GIS AND REMOTE SENSING AS A POTENTIAL TOOL TO SUPPORT DIGITAL SOIL MAPPING IN THE EASTERN CAPE PROVINCE IN SOUTH AFRICA

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GIS AND REMOTE SENSING AS A POTENTIAL TOOL TO SUPPORT DIGITAL SOIL MAPPING IN THE EASTERN CAPE PROVINCE IN SOUTH AFRICA

By

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Abstract

This study is based on assessing the potential use of GIS and Remote Sensing in trying to fill the various soil maps of selected regions at different scales with spatial soil data. A variety of processes are available for use. These include band ratios, principal component analysis as well as use of a digital elevation model (DEM). With the advent of GIS and Remote Sensing, these principles in the new niche of study are investigated to check if they can be used to augment the current processes available in soil mapping techniques. Such processes as band ratioing, principal component analysis and use of Digital Elevation Models (DEMs) are investigated to check if they can be used in soil mapping techniques. From the results produced it is evident that these processes have the potential to be used in the Digital Soil Mapping process. Despite the limitation of remote sensing to a few centimetres of the topsoil these processes can be used together with the soil mapping techniques currently being used to come up with soil maps.

Key words: digital soil mapping, band ratio, principal component analysis, digital elevation model.

Declaration by candidate

I, Tumelo Mathe, the undersigned candidate, declare that the content of this dissertation is my original work and has not been previously submitted to any other University for an award of a degree either in part or in its entirety.

Signature……………………………………..

Date……………………………………………

Acknowledgement

First and foremost, I would like to give thanks to God for making it possible for me to finish this thesis. If it was not for God I would not have made it because in Him I have my being and the strength, perseverance and wisdom.

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To the University of Fort Hare Volleyball Club Alice Campus team, affectionately known as SIXERS, I thank you guys for your support that you gave me.

Dedication

I dedicate this thesis to my family, Mathe, Bolamba, Gubado and Noko. Thank you for your faith you had in me to finish the Masters. I know I have made you very proud by adding yet another degree to the family tree. The thesis was completed at the time our brother, Moekejo "Tandala" Mate passed on from this world. As a family we are indebted to him for his life he shared with us.

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Abbreviation

AVHRR-Advanced Very High Resolution Radiometer

ASTER- Advanced Space borne Thermal Emission and reflection Radiometer

ARC-ISCW- Agriculture Research Council- Institute of Soil, Climate and Water

ARDRI-Agriculture Rural Development Research Institute

CLORPT-Climate, Organism, Relief, Parent material and Time

DN-Digital Number

DEM-Digital Elevation Model

DSA-Digital Soil Assessment

DSM- Digital Soil Mapping

DBMS-Database Management System

FAO-Food and Agriculture Organisation

GCP-Ground Control Points

GPS-Global Positioning System

GEOSS- Global Earth Observing System of Systems

IFOV-Instantaneous Field of View

IRS-India Remote Sensing

ISSS-International Soil Science Society

LUT-Look-up Table

MSS-Multispectral scanner

NASA-National Aeronautical Space Agency

NOAA-National Oceanic Atmosphere and Administration

NDVI-Normalised Difference Vegetation Index

PCA-Principal Component Analysis

RDBMS- Relational Database Management Systems

SOTER-Soil and Terrain database

SWIR-Short-wave infra-red

SPOT- Systéme Probatoire d'Observation de la Terre

TM-Thematic Mapper

TIR-Thermal Infra-Red

UNESCO-United Nations Education and Scientific Organisation

USDA-United States Department of Agriculture

USGS-United States Geological Society

UTM-Universal Transverse Mercator

VNIR-Visible Near Infra-Red

WG-DSM-International Working Group on Digital Soil Mapping

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CHAPTER 1: INTRODUCTION

1.1 Overview

Digital soil mapping can be described as "a tool that is used to create spatial soil information" (Behrens and Scholten, 2006). The International Working Group on Digital Soil Mapping defines the digital soil mapping process as "comprising the creation and population of a geo-referenced soil database" (http://www.digitalsoilmapping.org). This soil database can be generated at specific resolutions by coupling field and laboratory observation methods. Soil maps have been produced using soil surveys. The results from the laboratory are mapped to show where it would be possible to find the soil types analysed. This form of soil analysis has been referred to by many soil scientists as traditional soil mapping.

Traditional soil mapping is time consuming because it requires identification, characterisation of soils and fitting of mapping units in a classification system and their placement in a spatial context (Weber et al, 2008). The result is the production of very few maps. This is because the process is incapable of supporting optimal production of adequate maps. Consequently, it is increasingly essential to provide alternative strategies for rapid production of soil maps.

It is worth mentioning that the process of creating digital soil maps is different from soil mapping which is commonly known as soil survey. Soil mapping involves the compilation of thematic maps using criteria-based delineation of soil boundaries through digitising or thematic classification of remotely sensed imagery. The thematic maps do not become digital soil maps until soil related information has been added in a Geographic Information System (GIS) environment (Rossiter, 2005). Though digitisation has been used to compile maps at different scales, it often takes a lot of time to accurately capture the required information. Consequently, a lot of hard copy maps remain underutilised because of numerous constraints associated with their conversion into digital format. The Digital soil mapping procedure utilises the ability to convert these paper maps to digital format using GIS.

Remote sensing based soil mapping techniques offer viable alternatives to conventional soil mapping procedures. This is because soil maps can be accurately and rapidly produced through image classification. The process takes advantage in the technological and computational advances in the fields of digital soil mapping to come up with the desired digital maps. Technological advances include the use of Global Position System (GPS) receivers in ground truthing and field scanners. Computational advances include the use of GIS and digital elevation models as well as geo-statistical interpolation in the creation of the digital soil maps.

The creation of digital soil maps is essential because soil exhibits different behaviours, that is, each soil type has unique properties (Aksoy et al, 2006). These unique features are mapped and used to determine the soil type. Variations in the spectral characteristics of different soil types facilitate detailed mapping because each soil type reflects incident light differently. Digital soil maps provide information that is vital for soil management and most policy formulation policies have been widely used for agriculture and land use management by supporting the monitoring of erosion and tillage practices. They provide vital information on:

- Infiltrate/carbon storage capacity and the ability to support crop production.
- Geographical representations of soil constraints such as aluminium toxicity, carbon deficits and sub-soil restrictions. All this can be done with confidence to help farmers in determining levels of nutrient application.
- Spatial targeting for management recommendations and establishment of baseline conditions for change detection and impact assessment.

Digital soil maps are required in most activities related to land use management. They are important because they enhance our understanding of pedological processes by providing a site-specific/spatial information framework for land use management. The spatial dimension is important because of the need for accurate information on key environmental variables such as soil nutrient status, soil pH, texture, and salinity, vegetation and terrain. This information is also vital because it provides an objective basis for the creation of digital soil maps through the systematic classification.

To cost-effectively compile digital soil maps at any scale requires extensive use of both legacy soil data and soil landscape knowledge (Hansen et al, 2009). This compilation process largely relies on modelling relationships between measured soil properties, and environmental co-variables such as surface reflectance and digital elevation that can be derived from satellite imagery. Data for each digital soil mapping unit, are calibrated to fit the region of interest.

GIS has increasingly been used as a versatile means to store amounts of information contained is soil maps to overcome the problems associated with the storage of hard copy maps. GIS offers advantages over hard copies in that it provides digital storage of information in a database that can be easily accessed by different users at any given time. The same information can be used in creating other digital maps without the need of going to the field to acquire data or to the laboratory to analyse new soil samples. Digital soil mapping requires:

- A base map derived independently of other variables that will be used in subsequent analysis,
- Establishment of the relationship between the reference layer of interest and soil and determination error estimates and levels of accuracy.

GIS data can be coupled with satellite imagery for digital soil mapping. The choice of imagery is dependent on factors such as spatial and radiometric resolution. However, most digital soil maps have been created from the conventional satellite imagery data which include Landsat Thematic Mapper (TM) and Landsat Multispectral Scanner (MSS), ASTER, Advanced Very High Resolution Radiometer (AVHRR) from National Oceanic and Atmospheric Administration (NOAA) and Satellite Pour l' Observation de la Terre (SPOT) imagery. Soil properties, availability of collateral GIS data and scale at which the map is produced will determine the type of imagery to be used. Image resolution affects the scale of the map output. Using satellite imagery and other forms of GIS data is important in digital soil mapping as these types of data enhance the establishment of relationships between soil properties and spectral reflectance characteristics.

The increasing availability of state-of-the-art hardware and software that can be used in digital soil mapping has not done much to overcome limitation associated with the conversion of hard copy maps to digital format (Tomlinson and Boyle, 2001). Conventional soil mapping procedures have always required simultaneous verification of available information through field measurements and laboratory experiments. These are used to characterise soil samples. In more recent times, it has become increasingly possible to fast track the compilation of soil maps by tapping on remote sensing technology.

1.2 Problem statement

There is an incomplete coverage of soil maps by appropriate scale soil maps in South Africa. According to the Agriculture Research Council website, there are only 1:250 000 coverage of soil map in South Africa (http://www.arc.agric.za/arc-iscw/Product% 20Catalogue% 20 Library/Land%20Type%20Maps%20and%20Memoirs.pdf). Though soil maps are generally available for most parts of South Africa, some of these maps do not provide appropriately scaled information. This limitation is aggravated by the high costs of soil surveys and laboratory soil sample analysis. Though laboratory analysis provides indispensable information for soil mapping, remotely sensed data can be effectively used in lieu of conventional procedures that depend on the time-consuming and expensive field collection and analysis of soil samples.

1.3 Significance of the problem

There is a perceived need as well as rise for spatial soil information by multiple countries as well as provinces (Thompson et al, 2012). This information is needed to address resource issues that are needed to be solved. Local and global issues need to be solved by the availability of proper information on soils. Policy makers as well as environmental scientist need this information to assist them in giving proper decision on environmental issues. Failure to have properly managed spatial soil information may be disastrous as decisions may be passed from wrong information that has been provided from a given soil information database if the information it contains is not sufficient.

There are numerous environmental and socio-economic models that require the use of soil parameters to give a desired outcome such as estimating the changes in our future life conditions (Dobos et al, 2000). However, soil information has some issues that need to be solved before the information can be of use in any organisation. Such issues include:

i. Fixing the scale at which the soil information is viewed at,

ii. Giving proper names to the different soil types and properties being mapped and

iii. Improving on the quality of the soil data being mapped.

Most soil maps have been produced using field methods. This is where soil samples were collected from the field and studied in a laboratory. This process was slow and thus using the GIS and remote sensing it is envisaged that the process will be faster.

1.4 Justification of the problem

It is hoped that the methodology used in this project will provide a workaround strategy to increase the availability of soil maps in South Africa by offering affordable and user friendly procedures to fill gaps in spatial coverage. The methodology is versatile and robust because apart from saving time and reducing the prohibitively exorbitant costs associated with conventional mapping procedures, it is adaptable and user friendly and can be applied to maps at different spatial scales. These observations justify the need to make the proposed methodology more sharable by demonstrating its utility through a case study in which GIS and Remote Sensing techniques/data are synergistically used to compile soil maps that can be used to patch in gaps in different soil-map coverage.

Soil information is important for many regional land analysis methods where this information will be needed to be able to deal with challenges such as land degradation and productivity. This will be done by showing the land use management within a given soil type. It is known that traditional soil surveys do not provide quantitative data at detailed scale level and thus digital soil mapping should be able to rectify this by offering quantitative soil information at varying scales that have detailed soil information.

From the above statements, it is clear that unless there are digital soil maps that are produced with great care, there is a possibility of producing misleading maps. In this study the principles in GIS and remote sensing are used to produce a map of soil type or soil properties. The knowledge obtained from this study will thus aid in using this technology more efficiently so as to get the desired soil maps quicker than it would be.

1.5 Objectives of the study

1.5.1 Broad Based objectives

The broad based objective of this study is to investigate if GIS and Remote Sensing can be potential tool to support Digital Soil Mapping techniques.

1.5.2 Specific objectives

The objectives for this research are to:

a) Provide a cost-effective, user-friendly and adaptable methodology that will facilitate the rapid compilation of appropriately scaled soil maps from conjunctive use of GIS and Remote Sensing techniques/data.
b) Demonstrate the utility of the proposed methodology through a case study initiative in which the derived maps are used to seamlessly patch-up gaps in soil maps
c) Make recommendations for the way forward in order to facilitate adoption of the proposed gap-filling strategies by land-use planners and other stakeholders that routinely use soil maps in different ways and for multiple purposes.

1.6 Research Hypothesis

1.6.1 General Hypothesis

There is missing soil map information in the soil map of South Africa. This has led to lack of proper decision making processes.

1.6.2 Specific Hypothesis

Emerging from the above general hypothesis, the missing soil information on the property and types of soils have to some extent led to poor decision making processes for different organisation that use soil information.

Before a clearer appreciation of the major problems as outlined in the preceding sections can be grasped, it is essential to contextualise the problem by providing an outline of the biophysical setting of the study area. Chapter 3 therefore, provides some informative coverage of the physical characterisation of Tyume Valley.

To fill on these gaps of missing information there will be need to come up with methods that can be used to assist in adding soil information data on the gaps.

CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

This chapter provides a comprehensive overview of the literature on soil mapping with emphasis being placed on the general features of a) traditional and modern/digital soil mapping techniques and b) the specific features of the latter/modern/digital with particular reference to soil mapping in the Eastern Cape Province of South Africa.

2.2 Soil mapping Techniques

Soil mapping techniques can be subdivided into two broad categories. These comprise traditional (also known as conventional) soil mapping techniques and the more recent suit of techniques collectively referred to as modern soil mapping techniques. Soil mapping is often used in a manner that embraces digital soil mapping techniques because of the increased use of the latter in more recent times.

2.2.1 Traditional Soil mapping

Traditional soil mapping involves studying the soil profile only to come up with the desired soil maps for various users. The users vary depending on the purpose for which they want to use the map and its production scale. This type of soil mapping can also be described as knowledge-driven and data-driven models (Rossiter, 2005). The knowledge-driven model uses surveyors' knowledge of why each soil type is where it is while the data-driven model involves fieldwork and laboratory analysis.

When map compilation is done in a digital environment, the following steps are often involved:

i. Defining attributes of interest along with desired resolution and block size,
ii. Assembling attribute data related,

iii. Spatial analysis of existing data in accordance with the resolution and block size,
iv. Analysing data to determine field sampling plan and field compilation of geo-located soil samples,
v. Fitting quantitative relationships in cognisance of spatial structure and
vi. Compilation of predictive soil maps meet specific user requirements.

The fourth stage of analysis which field sampling and laboratory analysis, is often time consuming. The entire method may not be very useful since most soils do not always require the availability of field samples to verify the type of soil being mapped (Rossiter, 2005).

2.2.2 Remote Sensing and GIS soil mapping techniques

Soil maps are vital sources of information for many environmental and agro-economic analysis related fields (Henverlink, 2006). Most information on soils includes topography, geology and land use. Land use mapping substantially depends on the availability of satellite imagery which provides vital information on current and historic land management activities. Studies that can be done at the digital mapping level can be designed to:

i. Explore digital soil mapping techniques and to compare their advantages /disadvantages with those of traditional soil mapping techniques,

ii. Develop geostatistical methods that map a selected soil type and/ or property from auxiliary soil information or point data, and

iii. Applying modified digital soil mapping techniques to studies that involve the collection of validation data for soil classification accuracy assessment.

Optical remote sensing measurements record the radiation emitted from the soil surface as there is little penetration of electromagnetic radiation through the soil body (Matternich et al, 2003). Soil reflectance signals from the inherent spectral behaviour of the heterogeneous combination of the biochemical constituents, geometrical optical scattering and moisture conditions of the surface result from the presence or absence, as well as the position of certain absorption features of its constituents.

