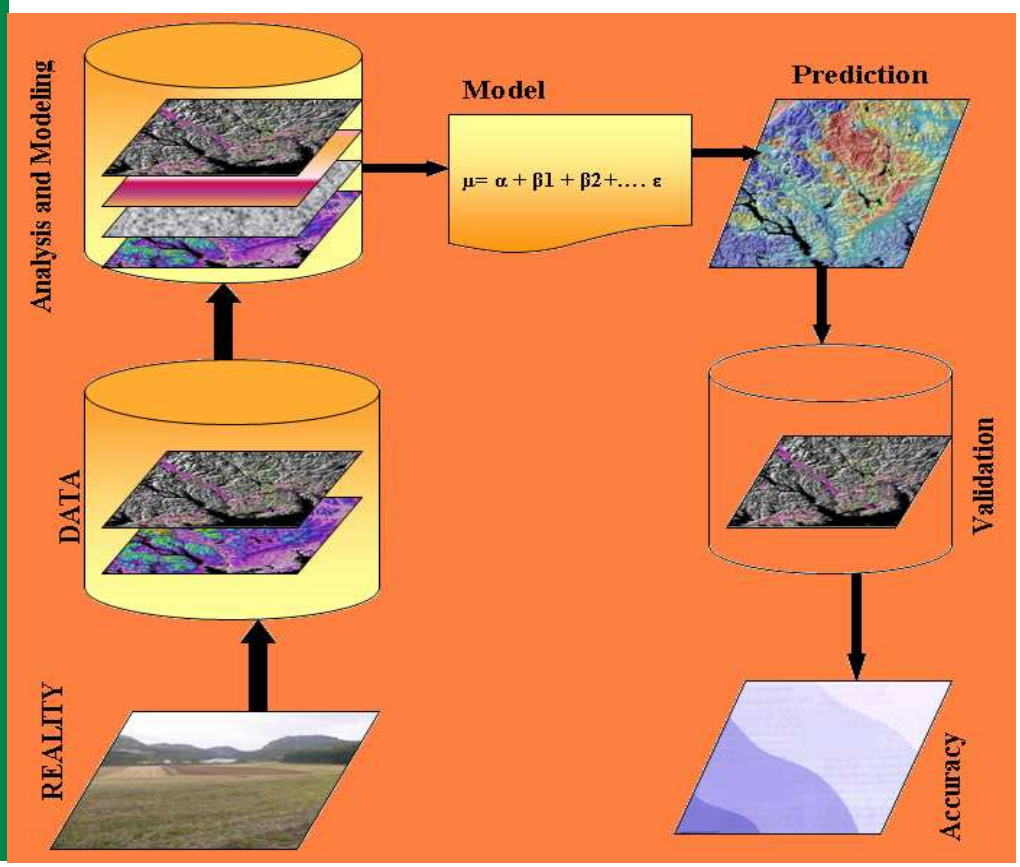
Master Thesis in Geosciences

# The Application of Digital Terrain Analysis for Digital Soil Mapping

*Examples from Vestfold County, South-Eastern Norway*

**Misganu Debella-Gilo**




UNIVERSITY OF OSLO
FACULTY OF MATHEMATICS AND NATURAL SCIENCES

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Misganu Debella-Gilo

Master Thesis in Geosciences

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Faculty of Mathematics and Natural Sciences

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Tutor(s): Prof. Dr. Bernd Etzelmuller (Geosciences, UiO)
Mr. Ove Klakegg (Norwegian Institute of Forest and Landscape)
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## Summary

Digital terrain modeling has revolutionized the way topography is characterized and analyzed. Its applicability has widened to almost anything where topography has a role to play. On the other hand, digital soil mapping has become the pedological paradigm of the time as it is making tremendous improvements in the ways soil information is obtained, stored, retrieved and manipulated. This research was conducted in Vestfold County of south-eastern Norway to use digital terrain analysis aided by statistical modeling and remote sensing image classification algorithms to make digital soil maps.

A digital elevation model of 25 meter resolution and digitized soil map of part of the study area accompanied by data on some analytical properties of soils were used as original data for the terrain and soil respectively. Fifteen terrain attributes were derived from the digital elevation model through digital terrain analysis. There were thirteen WRB soil classes in the surveyed area of the study site. Besides, five most important topsoil properties (the soils content of Clay, Organic carbon, Keldjahl's Nitrogen, $KNHO_3^-$ and pH) for limited number of soil profiles were also used.

The relationship between soil properties and the terrain attributes were analyzed using multiple linear regression in SPSS. The significant regression models were then fed into ARCGIS to predict the spatial distribution of the soil properties. The performance of this prediction was evaluated by comparing it with validation-based ordinary kriging interpolation of the soil properties, which was conducted in ARCGIS. The prediction of soil classes using digital terrain analysis was conducted using two conceptually different approaches. First, soil classes were considered as discrete objects and analysis of variance was used to check if there was significant difference among them in their terrain attribute values. Then, in analogy with satellite image channels, the terrain attributes were used as channels and object-oriented supervised classification algorithm was applied in eCgnition by collecting training areas from the reference soil map. To know the relative performance of this object-oriented approach, ordinary pixel-based supervised classification was conducted in ARCGIS using the same training areas. Second, the spatial variation of soil classes was conceptualized as gradual and fuzzy logic approach was employed for the prediction. Here, the relationship between the soil classes and the terrain attributes was first modeled using multinomial logistic regression in SPSS to identify the most influential terrain attributes and to construct logit models for each soil class. The logit models were used to derive probability prediction models which were then used in ARCGIS to predict the probability of existence of each of the soil classes as fuzzy variables. The reliability of this approach was evaluated qualitatively using expert knowledge, empirical soil map of the area and theoretical background of the soil classes, and quantitatively through correlation study of the probability values.

The result from the spatial prediction of topsoil properties using terrain attribute showed that the approach predicted topsoil clay content, KHNO3 content and extractible nitrogen content with better accuracy compared to the validation-based ordinary kriging. Besides, it showed that about 60% of each of their spatial variation can be attributed to terrain. On the other hand, insignificant correlation was found between the terrain attributes and organic carbon content and pH of the soils of the area.

All of the terrain attributes, with the exception of plan curvature, were found significantly influential in the spatial distribution of soils both by the ANOVA and the logistic regression analysis. Elevation, flow length, duration of daily direct solar radiation, slope, aspect and topographic wetness index were found to be the most significant terrain attributes. The crisp approach to the prediction of soil classes showed that the object-oriented approach performed better than the pixel-based terrain classification approach. The overall accuracy for the object-oriented approach was 30% while it was only 14% for the pixel-based. However, the accuracies of some soil classes reached up to 75% in the first approach. Higher accuracies were obtained for soil classes with higher spatial coverage in the area. The probability prediction for each soil class using logit models was found to be reliable when evaluated against the empirical soil maps except for those soil classes which are not greatly influenced by topography but by other factors such as human activity.

In general, the study revealed that digital terrain analysis has a great potential in digital mapping of soils and their properties. Fuzzy probability mapping and object-oriented approach were found to be reliable to a considerable extent in the prediction of soil classes and deserve further research and application.

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# 1 INTRODUCTION

## 1.1 Problem Statement

Digital Terrain Modelling has long replaced the qualitative and nominal characterisation of topography. It has shown its comparative advantages in that it gives quantitative measurement of elevation, enables to derive any other terrain attribute quantitatively, enables to visualise topography in more realistic way than ever before, and enables to store, update, proliferate and manipulate topographic data digitally (Li et al., 2005; Moore et al., 1993; Wilson and Gallant, 2000a). It further provides the possibility of deriving indices that can be used as indicators for environmental processes (Pike, 1988; Wilson and Gallant, 2000b).

On the other hand, the role topography plays in bio-physical processes and phenomena is increasingly unravelled. One of such bio-physical process is pedogenesis, i.e. the soil formation process. Due to the fact that topography influences endogenic and exogenic soil forming factors and processes, it plays crucial role in the spatial distribution of soils and their properties (Lark and Bolam, 1997; Schaetzl and Anderson, 2005). This is even more so in high latitude regions such as Norway.

Furthermore, the characterisation and investigation of the spatial distribution of soils and their properties, i.e. soil survey, is advancing due to the increasing need for knowledge about soils, triggered by their importance in the environmental well-being and agricultural activities. The conventional field investigation and laboratory analysis of soils at every site is becoming increasingly unaffordable in terms of financial cost, time, data deliverability, etc. That is why other paradigms such as pedometrics and digital soil mapping are widening their scope and depending their applicability (McBratney et al., 2003).

However, only few countries have made considerable transition to digital soil mapping. What has become more common is digitizing already available soil maps rather than digital approach to soil mapping. Norway is one of the few European countries that lack detailed soil information (Dobos et al., 2006). This might be partly due to the fact that agricultural activities and its environmental consequences are minimal as only 3 percent of the land area is used for agriculture (Solbakken et al., 2006). However, the rise in demand for detailed knowledge of soils at relatively low-cost from the public services is triggering the need for rapid, reliable and updatable soil information system.

Pedometrics and digital soil mapping involve the use of some soil data and auxiliary data on the biophysical factors such as topography, geology, climate, etc to predict soils and their properties (Dobos et al., 2006). On the other hand, digital terrain analysis enables to derive attributes that contain topographic information and indicators for other factors such as moisture, temperature and radiation implicating that it can provide most of the auxiliary data needed for the prediction. Such capability of digital terrain analysis and the increasing demand for reliable and readily distributable soil information make the application of digital terrain analysis for digital soil mapping a predetermined destiny.

Therefore, this thesis explored those technical possibilities in digital terrain modelling and demands for, and knowledge gaps in, digital soil mapping to investigate the possibility of using digital terrain analysis in the spatial prediction of some soil properties and soil classes. The study was conducted in Vestfold County, southern-eastern region of Norway, where there are relatively more agricultural activities, more environmental concerns, and where soil information is consequently more important.

## 1.2 Objectives and Research Questions

The major aim of this research was to make digital map of soil classes and soil properties through spatial prediction by using digital terrain analysis aided by statistical modelling and automated classification algorithms. To achieve this major goal, a number of specific research questions had to be answered. These were:

- Is there correlation between soil properties and terrain attributes? The general concept that soil properties and topography are related is a long established fact. However, the particular relationship that exists between a given soil property and a given terrain attribute is complicated because it varies across space and over time. Besides, the quantitative relationship is a relatively less studied matter. Thus, the aim here was to study the relationship between some topsoil properties and terrain attributes quantitatively.

