DEVELOPING A DIGITAL SOIL MAPPING PROTOCOL FOR SOUTHERN AFRICA USING CASE STUDIES

by

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Promoter: Prof. P.A.L Le Roux

To My Parents:

Wouter and Laurette van Zijl

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PREFACE

In creating a protocol intended for the use of the general soil scientist in southern Africa, one has to stay in touch with the realities faced when doing soil surveys. Therefore a case study approach was favoured above a theoretical approach for this research. The case studies cover different soil mapping challenges, displaying the protocols application in a variety of situations faced by soil surveyors. At each case study the protocol was updated and improved, and I believe the final protocol being reported here could be applied to all situations of large area soil mapping in southern Africa.

The core of the thesis is the four case studies (Chapters 3-6), being written up for publication in peer-reviewed journals. Chapter 1 gives a short literature review and highlights the soil mapping challenges in southern Africa. Chapter 2 introduces the software and covariates used in this research. Chapter 3, which is accepted by the *South African Journal of Plant and Soil*, shows how a research soil map was produced near Madadeni, South Africa. A land mine threat posed interesting challenges to soil mapping near Tete, Mozambique in Chapter 4. This chapter was published in the peer-reviewed proceedings of the 5th Global Digital Soil Mapping Workshop, 2012, Sydney, Australia. Staying in Mozambique, the soil maps produced in Chapter 5 played an integral role in planning a new forestry development near Namarroi. In Chapter 6 the soil map had a hydrological emphasis, with it being a base for the newly established 'Research Supersites' in the Kruger National Park. While discussing the protocol with other soil surveyors, the question which always came up is: "How many soil observations are enough?" Chapter 7 uses the data generated during this research to indicate an answer to the question. As there are not enough data available this work is only provisional and should be treated as such. The final chapter gives the protocol. In the appendices the usage of various individual software tools needed to use the protocol is explained. A moderate level of GIS expertise is necessary to apply the Appendices.

The case study approach together with the article style thesis naturally leads to some repetition between chapters. However, I trust that the diverse scenarios of the case studies will keep the reading interesting.

DECLARATION

I hereby declare that this thesis submitted for degree of 'Doctor of Philosophy' to the University of the Free Sate, is my own work and has not been submitted to any other University. Where use has been made of the work of others it is duly acknowledged in the text.

I also agree that the University of the Free State has the sole right to publication of this thesis.

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SUMMARY

Although there is an increasing need for spatial soil information, traditional methods of soil survey are too cumbersome and expensive to supply in that need. Digital soil mapping (DSM) methods can fulfil that need. Internationally, DSM is moving from the research to the production phase. As soil-landscape interaction and availability of data varies between locations, local DSM research is needed to make its application practical.

This research aims to produce a working DSM protocol which can be used for mapping large areas of land in southern Africa. The protocol must meet soil surveyors where they are at, being easy enough to follow, while also allowing for the creation of products needed by industry. To keep the link with industry's needs, a case study approach was followed. Four case studies were done in succession, with the protocol being improved with every case study. The case studies cover an array of challenges faced by soil surveyors.

In the first case study a baseline protocol was created when two land types near Madadeni were disaggregated in a series of soil maps. With each map, more information was incorporated when creating the map. For Map 1 only the land type inventory and terrain analysis were used. A reconnaissance field visit with the land type surveyor was added for the second map. Field work and a simplified soil association legend proved to improve the map accuracy for Maps 3 and 4, which were created using 30% and 60% of the observations points as training data respectively. The accuracy of the maps increased when more information was utilized. Map 1 reached an accuracy of 35%, while Map 4 achieved a commendable accuracy of 67%. Principles which emerged was that field work is critical to DSM, more data input improves the output and that simplifying the map legend improves the accuracy of the map.

An unrealistic demand for a soil survey of 37 000 ha of land in the Tete Province, northern Mozambique, possibly infested with land mines, in 8 working days by two persons, created an opportunity to apply the soil-land inference model (SoLIM) as a digital soil mapping tool. Dividing the area into smaller areas where unique soil distribution rules would apply (homogeneous areas, HA's) was introduced. A free survey was conducted along the available roads of the area. The final soil map for 15 000 ha had an accuracy of 69%. A principle which emerged was that inaccessible areas can be mapped, provided that they occur within surveyed HA's.

Near Namarroi, Mozambique, the potential of DSM soil survey methods to rapidly produce land suitability maps for a large area with acceptable accuracy was evaluated. Conditioned Latin hypercube sampling

(cLHS) was introduced to determine field observation positions. SoLIM was used to run an inference with soil terrain rules derived from conceptual soil distribution patterns. A restriction of the expert knowledge based approach was found in that only six soil map units (SMU's) could be determined per HA. The map achieved an overall accuracy of 80%. Land suitability maps were created based on the soil class map.

In the Kruger National Park a soil map was used to create and extrapolate 2-dimensional conceptual hydrological response models (CHRM's) to a 3-dimensional landscape. This is a very good example on how value could be added to a soil map. An error matrix convincingly identified problem areas in the map where future work could focus to improve the soil map.

The current data indicates that at least 28 soil observations are necessary to create a soil map to an acceptable standard. When minimum observation criteria are met, observation density is irrelevant. The cLHS method to pre-determine observation positions improved the usability of observations. Although more research is needed to accurately determine the minimum observation criteria, an observation strategy is suggested.

A 15 step protocol is produced with which it was shown that soil surveyors could produce a variety of maps in diverse situations. The protocol relies on the expert knowledge of the soil surveyor, combined with field observations. It has the advantages that fewer observations are necessary, map accuracy assessment is possible, problem areas are identified and under certain conditions unsurveyed areas can also be mapped. On the down side, there is a limitation of six SMU's per HA.

Further research needs to be done to determine the minimum criteria for soil observations, and soil distribution relationships between soil and remotely sensed covariates.

Keywords: conditioned Latin hypercube sampling, DEM, Expert knowledge, Hydropedology, Inference systems, Land type, Soil functions, Soil survey, SoLIM, Remote sensing, Terrain analysis

OPSOMMING

Ten spyte van 'n groeiende aanvraag vir ruimtelike grond inligting, is tradisionele metodes van grondopname te tydrowend en duur om in die behoefte te voorsien. Digitale grond kartering (DSM) metodes kan daardie leemte vul. Internasionaal beweeg DSM van die navorsings tot die produksie fase. Omdat grond-landskap interaksies en beskikbaarheid van data varieer tussen plekke, is plaaslike DSM navorsing nodig om die gebruik van DSM prakties uitvoerbaar te maak.

Hierdie navorsing poog om 'n werkende DSM protokol op te stel, wat gebruik kan word vir die kartering van groot land oppervlaktes in suidelike Afrika. Die protokol moet grondopnemers tegemoet kom, deurdat dit maklik genoeg moet wees om te volg, maar terselfdertyd toelaat dat produkte geskik vir die industrie geskep word. Om die skakel met die industrie te behou, is besluit om 'n gevallestudie benadering te volg. Vier gevallestudies is in opeenvolging gedoen en die protokol opgegradeer na elke gevallestudie. Die gevallestudies hanteer 'n verskeidenheid van uitdagings wat deur grondopnemers in die gesig gestaar word.

In die eerste gevallestudie is 'n basis protokol opgestel. Twee landtipes naby Madadeni was ontbind in 'n reeks grondkaarte. Met elke kaart is meer inligting gebruik tydens die skep van die kaart. Vir Kaart 1 is slegs die landtipe inventaris en terrein analise ingespan. Met Kaart 2 is die kennis van die landtipe opnemer vir die gebied getap tydens 'n verkenningsbesoek aan die studiegebied. Veld werk en 'n vereenvoudigde grond assosiasie legende het 'n toename in akkuraatheid vir Kaarte 3 en 4 veroorsaak. Dertig en 60 % van die observasiepunte is onderskeidelik gebruik as kwekingsdata vir Kaarte 3 en 4. Die akkuraatheid van die kaarte het toegeneem wanneer meer inligting benut is. Kaart 1 het 'n akkuraatheid van 35% bereik, terwyl Kaart 4 'n geloofwaardige 67% akkuraatheid bereik het. Beginsels wat tydens die projek ontluik het, is dat veldwerk krities is tot DSM, meer inligting insette verbeter die uitsette en dat die vereenvoudiging van die kaartlegende die kaart se akkuraatheid verbeter.

'n Onrealistiese eis vir 'n grondopname van 37 000 ha binne agt dae deur twee grondopnemers in 'n gebied met beperkte beweging a.g.v. 'n landmyngevaar het die geleentheid geskep om die grond-landskap inferensie model (SoLIM) vir gebruik as DSM gereedskap te toets. Die gevallestudie het afgespeel in die Tete Provinsie, Mosambiek. Verdeling van die gebied in kleiner areas waar unieke grondverspreidings reëls geld (homogene gebiede) is tydens die gevallestudie ingestel. 'n Vrye opname is geloods langs die beskikbare paaie van die gebied. Die finale grondkaart vir 'n gebied van 15 000 ha beskik oor 'n akkuraatheid van 69%. Die beginsel dat ontoeganklike gebiede gekarteer kan word, mits hulle in dieselfde homogene gebied as 'n gebied waar 'n opname wel kon plaasvind lê, is benut.

Naby Namarroi, Mosambiek, is die potensiaal van DSM grondopname metodes om vinnig landgeskiktheidskaarte op te stel vir 'n groot area getakseer. "Conditioned Latin hypercube sampling (cLHS)" is ingestel as metode om veld observasiepunte te bepaal. SoLIM is gebruik om 'n inferensie met grond-terrein reëls afgelei vanaf 'n konseptuele grond verspreidings model oor die hele gebied te dryf. 'n Beperking op die deskundige kennis gebaseerde benadering is raakgeloop. Slegs ses grondkaarteenhede kan bepaal word per homogene gebied. Die kaart het 'n algehele akkuraatheid van 80% behaal. Grondgeskiktheidskaarte is geskep gebaseer op die grond klas kaart.

In die Kruger Nasionale Park is 'n grondkaart gebruik om 2-dimensionele konseptuele hidrologiese reaksie modelle (CHRM) te skep en te ekstrapoleer na 'n 3-dimensionele CHRM landskap. Hierdie is 'n baie goeie voorbeeld van hoe waarde tot 'n grondkaart gevoeg kan word. Satellietbeelde is gebruik tydens die skep van die kaart. 'n Foutmatriks het doeltreffend probleemareas in die kaart uitgewys, waarop toekomstige verbeteringswerk op die kaart kan fokus.

Die huidige data dui aan dat ten minste 28 observasies per homogene area nodig is om 'n aanvaarbare grondkaart te skep. Wanneer die minimum observasie maatstaf vervul word, is observasie digtheid irrelevant. Die cLHS metode om observasie posisies te bepaal het die bruikbaarheid van observasies verhoog. Meer navorsing is nodig om die minimum maatstawwe vir observasies te bepaal.

'n Vyftien-stap protokol waarmee bewys is dat grondopnemers 'n verskeidenheid grondkaarte in diverse omstandighede kan skep is gelewer. Die protokol maak staat op die deskundige kennis van die grondopnemer, tesame met veld observasies. Die protokol het die voordele dat minder observasies nodig is, kaart akkuraatheid bepaal word, probleem areas uitgewys word en onder sekere toestande kan onbereikbare areas ook gekarteer word. Ongelukkig is daar 'n beperking van slegs ses grondkaarteenhede per homogene gebied.

Verdere navorsing is nodig om minimum maatstawwe vir grondobservasies en grondverspreidingsverhoudings met afstandswaarneming kovariate te bepaal.

Sleutelwoorde: Afstandswaarneming, cLHS, DEM, Deskundige kennis, Grond funksies, Grondopname, Hidropedologie, Inferensie sisteme, Landtipe, SoLIM, Terrein analise

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LIST OF SYMBOLS AND ABBREVIATIONS

2D – Two dimensional

3D – Three dimensional

AACN – Altitude above channel network

AfSIS – Africa Soil Information System

ASTER – Advanced spaceborne thermal emission and reflection radiometer

cLHS – conditioned Latin hypercube sampling

DEM – Digital elevation model

DN – Digital number

DSM – Digital soil mapping

EIA – Environmental impact assessment

ESRI – Environmental Systems Research Institute

ET – Evapotranspiration

GDSM – Global digital soil map

GIS – Geographical information systems

HA – Homogeneous area

ha – Hectare

HRU – Hydrological response unit

LS – Slope length factor

MAP – Mean annual precipitation

NDVI – Normalized difference vegetation index

SAGA – System for automated geoscientific analyses

SANSA – South African National Space Agency

SHRS – Stevenson Hamilton Research Supersite

SMU – Soil map unit

SoLIM – Soil land inference model

SPOT – Système Probatoire d'Observation de la Terre

SRTM – Shuttle radar topography mission

SUDEM – Stellenbosch University digital elevation model

TMU – Terrain morphological unit

WI – Wetness index

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ACKNOWLEDGEMENTS

CHAPTER 1:

INTRODUCTION

1.1. The need for soil maps

More than 95% of the world's food requires soil as a basic natural resource (FAOSTAT, 2003). In spite of this, the importance of soil in the food chain is often underestimated. The crop production potential of South African ecotopes[1] varies widely, and the lack of soil maps has been named as one of the biggest reasons for failure of many land reform projects, particularly in the Eastern Free State Province of South Africa (Gaetsewe, 2001). The benefit of doing a soil survey can be immense. According to calculations by Western (1978) in several countries, the cost benefit of doing a soil survey can be 1:125 or more. Thus for every rand invested in the soil survey, R125 can be gained from the knowledge achieved. According the Soil Science Society of South Africa (SSSSA) the cost benefit ratio in South Africa for dry land crop production is approximately 1: 20, with 1:10 as a minimum (Le Roux *et al.,* 1999). Soil suitability maps enable the farmer to optimize the potential of the land by providing guidance with regard to the planting of specific crops, the application of appropriate production techniques, and utilizing specific management practises on specific soils.

The role of soil in natural ecosystems has been ignored. Indications are that soil scientists world-wide focused on food security. The recent shift of focus to global health has drawn the attention of soil scientists. The focus is specifically on the impact of development on water supply to communities and the ecosystem. The ecosystem services supplied by individual soils and soilscapes are relevant. The need for soil maps in quantifying hydrology and assessing the role of soil on the impact of development on ecology and management have increased, due to an enlarged awareness of the role of soil in these processes. The fate of all precipitation, except what is stored in the canopy, is determined by the soil, as soil properties influence where the water will flow. The amount, seasonality and location of water in the landscape determine the vegetation and animal species and populations, thus directly controlling ecological functions. The extent of various sources of industrial pollution also depends on the soil properties' influence on water movement.

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[1]The crop production potential of a piece of land depends on three natural resource factors viz. climate, topography and soils. A piece of land where these three factors are reasonably homogeneous, is termed an ecotope.

Conventional methods of soil survey does not satisfy the growing demand for soil maps, due to being labour intensive and expensive (Zhu *et al.*, 2001). However, the cost of conventional soil surveys can be greatly reduced by digital soil mapping (DSM) (Hensley *et al.*, 2007). DSM harnesses the power of various new and rapidly developing technologies, including information technology, satellite imagery, digital elevation models (DEM's), pedometrics and geostatistics, and combines them in inference systems, incorporating the tacit knowledge gained during field soil surveys. DSM quantifies the huge amount of tacit knowledge gained during soil surveys, which simply went astray with conventional methods. DSM thus aims at utilising various different new technologies to apply expert tacit knowledge to produce the same or better quality soil maps as conventional soil survey at a fraction of the price.

Another challenge being addressed by the DSM community is the distribution of soil data. Traditionally soil scientists have struggled to communicate their findings within soil science and to other disciplines. (Hartemink and McBratney, 2008) This leads to the soil scientist's advice not being followed (Greenland, 1991). Products generated by DSM need to be used to benefit the community (McBratney *et al.,* 2012). For this to happen soil scientist must address issues faced in other disciplines, and communicate their findings in non-soil science language. Bouma (2009) called for a focus on soil functionality, while keeping the knowledge chain (Bouma *et al.*, 2008) intact, thus linking cutting edge research with the end users of the information. Therefore DSM should not only provide soil maps, but also extract the information relevant to the end user from the map and represent it in a way which is understandable to the non-soil scientist.

1.2. Digital soil mapping background

The concept of DSM emerged in the 1970's and because of technological advances in related fields accelerated in the 1980's. Research on different DSM technologies is converging and reaching a stage where operational systems are being implemented (Sanchez *et al.*, 2009). The industrious Global Digital Soil Map (GDSM, Sanchez *et al.*, 2009) project best showcases the theoretical potential of DSM. The aim of this project is to use both legacy and collected soil data to create a soil map of the world's soil properties to a depth of 1 m and at a resolution of 90 by 90 m (Minasny and McBratney, 2010).

Digital soil mapping produces predictions of soil classes or continuous soil properties in a raster format at various resolutions (Thompson *et al.*, 2010). At its core, a digital soil map presents a spatial database of soil properties, derived from a statistical sample of landscapes (Sanchez *et al.*, 2009).

The fundamental principal of digital soil mapping lies in drawing correlations between soil and other factors which are easier to map than the soil. Equation 1 shows this relationship mathematically.

$$S = f(Q) + e \qquad\qquad (1)$$

With S = soil class or property to be mapped

Q = other factors use to map S

e = the error involved with the prediction

The SCORPAN model of McBratney *et al.* (2003) (eq. 2) proposes seven factors which might be used as Q.

$$S = f (s, c, o, r, p, a, n) \qquad\qquad (2)$$

With S = soil class or property to be mapped

s = soil, or other properties of soil at a point

c = climate or climatic properties at a point

o = organisms, such as vegetation, fauna or human activity at a point

r = relief, topography and landscape attributes

p = parent material

a = age, the time factor

n = spatial variability.

The SCORPAN modal differs from Jenny's soil forming factors (Jenny, 1941) in that causality is not implied. Whatever correlation exists between soil properties or classes and the SCORPAN factors may be used to map soils, whether or not the SCORPAN factors influence the soil formation. Where there is evidence of a relationship it may be used (McBratney *et al.*, 2003). According to the effort principal, something should not be predicted if it is easier to measure than the predictor (McBratney *et al.*, 2002). Not all seven factors need to be used, but it is assumed that the more factors are included, the better the prediction will be (McBratney *et al.*, 2003).

As described by Zhu *et al.* (2001) conventional soil mapping occurs in the following steps: Firstly the soil mapper will conduct field work to establish the soil-landscape interaction for the specific area to be mapped. Thereafter the spatial extents of the different soils or soil groups will be mapped manually by aerial photography interpretation. In South Africa the conventional way of soil survey is to make observations on a grid basis, usually 150 m apart. After this the soil is mapped subjectively by drawing polygons around observations of the same type of soil, creating soil map units (SMU's). Shortcomings of both these methods are that they are time consuming and manual. They also incorporate a lot of tacit knowledge into the soil map, without providing a platform where it can be recorded. Thus the tacit knowledge stays with the soil surveyor and is not distributed to possible users of that knowledge. Lastly

the outcome of the conventional methods of soil mapping is map units as discrete polygons. This is labelled crisp logic by Zhu (1997), a term derived from the crisp boundary between map units which arises from this method. This occurs in spite of the realisation that soil classes have intermediate boundaries in both geographic and attribute space (Burrough, 1996). Crisp soil map boundaries have two main limitations. Firstly soil types which are smaller than the minimum mapping unit needs to be incorporated into other map units, which leads to loosing of data (Mulla and McBratney, 2000). Secondly it is assumed that the whole soil map unit has the same properties, although property variation does exist within soil map units. Zhu (2000) calls these limitations the generalization of soil in the spatial and parameter domain.

During a conventional soil survey tacit knowledge of individual and interactive relationships between all factors of SCORPAN, and individual and interactive relationships with surface properties *i.e.* vegetation, yield, surface colour, etc. is developed, but methodology to make it useful is not applied. DSM overcomes these shortcomings by using automated computer inference systems to apply all available data, including tacit knowledge to map soils, which speeds up the process considerably. The information whereby the inference system is run incorporates the expert tacit knowledge, thus providing a platform for it to be distributed to a wider audience. Furthermore a raster base is used for mapping. This means that the map is made up of pixels, each with an X, Y and Z value. The X and Y value is the spatial position of the pixel, whereas the Z value can be any soil property or class or environmental factor. This permits fuzzy transitions between mapping units, enabling a more real representation of soil boundaries.

There are some conflicting reports as to the accuracy of DSM and conventional soil maps. Because of the local variation within pixels and the uncertainty of environmental factor layers, it cannot be assumed that DSM will be more accurate than conventional maps (McBratney *et al.*, 2003). However, there are various reports of DSM projects with better accuracy than conventional maps, for the same area for both soil classes and properties (Zhu *et al.,* 2001; Zhu *et al.*, 2010). The benchmark for soil map accuracy is 65%, which is what Marsman and De Gruijter (1986) found the accuracy of conventional soil maps to be.

1.3. General framework of DSM; the SCORPAN-SSPFe broad methodology

A broad methodology to DSM has been generally accepted (McBratney *et al.*, 2003):
1.   Decide on what is to be mapped (soil classes or soil properties, and which soil properties) and at which scale it is to be done to meet land use requirements.
2.   Acquire the data layers necessary to represent Q.
3.   Spatial decomposition of lagging layers.
4.   Sampling of assembled data to obtain sampling sites.
5.   GPS field sampling and laboratory measurements.
6.   Fit quantitative relationships with auto correlated errors (observing Ockhams razor).

7.   Predict digital map.

8.   Field sampling and laboratory analysis for validation and quality testing.

9.   If necessary, simplify legend or decrease resolution by returning to 1 or improve map by returning
       to 5.

At each step, the soil mapper is free to choose which specific methodology he or she would like to use.
Several methods exist for each step. A general discussion of each step follows:

*Step 1: Decide on what is to be mapped (Soil classes or soil properties, and which soil properties) and at
which scale it is to be done.*
To answer the question what is to be mapped, one needs to know the specific requirements of the map.
DSM should not be an end to itself, but it rather should provide the input for a new framework for soil
assessment (Carré *et al.*, 2007). This statement implies a shift in focus from soil as a natural resource to
soil as a production unit. This asks for a diverse range of soil properties to be mapped depending on land
use requirements ranging from cropping to environment.

The scale at which the maps are to be drawn is usually decided by the resolution of the available input
variables. The finer the resolution the larger the scale will be.

Step 2: Acquire the data layers necessary to represent Q.
In South Africa, there is basic information available on all seven of the SCROPAN factors. This
information however varies from place to place and comes with different accuracies and at different
scales. The more data layers can be acquired, the larger the chance is that a good correlation will be
found between a data layer and the soil. Chapter 2 discusses the data layers used in this research.

Step 3: Spatial decomposition of lagging layers.
After the necessary environmental layers have been assembled, they need to be prepared to be worked
with. This step includes digitising and rasterising paper maps (normally for geological input), deriving
secondary terrain covariates from the DEM, radio transforming remotely sensed data (computing layers
such as the normalized difference vegetation index, NDVI) and interpolating all data layers onto the same
grid (Minasny and McBratney, 2007).

Step 4: Sampling of assembled data to obtain sampling sites.
To make the most of field work, observation positions must be in optimal places. Not only does an optimal
sampling strategy minimize costs by cutting back on sampling number, but it also provides accurate
representations of variability in environmental covariates and enough samples for predictive modelling
(Brungard and Boettinger, 2010).

Observations need to provide data that is adequate for the estimation of some statistical parameter or spatial predictions of soil properties over a specific area (Minasny and McBratney, 2006). A good sampling strategy will not necessarily cover the whole geographical area, but rather needs a good representation of the environmental factors. Minasny and McBratney, 2007, stated that: *"The general perception that good sampling requires a geographical spread is not well founded."* Bui *et al.* (2007) found that sampling must be representative of the whole region, or it will lead to gross mistakes when interpolating between sampling sites. Various sampling schemes exist, and it is up the soil mapper to choose the scheme best suited to the project's needs. In the research several schemes were used, including: hierarchical nested sampling (Vågen *et al.*, 2010; Chapter 3), conditioned Latin hypercube sampling (cLHS, Minasny and McBratney, 2006; Chapters 5 and 6), on-site determined sampling (Chapters 3, 4 and 5) and smart sampling (Chapter 6).

Step 5: GPS field sampling and laboratory measurements
In this step the soil data is collected with which soil classes or properties will be predicted in the rest of the studied area. Soil observations are made and samples taken for laboratory analysis on the locations determined in step 4. Observations necessary for validation purposes will also be made during this step.

Step 6: Fit quantitative relationships with auto correlated errors (observing Ockham's razor)
If DSM was a car, this step would be the engine. Here the observed data is correlated to the environmental factors with the soil surveyor's method of choice. For a general overview of these methods see McBratney *et al.* (2003). In this research these quantitative relationships will take the form of soil-landscape rules, derived based on the expert knowledge of the soil surveyor. The soil-landscape rules will be entered into the soil-landscape inference model (SoLIM; Zhu, 1997), which will also use the rules to predict the soil map (step 7). SoLIM is discussed in Chapter 2.

Step 7: Predict digital map.
The quantitative relationships determined in Step 6 are used to derive the soil map through an automated inference system. An inference model is a computer program which applies the defined quantitative relationship to the whole area to be mapped. Automated inference systems are more efficient, they reduce errors introduced through manual compilation, and they allow for constant application of the soil scientist's knowledge over the entire mapping area (Qi *et al.*, 2006). For a summary of inference systems, see McBratney *et al.*, 2003.

Step 8: Field sampling and laboratory analysis for validation and quality testing.
This step is required to determine the error term (*e*) in Equation 1. To be able to use any map well, it must be known what the uncertainty of the map is (Carré *et al.*, 2007). The error term could be random or have

spatial structure (McBratney *et al.*, 2003). When it is random, spatial variation is probably responsible. Lin *et al.* (2005) found short range hydrological and hillslope curvature variations to account for a great deal of local variability. When *e* has spatial structure various factors can be responsible; the SCORPAN model can by inadequate, too few environmental factors were used, interactions or f(Q) could be misspesified or something intrinsic such as spatial diffusion which influences the error (McBratney *et al.*, 2003). Errors can also be the result of the quality of the input data, which depends on laboratory analysis, experience of the surveyors, and date of sampling (Minasny and McBratney, 2010).

Zhu *et al.* (2010) validated their maps on three levels. Firstly the map must make conceptual sense. Secondly the accuracy must be determined with field observation and laboratory testing. This involves the same procedure as steps 4 and 5. Usually observations made for validation is taken at the same time as the observations made for training data. The validation observations are however set apart for validation and not used when mapping. Lastly the maps should be tested against existing soil maps or maps created with different methods.

Zhu *et al.* (2008; 2010) applied more than one sampling method in the validation step. Grid sampling, purposive sampling (the method they used at step 4) and transect sampling were used. This gives the assurance that the map is thoroughly validated.

Various statistical measures exist with which the accuracy of the map can be shown. For soil classes Ziadat (2001) used the common sense method of taking the accuracy of the map as the percentage of validation points that was predicted correctly. This method involves an error matrix, which gives an idea of the accuracy of prediction for soil class maps. For soil property maps statistical measures such as mean absolute error (MAE), root mean square error (RMSE), and agreement coefficient (AC) can be used to determine the accuracy of the map (Zhu *et al.* 2010).

Step 9: Assess the map. If necessary, simplify legend or decrease resolution by returning to 1 or improve map by returning to 5.

Decide if the map met the criteria set in Step 1. If not, either the map needs to be improved, which can be done by returning to Step 4, or the scale and properties can be simplified by returning to Step 1.

Generally speaking the SCORPAN-SSPFe method could be applied in two DSM approaches. The first approach relies on spatial statistics, with computer models generating soil predictions based on statistical relationships between the soil and covariates. Such processes are usually objective and fully automated, and thus require little time. On the downside, this approach is data hungry, needing plenty of observation points to fulfil statistical requirements (Hansen *et al.,* 2009). The second approach relies on expert

knowledge. With this approach, the soil mapper is required to create soil-landscape rules, which relate to the soil distribution of the area. Thus the soil mapper's knowledge of the soil distribution in the landscape is vital to the success of the soil survey (Qi *et al.*, 2006). Fewer observation points are required as quantitative information can be thoroughly integrated into the prediction system (McKenzie *et al.*, 1999). However, the process is only semi-automated and somewhat subjective, which might introduce bias when using expert knowledge to predict soils (McKenzie *et al.*, 1999).

1.4. DSM in South Africa

The challenge with DSM lies in creating site specific protocols which soil surveyors could follow to produce a quality product. Soil-landscape interaction varies between different locations and thus methodologies used in regional soil mapping might not be applicable at a different scale (Minasny and McBratney, 2010). Furthermore, available data sources vary in different parts of the world which complicates the implementation of DSM. This, together with unresolved research questions such as which data layer gives the best correlation to soil properties, what is the best way to model and reflect uncertainties (Minasny and McBratney, 2010), which sampling methods are best for which situations, how should validation and quality control be implemented, and the economic value of DSM (McBratney *et al.*, 2003) demands that research into DSM should be conducted locally.

In South Africa DSM is still an emerging research field, with only a few isolated reports and papers available. The Institute for Soil, Crop and Climate (ISCW) has compiled two reports (Van den Bergh and Weepener, 2008; Van den Bergh *et al.*, 2009) with regard to DSM, both focusing on the use of remote sensing and the land type soil profile database to produce soil maps for areas of KwaZulu-Natal. Schoeman (2005) also from the ISCW compiled some work on the theory of pedometrics. In the Free State Hensley *et al.* (2007) described a procedure for delineating land suitable for rainwater harvesting, using expert knowledge based DSM techniques. Stals (2007) mapped salt affected soils in the Orange River irrigation scheme with remote sensing, by mapping plants that had been affected by saline soils. Mashimbye *et al.* (2012) also mapped soil salinity using hyper spectral remote sensing data. We need a lot more research in South Africa to understand our local soil-landscape interaction, as well as to know how to optimally use the unique set of environmental layers that are available in our country.

Currently soil surveys in South Africa are industry driven. Clients pay soil surveyors to map soils for specific needs. The primary users of soils data are farmers, but developers (for environmental impact assessments), mines (for pollution studies), hydrologists (for hydrological purposes) and environmental consultants increasingly use soil maps. Regularly the areas to be mapped are fairly large (5 000 – 30 000 ha), and have very little or no existing data. Often budgets limit the input data. Southern African soil surveyors are generally very well trained in soil morphology and application of soil knowledge to specific needs. However, specialist skills in GIS applications and statistics, although part of university curricula,

are often lacking. Thus a DSM protocol for southern Africa should have an expert knowledge approach, with a relatively simple GIS and statistical background.

To keep the link with industry's needs, a case study approach was followed in this research. Four case studies were done in succession, which cover an array of challenges faced by soil surveyors. Figure 1.1 shows the locations, while Table 1.1 gives some features of the different case studies. Using these case studies a working DSM protocol for mapping large areas in southern Africa will be developed.

Figure 1.1: The locations of the case studies. A – Madadeni; B – Tete, C – Namarroi; D – Stevenson Hamilton Research Supersite.

Table 1.1: Features of the case studies used in this project

	Madadeni	**Tete**	**Namarroi**	**SHRS**
Map Aim	Research	Environmental Impact Assessment	Forestry Production Potential	Hydrological Modelling
Special feature	Land types	Land mines	LiDAR	Remote sensing
Sampling scheme	Hierarchical nested	Roads	cLHS	cLHS Smart sampling Hap-Hazard
Covariates	30 m DEM, interpolated from contours 1: 250 000 geological map Land types	25 m DEM, interpolated from contours 1 : 20 000 geological map	10 and 30 m DEM, interpolated from Lidar 1 : 1 000 000 geological map	10 and 30 m DEM, interpolated from 5 m SUDEM Landsat 7 SPOT 5 ET and Biomass
Geology	Sandstone and dolerite	Sandstone, shale and granitic gneiss	Granitic gneiss Basic intrusive rocks	Granite
MAP	858 mm	627 mm	1 770 mm	560 mm
Vegetation	Grassland	Bushland	Woodland Forest	Savannah
Area mapped	6 865 ha	15 000 ha	10 966 ha	4 001 ha

SHRS – Stevenson Hamilton Research Supersite; cLHS – conditioned Latin hypercube sampling; DEM – Digital elevation model; SUDEM – Stellenbosch University DEM; ET – Evapotranspiration; MAP – mean annual precipitation.

1.5. References

Bouma, J., de Vos, J.A., Sonneveld, M.P.W., Heuvelink, G.B.M., Stoorvogel, J.J., 2008. The role of scientists in multiscale land use analysis: lessons learned from Dutch communities of practice. Advances in Agronomy 97, 175–239.

Bouma, J. 2009. Soils are back on the agenda: Now what? Geoderma 150, 224-225.

Bui, E.N., Simon, D., Schoknecht, N., Payne, A., 2007. Adequate prior sampling is everything: Lessons from the Ord river basin, Australia. In: Lagacherie, P., McBratney, A.B. & Voltz, M. (eds.). Digital soil mapping; an introductory perspective. Elsevier, Amsterdam.

Brungard, C.W., Boettinger, J.L., 2010. Conditioned Latin hypercube sampling: Optimal sampling size for digital soil mapping of arid rangelands in Utah, USA. In: Boettinger, J.L., Howell, D.W., Moore,

A.C., Hartemink, A.E. & Kienast-Brown, S. (eds.). Digital soil mapping; bridging research, environmental application and operation. Springer, Dordrecht.

Burrough, P.A., 1996. Opportunities and limitations of GIS-based modelling of solute transport at the regional scale. In: Corwin, D.L. & Loague, K. (eds.). Applications of GIS to the modelling of non-point source pollutants in the vadoze zone. SSSA Special Publication 48, 19-38.

Carré, F., McBratney, A.B., Mayr, T., Montanarella, L., 2007. Digital soil assessments: Beyond DSM. Geoderma 142, 69-79.

FAOSTAT, 2003. Food and Agriculture Organization of the United Nations, Statistical databases. Available at: http://faostat.fao.org.

Gaetsewe, H.E., 2001. Evaluation of land reform projects in the south eastern Free State. M.Tech. Thesis. Technikon Free State, Bloemfontein.

Greenland, D.J., 1991. The contributions of soil science to society — past, present, and future. Soil Science 151, 19–23.

Hansen, M.K., Brown, D.J., Dennison, P.E., Graves, S.A., Bricklemyer, R.S., 2009. Inductively mapping expert-derived soil-landscape units within dambo wetland catenae using multispectral and topographic data. Geoderma 150, 72-84.

Hartemink, A.E., McBratney, A.B., 2008. A soil science renaissance. Geoderma 148, 123-129.

Hensley, M., Le Roux, P.A.L., Gutter, J., Zerizghy, M.G., 2007. Improved soil survey technique for delineating land suitable for rainwater harvesting. WRC Project K8/685/4. Water Research Commission, Pretoria.

Jenny, H., 1941. Factors of soil formation, a system of quantitative pedology. McGraw-Hill, New York.

Le Roux, P.A.L., Ellis, F., Merryweather, F.R., Schoeman, J.L., Snyman, K., Van Deventer, P.W., Verster, E., 1999. Riglyne vir kartering en interpretasie van die gronde van Suid-Afrika. Universiteit van die Vrystaat. Bloemfontein.

Lin, H., Wheeler, D., Bell, J., Wilding, L., 2005. Assessment of soil spatial variability at multiple scales. Ecological Modelling 182, 271-290.

Marsman, B.A., de Gruijter, J.J., 1986. Quality of soil maps, a comparison of soil survey methods in a study area. Soil Survey papers no. 15. Netherlands Soil Survey Institute, Stiboka, Wageningen, The Netherlands.

Mashimbye, Z.E., Cho, M.A., Nell, J.P., De Clercq, W.P., Van Niekerk, A., Turner, D.P., 2012. Model-based integrated methods for quantitative estimation of soil salinity from hyperspectral remote sensing data: A case study of selected South African soils. Pedosphere 22(5), 640-649.

McBratney, A.B., Minasny, B., Cattle, S.R., Vervoort, R.W., 2002. From pedotransfer functions to soil inference systems. Geoderma 109, 41-73.

McBratney, A.B., Mendoça Santos, M.L., Minasny, B., 2003. On digital soil mapping. Geoderma 117, 3-52.

McBratney, A.B., Minasny, B., Wheeler, I., Malone, B.P., Van der Linden, D., 2012. Frameworks for digital soil assessment. In: Minasny, B., Malone, B., McBratney, A.B., (eds.). Digital soil assessments and beyond. CRC Press, Boca Raton.

McKenzie, N.J., Ryan, P.J., 1999. Spatial prediction of soil properties using environmental correlation. Geoderma 89, 67-94.

Minasny, B., McBratney, A.B., 2006. A conditioned Latin hypercube method for sampling in the presence of ancillary information. Computers & Geosciences 32, 1378–1388.

Minasny, B., McBratney, A.B., 2007. Latin hypercube sampling as a tool for digital soil mapping. In: Lagacherie, P., McBratney, A.B. & Voltz, M. (eds.). Digital soil mapping; an introductory perspective. Elsevier, Amsterdam.

Minasny, B., McBratney, A.B., 2010. Methodologies for global soil mapping. In: Boettinger, J.L., Howell, D.W., Moore, A.C., Hartemink, A.E., Kienast-Brown, S. (eds.). Digital soil mapping; bridging research, environmental application and operation. Springer, Dordrecht.

Mulla, D.J., McBratney, A.B., 2000. Soil spatial variability. In: Sumner, M.E. (ed.). Handbook of Soil Science. CRC Press. Boca Raton.

