CHARACTERISATION OF SELECTED SOIL PROPERTIES USING REMOTE SENSING TECHNIQUES

By

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Contents

DECLARATION

I declare that the mini-dissertation hereby submitted to the University of Limpopo, for the degree of Master of Science in 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 that all material contained herein has been duly acknowledged.

25-03-2019

FISHA P.C (Mr) Date

DEDICATION

This study is dedicated to my sister Marble Kwena Fisha and my lovely parents Mr. and Mrs. Fisha.

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I give praise to the almighty God, the lion of Judah who has been with me all days of my life. I humbly extend my sincere gratitude to my supervisor Dr. M.G. Zerizghy for sharing his knowledge with me and guiding me about both academic work and life in general. I also like to appreciate the unconditional support I got from Ms MK Fisha, Mr PV Fisha, Ms MM Fisha and Ms MQ Mamodishe. It wasn't an easy journey but I made it with the help and courage from various people and I'm eternally grateful. My special thanks also go to my parents Mr and Mrs Fisha for their encouragement and faith they expressed in my studies. I'm grateful for the financial support that National Research fund (NRF) provided for me throughout my research.

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ABSTRACT

Many conventional laboratory methods are used to characterise spatial and temporal variation of soil properties in order to understand soil quality for different purposes. Currently there is a high demand for accurate soil information by land users. Therefore there is a need to develop a rapid, inexpensive, non-destructive and accurate technique that could compensate or replace conventional laboratory methodologies. Remote sensing has the potential to serve as an alternative approach to characterise soil properties due to its advantages over conventional laboratory methods such as it is rapid, non-destructive and it has low cost. The objectives of this study were to: (i) evaluate the ability of proximal soil sensing to characterise soil properties namely organic matter, soil moisture content, macronutrients, soil texture, cation exchange capacity (CEC), and pH. (ii) Identify bands of relevance from proximal soil sensing (300-2400 nm) that can provide acceptable reflectance variation for different levels of selected soil properties. (iii) Evaluate the performance of models developed from multispectral space-borne image in characterising selected soil properties. In this study spectroradiometer (proximal sensor) and worldview 2 satellite images (space-borne) were the two remote sensing techniques used to collect information about soil at Syferkuil experimental farm of the University of Limpopo. Visible and near infrared spectral data of 98 soil samples were collected at the study site using Analytical spectral device (ASD) field spectroradiometer. Spectral reflectance from spectroradiometer and those extracted from worldview 2 satellite image were used to develop prediction models of selected soil properties using Partial least square regression (PLSR). Bands of relevance were also identified from PLSR models developed from spectral data acquired by spectroradiometer. The results showed that estimation accuracy of PLSR models developed using spectral data from proximal soil sensing were excellent (Category A) for clay, sand, soil organic matter (SOM), and soil moisture content, while good prediction accuracy (Category B) was observed for other soil properties such as silt, ammonium, nitrate, active acidity (pH_w), calcium, magnesium, phosphorus, potassium, sulphur, CEC, and reserve acidity (pH_{KCl}). Then, relevant bands which contributed greatly in the prediction of these soil attributes were selected from the electromagnetic spectrum, the range was from 451 nm to 2400 nm. These bands fall within visible, shortwave infrared and near-infrared regions of electromagnetic spectrum. In addition all selected soil properties were approximately quantitatively estimated using spectral data from satellite image. Based on the results obtained it can be concluded that proximal soil sensing has the ability to predict selected soil properties with various accuracies and it can be used as an alternative technique to characterise soil properties of South African soils. Soil predicting models developed from proximal soil sensing data also showed that there are bands of relevance within spectral range of 451 nm to 2400 nm. However more work is required for space-borne sensing before it can be used as one of the soil characterisation methods since its prediction accuracy was low as compared to that of hyperspectral proximal soil sensing.

Keywords: Space-borne sensing; proximal soil sensing; soil characterisation.

CHAPTER 1
INTRODUCTION

1.1 Background

Soil characterisation is a way of revealing the nature of soil physical, chemical and biological properties. It is done for different purposes such as soil classification, land use planning, soil mapping and soil surveying (Morris *et al*., 2008). Conventional characterisation of soil can be done through in-situ assessment of soil which involves soil surveying, soil classification or it can be done through laboratory analysis which involves sampling of soil from the field and analyzing soil using standardized laboratory procedures (Manchanda *et al*., 2002).

Over the past decades, soil scientists used well-known conventional laboratory methods to characterise spatial and temporal variabilities of soil properties. However there are difficulties of conventional methods with regard to meeting high demands of detailed soil information in short time with reasonable cost (Steinberg *et al*., 2016). Soil scientists have started to search for alternative methods to characterise various soil properties rapidly, with high accuracy and low cost. Remote sensing has emerged as a promising alternative technique due to its advantages such as it does not require the use of chemical reagents in order to quantify soil properties, it can provide detailed information about soil variability rapidly without disturbing the soil, and it can also cover large areas with high accuracy depending on the resolution of the sensor (Genot *et al*., 2010).

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). Remote sensors are divided into three categories based on their platform of operations, namely airborne or air craft remote sensor, ground based or proximal sensors, and space-borne remote sensors (Jensen, 2007). Proximal soil sensing refers to the use of ground-based sensors to measure soil spectral reflectance when detector of the sensor is in close range (within 2 m) to the soil (Rossel *et al*., 2011). Space-borne remote sensing uses satellite sensors to detect and measure electromagnetic radiation reflected or emitted from the target object (Jensen, 2007).

All remote sensors either proximal sensors or space-borne sensors use electromagnetic radiation which has been reflected from the surface of the earth to interpret and identify various materials. This is due to the fact that various materials covering the surface of the earth reflect electromagnetic radiation differently (Chauhan, 2015). Thus it is postulated that information about soil can be revealed by remote sensing since the signals measured are in relation to the physical measures, which can be linked to soil properties (Rossel *et al*., 2011).

1.2 Problem statement

Many soil science laboratories around the world use conventional methods to characterise soil properties for various purposes. For instance, macro and micronutrients are normally characterised using conventional laboratory methods in order to monitor soil fertility. Such conventional characterisation of soil properties generally involves collection of soil samples at the field, transportation of soil samples to laboratory, soil sample preparation treatments such as drying and sieving, and using chemicals to quantify the soil parameters (Plaster, 2003). However, with the current demand of up to date soil information, these methods delay the process of acquiring necessary soil information of high accuracy at a short period, due to their long procedure (Ben-Dor, 2001). In this context, these methods have drawbacks since they are time consuming and costly in terms of sampling and analytical procedures and many of them are labour intensive and cause disturbance to the soil. This induces a challenge with regard to making rapid assessment, having up to date soil information and covering large area of land at an acceptable level of detail (Stenberg *et al*., 2010).

As a result, an alternative approach that will enable soil scientists to characterise soil properties, rapidly and at a reasonable cost is required. Soil scientists have identified remote sensing techniques as alternative approach for characterising soil properties due to their advantages over conventional methods. The advantages of using remote sensing techniques include the non-requirement of chemical reagents, lack of disturbance to the soil, and simultaneous characterisation of various soil properties using single spectrum from remote sensing spectral data (Rossel *et al*., 2011).

1.3 Motivation of the study

Remote sensing may offer the possibility to increase soil information in order to improve national digital soil map, food security and monitor environmental degradation. Remote sensing aims to provide advanced methods for data collection and analyses towards monitoring of soil properties (Manchanda *et al*., 2002). A large number of studies emphasise the ability of visible and near infrared analysis for the estimation of many chemical, physical, and biological soil properties (Stenberg *et al*., 2010). Remote sensing techniques such as the use of satellite image and aerial image spectroscopy are able to give excellent spatial coverage of a large area, making it easy to obtain information about spatial variation of soil properties. Furthermore, proximal soil sensors allow soil scientist to make expeditious and affordable collection of precise, quantitative soil information, fine-resolution soil data, which enable better understanding of soil spatial and temporal variability (Rossel *et al*., 2011).

According to Paterson *et al.* (2015), there is a shortage of up to date soil information about South African soils and there are lack of studies which address spatial distribution of soil properties. Remote sensing has been utilized in several locations around the world, but has not been fully tested on the unique and diverse soils of South Africa.

1.4 Purpose of the study

1.4.1 Aim

To characterise selected soil properties using remote sensing techniques.

1.4.2 Objectives

The objectives of the study are to:

I. Evaluate the ability of proximal soil sensing to characterise selected soil properties namely organic matter, soil moisture content, macronutrients, soil texture, CEC, and pH.

II. Identify bands of relevance from proximal soil sensing (0.3-2.4 μm) that can provide acceptable reflectance variation for different levels of selected soil properties.

III. Evaluate the performance of models developed from multispectral space-borne image in characterising selected soil properties.

CHAPTER 2

LITERATURE REVIEW

2.1 work done on problem statement

2.1.1 How soil properties are characterised by the use of spectral reflectance obtained from remote sensing techniques

Many studies have focused on using reflectance spectra within visible and near infrared (Vis-NIR) regions of electromagnetic spectrum to characterise soil attributes (Bilgili *et al*., 2010; Wenjun *et al*., 2014; Rossel *et al*., 2006; Shaddad *et al*., 2016). Information about soil properties is derived by studying the interaction between incident radiation and soil surface (Chang *et al*., 2001). The Vis-NIR spectra are influenced by the chemical composition and physical structure of the soil constituents. The main soil chemical and physical components that interact with electromagnetic radiation within the Vis-NIR range are called Chromophores (i.e. a parameter or substance either chemical or physical that significantly affects the shape and nature of a soil spectral reflectance) (Ben-Dor *et al*., 1999). Organic matter, water, primary minerals such as feldspar and carbonate, clay minerals, iron oxides and salts are some of the main soil Chromophores (O'Rourke *et al*., 2016). Apart from soil chemical components, physical properties of soil such as aggregate size, and particle size distribution may have influence on the spectral measurement due to radiation scattering or reflection (Du, 2009).

These chromophores contain chemical bonds or functional groups such as C-H, N-H, S-H and O-H which are spectrally active. The near infrared spectrum results from the weak overtones and combinations of fundamental vibrational bands which occurs when incident radiation energy interact with the chemical bonds in the molecules of soil constituents in the mid infrared region (Wetterlind *et al*., 2013; Zornoza *et al*., 2008). Visible spectrum is mainly influenced by electronic transitions of iron oxides which are caused by high incident radiation energy (Chang *et al*., 2001).

The overtones, stretching vibrations and combinations of these fundamental vibrational bands make it possible to characterise soil properties using reflectance spectra of NIR region (Xu *et al*., 2018). Several authors (Rossel *et al*., 2006; Ben-Dor *et al*., 2001; Stenberg *et al*., 2010) are of the opinion that remote sensing techniques can predict certain soil properties such as organic matter, total nitrogen, soil moisture and clay, since they are composed of functional groups (N-H, C-H, C-H, and O-H) which have known spectral signals. This means that these soil properties have direct spectral absorption features in the visible and near infrared region which make it possible to accurately estimate their contents in soil.