- Is it possible to spatially predict soil properties from terrain attributes? To tackle the expensive and time consuming measurement of soil properties at every site, predictive approaches are used very often. Most of the known predictive methods are interpolation (such as kriging) and pedotransfer functions that enable to derive one soil property from others. But, the question here was: If the relationship between terrain attributes and soil properties could be established, isn't it possible, and even better than the other approaches, to predict soil properties from terrain attributes?
- Are different soil types located under significantly different terrain characteristics? It is not just the soil properties that are known to be affected by topography, but the general soil type as well. However, what are the particular terrain attributes that significantly vary with soil types, at least for the particular study area?
- Is it possible to spatially predict soil types as discrete objects using automated terrain classification? Here, soil classes were perceived as discrete objects with spatially defined boundaries. The aim was then to know if these spatial soil objects could be related to terrain objects and if they could be predicted through classification of the terrain into soil-terrain objects using automated classification algorithms.
- Is it possible to spatially predict soil classes as fuzzy variables using digital terrain analysis? Refuting the notion that soil classes are discrete objects, this research question tried to address the issue of within soil unit uncertainty and approach the problem from the concept of gradual variation. The research goal here was then to predict the probability of the existence of a soil class at every site using digital terrain analysis aided by statistical modelling.

## 1.3 Scope and Layout of the Thesis

The springboard of this research was that since topography is known to have central role in influencing the existence, type and characteristics of soils, it is possible to quantitatively relate topographic attributes to soils and their properties and predict the spatial distribution of the later (McKenzie and Ryan, 1999; Thompson et al., 2006; Thwaites and Slater, 2000). The foundation of this principle is the morphometry-process relationship, which shows that surface processes are influenced by shape and size, i.e. morphometry, of the terrain (Etzelmüller and Sulebak, 2000).

The specific research questions of the thesis were as explained in the objectives section. However, its ultimate focuses were derivation of primary and secondary terrain attributes to fully and quantitatively characterise the topography of the area and to be able to make digital maps of soils and their properties based on just terrain information. Therefore, why and how the soil classes were created in the study area was not the focus of the study. It rather paid great deal of attention to as to how soils could be digitally mapped using terrain information and limited empirical soil information. It is well known that prediction of soil requires information on all soil forming factors. This research was not conducted with ignorance of that. It was rather aimed at determining how far one could go in using detailed terrain information to predict soils since the influence of other factors might, at least partly, be covered by terrain information. The lay out of the thesis is as follows.

The first chapter briefs the reader with the problem statement. It provides the background and the problems that led to this research idea. Besides, it states clearly what the objectives of the research were. This was supplemented by the research questions that this study tried to answer.

Chapter two explores the theoretical and empirical background of the research theme. It gives brief overview of the relationship between topography and soils after defining the two entities. It further explains the principles of digital terrain modelling and analysis. The chapter also introduces the most recent paradigms in soil survey, i.e. pedometrics and digital soil mapping. The roles that geomatics could play through its tools and techniques in digital soil mapping in particular and pedometrics in general have also been visited in this chapter. Since no geo-spatial analysis is without error, issues of uncertainties such as their sources and methods of estimation have also been explored in this chapter. This chapter is followed by Chapter three which introduces the study area. It describes the location, geology, climate, land use, and soils of the area briefly giving more attention to the definition of the soil classes of the area.

Chapter four gives detail step by step explanation of the methods and procedures used in this research. It starts with explaining the data set used and goes on by discussing the methods applied to tackle each of the research questions. Brief quantitative description of the methods is also given where necessary.

Chapter five presents the results of the research which includes tables, graphs, maps and text that explain the results of the study. It begins by giving quantitative characterisation of the terrain together with the uncertainties involved in the digital terrain modelling. The relationship between soil properties and terrain attributes follow with the prediction of the soil properties from terrain attributes. The prediction of soil classes from terrain attributes has been divided into the discrete and fuzzy approach. Accuracy estimates and reliability evaluation accompanied each result.

Chapter six gives explanation and reasoning to the results by connecting to theoretical and earlier empirical findings. The chapter is divided into two main sections. The first one reflects on the results focussing on the digital characterisation of the terrain, terrain and soil properties, and terrain and soil classes. The second section adds some general remarks that tried to connect the research outputs with practical applications.

Chapter seven concludes the whole thesis by extracting the main facts obtained from this study. It tries to answer the research questions posed in chapter one. The appendix and the CD-ROM attached give other information that could not be included in any part of this thesis but are believed to be of interest for the reader.

# 2 THEORETICAL AND EMPIRICAL BACKGROUND

## 2.1 The Soil-Terrain Relations

The soil topography relation is best understood when the two entities are defined first. Soil can be defined as the unconsolidated mineral or organic material on the surface and immediately beneath the surface of the earth that serves as a natural medium for the growth of land plants, that has been subjected to and shows effects of genetic and environmental factors of climatic, macro-and micro-organisms, conditioned by relief, acting on parent material on a period of time (USDA's NRCS: http://soils.usda.gov/education/facts/soil.html). This definition of soil by itself acknowledges the statement by Jenny (1941) that soil varies over space and time and is influenced by a range of environmental factors such as parent material, climate and topography.

Topography, sometimes known as landscape or relief, is a crucial factor in soil genesis because, with the exception of time, it modifies the role that the three other factors play in soil genesis (Brady and Weil, 2002). But, what exactly is topography? Hugget and Cheesman (2002) define topography more or less as the general configuration of the land surface and sea floor, including its relief and the location of its features, both natural and human-made. Basically it is described by locational and structural attributes. The main locational attributes are latitude, longitude and altitude. Where as, the structural attributes define the form of the land and are direct or indirect derivatives of the locational attributes. The major ones of them are slope, aspect, plan curvature, profile curvature, etc.

Topography plays both direct and indirect roles in surface and subsurface biophysical processes through its locational and structural attributes (Bell et al., 2000; Hugget and Cheesman, 2002; Wise, 2002). The direct impacts of the locational attributes becomes greater at greater scales such as regional and global, where as that of the structural attributes is already considerable at miner scales, especially at the toposcale (Burrough et al., 2001). All the discussions in this thesis with regard to topographic influences on soil are, therefore, implicitly at toposcale as the study is focused on the structural attributes

When a closer look at pedogenesis, i.e. soil formation process, and the role of each of the five environmental factors is taken, the soil-topography relation becomes more apparent. Investigation of the researches conducted on soil topographic relations (Crave and GascuelOdoux, 1997; Manning et al., 2001; McKenzie and Ryan, 1999; Webb et al., 1999; Webster, 2000), leads to the following three points which will become clearer with the subsequent discussions:

- First, topography dictates whether soil develops or does not develop at a given space;
- Second, if it develops, topography dictates the type of the soil;
- Third, even if the general soil type might be the same, topography affects the individual properties of the soil.

The first desirable condition for a soil to develop at a given space is the presence or absence of parent material (Brady and Weil, 2002; Schaetzl and Anderson, 2005). Decomposable organic material and/or weatherable inorganic materials have to first deposit in the area. This deposition takes place only if the topographic characteristics are suitable for deposition. Otherwise, the place may become a source of parent material for other places, itself being an erosion area. Once the parent materials start to deposit, pedogenic processes start to act on them. The type and the rate of these pedogenic processes are determined by environmental factors such as climate and organisms. Besides, just like any other process, pedogenic processes advance with time (Brady and Weil, 2002; Schaetzl and Anderson, 2005).

When we take the case of climatic influences, the major climatic components that play considerable role are precipitation, temperature and solar radiation as they influence decomposition of organic materials and weathering of minerals (Brady and Weil, 2002; Schaetzl and Anderson, 2005; Wakatsuki and Rasyidin, 1992). The spatial distribution of moisture and duration for which it prevails at a given space is dictated by the topographic characteristics of the area. The energy that comes from the sun, that is the source of radiation and heat, is not evenly distributed spatially and temporally. Its spatial distribution is related to the locational and structural attributes of topography (Hugget and Cheesman, 2002). This local variation in temperature, radiation and moisture regimes due to topography creates a kind of micro-climate (Hugget and Cheesman, 2002; Wilson and Gallant, 2000a)

Presence or absence and the type of macro- and micro-organisms, which are influenced by climatic conditions, influence the rate with which soils are formed, the type of soils that develop and the individual properties of the soils (Brady and Weil, 2002; Schaetzl and Anderson, 2005). The climatic and organic factors of soil formation are intertwined and are highly dictated by both the locational and structural attributes of topography. Consequently, other things being equal, 0the soils that might develop under the same macro-climatic zone vary immensely due to the fact that topography modifies climate and create a sort of micro-climate (Tromp-van Meerveld and McDonnell, 2006).

Most topographic attributes play significant role directly or indirectly in soil development as summarized by some researchers (Schaetzl and Anderson, 2005; Tromp-van Meerveld and McDonnell, 2006). All other things kept uniform, soils develop faster and deeper in flat areas compared to steep areas as their moisture regimes are favourable and materials tend to accumulate in flat areas but move away from steep areas. On the other hand, aspect modifies the influence of slope by exposing or obscuring the slope to and from solar radiation dictating the temperature and the moisture regimes. Curvature is as important as the slope because the concavity and convexity of the sloping area governs the storage and flow of water and solid materials over the slope.

Of the soil properties that vary spatially with topographic attributes, solum depth, horizon thickness, texture, moisture content, organic matter content, nutrient content, etc are the most important ones (Manning et al., 2001; Tromp-van Meerveld and McDonnell, 2006). The specific relationship between terrain attributes and soil properties is an issue still under continuous study. More precisely speaking, the quantitative functional relationships between terrain attributes and individual soil properties have not yet been established.

The fact that topography influences soil formation and soil properties has led to the development of the concept called the *soil-landform model*, .i.e. *the soil catena or the soil topo-sequence* (Schaetzl and Anderson, 2005). The concept is based on the principle that the continuous spatial variation of topographic features leads to a continuous spatial variation of soils, i.e. *the soil continuum*. The concept is complicated by the fact that soils are influenced by at least four other major factors than topography. The concept has, nonetheless, been helping in soil survey tasks. It has even been evolving to quantitative approaches and has consequently been part of the theoretical springboard of this research.

## *2.2* Digital Terrain Modelling and Analysis

### 2.2.1 Digital Terrain Modelling

In order to understand topography and its role in environmental processes and phenomena, there needs to be a technique for measuring, representing and characterising it reliably. On the other hand, measurement, representation and characterisation of such a vast and continuous feature are very challenging. Therefore, there needs to be a technique whereby the complexity is simplified and the vastness is scaled down. Such an objective is achieved through modelling. Modelling involves simplification and scaling down of reality to a comprehendible level with relative ease (Li et al., 2005).

There are many ways of modelling terrain, such as descriptive, pictorial, cartographic, physical and digital. Descriptive method simply involves describing topography using nominal terms of topographic parameters such as hills, hillslopes, valleys, concaves, convexes, undulating, steep, gentle, etc. The reality is then modelled only through mental perception. Pictorially, in the early days, painting was used to represent topography and accompanying features. Cartographic maps were later used for the same purpose especially with the invention of the topographic maps in the form of contours in the nineteenth century (Li et al., 2005). Physical modelling of topography is representation of terrain by physical objects as it is often used in the military. Digital modelling involves virtual realisation of terrain using computers (Li et al., 2005; Wilson and Gallant, 2000a).