Matternich et al, 2003 describes the composition of the soil as being not straightforward to evaluate, as soil is made up of both inorganic and organic constituents. This therefore may mean that some constituents of the soil may not be detected by different sensors from satellites that are used in the remote sensing technique of mapping soils or it may also mean that their spectral reflectance which these sensors receive may not be adequate in the soil mapping process. To quantify soil reflectance and determine the difference between soil reflectance spectra, early studies were done by Condit in 1970, Huete and Escadafal in 1991 and Stoner in 1981. These four researchers found that:

i. Under laboratory conditions there are three main types of soil curves in the range of 0.32 to 1µm,

ii. The five distinct soil reflectance curves are based on curve shapes, the presence or absence of absorption bands, the predominance of soil organic matter and iron oxide composition in the range of 0.50 to 2.32µm,

iii. The four spectral curves that were identified using spectral decomposition and mixture modelling technique in the range of 0.40 to 0.90µm represent soil brightness, red iron oxides, and organic carbon and reduced iron oxide (goethite) content.

The early researchers and soil scientists also found out that there was a good correlation between soil reflectance and soil properties such as organic matter, soil moisture, particle distribution, iron oxide content, colour, soil mineralogy, salts and parent material which they reported on.

The production of digital soil maps has been made possible by the advent of GIS, GPS and remote sensing technologies (Santhosh et al, 2011). These technologies have made it easier to integrate information from different sources and stimulated the development of numerous studies and projects. The scarcity of spatial data on soil has activated the development of digital modelling techniques that spatialise soil classes, types and properties. The main challenge confronting digital soil mapping is to make the process less time consuming than traditional method and shortage of GIS and remote sensing. These limitations have been aggravated by the general absence of techniques that provide dependable data on the exact nutrient compositions (range of nutrients and quantities) of different soils.

DEMs are of great importance in digital soil mapping because they can be manipulated to produce many kinds of data that can assist soil surveyors in the mapping and quantitative description of landform and soil variables (Aksoy et al, 2006). Information from DEMs can yield slopes, aspect and elevation maps that can be used with satellite imagery to enhance the soil mapping capabilities. A DEM can be used to predict soil types if information on surface and subsurface geology is available while slope class maps derived from DEMs can similarly be used in soil surveying and land use planning.

Remote sensing is now in a strong position to provide meaningful spatial data to soil science because of the advances that have taken place in soil science-related research (Anderson and Croft, 2009). Recent advances in the assessment of soil structure have emerged from the use of optical remotely sensed imagery from satellite platforms such as Landsat TM, MSS and Landsat Enhanced Thematic Mapper plus (ETM+) , SPOT and NOAA. Soil moisture studies have also benefited from the use of microwave remote sensed imagery from platforms such as RadarSAT due to the ability of radar waves to penetrate the soil surface.

GIS and remote sensing technologies involve mapping and characterisation of soils at different levels (Manchanda et al., 2002). The spatial dimension of soil and its components is used to derive information from remotely sensed data. From 1972 satellite image data in digital and analogue formats was used for making small scale resource maps that show oil sub groups and their associations. From the mid-1980s onwards, medium resolution Landsat TM and Indian Remote Sensing (IRS) satellite LISS II data became available. This availability enabled soil scientists to map soils at the 1:50 000 scale for district-level planning. At this scale soils can be delineated as associations of soils i.e. family level characterisation. The availability of SPOT and IRS-Pan data offered stereo capabilities that have improved soil mapping efforts. ASTER satellite imagery has also enhanced the mapping of individual minerals found in specific soil groupings because of its superior spectral resolution compared to with Landsat imagery.

The spectral behaviour of soils is determined by a number of properties that affect the spectral response curve. These properties include colour, texture, structure, mineralogy, organic matter content, concentration of free carbonates, salinity, moisture and the oxides/hydroxides of iron and manganese. Chemical composition influences spectral signatures by mediating the absorption processes. Most absorption occurs in the near infra-red and mid infra-red regions of the electromagnetic spectrum.

Molecular rotation and transition occurring in the soil pores where gas and water molecules reside and may also induce high absorption in the mid infrared regions of the spectrum. Soil water exhibits absorption peaks around 1450 nm, 1880nm and 266nm. Transition elements like iron, manganese and titanium decrease reflectance at lower wavelengths. Organic matter absorbs strongly in the short wave lengths and infrared regions because of the presence of various functional groups and conjugate bonds from different particles that make up the organic matter. Larger grain sizes exhibit wavelengths less than 1600nm and smaller grains exhibit fewer or less developed features in this region and well developed features at wavelengths greater than 1600nm.

A good soil dataset is a key factor to building an accurate Digital Soil Mapping function and to evaluate the quality of its outputs (Lagacherie et al., 2006). The collection of soil data has been and still remains a limiting factor that can break the DSM process severely. To overcome this problem, three ways can be explored:

i. Develop optimal sampling methods,

ii. Use as much as possible legacy soil data,

iii. Develop new soil sensors for accurate and cost-effective estimation of soil profiles.

Developing optimal sampling methods make use of methods aimed at optimising the coverage of geographical space, the coverage of soil covariate space or both. These methods are derived from well-known statistical and geostatistical techniques and they do not take into account more sophisticated sampling criteria that is often considered in classical soil survey. According Lagacherie (2006) the use of legacy soil data represents a large reservoir that can be used in many countries, thus, it can be used as input to the DSM procedure or in valuation tests. Most of this legacy data is in the form of existing soil maps or soil profiles. These two need to be first distinguished before they can be used as legacy data. However, the use of legacy soil data is made impossible in many countries by the unavailability of numeric data, lack of harmonisation and imprecision of soil description, imprecise geo-referencing and the non-optimal location of soil data.

Lagacherie (2006) explains the use of soil assessment framework in DSM as being crucial in soil related decision- and policy-making. This therefore requires the products of the DSM process to be of known quality. However, defining and applying a common accuracy assessment framework is one of the greatest challenges in the digital soil mapping process. As such some points described by Lagacherie (2006) will need to be taken into consideration as per the deliberations of the soil scientist at the Montpellier workshop on DSM. These are:

i. Defining precisely the type of quality indicators that are needed. Generic indicators are from the map maker point of view and these are well known (e.g. attribute accuracy, positional uncertainty). The quality must be assessed from the user point of view.

ii. DSM's advantage over other approaches such as classical survey is that it can predict the quality of the outputs. However, it is important to note that quality predictions are based on model assumptions that may hold in reality. These quality predictions are often calculated from the same data that was used to build DSM function.

Caution has to be taken to validate like data at like scales. This means that new error matrix must be proposed to compare area soil predictions with the "kind of truth" that represents soil maps used as validation data.

Soil properties are constantly being modified by internal factors and anthropogenic impacts generating complex spatial data (Grunewald, 2009). The ability to understand and describe soil properties has undergone tremendous changes with the introduction of digital technologies. Such technologies include remote sensing and soil survey, computer processing speed, management of spatial data, quantitative method to describe soil patterns and processes and the scientific visualisation methods (Grunewald, 2009). These have provided new opportunities to predict soil properties and processes. Numerous soil properties influence the suitability of the soil as a medium for rooting (Barnes et al, 2003). Some of these properties include soil water holding capacity, water infiltration rate, texture, structure, bulk density, organic matter, pH, fertility, soil depth, landscape features (slope and aspect), presence of resistive soil layers and the distribution and quality of crop residues. These properties are complex and vary spatially and temporally within the fields. However due to the emergence of variable-rate technologies, there is need to quantify the variations is soil properties at finer spatial resolutions and more emphasis is now being put on the use of remote sensing data to quantify the differences in soil physical properties.

According to Barnes et al, (2003) the characterisation of soil properties was one of the earliest applications of remote sensing in agriculture. Most studies have quantitatively examined relationships between remote sensed data and soil properties have focused on the reflective region of the electromagnetic spectrum (0.3-2.8µm). However, some relationships have been established from data in the thermal and microwave regions of the spectrum.

A variety of remote sensing imagery has been used to map a variety of soil characteristics. These range from Landsat MSS, TM and ETM+ to ASTER imagery (Abdi et al, 2012). In order to provide a better description of soil particles satellite that has more bands in the infra-red regions of the electromagnetic spectrum will be more desirable. Having a better spectral resolution means most soil particles will be able to be recognised and differentiated from the other association of soils. Landsat and ASTER have been used in soil mapping studies. However, ASTER has been used mostly due to its better spectral resolution as compared to Landsat group of satellite sensors. This is because ASTER has 14 bands while Landsat TM has 7 bands.

The availability and accessibility of 14-band multi-spectral data from ASTER has created new opportunities for geologists in mapping regolith, potentially mineralised rocks and alteration in mineral assemblages (Gozzard, 2006). This is due to the increased spectral resolution of the ASTER data in the geologically important short wave infrared (SWIR) and the thermal infrared (TIR) bands of the electromagnetic spectrum. ASTER data have the potential to provide detailed information on the mineralogy, chemistry and morphology of the earth's surface (Gozzard, 2006). The processing of the multi-spectral data to derive surface compositional information requires a chain of processes significantly different from image processing techniques of Landsat imagery. The ASTER satellite can therefore be considered as the geologic successor of Landsat TM due to its ability to provide more information on the composition of the Earth's surface at a higher spatial resolution (20m) than Landsat TM's 30m resolution. The ASTER instrument collects data in 14 bands by using one stereo backward-looking band. The instrument consists of 3 separate subsystems with each having its own telescope. These instruments capture up-whaling radiation in the visible and infrared (VNIR), short wave infrared (SWIR) and TIR. The composite ASTER instrument has a mixture of resolutions ranging from 15m in the visible part of the spectrum to 30m in the SWIR and 90m in the TIR regions of the spectrum. Like SPOT it has a 60km*60km swath width but it is on the same orbit as Landsat TM with a half hour delay. The instrument is able to map a range of minerals due to its higher spectra, and radiometric resolutions especially in the SWIR region of the spectrum.

Landsat's remotely sensed spectral data represent useful environmental covariates for digitally mapping soil distribution on the landscape (Boettinger et al, 2008). Unique soils are the products of unique sets of soil-forming factors. Landsat spectral data can represent environmental covariates for vegetation in the form of NDVI, fractional vegetation cover and parent material and /or soil (Hartemink et al., 2008).

The launch of Landsat1 in 1972 saw the use of digital image data becoming widely available and being used for land remote sensing applications even though at that time the theory and practice of digital image processing was at its infancy. The cost of digital computers was very high and their computational capabilities were very low when compared with the modern standards. Recently, access to low cost, efficient computer hardware and software is common and the sources of digital images are varied ranging from commercial and governmental earth resource satellites systems to the meteorological satellites, airborne scanner data, to digital camera data which are used to image data generated by photogrammetric scanners and other high resolution digitising systems.

Due to the advent of the internet in the 21st century, satellite imagery is now available for download on the web. These webpages provide the concerned users with options to view the images before downloading so that such things as noise, radiometry and geometry can be checked at hand before buying or downloading. Some of these images can be downloaded with some of radiometry and geometry having been corrected such that the processing time of this satellite imagery has been reduced for the different applications that researchers and users want to perform. This has also been made so that even the clients that have little or no knowledge on how satellite imagery are corrected for radiometry and geometry are able to use the data without having to apply the different equations or processes that are applied before ordering the various scene. However, raw satellite data can still be ordered but one has to be an expert on how to apply the above correction before the data can be used for the different applications.

Band ratio is a technique used to enhance contrast between high features of interest from the features with less interest (Ngcofe and Billay, 2008). Band ratios are effective in utilising the full potential of spectral formation. To generate a band ratio, the high digital reflectance values of a specific material is divided by the corresponding digital reflectance value with the lowest reflectance. This elevates the digital reflectance values of a specific material compared to its surroundings. This should produce a range of new values of pixels from zero to infinity.

Due to the limited range in each band and the strong correlation between bands, band ratios seldom fall outside the range 0.0-4.0. Displaying an image of the ratio requires rescaling the floating point values to the 0-255 range of integers, which is an 8-bit signed integer. Individual bands of remotely sensed images show the effect of varying illumination caused by topography. The sun illuminates a flat surface homogeneously. However, where there is any relief, the lighting of slopes away from the sun receives less or little radiation. As a result, a surface with uniform reflectance properties will show varying DNs across the scene. This can lead to added confusion especially in a surface that has different surface types.

Theoretically, any surface should receive the same properties of energy in all waveband irrespective of orientation to the sun (Drury, 2001). It should also reflect energy in the proportions controlled by its properties. The ratio between the two bands therefore should be the same for the pixels representing the same scene irrespective of the slope orientation. For this to be true the surface must reflect radiations equally in all directions. This is never possible in the natural conditions because reflections reach a maximum in a direction controlled by the structure of the surface and the angle of illumination. This is as shown in the figure below (Fig 2.1)

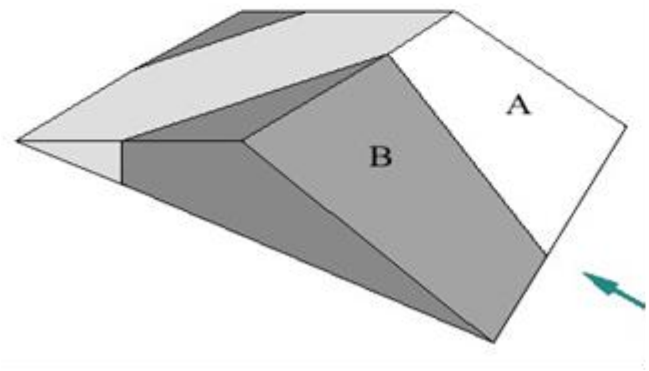


Fig 2.1: Effect of topography on band ratios. (The direction of the sun is shown by the green arrow).

In the diagram above the part that receives more sunshine and thus will reflect more radiation to the sensor is B. A receives little of the radiation from the sun and thus it will reflect little energy to the sensor. If a ratio is calculated for the red and near infrared region of the electromagnetic spectrum, for both the sun lit slope B and the shadowed slope we expect to have the same ratio for the two slopes. An example is as calculated on table 2.1 below.

Table 2.1: The ratios of the sunlit and shadowed side on the image in Fig 2.1

Unit	Red	NIR	R/NIR
A	45	60	0.75
B	20	40	0.50

Sunlight

Unit	Red	NIR	R/NIR
A	60	80	0.75
B	30	60	0.50

Dark side

The most important property of a ratio image is that it accentuates features in the spectral signature curve of a particular surface material. When combined in pairs as ratios, they express well aspects of a material’s spectral signature. Ratios between bands describe the spectral colour of an object although colour perceived by humans corresponds to the visible range.

Advantage of band rationing are that ratios do not reduce the effects of the slope and shadow to a marked degree. Atmospheric correction before ratio generation reduces the effect considerably. Band ratios enhance spectral difference between surface materials that are difficult to detect in raw RGB image bands. The information obtained from band ratios cannot be obtained from the individual bands. The disadvantages are that it's "ironing out" of topography effects and the suppression of differences in albedo. Rationing hides important information. Various classification and analysis methods, like optimum index factor, principal component analysis, supervised and unsupervised classification, can be used to recognise meaningful soil landscape patterns.

Training sites can be selected or the existing sites can be used to check the accuracy of the various classifications used. The use of Landsat scenes is because of their spatially explicit, physical representations of environmental covariates on the land surface. The 30m spatial resolution and fairly coarse spectral resolution may limit some applications. However, the wide availability and low expense should facilitate the utility of Landsat spectral data in digital soil mapping.

