, a threshold of %SMC could be selected to distinguish the wetland extent from the terrestrial extent. For wetland mapping, the criteria used to set a threshold were based on the principle of mapping the maximum extent of soil saturation of the wetland across multiple hydroperiods (Van Deventer *et al.,* 2018b). Following the examples of thresholds discussed in Chapter 2, it is likely that a threshold close to ±45 %VWC can be used to determine the extent of terrestrial area and ±50 %VWC can be used to determine the extent of wetland area based on studies conducted over grasslands done by Paloscia *et al*. (2013) and Holtgrave *et al*. (2018). In this study, a threshold was chosen based on the average mean %VWC across the terrestrial and wetland areas, however, were informed by a single season sampling to demonstrate the concept. The threshold were then applied to the predicted %SMC map and compared to the extent of the wetlands digitised by wetland experts in the National Wetland Map version 5 (NWM5) (Van Deventer *et al.,* 2018b). The extent of agreement and differences in wetland extent, in terms of their percentage of the extent of the study area, were explored between these two datasets to inform wetland inventorying.

Chapter 4 : RESULTS

4.1 Descriptive statistics analysis and normality testing for *in situ* volumetric water content measurements

The maximum percentage Volumetric Water Content (%VWC) was measured at 100 % while the minimum was measured at 4.5 % (Table 5). The range illustrates the spatial distribution of soil moisture across terrestrial and wetland areas for March and May 2018. Although there is noticeable variation across the study site, the standard deviation as a function of soil moisture indicates a relatively wide variability at 37 %. The distribution of the *in situ* %VWC measurements and the estimated percentage of Soil Moisture Content (%SMC) was not normally distributed (Figure 10). The non-normality was caused by the skewness to the right for *in situ* %VWC measurements measured on the 28 March 2018 and skewed to the left for *in situ* measurements at the time of the Sentinel-2B overpass on the 2 May 2018.

Table 5: Descriptive statistical analysis illustrating the variability of soil moisture across the study site during the March and May 2018 sampling campaigns

	Observed percentage of Volumetric Water Content (%VWC)
Number of samples (in total for 28 March 2018 and 2 May 2018 sampling campaigns)	400
Mean	61
Minimum	4.5
Maximum	100
Standard Deviation	37

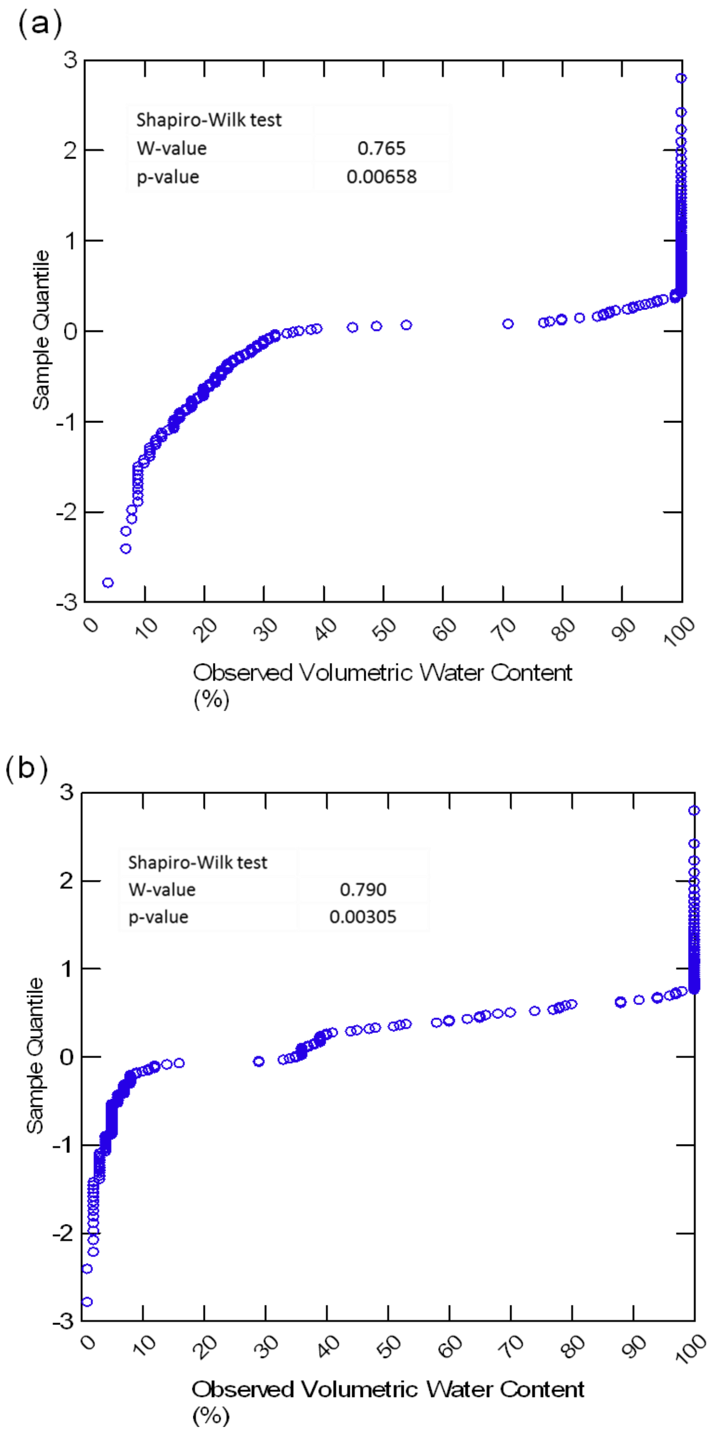

Figure 10: Graphs showing the distribution of the percentage Volumetric Water Content (%VWC) for (a) 28 March 2018 and (b) 2 May 2018. The results from the Shapiro-Wilk test indicates the *in situ* percentage Volumetric Water Content is not normally distributed ($p < 0.05$).

