ASSESSMENT OF SELECTED TYPES OF SOIL DEGRADATION IN SYFERKUIL FARM USING REMOTE SENSING TECHNIQUES

BY

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DECLARATION

I, Mamorobela Karabo, declare that the mini-dissertation hereby submitted to the University of Limpopo, for the degree of Bachelor of Science in Agriculture (Soil science) has not previously been submitted by me for a degree at this or any other University; that it is my work in design and in execution, and all material contained herein has been duly acknowledged.

23 March 2023

MAMOROBELA K.E (Mr) Date

DEDICATION

This study is dedicated to my lovely parents Mr. and Mrs. Mamorobela and my three siblings, Malego, Matome and Stanley Mamorobela.

ACKNOWLEDGEMENT

I would like to acknowledge my supervisor Dr. M.G Zerizghy who has been helping me with this dissertation from the beginning. I would not have managed to successfully complete this research without his assistance. He led me in the right direction where I seemed to go astray, and he never gave up on me. I would like to thank my parents Mr. and Mrs. Mamorobela and my three siblings for the unconditional support, love and their endless prayers and for motivating me to show dedication in everything I do. I would also like to acknowledge the University of Limpopo, School of Agricultural and Environmental Sciences for providing us resources whenever we visited the site where this research was conducted. I'm grateful for the funding that National Research Foundation (NRF) provided for me throughout my research. Finally, I would like to thank The Lord Almighty for being my rock, pillar and foundation. All praise and thanks unto God.

ABBREVIATIONS AND ACRONYMS

CEC	Cation Exchange Capacity
dS/m	DeciSiemens per metre
EC	Electrical conductivity
ESA	European Space Agency
FAO	Food and Agricultural Organization
GPS	Global positioning system
Landsat	Land Remote Sensing Satellite (system)
mS /cm	MilliSiemens per centimetre
PLSR	Partial Least Square Regression
QGIS	Quantum Geographic Information System
R^2	Coefficient of determination
RF	Random Forest
RIO	Region of Interest
RMSE	Root Mean Square Error
RPD	Relative Percentage Deviation
RS	Remote Sensing
SCP	Semi-Automatic Classification Plugin
SD	Standard Deviation
SOC	Soil Organic Carbon
SOM	Soil Organic Matter
SWIR	Short-Wave Infrared
VNIR	Visible Near-Infrared

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ABSTRACT

Soil degradation is a serious environmental threat facing the humanity today. Soil degradation in one or more of its forms has been labelled as a 'global pandemic'. This is because; soil degradation is a very serious world problem and affects all countries or continents. Thus there is an acute need to devise a way of reducing its vast advance. This is why, it is important to establish the magnitude and the extent of soil degradations in order to mitigate its effect. The objectives of this study were to: (i) Identify soils degraded by rill erosion with acceptable accuracy from remote sensing images. (ii) Determine soil organic carbon status with acceptable accuracy from remote sensing. (iii) Determine soil surface salt accumulation with acceptable accuracy from remote sensing images. The soil degradation forms considered in this study are soil salinity, rill soil erosion and soil organic carbon. Nutrient depletion is another significant chemical process of soil degradation. Soil organic carbon depletion is a chemical degradation and in most instances is influenced by human and natural activities. The assessment of these soil degradation forms has been done in three separate chapters and detailed abstract is given at the start of each chapter. However, the general findings revealed that the prediction of those soil degradation forms from remotely sensed images did not yield good results. Nonetheless, promising performance has been recorded. Recommendations for feature studies are also provided.

Keywords : Soil degradations, Remote sensing, Multispectral imagery (sentinel 2) , Regression analysis, Syferkuil farm.

CHAPTER ONE

1. THE GENERAL BACKGROUND

1.1 INTRODUCTION

Soil degradation is the most serious global environmental issue, which is why it is considered as a global pandemic, it is world problem. Soil degradation processes involves displacement of soil materials and internal soil physical and chemical deteriotation. Soil degradation is influenced by natural and human activities. However, soil degradation processes vary according to the land uses and management (DeLong *et al.*, 2015; Gopalakrishnan and Kumar, 2020). Soil degradation, mainly occurs in three forms namely, physical, chemical, and biological soil degradation. The physical degradation include (i.e. soil erosion, specifically rill erosion) and chemical degradations (i.e. depletion of organic carbon and salinization). In South Africa, soil degradations are predominant. Soil degradations pose a threat on agricultural land particularly in arid and semi-arid regions (Ren *et al.*, 2019). The dominating factors that initiate the development of soil degradation are accelerated by the soil type, topography, and climate (Lal, 2015).

In agriculture, soil degradation poses a threat to food security, food production and environment conservation. This can then force farmers to look for new productive land. Furthermore, monitoring soil quality degradation is a crucial step in practicing precision agriculture and making informed decisions with regards to the future land use and management for reclamation and rehabilitation of soils (Peng *et al.*, 2019). Therefore, it is of crucial importance to realise that soils are our most essential resources meaning that they must be used, improved and restored. In this study, remote sensing (RS) which is defined as the process of gathering information about an object through the use of electromagnetic radiation, from distance, without making physical contact with the object itself becomes a crucial tool for assessing, monitoring, and determining soil degradation forms (Chauhan, 2015 and Paterson *et al.*, 2015). Thus, this study aims to establish if soil degradation forms could be identified and quantified using remote sensing as an alternative method to the conventional methods (i.e., field work or survey).

Remote sensing techniques are able to provide rapid analysis of soil information and covering whole land surface at an acceptable level of details (Paterson *et al.*, 2015). In addition, remote sensing provides simultaneous collection of data systematically and non-requirement of chemical reagents (Chauhan, 2015). Remote sensing has the potential to reveal information about soils since the signals measured are in relation to the physical measures, which can be linked to soil properties (Mirzabaev *et al.*, 2016; Rossel *et al.*, 2011; and Zhou *et al.*, 2015).

1.2 PURPOSE OF THE STUDY

1.2.1 Aim

The realistic assessment of selected soil degradation forms in the Syferkuil farm.

1.2.2 Objectives

The objectives of this study are to:

i) Identify soils degraded by rill erosion with acceptable accuracy from remote sensing images.

ii) To determine soil organic carbon status with acceptable accuracy from remote sensing.

iii) To determine soil surface salt accumulation with acceptable accuracy from remote sensing images.

1.3 MOTIVATION OF THE STUDY

This study will be crucial in terms of increasing awareness on the importance of managing and restoring soil quality to minimise the risk of soil degradation forms. The results from this study will be crucial in land use management studies and soil reclamation programmes for environmental protection. Moreover, this study will help farmers to gain good understanding of the status of the soil which will help in coming up with precise management strategies for reclamation and rehabilitation of soils. The premise of maintaining and rehabilitating soil quality starts by establishing or assessing the existing condition (Lal, 2015). Hillel *et al.* (2015) pointed out that we cannot protect what we don’t understand. Therefore, the results of this study will provide a better understanding of assessing soil degradations using remote sensing.

Remote sensing techniques as an alternative tool to the conventional methods are able to assess and monitor selected types of soil degradations with acceptable accuracy (Paterson *et al.*, 2015). This is due to rapid analysis of soil information and covering whole land surface at an acceptable level of details for monitoring spatial variability of soil degradation forms. Conventional methods tend to be ineffective when dealing with the processing of large soil information due to their long procedure that delays the analysis of soil parameters (Chauhan, 2015).

According to Paterson *et al.* (2015), there is a shortage of up to date soil information about South African soils. Furthermore, there is little work done that utilizes remote sensing for assessing soil degradation in South Africa particularly in the Limpopo Province. However, majority of studies are undertaken in KwaZulu Natal and Eastern Cape Province (Mararakanye, 2015). Factors that influence the development of soil degradation tend to differ in regions and areas (Sonneveld *et al.*, 2005; Nazari Samani *et al.*, 2009). Additionally, the performance of the Partial Least Square Regression (PLSR) model varies with the location or study area and the soil parameter being investigated or assessed. Moreover, the need to study the use of remote sensing is important because the available literature mostly focused on the main factors that accelerate soil degradation rather than developing models that will assist in assessing soil degradation. This study will focus on accurate assessment of soil degradation using remote sensing techniques.

1.4 THE GENERAL STRUCTURE OF THE THESIS

The upcoming three chapters address one objective each and a final chapter that provides general summary at the end of the thesis (Figure 1.1). The content of each chapter is described briefly as follows:

Chapter one deals with the general background of soil degradation. I outlined the aim and objectives of the study. Furthermore, I explained the reasoning why this problem needs to be addressed and what will be learnt from it. Chapter two, deals with the assessment of soil surface salt accumulation (soil salinity). Chapter three, deals with the assessment of soils degraded by rill erosion. Chapter four, deals with the assessment of soil organic carbon depletion. Chapter five, deals with the summary and possible recommendations.

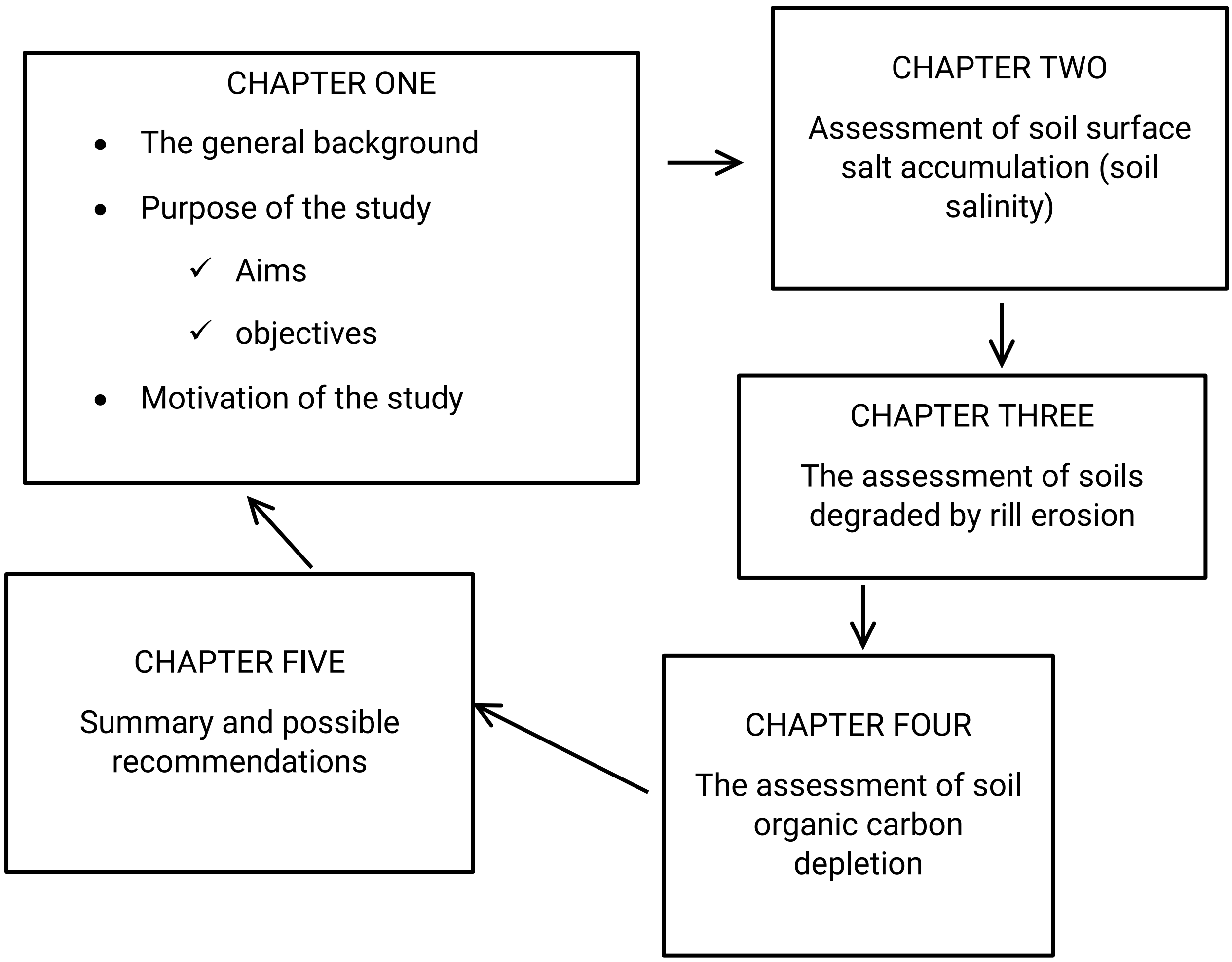

Figure 1.1: The general structure of the thesis.

CHAPTER TWO

ASSESSING SOIL SURFACE SALT ACCUMULATION USING MULTISPECTRAL IMAGES IN SYFERKUIL

ABSTRACT

Monitoring soil quality is an essential practice for agriculture and environmental protection. Soil salinization is one of the most globally significant environmental soil hazards, which results in severe land degradation and desertification. This is actually caused by both natural and human activities. The excess accumulation of soluble salts in the soil surface which basically referred to as salinization has severe impact on agricultural production, biodiversity and sustainable development. The objective of this study was to determine soil surface salt accumulation with acceptable accuracy from remote sensing images. The study was conducted in Syferkuil, experimental farm of the University of Limpopo. Fifty five soil samples were collected and a grid sampling of 50 m by 50 m was followed. Global positioning system (GPS) was used to record the exact location of each sampled point in each grid. The electrical conductivity (EC) of the soil samples was determined conventionally in the laboratory using Mettler Toledo EC meter. The standard laboratory (conventional) methods for determining soil texture and, pH were used. A multispectral image (Sentinel 2) with more than 10 bands ranging from the visible to shortwave infrared was used to predict the soil EC. The coordinates of the sampling points were used to extract spectral value from the image. The spectral values and the conventionally determined soil EC were modelled using partial least square regression (PLSR).

The PLSR model yielded a coefficient of determination (R^2) = 0.468 and the Root Mean Square Error (RMSE) = 0.44 ds/m. The result shows that approximately half of the EC variation could be explained by the reflectance values as recorded in the image. The deviation of the predicted values from the PLSR analysis was minimal as indicated by the low RMSE value. The low R^2 value indicates that there are confounding factors. The confounding factors might come in the form of noise and errors due to variations in soil surface roughness, geometric and atmospheric effects. Furthermore, the performance of models might be because of low spectral resolution of the image as compared to hyperspectral data, which have bands with

narrow wavelengths. Despite low prediction accuracy in this study, remote sensing techniques are efficient tools to monitor and detect soil salinity unlike in the old days, when conventionally laboratory methods were the only means of assessing soil salinity problems. Sentinel 2 could be used to make preliminary study of EC before detailed in situ assessment could be done. This is because; Sentinel 2 is able to provide excellent spatial coverage of a large area, and making it easy to obtain soil information (Gorji *et al.*, 2017). Thus, it is recommended that satellite image with better spectral resolution (hyperspectral) be investigated to see if there be an improvement in the model performance.

