The Identification of Natural Terroir Units in the Robertson Wine District using GIS and Remote Sensing

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DECLARATION

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SUMMARY

One of the main objectives of the South African Wine of Origin Scheme (SAWOS) is to guarantee the quality of wine products emerging from South Africa's viticultural production areas by preventing the abuse of names of products originating from outstanding viticultural areas. The study of terroirs contributes to knowledge that assists in delimiting potential viticultural areas in South Africa. Terroirs are areas with homogeneous groups of natural factors that, with the aid of effective management, have the potential to produce a unique product over a recognizable period. Natural terroir units (NTU) reflect the integration of relatively homogenous environmental factors, which include topography, climate, soil and geology.

This study investigates the use of geographic information systems (GIS) and remote sensing methods in the identification of NTU in the Robertson wine district. Existing topographical, soil, geological and climatic GIS data layers were collected at various scales. In addition to this spatial data, orthorectified and radiometrically corrected SPOT 5 and ASTER satellite imagery were used to classify the land use/cover using an object-based image analysis (OBIA) approach. Eight land use/cover classes were distinguished by a sequential ruleset and an overall accuracy of 81.2% was achieved.

The land use/cover layer was combined with the slope aspect and soil landscape to provide a three-component NTU description. One hundred and seventy NTU were identified, of which fifty five units exist for agriculture. These NTU can be used for site selection of agricultural produce and effective planning and management of land use. Climate was not included in the delimitation of NTU because the coarse resolution of climatic data could not be used to distinguish between different NTU. Therefore, all NTU identified in this research has similar climatic conditions.

The major drawback of GIS-assisted terroir studies is the difficulty of representing a number of NTU on one GIS map. Therefore, it is recommended to associate the NTU map with a table of the classes instead. Furthermore, the accuracy, scale and resolution of available GIS data in South Africa influence the delimitation of NTU. Although remote sensing was found to provide efficient methods for land cover mapping, the use of multiseasonal satellite images would classify vineyards more efficiently because such an approach accounts for the different growth cycles of grapevines.

KEY WORDS AND PHRASES

terroir, natural terroir units (NTU), geographical information systems, remote sensing, viticulture

OPSOMMING

Een van die hoof doelwitte van die Suid-Afrikaanse Wyn van Oorsprongskema (SAWOS) is om die kwaliteit van wynbouprodukte afkomstig van Suid-Afrikaanse wingerdbougebiede te verseker. Die studie van terroirs is geïdentifiseer as 'n metode om moontlike wingerdbougebiede in Suid-Afrika af te baken. Terroirs is gebiede met relatief homogene natuurlike faktore wat oor 'n erkenbare tydperk en met behulp van effektiewe bestuur die vermoë het om 'n unieke produk te lewer. Dié natuurlike faktore word, "natuurlike terroir eenhede" (NTE) genoem en sluit topografie, klimaat, grond en geologie in.

Hierdie navorsing ondersoek die gebruik van geografiese inligtingstelsels (GIS) en afstandswaarnemingstegnieke om NTE in die Robertson-wyndistrik te identifiseer. Bestaande ruimtelike topografiese-, grond-, geologiese- en klimaatdata is op 'n verskeidenheid skale versamel. Bykomend tot hierdie ruimtelike data, is ortogekorrigeerde en radiometries-gekalibreerde SPOT 5 en ASTER satellietbeelde gebruik om landgebruik/ -bedekking te klassifiseer. Objekgerigte beeldanalise (OGBA) is toegepas tydens hierdie klassifikasie en agt landgebruik/ -bedekkingsklasse is onderskei deur gebruik te maak van 'n stapsgewyse reëlstel. OGBA het 'n algehele akkuraatheid van 81.2% gelewer.

Die landgebruik/ -bedekkingsdata is gekombineer met hellingaspek en die grondlandskap om 'n drieledige NTE-beskrywing te lewer. Een honderd en sewentig NTE is geïdentifiseer waarvan daar vyf-en-vyftig eenhede vir landbou bestaan. Hierdie NTE kan aangewend word vir die selektering van geskikte terreine vir landbou-gewasse en effektiewe grondgebruikbeplanning en -bestuur. As gevolg van die bestaande klimaatdata se growwe resolusie, was dit ongeskik om te onderskei tussen verskillende NTE. Dus heers daar soortgelyke klimaatstoestande vir elke NTE wat in hierdie navorsing geïdentifiseer is.

Die grootste stremmende faktor wat GIS-verwante terroir navorsing beïnvloed, is die uitdaging om 'n groot getal NTE op een kaart voor te stel. Daarom is dit beter om die NTE kaart met 'n tabel te assosieer. Verder beïnvloed die akkuraatheid, skaal en resolusie van beskikbare digitale geografiese data in Suid-Afrika die afbakening van NTE. Alhoewel bevind is dat afstandwaarneming 'n effektiewe metode is om landbedekking te karteer, sal die gebruik van meerseisoenale satellietbeelde wingerde meer doelmatig karteer omdat dit verskeie siklusse in die groei van wingerde in ag neem.

SLEUTELWOORDE EN FRASES
terroir, natuurlike terroir eenhede (NTE), geografiese inligtingstelsels, afstandwaarneming, wingerdkunde

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ABBREVIATIONS

ARC	Agricultural Research Council
ASTER	Advanced spaceborne thermal emission and reflectance radiometer
B	Border
CGA	Centre for Geographical Analysis
CGS	Council for Geoscience
CSIR	Council for Scientific and Industrial Research
DEM	Digital elevation model
E	East
ESA	European Space Agency
F	Frame
FIR	Far infrared
FIS	Field-level geographic information systems
GCPs	Ground control point
GDD	Growing degree day
GIS	Geographical information systems
GPS	Global positioning system
HRG	High resolution geometric
HRS	High resolution stereoscopic
HRV	High resolution visible
HRVIR	High-resolution visible and infrared
ISCW	Institute for Soil, Climate and Water
LAI	Leaf area index
LIDAR	Light detection and ranging
LM	Local municipality
MFT	Mean February temperature
MSAVI	Modified soil-adjusted vegetation index
MRS	Multiresolution segmentation
N	North
NASA	National Aeronautics and Space Administration
NDSI	Normalized difference soil index
NDVI	Normalized Difference Vegetation Index
NGI	National Geo-Spatial Information
NIR	Near infrared
NTU	Natural terroir unit
OBIA	Object-based image analysis
PAN	Panchromatic

QUAC	Quick atmospheric correction
RGB	Red, green, blue
RMSE	Root mean square error
RWD	Robertson Wine District
S	South
SAVI	Soil-adjusted vegetation index
SAWB	South African Weather Bureau
SAWIS	South African Wine Industry Information and Systems
SAWOS	South African Wine of Origin Scheme
SPOT	*Le Systemé pour l'Observation de la Terre*
SWIR	Shortwave infrared
TIN	Triangulated irregular network
TIR	Thermal infrared
TMS	Table Mountain sandstone
USGS	United States Geological Survey
UTM	Universal Transverse Mercator
VNIR	Visible and near infrared
W	West
WCDEM	Western Cape digital elevation model
WD	Wine of Origin District
WGS84	World Geodetic System of 1984
WOSA	Wines of South Africa

CHAPTER 1: INTRODUCTION

Located at the southwestern tip of Africa, the Western Cape province of South Africa is the most renowned wine-producing province on the continent (Minnaar 2006). South African wines are of world-class quality and compete with the major wine-producing countries worldwide (WOSA 2006). Red and white grapes are harvested at various locations throughout the Western Cape, with Shiraz, Merlot, Cabernet Sauvignon, Chenin Blanc, Colombar, Chardonnay and Muscat d'Alexandrie being the most popular cultivars (SAWIS 2006).

As with all other wine-producing regions, the climate, topography and soil conditions of the Western Cape are the most influential factors in the production of wine in this region (Saayman 1973). Furthermore, although South Africa is relatively young compared to some European countries, the proud cultural history of longer than 350 years of grape-growing and wine-making, complements the natural conditions to produce some of the finest wines in the world (Carey 2005; Carey, Bonnardot & Knight 2003; Minnaar 2006).

In a country with an unemployment rate of 25% (StatsSA 2011), the wine industry of South Africa employs approximately 350 000 people on wine farms or in the cellars. Currently, the industry uses more than 112 000 ha of farmland for grapevine production (SAWIS 2010). In 2009, South Africa produced 805.1 million litres of wine, placing the country in the top ten countries regarding total volume production worldwide (SAWIS 2010). Approximately 389.1 million litres, or 48% of the total wine production, were exported in 2009, and the total revenue rendered from producers' sales and income exceeded R2.7 billion (SAWIS 2010). These statistics underline the important contribution of viticulture and oenology to South Africa's economy.

1.1 BACKGROUND

The marketing strategies and promotion of agricultural products such as wine, meat, cheese and fruit are increasingly focussing on the places where these products originate (Barham 2003). Studies show that the names of places renowned for outstanding agricultural products were abused in the past because of a lack of control over the origin and quality of such products (Barham 2003; Saayman 2003). The South African Wine of Origin Scheme (SAWOS), established in 1973, is concerned with this “label of origin” phenomenon and its main objective is to guarantee the quality of wine products emerging from South Africa’s viticultural production areas (Burger & Deist 1981). SAWOS demarcates areas of wine production into regions, districts, wards, estates and single vineyards, and is governed by a board that deals with all the administrative and legislative aspects regarding the marketing and promotion of wine and wine products originating from these viticultural areas (Saayman 2003; The Wine and Spirit Board 2006).

According to The Wine and Spirit Board (2006), areas of production are demarcated and defined as:

- *Single vineyards*, the smallest areas of production, with areas less than 5 hectares;
- *Estates*, production units consisting of one or more bordering farms and its own cellars where wine is farmed and produced;
- *Wards*, combination of different farms that are not necessarily part of a district provided that their soil, climate and ecological factors have a distinctive influence on the character of the wine. Their names are real geographical place names and the environmental features have the potential to produce wines with a distinctive character;
- *Districts*, defined in a similarly to wards, but are confined to broader macro geographical units such as rivers and mountains and can by definition have a wider variety of soil types than wards;
- *Regions*, combinations of different districts or parts of districts that are defined according to the encompassing area name.

Table A1 (Appendix A) distinguishes the demarcated regions, districts and wards of the Wine of Origin scheme. Figure A1 shows the geographical units of the wine-producing provinces in South Africa, while Figures A2 to A4 show the regions, districts and wards respectively of the wine-producing areas in South Africa.

This study is part of a research programme of Winetech (Wine Industry Network for Technology and Expertise) on the delimitation of viticultural terroirs in South Africa. Like wine-producing countries worldwide, the concept “terroir” has been identified as the basis for the delimitation of viticultural areas in South Africa (Carey 2001; Carey 2005). Terroirs are homogeneous or stable groups of natural factors that have the potential to produce a unique agricultural product over a period of time (Carey 2005). Natural terroir units (NTU) are groupings of land surfaces with homogeneous patterns in topography, climate, geology and soil (Carey *et al.* 2008). The mapping of these units is usually the first stage of data acquisition in terroir-related studies (Carey *et al.* 2008). The term “viticultural terroir” is appropriate when the terroir concept is specifically applied to the distinct quality of grapes and their wines from a viticultural area (Vaudour 2002). Although viticultural and oenological practices play an important role in the aroma and quality of a wine, the integration of natural factors such as climate, soil, topography and geology are considered the most important variables in determining the character and style of a wine (Carey 2001; Carey 2005; De Blij 1983).

Several methods have been used to identify viticultural terroirs. These include extensive lithological mapping, computational statistical methods and soil landscapes (Carey 2005). Computational statistical methods use multivariate techniques to generate a statistical view of terroirs (Carey 2006), while extensive lithological mapping makes use of detailed pedological investigations in areas with relatively constant microclimates to assess the agricultural potential of soils (Vaudour 2002). A soil landscape is the spatial combination of soil horizons and landscape elements such as vegetation, human activity, geomorphology, hydrology and substratum or bedrock to spatially determine a soil cover or a part of it (Girard & Girard 1998). No specific dominant methodology has yet been developed to identify viticultural terroirs.

1.2 AIM AND OBJECTIVES

The aim of this research is to investigate how GIS and remote sensing techniques can be used to identify natural terroir units by means of soil landscapes as a dominant methodology. To reach this aim, the following four objectives were set:

i) Identify and compile existing digital data and satellite imagery.
ii) Interpret satellite images using object-based image analysis (OBIA).
iii) Combine land cover, soil landscape and slope aspect maps to create a NTU map.
iv) Assess the NTU map by comparing it to Shiraz and Chardonnay reference plots.

1.3 RESEARCH METHODOLOGY AND AGENDA

This research is an exploratory study to investigate how GIS and remote sensing techniques can be qualitatively employed to identify natural terroir units. Figure 1.1 is a diagram of the step-by-step procedure followed.

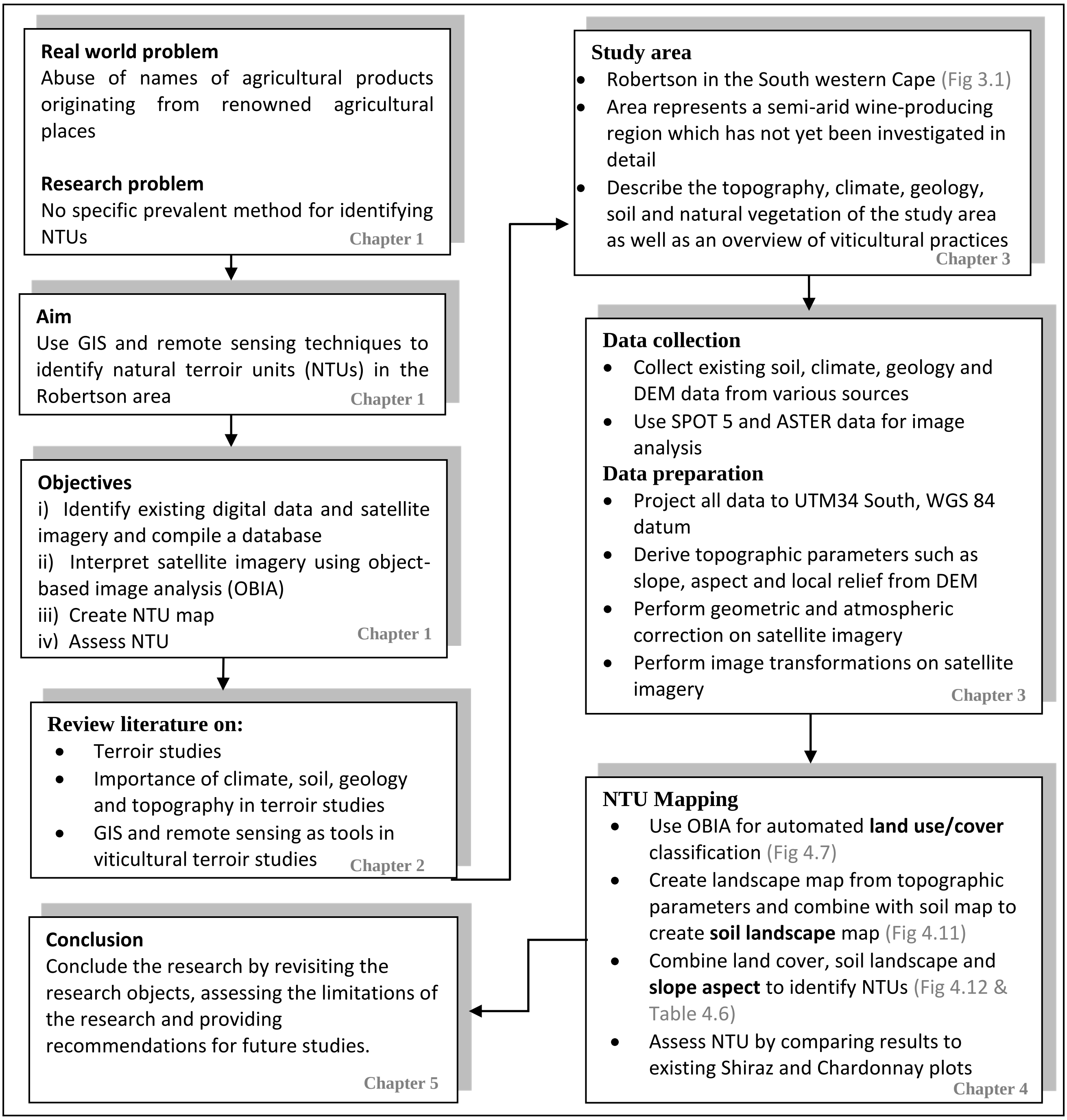


Figure 1.1: Research design for identifying natural terroir units

As illustrated in Figure 1.1, the research problem that was identified earlier in this chapter is the starting point of the research. The research problem is addressed by the aim and objectives that was also dealt with in Chapter 1. In Chapter 2, a literature review is presented to give more insight into the research problem, aim and objectives. The study area and data that is required for this study is identified in Chapter 3, as well as the data preparation processes and a description of the key environmental parameters that constitute a "terroir". Chapter 4 will look into the mapping of NTU. The land use/cover classification and the creation of a soil landscape map are sub processes that lead to the complete classification of NTU. The research is concluded in Chapter 5 where the research objectives will be revisited and further recommendations will be provided.

CHAPTER 2: TERROIRS AND THE APPLICATION OF GIS AND REMOTE SENSING IN VITICULTURE

Viticulture is the science of grape-growing and is distinguished from oenology the science of wines and winemaking (De Blij 1983). De Blij (1983) and Mouton (2006) suggest that natural factors such as climate, soil, topography and geology are the most important factors in grape-growing. As defined in the research problem, the combination of these natural factors into stable groups constitutes the term 'terroir'.

2.1 THE TERROIR CONCEPT

The concept of terroir in relation to viticultural zoning is examined in detail by Vaudour (2004), who describes two means of classifying terroir: the first defines terroir based on the geographical differentiation of wines, grapes and plant characteristics, while the second considers soil and climate as the key variables in determining geographical differentiation, land capabilities or vineyard suitability. The book *Terroir, zonazione, viticoltura* edited by Fregoni, Schuster & Paoletti (2003) is a collection of articles by viticulturists from various wine-producing countries in which aspects such as the history and importance of terroir, terroir factors, zoning of terroirs and vine diseases, among other viticultural issues, are discussed.

Deloire *et al.* (2005) have pointed out that the term "terroir" includes both spatial and temporal characteristics, hence the importance of tools such as geographical information systems (GIS), global positioning systems (GPS) and remote sensing when focussing on the spatial component of these studies. Furthermore, Deloire *et al.* (2005) agree with Vaudour (2004) that two types of terroir-related scientific studies can be distinguished:

(i) those that insist on the geographical differentiation of wines and grapes;

(ii) those that focus on the geographical differentiation of land capability or vineyard suitability.

The use of GIS and remote sensing as tools in terroir-related studies is discussed later in this chapter with the focus on the second type of terroir-related studies, namely investigations into the geographical differentiation of land capability or vineyard suitability. But first, attention is given to the individual components of the terroir: climate, soil, topography and geology.

2.2 THE ROLE OF CLIMATE, SOIL, TOPOGRAPHY AND GEOLOGY IN TERROIR MAPPING

Knowledge of the role of climate, slope and soil in the cultivation of the perfect vintage is an ancient art, mastered "perhaps as long as 8000 years ago" (De Blij 1983: 9). All the texts on viticulture and viticultural zoning consulted in this research, focussed on at least one of these environmental parameters. Carey (2005) and Carey, Archer & Saayman (2002) discuss the role of each of these environmental factors in detail. The emphasis placed on climate and soil in the literature underlines their importance for viticultural studies. According to De Blij (1983), Jones, Snead & Nelson (2004), Saayman (1973) and Saayman (2003), climate is the key environmental variable in determining the character and quality of a wine. Saayman (1973) proposed that, together with climate, soil has the greatest influence on the character and quality of a wine. Goussard (2008) has summarized the preferred environmental conditions and other cultivation characteristics for the production of various grape cultivars in South Africa. In the text by Goussard (2008), the influences of climatic conditions, soil conditions and terrain are discussed, as well as a general background to each of the cultivars, its morphology and phenology. The following subsections will discuss the influences of climate, soil, topography and geology in viticulture.

2.2.1 Climate

In viticulture, three levels of climate are relevant, namely macroclimate, mesoclimate and microclimate (Smart & Robinson 1991). Macroclimate describes the temperature variation of a region on a small scale whereas mesoclimate is the climate of a smaller region (usually a vineyard), but it accounts for the effect of other factors such as topography and the distance to large water bodies into account (Carey 2005). The microclimate is the climate around a plant and it can change within a short time or distance (Roux 2005). Although temperature is the most influential climatic component on a vineyard (De Villiers 1995), the effects of wind, relative humidity, rainfall and heat units are also important in the selection of vineyard locations (Carey 2001; Carey 2005; Roux 2005; Saayman 1973; Tait 1997).

Schulze's (1997) *South African atlas of agrohydrology and -climatology*, interpolates climatic parameters at a regional level. Climatic variables such as temperature, precipitation, solar radiation, heat units, humidity and evaporation are represented in the atlas as a 1×1 arc minute grid of South Africa, Lesotho and Swaziland. Each grid cell represents almost 2×2 km in metric units. In the texts by Schulze (1997) and De Villiers *et al.* (1996) it is apparent that degree-days (synonymously referred to as heat units) is an important climatic index in agriculture. In viticulture, this parameter is often described as growing degree days (GDDs) (Schulze 1997) and was first applied by Amerine & Winkler (1944) in California (Carey 2006; Vaudour 2004). Le Roux (1974) in Carey (2006) adapted the GDD index for the South Western Cape. Degree-days are based on the premise that below a threshold of accumulated daily temperatures, biological processes do not take place, and this impedes growth and development of plants and invertebrates (Schulze 1997). The opposite is also true, because above a certain threshold of accumulated daily temperatures, growth and development remain static or decline (Schulze 1997).

The basic equation for GDD is expressed as:

$$GDD = \frac{[T_{MAX} - T_{MIN}]}{2} - T_{BASE} \qquad \text{Equation 2.1}$$

where T_{MAX} is the daily maximum air temperature;

T_{MIN} is the daily minimum air temperature; and

T_{BASE} is the base temperature.

In viticulture, a base temperature of 10˚C is normally used (McMaster & Wilhelm 1997).

2.2.2 Soil

Carey (2001), Carey (2005), Maschmedt (1988), Mouton (2006), Roux (2005) and Saayman (2003) distinguish eight characteristics of soil as being most important in influencing viticultural performance, and thus the character and quality of wines, namely chemical composition, pH, colour, temperature, texture, structure, depth and water status. White (2009) has described the essential physical and chemical processes of soils and proposed methods to alleviate adverse soil conditions such as salinity, acidity and poor drainage among others. Maschmedt (1988) has listed the various soils used for the cultivation of grapevines in Australia, but no such list could be found for soils in the viticultural areas in South Africa.

2.2.3 Topography

Topography is a static feature of the landscape and is described by altitude and rate of altitude change over distance (Schulze 1997). Topography has a direct or indirect influence on other environmental parameters such as climate, soil and geomorphology and it is of special importance in viticulture as a slight change in topography may affect grape quality and consequently wine quality (Bryan 2003; Carey, Archer & Saayman 2002). Local relief, slope gradient, slope aspect and curvature are the topographic parameters most often used for the delimitation of terroirs (Carey 2001; Carey 2005; Roux 2005; Tait 1997). The rest of this subsection describes different terrain parameters and concludes with methods of how terrain can be mapped using a GIS.

2.2.3.1 Local relief

Local relief is the absolute difference in elevation between the highest and lowest points in a given land surface (Schloms 1975). Table 2.1 summarizes the categories frequently used for the classification of local relief.

Table 2.1: Description of local relief

Elevation (m)	Description
0-30	equal or no relief
31-90	unequal or slight relief
91-150	moderate relief
151-300	moderate steep relief
301-1500	high relief
>1500	very high relief

Source: Schloms (1975)

2.2.3.2 Slope gradient

Slope gradient is the rate of change in elevation in an x- and y-direction and is expressed in degrees, as a percentage or as a ratio (ARC 2000, Chang 2006). In ArcGIS 9.1, the slope of a DEM is described by the diagram shown in Figure 2.1.

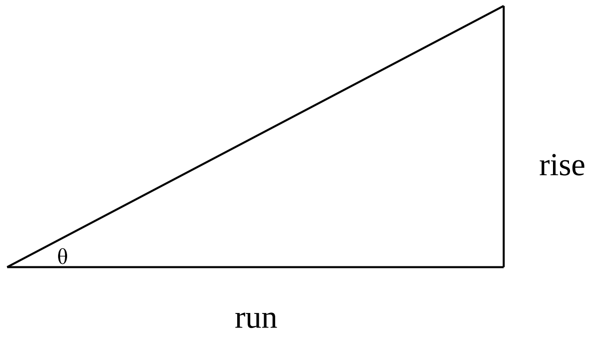


Figure 2.1: Derivation of slope in ArcGIS 9.1

Percentage slope and degree of slope are expressed by the following formulae:

$$\text{Percentage of slope} = \frac{rise}{run} \times 100$$ Equation 2.2

$$\text{Degree of slope} = \Theta$$ Equation 2.3

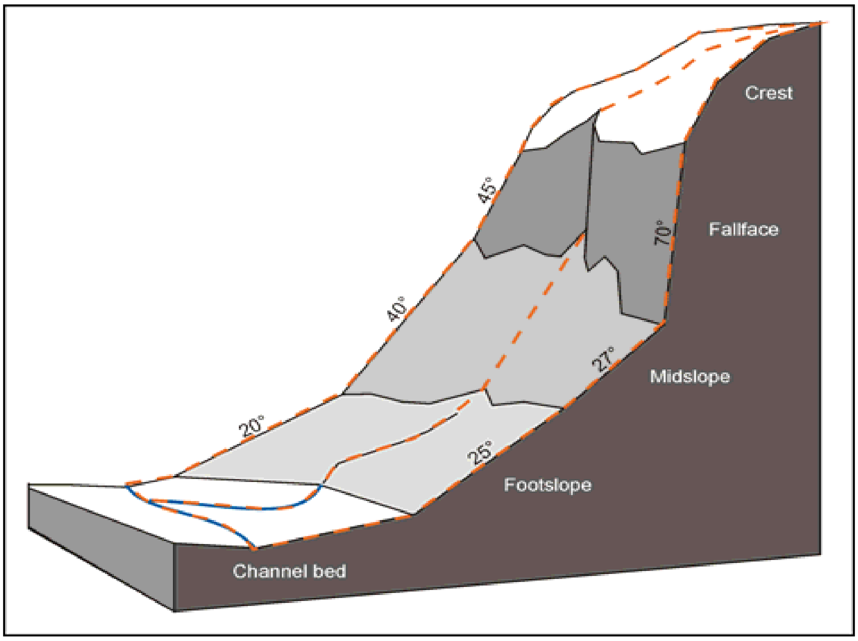
$$\tan\Theta = \frac{rise}{run} \qquad \left(0° \leq \Theta \leq 90°\right)$$ Equation 2.4

where *run* is the horizontal distance and
rise is the vertical distance.

Zietsman, Vlok & Nel (1996) found that a 20-25% slope gradient is critical for the cultivation of crops and they defined six categories for the classification of slope gradient, namely 1-5%, 6-10%, 11-15%, 16-20%, 21-25% and greater than 25%. The ARC (2000), Carey (2001; 2005), Roux (2005), Schloms (1975) and Tait (1997) on the other hand, made use of terrain morphological units to describe a landscape. These units are:

1. Crest (1-7% slope)
2. Scarp (> 90% slope)
3. Mid slope (16-75% slope)
4. Foot slope (1-15% slope)
5. Valley bottom (flat areas with 0% slope).

In some studies, mid slope is subdivided into a low mid slope (15-44% slope) and a high mid slope (45-75% slope) (Tait 1997; Schloms 1975). Figure 2.2 graphically illustrates how Van Niekerk & Schloms (2001) in Van Niekerk (2008) represent terrain components in the slope direction. This classification is known as a hillslope classification.



Source: Van Niekerk (2008)

Figure 2.2: Hillslope components illustrating sequences of five land components

Channel beds are synonymously referred to as either flood plains or valley bottom, while the fallface has been referred to as scarp by ARC (2000), Carey (2001, 2005), Roux (2005), Schloms (1975) and Tait (1997).

2.2.3.3 Slope aspect

Slope aspect is the compass direction of landslope faces (ARC 2000). Aspect measures are usually grouped in the four or eight principal directions listed in Table 2.2 (Chang 2006). Carey *et al.* (2008) divided aspect into four categories for their research on viticultural terroirs in Stellenbosch, namely east (46-135°), southwest (136-270°) and two categories for north west (271-360° and 0-45°) based on differing sunlight interception and the occurrence of local winds during the ripening period. In the southern hemisphere, slopes facing north, east and west receive more direct sunlight than south-facing slopes, and northern and western slopes are warmer than southern and eastern slopes.

Table 2.2: Eight principle compass directions of slope aspect

DIRECTION	DEGREES
North	1- 22.5 & 337.6 - 360
Northeast	22.6 - 67.5
East	67.6 - 112.5
South-east	112.5- 157.5
South	157.6 - 202.5
South-west	202.6 - 247.5
West	247.6 - 292.5
North-west	292.5 - 337.5
Flat areas	0

Source: ESRI (2005)

2.2.3.4 Curvature

Curvature is defined as the rate of change of slope gradient (Van Niekerk 2008). If the curvature of a surface is positive, then the surface is upwardly convex (Chang 2006). On the other hand, if the curvature of a surface is negative, then the surface is upwardly concave (Chang 2006). The curvature of a flat surface is neither concave nor convex (Chang 2006).

2.2.3.5 Terrain mapping

Most of the recent studies reported in the literature on terrain mapping used GIS to illustrate the importance of topographical variables in viticulture. Two methods, namely DEM and triangulated irregular networks (TIN) are frequently used for mapping terrain in GIS (Chang 2006). While Tait (1997) used a TIN, other GIS-related studies used DEM for mapping terrain (Bryan 2003; Carey 2001; Carey 2005; Carey, Bonnardot & Knight 2003; Jones, Snead & Nelson 2004; Martínez-Casasnovas & Sánches-Bosch 2000; NASA Vintage 2003; Pitcher-Campbell, Tuohy & Yule 2001; Scaglione *et al*. 2004; Slaymaker 2001). In some studies, DEM were created from high-resolution satellite imagery (NASA Vintage 2003), kinematic GPS data (Pitcher-Campbell, Tuohy & Yule 2001) or georeferenced aerial photographs (Bryan 2003; Martínez-Casasnovas & Sánches-Bosch 2000; Slaymaker 2001). The spatial resolutions of the DEM reviewed varied from 10 m (Bryan 2003; Jones, Snead & Nelson 2004; NASA Vintage 2003; Pitcher-Campbell, Tuohy & Yule 2001) to 50 m (Carey 2001; Carey 2005). LiDAR (light detection and ranging) and radar data can also be used for DEM creation. Spatial resolutions of up to 0.5 m for DEM have been achieved with LiDAR (Chang 2006). Bryan (2003) constructed nine hydrologically-corrected DEM with different cell resolutions (10 m – 200 m) and, although the effect of scale is the most important factor that influences the modelling of DEM, he found that a 50-m DEM revealed sufficient topographic detail to present the land surface acceptably while minimized computational costs for landscape planning.

2.2.4 Geology

The role of geology in viticulture has not been as comprehensively researched as that of climate, soil and topography (Carey, Archer & Saayman 2002). In the United States, geology has only been considered as a factor in viticulture since the mid-1980s when the terroir concept became popular (Witze 2005). Previously, geologists only mapped contacts between lithological units and provided 3D-models of vineyards (Witze 2005). Sever (2004) concluded that the analysis of soil is more important than the analysis of geology in regions where soils are very old, such as in South Africa. However, studies conducted by South African researchers (Carey 2001; Carey 2005; Carey, Bonnardot & Knight 2003; Saayman 1973; Saayman 2003) have provided broader descriptions of the geological history of study areas and acknowledge the role of geology in viticulture. Wooldridge (2000) evaluated several sources linking geology and viticulture, concluding that the role of geology in viticulture is unique to each specific (viticultural) environment. Wooldridge (2000) pointed out that role of geology has been neglected in terroir studies because parent material is usually covered by several metres of soil. Furthermore, he notes that geology impacts the morphology of the landscape and therefore has an indirect impact on the quality of wines. Wooldridge (2000) reports that the influences of geology in viticulture have not been comprehensively investigated in South African studies as have been done in French studies. Saayman (2003) has overviewed the geology and climatic conditions of the main South African wine-producing regions.

The combination of the environmental parameters comprising terroir is discussed next in relation to two tools, namely GIS and remote sensing.

2.3 GIS AND REMOTE SENSING AS TOOLS IN TERROIR STUDIES

The application of GIS in facilitating viticultural practices worldwide is becoming a widespread endeavour (Vaudour 2004). Several viticultural studies in the traditional wine-producing countries (referred to as the “Old World”) such as France (Fabre, Rodriguez Lovelle & Letessier 2003; Vaudour 2002; Vaudour 2004), Spain (Blanco, Alvarez & Queijeiro 2006; Gomez-Miguel & Sotes 2003) and Italy (Scaglione *et al*. 2004), as well as those in the younger wine-producing countries (the “New World”) such as South Africa (Carey 2001; Carey 2005; Carey, Bonnardot & Knight 2003; Tait 1997), Australia (Bryan 2003) and the United States (Jones, Snead & Nelson 2004; Pitcher-Campbell, Tuohy & Yule 2001; Welton 2004), has applied or recognized GIS technology as an essential tool in their research.

GIS and remote sensing are tools that have applications in a variety of disciplines (Barnard 2001; Campbell 2002). The field of viticulture, particularly viticultural terroir studies, is a multidisciplinary science with branches in soil science, geography (which includes climatology and geomorphology), geology and even cultural history (Carey 2001; Carey 2005; De Blij 1983; Scaglione *et al.* 2004). Although most of the sources reviewed are in the field of viticulture (Blanco, Alvarez & Queijerio 2006; Bryan 2003; Carey 2001; Carey 2005; Carey, Bonnardot & Knight 2003; Carey, Archer & Saayman 2002; Fregoni, Schuster & Paoletti 2003; Jones, Snead & Nelson 2004; Saayman 1973; Saayman 2003; Scaglione *et al*. 2004; Strever 2003; Vaudour 2002; Vaudour 2004; Wooldridge 2000; Tait 1997), it was difficult to classify them into specific disciplines because of the multidisciplinary nature of GIS, remote sensing and viticulture.

2.3.1 GIS applications

GIS is an effective and invaluable tool in a multidisciplinary approach to terroir studies, primarily because of its ability to superimpose various data layers (Scaglione *et al*. 2004). Climatic, topographical, pedological and/or geological data have been combined in GIS to identify natural terroir units in various locations throughout the world (Bryan 2003; Carey 2001; Carey 2005; Carey, Bonnardot & Knight 2003; Gomez-Miguel & Sotes 2003; Jones, Snead & Nelson 2004; Scaglione *et al*. 2004; Tait 1997). However, as noted by Vaudour (2002), GIS technology has only been applied in terroir-related studies since the 1990s.

In South Africa, Carey (2001), Carey (2005) and Carey, Bonnardot & Knight (2003) used GIS to identify viticultural terroirs in Stellenbosch. In these studies, a broad description of the viticultural history, climate, topography, soil and geology of the study area is discussed. Digital data of these environmental parameters were used in a GIS to assist the identification of natural terroir units. Slope gradient, slope aspect and altitude were derived from a 50-m DEM, while soil (at a 1:50 000 scale) and geological data (1:250 000 scale) were obtained from secondary data sources. Climatic data was obtained from automatic and mechanical weather stations in the vineyards and were interpolated by means of climate modelling.