An ideal terrain model is the one that can fully represent the reality of terrain. Although this is practically not possible to achieve, a good terrain model should have some desired qualities (Li et al., 2005; Pike, 1988; Wilson and Gallant, 2000a). First, it has to be able to give the perspective view of the physiography. Second, it has to be based on quantitative measurements. Third, it has to enable further quantitative analyses. Fourth, it should not be too complicated and too demanding. Fifth, it has to be duplicable and replicable. Such qualities are achieved through digital modelling since each of the others lack one or more of such qualities. As a result, the most common way of storing topographic information has now become the Digital Terrain Model (DTM) where elevation values, stream lines and other related terrain attributes are digitally stored together with their locational attributes (Li et al., 2005; Moore et al., 1993; Wilson and Gallant, 2000a).

The structure with which elevation is modelled digitally varies, and it has gone through transformations. Basically, there are three well-known data structures for terrain modelling which are explained in detail in (Hutchinson and Gallant, 2000; Li et al., 2005; Moore et al., 1993; Smith, 2005). The first one is the more traditional contour maps in which case elevation values are represented by isolines, i.e., lines connecting points of equal elevation values of fixed intervals that are digitized, stored and used to model topography. However, due to a number of reasons it is less favoured and less often used in digital terrain modelling although it is the most widely available terrain data source. It underrepresents areas between the contour lines. It is little suitable for further analysis. And, it is incompatible with other geographical data structures.

Another structure with which DTM represents topography is the Triangular Irregular Network (TIN). TIN is created by constructing a triangulation of the elevation data points, which form the vertices of the triangles, and then fitting local polynomial functions across each triangle (Wilson and Gallant, 2000a). This creates a very good result for visualization, requires less storage space and seems to represent the terrain more closely. However, triangulation methods are sensitive to the positions of the data points and the process needs to be constrained to produce optimal result. Besides, due to its rigidity in further analysis and its incompatibility with other spatial data structures it is less widely used.

The most widely favoured structure is the raster model where elevation values are represented by square grids of fixed size. This is easily used for further analysis and easily integrated with other spatial data structures (Hutchinson and Gallant, 2000; Moore et al., 1993; Wilson and Gallant, 2000a). This also does not come without drawbacks. First, the size of the grids often affects the storage requirements, computational efficiency and the quality of the result. Second, square grids can not handle abrupt changes in elevation easily, skipping important details. Third, the within grid variation is simply ignored.

The outcome of any model is dependent upon the original data that is used for the modelling. DTM is not an exception. The tools used for the capturing of numerical terrain data, too, have gone through tremendous progress (Hutchinson and Gallant, 2000; Wilson et al., 2000). Ground measurement of locational variables and some structural variables such as slope have been practically inadequate to cover large areas. The use of aerial photographs for civilian purposes brought in the art of photogrammetry as a tool for the measurement of topographic parameters. This technique has widely been used to capture topographic information at national levels around the world. However, the need for more accurate, faster, cheaper, reliable and repeatable method that can provide ready made numerical topographic information with global coverage has triggered the search for more advanced technologies. As a result, other air-borne and space-borne technologies have been brought in. To mention a few of such techniques: space borne optical satellites that employ photogrammetry, airborne radar and space-borne radar technologies that employ interferometry, airborne Lidar technology, global positioning system, etc. Although the desired qualities have not yet been achieved, they are on the progressive direction (Li et al., 2005) .

### 2.2.2 Digital Terrain Analysis

The mathematical analysis of terrain information including the derivation of the surface elevation data using computers is known as digital terrain analysis (Li et al., 2005; Pike Richard, 2000). In digital terrain analysis, the digitally stored elevation and other topographic features are used to derive other terrain attributes. The derivation of other attributes from elevation values is a follow up to the conversion of terrain information into a spatially connected surface data through interpolation or filtering depending on the data source (Li et al., 2005; Moore et al., 1993).

The terrain attributes are grouped into primary and secondary (Moore et al., 1993; Wilson and Gallant, 2000a). The primary terrain attributes are those which are directly derived from the elevation values, where as secondary terrain attributes, sometimes known as compound attributes, are those that are derived through functional combination of the primary terrain attributes. The main primary terrain attributes are surface derivates, slope, aspect, plan curvature, profile curvature, upslope contributing area, etc. The definitions and the ways they are derived are explained in depth by (Gallant and Wilson, 2000; Li et al., 2005; Moore et al., 1993) and are presented in table 4.1.

The terrain attributes so derived can be used to derive topographic indices that are indicators of pedological, geomorphological, hydrological, ecological and other surface and subsurface processes(Pike Richard, 2000; Wilson and Gallant, 2000b). These indices, i.e. the secondary topographic attributes, include topographic wetness index, sediment transport capacity index, the stream power index, the solar radiation index, etc. Their definition and methods of derivation are thoroughly discussed by (Moore et al., 1993; Wilson and Gallant, 2000a). Besides, both the primary and the secondary topographic attributes can be used to predict surface and subsurface processes. Derivation of both the primary and secondary terrain attributes is most often conducted using GIS tools based on the raster data structure.

### 2.2.3 Topographic Unit and Automated Terrain Classification

The fact that most of the environmental processes that take place on the surface of the earth vary with topography (Etzelmuller et al., 2001; Hugget and Cheesman, 2002; Moore et al., 1991), leads to the hypothesis that if processes vary when topography varies, they should remain uniform when topography is kept uniform. This leads to the goal of finding a unit in which topographic attributes do not vary significantly, and implicitly surface processes do not vary significantly as well.

The terms used for such a unit are many and confusing. Names such as landform unit, landscape element, landform element, land element, facet, etc are used. For example, Hugget and Cheesman (2002) used landform unit and landform element interchangeably and defined it as simply-curving geometric surfaces lacking inflections and are considered in relation to upslope, down slope and lateral elements. They also state that landform element is the same as facet and land element. Schmidt and Hewitt (2004) also define land element as small areas of land surface that are uniform in geomorphometric parameters such as slope, surface roughness, contour and profile curvature. Therefore, terms such as landform unit, landform element, land element and facet are geomorphometrically defined and are more or less the same.

Whatever the name might be, the idea here is to find a fundamental unit over which topographic variables, and implicitly surface processes too, do not vary significantly. However, it is known that most spatial processes and topographic attributes are continuous by nature and there is difficulty in setting boundaries. Although terrain is naturally continuous, discretisation simplifies the complication of the topographic attributes by using statistically set boundaries. The fact of the matter is that it is generally possible to create topographic unit using mixture of any of the topographic attributes. The question, however, is getting the topographically uniform unit which also indicates uniformity in process, i.e. form-process relation (Etzelmüller and Sulebak, 2000). If that is possible to identify, it might help to indirectly map processes through mapping topography.

Terrain classification has long been based on the qualitative description of the topographic attributes and the classes are also only of qualitative and nominal nature. Recently, the development of digital terrain analysis in GIS offered opportunity for quantitative and automated classification of terrain. As mentioned previously, topography is a continuous physical variable. Automated quantitative terrain classification in GIS provides the possibility of approaching the continuous nature of terrain in two ways. The first is classifying terrain into spatially discrete topographic units as stated earlier. The second approach is fuzzy classification to simulate the continuous reality of topography. In fuzzy classification terrain units may not be categorised into one terrain class, they are rather assigned with membership value expressing how much they belong to the given class (Schmidt and Hewitt, 2004).

Empirical attempts show that the outputs of terrain classification are dependent upon the algorithm used and the statistical rules set for the algorithms. Irvin et al. (1997) and Ventura and Irvin (2000) classified terrain into uniform units by applying the *iso-clustering* unsupervised classification algorithm using six terrain attributes as classification criteria. The result indicated that automated numerical classification classified terrain into more detail than the conventional qualitative method does. Moreno et al. (2005) also classified terrain automatically using GIS into land elements based on geomorphometry and concluded that it is less time consuming with a rewarding result compared to manual delineation of land elements, yet with unnecessarily too much detail. Such too much detail can be of advantage when further analysis is needed.

On the other hand, there are continuous classification attempts made based on the fuzzy logic theory (Irvin et al., 1997; Schmidt and Hewitt, 2004; Ventura and Irvin, 2000). In fuzzy classification topographic units are predefined and the whole area is classified based on numerical membership of each grid to each of the units. Therefore, a map is created for every landform unit depicting membership probability values of each pixel. Continuous classification provides more information about the character and variability of the topography compared to iso-clustering and manual delineation.

The advantages of the automated quantitative terrain classification over the conventional qualitative method are that: it can be more accurate if the data and parameters used for the classification are accurate, it can be used for quantitative studies of the relationship between topography and surface processes, it can easily be integrated into GIS, and it is readily transferable and interpretable. However, in both the discrete and continuous classification, the terrain attributes to be used as criteria for the classification have not yet been standardized. Besides, the terrain classes are expected to show some sort of process classes. The validity of the classification is thus dependent upon its ability in connecting to the variations in surface processes that are known to be affected by topography.

## *2.3* Pedometrics and Digital Soil Mapping

Soil is a *thematically* complex, *spatially* mosaic and *temporally* dynamic environmental variable. Therefore, ideally, its knowledge necessitates measurement of all soil properties, across all spaces continuously or periodically. However, reality does not allow such tasks due to technical, economical and logistic limitations. Consequently, what is practically possible is the measurement of some soil properties at selected sites at a given time or periodically. The big question is, then, how can we have knowledge about the rest of the soil properties at all other sites? Besides, how can we monitor them across time?

To tackle the above fundamental problems, researchers have come up with different approaches over time. By quantitatively modelling the relationships among the numerous soil properties, unmeasured soil properties could be predicted through pedotransfer functions (Shein and Arkhangel'skaya, 2006) thereby reducing the thematic complexity issue. Besides, spatial prediction of soil properties is most often dealt with through the combination of approaches such as interpolation, geostatistics and predictive modelling (Goovaerts, 1999; McBratney et al., 2000). Only few very dynamic soil properties such as soil moisture content and temperature are temporally monitored (Kang et al., 2000; Romano and Palladino, 2002). That might be due to the fact that the time span for the dynamism of some soil properties is too long for human life and that of others is too short and thus demand much material, time, finance and technique.

Most of the above approaches employ quantitative methods and deal with prediction, one way or another. Quantitative pedology was first proposed by Hans Jenny in the early 1940's (Jenny, 1941), although it peaked momentum in the 1960's. Such approaches have recently been re-disciplined under the umbrella of pedometrics. Pedometrics is defined as the application of mathematical and statistical methods for the study of the distribution and genesis of soils (Burrough, 1994). The term is analogous with geometry encompassing two Greek words, i.e. pedo means soil and metrics refers to measuring. The approaches of pedometrics are mathematical and statistical instead of the conventional field survey and qualitative modeling (Burrough, 1994; McBratney et al., 2000).