Keywords : Soil degradation, Soil salinity, Multispectral imagery (sentinel 2) , Regression analysis,

2.1 BACKGROUND

Soil salinity is defined as the build-up of salts mainly chloride, sulfates and carbonates of sodium, calcium, and magnesium in the soil surface (Smith and Doran, 1996). It is determined by measuring soil electrical conductivity (EC) due to its high correlation with soil salinity. Monitoring soil salinity or soil quality degradation in general, is an essential practice for precise management strategies for reclamation and rehabilitation of soils. It is determined by measuring soil electrical conductivity (EC) due to its high correlation with soil salinity. Monitoring soil salinity or soil quality degradation in general, is an essential practice for precise management strategies for reclamation and rehabilitation of soils.

In this study, one form of soil quality degradation - soil salinization is the centre of focus. It is considered as one of the leading causes of land degradation and has been found to be directly linked to the different natural processes and human activities (Gopalakrishnan and Kumar, 2020). Additionally, it has become one of the most serious global environmental issues, and as a result influencing agricultural production and food security since it leads to reduced soil and water quality especially in arid and semi-arid regions (Ren *et al.,* 2019). It predominates in these regions with the fact that evaporation rates are extremely high and water evaporates rapidly as a result leaving dissolved mineral salts in the topsoil (Pennock et al., 2015).

Despite the abundant evidence, regarding the damages that arise from salt affected soils, the problem is ever increasing rather than decreasing all over the world (Metternicht and Zinck, 2003). It should, however, be noted that assessing, monitoring and identifying areas that are mostly affected by soil degradation forms with acceptable accuracy from remote sensing is indeed a crucial step. Over the past decades, the conventional methods have been used by many soil scientists to characterise spatial and temporal variabilities of soil properties. The main difficulties of such methods lie on meeting high demands of detailed soil information in short period of time with reasonable cost (Steinberg *et al.*, 2016). Furthermore, conventional methods are time consuming and labour intensive particularly for regional level whereby data is required for large scale applications.

The complexity and cost of conventional methods in monitoring soil degradation forms has motivated the use of remote sensing techniques as an alternative method to the conventional methods. Remote sensing (RS) is defined as the process of gathering information about an object through the use of electromagnetic radiation, from distance, without making physical contact with the object itself (Chauhan, 2015). RS images can provide valuable information that might not be able to obtain using other methods since our visual perception is limited to some portions of electromagnet spectrum (EMS).

Remote sensing has the capability to cover different areas which might be difficult to cover using some other terrestrial means. In addition, remote sensing can help to observe change that might be occurring over time and to understand the spatial extent and rate of this problem. Lastly, remote sensing can provides records of soil degradation forms at those specific times the images were captured. The objective of this study was to determine soil surface salt accumulation with acceptable accuracy from remote sensing images. It is hypothesised that remote sensing images will enable accurate determination of soil surface salt accumulation.

2.2 PROBLEM STATEMENT

Soil salinity is considered as an environmental degradation and one of the leading causes of land degradation (Aldabaa *et al.,* 2015). It is a serious problem around the world due to the devastating impacts on agricultural farmlands. Thus, it is considered as a global pandemic since it affects the whole world and the problem is ever increasing rather than decreasing. Worldwide, productive and fertile soils are scarce resources and many farmers are looking at short term benefits and ignoring the long term consequences that arise from salt affected soils. In previous studies around the world, many soil scientists use conventional methods (i.e., laboratory methods or field surveys) for assessments of soil degradations. Conventional methods have drawbacks as they are time consuming and expensive. The main difficulties of conventional methods lie on meeting high demands of detailed soil information in short period of time with reasonable cost (Steinberg *et al.,* 2016). Furthermore, it is time consuming and labour intensive particularly for regional level whereby data is required for large scale applications. For instance, with the current demand for up to date soil information particularly for regional level whereby data is required for large scale applications, these methods delay the process of acquiring necessary soil information of high accuracy in a short period of time, due to their long procedure (Rossel *et al.*, 2011).

Conventional methods tend to be ineffective when dealing with the large soil information due to their long procedure that delays the analysis of soil parameters. This long procedure method, however, could be addressed by the use of remote sensing techniques. This is because soil scientists have identified remote sensing as an alternative method for assessment and monitoring of soil degradation forms due to their advantages over conventional methods. These includes, simultaneous collection of data systematically and non-requirement of chemical reagents (Chauhan, 2015). Moreover, it can provide rapid analysis of soil information and covering large land surface at an acceptable level of details.

Remote sensing images can provide valuable information that might not be able to obtain using other methods since human visual perception is limited to the visible range of the of EMS (Chauhan, 2015).This means that it can provide information beyond our human visual perception. Remote sensing images can provide the records of soil degradation forms at those specific times the images were captured (Forkuor *et al.,* 2017). This can help to observe change that might be occurring over time and to understand the spatial extent and rate of this problem. Moreover, it can cover different areas which might be difficult to cover using some other terrestrial means (Chauhan, 2015).

Advantages of using remote sensing technology include saving time, wide coverage (satellite remote sensing provides the only source when data is required over large areas or regions), are faster than ground methods, and facilitate long term monitoring. These techniques provide multispectral image with resolutions that can range from medium to high, as well as hyperspectral image. These remotely sensed data have been successfully used for monitoring and mapping soil salinity for decades with mixed results (Aldabaa *et al.*, 2015; Asfaw *et al.*, 2016). Many researchers have used different techniques to monitor and map soil salinity using remote sensing data, as discussed below. A multispectral imagery is able to provide excellent spatial coverage of a large area, and making it easy to obtain soil information (Gorji *et al.*, 2017).

2.3 LITERATURE REVIEW

2.3.1 Work done on the problem statement

2.3.1.1 The importance of assessing soil surface salt accumulation.

The accumulation of salts in the soil surface tend to affect the interaction between plants and soils which in turn influence the nutrient and water availability and thus affecting crop growth and productivity (Asfaw *et al.*, 2016; Gorji *et al.*, 2017). This can then force famers to abandon their farmlands due to the incidence of high accumulation of salts in the soil surface. Therefore, assessing, monitoring, and mapping salt affected areas will enable better understanding of the threat posed by soil salinization in different locations. Aldabaa *et al.* (2015) found that soil salinity leads to reduced crop productivity and in this case, it was inherent from parent materials (i.e. where the soil is formed from). These findings were supported by Clay *et al.* (2001) who found that salt surface accumulation tend to have devastating impacts on plant growth and production. Despite the awareness regarding the damages that arise from surface salt accumulation on agricultural soils, the problem is ever increasing rather than declining (Metternicht and Zinck, 2003). For example, Gao *et al.* (2021) monitored temporal and spatial dynamics of soil salinization changes using remote sensing and Geographic information system (GIS) in China. They found an increase in salt affected areas. Fey and Mashimbye *et al.* (2012) also found proof of increasing soil salinity in Western Cape Province.

2.3.1.2 The use of remote sensing in assessing, monitoring, and mapping soil salinity.

Al-Gaadi *et al.* (2021) mapped soil salinity in agricultural fields in Saudi Arabia using Sentinel 2 images. They found that the relationship between EC and Sentinel 2 data showed moderate to highly significant correlations (R^2 = 0.43 - 0.83). In a study by Gorji *et al.* (2019), the remote sensing techniques and methods were used to assess and map soil salinity. The results of which showed that RS data provides high precision salinity maps to monitor salt affected areas. Qu *et al.* (2008) used the Partial Least Square Regression (PLSR) method to assess the salinity using hyperspectral data. The results showed that the calibrated PLSR method could predict soil salinity with precise or accurate results. In a study by Zarei *et al.* (2021), they investigated soil salinity monitoring and EC mapping using sentinel 2 satellite images. The results of this study demonstrated that the remote sensing data could provide high-precision salinity maps to monitor soil salinity as an environmental problem.

A study by Leon *et al.* (2012) aimed at predicting soil properties using Partial least square regression (PLSR) and Visible Near-Infrared (NIR) spectroscopy in the Mediterranean soils from Southern Italy have been done. The results of this study showed that PLSR is very good in predicting soil properties. In addition, the results of the PLSR were in good agreement with the correlations between soil properties and reflectance at various wavelengths. These findings are in line with those of Wenjun *et al.* (2014) which reported that partial least square regression (PLSR) is a fast analytical tool to predict soil parameters such as soil salinity, total carbon, soil moisture, and cation exchange capacity (CEC) with high accuracy. Therefore, Stenberg *et al.* (2010) suggested that remote sensing techniques are effective tools in terms of providing rapid assessment, having up to date soil information and covering large area of land at an acceptable level of detail.

A study by Goossens *et al.* (1993) aimed at examining and comparing the accuracy of multispectral sensors (Landsat TM, MSS, and SPOT) for soil salinity mapping has been done in India. They found that Landsat TM was an effective tool for soil salinity mapping. Ahmed and Andrianasolo (1997) compared the performance of the Landsat TM and SPOT XS in Pakistan. Their results were opposite to that of Goossens *et al.* (1993). They found that the SPOT XS data were more helpful than Landsat TM as it provided finer details of various thematic variables. In a study by Huang *et al.* (2005) aimed at identifying saline areas dominated by sodium chlorides and sodium sulfates using ASTER imagery. The results of this study therefore showed a good correlation between surface salt concentrations and band 1 of the ASTER sensor, followed by bands 2 and 3.

A study by Mohammad *et al.* (2019) in the Kuh Sefid village, Qom Province, Iran has been done in assessing soil salinity using Sentinel-2 multispectral imagery. They have found that the Green, Red Edge 1, SI2, SWIR2, and BI, had the best performance in model development. Moreover, they emphasized that these features could be used as optimal salinity indicators for monitoring soil salinity through satellite imagery in future studies.

2.3.1.3 Factors affecting the prediction accuracy of multispectral satellite data.

Soil moisture content tends to influence the prediction accuracy of different sensors. This is because as soil moisture increases, the reflectance of soil decreases. This actively demonstrates that soil moisture is inversely proportional to the reflectance. For instance, if there is high amount of water in the soil, the reflectance will go down. However, drier soil such as sandy textured soil reflects more than wet soils (i.e. clay textured soils after same exposure of wetness) (Kumar and Sharma, 2020). The surface roughness is also considered as one of the main factors that influence the prediction accuracy. For instance, the smaller the local surface roughness, the greater the spectral reflectance. Therefore, Gorji *et al*. (2017) and Shahabi *et al.* (2017) pointed out that the performance of the models varies with the study site and the regression techniques used. Lastly, Allbed and Kumar (2013) stated that multispectral data has limitations because of the coarse spatial and spectral resolutions.

2.3.1.4 Human and environmental parameters related to soil salinity.

Aldabaa *et al*. (2015) reported that parent materials, soil types, and topography influence soil surface salt accumulation and constrain the growth of many crops. These natural factors tend to vary with location and farm management. The application of irrigation systems that contains high amount of magnesium and calcium results in high accumulation of salts in the soil surface. This can then compromise plant productivity and soil fertility since it affects soil properties. Furthermore, application of high amount of fertilizers can lead to high accumulation of salts in the soil surface and results in land abandonment and high economic costs for soil reclamation and rehabilitation (Aldabaa *et al*., 2015).

2.3.1.5 How soil properties are related with spectral reflectance obtained from remote sensing images.

Shrestha (2006) reported that humus, gypsum and water soluble salts are negatively correlated with spectral reflectance while carbonates are positively correlated with spectral reflectance. Visible, short wave, and near infrared bands have the ability to estimate chemical, physical, and biological soil properties (Stenberg *et al*., 2010). Moreover, spectral analysis illustrated the high potential of short-wave infrared (SWIR) bands to identify saline soils. The results from the study conducted by

Shrestha (2006) shows very weak correlation between soil salinity and V/NIR spectra.

2.3.2 Work not done on the problem statement

Over the past decades, majority of the studies have used multispectral sensors such as Landsat, SPOT, and Advanced Space borne Thermal Emission and Reflection Radiometer (ASTER) and IKONOS in assessing soil degradation forms (Dwivedi *et al.*, 2008). These broad-band sensors provide high spatial and spectral resolution imagery. Although various studies have been conducted under different regions to assess the ability of multispectral sensor (i.e. sentinel 2) not much work has been done on the Semi-arid area of Limpopo, particularly the Mankweng area. Most of the studies have focused on the main factors that influence soil degradation rather than developing models that will help in land management studies and soil reclamation programmes since soil degradation changes with space and time. This study will establish if soil salinity could be identified and quantified using remote sensing as an alternative method to the conventional or traditional methods (i.e., laboratory methods).

2.4. RESEARCH METHODOLOGY

2.4.1 Description of the study area

The study was conducted in Syferkuil, experimental farm of the University of Limpopo (Figure 2.1). The farm is about 1,650 ha in size in general. The study was conducted on the fields reserved for student experiments. The portion of the farm that was used for this study has an area of 61 ha. For the past years the study site has been cultivated coupled with occasional resting. The soils from Syferkuil farm are identified as sandy loam texture and the dominant soil forms on the site are Shortlands and Clovelly (Soil Classification Working Group, 1991). The research site is located in semi-arid region with average rainfall of 450-630 mm per annum.

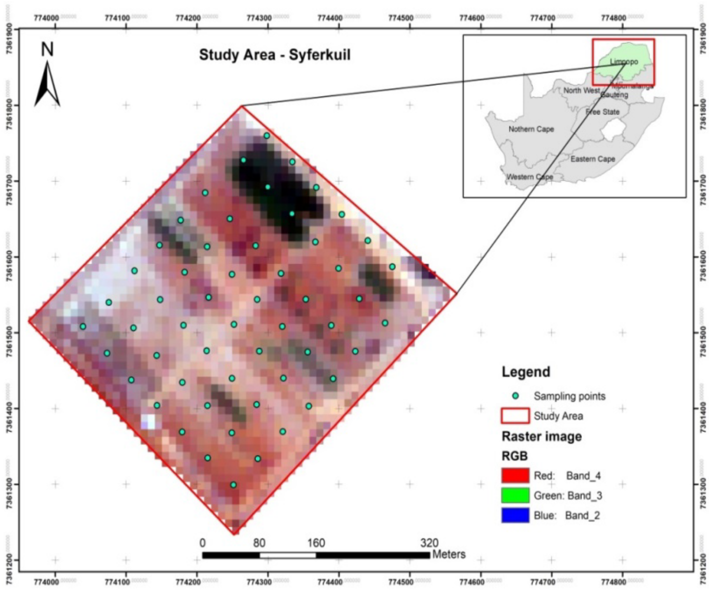

Figure 2.1: Study area and sampling points for extraction of spectral measurements

2.4.2 Data collection

2.4.2.1 Conventional methods

a) Field sampling

A grid sampling of 50 m by 50 m was followed to collect 55 soil samples. A shovel was used to take soil samples from the top 5 cm of soil surface. The soil samples are taken only in the top 5 cm soil layer for which the reflectance is thought to represent. Then samples were placed in plastic bags and were taken to soil laboratory. Global positioning system (GPS) was used to record the exact location of each sampled point in each grid.

b) Soil physiochemical properties

Soil samples were air-dried before analyzing for soil physiochemical properties. The electrical conductivity (EC) of the soil samples was determined conventionally in the laboratory using Mettler Toledo EC meter following a method from Jones (2001). Based on the classes determined by (Durand, 1983), five salinity classes were considered as shown in Table 2.1.