Landsat spectral bands, particularly in the short wave infrared (SWIR) region, can be used to represent the environmental covariates of the parent material and/or soil. Different mineral assemblages will have different spectral reflectance which may be separable by analysing bands 1-5 and 7. Landsat images can be visually interpreted only 3-bands at time, assigned to the red, green and blue guns. The 3-band combination has the maximum covariance and minimum duplication within the scene can be selected by calculating the optimum index factor (OIF). By using the OIF to select Landsat 7 ETM+ band combination; band 1, 5, 7 can be used to visually analyse areas with gypsum soils while band combination 4, 5, 7 can be used to visually analyse nitric soils. Soil enhancement ratios of Landsat spectral band ratios 3/2, 3/7, 5/7 have been interpreted to accentuate carbonate radicals, ferrous iron and hydroxyl radicals in exposed soils or geological materials (Hartemink, 2008). Normalised difference ratios of Landsat spectral bands, similar in form to NDVI, may be developed to target specific signatures of soils and/or parent material (Hartemink, 2008). Gypsum soils can be mapped by focusing on the spatial response of gypsum which can be analysed by using the high reflectance of band 5 and the low reflectance band 7 in the ratio [(5-7)/ (5+7)]. Band 5 and band 2 can be diagnostic for calcareous soils or rocks [(5-2)/ (5+2)] (Zeilhofer, 2006; Hartemink et al., 2008). Principal Component Analysis (PCA) can be valuable to enhance Landsat spectral data. Raw data are transformed into new PCA images that can compress vast amount of information contained in a data scene into few principal components. The transformation can make the image easier to interpret visually for distinguishing parent material as well as vegetation.

Principal component analysis is a technique which allows the production of images where the correlation between the images is zero. For *n*-dimensional dataset, *n* principal components can be produced. If one considers a system with six bands and assuming all bands carry equal amounts of information, even though it is never the case, then a standard false colour composite formed from the three input bands will display 50% of the information in the scene. If the PCA technique is applied to the images it is found that the first three principal components will have 98% variance of the total scene information from the six bands. A false colour composite formed by projecting Principal component 1 (PC1) on the red gun, PC2 on the green gun and PC3 on the blue gun, will contain a variance of the six input bands. Even though the highest principal component images (e.g. PC6) contain little variance and are usually noisy they should be examined because the information they contain may not well be represented at lower principal components.

A principal component can easily be visualised in two-dimensions. The DN plot for two bands can simply be represented in a feature-space by an ellipse. If the bands are highly related the ellipse will be very eccentric whereas, for less correlated bands the ellipse for bands 1 and 2 are x and y. It is however possible to create new axis principal components by means of rotation and translation. The long axis of the ellipse is the first principal component (PC1) and the variance (z) is along the axis along either if the two input bands. The second component is at right angles to the PC1.

The principal components transform the input digital numbers in the original bands in terms of the new principal components axes. The visualisation of principal components is simple, however to create the axis it is necessary to calculate the length of the principal components and their direction. These are computed by determining the eigenvalues (length) and eigenvectors (direction) from the covariance matrix. A number of minerals found in space can be mapped by the ASTER instrument making it easy to discriminate the various constituents of the soil material. In the SWIR region it is able to discriminate alunite, pyrophylite, kaolinite, and illite-muscovite-serite and MgOH-carbonate minerals. In the TIR region the instrument can discriminate feldspar, quartz, carbonate, amphibole and clay. The discrimination of these minerals requires complex processing to remove temperature and atmospheric effect from the data.

SWIR consists of 6 bands. Band 4 has a similar wavelength to Landsat TM band 5 and is located where most minerals have maximum reflectivity. Regions 5-9 cover a region of –OH bearing minerals and carbonate minerals that have absorption characteristics. Bands 5-8 approximately cover the wavelength limits of Landsat TM band 7.TIR bands measure radiance in the 8.1-11.7μm wavelength region and are the only available multi-spectral thermal data from space-borne systems like ASTER. The 90m resolution band is useful in identifying surface silification.

Spatial variations of soils are supposed to have an important impact on ecological process and vegetation distribution in any given area (Zeilhofer, 2006). Detailed map products with explicit statistical or rule-based models should be elaborated as a basis for the development of strategies for habitat preservation and sustainable land use. Remote sensing is the key technology for mapping soil classes or properties particularly in areas of difficult access and poor on-site information for prediction. In case where the soil surface is permanently and densely covered by vegetation or on a hilly landscape, no correlation can be made between backscatter and soil types and properties. This therefore means that there has to be other means of getting soil data in vegetation covered surfaces and on hilly landscapes.

There is need for quantitative soil mapping information for environmental monitoring and modelling (Minasny, 2008). The digital soil mapping process responds to this by producing digitally based variables. The Soil, Climate, Organisms, Parent Material, Age and Spatial position (SCORPAN) factors are derived from various sources like DEMs, satellite imagery and existing soil maps (Lagacherie, 2006). These are quantified and the data captured in digital format in the form of a database where most of the information consists of statistically optimal predictions.

Though soil scientists generate large quantities of soil data, the challenges associated with the management of these data have been alleviated by the development of methods and instruments that expedite data acquisition and facilitate, storage, retrieval, analysis, interpretation, manipulation, modelling, simulation, accessibility and distribution (Summer, 2000). With the rapid development and availability of powerful data acquisition facilities and the rapidly emerging technology and use of GIS and GPS, recurrent challenges are confronting soil scientists. These challenges relate to integration of new technologies into their efforts to provide objective decision-support systems for the soil management and monitoring so that they can be used by most soil scientists globally.

Institutions and organisations involved in applied research at a global scale have a definite need for soil information. These institutions and organisations include those involved in climate change, the greenhouse effect and other studies in the agriculture fields. This is because this data is of importance as input models that simulate crop growth and calculate anticipated yields and water balance or assess the environmental impact of land use practices. The different types of models and their soil data requirements can be summarised in table 2.2 below.

Table 2.2: Types of models and their soil parameter requirements

Model example	Key soil parameters used
Bio-geochemical	C, N, P, water retention, depth, clay, sand and stone content
Agriculture and Plant resource	
Agro-ecological zoning	Soil type, texture, slope, soil phase
Sediment yield	Texture, water retention, and transmission, depth, carbon, erodibility
Water balance	Water retention and transmission
Trace gas	C,N, texture, pH and redox potential
Landform history	Soil type, isotope
Carbon dioxide, methane,	C, bulk density, depth, soil moisture

nitrogen oxide inventories	
Climate	Water and heat capacity, surface reflectance
Environmental impact	Soil fertility, soil erodibility

In soil mapping, archived data is often sufficient and available at low cost. Integration of remote sensing within a GIS database can even decrease the cost, reduce the time and increase the information gathered for the soil survey to take place. Also research into digital soil mapping has indicated that methodologies such as those from pedometric techniques can be extended to a field setting where they could help enhance the quality and scientific foundation of soil surveys as well as time and money.

Reflectance and emission data can be analysed to extract information about the earth and its resources (Boettinger et al, 2008). This is because the physical and chemical properties of different surfaces vary across the electromagnetic spectrum. Conceptual models of soil information have been used to predict the patterns of soil map units in traditional soil surveys which were based on the interpretation of aerial photographs with field verification of soils and associated landscape features. However, with the increasing availability of spatial explicit digital data such as remotely sensed spectral data and digital elevation models, and the hardware and software for processing and analysing vast amount of spatial data, prediction on soil distribution on the landscape can be done quantitatively. McBratney et al., (2003) and Boettinger et al., (2008) proposed that to represent soil and the related environmental factors in a spatial extent and express these relationships, the SCORPAN model will have to apply and McBratney, 2003 says:

> *"At a point in space and time, soil (as either soil class,* ***Sc*** *or soil attribute,* ***Sa****) is an empirical quantitative function of the soil (****s****, as a class or as a directly or remotely*

*sensed property), climate****(c)****, organism* ***(o)****, relief****(r)****, parent material* ***(p)****, age* ***(a)*** *and spatial position* ***(n)****.”*

The increase in computation and information technology has resulted in vast amounts of data in the field of soil science where a vast creation of regional, national and world databases has not been left out in this evolution (McBratney et al., 2003). Understanding these large amounts of data, statistical tool have been created to analyse the data so that we get to understand the data better. These new tools in the field of statistics have spawned new areas such as data mining and machine learning. The increasing power of tools such as GIS and GPS, remote and proximal sensors and data sources such as those provided by Digital Elevation Models (DEMs) are suggesting new ways of gathering soil information. The availability of the new technologies has led to organisations using these new technologies to substitute for the old engine of soil survey where soil resource assessment using GIS is done with little costs. Production of digital maps is moving from research phase to production of maps for regions and catchments as well as whole countries. There are three resolutions that have been suggested for mapping soils at local, regional and national level. These are <20m, 20m-2km and >2km. Table 2.3 shows the scales that are used to choose the proper resolution that one would have to choose for the Digital Soil mapping procedures. These are based on the descriptions from USDA surveys (McBratney et al., 2003):

Table 2.3: Scales used to choose the proper resolution in DSM procedures.

Name	**USDA Order**	**Pixel Size**	**Cartographic Scale**	**Resolution**	**Nominal Spatial Res.**	**Extent**
D1	0	<5 x 5m	>1:5 000	<25x25m	<10x10m	<50x50km
D2	1,2	5x5-20x 20m	1:5000- 1:20 000	25x25-100x100m	10x10-40x40m	500x500-200x200km

D3	3,4	20 x 20-200 x200m	1:20 000-1:200 000	100x100m-1x1km	40x40-400x400m	2x2-2000x2000km
D4	5	200x200m-2x2km	1:200k-1:2m	1x1-10x10km	400x400m-4x4km	20x20-20000x20000km
D5	5	>2x2km	>1:2m	>10x10km	>4x4km	>200x200km

An assessment of the properties of soils and their response to management is required in agriculture and forestry for informed decision making in rural and urban planning, for feasibility and design studies in land development projects and many other engineering works (Dent and Young, 1981). For this objective to be achieved Allen Dent and Anthony Young (1981) suggest that there be a way to determine the pattern of the soil cover and divide the pattern to relatively homogeneous units and mapping these distribution units. This will enable the characterization of the mapped units in such a way that useful statements can be made about their land use potential and response to changes in management, thus, this process will be applied in an environment mostly dedicated to soil in an agriculture environment.

South Africa’s soil mantle is highly complex and diverse as a result of soil formation and weathering processes (de Villiers et al., 2010). As much as 81% of the land surface is characterized by eutrophic and calcareous soils often of shallow depth with 12% mesotrophic and 7% dystrophic. Over 30% comprise sandy soils, of which less than 10% are clay soils. Almost 60% of the soils have low organic matter content, conducive to low productivity and soil degradation. These soils de Villiers and his group say represent 70 different forms and thousands of ecosystems (de Villiers et al., 2010).

Eight percent of South Africa soils are arable which comprise 51.6% agricultural land which is underlain by coal deposits. Arable areas in the higher rainfall regions of South Africa are limited due to the large parts are steep underlying hills or are large mountains, or are covered by non-arable soils derived from parent materials giving unstable, highly erodible soils.

South Africa's estimate soil loss annually is 2.5 tons per hectare (de Villiers, 2010). This is mostly by erosion. This by far exceeds the estimated soil formation rate of 0.3 tons per hectare. This is in the case of 1m thick solum of tropical soil. More than half of South Africa's total surface area is under threat of desertification. Without proper soil management practices this may happen sooner than expected and thus the need for a soil management database that will help in educating the general population concerned with soil management on better soil management practices in South Africa (de Villiers et al., 2010). Arid, semi-arid and even sub-humid ecosystems are made poor by the combined effect of human activities and climatic conditions. There are many uncertainties around desertification but the country's soil and vegetation productive potential has already been greatly reduced. This must be reduced before desertification manifest in South Africa.

2.3 Advances and developments in Digital Soil Mapping

Modern Soil Information Systems make it possible not only to incorporate soil maps in digitised form but also to create new forms with the use of digital technologies at all stages of mapping (Kozlov and Konyushkova, 2009).

The International Working Group of Digital Soil Mapping holds biennial workshops to discuss advances in digital soil mapping in the world. The first global workshop was held in 2004 in Montpellier, France (Lagacherie, 2006).

At the Montpellier 2004 Soil Mapping Workshop, where the first workshop dedicated to digital soil mapping was held, different scientists from 17 countries discussed skills and tools that are expected to play a major role in the future of digital soil mapping. These skills and tools included soil surveying techniques, soil information systems, expert systems, GIS, pedometric and data mining techniques and remote sensing procedures. According to Lagacherie, 2008, the workshop recommended consideration of the following:

i. Use of a variety of environmental covariates and Digital Elevation Model (DEMs) as inputs for digital soil mapping. This conjunctive approach provided a workaround strategy worth exploring in the production of soil maps. The increased availability of multi-sensor/multi-resolution remotely sensed imagery makes the use of these data types and DEMs practically feasible. Remotely sensed data provide a valuable source of information because the conventional range of satellite imagery (Landsat, Spot ASTER and many others) has in more recent times been augmented by gamma ray spectrometry or hyper spectral images that offer enhanced soil-mapping capabilities.

ii. The environmental variables of elevation, slope and vegetation indices were to be used in the process of digital soil mapping and several pre-processing procedures conducted to produce sophisticated covariates that represent soil variations more accurately

    The most common pre-processing procedures comprise:

    - Derivation of soil covariates that represent the spatial variability of specific pedological processes,
    - Identification of soil mantle structuring elements such as landscape units and regolith catenary units and,
    - The decomposition of the initial image of a soil covariate into several spatial elements of variable resolution with multi-scaled soil landscape relations.

The theme for the workshop was: “Digital Soil Mapping: An Introductory Perspective.” The second such global workshop was held in 2006 in Rio de Janeiro, Brazil under the theme: “Digital Soil Mapping for regions and countries with sparse Soil Data Infrastructures.” The third global workshop was held at Logan State University in Utah, USA. The theme for this workshop was: “Digital Soil Mapping: Bridging research, production and environmental applications”. At the Utah workshop, the research output was aligned:

i. Exploring new sampling schemes and environmental covariates in DSM.
ii. Evaluating and using legacy data in DSM.
iii. Using integrated sensors or other new technologies for inferring soil properties or status.
iv. Innovative inference systems (new technologies for predicting soils classes and properties and estimating uncertainties)
v. Using DSM products and their uncertainties for soil assessment and environmental applications
vi. Protocol and capacity building for making DSM operational.

The fourth global workshop on DSM took place in May 2010 in Rome, Italy. It was held under the theme, “From Digital Soil Mapping to Digital Soil Assessment: Identifying key gaps from fields to continents”. Emphasis was made on the below domains of soil science:

i. From global to local DSM.
ii. Innovative Inference Systems, DSM issues and operational tools and dynamic assessment in DSM
iii. Quality Data Assessment, Modelling Uncertainties in DSM and DSA.

In scientific expeditions, issues pertaining to DSM were looked into and a new directive was achieved that the various scientists took to their respective countries to study and also guide them in the various research they are conducting. From the 2010 workshop attention is now shifting from global to local DSM where scientist will have to assess the data they have on soils to make sure that it can be used in a DSM process or application.

In South Africa, the Agriculture Research Council through its Institute of Soil, Climate and Water (ARC-ISCW) is involved in collecting soil data for the country. They have been involved in soil surveys since 1902 so as to gain knowledge on South Africa's soil mantle and to promote sustainable agricultural development. In 1971 a national systematic soil survey at 1:250 000 map scale, called the land type survey, demarcated homogeneous soil types, terrain forms and macro-climates to ensure sustainable land use and land use planning. The survey was completed in 2002 (Soil Classification Working Group, South Africa, 1991). This was following surveys in parts of the country which were formerly self-governing states. This prompted the development of a variety of soil-related structural databanks and a geographic system to provide structural framework for the acquisition, storage, retrieval, analysis and display of data within a spatial reference system. This led to the development of AGIS which ARC-ISCW maintained together with other national soil databanks including SOTER, national agricultural meteorological databank and the NOAA databank.

Based on the above review of the various works that been done by the different authors, it can be concluded that Digital Soil Mapping has a variety of techniques that can be used to achieve a desired result. The nature of the processes that the creator of DSM data proposes to use in coming up with DSM datasets will determine the results that will be produced at the end of the processing. The type of data also plays a major role in determining the type of products one would produce as well as the length of time to be taken in producing the desired results.