Multivariate calibration techniques are recommended in order to do quantitative analysis of visible and near infrared spectra in relation to soil properties since direct interpretation of Vis-NIR spectra is difficult due to overlaps of weak overtones and fundamental vibrational bands (Vagen *et al*., 2006).

2.1.2 Use of proximal soil sensors for soil analysis

Literature show that there has been growing interest in the use of different proximal soil sensing approaches including visible-near infrared (Vis-NIR) reflectance spectroscopy and diffuse infrared reflectance spectroscopy which use remote sensing tools such as Analytical spectral device (ASD) field spectroradiometer and diffuse reflectance spectroscopy (DRS) spectroradiometer to measure reflectance from soil surface (Brown *et al*., 2006; Gandariasbeitia *et al*., 2017; Iznaga *et al*., 2014).

Zornoza *et al*. (2008) evaluated the ability of near infrared (NIR) reflectance spectroscopy to estimate various physical, chemical and biochemical properties and reported good prediction of exchangeable calcium, magnesium, and water holding capacity. However pH and exchangeable phosphorus were poorly predicted.

A study was conducted in which in-situ measurement of soil properties was compared with laboratory-based spectra using Vis-NIR spectroscopy, and the results obtained indicated that soil attributes such as organic matter, organic carbon, total nitrogen, available nitrogen can be quantitatively predicted with various accuracies while available phosphorus and available potassium can be poorly predicted with laboratory-based visible and near-infrared spectra. Also concluded that laboratory based spectra using partial least square regression (PLSR) give better predictions of soil properties as compared to in-situ spectra (Wenjun *et al*., 2014).

Iznaga *et al*. (2014) reported successful predictions of organic matter and available phosphorus using support vector machine to model visible and near infrared spectra. However potassium was poorly predicted. Qi *et al.* (2017) conducted a study of comparing the performance of linear multi-task learning and PLSR for soil properties using field spectroscopy in visible and near infrared region. They concluded that linear multi-task learning models performed better than PLSR in predicting soil properties. Best prediction performance was observed for organic matter (OM) with ratio of performance to deviation (RPD) = 2.29, which means that the model had high accuracy, while nitrogen (N), phosphorus (P), soil moisture, and pH were reported to be moderately predicted with RPD values falling between 1.4 and 2. Furthermore potassium (K) and electrical conductivity (EC) were poorly estimated (RPD<1.4).

Bilgili *et al*. (2010) concluded that hyperspectral visible and near infrared spectroscopy was found to estimate soil organic matter (SOM) and clay well using both PLSR and multivariate adaptive regression splines (MARS). He *et al*. (2007) revealed that near-infrared reflectance spectroscopy has the potential to estimate N, OM and pH accurately suggesting that near infrared (NIR) spectroscopy could be a good technique for precision agriculture. However they also reported poor prediction of P and K in their study. Chang *et al*. (2001) suggested that near infrared reflectance spectroscopy could be used as a fast analytical tool to predict soil constituents such as total carbon, total nitrogen, soil moisture, cation exchange capacity (CEC) with high accuracy using principal component regression (PCR).

The applicability of using visible and near infrared spectra to predict various soil properties which play significant role in Chinese soil taxonomy was evaluated (Xu *et al*., 2018). They reported that PLSR models for pH, SOM, and total nitrogen (TN) showed good estimation accuracy (RPD>2.0; R^2 values between 0.70 and 0.90). On the other PLSR models for prediction of sand, silt, clay, CEC and available P obtained acceptable prediction accuracy with RPD values falling between 1.4 and 2.0 and R^2 values ranging between 0.56 and 0.72.

Rossel *et al*. (2006) compared simultaneous estimations of various soil constituents in three regions of electromagnetic spectrum (visible, near infrared, and mid infrared, respectively) and also the combined spectrum (Vis-NIR-MIR) using partial least square regression (PLSR) to develop models. Therefore concluded that the estimation accuracy of PLSR models for selected soil properties in each three individual regions and combined spectral region differ considerably amongst soil constituents. Also reported that mid-infrared region of the spectrum obtained more accurate prediction for pH, OC, CEC, soil texture, and P compared to other regions for electromagnetic spectrum. However combined spectrum showed little improvement in estimations of clay, silt and sand content.

2.1.3 The use of air or space-borne remote sensing for estimation of soil properties

Many studies have focused on the use of airborne hyperspectral images, but only few have looked into the use of satellite images to predict soil constituents. Zhang *et al*. (2013) compared the ability of laboratory measured spectra and Hyperion image spectra to predict soil constituents namely soil moisture, soil organic matter (SOM), total carbon, total phosphorus, total nitrogen, and clay content. They concluded that partial least square regression can predict all soil constituents using laboratory spectra while Hyperion reflectance spectra only gave good prediction for SOM, total carbon and total nitrogen. They suggest that spectral resolution had impacts on the PLSR performance in predicting soil constituents.

Liao *et al*. (2013) demonstrated that there is significant correlation between soil texture (Sand, silt and clay content) and Landsat ETM digital number of six bands from the visible to infrared portion (bands 1 to 5 and band 7). Digital number of band 7 showed most correlation. Paz-Kagan *et al*. (2015) conducted a study to assess the ability of airborne image spectroscopy in terms of evaluating soil attributes, and reported that image spectroscopy can effectively monitor soil quality.

A study was conducted which focused on determining estimation accuracy of models developed from simulated EnMAP (Environmental Mapping and Analysis Program) satellite data, and HyMap (Hyperspectral Mapper) airborne data. The conclusion reached was that both remote sensing techniques gave good predictions of clay and soil organic matter. However there was a slight decrease in estimation accuracy when using EnMAP as compared to HyMap (Steinberg *et al*., 2016).

Casa *et al*. (2013) corrected spectral reflectance obtained from space-borne CHRIS-PROBA and airborne MIVIS images to develop PLSR models to predict soil texture. The results showed a sufficient accuracy with RPD values greater than 1.4 for predicting clay and sand. Gomez *et al*. (2008) compared visible and near infrared and Hyperion hyperspectral sensor on-board satellite in terms of their ability to predict soil organic matter accurately. They concluded that the spectral resolution of the hyperspectral proximal sensor and Hyperion hyperspectral sensor did not affect prediction accuracy.

The performance of visible and near infrared (Vis-NIR) spectroscopy and Hyperion imagery for predicting soil organic carbon, pH, cation exchange capacity, and total phosphorus was assessed and the conclusion was reached that Hyperion image has the potential to be an alternative technique for modelling soil attributes (Lu *et al*., 2013).

Franceschini *et al*. (2015) used image spectroscopy to predict selected soil constituents taking into consideration fractional vegetation cover of the study area. They concluded that the prediction performance of model for clay, sand and CEC using spectral data from airborne sensor were satisfactory. Nowkandeh *et al*. (2017) also conducted a study where spectral reflectance derived from Hyperion image were used to develop predicting model for soil organic matter using various statistical methods to develop models including PLSR, PCR, Minimum Regression (MinR), and stepwise regression (SWR). The results obtained showed that good prediction accuracy of soil organic matter was found when PLSR and SWR statistical methods were used.

2.1.4 Factors affecting the prediction accuracy of remote sensing techniques

Numerus studies showed that remote sensing techniques operating at different remote sensing platforms namely ground-based, space-borne and airborne have the ability to accurately estimate several key soil properties (Wenjun *et al*., 2014; Franceschini *et al*., 2015; Gomez *et al*., 2008; Zhang *et al*., 2013). However external factors, such as ambient light, temperature, water content and atmospheric attenuation could have influence on spectral reflectance of soil surface. Therefore reducing the prediction accuracy of the model developed. Prediction accuracy can also be reduced by redundancy and multi-collinearity of spectral data (Qi *et al*., 2017).

There are no external interferences when proximal soil sensor collects soil reflectance measurements in the laboratory. However collection of soil reflectance measurement at the field, face challenges such as illumination change, soil surface roughness, and variations in sensor viewing angle. Estimation models built from space-borne and airborne spectral data normally have reduced estimation accuracies due to low spectral resolution, low signal to noise ratio, and partial coverage of soils with vegetation (Ben-Dor, 2001).

Remotes sensing techniques such as the use of satellite image and aerial image spectroscopy are able to give excellent spatial coverage of a large area. However measurements of reflectance are often limited to measuring the top 5 to 6 cm depth of the soil surface unless using radar. Coarse resolution also reduces the accuracy of predicting soil properties of interest at landscape scale. Therefore proximal sensing is normally used to overcome the challenges faced by space-borne sensor and airborne sensor (Rossel *et al*., 2011).

2.1.5 The importance of characterising soil properties

Land users characterise spatial and temporal variability of soil properties in the field to be able to monitor soil degradation, practise site specific management and evaluate soil fertility (Gandariasbeitia *et al*., 2017). Soil characterisation for soil fertility purpose involve quantification of soil macronutrients, soil texture and organic matter content. For example macronutrients such as nitrogen which play a vital role in plants growth because it is required in the creation of amino acids along with carbon, hydrogen, oxygen, and sulphur. These amino acids assist in forming protoplasm (Plaster, 2003). Deficiency of nitrogen may lead to stunted plant growth and early maturity in certain crops therefore resulting in decrease in yield and quality (Tolanur, 2006). Phosphorus is involved in key processes such as respiration and photosynthesis by storing and transferring energy as adenosine diphosphate (ADP) and adenosine triphosphate (ATP) (Brady and Weil, 2014). It is also important in developments of seeds, roots and fruits. Potassium is one of the primary soil macronutrients and it is essential for plant development by activating enzymes that lead to plants metabolism (Plaster, 2003).

It is essential to monitor the content of calcium and magnesium in soil since calcium assist in flocculation of soil particles and it is also a vital component in plant cell wall (Brady and Weil, 2014). On the other hand magnesium is needed for photosynthesis since it is an important component of chlorophyll (Akenga *et al*., 2014).

Determinations of soil organic matter (SOM) and soil texture are important in soil management since they influence soil structure, which in turn influence soil porosity. Soil particle size distributions affect soil bulk density (Shukla, 2014). Organic matter serves as the binding agent of soil particles leading to formation of soil structure. Clay soil particles and SOM affect the ability of soil to adsorb and release cations in soil solution and they also have influence on the ability of soil to hold water due to their negatively charged surface (Brady and Weil, 2014). Soil moisture enables nutrients movement in soil therefore allowing plants roots to absorb soluble soil nutrients (Scott, 2000). Soil pH regulates the solubility and availability of both macro and micronutrients cation in soil. For example at high pH, micronutrient cations get precipitated as insoluble hydroxides (Tolanur, 2006).

2.1.6 Current state and the future of remote sensing techniques as tools to predict soil properties

Due to advantages of application of remote sensing in characterising soil properties, there are Vis-NIR remote sensing instruments which operate at different platforms of remote sensing (space-borne, ground based, and airborne) (Jenson, 2010). Currently there are few remote sensing instruments which cover mid-infrared region of the electromagnetic spectrum.