Table 2.1: Classification of soil based on the electrical conductivity (EC) classification supplied by Duran (1983).

EC (ds/m)	Salinity classes
EC < 0.6	Non-saline soil
0.6 < EC >1.0	Slightly saline soil
1.0 < EC >2.0	Moderately saline
2.0 < EC >4.0	Very saline soil
EC > 4.0	Extremely saline

Note. EC = Soil electrical conductivity, (ds/m) = DeciSiemens per metre

Particle size distribution was determined using the hydrometer method (Bouyoucos, 1962). Soil pH was first measured in deionized water (1:2 soil, water) followed by 0.01 M calcium chloride ($CaCl_2$) using a calibrated glass electrode pH meter (Rhodes, 1982).

2.4.2.2 Remote sensing

a) Image acquisition

A multispectral image called sentinel 2 was downloaded from the European Space Agency (ESA). The image had more than 10 bands ranging from the visible to shortwave infrared and with 10 m spatial resolution. A multispectral satellite image of the study area was collected on 09 March 2021.

b) Image processing

Before the multispectral satellite image was used, it went through pre-processing in order to remove the effects of the atmosphere where radiance values received at the sensors where converted into reflectance or spectral values using Quantum Geographic Information System (QGIS). Before the multispectral satellite image was used, it went through pre-processing. This was done in order to correct any distortion inherent in the images due to the characteristics of the imaging system and conditions. The imagery was atmospherically corrected using QGIS. The coordinates of the sampling points were used in QGIS to extract spectral or reflectance values from the image using vector point extraction. The methodology for estimating soil salinity includes; the collection of soil samples from the study area and laboratory analysis to determine the soil physiochemical properties; determining the reflectance values of sentinel 2 bands ;and determining the relationship between the spectral values extracted from the Sentinel 2 imagery and the conventionally determined soil physiochemical properties(Figure 2.2).

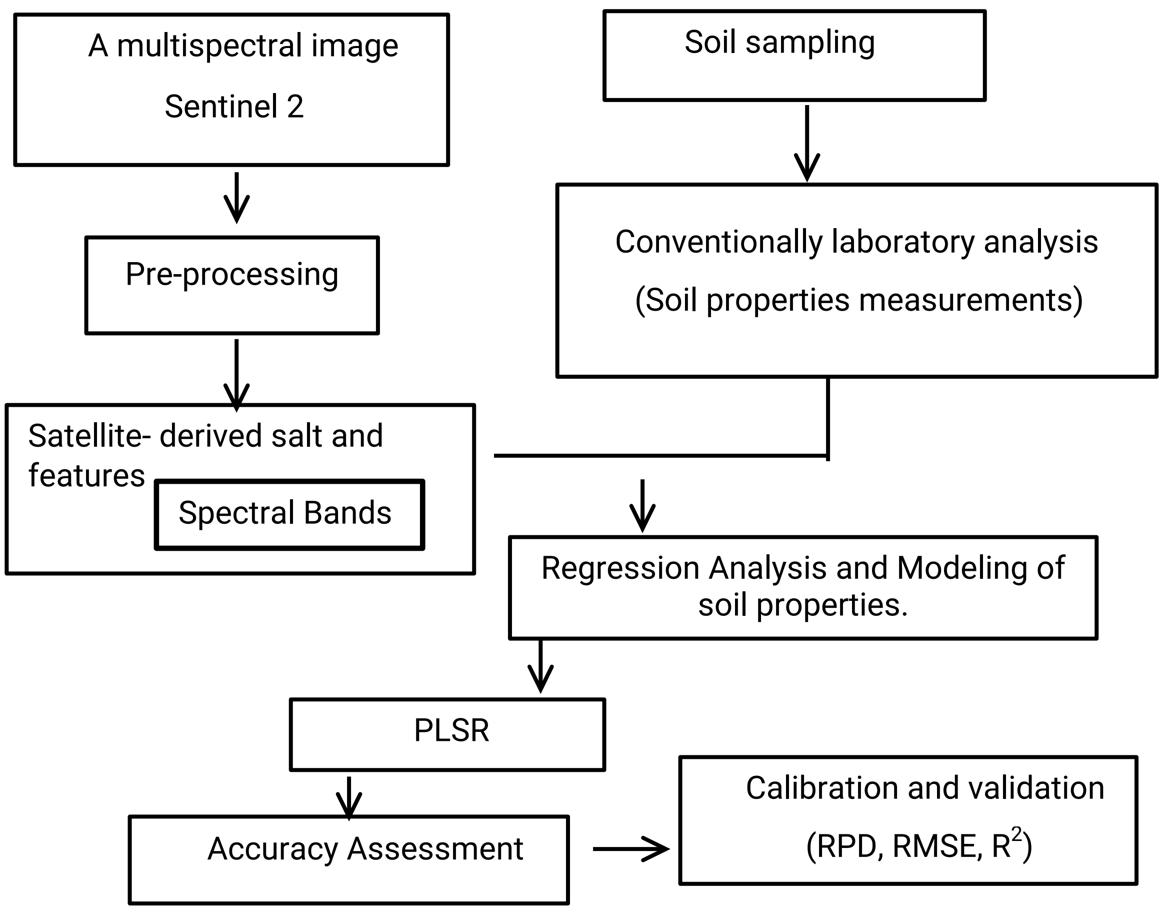

Figure 2.2: Flowchart indicating methodology for estimating the soil salinity in the Syferkuil farm, Limpopo, South Africa.

2.4.3 Data analysis

The soil samples were divided into calibration and validation group. Therefore, 70% was used for training or model development and 30% for testing or model validation. This study used one regression model which is Partial Least Square Regression (PLSR) model to estimate the relationship or correlation between the corresponding pixels or spectral values extracted from multispectral satellite imagery (Sentinel 2) and conventionally determined soil EC. The software used for PLSR is XLSTAT 2014. PLSR was chosen due to its capability to analyse large data, and it is more interpretable (Asfaw *et al.*, 2016). It is an effective tool for assessment of soil surface salt accumulation (Gorji *et al.*, 2016).

2.4.3.1 Calibration

Conventional laboratory measurement and their corresponding reflectance were used for calibrating a partial least square regression (PLSR) model. More than two thirds of the data were used in this exercise to select the spectral bands that provide best prediction of soil EC.

2.4.3.2 Validation

Validation of the developed models was done with independent set of data that was not used for calibration. The extracted spectral values from sentinel 2 and the conventionally determined soil EC were modelled using partial least square regression (PLSR), a method which reduces the variables, used to predict, to a smaller set of predictors. Soil EC is the dependent variables whereas the spectral or reflectance values from multispectral images are the independent variables. The Root Mean Square Error (RMSE), coefficient of determination (R^2) and relative percentage deviation (RPD) were used to test the predictive ability of the model. RMSE provides the absolute average error between the measured and the estimated values for samples (Leone *et al.*, 2012). The R^2 measures the proportion of the total variation accounted for and Table 2.2 shows the prediction of goodness of the model based on this parameter. RPD refers to the ratio of standard deviation (SD) to the RMSE prediction and predictive ability of the model was also based on the relative percentage deviation (Table 2.3).

Table 2.2: Prediction of goodness of the model based on the coefficient of determination (R^2) supplied by Mouazen *et al.* (2010)

R^2	Model performance
0.5 to 0.65	Poor prediction model
0.5 to 0.79	Good
0.80 to 1.00	Excellent

Note. R^2 = coefficient of determination

Table 2.3: Prediction of goodness of the model based on the relative percentage deviation (RPD) supplied by Duran (1983)

RPD	Model performance
RPD <1.0	Very poor model/ prediction
1.0 < RPD >1.4	Poor prediction model
1.4 < RPD > 1.8	Fair model/ Prediction
1.8 < RPD > 2.0	Good model
2.0 < RPD > 2.5	Very good model
RPD > 2.5	Excellent model

Note. RPD = relative percentage deviation;

2.5. RESULTS

2.5.1 Conventional laboratory analysis results for selected soil parameters.

The results obtained reveal that there is a great spatial variation of soil physiochemical properties in the study site. This is crucial especially when developing models and it ensures that the model is not biased. The results obtained shows that the soils at the portion where the soil samples are collected falls under slightly saline soils since it was found to be 1.03 ds/m (Table 2.4). The results show that soil surface salt concentration range from 0.003 to 2.36 ds/m. Therefore, the lower the soil surface salt accumulation, the lower the exchangeable and soluble

Calcium(Ca), the poorer the drainage conditions hence the lower the microbial activity, water holding capacity and soil fertility that results in reduced plant productivity (Sharma *et al.,* 2000). The results show that clay content range from - 3.71 to 20.16, sand percentage range from 0.064 to 90,72 and silt percentage range from 0,064 to 20,92. Based on the results obtained regarding soil particles distributions it shows that there is high variation across the field (Table 2.4).

Table 2.4: Statistical description of soil parameters analysed by conventional laboratory methods (n= 55) in Syferkuil farm, Limpopo, South Africa

Soil parameter	Max	Min	Mean	Median	SD	CV (%)
Soil salinity(EC)	2.36	0.003	1.03	0.35	0.54	52.43
Clay	20.16	3.71	8.18	8.36	5.77	70.54
Silt	20.92	0.06	10.34	11.05	4.42	42.75
Sand	90.72	0.06	80.77	81.28	6.08	7.53
pH(KCl)	8.02	5.23	7.07	7.14	0.53	7.49
pH(H_2O)	8.73	5.9	8.73	8.32	0.51	5.84

Note. SD = standard deviation; max = maximum; min = minimum; CV = coefficient of variation.

2.5.2 Prediction of soil salinity using models developed from multispectral satellite data.

The PLSR model yielded a coefficient of determination (R^2) of 0.468, the Root Mean Square Error (RMSE) of 0.44 ds/m and the RPD of 0.56 ds/m (Table 2.5). It also shows that the coefficient of determination is low. This actively demonstrates that the model performance was unsatisfactory.

Table 2.5: PLSR model performance for predicting soil EC using multispectral satellite in Syferkuil farm, Limpopo, South Africa

Soil parameter	R^2	RMSE	RPD	Model performance
Soil salinity(EC)	0 .468	0.44	0.56	Poor prediction model

Note. R^2 = Coefficient of determination; RMSE = The Root Mean Square Error; RPD = Relative Percentage Deviation.

2.6. DISCUSSION

2.6.1 Conventional laboratory analysis results for soil surface salt accumulation.

The results obtained demonstrate that there is high spatial variation at the research site because of statistical variables of soil parameters determined. The low soil EC in some portion of study area may possible be result of human activities (i.e., land use management, farm practices). This is because the portion of the farm that was used for this study has been cultivated for the past years and coupled with occasional resting. Conventional methods breakdown soil aggregates hence leading to soil being easily removed or eroded thus affecting soil quality. Furthermore, the natural factors such as the soil type and characteristics of terrain are the main drivers of the spatial variation of soil physiochemical properties. Taking into considerations that at the farm soils are identified as sandy loam texture and the dominant soil forms on the site are Shortlands and Clovelly (Soil Classification Working Group, 1991). Soils that have a higher content of clay conduct more concentration of soil EC than soils that have a higher content of silt and sand particles. Therefore, Shortlands soils do not present acidity issues and are productive. Irrigation and drainage is needed to reduce soil salinity because when irrigating, applying water can help to leach excess salts below the root zone and maintain the desired EC level for the crop growth. However, the application of irrigation systems that contains high amount of magnesium, aluminium and calcium can results in high accumulation of salts in the soil surface (Aldabaa *et al.*, 2015). In addition, at the farm soils are identified as sandy loam texture. Shortlands soils are typically associated with sweet grazing (Fey, 2010). Sandy loam texture is characterized by good drainage, low water holding capacity and high infiltration rate because of large macro pores.

Another possible reason may be due to climatic conditions (semi-arid for Limpopo, Mankweng area). Taking into consideration that the rainfall ranges from 450 to 630 mm per annum at the study sites.This actively demonstrate that there is high rainfall. In addition, rainfall is more effective in leaching salts or reducing salinity. However, in areas where there is little rainfall, evaporation rates are extremely high and water evaporates rapidly leaving dissolved mineral salts in the upper soil profile, which then build up progressively with space and time. A high concentration of salts at the surface can result in poor soil structure, low fertility and microbial activity and decrease the ability of the soil to support some plants (Sharma *et al.*, 2000).

2.6.2 The performance of model developed from multispectral satellite image (sentinel 2)

The PLSR model yielded a coefficient of determination (R^2) value ranging from 0.19 to 0.48; the relative percentage deviation (RPD) ranging from 0. 67 to 1.29; and the root mean square error ranging from 0.19 to 6.71 of all selected soil properties. The performance of the model was not excellent. Nonetheless, the result shows that approximately half of the soil properties variation could be explained by the reflectance values as recorded in the image. The average deviation of the predicted values from the multispectral images using the PLSR analysis is given by the magnitude of the RMSE value. The low R^2 value indicates that there are confounding factors. The confounding factors might come in the form of noise and errors due to variations in soil surface roughness, geometric and atmospheric effects (Casa *et al.*, 2013). Image noise is any unwanted disturbance in image data that is due to limitations in the sensing, signal digitization, or data recording process. Furthermore, the performance of models might be because of low spectral resolution of the image as compared to hyperspectral data, which have bands with narrower wavelengths (Qi *et al.*, 2017). The results showed low content of soil EC, this has influence on the reflectance spectra, and since soil which has low content of salt normally have high reflectance spectra (Lacerda *et al.*, 2016).