Qi, F., Zhu, A.X., Harrower, M., Burt, J.E., 2006. Fuzzy soil mapping based on prototype category theory. Geoderma 136, 774 – 787.

Sanchez, P.A., Ahamed, S., Carré, F., Hartemink, A.E., Hempel, J., Huising, J., Lagacherie, P., McBratney, A.B., McKenzie, N.J., Mendonça-Santos, M.L., Minasny, B., Montanarella, L., Okoth, P., Palm, C.A., Sachs, J.D., Shepherd, K.D., Vågen, T.G., Vanlauwe, B., Walsh, M.G., Winowiecki, L.A., Zhang, G.L., 2009. Digital soil map of the world. Science 325, 680-681.

Schoeman, J.L., 2005. Trends in soil survey and classification. Keynote address – Combined Congress, Potchefstroom.

Stalz, J.P., 2007. Mapping potential soil salinization using rule based object-oriented image analysis. M.Sc. thesis, Department of Geography, Stellenbosch University, Stellenbosch.

Thompson, J.A., Prescott, T., Moore A.C., Bell J.S., Kautz D., Hempel, J., Waltman, S.W., Perry, C.H., 2010.Regional approach to soil property mapping using legacy data and spatial disaggregation techniques.19th World Congress of Soil Science, Soil Solutions for a Changing World; 1 – 6 August 2010, Brisbane, Australia.

Vågen, T.G., Winowiecki, L., Desta, L.T., Tondoh, J.E., 2010. Land degradation surveillance framework: Field guide. AfSIS, Arusha.

Van den Bergh, H.M., Weepener, H.L., 2009. Development of spatial modelling methodologies for semi-detailed soil mapping, primarily in support of curbing soil degradation and the zoning of high potential land. Report no: GW/A/2009/01. ARC-ISCW. Pretoria.

Van den Bergh, H.M., Weepener, H.L., Metz, M., 2009. Spatial modelling for semi detailed soil mapping in Kwazulu-Natal. Report no: GW/A/2009/33. ARC-ISCW. Pretoria.

Western, S., 1978. Soil survey contracts and quality control. Oxford University Press, Oxford.

Zhu, A-X., 1997. A similarity model for representing soil spatial information. Geoderma 77, 217-242.

Zhu, A-X., 2000. Mapping soil landscape as spatial continua: the neural network approach. Water Resources Research 36, 663-677.

Zhu, A-X., Hudson, B., Burt, J., Lubich, K., Simonson, D., 2001. Soil mapping using GIS, expert knowledge and fuzzy logic. Soil Science Society of America Journal 65, 1463-1472.

Zhu, A-X., Yang, L., Li, B., Qin, C., English, E., Burt, J.E., Zhou, C., 2008. Purposive sampling for digital soil mapping for areas with limited data. In: Hartemink, A. E., McBratney, A.B., Mendonça-Santos, M. De L., (eds.). Digital soil mapping with limited data. Springer, Dortrecht.

Zhu, A-X., Yang, L., Li, B., Qin, C., Pei, T., Liu, B., 2010. Construction of membership functions for predictive soil mapping under fuzzy logic. Geoderma 155, 164–174.

Ziadat, F.E., 2007. Land suitability classification using different sources of information: Soil maps and predicted soil attributes in Jordan. Geoderma 140, 73-80.

CHAPTER 2:

Software and Covariates

In DSM various covariate layers are needed to predict soil distribution by using a variety of GIS tools in several software programs. As there are many ways to kill a cat, the available covariate layers and software programs can often be used for the same purposes. This chapter will briefly discuss those used in this research.

2.1. Software Programs

Different software programs were used, as they are specialized to do different functions, even though there are quite a bit functionality overlaps. A practical procedure was followed in the research. The appendices show step by step procedures on how to use some of the tools of the software packages.

2.1.1. ArcGIS 10

ArcGIS is probably the most widely used commercial GIS package. It is developed by Environmental Systems Research Institute (ESRI, www.esri.com). Although quite expensive (especially when compared to open source GIS packages) it is being used for GIS training by most universities in South Africa and is therefore the most commonly used GIS product. ArcGIS was used for the conversion of files, creating and assigning projections to map layers, viewing and drawing of maps. ArcGIS can be purchased at www.esri-southafrica.com.

2.1.2. SAGA

The System for Automated Geoscientific Analysis (SAGA, Böhner *et al.*, 2006; Böhner *et al.*, 2008) is an open source GIS package, developed by a research team from the Department of Physical Geography, Hamburg. The functionality of SAGA is very good for specific tasks, as the modules have been developed by scientists that need particular tasks done. Nearly all the terrain and image analysis in the final protocol is done in SAGA. The program can be downloaded from http://sourceforge.net/projects/saga-gis/files/, and various manuals and other useful material related to the operation of SAGA could be downloaded from http://www.saga-gis.org/en/index.html.

2.1.3. SoLIM

The Soil-Land Inference Model (SoLIM) (Zhu, 1997) is a software tool specifically designed for digital soil mapping, using an expert knowledge based approach. In this research it is used to enter the soil distribution rules, and to create a map from the rules. It also includes a method to determine observation positions called purposive sampling (Zhu *et al.*, 2008). Several scientific articles on the usage of SoLIM have been written (eg: Zhu, 2000; Zhu *et al.*, 2001; Zhu *et al.*, 2010). SoLIM can be

downloaded from http://solim.geography.wisc.edu/software. Manuals and publications of SoLIM can also be obtained from the website. A very good start-up tutorial is included in the software package. SoLIM is provided free of charge for non-commercial enterprises, however for commercial usage, please contact the developer Prof. A-Xing Zhu at mailto:azhu@wisc.edu.

2.1.4. Conditioned Latin Hypercube Sampling

Conditioned Latin hypercube sampling is adapted from Latin hypercube sampling (LHS) (see McKay *et al.*, 1979), a stratified random sampling method used for multivariate distributions. It provides a sampling scheme where the full range of each variable is represented by maximally stratifying the marginal distribution. Thus it gives a good spread of the feature space, and not necessarily of the geographical space (Minasny and McBratney, 2007). LHS follows the idea of a Latin square, with one sample in each row and column (Minasny and McBratney, 2006). In a Latin hypercube each environmental factor is stratified into n dimensions. The sample is maximally stratified when n = the sample size and the probability of a sample falling into each stratum is n^{-1} (Minasny and McBratney, 2006). Within each strata one sample is chosen randomly, which is then randomly paired with a sample from one strata of another environmental factor (Figure 2.1).
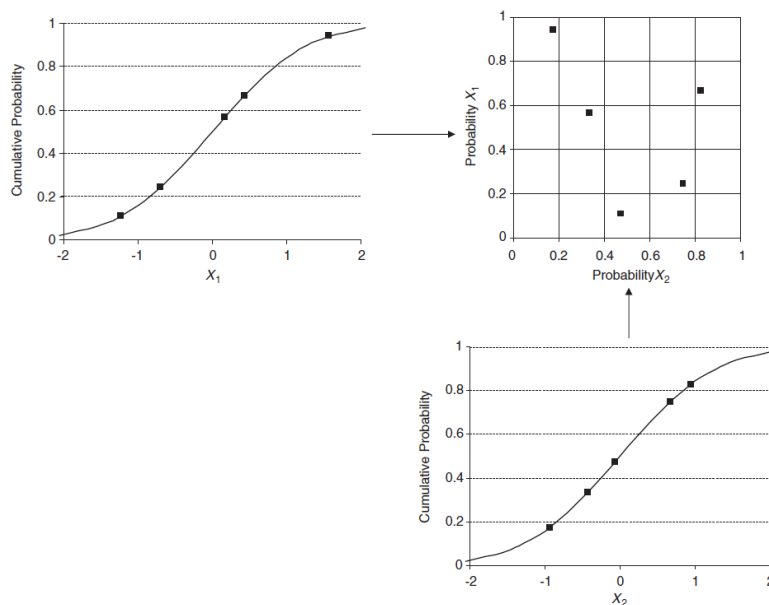
Figure 2.1: A graphic representation of the Latin Hypercube Sampling point selection (From Minasny and McBratney, 2006).

The problem with applying LHS is that the chosen samples do not necessarily exist in reality (Minasny and McBratney, 2006). Conditioned Latin hypercube sampling (cLHS) adds the condition that the samples chosen by LHS must exist in the landscape studied (Brungard and Boettinger, 2010). There are two ways to accomplish this. The first is to run LHS repeatedly until all the samples exist in the

landscape studied, or to include a seek function into the protocol. The latter option is performed by cLHS (Minasny and McBratney, 2006).

2.2. Covariate layers

Covariate layers can either be raster or polygon based. In raster based covariate layers, each pixel has an x, y and z value where the x and y values give the position of the pixel and the z value is the response. With a digital elevation model, the z value is height above sea level and for satellite images, the z value is the reflection of energy at a specific wavelength, usually expressed as a Digital Number (DN). It is the z values that are correlated with soil observations. Nearly all covariate layers are raster based, with the exception of geological maps, which is usually polygon based. These need to be converted to a raster format.

2.2.1. Digital elevation models

Correlations between soil and terrain variables are the most commonly used in DSM (McBratney, *et al.*, 2003). Several terrain variables can be computed from a DEM. DEM's can be obtained from various sources. The shuttle radar transmission (SRTM, Rodriguez *et al.,* 2005), has a resolution of 3 arc seconds, approximately 90 m. The ASTER Global DEM (Aster GDEM, undated) has a resolution of 30 m, but some problems with the data have been encountered. Another method to create a DEM is by interpolating the 20 m contours that is standard on the 1: 50 000 topographical maps of South Africa. Interpolation of contours gives varying resolutions dependant on relief. The larger the relief, the finer the resolution of the DEM will be. The DEM's for Chapters 3 and 4 were created in this way. The SUDEM (Van Niekerk, 2012), a DEM created by Stellenbosch University for the whole of South Africa was created by interpolation. They used the contours from the 1: 50 000 and 1: 10 000 (where available) topographical maps as well as the SRTM DEM to create the SUDEM. The SUDEM was used in Chapter 6. The best topographical information can be attained with a Lidar (light detection and radar) device, which is able to acquire point elevations with sub metre accuracies. The DEM's in Chapter 5 was acquired by interpolating Lidar data.

2.2.2. Geological maps

Geological maps at a scale of 1: 250 000 are available for South Africa (Geological Survey, 1988), which will provide the standard input for the parent material factor. These maps can be ordered from the Council for Geosciences (www.geoscience.org.za). The maps are quite expensive in digital format, so the most cost effective way to incorporate geological information into the equation is to order the printed map, scan it, and then georeference the map. A helpful portal for geological maps is One Geology (www.onegeology.org). From this website geological maps for large parts of the world can be downloaded. The geological information that was used in Chapter 5 was obtained in this way. Often, such as when the client is a mining company, the client provides very good geological data, as what happened in Chapter 4. The coarse scale of the geological maps can be limiting the accuracy of DSM, especially where dolerite dykes are present in an area (Chapter 6).

A further problem to address is the effect of colluvium. When two different geological formations exist, the colluvium from the top formation will influence soil formation on the bottom geology. This was encountered in Chapter 3.

2.2.3. Landsat satellite images

Landsat is the longest running satellite observation program. The latest satellite, Landsat-ETM 7 provides eight bands at varying resolutions (Table 2.1). The bands commonly used in DSM are 1 – 5 and 7. Various mathematical transformations with the data are possible, of which the most well-known is the normalized difference vegetation index (NDVI) (Rouse *et al.*, 1973; Tucker, 1979). These transformations provide an additional set of covariates with which the soils could be correlated. In Chapter 6 the NDVI proved valuable. Landsat images could be obtained free of charge from http://earthexplorer.usgs.gov/. The South African Space Agency (SANSA) also provides the images, with a level of pre-processing done on them, free of charge for educational and research purposes.

Table 2.1: Landsat 7 bands (From NASA, undated)

Band	Bandwidth (μm)	Resolution
1	0.45 - 0.52	30
2	0.52-0.6	30
3	0.63 - 0.69	30
4	0.76 - 0.9	30
5	1.55 - 1.75	30
6	10.4 - 12.5	60
7	2.08 - 2.35	30
Pan	0.5 - 0.9	15

2.2.4. SPOT 5 satellite images

The remote sensing covariates with the finest resolution are the Système Probatoire d'Observation de la Terre or SPOT images. It offers five bands, a 2.5 m panchromatic band, three multispectral bands (green, red and near infra-red) with a resolution of 10 m and a short wave infra-red band with a 20 m resolution. A pan sharpened image could be created, which is a fusion of the panchromatic and multispectral bands at a resolution of 2.5 m (SPOT image, undated). The three multispectral bands are used in DSM. As the multispectral bands include a red and infra-red band, the NDVI could be determined. SPOT images are available from SANSA. These images are provided free when used for educational and research purposes (terms and conditions apply), but are quite costly when used for commercial purposes. SPOT was used in Chapter 6.

2.2.5. Other remotely sensed layers

In Chapter 6, two further remotely sensed layers were used. These are commercially provided layers which measures biomass production and evaporation. The Inkomati Catchment Management Agency

on behalf of eLeaf (www.eleaf.com) and the WATPLAN EU project provided the images. When available, any layer which could be correlated to soil type could be used for DSM purposes.

2.2.6. Land type inventory

South Africa is blessed with the land type survey (Land Type Survey Staff, 1972-2006), whereby the whole country has been delineated into reasonably uniform land units at a scale of 1: 250 000. Each land type unit is described in the form of one representative catena per land type with percentages of soil forms per terrain morphological unit. The land type survey also included climate, parent material and topography to delineate the map units. The land type inventory gives an estimation of the percentage of each terrain morphological unit (TMU) which is occupied by a specific soil type. The soil classification was done according to MacVicar *et al.* (1977). The land type inventory is similar to the SOTER database (Oldeman and Van Engelen, 1993) (http://www.isric.org/projects/soil-and-terrain-database-soter-programme). In Chapter 3 the land type database was disaggregated into a soil association map.

2.3. References

ASTER GDEM, undated. http://www.ersdac.or.jp/GDEM/E/4.html. Accessed 2011-09-28.

Böhner, J., McCloy, K.R., Strobl, J. (eds.), 2006. SAGA - Analysis and Modeling Applications. Göttinger Geographische Abhandlungen, Vol.115, 130pp.

Böhner, J., Blaschke, T., Montanarella, L. (eds.), 2008. SAGA - Seconds Out. Hamburger Beiträgezur Physischen Geographie und Landschaftsökologie, Vol.19, 113pp.

Brungard, C.W., Boettinger, J.L., 2010. Conditioned latin hypercube sampling: Optimal sampling size for digital soil mapping of arid rangelands in Utah, USA. In: Boettinger, J.L., Howell, D.W., Moore, A.C., Hartemink, A.E. & Kienast-Brown, S. (eds.). Digital soil mapping; bridging research, environmental application and operation. Springer, Dordrecht.

Geological Survey, 1988. 1: 250 000 Geological Series. Geological Survey, Pretoria.

Land type survey staff, 1976-2006. Land type Survey Database. ARC-ISCW, Pretoria.

MacVicar, C.N., De Villiers, J.M., Loxton, R.F., Verster, E., Lambrechts, J.J.N., Merryweather, F.R., Le Roux, J., Van Rooyen, T.H., Harmse, H.J. von M., 1977. Soil Classification: A binomial system for South Africa. Department of Agriculture Technical Services, Pretoria.

McBratney, A.B., Mendoça Santos, M.L., Minasny, B., 2003. On digital soil mapping. Geoderma 117, 3-52.

McKay, M.D., Beckman, R.J., Conover, W.J., 1979. A comparison of three methods for selecting values of input variables in the analysis of output from a computer code. Technometrics 21, 239–245.

Minasny, B., McBratney, A.B., 2006. A conditioned Latin hypercube method for sampling in the presence of ancillary information. Computers & Geosciences 32, 1378–1388.

Minasny, B., McBratney, A.B., 2007. Latin hypercube sampling as a tool for digital soil mapping. In: Lagacherie, P., McBratney, A.B. & Voltz, M. (eds.). Digital soil mapping: an introductory perspective. Elsevier, Amsterdam.

NASA, undated. Landsat 7 science data users handbook. Available from http://landsathandbook.gsfc.nasa.gov/. Accessed 2011-09-28.

Oldeman, L.R., Van Engelen, V.W.P., 1993. A world soils and terrain digital database (SOTER) – An improved assessment of land resources. Geoderma 60, 309-325.

Rodriguez, E., Morris, C.S., Belz, J.E., Chapin, E.C., Martin, J.M., Daffer, W., Hensley, S., 2005. An assessment of the SRTM topographic products, Technical Report JPL D-31639, Jet Propulsion Laboratory, Pasadena, California.

Rouse, J.W., Haas, R.H., Schell, J.A., Deering, D., 1973. Monitoring vegetation systems in the great plains with ERTS. Proceedings, Third ERTS Symposium, 1, 48-62.

SPOT image, undated. SPOT satellite technical data. Available from http://www.spotimage.com/web/en/229-the-spot-satellites.php. Accessed 2011-09-28.

Tucker, C.J. 1979. Red and photographic infrared linear combinations for monitoring vegetation. Remote Sensing of Environment 8, 127–150.

Van Niekerk, A., 2012. Developing a very high resolution DEM of South Africa. Position IT, Nov-Dec: 55-60. http://www.eepublishers.co.za/images/upload/positionit_2012/visualisation_nov-dec12_developing-resolution.pdf.

Zhu, A-X., 1997. A similarity model for representing soil spatial information. Geoderma 77, 217-242.

Zhu, A-X., 2000.Mapping soil landscape as spatial continua: the neural network approach. Water Resources Research 36, 663-677.

Zhu, A-X., Hudson, B., Burt, J., Lubich, K., Simonson, D., 2001. Soil mapping using GIS, expert knowledge and fuzzy logic. Soil Science Society of America Journal 65, 1463-1472.

Zhu, A-X., Yang, L., Li, B., Qin, C., English, E., Burt, J.E., Zhou, C., 2008.Purposive sampling for digital soil mapping for areas with limited data. In: Hartemink, A. E., McBratney, A.B., Mendonça-Santos, M. De L., Digital soil mapping with limited data. Springer, Dortrecht.

Zhu, A-X., Yang, L., Li, B., Qin, C., Pei, T., Liu, B., 2010.Construction of membership functions for predictive soil mapping under fuzzy logic. Geoderma 155, 164–174.

CHAPTER 3:

Disaggregation of Land Types, using terrain analysis, expert knowledge and GIS methods

Abstract:

Soil maps' value is increasingly recognized for enabling the optimal management of ecosystems. Digital soil mapping (DSM) can overcome the cost constraints of traditional mapping methods, but requires local area specific research. As South Africa is blessed with the land type survey, local DSM research should start with the disaggregation of this resource. This paper shows how two land types (Ea34; Ca11) near Newcastle in KwaZulu-Natal were disaggregated using DSM methods. A series of soil maps were created. With each map, more information was incorporated when creating the map. For Map 1 only the land type inventory and terrain analysis were used. A reconnaissance field visit with the land type surveyor was added for the second map. Field work and a simplified soil association legend improved the map accuracy for Maps 3 and 4, which were created using 30% and 60% of the observations points as training data respectively. The accuracy of the maps increased when more information was utilized. Map 1 reached an accuracy of 35%, while Map 4 achieved a commendable accuracy of 67%. Thus DSM methods can be used to disaggregate land types into accurate soil association maps. Emerging principles include: Lithology rather than hard geology should be used as parent material input, field work is critical to obtain acceptable results and simplifying the map legend into soil associations improves the accuracy of the map.

Keywords: Digital Soil Mapping, Soil Survey, DEM, SoLIM Software

3.1. Introduction

Virtually all food except for fish requires soil as a natural resource. In spite of this, the importance of soil in the food chain is often underestimated. In South Africa, the lack of soil suitability maps has been named as one of the reasons for failure among upcoming farmers (Gaetsewe, 2001). However, it is known that the benefit of a soil survey for dryland cropping is between 10 to 125 times that of the cost (Western, 1978; Le Roux *et al.*, 1999). The value of soil survey in hydrology and the ecosystem has not been established.

Part of the reason for the lack of soil suitability maps is that traditional methods of soil survey are cumbersome and expensive. However, the cost of traditional soil surveys can be greatly reduced by digital soil mapping (DSM) methods (Hensley *et al.*, 2007), which is moving from the research into the operational phase (McBratney *et al.*, 2003). DSM harnesses the power of various new and rapidly developing technologies, including information technology, satellite imagery, digital elevation models (DEM's) and geostatistics, and combines them in computer inference systems, incorporating the tacit knowledge gained during field soil surveys. DSM thus aims at utilising various new technologies to produce better quality soil maps at a fraction of the price, while also improving the interpretation of soil maps to a wider range of specialist fields.

Soil-landscape interactions vary between different locations and thus methodologies used in regional soil mapping might not be applicable at a different scale or location (Minasny and McBratney, 2010). These, together with available data sources which vary in different parts of the world complicate the implementation of DSM and calls for local DSM research to be conducted.

In South Africa DSM is still in its infant stage (Stalz, 2007; Hensley *et al.*, 2007; van den Bergh and Weepener, 2009; van den Bergh *et al.*, 2009). The scientific potential of the Land Type database (Land Type Survey Staff, 1972-2006) has been emphasised in these efforts and has the potential to be exploited further (Hensley *et al.,* 2007), as the distribution of soil series (MacVicar *et al.*, 1977) in the landscape serves as the scientific backbone of the survey. Because of this resource, it seems logical that the starting point of DSM in South Africa should be the disaggregation of land types.

The land type survey (Land Type Survey Staff, 1972-2006) produced a 1: 250 000 scale map, showing relative homogeneous parcels of land in terms of terrain, climate and soil distribution pattern. Each such parcel of land is a different land type. Soil distribution is given as a rough estimate of the percentage of area of each Terrain Morphological Unit (TMU; also called terrain unit) covered by a specific soil series. Thus it is not a soil map, but rather a list of soil series' found within the land type and a rough estimation of where in the landscape they will occur. Bui and Moran (2001) successfully disaggregated a similar product, the Land Systems of western New South Wales, using expert knowledge and soil-landscape relationships.

The hypothesis expressed in this paper is that there is a sound scientific correlation between the local dominant soil forming factors, topography and parent material. This enables land types to be disaggregated into useful soil maps.

Two land types were disaggregated into a series of soil association maps, using DSM methods. The first map was created in office, using only terrain analysis and the land type inventory. The second map was created after a reconnaissance visit to the site, together with the land type surveyor. The last two maps were created after field work was conducted, using 30% and 60% of the observations as training data. Technically these last two maps are not produced by disaggregation, but rather

DSM. As the methodology of the different maps is different from each other, different map legends and accuracies are to be expected. This is not seen as a problem, as the aim of the paper is to determine the level of spatial soil information we can expect with different levels of input.

3.2. Material and methods

3.2.1. Site description

The study site of 6865 ha is north of Madadeni and Newcastle, in KwaZulu-Natal, close to the border with Mpumalanga and the Free State (Figure 3.1). Its geographical centre point is 29.95˚E and 27.62˚S. Two land types occur in this area, namely Ca11 and Ea34 (Land Type Survey Staff, 1986). The geology of land type Ea34 is dominated by dolerite lithology (Geological Survey, 1988), which weathers to swelling red or black clay soils. Land type Ca11 has sandstone as its main lithology (Geological Survey, 1988), which weathers to sandy soils, often with plinthic character in the deeper subsoil horizons. The mean annual precipitation is 858 mm (SAWS, 2012). The veld types in the area are the KwaZulu-Natal Highland Thornveld and Income Sandy Grassland (Mucina and Rutherford, 2006). Commercial cattle farming is the primary land use. Fields are burnt annually to provide regrowth as fodder for the cattle. This site is one of the sentinel sites for the Africa Soil Information Service project (AfSIS) (Vågen *et al.*, 2010), and thus it was chosen for this project, as a way to increase usage of the data already collected.
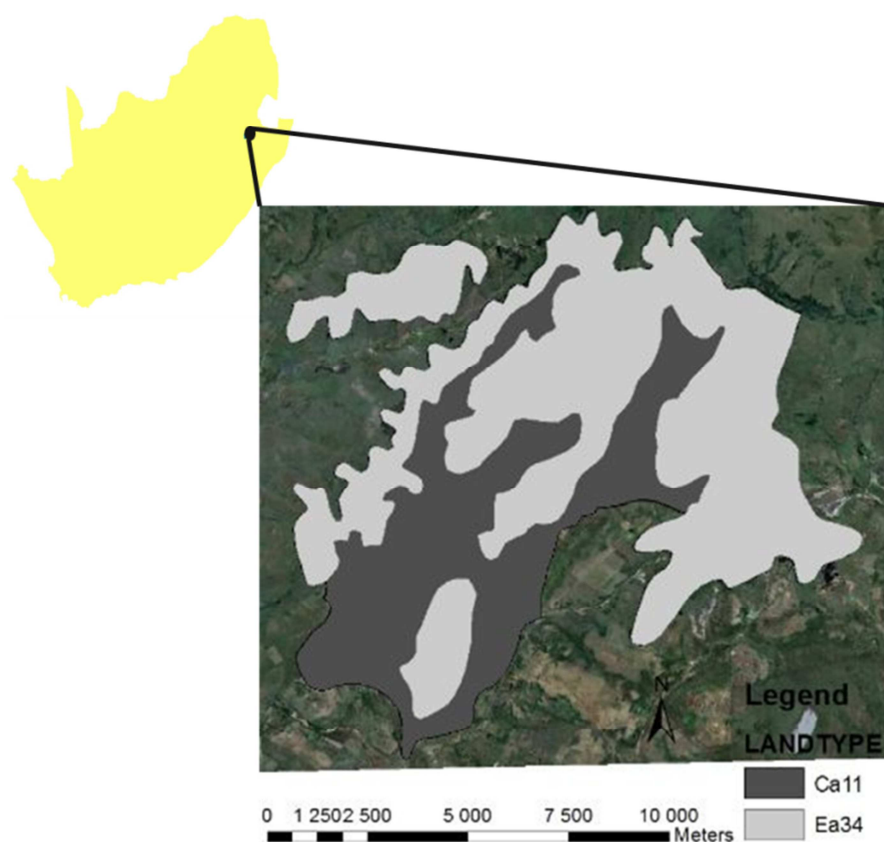
Figure 3.1: The Madadeni study site, showing the extent of the Ca 11 and Ea 34 land types.

The typical topography of the two land types varies (Figure 3.2). Land type Ea34 has all the topographical positions from crest to valley bottom, largely with short concave slopes. In contrast to this land type Ca11 has long concave slopes and is only comprised of crest, midslope and valley bottom positions.

Figure 3.2: Terrain sketches of Land Types Ca11 (Fig. 3.2a) and Ea34 (Fig. 3.2b) (Land Type Survey Staff, 1986).

3.2.2. Software used

The software used in this project is Arc Map 9.3 (Environmental Systems Research Institute Inc., 2010), 3dMapper (Terrain Analytics, L.L.C.; 2003) and the Soil-Land Inference Model (SoLIM, Zhu, 1997). 3dMapper and SoLIM have been specifically developed for use in DSM. SoLIM enables the user to capture soil terrain interactions as rules. Thus the user applies expert knowledge and writes specific terrain landscape rules for each soil map unit (SMU). SoLIM also runs an inference, whereby it assigns a specific SMU to each pixel, based on the rules the soil mapper created, thereby creating a soil map. Within 3dMapper terrain layers and maps created by SoLIM can be viewed in a 3d environment.

3.2.3. Methodology

Four different soil maps were drawn in hierarchical fashion, with each map having increasing levels of input.

Map 1

The first map was drawn in the office, by only using the land type inventory and a 30 m DEM interpolated from the 20 m contours of the 1: 50 000 topographic maps. As the DEM's resolution is 30 m, all products derived in this project also had a 30 m resolution. The terrain was divided by hand into TMU's, by drawing polygons in ArcGIS at the topographic knick points and the soil series listed in the land type inventory on each TMU divided into three soil associations, i.e. shallow soils, wet soils and intermediate soils. Soil associations were mapped by assigning shallow soils to the convex slopes, wet soils to the concave slopes and intermediate soils to the straight slopes. The soil associations were mapped by hand using 3dMapper and ArcGIS for land type Ca11 and with the SoLIM inference model for land type Ea34. SoLIM was used rather than the hand method, as it automated the process, making it much faster. Soil associations were assigned. The legend to this map shows the soil series abbreviations for these soil associations, as they vary between TMU's.

Map 2

For map 2 a reconnaissance field visit was undertaken to the study site, along with the land type surveyor of the area, to better grasp the soil genesis of the area. This resulted in including parent material as a factor to create the soil maps.

A lithology map (Figure 3.3b) was created for parent material input, as soil formation is influenced by the lithology and not hard geology (Figure 3.3a). Soil formation on sandstone hillslopes with dolerite colluviums especially underlined this statement. Therefore a Dol_Sand geological map unit was included in the lithology map for areas in the downslope colluvial positions where dolerite influence was noticed in the soil formation. The lithology map resulted in the map legend being changed considerably, as soil series' derived from sandstone were included in the same soil association with soils derived from dolerite in Map 1. Including lithology enabled the separation of such soil series'.
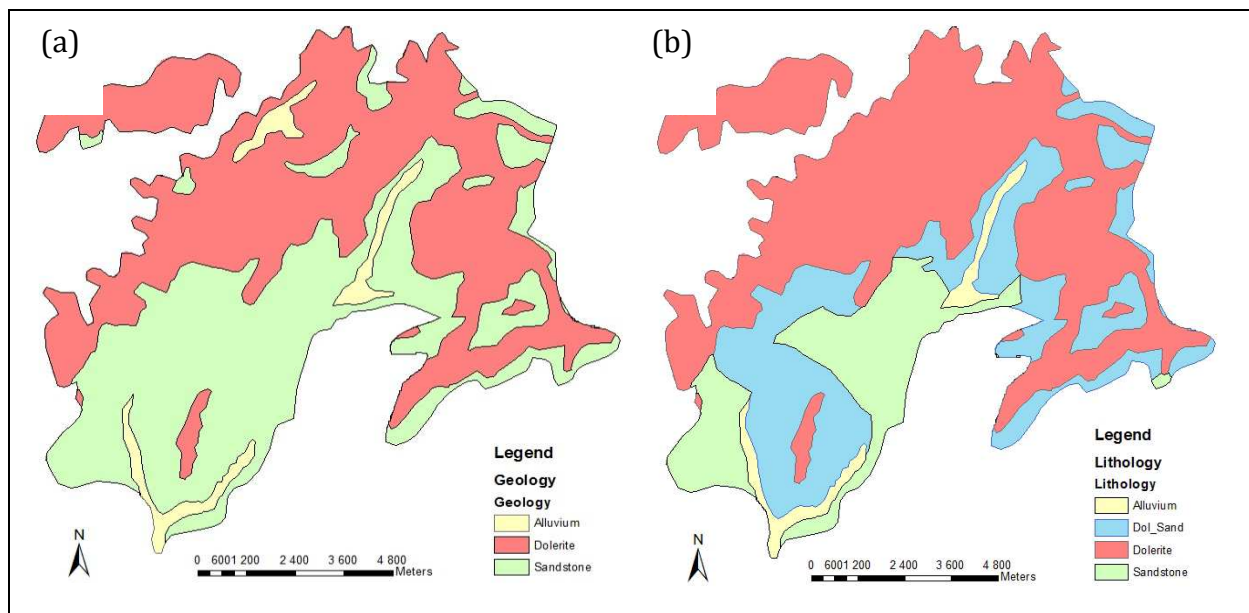
Figure 3.3: The geology (Geological Survey, 1988) (Fig. 3.3a) and the revised lithology maps of land types Ca11 and Ea34 (Fig. 3.3b).

The area was then divided into soilscapes, which are continuous areas with the same soil distribution patterns. From the soilscapes the soil associations were mapped by assigning the expected soil distribution pattern to each soilscape. The soil distribution pattern was determined by the soils series in the land type inventories on the different TMU's. This created a complex legend, as certain soilscapes stretched across both land types, while others were only confounded to one.

Maps 3 and 4

Field work included one hundred and eighteen auger observations (Figure 3.4), with the soils being classified according to the Soil Classification Working Group (1991). The observation points were determined in a hierarchical nested sampling plan, which is used by AfSIS (Vågen *et al.*, 2010). In this

sampling design a sentinel site of 10 000 ha is divided into 16 clusters of 2.5 by 2.5 km. Within each cluster 10 plots would be randomly chosen. These plots would be the observation points. Of the 10 000 ha and 160 observation points of the sentinel site 6 865 ha and 118 observation points fell within the Ca11 and Ea34 land types.
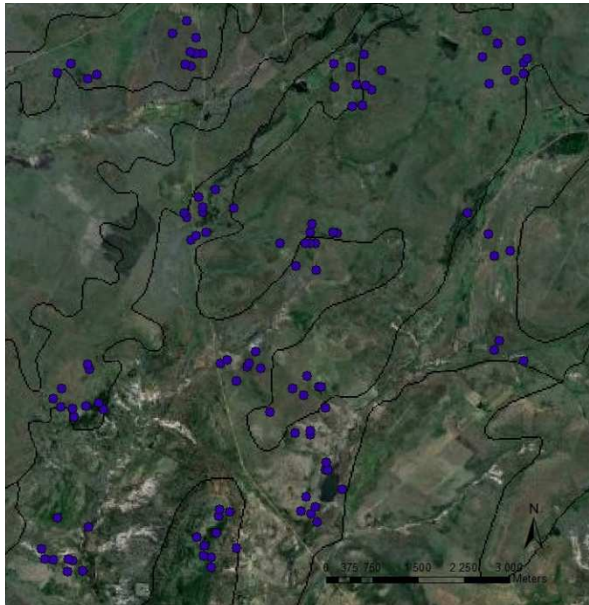
Figure 3.4: The observation points from the hierarchical nested sampling design.

The third and fourth soil maps were constructed using SoLIM with stratified randomly selected 30% and 60% of the observation points respectively. The observation points were stratified per cluster i.e. 30% and 60% of the observation points within a cluster were chosen at random as training data for Maps 3 and 4 respectively.

The map legend was simplified into six soil associations, following step 9 of the SCORPAN approach (McBratney *et al.*, 2003). The soil associations were formed by grouping soil forms of the Soil Classification Working Group (1991) into logical associations. Table 3.1 shows how these groupings, as well as the soil-landscape rules created for Map 4. Shallow soils and wet soils occur throughout the area and their distribution is determined by the topography. Red and dark clays occur on the dolerite parent material, which provides the basic cations needed for clay formation. Plinthic soils occur on the sandstone parent material. On the hillslopes where dolerite overlies sandstone and the dolerite colluvium plays a marked role in soil formation, the intermediate soils occur. These soils are not as clayey as pure dolerite derived soils, but also not as sandy as sandstone derived soils. Some soil forms fit into more than one soil association. This is because they have characteristics of both of the soil associations, and is probably a transitional zone between two soil associations.

Table 3.1: Soil map units for Maps 3 and 4

Soil Association	Soil Classification	IUSS Working Group,	Instance*	Soil-landscape rules				
					Covariates			
	Working Group, 1991	WRB, 2007		Slope	Profile Curvature	Planform Curvature	Aspect	Lithology
Wet soils	Katspruit, Kroonstad, Dundee, Rensburg, Willowbrook	Gleysols, Stagnosols	1	x < 2.6				
			2	3.3 < x < 5.2		x > 0.005		
			3	5.5 < x <10.7		x > 0.05		
Shallow Soils	Mispah, Milkwood, Glenrosa, Rock	Leptosols	1	x > 14.4				
			2	4.9 < x < 14.4		x < -0.005		Dolerite
Red Clay	Shortlands, Hutton	Nitisols, Ferralsols	1	8 < x < 13	x < 0.001			Dolerite
			2	4.5 < x < 8	x < -0.005			Dolerite
Dark Clay	Arcadia, Rensburg, Bonheim,	Vertisols,	1	4.2 < x < 8	x > -0.001			Dolerite
	Milkwood, Willowbrook	Mollisols	2	8.4 < x < 12.8	x > 0.005		South	Dolerite
Plinthic soils	Avalon, Westleigh, Dresden, Longlands, Glencoe, Wasbank	Plinthosols	1	3 < x < 14				Sandstone
Intermediate Soils	Bonheim, Valsrivier, Sepane	Luvisols, Lixisols	1	4.2 < x < 12.8				Dol_Sand

* An instance is a different set of rules for the same soil association.

Validation

Validation was done with the field observations. If the soil form as which the observation was classed, was part of the soil association on which it fell, the observation was deemed to be correct. Map accuracy was calculated by the percentage of observations that were predicted correctly. Observations of soil types which fitted into two soil associations were regarded as correct if it fell into either of those soil associations. Borderline observations were regarded as part of both soil associations, if it was unclear into which soil association the observation fell at a scale of 1 : 10 000. For Maps 1 and 2, all the observations were used, and for Maps 3 and 4 the observations which were not part of the training data were used. Thus for maps 1 and 2, 118 observations were used for validation, for map 3 it was 83 and for map 4 there were 47 validation observations.

3.3. Results and discussion

The four maps created and their accuracies can be seen in Figures 3.5 and 3.6. The accuracy of the maps improved with higher input into the maps. The first map included some illogical soil associations. Avalon soils (Av; WRB: Plinthosols) derived from sandstone and Arcadia soils (Ar, WRB: Vertisols) derived from dolerite were grouped together in the same soil association, since subdivision was only done on the basis of terrain forms. It would be desirable from a soil property and land use perspective to separate these soils.