In another study in the Stellenbosch area, Tait (1997) compiled maps of soils (obtained from a complete soil survey of the study area), slope gradient and slope aspect (derived from a TIN) in a GIS to identify optimal terrains for the cultivation of vineyards on one farm. Before identifying optimal terrains for different cultivars, Tait (1997) first investigated the theoretical environmental conditions (slope aspect, slope gradient, temperature and soil) of specific cultivars, then applied spatial analysis using GIS and finally identified areas suitable for the cultivation of specific cultivars.

Girard & Girard (1998) conducted a similar study to those of Carey (2001), Carey (2005), Carey, Bonnardot & Knight (2003) and Tait (1997) in which they mapped soil landscapes in Lorraine, France. In their study, land cover, geology and morphology were used as primary criteria in their soil mapping approach. The resulting map consisted of 54 soil landscape units, which were described by 15 different variables. The authors acknowledged difficulty of representing 54 units on a single map and proposed that a more simplified soil landscape map with broader zones should solve the problem.

The representation of many soil landscape units on a single map was partially solved by Gomez-Miguel & Sotes (2003) and Jones, Snead & Nelson (2004). In their studies, individual land suitability maps were created for, among other things, topography, soil, geology, vegetation and climate. Suitability values were created for each of the individual components and added to present a single suitability map.

2.3.2 Remote sensing applications

Remote sensing technology, which is often incorporated into GIS, has been recognized as an essential tool for agricultural applications (Campbell 2002). Many researchers have used this technology in applications ranging from soil science (Iqbaluddin *et al*. 1999; Martínez-Casanovas & Sánches-Bosch 2000; Mermut & Eswaran 2001; Mullers 1987; Pitcher-Campbell, Tuohy & Yule 2001; Slaymaker 2001; Verma, Cooke & Wendte 1997) and geology (Sever

2004; Witze 2005) to viticulture (ESA 2003; Goode 2004; Hall, Louis & Lamb 2003; Johnson *et al*. 2003; NASA Vintage 2003; Strever 2003; Vaudour, Carey & Gilliot 2010) and forestry (Lück 2004; Tuominen & Pekkarinen 2004).

Remote sensing technology has been widely applied in agricultural sciences since the introduction of the term precision agriculture in the early 1990s (Goode 2004). Precision agriculture is applied in crop management and is based on the monitoring of yield, growth, fertilizer application and other techniques (Strever 2003). Precision viticulture is a branch of precision agriculture (Goode 2004) and describes the "concept of monitoring and managing spatial variability in yield and quality factors within single vineyards" (Strever 2003: 18). The rest of this subsection will give a brief overview of how remote sensing has been used in viticultural studies and image classification techniques of satellite images, with a specific focus on object-oriented remote sensing.

2.3.2.1 Remote sensing in viticulture

Multi-spectral imagery obtained from aerial photography and satellite imagery has been widely applied in agricultural studies. The world leader in space technology, NASA, recognized this potential and has developed specific programmes to improve agricultural efficiency and increase the production and quality of agricultural products (NASA Vintage 2003). In one programme, NASA used high-resolution IKONOS satellite imagery to create map composites of normalized difference vegetation index (NDVI) values, to indicate active growth and productivity of vegetation of vineyards (Campbell 2002; NASA Vintage 2003). Other products generated in the NASA Vintage programme were a high-resolution DEM created from orthorectified aerial photography and a set of soil maps obtained from the satellite imagery (NASA Vintage 2003). The European Space Agency (ESA) mapped Europe's vineyards from space with the use of remote sensing and GIS to provide vineyard managers with the necessary guidelines to improve production management (ESA 2003). Satellite images with a spatial resolution of 0.65 m and aerial photographs with an even higher spatial resolution were used in the analysis to automatically detect vineyards and weeds (ESA 2003).

Johnson *et al*. (2003) suggest that remote sensing techniques are more efficient and cost-effective than traditional ground-based surveys and they used NDVI values calculated from high-resolution images to map leaf area index (LAI) values. The LAI is used as an indicator of fruit ripening rate, infestation, disease, water status, fruit characteristics and wine quality (Johnson *et al*. 2003). In a similar study, Strever (2003) used NDVI values to establish an experimental model to identify and classify within vineyard variability where the causes of variation within plants and its effect on plants are investigated. A sensor called *Fieldspec Pro FR Field Spectroradiometer* was used by Strever (2003) to hyperspectrally measure the reflectance values of vineyards in 12 spectral channels. By contrast, Hall, Louis & Lamb (2003) derived an algorithm called "Vinecrawler" to calculate key vine-canopy variables such as foliage, size, density and shape information from reflectance values of vineyards.

Vaudour, Carey & Gilliot (2010) mapped viticultural terroirs by using bootstrapped decision trees on morphometric data and SPOT 4 satellite images. Multidate and multiseasonal images were geometrically and radiometrically corrected to accurately map vineyards at different growth cycles of the grape vine and to characterize soil surface properties. In the bootstrapped approach, a number of classification trees were constructed and an algorithm with 100 iterations was run over the morphometric and satellite data using 25 training areas. The modal image of a "hyperclassified" image, consisting of 100 classified images, was used to finally map eight viticultural terroir units. The authors identified a few shortcomings in their research, including the need for scarce expert knowledge to define terroir units, the lack of additional data such as soil properties, heterogeneous soil management and viticultural practices which influence spectral surface characteristics, the unbalanced selection of sampling data and a lack of monitoring the viticultural network in the specific study area.

The method Vaudour, Carey & Gilliot (2010) used for the construction of classification trees was a supervised classification method. Campbell (2002) distinguished between three classification techniques, namely supervised classification, unsupervised classification and hybrid classification. Another method of image classification, namely object-oriented classification, can be added to this list. Supervised classification is a technique where training data of known classes are used to classify unknown pixels (Campbell 2002; Lillesand & Kiefer 1979). Unsupervised classification is the identification of groupings of pixels within multispectral data, while hybrid classification is a technique using both supervised and unsupervised classification methods (Campbell 2002). Object-oriented image analysis is discussed in greater detail in the following section.

2.3.2.2 Object-oriented remote sensing

Object-oriented remote sensing makes use of segments or image objects for image classification (Benz *et al.* 2004; Bock *et al.* 2005; Dragut & Blaschke 2006; Gamanya, De Maeyer & De Dapper 2007; Lück 2004). This means that objects, rather than single pixels, are the elementary processing units in object-oriented image analysis (Dutta, Serker & Warnitchai 2005). Contrary to what is implied in the bulk of the reviewed literature, object-orientation and image segmentation are not new concepts to either GIS (Camara *et al.* 1996) or remote sensing (Maxwell 2004). Recent literature on remote sensing image classification reveals a shift from the traditional pixel-based method to an object-oriented approach (Benz *et al.* 2004; Bock *et al.* 2005; Dragut & Blaschke 2006; Gamanya, De Maeyer & De Dapper 2007; Laliberte *et al.* 2004; Lück 2004; Maxwell 2004; Mueller, Segl & Kaufmann 2004; Rowlands & Lucas 2004). The eCognition software by Trimble, which was previously known as Definiens, has been the most widely used software for object-oriented image analysis for almost a decade ((Benz *et al.* 2004; Trimble 2011). Some of the traditional pixel-based image processing software, such as Erdas Imagine and IDRISI Taiga has also incorporated image segmentation in their latest versions (Clarke Labs 2008; Leica Geosystems 2008). Benz & Schreier (2001), Gao (2003), Lück (2004), Oruc, Marangoz & Buyuksalih (2004), and Walter (2003) used the eCognition software in their studies for image classification, and some of these studies (Gao 2003; Oruc, Marangoz & Buyuksalih 2004) compared object-based and pixel-based classification methods. Both Gao (2003) and Oruc, Marangoz & Buyuksalih (2004) reported that object-based classification provides higher accuracies than pixel-based classification.

2.3.2.3 Image segmentation

Image segmentation is the process by which an image is subdivided into smaller image objects or segments (Definiens Developer 2007a). Thus, image segmentation is the fundamental step of any eCognition project (Definiens Developer 2007b). Image objects are the elementary units on which classification is based and every segmented image consists of groups of homogeneous pixels which are related to each other (Baatz & Schäpe 2000; Gao 2003). Image segmentation in eCognition Developer provides five different segmentation algorithms, namely, chessboard segmentation, quad tree-based segmentation, contrast split segmentation, multiresolution segmentation (MRS) and spectral difference segmentation (Definiens Developer 2007a). The different segmentation algorithms operate as follows:

i) *Chessboard segmentation:* the image object or pixel domain is split into a grid of square image objects. The size of the image objects is defined as an input parameter.

ii) *Quad tree-based segmentation*: the pixel domain or image domain is split into a quad tree grid formed by square objects.

iii) *Contrast split segmentation:* defines bright and dark regions of an image object, based on threshold values.

iv) *Multiresolution segmentation (MRS):* locally minimizes the average heterogeneity of an image object for a given resolution by the application of an optimization procedure on the pixel-level domain or an image-object-level domain. Scale parameter and homogeneity criteria, based on colour and shape, are defined as input for this algorithm.

v) *Spectral difference segmentation:* uses the mean layer intensity values of neighbouring objects to merge the objects. A value of maximum spectral difference is used as an input parameter to distinguish between neighbouring objects.

Because of the underlying principle of the MRS algorithm, it has been the preferred segmentation algorithm at various scientific centres (Lewinski & Bochenek 2008). Baatz & Schäpe (2000) investigated several scenarios testing this algorithm and concluded that it yields optimal results in a wide variety of problems and using many different types of data. Another popular justification for the preference of this algorithm over others is that it produces highly homogenous segments over the image (Gao 2003).

The size of image objects in multiresolution segmentation depends on the scale parameter and values specified in the homogeneity criterion. As explained in Figure 2.3 the scale parameter determines the maximum allowed heterogeneity for the resulting image objects, i.e. image objects will be smaller in heterogeneous data sets (Definiens Developer 2007a). The homogeneity criterion is based on the weighting of colour and shape (Definiens Developer 2007a).

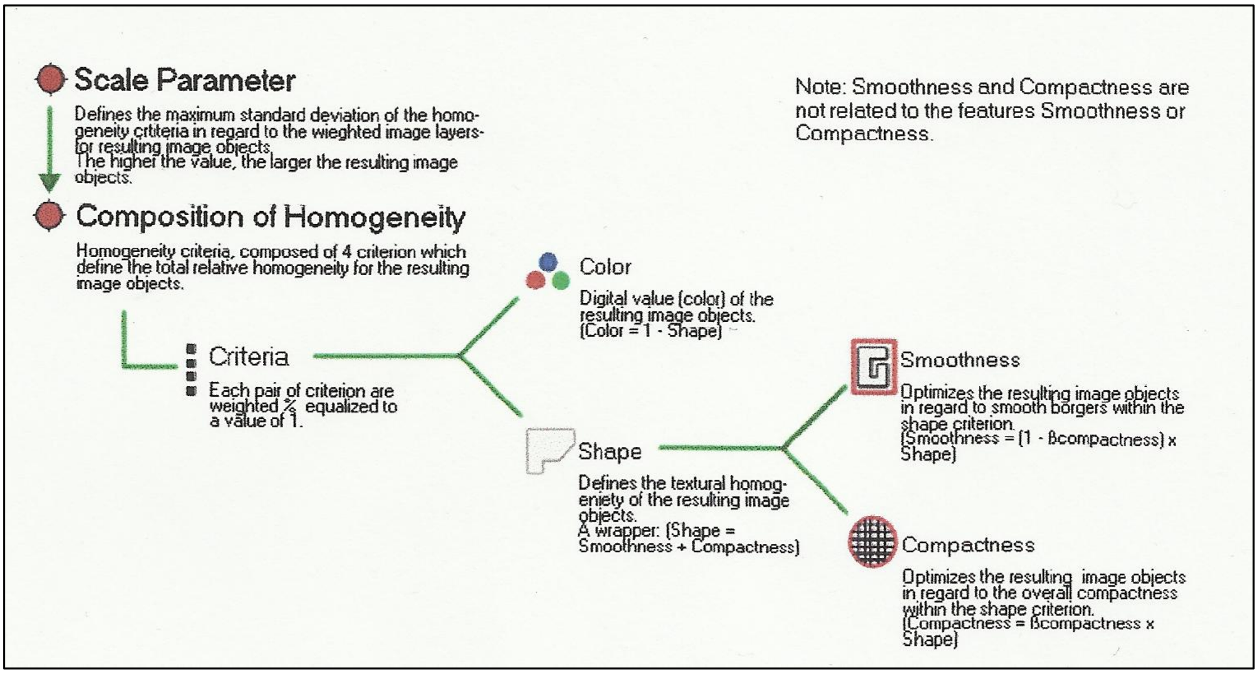


Figure 2.3: Concept flow diagram of the MRS algorithm

Source: Definiens Developer (2007a)

Colour takes the standard deviation of spectral colours into account, and the shape criterion takes smoothness and compactness into account (Definiens Developer 2007a). Furthermore, the multiresolution segmentation algorithm allows for the application of different weightings to different image layers, depending on the importance of the layer in the segmentation process, i.e. the higher the weight of a layer, the more information it uses during the segmentation process (Mitri & Gitas 2008). Image classification follows the segmentation process.

2.3.2.4 Image classification

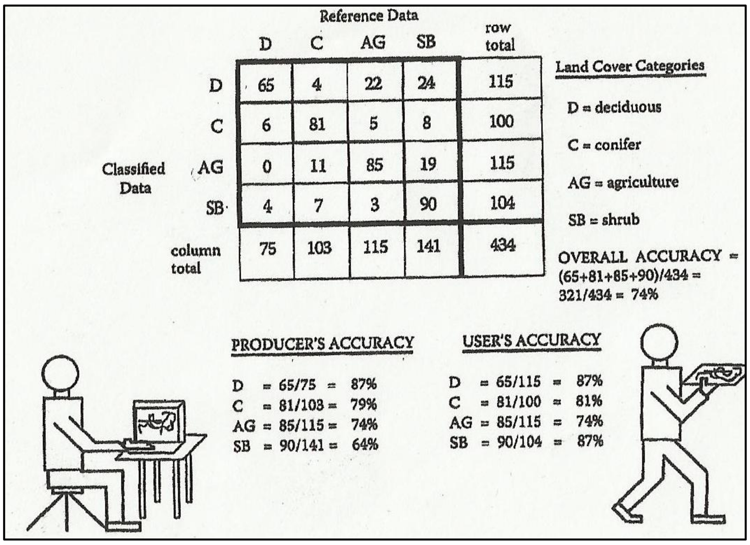
Various classification algorithms exist in the eCognition software (Definiens Developer 2007a). These algorithms are divided into basic and advanced classification algorithms (Definiens Developer 2007a). The basic classification algorithms allow users to classify objects based on criteria that best separate one class from the other, while the advanced classification algorithms uses special criteria to classify objects (Definiens Developer 2007a). De Kok & Wezyk (2006) demonstrated how a sequential rulebase can be executed in the eCognition software to classify objects by means of threshold values that meet certain conditions. Mitri & Gitas (2008) demonstrated a different technique where training data were used to develop the classification rules and to classify objects, while Benz *et al.* (2004) discussed how fuzzy classification can be used to classify images.

The results of image classification using satellite images are usually land use or land cover maps. Land cover is the natural or man-made cover on the earth's surface that can be directly observed at a specific instance of time, whereas land use is the functional use of land by humans (Campbell 2002). Examples of land cover include vegetation, water and built-up areas, while recreational, agricultural and mining activities are examples of land use.

2.3.2.5 Accuracy assessment

Accuracy assessment is the process by which the quality of the map created from remote sensing data is determined (Congalton & Green 2009). According to Congalton & Green (2009), the three critical steps to be taken during accuracy assessment are sample design, the collection of reference data and the use of error matrices to analyse the results.

An error matrix is an $n \times n$ array, where n is the number of categories or classes (Campbell 2002). The reference data (which is assumed to be the "correct" data) is listed on the *x*-axis, while the classified data is listed on the *y*-axis (Congalton & Green 2009). These two axes are interchangeable as Campbell (2002) notates axes differently to Cangalton & Green (2009) and mentions that there is no universal convention for labelling the axes. Figure 2.4 illustrates an example of an error matrix.



Source: Congalton & Green (2009: 17)

Figure 2.4: Example of an error matrix

The matrix is populated by numbers that compares the classified samples to the reference samples (Campbell 2002). The sum of the major diagonal divided by the number of sample units in the error matrix, gives the overall accuracy of the classification (Congalton & Green 2009). Two types of errors, namely the *errors of omission* and *errors of commission*, are usually described to examine the error matrix (Campbell 2002). An error of omission is when a classified sample does not correspond to its reference sample, i.e., the reference sample has been omitted, while an error of commission is the assignment of a reference sample to the wrong classified sample Campbell (2002). According to Campbell (2002), sources of classification error includes parcel size, variation in parcel size, parcel identities, number of categories, arrangement of categories, number of parcels per category, shapes of parcels and finally the radiometric and spectral contrast with surrounding parcels.

2.4 SUMMARY

The application of GIS to viticultural studies particularly related to viticultural zoning and terroir is relatively new. As a result, documented examples of GIS and/or remote sensing research in terroir-related studies are scarce. The earliest reported use of GIS in terroir-related studies in South Africa is by Tait (1997), while Vaudour, Carey & Gilliot's (2010) study is the most recent.

The literature review has identified the relevant data that are needed to identify NTU, namely climatic, soil, geological and topographical data, as well as satellite images. The availability and scale of digital GIS data are shortcomings identified in the literature, especially digital climatic and topographic data.

Concerning remote sensing methodologies to classify satellite imagery, it is clear that the eCognition software is the preferred choice of object-oriented software and the MRS algorithm is the preferred segmentation algorithm. Consequently, this software and segmentation algorithm will be used in the land cover classification process to pursue the second objective of this study. Accuracy assessment will be conducted as described by Congalton & Green (2009), with special attention being paid to the three critical steps of accuracy assessment.

Methods to incorporate the GIS data and remote sensing data in the identification of NTU are proposed in various studies, but the approaches followed by Carey (2001), Carey (2005), Carey, Archer & Saayman (2002), Carey, Bonnardot & Knight (2003), Girard & Girard (1998), Tait (1997) and Vaudour, Carey & Gilliot (2010) can be applied to achieve the third objective. The use of GIS as an essential tool to identify NTU is more widely applied than remote sensing, however Girard & Girard (1998) and Vaudour, Carey & Gilliot (2010) demonstrate how valuable remote sensing data are in this process. Girard & Girard (1998) named one important shortcoming in terroir-related studies, namely the difficulty to the represent a large number of classes on a single map. Gomez-Miguel & Sotes (2003) and Jones, Snead & Nelson (2004) provide a solution to this shortcoming by using suitability maps to indicate NTU for specific cultivars. Suitability maps however, do not address the research problem and will therefore be disregarded.

The work of Goussard (2008) and Tait (1997) will be used as guidelines to assess the viticultural potential of the NTU as these texts provide information on the preferred natural conditions for the cultivation of wine grapes. The following chapter will introduce the study area and data collection and -preparation procedures.

CHAPTER 3: STUDY AREA, DATA COLLECTION & PREPARATION

This chapter will introduce to the study area and will discuss the data that has been collected in order to identify NTU. A description of the data is provided and the methods to prepare the data for analysis are discussed in detail. The chapter concludes with a model that will be followed to identify NTU.

3.1 STUDY AREA

Robertson was chosen as the study area because it represents a different environment to that of terroir studies conducted in the Stellenbosch Wine District (Carey 2001; Carey 2005; Carey, Archer & Saayman 2002; Carey, Bonnardot & Knight 2003; Carey *et al.* 2008; Vaudour, Carey & Gilliot 2010). Where Stellenbosch represents coastal viticulture and forms part of the Coastal Region with irrigation being practiced conservatively, Robertson represents a fully irrigated semi-arid wine-producing region which is part of the Breede River Valley Region. Table A1 in Appendix A lists regions, districts and wards as demarcated by the Wine and Spirits Board, whereas Figures A1 to A4 shows the respective production areas in South Africa. The Coastal and Breede River Valley Regions are shown in Figure A2, while the Stellenbosch and Robertson districts are shown in Figure A3.

The Breede River Valley lies in the central part of the Cape Fold Belt and is located between the Langeberg in the north and the Riviersonderend Mountains in the south (Flügel & Kienzle 1989; Wooldridge 2005). The Breede River, which has its source in the mountains near Ceres, runs in a south-easterly direction through the study area and reaches the Indian Ocean near Witsand and Port Beaufort. The Western Cape is bordered by the Atlantic Ocean to the west and the Indian Ocean to the south (Flügel & Kienzle 1989). For this research, the study area (which encompasses an area of 158 897 ha) is demarcated by the municipal boundary of the Robertson local municipality (LM) as determined by the Municipal Demarcation Board of South Africa. The Robertson Wine District (RWD) is located in the interior of the south-western most part of the Western Cape province of South Africa (see Figure 3.1).

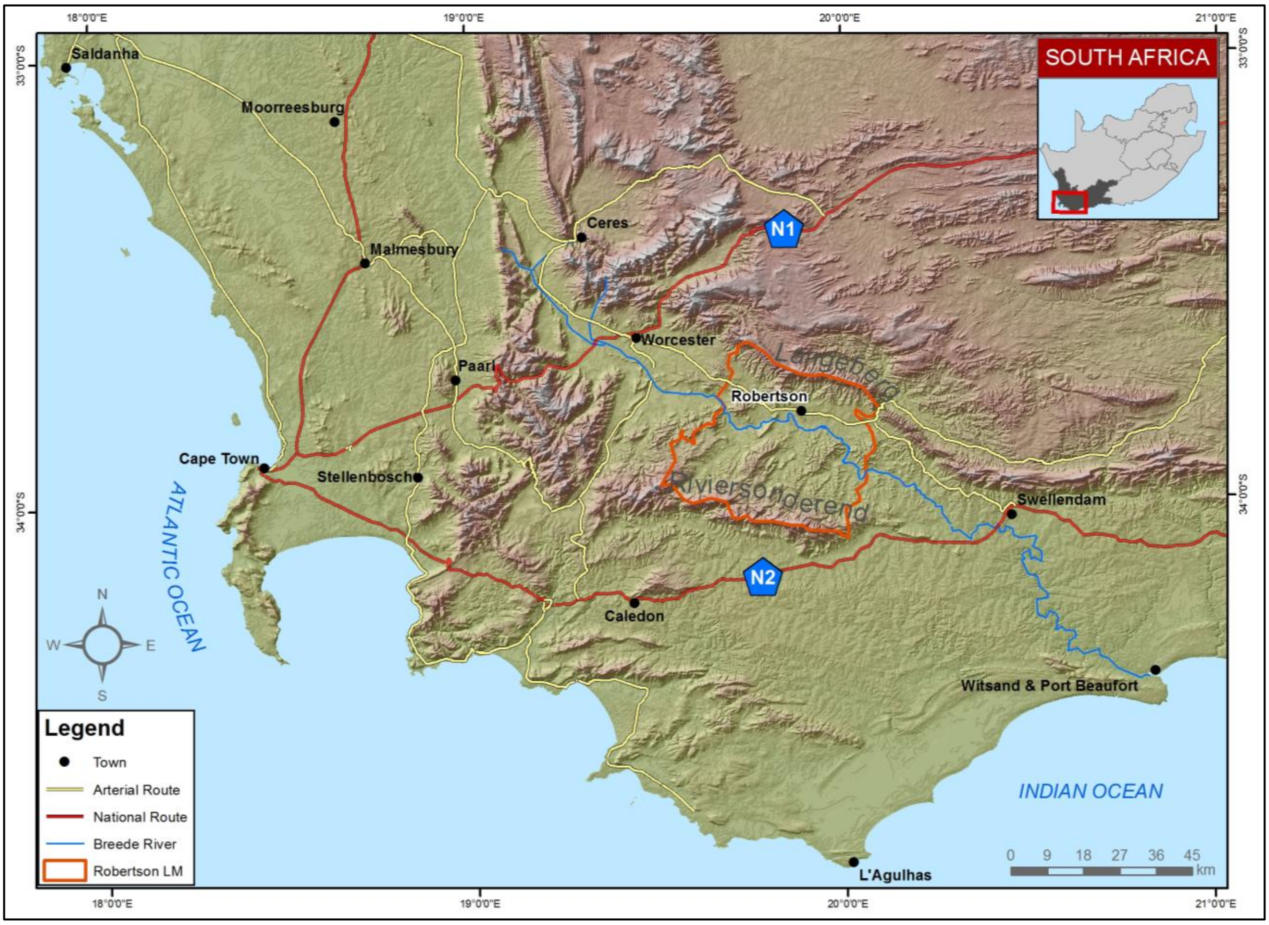
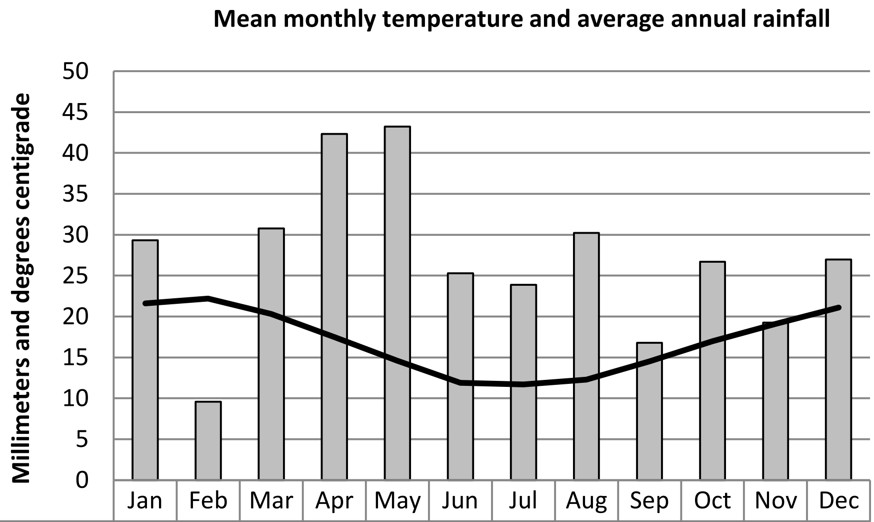


Figure 3.1: Location of Robertson in the Southwestern Cape

This boundary differs from that of the Robertson wine district (RWD) demarcated by the Wine and Spirit Board as it excludes the Bonnievale ward east of Robertson. Figure B1 in Appendix B indicates the Robertson LM and Robertson Wine of Origin District boundaries. The rest of the chapter comprises an exposition of the data used to study NTU, as well as the steps taken to prepare this data.

3.2 CLIMATE

The mean summer and winter temperatures of Robertson is 23°C and 14°C respectively (SAWB 1996). During summer, maximum temperatures of over 35°C are experienced and February is notably the warmest month. The A-pan evaporation of the area is about 1800 mm/yr, which is much higher than precipitation (Flügel & Kienzle 1989; Kirchner *et al.* 1997). Literature detailing the climatological conditions of the Robertson district is scarce. Information obtained from the Institute of Soil, Climate and Water (ISCW) on the weather conditions at 18 weather stations surrounding Robertson is appended in Tables B1 to B5. Rainfall and average temperatures were recorded on a monthly basis for each of these stations over a period of between one year and ten years. Most stations have records of five or more years of records, while only four stations have records for less than five years. Figure 3.2 is a climagram of the average temperature and total rainfall of the weather stations having records of five or more years.



	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Rainfall (mm)	29.3	9.6	30.8	42.3	43.2	25.3	23.9	30.2	16.8	26.7	19.2	27.0
AverageT (°C)	21.60	22.20	20.3	17.5	14.6	11.9	11.7	12.3	14.5	17	19.1	21.1

Figure 3.2: Monthly average temperature and mean rainfall from the automatic weather station network

According to Figure 3.2, February is the warmest and driest month, with a mean temperature of 22°C. June and July are the coldest months. With an annual rainfall of 323 mm, the climate of the Robertson area is classified as semi-arid (Grolier 1997; Kirchner *et al.* 1997). The area receives its highest precipitation during April and May. Because the information used in Figure 3.2 (and listed in Appendix B) was collected over a period of five to ten years only (1997 to 2006) it does not faithfully represent the general climate of the area. However, the numbers do not deviate significantly from those presented in other studies (Flügel & Kienzle 1989; Kirchner *et al.* 1997).

Figures 3.3 and 3.4 illustrate the mean February temperature (MFT) and the heat units acquired during the growing season respectively. From these figures it is clear that temperatures are higher in low-lying areas and decrease with increasing elevation.

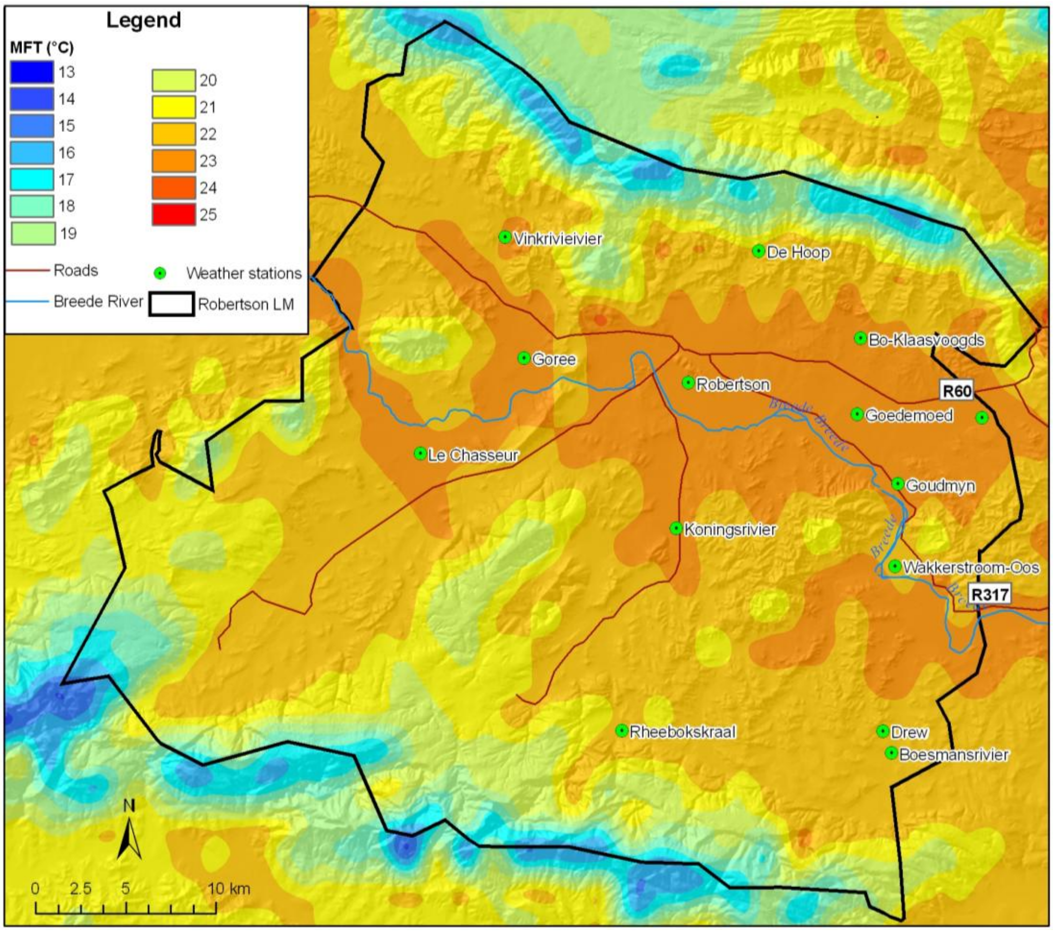


Figure 3.3: Mean February temperature of the study area resampled to 20 metres

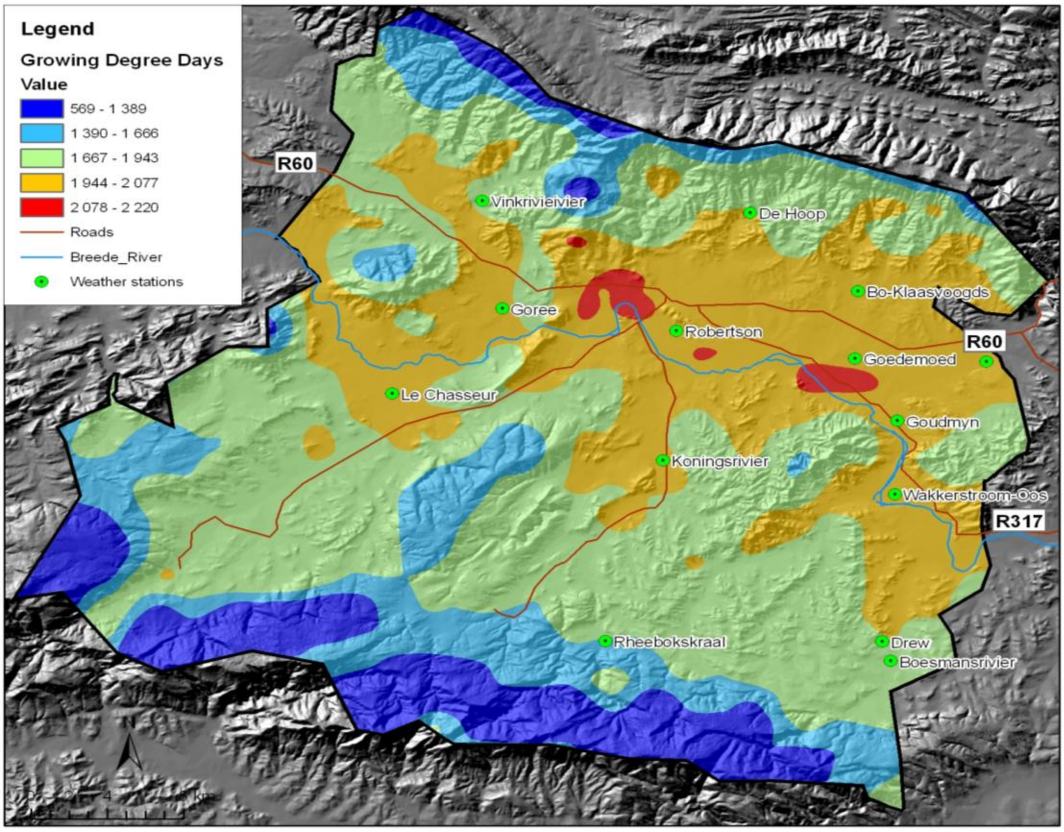


Figure 3.4: Heat units or growing degree-days from October to March of Robertson

Figure 3.5 shows that mean annual rainfall varies between 200 mm and 400 mm throughout the study area and generally increases with increasing elevation. The climate data represented in Figures 3.3, 3.4 and 3.5 were obtained from the *South African atlas of agrohydrology and -climatology* and were resampled in ArcGIS using the cubic convolution method. Cubic convolution calculates a weighted average of an input raster from the 16 nearest input cells and their values to create an output raster (ESRI 2005). Although this interpolation requires more computation, it creates smoother edges of the data compared to other interpolation methods such as the nearest neighbour and bilinear cubic interpolation methods (ESRI 2005).