The results obtained in this study, are in line with Mohammad *et al.* (2019) who compared the estimated EC values with ground-truth measurements to evaluate model consistency in Kuh Sefid (Iran). The performance of the PLSR model was unsatisfactory. Furthermore, the results were supported by Allbed and Kumar (2013) who highlighted that multispectral data has limitations because of the coarse spatial and spectral resolutions, which influences the quality and quantity of the information they provide. The results agree with those obtained by Liao *et al.* (2013) using spectral reflectance of Landsat ETM image to predict soil texture. The coefficient of determination reported for silt, sand and clay was found to be 0.32, 0.21 and 0.3, respectively. Soil texture and soil EC are related even though soil texture is a physical property and soil EC is a chemical property. This is because soils that have a higher content of clay have higher EC than soils that have a higher content of silt and sand particles. Clay textured soils which have high compaction can increase salinity and decrease the ability of soils to support some plants. Furthermore, Clay textured soils have low reflectance as compared to sandy loam textured soils because of high water holding capacity. This actively demonstrates that as soil moisture increases, spectral reflectance of soil decreases. This means that if there is high amount of water in the soil, the reflectance will go down. Therefore, drier soil such as sandy textured soil reflects more than wet soils (i.e., clay textured soils) (Kumar and Sharma, 2020).

Casa *et al.* (2013) also found that the PLSR model for CHRIS satellite image showed that the model prediction performance for clay, silt and sand estimations was unsatisfactory. Forkuor *et al.* (2017) observed poor estimation accuracy for model performance of the following soil constituents namely sand, silt, clay and CEC when using multispectral satellite image (R^2 of 0.35, 0.54, 0.21 and 0.36; RMSE of 7.57, 5.94, 6.95 and 4.79, respectively). Franceschini *et al.* (2015) also reported poor prediction of K, Ca and Mg using PLSR models developed with spectra data derived from airborne sensor (R^2 of 0.44, 0.52, 0.51; RMSE of 1.28, 7.6, 2.4; RPD of 1.28, 1.47, 1.45, respectively).

The results obtained in this study are however in contrasts with Al-Gaadi *et al.* (2021) who estimated soil salinity using Sentinel 2 satellite images and related conventional laboratory results of soil EC and spectral values using multiple regressions modelling. They found that the generated models show satisfactory results in predicting soil EC. Conforti *et al.* (2015) have reported that the sand percentage was successfully predicted by visible and near infrared spectroscopy with the R^2 of 0.81 and RMSE of 4.8% for validation dataset. De Santana *et al.* (2018), Curcio *et al.*

(2013), Xu *et al*. (2018), also obtained good R^2 in their studies (0.70, 0.74, and 0.67 respectively) for predicting the sand percentage of soil from visible and near infrared reflectance spectroscopy using partial least square regression. The difference in the results of these studies may possibly be due to the performance of the models which varies with the study site and the regression techniques used (Gorji *et al*., 2017; Shahabi *et al*., 2017).The performance of the models varies with study site because models are calibrated differently based on the soil parameters investigated. For instance, the model that is used in South Africa might not be adopted in some other countries. This is because of different climatic conditions and soil types.

2.7. CONCLUSIONS AND RECOMMENDATIONS

The study revealed the potential of using remote sensing techniques and understanding of soil surface salt accumulation. The results obtained showed that the performance of the model was not excellent or produced low prediction accuracy using multispectral imagery. The use of Sentinel 2 imagery did not give good prediction of all selected soil properties. To improve model performance, future studies should consider an image with better spectral resolution and narrower bands (hyperspectral) to see if there is an improvement in the model performance. The hyperspectral image covers spectral bands narrower than multispectral imagery and image data from several bands are recorded at the same time. Furthermore, hyperspectral image offer much greater spectral resolution than multispectral imagery (i.e., cover two or more spectral bands simultaneously typically from 0.3 m to 14m

CHAPTER THREE

ASSESSMENT OF RILL DEGRADED SOILS IN SYFERKUIL FARM USING REMOTE SENSING TECHNIQUES

ABSTRACT

Assessment and identification of soils degraded by rill erosion is essential for future land use management and planning. Rill erosion is one of the most globally significant environmental soil hazards, which results in severe threat on crop productivity and biodiversity since it can lead to loss of soil quality. The causes of rill erosion can either be natural or human factors. The objective of this study was to identify soils degraded by rill erosion with acceptable accuracy from remote sensing images. The study was conducted at the Syferkuil farm, Limpopo, South Africa. In this study, rill identification and dimensioning was done on a multispectral imagery (Worldview 2 satellite image) using supervised image classification. Quantum Geographic Information System (QGIS) software was used for the visual vectorization of individual rills. The Semi-Automatic Classification Plugin (SCP) in QGIS was used to identify soils degraded by rill erosion in Syferkuil. The classification was done using the spectral angle algorithm. The area was classified into two categories which is rill and no-rill. Raster object was converted to vector object using polygon trace tool for further object-based processing. For the purpose of assessing the accuracy of the supervised image classification, reference data was created, and the error matrix was calculated, and the results indicated the user's accuracy and producer's accuracy for no rill erosion and rill class were obtained.

The results of the study were not satisfactory using the supervised classification of the Worldview 2 satellite image. The possibility therefore exists that some soil erosion features may have been classified as non-erosion features. In addition, the low separability of classes limits the applicability of the supervised classification methods, particularly in spectrally complex erosion areas. The overall classification performance or accuracy of 47.91% with a Kappa coefficient of 0.41 was obtainable. Therefore, these remote sensing techniques, although there is much room for improvement, can contribute into identifying and quantifying soils degraded by rill erosion especially in data scarce environment and resources constrained province (i.e., Limpopo, Mankweng Area).

Keywords: Soil degradation, Rill erosion, Syferkuil, Remote sensing, Multispectral image (Worldview 2 satellite image), Supervised mage classification.

3.1 BACKGROUND

Monitoring soil quality degradation is essential towards land use management studies and reclamation programmes or rehabilitation strategies. The first step towards rehabilitation and reclamation of different soils is by providing accurate soil information and having an understanding of soil degradation forms. This will help in identifying high risk areas for future land use management and planning. This study will only focus on soils degraded by rill erosion. Rill erosion is a process of soil degradation that removes soil materials from one point on the earth to be deposited elsewhere through processes such as detachment, suspension, transportation and, mass movement (Vanmaercke *et al.*, 2021; Li *et al.*, 2016) .It is an important form of soil erosion that contributes greatly to soil degradation and loss in South Africa. Monitoring soil quality degradation can be precisely achieved through the usage of remote sensing as an alternative approach due to its advantages over conventional methods (i.e., Field surveys). Field surveys delay the process of acquiring necessary soil information of high accuracy in a short period of time and are limited to small areas (Rossel *et al.,* 2011; Odindi *et al.,* 2017).

In remote sensing (RS), data is collected using either passive or active remote sensing techniques, without making physical contact with the object itself (Chauhan, 2015). Active remote sensing, capture EM radiation in the visible spectrum and has its own source of light or emits its own energy. However, in passive remote sensing the source of signal is the sun, which emits EM at its highest intensity between the ultraviolet and infrared. Remote sensing has the capability to identify soils degraded by rill erosion with acceptable level of details (Kumar, 2013; Morshed *et al.,* 2016; Taghadosi *et al.,* 2018). Remote sensing is able to cover a large area of land especially when data is required for large areas. Moreover, remote sensing is faster, inexpensive, non-destructive, facilitate long term monitoring, and accurate monitoring tool. In addition, remote sensing allows for past, present, and near real time monitoring of objects of interests (Chauhan, 2015).

The multispectral satellite imagery has been widely studied in previous research and has been found to be a very promising tool for assessment rill degraded soils (Karydas *et al.,* 2020; Desprats *et al.,* 2013). The multispectral satellite imagery has the capability to provide improved spatial resolution and image acquisition is not costly which makes it effective in terms of classifying, analysing, monitoring and mapping soil degradation forms at different locations. RS images can provide detailed but much reduced version of reality or 3D view of object of interests. This can cover different areas which might be difficult to cover using some other terrestrial means (Karydas *et al.,* 2020; Desprats *et al.,* 2013).

To contribute to the valuable information and better understanding on the effects of soil degradation caused by rill erosion with the use of remote sensing, our study was focused on the Mankweng area (Syferkuil farm) in Limpopo province. This study will establish if rill degraded soils could be identified and quantified using remote sensing. The objective of this study was to identify soils degraded by rill erosion with acceptable accuracy from remote sensing images.

3.2 PROBLEM STATEMENT

Rill identification and assessment of intensity using field work can provide accurate results and have been preferred by most researchers, but they are only applicable to small areas. The main difficulties lie on meeting high demands of detailed soil information in short period of time with reasonable cost (Steinberg *et al.*, 2016). Field surveys are time consuming and labour intensive particularly for regional level in which data is required for large scale applications. Moreover, these traditional methods (i.e., field work or field surveys) are difficult to replicate and limited to small areas (Odindi *et al.*, 2017). Therefore, with the current demand for up to date and accurate soil information on soil degradation, these methods are ineffective. Moreover, they delay the process of acquiring necessary soil information of high accuracy in a short period of time (Rossel *et al.,* 2011).

The challenges of conventional methods, however, could be addressed by the use of remote sensing techniques. Many researchers have identified remote sensing as an alternative method for assessment and identification of soils degraded by rill erosion due to its advantages. This is because remote sensing techniques can provide rapid analysis of soil information, cover large land surface and facilitate long term monitoring at an acceptable level of detail (Chauhan, 2015). A multispectral imagery is able to provide excellent spatial coverage of a large area and making it easy to identify soils degraded by rill erosion (Gorji *et al.,* 2017). Remote sensing (RS) images can provide detailed, but much reduced version of reality or 3D view of object of interests. These imageries can provide valuable information that might not be able to obtain using other methods since our visual perception is limited to some portions of electromagnetic spectrum (EMS). This means that it can provide information beyond our human visual perception. Furthermore, it can provide the records of soil degradation forms at those specific times the images were captured and cover different areas which might be difficult to cover using field surveys. This can help to observe change that might be occurring over time and to understand the spatial extent and rate of this problem.

3.3 LITERATURE REVIEW

3.3.1 Work done on the problem statement

3.3.1.1 The importance of identifying soils degraded by rill erosion using remote sensing.

Soil erosion globally is an intense, poorly controlled process and there is lack of up-to-date soil information. Soil erosion is a serious problem in the entire world and a major threat of land degradation in South Africa particularly in Limpopo (Rahmati *et al.,* 2016; Le Roux and Sumner, 2012). It is also considered as one of the most critical environmental issues due to the devastating impacts on agricultural lands. Therefore, soil erosion is a dynamic process requiring constant monitoring while keeping up-to-date information on its spatial distribution. Soil conservation and rehabilitation measures and understanding the dynamics of soil degradation and driving factors is a crucial step (Nwilo *et al.*, 2021; Le roux and Sumner, 2012). It is important for modelling erosion hazard of the area or high-risk area for future land uses management and planning (Ogbonna, 2012).

Rill erosion can lead to land abandonment and threaten food security since soil fertility or nutrient status of the soil might be compromised. In turn, many farmers abandoning their farmlands due to the threats posed by rill erosion and then cause economic effects on farming communities. In addition, rill erosion can results in decline soil fertility, poor soil structure, poor drainage conditions. This is because during heavy rainfall essential nutrients are leached away, and as a results leading to decreased soil quality and capability to sustain crops (Dewitte *et al.*, 2015).

3. 3.1.2 Rill degraded soils monitoring, identification and assessment using remote sensing.

Various studies have been done for rill identification and assessment of intensity using remote sensing. Saadat *et al*. (2014) conducted a study of mapping rill erosion using Landsat in Iran. The results obtained showed that the proposed method is able to produce a rill erosion intensity map with an accuracy of 96% at this study location.

Desprats *et al*. (2013) conducted a study of mapping rill erosion using Quick Bird and SPOT satellite imagery in Tunisia. They found that the high-resolution imagery (Quick Bird) is a valuable tool from which one can extract the consequences of soil degraded by rill erosion whereas it remained fairly insignificant with the SPOT type. However, this methodology used demonstrates the potential for extracting rill erosion features from the imagery, but more importantly it discusses a GIS analysis that can identify elements with soil erosion traits from among all the linear features.

Fiorucci *et al*. (2015) conducted a study of mapping and measuring rill erosion using GeoEye -1 panchromatic stereo images in Italy. In this study, they found that the proposed method is faster than field work, improves the ability to map these features over large areas, which are applicable to detailed scales and analyses, and other more traditional method. Karydas *et al*. (2020) conducted a study of mapping rill erosion in which data from sentinel 2 images was used. They have found that the multispectral imagery (sentinel 2) is suitable for future erosion assessments with G2 model. Basically, G2 is quantitative algorithm for mapping soil loss and sediment yield rates on month-time intervals. G2 model proved to work as a rapid and at the same time flexible mapping tool.

Gafurov (2022) conducted a study using the trained rill erosion convolutional neural network (RECNN) for automated rill erosion detection from remote sensing data in Russia. The results of this study showed accuracy level of 0.62, F1-measure was 0.76, and loss-function was 0.27. Furthermore, it was found that not a single case of detection of gullies or ground roads, which are abundant in the study area, instead of rills, was recorded.

3.3.1.3 The use of supervised image classification for identification and assessment of rill degraded soils.

In supervised image classification, there is no limited control over identity of classes. Training area is referred as an area of known identity delineated on the digital image within its coordinate system. The key characteristics of training areas are number of pixels, size of the training area, shape of the training area, location of the training area, and number of training area (Eastman, 2003). However, the training data not often defined spectrally, and the training areas must be selected carefully to minimize errors. Moreover, not all spectral classes may be known to the users. In most instances, the decision to utilize this image classification depends on the study area, the skills of individual processing the image, and the spectral distinctness of the classes. The spectral class are inherent in the multispectral imagery or remotely sensed data whereas the information class are defined by human beings (Eastman, 2003).

3.3.1.4 Factors affecting the spectral signatures of rill degraded soils.

According to Taruvinga, (2008), the spectral signature of soil erosion forms differs. In addition, the spectral signature of soils depends on the moisture content, organic matter content, texture, structure and iron oxide content (Aggarwal, 2004). Spectral characteristics of vegetation differ with wavelength and the pigment leaves of plant reflect green wavelengths and strongly absorb red and blue wavelengths. Bare soil and vegetation have different spectral characteristics and are completely different and need to be dealt with separately when selecting training areas. The heterogeneous nature of soil degraded by rill erosion makes it complex to differentiate with the surroundings, thereby posing a challenge to the classification technique (Aggarwal, 2004).

3.3.1.5 The possible human and environmental factors that influence rill erosion initiation and development.

According to Chaplot *et al.* (2013) and Mararakanye and Summer, (2017), Soil erosion forms are influenced by soil type, bedrock lithology and structure, precipitation, slope angle, vegetation and land use. Although, rill erosion is a natural process, it is accelerated by human activities and rainfall or climatic conditions (Vanmaercke *et al.*, 2021; Li *et al.*, 2016).