4.2 Ability of Sentinel-1 and Sentinel-2 to estimate soil moisture content

The Sentinel sensors were capable of predicting the %VWC with correlation coefficients (R^2) > 0.7 and RMSEs < 17 %. Of the four sensors, Sentinel-1B (S1B) produced a high correlation coefficient (R^2) of 0.92—0.94 and the lowest Root Mean Square Error (RMSE) of 10 %. Sentinel-2B (S2B) achieved the second-highest results with an R^2 of 0.92—0.94 and RMSE of 12 %-14 %. Sentinel-2A (S2A) produced slightly better results (R^2 = 0.8—0.86; RMSE = 15 %—16 %) than Sentinel-1A (S1A) which resulted in the lowest R^2 of 0.76—0.8 and highest error at RMSE = 13 %—17 % (Table 6).

Of the three polarization modes (vertical-receive, vertical-transmit (VV); vertical-receive, horizontal-transmit (VH); and VH+VV associated with the two Sentinel-1 (SAR) sensors the VH polarization mode and the VH+VV modelling scenario yielded higher accuracies (R^2 > 0.72) and lower errors (RMSE < 19 %) compared to the VV polarization (Table 6). S1B showed the highest coefficient of determination (R^2 > 0.9) when the VH polarization and VH+VV modelling scenario were used, with an RMSE of 10 % in both instances. The results for S1A were slightly lower at R^2 = 0.79 and a slightly higher RMSE of 13 % for VH and 16 % for VH+VV modelling scenario. The single VV polarization showed the lowest coefficient of determination and highest error (R^2 = >0.2; RMSE = >35 %) for both of the Sentinel-1 sensors. The VH polarization mode, however, contributes more to the accuracies of the combined VH+VV modelling scenario inputs than the single polarization (VV) mode.

A combination of all the bands for the optical sensors S2A and S2B, in general, resulted in high accuracies (R^2 > 0.7 and RMSE < 20%) across algorithms and validation approaches (Table 6). Some exceptions are evident where the use of the blue, green, red and vegetation red edge (VRE) bands produced comparable results to the combined bands, most noticeably when the RF algorithm is used (R^2 = 0.8 for S2A, or even higher for S2B (R^2 > 0.84). Five of the individual bands resulted in high coefficient of determinations in estimating %SMC (R^2 = >0.9; RMSE = 12%), namely, blue (band 2:496–492 nm), green (band 3: 560–559 nm), red (band 4: 664–665 nm), NIR (band 8: 833–835 nm) and SWIR (band 12: 2185–2204 nm).

When comparing the modelling approaches, the non-parametric Random Forest (RF) algorithm outperformed the parametric Simple Linear Regression (SLR) and non-parametric Support Vector Machine (SVM). RF achieved ranges of the coefficients of determination from $R^2 = 0.58$ to $R^2 = 0.94$ and RMSE values between 10 % and 24 % (Table 6). In contrast, SVM had lower accuracies ranging from $R^2 = 0.01$ to $R^2 = 0.66$ and RMSE values between 24 % and 50 %. The SLR algorithm showed similar ranges of coefficients of determination to that of the non-parametric SVM algorithm (from $R^2 = 0.01$ to $R^2 = 0.6$) and RMSE values ranging from 29 % to 40 %. The data split method, in general, showed better results ($R^2 = \geq 0.1$; RMSE = ≤ 41 %) as compared to the cross validation method ($R^2 = > 0.5$; RMSE = ≤ 50 %).

Table 6: Comparison of the different modelling approaches and validation models, using coefficient of determination (R^2) and Root Mean Square Error (RMSE) between the percentage Volumetric Water Content (%VWC) and predicted percentage of Soil Moisture Content (%SMC), across the four Sentinel sensors evaluated, using simple linear regression, support vector machine and random forest modelling algorithms. S1A = Sentinel 1A; S1B = Sentinel 1B; S2A = Sentinel 2A; S2B = Sentinel 2B; VV = vertical-receive, vertical-transmit; VH = vertical receive, horizontal-transmit; VRE = Vegetation Red Edge; SWIR = Short Wave Infrared; SLR = simple linear regression; SVM = support vector machine; RF = random forest.

		SLR				***SVM***				***RF***			
		Data Split		Cross validation		Data Split		Cross validation		Data Split		Cross validation	
		R^2	RMSE	R^2	RMSE	R^2	RMSE	R^2	RMSE	R^2	RMSE	R^2	RMSE
S1A	VV	0.01	40	0.04	36	0.01	50	0.18	39	0.58	24	0.76	17
	VH	0.10	34	0.09	25	0.10	35	0.15	35	0.72	19	0.79	13
	VV+VH	0.01	40	0.08	35	0.03	48	0.1	37	0.69	23	0.8	16
S1B	VV	0.05	39	0.18	39	0.05	32	0.06	35	0.86	15	**0.92**	**10**
	VH	0.12	36	0.15	35	0.12	37	0.15	37	0.88	14	**0.94**	**10**
	VV+VH	0.16	34	0.83	36	0.16	36	0.14	37	0.88	13	**0.94**	**10**
S2A	2-Blue	0.09	34	0.06	36	0.30	37	0.23	41	0.82	13	0.82	15
	3-Green	0.25	32	0.17	34	0.50	33	0.44	37	0.86	18	0.82	15
	4-Red	0.28	31	0.21	33	0.53	32	0.49	36	0.86	18	0.80	16
	5-VRE	0.23	32	0.15	34	0.48	33	0.42	35	0.86	18	0.82	15
	6-VRE	0.1	37	0.6	37	0.14	41	0.14	40	0.72	19	0.84	15
	7-VRE	0.25	37	0.6	36	0.25	41	0.5	38	0.7	19	0.83	15
	8-NIR	0.7	35	0.13	34	0.7	38	0.13	37	0.74	19	0.84	15
	11-SWIR	0.11	35	0.2	33	0.11	39	0.12	37	0.72	20	0.84	15
	12-SWIR	0.45	27	0.4	29	0.45	27	0.4	39	0.74	19	0.84	15
	All bands	0.53	25	0.5	26	0.6	25	0.67	28	0.75	19	0.85	15
S2B	2-Blue	0.41	29	0.64	31	0.45	30	0.62	32	**0.94**	12	0.90	13
	3-Green	0.40	29	0.64	31	0.40	29	0.64	31	**0.94**	13	0.90	13