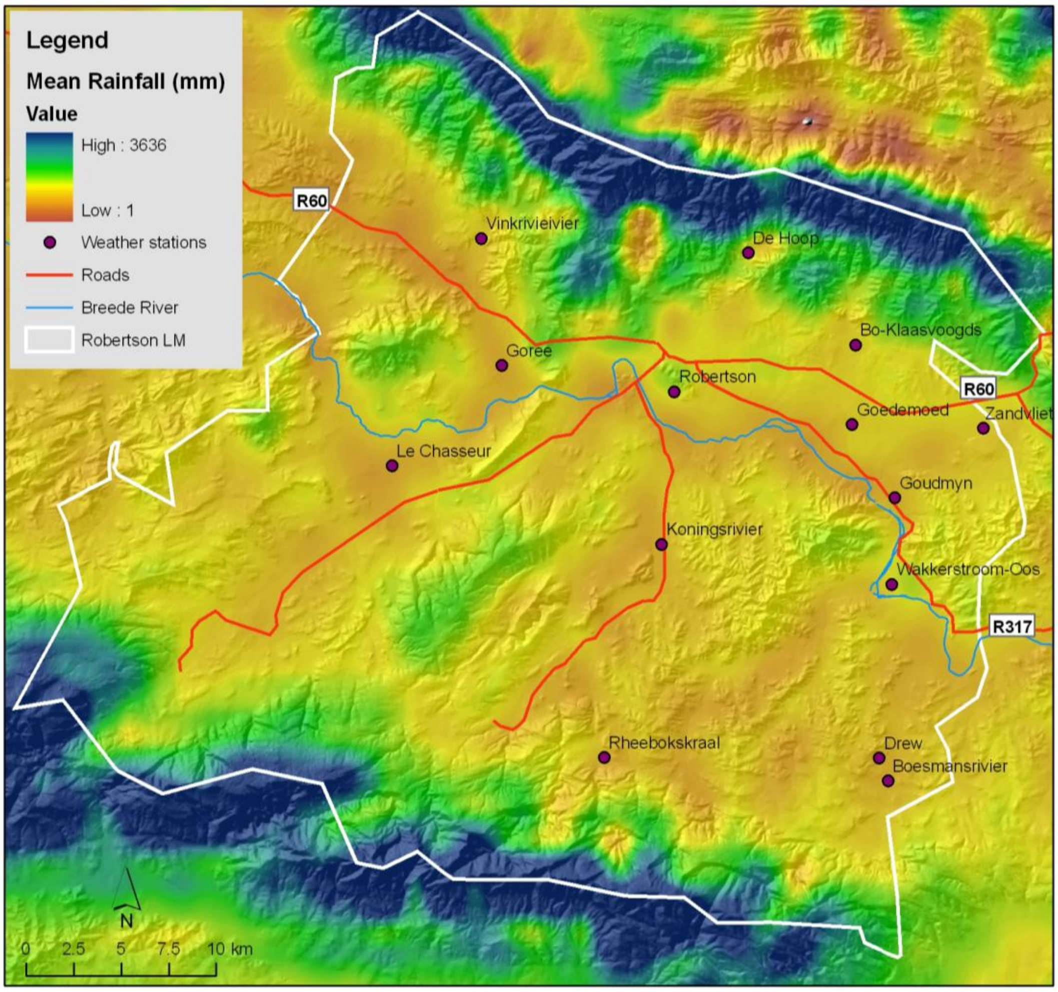


Figure 3.5: Mean annual rainfall of Robertson

Information regarding wind direction and speed is not captured by the weather stations in the area. However, the warm summer months are associated with south-easterly winds; while westerly to north-westerly winds is the norm during the rainy winter months (SAWB 1996; Schloms 1975). Frost is restricted to between 30 and 60 days a year for the entire Breede River valley (Schloms 1975).

This section has established that Robertson has a semi-arid climate and demonstrated how topography influences climate. There is a general decrease in temperature with an increase in elevation and an increase in precipitation from the valley towards the mountains. The following section describes the topography and the different topographic parameters of the study area in more detail.

3.3 TOPOGRAPHY

All topographic parameters (local relief, slope gradient and slope aspect) set out in this section were computed by means of the Western Cape digital elevation model (WCDEM) in the ArcGIS 9.2 software. This DEM, developed by the Centre for Geographical Analysis (CGA) at Stellenbosch University, was interpolated from the contours of the 1:50 000 topographical map series and has a 20-m cell resolution (Van Niekerk 2008). Slope gradient and slope aspect of the study area will be described in the following subsections.

3.3.1 Slope aspect

Table 3.1 shows that most slopes in the study area are north-facing, followed by those facing to the south-east and north-west. West-facing slope aspects occur least. Figure 3.6 shows the slope aspect of the terrain computed with ArcGIS 9.2 software.

Table 3.1: Percentage area of the slope aspect of the terrain

Direction	Degrees	Area (ha)	Percentage
North	0 - 22.5 & 337.6 - 360	24 586	15.6
North-east	22.6 - 67.5	18 937	12.0
East	67.6 - 112.5	18 371	11.7
South-east	112.6 - 157.5	21 339	13.56
South	157.6 - 202.5	18 109	11.5
South-west	202.6 - 247.5	18 204	11.6
West	247.6 - 292.5	16 952	10.8
North-west	292.6 - 337.5	20 755	13.2
Total		157 253	100.00%

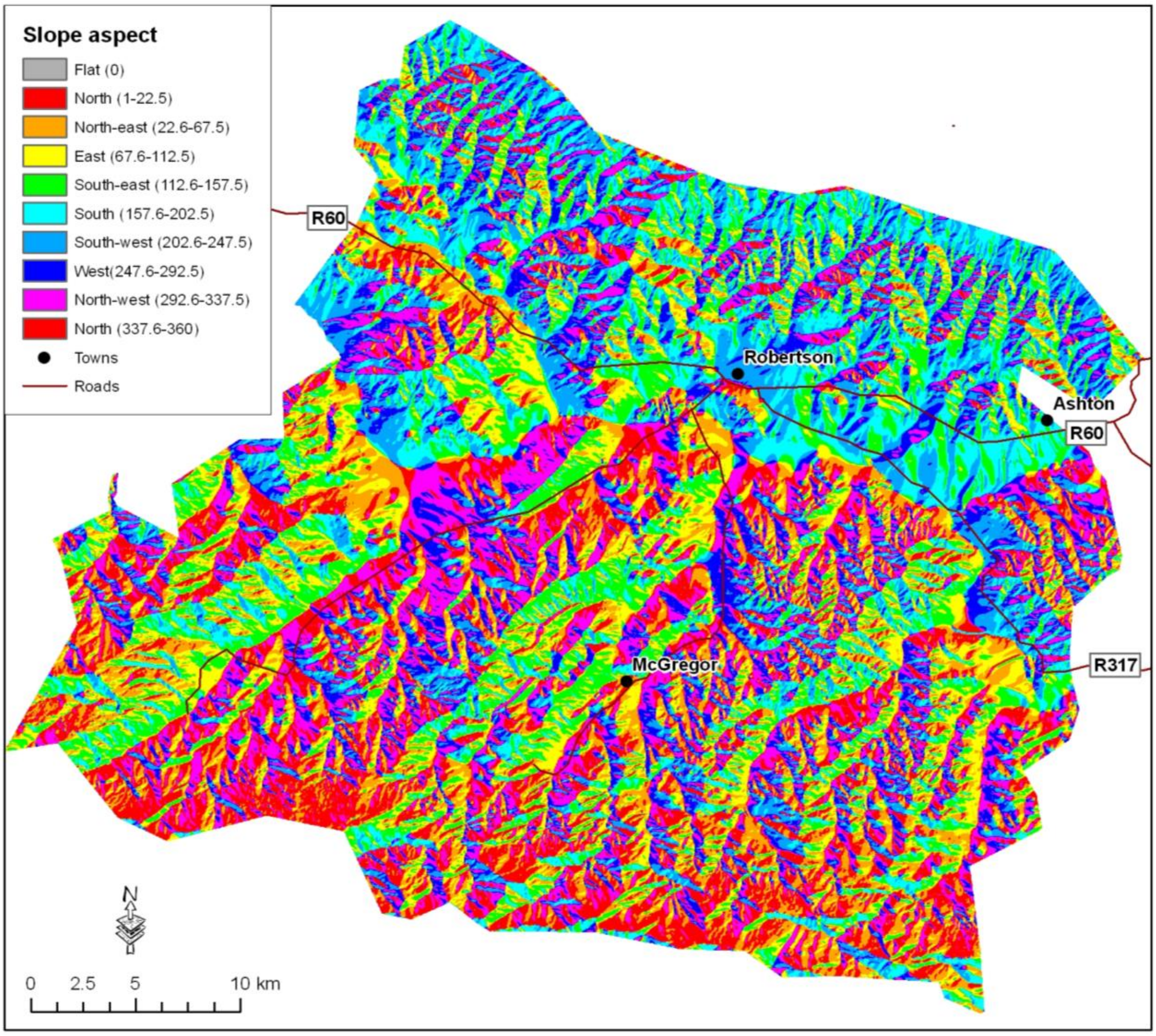


Figure 3.6: Slope aspect

3.3.2 Slope gradient

The slope gradient was computed with the ArcGIS 9.2 software. A total area of 57 245 ha or 36% of the study area has a slope gradient of more than 25%, which is greater than the limit for the cultivation of crops (Zietsman, Vlok & Nel 1996). Figure 3.7 illustrates the slope percentage of the study area using the classification suggested by Zietsman, Vlok & Nel (1996).

The topography of the study area varies dramatically, with the majority of the terrain being steep and rocky. The following two sections will investigate the geology and soil of the study area and will give insight into the parental material underlying the landscape and its subsequent soil formations.

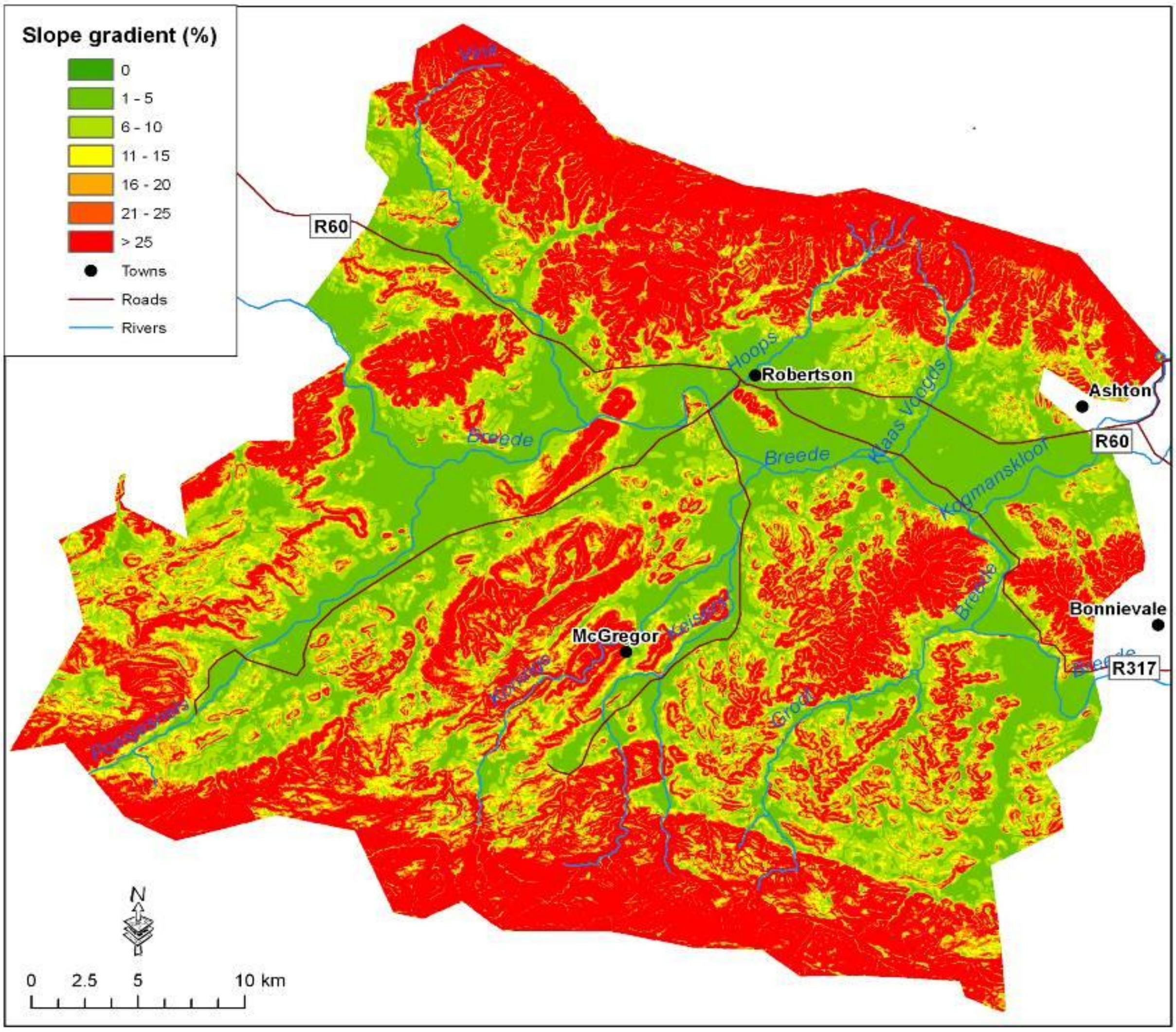


Figure 3.7: Slope percentage

3.4 GEOLOGY

The study area's geology is dominated by formations of the Cape Supergroup which were formed between the Ordovician (500 mya[1]) and the Devonian (360 mya) (Wickens 2004; Flügel & Kienzle 1989). At the foot slopes of the Langeberg, formations of the Malmesbury Group occur which are of Precambrian age (Kirchner *et al.* 1997; Wooldridge 2005). Figure 3.8 illustrates the geological deposits of Robertson as described by Wooldridge (2005).

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[1] Mya = million years ago

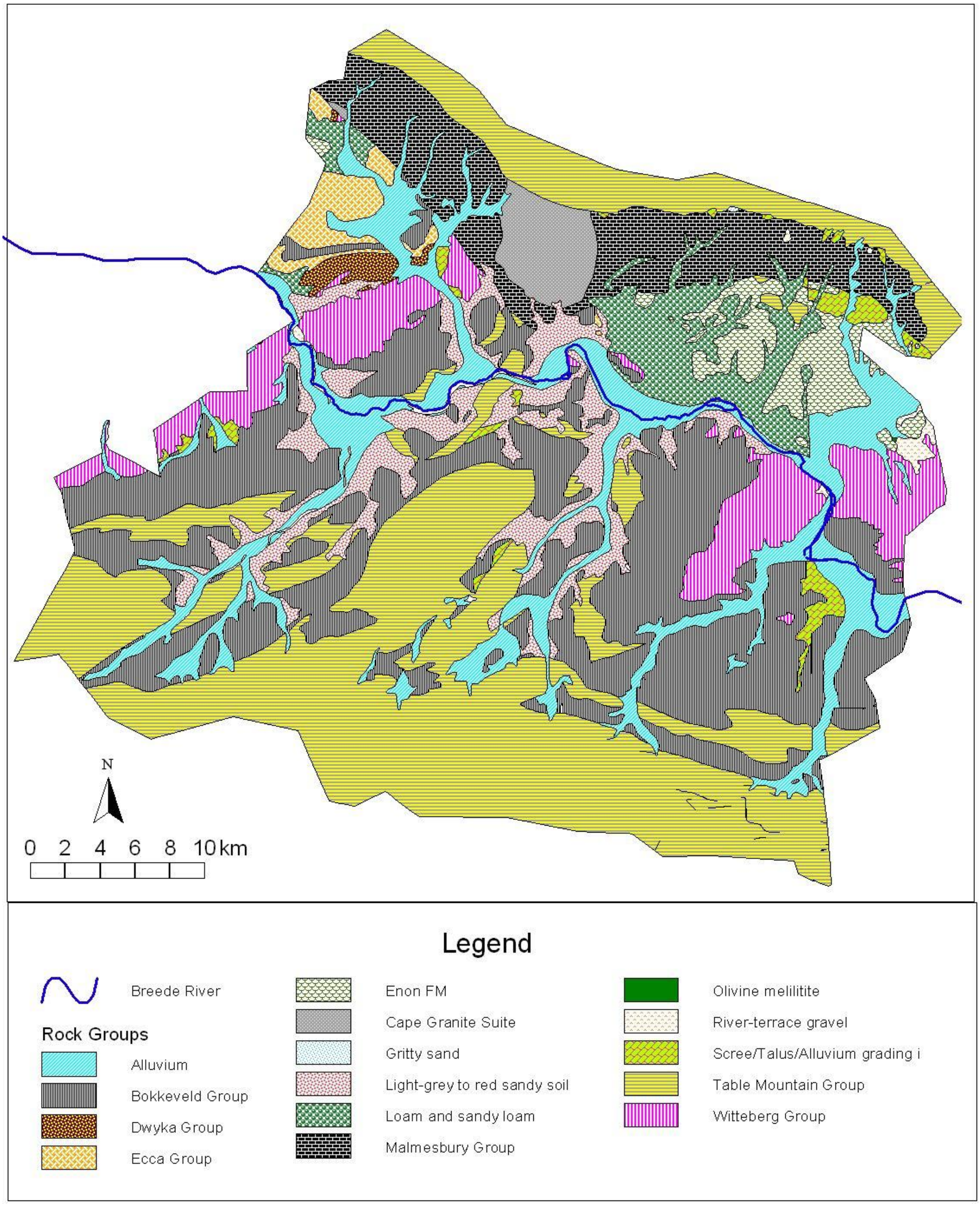
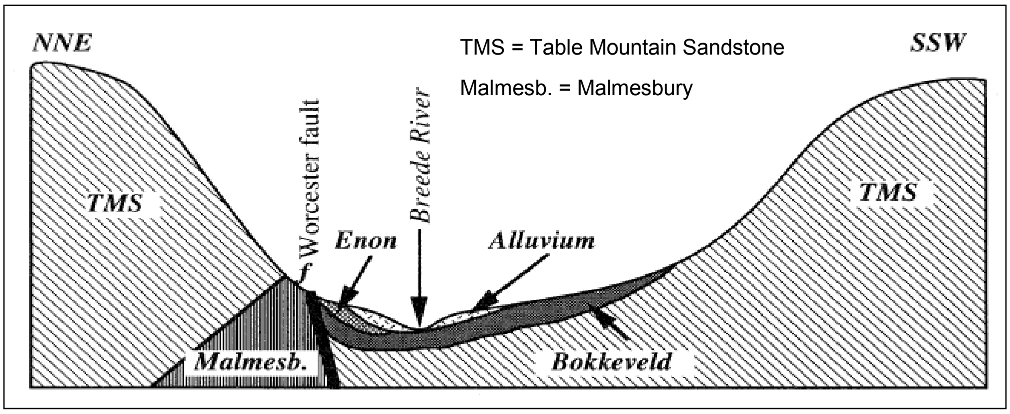


Figure 3.8: Generalized description of the geological deposits

These formations have a northerly dip and a general strike of WNW-ENE (Kirchner *et al.* 1997; Flügel & Kienzle 1989). Figure 3.9 illustrates that a set of related faults comprising the Worcester fault stretches south of the Langeberg range in an easterly direction through the study area (Wooldridge 2005). The Worcester Fault was formed during the early Cretaceous (135-130 mya) when South America and Southern Africa separated from each other (Wickens 2004; Wooldridge 2005).



Source: Flügel & Kienzle 1989

Figure 3.9: Geological cross-section through the Breede River Valley

The Langeberg in the north and the Riviersonderend Mountains in the south of the study area consist of erosion-resistant quartzitic sandstones (Figures 3.8 and 3.9) also known as Table Mountain sandstone (TMS) (Flügel & Kienzle 1989; Wooldridge 2005). These sediments belong to the Table Mountain Group of the Cape Supergroup. Water originating from this sandstone is of a high quality and has a very low salinity (Kirchner *et al.* 1997).

Underlying the TMS of the Langeberg are the much older meta-sediments of the Malmesbury Group (Kirchner *et al.* 1997; Wooldridge 2005). Rocks from the Malmesbury Group are rich in carbonates such as limestone and dolomite; those on the upper slopes are rich in clay minerals derived from phyllites (Wooldridge 2005). The Robertson Granite intrusion in the Malmesbury Group west of Robertson is evidence of a period of igneous events during the Precambrian (Wooldridge 2005).

In a northerly direction from the TMS of the Riviersonderend Mountain range to the south of the Breede River, the geology is dominated by formations of the Bokkeveld Group. These formations, mainly consisting of darker-coloured shale and sandstone, were deposited under marine conditions during the Devonian (390-340 mya); hence its high salt content (Kirchner *et al.* 1997; Wooldridge 2005).

The Witteberg Group overlies the formations of the Bokkeveld Group (Wooldridge 2005). It is younger (Carboniferous, i.e. 340-280 mya) than the formations of the Bokkeveld Group and usually consists of lighter-coloured, very hard quartzitic sandstones (Wooldridge 2005).

The Dwyka and Ecca groups of the Karoo Supergroup were deposited after the formations of the Witteberg Group (Wooldridge 2005). The Dwyka Group is evidence of a glacial ice period during the early Permian (290-278 mya) (Wooldridge 2005). Rocks were formed in four cycles because of the advance and retreat of ice sheets, and are usually massive tillites with varved[2] shale, mudstone with dropstones, and sheet and shoestring sandstone bodies (Wickens 2004). Formations of the Ecca Group were created during the mid-Permian (278-265 mya) and common rocks of this group are siltstone, shale and mudstone (Wooldridge 2005). The Enon Formation of the Uitenhage Group follows unconformably on the formations of the Ecca Group (Wickens 2004). The Enon Formation is of Jurassic age (190-135 mya) and common rocks are reddish conglomerates, subordinate lenticular sandstones and greenish shale (Wickens 2004; Wooldridge 2005).

Alluvial, sandy, loamy and gravelly deposits (Figure 3.9) occur adjacent to rivers and streams, or where drainage systems converge (Wooldridge 2005). Wooldridge (2005: 37) calls these deposits “superficial deposits” and defines them as “unconsolidated accumulations of mineral material derived from rock by weathering and erosion.” These superficial deposits and other soil formations will be discussed in the following section.

3.5 SOIL

The Malmesbury shale, Cape Granite rocks, Table Mountain sandstones, Bokkeveld shale and Enon conglomerates are the major parent materials from which soils in the study area were derived (Schloms 1975; Wooldridge 2005). The mineral composition of a soil’s parent materials and its interaction with the natural environment (climate, topography, geology, organisms) eventually determines the chemical and physical properties of the soil (Carey, Archer & Saayman 2002; Wooldridge 2005).

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[2] Shales deposited from melted ice in a lake in which the depositional layers appear in pairs which represents a seasonal deposit (Babylon 2009).

Figure 3.10 shows the soil groups documented in the GIS database of the Department of Agriculture at Elsenburg and Table 3.2 summarize the area and percentage distribution of soil groups in the study area. Because of the study area's location in a valley between two mountain ranges, more than 63% of the area has no soil cover, has relatively shallow soils (less than 500 mm to bedrock) or is covered by tallus rocks. About 25% of the area is covered by red soils and the remainder is covered by dry, saline, cutanic, yellow-brown or gravelly soils.

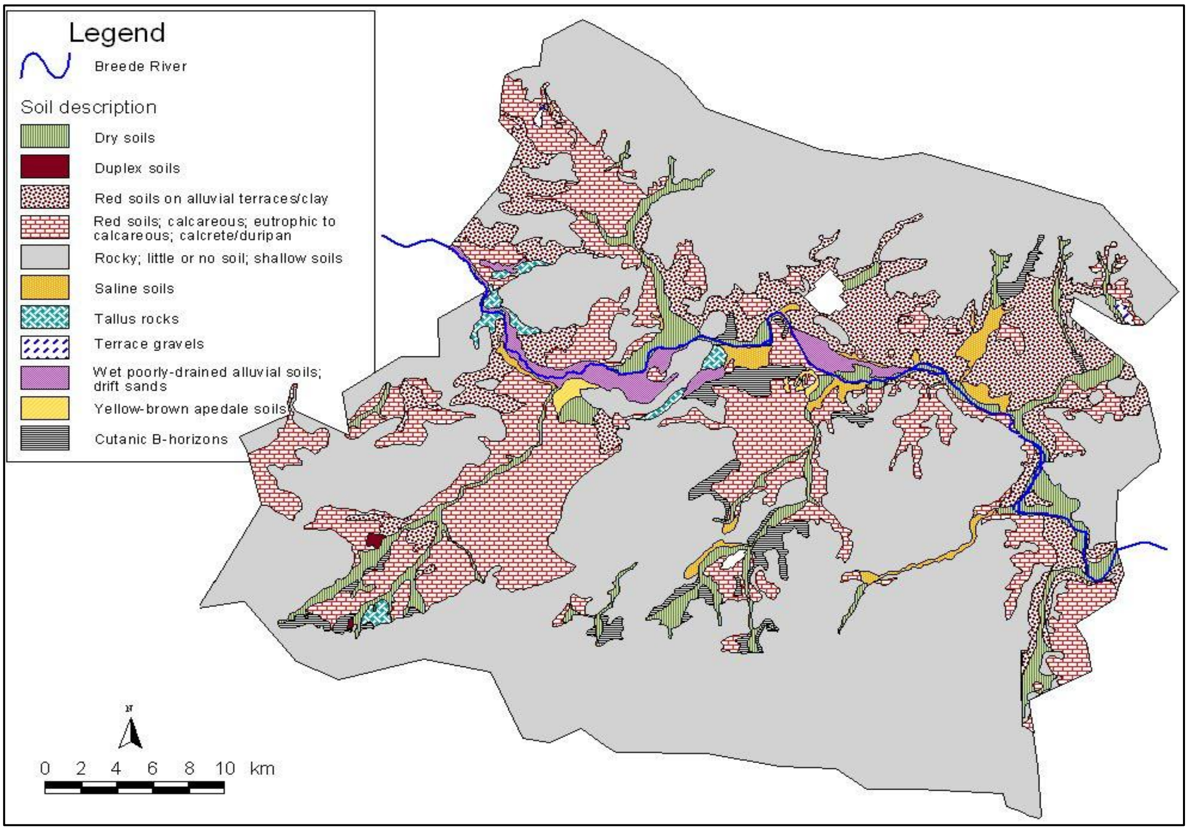


Figure 3.10: Soils of the Robertson LM

Table 3.2: Description of soil groups in the study area and the total area covered

Soil description	Area (ha)	Percentage
Rocky; little or no soil; shallow soils	99 859	62.8
Red soils; calcareous; eutrophic-calcareous; calcrete/duripan	26 997	17.0
Red soils on alluvial terraces/clay	14 643	9.2
Dry soils	8 349	5.3
Cutanic B-horizons	2 833	1.8
Wet poorly-drained alluvial soils; drift sands	2 274	1.4
Saline soils	1 969	1.2
Tallus rocks	927	0.6
N/A (Built-up areas)	471	0.3
Yellow-brown apedal soils	366	0.2
Terrace gravels	126	0.1
Duplex soils	85	0.1
Total	158 899	100

Schloms (1975) broadly describes the soil forms and series of the study area. Alluvial material and Dundee, Clovelly, Oakleaf, Hutton, Fernwood and Westleigh soil forms are found on the flood plains adjacent to rivers. Shallow Mispah forms are typically found on the crests where the bedrock is not exposed, while Mispah, Swartland and Glenrosa soil forms are found on the mid slopes. Shortlands, Sterkspruit, Estcourt, Oakleaf and Hutton forms are found on the foot slopes. Table 3.3 details the main characteristics of the soil forms and series of the study area.

Table 3.3: Characteristics of main soil forms

Soil form	Occurrence	Soil colour	Parent material	Clay content	Sand particle size	Other characteristics
Dundee	Flood plain	Yellow-brown	Alluvium from Table Mountain sandstone	Low	Medium-coarse	Well drained; acidic
Clovelly	Flood plain	Yellow-brown	Table Mountain sandstone	Low	Medium-coarse	Low water-carrying capacity; eutrophic-mesotrophic; lime
Oakleaf	Flood plain / foot slope	Red to brown	Enon shale and alluvium from Table Mountain sandstone	Low-medium	Fine-medium	Low-neutral pH
Hutton	Flood plain / foot slope	Red	Bokkeveld shale and Enon sediments	Low-high	Fine-coarse	Lime
Fernwood	Flood plain	Yellow-brown	Alluvium from Table Mountain sandstone		Medium-coarse	Acidic
Westleigh	Flood plain	Yellow to yellow-brown	Alluvium from Table Mountain sandstone	Low	Low-medium	Poor drainage
Mispah	Crest / mid slope	light-grey to red brown	Malmesbury- and Bokkeveld shale	Low	Fine	Lime; ferricrete; laterite
Swartland	Mid slope	yellow-red to dark brown	Dwyka shale	Medium-high		Saline
Glenrosa	Mid slope	Light-brown to grey	Malmesbury- and Bokkeveld shale	Low-medium	Fine-medium	
Shortlands	Foot slope	Red	Bokkeveld shale and Enon sediments	Medium-high		Lime-rich; eutrophic
Sterkspruit	Foot slope	Red	Alluvium from Table Mountain sandstone and Bokkeveld shale and Enon sediments	Low-medium	Fine-medium	High pH; High in Na and Mg
Estcourt	Foot slope	Pink-white to yellow-red	binary parent material	Low	Fine-coarse	High in Na and Mg

According to Schloms (1975), the Clovelly, Hutton and Shortlands soil forms are well-drained, uniform red or yellow soils. The yellow to yellow-brown soils of the Clovelly form have their origins in the Table Mountain sandstones and have low clay content. The Hutton form is a firm red apedal soil form with a low to medium clay content. At some places, the Hutton form is calcareous and has the Bokkeveld shale and Enon sediments as parent material. The Shortlands forms are red soils with structured B-horizons. These eutrophic soils are derived from Bokkeveld shale and Enon sediments, and they have a medium to high clay content, as well as high lime content.

The Westleigh soil form has poor drainage, occurs on the flood plain and has a grey to almost black colour. Dundee, Fernwood and Oakleaf are relatively young soils which occur on transported material. Mispah and Glenrosa are poorly-developed residual soils. Swartland, Estcourt and Sterkspruit are soils with structured cutanic subsurface horizons. The natural vegetation growing on these soils will be discussed in the following section.

3.6 NATURAL VEGETATION

A wide variety of *Macchia (*fynbos*)* is found along the slopes of the mountains in the study area (Greeff 1991). These include various species from the *Proteaceae* family such as *Protea repens*, *Protea nerifolia* and *Leucodendron imbricatum* (Schloms 1975). Towards the valley succulent plants of the Succulent Karoo Biome occur. These succulent plants are adapted to hot and dry environments such as the Little Karoo and Robertson (Greeff 1991; Rutherford, Mucina & Powrie 2002; Schloms 1975). Natural vegetation in the study area has been cleared for the production of wine grapes, peaches, apricots and vegetables, of which the production of wine grapes is the heart of the region's economy (Kirchner *et al.* 1997). The region's viticulture will be discussed in the following section.

3.7 VITICULTURE

The warm climate and well-drained lime-rich soils of Robertson is ideal for the cultivation of wine grapes but only on the completion of the Brandvlei Dam in 1923 did the wine industry start to flourish in the area (Roux 2005). Initially, production was limited to brandy and standard wines, but the development and application of new irrigation methods since 1985 has led to the improvement of wine quality (Roux 2005)

The Robertson Wine District is part of the Breede River Valley Region and consists of nine wards (see Table A1). The study area comprises an area of 158 897 ha and is the fourth largest wine-producing region in South Africa (SAWIS 2010). In 2009, approximately 48 000 000 vines were counted in the study area (including Bonnievale), which accounted for 16% of all vines in the country, making Robertson the third largest wine district in number of vines (Table 3.4).

Table 3.4: *Geographical distribution of South African wine grape vineyards per wine region, 2009*

Wine region	Number of vines	% of total vines	Area (ha)	% of total hectares
Stellenbosch	52 379 700	17.2	17 117	16.9
Paarl	51 014 900	16.8	16 673	16.5
Malmesbury	36 647 500	12.1	14 448	14.3
Robertson	47 914 300	15.8	13 994	13.8
Breedekloof	40 780 900	13.4	12 427	12.3
Olifants River	27 494 600	9.1	9 964	9.8
Worcester	27 878 300	9.2	8 658	8.6
Orange River	10 732 900	3.5	5 075	5
Little Karoo	8 956 700	2.9	2 904	2.9
TOTAL	303 799 800	100	101 260	100

Source: SAWIS (2010)

Table 3.5 indicates the varietal composition of red and white wines in the Robertson wine district. The majority of wine varieties planted in the region are white, of which Chardonnay and Colombar are the top two varieties.

Table 3.5: Varietal composition for the Robertson wine district

Red varieties	%	White varieties	%
Cabernet Sauvignon	10	Chardonnay	16
Cinsaut noir	1	Chenin blanc	12
Merlot	5	Colombar(d)	16
Pinot noir	1	Hanepoot	1
Pinotage	3	Sauvignon blanc	11
Ruby Cabernet	5	Sémillon	1
Shiraz	8	Other white	8
Other red	2		
Total	35		65

Source: SAWIS (2010)

The next section discusses how the climate, topography, geology, soil, natural vegetation and viticultural data, described in this section was prepared to reach the study aim and objectives.

3.8 DATA PREPARATION

The maps that are illustrated in the previous sections of this chapter were all produced with ESRI ArcMap 9.2 software. Because these data sets were collected from various sources, the projection information differed. This section describes the steps that were taken to prepare the data for effective analyses. Figure 3.11 illustrates the processes involved to prepare the data for NTU mapping.

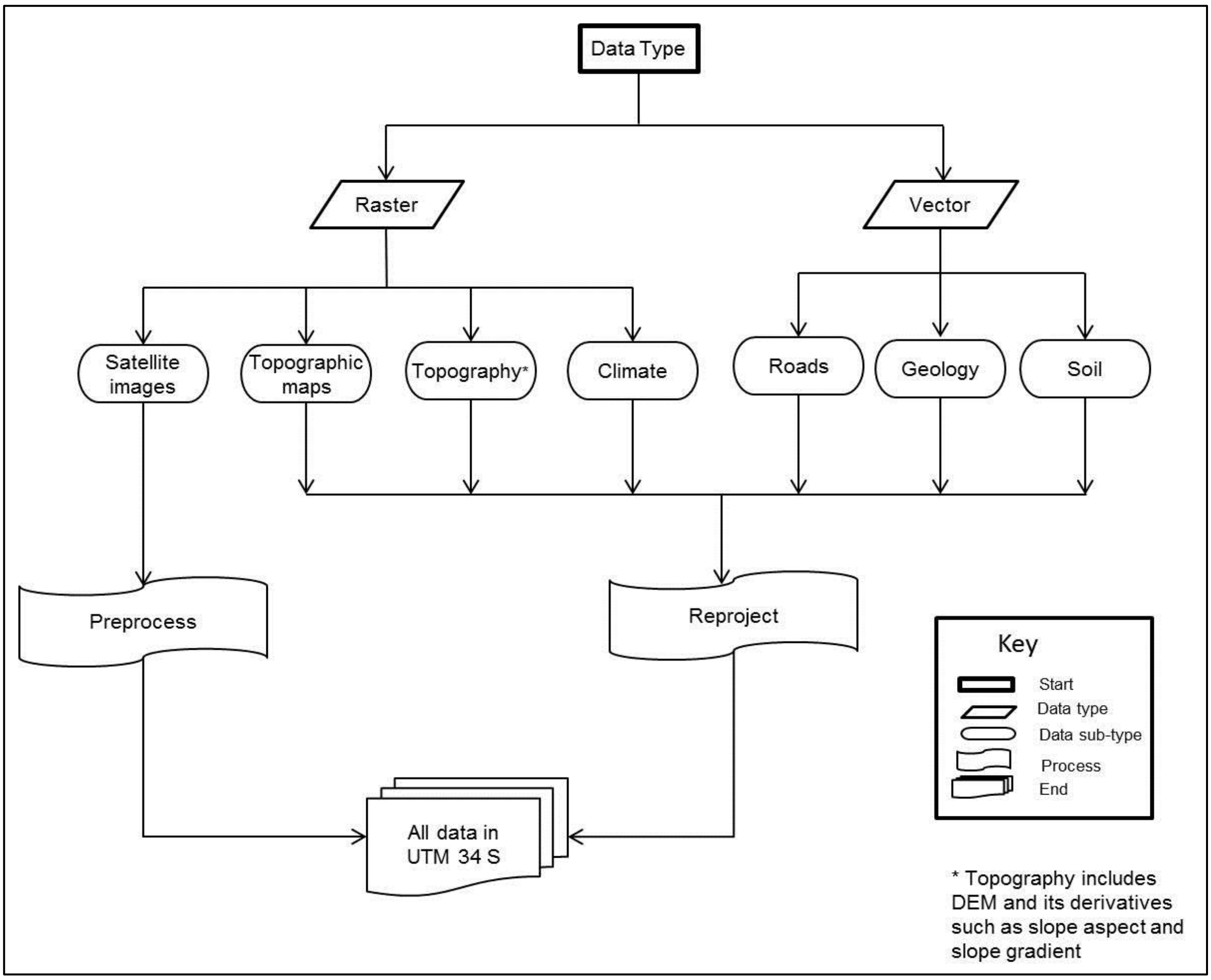


Figure 3.11: Data preparation procedure

All the GIS data were reprojected to zone 34 of the Universal Transverse Mercator (UTM) map projection. Table 3.6 summarizes the custodians and key characteristics of the data that is described in this section and that was used in this study.