Any kind of spatially variable environmental object is best described through mapping. Mapping is a medium of communication that is concise, explicit and implicit at the same time. Soil is one of such environmental objects perceived as spatially variable. Consequently, soil mapping is an integral part of soil survey. There is a discipline called soil geography (pedogeography) that focuses on the location, distribution and pattern of soils on the landscape (Scull et al., 2003). However, the conventional approaches to soil geography have a number of drawbacks that needed to be dealt with. First, they rely on field observation and laboratory data on soils and their spatial extent, which are costly and slow to acquire (Schuler, 2006). Second, the outcomes have mostly been produced as paper maps which are not easily stored, replicated and distributed, and thus lack the quantitative aspects needed for interpretation and further uses. Third, in almost all cases, soil classes are treated as discrete objects and the spatial continuity of soils is not often taken into consideration.

Dealing with the above drawbacks of conventional soil mapping, the quantitative and predictive approaches of pedometrics combined with the advancements in the analytical capabilities of computers triggered the birth of digital soil mapping. Digital soil mapping has achieved such a global attention that a global working group that deals with promoting the approach has been setup (http://www.digitalsoilmapping.org). The European branch of this working group defines digital soil mapping as follows:

> *Digital soil mapping is the computer-assisted production of digital maps of soil type and soil properties. It typically implies use of mathematical and statistical models that combine information from soil observations with information contained in correlated environmental variables and remote sensing images (Dobos et al., 2006).*

In digital soil mapping, observed soil data and auxiliary data are integrated to predict soil properties and soil classes. The observed soil data may include soil profile description, laboratory data and soil classification. On the other hand, auxiliary data may include terrain parameters, remote sensing images, soil and other auxiliary maps. These are needed because soil mapping generally requires predefined model of soil formation and data on soil properties and other environmental variables that have significant impact on soil formation and thus on the spatial distribution of soils and their properties (McBratney et al., 2003). Nonetheless, digital soil mapping has advantages over digitizing soil maps as it avoids or minimizes the lengthy and costly procedures of field investigation and laboratory analysis.

There are different and numerous tools used in digital soil mapping. These are state-factor models, pedotransfer functions, geostatistics, statistically set empirical models, discrete and fuzzy classification, decision trees, artificial neural networks, etc (Behrens and Scholten, 2006; McBratney et al., 2003). Behrens et al. (2005) used artificial neural network to digitally map soil classes based on the digital data of geology, terrain and land use. They concluded that using data on relief, land use and geology artificial neural network has a very high predictive power. Behrens and Scholten (2006) reviewed digital soil mapping in Germany and state that the approach is reliable and can be used intensively. There are also other researches done on spatial prediction of soil properties such as organic carbon (Ping and Dobermann, 2006; Simbahan et al., 2006), pH, nitrogen, carbon, Phosphorous and clay content (Henderson et al., 2005). They also came up with encouragingly satisfactory results. However, since the approach is relatively new methodological aspects have not been well explored yet. Besides, only few selected terrain parameters were used in most of these studies. There needs to be inclusion of as many parameters as possible in the analysis. Besides, more predictive approaches need to be explored.

## 2.4 Geomatics in Digital Soil Mapping and Pedometrics

Dealing with spatial data needs tools that are well advanced in capturing, storing and analysing spatial data. That is just what geomatics is capable of doing. Geomatics is the discipline of gathering, storing, processing, and delivering of geographic information, or spatially referenced information (http://en.wikipedia.org/wiki/Geomatics#Overview). Due to such capabilities, geomatics plays central role in pedometrics in general and digital soil mapping in particular.

Techniques and tools employed by geomatics that are relevant to pedometrics and/or digital soil mapping are digital terrain analysis, remote sensing, Global positioning system, geostatistics, spatial analysis, etc. Global positioning system and remote sensing provide information about some of the environmental factors and their positions on the surface of the earth. Geostatistics and spatial statistics are tools used to establish and study the relationships among soil properties and between soil properties and environmental factors. On the other hand, digital terrain analysis provides data and analytical capabilities with respect to one of the most crucial environmental factors that influence soils and their properties, i.e. topography.

Of those tools used in geomatics, digital terrain analysis stands out because it is relevant to a well established conceptual model in pedometrics, i.e. the soil-landscape model. Earlier it has been discussed that primary and secondary topographic attributes can quantitatively be derived in geomatics through the process of digital terrain analysis. This terrain attributes are interesting because they affect soil development and other surface and subsurface processes (Etzelmuller et al., 2001; Florinsky et al., 2002; Moore et al., 1993; Wilson and Gallant, 2000a).

The terrain attributes in particular and digital terrain analyses in general are widely used in soil-landscape modeling which is central in spatial prediction of soils and their properties. Some of the applications include prediction of soil moisture content (Blyth et al., 2004; Romano and Palladino, 2002; Sulebak et al., 2000) soil moisture deficit (Krysanova et al., 2000), level of water table (Rodhe and Seibert, 1999), soil organic carbon content (Bell et al., 2000; Florinsky et al., 2002). The case studies indicate that the performance of digital terrain analysis in predicting soil properties seems to depend on the terrain attributes used, the algorithms employed and the types of landscape on which the application is conducted.

Earlier the concepts of topographic units and automated terrain classification have been briefly explained. These concepts are very relevant to digital soil mapping. For long time, landscape classification has been used to define soil spatial units (Bartsch et al., 2002; Dragut and Blaschke, 2006; Hengl and Rossiter, 2003; Irvin et al., 1997; Ventura and Irvin, 2000). Geomatics with its possibility of dealing with spatially continuous quantitative data offers the opportunity of classifying terrain into either discrete units or fuzzy memberships. Besides, it offers the opportunity of quantitatively relating spatially variable attributes to soil properties.

Many of the case studies that tried to delineate landscape unit through terrain attributes have come up with encouraging results (Etzelmuller et al., 2001; Ippoliti et al., 2005; Irvin et al., 1997; Park et al., 2001; Schmidt and Hewitt, 2004; Schmidt et al., 2005). The results have shown that topographic units that are delineated by using terrain attributes implied either homogeneous units in certain aspects such as soil properties or even homogeneous soil classes.

Review of the theoretical principles and empirical evidences has shown that geomatics plays crucial role in quantitative prediction of soils and their properties. This might even lead to the evolution of a unique branch of soil geography, i.e. *pedogeomatics*? *Pedogeomatics* could be defined as a technique whereby spatially referenced data on the environmental factors of pedogenesis are gathered, stored and processed quantitatively to predict the spatial distribution of soils and their properties. This research deals with a part of this theme.

## 2.5 Issues of Uncertainties in Spatial Data Analyses

### 2.5.1 Uncertainties and Their Sources in Geo-Spatial Analysis

It has been recognised from the early days of modern science dating back to over three centuries that representation of realities through measurement and modelling seldom fully duplicate the reality (Rouvray, 1997). That means scientific analyses are seldom free of uncertainties. Uncertainties in geo-spatial analyses are recognised to be significant and are likely to be just as important as the estimated or simulated outputs (Atkinson, 1999).

There are a number of confusing terms related to the indicators of the (mis)representation of reality such as error, uncertainty, accuracy, precision, quality, vagueness, fuzziness, etc. One thing they have in common is that they express the correctness or non-correctness of the representations of reality. Even though the terms mentioned above have some differences, most scientific articles do not make clear distinction among most of them. Wechsler and Kroll (2006) define error as the departure of a measurement from its true value. They define uncertainty as the lack of knowledge about the reliability of a measurement in its representation of the true value, i.e. the lack of knowledge about the error values. It is not the same as the laymen's language of 'mistake' and 'blunder' for it can not be corrected by carefulness. The definitions given by (Fisher, 2006) are also similar to these. Accuracy is a measure of how close the measurement is to the real value. Precision indicates how good or how repeatable the measurement is. It often refers to the decimal digits of the measurement values. Vagueness and ambiguity are terms related to uncertainties in nominal attributes such as naming, boundary setting, indicator selection, etc (Longley, 2005).

Geospatial analyses such as this research topic involve conceptualisation of the reality, its measurement, representation, analysis, and interpretation. Uncertainty is involved in all these stages as summarised by Longley (2005) graphically (figure 2.1). Here it is shown that reality gets blurred as it passes through each of those processing steps.

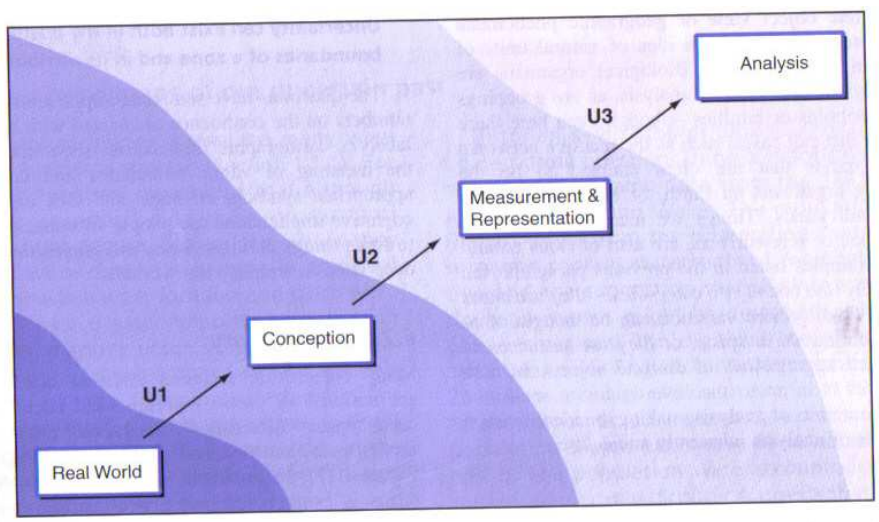



**Figure 2.1** A conceptual view of reality getting blurred by uncertainties (Source: **Longley, 2005).**

- ***Uncertainties in conceptualisation of the reality:*** Relevant examples here include conceptualising terrain as a continuous or discrete variable, conceptualising soil as continuous or discrete variable, conceptualising the relationship between terrain and soils, and many more. This introduces uncertainty into the representation since the within unit variation is ignored and the boundaries are vague. Besides, the scale at which a geographic object such as soil or terrain is conceptualised is also very ambiguous.

- ***Uncertainties during representation/measurement:*** The choice of using raster or vector data model pretty much depends on the conceptualisation of the reality as discrete object or field (Longley, 2005). Therefore, representation of soils by vector polygons with sharp boundaries involves strong simplification of reality. Even, the use of raster grids to represent soil classes or terrain values constitutes uncertainty as the within grid variation is simply ignored.

Data acquisition (measurement) introduces other sources of uncertainties. There can be simple errors due to 'mistakes' made by the measurer, accuracy and precision of the equipments used, type and unit of the indicator to be measured, etc. Besides, uncertainties related to the measurement and data model precision may arise. Data may be measured as interval or ratio. The data model used for interval data is integer where as that of ratios is floating or real number. Representing a ratio data by integers leads to lose of values leading to reduced precision and increased uncertainty.