Clay textured soil is more compacted and has higher structural stability that resists soil erosion whereas sandy or silty textured soils are less susceptible to soil erosion because of larger pores and high infiltration rate which results in high leaching of soil materials (Gandariasbeitia *et al*., 2017). Overgrazing can reduce ground cover and enable erosion by wind and rain. Therefore, vegetation plays a crucial role in reducing rill erosion because plants roots bind soil particles together and increase structural stability of soils that are not easily leached out or eroded by soil erosion agents (i.e., water or wind). Therefore, the more water flowing over the surface or land, the more soil particles are leached out or transported from one place to another. Meaning that farmland that has no vegetation is vulnerable to rill erosion as compared to the one having vegetation cover. Land use practices can influence rill erosion. For instance, the conversion of natural ecosystem to pasture land can lead to high rates of rill erosion and loss of top soil and nutrients. The slope can have a major influence on rill erosion. Meaning that when the slope is longer (length), surface area of water collection increases and therefore increase the water surface runoff (Le Roux and Sumner, 2012).

3.3.2 Work not done on the problem statement.

The study is done at a farm level requiring much detail with a potential to apply on a large scale. The remote sensing technique used can vary with the location or study area and the feature being observed. Most of the studies have focused on the soil erosion origin and contributing factors. Moreover, there is little work done that utilizes remote sensing for assessing soil degradation on South African soils and particularly in Limpopo. Therefore, this study will establish if soils degraded by rill erosion could be identified and quantified using remote sensing as an alternative method to the traditional methods (field work or surveys).

3.4 RESEARCH METHODOLOGY

3.4.1 Description of the study area

The study was conducted in Syferkuil, experimental farm of the University of Limpopo (Figure 3.1). The farm is about 1,650 ha in size and 13 km from the main campus of the University. The climate is semi-arid with rainfall of relatively 450-630 mm per annum, experiencing about 400 mm of summer rainfall. The farm is exposed to temperatures ranging between 14°C during winter periods and 35°C in summer. The soil forms are Hutton and Glenrosa and composed of seven minerals which include plagioclase, K-feldspar, amphibole, quartz, interstratified illite or smectite, talc and kaolinite dominated by quartz and interstratified illite or smectite (Molepo *et al.,* 2017). The soils from Syferkuil farm is moderately shallow to deep and consists of the following texture classes; sandy loam, loamy sand and sandy clay loam (Phefadu and Kutu, 2016).

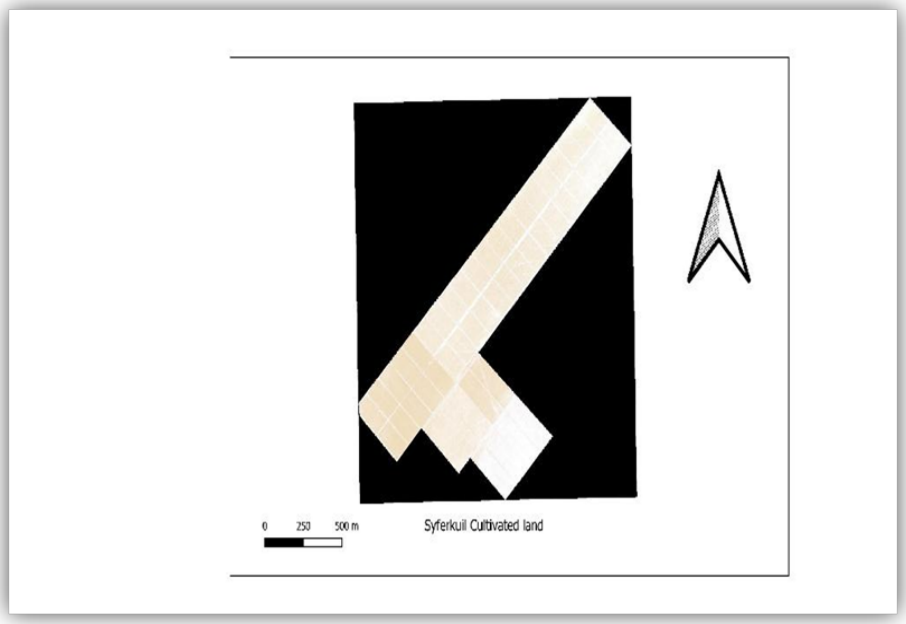

Figure 3.1: Study site in the Syferkuil farm, Limpopo

3.4.2 Data collection

3.4.2.1 Remote sensing

a) Identification of soils degraded by rill erosion using supervised image classification

In this study, the Quantum Geographic Information Science (QGIS) software was used for the visual vectorization of individual rill erosion forms. The Semi-Automatic Classification Plugin (SCP) in QGIS was used for identification or assessment of soils degraded by rill erosion. Supervised image classification was done using QGIS to identify soils degraded by rill erosion in Syferkuil. The classification was done using the spectral angle algorithm. The portion of the farm that was used for this study has an area of 61 ha. The area was classified into two categories which is rill and no rill. Raster object was converted to vector object using polygon trace tool for further object-based processing. The SCP is defined as a free open source plugin for QGIS (Congedo, 2016) that allows for the semi-automatic classification of remote sensing images for the visual vectorization of individual rills. Supervised image classification involves collecting data from the training area followed by a classification step or stage then output stage (Figure 3.2). Rill identification and assessment was done on multispectral satellite imagery [Worldview 2 satellite image] as a form of feature extraction. This image multispectral imagery had one panchromatic band with 46 cm spatial resolution and eight bands with 1.85 m spatial resolution. This satellite image had wavelengths covering from 400 nm to 1040 nm. The supervised remote sensing image classification approach was used based on only two categories which are rill and no rill. It is the digital image processing that commonly group pixels to represent land cover attributes. The sample size was selected in an image that represents the specific classes and then directed the image processing software to use these training sites as references for the classification of all other pixels in the image. It used the spectral information represented by the digital numbers in many spectral bands and attempt to classify each individual pixel based on this information. The computer used an algorithm in order to determine spectral signatures for each training class and then compares each pixel in the image to these signatures and labels it as the class it most closely resembles digitally. The training areas were selected based on what it is known on the ground then digitizes a polygon within that particular area. The spectral signature of each pixel was matched with the training signatures and the image was classified accordingly. Pixels which have the same spectral characteristics were identified as belonging to the same class and assigned or given unique number or colour. Pixels are defined as the small representation of reality or objects of interest.

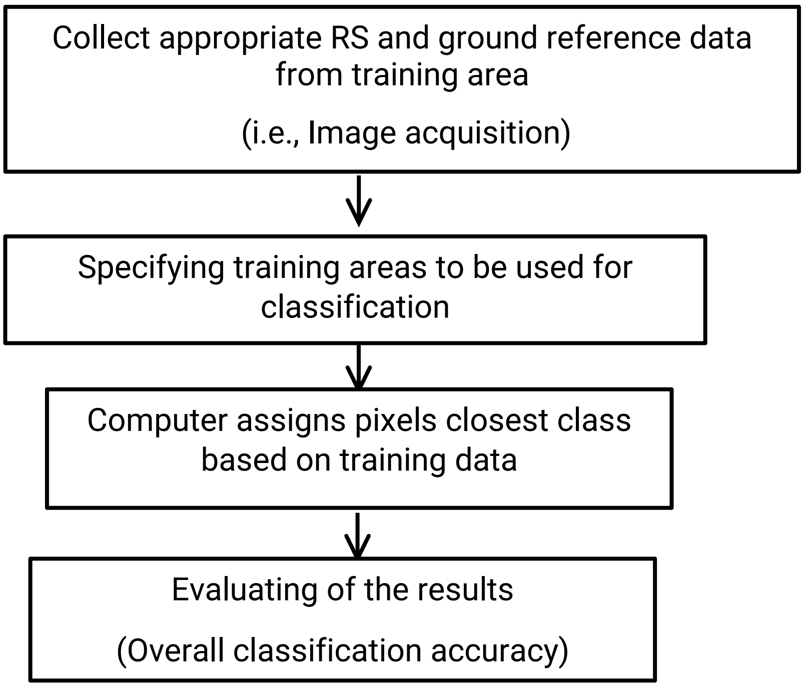

Figure 3.2: Flow charts showing supervised image classification.

3.4.3 Data analysis

The multispectral imagery (Worldview 2 imagery) was used to discriminate rill and no rill erosion in Syferkuil farm. The SCP in QGIS was used to classify the image or for the visual vectorization of individual rills to generate statistical results of the map accuracy. SCP has the ability to discriminate land cover feature and offers a potential for mapping individual rills.

3.4.3.1 Accuracy assessment

Accuracy assessment and check was done by generating validation points. The error matrix is the method used for assessing the degree of accuracy (Mather, 2004) and has been widely used in classification accuracy assessment. Error matrix is a square which contains rows and columns that are equal to the number of categories whose classification accuracy is being assessed (Lillesand *et al.*, 2008). The results of the error matrix were interpreted using the producer’s accuracy, user’s accuracy, overall classification accuracy and the Kappa classification. The overall classification accuracy summarises the producer's accuracy as well as the user's accuracy. The user's accuracy measures the errors of commission while the producer's accuracy measures the errors of omission. The Kappa coefficient is the difference between the actual agreement in the error matrix and the agreement occurring by chance (Persello and Bruzzone, 2010).

RESULTS AND DISCUSSION

3.5 RESULTS

The results of the digital image processing (supervised image classification) of the area classified into two categories which is rill and no rill erosion showed a low overall accuracy of up to 47.91%. The accuracy results produced is very low and the kappa statistic of 0.41 indicates none to slight agreement.

3.5.1 Supervised image classification results

The map shown in Figure 3.3 illustrates the cultivated area with the selected training areas created by using Region of interest (ROI) polygon.

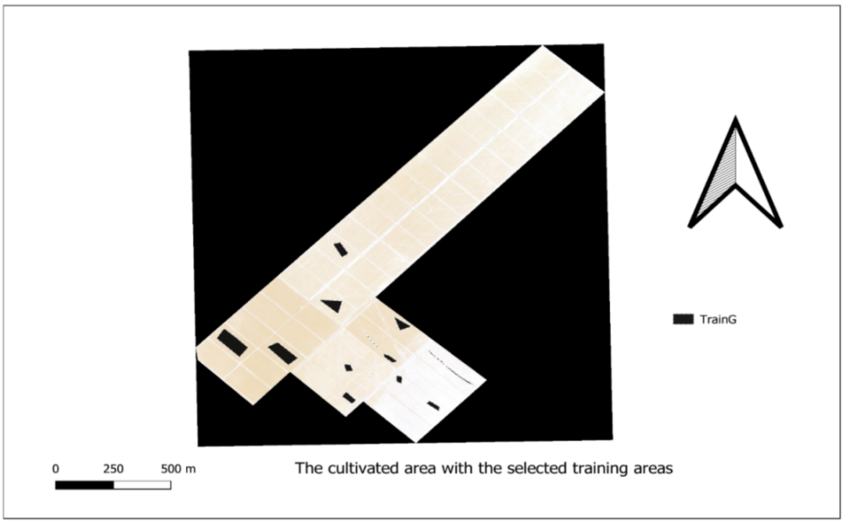

Figure 3.3: The cultivated area with the selected training areas

Figure 3.4 below illustrates the validation points selected randomly to provide information and evidence that the classification produced the expected results. The random selection was done automatically by SCP and this map shows that it covers the entire study area.

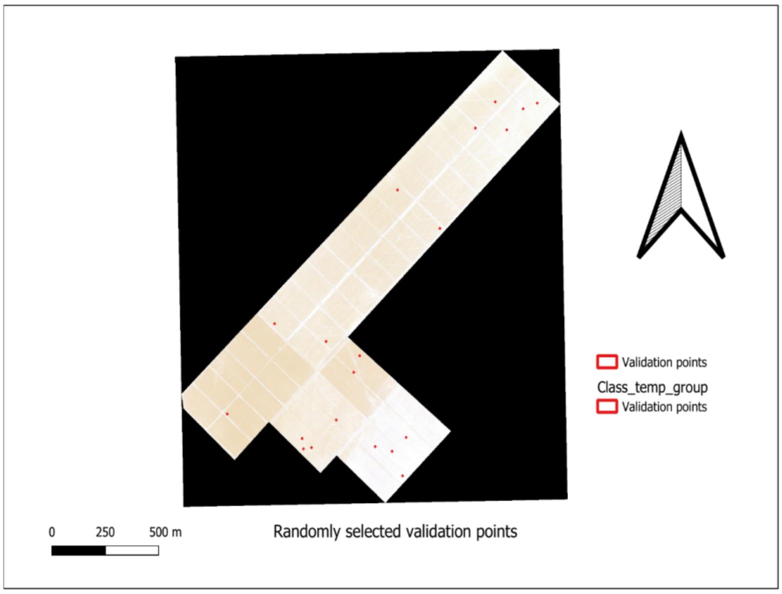

Figure 3.4: Randomly selected validation points

Figure 3.5 below shows the classification done with spectral angle algorithm. The classification is showing the rill and no-rill regions. It shows that areas affected by rill are identified positively. Areas like inter-plot paths are also identified as rill regions. Furthermore, some whole plots are also depicted as representing rills. The veracity of the model prediction is clearly conveyed by the accuracy results. This means that the predictive ability of the model depends on the accuracy of the results. The higher accuracy means better performance.

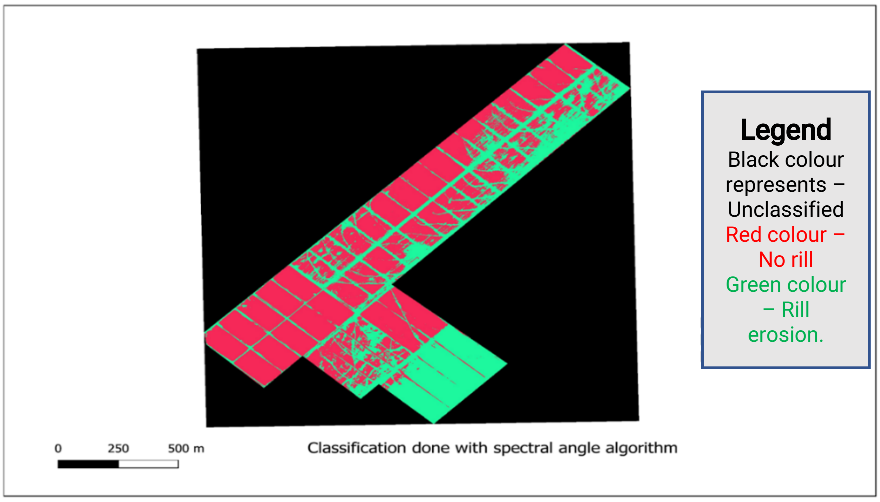

Figure 3.5: Classification done with spectral angle algorithm.