Table 3.6: Data needs and sources

Data category	Type	Custodian
Satellite imagery	SPOT 4 and 5	CSIR Satellite Applications Centre
	ASTER	USGS
Climate data	Historical data	ARC ISCW
	Climate grids	South African atlas of agrohydrology and -climatology
Digital elevation model (DEM)	20-m resolution	Centre for Geographical Analysis (CGA)
Soil	1:25 000	Department of Agriculture (Elsenburg)
Geology	1:250 000	Council for GeoScience (CGS)
Topocadastral	1:50 000	National Geo-Spatial Information (NGI)

The following subsection provides an overview of the satellite imagery that was chosen for this study. The methods to pre-process these images will be discussed in detail.

3.8.1 Satellite imagery acquisition

Satellite images were used to map the current land cover/land use which will subsequently be combined with the other environmental parameters to describe the NTU. Factors such as the availability of images, cost, spatial resolution, swath width and spectral range were considered when these images were selected.

3.8.1.1 SPOT

Three satellite images were obtained from the Systeme Pour l'Observation de la Terre (SPOT) satellite system, two of which were from the SPOT 4 system and one from the SPOT 5 system. The SPOT 4 satellite was launched in 1998 and the high-resolution visible and infrared (HRVIR) instruments on-board this sensor was a modification on the high resolution visible (HRV) instrument on-board previous SPOT missions (Campbell 2002). Both the HRV and HRVIR instruments provide off-nadir viewing modes, which allows for the acquisition of images in stereoscopic mode (CRISP 2003). Compared to the HRV, the HRVIR instruments provide an additional mid-infrared band and it has a narrower panchromatic band which functions in both 10 m and 20 m modes (CRISP 2003).

The main objective of the SPOT 5 satellite, which was launched in May 2002, was to ensure the continuity with previous SPOT missions and to improve the quality of the data and images (CNES 2011). Two new instruments were fitted onto the satellite which was a modification of the HRVIR instrument of the SPOT 4 satellite. These are the high resolution geometric (HRG) and the high resolution stereoscopic (HRS) instruments. The HRG instrument acquires panchromatic images at a resolution of 2.5 m and 5 m as opposed to the 10 m that the HRVIR acquires. It also acquires multispectral images at 10 m instead of 20 m. The HRS instrument was designed to capture high resolution (10 m) images in forward and back mode to enable stereoscopic image acquisition (CNES 2011).

Both SPOT 4 and 5 have four multi-spectral bands and one panchromatic band. The first three multi-spectral channels on both sensors cover the green, red and near-infrared spectrum, while the fourth channel covers the shortwave infrared (SWIR) spectrum. Table 3.7 summaries the spatial and spectral properties produced by the SPOT 4, SPOT 5 and Landsat 7 systems. The cost of a raw ASTER scene is also relatively inexpensive compared to other satellite images (Fugro-NPA 2011).

Table 3.7: Spatial and spectral resolutions of SPOT 4, SPOT 5 and Landsat 7 imagery

Band No.	SPOT 4			SPOT 5			Landsat 7		
	Spectral range (µm)	Spatial resolution (m)	Electro-magnetic spectrum	Spectral range (µm)	Spatial resolution (m)	Electro-magnetic spectrum	Spectral range (µm)	Spatial resolution (m)	Electro-magnetic spectrum
1	0.50 – 0.59	20	green	0.50 – 0.59	10	green	0.45 – 0.515	30	blue-green
2	0.61 – 0.68	20	red	0.61 – 0.68	10	red	0.525 – 0.605	30	green
3	0.79 – 0.89	20	NIR	0.79 – 0.89	10	NIR	0.63 – 0.690	30	red
4	1.58 – 1.75	20	SWIR	1.58 – 1.75	20	SWIR	0.75 – 0.90	30	NIR
5							1.55 – 1.75	30	SWIR
6							10.4 – 12.5	60	FIR
7							2.09 – 2.35	30	SWIR
Pan	0.61 - 0.68	10 x 10		0.51 - 0.73	2.5		0.52 – 0.90	15	

3.8.1.2 ASTER

Two images of the *Advanced Spaceborne Thermal Emission and Reflectance Radiometer* (ASTER) were used in addition to the SPOT imagery. The ASTER sensor is on board the *Terra* satellite, which was launched in December 1999. ASTER operates in the visible and near infrared (VNIR), shortwave infrared (SWIR) and thermal infrared (TIR) spectra, and essentially covers wavelengths that the SPOT systems do not cover. The ASTER sensor has 15 spectral channels, including channel 3b, which is a back-looking band in the VNIR to create parallax (Bonneau 2007). Table 3.8 summaries the ASTER system. When compared to the SWIR spectrum of the SPOT 5 and Landsat 7 sensors, bands 4 to 9 of the ASTER sensor covers a broader spectral range than band 4 of SPOT and bands 5 and 7 of Landsat 7. This broader SWIR spectral range makes ASTER an ideal platform for soil mapping and the identification of minerals and mineral groups (Gao 2003; Kalinowski & Oliver 2004). ASTER images are relatively inexpensive (Fugro-NPA 2011) and provide a higher overall spatial resolution than Landsat ETM+ (Campbell 2002; Gao 2003).

Table 3.8: Overview of the ASTER system

Spectral channel	Spectral range (μm)	Electromagnetic spectrum	Spatial resolution (m)	Quantisation (bits)
Band 1	0.52 - 0.6	VNIR	15	8
Band 2	0.63 - 0.69			
Band 3	0.76 - 0.86			
Band 3b	0.76 - 0.86			
Band 4	1.600 - 1.700	SWIR	30	8
Band 5	2.145 - 2.185			
Band 6	2.186 - 2.225			
Band 7	2.235 - 2.285			
Band 8	2.295 - 2.365			
Band 9	2.360 - 2.430			
Band 10	8.125 - 8.475	TIR	90	12
Band 11	8.476 - 8.825			
Band 12	8.925 - 9.275			
Band 13	10.25 - 10.95			
Band 14	10.96 - 11.65			

In order to reach the aim of this study, the satellite images required should have a high spatial resolution and wide spectral range to distinguish between different land cover classes. Furthermore, the images should be inexpensive and should have frequent ground coverage.

The SPOT 4 and 5 images were selected because they have better spatial resolutions than images of other popular optical sensors (e.g. Landsat). SPOT 5 imagery has a high spatial resolution (2.5 m) and can consequently be compared to other very-high resolution imagery such is QuickBird and IKONOS. Compared to QuickBird and IKONOS images, SPOT images are inexpensive (Fugro-NPA 2011) and have a wider swath width (60×60 km). Table 3.7 shows that SPOT 5 has better spatial resolutions than both SPOT 4 and Landsat 7. Landsat 7 has a better spectral coverage in the SWIR region than SPOT 4 and 5. However, the Landsat 7 was not used because the ASTER sensor has a superior spectral coverage and has a better spatial resolution.

Summer and winter images were acquired because they represent different growth cycles of the grape vine (Vaudour, Carey & Gilliot 2010). The SPOT 4 summer image was overlooked in this research, because the SPOT 5 image, which has a higher resolution, was acquired over the same period. The SPOT 4 winter image was overlooked, because the ASTER image was acquired over the same period and because of ASTER's superior coverage in the SWIR spectrum.

The preprocessing of the SPOT 5 and ASTER images will be discussed in the next two sub sections, where geometrical and atmospherical corrections be discussed.

3.8.2 Geometrical corrections

The SPOT 5 images (panchromatic and multispectral) were received in Level 1A format and the ASTER image in Level 1B format. Level 1A data products are not geometrically corrected, meaning the data were still in an almost raw form (SPOT Image 2006). The Level 1B ASTER product also required geometric correction.

Geometric correction takes into account the earth's rotation and curvature, variations in the satellite's orbital altitude and panoramic distortions (SPOT Image 2006). This process is also called orthorectification. Orthorectification was performed with the Erdas Imagine 8.7 software and all data sets in this research were georeferenced to UTM zone 34. The WGS 84 datum and ellipsoid were used. Similar steps were taken to geometrically correct the SPOT and ASTER images.

Twenty-five evenly-spread ground control points (GCP) were collected over the study area. A 2.5m resolution mosaic of orthorectified aerial photographs of the study area was used as a reference image to locate X- and Y coordinates on the SPOT 5 panchromatic image. The DEM (Section 3.3) was used to extract elevation (Z-value). A total root mean square error (RMSE) of less than one metre was maintained for the SPOT 5 panchromatic image. The SPOT 5 multi-spectral image and the ASTER images were georeferenced to the orthorectified SPOT 5 panchromatic image. The RMSE was kept below three metres for the SPOT 5 multi-spectral image and below five metres for the ASTER image. This is better than the generally accepted RMSE of half the ground resolution of the satellite image (Reinartz *et al.* 2011).

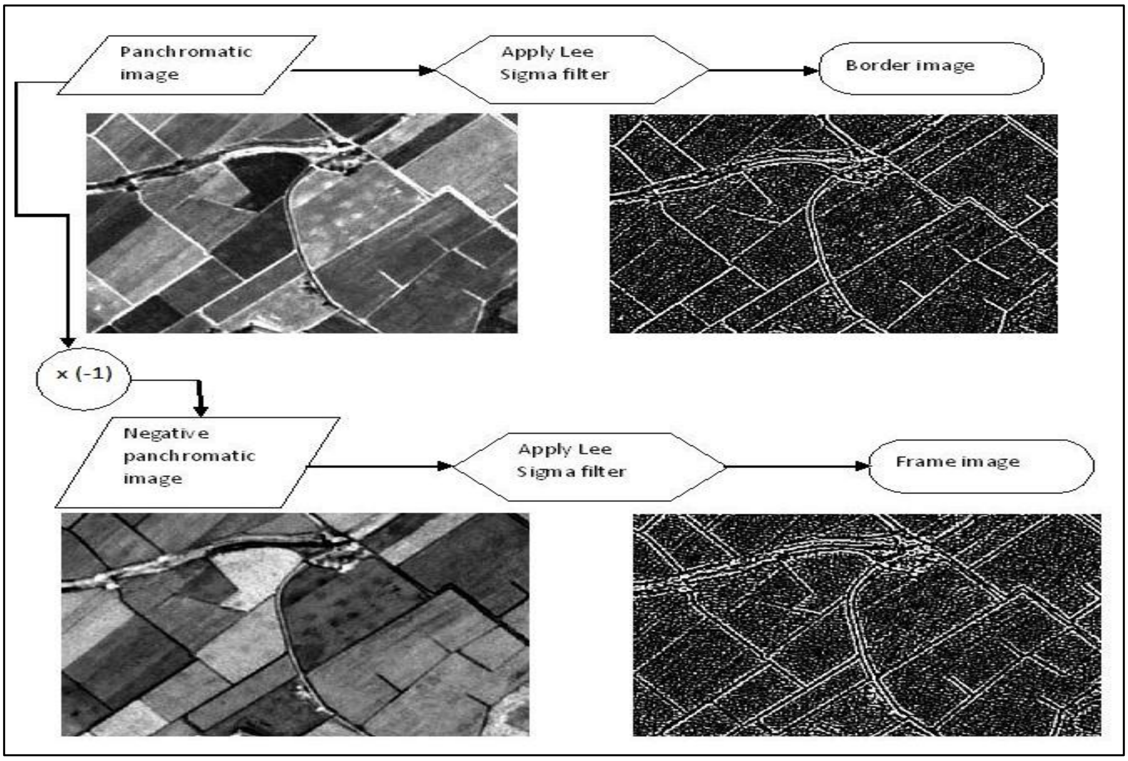
3.8.3 Atmospherical corrections

Atmospheric correction is the process by which atmospheric interference, motion of the sensor, and system noise is eliminated (Campbell 2002). This procedure is particularly important in multi-temporal image analysis (Campbell 2002; Chavez 1996; Gao 2003). The ASTER and SPOT images were radiometrically corrected with the quick atmospheric correction (QUAC) algorithm in the ENVI software. QUAC is an atmospheric correction method in the visible near-infrared to shortwave infrared spectrum of multispectral and hyperspectral imagery (ENVI 2009). Atmospheric compensation parameters are directly determined from the radiometric and wavelength properties of the scene information to create surface reflection of the image. The wavelengths of the SPOT 5 and ASTER multispectral images were entered into the software module which determines which gain and bias parameters should be used to apply atmospheric correction.

3.8.4 Edge detection layers

Edge detection layers were created to supplement the SPOT 5 panchromatic band to intensify the shape information of specific objects (De Kok & Wezyk 2006). Mueller, Segl & Kaufmann (2004) developed an object-oriented segmentation approach by which man-made objects were extracted from high-resolution satellite imagery based on shape-analysis. Additionally, De Kok & Wezyk (2006) discuss how homogeneous regions with regular shapes such as agricultural fields, forest stands and infrastructure, are distinguished from each other by taking into account the spectral differences of edge features separating the different regions. Wezyk & De Kok (2005) presented a method using the SPOT 5 panchromatic band in creating 'artificial image layers'. These artificial layers amplify edge features and divide the image into edge and non-edge regions which range between values of 0 (for non-edge or smooth, homogenous regions) and 2^n-1 (for edge features), where n is the bit number of the panchromatic band.

The edge layers were created as a preprocessing step, which included techniques such as edge detection filtering, spectral unmixing and textural derivatives (Wezyk & De Kok 2005). The edge image (or border image) was produced by applying the Lee-Sigma filter to the panchromatic image, which is then subtracted from the original panchromatic image. A frame image is similarly created by applying the Lee-Sigma filter to the negative of the panchromatic image and then subtracting the resultant filtered image from the negative panchromatic image. Figure 3.12 illustrates the steps taken to create the edge layers.



Adapted from Wezyk & De Kok (2005)

Figure 3.12: Processing steps for creating artificial edge layers, border and frame

The border and frame images were created with a model in the 'Model Maker' of Erdas Imagine 9.1. The example in Figure 3.12 shows that the edge images enhance the sharp contrast which separates homogeneous objects (individual vineyard blocks in this example) from neighbouring objects. The data that was discussed in this section will be used as input to identify NTU in the following chapter.

CHAPTER 4: NATURAL TERROIR UNIT MAPPING

In the previous chapter the study area and data needs were identified, and the data preparation procedures were described. This chapter contains the bulk of the research and describes the image analyses that were performed, the combination of the soil map and terrain map into a soil landscape map, the creation of a NTU map of the study area and finally and the assessment of the NTU based on the preferred natural conditions for two of the study area's top cultivars. Figure 4.1 illustrates the steps that were followed for NTU identification. These steps are discussed in the next sections.

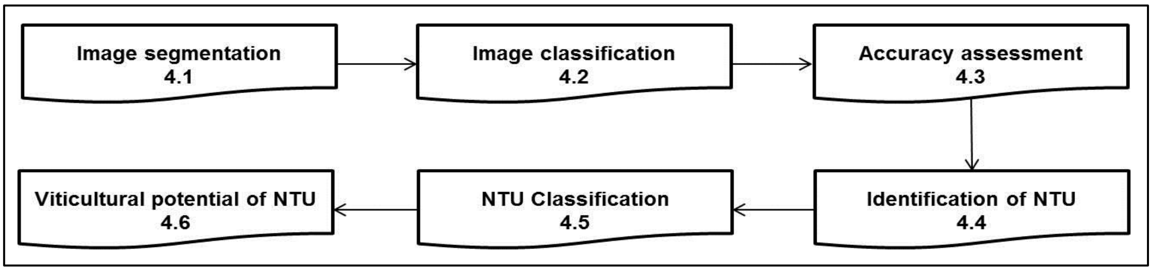


Figure 4.1: Modelling diagram for the identification of NTU

4.1 IMAGE SEGMENTATION

Image analysis was performed by using the Definiens Developer 7.0.3 software. This software, also known as eCognition, is the market leader in object-based image analysis (OBIA) (Benz *et al*. 2004; Trimble 2011). As described in Section 2.3.2, the classification process of OBIA differs from the traditional supervised and unsupervised classification in that image objects or segments, rather than single pixels, are the elementary processing units (Benz & Schreier 2001; Bock *et al.* 2005; Definiens Developer 2007a; Dragut & Blaschke 2006; Gamanya, De Maeyer & De Dapper 2007; Gao 2003; Lück 2004). eCognition offers five main image segmentation algorithms of which multiresolution segmentation (MRS) is considered the most powerful. Consequently, MRS was selected as the segmentation algorithm for this study. This algorithm produces highly homogeneous pixels over an image depending on the input parameters (Gao 2003). After testing various values for the scale parameter and homogeneity criterion, the most optimal values to create discernible image objects were selected. These optimal values are discussed below.

The SPOT 5 panchromatic, red and near-infrared layers, as well as edge layers were selected as input for the MRS algorithm. The wavelength (see Table 3.7) of the red layer (2nd SPOT 5 band) is in that part of the electromagnetic spectrum that allows the absorption of chlorophyll. It was selected because it differentiates between different plant types, whereas the near-infrared layer (3rd SPOT 5 band) was selected because it is a good indicator of plant cell structure, biomass and plant vigour (Campbell 2002). Together, these two multispectral layers satisfy the colour criterion of the MRS algorithm and are important for distinguishing between agricultural fields and natural vegetation.

Because of its higher spatial resolution, the panchromatic band, supplemented with the edge layers (Section 3.8.4), are ideal candidates to satisfy the shape criterion in the MRS algorithm. The high resolution of the panchromatic image and the enhancement of edges between different objects define clearer boundaries between objects during segmentation, which makes it easier to define between the shape of objects.

Following experimentation with various parameters, the following were found to generate objects suitable for differentiating between land use/cover classes in the study area:

- scale parameter = 30;
- shape = 0.2;
- compactness = 0.5;
- weight of SPOT 5 panchromatic (PAN), border and frame = 1; and
- weight of SPOT 5 red and SPOT 5 NIR = 0.5.

The layers that satisfy the shape criterion (SPOT 5 PAN, border and frame) were assigned a higher weight than the layers specified by the colour criterion (SPOT 5 red and SPOT 5 near infrared) so as to define clearer boundaries between objects. A lower value was consequently selected for the shape criterion. A low-value shape criterion compensates for the higher contribution of the colour criterion. Compactness was set to 0.5 to generate objects that are equally smooth and compact. A digitized roads layer identifying the major roads in the study area was used as a thematic layer during segmentation because the panchromatic and edge layers could not clearly segment roads. The roads layer was obtained from the South African 1:50 000 topocadastral maps as a vector (line) layer. A buffer of 15 m was applied to roads to create suitable objects during segmentation. A comparison between the SPOT 5 image and the segmented result is provided in Figure 4.2.

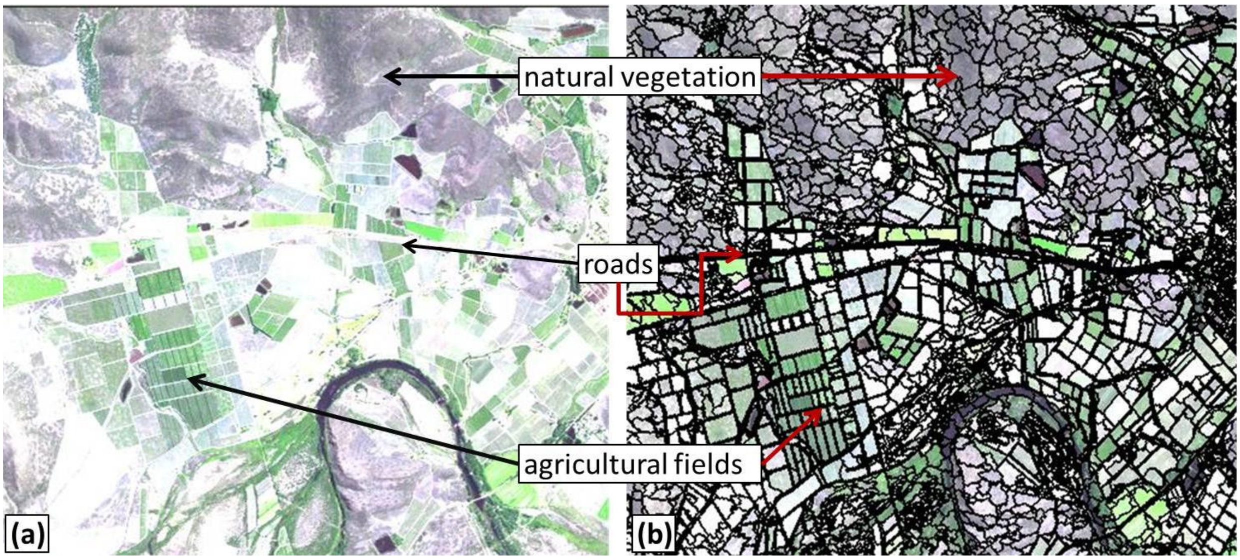


Figure 4.2: Comparison between the SPOT 5 (a) natural colour image and (b) segmented image

The segmented image in Figure 4.2 clearly illustrates that natural features such as natural vegetation have irregular shapes, whereas mad-made features such as agricultural patches and roads have more regular shapes. The objects having been created, the next step is to classify the land use/cover.

4.2 CLASSIFICATION

A rule-based classification methodology was followed to classify the image objects into land use/cover classes. This method is based on a sequence of operations that uses spectral, hierarchical, shape and textural attributes to derive land use/cover classes. These attributes are called 'features' in eCognition and examples include the mean or standard deviation of an object (spectral), the relationship of one object to its super- or sub-objects (hierarchical), an object's width, length or rectangular index (shape) and variability within an object (textural). The eCognition software also allows users to define customized features based on arithmetic or relational algorithms.

Five land cover and three land use classes were defined for the study area. Image classification was based on threshold values separating one image object from another using various features. The five land cover classes are *water, built-up areas, natural vegetation, bare surfaces* and *roads*, while the three land use classes are *agricultural land, recreational areas* and *mining areas*. For the rest of the research, *built-up areas* will be referred to as "*built-up*", *agricultural land* as "*agriculture*" and *recreational* and *mining areas* as "recreation" and "*mining*" respectively. The land use classes *agriculture*, *recreation* and *mining* were brought into the land cover classification to show the extent to what the land surface has been used and to separate land with the most agricultural potential from land with limited/unexploited agricultural potential (*bare surfaces* and *natural vegetation*) and land with no agricultural potential (*roads, water, recreation* and *mining*) in NTU mapping. For the purposes of this research, the eight land use/cover classes are defined as shown in Figure 4.3.

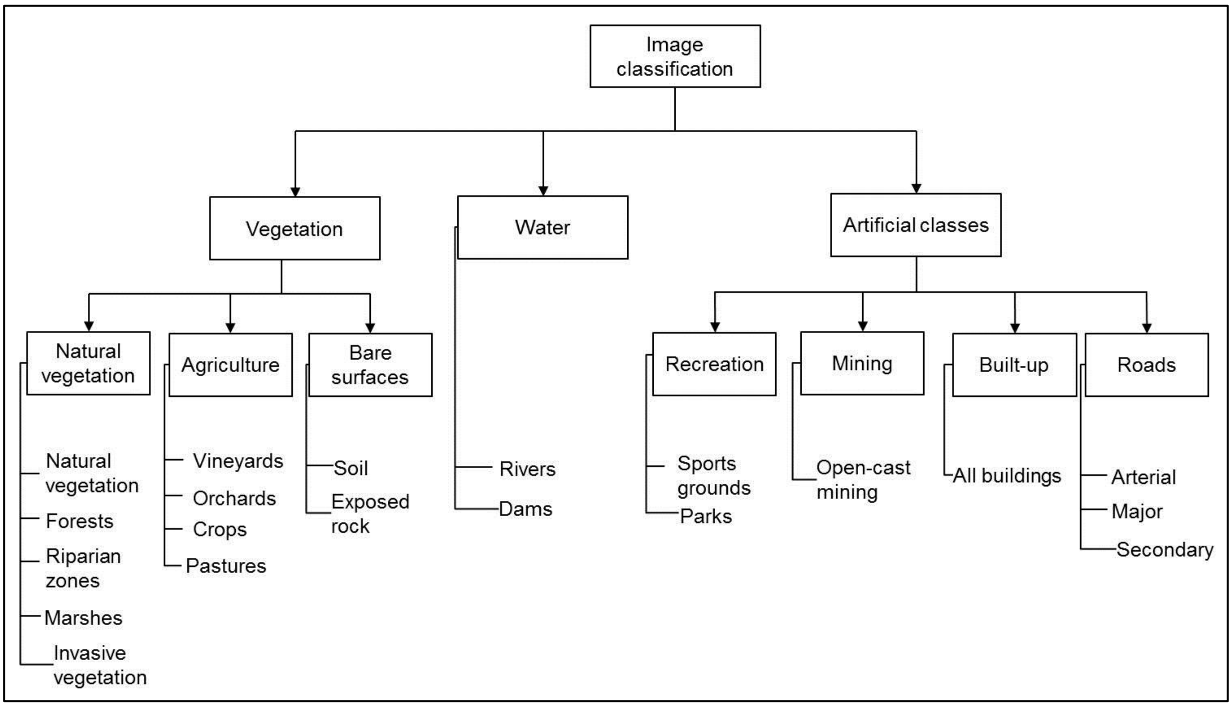


Figure 4.3: Hierarchal structure of land use/cover classes

The complete ruleset used in the land use/cover classification is provided in Appendix C. The ruleset is divided into six sections, namely classes, customized features, segmentation, classification, clean-up and export. The classes section refers to classes that were defined in Figure 4.3. Only the eight final classes were exported to vector format at the conclusion of the classification process. A number of temporary classes were derived before the final classification. The customized features are theoretical indices that have been used to derive certain classes. A complete list of the customized features that were created is listed in Table 4.1.

Table 4.1: List of customised features used in the classification

Customized algorithm	**Formula**	**Eq. no**	**Reference**
Ratio Green_AST	$\frac{G}{G+B+R+SWIR4+SWIR5+SWIR6+SWIR7+SWIR8+SWIR9}$	4.1	Adapted from Ratio Red (De Kok & Wezyk2006)
Brightness_SPOT5	$\frac{BG+R+NIR+SWIR}{4}$	4.2	Definiens Developer (2007a)
Brilliance Index_SPOT5	$\frac{R^2+NIR^2}{10000}$	4.3	Deshayes & Maurel (1990)
Difference_SPOT5	$R-NIR$	4.4	Girard & Girard (2008)
MSAVI	$\frac{(1+L)(NIR-R)}{NIR+R+L}+L$	4.5	Jensen (2005)
NDSI	$\frac{SWIR-NIR}{SWIR+NIR}$	4.6	Takeuchi & Yasuoka (2004)
NDVI	$\frac{(NIR-R)}{(NIR+R)}$	4.7	Campbell (2002)
PAN B_FSPOT5	$\frac{PAN}{Border+Frame}$	4.8	Wezyk & De Kok (2005)
Ratio (SPOT$_{nir}$/SPOT$_{swir}$)	$\frac{(NIR)}{(SWIR)}$	4.9	Adapted from Simple Ratio (Jensen 2005)
Ratio_Green_SPOT5	$\frac{BG}{BG+R+NIR+SWIR+PAN}$	4.10	Adapted from Ratio Red (De Kok & Wezyk (2006)
Ratio NIR_SPOT5	$\frac{NIR}{BG+RED+NIR+SWIR+PAN}$	4.11	Adapted from Ratio Red (De Kok & Wezyk2006)
Ratio_8/9_AST	$\frac{SWIR8}{SWIR9}$	4.13	Adapted from Simple Ratio (Jensen 2005)
SAVI	$\frac{(1+L)(NIR-R)}{NIR+R+L}$	4.14	Jensen (2005)
Zabud1_SPOT5	$\sqrt{[((BG)-(R))^2+((R)-(NIR))^2+((NIR)-(SWIR))^2]}$	4.15	Lewinski (2006)

The following naming conventions are used in Table 4.1 and the rest of the thesis:

- the name of the algorithm can be succeeded by the subscripts SPOT, AST (Aster) and Topo (Topocadastral layer) to indicate the source layer;
- R, G, B refers to the red green and blue spectral bands respectively;
- BG refers to the first SPOT band;
- NIR refers to the near infrared band;
- SWIR refers to the shortwave infrared band;
- L is the soil background adjustment factor;
- PAN refers to the panchromatic band;
- B refers to the border image; and
- F refers to the frame image.

Table 4.2 lists the standard eCognition algorithms that was used in the classification.

Table 4.2: List of eCognition Developer standard algorithms used in the classification

Name	Definition
Shape Index	"Mathematically the shape index is the border length e of the image object divided by four times the square root of its area A. Use the shape index s to describe the smoothness of the image object borders" (Definiens Developer 2007a: 124).
Existence of	"Existence of an image object assigned to a defined class in a certain perimeter (in pixels) around the image object concerned. If an image object of the defined classification is found within the perimeter, the feature value is 1 (= true), otherwise it would be 0 (= false). The radius defining the perimeter can be determined by editing the feature distance" (Definiens Developer 2007a: 164).
Border to	"The absolute border of an image object shared with neighbouring [sic] objects of a defined classification. If you use georeferenced data, the feature value is the real border to image objects of a defined class; otherwise it is the number of pixel edges shared with the adjacent image objects, as by default the pixel edge-length is 1" (Definiens Developer 2007a: 164).

The segmentation and classification sections in Appendix C contain the rules used for segmenting and classifying the imagery respectively. The clean-up section provides the code for cleaning the image objects by merging neighbouring objects of the same class into bigger objects, while the export section represents the code to export these objects to a GIS vector layer.

The ruleset for the classification of each of the land use/cover classes is illustrated in more detail as compound models in the following subsections. The decision tree starts with the unclassified image objects, followed by logical statements to derive the classes. Three models, namely hydrological features (*water),* artificial features (*roads, built-up, recreation* and *mining*) and vegetation features (*agriculture, natural vegetation* and *bare surfaces*) were created.

Initially, the 'No data' values outside the boundaries of the study area were classified as *null* by using values less than 0 in the SPOT 5 blue-green band and the slope percentage raster. The *null* class was then merged into a single object and eliminated from the rest of the classification. Classification of the eight land use/cover classes are considered next.

4.2.1 Water

The compound model to illustrate the classification of water is shown in Figure 4.4. The customized feature, 'ratio green' (see Equation 4.10) was found to be a better index to distinguish between classes than indices usually used in image classification, e.g. normalized difference vegetation index (NDVI). Features such as water, buildings, shadows, dark soils, roads and open-cast mining areas yield high values when this index is applied, whereas features such as vegetation and cultivated soils have lower values. Thus, objects with a "ratio green" value greater than 0.142 were temporarily classified as 'water container.'

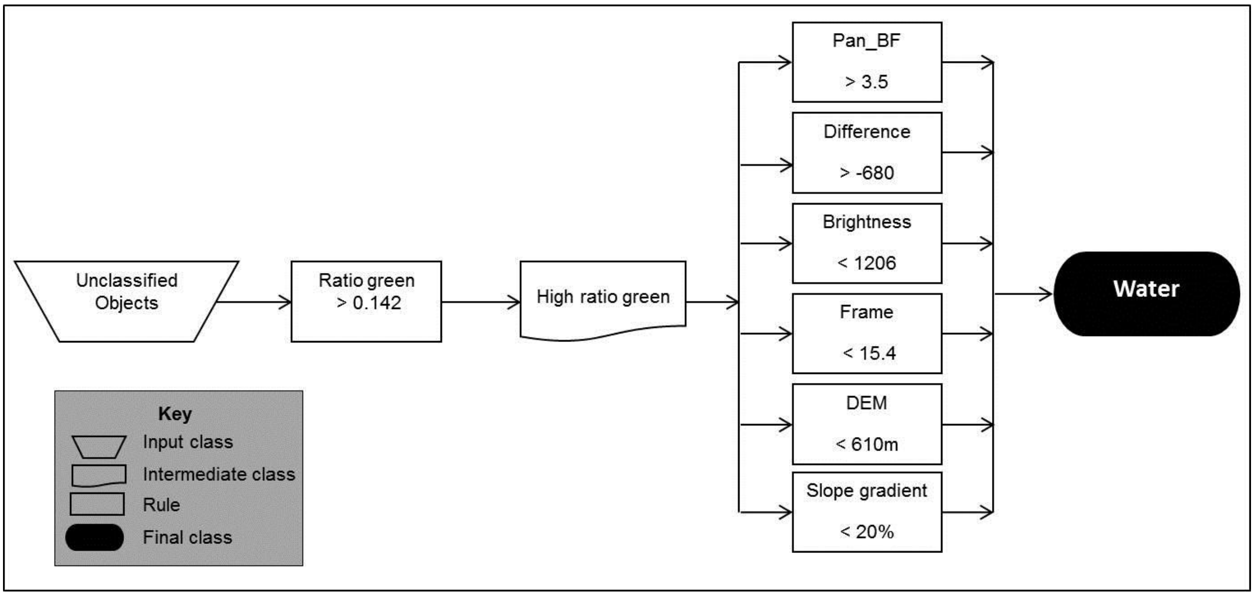


Figure 4.4: Compound 1: Classification of water

Non-water features such as buildings, bright soils, open-cast mining areas, roads and shadows were sequentially removed from the water container by applying different features. Buildings, bright soils and open-cast mining areas can be separated from water because they have higher 'brightness' and/or 'frame' values and lower 'Pan_BF' and 'difference' values. As indicated in

Table 4.1, brightness is defined as the average of the SPOT 5 multispectral layers (i.e. the sum of the four multispectral bands divided by four). The customized feature Pan_BF will be discussed in more detail in Section 4.2.2.3. After the elimination of non-water classes, only water and shadow objects remained in the water-container class. Shadows were removed from the water-container class by using high elevation (DEM) and slope gradient values because in very mountainous areas, darker pixels are more frequently represented by shadow rather than water.

4.2.2 Artificial classes

The compound model used to classify artificial classes such as *roads*, *recreation*, *built-up* and *mining* is illustrated in Figure 4.5. This model is discussed in the following subsections.