4-Red	0.34	31	0.56	33	0.34	30	0.56	34	**0.94**	12	0.90	13
5-VRE	0.30	31	0.55	33	0.30	31	0.50	36	**0.92**	13	0.90	13
6-VRE	0.25	32	0.50	34	0.25	33	0.48	36	**0.92**	13	0.90	13
7-VRE	0.18	34	0.44	36	0.18	34	0.41	37	**0.92**	14	0.90	13
8-NIR	0.09	36	0.29	38	0.09	36	0.30	39	**0.94**	14	0.90	13
11-SWIR	0.36	30	0.59	32	0.36	31	0.59	33	**0.92**	14	0.90	13
12-SWIR	0.42	28	0.64	30	0.42	29	0.66	32	**0.94**	13	0.90	13
All bands	0.36	30	0.64	30	0.45	30	0.66	32	**0.94**	12	0.90	12

4.3 Differences in soil moisture content between wetland and terrestrial ecosystem types

The *in situ* %VWC and predicted %SMC values derived from S1B and S2B showed significant differences (p < 0.05) between the wetland and terrestrial areas (Table 7). On 28 March 2018, higher levels of soil moisture ranging from > 60 % were observed in the wetland sampling area and a lower range of soil moisture, less than ±30 % (rounded off to the nearest 10th digit) were observed in the terrestrial sampling area (Figure 11a). Similarly, a higher range of soil moisture levels occurred in the wetland sampling area (> 45 %) as compared to the terrestrial sampling area (< ± 45 %) for both the *in situ* %VWC and predicted %SMC of 2 May 2018 (Figure 11b). There is a much larger variability between the *in situ* %VWC measurements as compared to predicted %SMC measurements.

Table 7: Differences between the wetland and terrestrial areas for in situ percentage Volumetric Water Content (%VWC) and Soil Moisture Content (%SMC) resulting from the Sentinel 1B and 2B predictions.

Date	***In situ* measurements**	**Sensor**	**Predicted soil moisture measurements**
28 March 2018	0.0000000000000023	**Sentinel-1B**	0.0000000000000027
2 May 2018	0.0000000000000024	**Sentinel-2B**	0.0000000000000029

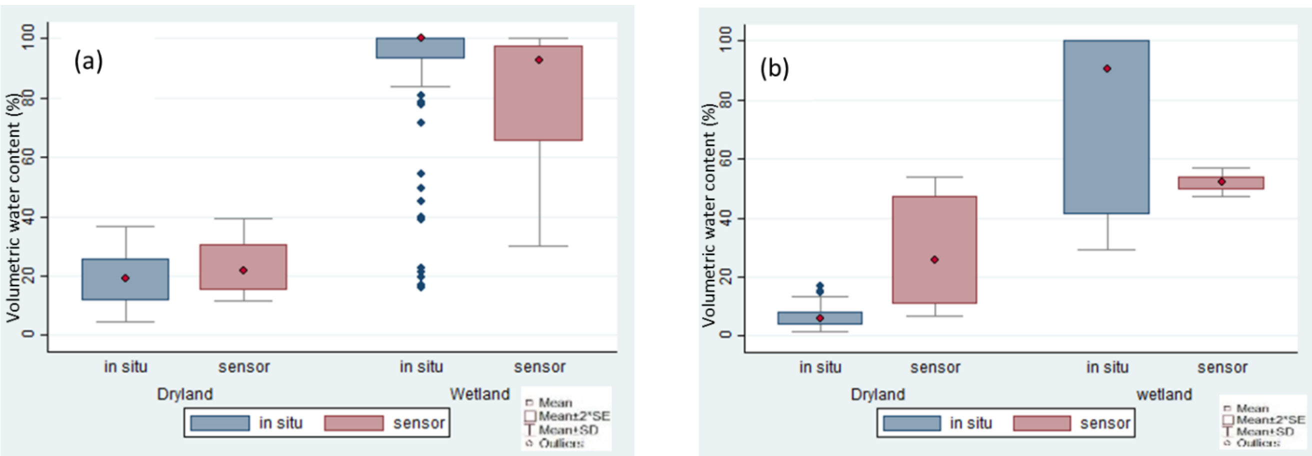

Figure 11: Percentage Volumetric Water Content and predicted percentage of Soil Moisture Content levels between drylands and wetlands for (a) 28 March 2018 and (b) 2 May 2018.

The coefficient of variation (COV) and mean values for *in situ* observed %VWC for the wetlands sample plots were low for the 28 March 2018 (COV = 1.2; mean = 90.7) and high for the in situ sampling period on the 2 May (COV = 5.6; mean = 74.3). Whereas, in comparison to the in situ %VWC, the COV and mean values for S1B predicted SMC Values (COV = 0.7; mean = 80.7) and S2B predicted SMC (COV = 0.05; mean = 51.9) were low. The coefficient of variation (COV) and mean of the %VWC values measured for the terrestrial areas are low for both those corresponding to the dates on which S1B (COV = 1.7; mean = 20.3) and S2B (COV = 2.2; mean = 5.8) were acquired, whereas COV and mean values of the predicted SMC values for S1B (COV = 0.6; mean = 23.3) and S2B (COV = 2.3; mean = 28.6) were relatively high in comparison (Table 8).