Advances in geomorphology and hydrology have further laid foundations for the spatial exploration of soil system dynamics within a landscape context. Information on soils is needed spatially and temporally to assist in erosion and runoff simulation models and in the agriculture engineering land management sectors.

With all these remote sensing processes mentioned in this section, it is advantageous to use remote sensing processes in the DSM process. The obvious reasons being that they will cut the time in which the results were obtained and that there will be less pollution as this will be a desktop process.

In this thesis a variety of techniques and processes will be proposed to be used in the study area. However, the reader of this work should take note that not all of the named processes were completed in time for inclusion in this thesis. This is due to other factors such as availability of the data and the length of processing of the data. The nature of the data and the processes to be undertaken will be discussed in the coming chapters.

CHAPTER 3: STUDY AREA

3.1 Introduction

This chapter describes the location of the study area. The explanation includes the types of soils that would be expected to be found on the area.

3.2 Location of the study area

The area (~1 068 531 km²) is drained by two rivers namely Tyume and Keiskamma. The extents of where the study area is situated are 26º49 E and 27º 02’E and; 32º 44’ 22S and 32º 55S. The satellite path and row are 170 and 083 respectively.

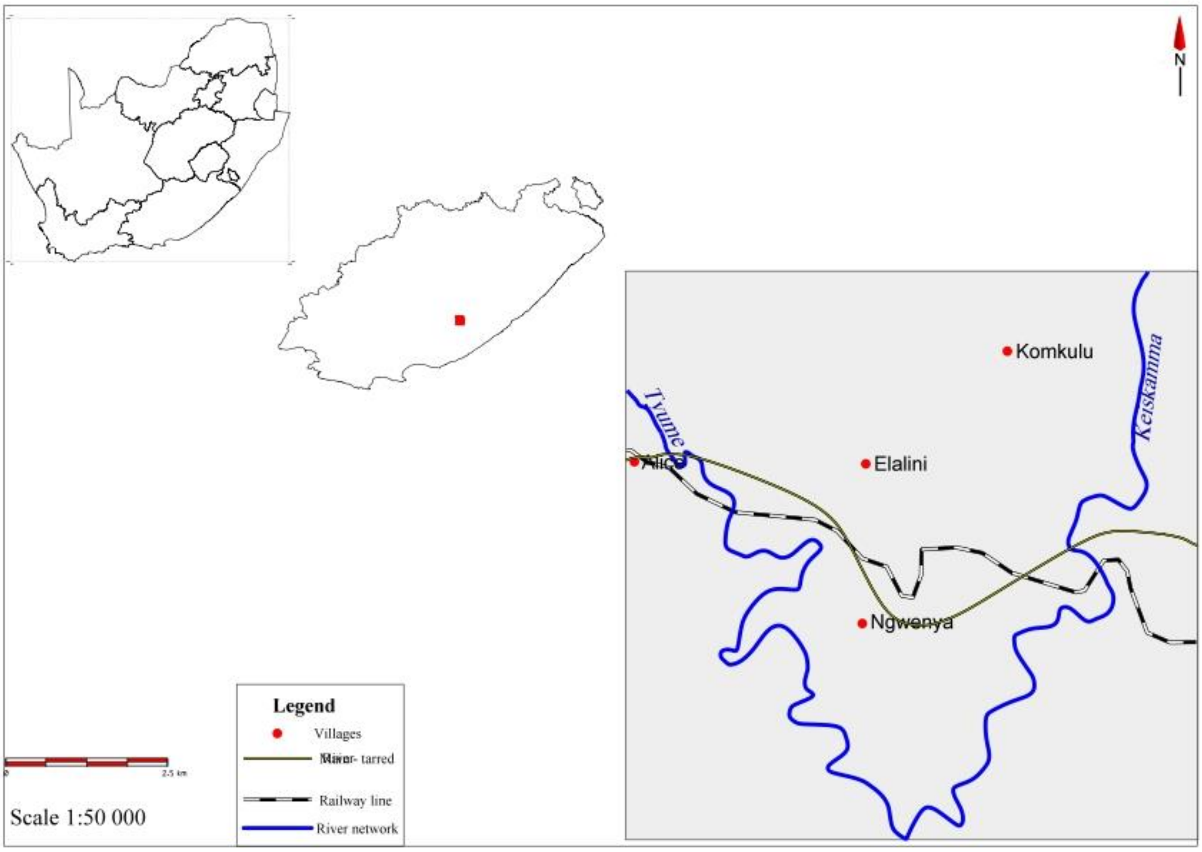


Figure 3.1: Map of study area

3.3 Description of the Study Area

Four villages are found within the study area and these are Alice, Ngwenya, Komkhulu and Elalini. Two rivers make up the study area namely Tyume and Keiskamma River.

3.3.1 Physiographic properties of the Study Area

Medium-textured shallow, young soils, generally on shale or sandstone predominate in areas around Alice town in the Eastern Cape Province (INCO-DC, 1998-99 report). This area also covers the areas intended for this study in this research. According to the South African Soil Classification System 1991, the majority of the soils are of the Glenrosa form which correspond to Dystric Cambisols and Regisols in the FAO Classification, Mayo form and Mispah form. Mayo soils can be moderately fertile if adequately deep, while the others are normally very shallow with limited water storage capacities and poor chemical fertility.

In the more densely populated areas, overgrazing is a serious problem, leading to soil degradation and high erosion hazard. However, patches of moderate to fairly deep and potentially productive soils occur in the valleys of the major river systems like the Tyume and Keiskamma. These patches are typically used for the intensive production of maize, pumpkins, vegetables and fruits (citrus) under irrigation. The soils in these areas are mainly of the Hutton, Oakleaf and Westleigh forms. Some of these alluvial soils are among the best soils in Ciskei.

Based on information from Agriculture Research Council’s Institute of Soil, Water and Climate (ARC-ISCW), about 17 land types are found in the selected study area. These include Fb816, Fb818, Ea366, Ia225, Ae380 and Bd64. These land types are comprised of a variety of soil series/land classes which are mainly composed of mudstone, shale or sandstone from the Balfour Formation with grey or red mudstone or both and/ or sandstone from the Middleton Formation of the Adelaide Subgroup from the Ecca Group. Dolerites and sills are common volcanic intrusions that are found within this study area as well.

These land classes cover different depths of the soil profiles of the sites where they were collected. However, most of these land types have their deepest land class at 1.2m deep. Some of the common land classes that are common for each land type include Mispah Ms10, Shorrocks Hu36, Jozini Oa36 and Limpopo Oa46. The details of the different land type and their associated land classes are available on the appendix section.

3.4 Developments in Digital Soil Mapping

In the Eastern Cape Province, there are digital soils maps that have been produced in the study area. The Agriculture Research Council's Institute of Soil, Climate and Water have produced some soil maps at varying scales. However, these soil maps that ARC-ISCW has are land type maps where information from the last paragraph was obtained from for the study area.

The other information that can be obtained on soils is at the Soil Science Department at University of Fort Hare. However, most of this information cannot be used in a GIS application as the coordinates of where the soil samples were collected are not available. This information is crucial so that any user of the data can be able to go to the point where the samples were collected to verify the data but if these coordinates are not available it renders the soil data unusable for this dissertation. Most information on soils for the study area will be collected from satellite imagery and processed.

CHAPTER 4: METHODOLOGY

4.1 Introduction

This chapter discusses how the data collected was used to come up with the results. It begins by discussing how the data was collected and processed to get the desired results.

4.2 Data used and how it was acquired

Studies related to the study of minerals and/or soils require satellite imagery that will be able to distinguish the various mineral assemblages that can be found in a given unit of soil. Failure to get such imagery will lead to undesirable results being obtained from the various processing techniques that will have to be applied on the data. Landsat and ASTER satellite data are one of the common data sets that have been used in these kinds of studies with the latter being the most of the two due to its better spectral resolution as compared to the former. ASTER covers a wider range of the electromagnetic spectrum when compared with Landsat which mostly covers the visible part of the spectrum. Due to the numerous bands in the infrared region of the spectrum, ASTER is able to discriminate most mineral assemblages in the soil.

In this study the use ASTER imagery was therefore the preferred choice. However, due to the unavailability of ASTER imagery, Landsat ETM+ imagery was used. The cause of unavailability of ASTER was due to an error with the Terra the instrument which carries ASTER developed by NASA (National Aeronautical Space Agency, www.nasa.gov), and also reported on their 1B datasets. These are data sets that have been corrected for errors from the sensor’s radiance values and the data has been geo-referenced and corrected radiometrically. Due to this error, the ASTER dataset was not available for download.

The details of Landsat satellite data download are given in table 4.1:

Table 4.1: Details of satellite images downloaded

Type	Path/Row	Date collected
Landsat 7 ETM+	170/083	23 September 1999
Landsat 7 ETM+	170/083	04 September 2008

In this study, satellite imagery that was downloaded from the United States Geological Society (USGS) satellite was Landsat ETM+. This data archive had radiometry and geometry corrections already applied as well as geo-referencing. The details of the data downloaded are as shown in the next page (Table 4.2).

The two satellites images downloaded were checked for their quality to check if they could be used in this study. The 4 September 2008 images had many stripes making it unsuitable for use in this project. De-striping the images was not also going to help since the images were not usable at all.

The Landsat 7 ETM+ bands that were collected have the following characteristics shown in Table 4.2.

4.4 Image Pre-processing done

The software that was used to process the satellite imager was TNTMips. The following image pre-processing techniques were applied to the satellite imagery acquired from USGS:

- Removal of the Imported contrast stretch
- Auto normalise contrast stretch
- Sub setting
- Masking
- Ground truthing

Table 4.2: Landsat 7 ETM+ bands information

Satellite Altitude		705km
Sensor		Digital 7 multispectral scanner with a panchromatic band (ETM+)
Size of Full Scene		185 * 185 km
Temporal Resolution (Repeat coverage interval)		16 days
Radiometric resolution		8 bits
Inclination		98.2º
Bands		**Pixel size**
Spatial Resolution	Band 1 (blue)	30m
	Band 2(green)	30m
	Band 3 (red)	30m
	Band 4 (near infra-red)	30m
	Band 5 (near infrared)	30m
	Band6(thermal infrared)	60m
	Band 7 (mid infra-red)	30m
	Band 8 (panchromatic)	15m

4.4.1 Sub setting

In some cases, Landsat TM scenes are much larger than a project study area. In these instances it is beneficial to reduce the size of the image file to include only the area of interest. This does not only eliminate the extraneous data in the file, but it speeds up processing due to the smaller amount of data to process. This is important when utilizing multiband data such as Landsat TM imagery. This reduction of data is known as subsetting.

This process cuts out the preferred study area from the image scene into a smaller more manageable file. In this study a subset of the study area was extracted from the original satellite imagery. This sub set was used in the processing techniques that were applied in this study.

4.4.2 Contrast Stretching

Many natural features within a given landscape have a low range of reflectance in a specific waveband (Gibson and Power, 2000). Sensors onboard remote sensing satellites such as Landsat and MSS are designed to read the reflectance of any surface that they image. An 8 bit detector can be able to record 255 grey levels where a value of 255 being the highest may represent snow as an example and a value of 0 may represent a darkest rock. It has been noted however that the average scene of reflectance Digital Number (DN) in sensor data rarely extends over the entire image. In order to view an image, it is therefore necessary to stretch the data. This is so that the range of 0 to 255 is filled by the DNs from the scene being viewed.

When the images were downloaded from the USGS website they came up with an imported contrast stretch already applied on the imagery. This contrast stretch was removed so as to be able to view the images in TnT MIPS software. Failure to remove this contrast stretch was going to make it impossible for any other form of contrast stretch to be applied on the imagery. After the removal of the IMPORTED contrast enhancement, an AUTO-NORMALIZE contrast stretch was applied on all the seven bands for the image to appear in the same way as it was downloaded and the only difference being that the lighter pixels will appear brighter and this will be the same with darker pixels in the satellite imagery.

4.4.3 Masking buildings

A building mask was created to mask all the built up areas so that the results obtained are not affected by the presence of the built up areas. A 321 natural colour composite was used. This was so that the built- up areas could be visible. The identification of the building was done using visual image interpretation techniques. These are association, detection, recognition, identification, tone, shape, texture, shadow, size and pattern.

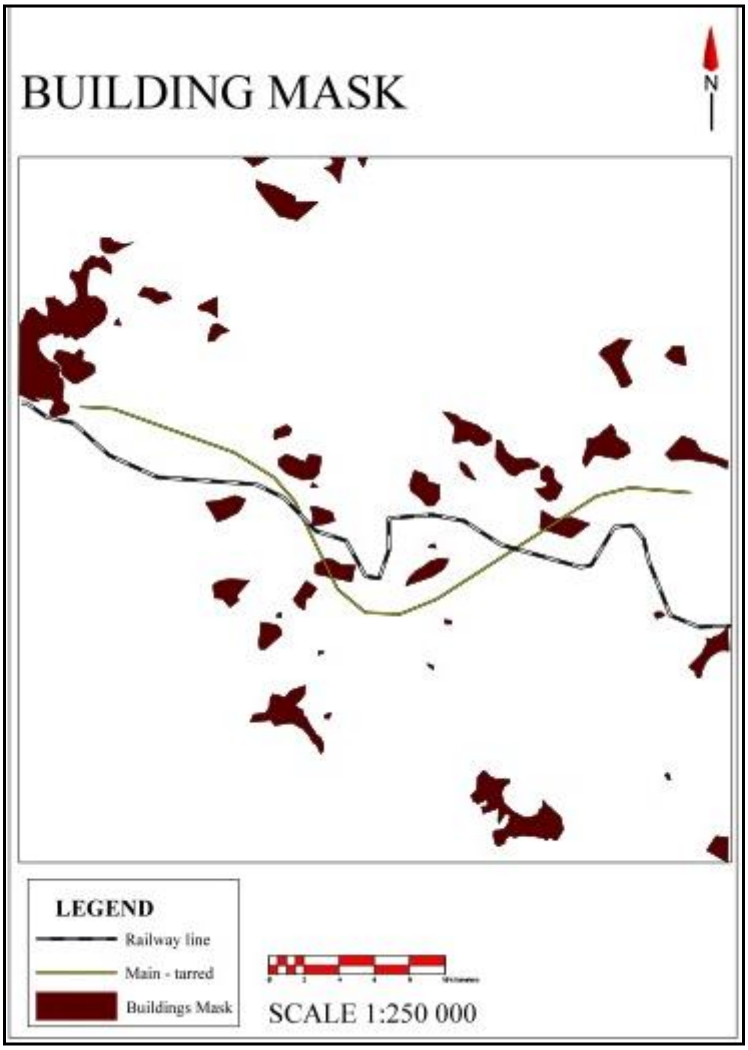


Figure 1: Building Mask

4.4.4 Ground truth

Using Land type data obtained from ARC-ISCW, about 200 points were assigned within the study areas. These points were used as a way of validating the results from the processing that was done on the satellite imagery. The points were placed within the study area based on the size of each land type.