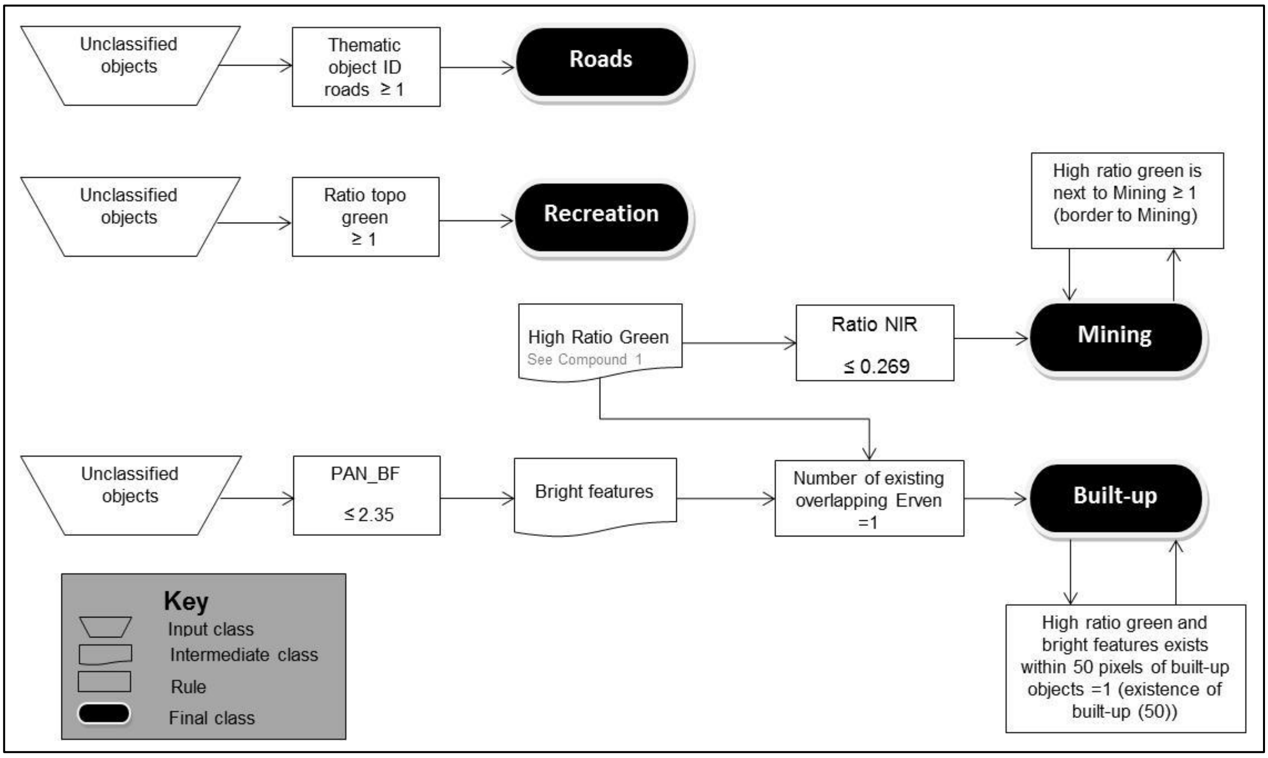


Figure 4.5: Compound 2: Classification of artificial classes

4.2.2.1 Roads

A thematic vector layer of roads was used in the segmentation algorithm. The attributes of this thematic layer were also used to classify *roads*. Objects were classified based on the ID field in the thematic layer's attribute table and therefore all objects with an ID greater than or equal to 1 were classified as roads.

4.2.2.2 Recreation

The 1:50 000 topocadastral map sheets were used to extract recreational areas such as golf courses and sports fields. The extent of the study area is covered by nine 1:50 000 topocadastral map sheets: 3319DA, 3319DB, 3319DC, 3319DD, 3320CA, 3320CC, 3419BA, 3419BB and 3420AA. These map sheets were scanned in as an RGB raster and indicate recreational areas with a solid green colour which exhibits high values in the green band. The ratio of the green band (‘ratio topo green’) to the sum of the red, green and blue bands was used to classify recreational features because recreational areas exhibit high values for this ratio. Areas with ratio topo green values of greater than 0.375 were classified as *recreation.*

4.2.2.3 Built-up

The ratio green customized feature as described in Section 4.2.1 proved to be a useful index to separate vegetation from non-vegetation. Areas with high albedos such as buildings, bright soils, and open-cast mines also display high values with this index. The separation between buildings and mining areas with high ratio green values is discussed in the next section.

De Kok & Wezyk (2006) described how the panchromatic band divided by the sum of the two edge layers could delineate built-up areas, shadows and high vegetation. A customized feature called ‘Pan_BF’ was created and low values of this algorithm were used to classify a temporary class, ‘bright features’. Objects with sharp contrast to their neighbours, such as buildings, bare surfaces between agricultural patches and very bright, unvegetated areas had high values in this temporary class.

The DEM was used to eliminate bright objects in areas of high elevation to separate built-up areas from bare surfaces. Furthermore, a thematic layer of the cadastral information of the study area was used to separate objects with high PAN_BF and high ratio green values within cadastral units (buildings in towns) from bright features outside cadastral units (bare surfaces or soil between agricultural patches). Bright objects within cadastral units were classified as *built-up* and all other objects with high ratio green and high PAN_BF values within 50 pixels of the *built-up* class were amalgamated into the *built-up* class.

4.2.2.4 Mining

Low values of the ratio of the NIR SPOT 5 band to all other SPOT 5 bands separated open-cast mining areas from built-up areas. The ‘ratio NIR’ customized feature is the NIR band divided by the sum of the NIR, blue-green, red and SWIR bands. Both heavy industries and open-cast mines have low ‘ratio NIR’ values, but because the former was classified as *built-up*, only open-cast mines remained with low NIR values. Therefore, a new class, *mining*, was created. The *mining* class was expanded by amalgamating neighbouring ‘high ratio green’ objects into it with the ‘border to’ feature.

4.2.3 Vegetation

The vegetation class include *natural vegetation, agriculture* and *bare surfaces*. The *bare surfaces* class includes natural bare areas such as exposed rock and bare soil (see Figure 4.3). The compound model for the four vegetation classes is illustrated in Figure 4.6 which are examined in turn.

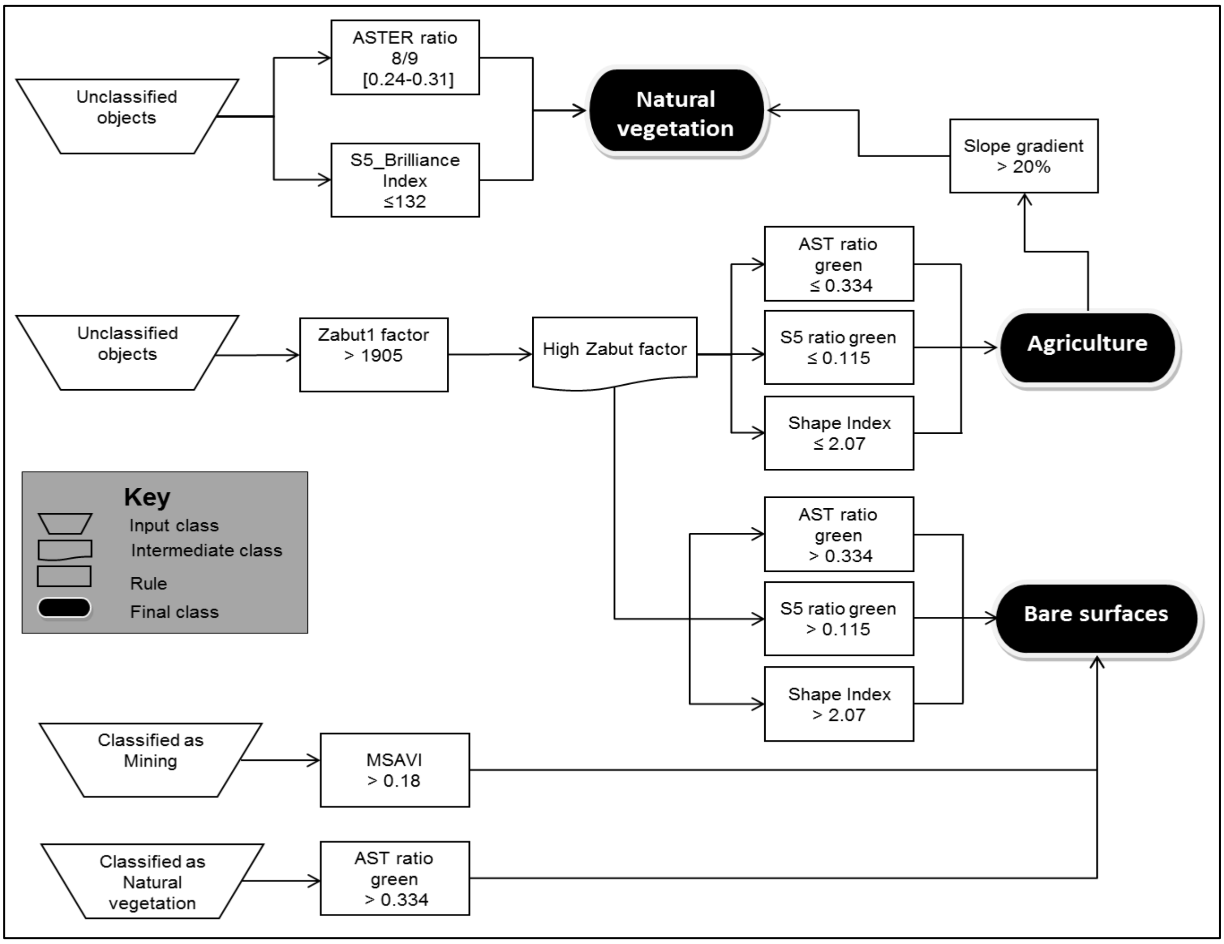


Figure 4.6: Compound 3: Classification of vegetation

4.2.3.1 Natural vegetation

The SPOT 5 brilliance index (Equation 4.3) and the ratio of the sixth and seventh SWIR bands (see SWIR spectral channels in Table 3.8) of the ASTER image (‘ASTER_ratio_8/9’) were used to classify *natural vegetation*. As indicated by Equation 4.3 in Table 4.1, the brilliance index is the sum of the square of the red and NIR bands. It was divided by a factor of 10 000 to compensate for the high values of pixels produced after the application of the QUAC method during atmospheric correction. The brilliance index is traditionally used to indicate changes in the colour of exposed soil and rocks (Deshayes & Maurel 1990), but in the classification of natural vegetation, low values of this index were used to identify arid renosterveld vegetation in the study area. The index returns high values for exposed soil and rocks, while low values are indicative of high soil moisture and soil roughness (Deshayes & Maurel 1990). Note that the brilliance index is not abbreviated to ‘BI’ as this can create confusion with the brightness index that is often abbreviated as such in other studies. Objects in the range of 0.24-0.31 in the ‘ratio_AST_8/9’ feature were added to the *natural vegetation* class.

4.2.3.2 Bare surfaces

In the beginning of this subsection (Section 4.2.3), the class, *bare surfaces*, were defined as natural bare surfaces such as bare rock and soil. A number of bare surface objects were misclassified as natural vegetation using the brilliance index feature, because of high soil moisture. Another feature, the ‘ASTER ratio green’, was consequently used to eliminate misclassified bare objects. With the ASTER ratio green feature, *bare surfaces* have higher values than natural vegetation and were therefore eliminated from the natural vegetation class. The modified soil-adjusted vegetation index (MSAVI) was used to classify bare areas surrounding open-cast mining areas. MSAVI is derived from the soil adjusted vegetation index (SAVI) which is a vegetation index that minimizes the brightness variations of soils in satellite imagery (Jensen 2005). The dynamic range of SAVI is modified by applying an iterative, continuous function (Jensen 2005).

4.2.3.3 Agriculture

The Zabud1 factor was used to identify bright objects such as bright soils, exposed rocks and cultivated land. These classes have high Zabud1 values and were temporarily classified as ‘high_Zabud’. The Zabud1 factor was used by Lewinski (2006) to classify built-up areas on a

Landsat TM image. The same equation (Equation 4-15 in Table 4.1) was applied on the SPOT 5 image. The 'high_Zabud' class was further refined to separate *agriculture* and *bare surfaces* from each other. Agricultural patches has low ratio green values in the SPOT5 and ASTER images and ratio green was successfully used to separate vineyards, orchards, crops, cultivated land, and bare surfaces from mining areas. Low Ratio Green values in the ASTER image were directly classified as *agriculture*, while low ratio green values of the SPOT 5 image were temporarily classified as 'agriculture_container'.

The 'shape index' was applied to the 'high_Zabud' and 'agriculture_container' classes to separate these two temporary classes from natural bare surfaces. As defined in Table 4.2, this index describes the smoothness of an image object's boundary. Objects of the class, *agriculture*, normally have more regular shapes than natural vegetation and were consequently classified as such. Furthermore, a visual interpretation of the SPOT 5 image revealed that agricultural land in the study area does not exceed a slope percentage of 20%. Therefore, objects of the class *agriculture* that have a slope gradient of more than 20% were reclassified as *natural vegetation*.

Once the classification was completed, objects of the same class were merged into bigger objects and exported as vector layers. The vector export algorithm was set so that the exported objects have smooth boundaries. The attribute table of the exported vector layer included a 'land cover' field that identifies each of the eight classes.

Figure 4.7 shows the results of the object-based image classification. The product is draped over a hillshade grid generated from the 20-m DEM in ArcGIS. From Table 4.3 it is clear that the majority of the study area (75%) is composed of natural vegetation. Agriculture is the second largest class (13%), while bare surfaces represent 10% of the area. The other land cover classes make up smaller portions of the total area.

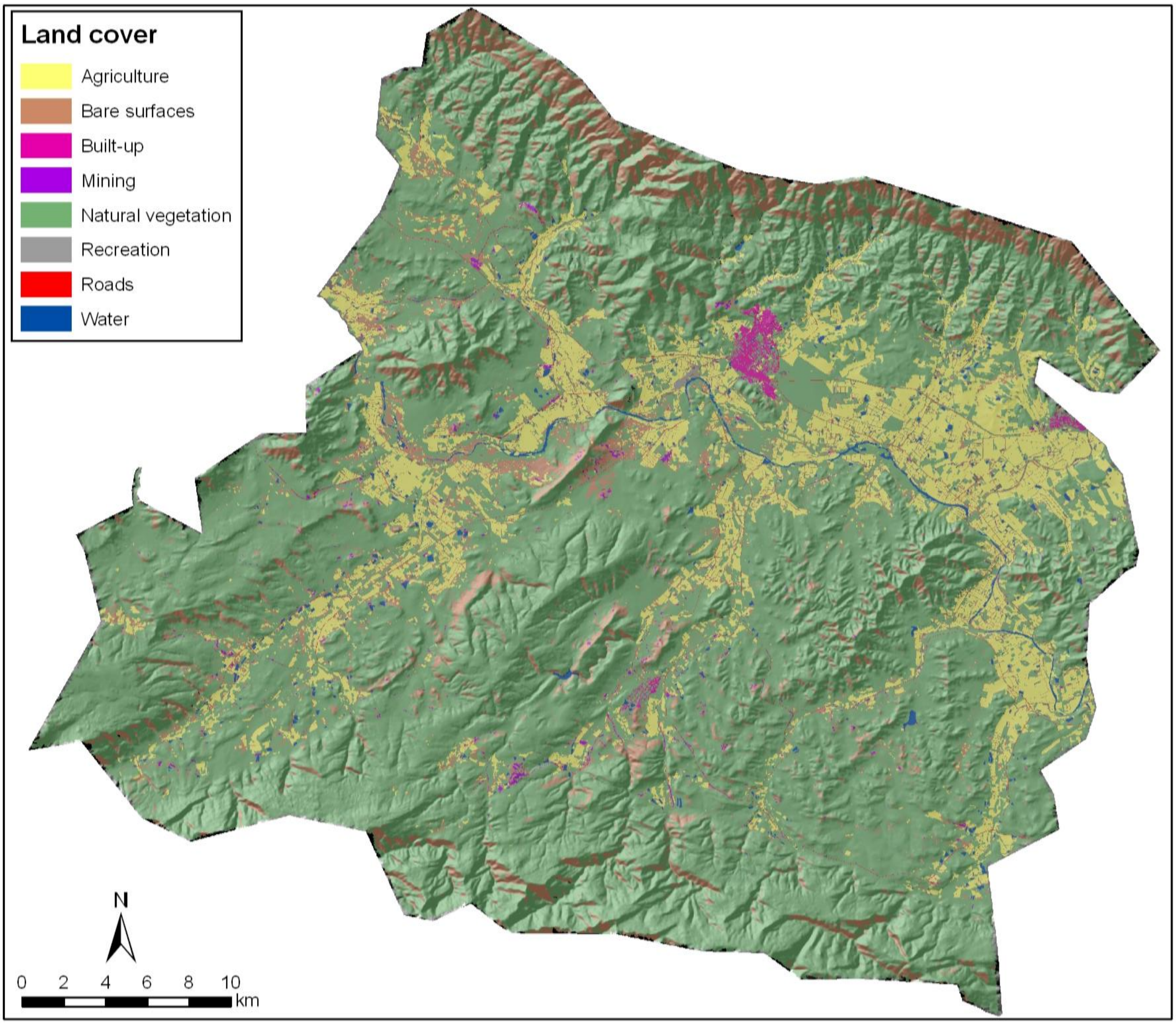


Figure 4.7: Result of object based image analysis for land cover classification of Robertson LM

Table 4.3: Land use/cover composition of Robertson LM

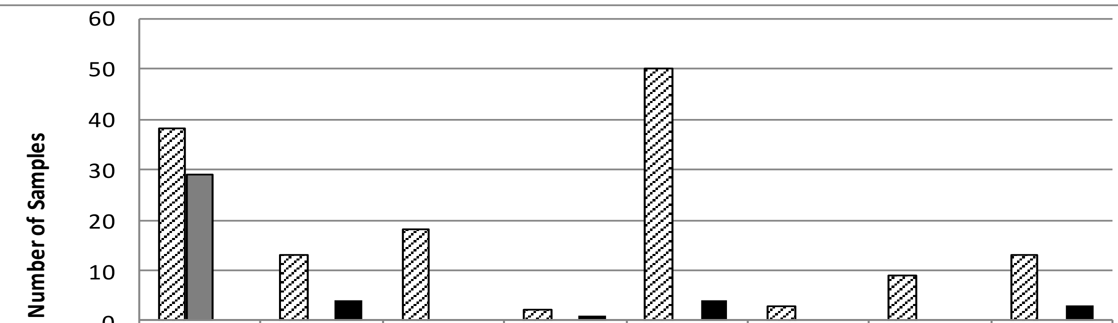
Land use/cover	**Area (ha)**	**% of area**
Agriculture	19 368	12.5
Bare surfaces	16 687	10.7
Built-up	530	0.3
Mining	469	0.3
Natural vegetation	116 936	75.2
Recreation	93	0.1
Roads	311	0.2
Water	1 095	0.7
Total	**155 489**	**100**

The accuracy of the classification is assessed in the next section and some of the pitfalls of the rule-based classification are considered.

4.3 ACCURACY ASSESSMENT

This section briefly investigates the three critical steps taken during the accuracy assessment as suggested by Congalton & Green (2009). The sample design, collection of reference data and the use of an error matrix will be discussed. Furthermore, the error matrix will be analysed and possible sources of error will be listed.

A stratified random sampling technique was used to verify the classification results of the land use/cover types. Samples were taken at 5 km intervals along the major routes of the study area. Given that the road network is 267 km, a total of 53 sample points (267/5) were visited. When more than one land use/cover class were observed within walking distance, multiple samples were collected by recording the exact XY coordinate (with a GPS) for every different land use/cover class. Photographs were also taken in all four major directions of the area surrounding each point. A shapefile of the XY coordinates was created. The photos were hyperlinked in ArcGIS to the shapefile and a field was created for the corresponding land use/cover type. A total of 146 samples were collected in this way. Twelve additional samples (virtual sampling) representing classes in areas that were inaccessible by car and verified by high resolution aerial photography, as well as twenty-nine points of known Shiraz and Chardonnay vineyard blocks were appended to the field samples. This shapefile served as the independent reference dataset for the accuracy assessment. The number of samples for the three different methods for collecting the reference data is shown in Figure 4.8.



	Agriculture	Bare surfaces	Built-up	Mining	Natural vegetation	Recreation	Roads	Water
	67	17	18	3	54	3	9	16
Fieldwork	38	13	18	2	50	3	9	13
Known vineyards	29	0	0	0	0	0	0	0
Virtual sampling	0	4	0	1	4	0	0	3

Figure 4.8: Total number of samples per class for the different collection methods

An error matrix and kappa coefficient was produced in ArcView 3.2 with the 'Kappa Tool extension' to validate the classification result. This extension is freely available from www.esri.com and was created by Jennes & Wynne (2007). The Kappa coefficient (κ) is widely used in accuracy assessment in the remote sensing community to statistically determine whether the results of one error matrix significantly differ from any other error matrix (Chen, Yamauguchi & Chen 2010; Congalton & Green 2009). Kappa values range between +1 and -1, where values greater than 0.8 represents strong agreement, values of between 0.4 and 0.8 represents moderate agreement and values less than 0.2 represents poor agreement (Congalton & Green 2009). The reference data set was compared with the land use/cover classification in the error matrix. The resulting statistics are presented as an error matrix in Table 4.4. In the error matrix, the classes produced by the OBIA are presented as rows, while the reference data are presented as columns.

Table 4.4: Error matrix based on samples

		Reference data								
	ID	Agriculture	Bare surfaces	Built-up	Mining	Natural vegetation	Recreation	Roads	Water	SUM
Classification	Agriculture	58	4	2	0	2	0	1	0	67
	Bare surfaces	0	12	2	0	1	0	1	1	17
	Built-up	0	0	18	0	0	0	0	0	18
	Mining	0	0	0	2	0	0	0	1	3
	Natural vegetation	11	4	3	0	34	2	0	0	54
	Recreation	0	0	0	0	0	3	0	0	3
	Roads	0	0	0	0	0	0	9	0	9
	Water	0	0	0	0	0	0	0	16	16
	SUM	69	20	25	2	37	5	11	18	187
	PRODUCER	0.84	0.60	0.72	1.00	0.92	0.60	0.82	0.89	
	USER	0.87	0.71	1.00	0.67	0.63	1.00	1.00	1.00	
	Overall Accuracy	0.8128342								
	Kappa coefficient (κ)	0.758932								

The overall accuracy if the OBIA was 81.3% with a kappa coefficient of 0.76. Because the kappa coefficient is between the ranges of 0.4 - 0.8, it means that the classification represents a moderate level of agreement (Congalton & Green 2009). The producer's accuracy ranged between 60% for bare surfaces and recreation and 100% for *mining*. Classes such as *natural vegetation* (92%), *water* (89%), *agriculture* (84%) and *roads* (82%) achieved producer's accuracies greater than 80%, which means that of the actual landscape of the area more than 80% of the objects were correctly classified for these classes (Campbell 2002). Other than *bare surfaces* and *recreation*, the *built-up* class (72%) is the only class that had an accuracy of less than 80%. The user's accuracy ranges from 63% for *natural vegetation* to 100% for *built-up*, *recreation*, *roads* and *water*, while *agriculture* had an accuracy of 87%. According to Campbell (2002), the difference obtained between the producer's and user's accuracy is the base from which the error is assessed. The base of the producer's accuracy is the area in each class of the final map, while the user's accuracy is a measure of the reliability of the map as a predicted device (Campbell 2002).

The 100% producer's accuracy for the *mining* class is attributable to there being only two open-cast mines in the study area. Both areas were selected as samples and were classified correctly. The 67% user's accuracy of *mining* is because one object that was classified as *water* was misclassified as *mining*.

More samples were selected for *agriculture* than any other class because agricultural fields often occur adjacent to the major routes in the study area and were therefore the most likely class to be sampled. A very high (84%) producer's accuracy was achieved for *agriculture*. However, it seems that some (11) agricultural patches that were misclassified were misclassified with *natural vegetation*. This is an example of an 'error of omission', i.e. samples of the agriculture class were omitted from the classification (see Section 2.3.2.5). This misclassification is likely caused by the inability of the features that were used to classify *natural vegetation*, specifically the SPOT 5 brilliance index and/or the ratio of the 8th ASTER band over the 9th ASTER band.

Agriculture also achieved a very high user's accuracy (87%). Four classes namely *bare surfaces*, *built-up* areas, *natural vegetation* and *roads*, were misclassified as *agriculture*. The misclassification of *bare surfaces* as *agriculture* is likely due to the difference in image acquisition dates and the date on which fieldwork was carried out. For instance, a bare land parcel which was misclassified as *agriculture* on the SPOT 5 and ASTER images may have been cultivated on the date that the fieldwork was done and the land parcel of that object may have been less fractal (i.e. it has a lower shape index than was specified in the ruleset). The misclassification of *built-up* areas is attributed to the use of a cadastral vector layer to distinguish between bright objects such as buildings, mining areas and bare surfaces. Buildings on farms were consequently classified incorrectly. The misclassification of the *roads* objects as *agriculture* is most likely due to the positional inaccuracy of either the roads vector layer or the inaccuracy of the GPS readings, particularly where an agricultural field is adjacent to the road.

The largest error of omission, or inversely error of commission, was between *natural vegetation* and *agriculture*. These were the most sampled classes and they make up nearly 88% of the classified image. There was a marked difference (29%) between the producer's and user's accuracies for natural vegetation, a difference mainly attributable to the misclassification of agricultural objects. *Natural vegetation* objects that were incorrectly classified as *agriculture,* is likely because of the similar spectral properties of these classes. To a lesser extent, *bare surfaces, built-up* and *recreation* were misclassified as *natural vegetation*.

The 60% producer's accuracy and 71% user's accuracy for *bare surfaces* is an indication that this class was classified least accurately overall. Objects of this class were misclassified as either *agriculture* or *natural vegetation*. The main problem with a bare patch of land is that vegetation, whether it is natural vegetation or agriculture, can cover the surface within a short period of time. The accuracy of this class will always be influenced by the image acquisition date and the date the fieldwork was conducted. This class should therefore be confined to areas where vegetative growth is limited.

Built-up objects had a producer's accuracy of 72%. Objects of this class were often misclassified as *natural vegetation, bare surfaces* or *agriculture*. The reason for the confusion with *agriculture* and *natural vegetation* could be attributed to the cadastral thematic layer that was used to separate built-up areas from other classes with similar spectral characteristics. *Built-up* areas have a very similar spectral response to *bare surfaces*, hence the misclassification. Another possible reason for the misclassification could be related to the object size, i.e. the parameters specified in the MRS algorithm. A smaller scale parameter would have classified sparsely separated *built-up* objects more accurately. However, reducing the scale parameter may have resulted in undergeneralization (i.e. noise).

Water had a very high producer's accuracy (89%). *Bare surfaces* and *mining* were misclassified as *water* on two occasions. This misclassification may be due to the ratio green customized feature used to separate non-vegetated from vegetated areas. Furthermore, the linear shape of rivers and roads makes the textural separation of these classes difficult.

Where possible these small errors were corrected manually to improve the overall quality of the land use/cover map. This map was then combined with other environmental parameters to identify NTU, as explained in the next section.

4.4 IDENTIFICATION OF NATURAL TERROIR UNITS

Natural terroir units (NTU) were defined earlier as the grouping of land surfaces with homogeneous patterns in topography, climate, geology and soil (Carey 2005). To combine these natural factors with the current land cover, a single GIS layer was created by multiplying each of these natural factors with every other natural factor in order to define a unique unit of the land surface. This is theoretically possible but it would be difficult to represent the different units on one map, especially if the individual units are diverse. Consequently, the data needed to be generalized to limit the number of classes. This section describes the process of identifying the NTU in the study area. Two important constituents of NTU, namely land use/cover and soil landscape, will be discussed individually and then combined with slope aspect to classify NTU.

4.4.1 Land use/cover

The land use/cover map (Figure 4.7) served as the basis for the delimitation of NTU. Only *agriculture*, *natural vegetation* and *bare surfaces* are considered for NTU mapping. *Natural vegetation* and *bare surfaces* areas can potentially be exploited for *agriculture*, provided that the environmental conditions are favourable. These land use/cover classes will be combined with the soil landscape and slope aspect to delimit NTU. The following subsection will describe the soil landscape of the study area.

4.4.2 Soil landscape

This section describes how the soil map was combined with the landscape to create a soil landscape map. Terrain elements such as slope gradient, elevation and curvature are combined to define landscape elements.

The landscape was represented by creating hillslope components from the terrain data. The eCognition Developer 7.0 software was used for the hillslope classification. The method used was based on the approach followed by Dragut & Blaschke (2006) in which a normalized elevation layer, the slope gradient, plan curvature and profile curvature were derived from a DEM and used as input layers for segmentation. The same weight was applied to all the layers and homogeneous objects were created by segmenting the layers with a scale parameter of 50 in the MRS algorithm. The classification procedure is described in Figure 4.9.

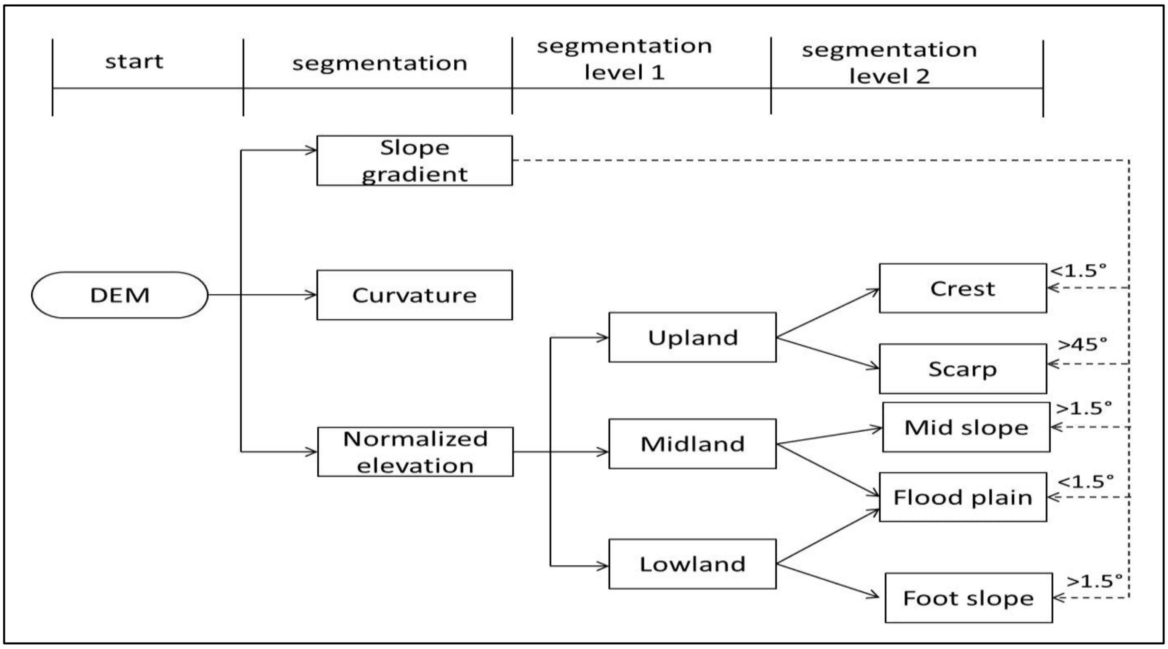


Figure 4.9: Hierarchy for classifying landscape elements

A normalized elevation layer was created by transforming the 16-bit 20-m resolution DEM into an 8-bit elevation layer with values ranging from 0-255. This 8-bit layer was segmented and classified as upland (59-255), midland (38-58) and lowland (0-37). These values were defined using the fuzzy membership classification function in eCognition. Because of the abrupt change in terrain, the fuzzy membership values were slightly adjusted so that it can be more representative of the terrain of the study area.

Next, the segmentation was refined according to the position of the objects on the hillslope. This position was determined by the five land components illustrated in Figure 2.2. Henceforth, the term 'channel beds' is replaced by 'flood plains' and 'fallface' by 'scarp'. Although Dragut & Blaschke's (2006) classification takes curvature into account, this research omits this parameter and the subsequent classes derived from it because it has neither been consistently described in the delimitation of land components, nor in the classification of NTU. On the second level of terrain classification, the upland was classified into crests (objects with flat areas on upland and objects that are higher than their neighbours) and scarps (objects with slope gradients greater than 45°). The midland was subdivided into areas with gentle slopes (objects with slope gradients less than 1.5°) and mid slopes (objects with slope gradients greater than 1.5°). The lowland was subdivided into flood plains (objects with slope gradients less than 1.5°) and foot slopes (areas with slope gradients greater than 1.5° on low-lying areas). Areas with gentle slopes on the midlands were reclassified as flood plains (Figure 4.10).

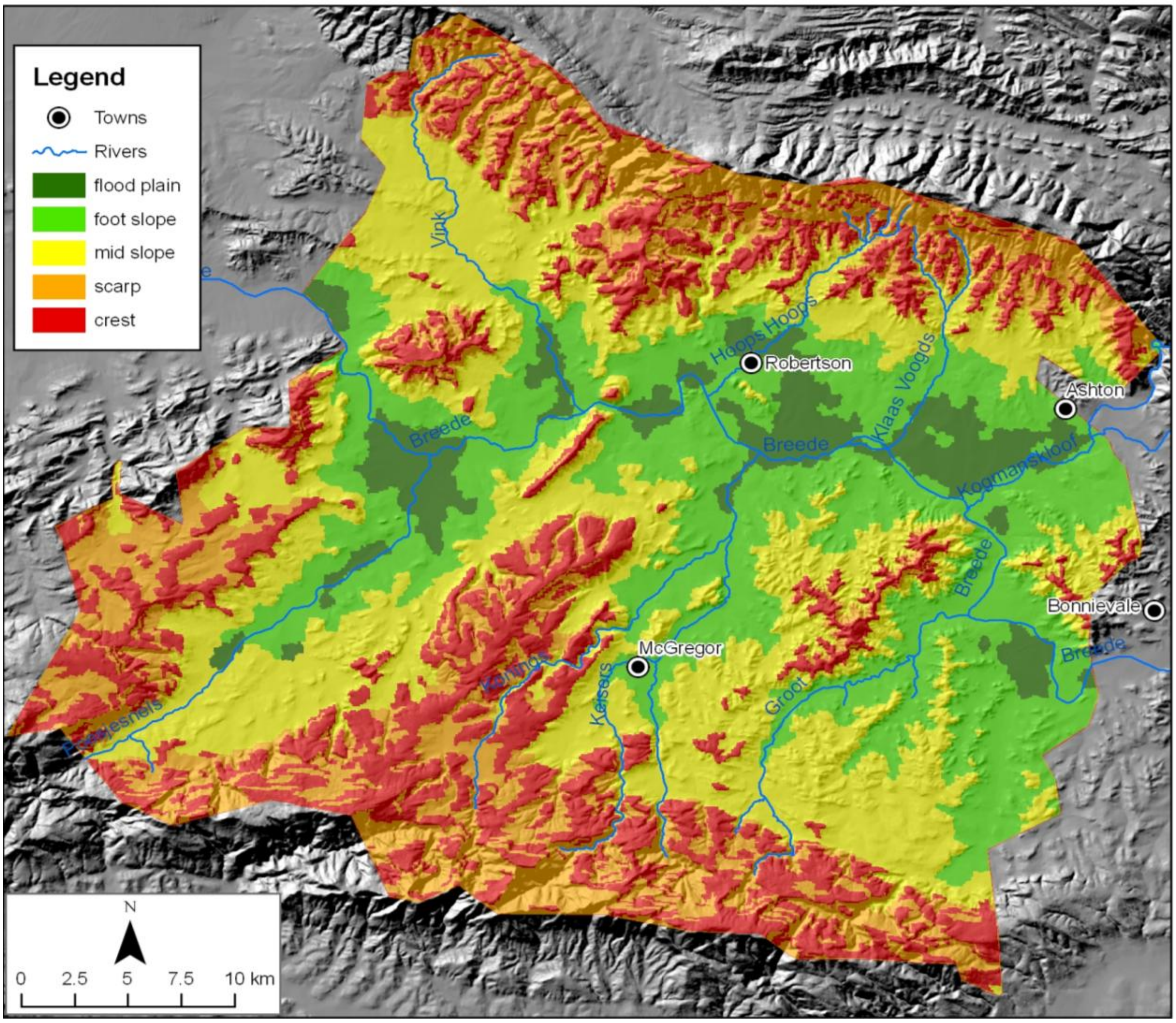


Figure 4.10: Landscape elements subdivided into hillslopes

Mid slopes comprise an area of 47 730 ha, foot slopes 37 970 ha, crests 33 630 ha, scarps 30 140 ha and flood plains 9 970 ha.