Separation of soils from different geologies was done by including a lithology map for the area. This immediately improved the map legend, as soil series' which are more alike were grouped together in the same soil associations. However, the use of soilscapes as the basis for mapping soil associations complicated the map legend with too many mapping units. The accuracy of the map also did not improve much. The simplification of the map legends of Maps 3 and 4, together with the usage of field work, immediately improved the accuracy of the maps. The fourth map achieved an accuracy of 67%, which is comparable to the average traditional soil map accuracies of 65% as quoted by Marsman and De Gruijter (1986) and the 69 % map accuracy which was achieved in another project also using SoLIM (Van Zijl *et al.*, 2012). In addition to being more accurate, the fourth map shows a lot more intricacy than the third map. This should closer represent the real situation at a large scale, showing differences in mapping units across short distances. As all the maps were evaluated at a scale of 1: 10 000, the larger measure of intricacy probably contributed to the higher accuracy of the map. It is clear that using more observations as training data improved the final product.

The comparable map accuracy of Map 4 to conventional soil survey, although using a lot less observations (3 430 observations is necessary for conventional mapping on a 2 ha grid) shows that combining land types, terrain analysis and expert knowledge optimises the field work necessary for soil survey. The desktop study done for Map 1 can be applied to give some idea of the soil distribution, for projects where exact soil information is not necessary. As the whole country is included in the land type survey, this method has great potential to aid future soil surveys.

a) Map 1, Accuracy 35%
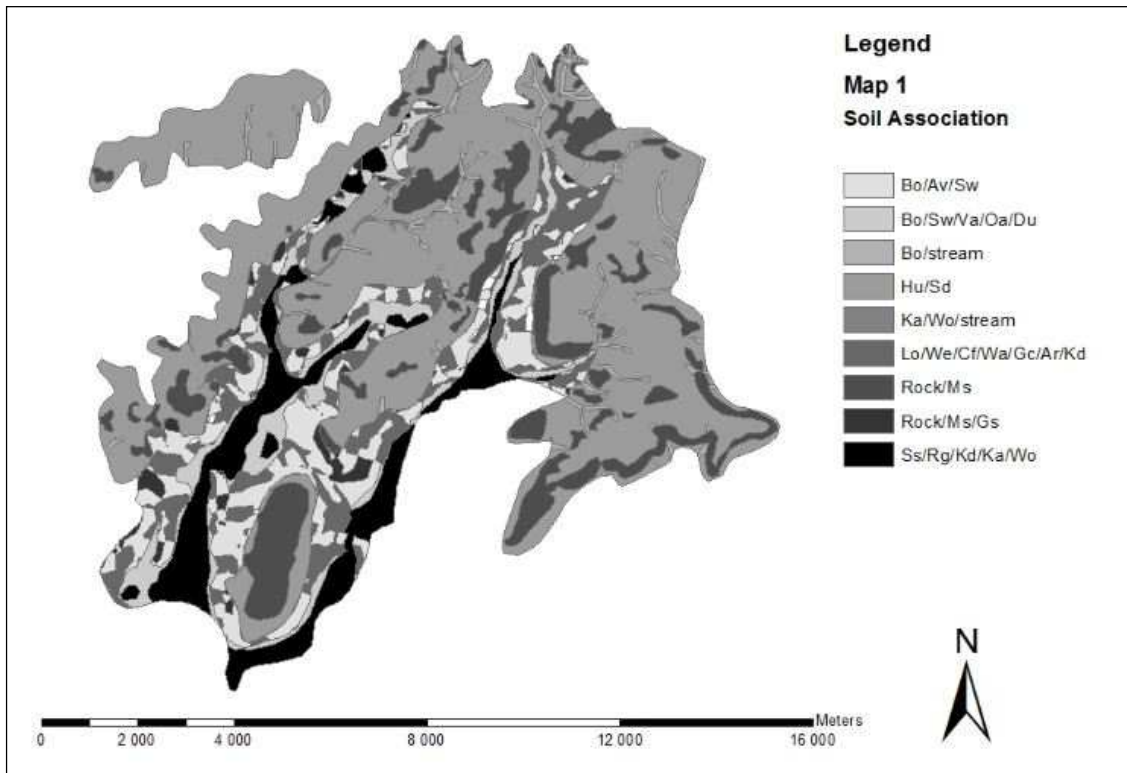
b) Map 2, Accuracy 36%
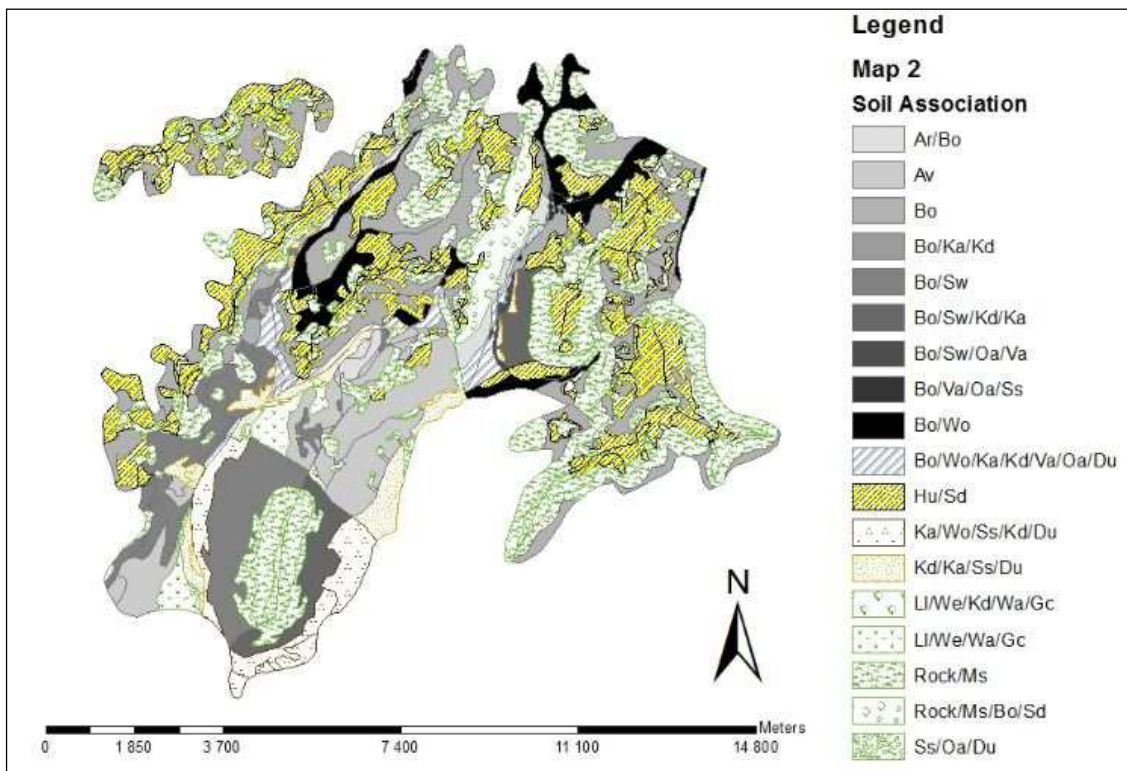
Figure 3.5: Maps 1 and 2. The map legend shows the abbreviations for the soil forms according to the Soil Classification Working Group, 1991.

a) Map 3, Accuracy 49%
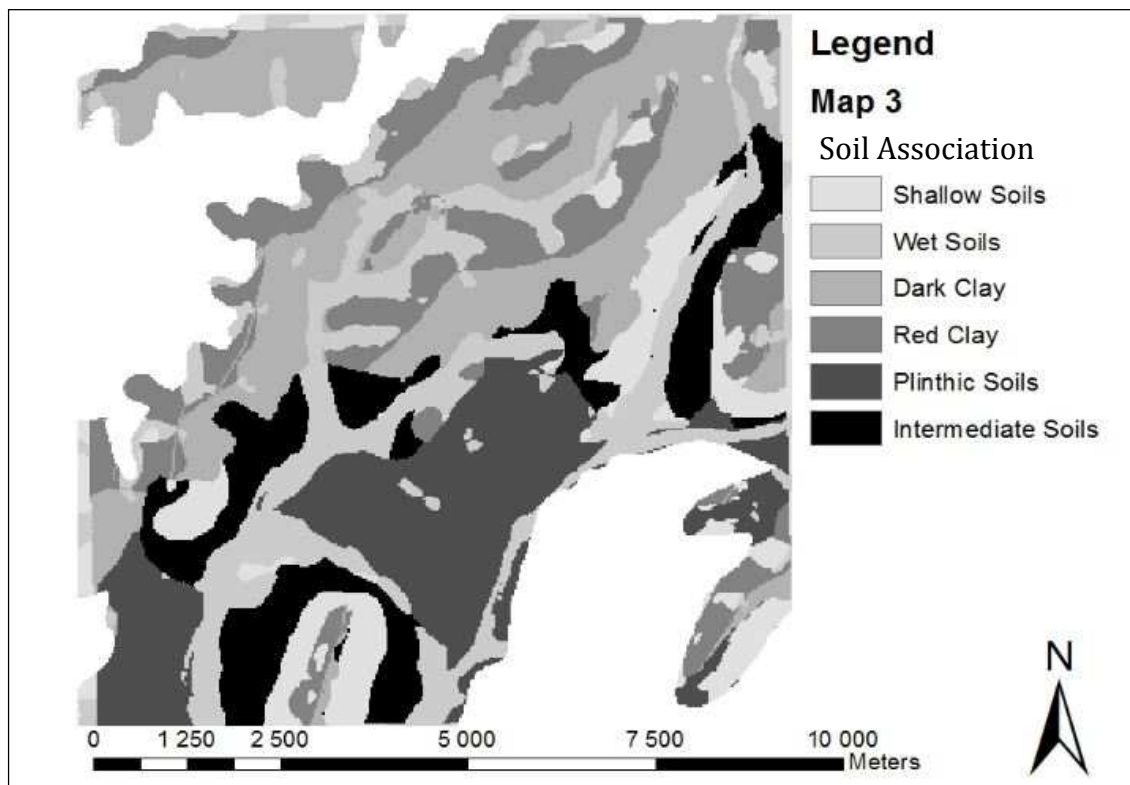
b) Map 4, Accuracy 67%
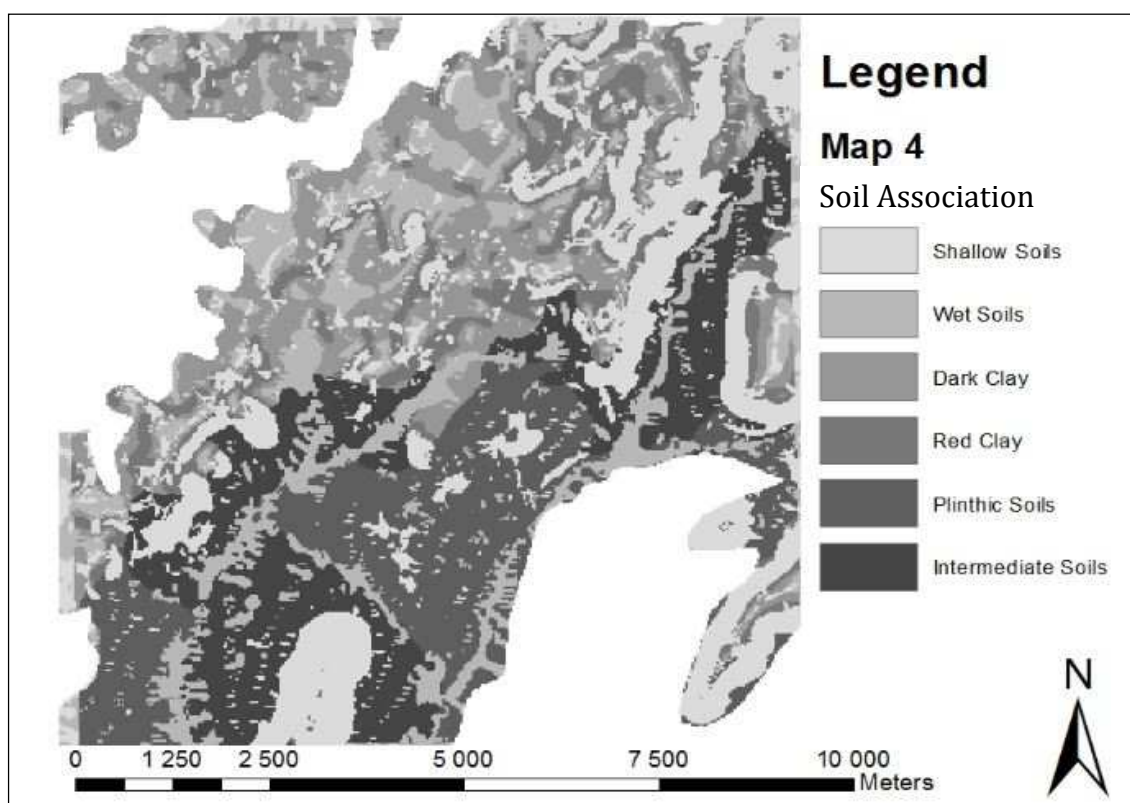
Figure 3.6: Maps 3 and 4. The descriptions for the soil associations are shown in Table 3.1

An error matrix for Map 4 (Table 3.2) shows the specific accuracy of the different soil associations. The Wet (W) and Shallow soils (SS) map units are very accurate with barely any other observations made in them, although they did not include all the Wet and Shallow soils observations. This shows that the rules for the Wet and Shallow soils map units might be widened slightly. Seventy seven per cent of the dark clay (DC) observations were mapped correctly, but the map unit included a small number of plinthic soils (P), indicating possible small inaccuracies in the lithology map. The presence of shallow soils in the dark clay mapping unit is to be expected and may not be due to mapping errors as rock outcrops will commonly occur in this mapping unit.

Table 3.2: An error matrix of Map 4

Validation				*Observations*						
		RC	*DC*	*I*	*P*	*SS*	*W*	*Correct (#)*	*Total*	*Correct (%)*
	RC	1	2	0	0	0	0	1	3	33
	DC	1	10	0	1	3	0	10	15	67
	I	0	1	1	2	0	0	1	4	25
Map	*P*	1	0	2	6	1	1	6	11	55
	SS	1	0	0	0	10	0	10	11	91
	W	0	0	0	0	0	4	4	4	100
	Correct (#)	1	10	1	6	10	4	32		
	Total	4	13	3	9	14	5		48	
	Correct (%)	25	77	33	67	71	80			67

The plinthic soil observations were mapped to an acceptable accuracy, but the map unit included five other observations, indicating that the map unit is too broadly defined by the soil-landscape rules. The rules governing the delineation between the plinthic and intermediate (I) soil associations should be improved. Sixty six per cent of the intermediate observations lie on the plinthic map unit and 50% of the observations on the intermediate map unit are plinthic soils. This might not be a true reflection of the map units' accuracy, as there were only 4 observations made on the intermediate soil association.

The combination of soil forming factors giving rise to red structured clay on the one hand and dark swelling clays on the other hand are not well understood in quantitative terms. Although both soils are commonly derived from basic igneous rocks, it is still unknown how soil forming factors determine which type of soil will form at a specific location. Thus, it is no surprise that there are dark clay observations on the red clay (RC) map unit and vice versa.

3.4. Conclusions

Digital soil mapping methods, and specifically the SoLIM software combined with expert knowledge and soil observations can be used to disaggregate land types into accurate soil association maps. The more information used when creating the maps, the better the map accuracy will be.

The land type survey proved to be a good basis to start DSM. Using only terrain analysis, soil series

distribution could be predicted from this platform, to a reasonable accuracy, however, some illogical soil associations were mapped. Including parent material as input variable improved the usability of the soil map, but not its accuracy. A revised lithology map represented the real parent material better than hard geology did, especially in soilscapes where dolerite colluvium influenced soil formation on sandstone geological map units. Simplifying the map legend into soil associations improved the accuracy of the map. Field work is critical to obtain acceptable results. Results improved when more observations were used as training data.

Research is needed to determine optimal sampling strategies which will include adequate observation points of all soil types present; a way to map the lithology accurately; and to utilize these soil association maps to create soil property maps.

3.5. References

Bui, E.N., Moran, C.J., 2001. Disaggregation of polygons of surficial geology and soil maps using spatial modelling and legacy data. Geoderma 103, 79-94.

Environmental Systems Research Institute Inc., 2010. ArcGIS version 9.3. www.ESRI.com.

Gaetsewe, H.E., 2001. Evaluation of land reform projects in the south eastern Free State. M.Tech. Thesis. Technicon Free State, Bloemfontein, South Africa.

Geological Survey. 1988. 1: 250 000 Geological Series 2730 Vryheid. Geological Survey, Pretoria.

Hensley, M., Le Roux, P.A.L., Gutter, J., Zerizghy, M.G., 2007. Improved soil survey technique for delineating land suitable for rainwater harvesting. WRC Project K8/685/4. Pretoria: Water Research Commission.

IUSS Working Group WRB, 2007. World reference base for soil resources 2006, first update 2007. World Soil Resources Reports No. 103. FAO, Rome.

Land Type Survey Staff. 1976-2006. Land Type Survey Database. ARC-Institute for Soil, Climate and Water, Pretoria

Land Type Survey Staff. 1986. Land types of the map 2730 Vryheid. Memoirs Agric. Nat. Resour. S. Afr. No. 7. ARC - Institute for Soil, Climate and Water, Pretoria.

Le Roux, P.A.L., Ellis, F., Merryweather, F.R., Schoeman, J.L., Snyman, K., Van Deventer, P.W., Verster, E., 1999. Guidelines for mapping and interpretation of the soils of South Africa. University of the Free State, Bloemfontein.

MacVicar, C.N., De Villiers, J.M., Loxton, R.F., Verster, E., Lambrechts, J.J.N., Merryweather, F.R., Le Roux, J., Van Rooyen, T.H., Harmse, H.J. von M., 1977. Soil Classification: A binomial system for South Africa. Department of Agriculture Technical Services, Pretoria.

Marsman, B.A., de Gruijter, J.J., 1986. Quality of soil maps, a comparison of soil survey methods in a study area. Soil Survey papers no. 15. Netherlands Soil Survey Institute, Wageningen.

McBratney, A.B., Mendoça Santos, M.L., Minasny, B., 2003. On digital soil mapping. Geoderma 117, 3-52.

Minasny, B., McBratney, A.B., 2010. Methodologies for global soil mapping. In: Boettinger, J.L., Howell, D.W., Moore, A.C., Hartemink, A.E., Kienast-Brown, S. (eds.). Digital soil mapping; bridging research, environmental application and operation. Springer, Dordrecht.

Mucina, L., Rutherford, M.C. (eds.). 2006. The vegetation of South Africa, Lesotho and Swaziland, Strelitzia 19. South African National Biodiversity Institute, Pretoria.

SAWS. 2012. Climate data provided by South African Weather Service. Pretoria, South Africa

Soil Classification Working Group. 1991. Soil classification: A taxonomic system for South Africa. Department of Agricultural Development, Pretoria.

Stalz, J.P., 2007. Mapping potential soil salinization using rule based object-oriented image analysis. MSc thesis, Stellenbosch University, Stellenbosch, South Africa.

Terrain Analytics, L.L.C., 2003. 3d Mapper version 4.02. http://www.terrainanalytics.com.

Vågen, T.G., Winowiecki, L., Desta, L.T., Tondoh, J.E., 2010. Land degradation surveillance framework: Field guide. AfSIS, Arusha.

Van den Bergh, H.M., Weepener, H.L., 2009. Development of spatial modelling methodologies for semi-detailed soil mapping, primarily in support of curbing soil degradation and the zoning of high potential land. ARC-ISCW Report No GW/A/2009/01. ARC - Institute for Soil, Climate and Water, Pretoria.

Van den Bergh, H.M., Weepener, H.L., Metz, M., 2009. Spatial modelling for semi detailed soil mapping in KwaZulu-Natal. ARC-ISCW Report No GW/A/2009/33. ARC - Institute for Soil, Climate and Water, Pretoria.

Van Zijl, G.M., Le Roux, P.A.L., Smith, H.J.C., 2012. Rapid soil mapping under restrictive conditions in Tete, Mozambique. In: Minasny, B., Malone, B.P., McBratney, A.B. (eds.). Digital soil assessments and beyond. CRC Press, Boca Raton.

Western, S., 1978. Soil survey contracts and quality control. Oxford University Press, Oxford.

Zhu A-X., 1997. A similarity model for representing soil spatial information. Geoderma 77, 217-242.

CHAPTER 4:

Rapid soil mapping under restrictive conditions in Tete, Mozambique

Abstract:

The necessity to do large area soil surveys that conform to specified requirements is increasing, especially in areas with little baseline information. An unrealistic demand for a soil survey of 37 000 ha of land in the Tete Province, northern Mozambique, possibly infested with land mines, in 8 working days by two persons, created an opportunity to apply the soil-land inference model (SoLIM) as a digital soil mapping tool. A free survey was conducted along the available roads of the area. Based on geology and topography, the area was divided into seven homogeneous areas (HA's). SoLIM was used to derive different soil-landscape rules and create a final soil map for the area. Independent observations were made for validation. A fifteen thousand ha area was mapped with a validation accuracy of 50%. When including borderline observations within one pixel of the correct soil map unit, the accuracy increased to 69%. When including the training data, the overall accuracy was 58% and the borderline accuracy 72%. Several principles emerged in the study. Expert knowledge is necessary to conduct DSM. Inaccessible areas can be mapped, provided that they occur within surveyed sub-areas. Field work is essential. Identical soil forms from different HA's could be lumped together, even if they were predicted with different rules. The better the data used, the better the results will be. Currently the methodology is surpassing the affordable technology, as finer resolution DEM's will improve the quality of the products, created with the same methodology.

Keywords: DEM, DSM, Expert knowledge, SoLIM, Terrain analysis

4.1. Introduction

Quick and accurate soil maps for vast areas are becoming increasingly sought after, especially as awareness of the role of soil in the environment spreads. Environmental impact assessments (EIA's) are required by the International Finance Corporation for funding of new developments (IFC, 2012). Such developments covering large areas are often situated in remote areas and supported by little infrastructure. An EIA requires a soil map to provide guidelines for rehabilitation. For open cast mining the soil map provides guidelines for stockpiling of soil before mining commences. Soil is replaced after mining to facilitate rehabilitation to the original agricultural potential. To achieve this, the soil types are grouped

and stockpiled. It is specifically important to avoid mixing soils with different textures. Thus soil map units (SMU's) should differentiate between soil types as well as soils with different textures.

The production of conventional soil maps are slow and costly (Zhu *et al.*, 2001). Digital soil mapping (DSM) greatly increases the speed and decreases the cost of soil mapping (Hensley *et al.*, 2007). This is improving with growing correlation of soil observations with an array of new, rapidly developing technologies, including information technology, satellite imagery, digital elevation models (DEM's) and pedometrics. Topographical analysis specifically considers soil-landscape interaction, using a DEM. Such methods can rely on legacy data (Mayr *et al.*, 2010) or site specific sampling (Zhu *et al.*, 2008; Minasny & McBratney 2010), to provide knowledge of the soil-landscape interaction necessary to create a soil map.

In this project a soil map had to be created as part of an EIA for an open coal mine in an area of 37 000 ha near Tete, Northern Mozambique. Two restrictive conditions challenged the soil survey. Firstly, a threat of land mines in the area confined observations to be made in safe areas along the explorations roads. Secondly, only 8 days were allocated for two surveyors to do the job.

Thus site specific sampling could not be done due to the land mine threat, conventional soil mapping methods was not considered due to time restrictions and no legacy data exists for the area. As development in Africa increases, such challenges will be faced more frequently by soil surveyors.

This paper aims to assess the potential of DSM methods to produce acceptable soil maps under these very restrictive conditions, specifically using SoLIM (Zhu *et al.,* 1997), hard geology inputs and topographical analysis.

4.2. Site description

The site lies in the Tete province, in the North West of Mozambique, adjacent to the Ncondezi River (Figure 4.1). The geographical centre point is 33.93˚E and 15.85˚S. The elevation ranges between 235 and 380 m above sea level. The area is very hot, with summer temperatures ranging between 23 and 36 ˚C and winter temperatures between 16 and 29 ˚C. The mean annual precipitation is 627 mm. The vegetation type is bushland, with *Colophospermum mopane* and *Adansonia digitata* trees dominating. The main geological formations include sandstone, shale and granitic gneiss. Small areas overlain with Basalt and Rhyolites also occur. Vegetation and climate are uniform throughout the survey area.
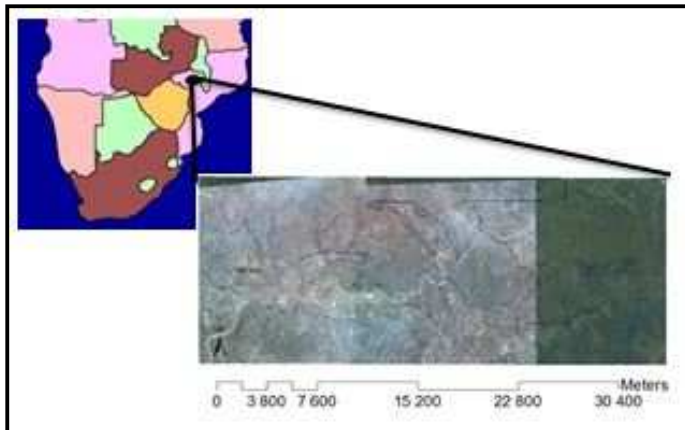
Figure 4.1: The Ncondezi study site, and its location in Southern Africa

4.3. Material and methods

A 25 m pixel size DEM was constructed in ArcGIS9.3, using the 90 m SRTM DEM and a 20 m contour map. A 1: 20 000 hard geology map was rasterized to the same grid as the DEM. Unfortunately this map was created for coal exploration purposes, and had all igneous rocks and sedimentary rocks lumped together. Thus neither mavic and felsic igneous rocks nor coarse or fine grained sedimentary rocks could be distinguished. As vegetation and climate do not vary within the area, parent material and topography was used to divide the area into 7 more environmentally homogeneous sub-areas (Table 4.1), following MacMillan *et al.* (2010).

Due to the land mines restricting the areas where observations could be made, the 131 auger observations used for training data was made along the mine exploration roads, while attempting to cover as large an area as possible. Ideally one would do site specific sampling, but under the circumstances this is the best that could be done. Soils were classified according to the South African soil classification system (Soil Classification Working Group, 1991) and for purposes of this paper converted into WRB reference soil groups (IUSS Working Group WRB, 2007). While doing the field work, a conceptual soil distribution model was postulated for each HA.

The Soil-Land Inference Model (SoLIM; Zhu *et al.*, 1997) was used to create soil-landscape rules for each soil type of each sub-area. The conceptual soil distribution model and soil-landscape rules were created with expert soil pedogenesis knowledge. An inference was run with these rules, and the final map hardened (hardening of a map is when each pixel is assigned the map unit with the highest membership value on that pixel). Validation was done using data from a fresh set of 52 independent observations, collected after the 131 training data observations, but sampled in the same way. The map accuracy was calculated by the percentage of observations which was predicted correctly.

Table 4.1: General descriptions of the sub-areas

Sub-area	Topographical description (Based on visual inspection of the DEM)	Geology (From 1: 20 000 mine exploration geological map)	No. of observations in sub-area
1	Large flat plains with some small ridges	Gabbro, Granitic Gneis	38
2	Wavy, with frequent ridges	Gabbro, Granitic Gneis	16
3	Wavy, with frequent ridges	Sandstone, Shale, some Basalt	36
4	Medium flat plains, with common ridges	Sandstone, Shale, some Basalt	20
5	Hilly, frequent ridges	Gabbro, Granitic Gneis	5
6	Hilly, frequent ridges	Sandstone, Shale	10
7	Large flat plains with some small ridges	Sandstone, Shale	6

4.4. Results and discussion

An example of a postulated conceptual soil distribution model is shown in Figure 4.2. This example accounts for sub-areas 5, 6 and 7. In this model, Leptosols occur on the ridges, while Cambisols will occur on the flat plains. The same model holds for the other sub-areas areas, however Arenosols (sub-areas 1 and 2) and Luvisols (sub-areas 3 and 4) replace the Cambisols in the other HA's. In general, the clay content of the soil increases from east to west.
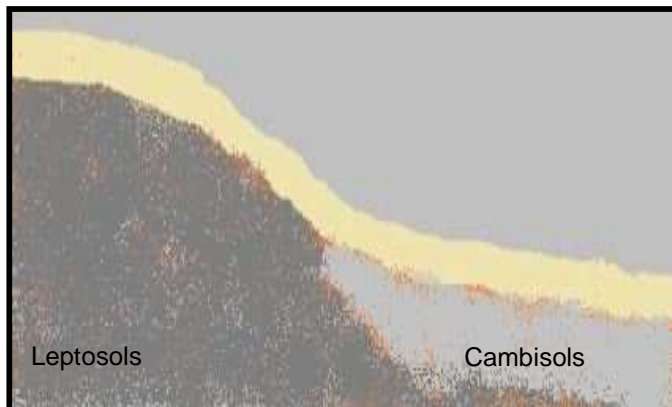
Figure 4.2: The postulated conceptual soil distribution model for areas 5, 6 and 7. Leptosols occur on the ridges, while Cambisols occupy the plains.

The soil-landscape rules differ between sub-areas, but within all sub-areas a general trend exists. If the slope is steep, then the soil will be a Leptosol. If the slope is flat, then Arenosols, Luvisols or Cambisols will occur, depending on the sub-area. The tops of the ridges, which have flat slopes but very convex curvature, will also be predicted as Leptosols. On intermediate slope gradients, if the curvature is convex, Leptosols will also be predicted, while concave intermediate slopes will be assigned to Arenosols, Luvisols or Cambisols. The specific slope and curvature values where the map unit boundary lines occur differ between sub-areas, but the trend is the same throughout the whole area.

By combining the soil maps created within each of the sub-areas, the final soil map was created (Figure 4.3). It has four map units, Leptosols, Cambisols, Arenosols and Luvisols. Thus the same soils occurred in different sub-areas, even though the specific soil-landscape interactions differed slightly. For the EIA it was recommended that the four map units should be stockpiled separately, to avoid mixing soils with different textures.

Figure 4.3 also shows that areas were mapped which could not be surveyed. Large areas were mapped without observations by extrapolation of data. This was possible because these areas were part of sub-areas that could be surveyed. The same soil-landscape rules should apply across sub-areas. However, soil observations are critical. Inaccessible areas topographically or geologically different to HA's were not mapped, lacking a scientific base to predict the soil distribution patterns. Thus only 15 000 ha of the total area were mapped.
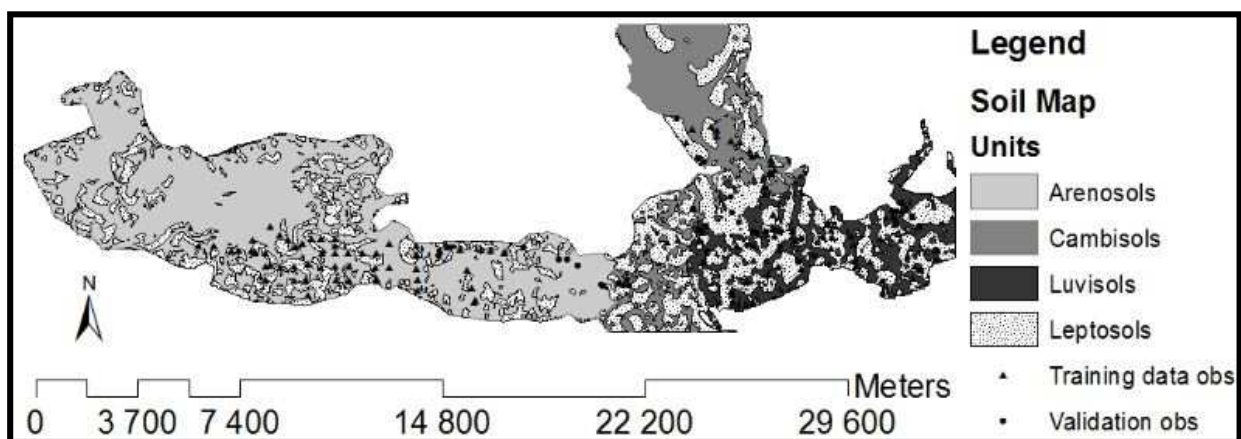
Figure 4.3: The soil map of the Ncondezi area, showing the training and validation observations.

The accuracy of the map was sufficient (Table 4.2) to be accepted by the company conducting the EIA. The validation accuracy of 50% means that one can have 50% certainty of the soil type for a 15 000 ha area after sixteen working days.

Table 4.2: Accuracy assessment of the soil map.

	Training Observations	Validation Observations	All Observations
Observations	131	52	183
Correct	80	26	106
% Correct	61	50	58
Borderline	15	10	25
% Borderline	11	19	14
% Correct + Borderline	73	69	72

Borderline observations were incorrectly mapped observations, but fell within one pixel of the correct map unit

When including the training data observations, the accuracy increased to 58%. This is lower than the accepted 65% of conventional soil maps (Marsman and De Gruijter, 1986). The acceptance of the map was due to the large number of borderline observations. These are observations which were mapped incorrectly, but which fell within one pixel of the correct SMU. Including them raised the validation accuracy to 69%, slightly above the accepted accuracy. Thus there is a 69% certainty of correctly predicting the soil type or being within 25 m of the correct SMU. This accuracy percentage is comparable to other DSM projects across various scales, such as 69% by MacMillan *et al*. (2010) and 76% by Zhu *et al*. (2008).

Borderline observations could occur for various reasons. Firstly, real map unit boundaries do not follow the straight lines and right angles that pixels do, but could actually occur within a pixel. The larger the pixel, the larger the chance is of this happening. While making observations close together to create the conceptual soil distribution model, different soil types were observed within the same pixel. Secondly, first and second derivative terrain attributes (slope and curvatures) could be incorrect due to the large distance (3 pixels, thus 75 m) by which they were calculated. Lastly, slightly incorrect soil-landscape rules could be another reason for the large number of borderline observations.

Evidence that the mispresentations are due to the large pixel size of the DEM, can be seen in the accuracy of the individual soil types (Table 4.3). The boundaries between the Luvisols and the Leptosols are poorly defined, as 46% of the Luvisol observations fell on the Leptosol mapping unit and 41% of the Leptosol observations fell on the Luvisol mapping unit. However, those percentages dropped to 38% and

17% respectively when including borderline observations. Thus the borderline observations account for a large proportion of the inaccuracy of these two mapping units. When determining the spatial position of the Luvisol borderline observations, it shows that 29% of the total observations in sub-area 3 are borderline observations, while in sub-area 4 it is only 15%. Sub-area 3 has the more incised landscape of the two sub-areas, which creates smaller ridges and flat plains, resulting in smaller continuous mapping units. This increases the chances of soil boundaries occurring within pixel boundaries, amplifying the error due to a too coarse DEM.

Table 4.3: An error matrix for all the validation observations

		Observations							
		Leptosols	Arenosols	Cambisols	Luvisols	Vertisols	Total	Correct	% Accuracy
Map Units	Leptosols	13 (21)		2 (1)	6 (5)	1 (1)	22 (28)	13 (21)	59 (75)
	Arenosols	2 (1)	4 (4)		1 (1)		7 (6)	4 (4)	57 (67)
	Cambisols	2 (2)		3 (4)			5 (6)	3 (4)	60 (67)
	Luvisols	12 (5)			6 (7)		18 (12)	6 (7)	33 (58)
	Total	29 (29)	4 (4)	5 (5)	13 (13)	1 (1)	52 (52)	26 (36)	50 (69)
	Correct	13 (21)	4 (4)	3 (4)	6 (7)	0 (0)	26 (36)		
	% Accuracy	45 (72)	100 (100)	60 (80)	46 (54)	0 (0)	50 (69)		

Values are number of observations. Values between brackets include borderline observations. Borderline observations are incorrectly mapped observations, but fell within one pixel of the correct map unit.

The current terrain analysis methodology is ahead of the affordable DEM technology. As high resolution DEM technology such as Lidar becomes more affordable, the same methodology could be applied to such DEM's and the results will be improved.

However, an inadequate DEM is not the only reason for mapping inaccuracies. Even after including borderline observations, the prediction of the Luvisols was only 54% correct. Also, in the most incised sub-area, sub-area 5, where one would expect the largest effect of the coarse DEM, the mapping accuracy was 80%. Thus even with the current DEM, one could define soil-landscape rules which will represent the reality better. Ideally one would have chosen better situated observation sites, but this was not possible due to the land mine threat.

The large accuracy difference between the training and validation observations is to be expected. The data used to create the soil-landscape rules will naturally be better represented by these rules than other

independent observations. However, the large number of borderline validation observations shows that the misrepresentation of the validation data is only slight.

4.5. Conclusions

Even under access restricted conditions topographical analysis using SoLIM was adequate to map an area of 15 000 ha within 16 working days, to an accepted standard to provide stockpiling guidelines. The absolute validation map accuracy was 50%, while another 19% of the observations fell within 1 pixel of the correct map unit. The inputs used were a DEM and a 1: 20 000 coal mining exploration hard geological map.

Various principles emerged during the project. 1) Expert knowledge plays a vital role in creating the conceptual soil distribution model as well as the soil-landscape rules from which the map is created. 2) It is possible to map un-surveyed areas, provided that these areas occur within sub-areas which had been surveyed in parts, from which soil-landscape rules could be devised. 3) Field work within sub-areas is critical to enable mapping. Extrapolation of soil-landscape rules to unsurveyed areas outside of the sub-area where the rules were created is erroneous. Because of this, the whole area was not mapped. 4) The same soil types from different sub-areas can be lumped together in the final map, even though they were predicted using different soil-landscape rules. 5) Better quality input data, especially DEM's, will improve the accuracy of the map. At this stage the methodology is surpassing the affordable technology, as finer resolution DEM's will enable better mapping.