- ***Uncertainties during Analysis:*** In spatial analysis, raw spatial data are turned into useful spatial information. Geo-spatial analysis involves models and stacks of spatial and non-spatial input data. Uncertainties or errors contained in the model and its input will therefore propagate to the output of the analyses (Bishop et al., 2006; Heuvelink, 1998). For example spatial analysis on DEM such as derivation of slope, involves errors of the input DEM and uncertainties in the calculation procedure propagated into the result (Wechsler and Kroll, 2006).

- ***Uncertainties during Interpretation***: in addition to the graphical presentation of Longley (2005) the discussion given by Lark (1997) points out that uncertainty might even be involved during interpretation. For instance, the meanings that a map may give vary depending on the background of the user. This ambiguity is much more complicated in the case of fuzzy logic maps. Their meanings are mostly clear only to the professional reader. One has to also be reminded of the fact that the interpretations are based on maps which may contain uncertainties of themselves. This leads to the notion of '*uncertainties of interpreting an uncertain value*' (Lark, 1997).

### 2.5.2 Dealing with Uncertainties

Given the sources and modes of uncertainties discussed above, the question that naturally popes up into anyone's mind is: how is it possible to trust the results of any geo-spatial analysis? Uncertainties are not just mistakes to be totally avoided through carefulness or equipment adjustment (Wechsler and Kroll, 2006). Possible ways of dealing with them as summarised by Bishop et al. (2006) and Fisher (2006) are:

- ***Estimating their values and reporting them with the data or analysis report***: Error estimation is possible only where the true values are known. In the case of uncertain values, the true value itself is not known. In digital terrain modelling, most often RMSE (Root Mean Square Error) is used to estimate the error values. *RMSE* is usually reported as a single, positive, aspatial global statistic per DEM based on comparison with a limited sample of points (Fisher, 2006). Since it is the only error report that accompanies most DEM data it is nonetheless valuable.

- ***Modelling uncertainties in order to understand their statistical and spatial behaviour:*** Error values may vary spatially, temporally and depending on the data source and the applied analytical process. To know how error values behave in relation to all these factors, error and/or uncertainty modelling is used. There are many approaches used to model error: the most common of them are stochastic (Wechsler and Kroll, 2006), Monte Carlo approach (Fisher, 2006; Oksanen and Sarjakoski, 2005), etc. Modelling and simulation are the only ways of estimating errors in cases where the real values can not be known.

- ***Investigating how uncertainties propagate from input and model to analysis result***: There are many researches that aimed at propagating errors involved in geo-spatial data analysis in general (Arbia, 1998; Atkinson, 1999; Fisher, 2006; Oksanen and Sarjakoski, 2005) and soil-terrain modelling in particular (Bishop et al., 2006; Hengl et al., 2004). They either used or suggested the use of modelling and analytical approaches to estimate how errors in input data and in models propagate to the outputs of geo-spatial analysis.

- ***Trying to correct or reduce Uncertainties***: Even if accurately estimated, there may not be possibilities to completely remove errors. What is more common to do is reducing the errors and uncertainties contained in data and models. To reduce them the sources of error during conceptualisation of reality, its representation, data acquisition and analysis should be sought. Once the sources are known, remedial procedures may be applied. For example, one of the sources of errors involved in soil-terrain modelling is conceptualising soil and terrain as discrete objects and trying to classify them. This source of uncertainty can be reduced by conceptualising them as continuous variable and modelling them through fuzzy logic approach (McBratney and Odeh, 1997). Likewise, errors during measurement, modelling and analysis can be reduced if the sources are known, e.g. removal of artificial pits in digital elevation models.

# 3 STUDY AREA DESCRIPTION

**Location**

This research was conducted in Vestfold County, in the south-eastern part of Norway (figure 3.1). The area extends over the municipalities of Sandefjord, Larvik, Andebu, and partly those surrounding them. It covers an area of 1835 square kilometre (35.05km by 52.35km). The area was selected based on the availability of most of the necessary data and its representativeness for the majority of the Norwegian agricultural landscape, especially for areas below the marine limit.

Vestfold is the second smallest of the nineteen Norwegian counties. However, it has the highest proportion of agricultural land compared to all the other counties (Nyborg and Solbakken, 2003). The favourability of the area for agriculture is due to its historical and contemporary climate, geology and landform.

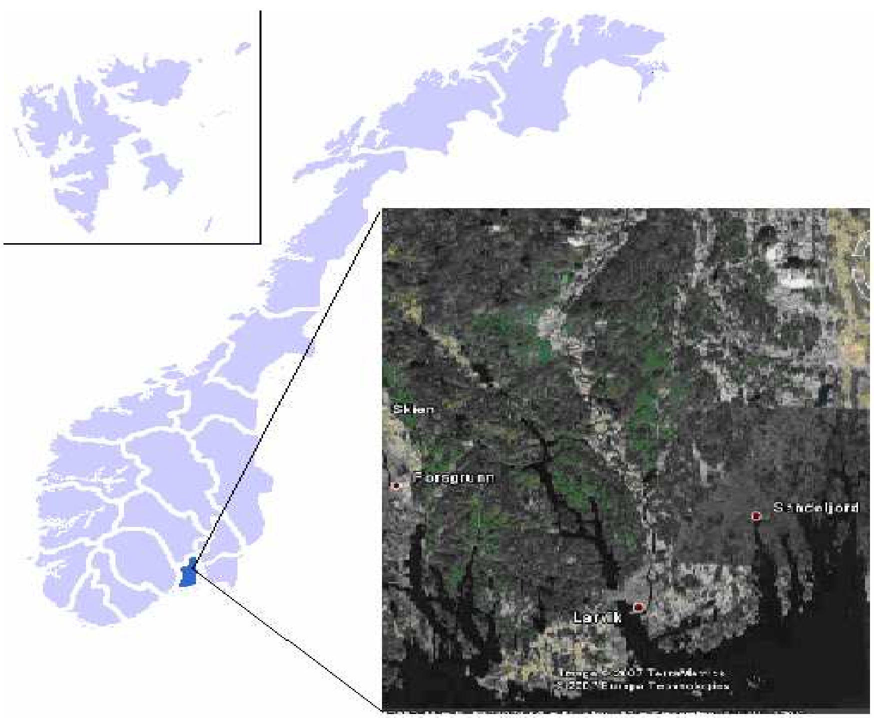



**Figure 3.1** The Vestfold County and the study area in relation to the country map of Norway

## Geology

The geology of Vestfold belongs to the south-western gneiss province of the Fennoscandian shield and makes the western part of the Oslo Graben, a rift basin of Carboniferous-Permian age (Sorensen, 1988). The geological history of this area began 280 million years ago when volcanic lava started to deposit over the region during the Permian period although there are some traces of earlier activities from about 600 million years ago. Throughout the later time the volcanically created hills were subjected to erosion by climate related activities and metamorphism. The major noticeable climatic activity that played great role in the creation of the landscape of the study area is the events that took place around 10000 to 12000 years ago (Solbakken et al., 2006; Sorensen, 1988). During that period the Ra Moraine was formed as a result of the re-advancement of the Scandinavian inland ice. The melting of the ice, that occurred later on, was followed by the uplifting of the land bringing the former sea bottom up to dry land. The mark of the ocean line, i.e. the boundary between former sea and land, can be clearly seen on the landscape today. That boundary is approximated with the thick dark line on the lower part of figure 3.2.

Due to the past volcanism, metamorphism, tectonics, glaciation and deglaciation, the geological makeup of the area are today classified into three main groups: the eruptive rocks of volcanic origin, sedimentary rocks of the erosion and deposition, and metamorphic rocks (Sorensen, 1988). The lower part consists of Palaeozoic marine and continental sediments of Cambro-Silurian age; where as, the upper part consists of Palaeozoic igneous and sedimentary rocks of Carboniferous-Permian age. Igneous extrusive and intrusive rocks are dominating. The bedrock types of the area are dominated by monzonites, sianites and larvikites with some others as can be observed in figure 3.2.

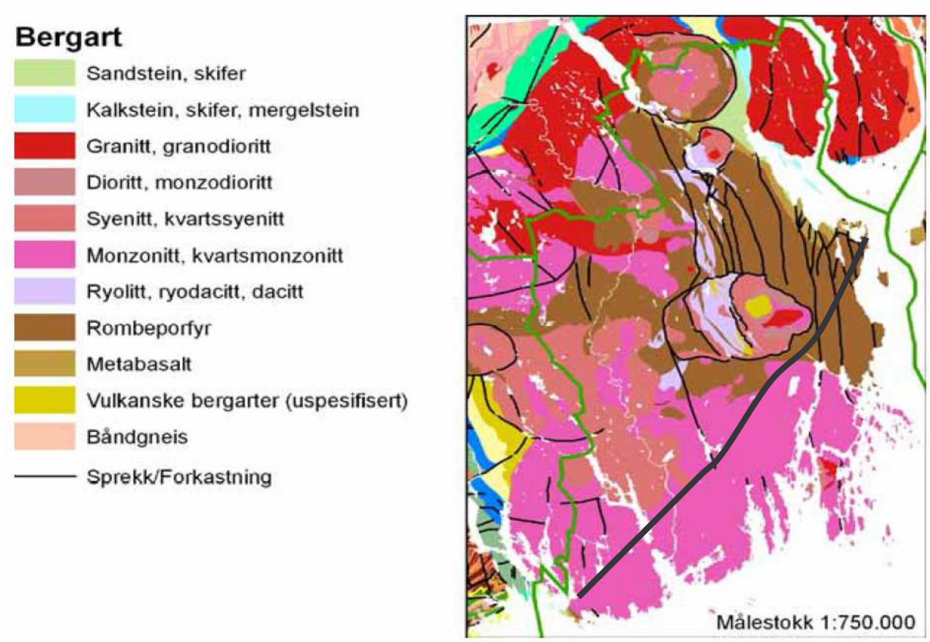



**Figure 3.2** The geological map of the study area showing the bedrock types (Source: Solbakken et al., 2006)

## Land use and climate

The county is known for its agricultural activities such as cereal crops, vegetables and animal fodder. The reason for the agricultural activity lies mainly in the climatic condition of the county. The growing season is longer; winter is milder; spring comes earlier; and, autumn comes later, compared to most places in Norway. Figure 3.3 gives overview of the mean normal temperature and precipitation over three decades (1961 to 1991) averaged from the stations within the study area.