The maximum %VWC was recorded as 100% for *in situ* measurements on 28 March 2018 at 05:33. The mean modelled %SMC for S1B (mean±standard deviation = 80.7±21.4;23.3±7.5) compares well with the observed mean %VWC (mean±standard deviation = 90.7±20.8;20.3±7.9) in the wetland and terrestrial areas, respectively (Table 8). The S2B predicted SMC map was unable to model very high values (close to 100) that had been recorded during the sampling date (Table 8).

Since S1B and S2B produced the best results, predicted SMC maps were generated for the two sensors using the data-split method. The maximum observed %VWC and/or modelled %SMC in the terrestrial area is less than 50 %VWC, which are therefore suggested as the threshold for mapping wetland extent (Figures 12 and 13). The predicted %SMC maps for the S1B and S2B sensors show a distinct difference in the extent of soil saturation. The SMC map predicted from SAR VH taken on 28 March 2018 at 05:33 overpass, showed that 41 % (28,5 Ha) of the extent of the study area could be wetland (Figure 12), with %SMC values below the chosen threshold value of 50 % predicted %SMC. The S2B SMC map, in contrast, indicated a larger extent of wetland area (approximately 72 % or 50,3 Ha) with the predicted SMC values > 50 % (Figure 13). S1B shows relatively high SMC values around the south of Hartebeesspruit River and along the railway lines whereas S2B show higher SMC values (50 %—100 %) indicating more soil saturation.

Table 8: Descriptive statistics for in situ observed percentage of Volumetric Water Content (%VWC) and predicted percentage of Soil Moisture Content (%SMC) at the time of Sentinel sensors overpass on the 28 March 2018 for Sentinel-1B and on 2 May 2018 for Sentinel-2B.

		S1B: 28 March 2018		**S2B: 2 May 2018**	
		Observed %VWC	**Predicted %SMC**	**Observed %VWC**	**Predicted %SMC**
Wetland	Minimum	16.2	30.1	35	47.1
	Maximum	100	100	100	56.9
	Mean	90.7	80.7	74.3	51.9
	Standard Deviation	20.8	21.4	28.0	20.5
	Coefficient of Variation	1.2	0.7	5.6	0.05
Terrestrial	Minimum	4.5	11.4	1.3	6.6
	Maximum	36.9	39.4	16.9	54
	Mean	20.3	23.3	5.8	28.6
	Standard Deviation	7.9	7.5	2.9	15.8
	Coefficient of Variation	1.7	0.6	2.2	2.3
Terrestrial and wetland	Minimum	4.5	11.4	1.30	6.6
	Maximum	100	100	100	56.9
	Mean	57.3	52.0	42.4	40.3
	Standard Deviation	38.7	32.9	39.9	16.2
	Coefficient of Variation	8.6	2.8	30.7	2.4