Literature show that in the near future there will be space-borne sensors that will provide hyperspectral reflectance data such as EnMap developed from Germany, HSUI built in Japan, PRISMA from Italy and SHALOM from Israel which cover visible and near infrared range and also those which cover thermal infrared region such as HyspIRI (Nocita *et at*., 2015). These instruments could make it easier to characterize the spatial variation of soil properties over a large area.

2.2 Work not done on problem statement

Literature show that many studies focused on the use of remote sensing to characterise soil properties such as soil texture, primary macronutrients, soil moisture, and organic matter (Franceschini *et al*., 2015; Conforti *et al*., 2015; Xu *et al*., 2018). But few studies have been done on assessing the ability of proximal sensor and space-borne on characterising primary and secondary essential macronutrients especially on South African soils. Therefore this study will cover characterisation of primary and secondary macronutrients among other important soil properties.

CHAPTER 3
RESEARCH METHODOLOGY

3.1 Description of study area

The study site was Syferkuil experimental farm of the University of Limpopo (23°50'36.86"S and 29°40'54.99"E). It is about 13 km from the main campus of the University. The research site is located in semi-arid region with average annual rainfall of 500 mm. 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 72 ha and this portion has been cultivated since from 2011 coupled with occasional resting. The study was conducted during winter season from 16th to 17th June 2017, when the field was not covered by vegetation.

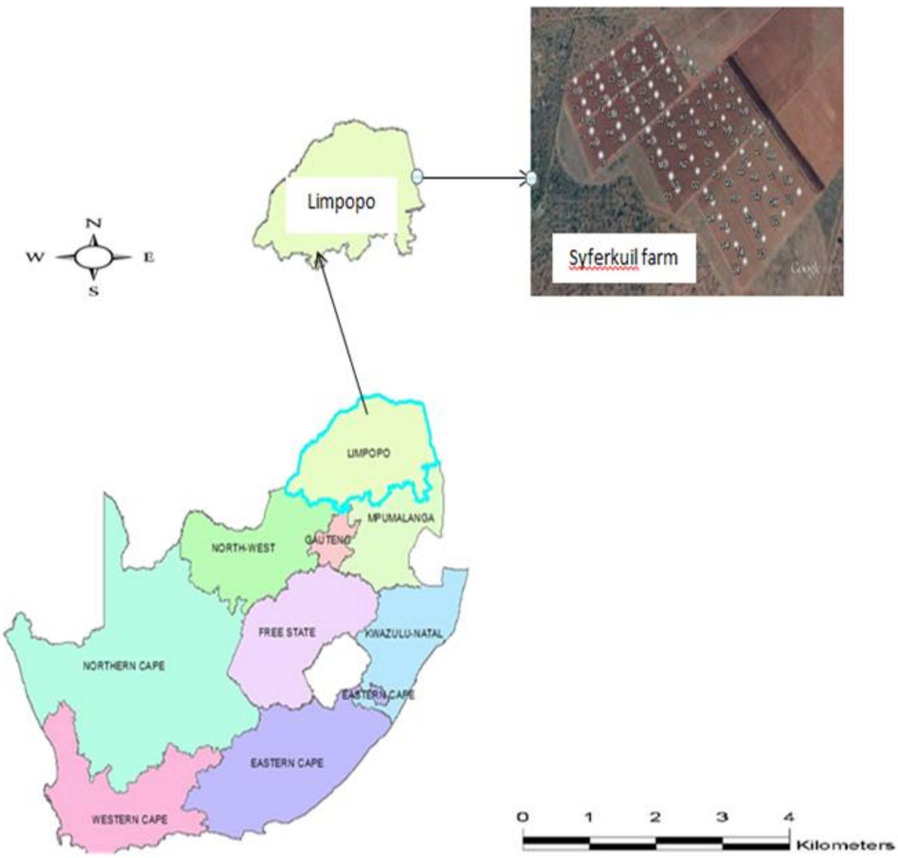

Figure 1: Measure soil reflectance using ASD fieldspec spectroradiometer

3.2 Procedures

Remote sensing techniques used to conduct the study are spectroradiometer (hyperspectral proximal sensor) and a satellite image. In achieving objective one, the field study was segmented into grid of 50 m X 100 m in order to cover lots of spatial variation. Having a wide range of spatial variation in the field is important since it tests the prediction ability of models developed and it reduces biasness of models. A sampled point at the centre of each grid was used for measurement of soil surface reflectance using Analytical spectral device (ASD) FieldSpec spectroradiometer (figure 1). The field reflectance measurement was replicated 4 times by randomly pointing the gun in a diameter of 10 cm around the sampled point. The spectroradiometer also ensures the repeatability of the measurement by taking 5 different measurements (pseudo-replicate) for every replication. The reflectance readings were taken between 10h00 and 14h00. Since the ideal time to take adequate measurements of the reflectance from the field is when the sun angle is between 30° and 52° above the horizon. After that, soil samples were taken at the sampled point of each grid for conventional characterisation of the selected soil properties which was done with soil laboratory. A shovel was used to take soil samples from the top 5 cm of soil surface, 98 soil samples were taken. 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.

For conventional characterisation of soil properties, the standard laboratory (conventional) methods for determining soil organic matter, soil moisture content, macro-nutrients, soil texture, CEC and pH were used. The results from these conventional methods were used together with reflectance measurements of spectroradiometer to develop models for characterising the selected soil properties. The developed models were used to achieve objective two since they highlight bands of relevance for predicting each selected soil property.

To achieve objective three, a multispectral satellite image called worldview 2 was purchased at digital globe; the image 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. Before the satellite image was used to achieve objective three, it went through pre-processing where digital numbers of radiometrically corrected image pixels were converted into top of atmosphere (TOA) spectral radiance. Furthermore the TOA spectral radiances were converted to surface reflectance using raster calculator of ArcMap version 10.3 (Comp and Updike, 2010). The geographic references of the sampled points were used in ArcMap version 10.3 to extract reflectance values from the remote sensing images using multiple point extraction. Extracted reflectance values from worldview 2 were used together with results of conventional laboratory analysis results to develop prediction models for the selected soil properties. Thereafter the prediction performance of these models were evaluated based on the coefficient of determination (R^2), root mean square error of prediction (RMSE) and ratio of prediction deviation (RPD) of each model.

3.3 Data collection

3.3.1 Remote sensing

The spectroradiometer recorded reflectance data between the wavelengths of 350 nm and 2500 nm. Reflectance data collected by way of extraction from the satellite image is described above. Spectroradiometer measurements at the field were taken on 16th and 17th June 2017 while a multispectral satellite image of the study area was collected on 17th June 2017.

3.3.2 Conventional methods

Extractable phosphorus (P) was determined using Bray 1-P method (Bray and Kurtz, 1945). Nitrate (NO_3^-) and ammonium (NH_4^+) content of soil were determined using colorimetric method of nitrate and ammonium determination (Ryan *et al*., 2001). Soil pH of both H_2O and KCl solutions were determined using the electrode method (Thomas, 1996). Particle size determination was performed using Bouyoucos Hydrometer method (Bouyoucos, 1962). Exchangeable cations namely Potassium (K), Magnesium (Mg), Sodium (Na) and Calcium (Ca) were determined using ammonium acetate extraction method. Cation exchange capacity (CEC) was estimated by summing the major exchangeable cations (K, Ca, Mg, and Na) (Reeuwijk, 2002). Soil organic carbon was determined using Walkley-Black method. Organic matter was determined by multiplying the value of organic carbon with 1.72 (Walkley, 1935). Sulfur (S) content of soil was determined using phosphate extractable sulphate method (Nieto and Frankenberger, 1885). Moisture content of soil was determined using gravimetric method (Black, 1965)

3.4 Data analysis

The soil samples were divided into calibration and validation groups. Two third of the samples were randomly selected to be used for calibration and the rest were used for validation. Partial least square regression (PLSR) was conducted as the main statistical analysis and SPSS statistical software was used to compute Pearson correlation matrix with the aim of supporting discussion of results. PLSR was chosen due to its ability to analyse large data, handle data which have more descriptors variables than compound and it produce high prediction accuracy (Cramer, 1993).

3.4.1 Calibration

The replications and pseudo-replications of the spectroradiometer measurements were averaged using the ViewSpec pro version 6.0 to obtain one reflectance curve representing one sampled point. Conventional laboratory measurement of soil properties allocated for calibration and their corresponding reflectance values were used for calibrating models using partial least square regression (PLSR), a 30 days trial Unscrambler X software version 9.0 (CAMO, Norway) was used to perform PLSR. The software also identified individual bands from spectral data that contribute highly to PLSR model developed for estimation of the different soil parameters based on the reflectance variation.

3.4.2 Validation

Conventional laboratory measurement of soil properties selected for validation and the corresponding reflectance values were used to test the model. The coefficient of determination (R^2), root mean square error of prediction (RMSE) and ratio of prediction deviation (RPD) were used to measure the goodness of the prediction. RPD was obtained by dividing the standard deviation of analysed data by the value of RMSEP. Chang *et al*. (2001) developed a method to classify models based on their estimation accuracy, looking at their RPD value and R^2 value: Models which had RPD value greater than 2.0 and R^2 value starting from 0.80 to 1.00 were considered to be excellent (category A). Furthermore models which had RPD value starting from 1.4 to 2.0, with an R^2 value starting 0.50 to 0.79 was considered to be good (category B). A model which had RPD value lower than 1.4 and R^2 value lower than 0.5, indicate approximate quantitative prediction (category C). Models which are classified as category C are considered not to be reliable to predict soil properties.

CHAPTER 4
RESULTS AND DISCUSSIONS

4.1 RESULTS

4.1.1 Conventional laboratory analysis results for selected soil properties

The results obtained reveal that there is a great spatial variation in the study site (Table 1). This is important when developing predictive model since it tests the predicting ability of model under varying soil conditions and it ensures that the model is not biased. For example the results show that clay content range from 0.16 to 31.20, sand percentage range from 51.2 to 88.8 and silt percentage range from 0.16 to 40.16. This shows that there is high variation of clay, sand and silt percentage across the field, it may be as the result of parent material of the study area. Dolomite and Shale were found to be the dominated parent material at the study area. The results showed low content of organic matter; this has influence on the reflectance spectra, since soil which have low organic matter normally have high reflectance spectra (Lacerda *et al*., 2016). Both active and reserved soil pH of the study area were found to range between 7 and 6, which is suitable for most agronomic crops and phosphorus availability for plants absorption. This soil pH may have been influenced by the concentration of magnesium and calcium in the soil since magnesium and calcium are base cations which makes pH of the site to slightly neutral. NH4+ and NO_3^- have skewness values of 3.24 and 3.87, respectively above -0.5 and +0.5 threshold, this indicate that they are not normally distributed. From Clay, silt, sand, soil pH, cation exchange capacity (CEC), Sulphur (S), and phosphorus (P) were found to be approximately symmetric since their skewness value lies between -0.5 and +0.5, this means these soil parameters are normally distributed. Sand content is the only soil property that was found to be negatively skewed. This may be due to the influence of slope since the study site was at mid-slope therefore during rainfall other soil texture such as silt and clay may be carried by water to the lower area of slope. On the other hand soil organic matter (SOM) was found to be moderately skewed while other soil parameters were found that the distributions are highly skewed since their skewness values fall between +0.5 and 1, respectively (Bulmer, 1979).