3.5.2 Accuracy results

The supervised image classification was used for classification of soils degraded by rill erosion. The Kappa statistic of 0.41 indicates moderate agreement (Table 3.1). The overall classification accuracy calculated of 47.91% indicates that only 47.91% accuracy was classified correctly (Table 3.2). The user's and producer's accuracy indicate the performance of supervised image classification for rill erosion and no rill erosion identification. However, a 47.23% of producer's accuracy in rill class indicates more errors of omission while 45.80% of producer's accuracy in no rill erosion class. Kappa is the most used indicator of classification accuracy and is used to assess the agreement between the dependent variable and independent variable. In addition, Kappa coefficient can also be used to assess the performance of a classification model (Persello and Bruzzone, 2010). A Kappa value of 0.41 in rill class is problematic because the classification accuracy indicates moderate agreement rill and no rill erosion. The accuracy results produced is very low as indicated in Table 3.3.

Table 3.1: Showing the classification to interpret the strength of agreement based on the Cohen's Kappa value (Altman, 1997; Landis, 1977)

Kappa coefficient	Strength of agreement
≤ 0	No agreement
0.01 - 0.20	None to slight agreement
0.21 - 0. 40	Fair agreement
0.41 - 0.60	Moderate agreement
0.61 - 0.80	Substantial agreement
0.81 - 1.00	Almost perfect agreement

Table 3.2: Showing area-based error matrix, reference, standard error, confidence interval, producers' accuracy, users' accuracy and kappa classification values.

>AREA BASED ERROR MATRIX

> REFERENCES

V_ classified	0	1(rill)	2(no rill)	Area	Wi
0	0.00	0.00	0.00	2529015.50	0.69
1	0.00	0.012	0.11	440931.25	0.12
2	0.00	0.019	0.17	712232.00	0.19
Total	0 .00	0.031	0.28	3682178.75	
Area (metre^2)	0.00	0.0	0.28	3682178.75	
SE	0.00	0.02	0.02		
SE area	0	83767	83769		
95% Cl area	0	164184	164184		
PA[%]	nan	47.24	45.76		
UA [%]	nan	49.40	50.03		
Kappa coefficient		0.41	0.41		

Note. PA = producer's accuracy, UA = user's accuracy, SE= standard error and, CL = confidence interval.

Overall accuracy [%] = 47.91

Kappa coefficient = 0.41

Table 3.3: Worldview 2 satellite image accuracies (%) for rill erosion and no rill erosion.

Two categories	Producer's accuracy (%)	User's accuracy (UA)	Overall Accuracy (%)
Rill erosion	47.24	49.40	48.31
No rill erosion	45.76	50.03	47.52
Overall Accuracy (%)	47.91		

3.6 DISCUSSION

The results obtained reveal that the digital image processing (supervised image classification) of the area classified into two categories which is rill and no rill erosion showed a low overall accuracy of 47.91% and the total Kappa coefficient of 0.41. The accuracy results produced is very low and the Kappa statistic of 0.41 indicates moderate agreement between rill and no rill erosion. Therefore, the results were not satisfactory using multispectral satellite image [Worldview 2 satellite image]. This may be due to limited spectral bands, atmospheric conditions and soil properties (Shruthi *et al.,* 2011; Taruringa, 2008). The heterogeneous nature of soil degraded by rill erosion makes it complex to differentiate between soil erosion feature and non-erosion features, thereby posing a challenge to the classification technique. The error matrix (pixel count values), Reference, Classified and Pixel Sum values are in Appendixes 1 and 2.

In a previous study by Torkashvand and Alipour (2009) using supervised image classification for assessment of rills using remote sensing techniques in plain physiography of Iran , the researchers found out that the accuracy decreases where there are other land uses such as cultivation due to similarity in spectral characteristics. Thus, it is important to classify where there is bare soil in order to increase the accuracy. Furthermore, within the study area, the spectral reflectivity of soil erosion varies considerably, and in some cases tends to be similar to non-erosion features (for example bare soil). The possibility therefore exists that some soil erosion features may have been classified as non-erosion features. Similarly, Sepuru and Dube (2017) emphasised that the low separability of classes limits the applicability of the supervised classification methods, particularly in spectrally complex erosion areas.

Another possible reason is that the supervised image classification depends on the training sites, the skill of the person processing or classifying an image and the spectral distinctness of the classes. This method of classification requires close attention to the development of training data and if the data is poor and not representative, the classification results will also be poor decreasing the accuracy of results. However, the training data not often defined spectrally, and the training areas must be selected carefully to minimize errors. Moreover, not all spectral classes may be known to the users. The spectral class are inherent in the multispectral imagery or remotely sensed data whereas the information class are defined by human beings.

These results are however in contrast with those obtained by Floras and Sgouras. (1999) who found high overall accuracy of 83.94% using supervised image classification method (The Gaussian maximum likelihood classifier). This is because their classification was assisted by Digital Elevation Model (DEM). Moreover, they used the Landsat 5 images while we used the worldview imagery. Landsat 5 image is easy to obtain and has a wide coverage and, is suitable for the large-scale land cover studies (Wang *et al.*, 2019)

This is supported by various studies (Phinzi and Ngetar (2017); Munyati and Ratshibvumo (2011); Singh *et al.* (2015) using Landsat 5 in assessing rills erosion. The results of these studies indicated that an overall classification performance or accuracy of above 81% was obtainable. The results are in line with those obtained by Sepuru and Dube (2018) in mapping spatial distribution of three eroded area using Sentinel 2, achieving an overall classification accuracy of 81,90%. In another study by Azad (2019), the author found a high overall accuracy of surface erosion classification of 69% using the supervised image classification. Therefore, higher spatial resolution allows finer grain details to be discerned in the imagery. Satellite imagery with relatively higher spatial resolution allows the classification technique to detect the smaller rills which were omitted from low spatial resolution imagery. The image acquisition is costly and limited due to their small swath width (Seutloali *et al.*, 2016, Shruthi *et al.,* 2011; Ranga *et al.*, 2015; Le Roux and Marakanye, 2012).

3.7 CONCLUSION AND RECOMMENDATIIONS

This study focused on identifying soils degraded by rill erosion using remote sensing techniques. In this study, the results were not satisfactory from multispectral satellite image [Worldview 2 satellite image] using digital image processing called supervised image classification. Despite low prediction accuracy in this study, remote sensing is a promising tool since it can provide information beyond our human visual perception. Furthermore, remote sensing can provide the record of soil degradation form at those specific times the images were captured and cover different areas which might be difficult to cover using field based methods.

Even though the results were not satisfactory, remote sensing can serve an alternative method to field based methods because the results of this study can be greatly improved through the use of much higher spatial resolution imagery and narrow bands (hyperspectral satellite image) to see if there is an improvement in the accuracy level. This is because satellite imagery with relatively higher spatial and spectral resolution (i.e., hyperspectral imagery) allows the classification technique to detect the smaller rill erosion features which were omitted from low spatial resolution imagery.

CHAPTER FOUR

ASSESSING SOIL ORGANIC CARBON STATUS USING MULTISPECTRAL IMAGES IN SYFERKUIL FARM

ABSTRACT

Soil organic carbon (SOC) depletion which is directly linked to human and natural activities poses a major threat to agricultural productivity since it can lead to reduced soil and water quality, soil fertility and nutrient status. Assessing and monitoring soil quality degradation is vital in terms of practicing precision agriculture and future land use management and planning. The main objective of this study was to determine SOC status with acceptable accuracy from a remotely sensed image. The size field area of the plot sampled is 61 ha. Ninety seven soil samples were collected and a regular sampling grid strategy of 50 m by 100 m was followed in Syferkuil Farm, South Africa, Limpopo. Global positioning system (GPS) was used to record the exact location of each sampled point in each grid. In this study, the SOC of the soil samples was determined conventionally in the laboratory using a Walkley Black method. The coordinates of the sampling points were used to extract spectral value from the multispectral image (Sentinel 2) using QGIS. The spectral values and the conventionally determined SOC were modelled using partial least square regression (PLSR). The results showed low prediction accuracy of SOC with R^2 of 0.41, Root Mean Square Error (RMSE) of 0.53%, and the relative percentage deviation (RPD) of 1.21 using the PLSR model developed from the multispectral image (Sentinel 2). The result shows that approximately half of the SOC variation could be explained by the reflectance values as recorded in the image. Despite low prediction accuracy, remote sensing techniques are potential tools to monitor and detect SOC unlike in the old days, when conventionally laboratory methods were the only means of assessing soil organic carbon depletion or status. Sentinel 2 could be used to make preliminary study of SOC before detailed in situ assessment could be done. Thus, it is recommended that an image with better spectral resolution (hyperspectral) be investigated to see if there be an improvement in the model performance.

Keywords: Soil degradation, Soil organic carbon, Remote sensing, Multispectral image (Sentinel 2 imagery), PLSR, Syferkuil farm

4.1 BACKGROUND

Soil degradation has become the most serious global environmental issue that needs a serious attention due to its devastating impacts on agricultural productivity. This can lead to reduced water quality, soil fertility and nutrient status especially in arid and semi-arid regions (Shi *et al.*, 2019). Thus, it is of crucial importance to monitor and assess soil quality degradation for sustainable and precision agriculture. This can help with reclamation and rehabilitation of soils and minimizing the risks of soil degradation forms in different regions. In this study, one form of soil quality degradation to monitor or assess is soil organic carbon (SOC) depletion. Assessing SOC status is vital in terms of soil health monitoring and environmental management. SOC depletion is directly linked to human and natural factors (FAO of United Nations, 2012). In agricultural land, SOC is a key indicator of soil fertility due to its beneficial effects on soil properties. This is because SOC has potential to increase soil fertility, quality, and cation exchange capacity and enhances the water holding capacity (Mccauley *et al.*, 2017; Zhu *et al.*, 2018; Bangroo *et al.*, 2020). Moreover, SOC can contribute to high stable aggregate structures, that are resistant to soil degradation forms hence binds soil particles together. Soil carbon contains a major proportion of carbon that is considered to be three times larger than in the atmosphere and terrestrial vegetation (Houghton, 2007).

Over the past decades, conventional laboratory methods were the only means of assessing SOC depletion. These methods delay the process of acquiring necessary soil information of high accuracy in a short period of time, due to their long procedure (Rossel *et al.*, 2011). Moreover, they are difficult to replicate, time consuming, labour intensive, and are limited to small localized scales (Odindi *et al.*, 2016, Angelopoulou *et al.*, 2019). Remote sensing techniques have the potential to serve as an alternative approach due to its advantages over conventional laboratory methods (Kumar *et al.*, 2016). In previous research, remote sensing have been widely used and found to be a promising tool for assessment of soil degradation forms. These include simultaneous collection of data systematically, inexpensive, non-destructive, facilitate long term monitoring and non-requirement of chemical reagents (Chauhan, 2015; Angelopoulou *et al.*, 2019). In addition, it can provide rapid analysis of soil information and covering large land surface at an acceptable level of detail. In this study, the multispectral imagery (i.e. Sentinel 2 satellite imagery) was used to extract spectral values using the coordinates of the sampling points in QGIS. The multispectral image has the capability to provide improved spatial resolution and excellent perspectives on land related studies and have the capability to produce significant results in SOC estimation and soil health monitoring (Wang *et al.*, 2018; Odindi *et al.*, 2016; and Zhou *et al.*, 2020). Therefore, the purpose of this study is to determine SOC status with acceptable accuracy from remote sensing. The study was focused on the Syferkuil farm in the Limpopo province.

4.2 PROBLEM STATEMENT

Soil carbon is a key indicator of soil fertility or quality since it can influence the three categories of properties (physical, chemical and biological) (Houghton, 2007). For instance, water holding capacity, microbial activity and cation exchange capacity of soils (Mccauley *et al.*, 2017; Zhu *et al.*, 2018; Bangroo *et al.*, 2020). In addition, it can contribute to high stable aggregate structures, that are resistant to soil degradation forms. This is because SOC has the capability to bind soil particles together.

Since there is higher demand of detailed soil carbon information, remote sensing techniques have the ability to provide soil carbon information in short period of time with reasonable cost. Remote sensing (RS) could be used as an alternative method to the conventional laboratory methods due to its advantages. It can provide rapid analysis of soil information and covering large land surface at an acceptable level of details (Chauhan, 2015). It has the potential to provide valuable information that might not be able to obtain using other methods since our visual perception is limited to some portions of EMS (Electromagnetic spectrum). This means that it can provide information beyond our human visual perception. Furthermore, it can provide the records of soil degradation forms at those specific times the images were captured and cover different areas which might be difficult to cover using some other terrestrial means. This can help to observe change that might be occurring over time and to understand the spatial extent and rate of this problem. RS images can provide detailed but much reduced version of reality or 3D view of object of interests (Gorji *et al.*, 2017).

Multispectral imagery is able to provide excellent spatial coverage of a large area, and making it easy to obtain soil carbon information (Gorji *et al.*, 2017). Despite the wide use of conventional laboratory methods, these methods are time consuming, expensive, and labour intensive especially when data is required for large farmlands (Rossel *et al.,* 2011). Therefore, with the current demand for up to date soil carbon information, conventional methods are ineffective.

4.3 LITERATURE REVIEW

4.3.1 Work done on the problem statement

4.3.1.1 The importance of assessing soil organic carbon status.

Soil organic carbon depletion as a result of natural and human activities can lead to reduced crop productivity due to lower moisture retention and nutrient status (FAO of United Nations, 2012). This is because, high level of SOC depletion influences water retention properties and cation exchange capacity (Franzluebbers, 2002). Soil organic matter (SOM) plays a crucial role in physical, chemical and biological functions of agricultural soils (Houghton, 2007). SOC is a key indicator of soil fertility due to its beneficial effects on soil properties and contributes to high stable aggregate structures, that are resistant to soil degradation forms (i.e. soil erosion) because SOM binds soil particles together. In addition, aggregates stability tends to determine soil erodibility and influence water infiltration since it gives the best prediction of erosion.

4.3.1.2 The use of remote sensing in assessing, monitoring, and mapping soil organic carbon depletion.

A study was conducted by Mallik *et al*. (2022) in India to map and predict soil organic carbon (SOC) using remote sensing and terrain data. The results showed that the mean value of SOC status was 0.77% with value ranging from 0.043% to 2.87%. The results indicated that the EBKR (Empirical Bayesian Kriging Regression) model is unbiased and accurate. In this work, the root mean square error (RMSE) and the coefficient of determination (R^2) which were used for validation of model outputs was found to be 0.094 and 0.936 respectively. In addition, they found that the composite, band 6 (vegetation red edge) of sentinel 2, slope and elevation gives the best prediction for SOC.