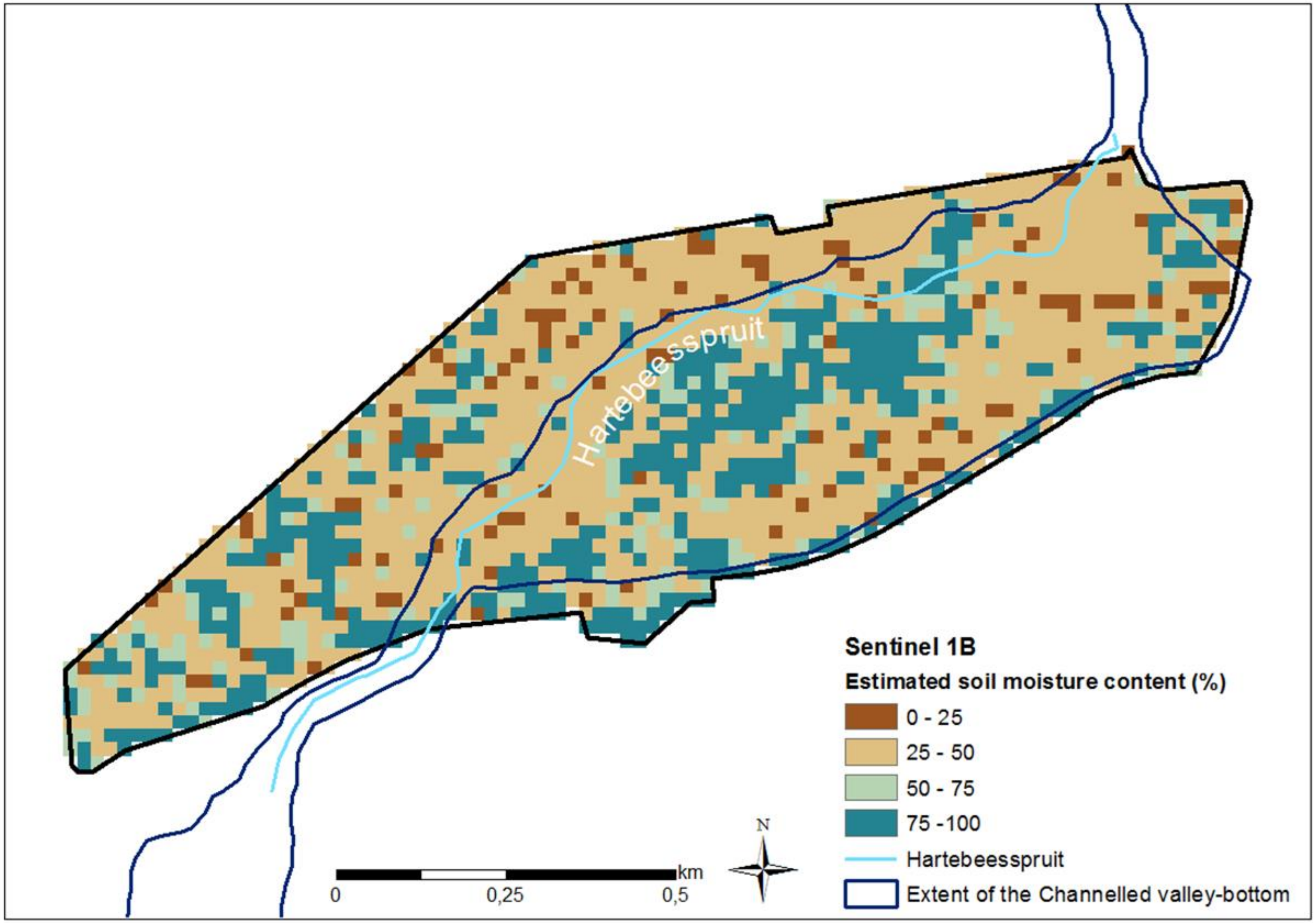

Figure 12: Predicted percentage Soil Moisture Content (%SMC) map derived from Sentinel-1B showing the variation in soil moisture on 28 March 2018 sampling campaign.

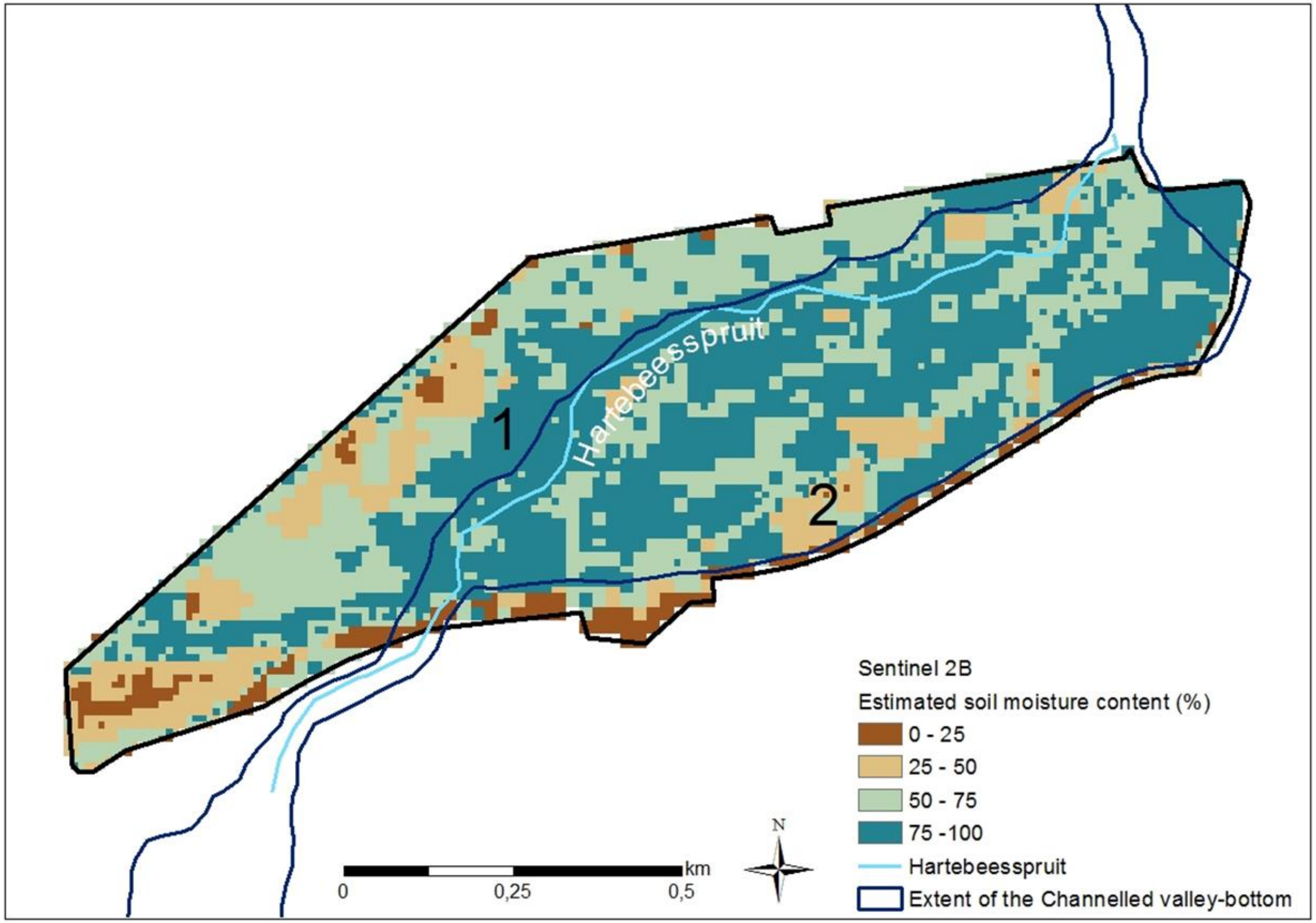

Figure 13: Predicted percentage Soil Moisture Content (%SMC) map derived from Sentinel-2B showing the variation in soil moisture for 2 May 2018 sampling campaign.