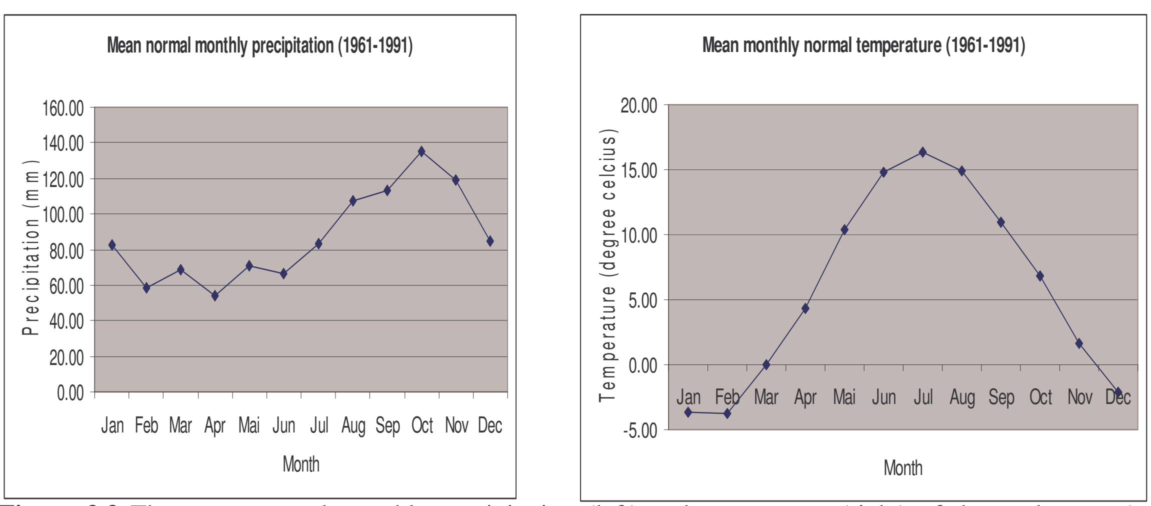



**Figure 3.3** The mean normal monthly precipitation (left) and temperature (right) of the study area (source: www.met.no).

**Soils**

A number of pedogenic processes that are active in Norway and that led to the today's soil cover of the country in general and the study area in particular are summarised by Solbakken et al. (2006). The soils of this area are known to have been highly influenced by the parent material and topography of the area. This is partly due to the fact that the parent materials are relatively young. The definition, characteristics and environmental domains of these soils are as explained in FAO (1998) and as modified for Norway in (Nyborg and Solbakken, 2003).

*Decomposition* of organic materials such as plant and animal remains lead to the formation of soils with high organic carbon content such as Phaeozem and Umbrisols. Phaeozems are intensively leached soils of wet grassland and forest areas that consequently have dark humus rich surface horizons. Umbrisols have high organic matter content in their mineral horizon and have low base saturation. They are mostly dominant in humid mountainous regions. When the rate of *accumulation* is greater than its rate of decomposition, organic materials such as peat mosses accumulate leading to the formation of Histosols. These are soils that are formed on organic materials of moss and peat and are characterised by having dark colour and very high organic matter content.

The chemical weathering of inorganic parent materials, i.e. *transformation*, leads to the creation of brownish or reddish coloured soils. In temperate environments such as Norway, the resulting soil types are usually Cambisols. Cambisols are soils with at least the beginnings of horizon differentiation in the subsoil, evident in changes in structure, colour, and clay content or carbonate content.

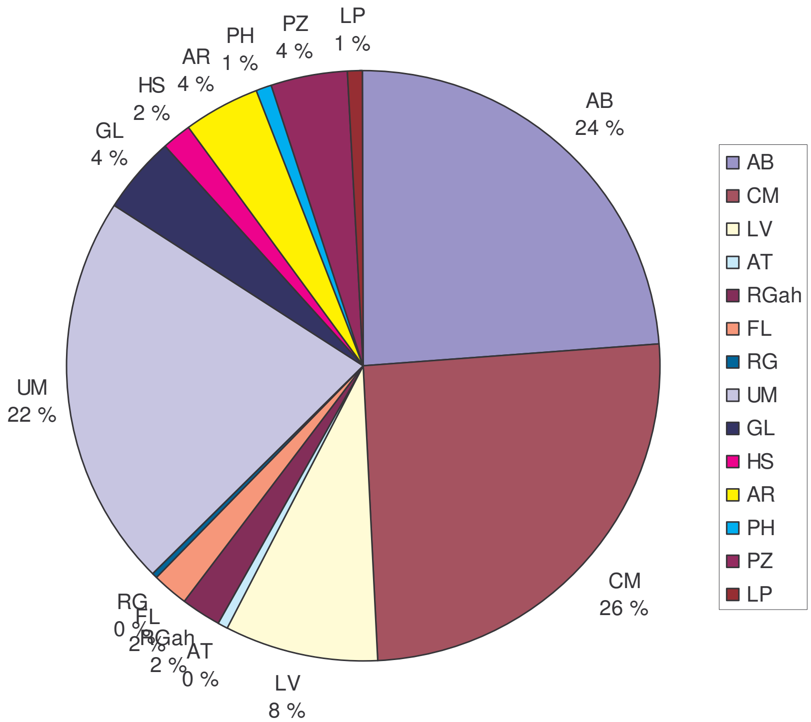
The movement of water down the profile, i.e. *translocation*, can transport materials such as basic ions, iron, aluminium, and clay from upper horizons to much lower horizons. When the horizons are completely washed of the basic ions, iron and aluminium, only silica remains behind making the horizon bright in colour. Such process is called podzolization and leads to the formation of Podzols. On the other hand, when the translocated material consists mainly of clay, and sand remains behind in the upper horizon, the process is called clay elluviation and leads to the formation of soils such as Luvisols and Albeluvisols. Albeluvisols are soils that have, beginning within 1 m of the soil surface, a clay illuviation horizon with an irregular or broken upper boundary resulting in tonguing of bleached soil material into the illuviation horizon. Where as Luvisols are soils that have higher clay content in the subsoil than in the topsoil as a result of pedogenic processes (especially clay migration) leading to a subsoil horizon with high clay content. Podzols are soils with a typically ash-grey upper subsurface horizon, bleached by loss of organic matter and iron oxides, on top of a dark accumulation horizon with brown, reddish or black illuviated humus and/or reddish Fe compounds (figure 3.4 right).

In areas where there is at least periodic water-logging, reduction process dominates and creates gleyic flecks which are characterised by reddish, brownish or yellowish color. Such process can be created due to shallow groundwater table leading to the formation of Gleysols and stagnated surface water leading to the formation of Stagnosols. Stagnosols were not part of the WRB classes used in the classification of the area until the 2006 publication of the institute (Solbakken et al., 2006). Gleysols are characterised by having the gleyic flecks on the ped surfaces and/or in the upper soil layer, in combination with greyish/bluish colors inside the peds and/or deeper in the soil. Besides, human activities have led to the creation of Anthrosols and Anthropic soils such as Anthropic Regosols in the area. Such soils are characterised by the presence of evidences of intensive human interferences such as addition of organic matter, household wastes, remains of artefacts, etc. in addition to all those mentioned, Regosols, that includes weakly developed soils that taxonomically can not be classified into any of the other WRB soil classes, are also found in the area.

There are also sandy soils formed due to the accumulation of sandy materials on the beaches and sands that are left behind due to selective erosion. Such soils are called Arenosols. There are also Fluvisols created on alluvial and marine deposits. These include predominantly young soils of recent deposit. As shown on the pie-chart of figure 3.5 they are less abundant in the area.

Figure 3.4 shows the vertical profiles of three very different soil classes. One can easily observe the differences visually. Those visual differences say a lot about their genesis as explained earlier. The brownish Cambisol is basically made of inorganic minerals through weathering, where as the dark histosol results from mainly organic materials. On the other hand, podzols are formed as a result of the removal of basic ions and organic matter from the upper horizon leaving behind the light coloured silica as can be seen in the figure. The soil types and the proportion of their area coverage in the study area are presented in the pie chart of figure 3.5. One has to bear in mind that since it is only the agricultural areas that has been surveyed and mapped, the chart does not show the complete picture of the area. It is based on the soil map used for this research. The pie-chart shows that Albeluvisol, Cambisol, Luvisol and Umbrisols together cover about 80% of the surveyed area.

**Figure 3.4** Example profile for three soil classes of the study area: left (Cambisol), Middle (Histosol) and right (Podzol) (Source: Solbakken et al., 2006)




**Keys**
AB = Albeluvisols
AR = Arenosols
AT = Anthrosols
CM = Cambisols
FL = Fluvisols
GL = Gleysols
HS = Histosls
LP = Leptosols
LV = Luvisols
PH = Phaeozem
PZ = Podzol
RG = Regosols
RGah = Anthropic Regosls

**Figure 3.5** Area distribution of the soil classes in the study area

# 4 METHODOLOGY

## 4.1 Data

The data used in this research were not collected based on pre-designed sampling strategy. They were rather obtained from different sources which apparently collected and stored their data for different purposes. The data type, their sources and how they were originally collected are explained hereunder case by case. The data include digital elevation model, soil maps, soil databases, satellite images, etc.

***Digital Elevation Model (DEM):*** DEM of the area at the resolution of 25m created by the Norwegian Mapping Authority was obtained from the database of the Institute of Geosciences of the University of Oslo. The Authority states that the source data for the DEM were contour maps, elevation points, streamlines and road maps (http://www.statkart.no/?module=Articles;action=ArticleFolder.publicOpenFolder;ID=2717). These source maps were originally made as the Norwegian N50 map series (topographic maps at the scale of 1:25 000 to 1:100 000).

Details of the procedures used by the Norwegian Mapping Authority are not available. However, it is briefly stated that TIN (Triangular Irregular Networks) were first derived from the source data. The TIN model was later converted to the grid based DEM model. The format in which the data was obtained for this study was therefore in USGS DEM format. This was converted to grid format in ARCGIS. Since the study area was not completely covered with one DEM file, merging and clipping were carried out to extract the DEM that extends over the study area.

***Soil Maps and Accompanying Soil Databases:*** The soil maps were obtained from the then Norwegian Institute of Land Resources Inventory (NIJOS) which has now become Norwegian Institute of Forest and Landscape. The institute conducted the classification and mapping of the soils there in the field following field guide for soil survey and classified the soil using FAO (WRB) soil classification system (FAO, 1998). They used stereo aerial photographs of the areas to delineate soil units in the field. Reference and site data were also collected and *in-situ* profile description was carried out. The soil unit maps were digitized using an AP190 Analytical Plotter and converted into SOSI and ESRI file formats.

The soil maps used for this research were in ESRI shape file format. There were 13 soil classes found in the area whose proportion is displayed in figure 3.5. The accompanying soil database which was obtained in Oracle dump database format contained generic and empirical profile databases and site descriptions. The empirical databases contained description of the site, some profiles, their horizons and analytical data on topsoil and subsoil samples and the soil classification in FAO-WRB system (FAO, 1998).

***Satellite Image:*** The Enhanced Landsat Thematic Mapper image from May 2000 was downloaded from the USGS website. The image was radiometrically corrected and geometrically orthorectified by NASA (Tucker et al., 2004). The image was subsequently analysed to make land cover maps of the area. This land cover map was later used to mask areas covered by water bodies such as lakes and sea during the digital mapping of soils.