4.6. References

Hensley, M., Le Roux, P.A.L., Gutter, J., Zerizghy, M.G., 2007. Improved soil survey technique for delineating land suitable for rainwater harvesting. WRC Project K8/685/4. Water Research Commission, Pretoria.

IFC, 2012.Performance standard 1: Assessment and management of environmental and social risks and impacts. International Finance Corporation, World Bank Group, http://www.ifc.org.

IUSS Working Group WRB. 2007. World reference base for soil resources 2006, first update 2007. World Soil Resources Reports No. 103. FAO, Rome.

MacMillan, R.A., Moon, D.E., Coupé, R.A., Phillips, N., 2010. Predictive ecosystem mapping (PEM) for 8.2 million ha of forestland, British Columbia, Canada. In: Boettinger, J.L., Howell, D.W., Moore, A.C., Hartemink, A.E. & Kienast-Brown, S. (eds.). Digital soil mapping; bridging research, environmental application and operation. Springer, Dordrecht.

Marsman, B.A., de Gruijter, J.J., 1986. Quality of soil maps, a comparison of soil survey methods in a study area. Soil Survey papers no. 15. : Netherlands Soil Survey Institute, Wageningen, The Netherlands

Mayr, T., Rivas-Casado, M., Bellamy, P., Palmer, R., Zawadzka, J., Corstanje. R., 2010. Two methods for using legacy data in digital soil mapping. In: Boettinger, J.L., Howell, D.W., Moore, A.C., Hartemink, A.E. & Kienast-Brown, S. (eds.). Digital soil mapping; bridging research, environmental application and operation. Springer, Dordrecht.

Minasny, B., McBratney, A.B., 2010. Methodologies for global soil mapping. In: Boettinger, J.L., Howell, D.W., Moore, A.C., Hartemink, A.E., Kienast-Brown, S. (eds.). Digital soil mapping; bridging research, environmental application and operation. Springer, Dordrecht.

Soil Classification Working Group, 1991. Soil classification: A taxonomic system for South Africa. Department of Agricultural Development, Pretoria.

Zhu, A-X., Band, L.E., Verteasy, R., Dutton, B., 1997. Derivation of soil property using a soil-land inference model (SoLIM). Soil Science Society of America Journal 61, 523-533.

Zhu, A-X., Hudson, B., Burt, J., Lubich, K., Simonson, D., 2001. Soil mapping using GIS, expert knowledge and fuzzy logic. Soil Science Society of America Journal 65, 1463-1472.

Zhu, A-X., Yang, L., Li, B., Qin, C., English, E., Burt, J.E., Zhou, C., 2008. Purposive sampling for digital soil mapping for areas with limited data. In: Hartemink, A. E., McBratney, A.B., Mendonça-Santos, M. De L. (eds.). Digital soil mapping with limited data. Springer, Dordrecht.

CHAPTER 5:
Functional digital soil mapping: a case study from Namarroi, Zambezia Province, Mozambique

Abstract:

The value of soil is often neglected in developing countries, partially due to a lack of spatial soil data. Traditional methods of soil survey are too cumbersome and expensive to fulfill the need for soil maps. Expert knowledge based digital soil mapping (DSM) methods provides the answer to deliver in-time spatial soil information in developing countries. The objective of this study was to evaluate the potential of DSM soil survey methods to rapidly produce land suitability maps of a large area with acceptable accuracy. An expert knowledge approach was used, with soil surveyors creating conceptual soil distribution patterns, and populating the patterns with covariate values to create soil-landscape rules. A soil class map was created by running an inference with those rules. The map achieved an accuracy of 80%. Land suitability maps were created based on the soil class map. Furthermore the data indicated that more than 13 soil observations are needed per homogeneous area to achieved acceptable results, the sampling scheme used worked very well for mapping purposes, but did not represent soil diversity very well, and multiple scale covariates were useful to map different parts of the landscape.

Keywords: Lidar, Production potential, SoLIM, Terrain analysis

5.1. Introduction

More than 95% of the world's food comes from the soil (FAOSTAT, 2003). Despite this, the value of soil is often neglected in the food chain, especially where spatial soil data is scarce. In South Africa the return on investment for a soil survey is estimated to be 1:20 in the first year for dryland crop production (Le Roux *et al.*, 1999). One reason for the lack of soil maps is that traditional methods of soil survey are cumbersome and expensive (Hensley *et al.*, 2007). In South Africa the traditional soil survey method is to make soil observations on a 100 - 200 m grid, dependant on soil variation, and grouping similar observations together. It works well on small fields, but cannot produce maps for large areas which often need to be mapped in developing countries. With stereoscopy soil mapping is supported by using overlapping stereo pairs of black and white photographs to delineate terrain units for application as mapping units representative of soils, after making observations in those areas (Zhu *et al.,* 2001). However, for this one needs aerial photographs, which is often not available, and it remains a time consuming manual process limiting the application of quantitative expert knowledge.

Expert knowledge based digital soil mapping (DSM) methods provides the answer to deliver in-time spatial soil information in developing countries (Van Zijl *et al.*, 2012). It also has the advantages that the expert knowledge of the soil surveyor is captured and constantly applied, the process is automated, saving time and reducing errors, and it allows for higher levels of soil detail to be represented (Qi *et al.,* 2006).

Soil survey for quantification of soil as a natural resource has decreased dramatically and surveys are now driven by industrial needs, implying that the map has to serve a specific aim, comply to a budget and fit a time frame. The survey often cover large areas (10 000 ha and more) with limited accessibility, little legacy data and variable ancillary data (dependent on the resources of the client). Requirements for land uses vary and they need to be matched with land qualities to produce an easily understandable map legend, for the map to be usable by the client (Bui, 2004). To apply site specific management, detailed application orientated and functional soil maps are needed (Zhu *et al.*, 2013).

The objective of this study was to evaluate the potential of DSM soil survey methods to rapidly produce land suitability maps of a large area with acceptable accuracy. The area to be mapped is near Namarroi, Zambezia Province, Mozambique, where a forestry company aims to establish forestry plantations. The soil map is a primary input to determine where the trees will be planted, and which soil preparation works are necessary. Specific research questions include:

1. What is the minimum observation density to achieve acceptable map accuracy?
2. How well does the sampling scheme represent the real soil diversity?
3. Which covariates are the most important in predicting soil classes?

The hypothesis is that a soil map for a large area, suitable for forestry, can be produced using DSM methodology.

5.2. Site Description

The site (Figure 5.1) is located in the Namarroi district, Zambezia Province, Mozambique, with 15.7˚S; 36.6˚E as its centre point. The site is divided into two areas, Nammarua (6 820 ha) to the South, and Cassarano to the North (4 150 ha). The vegetation forms part of the Miombo Woodland Forest (Snyman, 2012). The area is burnt annually by the locals to catch moles and mice for food. Subsistence crop production takes place, with cassava and maize being the most popular crops.
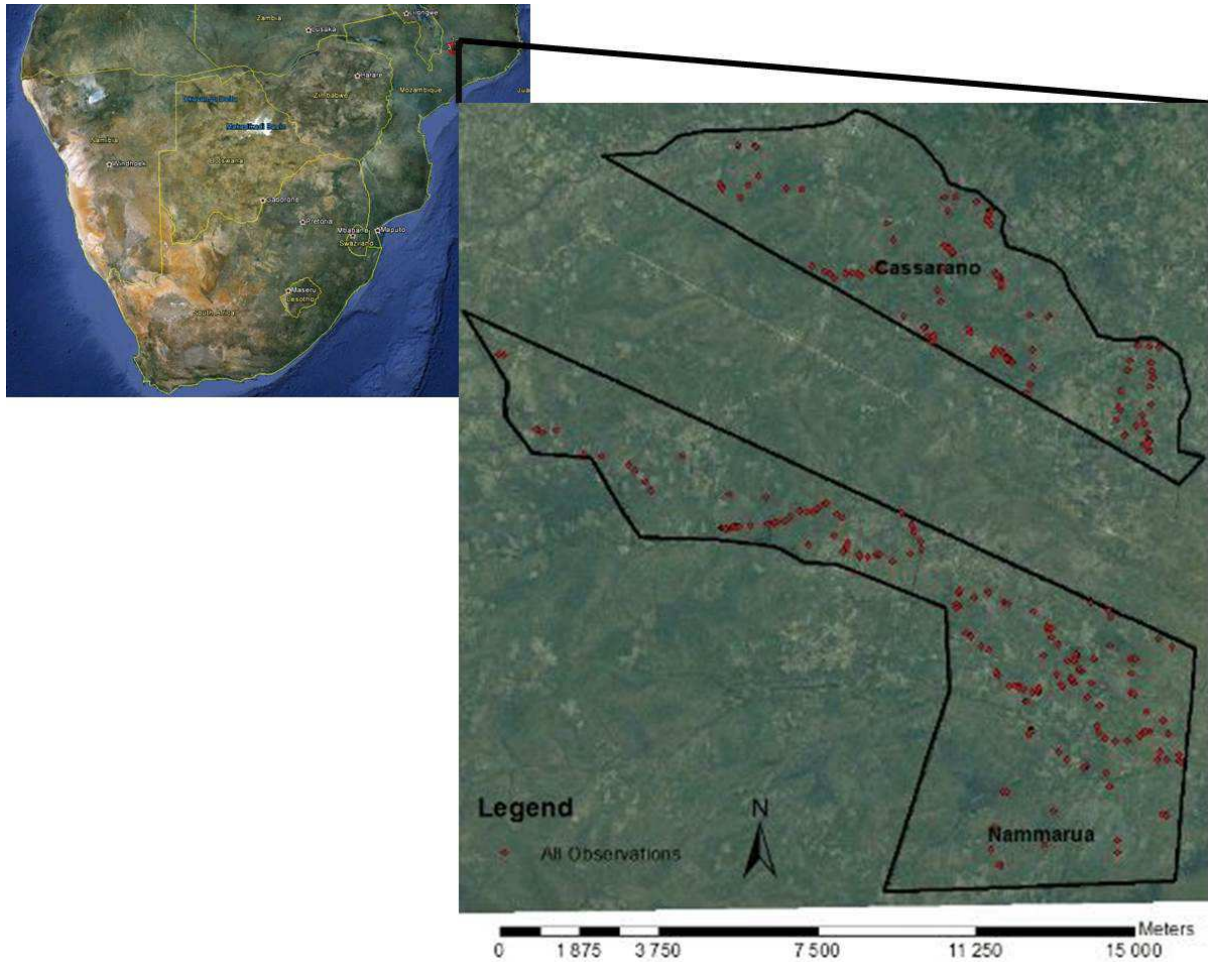
Figure 5.1: The study area. Nammarua is to the South and Cassarano to the North. Soil auger observation points are displayed as red dots.

The area is very hot and humid. Figure 5.2 shows the rainfall and mean temperatures for the period 1951 – 1968, the only period for which climate data exist. The climate is marked by a distinct wet and dry season. Very little rain falls between May and October, which places a specific emphasis on the water holding capacity of soils to bridge the dry season.

Granite and gneiss are the main geological formations, both of which weathers to very coarse, bleached, sandy soils. There are some basic igneous rock intrusions, which produces red structured clayey soils. Unfortunately the existing geological map (Direcção Nacional de Geologia (DNG), undated), at a small scale of 1:1 000 000, does not show all of these intrusions. Thus a makeshift geological map had to be produced while doing field work, as in Van Zijl *et al.* (2013). Large steep granite inselbergs are common, while the rest of the terrain is relatively flat, often dipping steeply near the streams.
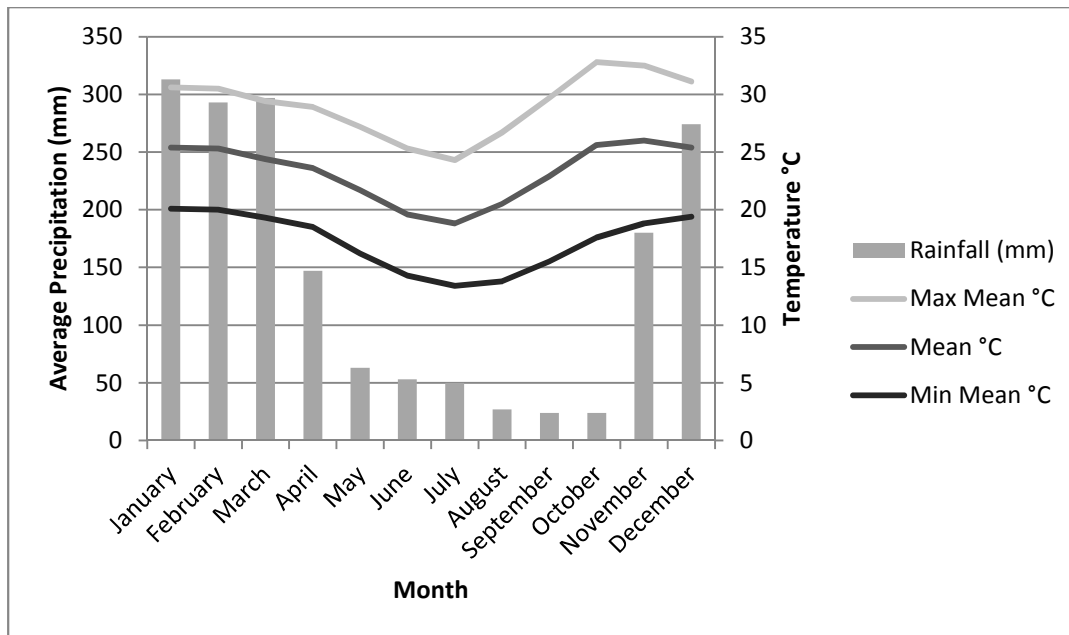
Figure 5.2: Rainfall and temperature for Namarroi, Zambezia, Mozambique for the period 1951 – 1968 (Obtained from ATFC, 2013).

5.3. Material and Methods

Two Lidar interpolated DEM's (10 m and 30 m) were used as ancillary data. Multiple resolutions were used, as multi scale terrain analysis is known to improve prediction accuracy (Behrens *et al.*, 2010). Terrain variables were derived in SAGA (SAGA User Group Association, 2011) with the "Basic Terrain Analysis" module. Conditioned Latin Hypercube Sampling (cLHS; Minasny and McBratney, 2006) were used to determine pre-determined field observation points. The cLHS method allows for observations at positions representing the entire attribute space. For the Nammarua site, cLHS was conducted on the 30 m resolution grids using Slope, Profile curvature, Planform curvature, Wetness index and Altitude above channel network (AACN) as ancillary data. For the Cassarano site, principal component analysis was conducted on all the 30 m resolution derived topographic layers and the resulting three layers were used to perform the cLHS. Forty two and thirty observation points were determined for the Nammarua and Cassarano sites respectively.

Field work was done in a period of six work weeks. Field observations were made at pre-determined observation positions, and at on-site determined transects and positions when moving from one pre-determined observation position to the next. The on-site determined observations were made to gain understanding of soil distribution patterns in order to build pedogenetic knowledge of the area; a crucial prerequisite for creating the soil map. Conceptual soil distribution patterns were constructed based on the pedogenetic knowledge obtained during field work. Soils were classified according to the South African Soil Classification System (Soil Classification Working Group, 1991). Field estimated texture, structure, mottles and depth were noted for each soil horizon.

The area was divided into homogeneous areas (HA's), with the same geology and pattern of topography using applicable methodology (MacMillan *et al.*, 2007; Van Zijl *et al.*, 2012). SMU's (SMU's) were derived for each HA, by grouping soil observations with the similar morphological properties together. Because of the distinct dry season of the area, the water holding capacity of a soil determines its production potential. Soil texture and depth were the main determining factors. The observations were divided into training and validation data. For SMU's which had enough observations within a HA, roughly a quarter of the observations were chosen at random as validation observations. Validation observations were not used to develop rules for delineating SMU's. Within each HA, unique soil-landscape rules were created by adding terrain covariate values to the conceptual soil distribution patterns, using the training observations. A soil map was created by running an inference in the Soil Land Inference Model (SoLIM, Zhu, 1997), using the soil-landscape rules.

The map was validated using the selected independent validation observation data. Map accuracy was calculated as a percentage of correctly predicted observations. A one pixel buffer was included around SMU's, as in Van Zijl *et al.* (2012). Thus the accuracy shows the percentage of soil observations which occur within 30 m (one pixel) of the same SMU. The Shallow Soil (Leptosols) observations and the Clovelly Shallow (Arenosols) observations were not included in the validation, as rock outcrops around which these SMU's occur are seemingly randomly distributed and smaller than the mapping resolution of 30 m, making it impossible to map. This does not hinder the operations of the client though, rock outcrops will easily be identified while planting. A 15 m radius area around the rock outcrops should not be planted, as the soils within this area will still be too shallow for tree production. Large rock outcrops, generally the granite inselbergs, were mapped.

After validation the raster file was converted to a shapefile in ArcGIS. Polygons smaller than 0.81 ha (9 pixels) were incorporated into surrounding polygons, to yield a soil map product which has a minimum mapping unit size of 0.81 ha, and definite soil boundaries which could be used by the client.

Land suitability evaluation included production potential, compaction risk and soil erodibility risk. This was mapped by assigning a semi-quantitative value for each of these properties to each SMU, on a scale of 1 to 5. For production potential the scale was relative, with the most productive soils being assigned a 5 rating and less productive soils lower values. Soil texture and depth are the dominant soil properties taken into account for assigning a production potential value to SMU's. For compaction and soil erodibility risk, the scale was absolute, with values being assigned to SMU's based on the expected risk. Texture is the main determinant of compaction risk, with sandy soils being more susceptible to compaction. Soil erodibility risk is determined by the water infiltration rate and clay stability. Thus the topsoil texture and presence of cutans (which suggest clay dispersibility) were considered when assigning erosion risk values. Soils with a coarse texture and absence of cutans received low erosion risk values. Continuous land suitability maps were created with the "Property Map" tool in SoLIM, using the equation:

$$V_{ij} = \frac{\sum_{k=1}^{n} S_{ij}^{k} \cdot V^{K}}{\sum_{k=1}^{n} S_{ij}^{k}}$$

Where S_{ij} is the estimated soil property value at location (i;j)

S_{ij}^{k} is the fuzzy membership value for kth soil at location (i;j) and

Vk is the representative property value for kth soil.

To answer the specific research questions further data analysis was done. Observation numbers and densities were plotted against map accuracy for each HA, the percentage of SMU's observed in sampling was correlated with the percentage map areas of the different SMU's and a survey was made into the number of soil-landscape rules used in each covariate layer.

5.4. Results and discussion

Identification of homogeneous areas

Topography was used to delineate six HA's. Lithology was used to delineate the other four. The geological map scale limited application of lithology as diagnostic rule and only one HA (N2) was delineated on geology indicated by the map. Three more HA's (N3, N4 and N5) with soils with a high clay content were delineated (Figure 5.3). The clayey texture is probably related to lithology.

Soil map units

Ten SMU's were determined based on their classifications according to the South African soil classification system (Soil Classification Working Group, 1991) and their properties. The SMU descriptions are presented in Table 5.1. For purposes of this publication the SMU's classification according to the World Reference Base classification system (IUSS, 2007) is included. Soils were divided into SMU's with its production potential and management in mind. Thus separation occurred based on depth and subsoil characteristics, resulting in similarities between map units.
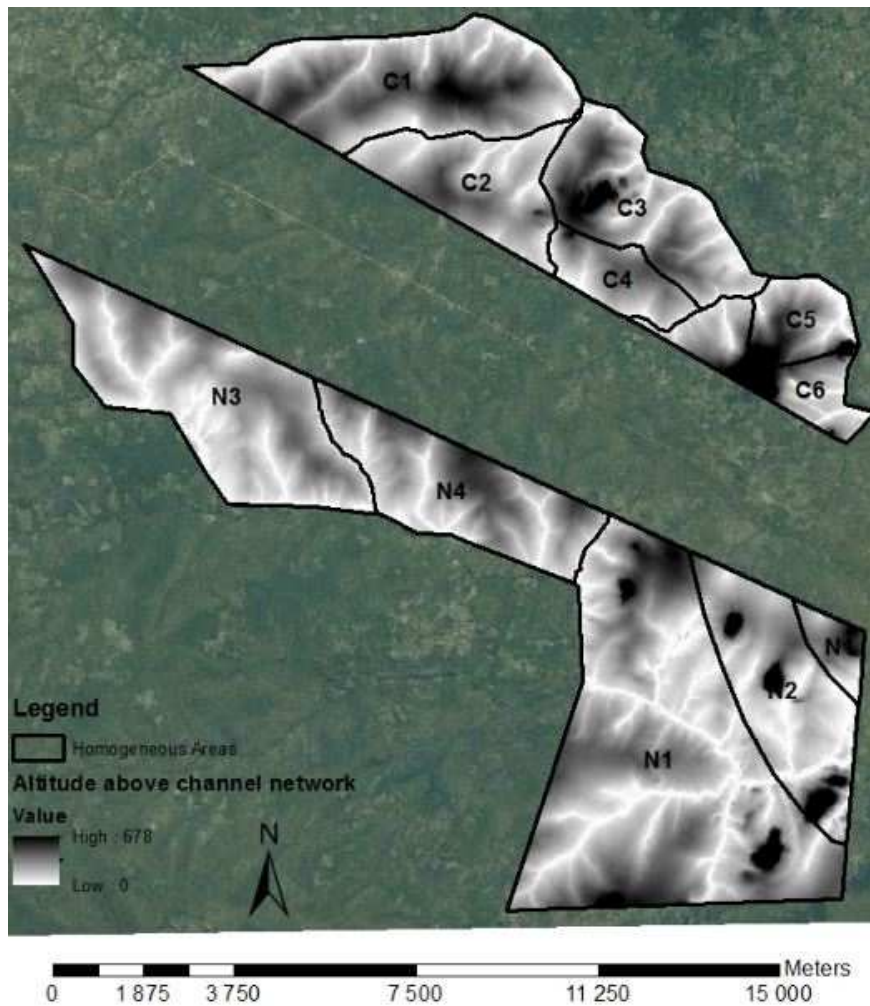
Figure 5.3: The homogeneous areas superimposed on a 30 m 'Altitude above channel network' background. Areas N2, C3, C4 and C5 were differentiated by lithology, while the other areas were differentiated by topography.

Conceptual Soil Distribution Patterns

The three conceptual soil distribution patterns are shown in Figure 5.4 (a, b and c). In the first distribution pattern (Figure 5.4a) there are steep inselbergs sloping to a level plain. The plain slopes steeply to the river. On the inselbergs the Shallow Soils class (Leptosols) and rock outcrops dominate. Several SMU's occur on the plains and the Wet Soil class (Gleysols) borders the river. On rock outcrops occurring randomly on the plains, the Shallow Soil class (Leptosols), and the shallow variants of the Clovelly and Oakleaf soils (Arenosols and Cambisols) dominate. The second soil distribution pattern (Figure 5.4b) is similar to the first, excluding the inselbergs. The third soil distribution pattern has shorter hillslopes with a low gradient (Figure 5.4c). This topography occurs in areas with only granite lithology. The ridges are overlain with some of the Clovelly SMU's (Arenosols), while the Fernwood Soil class (Arenosols) occurs on the midslopes and footslopes. The Wet Soil class (Gleysols) occurs near the stream. The training data observations were used to distinguish between SMU's on areas where more than one can occur. As an example, the final rules for HA N1 can be seen in Table 5.2.

Table 5.1: Soil map units

Soil Map Unit	WRB Classification	Rooting Depth (mm)	Clay Content	Production Potential	Erosion Risk	Compaction Risk	Determining characteristic
Shallow Soils	Leptosols	< 450	Any	0	0	0	Shallow depth
Wet Soils	Gleysols	< 500	Any	0	0	0	Root depth inhibited by water logging
Fernwood	Arenosols	> 900	B horizon < 5 %	2	2	4	Lateral subsurface water flow
Shortlands	Nitisols	> 1000	B horizon > 20 %	5	1	2	Red, clayey structured soils
Clovelly Shallow	Arenosols	500 - 900	B horizon < 10 %	1	3	4	Shallow sandy soil on shallow rock
Clovelly Clayey	Acrisols	> 1200	B horizon < 10 % C horizon > 20 %	4	1	4	Sandy horizon on clayey saprolite
Clovelly Sandy	Arenosols	> 1200	B + C horizon < 12 %	3	2	4	Sandy horizon on sandy saprolite
Clovelly Deep	Arenosols	> 1000	B horizon < 10 %	3	2	4	Deep sandy soil
Oakleaf Shallow	Cambisols	< 800	B horizon > 10 %	2	2	2	Shallow moderately clayey soil
Oakleaf Deep	Cambisols	> 1000	B horizon > 10 %	4	1	2	Deep moderately clayey soil

Table 5.2: Soil-landscape rules for homogeneous area N1, as an example of how the rules are constructed. Values in brackets show the resolution of the covariate

Soil map unit	Instance	Altitude above channel network (10)	Altitude above channel network (30)	Wetness index (30)	Slope % (30)
Shallow Soils	N1.1				x > 12
	N1.2		x > 39		
Wet Soils	N1.1	x < 0.1			
	N1.2			x > 10.3	
Clovelly Clayey	N1.1		2.3 < x < 39	x < 10	7.5 < x < 10.5
	N1.2		2.3 < x < 39	x < 10	x < 4.3
Clovelly Sandy	N1.1		2.3 < x < 39	x < 10	4.4 < x < 7.5

a.

Inselberg	Clovelly Shallow	Shallow Solls	Clovelly Shallow	Wet Solls
Shallow solls	Clovelly Sandy	Clovelly Shallow	Clovelly Sandy	
	Clovelly Clayey	Oakleaf Shallow	Clovelly Clayey	
	Clovelly Deep		Clovelly Deep	
	Shortlands		Shortlands	
	Oakleaf Deep		Oakleaf Deep	
	Oakleaf Shallow		Oakleaf Shallow	

b.

Clovelly Shallow	Shallow Solls	Clovelly Shallow	Wet Solls
Clovelly Sandy	Clovelly Shallow	Clovelly Sandy	
Clovelly Clayey	Oakleaf Shallow	Clovelly Clayey	
Clovelly Deep		Clovelly Deep	
Shortlands		Shortlands	
Oakleaf Deep		Oakleaf Deep	
Oakleaf Shallow		Oakleaf Shallow	

c.

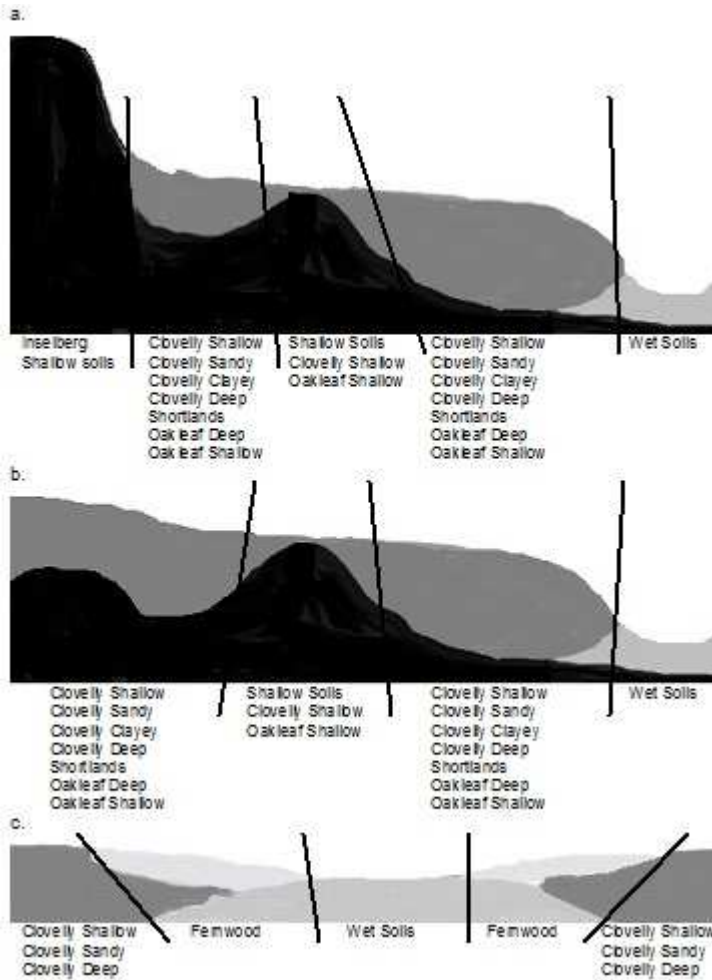| Clovelly Shallow | Fernwood | Wet Solls | Fernwood | Clovelly Shallow |
| Clovelly Sandy | | | | Clovelly Sandy |
| Clovelly Deep | | | | Clovelly Deep |

Figure 5.4: Conceptual soil distribution patterns for the main topographic shapes.

The soil map

The boundaries of the soil map (Figure 5.5) follow natural looking lines, except for the Shortlands SMU (Nitisols) from the HA N2. The reason for this is that the boundaries for this HA were determined by the geological map, which is crisp. This shows a challenge faced by all soil surveyors working in areas with more than one geological formation. How does one determine the extent to which the colluvium from the upper geological formation influences the soil formation on the lower geological formation? In this case, the boundary was taken as the furthest Shortlands observation, as basic igneous rocks are required for formation of this soil form. However the soil boundary does then stay abrupt, as the HA's boundary is abrupt. The division of the other HA's is more natural, as they follow rivers.
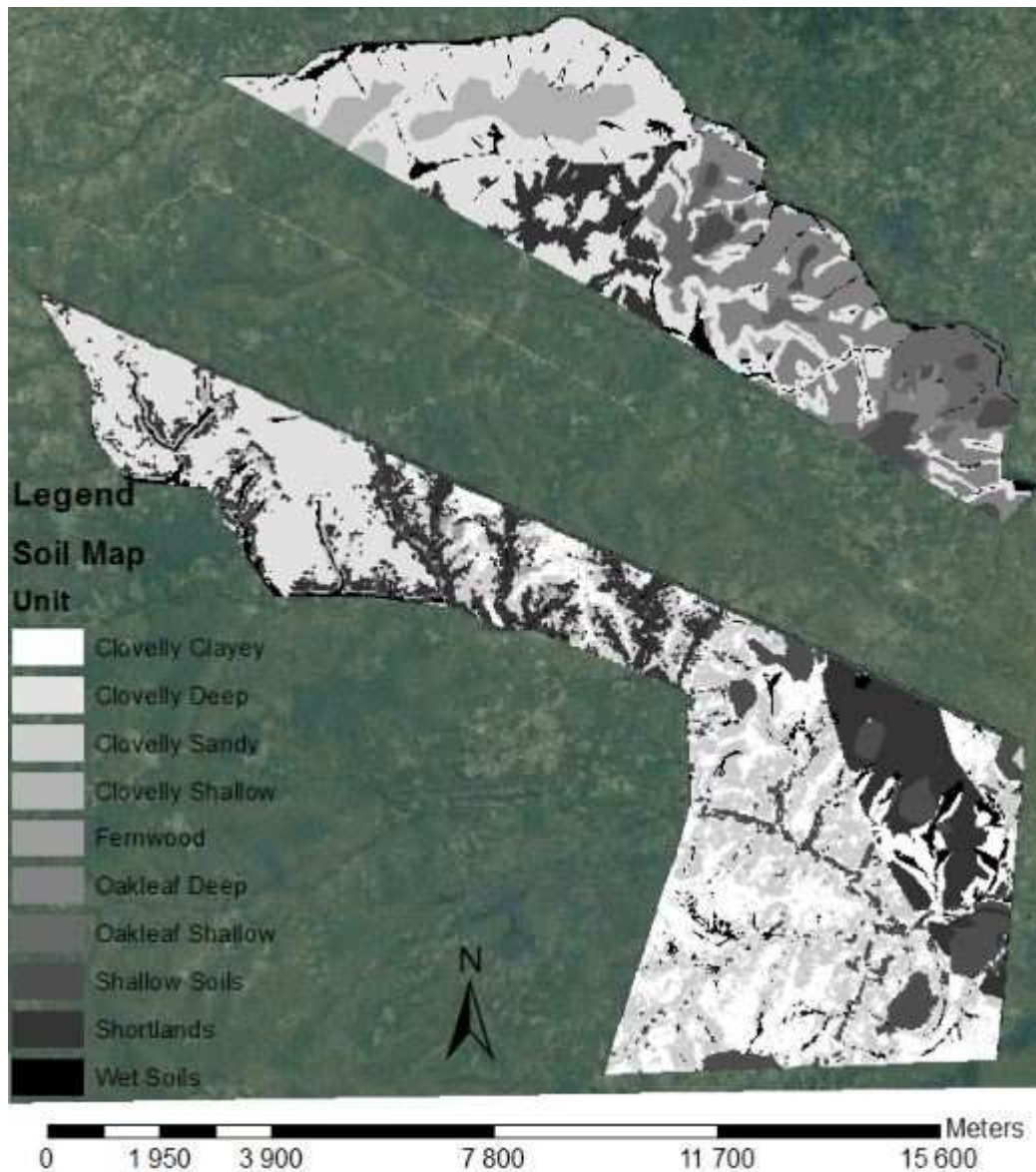
Figure 5.5: Soil map for both the Nammarua and Cassarano study sites.

Only six SMU's could be mapped within each HA. Using SoLIM Zhu *et al*. (2010) also only delineated six SMU's. However Zhu *et al*. (2001) created a soil map with 18 SMU's. Geology was one of the input variables in Zhu *et al*, (2001), thus it could be assumed that geology was used to divide the area into HA's. However, the number of SMU's which were mapped per HA are uncertain. Our experience is that when one tries to add more SMU's, the map becomes too cluttered, with very small and fragmented SMU's. This is one practical limitation to the methodology. A solution could be to decrease the size of the HA's, but that would mean more observations will be necessary, and this will increase costs.

Validation

The overall accuracy (Table 5.3) achieved a very good 80%. This compares well with the accuracy of traditional soil maps (65%, Marsman and De Gruijter, 1986), and other DSM projects which use the same kind of approach, such as Van Zijl *et al.* (2012), 69%, Zhu *et al.* (2001) 81% and Zhu *et al*, (2010), 76%. The omission of the shallow soils in the validation increased the accuracy, and the client should acknowledge this when planting. However, it is impossible to map those soil areas, due to the seeming randomness of small rock outcrops.

**Table 5.3: Map accuracy for the different homogeneous areas as presented in Figure 5.3**

Homogeneous Area	Validation observations		Training observations		Total observations	
	#	% Correct	#	% Correct	#	% Correct
Nammarua 1	14	86	18	89	32	88
Nammarua 2	***	***	31	77	31	77
Nammarua 3	8	88	14	79	22	82
Nammarua 4	8	63	24	88	32	81
Cassarano 1	4	75	10	90	14	86
Cassarano 2	4	100	10	60	14	71
Cassarano 3	7	86	17	71	24	75
Cassarano 4	4	100	16	75	20	80
Cassarano 5*	1	0	3	67	4	50
Cassarano 6	5	60	8	88	13	77
All	55	80	151	79	206	80

*** For the Nammarua 2 homogeneous area, no independent validation was done
*The very small number of observations for the Cassarano 5 homogeneous area is due to the shallow soil observations not being part of the accuracy assessment, and a large part of the area has bare rock or shallow soils. If one includes them, there are 9 validation observations with accuracy of 89%.

Land suitability assessment

The production potential, compaction risk and soil erodibility maps (Figure 5.6) show that the areas with the highest production potential (light colours) also has low erosion and compaction risk (dark colours) This is good news for the client, as it means less soil preparation for the areas where cultivation is most likely to take place. Black areas on all three maps denote areas of the Wet Soil (Gleysols) or Shallow Soils (Leptosols) classes. The Wet Soil class (Gleysols) cannot be planted due to wetland protection laws, while the Shallow Soil class (Leptosols) is too shallow to be planted. Table 5.4 shows the areas which each of these property classes occupy. This shows that the largest part of the area should have an above average production potential, as 8 266 ha, or 76% of the area has a production potential of three or above. The largest risk is compaction, with 6 846 ha falling into risk category 4. This is due to the coarse textured soils in all four Clovelly type SMU's (Arenosols and Acrisols).
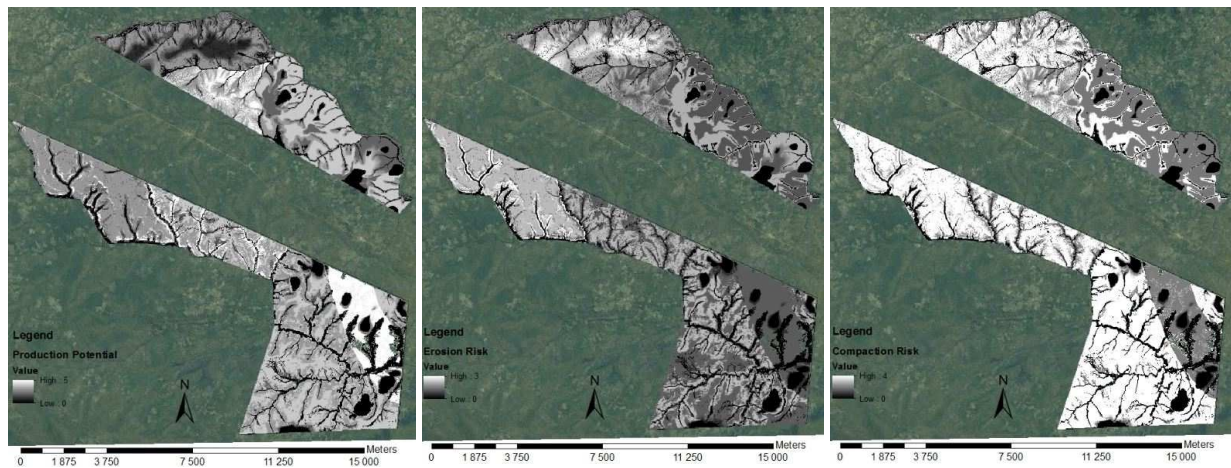
a) Production Potential   b) Erosion Risk   c) Compaction Risk

Figure 5.6: Soil property maps derived from the soil map. a) Production potential, b) Erosion risk and c) Compaction risk. Black areas on all three maps denote areas the wet or shallow soils, which cannot be planted.