This was supported by Suleymanov *et al*. (2021) who estimated and mapped the spatial distribution of organic carbon using remote sensing. In this work, they used the Sentinel-2A satellite data and the linear regression method. The results show that the coefficient of determination (R^2), RMSE, and the RPD was found to be 0.58, 0.56, and 1.61 respectively. The linear regression model performance for SOC prediction was found to be satisfactory. This was supported by various studies using Sentinel 2 (e.g. a study by Vaudour *et al.* 2019 in France with the RPD of 1.51 and a study by Castaldi *et al.* (2019) in Germany, Belgium, and Luxembourg in evaluating the capability of the Sentinel 2 data for SOC prediction based on PLSR and RF models. The ratio of performance to deviation (RPD) was higher than 2 in Luxembourg (2.6) and German (2.2) site, while it was 1.1 in the Belgian area. According to Castaldi *et al.* (2019) the prediction accuracy obtained by Sentinel 2 data is generally slightly lower than that retrieved by airborne hyperspectral data. According to Shen *et al*. (2015) the PLSR model achieves better accuracy within the laboratory spectral data than in the field data.

Nabiollah *et al*. (2019) conducted a study in Iran in assessing SOC under land-use change using random forest models. In this study, spectral data was derived from Landsat imagery. In their findings, Nabiollah *et al*. (2019) found that the accuracy was good with RMSE of 3.53 and coefficient of determination of 0.67.

4.3.1.3 The spectral bands to predict soil organic carbon

Wang *et al*. (2010) reported 440, 560, 625, 740, and 1336 nm as the principal spectral bands to predict SOC. Nocita *et al*. (2014) suggested that the spectral region between 580 and 680 nm was sufficient to predict SOC. Bangelesa *et al.* (2020) found that that important wavelengths at around 2000–2200 and 1400–1500 nm are key to predict SOC and The best model results were obtained with transformed spectral data, with the key wavelengths to predict SOC values mostly localised around the visible range (400–700 nm).

4.3.1.4 The limitations of remote sensing techniques in soil organic carbon assessment

The main drawbacks of remote sensing techniques include low signal to noise ratio due to a short integration time over target area and the atmospheric absorptions interfering with the spectral measurements. Furthermore, mixed pixels contains more than bare soil surface and there is a need for geometric and atmospheric corrections (Minu *et al.,* 2017). Remote sensing techniques are mainly affected by external factors such as moisture, surface roughness, vegetation cover, structure, and change in atmospheric conditions. Soil moisture content tends to influence the prediction accuracy of different sensors. This is because as soil moisture increases, the reflectance of soil decreases. This actively demonstrates that soil moisture is inversely proportional to the reflectance. For instance, if there is high amount of water in the soil, the reflectance will go down. However, drier soil such as sandy textured soils reflects more than wet soils .The surface roughness is also considered as one of the main factors that influence the prediction accuracy. For instance, the smaller local surface roughness, the greater the spectral reflectance (Ben-Dor, 2002; Guerschman *et al.*, 2009).

4.3.1.5 Human and environmental parameters related to soil organic carbon depletion.

The natural factors (i.e., slope, rainfall and soil type) and human factors (i.e., tillage practices) leads to the development and initiation of soil degradation forms and results in decline in SOC status (Phinzi *et al.*, 2020 ; Mohammed *et al.*, 2020). This means that the upper portions of the topsoil which composed of high concentration of organic materials can be easily removed and results in decline in SOC status. Furthermore, low areas have high SOC status due to high concentration of clay content as compared to high areas with low clay content and high erosion rates. The above mentioned natural factors can limit the soil ability to provide essential nutrients that play a crucial role in plant productivity and growth. These natural factors tend to vary with location and farm management. Furthermore, soil organic carbon depletion can result in land abandonment and high economic costs for soil reclamation and rehabilitation (Phinzi *et al.*, 2020; Mohammed *et al.*, 2020).

4.3.2 Work not done on the problem statement.

In the available literature, many researchers have used remote sensing in monitoring soil degradation in different regions that differ with climate, soil, and land use management. It is used as an alternative method to the conventional laboratory methods due to its advantages. Despite various studies conducted for assessing SOC status with the use of remote sensing techniques. There is little work done that utilizes remote sensing and models for assessing soil degradation forms on South African soils and particularly in Limpopo. Most of the studies have focused on the main factors that influence soil degradation rather than developing models that will assist in soil health monitoring and land use management studies. However, the performance of the models varies with the location or study area and the feature being observed. The objective of this study is to determine SOC status with acceptable accuracy from remote sensing.

4.4 RESEARCH METHODOLOGY

4.4.1 Description of the study area

The study was conducted in Syferkuil, experimental farm of the University of Limpopo (23°51'0" S and 29°42'0" E) with an elevation of 1.325 meters (Figure 4.1). The farm is about 1.650 ha in size and 13 km from the main campus of the University. The research site on which this study focused on had an area of 62 ha, a part of the farm leased to ZZ2. The study site falls under semi-arid climate consisting of annual rainfall varying from 450 mm to 630 mm most of which is received from November to March (Molepo *et al.,* 2017). The soil at the farm is identified as sandy loam texture and the dominant soil forms on the site are Shortlands and Clovelly (Soil Classification Working Group, 1991). The portion of the farm that was used for this study has an area of 61 ha, a part of the farm leased to ZZ2. The research site has been cultivated since from 2011 coupled with occasional resting.

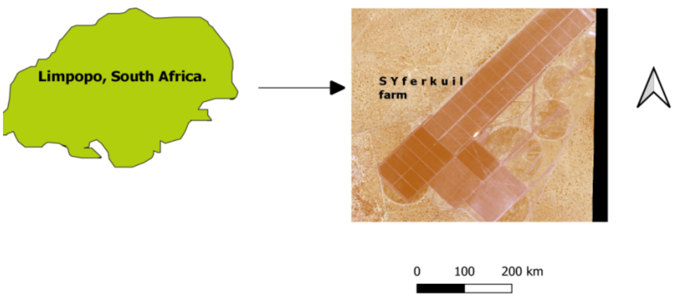

Figure 4.1: A map of Syferkuil farm, Limpopo, South Africa.

4.4.2 Data collection

4.4.2.1 Conventional methods

a) Field sampling

A grid sampling of 50 m by 100 m was followed to collect 98 soil samples. A shovel was used to take soil samples from the top 5 cm of soil surface. Then samples were placed in plastic bags and were taken to soil laboratory. Global positioning system (GPS) was used to record the exact location of each sampled point in each grid. This was done to be able to locate each sample point.

b) Soil organic carbon (SOC) analysis

Upon the arrival at the soil science laboratory of the university of Limpopo, the gravel fraction was removed, and the samples were left to dry for about a week. After drying, the soil samples were sieved using a 2 mm sieve for soil organic carbon determination. The soil organic carbon of the soil samples was determined conventionally in the laboratory using the Walkley-Black method (Walkley and Black, 1934). This method provides precise and accurate results for soil organic carbon (SOC) determination. Table 4.1 below shows the classification of soil based on the soil organic carbon levels. Low SOC level indicates lower moisture retention and nutrient status (FAO of United Nations, 2012) whereas high level of SOC influences soil properties which results high soil quality or fertility.

Table 4.1: Classification of soil based on the SOC (Feller and Beare, 1997)

SOC (%)	SOC levels
0.00 – 0.5	Extreme low
0.5 – 1.0	Low
1.0 – 2.5	Moderately low
2.5 – 6.0	Moderate
>6.0	Very high

Note. SOC= Soil organic carbon

SOM is usually estimated through a measure of SOC and the different soils can be classified based on SOM matter content (Table 4.2). It is determined by multiplying the value of organic carbon with 1.72 (Walkley, 1935).

The soil organic matter (SOM) equation is:

$$SOM = C \times 1.72$$

Whereby: C is the soil organic carbon, expressed in percentage (%).

1.72 is the Bemmelen factor

Table 4.2: Classification of soil based on the SOM content (Feller and Beare, 1997).

SOM level (%)	Description
0.00 – 0.5	Extreme low; soil is deprived of residues
0.5 – 1.0	Low ; soil needs more organic residues
1.0 – 2.5	Moderately low ; soil has been cropped very heavy
2.5 – 6.0	Moderate; soil is being maintained in optimal desired range.
>6.0	Soil is accumulating organic matter in high addition rate; rich organic soil.

Particle size distribution was determined using the hydrometer method (Bouyoucos, 1962). Soil pH was first measured in deionized water (1:2 soil, water) followed by 0.01 M calcium chloride ($CaCl_2$) using a calibrated glass electrode pH meter (Rhodes, 1982).

4.4.2.2 Remote sensing data

Multispectral imagery (sentinel 2)

In this study, the Sentinel-2 multispectral imagery was used in assessing SOC. This imagery is able to provide excellent spatial coverage of a large area, and making it easy to obtain soil information (Gorji *et al.*, 2017). The multispectral image is a type of raster data in which raster files are grid of pixels (cells) and each pixel contains a single value (references) that provide valuable information. The multispectral imagery is able to provide valuable information that might not be able to obtain using conventional methods since our visual perception is limited to some portions of EMS (Electromagnetic spectrum).

a) Image acquisition

A multispectral satellite image of the study area was collected on 09 March 2021. This imagery (Sentinel 2) was downloaded from the European Space Agency (ESA); the image had more than 10 bands ranging from the visible to shortwave infrared and with 10 m spatial resolution.

b) Image processing

Before the multispectral satellite image was used, it went through pre-processing. Then images went through the stages of atmospheric and radiometric correction using Quantum Geographic Information System (QGIS). This was done in order to extract specific or valuable information. The imagery was atmospherically corrected using QGIS.

4.4.3 Data analysis

This study used one regression model (PLSR model) to estimate the relationship or correlation between the corresponding pixels or spectral values extracted from multispectral satellite imagery (Sentinel 2) and conventionally determined SOC. The coordinates of the sampling points were used in QGIS to extract spectral or reflectance values from the image using vector point extraction. PLSR is a method that specifies a linear relationship between a set of dependent variables, Y, and a set of predictor variables, X (Farifteh *et al.*, 2007). It reduces the variables, used to predict, to a smaller set of predictors. The general idea of the PLSR is to extract the orthogonal or latent predictor variables, accounting for as much of the variation of the dependent variables as possible. PLSR was chosen due to its capability to analyse large data, and it is more interpretable (Asfaw *et al.*, 2018). It is an effective tool for assessment of soil degradation forms (Gorji *et al.*, 2017).

Soil organic carbon (SOC) is the dependent variable whereas the spectral or reflectance values from multispectral images are the independent variable. The prediction performance of this model was evaluated based on the coefficient of determination (R^2), root mean square error of prediction (RMSE) and ratio of prediction deviation (RPD). The soil samples were divided into calibration and validation group. Therefore, 70% was used for training or model development and 30% for testing or model validation.

a) Calibration

Conventional laboratory measurement and their corresponding reflectance were used for calibrating models using partial least square regression (PLSR) to verify the results and test the goodness of the model or performance. Conventional laboratory measurement of SOC for validation was used to test the goodness of the model or performance. PLSR model was developed for estimation of the SOC based on the reflectance or spectral variation.

b) Validation

The Root Mean Square Error (RMSE), coefficient of determination (R^2) and relative percentage deviation (RPD) were used to test the predictive ability or accuracy of the model. RMSE provides the absolute average error between the predicted values and the measured results of conventional laboratory analysis (Leone *et al.*, 2012). The coefficient of determination (R^2) measures the proportion of the total variation accounted for and it has the capability to test the goodness of the model (Table 4.3). RPD refers to the ratio of standard deviation (SD) to the RMSE prediction. It was obtained by dividing the standard deviation of analysed data by the value of RMSE and it was used to test Prediction of ability of the model (Table 4.4). RMSE is used to measure the difference between the values predicted and the values observed. Chang *et al.* (2001) and Mouazen *et al.* (2010) developed a method to classify models based on their estimation accuracy, looking at their RPD value and R^2 value respectively.

Table 4.3: Prediction of goodness of the model based on the coefficient of determination (R^2) supplied by Mouazen *et al.* (2010)

R^2	Model performance
0.5 to 0.65	Poor prediction model
0.5 to 0.79	Good
0.80 to 1.00	Excellent

Note. R^2 = coefficient of determination

Table 4.4: Prediction of goodness of the model based on the relative percentage deviation (RPD) supplied by Duran (1983)

RPD	Model performance
RPD <1.0	Very poor model/ prediction
1.0 <RPD >1.4	Poor prediction model
1.4 < RPD > 1.8	Fair model/ Prediction
1.8 < RPD > 2.0	Good model
2.0 < RPD > 2.5	Very good model
RPD > 2.5	Excellent model

Note. RPD = relative percentage deviation;