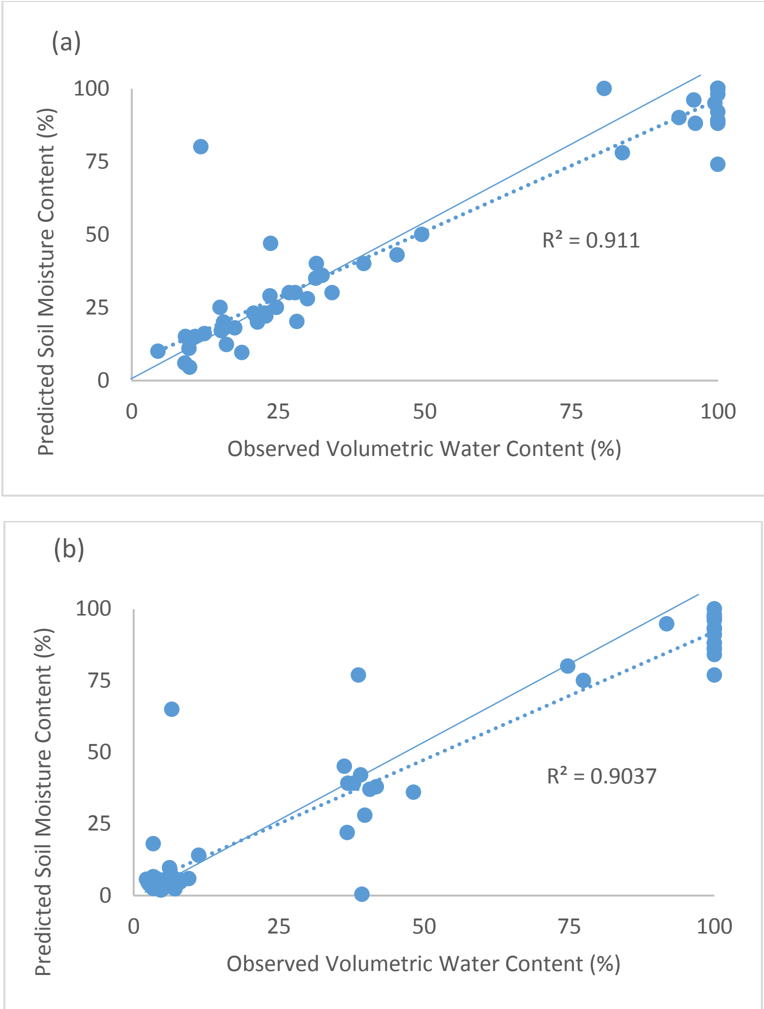

Figure 14: Standard error regression graphs displaying how well Sentinel 1B (a) and Sentinel 2B (b) captured the variability of the soil moisture content across the study area.

The standard error graphs illustrating the observed *in situ* measurements against the predicted SMC measurements represent the level of over estimation and under estimation of the model (Figure 14). The results displayed show a correlation of determination for S1B of R^2 = 0.94 and for S2B, R^2 = 0.93. From the ±5 % to ±30 % range the estimated %SMC measurements for S1B are showing an overestimation and from > ±30 % it is showing an underestimation. For S2B, the overestimation falls in the range of ±2 % to ±15 % and %SMC is underestimated from ±25 %. The inflection shows typical performance of machine learning algorithms.

Chapter 5 : DISCUSSION

The results showed that C-band Synthetic Aperture Radar (SAR) Sentinel-1 (S1) and optical sensor, Sentinel-2 (S2), were able to estimate soil moisture content (SMC) for a palustrine wetland in the grassland biome of South Africa. S1 produced a high correlation coefficient of R^2 = > 0.76 and a low Root Mean Square Error (RMSE = < 24 %) and S2 produced an accuracy of R^2 = 0.8 and low RMSE of < 20 %. Several studies have made use of C-band to estimate SMC. A study by Dabrowska-Zielinska *et al.* (2018) used the ERS-1/2 SAR VV and ENVISAT to monitor SMC over the Bierbza wetlands in northeast Poland, cover by grassland and marshland. Their findings show a reasonable error (RMSE) of 10 %. Holtgrave *et al.* (2018) estimated soil moisture using the Sentinel-1 data in grassland floodplain Peene and Elbe, Germany. The results showed high accuracies of R^2 = > 0.72 and average RMSE of 13 % over the two sites. In another study conducted in the plains of Italy in a semi-arid region, RADARSAT-2 estimated SMC with really high accuracies of R^2 = 0.85 (Filion *et al.,* 2015). In a recent study, Sadeghi *et al.* (2017) estimated soil moisture using S2 over a watershed in Southern Arizona, in which low estimation errors of 0.04 $cm^3\ cm^{-3}$ were derived. The results of this study therefore compares well in terms of the coefficient of determination, though higher RMSE percentages were recorded to all these comparable studies. All of these studies were conducted in temperate climatic regions or over areas with grassland cover, and some include palustrine wetlands which demonstrate that the C-band SAR sensors are capable of predicting %SMC. This study shows that the freely available Sentinel-1 and optical Sentinel-2 remote sensors can also estimate near surface SMC, to a depth of 5 cm, for palustrine wetlands in the grassland biome of a semi-arid region.

A significant difference ($p < 0.05$) in soil moisture ranges was observed between the wetland and terrestrial areas. *In situ* percentage Volumetric Water Content %VWC ranged from 4.5 % to 100 %, while predicted %SMC ranged from 1.3 % to ±50 %. The results showed that the mean soil moisture levels for the *in situ* %VWC measured in the wetland (90.7 %; 74.3 %) was significantly higher ($p < 0.05$) compared to the mean %VWC measured in the terrestrial area (20.3 %; 5.8 %) on the 28 March and 2 May 2018, respectively. Similarly, the Sentinel sensors (S1B and S2B) were able to pick up similar trends. Continuous assessment of the different soil moisture ranges over multiple hydrological regimes would provide insight into determining the maximum extent of a wetland (Van Deventer *et al.,* 2018b). In this study 50 % of the measured %VWC or predicted %SMC is suggested as a possible threshold for determining the maximum extent of a wetland. Other studies such as Holtgrave *et al.* (2018) measured %VWC ranging between ±30—99.1 % with a mean value of close to 50 % of over a floodplain made up of grassland also reaching up to 2 m in height, in Germany. In another study, Paloscia *et al.* (2013) acquired %VWC measurements with a mean of 45 % in terrestrial lands comprised of dense grasses, in Italy. Both these studies took place at the end of the growing period of the vegetation. In another instance, a study conducted by Lang *et al.* (2007) in the coastal plains of Washington D.C. (United States of America), also attained similar trends in the differences in the soil moisture ranges between the wetland and the terrestrial area, with an average of 59 % and 24 % (%VWC), respectively. It appears that these ranges have a similar trend, although in different biomes and regions. In addition, for the Colbyn Valley Nature Reserve (CVNR) study area, on-site variation in SMC values may be attributed to a number of factors. The vegetation in the wetland area causes a decrease in velocity of flow due to the water holding capacity of the plants as well as their high friction value. Also, the nature of palustrine type wetlands is relatively flat which naturally decreases the velocity of flow, even if there was no vegetation present at the time of sampling and overpass of the sensor (Enviroguard Ecological Services cc. 2014). Other factors include sub-surface fractures, groundwater flow, or alterations which have resulted in the accumulation of water. As a result of the build-up of SMC in the valley-bottom, patterns of high SMC across the wetland has in some instances linear appearances (marked 1 and 2 in Figure 13), following old drains. In addition, the construction and filling of the area for the road and railway line may have caused accumulation of water adjacent to these areas (Figure 5).