## 4.2 Digital Terrain Analysis

### 4.2.1 Pre-Evaluation and Pre-Processing of the DEM

Before doing anything with the DEM, quality assessment was conducted on the DEM. The mapping agency claims that the DEM has an RMSE of 5 to 6 meters. There are some acceptable procedures used to evaluate the overall quality of DEM other than the accompanying standard error report (Li et al., 2005; Liu et al., 2006; Wise, 2002; Zhou and Liu, 2004). Some of these approaches were employed in this study to investigate and improve the quality of the DEM before analytical procedures were applied. First, the histograms of the elevation data itself and that of aspect were investigated. Second, the shaded relief of the DEM was visually investigated to see artificial structures. Third, depression were derived from the DEM and investigated to identify if they were natural lakes or artificially introduced sinks.

Some measures were taken to improve the quality of the DEM. Artificial depressions were removed from the DEM using (Planchon and Darboux, 2002; Planchon, 2001) method accompanied with drainage enforcement in flat areas. Spikes, i.e. unusually high elevated pixels in relation to their surroundings, were also removed. All the subsequent analytical procedures were applied on the so smoothed DEM.

### 4.2.2 Derivation of Terrain Attributes

All the important primary and secondary terrain attributes were derived using ARCGIS and a program called TAS (Terrain Analysis Systems) developed by John Lindsey of the University of Manchester (Lindsay, 2005). In table 4.1, the definition, methods used to derive the values and the units of the terrain attributes used in this research are given based on figure 4.1 and the accompanying formulae as modified from (Gallant and Wilson, 2000; Wilson and Gallant, 2000b). Such three by three windows are used only to derive local terrain attributes. Those attributes that include pixels beyond such windows are the flow related attributes and are determined by specific algorithms as stated in table 4.1.

| | | |
|---|---|---|
| $Z_7$ | $Z_8$ | $Z_1$ |
| $Z_6$ | $Z_9$ | $Z_2$ |
| $Z_5$ | $Z_4$ | $Z_3$ |

$Z_X = (Z_2 - Z_6)/2h$

$Z_y = (Z_8 - Z_4)/2h$

$Z_{xx} = (Z_2 - 2Z_9 + Z_6)/h^2$

$Z_{yy} = (Z_8 - 2Z_9 + Z_4)/h^2$

$Z_{Xy} = (-Z_7 + Z_1 + Z_5 - Z_3)/4h^2$

$P = Z^2_X + Z^2_y$

$q = p + 1$

**Figure 4.1** A three by three grid window and the formulae for surface derivatives (modified from Gallant and Wilson, 2000)

**Table 4.1** The terrain attributes, their definition and methods of analysis (the symbols are as given in figure 4.1)

| Parameter | Definition | Method Used | Unit |
|---|---|---|---|
| Elevation | Height above sea level | DEM | Meter |
| Slope | The rate of change of elevation in the direction of the steepest descent | SD8 = Max$(Z_9 - Z_i)/h\phi(i)$ $\phi(i)$ is 1 for cardinal and $\sqrt{2}$ for diagonal directions | Percent |
| Mean Upslope slope | The mean upstream gradient found between the pixel and the ridge above it | Mean value of slope of the upstream area | Percent |
| Aspect | The direction of the line of the steepest descent | 180-arctan$(Zy/ Zx)+90(Zx/\|Zx\|)$ | Degrees but the product of the sin and cosine of aspect was used to deal with the cyclic nature of aspect values |
| Total Curvature | a measure of total curvature within a group of grid cells | $Z^2{}_{xx}+2Z^2{}_{xy}+{}_yZ^2{}_{yy}$ | Degrees per 100 meter |
| Profile Curvature | The rate of change of slope down a slope line | $(Z_{xx}Z^2{}_x+2Z_{xy}Z_xZ_y+Z_{yy}Z^2{}_y)/pq^{3/2}$ | Degrees per 100 meter |
| Plan Curvature | The rate of change of aspect along a contour | $(Z_{xx}Z^2{}_y-2Z_{xy}Z_xZ_y+Z_{yy}Z^2{}_x)/pq^{3/2}$ | Degrees per 100 meter |
| Tangential Curvature | Plan curvature multiplied by the sine of the slope angle | $(Z_{xx}Z^2{}_y-2Z_{xy}Z_xZ_y+Z_{yy}Z^2{}_x)/pq^{1/2}$ | Degrees per 100 meter |
| Specific catchment area (As) | The area above a unit length of contour or grid width that contributes flow to it | FD8 Flow routing algorithm (Gallant and Wilson, 2000) | Meter squared per meter ($m^2/m$) |
| Downstream flow length | The length between the pixel and the catchment outlet point | D8 flow routing algorithm downstream (Gallant and Wilson, 2000) | Number of pixels but converted to kilometre |
| Mean Upstream flow length | The average distance between the pixel and the furthest pour points that flow down to the pixel | D8 flow routing algorithm upstream (Gallant and Wilson, 2000) | Number of pixels but converted to kilometre |

| | | | |
|---|---|---|---|
| Topographic Wetness index | A measure of the topographic control on soil wetness | ln(As/tan Slope) | none |
| Sediment Transport capacity index (LS) | A measure of the topographic control on the sediment transport (USLE's LS factor) | $(As/22.13)^{0.6}X(sinSlope/0.0896)^{1.3}$ | none |
| Stream power index | The topographic index for stream forming power of flow | As*tan Slope | none |
| Mean daily Direct shortwave radiation | The amount of direct shortwave radiation received per day | The sloarflux model (Rich et al., 1995) | Watts per square meter (W/ $m^2$) |
| Mean daily duration of direct radiation | The mean duration for which direct radiation is received per day | The solar flux model (Rich et al., 1995) | Hours |

Terrain attributes are basically derived from the combination of the position and elevation data. Some terrain attributes may be correlated and may not contain any different information from each other. To identify which terrain attributes are related, correlation coefficients among the different terrain attributes were determined in ARCGIS. The Pearson's Product Moment Correlation was used to study the correlation among the terrain attributes.

## 4.3 Terrain Attributes and Soil properties: *Correlation and Regression*

The first step here was to re-project all maps to the same projection, i.e. WGS84 UTM zone 32N. Then the values of the terrain attributes for each of the soil profiles were extracted. Since not all soil analysis data were available for the profiles in the study area, those soil properties which are agriculturally and environmentally important and for which analytical data were available were included into the analysis. These were clay content, pH, organic carbon content, $KHNO_3^-$ and extractible (Kjeldahl's) nitrogen content. These properties are crucial soil properties as they are related to many other soil properties through pedotransfer functions (Shein and Arkhangel'skaya, 2006) and as they are fundamental in plant growth and environmental processes.

The terrain attribute data and the soil analysis data were linked using the database query capabilities of ARCGIS and Microsoft ACCESS. The output of the database query was later used in SPSS for further analysis. The soil analytical properties were divided into the topsoil and subsoil section of the soil profile. The focus was made on the topsoil data. There were only 29 soil profiles with topsoil analytical data available for the study area. This number is obviously too few for such an environmental variable with known spatial dependence and complex variability over such a large area. The interpretation of the result should therefore be considerate of this sample size.

If and to what extent soil properties and terrain attributes are related seems to be relatively easy to study assuming that: first, both the soil properties and the terrain attributes are measurable quantitative variables. Second, the relationship, if exists, is linear which can be expressed through correlation coefficients. In such cases, the samples used for the model building are assumed to be random and normally distributed with constant and estimable first (mean) and second (variance) moments.

In this study, each of the dependent variables (soil properties) was regressed against the independent variables (terrain attributes) using multiple linear regression analysis in SPSS to see how much of the variations of each soil attribute can be ascribed to each terrain attribute and to predict the values of the soil properties from terrain attributes. All of the options (i.e. enter, forward inclusion, backward elimination) were tried to arrive at the most significant regression model. Besides, the Pearson's product Moment Correlation Coefficient between each terrain attribute and each soil property was determined to see the bivariate correlation between them. Regression models were created for each soil property using the significant terrain attribute for that soil property. The models show how soil properties are related to terrain attributes quantitatively. The models were used in raster calculator module of ARCGIS to predict the spatial distribution of the soil properties. The generic format of the regression models are given as:

$S_i = a + b_1X_1 + b_2X_2 + \ldots.+b_nX_n + \varepsilon$

Where:

- $S_i$ denotes the value of the soil property at point (or pixel) i,
- a denotes the intercept of the regression curve
- $b_{1\ldots.n}$ denote the regression coefficients of the terrain attributes $X_{1\ldots n}$ respectively
- $\varepsilon$ stands for normally distributed random error (assuming there is no systematic error)

To know the relative performance of the regression-based perdition, comparison was made with the most often used interpolation technique, i.e. ordinary kriging. Kriging interpolates the value of a spatial variable at a location through weighted linear combinations of the available values of the nearby points. The weights assigned to each available value is a function of the distance of that point from the point whose value is to be estimated (van Beers and Kleijnen, 2003; Virdee and Kottegoda, 1984). Besides, the weights have to add up to just 1. Mathematically:

$$s(r) = \sum \lambda_i(r)S(ri)$$

$$\sum \lambda i(r) = 1$$

Where: s(r) is the estimated value of the variable S at location r,

$S(r_i)$ is the values of S at locations i surrounding r, and

$\lambda_i(r)$ is the weight given to every point i based on its distance from location r.

The weights, $\lambda_i(r)$, in the kriging model are estimated through structural analysis of the behaviour of the variable with respect to distance. What makes kriging different from other interpolators is this fact that the weights are not estimated solely based on distance but based on the behaviour of the values of the variable with respect to distance as well. Details of how these weights are estimated are discussed in (Virdee and Kottegoda, 1984; Webster and Oliver, 2001) will not be discussed here.

Ideally, if the value is perfectly estimated, there will be no deviation between the true value of S(r) and its estimated value s(r). Since there is no way of perfectly estimating an unknown value, minimisation of the deviation is the guiding rule. That means the mean square of the error should be minimal.

Kriging is known to be an unbiased exact estimator, which means the data that were used in the kriging are exactly replicated (van Beers and Kleijnen, 2003; Virdee and Kottegoda, 1984). Consequently, validation data and sample data should be kept apart. Therefore, for comparison with the regression-based prediction, the validation-based approach was used. Here, one data value was kept out of the kriging and its value was estimated by kriging and the deviation was calculated. This was repeated until all the data values had been through. This procedure was carried out automatically in ARCGIS.

The comparison between the regression-based prediction and the validation-based kriging was conduced using three parameters. The parameters were:

- First, the mean values of the error of the prediction and the interpolation are calculated as:

$$\partial_{\text{mean}} = (\sum (S_i - s_i))/n$$

Where: $\partial_{\text{mean}}$ is error mean, $S_i$ is the measured value of the soil property, $s_i$ is the predicted/interpolated value of the soil property, n is the total number of samples used in the evaluation. The closer this value is to zero the better the prediction is.