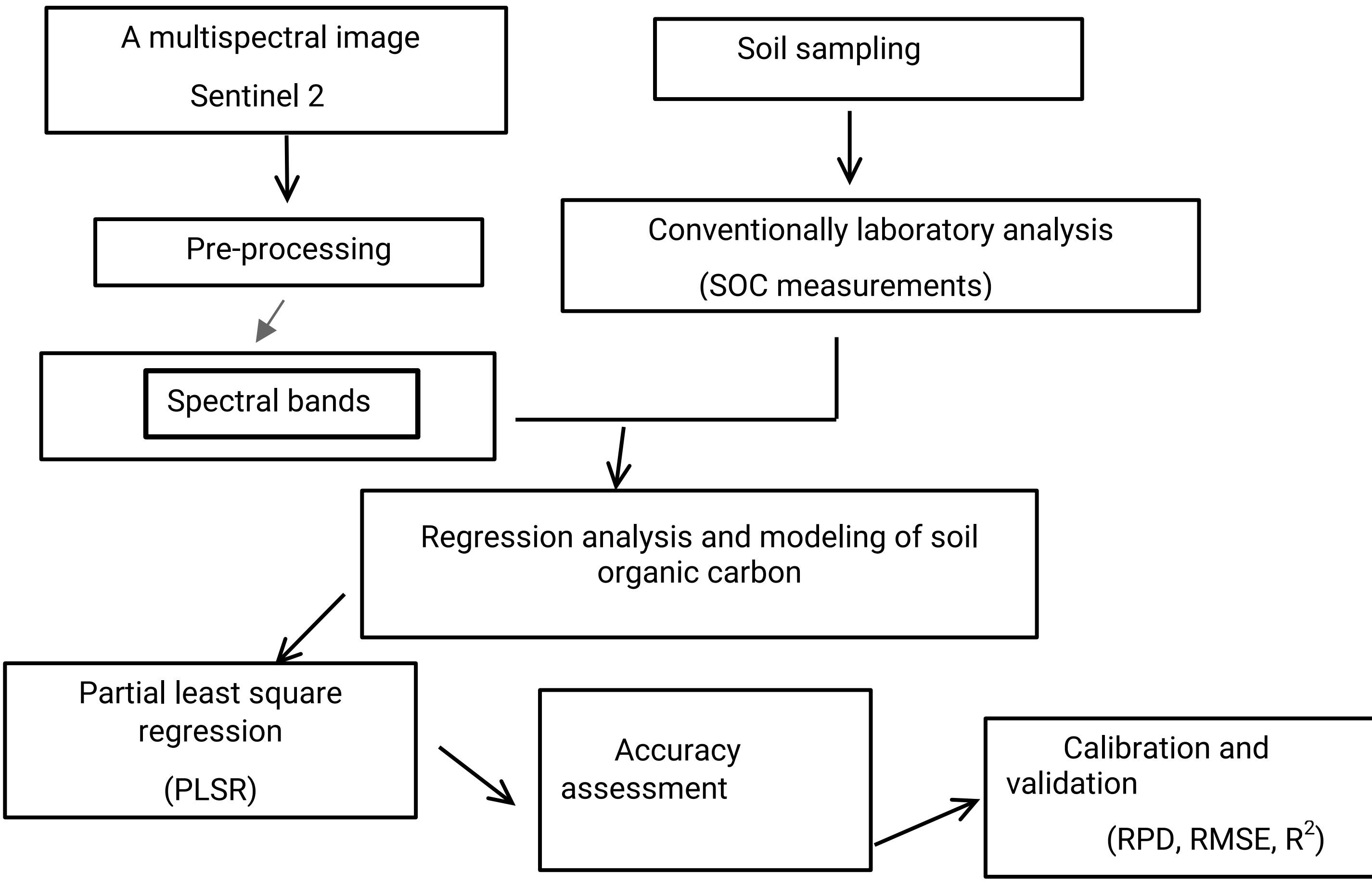

Figure 4.2: Flowchart of methodology used in this study

4.5 RESULTS

4.5.1 Conventional laboratory analysis results for soil physical and chemical properties.

Based on the results obtained there is a great spatial variation of SOC in the study site (Table 4.5). The mean SOC and SOM were found to be 1.66% and 2.86% respectively. The highest SOC was found to be 3.56% while the lowest to be 0.76%. The highest SOM content was found to be 6.12 and the lowest to be 1.30. The low SOM content will results in poor water and nutrient retention. The high SOM content inhibits soil erosion because SOM binds soil particles together. The standard deviation of SOC and SOM is 0.48 and 0.82 respectively. The coefficient of variation was found to be 28.92 and 28.67 percentages for SOC and SOM respectively. The results show that clay content range from 0.18 to 30.31, sand percentage range from 49.86 to 79.40 and silt percentage range from 0.21 to 37.86. This shows that there is variation across the field and may possibly be as a result of human and natural factors.

Table 4.5: Statistical description of soil information analysed (n =98) in Syferkuil farm, Limpopo, South Africa

Soil parameter	Max	Min	Mean	Median	SD	CV (%)
SOC (%)	3.56	0.76	1.66	1.62	0.48	28.92
SOM (%)	6.12	1.30	2.86	2.77	0.82	28.67
Clay (%)	30.31	0.18	18.38	12.30	7.05	38.36
Sand (%)	79.40	49.86	62.32	69.45	6.89	11,06
Silt (%)	37.86	0.21	20.60	16.38	8.34	40.49
pH(KCl)	7.06	6.06	6.31	6.30	0.27	4.28
pH(H_2O)	7.49	6.7	6,71	6.72	0.31	4.619

Note. SD = standard deviation; max = maximum; min = minimum; CV = coefficient of variation.

4.5.2 Prediction of soil organic carbon using PLSR model

The results obtained showed the poor estimation accuracy for model performance of SOC when using multispectral satellite image (R^2 of 0.41, RMSE of 0.53 and; RPD of 1.21(Table 4.6). The PLSR model performance for SOC prediction was found to be unsatisfactory. The bands which were used in SOC prediction fall within the visible, shortwave infrared and near-infrared regions of the electromagnetic spectrum.

Table 4.6: PLSR model performance for soil organic carbon prediction

Soil parameter	R^2	RMSE	RPD	Model performance
SOC	0 .41	0.53	1.21	Not excellent

4.6 DISCUSSION

4.6.1 Soil organic carbon and soil degradation forms

The results obtained show that soil organic carbon (SOC) status was lower and higher in some other parts in the study area. The areas of low SOC status (1.5% and less) observed in the study area may have influenced by low elevation, slope and agricultural land use (Phinzi *et al.*, 2020; Mohammed *et al.*, 2020). Therefore, the low SOC status may possibly be a result of frequent deep ploughing which disturb the soils extensively. Taking into considerations that the conventional method (i.e. tillage practice) was practiced in the portion were soil samples collected. Conventional practices breakdown soil aggregates hence leading to depletion of SOM, thus reducing carbon inputs into the soil. However, no tilled soils tend to store more carbon than the one found on similar conventional soils because of the formation of strong structure that limit soil erosion hence increases crop productivity and development. For instance, Bayer *et al.* (2006) have pointed out that those soils under no till method store more carbon due to increased dead matter accumulation and amount of undisturbed biomass. The conventional laboratory analysis results for soil organic carbon and soil organic matter are in Appendix 3.

Conventional methods can also influence SOC status since it will results in soils left exposed and the upper profile be easily removed (Phinzi and Ngetar 2017; and Sepuru and Dube, 2018). This is why vegetation cover is considered as one of the most important factors controlling soil erosion and can considerably decrease soil loss, due to its ability to bind soil particles, thereby protecting the soil (Jain and Goel, 2002). The results of this study can differ with other studies possibly due to the differences in the climatic conditions or rainfall patterns and the period at which tillage system has been in practice. Conventional methods are currently threatened by population growth, agriculture and increased demand for food production. This means that when the ever growing population increases, there is higher demand for food production to feed the human population hence limited time to practice sustainable agriculture. This is supported by Pacione (2013), who pointed out that an increase in the number of human population results in higher demand for food to feed the ever-growing global population and thus accelerate land degradation.

Poor agricultural and land management practices without taking into considerations sustainable conservation practices lead to accelerated soil erosion (Le Roux *et al.*, 2007). This means that the upper portions of the top soil can be easily removed and results in decline in soil organic carbon content. Another possible reason may be due to natural factors (i.e. slope, rainfall and soil type) which lead to the development and initiation of soil degradation forms and results in decline in soil organic carbon status (Suleymanov *et al.*, 2021 ; Mallik *et al.*, 2022). This is because at the research site the soils are prone to erosion due to permeability or infiltration rate which results in increased surface runoff then remove the upper top layer that is composed of high concentration of organic materials.

The lack of knowledge and resources may also possibly result in decline in SOC status. This is supported by Seutloali *et al.* (2017) who emphasized that poor decisions and mismanagement of soils can be able to accelerate soil degradation forms. This will then lead to inefficient land use planning and management. Population growth is also driving force for changes in land use management. This is supported by Pacione. (2013), who pointed out that an increase in the number of human population results in higher demand for food to feed the ever growing global population and thus accelerate soil degradation forms.

The high SOC status in some portion of study area observed can also be caused by high concentration of clay content as compared to high areas with low clay content and high erosion rates. This is supported by various studies by Ben-Dor, 2002 and Guerschman *et al.* (2009). They found that the high concentration of clay content plays a crucial role in plant productivity and growth. This is because high SOC is associated with high concentration of clay content which then influences water holding capacity, infiltration and nutrients availability. Clay textured soils are more compacted and essential nutrients are not easily leached out during heavy rainfall. Furthermore, high SOC can increase soil fertility and improve yields and food security (Ben-Dor, 2002; Guerschman *et al.*, 2009).

4.6.2 The performance of model developed from multispectral satellite image.

The performance of the model was not excellent. The result shows that approximately half of the SOC variation could be explained by the reflectance values as recorded in the image. The deviation of the predicted values from the PLSR analysis was minimal as indicated by the low RMSE value. The low R^2 value indicates that there are confounding factors. The confounding factors might come in the form of noise and errors due to variations in soil surface roughness, geometric and atmospheric conditions (Casa *et al.*, 2013). Furthermore, the performance of models might be because of low spectral resolution of the image as compared to hyperspectral data, which have bands with narrow wavelengths (Qi *et al.*, 2020). The results of this study are supported by Allbed and Kumar (2013) who highlighted that multispectral data has limitations because of the coarse spatial and spectral resolutions, which influences the quality and quantity of the information they provide. This may be due to low swath width when using multispectral imagery which does not permits large area coverage and frequent mapping as compared to Land sat imagery (Odindi *et al.*, 2015). However, the performance of the models varies with the study site and the regression techniques used (Gorji *et al.*, 2017; Shahabi *et al.*, 2021).

4.7 CONCLUSION AND RECOMMENDATIONS

This study focused on the use of remote sensing techniques in assessing soil organic carbon status. The extracted reflectance values from Sentinel 2 were used together with results of conventional laboratory analysis results for prediction performance of PLSR models. In this study a multispectral satellite image was used and it did not give satisfactory results. Despite that the performance of the model was unsatisfactory, remote sensing techniques are considered as efficient tools to monitor and detect SOC unlike in the old days, when conventionally laboratory methods were the only means of assessing SOC status even though it produced low prediction accuracy. Thus, it is recommended that an image with better spectral resolution and narrower bands (hyperspectral) be investigated to see if there is an improvement in the model performance. This study can be helpful for land use management and planning and increases awareness on the importance of managing and restoring soil quality to minimise the risk of soil degradation forms.

CHAPTER FIVE

SUMMARY AND RECOMMENDATIONS

The study revealed the potential of using remote sensing as an alternative method to the conventional methods in assessing soil degradation forms. PLSR models developed using spectral reflectance extracted from Sentinel 2 imagery and the conventional laboratory results (i.e., soil organic carbon and soil salinity analysis) did not give satisfactory results in chapter two and four. Based on the results, this might be due to noise and errors due to variations in soil surface roughness, geometric and atmospheric effects. Image noise is any unwanted disturbance in image data that is due to limitations in the sensing, signal digitization, or data recording process. In addition, the performance of PLSR models might be influenced by the spatial and spectral resolution of the image. This is because the multispectral imagery used in this study has low spectral and spatial resolution as compared to higher spatial resolution imagery and narrow bands (hyperspectral satellite image). The satellites imagery with relatively higher spatial and spectral resolution allows the classification technique to detect the smaller rill erosion features which were omitted from low spatial resolution imagery (Qi *et al.*, 2017). In chapter three, the results were not satisfactory from multispectral satellite image [Worldview 2 satellite image] using digital image processing called supervised image classification. Despite low prediction accuracy, the potential of remote sensing techniques are evident. Remote sensing has the potential to serve as an alternative tool in monitoring and identifying soils degraded by rill erosion and could reduce the field based work.

Based on the results obtained and with the current demand for valuable or precise up to date soil degradation forms, remote sensing is a crucial or effective tool. It can be utilized with the upcoming studies and it has the potential to identify and monitor soil degradation form. Thus, it is recommended that an image with a better spatial and spectral resolution (i.e. hyperspectral remote sensing data) be investigated to see if there is improvement in the model performance. This is because in remote sensing application there is much room for improvement, and can be valuable particularly in data scarce environment like Limpopo. Lastly, it is also recommended that the entire area should be put under careful monitoring, and emphasis should be given to sustainable land management measures.

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APPENDICES

APPENDIX 1: Showing Error Matrix Code, Reference, Classified and Pixel Sum values

Error Matrix Code	Reference	Classified	Pixel Sum
4	1	1	1
5	1	2	1
4	2	1	9
7	2	2	9

APPENDIX 2: Showing Error matrix (pixel count values)

> ERROR MATRIX (pixel count)				
> Reference				
V_Classified	0	1	2	Total
0	0	0	0	0
1	0	1	9	10
2	0	1	9	10
Total	0	2	18	20

APPENDIX 3: Conventional laboratory analysis results for soil organic carbon and soil organic matter.

Soil samples	Organic C%	Organic matter %
A1	1.87	3.22
A2	1.57	2.70
A3	2.29	3.94
A4	1.25	2.14
A5	1.56	2.68
B1	1.26	2.16
B2	2.25	3.88
B3	1.95	3.36
B4	1.64	2.82
B5	1.23	2.12
C1	2.47	4.25
C2	1.63	2.80
C3	1.27	2.19
C4	2.23	3.83
C5	1.65	2.85
D1	1.51	2.60
D2	1.61	2.76
D3	1.50	2.58
D4	2.17	3.73

Soil samples	Organic C%	Organic matter %
D5	1.59	2.74
F1	1.63	2.80
F2	2.00	3.44
F3	1.52	2.62
F4	1.09	1.88
F5	1.63	2.80
G1	1.83	3.15
G2	1.34	2.31
G3	1.62	2.78
G4	1.51	2.60
G5	1.44	2.47
H1	1.69	2.91
H2	1.87	3.22
H3	1.95	3.36
H4	1.62	2.78
H5	1.82	3.13
I1	2.10	3.61
I2	1.55	2.66
I3	1.40	2.41
I4	2.31	3.98
I5	2.59	4.45
J1	2.35	4.04
J2	1.75	3.01
J3	1.50	2.58
K1	1.14	1.96
k2	1.99	3.42
K3	2.31	3.98
L1	2.39	4.10
L2	1.58	2.72
L3	1.51	2.60
M1	1.63	2.80
M2	1.53	2.64
M3	2.25	3.88
N1	1.16	2.00
N2	1.51	2.60
N3	1.75	3.01
O1	0.91	1.57
O2	1.32	2.27
O3	1.77	3.05
P1	0.98	1.69
P2	1.69	2.91
P3	1.71	2.95
P4	1.02	1.75
O1	1.57	2.70
O2	1.51	2.60
O3	1.93	3.32
O4	1.79	3.07
R1	1.03	1.77
R2	1.39	2.39
R3	1.38	2.37
R4	2.86	4.93
S1	1.51	2.60
S2	1.65	2.85
S3	1.99	3.42
S4	1.39	2.39
T1	1.27	2.19
T2	3.56	6.12
T3	2.19	3.77

Soil samples	Organic C%	Organic matter %
T4	1.88	3.24
U1	1.27	2.19
U2	1.17	2.02
U3	0.99	1.71
U4	1.15	1.98
J-1	0.92	1.59
J-2	1.15	1.98
K-1	2.23	3.83
K-2	1.73	2.97
L-1	0.90	1.55
L-2	1.44	2.47
M-1	2.35	4.04
M-2	2.54	4.37
N-1	2.06	3.55
N-2	1.94	3.34
O-1	0.76	1.30
O-2	1.59	2.74
F-1	0.96	1.65
G-1	1.88	3.24
H-1	0.91	1.57
I-1	1.46	2.52