The soil landscape map (Figure 4.11) was compiled by combining the landscape element map (Figure 4.10) with the soil map (Figure 3.10) in ArcGIS 9.2. Arbitrary rules were applied when the soil landscape classes were defined. Wet, poorly-drained alluvial soils were assigned to the flood plain only. Duplex soils were assigned to landscapes on the mid slopes, while dry soils were assigned to landscapes on the flood plains, foot- and mid slopes. Red soils on alluvial terraces or clay were reclassified as soils with red B-horizons, and they occur on the flood plains and on foot- and mid slopes of the terrain. Soils classified as ‘red soils; calcareous; eutrophic-calcareous, calcrete and duripan’ were reclassified as ‘lime-rich soils’ and they occur on the flood plains, foot- and mid slopes. ‘Rocky; little or no soil; shallow soils’ were reclassified as landscapes on scarps and crests. Saline soils occur on the flood plain and foot slopes, while terrace gravels and yellow-brown apedal soils occur on the foot slopes only. Tallus rocks occur on both the foot- and mid slopes of the hillslope. The soil landscap map that was subsequently created consists of 18 classes as illustrated in Figure 4.11.

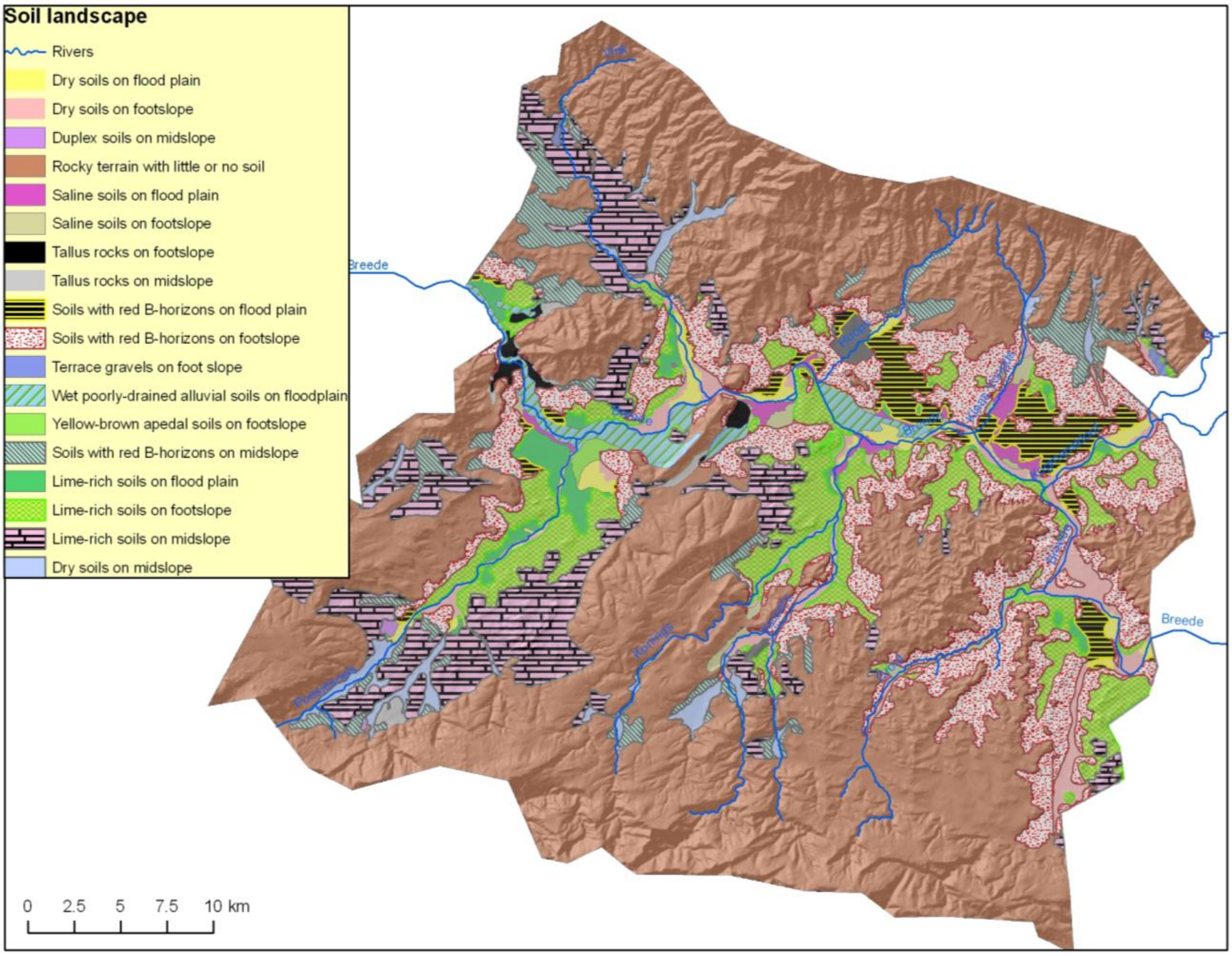


Figure 4.11: Soil landscapes of the Robertson LM

Excluding rocky terrain on scarps and crests, most of the soil landscape is covered by soils with red B-horizons on foot slopes, lime-rich soils on mid slopes and on foot slopes, soils with red B-horizons on mid slopes and dry soils on foot slopes.

4.5 NTU CLASSIFICATION

The land use/cover map and the soil landscape map were rasterized in ArcGIS to the resolution of the slope aspect map (Figure 3.6) that is 20×20 m. Natural components in the delimitation of the NTU are therefore based on land use/cover, soil landscape and slope aspect. The number of land use/cover classes was reduced from eight to three, because only *agriculture*, *natural vegetation* and *bare surfaces* are land that has the potential to produce NTU. The slope aspect classes were reduced to the four major directions, namely north, east, south and west. After rasterization of the land use/cover and soil landscape maps, each of the components were assigned a code to uniquely identify it. The three land use/cover classes were reclassified to values ranging from 1000 to 3000; the four directional classes of the slope aspect were reclassified to values ranging from 100 to 400, and the 18 soil landscape classes were reclassified to values ranging from 1 to 18. Table 4.5 shows the code system applied to uniquely identify each NTU.

Table 4.5: Code system used to describe NTU

Land use/cover		
Class #	**Class name**	**NTU code**
1	Natural vegetation	1000
2	Agriculture	2000
3	Bare surfaces	3000

Slope aspect		
Class #	**Class name**	**NTU code**
1	North	100
2	East	200
3	South	300
4	West	400

Soil landscape		
Class #	**Class name**	**NTU code**
1	Dry soils on flood plain	1
2	Dry soils on foot slope	2
3	Duplex soils on mid slope	3
4	Rocky terrain with little or no soil	4
6	Saline soils on foot slope	6
7	Tallus rocks on foot slope	7
8	Tallus rocks on mid slope	8
9	Terrace gravels on foot slope	9
10	Wet poorly-drained alluvial soils on flood plain	10
11	Yellow-brown apedal soils on foot slope	11
12	Dry soils on mid slope	12
13	Lime-rich soils on flood plain	13
14	Lime-rich soils on foot slope	14
15	Lime-rich soils on mid slope	15
16	Soils with red B-horizons on flood plain	16
17	Soils with red B-horizons on foot slope	17
18	Soils with red B-horizons on mid slope	18

The first digit in the code indicates the land use/cover, the second digit indicates slope aspect and the third and fourth digits indicate the soil landscape. If, for example, the NTU code starts with a ‘2’ it means that the land use/cover class is agriculture. A ‘1’ as first digit indicates natural vegetation and a ‘3’ indicates bare surfaces. If the second digit is a ‘1’, it means that the NTU class has a northerly slope aspect and a second digit with the value of ‘3’ indicates NTU classes with southerly slopes aspects, and so forth. If the code ends with ‘1’, it indicates an NTU with a soil landscape class of ‘dry soils on flood plains’. A NTU code of ‘2101’, for example, is a NTU classified as agriculture, with a northerly slope aspect, which is on dry soils on flood plains. Potentially, 216 classes (3 land use/cover classes × 4 slope aspect classes × 18 soil landscape classes) can be described with this method of terroir delimitation. Hence, some generalizations had to be made to limit the number of NTU classes. The slope aspect and soil landscape for classes such as built-up, roads, water, recreation and mining were omitted as they would be irrelevant in NTU mapping. The slope aspects for terrain on the flood plain were also omitted in the NTU description because these areas are relatively flat. A raster layer with unique codes to represent NTU was calculated after the summation of the three layers and the generalization of the classes. The raster dataset was vectorized and the attribute table was populated with the description of the NTU codes. A total 170 NTU classes were described. Water, built-up areas, recreation and roads are also accounted for. The spatial distribution of NTU Robertson LM is shown in Figure 4.12.

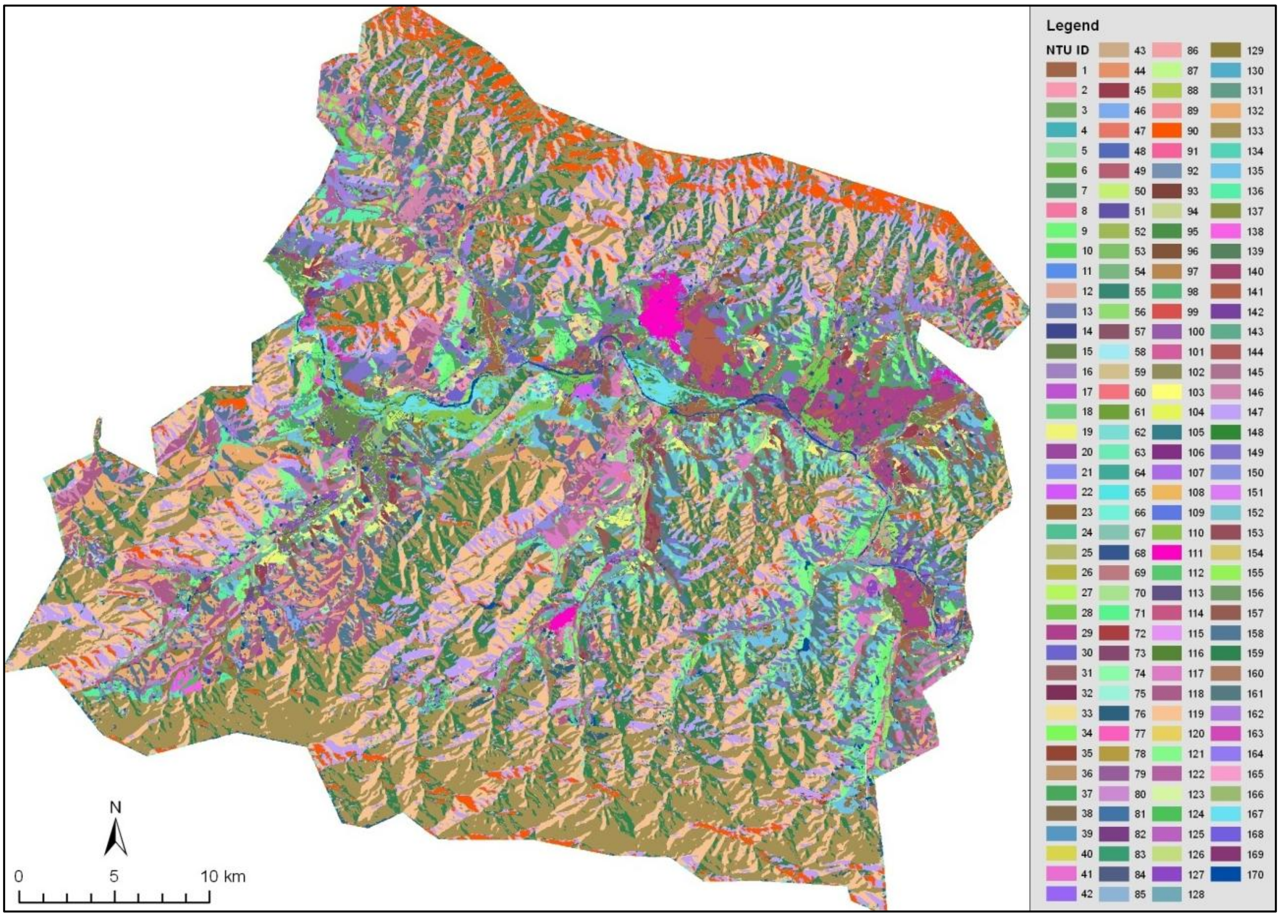


Figure 4.12: NTU map of Robertson. The description associated with the legend can be found in Table 4.6

Providing a legend comprehensible for 170 classes on a single map is a major limitation of NTU mapping as pointed out by Girard & Girard (1998). Therefore, the description of each of the 170 NTU is tabulated in Table 4.6. For each NTU, three parameters are described, namely land use/cover, slope aspect and soil landscape. Further generalization of the individual NTU components would be necessary to reduce the number of classes to categorize them in an intelligible legend. The number of soil landscape classes can be reduced, but the expert knowledge of soil scientists and/or geomorphologists would be required to do the task.

Table 4.6: Description of the 170 NTU of Robertson sorted alphabetically

NTU ID	NTU Description	Area (ha)
1	Agriculture; dry soils on flood plain	968.1
2	Agriculture; easterly slope aspect; dry soils on foot slope	376.8
3	Agriculture; easterly slope aspect; dry soils on mid slope	179.6
4	Agriculture; easterly slope aspect; Duplex soils on mid slope	25.4
5	Agriculture; easterly slope aspect; lime-rich soils on foot slope	990.7
6	Agriculture; easterly slope aspect; lime-rich soils on mid slope	188.9
7	Agriculture; easterly slope aspect; rocky terrain with little or no soil	250.6
8	Agriculture; easterly slope aspect; saline soils on foot slope	56.3
9	Agriculture; easterly slope aspect; soils with red B-horizons on foot slope	1 337.4
10	Agriculture; easterly slope aspect; soils with red B-horizons on mid slope	184.8
11	Agriculture; easterly slope aspect; tallus rocks on foot slope	40.2
12	Agriculture; easterly slope aspect; tallus rocks on mid slope	13.0
13	Agriculture; easterly slope aspect; terrace gravels on foot slope	14.5
14	Agriculture; easterly slope aspect; yellow-brown apedal soils on foot slope	14.2
15	Agriculture; lime-rich soils on flood plain	1219.3
16	Agriculture; northerly slope aspect; dry soils on foot slope	357.7
17	Agriculture; northerly slope aspect; dry soils on mid slope	140.9
18	Agriculture; northerly slope aspect; duplex soils on mid slope	8.1
19	Agriculture; northerly slope aspect; lime-rich soils on foot slope	929.1
20	Agriculture; northerly slope aspect; lime-rich soils on mid slope	275.6
21	Agriculture; northerly slope aspect; rocky terrain with little or no soil	207.3
22	Agriculture; northerly slope aspect; saline soils on foot slope	140.3
23	Agriculture; northerly slope aspect; soils with red B-horizons on foot slope	811.4
24	Agriculture; northerly slope aspect; soils with red B-horizons on mid slope	166.2
25	Agriculture; northerly slope aspect; tallus rocks on foot slope	6.5
26	Agriculture; northerly slope aspect; tallus rocks on mid slope	5.8

Continued overleaf

Table 4.6 continued

NTU ID	NTU Description	Area (ha)
27	Agriculture; northerly slope aspect; yellow-brown apedal soils on foot slope	81.1
28	Agriculture;saline soils on flood plain	523.3
29	Agriculture; soils with red B-horizons on flood plain	2 315.7
30	Agriculture; southerly slope aspect; dry soils on foot slope	529.6
31	Agriculture; southerly slope aspect; dry soils on mid slope	146.0
32	Agriculture; southerly slope aspect; duplex soils on mid slope	4.4
33	Agriculture; southerly slope aspect; lime-rich soils on foot slope	513.3
34	Agriculture; southerly slope aspect; lime-rich soils on mid slope	291.6
35	Agriculture; southerly slope aspect; rocky terrain with little or no soil	201.2
36	Agriculture; southerly slope aspect; saline soils on foot slope	120.0
37	Agriculture; southerly slope aspect; soils with red B-horizons on foot slope	1 553.1
38	Agriculture; southerly slope aspect; soils with red B-horizons on mid slope	285.5
39	Agriculture; southerly slope aspect; tallus rocks on foot slope	3.8
40	Agriculture; southerly slope aspect; tallus rocks on mid slope	0.1
41	Agriculture; southerly slope aspect; terrace gravels on foot slope	22.9
42	Agriculture; southerly slope aspect; yellow-brown apedal soils on foot slope	1.5
43	Agriculture; westerly slope aspect; dry soils on foot slope	530.2
44	Agriculture; westerly slope aspect; dry soils on mid slope	163.3
45	Agriculture; westerly slope aspect; lime-rich soils on foot slope	689.3
46	Agriculture; westerly slope aspect; lime-rich soils on mid slope	294.2
47	Agriculture; westerly slope aspect; rocky terrain with little or no soil	168.7
48	Agriculture; westerly slope aspect; saline soils on foot slope	94.6
49	Agriculture; westerly slope aspect; soils with red B-horizons on foot slope	1 075.2
50	Agriculture; westerly slope aspect; soils with red B-horizons on mid slope	233.4
51	Agriculture; westerly slope aspect; tallus rocks on foot slope	38.8
52	Agriculture; westerly slope aspect; tallus rocks on mid slope	2.2
53	Agriculture; westerly slope aspect; terrace gravels on foot slope	15.3
54	Agriculture; westerly slope aspect; yellow-brown apedal soils on foot slope	44.6
55	Agriculture; wet poorly-drained alluvial soils on Flood plain	333.2
56	Bare surfaces; dry soils on flood plain	289.2
57	Bare surfaces; easterly slope aspect; dry soils on foot slope	103.1

Continued overleaf

Table 4.6 continued

NTU ID	NTU Description	Area (ha)
58	Bare surfaces; easterly slope aspect; dry soils on mid slope	87.3
59	Bare surfaces; easterly slope aspect; duplex soils on mid slope	16.3
60	Bare surfaces; easterly slope aspect; lime-rich soils on foot slope	328.1
61	Bare surfaces; easterly slope aspect; lime-rich soils on mid slope	293.5
62	Bare surfaces; easterly slope aspect; rocky terrain with little or no soil	926.1
63	Bare surfaces; easterly slope aspect; saline soils on foot slope	29.8
64	Bare surfaces; easterly slope aspect; soils with red B-horizons on foot slope	409.2
65	Bare surfaces; easterly slope aspect; soils with red B-horizons on mid slope	116.8
66	Bare surfaces; easterly slope aspect; tallus rocks on foot slope	72.0
67	Bare surfaces; easterly slope aspect; tallus rocks on mid slope	10.5
68	Bare surfaces; easterly slope aspect; terrace gravels on foot slope	3.0
69	Bare surfaces; easterly slope aspect; yellow-brown apedal soils on foot slope	9.8
70	Bare surfaces; lime-rich soils on flood plain	242.0
71	Bare surfaces; northerly slope aspect; dry soils on foot slope	161.2
72	Bare surfaces; northerly slope aspect; dry soils on mid slope	83.3
73	Bare surfaces; northerly slope aspect; duplex soils on mid slope	0.2
74	Bare surfaces; northerly slope aspect; lime-rich soils on foot slope	367.6
75	Bare surfaces; northerly slope aspect; lime-rich soils on mid slope	339.8
76	Bare surfaces; northerly slope aspect; rocky terrain with little or no soil	1 246.1
77	Bare surfaces; northerly slope aspect; saline soils on foot slope	51.5
78	Bare surfaces; northerly slope aspect; soils with red B-horizons on foot slope	415.4
79	Bare surfaces; northerly slope aspect; soils with red B-horizons on mid slope	127.1
80	Bare surfaces; northerly slope aspect; tallus rocks on foot slope	8.4
81	Bare surfaces; northerly slope aspect; tallus rocks on mid slope	10.3
82	Bare surfaces; northerly slope aspect; yellow-brown apedal soils on foot slope	33.4
83	Bare surfaces; saline soils on flood plain	179.4
84	Bare surfaces; soils with red B-horizons on flood plain	396.9
85	Bare surfaces; southerly slope aspect; dry soils on foot slope	117.7
86	Bare surfaces; southerly slope aspect; dry soils on mid slope	60.5
87	Bare surfaces; southerly slope aspect; Duplex soils on mid slope	1.3
88	Bare surfaces; southerly slope aspect; lime-rich soils on foot slope	148.0

Continued overleaf

Table 4.6 continued

NTU ID	NTU Description	Area (ha)
89	Bare surfaces; southerly slope aspect; lime-rich soils on mid slope	314.0
90	Bare surfaces; southerly slope aspect; rocky terrain with little or no soil	6 029.0
91	Bare surfaces; southerly slope aspect; saline soils on foot slope	24.4
92	Bare surfaces; southerly slope aspect; soils with red B-horizons on foot slope	428.4
93	Bare surfaces; southerly slope aspect; soils with red B-horizons on mid slope	119.2
94	Bare surfaces; southerly slope aspect; tallus rocks on foot slope	14.4
95	Bare surfaces; southerly slope aspect; tallus rocks on mid slope	9.1
96	Bare surfaces; southerly slope aspect; terrace gravels on foot slope	5.3
97	Bare surfaces; southerly slope aspect; yellow-brown apedal soils on foot slope	4.1
98	Bare surfaces; westerly slope aspect; dry soils on foot slope	158.0
99	Bare surfaces; westerly slope aspect; dry soils on mid slope	81.2
100	Bare surfaces; westerly slope aspect; lime-rich soils on foot slope	232.9
101	Bare surfaces; westerly slope aspect; lime-rich soils on mid slope	303.8
102	Bare surfaces; westerly slope aspect; rocky terrain with little or no soil	3 487.1
103	Bare surfaces; westerly slope aspect; saline soils on foot slope	26.8
104	Bare surfaces; westerly slope aspect; soils with red B-horizons on foot slope	310.5
105	Bare surfaces; westerly slope aspect; soils with red B-horizons on mid slope	116.8
106	Bare surfaces; westerly slope aspect; tallus rocks on foot slope	33.6
107	Bare surfaces; westerly slope aspect; tallus rocks on mid slope	5.5
108	Bare surfaces; westerly slope aspect; terrace gravels on foot slope	5.1
109	Bare surfaces; westerly slope aspect; yellow-brown apedal soils on foot slope	17.6
110	Bare surfaces; wet poorly-drained alluvial soils on Flood plain	852.1
111	Built-up	718.9
112	Mining	469.3
113	Natural vegetation; dry soils on flood plain	448.3
114	Natural vegetation; easterly slope aspect; dry soils on foot slope	272.3
115	Natural vegetation; easterly slope aspect; dry soils on mid slope	365.4
116	Natural vegetation; easterly slope aspect; duplex soils on mid slope	10.5
117	Natural vegetation; easterly slope aspect; lime-rich soils on foot slope	1 872.4
118	Natural vegetation; easterly slope aspect; lime-rich soils on mid slope	2 783.2
119	Natural vegetation; easterly slope aspect; rocky terrain with little or no soil	19 556.0

Continued overleaf

Table 4.6 continued

NTU ID	NTU Description	Area (ha)
120	Natural vegetation; eas terly slope aspect; saline soils on foot slope	112.1
121	Natural vegetation; easterly slope aspect; soils with red B-horizons on foot slope	3 577.8
122	Natural vegetation; easterly slope aspect; soils with red B-horizons on mid slope	691.7
123	Natural vegetation; easterly slope aspect; tallus rocks on foot slope	115.0
124	Natural vegetation; easterly slope aspect; tallus rocks on mid slope	92.6
125	Natural vegetation; easterly slope aspect; terrace gravels on foot slope	7.4
126	Natural vegetation; easterly slope aspect; yellow-brown apedal soils on foot slope	34.0
127	Natural vegetation; lime-rich soils on flood plain	418.2
128	Natural vegetation; northerly slope aspect; dry soils on foot slope	474.2
129	Natural vegetation; northerly slope aspect; dry soils on mid slope	580.2
130	Natural vegetation; northerly slope aspect; duplex soils on mid slope	7.3
131	Natural vegetation; northerly slope aspect; lime-rich soils on foot slope	2 055.5
132	Natural vegetation; northerly slope aspect; lime-rich soils on mid slope	3 756.7
133	Natural vegetation; northerly slope aspect; rocky terrain with little or no soil	26 177.4
134	Natural vegetation; northerly slope aspect; saline soils on foot slope	127.6
135	Natural vegetation; northerly slope aspect; soils with red B-horizons on foot slope	3 356.7
136	Natural vegetation; northerly slope aspect; soils with red B-horizons on mid slope	952.6
137	Natural vegetation; northerly slope aspect; tallus rocks on foot slope	31.6
138	Natural vegetation; northerly slope aspect; tallus rocks on mid slope	128.6
139	Natural vegetation; northerly slope aspect; yellow-brown apedal soils on foot slope	47.9
140	Natural vegetation; saline soils on flood plain	202.1
141	Natural vegetation; soils with red B-horizons on flood plain	1071.6
142	Natural vegetation; southerly slope aspect; dry soils on foot slope	271.9
143	Natural vegetation; southerly slope aspect; dry soils on mid slope	216.1
144	Natural vegetation; southerly slope aspect; duplex soils on mid slope	2.0
145	Natural vegetation; southerly slope aspect; lime-rich soils on foot slope	1 023.8
146	Natural vegetation; southerly slope aspect; lime-rich soils on mid slope	2120.5
147	Natural vegetation; southerly slope aspect; rocky terrain with little or no soil	14776.9
148	Natural vegetation; southerly slope aspect; saline soils on foot slope	106.8
149	Natural vegetation; southerly slope aspect; soils with red B-horizons on foot slope	3 116.7

Continued overleaf

Table 4.6 continued

150	Natural vegetation; southerly slope aspect; soils with red B-horizons on mid slope	906.3
NTU ID	**NTU Description**	**Area (ha)**
151	Natural vegetation; southerly slope aspect; tallus rocks on foot slope	45.6
152	Natural vegetation; southerly slope aspect; tallus rocks on mid slope	37.5
153	Natural vegetation; southerly slope aspect; terrace gravels on foot slope	24.3
154	Natural vegetation; southerly slope aspect; yellow-brown apedal soils on foot slope	21.3
155	Natural vegetation; westerly slope aspect; dry soils on foot slope	448.2
156	Natural vegetation; westerly slope aspect; dry soils on mid slope	350.4
157	Natural vegetation; westerly slope aspect; lime-rich soils on foot slope	1 391.2
158	Natural vegetation; westerly slope aspect; lime-rich soils on mid slope	3 035.6
159	Natural vegetation; westerly slope aspect; rocky terrain with little or no soil	15 037.0
160	Natural vegetation; westerly slope aspect; saline soils on foot slope	100.3
161	Natural vegetation; westerly slope aspect; soils with red B-horizons on foot slope	3 089.5
162	Natural vegetation; westerly slope aspect; soils with red B-horizons on mid slope	837.2
163	Natural vegetation; westerly slope aspect; tallus rocks on foot slope	118.0
164	Natural vegetation; westerly slope aspect; tallus rocks on mid slope	71.3
165	Natural vegetation; westerly slope aspect; terrace gravels on foot slope	20.6
166	Natural vegetation; westerly slope aspect; yellow-brown apedal soils on foot slope	49.8
167	Natural vegetation; wet poorly-drained alluvial soils on Flood plain	965.3
168	Recreation	98.2
169	Roads	326.7
170	Water	1 125.9

According to Table 4.6, the most extensive NTU in the study area is natural vegetation on steep rocky terrain. Of the 170 classes, 55 NTU were described for agriculture and 54 each for natural vegetation and bare surfaces. Of the 55 agricultural NTU, 35 units have areas of more than 100 ha. Agriculture practiced on soils with red B-horizons that occur on flood plains, has the largest area (2315 ha), followed by areas with southerly slope aspects and soils with red B-horizons on the foot slopes of the terrain (1550 ha). Figure 4.12 and the NTU description in Table 4.6 can be used to assess the viticultural potential of these NTU. NTU with a land use/cover component of agriculture are used in this assessment, as this class is most likely to include the ideal conditions for viticulture. Existing locations of two of Robertson's award-winning cultivars, Chardonnay and Shiraz, will be assessed to determine whether their locations correspond with the research findings. But before this assessment is made, the viticultural potential of the NTU components are explored.

4.6 VITICULTURAL POTENTIAL OF THE NTU

This section examines the preferred climate, soil and topographic conditions for the cultivation of Shiraz and Chardonnay grapes. The data acquired and generated in Chapters 3 and 4 are compared to the preferred natural conditions for the cultivation of these two cultivars as described in literature sources.

4.6.1 Climatic potential

The MFT and heat units (or degree-days) maps (Figure 3.3 and Figure 3.4) indicated that there is a decrease in temperature from the valley towards the mountains. The determination of the climatic potential of the region is based on the potential of the Western Cape's viticultural areas according to the MFT and heat units as discussed by De Villiers *et al.* (1996). This is tabulated in Table 4.7.

Table 4.7: Viticultural potential for Robertson's major cultivars based on climatic parameters

Climatic index					
Degree-days	**<1389**	**1389-1666**	**1667-1943**	**1944-2220**	**>2220**
MFT	**17-19°C**	**19.1-21°C**	**21.1-23°C**	**23.1-25°C**	**>25°C**
Climate Desc	**Cold**	**Cool**	**Moderate**	**Hot**	**Very hot**
White varieties	Chardonnay	Chardonnay Chenin Blanc Sauvignon blanc	Chardonnay Chenin Blanc Colombar, Sémillon Sauvignon blanc		
Red varieties	Pinot Noir	Cabernet Sauvignon Merlot, Pinot Noir Pinotage, Shiraz Ruby Cabernet	Cabernet Sauvignon Cinsaut, Merlot, Shiraz Pinot Noir, Pinotage Ruby Cabernet	Cinsaut Ruby Cabernet	
Potential	High-quality white table wine	High quality red and white table wine	High-quality red table wines	Standard quality table wine	Dessert wine and brandy

Source: De Villiers *et al.* (1996) in Carey (2006)

Figure 3.2 and Figure 3.3 in the previous chapter shows that Robertson has a moderate MFT (21-23°C) according to Table 4.7 and consequently has the potential for the cultivation of high-quality red table wines. Moreover, Table 4.7 indicates that at moderate temperatures, there is an overlap between high quality red table wines such as Shiraz and high quality white table wines such as Chardonnay. This means that the climatic data could not be used to distinguish between Shiraz and Chardonnay growing areas based on MFT or GDD. Other environmental parameters, such as prevailing winds, the proximity of large water bodies and the effect of a sea breeze were omitted as there is not enough information to represent such data spatially. Although the literature (Section 2.2.3.3) suggests that northern and western slopes are warmer than southern and eastern slopes, the resolution of the climate data in Figure 3.3 and Figure 3.4 is too coarse (1.6 × 1.6 km) to distinguish between these slopes.

4.6.2 Topographic potential

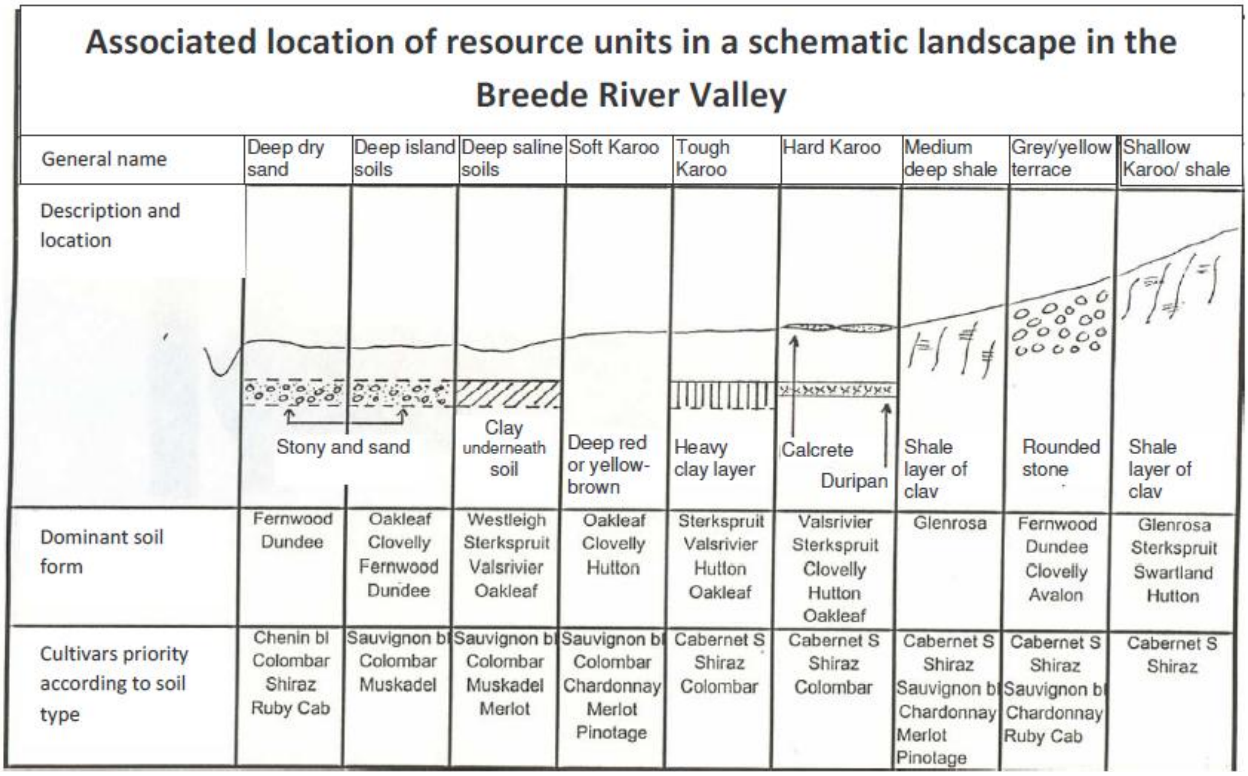
Slope gradient and slope aspect are important topographical parameters which play significant roles in the assessment of the viticultural potential of NTU (Dry & Coombe 1988). In the southern hemisphere, slope gradients with north-, west- and east-facing slope aspects receive more direct sunlight than slope gradients with south-facing slope aspects. In this research the four principal directions were used to describe slope aspect of the NTU. Northern and western slopes are warmer than eastern and southern slopes in the southern hemisphere because they receive the most direct radiation (Carey 2008). Both Goussard (2008) and Tait (1997) have pointed out that Chardonnay grapes prefer cooler slopes, i.e. preferably southern slope aspects, while Shiraz grapes prefer slightly warmer easterly slope aspects.

Another key factor to consider is that temperature generally decreases by 0.6°C per 100-m increase in elevation (Carey 2006). This is evident in Figure 3.3 where a decrease is shown in the MFT from the low-lying areas in the valley towards the high-lying slopes along the mountains. Tait (1997) reported that Shiraz grapes prefer terrain along the foot slope of hills, while Goussard (2008) affirms that Shiraz prefer mid slopes, or even flood plains if diseases are monitored carefully. Chardonnay grapes, in contrast, prefer lower slopes such as foot slopes and low mid slopes (Goussard 2008).