Table 1: Statistical description of selected soil properties analysed by conventional laboratory methods (n= 98)

Soil parameters	Max	Min	SD	Median	Mean	Skew	Q_1	Q_3
Clay (%)	31.20	0.16	7.13	12.32	13.43	0.51	8.16	18.16
Sand (%)	88.8	51.2	7.62	71.20	69.35	- 0.28	64.16	75.2
Silt (%)	40.16	0.16	8.64	17.60	17.22	0.02	11.04	24.16
SOM (%)	6.12	1.55	0.82	2.78	2.90	0.87	2.39	3.36
Soil moisture (%)	45.20	23.7	2.23	1.14	1.28	1.02	2.56	3.02
NH_4^+ (mg/kg)	25.32	5.12	2.23	1.14	4.64	3.24	4.41	2.31
NO_3^-	24.01	4.58	12.0	4.45	5.12	3.87	3.41	2.89
P (mg/kg)	9.98	1.33	2.61	4.81	4.40	0.43	2.05	6.14
K (mg/kg)	20.1	4.31	3.56	4.84	6.23	4.12	2.27	5.94
Mg (mg/kg)	38.90	4.42	7.24	13.80	14.50	1.09	8.97	18.20
Ca (mg/kg)	23.8	3.05	4.33	7.84	9.36	1.50	6.51	11.10
S (mg/kg)	4.98	1.09	0.58	2.98	2.81	0.02	2.46	3.20
CEC (cmol(+)/100g)	14.30	3.74	1.71	8.36	8.28	0.26	7.26	9.24
pH_w	7.49	6.7	0.31	6.72	6.71	0.14	6.48	6.91
pH_{KCl}	7.06	6.06	0.27	6.30	6.31	0.43	6.12	6.49

SD=standard deviation, max=maximum, min=minimum, Q_1=first quartile, Q_3= third quartile

4.1.2 The reflectance curves of the sampled points in the study area

The Vis-NIR spectra of all soil sampled points were similar in shape. However differ slightly with the level of reflectance. The reflectance increases with the wavelength from the visible portion (250 nm) of the spectrum then it starts to decrease when approaching 2200 nm which is within the near infrared region. All the visible and near infrared spectra of the soil sampled points showed slight absorption troughs of the reflectance on the wavelength of approximately 1000 nm, 1400 nm and 2200 nm. The spectra also showed noise between wavelength of 1800 nm and 1900 nm from the surrounding environment which was recorded during the measurements.

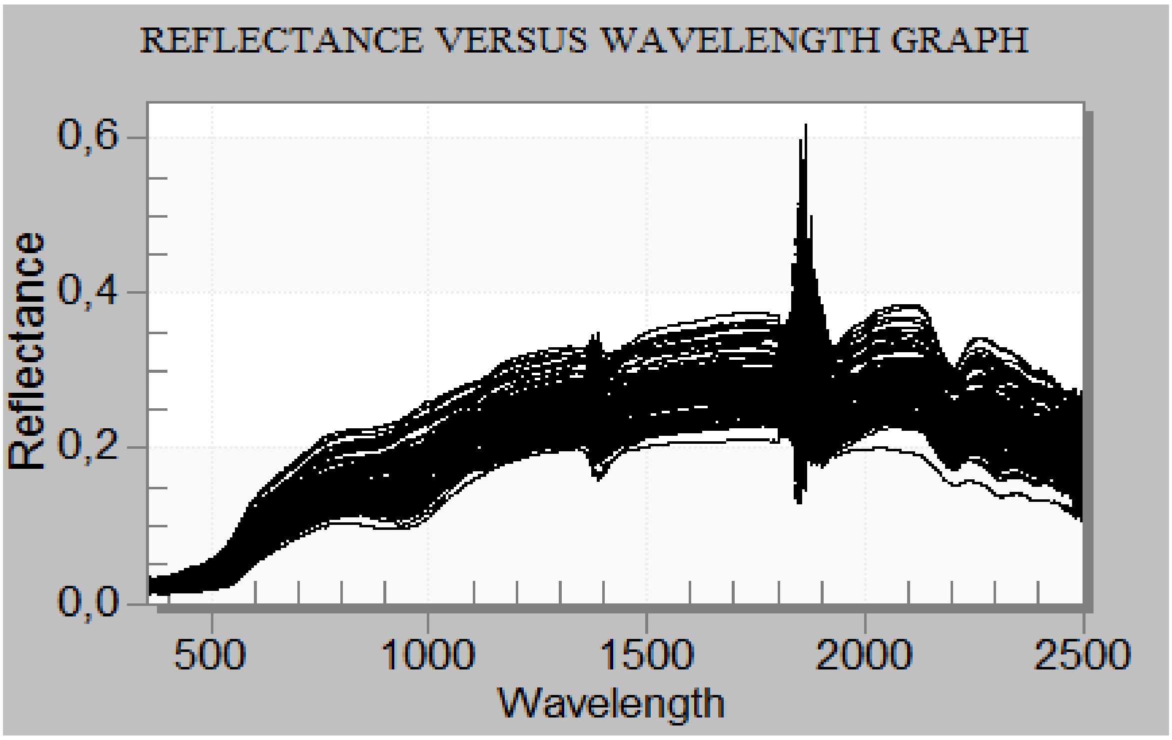

Figure 2: The spectral reflectance curves of all 98 soil sampled points taken at Syferkuil experimental farm covering visible and near infrared range (350 - 2500 nm) of electromagnetic spectrum

4.1.3 Pearson correlation between selected soil properties

Correlation matrix (Table 2) revealed that both clay content and SOM of the study site were significantly correlated to the other soil properties (soil moisture content (SM), Phosphorus (P), potassium (K) , magnesium (Mg), reserved acidity (pH_{KCl}), active acidity (pH_w), silt percentage, sand percentage, ammonium (NH_4^+), nitrate (NO_3^-), Calcium (Ca), and CEC) with $P < 0.05$. However pH_w and NO_3^- showed weak positive correlation with clay content ($r = 0.42$ and 0.43 with $P < 0.05$, respectively). It is observed that K, P, CEC and SM have strong positive correlation with Clay content and SOM as evidenced by their correlation coefficient ranging from 0.70 to 0.91 with $P < 0.05$.

Table 2: Pearson correlation matrix among selected soil properties

	pH_{kcl}	OM	Ca	Mg	K	pH_w	NO_3^{2-}	NH_4^+	P	Silt	Clay	Sand	CEC	SM
pH_{kcl}	1													
OM	**0.78**	1												
Ca	-0.24	**0.54**	1											
Mg	**0.50**	**0.55**	0.22	1										
K	-0.24	**0.74**	0.33	0.30	1									
pH_w	**0.54**	**0.62**	0.26	**0.52**	0.14	1								
NO_3^-	0.28	**0.64**	0.08	-0.06	0.21	0.30	1							
NH_4^-	0.30	**0.62**	0.10	-0.12	0.23	0.27	**0.65**	1						
P	**0.65**	**0.86**	0.03	0.05	0.12	**0.63**	-0.20	-0.25	1					
Silt	-0.04	**0.60**	0.33	0.26	0.02	-0.03	-0.14	0.37	0.23	1				
Clay	**0.69**	**0.80**	**0.55**	**0.50**	**0.70**	0.42	0.43	**0.55**	**0.73**	**0.63**	1			
Sand	0.20	**0.56**	0.15	0.17	0.32	-0.29	-0.15	-0.23	0.02	**0.63**	**0.69**	1		
CEC	0.42	**0.85**	**0.68**	**0.59**	0.42	0.46	0.38	0.40	0.32	0.26	**0.71**	0.32	1	
SM	-0.23	**0.91**	0.04	0.06	0.24	-0.25	0.03	0.09	0.11	**0.62**	**0.85**	**0.74**	0.44	1

The bold numbers indicate significant correlation among soil properties when $p<0.05$

om(%); Ca, Mg, K, NO_3^- ,NH_4^-, P (mg/kg); Sand, silt, clay (%), CEC (cmol(+)/100g) , moisture (%)

4.1.4 Prediction of soil properties using models developed from hyperspectral proximal data

The results show that PLSR (partial least square regression) models developed to predict soil properties obtained excellent predictions for clay, sand, SOM, and soil moisture content. Their R^2 values range from 0.83 to 0.87 (Table 3) and their RPD values are above 2.0 therefore their prediction performance of PLSR models are classified as category A (Table 3). Good prediction performance (Category B) of PLSR models was reported for estimation of silt, Phosphorus (P), Potassium (K), cation exchange capacity (CEC), pH_{KCl}, ammonium (NH_4^+), NO_3^- (nitrate), $pH_{w,}$ Sulphur (S), Calcium (Ca), and Magnisium (Mg). Since their models showed R^2 values ranging from 0.54 to 0.76 and their RPD values range from 1.5 to 2.0 (Table 3). Full descriptions of the performance of these models are in Appendixes 1 to 15.

PLSR models developed using proximal soil sensing identified bands of relevance for prediction of selected soil properties. Those selected bands with the greatest contribution for predictions of soil attributes ranged from 451 nm to 2400 nm (Table 3). These bands fall within visible, shortwave infrared and near-infrared regions of the electromagnetic spectrum.

Table 3: PLSR model performance for predicting of soil properties from hyperspectral proximal sensor data

Parameters	R^2	RMSE	RPD	Accuracy classification	Relevant spectral bands (nm)
Clay (%)	0.83	2.70	2.6	A	540, 1100, 1401, 2200
Silt (%)	0.64	1.20	1.5	B	1320, 1080, 1900, 2220, 2205
Sand (%)	0.84	2.73	2.9	A	1320, 1900, 1940, 2220, 2205
OM (%)	0.83	0.35	2.7	A	1225, 1315, 1900, 2200
Moisture content (%)	0.87	0.39	2.6	A	1400, 1900, 2400
NH_4^+ (mg/kg)	0.64	9.7	1.6	B	451, 510, 675, 1915, 2200
NO_3^- (mg/kg)	0.67	7.28	1.6	B	451, 510, 675, 1915, 2200
P (mg/kg)	0.76	1.28	2.0	B	1100, 1120, 1150, 1155
K (mg/kg)	0.74	4.0	2.0	B	1100, 1120, 1150, 1155
Mg (mg/kg)	0.56	3.02	1.6	B	540, 1400, 1566, 2205
Ca (mg/kg)	0.54	2.31	1.5	B	540, 1400, 1566, 2205
S (mg/kg)	0.75	0.31	2.0	B	1100, 1120, 1150, 1155
CEC (cmol(+)/100g)	0.72	0.80	2.0	B	540, 1400, 1566, 2205
pH_{KCl}	0.70	1.14	2.0	B	1120, 1125, 1910, 2201
pH_w	0.63	0.18	1.7	B	1120, 1125, 1910, 2201