4.5 Processing Done

The processing done for this study is a shown in the flow chart below:

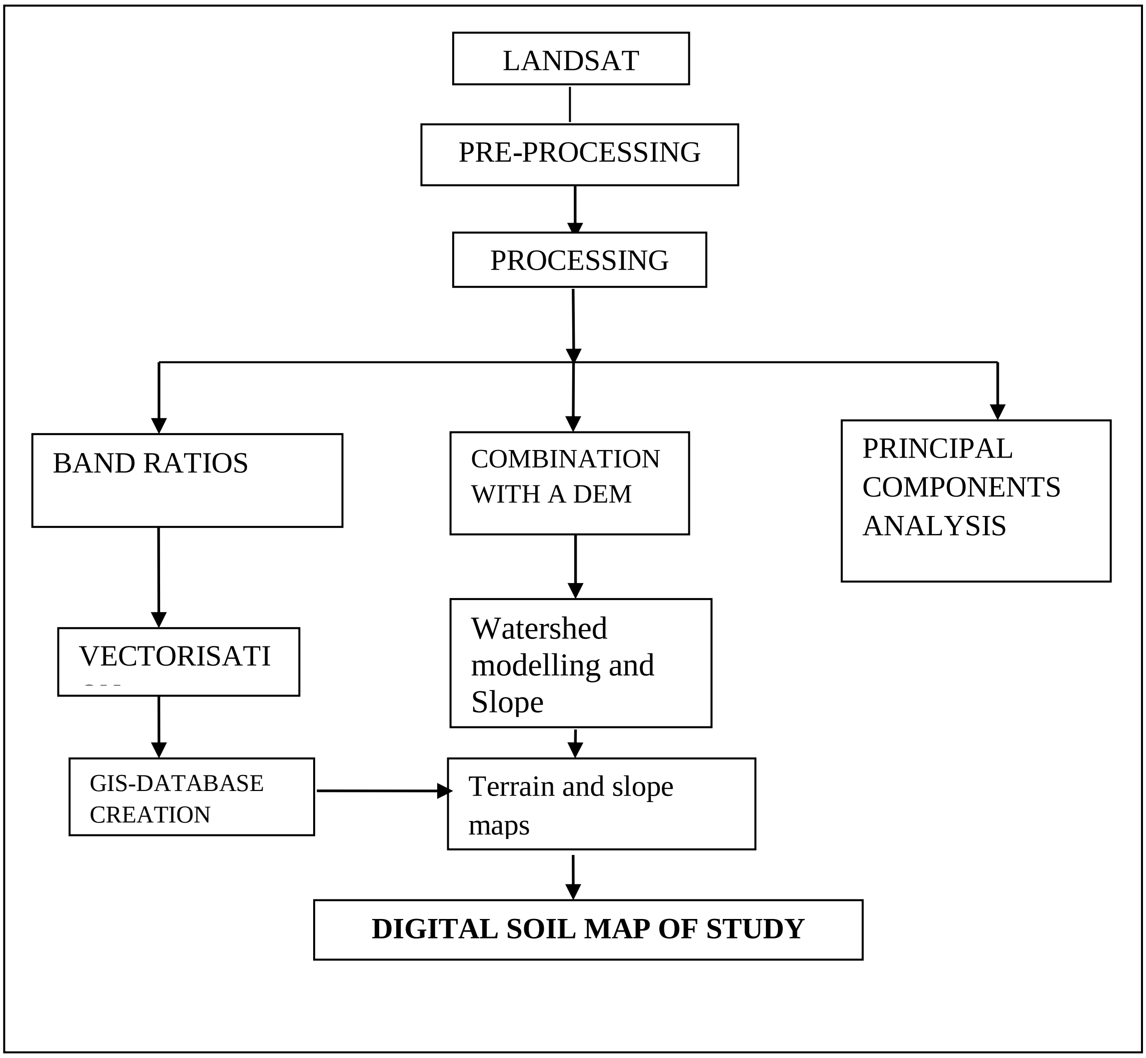


Fig 4.2: Flow chart for the processing done

Image processing which was done includes:

1. Band rationing
2. Principal components analysis
3. Masking of buildings

4.5.1 Band ratios

In this study different kinds of band ratios were applied to check the different kinds of soil minerals present in the study area. These band ratios included:

- TM 5/ TM 7 which was used to map areas where clay minerals were common
- TM 3/TM 1 was used to map all red soils which were dominated by iron (II) oxide(Fe_2O_3)- hematite
- TM 5/TM 4 was used to map areas of ferrous mineral hematite.
- TM 4/ TM 3-was used to map areas with geothite minerals
- TM 4/ TM 5- was used to map areas with hydroxyl minerals

All these ratios were processed and colour palettes were applied to each one of them showing that they were found within the study area. The results from the band ration process was in the form of raster imagery. To aid in further analysing the soil minerals mapped form the band ration process, vectorisation was applied on all the results.

4.5.2 Principal component Analysis (PCA)

In Landsat TM, which is the satellite imagery used in this study, six bands (TM 1, TM2, TM3 TM4, TM5 and TM7) were used as inputs to the PCA technique. TM band 6 due to its different spatial resolution (120 km while other TM bands are 30 km) was not used in the PCA process.

According to Rajesh (2004) a variety of PCA techniques can be used for n-bands. An example is in the identification of hydroxyl-minerals where a variant PCA on TM bands 1, 4, 5 and 7 will enhance the hydroxyl-rich minerals. The analysis of the PCAs of the four bands' eigenvectors should allow the identification of principal components that contain spectral information about specific minerals as well as the contribution of each specific original bands to the components in relation with the spectral response of the minerals of interest (Kariuki et al., 2004). The PCA technique to enhance the hydroxyl- rich minerals was undertaken together with the general PCA of the six bands.

CHAPTER 5: FINDINGS AND RESULTS

5.1 Introduction

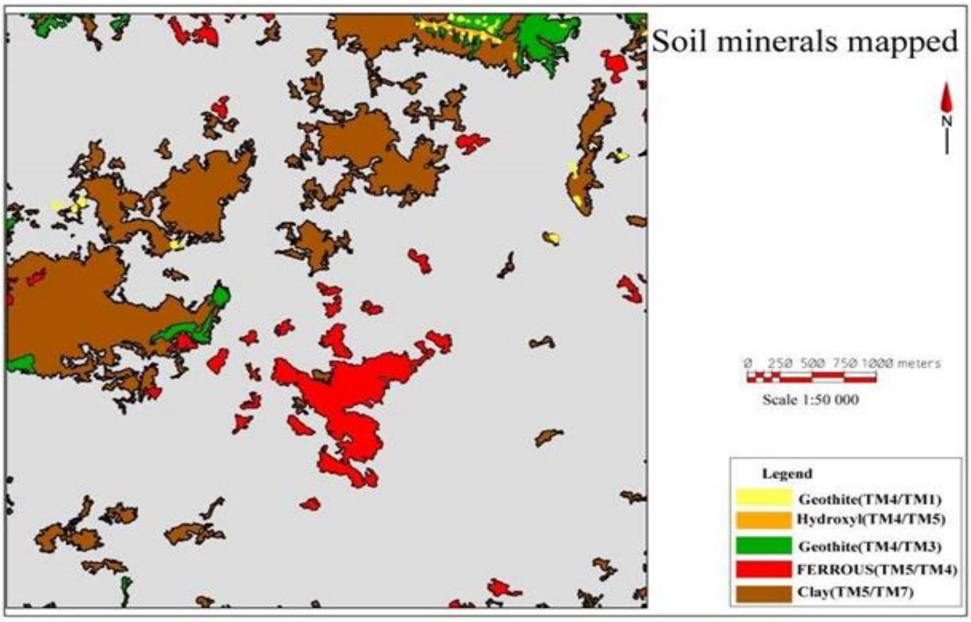
In this chapter the finding and results that were obtained from the methodology in the previous chapter are presented. The reason for using these techniques is also given in the explanation.

5.2 Results

5.2.1 Band ratios

The results from the band ratio process were presented in a map. The map showed the relative location of each of the soil mineral mapped. Fig 5.1 on shows that the location of the various minerals. These results show that the study area is predominantly composed of clay minerals which dominate the low lying areas. The minerals from iron namely goethite and ferrous were located in the mountainous areas and on the low lying areas alongside the rivers. In most areas, the minerals were not and these are shown as greys areas in the map.

Fig 5.1: Soil minerals mapped



5.2.2 Building masking

It can be said with about 80% confidence that the visual interpretation that was used in identifying the various built up areas was correct. The 321 colour composite was used in this visual interpretation. The map of the building masks overlaid with the minerals mapped is shown on Fig 5.2.

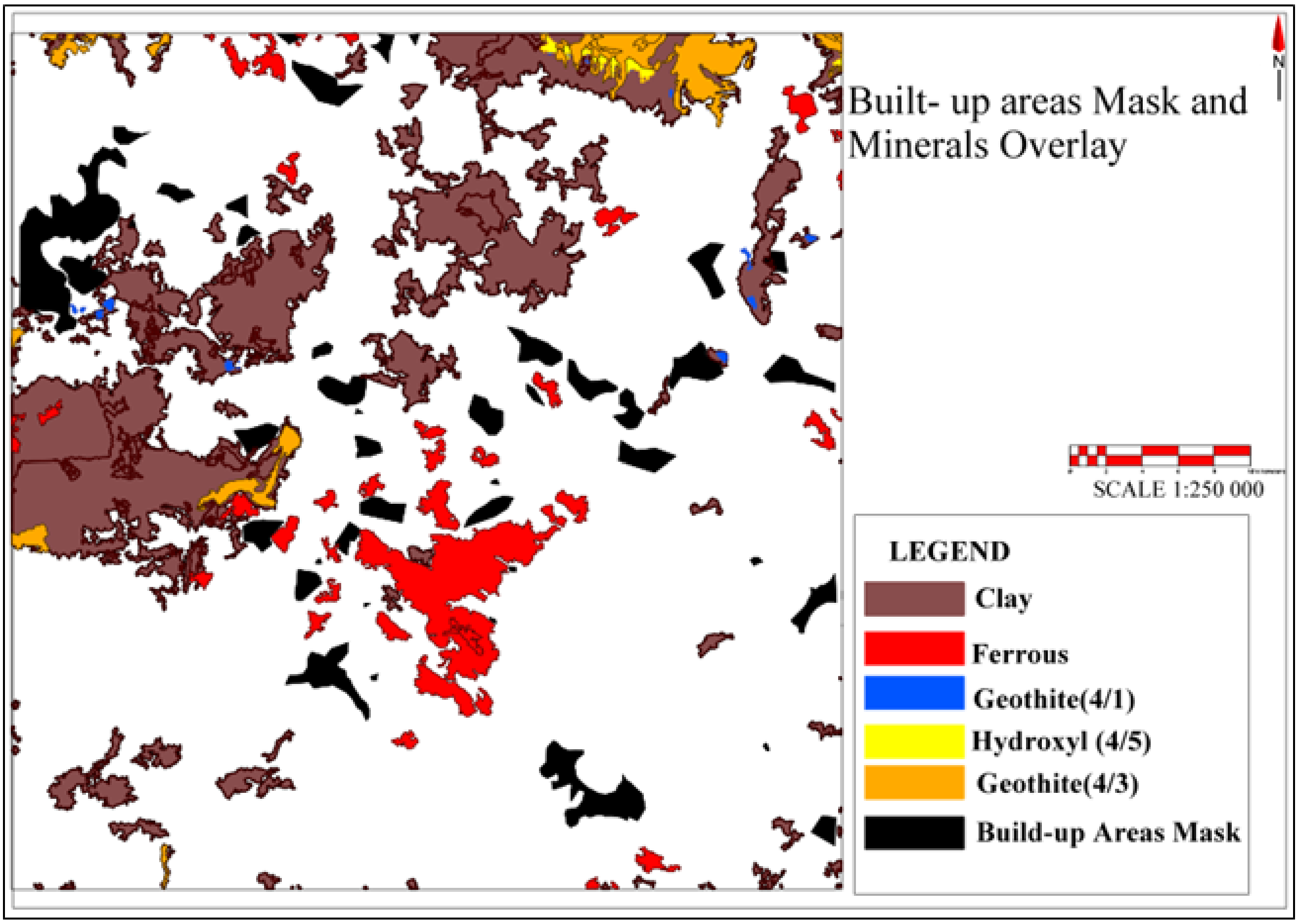


Fig 5.2: Building mask overlaid with minerals mapped

The previous section results on band ratios indicate that, the building mask does not affect the result that was produced from the band ratio process.

5.2.3 Principal Component Analysis

The Principal Component Analysis process used two types of techniques. These techniques were the Crosta PCA which used 4 band as input and the normal PCA which used 6 band as input.

The results from Crosta technique show that:

- Component 1 was able to show the features in the image better than the other components.
- Component 2 showed a mixture of darker features with light features in the mid and upper parts of the image.
- Component 3 showed linear feature partially visible. The one that could be distinguished were roads.
- Component 4 managed to show linear feature of rives.

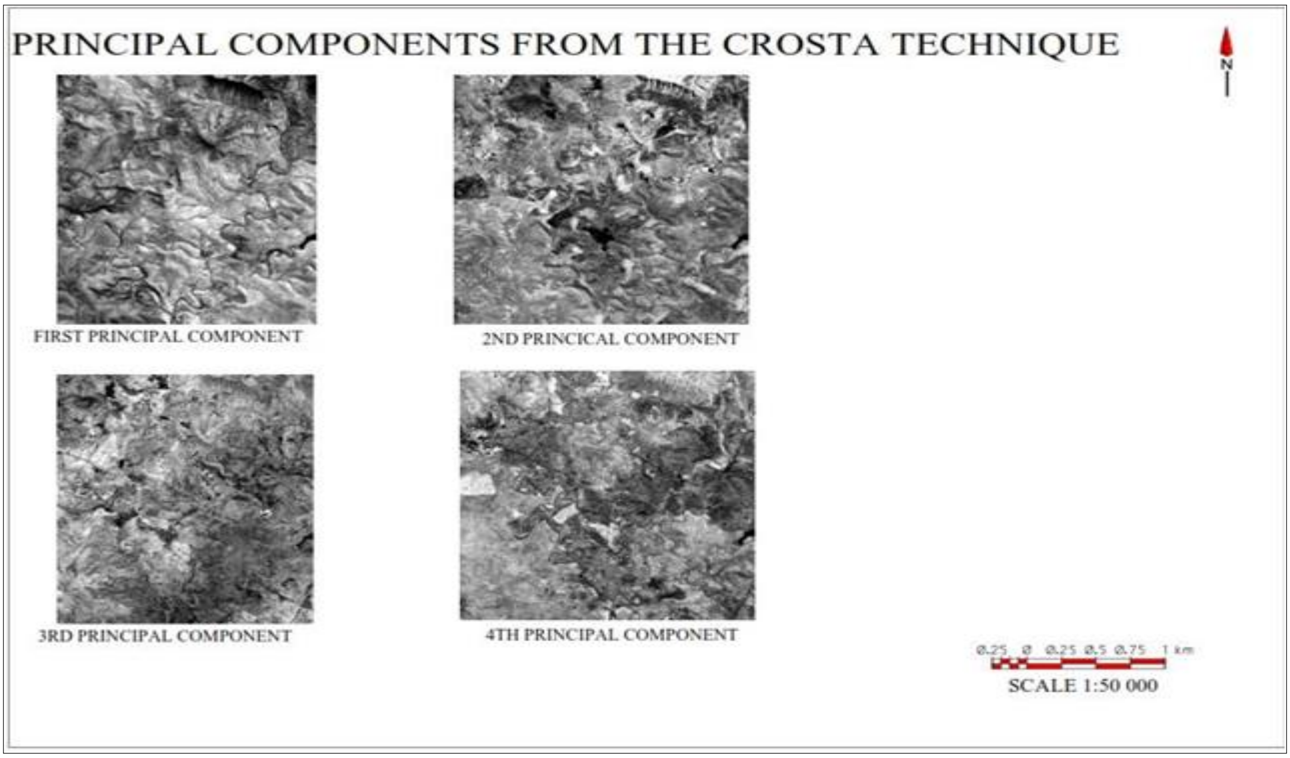


Fig 5.3: Results from Crosta technique PCA

The results from the PCA with 6 input bands showed that:

- Component 1 was able to show the features in the image better than the other components. This component had a clear image.
- Component 2 showed a mixture of darker features with light features in the upper parts of the image.
- Component 3 showed linear features. These included both rivers and roads.
- Component 4 managed to show darker features in the image.
- Components 5 and 6 images were fuzzy and the "salt and pepper" affected them. There was nothing from these components.