4.6.3 Soil potential

Significant soil parameters, such as pH, chemical composition, soil depth, soil texture and soil structure are not uniformly described by the existing GIS datasets. One can conclude from Figure 4.8 that most soils in the study area have good viticultural potential because these general soil classes have been successfully managed to produce outstanding quality wines.

Figure 4.13 presents a guideline followed by VinPro (2010, pers com), an independent wine-producer's organization, in the Breede River valley for assessing the viticultural potential based on soil description and location of the area's major cultivars.



Associated location of resource units in a schematic landscape in the Breede River Valley

General name	Deep dry sand	Deep island soils	Deep saline soils	Soft Karoo	Tough Karoo	Hard Karoo	Medium deep shale	Grey/yellow terrace	Shallow Karoo/ shale
Description and location	Stony and sand		Clay underneath soil	Deep red or yellow-brown	Heavy clay layer	Calcrete Duripan	Shale layer of clav	Rounded stone	Shale layer of clav
Dominant soil form	Fernwood Dundee	Oakleaf Clovelly Fernwood Dundee	Westleigh Sterkspruit Valsrivier Oakleaf	Oakleaf Clovelly Hutton	Sterkspruit Valsrivier Hutton Oakleaf	Valsrivier Sterkspruit Clovelly Hutton Oakleaf	Glenrosa	Fernwood Dundee Clovelly Avalon	Glenrosa Sterkspruit Swartland Hutton
Cultivars priority according to soil type	Chenin bl Colombar Shiraz Ruby Cab	Sauvignon bl Colombar Muskadel	Sauvignon bl Colombar Muskadel Merlot	Sauvignon bl Colombar Chardonnay Merlot Pinotage	Cabernet S Shiraz Colombar	Cabernet S Shiraz Colombar	Cabernet S Shiraz Sauvignon bl Chardonnay Merlot Pinotage	Cabernet S Shiraz Sauvignon bl Chardonnay Ruby Cab	Cabernet S Shiraz

Source: VinPro (2010, pers com)

Figure 4.13: Viticultural potential for the Breede River valley's major cultivars based on soil description

It is clear from Figure 4.13 that most cultivars are suitable for the cultivation on a variety of soil landscapes. For example, Shiraz grapes can be cultivated on flood plains, foot- and mid slopes on most soils of the terrain. Chardonnay grapes, in contrast are most suited for the cultivation on foot- and mid slopes with gravelley, clayey or deep red or yellow-brown soils. The soil description in Figure 4.13 does not entirely correspond to the GIS data in Figure 3.10 so that some assumptions will have to be made to assess the soil potential of the region.

4.6.4 Geological potential

No references could be found to link the role of geology directly to specific cultivars. As cited in Section 2.2.4, Sever (2004) stated that because soils are very old in South Africa, it plays a much more important role than geology, although other studies acknowledge the indirect role of geology in the aroma and quality of wines.

4.6.5 NTU for Shiraz cultivars

Shiraz performs well on mid slopes with eastern slope aspects and medium- to high-potential soils in various climatic conditions (Goussard 2008). According to Figure 4.13, this cultivar does well on various soils throughout the region, except for deep saline soils, deep island soils and deep red or yellow-brown soils. There are six NTU that meet this condition i.e. agriculture with easterly slope aspects, on mid slopes. These NTU cover a combined area of 842 ha.

In addition Goussard (2008) has noted that if plant diseases are well controlled, Shiraz can perform well in valleys. NTU on flood plains satisfy this condition and these landscapes cover a total area of 3535 ha in the study area. NTU with easterly slope aspects on mid slopes and those on flood plains were combined in a single layer to indicate areas that are most suitable for the cultivation of Shiraz grapes- an area totalling 4377 ha. The NTU description of this layer is given in Table 4.8 and shown in Figure 4.14. Table 4.8 shows that there are eight NTU most suitable for the cultivation of Shiraz grapes, of which the largest area (80.8%) occurs on flood plains. The NTU in size range between 13 and 2316 ha with an average size of 550 ha.

Table 4.8: Description of NTU most suitable for the cultivation of Shiraz grapes

NTU ID	NTU Description	Area (ha)	% of area
3	Agriculture; easterly slope aspect; dry soils on mid slope	179.6	4.1
4	Agriculture; easterly slope aspect; duplex soils on mid slope	25.4	0.6
6	Agriculture; easterly slope aspect; lime-rich soils on mid slope	188.9	4.3
7	Agriculture; easterly slope aspect; rocky terrain with little or no soil	250.6	5.7
10	Agriculture; easterly slope aspect; soils with red B-horizons on mid slope	184.8	4.2
12	Agriculture; easterly slope aspect; tallus rocks on mid slope	13.0	0.3
15	Agriculture; lime-rich soils on flood plains	1 219.3	27.9
29	Agriculture; soils with red B-horizons on flood plains	2 315.7	52.9
Totals		4 377.3	100.0

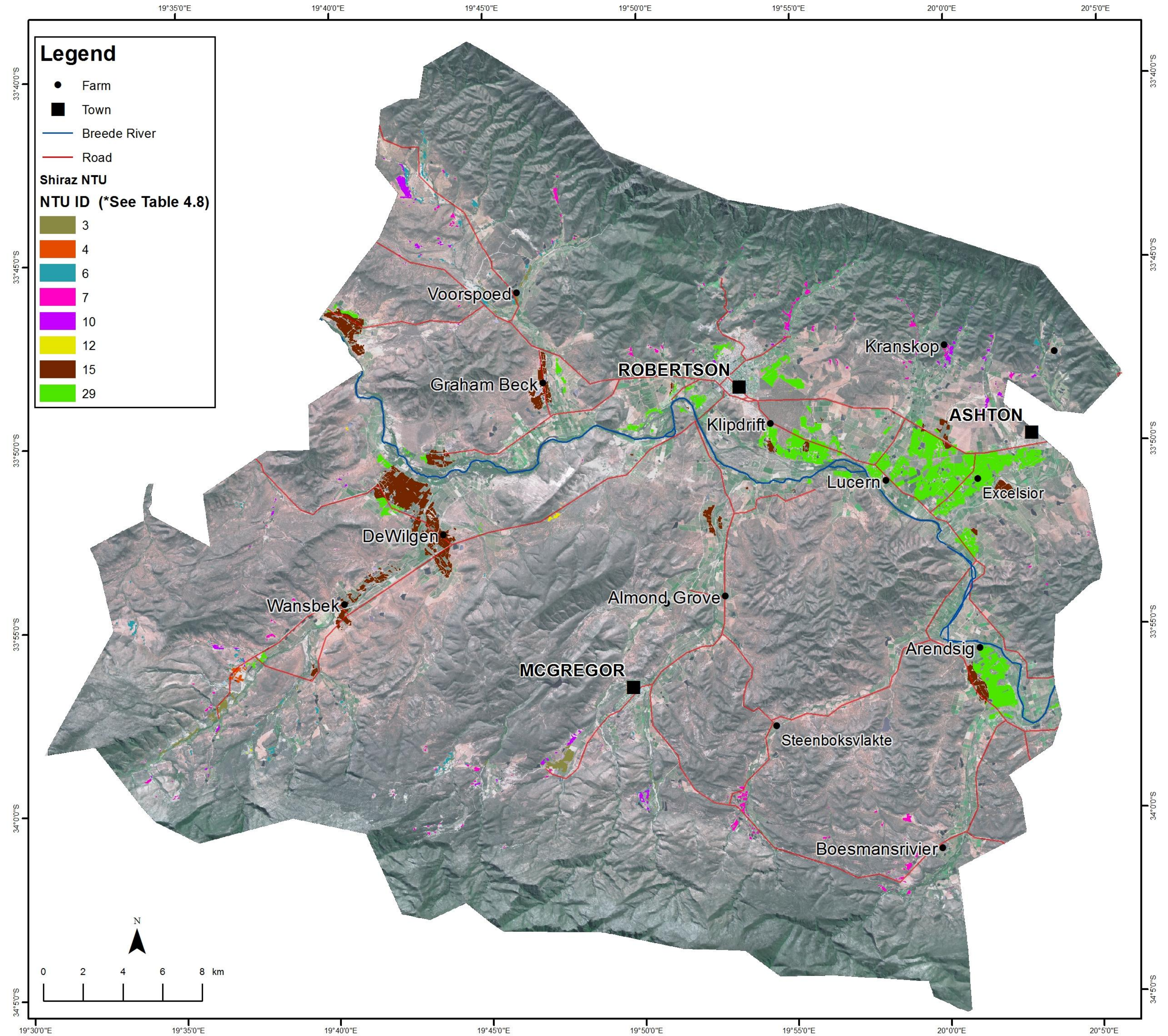


Figure 4.14: NTU most suitable for the cultivation of Shiraz grapes

Fourteen reference plots of known Shiraz vineyard blocks were used to determine whether existing plots are located on terrain with the most suitable environmental conditions for the cultivation of the cultivar as determined by this research. The suitability of the reference plots is summarized in Table 4.9.

Table 4.9: Reference plots of current Shiraz vineyard blocks

No.	Reference plot	Suitability*	Reason why reference plot is unsuitable
1	Almond Grove	0	Occurs on westerly slope aspect and foot slope
2	Arendsig	1	
3	Boesmansrivier	0	Occurs on southerly slope aspect and foot slope
4	DeWilgen	1	
5	Excelsior	1	
6	Graham Beck	1	
7	Klipdrift	1	
8	Koringsrivier	0	misclassified land use/cover class
9	Kranskop	1	
10	Lucern	1	
11	Steenboksvlakte	0	Occurs on foot slope
12	Voorspoed	1	
13	Wansbek	1	
14	Wilde Paarde Kloof	0	Occurs on westerly slope aspect

*Note: Value of ‘1’ indicates that the current Shiraz block is a suitable NTU candidate and value of ‘0’ indicates an unsuitable NTU candidate.

Of the fourteen reference plots, nine are the most suitable locations for the cultivation of Shiraz grapes according to the guideline specified by Goussard (2008). The reason why the other five Shiraz vineyard blocks are unsuitable according to this research is that these vineyards either have slope aspects other than east, occur on landscapes other than the flood plain or mid slopes or due misclassification in the OBIA.

4.6.6 NTU for Chardonnay cultivars

Chardonnay performs well on any terrain, but prefers lower southern slope aspects on medium- to high-potential soils where the climate is cool to moderate (Goussard 2008). A total of 7855 ha of NTU is suitable for the cultivation of Chardonnay grapes, of which the largest share (57%) occurs along the flood plains (4503 ha). NTU with southerly slopes along the foot- and mid slopes with medium- to high-potential soils contribute 3352 ha (43%).

There are 14 NTU that meet these requirements. The spatial distribution of these NTU is described in Table 4.10 shown in Figure 4.15.

Table 4.10: Description of NTU most suitable for the cultivation of Chardonnay grapes

NTU ID	NTU description	Area (ha)	% of area
1	Agriculture; dry soils on flood plain	968.1	12.3
15	Agriculture; lime-rich soils on flood plain	1 219.3	15.5
29	Agriculture; soils with red B-horizons on flood plain	2 315.7	29.5
30	Agriculture; southerly slope aspect; dry soils on foot slope	529.6	6.7
31	Agriculture; southerly slope aspect; dry soils on mid slope	146.0	1.9
32	Agriculture; southerly slope aspect; duplex soils on mid slope	4.4	0.1
33	Agriculture; southerly slope aspect; lime-rich soils on foot slope	513.3	6.5
34	Agriculture; southerly slope aspect; lime-rich soils on mid slope	291.6	3.7
37	Agriculture; southerly slope aspect; soils with red B-horizons on foot slope	1 553.1	19.8
38	Agriculture; southerly slope aspect; soils with red B-horizons on mid slope	285.5	3.6
39	Agriculture; southerly slope aspect; tallus rocks on foot slope	3.8	<0.1
40	Agriculture; southerly slope aspect; tallus rocks on mid slope	0.1	<0.1
41	Agriculture; southerly slope aspect; terrace gravels on foot slope	22.9	0.3
42	Agriculture; southerly slope aspect; yellow-brown apedal soils on foot slope	1.5	<0.1
Totals		7854.9	

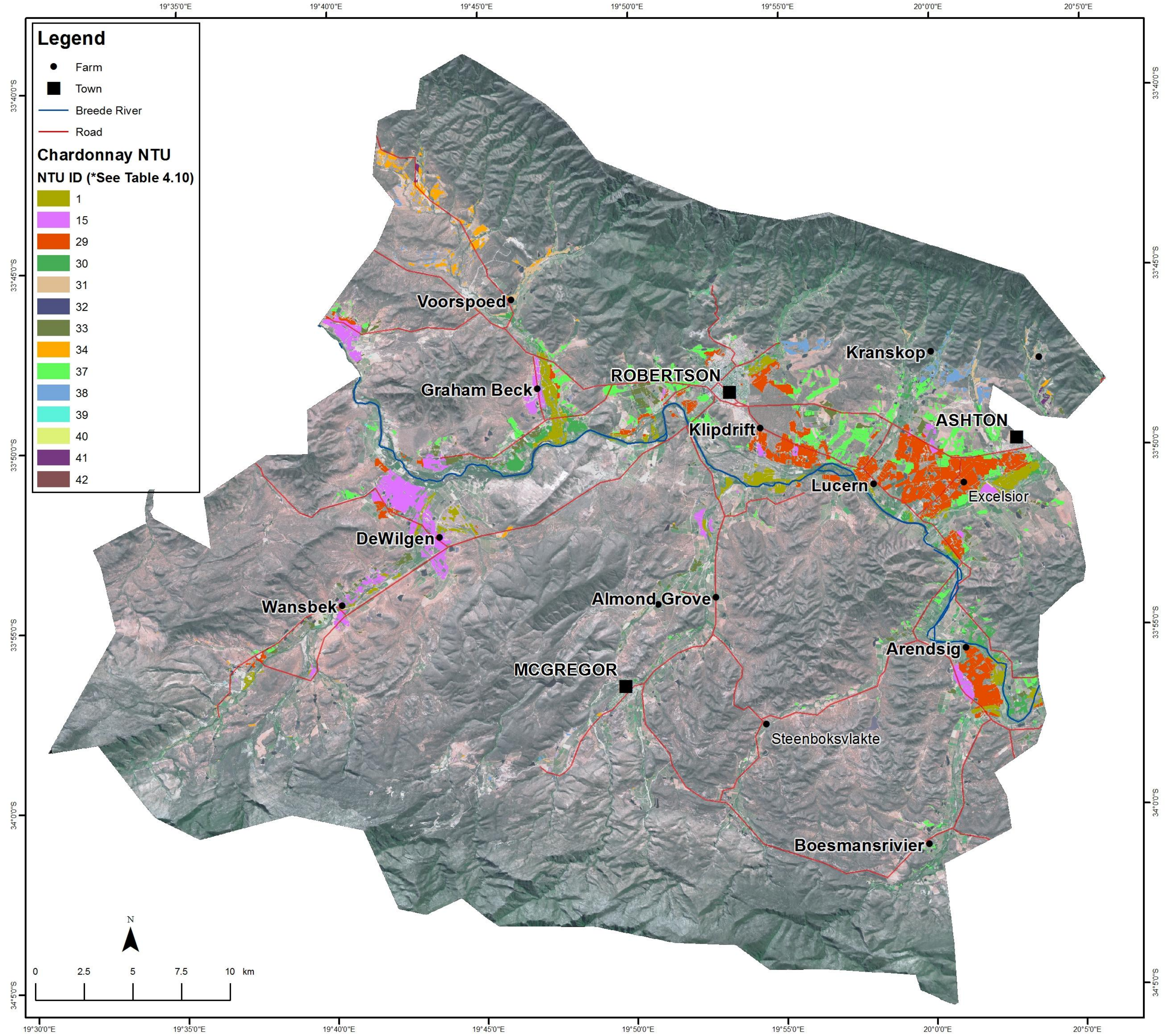


Figure 4.15: NTU most suitable for the cultivation of Chardonnay grapes

The location of 15 known Chardonnay reference plots were used to determine whether these existing plots are located on terrain with the most suitable environmental conditions for the cultivation of this cultivar as determined by this research. The suitability of the reference plots is summarized in Table 4.11.

Table 4.11: Reference plots of current Chardonnay vineyard blocks

Reference Plot	**Suitability**	**Reason why reference plot is unsuitable**
Almond Grove	0	Occurs along westerly slope aspect
Arendsig	0	Occurs along northerly slope aspect
Boesmansrivier	0	Occurs along easterly slope aspect
Excelsior	1	
Graham Beck	1	
Klipdrift	1	
Koringsrivier	0	Misclassified landcover and occurs along northerly slope aspect
Kranskop	0	Occurs along easterly slope aspect
Lucern	0	Occurs on saline soils
Steenboksvlakte	0	Misclassified landcover and occurs along northerly slope aspect
Voorspoed	0	Occurs along westerly slope aspect
Wansbek	0	Occurs along westerly slope aspect
Wel van Pas	0	Occurs along northerly slope aspect
Weltevrede RS	1	
Wilde Paarde Kloof	0	Occurs along westerly slope aspect

*Note: Value of ‘1’ indicates that the current Shiraz block is a suitable NTU candidate and value of ‘0’ indicates an unsuitable NTU candidate.

Only four of the 15 reference plots for Chardonnay grapes are located at NTU that are most suitable for this cultivar, as determined by this research. Two of the reference plots were misclassified as natural vegetation, while the other eight plots are unsuitable because they occur either on slope aspects other than south or on soils that are not generally suitable for the cultivation of Chardonnay grapes as determined by Goussard (2008).

4.7 SUMMARY

SPOT 5 panchromatic and edge layers derived from the panchromatic band were used in conjunction with SPOT 5 red and NIR layers in the MRS algorithm to derive meaningful image objects in the eCognition Developer software. These objects were classified using layer values, various indices and classification algorithms to classify eight different land use/cover classes. Indices such as the Brilliance index, ratio green and Zabud1 were more successful in discriminating between the eight classes than commonly used indices such as NDVI and SR. An overall accuracy of 81.2% was achieved with the land use/cover classification.

The land use/cover was combined with slope aspect and soil landscape to delineate NTU. A total of 170 NTU were described for the study area after a few generalizations were made. Because it is a difficult task to illustrate 170 different units on one map, the NTU were tabulated separately. These NTU vary in size from 0.1 ha to 26 170 ha. Of the 55 NTU classified as agriculture, 35 units have an area greater than 100 ha, which indicates that large areas of existing agricultural land are suitable to produce a unique product.

NTU that have a land use component of agriculture were assessed to evaluate their viticultural potential according to the optimal environmental conditions for the cultivation of Shiraz and Chardonnay grapes. Climate could not be used as an environmental parameter to distinguish Shiraz from Chardonnay because there is too much overlap in both MFT and GDD for these two cultivars. The moderate climate of the study area is nonetheless suitable for the cultivation of a variety of cultivars.

According to the guidelines followed by the independent wine producer’s organization, VinPro, various grape cultivars are well adapted to the variety of soil conditions in the study region. This guideline was used to identify soil conditions that the respective cultivars prefer. The soil descriptions in the VinPro (2010, pers com) guideline and the GIS information do not correspond fully and some assumptions had to be made.

The topographic suitability of Shiraz and Chardonnay was assessed against the cultivar characteristics described by Goussard (2008). The preferred slope aspects and location on the hillslope of various cultivars are the most important characteristics described by Goussard (2008). According to these guidelines, the preferable locations for the cultivation of Shiraz grapes are limited to terrain with eastern slope aspects on mid slopes and flood plains while those for Chardonnay are limited to terrain on the foot- and mid slopes with southern slope aspects, as well as terrain on flood plains.

This research found that, of the fourteen reference plots assessed for Shiraz grapes, nine occur on terrain that has ideal NTU for this cultivar, whereas only four of the fifteen reference plots for Chardonnay grapes occur on terrain with ideal NTU. Different hillslope location, soil description, slope aspect and misclassified land cover classes were the reasons why the reference plots were found to be unsuitable. Besides the slope aspect that was computed automatically, the land cover, hillslope and soil descriptions had some or other user intervention and therefore have an influence on the NTU that were identified.

This chapter constituted the bulk of the research and the findings of this chapter and those of the previous two chapters will determine whether the objectives that was identified in the first chapter was met and whether the aim of the research was reached. This will be discussed in the next chapter.

CHAPTER 5: GENERAL DISCUSSION AND CONCLUSIONS

The aim of this study was to investigate how GIS and remote sensing techniques can be used to identify natural terroir units by means of soil landscapes in the Robertson Wine District. This chapter considers whether the objectives have been met, reports on potential applications of the research, points out some limitations of the study and suggests recommendations for future research.

5.1 REVISITTING THE RESEARCH OBJECTIVES

This section examines whether the research objectives were met and reports on some difficulties that were experienced in reaching these objectives.

5.1.1 Objective 1: Identify and compile existing digital data and satellite imagery

Topographic, climate, geology, soil and vegetation data were collected from various sources (Table 3.6). Topographic parameters such as slope aspect and slope gradient were derived from a 20-m digital elevation model (DEM). Digital climate data were extracted from the *South African atlas of agrohydrology and -climatology* where temperature, precipitation, heat units and humidity are represented in the atlas as 1.6 × 1.6 km grids for the whole of South Africa. Compared to the 20-m DEM, the resolution of the atlas grids was too coarse and therefore the data was resampled to 20 m by means of cubic convolution resampling. Unfortunately, no spatial information on wind speed or wind direction could be found.

Geographical information system (GIS) data for geology and soil were received from the Council for Geoscience (CGS) and the provincial Department of Agriculture (Elsenburg) respectively. The pH, texture, structure, colour, clay content and lime content of the various soil classes are not uniformly described by the GIS dataset used in this study. In order for NTU identification, complete soil surveys have to be done to capture this information.

SPOT 5 and ASTER satellite images were identified as the best satellite imagery available to do a land use/cover classification. Overall, SPOT 5 imagery is a good source due to a combination of its spatial resolution, swath width and low cost while ASTER is a good data source owing to its wide spectral coverage in the shortwave infrared (SWIR) spectrum, swath width and low cost.

The latter was selected to complement shortfalls in the SPOT 5 imagery. Both images were geometrically and radiometrically corrected.

5.1.2 Objective 2: Interpret satellite images using OBIA

The second objective was to interpret the satellite images by means of object-based image analysis (OBIA). The multiresolution segmentation (MRS) algorithm was used to create image objects (Section 4.1). A sequential ruleset was developed to classify image objects based on their spectral, textural and topological properties (Section 4.2). Seven indices, two edge layers (border and frame), a combined edge layer (PAN_BF), topographic parameters (DEM and slope gradient), two thematic layers (roads and cadastral data) and a standard algorithm (shape index) were used in the classification process to distinguish eight land use/cover classes. The seven indices are the Zabud1 factor, brilliance index, ratio near infrared (NIR), ratio green (of SPOT, ASTER and topocadastral maps), modified soil-adjusted vegetation index (MSAVI), ratio of the 8th and 9th ASTER bands and brightness. These indices could separate the classes better than popular indices such as NDVI and SR. The land use/cover classes that were produced are *agriculture, natural vegetation, bare surfaces, built-up, mining, roads* and *recreation*. An overall accuracy of 81.3% was achieved for the land use/cover classification (Section 4.3).

5.1.3 Objective 3: Identify NTU

Land use/cover, combined with climate, soil, topography and geology were identified as environmental parameters for identifying natural terroir units (NTU) (Section 4.4). Geology, was however, not used because the literature review did not provide sufficient proof of the direct role of geology in terroir studies. Geological processes play an important role in topography and the physical and chemical properties of soil and therefore, the indirect role of geology on wine quality should not be underestimated. The coarse resolution of the climate data was another limiting factor and the influence of slope gradient and slope aspect on temperature could not be established with the available climate data.

Landscape was defined in terms of hillslope components as proposed by Dragut & Blaschke (2006). The topographic parameters elevation, slope gradient and curvature were segmented to define homogenous terrain objects which were classified according to slope gradient and normalized elevation values. The hillslope components were combined with the soil data to define the soil landscape. Eighteen soil landscape classes were defined.

These soil landscape classes were combined with three land use/cover classes and four slope aspect classes to describe the study area's NTU. A code system consisting of 4 digits was used to uniquely describe each NTU. The first digit indicates the land use/cover class, the second identifies the slope aspect and the last two digits relate to the soil landscape. One hundred and seventy distinct NTU were distinguished using this method, of which 55 units exist for agriculture. The large number of classes is a severe limitation as it is impractical to illustrate all of these units on a single map. The alternative was to list each NTU in a table.

5.1.4 Objective 4: Assess the NTU

Existing vineyards of Shiraz and Chardonnay grapes were used to verify the identified NTU. The viticultural potential of these two cultivars was specified according to the particular cultivar characteristics described by Goussard (2008). These characteristics are climate, soil, slope aspect and the cultivar's preferred location on hillslopes.

Climate could not be used as a distinguishing parameter between the various optimal environmental conditions for the cultivation of Shiraz and Chardonnay grapes because of the coarse resolution of the climate data and the constant climatic conditions prevailing throughout the study area (Section 4.6.1). Similarly, soil could not be used to pinpoint the respective cultivars' preferred soil type due to inconsistencies in the GIS data and the guidelines followed by viticulturists in the area (Section 4.6.3). Given that a moderate temperature of between 21.1 and 23˚C prevail throughout the study area, this research could only use slope aspect and hillslope to distinguish optimal NTU for Shiraz and Chardonnay respectively.

Nine out of fourteen reference Shiraz plots are at locations most conducive to Shiraz cultivation and four of the fifteen reference plots for Chardonnay grapes exist at most favourable locations. Misclassification of land use/cover classes and the occurrence of these reference plots on hillslope and slope aspect locations other than the preferred locations as specified by Goussard (2008) are reasons why some reference plots were unsuitable for the cultivation of the specific cultivars. One location was unsuitable because of its occurrence on saline soils.

5.2 LIMITATIONS AND RECOMMENDATIONS

To describe an NTU thoroughly, every single environmental component has to be included in the description. This means that the more diverse the environmental component, the more NTU will be generated and the more difficult it will be to illustrate the NTU on a single map. The literature suggests that generalization should be used to limit the number of classes. If generalization is required, it is imperative that expert knowledge is incorporated to avoid ambiguity or incorrectness in the definition of classes. Because soil data is so diverse, it is recommended that soil potential maps be compiled to describe NTU and to restrict the number of classes. Geology was not included as a component in the identification of NTU.

The extent, availability and accuracy of spatial data in South Africa limit the identification of NTU. This limitation has also been recognised in other terroir-related studies in South Africa (Carey 2001; Carey 2005; Carey, Archer & Saayman 2002). The climatic data used in this research have a resolution of 1.6 × 1.6 km, a degree of detail too coarse to map temperature differences in slope gradient and slope aspect. This had a major impact on the mapping of NTU because the coarseness could not distinguish differences in the mesoclimate. An updated version of the *South African atlas of agrohydrology and -climatology* was published in 2007, however, the resolution of the climate grids remained the same (Schulze 2007). Van Niekerk & Joubert (2011) created 90×90 m climatic grids of the Western Cape using ANUSPLIN software. These grids are able to address the coarse resolution of the climatic data that was used in this study. An accuracy assessment by Van Niekerk and Joubert (2011) proved that their climate grids are also more accurate than existing climate interpolations. The authors, however, recommended that a combination of different input variables for climate modelling could further enhance existing climate modelling algorithms.

Multi-temporal, multi-seasonal satellite images are required for accurate land use/cover mapping. Normalized values for indices and ratios can be calculated for multi-date imagery, provided that satellite images are radiometrically and atmospherically corrected. Using atmospherically corrected imagery, rulesets developed by object-based classification can be transferred to different images irrespective of area or date. The ruleset developed in this research has not been applied to other images and it is expected that the threshold values used in this research might need some adjustments, specifically for rules where area-specific values such as elevation and slope gradient were applied in the classification process. The research by Vaudour, Carey & Gilliot (2010) is a prime example why multi-seasonal images should be selected. They contend that by selecting images during different growth cycles of the grapevines, vineyards can be classified more accurately. If this argument had been tested in this research, the accuracy of the land use/cover map and, consequently, that of NTU could have been greater.

Although the OBIA has delivered accurate results, the number and definition of land use/cover classes may influence the overall accuracy. Vineyards, orchards and other crops in the study area were not distinguished. Textural information of very-high resolution satellite imagery or aerial photographs can be used in conjunction with spectral and structural properties to distinguish between different agricultural classes, but the cost of very high-resolution satellite imagery can be an inhibiting factor. Furthermore, OBIA can add more value to information in existing viticultural databases. For example textural information can be obtained from very-high resolution satellite images or aerial photography to digitally separate vineyard blocks from each other and to determine the number of rows per vineyard block and the row orientation (De Kok 2009, pers com; Smit, Sithole & Strever 2010).

Newer versions of the eCognition Developer software have been released since the development of the ruleset. The ruleset developed for this study behaved inconsistently when it was tested on the latest versions of the software. Care must be taken when rulesets developed in one version of the software are applied in other versions.

5.3 CONCLUSION

In conclusion, this study provided a methodology for using GIS and remote sensing techniques to identify homogenous groups of natural factors (defined as natural terroir units) in Robertson, an area renowned for producing quality red and white wine varieties. The NTU identified in this research can be exploited by viticulturists and oenologists to grow grapes in optimal environmental conditions to produce outstanding wines. Furthermore, NTU can be used to demarcate production areas such as single vineyards, estates and wards within the Robertson wine district to ultimately certify that wines originating from these production areas. This would avoid the abuse of the names of wines originating from Robertson. The results obtained can be used as a guideline for showing where the most suitable locations are for the cultivation of vineyards and other agricultural crops. Furthermore, the results can be used in the planning and management of land use in the study area.

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APPENDICES

APPENDIX A: WINE-PRODUCTION AREAS IN SOUTH AFRICA

Table A1: Map of wine production areas in South Africa

REGION	DISTRICT	WARDS
BREEDE RIVER VALLEY	ROBERTSON	Agterkliphoogte
		Bonnievale
		Boesmansrivier
		Eilandia
		Hoopsrivier
		Klaasvoogds
		Le Chasseur
		McGregor
		Vinkrivier
	WORCESTER	Aan-de-Doorns
		Goudini
		Nuy
		Scherpenheuvel
		Slanghoek
	SWELLENDAM	Buffeljags
		Stormsvlei
KLEIN KAROO	-	Montagu
	-	Tradouw
	CALITZDORP	-
	-	Upper Langkloof
	-	Outeniqua
COASTAL REGION	CAPE POINT	-
	-	Constantia
	TYGERBERG	Durbanville
		Philadelphia
	PAARL	Franschhoek Valley
		Wellington
		Simonsberg-Paarl
		Voor Paardeberg
	STELLENBOSCH	Jonkershoek Valley
		Papegaaiberg
		Simonsberg-Stellenbosch
		Bottelary
		Devon Valley
		Banghoek
	DARLING	Groenekloof
	SWARTLAND	Riebeekberg
		Malmesbury
	TULBAGH	-

Continued overleaf

Table A1 continued

REGION	DISTRICT	WARD
OLIFANTS RIVER	LUTZVILLE VALLEY - - CITRUSDAL MOUNTAIN - CITRUSDAL VALLEY	Koekenaap Spruitdrift Vredendal Piekenierskloof Bamboes Bay -
No Region	OVERBERG	Elgin Klein River
No Region	CAPE AGULHAS	Elim
No Region	WALKER BAY	-
No Region	DOUGLAS	-
No Region	PLETTENBERG BAY	-
No Region	No District	Hartswater Lower Orange Cederberg Ceres Herbertsdale Rietrivier FS Ruiterbosch Swartberg Prince Albert Valley

Source: The wine and Spirit Board (2006)

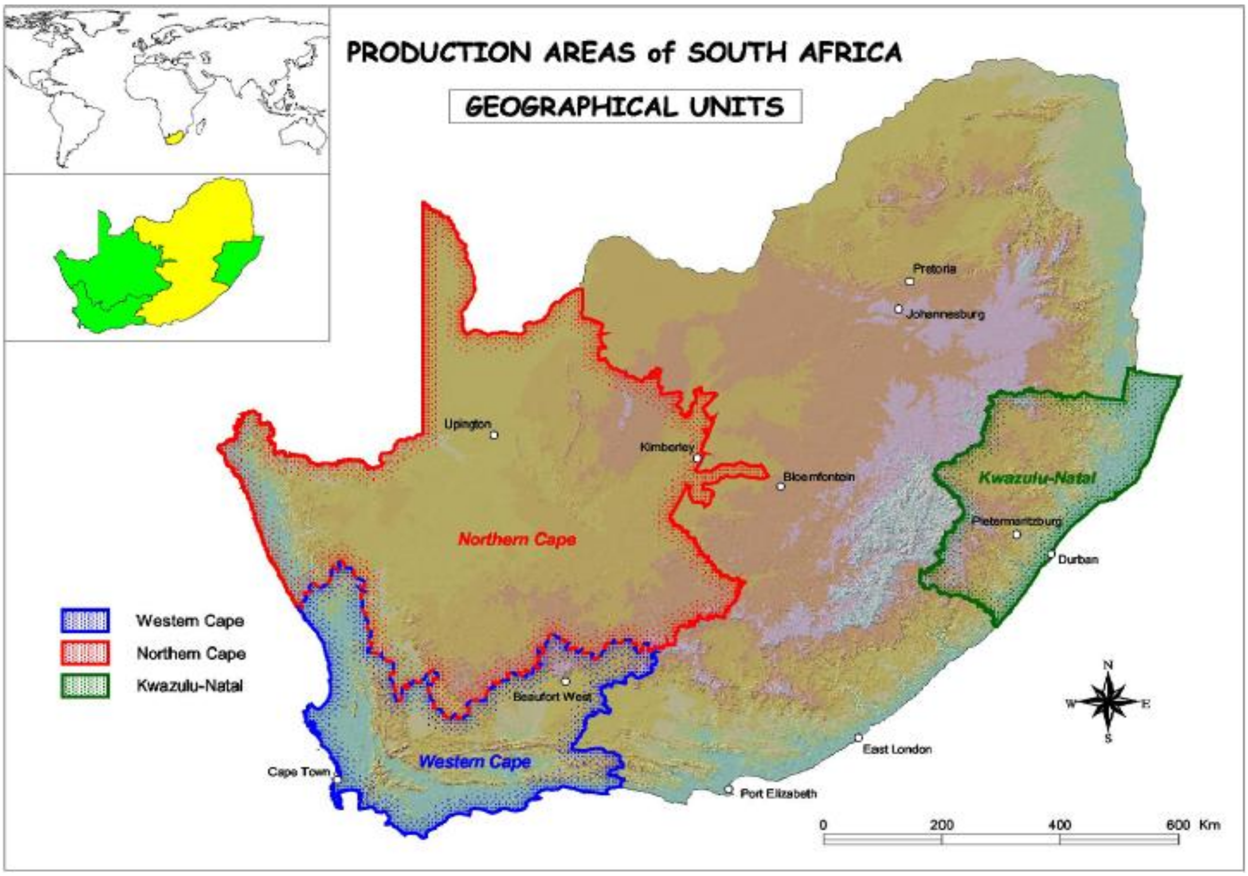

Figure A1: Map indicating South Africa's geographical units as demarcated by the Wine and Spirits Board