Differences between the two sampling campaigns of this study in the CVNR may relate to changes in the hydrological period. The sampling campaign on 28 March 2018 took place shortly after an intense rainfall storm (22 March 2018) whereas the sampling campaign on 2 May 2018 took place approximately two weeks after a less intense rainfall period (Figure 15). Despite the fact that the first campaign (28 March 2018) took place soon after an intense storm, the extent of soil saturation was much wider (30 % or 21 Ha) from the image derived on 2 May 2018 associated with the second campaign. The continuous rainfall events over summer (rainfall started mid-

February of 2018) lead to progressively accumulated water in the wetland through surface run-off and groundwater accumulation. The accumulation of water would have resulted in an increase dielectric constant, resulting in higher backscatter and reflectance values. These results are evidence from the comparison of the predicted SMC maps for S1B sensor and S2B sensor to one another, which suggests that changes in soil saturation could be detected across the wetland's hydroperiod. This study, however, was limited to an inter-annual analysis at the peak and end of the rainfall season and respective hydroperiod, limiting full understanding of the variation of %SMC over the hydroperiod and extent of the wetland. Since palustrine wetlands are dynamic ecosystems, they require frequent monitoring. Very high spatial (~ 1.2 m) and temporal resolution (1 – 3 days) imagery from WorldView or IKONOS, for example, are most suitable for such an application, however, acquiring information from these remote sensing platforms comes at a high cost which makes them insufficient for regional monitoring of SMC. The Sentinel series surpasses this limitation by offering freely available imagery with a relatively low revisit time of 5 – 6 days.

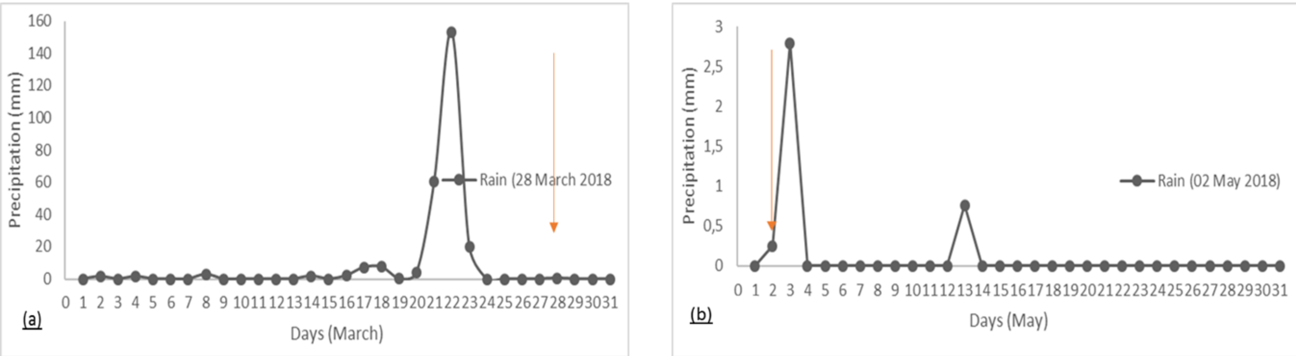

Figure 15: Precipitation readings for the duration of the sampling period. Graphs (a) shows a rainfall period shortly before the acquisition for S1B on the 28 March 2018 (indicated by red arrow) and graph (b) shows the S2B acquisition on 2 May2018 (indicated by red arrow). Scale ranges are different to account for differences in the maximum precipitation of the two sample dates.

The estimated %SMC based on the interpretation from Sentinel-1 recorded in the cross-polarization mode, found vertical-receive, horizontal-transmit (VH) to be more sensitive to vegetation cover, surface roughness and SMC (R^2 = 0.79; RMSE = 13 for S1A and R^2 = 0.94; RMSE = 10 for S1B) compared to the single polarization mode, vertical-receive, vertical-transmit (VV) (R^2 = 0.76; RMSE = 17 for S1A and R^2 = 0.92; RMSE = 10 for S1B) and the VV+VH modelling scenario obtained the same result as the VH polarization mode. The CVNR showed comparable results, recommending the use of VH above that of VV. For instance, Dabrowska-Zielinska *et al.* (2016) found that VH was able to estimate SMC with a higher accuracy (R^2 = 0.72) than VV (R^2 = 0.63) over a vegetated wetland area comprising of sedges, reeds and grasses. By using the cross-polarization VH as well as integrating it into the VV+VH modelling scenario, it was assumed that the influence from the vegetation cover and surface roughness was reduced and the possibility of receiving backscatter from the soil surface was increased.