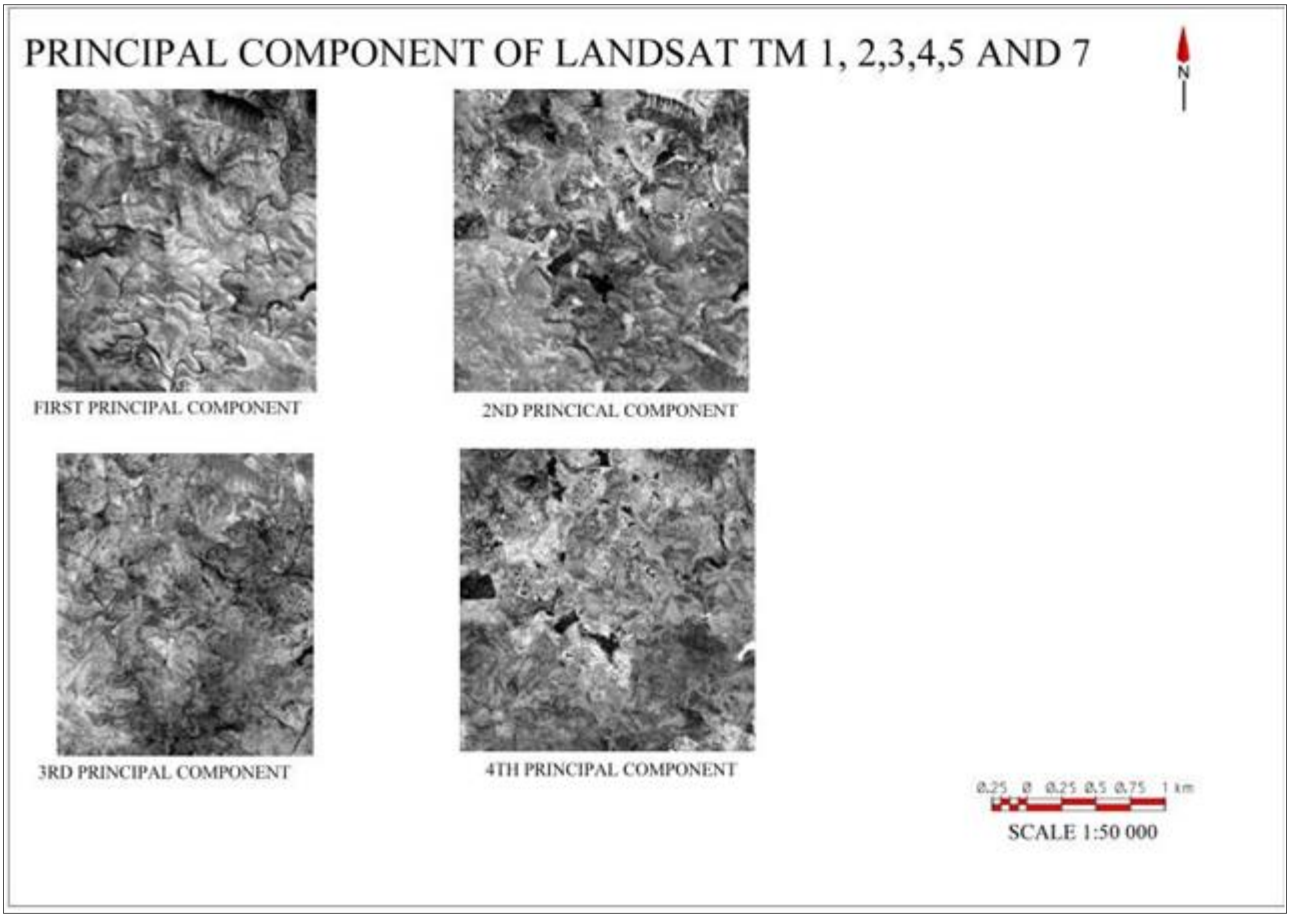


Fig 5.4: Results from PCA with 6 input bands

CHAPTER 6: DATA ANALYSIS

6.1 Analysis

Remote Sensing data can only penetrate a few micrometres in the very near infra-red region, to a few centimetres in the thermal infra-red region and some metres in the microwave region. A remote sensing data interpreter will have to rely on incident clues such as the general geologic setting of the study area, the alteration zones, associated rock structure, lineaments, oxidation products, morphology, and drainage and vegetation anomaly. This is because it is rarely impossible to directly pin point the occurrence and mineralogy of a deposit, even soils based solely on remote sensing data. Therefore, this data analysis shows the minerals mapped from the band ratio methods as well as the principal component method. It also gives an explanation as to why where these minerals mapped in these location. The chapter will end by validating the data using the accuracy assessment method.

6.2 Band Ratios

The remote detection of iron oxide and clay zones in the presence of vegetation proved to be difficult. This was due to the similarities in the reflectance spectra of these minerals. If Landsat was used to provide information regarding the distribution of ferric oxide minerals, the effects of vegetation need to be minimised. Different techniques for image processing of Landsat TM to detect and map minerals in soils are aimed at reducing substantially the effects of vegetation from the underlying substrate. The absorption feature at wavelengths less than 0.55µm and is responsible for the strong red coloration of rocks rich in iron oxide and hydroxides. This coloration is at times masked by mixing iron materials with large amounts of other minerals which reflect strongly in all wavelengths, for example quartz. The albedo of such a mixture will be so high such that it appears white in natural or false colour images. However, if we use the Landsat TM image ratio of red (TM3) to blue (TM1) reflectance, we will enhance the small contribution of iron minerals; given the pixels of iron bearing rocks have a higher value when compared to those of quartz. The position of Fe-O feature is different for haematite and geothite with haematite being the absorbent in the green part of the visible spectrum of the electromagnetic spectrum. This results in haematite being cherry red and geothite being orange brown. The red/green (TM3/TM2) can be used to discriminate between the two minerals (Rajesh, 2004: Kiriuki et al., 2004). In this study area the band ratio TM3/TM1 shows little amount of the occurrence of the mineral haematite but there is an abundance of geothite in the mountains of Hogsback mountain range (top right corner in the study area).

Several airborne and orbital imagery studies have shown that the feasibility of remote sensing techniques to detect certain minerals that are associated with hydrothermal processes and these include:

- Iron-bearing minerals (haematite, geothite and jarosites)
- Hydroxyl-bearing minerals (clays and micas)
- Hydrate sulphate (gypsum and alunite)

These show diagnostic spectral features that permit their remote identification.

Iron produces an absorption band between 0.85 and 0.92µm owing to an electron transfer transition within this region of the electromagnetic spectrum. This feature fell within the Landsat TM band 4. The high reflectance for all minerals fell within the Landsat TM band 5. Therefore, the ratio of band 5 to band 4 showed higher values of oxidised iron rich rocks than for other types. The Al-OH and Mg-OH rotational transition associated with clays and other hydroxylated minerals resulted in absorption within Landsat TM band 7. Therefore, dividing band 7 by band 5 resulted in clay rich minerals being mapped.

The limitation of using Landsat TM or ETM+ according to Steve Drury (2006) is that only four spectral band ratios form the spectral limit to surface discrimination using ratio techniques, even though there are about 30 possible combinations of the six reflected TM bands (TM1, TM2, TM3, TM4, TM5 and TM7) that can be chosen to discriminate different surface features. An example was the ratio TM4/TM3 which was used to show the regions where geothite was likely to be found.

TM band 6 due to its different spatial size (60m and the other 6 TM band are 30m) is not used in the band ratio processes. However, using JERS-1, ASTER and hyper spectral devices, many other features can be investigated using narrower bands within the same reflected range as in Landsat TM or ETM+. Advantages of using ratios are that they do not reduce the effects of slope and shadows to a marked degree. Atmospheric correction before ratio generation reduces this effect considerably. The disadvantages in band rationing are in the "ironing out" of topographic effects and the suppression of differences in albedo.

6.3 Principal Component Analysis

The Principal Component Analysis process used two types of techniques. These techniques distinguished the hydroxyl minerals from vegetation as well as iron oxide.

These bands were selected due to their ability to characterise the OH and the vegetation. The table below shows the Landsat TM bands used for high reflectance and absorption for hydroxyl, iron oxide and vegetation. The bands were selected and inputted in the PCA process to discriminate the hydroxyl minerals from other bands as well as vegetation.

Table 6.1: Absorption and reflectance bands for iron oxide, hydroxyl and vegetation

Material	High reflectance	Absorption
Iron oxide	TM 3,TM5 and TM7	TM1 and TM2
Hydroxyl	TM5	TM7
Vegetation	TM2 and TM4	TM1,TM3 and TM7

6.3.1 Statistics from the Crosta technique PCA

From the analysis of resulting principal components in the Crosta technique it is found that:

- PC1 had high loadings from band 5 (72.72% of the data covariance) and this was assigned to its albedo
- PC2 gave dark pixels due to the positive contribution from band 4 and negative from band 1
- PC3 gave strong positive loadings for TM7 and relatively strong negative for PC4 and thus were assumed to show hydroxyl pixels as dark pixels.

The results from the above analysis are supported by the statistics obtained from the PCA process. These are represented by the eigenvectors in table 6.2 below

Table 6.2: Eigenvectors from the Crosta technique

AXIS	BAND 1	BAND 2	BAND 3	BAND 4
1	0.1437	0.3242	0.7272	0.5877
2	-0.0362	0.8765	0.0043	-0.4800
3	-0.3686	-0.3243	0.6687	-0.5548
4	-0.9177	0.1465	-0.1548	0.3352

From the mean raster values, Band 5 of Landsat ETM+ influenced the way the Crosta technique PCA was processed. The mean value of this band was found to be 92.7%. Table

6.3 shows the mean value of each input band. These values show that the percentage influence that each band had on the final components produced from the Crosta technique.

Table 6.3: The Mean raster values from Crosta technique

Raster	**Mean**
Band 1	65.8
Band 4	70.5
Band 5	92.7
Band 7	66.3

The correlation between the input bands and the principal components shows that all bands had an influence in the PC 1. However, band 5 had a slight advantage as it dominated more in this PC. Table 6.4 show the correlation of the input bands and the principal components.

Table 6.4: The correlation between the input bands and the principal components

AXIS	**BAND 1**	**BAND 4**	**BAND 5**	**BAND 7**
1	0.8367	0.8367	0.9931	0.9742
2	-0.0493	0.5317	0.0014	-0.1864
3	-0.2723	-0.1066	0.1159	-0.1175
4	-0.4726	0.0336	-0.0187	-0.0492

6.3.2 Statistics from the PCA with 6 input band

Six bands of Landsat TM or ETM+ (bands 1, 2, 3, 4, 5 and 7), were taken as inputs to the PCA. This being the normal or the most common PCA, it would be expected that it will show better results than the Crosta technique.

On analysing the resultant Principal component and the resulting statistic of the 6 bands:

- PC1 was assumed to consist of information on the albedo the major contributing factor being from TM5 (66.24%)
- PC2 gave a stronger contribution from band 5 and gave built up areas as bright pixels.
- PC3 gave a strong loading from PC4 (62.48%) thus assigned to healthy vegetation.
- PC4 is thought to map hydroxyl minerals as bright pixels due to high negative contribution by TM7 (70.20%)
- PC5 and PC6 were incoherent due to a lot of noise in the form of "salt and pepper" effect, which is the overall noise from the six bands. These two principal components were not used.

The above analysis is supported by table 6.5 which shows the eigenvectors from the PCA with 6 input bands.

Table 6.5: Eigenvectors from PCA with 6 input bands

AXIS	BAND 1	BAND 2	BAND 3	BAND 4	BAND 5	BAND 7
1	0.1362	0.2066	0.3481	0.2959	0.6624	0.5397
2	-0.0857	-0.0601	-0.2217	0.8608	0.1187	-0.4300
3	-0.3023	-0.4545	-0.6248	-0.2082	0.4911	0.1647
4	0.1563	0.1140	0.2068	-0.3499	0.5519	-0.7020
5	0.7298	0.3523	-05821	-0.0219	0.0046	0.0628
6	0.5706	-0.7810	0.2404	0.0722	-0.0372	0.0059

From the mean raster values, Band 5 of Landsat ETM+ influenced the way the PCA was processed. The mean value of this band was found to be 92.7%. Table 6.6 shows these mean value of each input band. This values shows the percentage influence that each band had on the final components produced from the 6 input band PCA technique.

Table 6.6: The Mean raster values from the 6 input band PCA

Raster	Mean
Band 1	65.8
Band 2	54.4
Band 3	59.4
Band 4	70.5
Band 5	92.7
Band 6	66.3

The correlation between the input bands and the principal components shows that all bands had an influence in the PC 1. However, band 5 had a slight advantage as it dominated more in this PC. Table 6.7 show the correlation of the input bands with the principal components.

Table 6.7: The correlation between the input bands and the principal components

AXIS	BAND 1	BAND 2	BAND 3	BAND 4	BAND 5	BAND 7
1	0.8649	0.9109	0.9341	0.8358	0.9864	0.9756
2	-0.1183	-0.0577	-0.1293	0.5284	0.0384	-0.1690
3	-0.3576	-0.3755	-0.3123	-0.1095	0.1363	0.0555
4	0.1007	0.0510	0.0563	-0.1002	0.0834	-0.1287
5	0.2876	0.0964	-0.0970	-0.0038	0.0004	0.0070
6	0.1311	0.1247	0.0233	0.0074	-0.0020	0.0004

6.2 Data Validation

The data that was used in this thesis was mainly Landsat satellite imagery collected from the earth explorer website. To prove the results collected from the processing and analysis of this satellite imagery, there was need to collect samples from the study area so as to verify if the topsoil mapped by the remote sensing process was coinciding with the information obtained from the soil samples. Due to little or no experience in the study of soils of the author of this thesis, ancillary data in the form of soil profiles were obtained from the Soil Science department and the Agriculture and Rural Development Research Institute (ARDRI) at the University of Fort Hare. These were used to validate if the results were to some degree agreeing on the types of soils mapped.

Through the help of Mr Allan Manyevere (at the completion of this thesis he had moved to North West University) who has been involved in the study of soils using remote sensing before and being a PhD student in the soil science department, he provided his expertise in the validation. Dr J van Tol, a lecturer at the department of Soil Science also provided soil profiles which were used in the validation process. The advantage of using soil profile information from the soil science department was that the information contained the composition of each mineral mapped within each land type obtained from ARC-ISCW data used.