Classification of accuracy of models for prediction performance was grouped into three categories namely: A, B and C, where each category means; A, excellent (RPD >2.0 and 0.80≤ R^2≤1.00); B, good (1.4 ≤RPD ≤2.0 and 0.50≤ R^2 ≤0.79); C, approximate quantitative prediction (RPD<1.4, R^2<0.50 (Chang *et al*., 2001). RPD=ratio of performance to deviation, RMSE=root mean square error, R^2=coefficient of determination

4.1.5 Prediction of soil properties using models developed from space-borne remote sensing data

Soil properties which are predicted using spectral data obtained from space-borne sensor showed approximate quantitative predictions for all selected soil properties. PLSR models are classified as category C since their RPD values were less than 1.4 and their R^2 values were less than 0.50 (Table 4). Although all soil properties were approximately quantitatively estimated, soil constituents such as clay content, sand percentage, soil organic matter, and soil moisture showed better estimation performance as compared to other selected soil properties since their models obtained R^2 values ranging from 0.32 to 0.45 (Table 4)

Table 4: PLSR models performance for predicting soil properties using space-borne remote sensing data (Worldview 2 satellite image)

Soil parameters	R^2	RMSE	RPD	Model accuracy
Clay (%)	0.45	5.32	1.34	C
Sand (%)	0.32	5.89	1.29	C
Silt (%)	0.21	7.41	1.17	C
Soil organic matter (SOM) (%)	0.42	0.68	1.21	C
Soil moisture	0.40	4.91	1.41	C
NO_3^-	0.13	7.14	1.34	C
NH_4^+	0.12	6.26	1.25	C
P (mg/kg)	0.23	2.32	1.23	C
K (mg/kg)	0.11	7.32	1.28	C
Mg (mg/kg)	0.23	5.80	1.25	C
Ca (mg/kg)	0.18	3.41	1.27	C
S (mg/kg)	0.14	7.28	1.18	C
CEC (cmol(+)/100g)	0.16	1.52	1.23	C
pH(KCl)	0.23	0.23	1.17	C
pH(H_2O)	0.10	0.26	1.19	C

4.2 DISCUSSION

4.2.1 Assessing performance of models developed from hyperspectral proximal sensor data

In this study excellent prediction performance of PLSR models were reported for clay content, sand percentage, soil organic matter content, and soil moisture content. Successful predictions of clay, SOM, and soil moisture content might be because these properties have direct spectral responses in visible and near infrared spectral range, which may be linked to overtones and combinations of fundamental vibrations as the result of stretching and bending N-H, C-H, S-H, and O-H bonds. This means that these soil properties have direct spectral absorption features in the visible and near infrared range, which enable successful estimation of these properties (Stenberg *et al*., 2010; Chang *et al*., 2001; Rossel *et al*., 2006).

The predictions of these properties are comparable to previous studies elsewhere. 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), Paz-kagan *et al*. (2015) also obtained good R^2 in their studies (0.70, 0.74, 0.67,and 0.78, respectively) for predicting the sand percentage of soil from visible and near infrared reflectance spectroscopy using partial least square regression. The results obtained by Zornoza *et al*. (2008) demonstrated that the visible and near infrared spectroscopy might be useful to estimate soil moisture since they obtained PLSR model with R^2 value of 0.96 and RPD value of 4.88 which indicate excellent prediction. Conforti *et al*. 2015 obtained excellent prediction of soil organic matter with R^2 of 0.89 using 9 PLSR latent factors and RMSE of 0.60%. Vohland *et al*. (2014) also obtained PLSR model with good R^2 of 0.78, RMSE of 0.31% and RPD of 2.12 for soil organic matter estimation in their study using DRIFT(Diffuse reflectance infrared Fourier transform) in the mid-infrared range. Results obtained in this study for prediction of soil organic matter correspond with those reported by Pinheiro *et al.* (2017), and Bilgili *et al*. (2010) with R^2 ranging from 0.74 to 0.80.

The results of PLSR models further showed good prediction of silt, P, K, CEC, pH_{KCl}, NH_4^+, NO_3^- , pH_w, S, Ca, and Mg. Therefore these models were classified as category B since the R^2 values fell between 0.50 and 0.79 while the RPD values were within the range of 1.4-2.0. Although these soil properties do not have direct spectral response in the Vis-NIR region, they are well predicted. This may be as the result of covariation through other soil constituents such clay and organic matter which have direct spectral responses in the near infrared region (Stenberg *et al*., 2010). Chang *et al*. (2001) and de Santana *et al*. (2018) postulated that the ability to predict soil properties which do not have direct spectral response such as K, Ca and Mg using visible and near infrared spectroscopy is due to correlations of these parameters with spectrally active soil constituents. Clay and soil organic matter showed varying positive correlations with silt, P, K, CEC, pH_{KCl}, NH_4^+, NO_3^- , pH_w, Ca, and Mg (Table 2). The correlation of clay and organic matter with exchangeable cations may be due to the fact that clay and organic matter tend to adsorb exchangeable cations on their negatively charged surfaces. The ability of PLSR models to predict soil pH may be due to covariation of pH with clay and soil organic matter (Chang *et al*., 2001). Kuang *et al.* (2012) suggested that the accuracy of nitrogen estimation using Vis-NIR reflectance depends on the form of nitrogen that will be quantified since nitrogen content in soil can be measured as organic, inorganic or total nitrogen. Results found in this study are consistent with results obtained in previous studies. Xu *et al*. (2018) reported slightly similar results for estimation of silt using near infrared spectral data. Rossel *et al*. (2006) and Wenjun *et al*. (2014) reported successful prediction of soil pH_w. Franceschini *et al*. (2015) obtained good prediction of Mg based on laboratory derived spectra (R^2 of 0.59, RMSE of 2.2 mmolc kg^{-1} and RPD of 1.58). Many studies reported high prediction accuracy of soil nitrogen content in the visible and near infrared region (Chang *et al*., 2001; Zornoza *et al.*, 2008; He *et al*., 2007).

4.2.2 Identifying bands of relevance from hyperspectral proximal soil sensing

Bands which were selected as major contributors to the PLSR model for predicting soil organic matter (Table 3) correspond with those observed by Qi *et al*. (2017) who reported that bands 1225 nm and 1315 nm are important for estimation of organic matter. Rossel and Behrens (2010) suggested that these bands may be associated with carbonic acids found in organics. Important bands for prediction of Clay content were found to be 540, 1100, 1401 and 2200 nm. Selection of important bands for prediction of clay content in near infrared region is mainly due to overtones and combination of vibrational bands of H_2O, Mg, Al and Fe hydroxides, and band 540 nm which is within the visible range of electromagnetic spectrum is associated with hematite clay mineral (de Santana *et al*., 2018). The wavelengths 1400, 1900 and 2400 nm were reported as most relevant bands for estimation of soil moisture content. These bands may be related to OH features of soil water (Bilgili *et al*., 2010).

For estimation of pH_W and $pH_{KCl,}$ the following bands 1120, 1125, 1910, and 2201 nm (Table 3) were selected as bands with the greatest contribution in PLSR model. Xu *et al*. (2018) also reported similar bands for estimation of pH based on selective ratio values of individual bands. PLSR model selected the following bands 540, 1400, 1566 and 2205 nm of electromagnetic spectrum as relevant wavelengths for prediction of CEC. According to de Santana *et al.* (2018) organic matter and clay minerals are two important soil constituents that play vital role in quantification of CEC due to their exchange surface, therefore band 540 nm and 1400 nm are considered as important variables due to hematite mineral and organic compound such as aromatics, respectively. Significant bands for estimation of available nitrogen both NO_3^- and NH_4^+ were found to be 451, 510, 675, 1915 and 2200 nm. The selection of these wavelengths may be associated with electronic transitions of Fe oxides (Fe^{2+} or Fe^{3+}) which occur in the visible portion of electromagnetic spectrum and may also be due to O-H combination band of clay minerals which generally occur in the near infrared region (Vohland *et al*., 2014).

Wavelengths which showed greatest contribution in the PLSR models developed for estimation of silt and sand percentage include bands in the shortwave infrared (1320,1080, 1900, 1940, 2220, and 2205 nm) (Table 3). Bands 1080 nm and 1900 nm are the only relevant bands which correspond to similar wavelengths selected by Paz-Kagan *et al*. (2015) and Xe *et al*. (2018). For estimation of P, S and K using visible and near infrared spectral data measured by proximal soil sensing, bands of relevance were found to be 1100, 1120, 1150, and 1155 nm. According to Qi *et al*. (2017) P, S and P can be estimated because 1120 nm and 1155 nm wavebands are associated with S-O stretching bands of sulphate.

4.2.3 Evaluate performance of models developed from space borne sensor data

The results showed poor predictions of selected soil properties using Vis-NIR spectral reflectance obtained from worldview-2 satellite image (Table 4). PLSR models of selected soil properties obtained R^2 value ranging from 0.1 to 0.45 which means that the models are not reliable for prediction and the model accuracy is low. This may be the results of the effect of noise and errors due to variations in soil surface roughness, geometric and atmospheric effects (Casa *et al.,* 2013). Even though atmospheric and geometric corrections has been done on the image before extracting spectral reflectance, there may still be some effects remaining which was caused by atmosphere, geometric and surface roughness effects which influence the model performance. The poor performance of models may also de due to wide spectral resolution of the image (low resolution compared to hyperspectral data). Studies show that good prediction performance of models is obtained when satellite image which have bands with narrow wavelengths (hyperspectral image) are used (Lu *et al*., 2013; Franceschini *et al*., 2015; Gomez *et al*., 2008; Qi *et al*., 2017).

Prediction performance of PLSR model for estimations of Clay, sand, SOM, and soil moisture (Table 4) was found to be better as compared to other soil parameters predicted using reflectance from worldview-2 satellite image. 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 (R^2) reported for silt, sand and clay was found to be 0.32, 0.21 and 0.3, respectively. 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).

CHAPTER 5

CONCLUSIONS AND RECOMMENDATIONS

This study focused on the use of remote sensing techniques as an alternative approach to characterize soil properties. The results demonstrated that proximal soil sensing has the ability to predict selected soil properties with various accuracies and can be used as alternative method to characterise soil properties. Selected soil properties (clay, sand, SOM, and soil moisture content) which are spectrally active in the Vis-NIR region due to their molecular bonds such as C-C, N-H, C-H and O-H were excellently predicted using spectral data of proximal soil sensor, while good prediction performance of PLSR models were observed for silt, NH_4^+, NO_3^-, $pH_{w,}$ S, Ca, Mg, P, K, CEC, and pH_{KCl} due to their strong positive correlation with SOM and Clay which have direct spectral response in the Vis-NIR range.

Bands of relevance for prediction of each selected soil constituents were also identified. Results show that most of bands that contribute highly to PLSR models were found in the near infrared region, with few bands only found in the visible range. Furthermore PLSR models developed using spectral reflectance extracted from worldview 2 satellite image (space-borne sensor) showed that all selected soil properties were approximately quantitatively estimated. This means that they have low prediction accuracy. Based on the results obtained in this study, it is clear that proximal soil sensing which is a ground based hyperspectral remote sensing technique can be used as an alternative tool to accurately characterise soil properties.