Table 5.4: Areas which each of the property classes occupy

Rating	Production Potential (ha)	Erosion Risk (ha)	Compaction Risk (ha)
5	1201	0	0
4	2835	0	6846
3	4230	552	0
2	488	4718	2461
1	552	4037	0
0	1660	1660	1660

Minimum number of observations needed

In some HA's there were not enough observations to have validation observations of all the SMU's. This, together with the different number of observations in the different HA's ask the question "how many observations are enough?" The graph of total number of observations against map accuracy per HA (Figure 5.7a) indicates that more than 13 observations are necessary per HA to achieve an accuracy of more than 65%. The total number of observations seem to be more important that observation density. Figure 5.7b shows that in all the areas with more than 13 observation points an accuracy of more than 65% was achieved, regardless of observation density. Observation densities of between 17 and 99 ha per observation were observed. This implies that the number of observations needed to map an area to an adequate standard depends on the heterogeneity of the area (which determines the number of HA's), rather than the size of the area.
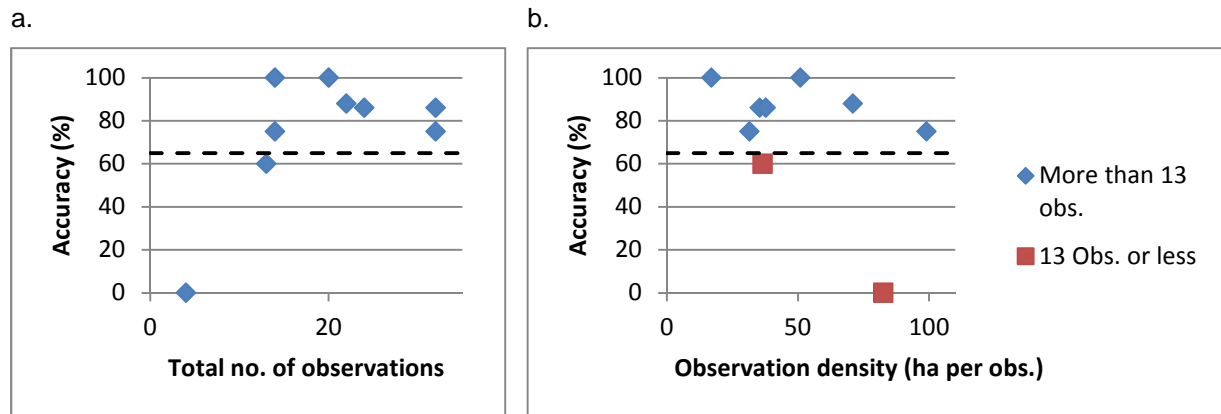
a.

b.

Figure 5.7: Observations against map accuracy. Figure 5.7a depicts the total number of observations, while Figure 5.7b shows the observation density. Each data point represents a homogeneous area. The dashed line represents an accuracy of 65%.

Sampling vs. Soil diversity

Although the soil map was created to an adequate standard, the sampling scheme does not represent the soil diversity very well. In Figure 5.8 the percentage of observations of the different SMU's were plotted against the percentage of area which the SMU's represent. The understanding is that in a good sampling scheme the percentage of observations will closely represent the percentage of the area of each SMU. For Cassarano (Figures 5.8 d, e and f) the expected trend of improving the sampling scheme when adding more observations was observed. For the cLHS only two SMU's were observed within the 65% confidence level. This low number is probably due to the low number of observations made. For the on-site determined observations, being a lot more, the number increased to four. When the two sampling schemes were combined, the number was raised to five. Nammarua (Figures 5.8 a, b, and c) shows a different trend. The cLHS sampling method caused four of the eight SMU's being represented within the 65% confidence levels. The on-site determined observations only had three, and probably due to the much larger number of on-site determined than cLHS observations the total number of observations also only had three data points within the 65% confidence intervals.

The fact that the sampling scheme does not represent the soil diversity very well does not necessarily mean it is not useful for DSM. Grinand *et al.* (2007) found that classification accuracy was not largely influenced by having an observation intensity in proportion to class extent. The cLHS method is supposed to ensure full coverage of the attribute space. In doing this very good conclusions for the soil formation could be drawn for the whole area, as it is mapped by determining soil attribute interactions. However, attribute space does not automatically imitate spatial extent. The aim of the on-site determined sampling scheme is to gain a good understanding of soil-landscape interactions. Thus, for complex soil boundaries, more observations would be made near the boundaries, increasing the observations for specific SMU's, which might not have a very large spatial extent. This confirms the statement of Minansy and McBratney (2007): *"The general perception that good sampling requires a geographical spread is not well founded."*
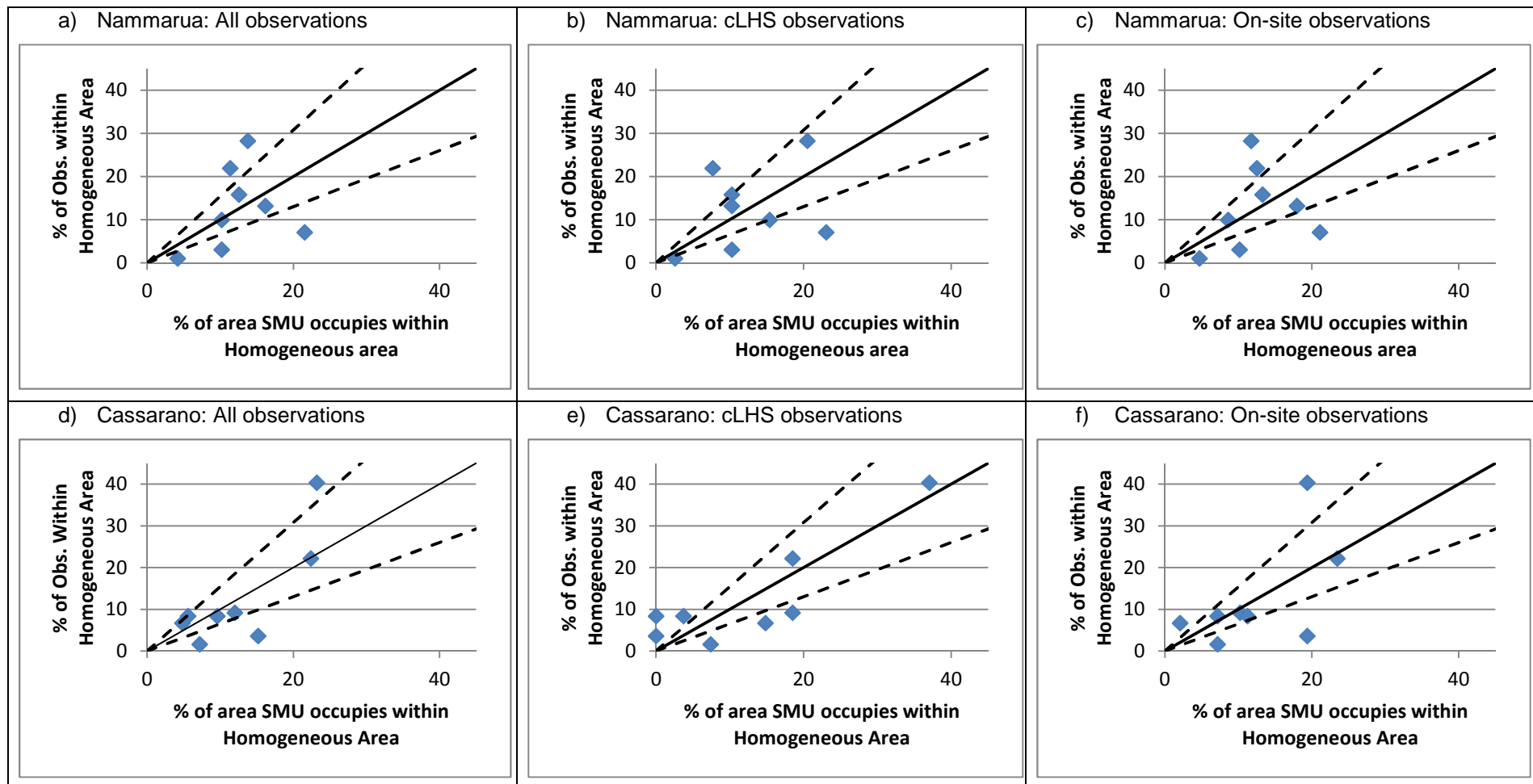
Figure 5.8: Graphs depicting percentage of observation points for soil map units against percentage of area covered by the same soil map unit. The solid lines depict the 1:1 line and the dashed lines a 65% confidence interval.

To improve the sampling scheme, we suggest that cLHS should be done on each HA individually. This will of course only be possible for HA's determined on topographical patterns or from the geological map. Areas could only be differentiated due to perceived differences in parent material after field work has been completed. Determining observation positions for each HA will ensure enough observation points within each HA. The data from this project suggest that more than 13 observations should be made within each HA.

Covariates

The most valuable covariate in this project was the Wetness Index at 30 m resolution, which was used for seven out of eight SMU's in Nammarua and eight out of eight SMU's for Cassarano (Table 5.5). Other important covariates include AACN (both 10 m and 30 m resolution) and Slope (30). The impact which the AACN and Wetness index covariates had at both 10 m and 30 m resolution shows the value of using multi resolution DEM's. Near small streams, which were not picked up as streams on the 30 m DEM, the 10 m covariates proved invaluable. When moving further away from the streams, the generalization of the larger resolution covariates managed to smooth any noise in the soil-landscape relation. This agrees with Smith *et al.* (2006) that higher resolution DEM's do not always lead to higher accuracies, but that it is more important to match terrain characteristics with characteristics of the real world landscape. Behrens *et al.* (2010) also found that soil classes were best predicted using different combinations of covariates at different scales. The fact that only seven out of a possible 24 covariate layers were used concurs with Behrens *et al.* (2010) that only a small number of covariates are needed to achieve a good prediction.

Table 5.5: The covariates used in the soil-landscape rules. This table shows in which homogeneous areas they were used, for how many rules, and for how many soil map units.

Covariate	Homogeneous Areas	Rules	SMU's
Nammarua			
AACN (30)	1,2,3,4	12	7
AACN (10)	1,2,4	6	5
LS (30)	1	2	2
Profile Curvature (30)	3	2	2
Slope (30)	1,2,3,4	15	7
Wetness Index (30)	1,2,3	13	7
Wetness Index (10)	1,3	2	1
Cassarano			
AACN (30)	1,3,4,5,6	10	6
AACN (10)	3,4,5,6	10	6
Wetness Index (30)	1,2,3,4,5,6	14	8

AACN – Altitude above channel network; LS – Length of Slope factor; SMU's – Soil map units. The values in brackets depict the resolutions of the layers.

5.5. Conclusions

The DSM method used proved adequate to rapidly create functional land suitability maps for a large area with little legacy data. The overall map accuracy is 80%. Production potential, soil compaction risk and soil erodibility risk maps were created.

To evaluate the approach used in this project, it has to be compared with other possible approaches. This project took 12 work weeks to be concluded, six weeks for field work and another six for creating the maps and writing the report. In the South African traditional approach with soil observations on a 150 X 150 m grid 5 000 observations would have been needed. It is estimated to need at least 30 work weeks for field work and another two for drawing the map and writing the report. Thus the time cost would have been 2.6 times more. Added to that, the extra field work costs (accommodation, food and labour) would have been 5 times higher. Thus the current approach resulted in substantial financial and time savings. Added to that, with the traditional approach, no independent validation is possible, as all the grid points are needed to create the soil map. With the aerial photo interpretation approach, the dividing of the area into mapping units would be manual, and thus more time consuming than this automated approach. Also, no validation would be possible. Geostatistical DSM methods are data hungry. To provide for this, an increased amount of time for field work should be allowed, which is the most expensive part of the project. By using pedogenetic knowledge fewer observations are necessary, thus saving on costs

A limitation to the method is that SMU's are limited to six per HA. One option to increase the number of SMU's is to have smaller HA's. However, this will increase the number of observations required, which in turn will increase the costs.

Data from this project indicates that more than 13 observations must be made to create soil maps to an adequate standard. Even though the soil maps were completed to an adequate standard, the sampling scheme did not represent the soil diversity well. By dividing the area into HA's before determining the observation positions per HA, one can ensure that there will be enough observations within each HA.

Covariates of different resolutions (10 m and 30 m) were critical to delineate specific SMU's. The smaller resolution covariates worked well near small streams, that were too small to be picked up with the 30 m DEM, while the larger covariates succeeded in filtering out noisy soil-landscape interactions evident with the smaller resolution covariates.

5.6. Acknowledgements

5.7. References

ATFC, 2013.Land Optimization Plan and Implementation Schedule for 21,375 ha of lease title area in the District of Namarroi, Zambezia Province, Mozambique. ATFC, Gurue.

Behrens, T., Zhu, A-X., Schmidt, K., Scholten, T., 2010. Multi-scale digital terrain analysis and feature selection for digital soil mapping. Geoderma 155, 175-185.

Bui, E.N., 2004. Soil survey as a knowledge system. Geoderma 120, 17–26.

Direcção Nacional de Geologia (DNG), undated. Mozambique DNG 1M Bedrock and Structural Geology. Obtained through http://portal.onegeology.org/.

FAOSTAT, 2003. Food and Agriculture Organization of the United Nations, Statistical databases. Available at: http://faostat.fao.org.

Grinand, C., Arrouays, D., Laroche, B., Martin, M.P., 2008. Extrapolating regional soil landscapes from an existing soil map: Sampling intensity, validation procedures, and integration of spatial context. Geoderma 143, 180-190.

Hensley, M., Le Roux, P.A.L., Gutter, J., Zerizghy, M.G., 2007. Improved soil survey technique for delineating land suitable for rainwater harvesting. WRC Project K8/685/4. Water Research Commission, Pretoria.

IUSS Working Group WRB. 2007. World reference base for soil resources 2006, first update 2007. World Soil Resources Reports No. 103. FAO, Rome.

Le Roux, P.A.L., Ellis, F., Merryweather, F.R., Schoeman, J.L., Snyman, K., Van Deventer, P.W., Verster, E., 1999. Riglyne vir kartering en interpretasie van die gronde van Suid-Afrika. Universiteit van die Vrystaat, Bloemfontein.

MacMillan, R.A., Moon, D.E., Coupé, R.A., 2007. Automated predictive ecological mapping in a forest region of B.C., Canada, 2001-2005. Geoderma 140, 353-373.

Marsman, B.A., de Gruijter, J.J., 1986. Quality of soil maps, a comparison of soil survey methods in a study area. Soil Survey papers no. 15. Netherlands Soil Survey Institute, Stiboka, Wageningen, The Netherlands.

Minasny, B., McBratney, A.B., 2006. A conditioned Latin hypercube method for sampling in the presence of ancillary information. Computers & Geosciences 32, 1378–1388.

Minasny, B., McBratney, A.B., 2007. Latin hypercube sampling as a tool for digital soil mapping. In: Lagacherie, P., McBratney, A.B. & Voltz, M. (eds.). Digital soil mapping; an introductory perspective. Elsevier, Amsterdam.

Qi, F., Zhu, A-X., Harrower, M., Burt, J.E., 2006. Fuzzy soil mapping based on prototype category theory. Geoderma 136, 774-787.

SAGA User Group Association, 2011.SAGA GUI 2.0.8. http://www.saga-gis.org.

Smith, M.P., Zhu, A-X., Burt, J.E., Stiles, C., 2006. The effects of DEM resolution and neighborhood size on digital soil survey. Geoderma 137, 58-69.

Snyman, K., 2012. Exploratory assessment of afforestation potential of the Regone and Rumala areas – Namarroi district, Mozambique. Report prepared for ATFC II Lda. Gurue, Mozambique.

Soil Classification Working Group, 1991. Soil classification: A taxonomic system for South Africa. Department of Agricultural Development, Pretoria, South Africa.

Van Zijl, G.M., Le Roux, P.A.L., Smith, H.J.C., 2012. Rapid results with digital soil mapping, Mozambique. In: Minasny, B., Malone, B., McBratney, A.B., (eds.). Digital soil assessments and beyond. CRC Press, Boca Raton.

Van Zijl, G.M., Le Roux, P.A.L., Turner, D.P., 2013. Disaggregation of land types, using terrain analysis, expert knowledge and GIS methods. South African Journal of Plant and Soil. Article in Press.

Zhu, A-X., 1997. A similarity model for representing soil spatial information. Geoderma 77, 217-242.

Zhu, A-X., Hudson, B., Burt, J., Lubich, K., Simonson, D., 2001. Soil mapping using GIS, expert knowledge and fuzzy logic. Soil Science Society of America Journal 65, 1463-1472.

Zhu, A-X., Yang, L., Li, B., Qin, C., Pei, T., Liu, B., 2010. Construction of membership functions for predictive soil mapping under fuzzy logic. Geoderma 155, 164–174.

Zhu, Q., Lin, H.S., Doolittle, J.A., 2013. Functional soil mapping for site specific soil moisture and crop yield management. Geoderma 200-201, 45-54.

CHAPTER 6:

Creating a hydrological soil map for the Stevenson Hamilton Research Supersite, Kruger National Park

Abstract:

Water probably plays the defining role in ecosystems, directly influencing the vegetation and animal distributions. Therefore the understanding of hydrological processes is a vital building block in managing ecosystems. Conceptual hydrological response models (CHRM's) are the basic expressions of hydrological flowpaths. Unfortunately they exist as 2-dimensional expressions, and landscapes are 3-dimensional units. This research uses a soil map to create and extrapolate 2D CHRM's to the 3D landscape of the Stevenson Hamilton Research Supersite. The soil map is produced with an expert knowledge based digital soil mapping (DSM) approach. One hundred and thirteen soil observations were made in the 4 001 ha area. Fifty-four of these observations were pre-determined by smart sampling and conditioned Latin hypercube sampling. These observations were used to determine soil distribution rules, from which the soil map was created in SoLIM. The map was validated by the remaining 59 observations. The soil map achieved an overall accuracy of 73%. The soil map units were converted to hydrological response units. Using GIS terrain analysis, the area was divided into hillslopes. The hillslopes, together with the hydrological response map, were used to create a CHRM map for the whole area. The CHRM map is a 3D representation of 2D CHRM's, and is a valuable input into understanding the hydrology of the area.

Keywords: Digital Soil Mapping, Terrain analysis, Ecosystem Services, Conceptual Hydrological Response Models

6.1. Introduction

Water is probably the defining element in all ecosystems. Hydrological processes determine the amount, seasonality and location of water, therefore rendering ecological system services, by directly influencing vegetation and animal distribution. The importance of a clear understanding of the hydrological processes in the management of water resources is augmented in the highly variable hydrological environment of southern Africa (Wenninger *et al.*, 2008). The identification, definition and quantification of the flowpaths and residence times of the different components of flow are central to the understanding of hydrological processes. There exists an interactive relationship between soil and

hydrology. As soil formation is influenced by climate, vegetation/land use, topography, parent material and time (Jenny, 1941), soil properties incorporates the influence of these factors on hydrologic flow paths. Therefore soil can be a first order control in partitioning hydrological flow paths, residence times and distributions and water storage (Soulsby *et al.*, 2006). Thus soil properties contain unique signatures of the hydrologic regime under which they formed. By interpreting these signatures, hillslope conceptual hydrological response models (CHRM's) can be created (Ticehurst *et al.*, 2007; Van Tol *et al.,* 2010; Kuenene *et al.,* 2011). CHRM's are the basic expression of the understanding of hydrological flowpaths. Unfortunately CHRM's only give a 2-dimensional (2D) expression of hydrological behaviour (Van Tol *et al.*, 2012), and landscapes are 3-dimensional (3D) units.

Soil distribution patterns, expressed as soil maps, can provide a means by which 2D CHRM's are extrapolated to 3D landscapes. As traditional methods of soil mapping is time consuming and expensive, digital soil mapping (DSM) methods, which reduces the cost and time needed for soil survey (Hensley *et al.*, 2007) will be used. DSM harnesses the power of various new and rapidly developing technologies, including information technology, remote sensing, digital elevation models (DEM's), pedometrics and geostatistics, and combine them in inference systems, to produce soil maps in considerably less time than traditional soil survey methods. The hypothesis expressed in this paper is that a soil map derived from DSM could be the used to create and extrapolate the 2D CHRM's to 3D landscapes.

6.2. Site description

The study site is the 4001 ha Stevenson Hamilton Supersite, approximately 7 km's South of Skukuza in the Kruger National Park (Figure 6.1). The mean annual precipitation is 560 mm/a (Smit *et al.*, 2013), and the geological formation is granite and gneiss of the Nelspruit Suite (Venter, 1990). It lies in the Renosterkoppies land type (Venter, 1990). Furthermore it has a highly dissected landscape, with a high stream density (Smit *et al.*, 2013), with a few prominent inselbergs occurring as rock outcrops. *Combretum apiculatum* and *Combretum zeyher* dominate the woody vegetation on the crests. A distinct seepline commonly occurs between the crest and the midslopes, where *Terminalia sericea* is noticeable. *Acacia nilotica* and other fine leaved woody species are most abundant on the midslopes and footslopes. Sodic sites frequently occur, where of *Eucleadi vinoriumis* occurs commonly (Smit *et al.,* 2013).There is a very good correlation between the vegetation and soil type (Venter, 1990), which makes the use of satellite images to map soils very worthwhile.
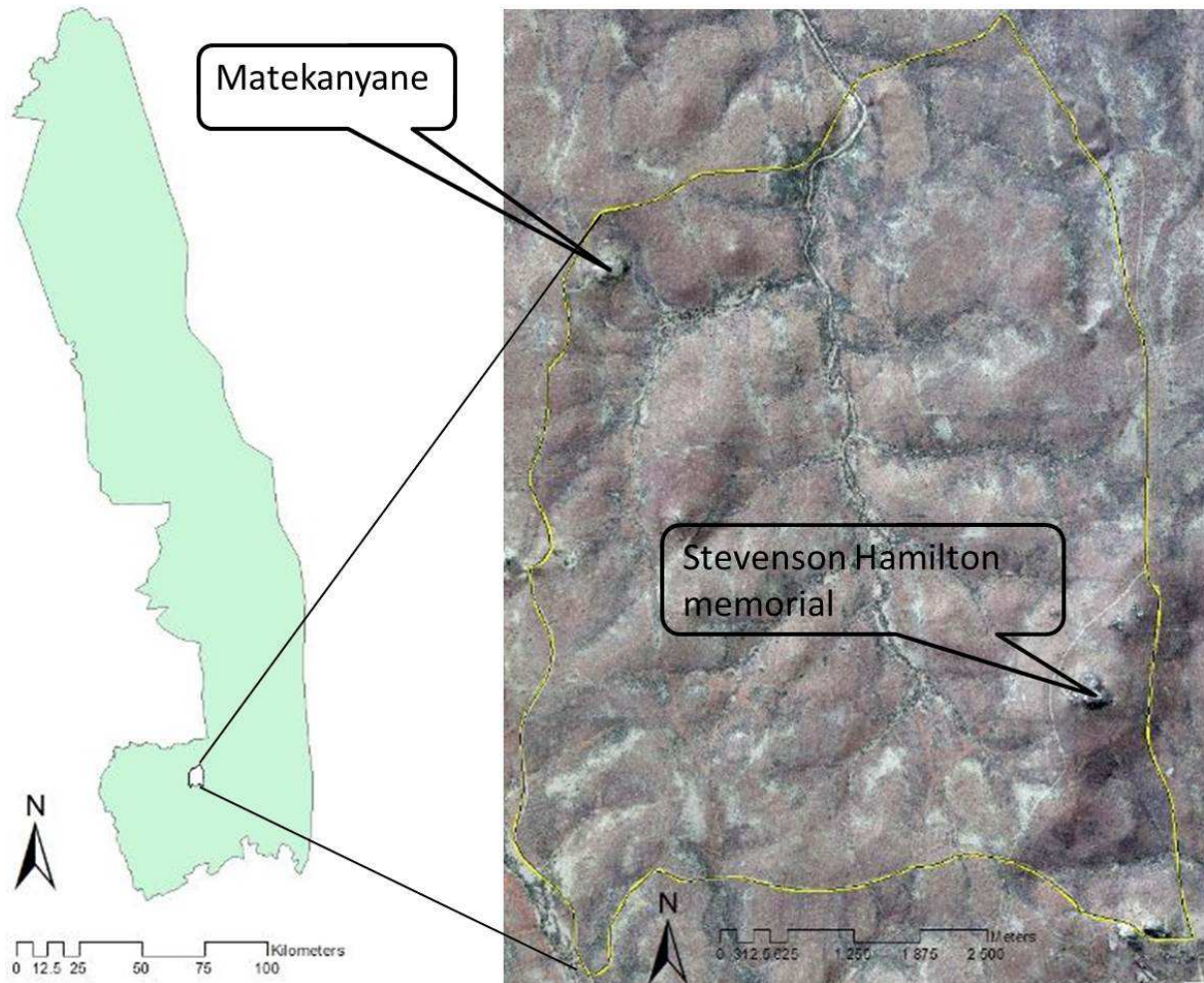
Figure 6.1: The Stevenson Hamilton Research Supersite.

6.3. Material and methods

A suite of environmental covariates were assembled including Spot 5 (SPOT images, undated), Landsat (USGS, undated) satellite images, remotely sensed biomass and evapotranspiration (ET) for a series of dates (eLeaf, undated) and the SUDEM (Van Niekerk, 2012) digital elevation model (DEM). The SUDEM was re-interpolated to a 10 m and 30 m resolution, as multi-resolution elevation layers are useful for soil mapping (van Zijl *et al.*, 2013). Topographic variables were derived from both DEM's with the basic terrain analysis tool in SAGA (SAGA User Group Association, 2011). Several additional co-variate layers, such as NDVI, were created by mathematical manipulation of the different bands of the Landsat and SPOT 5 images.

Three different sampling strategies were followed. For the training observations, both "smart sampling" and conditioned Latin hypercube sampling (cLHS) (Minasny and McBratney, 2006) were used. For the smart sampling a colour aerial photograph was subjectively divided into 5 classes, and observation positions were chosen to include all 5 of the classes. Twenty-five smart sampling observations were made. Six co-variate layers were included into the cLHS. These layers were the principal component analysis (PCA) results of the ET, biomass, Landsat images, SPOT 5 images and

both the resolutions topographic variable layers. Thirty observation positions were selected, of which one was rejected due to being too close to a road. Thus 29 observations were made by cLHS. The position of 59 validation observations were determined on-site, with soil surveyors walking transects through the study site, visually selecting representative sites where observations could be made. In this way, the entire study site was covered. The smart sampling and cLHS ensured that the whole attribute space was sampled, whereas the on-site determined sampling ensured full spatial coverage (Figure 6.2). Soil observations were classified according to the South African soil classification system (Soil Classification Working Group, 1991). Hand estimated texture, structure, mottles and stoniness were also observed per soil horizon.

Figure 6.2: Soil observation positions.

The soil observations were divided into soil map units (SMU's) based on texture and the occurrence of a horizon with signs of wetness. Seven SMU's were determined. The SMU's were mapped by creating soil-landscape rules for each in SoLIM (Zhu, 1997). Central to these rules is an understanding of the soil distribution, based on the expert knowledge gained during field work. Specific values for the rules were obtained from the values for the different covariates of the different soil observations. The rules were derived by starting with the easiest identifiable SMU, the Sodic Soils. Once this SMU was mapped satisfactorily, the rules which defined its distribution were inverted for the other SMU's. Then the Clayey soils were separated from the Sandy soils. Lastly within both the Clayey and Sandy soils the interflow soils were separated from the recharge soils. By running an inference of the soil map rules, SoLIM created a soil map for the area. The raster layer soil map was converted to a shapefile, and filtered using a majority filter with a square radius of 2 pixels and a 20 % threshold. Polygons smaller than four pixels were manually included into larger, surrounding polygons. Alluvial soils were mapped by setting buffers around the stream network. The distance of the buffers were determined by the observations of how far alluvial soils occurred around the different stream orders. Rock outcrops were mapped manually from an aerial photograph, following the effort principal that it is better to map areas than to predict it when it is easier to map it (McBratney, 2002).

The map was validated using the independent validation observations. Map accuracy was calculated as a percentage of correctly predicted point observations. A one pixel buffer was included around SMU's, as in Van Zijl *et al.* (2012). An accuracy matrix was created to evaluate the accuracy of each SMU.

To create a hydrological soil map, a conceptual hydrological response was assigned to each SMU according to Le Roux *et al.* (2011). To convert this map to a conceptual hydrological response model map, the entire area was divided into hillslopes in SAGA. Firstly the SUDEM was pre-processed with the 'fill sinks' module. Then the pre-processed DEM was used in the 'Catchment area' module to create a catchment area grid layer. This layer was used as the initiation grid in the 'Channel Network' module with an initiation threshold of 40 000, to determine the channel network. The channel network and the pre-processed DEM were used in the 'Watershed basins (extended)' module to produce subbasins. The polygon subbasins were divided into hillslopes along the channel network with the 'polygon-line interception' module. By superimposing the hillslope layer on the hydrological soil map, a conceptual hydrological response model was subjectively predicted for each hillslope. This allowed the area and size of each conceptual hydrological response model to be known.

6.4. Results and discussion

The observation positions give a good spatial coverage of the study area. The clusters that formed are due to the on-site determined sampling. The total of 113 observations is very little compared to the 2000 which would have been necessary to draw a soil map with conventional methods. Thus a considerable cost and time saving was made.

The SMU's (Table 6.1) were divided on the basis of hydrological response. Therefore soil forms could be allocated to more than one SMU, based on its hydrological response. The Bonheim soil form fits into both the Clayey Interflow and Clayey Recharge SMU's. The division was made on the basis of whether or not the C-horizon had signs of wetness. The Oakleaf and Tukulu soil forms also fit into two SMU's. Only when it was clear that the soil had formed due to alluvial deposits, was it added to the alluvial SMU, otherwise the observation was added to the Sandy Interflow or Sandy Recharge SMU's respectively. The distinct seepline where _Terminalia sericea_ is noticeable commonly occurs above the Sodic site SMU. Here the Glenrosa soil form (Leptosols) is dominant. It was not mapped as it is too thin to be picked up at a 30 m resolution.

Table 6.1: Descriptions of the soil map units

Soil Association	Soil forms[1]	WRB Reference Groups[2]	Determining characteristics	HRU
Sodic Site	Sterkspruit, Estcourt	Solonetz	Abrupt textural transition between the top and subsoil. Signs of wetness in C horizon	Responsive
Clayey Interflow	Sepane, Bonheim	Phaeozems, Luvisols	High clay percentage in B horizon. Signs of wetness in C horizon	Interflow
Clayey Recharge	Bonheim, Valsrivier, Swartland, Milkwood, Mayo	Phaeozems, Luvisols, Leptosols	High clay percentage in A and/or B horizon. No signs of wetness in C horizon	Recharge
Sandy Interflow	Tukulu, Pinedene, Westleigh, Avalon	Arenosols	Coarse textured A and/or E horizon. Signs of wetness in C horizon	Interflow
Sandy Recharge	Clovelly, Oakleaf, Mispah, Glenrosa	Arenosols, Leptosols	Coarse textured A horizon. No signs of wetness in C horizon	Recharge
Rock Outcrops	Rock	Rock	Rock outcrop	Recharge
Alluvial Soils	Dundee, Oakleaf, Tukulu	Fluvisols, Arenosols	Coarse textured soils, from alluvial deposits	Recharge

WRB – World Reference Day; HRU – Hydrological Response Unit
[1] Soil Classification Working Group, 1991
[2] IUSS, 2007

The SoLIM rules for the five SMU's mapped with SoLIM is shown in Table 6.2. The hierarchical fashion of the rule creating and the exclusion from lesser distinct SMU's from ones mapped earlier is evident when one considers the values of the rules. Both topographic and vegetation indicating covariates were used, indicating that of the five soil forming factors, not one dominates soil formation in this area. Vegetation is determined by the soil type, rather than playing a big role in the soil formation in this area. However, the parent material plays a dominant role in soil formation. The main geological formation of the area is granite, which weathers to a coarse sandy material, except in extreme cases where Sodic Sites develop. It is however highly unlikely for soils with melanic A

horizons (Bonheim, Milkwood, Mayo) to occur. These soils are associated with basic intrusive rocks (Le Roux *et al.*, 2013). Unfortunately the scale of the geological map did not allow for dolerite dykes (which is known to occur in the area) to be mapped. The soil map (Figure 6.3) shows that there are considerable areas of Clayey Recharge and Clayey Interflow soils, which are largely comprised of soil forms with melanic A horizons. Thus the soil map could be improved if the location and extent of the influence of the dolerite dykes can be mapped.

Table 6.2: Soil distribution rules for the soil map units

Soil Map Unit	Instance	Co-Variate							
		Biomass PCA	Biomass 2012-01-11	ET 2012-03-14	Landsat band 4	NDVI	AACN (10)	DEM (30)	Profile Curvature (30)
Sodic	1			x < 23.6					
	2				x > 63				
	3					x < 0.18			
Clayey Recharge	1	x > -32		x > 23.6	x < 63	x > 0.18	x < 7.6	x < 362	
Clayey Interflow	1	x < -32		x > 23.6	x < 63	x > 0.18	x < 7.6		
	2			x > 23.6	x < 63	x > 0.18	x < 7.6	x > 362	
Sandy Recharge	1		x < 197	x > 23.6	x < 63	x > 0.18	x > 7.6		
	2			x > 23.6	x < 63	x > 0.18	x > 7.6		x > 0.199
Sandy Interflow	1		x > 197	x > 23.6	x < 63	x > 0.18	x > 7.6		x < 0.199

PCA – Principal component analysis, ET – Evapotranspiration, NDVI – Normalized difference vegetation index, AACN – Altitude above channel network, DEM – Digital elevation model. Numbers between brackets denote topographical layer's resolutions.
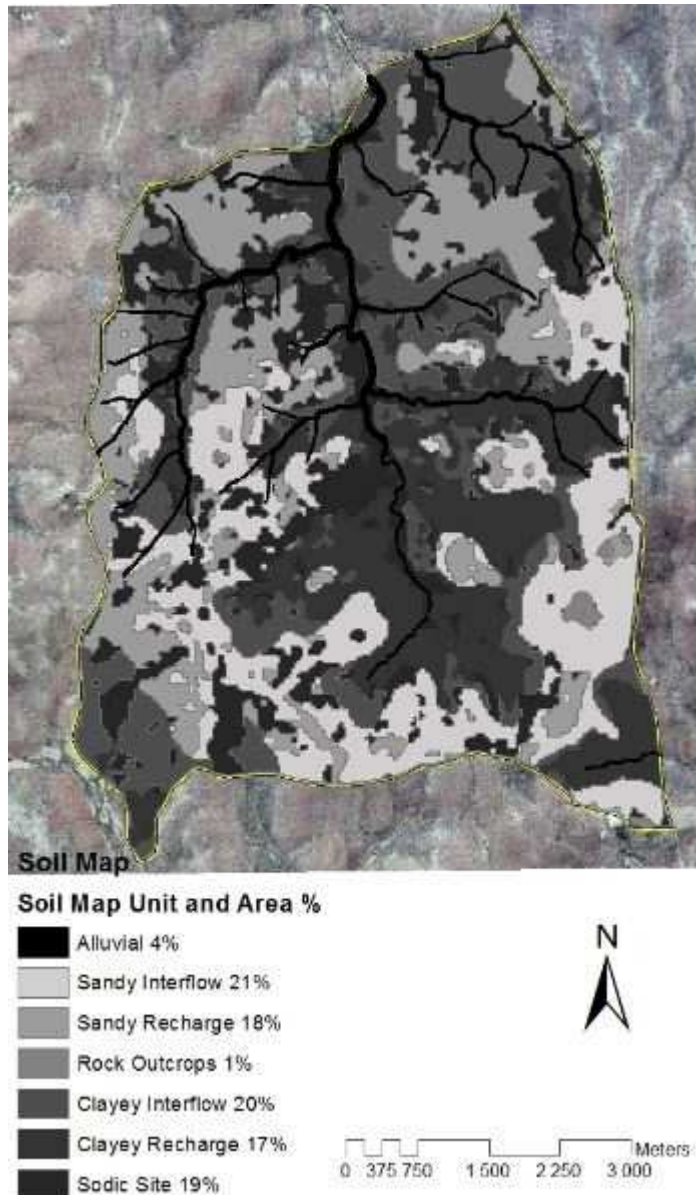
Figure 6.3: The soil map for the study site, showing the percentage of area which each soil map unit occupies.

The overall soil map accuracy of 73% (Table 6.3) is acceptable. This is higher than the 65% commonly accepted as the map accuracy of conventional soil maps (Marsman and De Gruijter, 1986). It also compares well with other studies using comparable methodology, such as MacMillan *et al.* (2010), 69%, Van Zijl *et al.* (2012), 69% and Zhu *et al.* (2008), 76%.