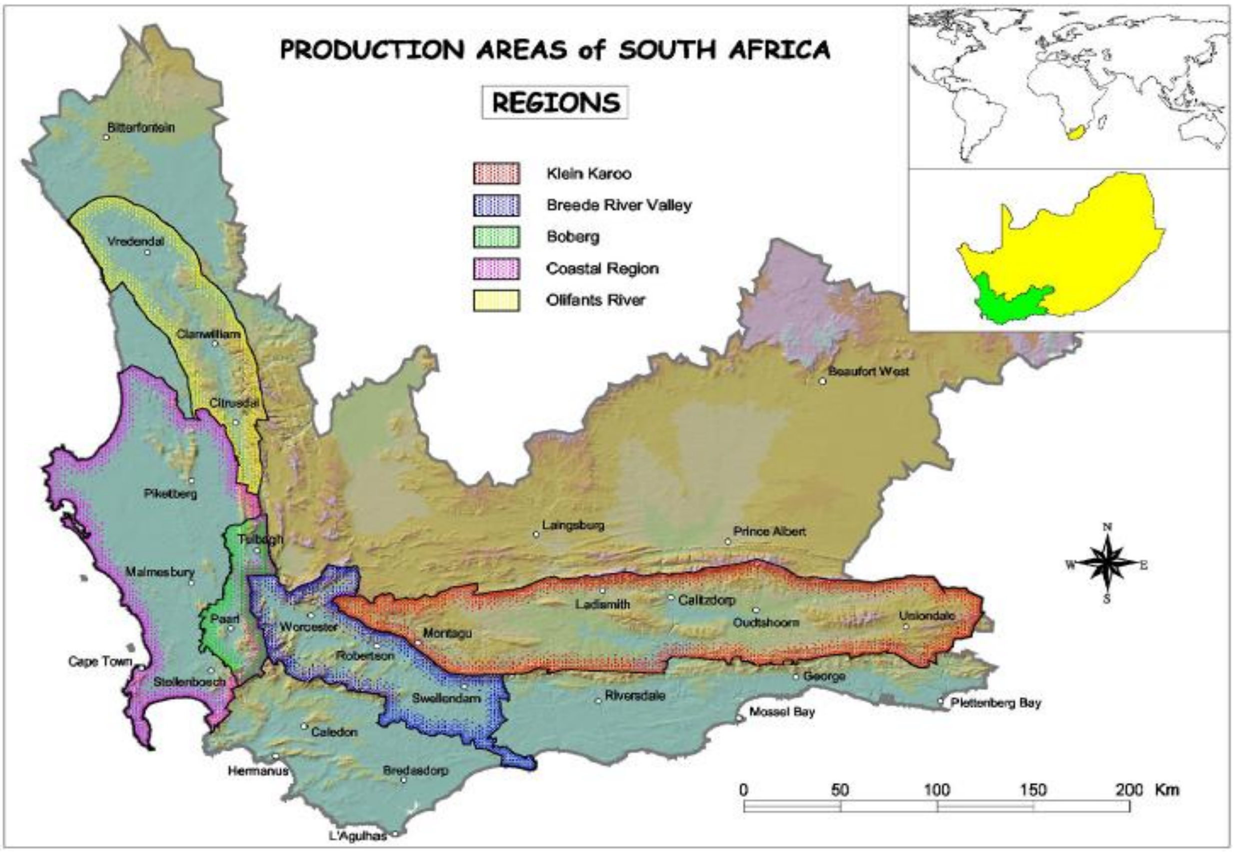

Figure A2: Wine-producing regions in South Africa

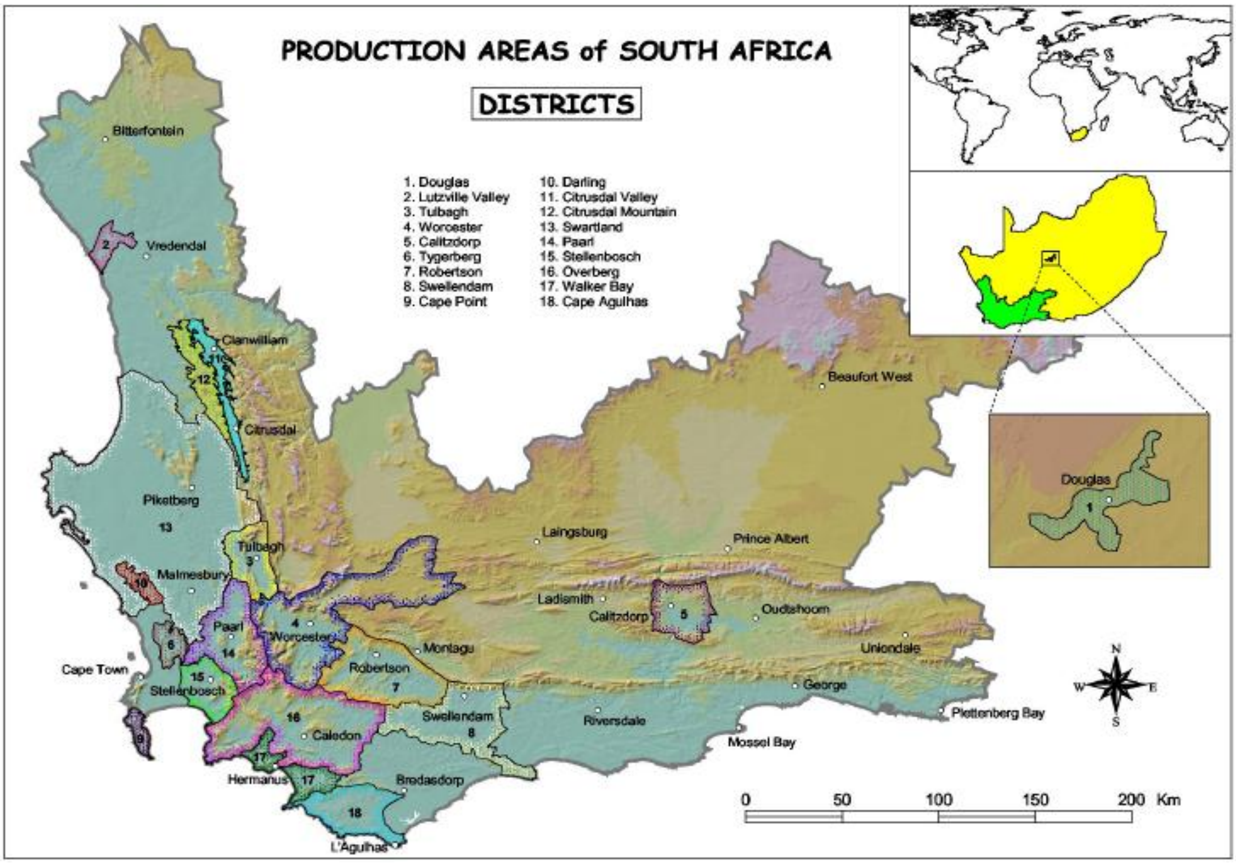

Figure A3: Wine-producing districts in South Africa

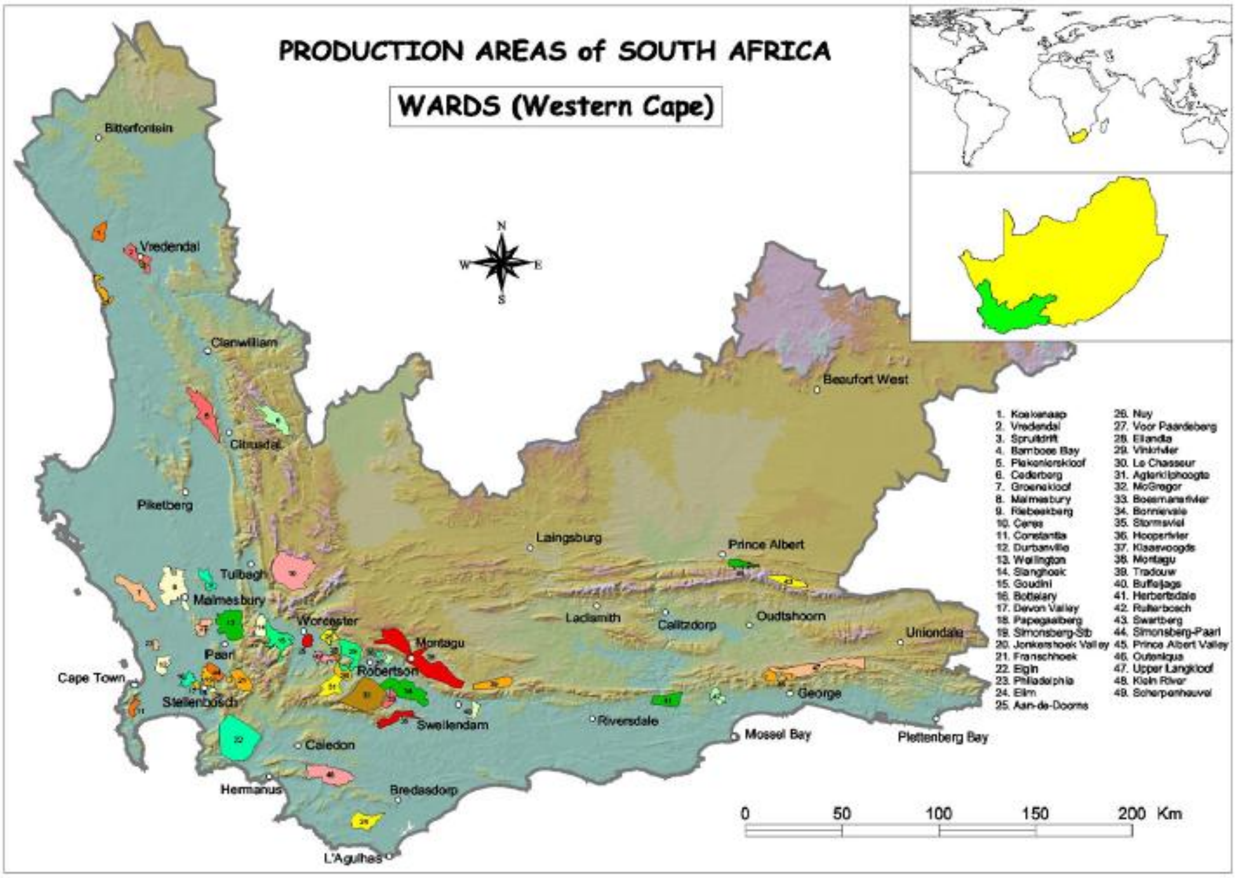

Figure A4: Wine-producing wards in the Western Cape

APPENDIX B: DATA GATHERED AT WEATHER STATIONS IN ROBERTSON

Table B1: Location and average weather conditions at weather stations over a number of years

No	WEATHER_STATION	LAT	LON	ALT	# yrs	Rain (mm)	Tmax (°C)	Tmin (°C)	Tave (°C)
							Annual average		
1	Boesmanspad	-33.92216	20.20257	203	8	504.84	24.33	11.52	17.16
2	Boesmansrivier **	-34.01068	20.00495	187	6	379.35	27.27	11.37	16.82
3	Bo-Klaasvoogds	-33.80748	19.98874	230	10	308.23	24.66	10.57	16.75
4	De Hoop	-33.76408	19.92829	276	8	448.28	24.27	10.03	16.21
5	Drew 1	-34.01903	20.21664	122	2	370.15	25.02	11.89	17.69
6	Drew	-34.00370026	20.21660042	98	4	467.61	24.79	10.96	16.99
7	Goedemoed	-33.84459	19.98644	174	7	273.40	24.99	10.79	17.02
8	Goree	-33.81532	19.78711	182	10	244.04	24.62	10.15	16.72
9	Goudmyn	-33.87896	20.01030	144	10	333.90	25.05	10.69	17.02
10	Koningsrivier	-33.89938	19.87706	185	10	239.24	25.21	10.44	17.03
11	Le Chasseur	-33.86141	19.72400	184	10	262.53	25.34	10.18	17.05
12	Merwespont	-33.97287	20.15524	118	10	322.29	24.94	10.95	16.99
13	Rheebokskraal	-33.99826	19.84301	296	5	331.87	24.67	10.81	17.17
14	Robertson PP	-33.82835	19.88537	154	4	251.45	25.17	10.80	17.28
15	Vaandrigsdrift	-34.06021	20.23166	145	1	213.80	24.44	11.73	17.21
16	Vinkrivier	-33.75599	19.77653	267	10	390.58	24.81	9.83	16.58
17	Wakkerstroom-Oos	-33.91914	20.00816	127	6	216.00	25.14	11.34	17.24
18	Zandvliet	-33.84680	20.06113	158	10	270.63	25.09	10.26	16.94
	TOTAL					323.79			
	AVERAGE						24.99	10.79	16.99

Source: ISCW

** According to the data, the average maximum temperature at the Boesmansrivier weather station for December is over 56 °C. This is an error

Table B2: Rainfall and temperature at weather stations for the first quarter

	Jan				Feb				Mar			
WEATHER_STATION	Rain (mm)	Tmax (°C)	Tmin (°C)	Tave (°C)	Rain (mm)	Tmax (°C)	Tmin (°C)	Tave (°C)	Rain (mm)	Tmax (°C)	Tmin (°C)	Tave (°C)
Boesmanspad	50.81	28.66	15.74	21.22	22.04	29.36	16.3	21.51	57.58	27.6	14.57	20.15
Boesmansrivier	22.43	28.77	15.54	21.35	19.88	30.23	16.41	21.92	42.16	28.41	13.43	20.1
Bo-Klaasvoogds	24.87	29.23	15.14	21.29	8.75	29.94	15.98	21.74	35.51	28.26	14.31	20.14
De Hoop	39.53	28.6	14.5	20.57	20.71	29.63	15.41	21.27	54.01	27.58	13.76	19.71
Drew 1	47.15	29.32	17.53	22.51	11.7	30.28	17.85	22.87	7.65	28.84	14.6	20.52
Drew	23.73	29.02	16.13	21.55	14.8	29.51	16.52	21.62	69.4	28.22	14.33	20.28
Goedemoed	31.74	30.11	15.82	21.97	5.97	30.43	16.6	22.24	29.26	28.41	14.12	20.23
Goree	20.91	29.2	15.18	21.41	2.44	30.09	16.18	21.91	19.76	28.14	13.96	20.33
Goudmyn	22.9	29.26	15.82	21.67	6.21	30.68	16.86	22.41	28.25	28.63	14.82	20.68
Koningsrivier	35.98	30.03	15.44	21.8	4.87	30.21	16.26	22.12	20.36	28.4	14.11	20.42
Le Chasseur	23	30.31	15.44	21.44	3.69	31.29	16.29	22.77	15.42	28.85	14.22	20.85
Merwespont	25.12	29.04	15.49	21.27	8.44	29.88	16.5	21.9	36.66	28.13	14.61	20.29
Rheebokskraal	20.06	29.04	15.9	21.81	3.64	30.39	16.77	22.71	53.26	28.5	14.1	20.66
Robertson PP	33.93	30.48	16.6	22.81	3.27	30.78	16.98	23.27	8.8	28.7	13.75	20.39
Vaandrigsdrift	23.2	28.97	17.35	21.9	13.4	30.06	17.93	22.5	14.8	27.37	13.69	19.49
Vinkrivier	37.92	29.6	14.69	21.38	10.42	30.64	15.74	22.08	24.69	28.59	13.65	20.32
Wakkerstroom-Oos	24.7	29.16	16.37	21.53	5.58	30.8	17.1	22.34	18.23	28.47	14.52	20.39
Zandvliet	20.07	29.52	15.21	21.56	6.79	30.36	15.98	22.06	18.14	28.6	14.31	20.62
Average	29.34	29.35	15.77	21.61	9.59	30.25	16.54	22.18	30.77	28.32	14.16	20.31

Table B3: Rainfall and temperature at weather stations for the second quarter

	Apr				May				Jun			
WEATHER_STATION	Rain (mm)	Tmax (°C)	Tmin (°C)	Tave (°C)	Rain (mm)	Tmax (°C)	Tmin (°C)	Tave (°C)	Rain (mm)	Tmax (°C)	Tmin (°C)	Tave (°C)
Boesmanspad	66.76	24.53	12.35	17.59	57.51	21.43	9.84	15.09	42.21	19.95	7.77	13.52
Boesmansrivier	41.86	25.47	11.44	17.78	46.12	22.76	7.89	14.47	18.47	20.54	4.8	11.54
Bo-Klaasvoogds	51.92	24.9	11.66	17.34	39.62	21.83	8.6	14.37	18.29	19.51	5.42	11.66
De Hoop	54.75	24.46	11.21	16.75	41.38	21.5	8.2	13.78	28.99	19.48	5.24	11.17
Drew 1	77.95	24.47	12.77	17.83	48.45	21.32	10.17	15.21	39.6	19.64	7.19	13.05
Drew	37.93	26.02	12.37	18.05	44.5	22.42	9.33	14.98	30.4	20.17	5.24	11.67
Goedemoed	34.19	25.18	11.53	17.49	37.1	21.95	8.55	14.57	15.41	20	5.57	11.89
Goree	24.34	24.83	10.79	17.19	38.28	21.61	7.44	13.98	21.22	19.55	4.18	11.2
Goudmyn	42.17	25.05	11.76	17.57	41.53	22.14	8.07	14.39	27.52	19.9	4.29	11.25
Koningsrivier	27.7	25.11	11.21	17.38	31.06	22.44	7.76	14.22	16.03	20.1	4.82	11.69
Le Chasseur	37.62	25.55	11.08	17.67	29.15	22.11	7.52	14.32	15.88	20.04	3.94	11.35
Merwespont	43.68	25.06	12.09	17.57	39.9	22.23	8.94	14.68	26.71	20.35	5.78	12.04
Rheebokskraal	55.54	25.2	11.77	17.87	32.1	21.76	9.14	14.85	23.4	19.53	6.17	12.23
Robertson PP	34.6	24.89	11.06	17.53	33.92	22.67	8.61	15.06	18.2	19.97	4.75	11.88
Vaandrigsdrift	24	23.85	12.24	17.18	52.7	20.61	10.61	14.99	27.5	18.64	7.6	12.82
Vinkrivier	36.78	25.19	10.69	17.13	96.55	21.81	7.59	13.96	46.14	19.49	4.61	11.17
Wakkerstroom-Oos	26.97	25.42	12.34	17.95	27.9	22.38	9.33	15.04	14.03	20.33	6.12	12.2
Zandvliet	43.48	25.22	11.3	17.35	40.1	22.4	8.08	14.58	25.24	20.3	4.76	11.71
Average	42.35	25.02	11.65	17.51	43.22	21.97	8.65	14.59	25.29	19.86	5.46	11.89

Table B4: Rainfall and temperature at weather stations for the third quarter

	Jul				Aug				Sep			
WEATHER_STATION	Rain (mm)	Tmax (°C)	Tmin (°C)	Tave (°C)	Rain (mm)	Tmax (°C)	Tmin (°C)	Tave (°C)	Rain (mm)	Tmax (°C)	Tmin (°C)	Tave (°C)
Boesmanspad	27.1	19.39	7.28	13.01	44.73	19.75	7.61	13.17	37.2	21.44	8.78	14.4
Boesmansrivier	22.66	19.83	4.5	11.38	33.74	19.84	5.34	11.86	18.8	22.72	7.94	14.6
Bo-Klaasvoogds	19.93	19.17	5.08	11.47	24.49	19.65	6.09	12.09	13.84	21.96	7.89	14.1
De Hoop	36.14	18.98	4.72	10.99	34.41	19.35	5.69	11.56	28.71	21.32	7.19	13.48
Drew 1	2.6	21	7.1	13.48	33.4	19.85	6.34	12.6	13.3	23.35	9.26	15.55
Drew	34.03	19.18	4.45	11.23	42.87	19.87	5.65	12.36	29.3	22.68	8.23	14.92
Goedemoed	26.53	19.36	5.16	11.55	24.76	19.96	6.33	12.43	13.93	22.15	8.34	14.42
Goree	24.43	18.83	3.84	10.75	28.86	19.51	5.83	12.14	11.06	22.08	7.58	14.3
Goudmyn	50.63	19.22	4.15	11.12	28.38	20.02	5.87	12.42	13.39	22.53	8.08	14.62
Koningsrivier	35.48	19.62	4.58	11.4	20.27	20.18	6.08	12.52	8.72	22.73	7.78	14.61
Le Chasseur	24.17	19.19	3.65	10.87	32.92	19.95	5.52	12.27	10.57	22.58	7.32	14.46
Merwespont	32.34	19.56	5.33	11.68	29.02	20.27	6.61	12.69	14.59	22.5	8.14	14.4
Rheebokskraal	12.6	19.71	5.29	12.11	37.9	18.98	5.86	12.06	13.38	22.33	8.13	14.75
Robertson PP	19.93	19.17	5.08	11.47	24.49	19.65	6.09	12.09	13.84	21.96	7.89	14.1
Vaandrigsdrift	5.8	20.19	7.7	13.35	21.2	19.14	6.49	12.21	14.2	23.06	9.39	15.29
Vinkrivier	15.81	18.96	3.71	10.67	36.16	19.6	5.34	11.77	18.17	21.87	6.98	13.77
Wakkerstroom-Oos	19.77	19.63	5.51	11.72	19.78	20.13	6.99	12.9	13.92	22.6	8.89	14.9
Zandvliet	19.79	19.72	4.4	11.5	26.8	20.2	5.77	12.31	15.33	22.58	7.48	14.4
Average	23.87	19.48	5.09	11.65	30.23	19.77	6.08	12.30	16.79	22.36	8.07	14.50

Table B5: Rainfall and temperature at weather stations for the fourth quarter

	Oct				Nov				Dec			
WEATHER_STATION	Rain (mm)	Tmax (°C)	Tmin (°C)	Tave (°C)	Rain (mm)	Tmax (°C)	Tmin (°C)	Tave (°C)	Rain (mm)	Tmax (°C)	Tmin (°C)	Tave (°C)
Boesmanspad	42.34	24.78	10.75	16.78	28.03	26.66	12.61	18.73	28.54	28.37	14.66	20.75
Boesmansrivier **	39.7	25.2	10	16.74	38.57	27.42	12.57	19.24	34.97	**56.02	26.58	20.9
Bo-Klaasvoogds	23.61	25.27	10.17	16.91	20.41	27.12	12.24	18.84	26.99	29.05	14.21	20.99
De Hoop	26.23	24.68	9.41	16.26	29.79	27.06	11.37	18.45	53.64	28.55	13.62	20.56
Drew 1	58	25.39	11.33	17.61	1.9	27.39	13.31	19.57	28.45	29.35	15.17	21.51
Drew	68.85	24.62	10.78	16.72	30.7	27.35	12.96	19.13	41.1	28.38	15.56	21.35
Goedemoed	20.18	25.52	10.62	17.17	10.2	27.51	12.13	18.92	24.14	29.34	14.75	21.4
Goree	12.61	25.3	10.01	17.03	19.48	27.16	12.22	19.08	20.66	29.09	14.62	21.27
Goudmyn	19.13	25.81	10.61	17.35	18.3	27.74	12.82	19.31	35.49	29.61	15.11	21.46
Koningsrivier	11.78	25.84	10.23	17.3	10.58	27.6	12.34	19.2	16.42	30.25	14.65	21.74
Le Chasseur	19.97	26.05	10.04	17.39	16.44	28.08	12.39	19.5	33.7	30.05	14.77	21.73
Merwespont	16.6	25.67	10.55	17.05	19.13	27.36	12.64	19.07	30.09	29.19	14.75	21.22
Rheebokskraal	37.13	24.75	10.03	16.96	15.63	27.22	11.91	19.12	27.24	28.6	14.64	20.96
Robertson PP	23.61	25.27	10.17	16.91	20.41	27.12	12.24	18.84	26.99	29.05	14.21	20.99
Vaandrigsdrift	2.2	26.44	10.88	17.54	14.6	26.84	13.11	19.22	0.2	28.07	13.77	20.04
Vinkrivier	16.4	25.21	9.56	16.76	25.81	27.22	11.53	18.72	25.73	29.51	13.92	21.22
Wakkerstroom-Oos	21.1	25.46	10.77	17.07	13.77	28.13	13.28	19.59	10.25	29.17	14.89	21.25
Zandvliet	21.07	25.75	9.85	17.06	12.69	27.18	11.88	18.88	21.13	29.29	14.07	21.25
Average	26.70	25.39	10.32	17.03	19.25	27.34	12.42	19.08	26.99	29.11	15.22	21.14

** According to the data, the average maximum temperature at the Boesmansrivier weather station for December is 56 °C. This is an error

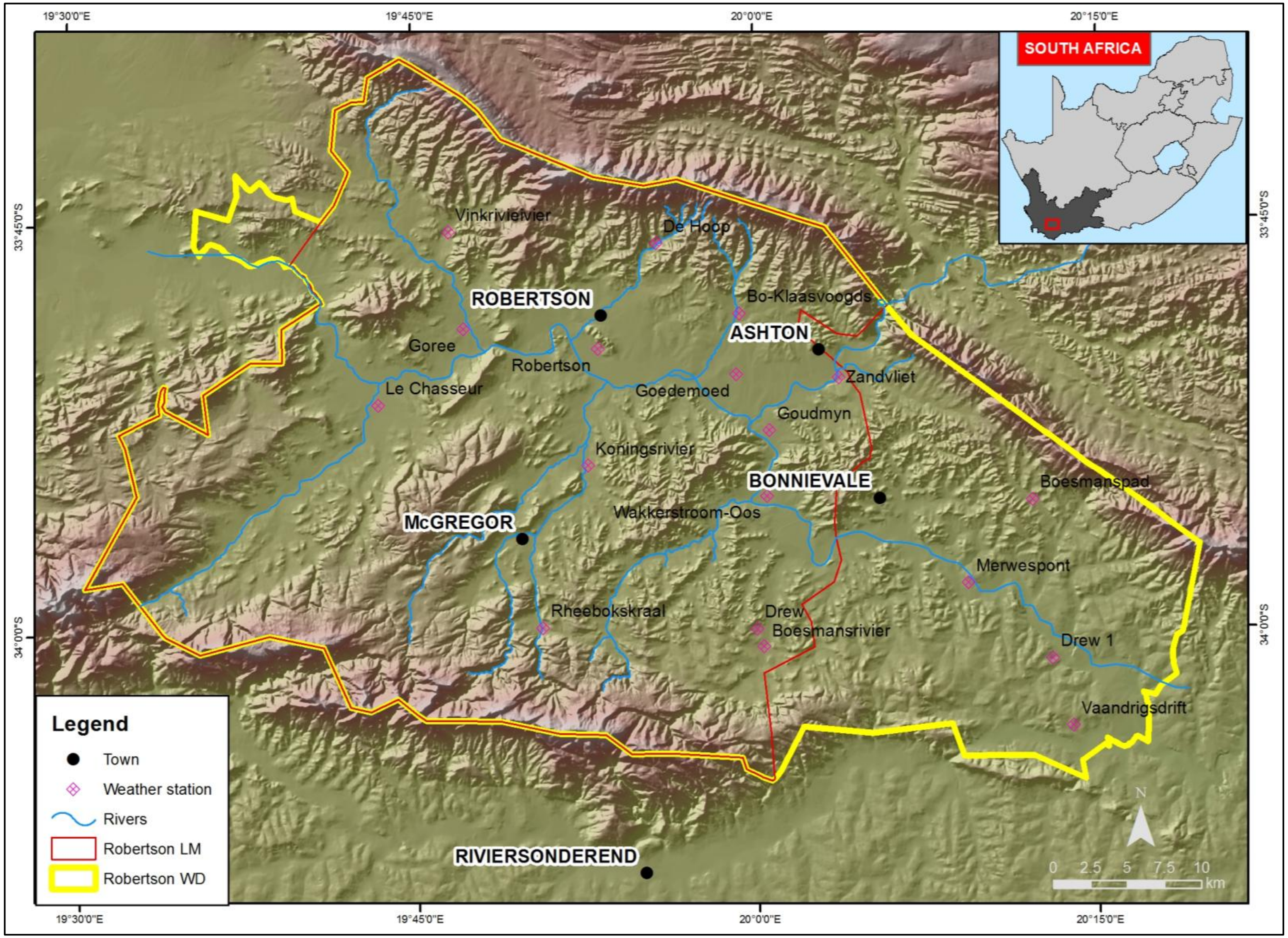

Figure B1: Location of weather stations and the boundaries of Robertson LM and Robertson WD

*Note. Robertson LM is the Robertson Local Municipality boundary as demarcated by the Municipal Demarcation of Board South Africa and Robertson WD is the Robertson Wine of Origin District as demarcated by the Wine and Spirit Board

APPENDIX C: RULESET FOR LAND USE/COVER CLASSIFICATION

OBIA RULESET

Temporary CLASSES

agriculture_cointainer

bright_features

high ratio green

high_NIR

High_Zabut

high-border

high_ASTER_ratio 8/9

Null

Urban

urban_container

_urban_container

water_container

FINAL CLASSES

Agriculture

bare surfaces

built-up

mining

natural vegetation

Recreation

Roads

Water

CUSTOMIZED FEATURES

Aster_Built-up: [Aster_NDBI]-[aster_NDVI]

Aster_NDBI: ([Mean aster_swir4]-[Mean aster_nir3])/([Mean aster_swir4]+[Mean aster_nir3])

Border_Frame: [Mean border]+[Mean frame]

Difference: [Mean S5_R]-[Mean S5_NIR]

MSAVI: ([Mean S5_NIR]-[Mean S5_R])/([Mean S5_NIR]+[Mean S5_R]+0.5)

NDVI: ([Mean S5_NIR]-[Mean S5_R])/([Mean S5_NIR]+[Mean S5_R])

PAN_BF: [Mean S5_pan]/([Mean border]+[Mean frame])

Ratio_Green: [Mean S5_BG]/([Mean S5_pan]+[Mean S5_BG]+[Mean S5_R]+[Mean S5_NIR]+[Mean S5_SWIR])

Ratio_Nir: [Mean S5_NIR]/([Mean S5_pan]+[Mean S5_BG]+[Mean S5_R]+[Mean S5_NIR]+[Mean S5_SWIR])

S5_Brillance_Index: ([Mean S5_NIR]^2+[Mean S5_R]^2)/100000

Weighted Brightness (S5): ([Mean S5_BG]+[Mean S5_NIR]+[Mean S5_R]+[Mean S5_SWIR]+[Mean S5_pan])/5

Zabut: ((([Mean S5_BG]-[Mean S5_R])^2)+(([Mean S5_R]-[Mean S5_NIR])^2)+(([Mean S5_NIR]-[Mean S5_SWIR])^2))^(0.5)

aster_NDVI: ([Mean aster_nir3]-[Mean aster_red2])/([Mean aster_red2]+[Mean aster_nir3])

ratio_TOPOGREEN: ([Mean topo_green])/([Mean topo_blue]+[Mean topo_green]+[Mean topo_red])

ratio_ast_8/2: [Mean aster_swir8]/[Mean aster_red2]

ratio_ast_green: [Mean aster_green1]/([Mean aster_green1]+[Mean aster_nir3]+[Mean aster_red2])

spot_3/4: [Mean S5_NIR]/[Mean S5_SWIR]

SEGMENTATION

multiresolution segmentation: 30 [shape:0.2 compct.:0.8] creating 'image_seg'

multiresolution segmentation: at image_seg_100: 100 [shape:0.2 compct.:0.5]

CLASSIFICATION

<u>Image Border</u>

assign class: unclassified with Mean S5_BG <= 0 at image_seg: null

assign class: unclassified with Mean slope < 0 at image_seg: null

multiresolution segmentation: null at image_seg: 10000 [shape:0.8 compct.:0.1]

merge region: null with Classified as null = 1 at image_seg: merge region

<u>Water</u>

assign class: unclassified with Ratio_Green > 0.142 at image_seg: _high ratio green assign class: _high ratio green with PAN_BF <= 3.55 at image_seg: unclassified

assign class: _high ratio green with Difference <= -680 at image_seg: unclassified

assign class: _high ratio green with Brightness >= 1206 at image_seg: unclassified

assign class: _high ratio green with Mean frame >= 15.4 at image_seg: unclassified

assign class: _high ratio green at image_seg: water

assign class: water with Mean DEM >= 610 at image_seg: unclassified

assign class: water with Mean slope >= 20 at image_seg: unclassified

<u>Man-made features (Built-up, roads and mining)</u>

assign class: unclassified with Thematic object IDroads >= 1 at image_seg: roads

assign class: unclassified with Ratio_Green > 0.141 at image_seg: high ratio green

assign class: high ratio green with Ratio_Nir <= 0.269 at image_seg: mining

assign class: high ratio green with Border to mining >= 1 m at image_seg: mining

assign class: high ratio green Mean DEM >= 610 at image_seg: unclassified

assign class: high ratio green at image_seg: unclassified

assign class: unclassified with PAN_BF <= 2.35 at image_seg: bright_features

Assign class: bright_features, high ratio green with number of existing overlapping Erven =1: urban

assign class: urban with Border to water > 0 at image_seg: unclassified

assign class: loop: urban with Existence of _urban_container (50) = 1 at image_seg: _urban_container

assign class: high brightness, high ratio green at image_seg: unclassified

<u>Vegetation</u>

assign class: unclassified with Zabut > 1905 at image_seg: High Zabut

assign class: unclassified with ASTER Ratio 8/9 > 0.24 at image_seg: _high_ASTER Ratio 8/9

assign class: _high_ASTER Ratio 8/9 with ASTER Ratio 8/9 <= 0.31 at image_seg: Natural Vegetation

assign class: unclassified with S5_Brilliance Index <= 132: Natural Vegtation

assign class: Natural Vegetation with ASTER Ratio-Green > 0.334: Bare Surfaces

assign class: with ratio_TOPOGREEN >= 0.375 at image_seg: recreation

assign class: mining with Border to water >= 1 at image_seg: bare surfaces

Assign class mining with MSAVI > 0.18 at image_seg: Bare_Surfaces

assign class: 3x: bare surfaces with Border to mining = 1 at image_seg: mining assign class: unclassified at image_seg: Natural Vegetation

Agriculture

assign class: High_Zabut with ASTER Ratio Green <= 0.334 at image_seg: Agriculture

assign class: High_Zabut with SPOT 5 Ratio Green <= 0.115 at image_seg: agriculture_container

assign class: High_Zabut, agriculture_container with Shape index <= 2.072 at image_seg: Agriculture

assign class: agriculture_container at image_seg: Bare surfaces

assign class: agriculture with Mean border >= 28 at image_seg: bare surfaces

assign class: High_Zabut at image_seg: bare rock / soil

assign class: mining with MSAVI > 0.14 at image_seg: bare rock / soil

assign class: agriculture with Mean slope > 20 at image_seg: Natural Vegetation

CLEAN-UP

multiresolution segmentation: _urban_container at image_seg: 1000 [shape:0.1 compct.:0.3]

multiresolution segmentation: mining at image_seg: 100 [shape:0.1 compct.:0.5]

assign class: _urban_container at image_seg: built-up

assign class: urban at image_seg: built-up

multiresolution segmentation: 2x: recreation at image_seg: 500 [shape:0.3 compct.:0.2]

multiresolution segmentation: Natural Vegetation at image_seg: 1000 [shape:0.1 compct.:0.5]

multiresolution segmentation: agriculture at image_seg: 1000 [shape:0.1 compct.:0.5]

multiresolution segmentation: mining at image_seg: 1000 [shape:0.1 compct.:0.5]

find enclosed by class: recreation at image_seg: enclosed by null: null +

EXPORT

image

update variable: agriculture with Classified as agriculture = 1 at image_seg: Type = Agriculture

update variable: water with Classified as water = 1 at image_seg: Type = water

update variable: mining with Classified as mining = 1 at image_seg: Type = mining

update variable: Natural Vegetation with Classified as Natural Vegetation = 1 at image_seg: Type = Natural Vegetation

update variable: bare rock / soil with Classified as bare rock / soil = 1 at image_seg: Type = Bare surfaces update variable: roads with Classified as roads = 1 at image_seg: Type = roads

update variable: built-up with Classified as built-up = 1 at image_seg: Type = built_up

Vector layers created

roads, agriculture, natural vegetation, water, mining, bare surfaces, recreation, built-up

.