Further research should be conducted to evaluate of the ability of space-borne sensor to characterise soil properties using hyperspectral satellite image. In this study a multispectral satellite image was used and it did not give satisfactory results.

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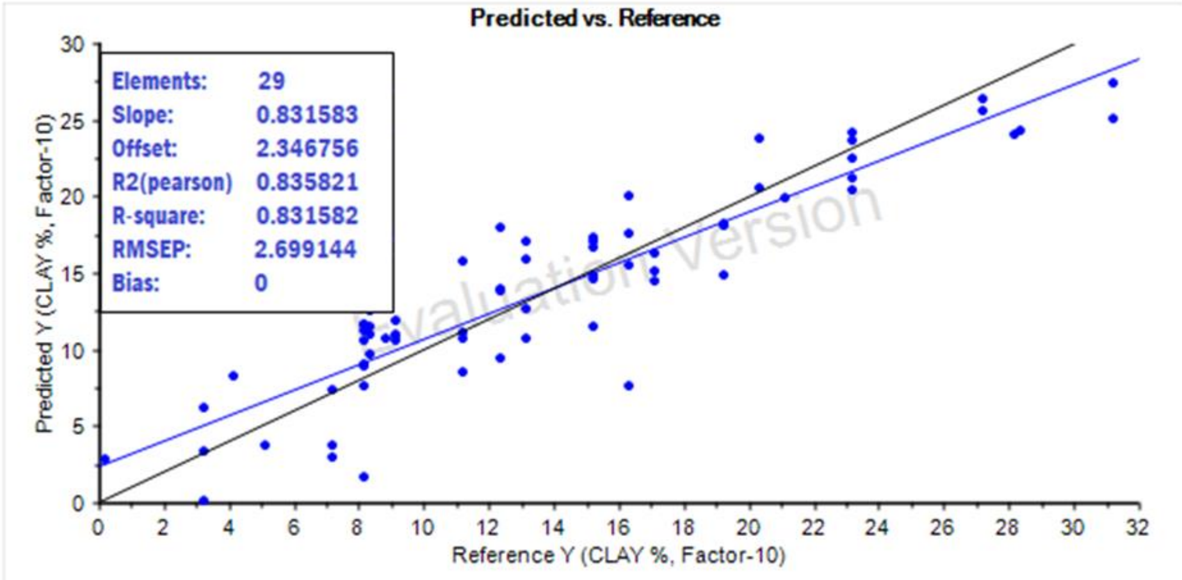
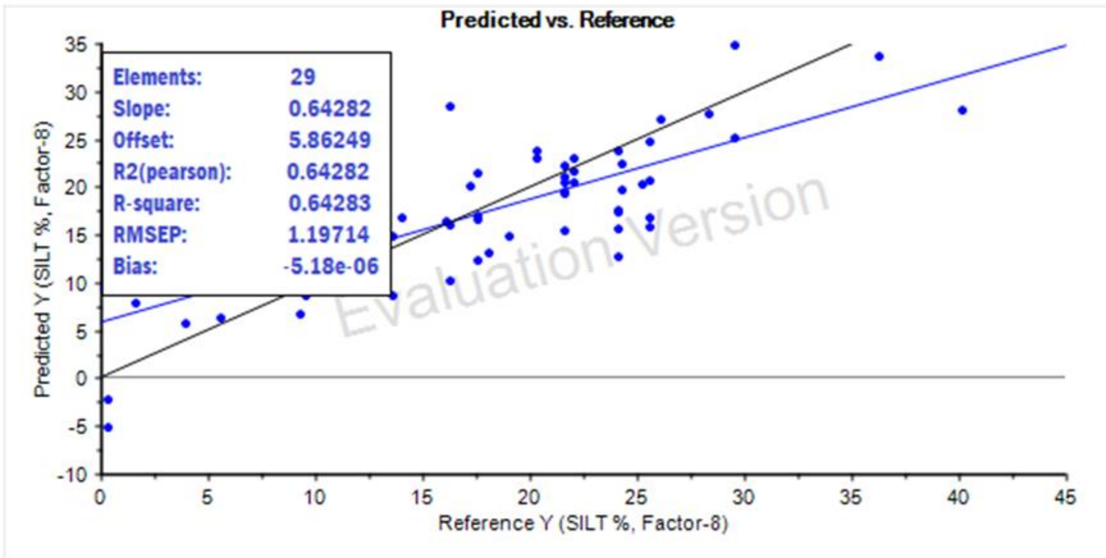
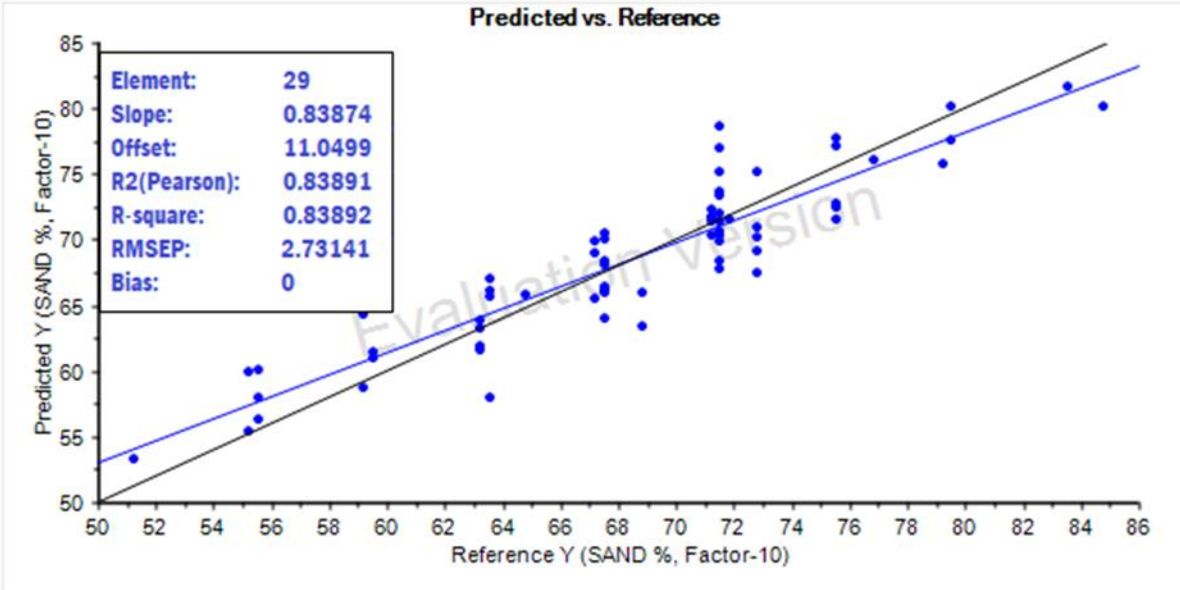
APPENDICES



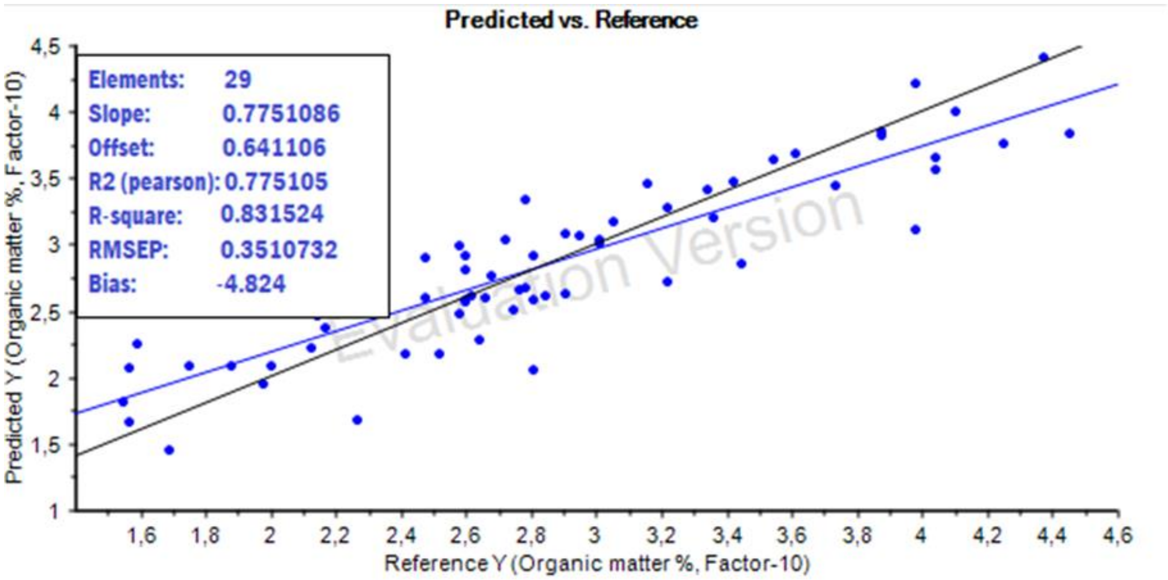
Appendix 1: PLSR model for prediction of soil clay content using spectral data from proximal sensor



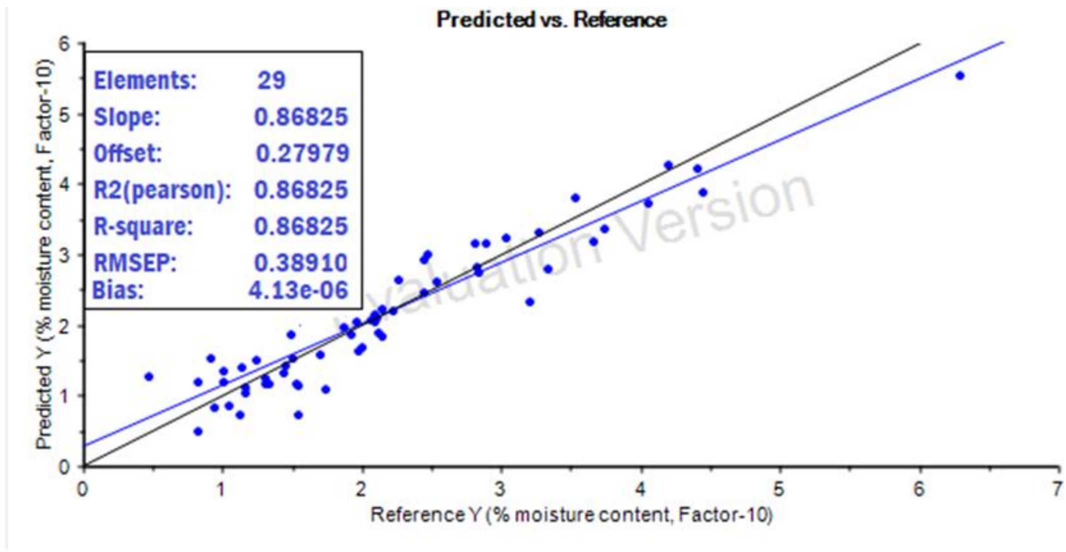
Appendix 2: PLSR model for prediction of soil silt content using spectral data from proximal sensor