A concern though is the low accuracy values for the Clayey Interflow and Sandy Interflow map units. Seven of the soil observations made on the areas of these map units are actually Clayey Recharge soil observations. Thus the Clayey Interflow and Sandy Interflow SMU's are too large and the Clayey Recharge SMU is too small. To improve the map, more observations should be made along these map units' boundaries. This will enable the improvement of the rules predicting the three map units.

Table 6.3: An accuracy matrix of the soil map

| | | Map units | | | | | | | | |
		Sodic Site	Clayey Interflow	Clayey Recharge	Sandy Interflow	Sandy recharge	Alluvial	Total	Correct	%
Observations	**Sodic**	18	1	2	1	0	1	23	18	78
	Clayey Interflow	0	3	0	0	0	0	3	3	100
	Clayey Recharge	0	3	11	4	0	0	18	11	61
	Sandy Interflow	0	0	1	5	0	0	6	5	83
	Sandy Recharge	0	0	2	0	4	0	6	4	67
	Alluvial	1	0	0	0	0	2	3	2	67
	Total	19	7	16	10	4	3	59	43	73
	Correct	18	3	11	5	4	2	43		
	%	95	43	69	50	100	67	73		

From the hydrological soil map, which also shows the hillslopes, (Figure 6.4) it is clear that various different hydrological responses function in the different hillslopes. The seventeen different conceptual hydrological response models are shown in Figure 6.5, and the final CHRU map in Figure 6.6. There are five hillslopes in which the hydrological soil map is too complex to predict a hydrological response. These hillslopes were mapped as such. The two most common hydrological responses account for 40% of the area and are: 'Recharge-Interflow-Recharge' and 'Interflow-Recharge'. This shows the interchanging nature of recharge and interflow soils. It is suspected that the character of underlying bedrock (whether it is cracked or not) and the position in the topography (whether it can release water to lower lying soils or receive water from higher lying land) determines the hydrological response of the soil. This argument is strengthened by the observation that large trees are often clumped together in recharge areas, and seldom occur in interflow areas. The roots of the trees probably grow into the cracks and can extract water from the fractured rock. Where the rock is not cracked, interflow occurs at the soil-rock interface, but the roots can also not penetrate the rock. The water holding capacity of the soil is then too low to sustain large tree growth. The fact that interflow and responsive hydrological response units occur in high lying terrain positions is an indication that the storage capacity of the granites is high and control hydrological response.

Figure 6.4: Hydrological soil map of the study site, showing the areas which each hydrological unit occupies, as well as the hillslopes of the area.
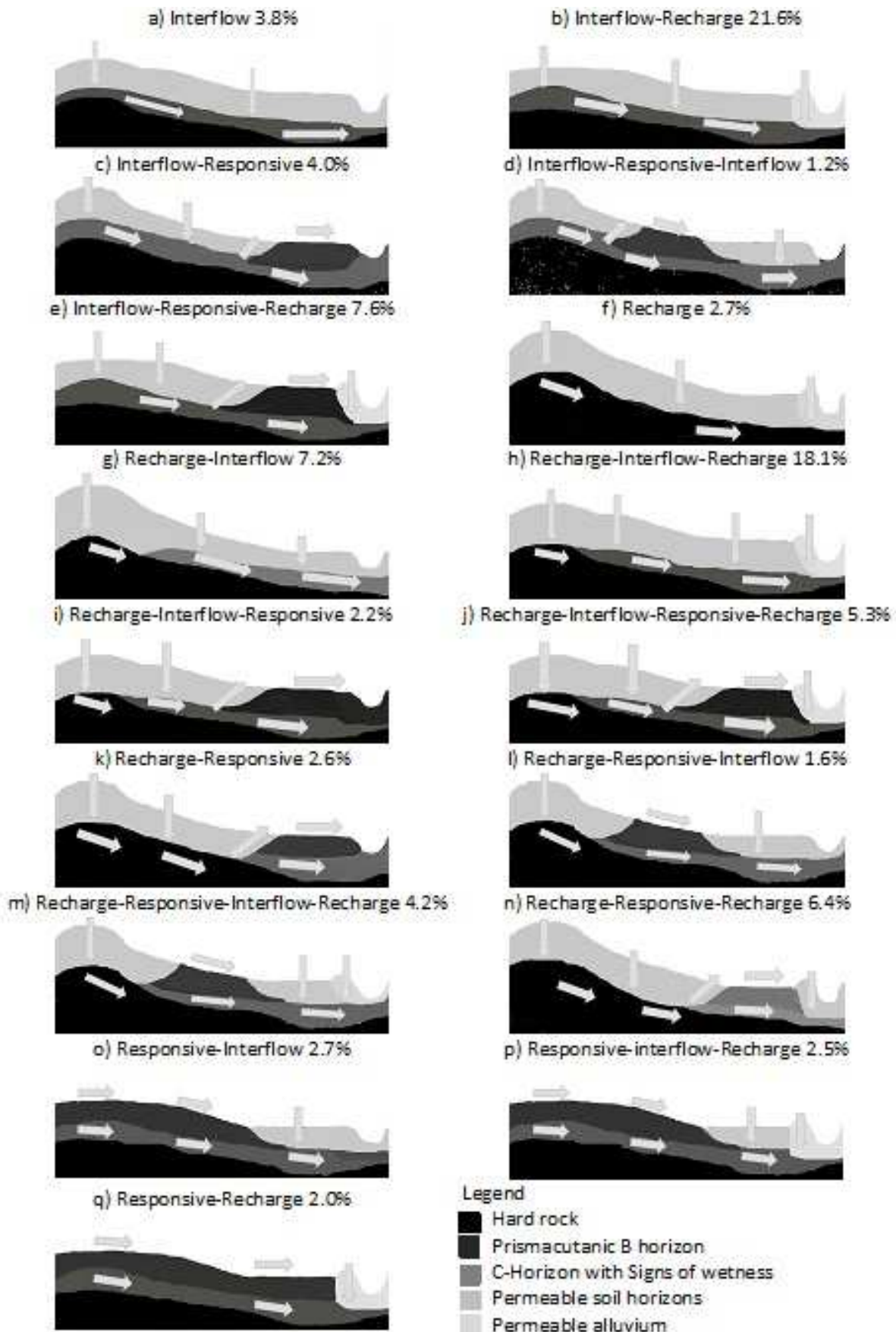
a) Interflow 3.8%

b) Interflow-Recharge 21.6%

c) Interflow-Responsive 4.0%

d) Interflow-Responsive-Interflow 1.2%

e) Interflow-Responsive-Recharge 7.6%

f) Recharge 2.7%

g) Recharge-Interflow 7.2%

h) Recharge-Interflow-Recharge 18.1%

i) Recharge-Interflow-Responsive 2.2%

j) Recharge-Interflow-Responsive-Recharge 5.3%

k) Recharge-Responsive 2.6%

l) Recharge-Responsive-Interflow 1.6%

m) Recharge-Responsive-Interflow-Recharge 4.2%

n) Recharge-Responsive-Recharge 6.4%

o) Responsive-Interflow 2.7%

p) Responsive-interflow-Recharge 2.5%

q) Responsive-Recharge 2.0%

Legend
- Hard rock
- Prismacutanic B horizon
- C-Horizon with Signs of wetness
- Permeable soil horizons
- Permeable alluvium

Figure 6.5: The different CHRM's and the percentage of area they occupy of the study site.
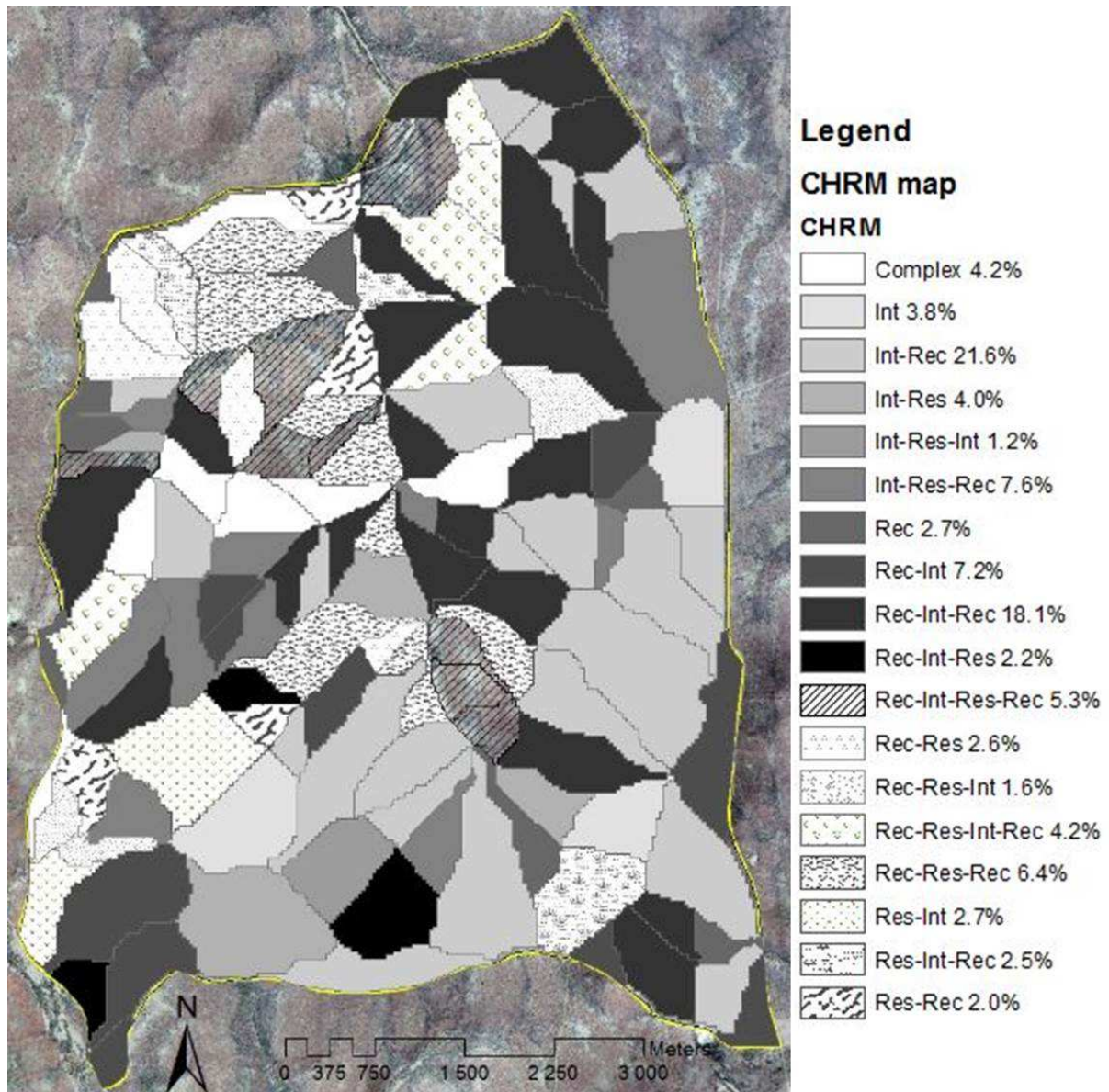
Figure 6.6: The CHRM map for the study site.

6.5. Conclusions

The spatial identification and quantification of CHRM's presented as a map, could be valuable input data into hydrological models.

Digital soil mapping is a tool with which 3D hydrological soil maps can be created in a timely cost effective way. One hundred and thirteen soil observations were made to create a soil map which was 73% accurate. In contrast to this, 2000 soil observations would have been necessary in conventional soil mapping. The map could be improved with a geological map showing the dolerite dykes, as well as by making more observations on the boundaries between the Sandy Interflow, Clayey Interflow and Clayey Recharge SMU's, as pointed out by the error matrix.

By combining terrain analysis to the soil map, a CHRM could be devised for each individual hillslope. Based on these CHRM's it is clear that topography alone does not determine the soil's hydrological response, as each hydrological soil type occurs on each terrain position. It is thought that geology plays a larger role in this, due both to the occurrence of dolerite dykes, as well as the varying character of the bedrock.

6.6. Acknowledgements

6.7. References

eLeaf, undated. Data supplied by the Inkomati Catchment Management Agency on behalf of eLeaf (www.**eleaf**.com) and the WATPLAN EU project.

Hensley, M., Le Roux, P.A.L., Gutter, J., Zerizghy, M.G., 2007. Improved soil survey technique for delineating land suitable for rainwater harvesting. WRC Report K8/685/4, Water Research Commission, Pretoria.

Jenny, H., 1941. Factors of soil formation, A system of quantitative pedology, McGraw-Hill, New York.

Kuenene, B.T., Van Huyssteen, C.W., Le Roux, P.A.L., Hensley, M., 2011. Facilitating interpretation of the Cathedral Peak VI catchment hydrograph using soil drainage curves. South African Journal of Geology 114, 525-234.

Le Roux, P.A.L., Van Tol, J.J., Kuenene, B.T., Hensley, M., Lorentz, S.A., Everson, C.S., Van Huyssteen, C.W., Kapangaziwiri, E., Riddell, E.S., 2011. Hydropedological interpretations of the soils of selected catchments with the aim of improving the efficiency of hydrological models. Report to the WRC on project K5/1748, Water Research Commission, Pretoria.

Le Roux, P.A.L., Du Plessis, M.J., Turner, D.P., Van Der Waals, J., Booyens, H.B., 2013. Field Book for the classification of South African soils. South African Soil Surveyors Organization, Bloemfontein.

MacMillan, R.A., Moon, D.E., Coupé, R.A., & Phillips, N., 2010. Predictive ecosystem mapping (PEM) for 8.2 million ha of forestland, British Columbia, Canada. In: Boettinger, J.L., Howell, D.W., Moore, A.C., Hartemink, A.E., Kienast-Brown, S. (eds.). Digital soil mapping; bridging research, environmental application and operation. Springer, Dordrecht.

Marsman, B.A., de Gruijter, J.J., 1986, Quality of soil maps, a comparison of soil survey methods in a study area, Soil Survey papers no. 15, Netherlands Soil Survey Institute, Stiboka, Wageningen, The Netherlands.

McBratney, A.B., Minasny, B., Cattle, S.R., Vervoort, R.W., 2002, From pedotransfer functions to soil inference systems. Geoderma 109, 41-73.

Minasny, B., McBratney, A.B., 2006., A conditioned Latin hypercube method for sampling in the presence of ancillary information. Computers & Geosciences 32, 1378–1388.

SAGA User Group Association, 2011. SAGA GUI 2.0.8. http://www.saga-gis.org.

Smit, I.P.J., Riddell, E.S., Cullum, C., Petersen, R., 2013. Kruger National Park research supersites: Establishing long-term research sites for cross-disciplinary, multiscaled learning. Koedoe 55 (1), Art. #1107, 7 pages. http:// dx.doi.org/10.4102/koedoe. v55i1.1107.

Soil Classification Working Group, 1991. Soil classification: A taxonomic system for South Africa. Department of Agricultural Development, Pretoria, South Africa.

Soulsby, C., Tetzlff, D., Rodgers, P., Dunn, S., Waldron, S., 2006. Runoff processes, stream water residence times and controlling landscape characteristics in a mesoscale catchment: An initial evaluation. Journal of Hydrology 325, 197-221.

SPOT image, undated. SPOT satellite technical data. Available from http://www.spotimage.com/web/en/229-the-spot-satellites.php.

Ticehurst, J.L., CresswelL, H.P., McKenzie, N.J., Glover, M.R., 2007. Interpreting soil and topographic properties to conceptualize hillslope hydrology. Geoderma 137, 279-292.

USGS, undated. Landsat images, http://landsat.usgs.gov.

Van Niekerk, A., 2012. Developing a very high resolution DEM of South Africa. Position IT, Nov-Dec, 55-60. http://www.eepublishers.co.za/images/upload/positionit_2012/visualisation_nov-dec12_developing-resolution.pdf.

Van Tol, J.J, Le Roux, P.A.L., Hensley, M., 2010. Soil indicators of hillslope hydrology in Bedford catchment. South African Journal of Plant and Soil 27(3), 242-251.

Van Tol, J.J., Le Roux, P.A.L., Hensley, M., 2011. Soil indicators of hillslope hydrology, In: Gungor, B.O. (ed.), Principles-Application and Assessments in Soil Science. Intech, Turkey.

Van Zijl, G.M., Le Roux, P.A.L., Smith, H.J.C., 2012. Rapid soil mapping under restrictive conditions in Tete, Mozambique. In: Minasny, B., Malone, B.P., McBratney, A.B., (eds.). Digital soil assessments and beyond. CRC Press, Boca Raton.

Van Zijl, G.M., Le Roux, P.A.L., Turner, D.P., 2013. Disaggregation of land types, using terrain analysis, expert knowledge and GIS methods. South African Journal of Plant and Soil. Article in Press.

Venter, F.J., 1990. A classification of land management planning in the Kruger National Park. PhD thesis, Department of Geography, University of South Africa, Pretoria.

Wenninger, J., Uhlenbrook, S., Lorentz, S., Leibundgut, C., 2008. Identification of runoff generation processes using combined hydrometric, tracer and geophysical methods in a head water catchment in South Africa. Hydrological Sciences Journal – des Sciences Hydrologiques 53, 65 – 80.

Zhu, A-X., 1997. A similarity model for representing soil spatial information. Geoderma 77, 217-242.

Zhu, A-X., Yang, L., Li, B., Qin, C., English, E., Burt, J.E., Zhou, C., 2008. Purposive sampling for digital soil mapping for areas with limited data. In: Hartemink, A. E., McBratney, A.B., Mendonça-Santos, M. De L. (eds.). Digital soil mapping with limited data. Springer, Dordrecht.

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CHAPTER 7:

Observation Optimization

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7.1. Introduction

The main advantage of the expert knowledge DSM approach is that it adds value to each observation. In the traditional grid method, a point observation is just another observation of soil type which could be grouped together with identical soil types. In geostatistical based DSM methods an observation is merely a statistical sample with which statistical correlations could be drawn with the covariates. In contrast to these two methods rule based systems allow for the integration of quantitative information into a prediction system (McKenzie *et al.*, 1999), as well as allowing for the soil surveyors mental model to be expressed qualitatively. This enables the optimal use of point observations, thus requiring fewer observations. The expected trend (Figure 7.1) is that with more observations the map accuracy would increase, up to a point where the accuracy will reach a plateau and more observations will not have a meaningful effect on the map accuracy.
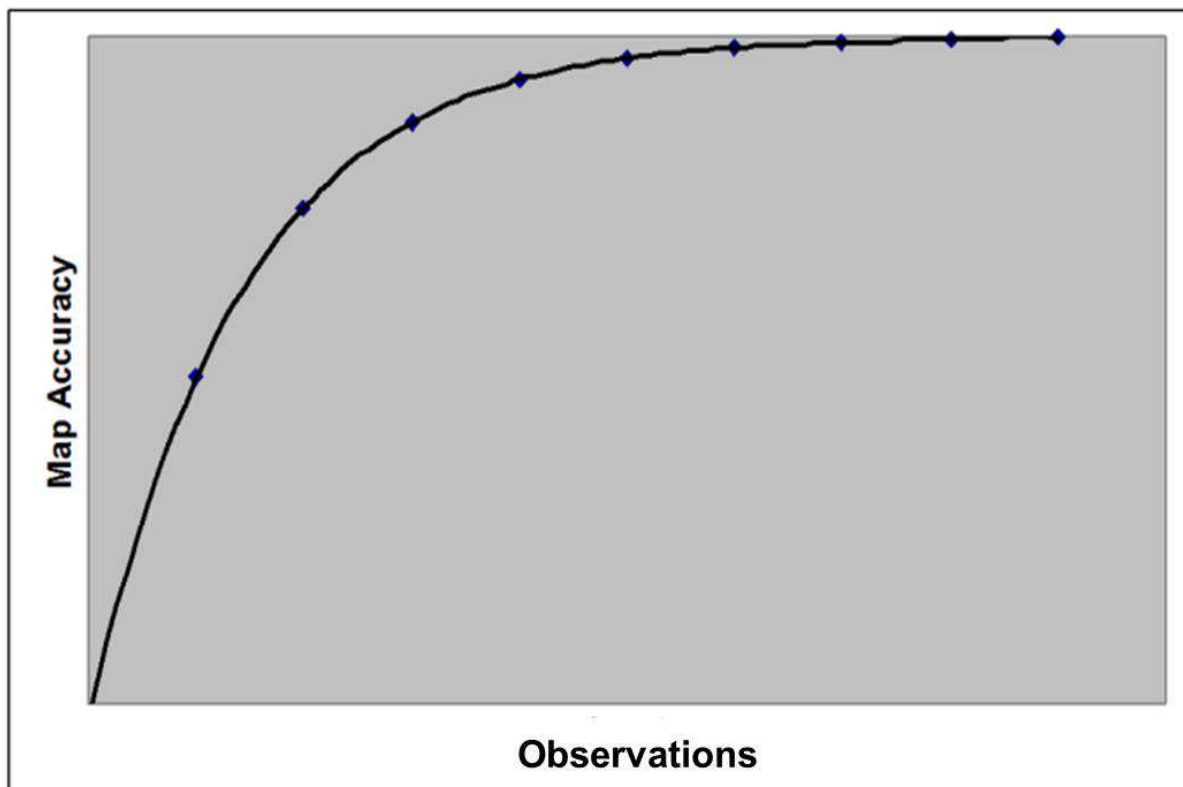
Figure 7.1: The theoretical relationship between map accuracy and number of observations.

To optimize field work one would like to make a number of observations which is close to the optimal inflection point where an acceptable accuracy will be obtained. Vašát *et al.* (2010) found this to be

challenging and concluded that an optimal sampling design for one soil variable is suboptimal for another.

In other expert knowledge approaches for soil classification mapping, a large range of observation numbers was used. Zhu *et al.* (2000) mapped roughly 4 000 ha with three homogeneous areas (HA's), using 150, 140 and 90 training observations for the three HA's respectively. For validation purposes they took a further 90, 80 and 60 observations. This constitutes a total observation density of 6.5 ha per observation. In a later article, using the purposive sampling design, Zhu *et al.* (2008) used 23 training and 45 validation observations to map an area of 6000 ha, which constitutes a total observation density of 88 ha per observation.

Training data observations and validation observations serve a different purpose. With training data observations one would like to be able to determine realistic soil distribution patterns and derive covariate values for the SMU boundaries. Chapter 5 confirmed that a good representation of soil diversity is not necessary for training data. However, this is exactly what is needed from validation observations. When deciding on a sampling scheme and the number of observations needed, the purpose of the observations should be kept in mind.

In Chapter 5 the data indicated that total observations are more important than observation density and at least 13 observations are necessary per HA. In this chapter, the data from Chapters 4, 5 and 6 will be evaluated to obtain a better indication of the minimum requirements for observations needed (Chapter 3 was left out, as no HA's were defined in that project, while the subareas from Chapter 4 were combined into three HA's, to make the data applicable to the current chapter). Based on the indications from Chapter 5, the following three hypotheses are made:

1. A total observation size of at least 13 per HA is needed to obtain an acceptable mapping accuracy.
2. The observation density does not matter if the minimum number of observations is adhered to.
3. Whether or not the observations are determined on-site or with a specific sampling scheme does not matter, as long as a sufficient number of observations are made.

To obtain statistically correct guidelines for sampling schemes would require at least 50 HA's to be able to apply quantile regression to the data points (Cade and Noon, 2003; Mills *et al.,* 2006) Therefore the results presented in this chapter are only preliminary, although they do give a good indication of observation requirements.

7.2. Material and Methods

The sampling schemes from Chapters 4, 5 and 6 (Table 7.1) are analyzed, with various subsets of sampling data correlated with map accuracy. Minimum criteria for observation quantity are interpreted from these graphs. Two assumptions are made. Firstly, that the target map accuracy is 65% and

Table 7.1: Sampling schemes analysed in this Chapter

Chapter	Sampling scheme	HA	Size (ha)	Training obs (#)	Training obs density (ha/obs)	Validation obs (#)	Validation obs density (ha/obs)	Total obs (#)	Total obs density (ha/obs)	Map Accuracy (%)
4: Tete	On-site	1	8515	54	158	10	852	64	133	90
		2	3686	21	176	6	614	27	137	50
		3	3149	56	56	36	87	92	34	72
5: Namarroi	cLHS + On-site	N1	1137	18	63	14	81	32	36	86
		N2	3115	31	100			31	100	
		N3	1561	14	111	8	195	22	71	88
		N4	1010	24	42	8	126	32	32	75
		C1	1387	10	139	4	347	14	99	75
		C2	714	10	71	4	179	14	51	100
		C3	906	17	53	7	129	24	38	86
		C4	342	16	21	4	85	20	17	100
		C5	330	3	110	1	330	4	83	0
		C6	475	8	59	5	95	13	37	60
6: Kruger National Park	cLHS + Smart + On-site	1	4001	59	68	54	74	113	35	73

HA – Homogeneous area; obs – observations; cLHS – conditioned Latin hypercube sampling

secondly, a minimum criterion is applied. Values for numbers of observations are derived from the maximum observation size which did not meet the required map accuracy. This leads to conclusions being drawn such as: "More than *x* number of observations are needed".

To develop an indication of validation observation number norms, the percentage of validation observations of the different soil map units were plotted against the ratio of map unit to total map area in percent. With a sampling scheme which closely represents reality, the percentage of observations will represent the ratio of area of each SMU. The data was divided into three groups. The first group represents the HA's which do not meet the minimum validation criteria as suggested by the correlations with map accuracy. They have 6 or less validation observations. In the second group is the HA's with between 7 and 14 validation observations. Lastly there is the group of HA's with more than 15 validation observations.

7.3. Results and Discussion

Total observations
The total number of observations needed with all sampling schemes to obtain acceptable results is more than 27 (Figure 7.2a). This is more than the 13 observations that is indicated in Chapter 5, showing that under different conditions, more observations could be necessary. The reason for this higher number of observations needed is probably due to the sampling strategy followed in Chapter 4, where, due to the land mine threat, no pre-determined observations could have been made. The area where observations could have been made was also limited, therefore forcing observations to be made in less optimal positions. This invariably led to requiring a higher number of observations. Other factors which could influence the number of observations necessary include complexity of terrain and the quality of covariate layers.

At least 22 of the observations should be used as training data, with more than six validation observations (Figure 7.2b and c). As in Chapter 5, the observation density is irrelevant (Figure 7.2d), as long as the minimum criteria for the total, training and validation observations are adhered to. This concurs with Grinand *et al.* (2007), who found that observation density did not largely influence classification accuracy. Thus the number of observations is determined by the complexity of the area, which is expressed as HA's. Within each HA it seems that a certain number of observations are needed to sufficiently grasp the soil distribution pattern.

cLHS
Usage of cLHS to pre-determine observation positions improved the usage of the soil observations. Only 4 or more cLHS observations are needed per HA for acceptable results (Figure 7.3a), while more than 27 on-site determined observations are needed (Figure 7.3c). With cLHS observation densities also do not play a role, when the minimum criteria are adhered to, for observation densities varying between 63 and 310 ha per observation (Figure 7.3b and d). When cLHS was performed, only 11 or more additional on-site determined observations were required (Figure 7.4). Unexpectedly, the

percentage of training data observations determined by cLHS does not play a major role (Figure 7.5a) as acceptable map accuracies were obtained with a wide range of cLHS percentages. It also does not matter which percentage the cLHS determined observations contribute to the total observations (Figure 7.5b). Therefore it seems that the advantage of the cLHS observations lies in the sampling of the entire attribute space, which allows for conceptual soil distribution patterns to be created which cover the whole area.

Training vs. Validation observations

There is a slight trend suggesting that when the minimum observation requirements are adhered to, a larger percentage of training observations increases the map accuracy (Figure 7.6). This could be expected, as more training data observation points will lead to more accurate covariate values at SMU boundaries. However, this is not a rule to be adhered to, but rather an interesting observation. Minimum requirements for both training and validation observations are more important.
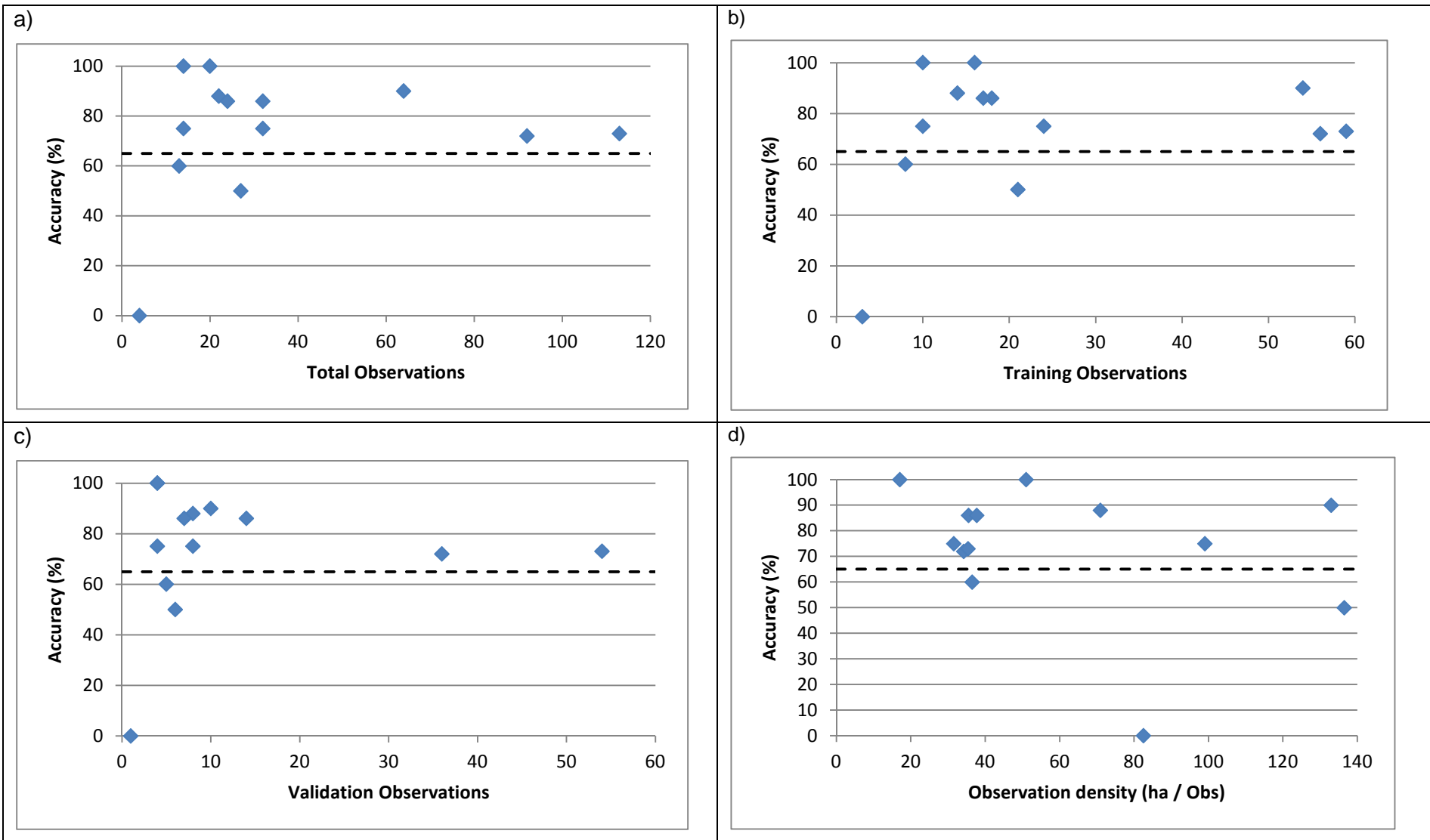
Figure 7.2: Sampling schemes against map accuracy. Figure 7.2d shows the observation density of the total observations.
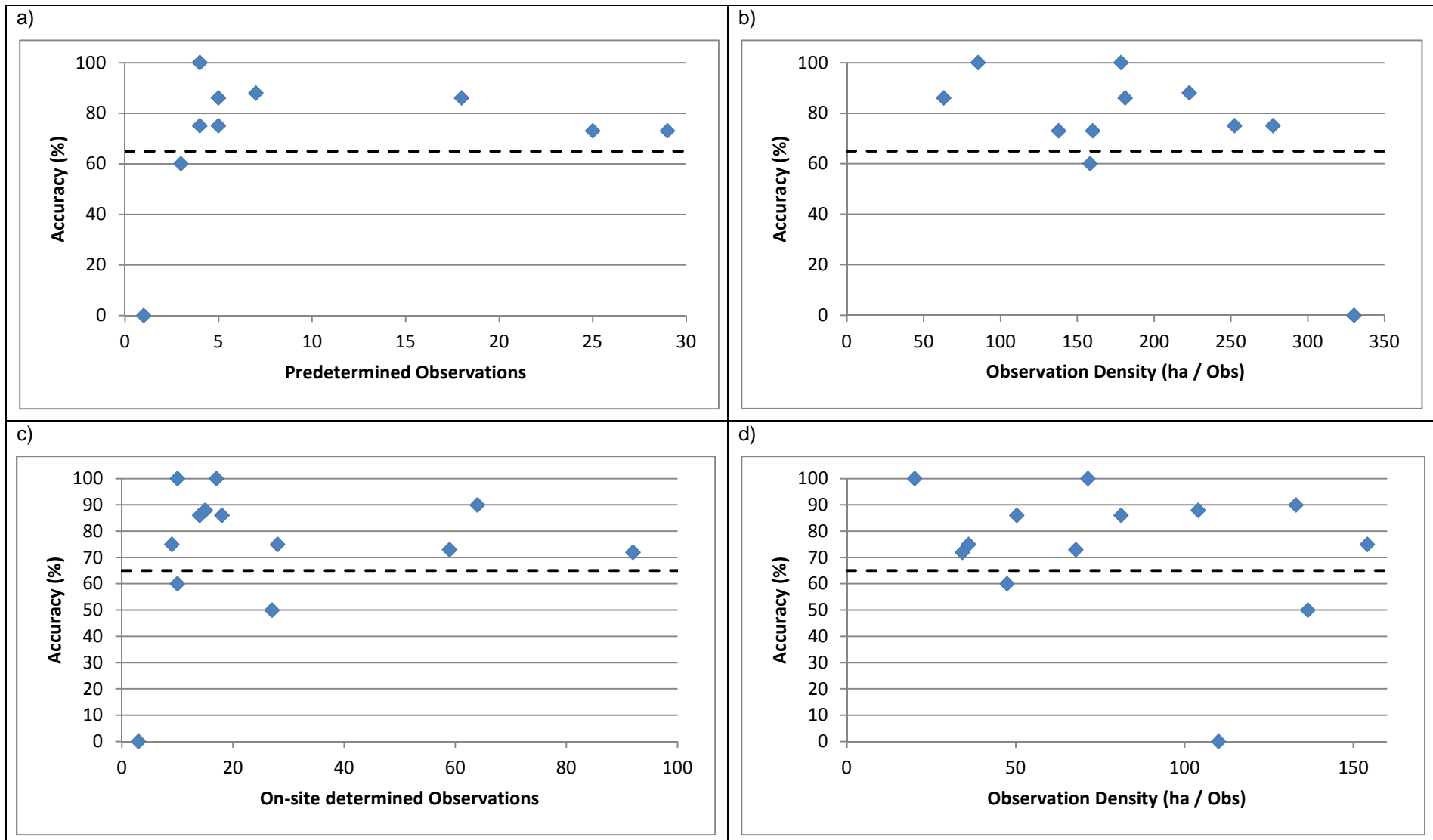
Figure 7.3: Different sampling schemes against map accuracy. Figures a and b is for predetermined observations, while Figures 7.3c and 7.3d shows the data for on-site determined observations.
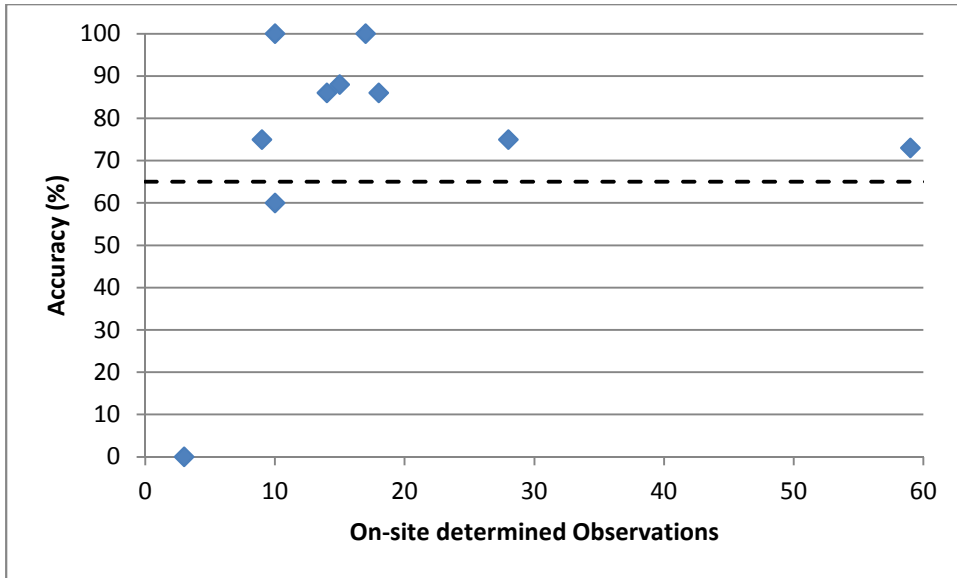
Figure 7.4: On-site determined observations for HA's where cLHS has been applied, against map accuracy.

a)

b)
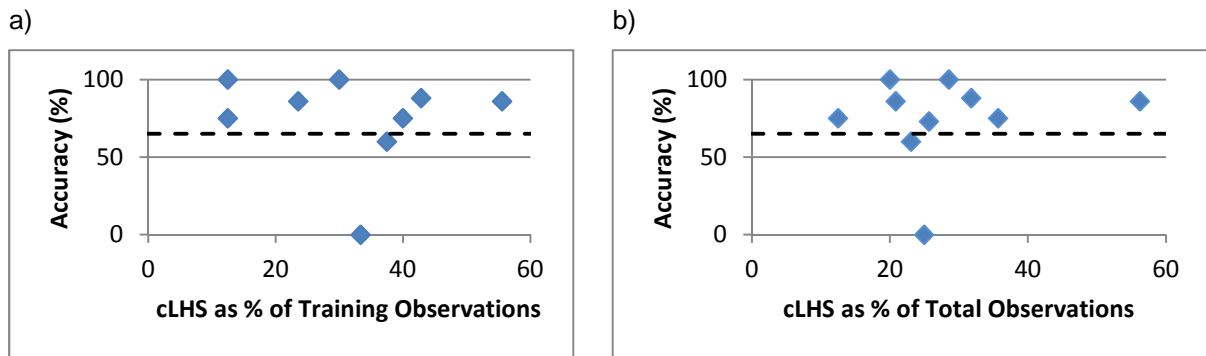
Figure 7.5: cLHS as percentage of Training observations (a) and Total observations (b) against map accuracy.

y = 0.499x + 50.267
R² = 0.2364
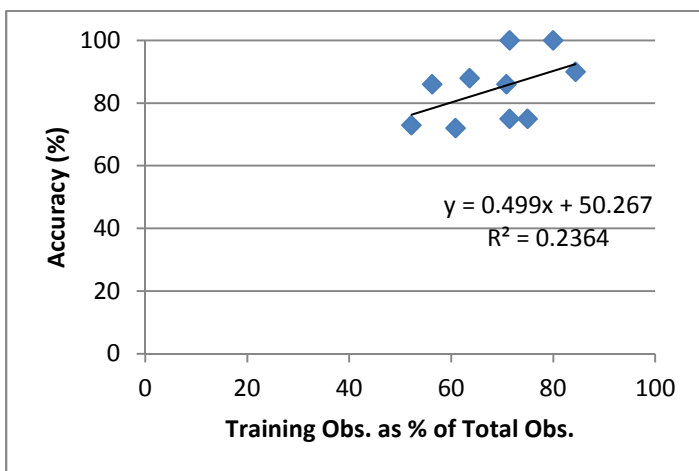
Figure 7.6: Training observations as percentage of total observations, against map accuracy. Only data points which meet the minimum criteria are shown.