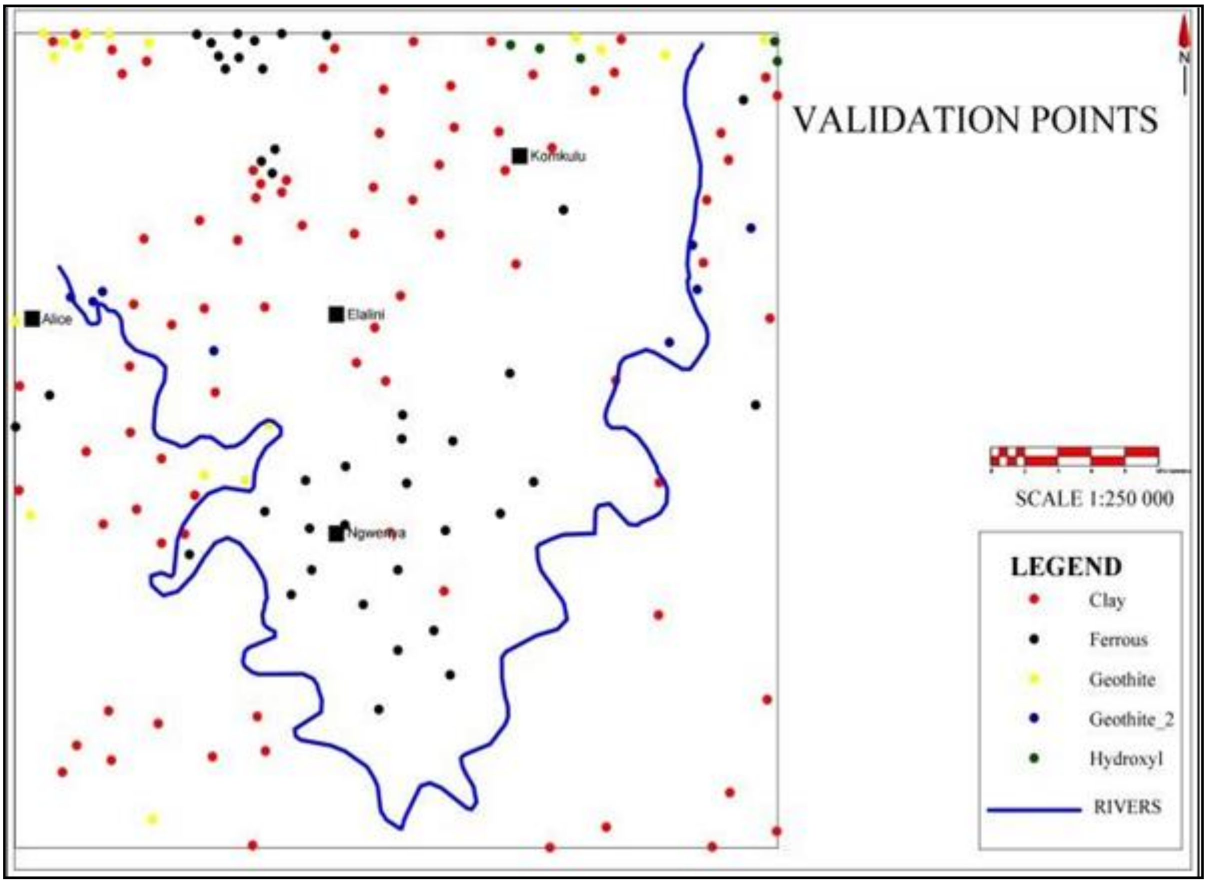


Fig 6.9: Validation points

To validate if the minerals mapped were correctly mapped, a Kappa coefficient was used to check the level of significance of the mapped minerals to the information obtained by the soil science department. Each mineral was validated using validation points which were covering the study area. To check on the validity of the data collected from the 200 points, for each mineral mapped, it was checked if it coincided with a given land type within the study area. Each land type was studied to check if it contained the mineral being mapped. If the pointed showed that the mineral being mapped coincided with the respective point then a score of 1 was given to the corresponding point. If the point did not coincide with the mapped mineral a point was not allocated to that point. These values were then added to the Kappa co-efficient to calculate the level of validity of the results. The Kappa coefficient (also called the K static) is used to check the percentage of errors that were avoided in the study. These errors are calculated from the results obtained from the methodology as discussed in chapters 4 and 5. The calculation is as below:

Table 6.8: The classification accuracy assessment of the band ratioing process

	CLAY	FERROUS	GEOTHITE	GEOTHITE_2	HYDROXYL	TOTAL	Pa	Ua
CLAY	87	40	17	8	5	157	54.4%	54.4%
FERROUS	40	40	40	40	40	200	36.4%	20%
GEOTHITE	17	17	17	17	17	85	19.5%	20%
GEOTHITE_2	8	8	8	8	8	40	47.1%	20%
HYDROXYL	5	5	5	5	5	25	6.66%	20%
TOTAL	**157**	**110**	**87**	**78**	**75**			

Grand Percentage correct= $\frac{\text{sum of diagonal entries}}{\text{Total observations}} = \frac{157}{200}$ = 78.50%

Expected agreement by chance= $\frac{\text{total diagonal entries}}{\text{Grand total}} = \frac{157}{1014}$ = 0.1548

K= $\frac{\text{observed- expected}}{\text{1- Expected}} = \frac{0.7850- 0.1548}{1-0.1548} = \frac{0.6302}{0.8452}$ = ***0.7456***

From the above K-statistic calculation it can be concluded that about 74.56% of errors in the methodology used were avoided. These errors could have been generated from the band rationing processes where the band could have not produced the desired results. This accuracy assessment shows that the accuracy obtained from the band rationing process indicates that the performance of the proposed methodology was satisfactory. This therefore, shows that there is possibility of potentially using GIS and Remote Sensing in the Digital Soil Mapping process. The data from soil science department showed that there are two dominant minerals in this study area. This was shown from the 5 land types that were in the study area to contain some soil information from the ARC-ISCW. The iron minerals could not be split between goethite and ferrous but it was assumed that iron content in the soil could contain both ferrous and goethite. The hydroxyl mineral could not be validated if it was present in the minerals mapped from the remote sensing process. From the analysis of the table 6.9 below it is evident that clay minerals dominate the study area with a few traces of iron and other minerals like Al and CO. According to Soil Science department data found in the soil profile of some of the land type in the study area.

Table 6.9: Mineral composition for each land type

Profile number	**Land type**	**Mineral composition (%)**	
		Fe(iron)	**Clay**
12803	Ea366	4.25	60
12808	Fb816	3.4	47.5
12809	Fb820	2.89	64
12810	Fb819	1.25	32.1
12811	Ae380	2.96	70.1

The challenge with the ancillary data that was used to validate and verify that the remote sensing process was correct in the location of the points used in the study by van Averbeke and Marais. Their study concentrated mostly on the Fort Hare farm and the surrounding agricultural lands under irrigation namely Phandulwazi Agricultural farm. The points statistically never covered most of the studies area and from the remote sensing process, the points seem to be in two minerals namely clays and ferrous minerals. This is a shown in Fig 6.1 above. If there was a way of getting these points covering a bigger part of the study area a proper validation and verification could have given a better picture on the effectiveness of using the remote sensing and GIS techniques in mapping soils. Another challenge was the use of the data was in the year that it was produced. The data was collected in 1989 and the document published in 1991. Since then some of the land uses in this area have changed and there is no recent data that could have been used.

CHAPTER 7: CONCLUSION AND DISCUSSION

7.1 Introduction

After having done the processing and analysis in chapter 5, this chapter concentrates on the discussion of the results obtained. The chapter proceeds to look into the limitations of the study and the project before looking at the recommendations based on what was noticed during the course of the studies in this thesis work. The chapter proceeds by linking all the chapters with a conclusion.

7.2 Discussion

The aim of this study was to find if it is possible to use GIS and Remote Sensing processes in the Digital Soil Mapping process. This was done through the use of different Remote Sensing techniques to map soils in the Hogsback area near Alice. The main objectives was to generate fill the missing soil maps in the Amatole District Municipality of Eastern Cape Province. This was going to help to demonstrate the advantages of remote sensing in the Digital Soil Mapping process.

The specific objectives of this study were (a) to investigate if GIS and Remote Sensing can be potential tool to support Digital Soil Mapping techniques and (b) to provide a cost effective, user friendly and adaptable methodology that will facilitate the “rapid” compilation of appropriately scaled soil maps through the conjunctive use of GIS and Remote Sensing techniques/data. This method was used to demonstrate the utility of the proposed methodology through a case study initiative in which the derived maps would be used to seamlessly patch-up gaps in soil maps. The hypothesis of this thesis was that there was a missing soil map information in the soil map of South Africa. The lack of information has led to improper decision as regards processes pertaining to soils. There was a need to come up with a solution that could assist in the filling of the gaps in the Eastern Cape soil map.

The methodology that was used in this thesis was based on the band ratio as well as principal component analysis. The band ratio process showed that there is a concentration of clay minerals in the study area. This was so as there was some evidence of commercial agricultural activity. This was identified as the Fort hare farm.

Most iron minerals and hydroxyl mineral were found in the high lying and low lying areas within the study area. This was attributed to the weathering processes in the area in and around the Hogsback mountain range. The area also receive a substantial amount of rainfall. Thus the mixing of rainfall water with the weathered residue could have caused these minerals to be exposed. These minerals were also carried downstream and resulted in them being mapped in the low lying areas. The PCA process only proved to show the difference between vegetation, iron oxide as well as hydroxyl mineral.

The results of this study showed that the DSM process can utilise the remote sensing process in mapping soils. The Kappa coefficient showed that about 74.56% of errors were avoided in the methodology that was used in this study. This means that the results obtained from the methodology used in the study were satisfactory. The aim of the study was to show the potential use of GIS and Remote Sensing techniques in mapping soils. The result therefore shows that these techniques can be used in the DSM process.

The only challenge was that the technique can only map the top soils of any soil type or profile. Optical Remote Sensing processes or techniques can only detect reflected energy or radiation from a few centimetres of the top soil. This therefore means that there will be need to have some ancillary data to be able to supplement the data collected from the remote sensing process.

The advantage of using remote sensing techniques is that it facilitates mapping of inaccessible areas by reducing the need for excessive time-consuming and costly field surveys. The ability to apply remote sensing methods to improve coherence in soil and terrain mapping on a global scale could contribute to the Global Earth Observing System of Systems (GEOSS) to meet the need for land resource information.

It should be noted however that regardless of whether the data is collected in various forms, a GIS system will be needed in the storage of the data so as for various people and communities concerned with soil management can be able to access the GIS database and be able to view where the various soils were collected.

It should be noted that the remote sensing process of mapping the soil minerals is only limited to the top soils of any soil profile. This process therefore means that the remote sensing process may need to be couple.

The authors that were used in the literature review section of this document have agreed to the notion that GIS and remote sensing can be used in the DSM process. These include Gibson and Power, 2000; Mather, 1987; Rajesh, 2004 and Scull et al, 2003. They have shown through various process as that GIS and remote sensing can use in the DSM process. Some of these processes include the PCA and band ratio process as used in this thesis. However, there is still need to check other remote sensing processes such as active remote sensing. These can help in mapping the soil as they can penetrate the soil body further than in optical remote sensing.

7.3 Limitations

The only limitation with remote sensing data is in its penetration to the ground surface, the incident light can only penetrate a few centimetres of the ground. This makes it possible to study only the topsoil and not the whole profile of the soil. Therefore there will be need for ground verification of all the data that will be produced through remote sensing techniques.

There was no funding that was involved in this study that could have necessitated the author to collect some soil samples from the study area and use them to validate data produced from remote sensing processes. Most data used was downloaded from the internet, collected from other Masters students, some departments and research institutes within the university as well from my supervisors. This was one limitation that could have made this thesis and project not to be a success but thanks to the Soil Science department and ARDRI for providing the ancillary data that was used in the validation of the data produced.

Remote sensing may offer possibilities for extending existing soil maps and survey data. There are many ways of doing this and these may include:

- Segmenting the landscape into internally more or homogeneous soil-landscape units for which soil composition can be assessed by sampling using classical or more advanced methods
- Using physically based or empirical methods to derive soil properties.
- As data source supporting digital soil mapping.

7.4 Recommendations

Based on the results that were produced from the study area, it is possible to use remote sensing techniques as a way of mapping the soil in a given landscape and terrain. However, without validating the results obtained from the remote sensing processes, the whole process may seem impossible as the results may not coincide with what is on the ground. It should be noted that remote sensing only makes use of satellites that are mounted many kilometres away from the surface of the earth. Their interaction with the surface of the earth is through sending beams of light which are also affected by various conditions upon reaching earth before and after interacting with the target. Thus the results may not really show what was mapped. There is also need to consider other mapping techniques which soil scientists use. Though their methods are costly they come up with results which are usable as well.

There are many remote sensing techniques that can be used to come up with soil maps. Some of these techniques may require some degree of expertise to be able to manipulate the processes they involve. It is essential for the various remote sensing technicians and professional to be familiar with the process they want to use and make sure that they will produce the results they want.

If the study of soils is going to be very effective there is need for funding so as to aid in the data collection and processing within the study area. This will assist in verifying what the GIS and Remote Sensing processes produce with the data collected in the field.

7.5 Conclusion

In conclusion remote sensing and GIS techniques can be used to support digital soil mapping within South Africa. However, there is need for the remote sensing experts to have some knowledge of soils and geology so as to understand how to map the soils. There are a variety of ways of mapping soils and it is up to the author and designer of a given project to choose the processes that will be suitable for a given location of the study area.

It can also be said that the slope and occurrence of soil minerals influence the spatial distribution of soils within the study area. This is because most of these minerals mapped have either been found along the valleys or following a stream meaning that the flow of the river or on the crests. Also the slope influenced the type of minerals where deposited within the spatial extent of the study area. The relief of the area and the area having shown the occurrence of some weathering, could have influenced which type of minerals were detected by the sensor on the band ratio process.

Coupling results obtained from the remote sensing techniques with soil science or geomorphology principles or analysing soils shows that a credible result is possible to get. Therefore, the soil survey processes which though they take time, can be put into good use when validating the results of remote sensing techniques.

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APPENDICES

APPENDIX 1: PRINCIPAL COMPONENT ANALYSIS STATISTICS

<u>For the six input bands</u>

Table 1: Mean Raster Values

Landsat Band	**Mean**
Band 1	65.8
Band 2	54.4
Band 3	59.4
Band 4	70.5
Band 5	92.7
Band 7	66.3

Table 2: Variance / Covariance Matrix

Raster	**Band 1**	**Band 2**	**Band 3**	**Band 4**	**Band 5**	**Band 7**
Band 1						
Band 2	24.0956					
Band 3	38.3864	58.2742				
Band 4	27.4532	43.8851	69.8794			
Band 5	61.0337	92.4211	156.9994	139.4733		
Band 7	51.8323	78.0922	133.6713	102.5187	252.7120	

Table 3: Correlation Matrix

Raster	Band 1	Band 2	Band 3	Band 4	Band 5	Band 7
Band 1	1.0000					
Band 2	0.9448	1.0000				
Band 3	0.9158	0.9656	1.0000			
Band 4	0.6894	0.7654	0.7416	1.0000		
Band 5	0.8081	0.8500	0.8785	0.8215	1.0000	
Band 7	0.8330	0.8718	0.9079	0.7329	0.9527	1.0000

Table 4: Eigenvalues and Associated Percentages

Axis	Eigenvalues	Percentages	Cumulative
1	714.1083	91.1235	91.1235
2	33.7425	4.3057	95.4292
3	24.7876	3.1630	98.5922
4	7.3454	0.9373	99.5295
5	2.7518	0.3511	99.8807
6	0.9353	0.1193	100.0000

Table 5: Eigenvectors

Axis	Band 1	Band 2	Band 3	Band 4	Band 5	Band 7
1	0.1362	0.2066	0.3481	0.2959	0.6624	0.5397
2	-0.0857	-0.0601	-0.2217	0.8608	0.1187	-0.4300
3	-0.3023	-0.4545	-0.6248	-0.2082	0.4911	0.1647
4	0.1563	0.1140	0.2068	-0.3499	0.5519	-0.7020
5	0.7298	0.3523	-0.5821	-0.0219	0.0046	0.0628
6	0.5706	-0.7810	0.2404	0.0722	-0.0372	0.0059

Total variance = 783.6708

Determinant = 11291651.5246

Translation vector = 158.9783 21.0921 -39.9587 8.7150 35.6388 11.3133

Table 6: Transformation Matrix

Axis	Band 1	Band 2	Band 3	Band 4	Band 5	Band 7
1	0.0622	0.0944	0.1590	0.1352	0.3026	0.2466
2	-0.0482	-0.0338	-0.1248	0.4844	0.0668	-0.2420
3	-0.1346	-0.2024	-0.2782	-0.0927	0.2187	0.0733
4	0.0751	0.0548	0.0994	-0.1682	0.2652	-0.3373
5	0.4162	0.2009	-0.3319	-0.0125	0.0026	0.0358
6	0.3342	-0.4575	0.1408	0.0423	-0.0218	0.0034