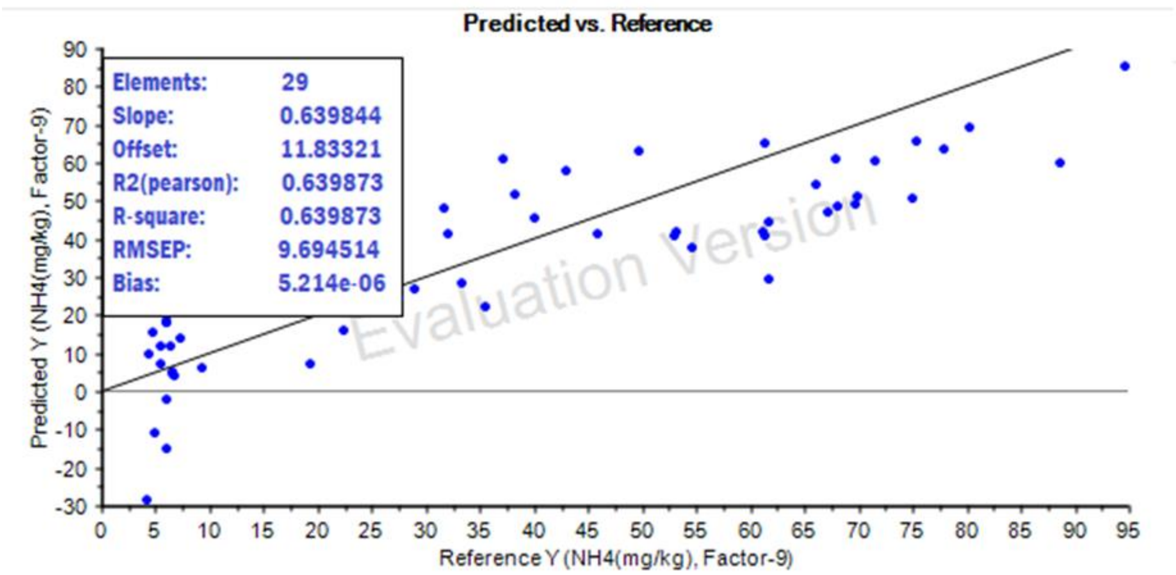
Appendix 3: PLSR model for prediction of soil sand content using spectral data from proximal sensor



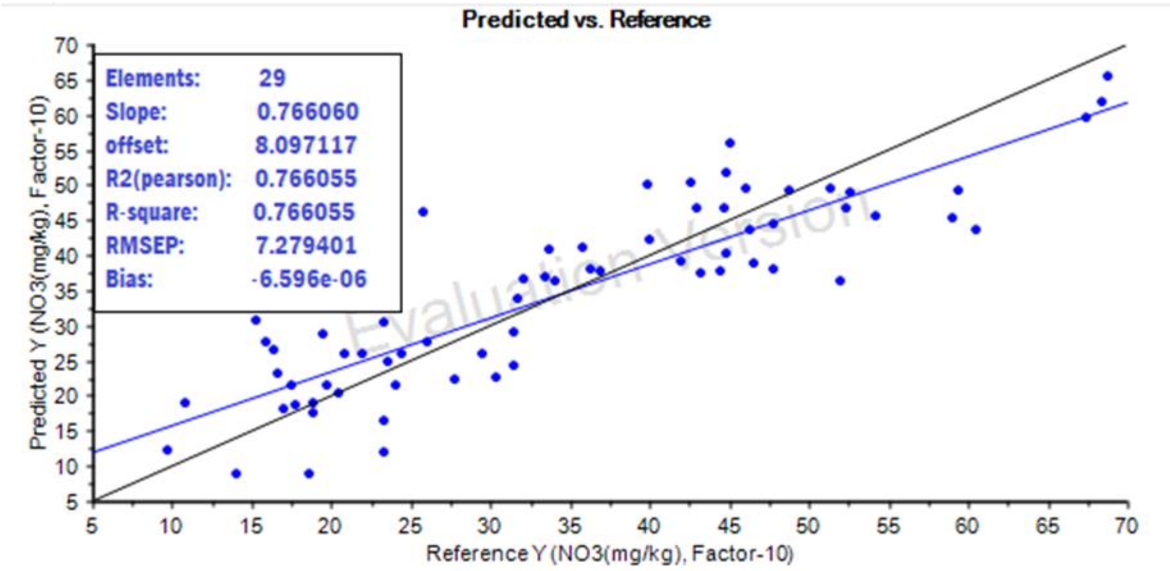
Appendix 4: PLSR model for prediction of soil organic matter content using spectral data from proximal sensor



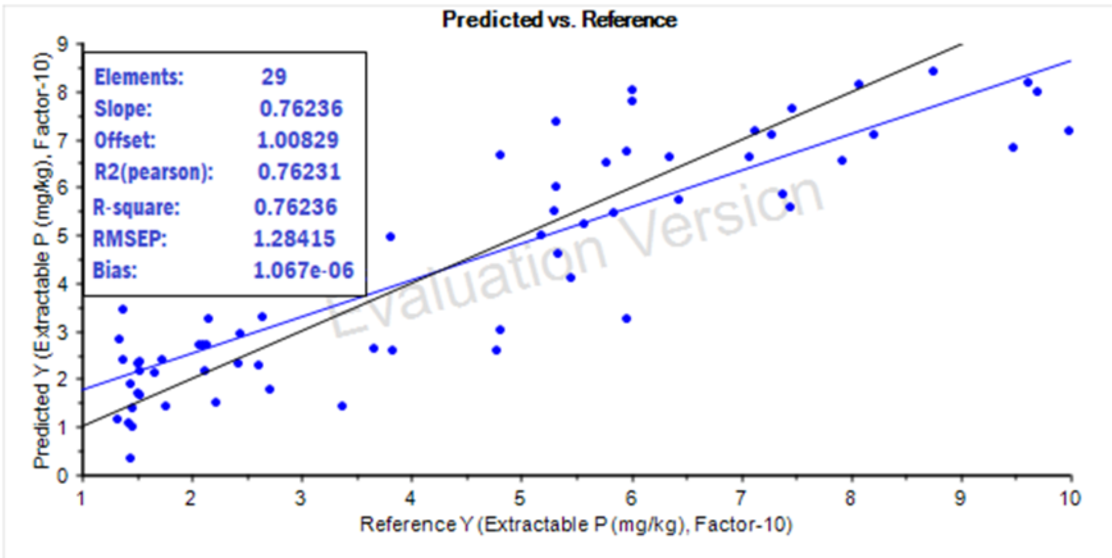
Appendix 5: PLSR model for prediction of soil moisture content using spectral data from proximal sensor



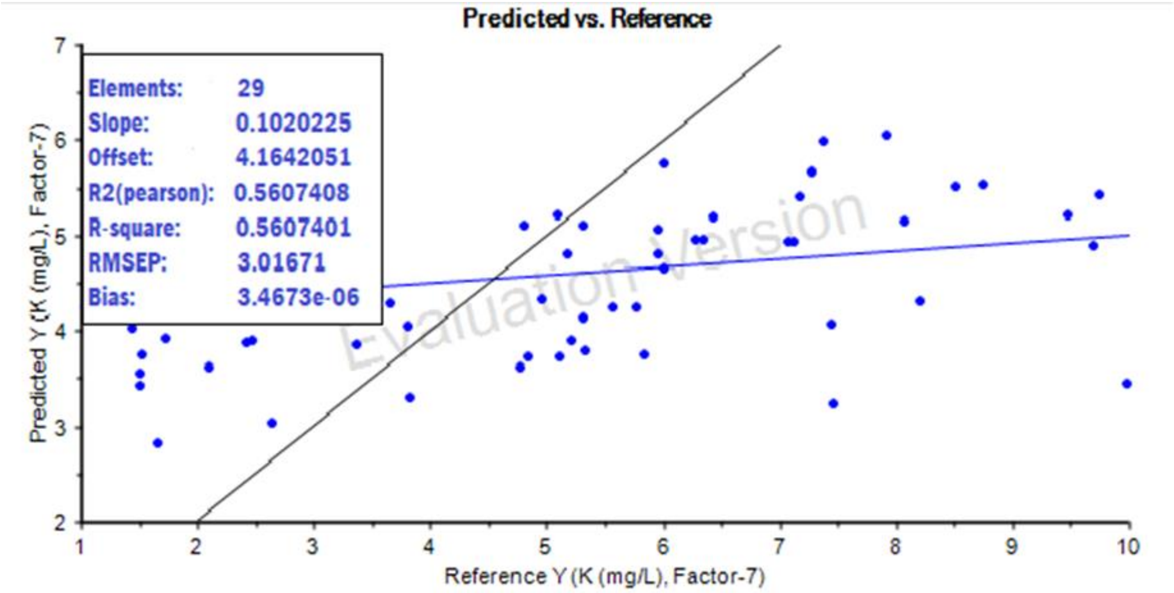
Appendix 6: PLSR model for prediction of ammonium content (NH_4^+) in soil using spectral data from proximal sensor



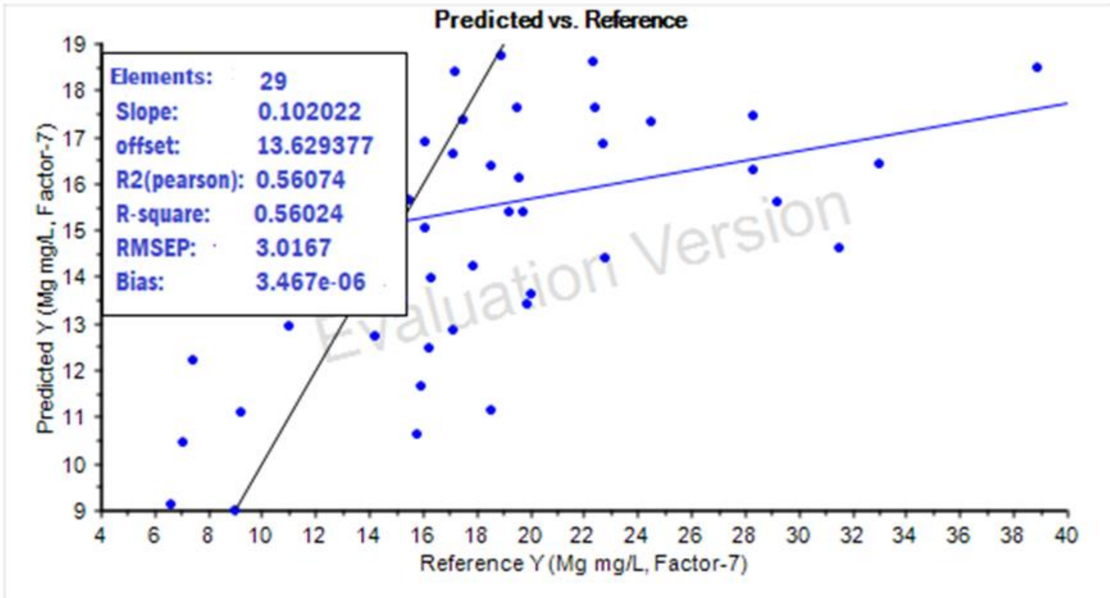
Appendix 7: PLSR model for prediction of nitrate content (NO_3^-) in soil using spectral data from proximal sensor