Validation observations

The group of HA's with six or less validation observations had 6 out of 21 SMU's that were represented between the 65% confidence intervals (Figure 7.7a). Understandably there are 7 SMU's with no validation observations, due to the very few observations. The group of HA's with between 7 and 14 validation observations were better represented, with 9 out of 19 SMU's being represented within the 65% confidence levels (Figure 7.7b). However this group also had 4 SMU's with no validation observations at all. Surprisingly, the group of HA's with more than 14 validation observations were represented far worse with only 2 out of 9 SMU's being represented within the 65% confidence levels (Figure 7.7c). There was also one SMU with no validation observation. Thus more validation observations do not necessarily mean a better representation of reality, placing more emphasis on the placement of validation observations. Unbiased field observations are necessary to assess accuracy (MacMillan *et al.*, 2007). This, together with the irrelevancy of whether the cLHS observations are included into the training or validation data sets, make using the cLHS observations as validation data observations a logical improvement to the current sampling scheme. However, it is a more complex problem, as all SMU's must be represented in the validation data set. More research is needed on how to determine where and how many validation observations should be made.

a) Six or less validation observations
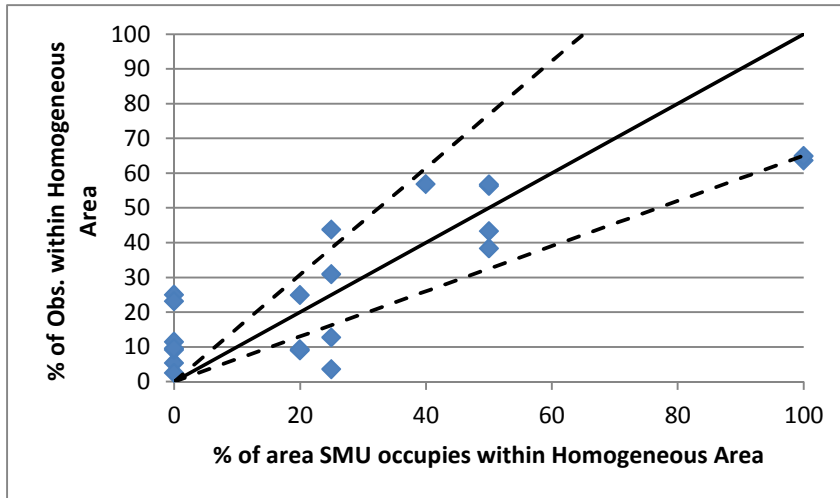
b) Between six and fourteen validation observations
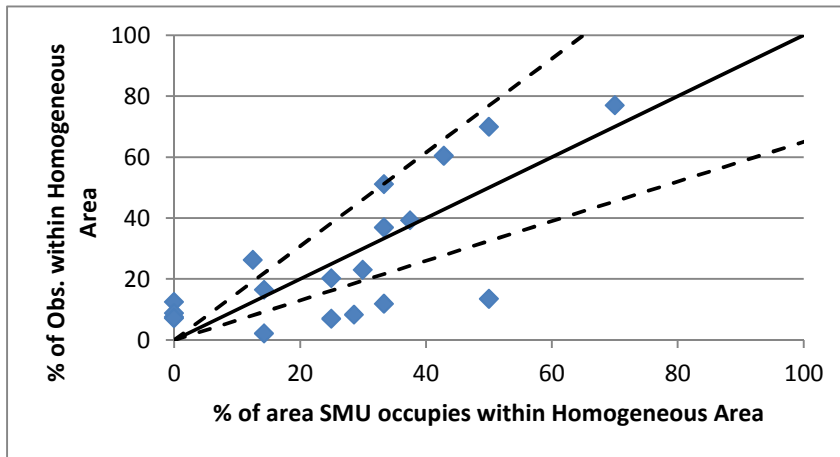
c) More than fourteen validation observations
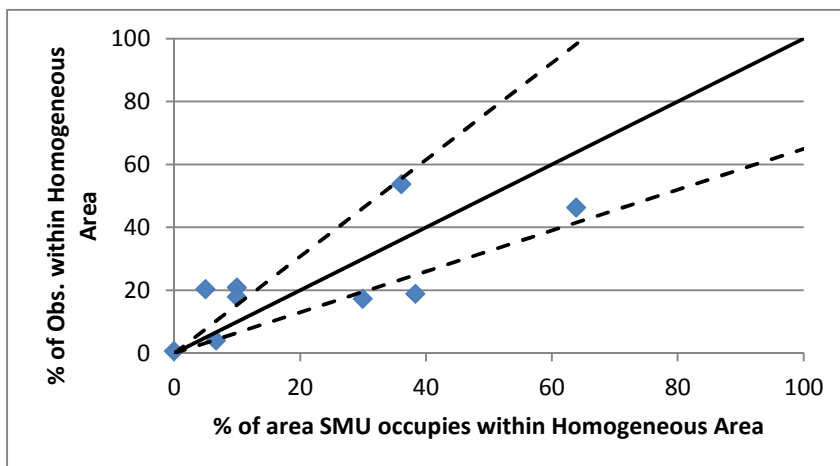
Figure 7.7: Graphs depicting percentage of observation points for soil map units against percentage of area covered by the same soil map unit. The solid lines depict the 1:1 line and the dashed lines a 65% confidence interval.

7.4. Conclusions

The current data indicate that more than 27 observations, with at least 22 training data observations and more than 6 validation observations are necessary to obtain acceptable results. This is less than the hypothesized 13 observations, thus the first hypothesis is rejected. However, when using cLHS to pre-determine some of the observation points, the first hypothesis holds true, and only 14 or more observations are needed. The improvement could be ascribed to the fact that cLHS allows the entire attribute space to be observed, allowing for conceptual soil distribution patterns to be created which represent the entire area. The fact that cLHS improved the sampling scheme rejects the third hypothesis as well, as it does matter which sampling scheme is used.

The second hypothesis is accepted, because in none of the subsets of data did observation density play a role. Thus the total number of observations is not dependent on the size of the area to be mapped, but rather on the heterogeneity of the area, which is expressed by the number of HA's present in the area.

To gain a good representation of reality, which is necessary for validation observations, both the number and positions of observations play a role. Validation observations need to be pre-determined to prohibit bias. More research is needed into where and how many validation observations should be made.

These conclusions are only indications as statistically proving the observation requirements would necessitate at least 50 HA's, in order to apply quantile regression. This will take another 5 – 10 projects to be achieved. However, based on the current data, the following sampling scheme could be suggested:

Within each HA, determine 10 cLHS observation points. This allows for enough stratification to ensure sampling the entire attribute space. In the field make at least another 25 on-site determined observations. This will give at least 35 observations, which will ensure that the minimum criteria of at least 22 training data observations and six validation observations will be met. When dividing the observations between the training and validation data sets, include roughly a third of each SMU's observations in the validation data set, giving preference to the cLHS observations. This will decrease the bias in the validation data set.

7.5. References

Cade, B.S., Noon, B.R., 2003. A gentle introduction to quantile regression for ecologists. Frontiers in Ecology and the Environment 1, 412-420.

Grinand, C., Arrouays, D., Laroche, B., Martin, M.P., 2008. Extrapolating regional soil landscapes from an existing soil map: Sampling intensity, validation procedures, and integration of spatial context. Geoderma 143, 180-190.

Mills, A.J., Fey, M.V., Gröngröft, A., Petersen, A., Medinski, T.V., 2006. Unravelling the effects of soil properties on water infiltration: segmented quantile regression on a large data set from arid south-west Africa. Australian Journal of Soil Research 44, 783–797.

MacMillan, R.A., Moon, D.E., Coupé, R.A., 2007. Automated predictive ecological mapping in a forest region of B.C., Canada, 2001-2005. Geoderma 140, 353-373.

McKenzie, N.J., Ryan, P.J., 1999. Spatial prediction of soil properties using environmental correlation. Geoderma 89, 67-94.

Vašát, R., Heuvelink, G.B.M., Borůvka, L., 2010. Sampling design optimization for multivariate soil mapping. Geoderma 155, 147-153.

Zhu, A-X., 2000. Mapping soil landscape as spatial continua: the neural network approach. Water Resources Research 36, 663-677.

Zhu, A-X., Yang, L., Li, B., Qin, C., English, E., Burt, J.E., Zhou, C., 2008. Purposive sampling for digital soil mapping for areas with limited data. In: Hartemink, A. E., McBratney, A.B., Mendonça-Santos, M. De L. (eds.). Digital soil mapping with limited data. Springer, Dortrecht.

CHAPTER 8:

Conclusions

8.1. Conclusions

Using the four diverse case studies, a working expert knowledge based DSM protocol was developed which can be used to create soil maps of an adequate standard for a variety of uses under different conditions in southern Africa. The understanding of the soil distribution pattern in the landscape is central to the protocol, thus it capitalizes on the strengths of the general local soil surveyor.

Although still an integral part of the protocol, field work is limited, as the expert knowledge approach allows for the quantification of the expert knowledge extracted by the soil surveyor from the soil observations. Provisional results showed that at least 28 soil observations are needed per HA to achieve acceptable soil map accuracies, irrespective of the observation density. Thus landscape heterogeneity, expressed as number of HA's, determines the number of soil observations required. Using the cLHS method to pre-determine observation locations improved the amount of information gained per observation, therefore decreasing the number of observations needed.

The protocol includes an accuracy assessment of the map, allowing for controlled utilization of the map by end users. The error matrix which is used to assess the accuracy pinpoints problem areas, which can be addressed in future mapping work. As expert knowledge is stored in its quantified form, improvement of the map concerns the refinement of expert knowledge soil-covariate interaction values. The protocol allows for soil mapping in inaccessible areas, as extrapolation of the soil map to unsurveyed areas is possible when the unsurveyed area is in the same HA as a surveyed area. Attributed soil properties (such as production potential) could be mapped. However, mapping of soil properties which need to be determined in a laboratory was unsuccessful. This is ascribed to a lack of soil samples taken in the field.

A limitation of the protocol is that only six SMU's per HA could be mapped. This practically means that functional soil groups rather than soil forms are mapped. However, for management purposes, six SMU's per HA are sufficient.

Further research is required to more precisely determine optimal soil observation numbers and positions, create a method to delineate HA's and to define survey needs to enable the mapping of all soil properties.

8.2. The Protocol

Step 1: Decide on purpose of the map and scale.
The purpose of the map is prescribed by the client and the scale is limited by the resolutions of the available data layers. The resolution of the largest pixel size covariate is used. The resolution of the soil map should facilitate the purpose of the map.

Step 2: Accumulate different covariate layers needed to represent Q.
In this step all the covariate layers should be assembled. This means practically that the DEM should either be downloaded or interpolated from contours or points, satellite imagery should be downloaded and geological maps must be digitized. Every covariate must be prepared to be imported into the GIS software.

Step 3: Spatial decomposition of lagging layers
To enable working with different layers in a GIS, the different layers are converted to a common projection (Appendix 1.3). The user is free to choose any projection, as long as it is in meters, as this enables derivation of terrain attributes and areas of polygons. In southern Africa the projection 'WGS_1984_UTM_Zone_36S' works well. The different covariate layers assembled will not have the same spatial resolution and extent. Even if pixel sizes are the same, the positions of the pixels will differ, therefore resampling of the covariate layers into a common raster system (Appendix 2.3) is necessary when using the covariates to pre-determine observation positions. When using multi resolution covariates, it is only necessary to resample the covariates with the resolution at which the observation positions will be determined. Polygon based layers are converted into raster layers of the same common system (Appendix 1.6). Thereafter the derivation of further covariate layers can occur. Terrain derivatives are derived from the DEM (Appendix 2.4), while mathematical manipulation (Appendix 2.5) of satellite imagery provides additional imagery indices, such as the NDVI.

Step 4: Divide area into homogeneous areas.
In this step the whole area is stratified into smaller areas with homogeneous vegetation, topographic patterns and geology. Within each HA unique soil distribution rules apply. Division on the basis of geology is quite easy, as the geological map will determine the boundaries of the HA's, unless a colluvium effect plays a role, such as in Chapter 3. Then the soil observations are used to determine the extent of the colluvium impact. To determine HA's by vegetation and/or topography, one visually inspects several vegetation and/or topographical layers. Where the pattern differs, a separation should be made. Currently this is done by hand drawing polygons (Appendix 1.4) where the HA's boundaries should be. The development of a method on which basis HA's could be determined is a future research need.

Step 5: Determine observation points

This step is probably the most important, as it determines the effect which the field work will have. The aim is to choose observation points for their intended use. Training data observations need to give the soil surveyor a very good understanding of the soil genesis and spatial distribution for the area, as well as allow for covariate values at SMU boundaries to be determined. Validation observations need to represent the real soil distribution. Any sampling scheme which fulfills these pre-requisites can be used.

A combination of the cLHS method (Minasny and McBratney, 2006) and on-site determined sampling worked very well in this research (Chapters 5 and 6). cLHS ensures full attribute coverage of the area, while the on-site determined observations provide a good understanding of the soil distribution. On-site determined observations also allow for optimal usage of time in the field, while allowing the freedom to investigate specific conditions in the field, as they are not linked to specific positions.

The suggested method of determining observation points is to run cLHS (Appendix 3.1) within each HA, to generate at least 10 points for a reasonable stratification of covariates. Use principal component analysis layers as input (Appendix 2.6). If there are more than one type of data input (as in Chapter 6), create one PCA layer for each type of input. If only topographical data could be obtained, then three PCA layers should be created.

Another 25 on-site determined observations per HA should be made, spread out between the cLHS points. This will give 35 total observations, which is more than the 28 suggested in Chapter 7, and should ensure enough observations to meet the minimum criteria for both the training (at least 22 observations) and validation (at least seven observations) datasets. More research is needed into how many observations are optimal.

Other sampling schemes can be used. Purposive sampling (Zhu *et al.*, 2008) is one which have been used to good effect. It is built into the SoLIM software. It was not used in this research, as the software had some problems and predicted points outside of the study area. However, the developers of SoLIM continually fix bugs in the software and it will be worthwhile to investigate purposive sampling and other sampling schemes.

Step 6: Field work

During field work, all observations should be entered into a GPS, so that the exact location is known. Describe soil profiles in as much detail as possible and take soil samples as necessary for the purpose of the map.

Step 7: Divide observations into soil map units.

As SMU's are limited to six per HA, one cannot map soil forms, therefore soil form observations should be aggregated into functional SMU's. This is done by matching soil qualities to land-use requirements. The research covers crop production suitability (Chapter 5) and hydrological response models (Chapter 6). For crop production suitability maps, soil forms with the same crop production potential and management requirements are grouped, while for a hydrological response model map, the grouping is determined by similar hydrological responses. Groupings are strictly land-use requirement related. As in Chapter 5, it often happens that soil observations with the same soil form will be divided into different SMU's based on functionality.

SMU's are derived individually for each HA and are based on the observations within that HA. There should be at least four observations for each soil SMU to ensure enough observations for training and validation observations.

Step 8: Set apart validation observations

When dividing the observations between the training and validation data sets, include roughly a third of each SMU's observations in the validation data set, giving preference to the cLHS observations. This will decrease the bias in the validation data set. Ensure that there are at least seven validation observations. These observations are not used in determining the soil distribution rules. More research into the number and positions of validation observations are needed.

Step 9: Create rules for soil map

The rules carry the information with which the map will be created. It is the quantitative expression of the expert knowledge of the soil surveyor. Thus it provides a platform where expert knowledge can be retained. Thus improvement of soil maps can be done by updating the soil distribution rules. When only topographical covariates are available, a conceptual soil distribution model is a pre-requisite to create the rules. Then, with the model in mind, the values of the covariates at the SMU boundaries are obtained from the training data. To do this, covariate values are added to the point data set (Appendix 2.7). It is more difficult to create soil distribution patterns with satellite imagery, as correlations between soil and vegetation, and vegetation and satellite imagery are not well known. However the training data observations can still be used to determine the covariate values at SMU boundaries. The soil distribution rules are created in SoLIM. See Appendix 4 to see how to apply SoLIM.

Step 10: Run inference with rules to create soil map.

Using the soil distribution rules, SoLIM will create a soil map by running an inference over the study site.

Step 11: Filter out small map units into larger map units.

Inevitably, very small areas of only a few pixels will be delineated as SMU's. Although this might be representative of the real situation, it is not functional. A filter tool is applied to filter small map units into larger ones (Appendix 2.8). Thereafter the raster based soil map is converted to a polygon based shapefile (Appendix 1.5).

Step 12: Validate the map.

The map is validated using an accuracy matrix. The advantage of an accuracy matrix is that it points out where inaccuracies in the map exist. For example, in Chapter 6 the accuracy matrix showed that the largest concern with the map is the map boundaries between the Clayey Recharge and Clayey and Sandy Interflow SMU's. The map can be improved by making more observations along the borders of these SMU's, and in that way improve the covariate values of the border.

To create an accuracy matrix, the map unit of the pixel where the location is located for each validation observation should be noted. When the correct SMU falls within one pixel of the observation, the observation is deemed to be correct. Purists would argue that this creates bias towards higher accuracy values. However, this is done to correct a systemic bias towards lower accuracy values. The bias towards lower accuracy values occurs in the following ways:

1. It is easy to predict soil distribution in the centre of the SMU's. However, with on-site determined sampling, one makes observations at the boundaries of SMU's to determine the covariate values at which boundaries occur. This leads to more validation observations at the SMU boundaries, leading to perceived lower map accuracies.

2. When filtering small SMU's into larger units, some detail of the map is lost. Thus the map could be predicted correctly, but because of the small area of the map unit, it is incorporated into a larger unit, and the accuracy decreases. This is the inclusion problem also encountered in traditional grid based surveys.

3. Natural soil boundaries do not follow the right angles of pixels. As in Figure 8.1 a situation can exist where an observation can be classified correctly and the correlating pixel be predicted correctly, but where the observation is deemed to be mapped incorrectly. The chance of this happening is larger at SMU boundaries, where on-site determined observations tend to concentrate.
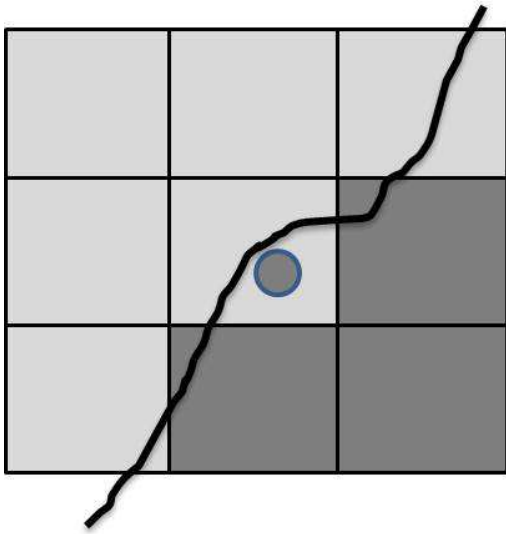
Figure 8.1: Natural soil boundaries vs. pixels. A hypothetical situation where soil map boundaries do not follow pixel boundaries, and bias towards lower accuracies occur as a result thereof.

The one pixel buffer around validation observations is a way to somewhat rectify this systemic bias towards lower map accuracies.

Step 13: Evaluate the map.
Based on the accuracy assessment and the initial aim of the map set out in Step 1, the map is assessed to determine whether or not the aims have been met. If it does, proceed to Step 14 and if not, either redefine the aims (Step 1) or do more field work in problem areas. To do this, return to Step 5.

Step 14: Add value.
Soil maps in general are not very good vehicles to convey soil information to non–soil scientists. To convey soil information to the client, some value adding must be done. In Chapter 5 soil property maps and in Chapter 6 a hydrological response model map were developed. After value adding data was easily accessible for the users. During value adding soil related terminology are converted to land use terminology.

Step 15: Extrapolate data.
This step is done in special scenarios. When the area surveyed is similar to areas around it, one could apply the soil distribution rules to the new areas. However, no validation of the new area is possible. Caution must be applied when extrapolating, as incorrect soil information could lead to wrong management decisions. Grinand *et al*. (2007) found strong differences in accuracies between training and

extrapolated areas. A situation where extrapolation could occur reasonably safely is in Chapter 6, where the soil map could be extrapolated to the extent of the Renosterkoppies land type.

8.3. References

Grinand, C., Arrouays, D., Laroche, B., Martin, M.P., 2008. Extrapolating regional soil landscapes from an existing soil map: Sampling intensity, validation procedures, and integration of spatial context. Geoderma 143, 180-190.

Zhu, A-X., Yang, L., Li, B., Qin, C., English, E., Burt, J.E., Zhou, C., 2008. Purposive sampling for digital soil mapping for areas with limited data. In: Hartemink, A. E., McBratney, A.B., Mendonça-Santos, M. De L. (eds.). Digital soil mapping with limited data. Springer, Dortrecht.

Appendices

Appendix 1: ArcGIS

1.1 ArcGIS Interface

The basic interface of ArcGIS is shown in Figure A1.1. Various toolbars are at the top, the table of contents is on the left, the map view is in the middle and the toolboxes are on the right. The exact position of all of these functions can vary. The toolboxes are the main function that is focused on in the appendices.
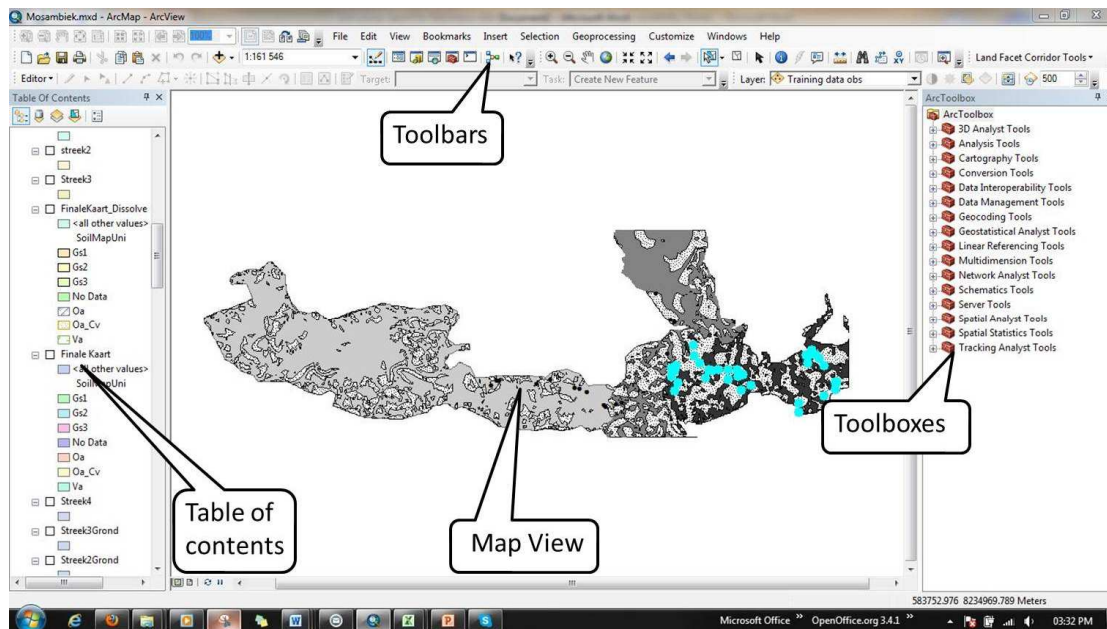
Figure A1.1: The basic interface of ArcGIS.

1.2: Importing layers into ArcGIS

In ArcGIS it is the easiest of all the software that are used to import layers, as it can accommodate nearly all file types. Left click on the icon with a black plus over the yellow layer (FigureA1.2) and select the layer required.
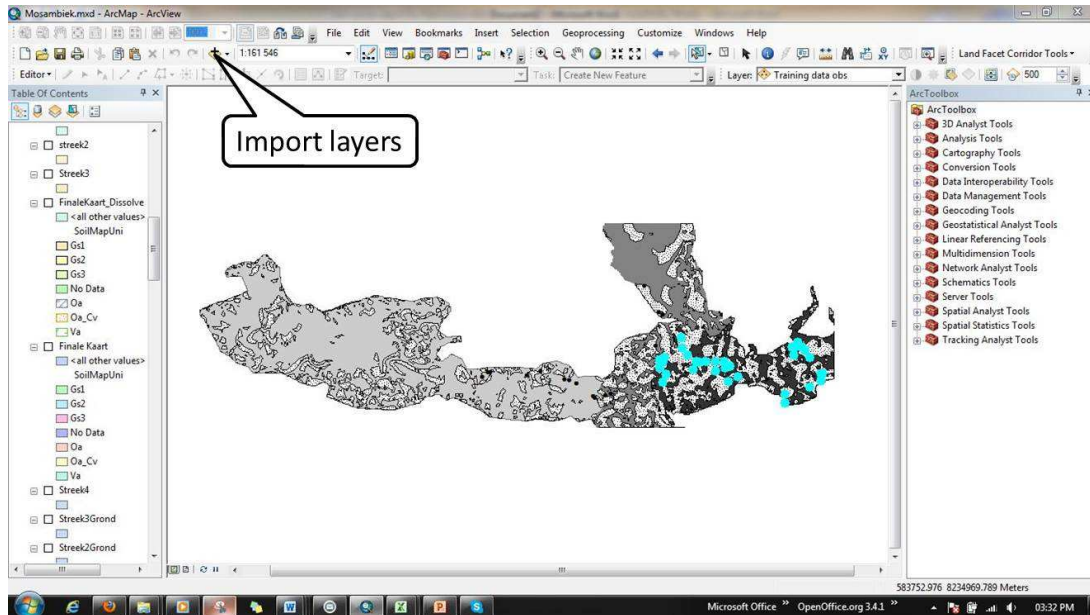
Figure A1.2: Import layers.

1.3: Project layers

Using a uniform projection enables multiple datasets to be used. To re-project a raster layer, use the 'Data Management Tools' – 'Projections and Transformation' – 'Raster' – 'Project Raster' toolbox. To re-project a shapefile use the 'Data Management Tools' – 'Projections and Transformation' – 'Feature – Project' toolbox. The dialogue screen that will appear (Figure A1.3) is similar for projecting both rasters and shapefiles.
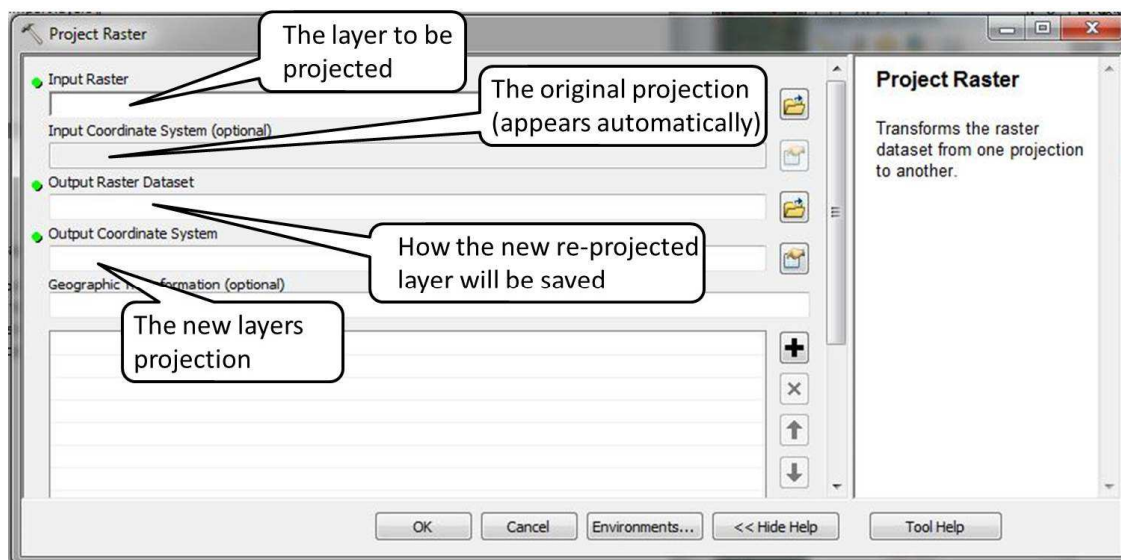
Figure A1.3: The re-projection dialogue window.

A projection where the coordinates are in meters should be used. In South Africa, WGS_1984_UTM_Zone_36S is a good projection to use. When the coordinates are in degrees, the coordinate system used is usually GCS_WGS_1984. ESRI provides a good tutorial on understanding map projections. It is available at:

http://downloads2.esri.com/support/documentation/ao_/710Understanding_Map_Projections.pdf

1.4: Drawing polygons by hand

To divide the area into HA's, one needs the boundary of the area as a shapefile, which is usually provided by the client. One way to create a duplicate boundary shapefile is to use the 'Conversion Tools' – 'To Shapefile' – 'Feature Class To Shapefile' toolbox. To divide this duplicate boundary shapefile into HA's it needs to be edited. This is done with the 'Editor Toolbar' (Figure A1.4) (Right click on any toolbar and select the 'Editor Toolbar' from the dropdown menu to activate it).
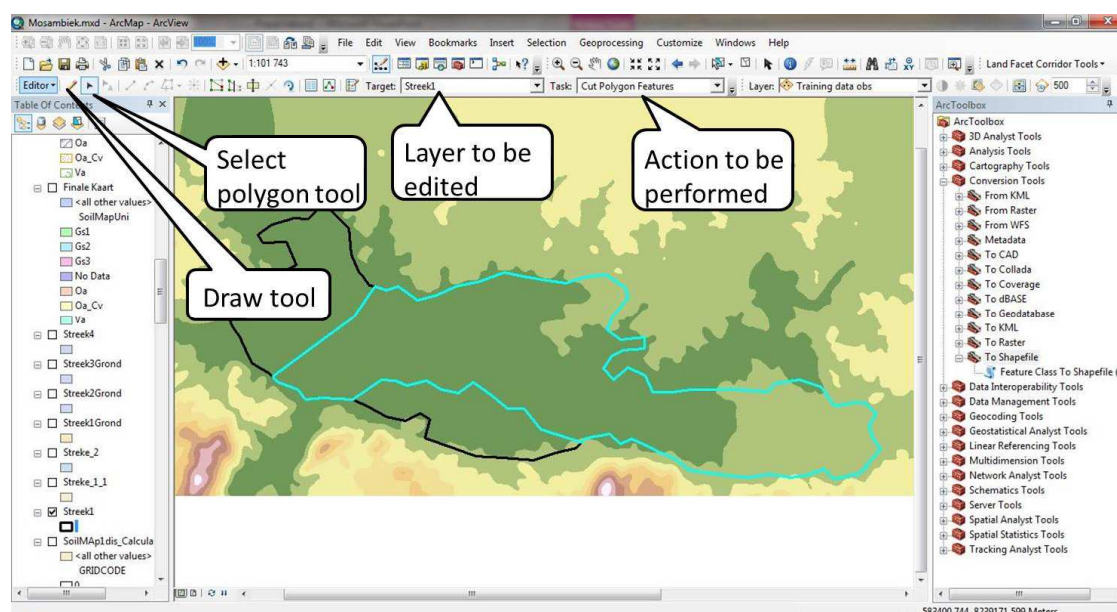
FigureA1.4: The Editor Toolbar.

Left click on the down arrow next to the word 'Editor', and left click on 'Start Editing' button in the drop down menu. Make sure the desired layer is in the 'Layer to be edited' box, and that the 'Action to be performed' is 'Cut Polygon Features'. Then select the polygon to be cut with the 'Select polygon tool'. Left click on 'Draw tool' and divide the desired polygon into smaller units by left clicking where one wants to divide the polygon. One has to start and end by clicking on the outside of the polygon being divided.

1.5: Convert raster to polygon

To convert a raster layer to a polygon layer, use the 'Conversion Tools' – 'From Raster' – 'Raster To Polygon' toolbox (Figure A1.5). Name the raster being converted, the field by which conversion takes place and how the new shapefile is saved.
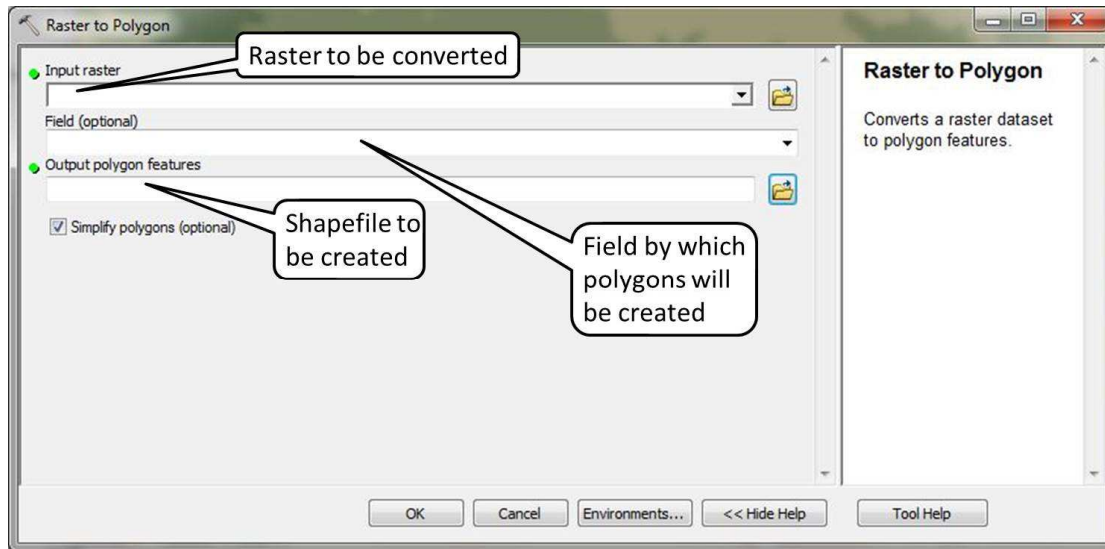
Figure A1.5: Raster to Polygon dialogue window.

1.6. Convert polygon to raster

To convert a polygon shapefile to a raster, use the 'Conversion tools' – 'To Raster' – 'Polygon To Raster' toolbox. In the dialogue window (Figure A1.6), enter the shapefile to be converted, the field from which the new raster's *z* value is determined, and where and as what the new raster is saved. One can specify the method by which pixel values are assigned ('Cell_Center' works well) and the new raster's resolution. Enter a resolution which is the same as the soil map's resolution.
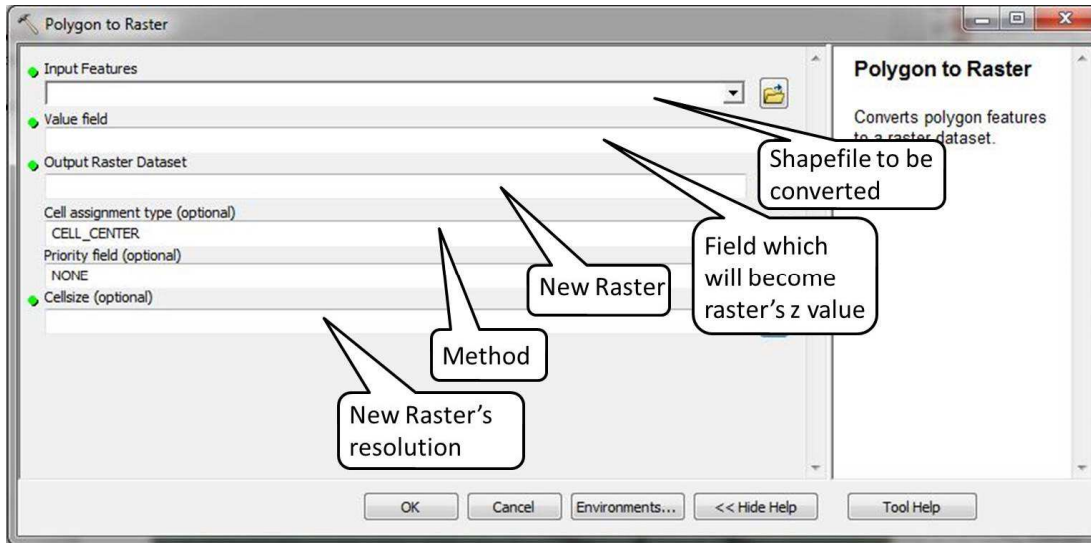
Figure A1.6: The 'Polygon To Raster' dialogue window.