The combination of all the optical S2 bands, resampled to 10 m spatial resolution (excluding the 60 m spatial resolution bands), produced high accuracies of predicting %SMC (R^2 = > 0.7; RMSE = ≤ 15 %). S2B stacked bands showed the highest R^2 (0.94) with the lowest RMSE (12 %). The accuracy in the %SMC estimation is probably enhanced by the contribution of the visible range bands (blue (496–492 nm), green (560–559 nm), red (664–665 nm)), the NIR (band 8, 833–835 nm) and the SWIR (band 12, 2185–2204 nm), where the spectrum in these bands were absorbed by water molecules, based on the results of the random forest's (RF) model ranking of the bands. These bands also produced a high R^2 = 0.94 and low RMSE = 13 %. Various other studies found that surface soil moisture the NIR and SWIR was important for predicting soil moisture (Barret *et al.*, 1993; Lobell and Asner, 2002; Wang *et al*., 2009). For the CVNR, the use of bands across the visible, NIR and SWIR all contributed to the optimisation of the prediction of %SMC.

The findings of our study indicated that non-parametric models (Support Vector Machine (SVM) and RF) produced a better outcome as compared to the parametric model (Simple Linear Regression (SLR)). The results from the Shapiro-Wilk test indicate the *in situ* %VWC for the 28 March and 2 May 2018 sampling campaigns are not normally distributed ($w < 0.8$; $p < 0.05$) (Figure 10 (a) and (b)). These results are in agreement with other studies which also found non-parametric algorithms to outperform parametric algorithms. For example, Ali *et al.* (2015) made a comprehensive comparison between different machine learning methods and concluded that non-parametric models such as SVM or Artificial Neural Network (ANN) have great potential for measuring SMC for vegetated environments because they require less amounts of training data. Liu *et al.* (2017) compared four different machine learning approaches for observing monthly SMC satellite data over grain crop regions in northeast China. They found that of all the four methods, RF showed to have produced the best results with R^2 generally greater than 0.92 (RMSE = 0.009 m^3m^{-3}). Cross-validation can be used when the number of samples doesn't capture the variability of the data. It appears as if the number of samples used in this study did capture the variability and therefore where the data split was used, the results were generally higher than the cross-validation approach.

Despite vegetation canopy cover influencing backscatter from C-band data, in this study it can be argued that the vegetation may have very little impact on the radar signal from C-band Sentinel-1 SAR. Several studies have attempted to compensate for the influence of vegetation and surface roughness through incorporating it in their models. Some methods included using sensors at different frequencies, polarization modes and incident angles and assessing temporal variations across a part of the phenological period when the biomass and texture remained the same (Zribi and Dechambre, 2002; Baghdadi, *et al.,* 2008; Paloscia *et al.,* 2013). The most commonly used index for incorporating the influence of vegetation in the estimation of SMC, is the Normalization Difference Vegetation Index (NDVI). Paloscia *et al.* (2013) and Holtgrave *et al.* (2018) both showed that the estimation of SMC without NDVI resulted in the increase of RMSE values by 7–40 percentile points (pp). In Polascia *et al.* (2013) study, the RMSE increased by 8–40 pp when NDVI was not used. Research done by Hornacek *et al.* (2013) suggests that grassland above ground biomass (AGB) ≤ 1 kg/m^2 have very little influence on the estimation of SMC estimation. As a result, the estimation of SMC in the CVNR were not adjusted since the AGB of grasses and sedges in the study area is likely < 850 g/m^2, following AGB values of palustrine and terrestrial systems in the grassland biome (Naidoo *et al.,* 2019).

This study showed that the Sentinel-1 and -2 sensors have the potential to estimate and monitor %SMC of palustrine wetlands at a regional scale. Few studies have compared the estimations of %SMC between different microwave bands of sensors, such as the C- and L-band sensors. While L-band sensors have the advantage of deeper penetration through canopy cover (in case of densely vegetated lands, for example, forests), some L-band sensors are limited by their spatial resolution to estimate SMC in palustrine wetlands in temperate and semi-arid regions because these wetlands are small, such as SMOS satellite (spatial resolution of 35 km); other

L-band sensors have a high spatial resolution (10 m) but are limited by their revisit time, such as ALOS (46 days temporal resolution); and in some cases, the high cost associated with acquiring radar imagery limits its broader use. Since SMC is considered an Essential Climate Variable and therefore monitoring SMC in palustrine wetlands could lead to positive outcomes in conserving these important ecosystems. Future L-band sensors such as the Advanced Land Observing Satellite-4 (ALOS-4) from the Japan Aerospace Exploration Agency (JAXA), NASA ISRO Synthetic Aperture Radar (NISAR) from NASA/ ISRO and TanDEM-L from the German Space Agency or Deutsches Zentrum Fur Luft-und Raumfahrt e.V. (DLR) will greatly improve the efforts for monitoring SMC (The CEOS Database – Catalogue of Satellite Missions, 2019). However, future research needs to be carried out to assess the potential of the different sensors for estimating %SMC across different climatic zones and wetland types.

Chapter 6 : CONSCLUSION

This study proves that the freely available Sentinel-1 (SAR) and 2 (optical) sensors have potential in estimating the extent and degree of soil saturation of palustrine wetlands in the grassland biome of South Africa. The Sentinel 1 SAR and optical sensors were able to predict the percentage of Soil Moisture Content (SMC) with a high coefficient of determination ($R^2 > 0.7$) and low Root Mean Square Error (RMSE) < 15 % for a vegetated channelled valley-bottom wetland located in the grassland biome and Gauteng Province of South Africa. The VH polarization mode of the Sentinel-1 and optical bands 2 (Blue), 3 (Green), 4 (Red), 8 (NIR) and 12 (SWIR) of Sentinel-2 sensors, contributed to the highest accuracies, when a non-parametric Random Forest regression model was used. An SMC threshold of ≥ 50 % is suggested as a potential threshold to determine the extent of the wetland area, though further work would be required to confirm whether this is relevant across the hydroperiod and other grassland sites. The results therefore suggest that the prediction of SMC in the grassland biome of South Africa can play a significant role to improve the representation and monitoring of palustrine wetlands in the face of global and changing climate.

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