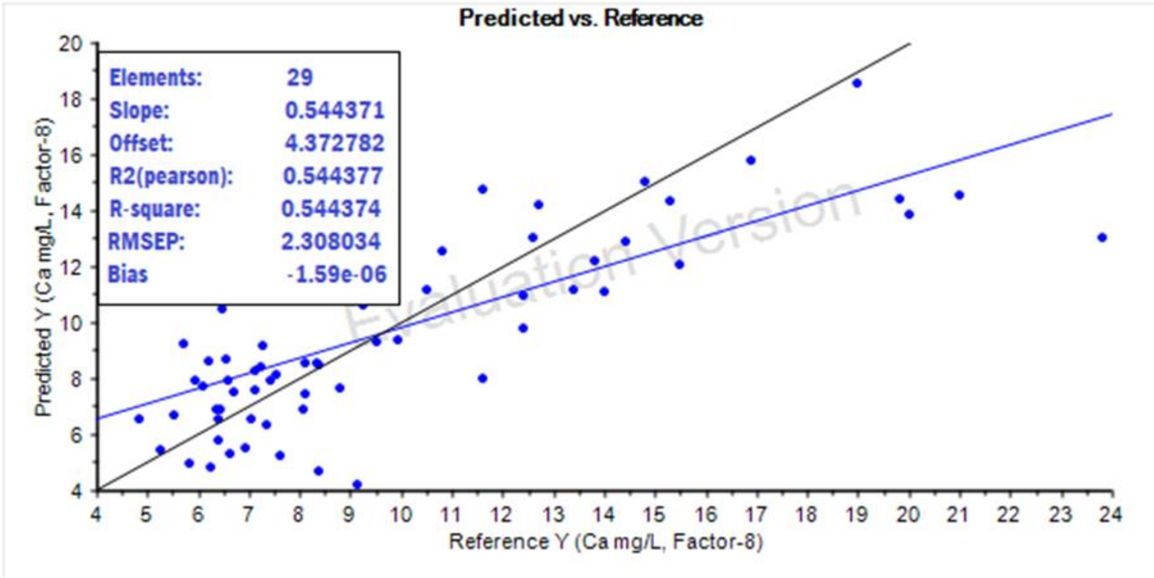
Appendix 8: PLSR model for prediction of available phosphorous (P) content in soil using spectral data from proximal sensor



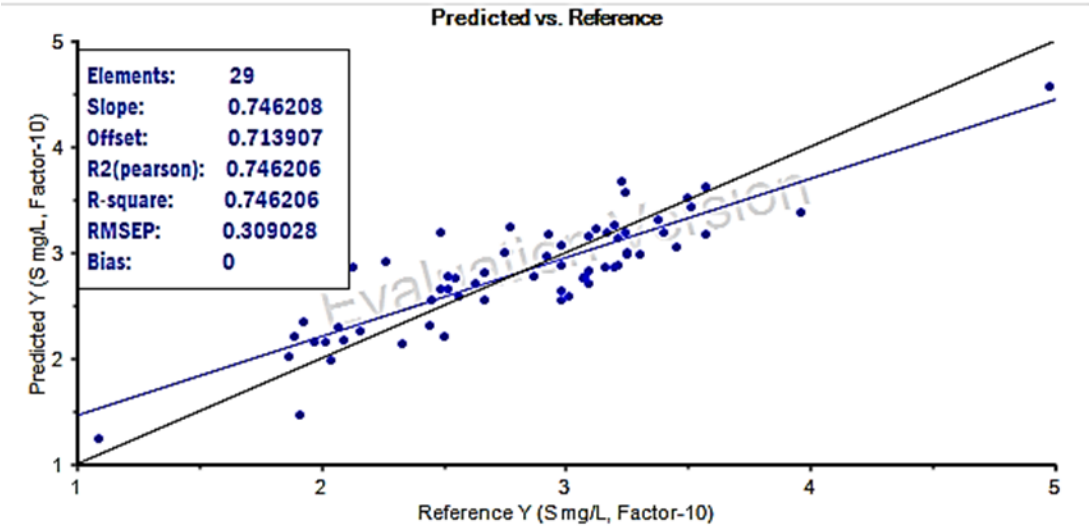
Appendix 9: PLSR model for prediction of potassium (K) content in soil using spectral data from proximal sensor



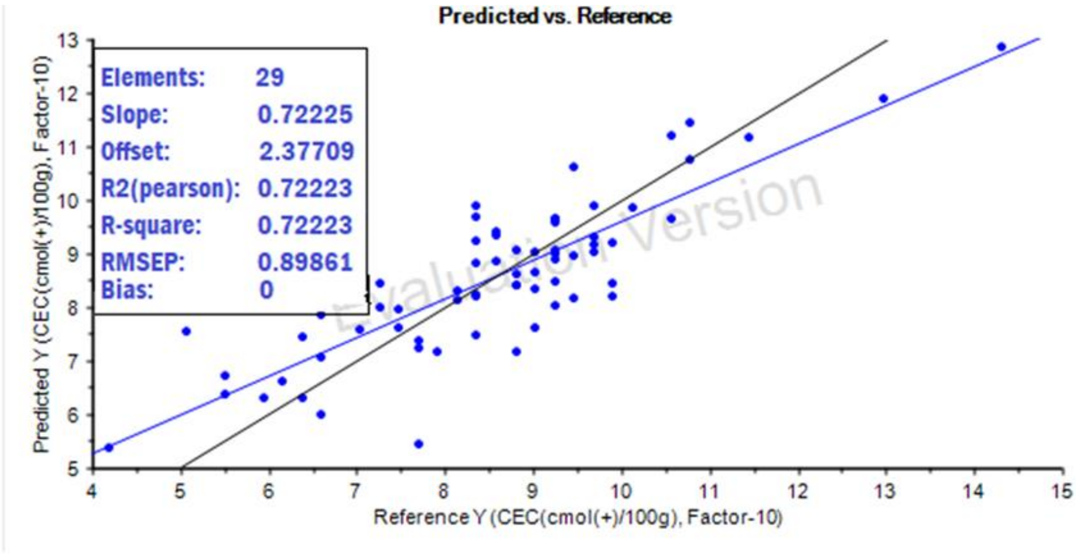
Appendix 9: PLSR model for prediction of Magnesium in soil using spectral data from proximal sensor



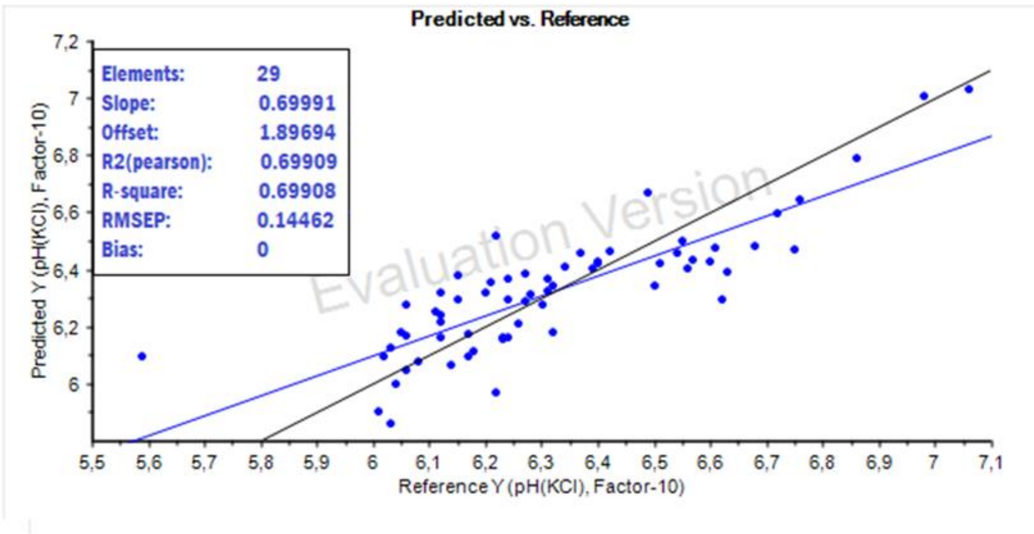
Appendix 10: PLSR model for prediction of calcium in soil using spectral data from proximal sensor



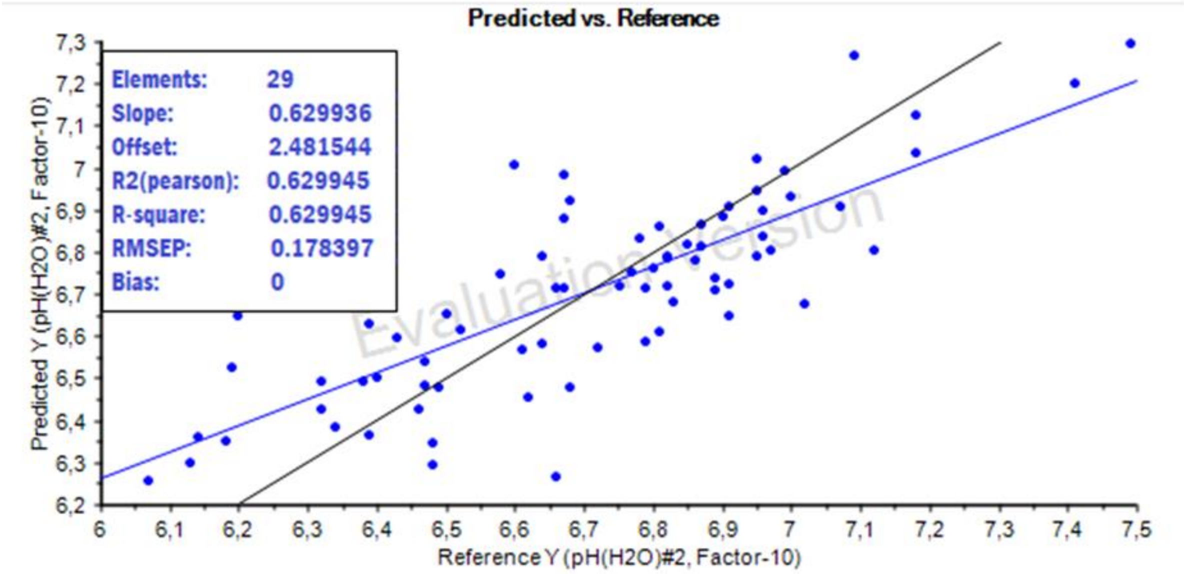
Appendix 11: PLSR model for prediction of sulphur in soil using spectral data from proximal sensor



Appendix 12: PLSR model for prediction of cation exchange capacity (CEC) in soil using spectral data from proximal sensor



Appendix 13: PLSR model for prediction of pH_{KCl} in soil using spectral data from proximal sensor



Appendix 14: PLSR model for prediction of pHw in soil using spectral data from proximal sensor