1.7. Convert rasters to Ascii

To convert a raster file to Ascii file, use the 'Conversion Tools' – 'From Raster' – 'Raster to Ascii' toolbox. In the dialogue window (Figure A1.7), enter the raster to be converted and where and how the new Ascii file is saved.
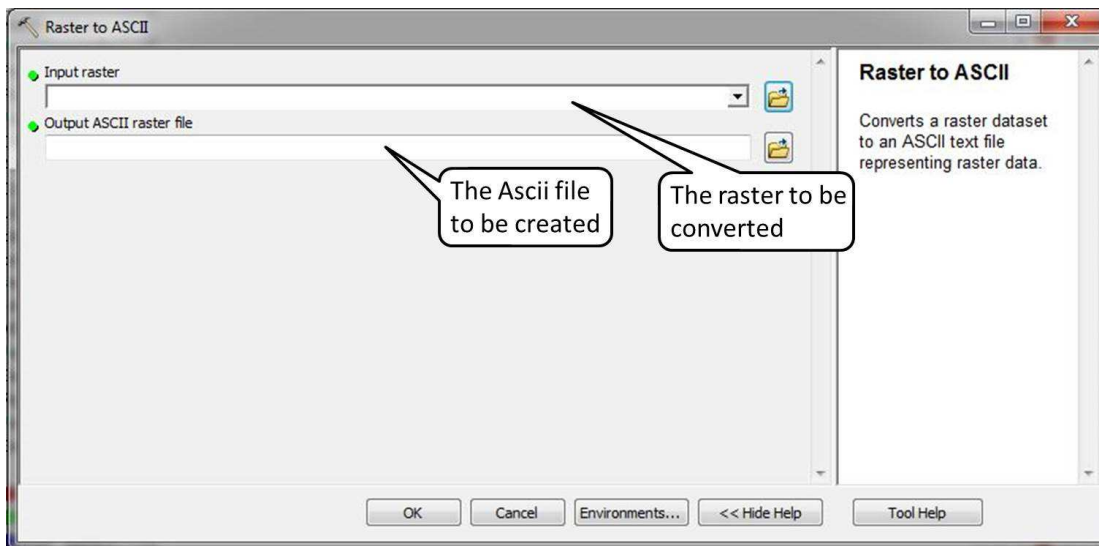
Figure A1.7: The 'Raster to Ascii' dialogue window.

1.8. Converting a text file to a shapefile

Firstly, convert the text file (.txt) to a Microsoft Excel file (.xls) by simply saving it as an '.xls' file, using the 'save as' command. Then import the sheet into ArcGIS (Appendix 1.2). The Excel sheet will appear as a layer in the 'Table of Contents' part of the ArcGIS interface, but not on the map. Right click on the layer in the 'Table of Contents' and select 'Display XY Data'. Set the columns for the X and Y coordinates and choose the coordinate system and then left click on 'OK'. The points will appear as a new layer in the 'Table of Contents' and in the 'Map View'. Right click on the new layer (its name is in the format: 'oldname Events'), and select 'Data' – 'Export Data'. In the following dialogue window select the location and name of the shapefile being created. After creating the shapefile, a pop up window will appear, asking: 'Do you want to add the exported data to the map as a layer?' Left click on 'Yes'. The shapefile will appear in the 'Table of Contents' and in the 'Map View'.

Appendix 2: SAGA

2.1: SAGA interface

The SAGA interface is shown in Figure A2.1. At the top are toolbars where some commands for the maps can be performed. At the left is the 'Workspace Window', where one can toggle between the 'Modules', 'Data' and 'Maps' menu's. Modules are similar to toolboxes in ArcGIS and are referred to the most in the appendices. In the 'Data' menu, all the data layers are shown while the 'Maps' menu contains the layers of the different maps (multiple sets of maps can be open). To the right is the 'Object Window', where properties of the layers can be seen and at the bottom, in the 'Message Window' the tasks which are performed are shown.

Raster layers (as used in this research and in ArcGIS), are called grids in SAGA. SAGA also groups the grids based on the grid system to which they belong to. The grid system is determined by the grid extent and resolution.
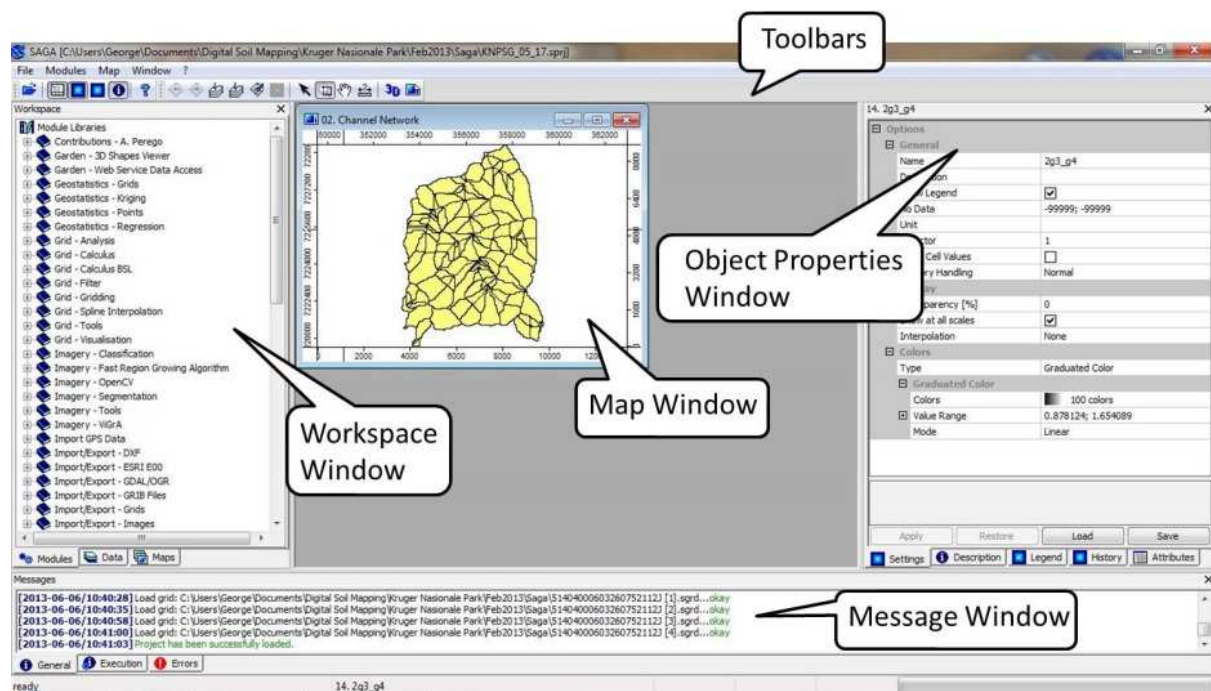
Figure A2.1: The SAGA interface.

2.2: Import layers into SAGA

The easiest way to import raster layers into SAGA is to convert them to Ascii files in ArcGIS (Appendix 1.7) and then import the file using the 'Import/Export – GDAL/OGR' – 'GDAL: Import Raster' module. The 'Import Raster' dialogue window is shown in Figure A2.2. Left click on the three dots on the right and

select the file to be imported. If the three dots do not appear, left click in the bigger block around the area where they should appear, and they will.
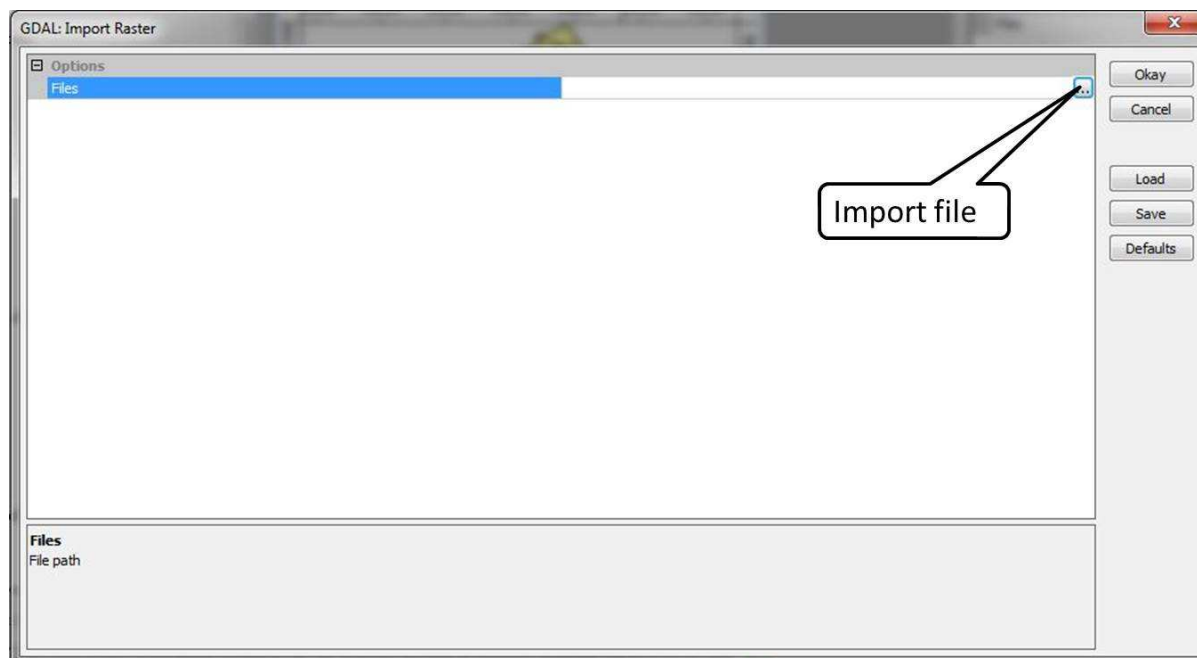
Figure A2.2: The 'Import Raster' dialogue window.

To import a shapefile, use the module 'Import/Export – GDAL/OGR' – 'OGRL: Import Vector Data', the dialogue window is the same as the 'Import Raster' dialogue window.

2.3 Resampling

Resampling of rasters allows for the raster extent and resolution to be changed. To do this, use the 'Grid – Tools' – 'Resampling' module. In the following dialogue window (Figure A2.3) set the grid system, target grid, additional grids and the new grid system. When keeping the new grid system as 'user defined' a new dialogue window will appear where the extent and resolution of the new grid can be set. If it is changed to 'grid' a grid to which the new grid system will be set must be chosen.
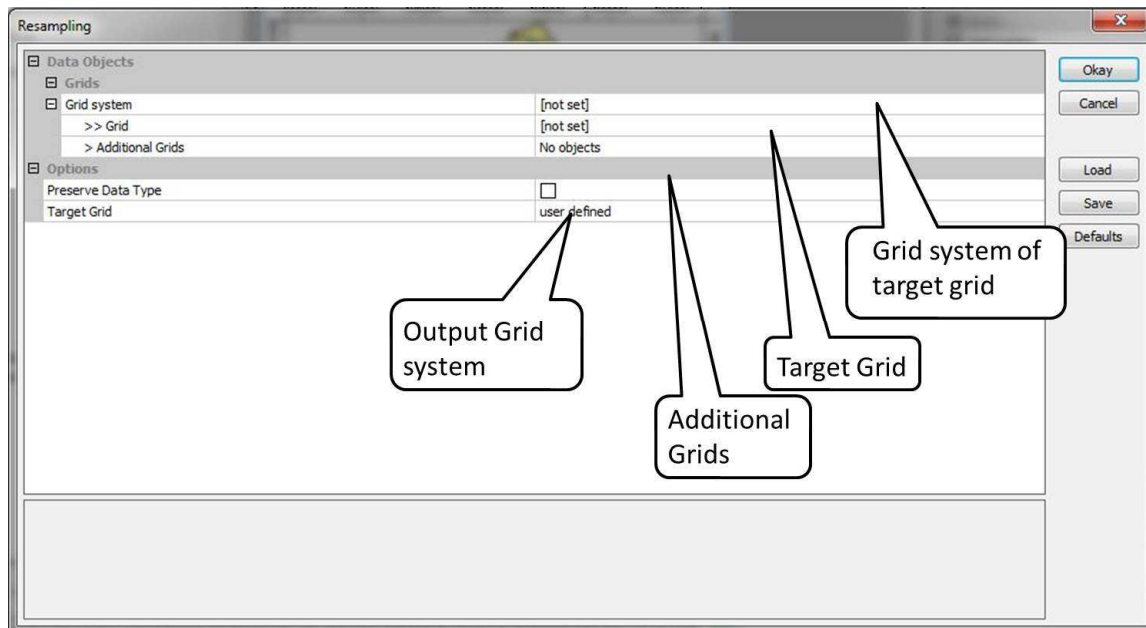
Figure A2.3: The 'Resampling' dialogue window.

2.4: Terrain derivatives

Although an array of terrain derivatives can be derived, in this research the 'Terrain Analysis – Compound Analyses' – 'Basic Terrain Analysis' module are used. In the dialogue window (Figure A2.4), the input grid system and DEM need to be entered. Thirteen terrain variable layers are derived.
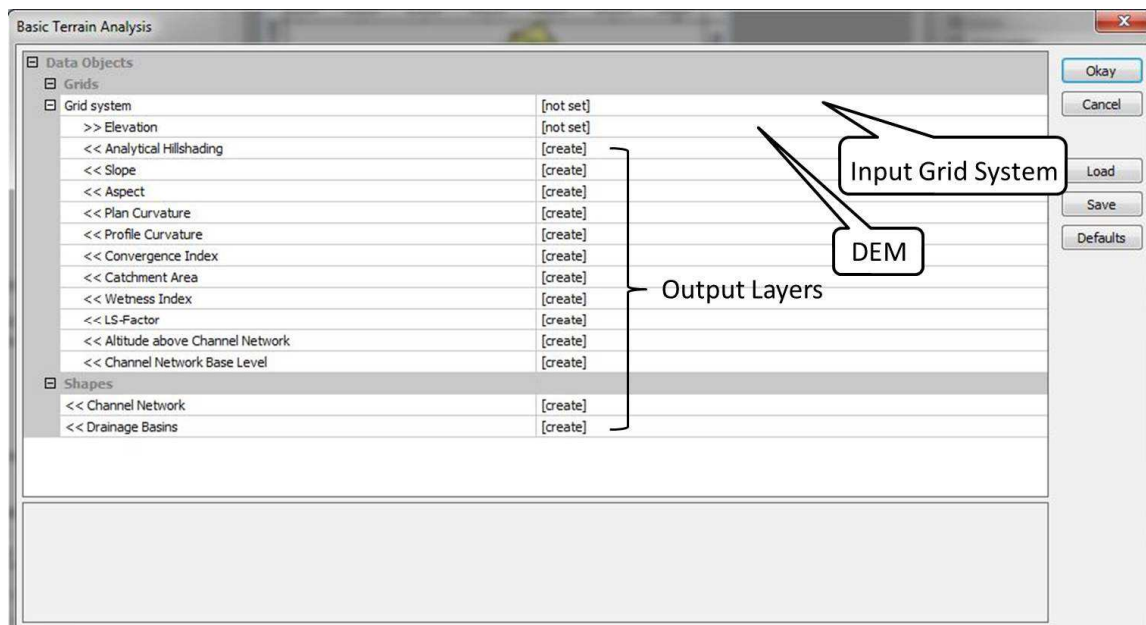

Figure A2.4: The 'Basic Terrain Analysis' dialogue window.

2.5: Mathematical manipulation

The module 'Grid-Calculus' – 'Grid Calculator' allows the mathematical manipulation of grids. In the example dialogue window (Figure A2.5), the NDVI is calculated. The inputs needed are the input grid system, the input grids and the equation which needs to be performed. Set the new created grid to '[create]', and enter a name for the new grid. In the formula, g1 refers to the first entered grid, g2 to the second entered grid and so forth.
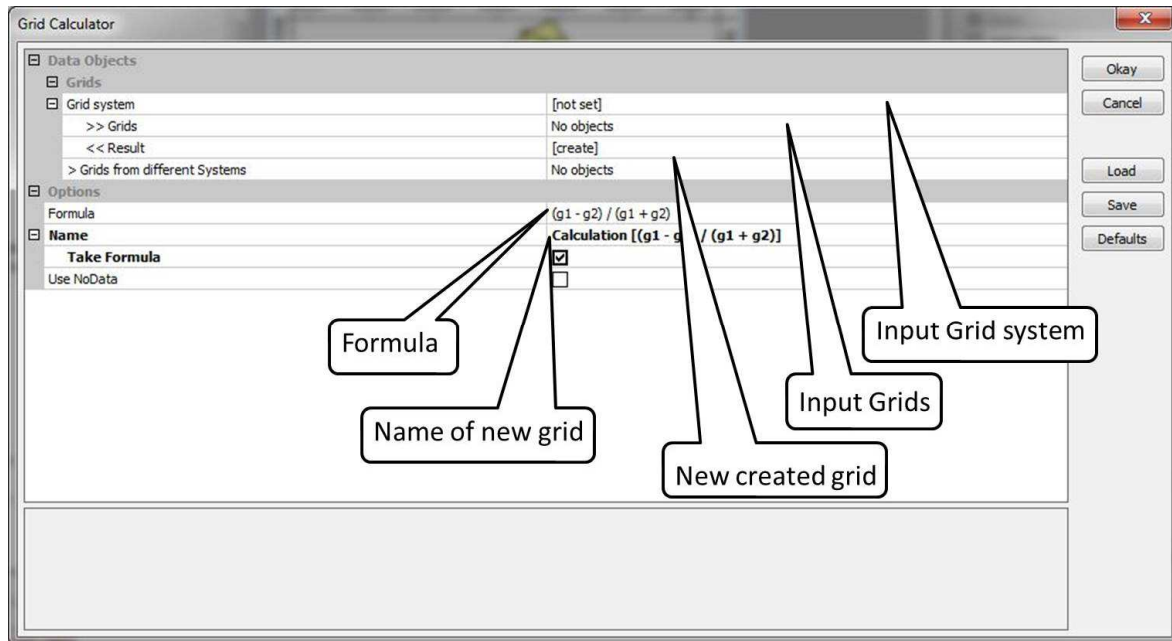
Figure A2.5: The 'Grid Calculator' dialogue window.

2.6 Principal component analysis (PCA)

To perform PCA use the 'Geostatistics – Grids' – 'Principle Component Analysis' module. In the dialogue window (Figure A2.6), specify the input grid system, the input grids and the number of components in the output. Each component is created as a separate covariate layer. The method to determine the PCA can be stipulated. In this research the default method was used.
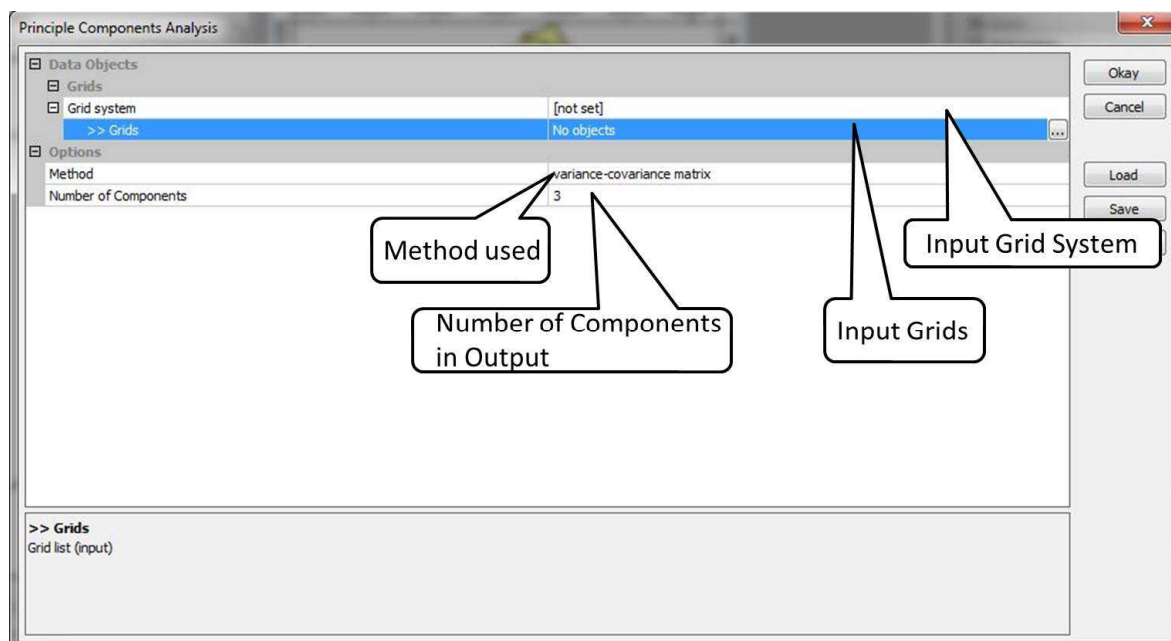
Figure A2.6: The 'Principal Component Analysis' dialogue window.

2.7 Adding covariate values to point data

To add covariate layers values to a point shapefile, the 'Shapes- Grid' – 'Add Grid Values to Points' module is used. In the dialogue window (Figure A2.7) the points to which the covariate values are added and the grids which values are added must be set. Set the output shapefile to '[create]' and the method used to 'Nearest Neighbor'. A point shapefile is created with the covariate values added in the attribute table.
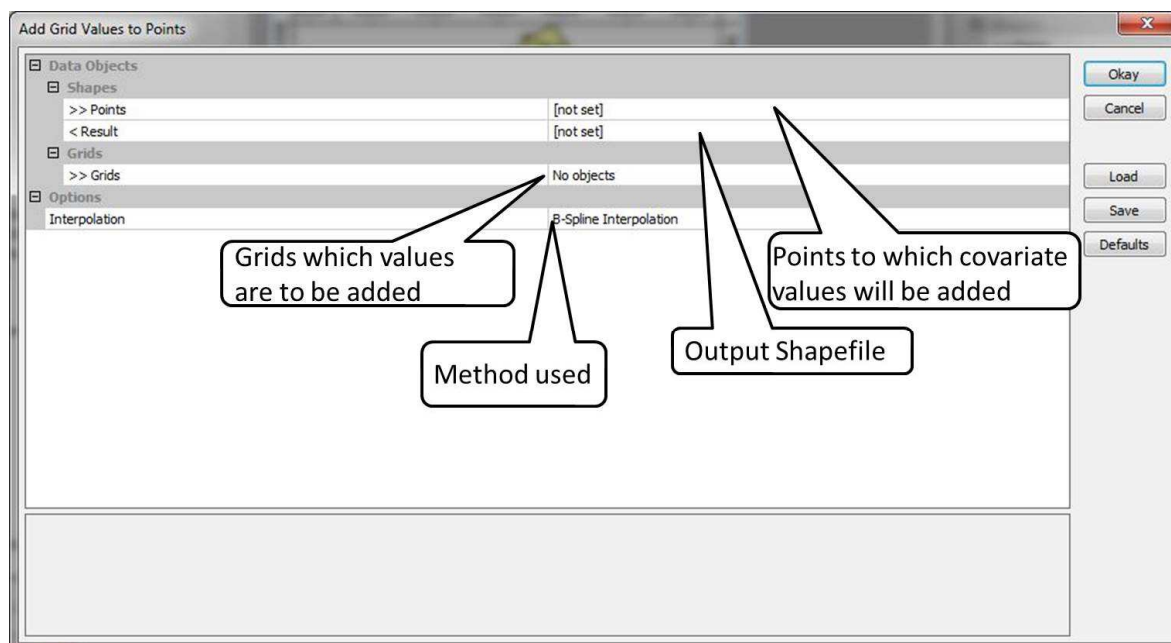
Figure A2.7: The 'Add Grid Values to Points' dialogue window.

2.8 Filter

To filter small map units into larger ones, use the 'Grid – Filter' – 'Majority Filter' module. In the dialogue window enter the input grid system and grid. Set the output grid to '[create]'. The search mode establishes whether the search mode is square or circular. The pixel radius determines how many pixels are included in the smoothing. The larger the pixel radius, the larger the size of SMU's which are incorporated into other SMU's. The threshold sets a percentage which influences how much detail is retained. A larger percentage allows for more detail to be retained and a lower percentage for a smoother output. In Chapter 6 a square search mode was used with a pixel radius of 2 and a threshold percentage of 20.
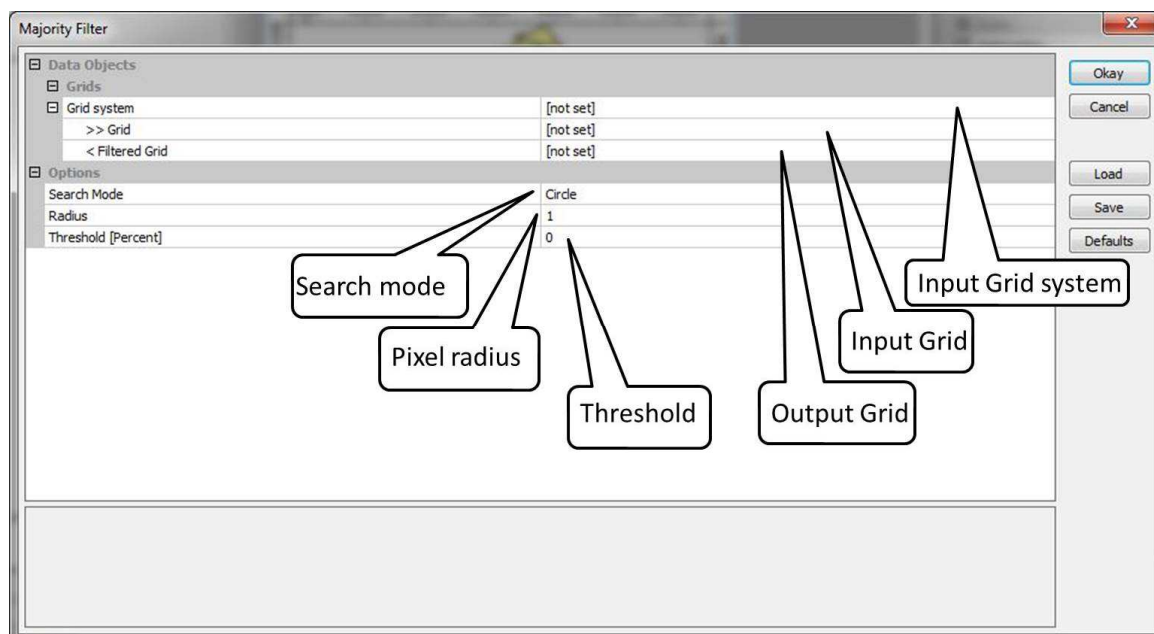
Figure A2.8: The 'Majority Filter' dialogue window.

2.9: Export Grid to XYZ

As input for the cLHS, the input grids must be in a text file format (.txt). Use the 'Import/Export – Grids' – 'Export Grid to XYZ' to do this. The input grid system and input grids must be specified, and an output file name can be chosen.
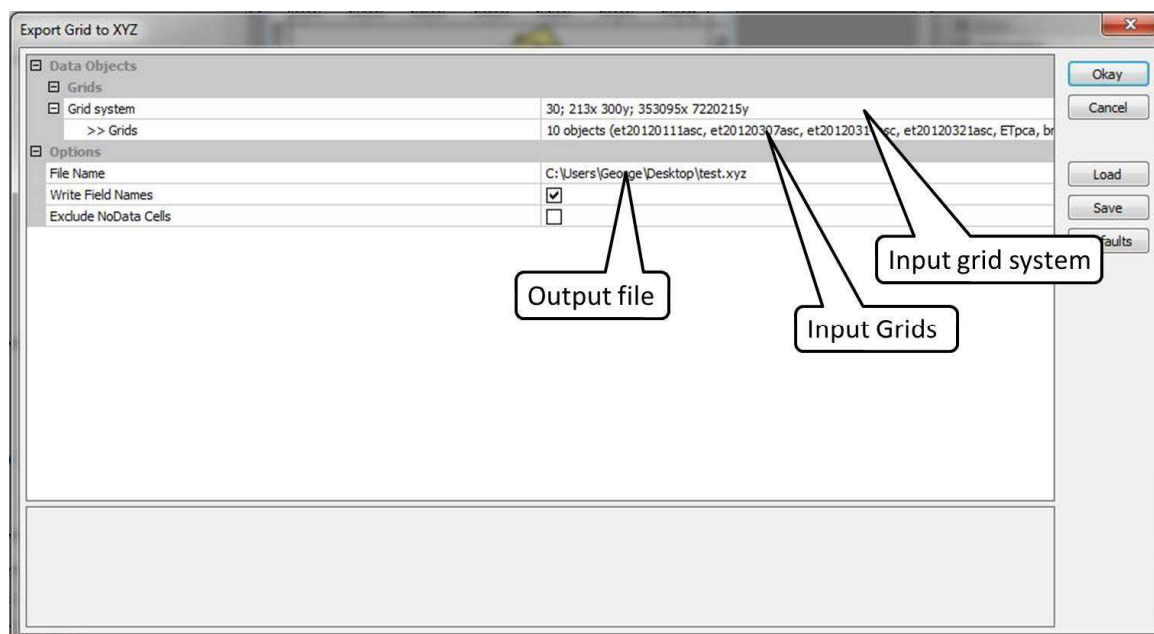

Figure A2.9: The 'Export Grid to XYZ' dialogue window.

Appendix 3: Conditioned Latin hypercube sampling (cLHS).

Within the cLHS file, one would find the files such as in Figure A3.1. All inputs must be set to correlate with the names given in the clhs_input.txt file (Figure A3.2). The 'infile' is the file where all the grid data is, which was created in Appendix 2.9. The 'outfile' is the output grid file and 'nvar' is the number of grids included in the 'infile'. 'nsam' is the desired number of observations and 'icord' must be set to 1. Leave 'w1', 'w2' and 'tfactr' as they are. The number of iterations is set with 'niter'. In this research a value of 20 000 was used.
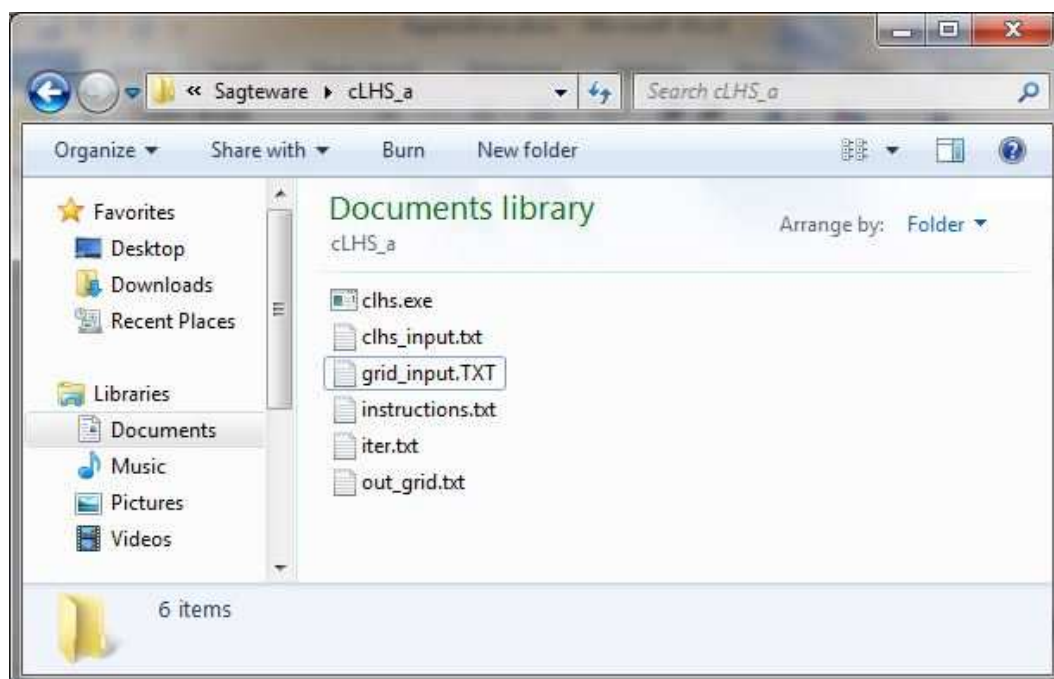

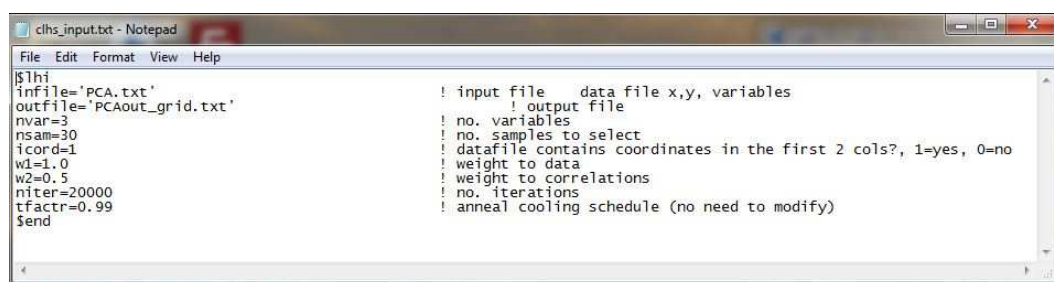**Figure A3.1: The files included in the cLHS file.**

Figure A3.2: The 'clhs_input.txt' window.

After entering the data in the 'clhs_input' file, the file should be saved. Then click on the 'clhs.exe' icon in the cLHS file (Figure A3.1). The program will run and the output occur as the 'outfile' specified in the 'clhs_input.txt' window. To create a shapefile from the data, refer to Appendix 1.8.

Appendix 4: SoLIM

The functionality of SoLIM is explained beautifully in the 'Quick Tutorial' which is included in the help manual. The help manual goes with the SoLIM 2010 program. Refer to this document when starting out on SoLIM. Appendix 4.1 explains how to export maps created in SoLIM.

4.1. Exporting maps from SoLIM

SoLIM derives products in the '.3dr' SoLIM format. To view these maps in ArcGIS, it needs to be converted back to an Ascii file. On the 'Menu Toolbar' (Figure A4.1) left click on the 'Utilities' button and then in the drop down menu select 'Data Format Conversion' – '3dr -> Grid Ascii'. In the following dialogue window, the 'Input File' is the map created by SoLIM, and the 'Output File' is the name of the new Ascii file being created. Left click on 'OK' and the map will be converted to the Ascii format. This file can be opened in ArcMap and SAGA by following the import instructions in Appendix 1.2 or 2.2.
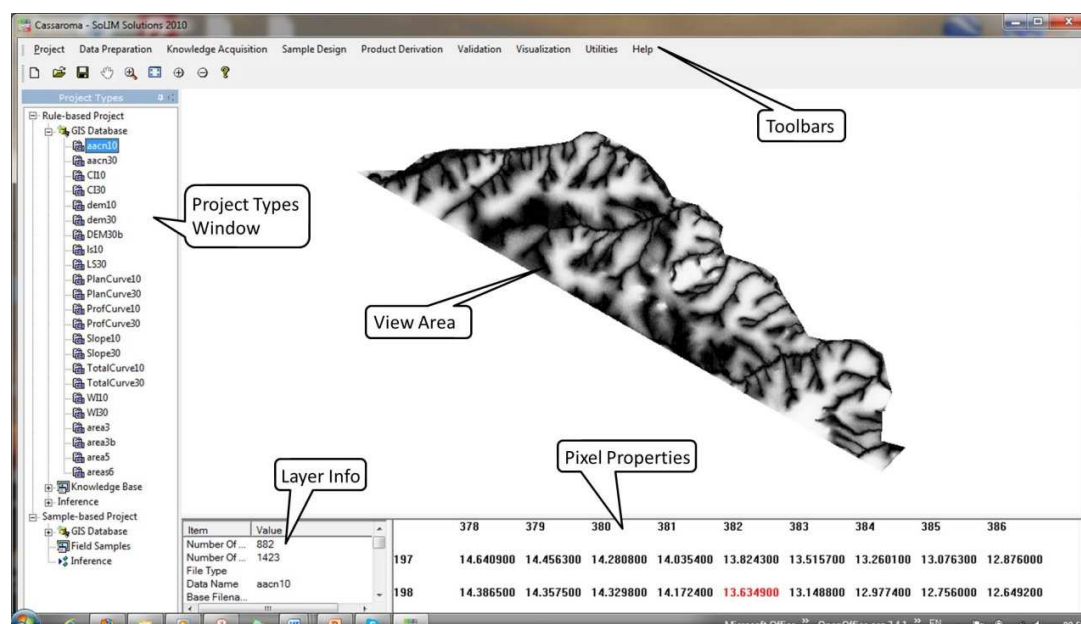

Figure A4.1: The SoLIM interface.