Table 7: Correlation between Input raster and Principal Components

Axis	Band 1	Band 2	Band 3	Band 4	Band 5	Band 7
1	0.8649	0.9109	0.9341	0.8358	0.9864	0.9756
2	-0.1183	-0.0577	-0.1293	0.5284	0.0384	-0.1690
3	-0.3576	-0.3735	-0.3123	-0.1095	0.1363	0.0555
4	0.1007	0.0510	0.0563	-0.1002	0.0834	-0.1287
5	0.2876	0.0964	-0.0970	-0.0038	0.0004	0.0070
6	0.1311	-0.1247	0.0233	0.0074	-0.0020	0.0004

For the Crosta Technique

Table 8: Mean Raster Values

Landsat Band	Mean
Band 1	65.8
Band 4	70.5
Band 5	92.7
Band 7	66.3

Table 9: Variance / Covariance Matrix

Raster	Band 1	Band 4	Band 5	Band 7
Band 1				
Band 4	27.4532			
Band 5	61.0337	139.4733		
Band 7	51.8323	102.5187	252.7120	

Table 10: Correlation Matrix

Raster	Band 1	Band 4	Band 5	Band 7
Band 1	1.0000			
Band 4	0.6894	1.0000		
Band 5	0.8081	0.8215	1.0000	
Band 7	0.8330	0.7329	0.9527	1.0000

Table 11: Eigenvalues and Associated Percentages

Axis	Eigenvalues	Percentages	Cumulative
1	600.4562	92.6962	92.6962
2	32.9432	5.0856	97.7818
3	9.6700	1.4928	99.2747
4	4.6985	0.7253	100.0000

Table 12: Eigenvectors

Axis	Band 1	Band 4	Band 5	Band 7
1	0.1437	0.3242	0.7272	0.5877
2	-0.0362	0.8765	0.0043	-0.4800
3	-0.3686	-0.3243	0.6687	-0.5584
4	-0.9177	0.1465	-0.1548	0.3352

Total variance = 647.7679

Determinant = 898734.7288

Translation vector = 138.7307 27.9881 -22.1355 -42.1426

Table 13: Transformation Matrix

Axis	Band 1	Band 4	Band 5	Band 7
1	0.0806	0.1818	0.4079	0.3297
2	-0.0259	0.6274	0.0031	-0.3436
3	-0.1920	-0.1689	0.3483	-0.2908
4	-0.5905	0.0942	-0.0996	0.2157

Table 14: Correlation between Input raster and Principal Components

Axis	Band 1	Band 4	Band 5	Band 7
1	0.8367	0.8395	0.9931	0.9742
2	-0.0493	0.5317	0.0014	-0.1864
3	-0.2723	-0.1066	0.1159	-0.1175
4	-0.4726	0.0336	-0.0187	0.0492

APPENDIX II: DESCRIPTION OF SOILS OF THE STUDY AREA

A. Description of the Fort Hare Jozini ecotope

Soil Name

South Africa name: Oakleaf Jozini

FAO name: Orthic Luvisol

Soil Taxonomy: Typic Haplustalf

Location

Alice, Fort Hare Research Farm.

Latitude: 32º 47' 51S and Longitude: 26º50'55E

Altitude: 508m

Landform

General: dissected coastal plateau

Regional: alluvial valley of the Tyume River

Local: Most recent alluvial terrace

Slope

Flat or nearly flat land, sloping gently down in a south eastern direction with a gradient of 0.5%

Vegetation and land use

Annually cropped land, which has been under irrigation for at least the past 50 years.

Climate

Mean annual temperature: 18.1ºC

Mean Annual rainfall

575mm with a distinct winter minimum and more or less pronounced spring and autumn maximum.

Parent material

Alluvial deposit which consists mainly of fine sand and silt, and contains significant amounts of clay. Mineralogically the sand fraction consists mainly of quartz and lesser amounts of plagioclase, rock fragments and iron and manganese oxides. In the clay fraction both 1:1 and 2:1 clay minerals are present.

Description of top soil

Depth 0-300mm

Dry: dark brown

Moist: brown

Fine sandy loam, generally massive buy in places weak medium sub angular blocky, hard (dry), friable (moist), slightly sticky and slightly plastic (wet) many fine roots, clear smooth transition, broken in places.

B. Description of the Alice Bluebank ecotope

Locality: Fort Hare Farm

Coordinates: 32º47’ 50” S and 26º51’55”E

Climate: Semi-arid

Parent material

No. of kinds: single

Lithology: mudstone

Underlying material: mudstone

Topography

Altitude: 510m

Terrain morphological unit: 4

Slope: 1.5%

Kind: Concave

Aspect: 280ºW

Mode of accumulation: colluvium

Factors of soil formation

Chemical weathering: strong

Physical weathering: strong

Vegetation: open tree veld

Description of topsoil

Depth: 0-160mm

Dry; dark greyish brown moist and light grey dry; silt loam; weak fine and medium sub angular blocky in places tending to coarse granular due to faunal (animal) activity. Hard (dry) friable (moist); slightly sticky; non plastic (wet); many to very fine roots; clear smooth boundary.

C. Description of the Alice Jozini Ecotope

Form: Oakleaf

Series: Jozini

Locality: Fort hare farm, Alice

Coordinates: 32º47'30"S and 26º50'45"E

Climate: Semi-arid

Parent material

No of kinds: single

Lithology: alluvium

Underlying material: alluvium

Mode of accumulation: river deposit

Weathering

Physical: weak

Chemical: weak

Topography

Altitude: 508m

Terrain morphological unit: 5, valley bottom

Slope: 0.5%

Kind: plane

Aspect: 90ºE

Vegetation

Cultivated land

Description of topsoil

Depth: 0-200mm

Moist/dry, dark brown, moist and brown dry, fine sandy loam; weak fine to medium sub-angular blocky, medium sized crumbs also present. Slightly hard (dry), very friable (moist), slightly sticky and slightly plastic (wet), many fine roots with gradual smooth transition.

D. Description of the Alice Limpopo ecotype

Form: Oakleaf

Series: Limpopo

Location: Fort hare Farm, Alice

Coordinates: 32º48’00”S and 26º51’ 30’E

Climate: Semi-arid

Parent material

No of kinds: single

Lithology: alluvium

Underlying material: old alluvium

Mode of accumulation: river deposit

Soil formation factors

Physical weathering: weak

Chemical weathering: weak

Topography

Altitude: 498m

Terrain morphological unit: 5, valley bottom

Slope: 0%

Kind: flat

Aspect:-

Vegetation

Cultivated land

Description of topsoil

Depth: 0-200mm

Dry brown, moist and brown dry, loam, massive to weak fine and medium sub-angular blocky, hard(dry), many fine roots with gradual smooth transition.

E. Description of the Alice Lindley ecotope

Form: Valsrivier

Series: Lindley

Location: Fort hare Farm, Alice

Coordinates: 32º47’30”S and 26º51’ 45’E

Climate: Semi-arid

Parent material

No of kinds: probably binary

Lithology: mudstone and probably influence of dolerite

Underlying material: mudstone

Mode of accumulation: colluvium

Soil formation factors

Physical weathering: strong

Chemical weathering: strong

Topography

Altitude: 530m

Terrain morphological unit: 3, middle slope

Slope: 7.5%

Kind: slightly concave

Aspect: 240ºSW

Vegetation

Thorn bush veld

Description of topsoil

Depth: 0-155mm

Dry and very dark brown moist; very dark greyish brown and dry with upper 30mm dark greyish brown dry, silt loam. Weak to moderate fine sub-angular blocky in upper 30mm and moderate medium sub-angular blocky lower down, hard (dry) many fine roots with gradual smooth transition.

F. Description of the Alice Robmore ecotope

Form: Glenrosa

Series: Robmore

Location: Fort hare Farm, Alice

Coordinates: 32º48'00"S and 26º52' 00'E

Climate: Semi-arid

Parent material

No of kinds: single

Lithology: mudstone

Underlying material: mudstone

Mode of accumulation: colluvium and in situ weathering of rock

Soil formation factors

Physical weathering: strong

Chemical weathering: weak

Topography

Altitude: 518m

Terrain morphological unit: 3, middle slope

Slope: 5%

Kind: straight

Aspect: 270º

Vegetation

Cultivated land

Description of topsoil

Depth: 0-260mm

Dry and very weak greyish brown, dry loam. Moderate, fine angular blocky, hard dry with many fine roots. Few small Fe/Mn concentrations and mudstone fragments with clear wavy transition.

G. Description of the Alice Rosemead ecotope

Form: Escourt

Series: Rosemead

Location: Fort hare Farm, Alice

Coordinates: 32º47'00"S and 26º51' 00''E

Climate: Semi-arid

Parent material

No of kinds: single

Lithology: mudstone

Underlying material: mudstone

Mode of accumulation: combination of colluvium and weathering in situ

Soil formation factors

Physical weathering: strong

Chemical weathering: strong

Topography

Altitude:

Terrain morphological unit: 4, old terrace

Slope: 3.8%

Kind: straight

Aspect: 120º ESE

Vegetation

Annually cropped land

Description of topsoil

Depth: 0-230mm

Dry dark brown, moist and greyish brown dry, loam, massive to weak; fine to medium sub-angular blocky, hard(dry), very small Fe/Mn concentrations; many fine roots with gradual smooth transition.

H. Description of the Alice Sterkspruit ecotope

Form: Sterkspruit

Series: Sterkspruit

Location: Fort hare Farm, Alice

Coordinates: 32º47’30”S and 26º50’ 45’’E

Climate: Semi-arid

Parent material

No of kinds: binary

Lithology: old alluvium covered by recent colluvium

Underlying material: old alluvium

Mode of accumulation: old alluvium deposit with a more recent colluvium cover.

Soil formation factors

Physical weathering: strong

Chemical weathering: strong

Topography

Altitude: 510m

Terrain morphological unit: 3/4, old river terrace

Slope: 4%

Kind: slightly convex

Aspect: 270º W

Vegetation

Cultivated land

Description of topsoil

Depth: 0-170mm

Dry: dark yellowish brown, moist and yellowish brown dry, loam, weak fine and medium sub-angular blocky, slightly hard (dry), many fine roots with clear smooth transition.

D. Description of the Ngwenya Swartland ecotope

Form: Swartland

Series: Swartland

Location: Ngwenya

Coordinates: 32º51’20”S and 26º56’ 10’’E

Climate: Semi-arid

Parent material

No of kinds: single

Lithology: mudstone

Underlying material: mudstone

Mode of accumulation: colluvium plus weathering in situ

Soil formation factors

Physical weathering: strong

Chemical weathering: moderate

Topography

Altitude: 585m

Terrain morphological unit: 3, middle slope

Slope: 3.7%

Kind: plane

Aspect: 45º NE

Vegetation

Cultivated land

Description of topsoil

Depth: 0-200mm

Moist: very dark greyish brown, dry loam, massive to very weak fine and medium sub-angular blocky, friable (moist), many fine roots with gradual smooth transition.

D. Description of the Ncera Kinross ecotope

Form: Shortlands

Series: Kinross

Location: Ncera

Coordinates: 32º44’ 45”S and 26º51’50’’E

Climate: Semi-arid to sub humid

Parent material

No of kinds: 1

Lithology: dolerite

Underlying material: dolerite

Mode of accumulation: colluvium and weathering in situ

Soil formation factors

Physical weathering: weak

Chemical weathering: strong

Topography

Altitude: 700m

Terrain morphological unit: 1/3, upper middle slope

Slope: 5.5%

Kind: slightly convex

Aspect: 45º NE

Vegetation

Ploughed land

Description of topsoil

Depth: 0-200mm

Dry: dark reddish brown, moist, yellowish red dry clay loam. Weak medium sub-angular blocky, hard (dry), few fine roots with clear smooth transition.

APPENDIX III: **Selected platforms by instrumentation, operation status, spatial coverage, spatial and temporal resolution**

(Table provided courtesy of Prof. Hamandawana)

	Instrumentation	Service period		Spatial coverage	Resolution	
		From	To		Spatial	Temporal
SPOT 1	HRV	1986	Present	6400 km2	10-20m	26 days
SPOT 2	HRV	1990	Present	6400 km2	10-20m	" "
SPOT 3	HRV	1993	Failure	6400 km2	10-20m	" "
SPOT 4	HRVIR	1998	Present	14 400 km2	10-20m	" "
TERRA	ASTER	1999	Present	3600 km2	15-90m	5-16 days
TERRA	MODIS	1999	Present	No data	250-1000m	1-2 days
IKONOS	No data	1999	Present	121 km2	1-4m	No data
QuickBird	No data	2001	Present	484 km2	0.61-0.73m	" "
Landsat 1	MSS	1972	1978	34225 km2	79m	14 days
Landsat 2	MSS	1975	1982	34225 km2	57m	" "
Landsat 3	MSS	1978	193	34225 km2	57m	" "
Landsat 4	MSS + TM	1982	1993	34225 km2	57m (MSS)	" "

Landsat 5	MSS + TM	1984	Present	(MSS) 34 000 km2 (TM)	30-120m (TM)	" "
Landsat 6	ETM	1993	Failure	Not applicable	Not applicable	" "
Landsat 7	ETM+	1999	2003	34 000 km2	15, 30, 120m	" "
Abbreviations						
MSS = Multispectral Scanner						
ETM = Enhanced Thematic Mapper						
HRVIR = High Resolution Visible and Infrared						
MODIS = Moderate Resolution Imaging Spectro-radiometer						
HRV = High Resolution Visible	IRS = Indian Remote Sensing Satellite					
ASTER = Advanced Spaceborne Thermal Emission and Reflection Radiometer						
Temporal coverage						
SPOT: 18 yrs	ASTER:5 yrs	MODIS:5 yrs	IKONOS: 5 yrs	QuickBird: 3 yrs	Landsat: 32 yrs	
Sources: MTPE/EOS 1997; Mather, 2004; Lauer et al., 1997; Lillesand and Kiefer, 2000; Drury, 1998.						

Criteria table used to guide data-type selection from individual platforms

<table>
<tr><td rowspan="3">Platform/ Sensor</td><td></td><td colspan="9">Criteria</td></tr>
<tr><td rowspan="2"></td><td colspan="2">Spatial</td><td colspan="2">Temporal</td><td rowspan="2">Spectral Resolution</td><td rowspan="2">Software compatibility</td><td rowspan="2">Cost</td><td rowspan="2">Total score</td><td rowspan="2">Decision</td></tr>
<tr><td>Res</td><td>Cov</td><td>Res</td><td>Cov</td></tr>
<tr><td></td><td rowspan="7">Criteria score</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>Spot</td><td>1</td><td>1</td><td>1</td><td>1</td><td>1</td><td>1</td><td>0</td><td>6</td><td>R</td></tr>
<tr><td>Terra/Aster</td><td>1</td><td>1</td><td>1</td><td>0</td><td>1</td><td>1</td><td>1</td><td>6</td><td>R</td></tr>
<tr><td>Terra/MODIS</td><td>0</td><td>2</td><td>0</td><td>0</td><td>1</td><td>0</td><td>1</td><td>4</td><td>R</td></tr>
<tr><td>IKONOS</td><td>0</td><td>0</td><td>0</td><td>0</td><td>1</td><td>1</td><td>0</td><td>2</td><td>R</td></tr>
<tr><td>QuickBird</td><td>0</td><td>0</td><td>0</td><td>0</td><td>1</td><td>1</td><td>0</td><td>2</td><td>R</td></tr>
<tr><td>Landsat</td><td>1</td><td>1</td><td>2</td><td>2</td><td>1</td><td>1</td><td>1</td><td>8</td><td>A</td></tr>
<tr><td rowspan="2">Platform categories</td><td colspan="4">Category 1</td><td colspan="4">Category 2</td><td colspan="2">Category 3</td></tr>
<tr><td colspan="4">SPOT and ASTER</td><td colspan="4">MODIS, IKONOS and Quick Bird</td><td colspan="2">Landsat</td></tr>
<tr><td>Score ratings</td><td colspan="6">Very suitable = 2; Suitable = 1; Unsuitable = 0</td><td colspan="4">Decision: R = reject; A= accept</td></tr>
</table>