- Second, the root mean squared (RMSE) values were estimated as:

$$\text{RMSE} = \sqrt{((\sum (S_i - s_i)^2)/n)}$$

Again, the smaller this number is, the better is the prediction.

- Third, the $R^2$ of the correlation between the predicted and observed values were also used for the comparison. This tells by how much percentage the predictions are correct.

## 4.4 Discrete Approach to Spatial Prediction of Soil Classes

### 4.4.1 Testing Topographic Differences among Soil Classes

Basically, discrete classification presupposes that the different soil groups are different in terrain attributes, i.e. they are located under different topographic conditions. The logic behind this is that it is possible to map soils based on terrain attributes if and only if the soils are significantly different from each other in the kind of terrain attribute they are located in. To test if this presupposition (hypothesis) holds, analysis of variance (ANOVA) and mean comparison for each of the terrain attributes among the different soil groups was carried out in SPSS.

ANOVA was conducted by treating the soil classes as factor variables and the terrain attributes as dependent variables. ANOVA tests the significance of the mean differences due to the factor variable using the F-test (Anderson, 2001). There is no need of going into the details of ANOVA here. It suffices to indicate how the significance test of the difference between two categories is conducted using the F statistic. The F statistic is calculated as the ratio of the between groups (soil classes) variance to the error variance, i.e.:

$$F = \frac{(\Sigma(Xi - X_{Cmean})^2/df_B)}{(\Sigma(Xi - X_{Tmean})^2/df_W)}$$

Where: Xi indicates the value of a terrain attribute X at observation i,

$X_{Cmean}$ is the mean value of X within the given soil class C

$X_{Tmean}$ is the global mean value of X,

$df_B$ is the between classes degrees of freedom, i.e. the total number of classes or factors minus one.

$df_W$ is error degree of freedom, i.e. the total number of observations minus the total number of classes or factors.

Large F value indicates larger between-group variance and smaller error (within-group) variance. The error variance can actually be thought of as variance due to other factors apart from the ones in the analysis. Basically, the F-statistic tests hypotheses which for this research were defined as:

- *The Null hypothesis*: there is no difference among soil classes in their terrain attribute values, i.e. mean values of terrain attributes for the soil classes are equal.
- *The alternative hypothesis*: there is difference among the soil classes in the values of their terrain attributes, i.e. at least the mean value of one terrain attribute is different.

We reject the null hypothesis if the F value is greater than the F-critical for the given degree of freedom and at that level of significance, i.e. 0.05. Otherwise, we accept it. The F-critical is obtained from an F-table with the given degree of freedom and the given level of significance.

### 4.4.2 Digital Soil Mapping Using Automated Terrain Classification

The prediction of discrete soil classes from terrain attributes relies on the presumption that terrain units correlate with soil units which could be verified using ANOVA as explained earlier. Once, it has been learnt that there are significant differences among soil units in their terrain characteristics, the prediction can follow. Since it is assumed that different soil classes develop under different ranges of terrain attribute values, the prediction can be achieved through classification of terrain. The classification can take place in such a way that, the values of all the terrain attributes of sample soil classes are determined and the rest of the area is categorised into one of the soil classes based on its similarity to that class with regard to its terrain attribute values.

Although, theoretically it can be achieved as stated above, the practical approaches can vary. Automated classification of terrain using remote sensing image classification algorithms is the most suited tool for such purposes. Unsupervised and supervised classification algorithms that are used for remote sensing image classification (McCloy, 2006) can be adapted for this purpose. In the unsupervised case, terrain can automatically be classified into a number of classes based on the characteristics of the terrain attributes, and the classes can then be identified with respect to the soil types. In the supervised classification, empirical soil data on at least some areas is needed. The locations of the sample soil data are identified as training areas and one of the classification algorithms is applied to the terrain attribute maps to classify every pixel into a certain soil type. This approach classifies every pixel into a predefined soil class based on the values of its terrain attributes. Two conceptually different methods of supervised terrain classification algorithms were used in this study. These were object-oriented and pixel-based approaches which are explained next.

**Object-oriented Approach**

Pixel-based classification methods purely depend on the digital values (the values of the terrain attributes) of the individual pixel. There is no consideration of the neighbourhood and the geometry of the pixel as all pixels have the same geometry. The result of such classification method lacks spatial connectivity and fails to represent reality. Besides, the scale of classification is fixed to the original one. These drawbacks can be tackled through object-oriented classification. In object-oriented classification, it is not only the digital values of individual pixel that matter but object characteristics such as shape, texture, neighbourhood, etc.

In this research, all of the grids of the terrain attributes were treated as channels in analogy with satellite images and the following procedures were applied on them in eCognition. First, the entire area was segmented into terrain objects. A terrain object here is a collection of adjacent pixels of similar terrain characteristics at a given scale. The segmentation process starts with a single pixel and grows it by adding neighbouring pixels with similar characteristics, hence forming objects. The segmentation in eCognition is conducted at a defined scale and thematic (colour) – shape factor. It combines the channel digital values, scale factor, shape factor and their respective weights to define the boundaries of heterogeneity and homogeneity as explained in detail in Baatz et al. (2000). In this particular application, those parameters were changed now and then until the appropriate segmentation was attained. All the terrain attributes were first weighted to 1, that means all of them were fully and equally used in the segmentation process. Then the colour weight was given 0.9 leaving 0.1 as a weight for the shape parameter. The scale parameter was varied every now and then with values between 10 and 200 to see their effects on the accuracy of the classification.

Second, sample objects were collected for each soil class using the digitized empirical soil map on the background. Attempt was made to keep the number of samples proportional to the distribution of soil classes in the area. In general, between 10 and 80 sample objects were identified for each soil class with great care to evenly distribute them spatially.

Third, the parameters to be used for the classification (features) were defined. In eCognition, it is possible to use layer related, object related, class related and scene related features. However, selecting the most distinguishing features is not a straight forward task. Automatic feature selection was used as selecting them manually was found to be not effective. All the features thought to be important were included, and the automatic feature optimisation module was run to identify how many and which features separated the soil classes optimally.

Fourth, after defining sample objects and identifying features, the classification algorithm had to be defined. eCognition offers two classification algorithms: the nearest neighbour classifier and the fuzzy classifier. The former was used for this purpose. It is actually based on the principle of fuzzy classification and fuzzy combination (Baatz et al., 2000). An object is classified into the class to which it is closer in the n-dimensional feature space created using the sample objects. Values between 0 and 1 are assigned to each object with respect to each class depending on its distance to the mean centre of that class in the n-dimensional feature space. Then, the object is assigned to the class for which it has the highest value, i.e. to which it is closest. An object belongs to just one class and a class can have as many objects as possible. Therefore, in database language, there is one-to-many relationship between class and object.

Fifth, the classification accuracies were assessed using the empirical soil map as reference. The user, producer and overall accuracies were calculated automatically by the program. User accuracy, for a given class i, is the proportion of the total number of pixels predicted as that class which are actually that class in the reference map. Producer accuracy, for a given class i, is the proportion of the total number of pixels of that class in the reference that are correctly classified. The overall accuracy shows the proportion of all reference pixels which are classified correctly.

The producer accuracy, user accuracy and overall accuracy are calculated as (Baatz et al., 2000; Stehman, 1998):

- Producer Accuracy (%) = $n_{ci}/n_{ai}$ X 100
- User Accuracy (%) = $n_{ci}/n_{pi}$ X 100
- Overall Accuracy (%) = $(\Sigma n_{ii})/n$ X 100

Where: $n_{ci}$ = the number of correctly classified pixels for class i,

$n_{ai}$ = the total number of pixels of class i in the reference,

$n_{pi}$ = the total number of pixels of class i in the predicted map

$\Sigma n_{ii}$ = the total sum of all of the correctly classified pixels

n = the overall total number of pixels

The classification was rerun many times after changing one or more parameters until the classification accuracies were no more improving. When the final classification was obtained, it was exported in tiff format. The flow chart of figure 4.2 presents the workflow of the object-oriented automated terrain classification approach to digital soil mapping.

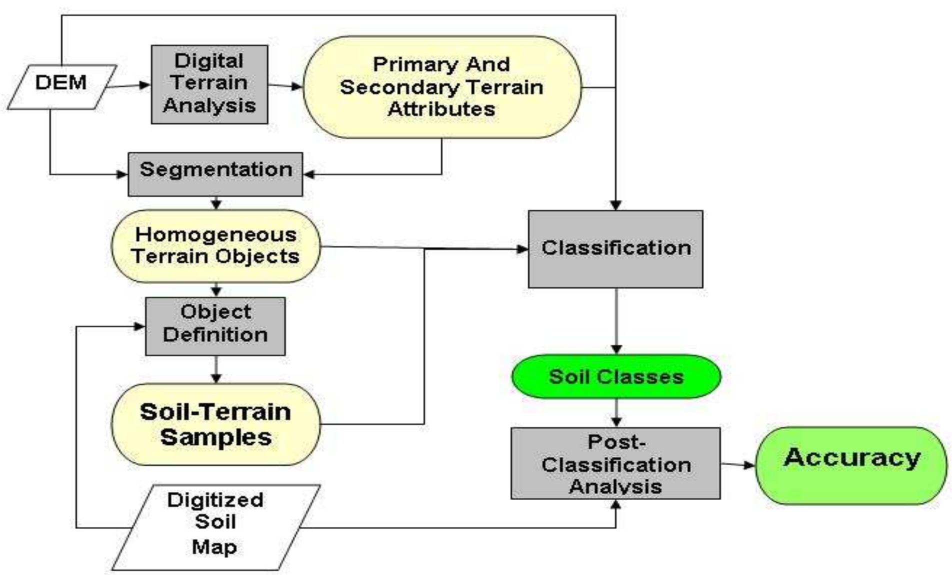



**Figure 4.2** Flowchart showing the procedures employed in the object-oriented classification

### Pixel-based supervised classification approach

To know if the object-oriented approach had any additional advantage over the less complicated conventional supervised classification, pixel-based supervised classification was carried out. The conventional pixel-based classification classifies a pixel (not an object) to a class to which it is closer in an n-dimensional feature space (McCloy, 2006). The most effective algorithms of all, is known to be the Maximum Likelihood Classifier (MLC).

MLC classifies a pixel to the class where the pixel has the maximum probability of belonging. MLC was applied using the multivariate analysis module of ARCGIS. First, the class signatures had to be defined. The samples and classes that were used in the object-oriented approach were imported and signatures were made for the samples. Using the signature file and all the terrain attribute layers, MLC algorithm was applied. The accuracy of the classification was assessed using the vector based empirical soil map as reference and cross-tabulating that with the newly made soil map. A confusion matrix with producer, user and overall accuracies was then made in Microsoft EXCEL and compared with that of the object-oriented approach.

## 4.5 Fuzzy Approach to Spatial Prediction of Soil Classes

### 4.5.1 Statistical Modelling of the Continuous Relationship between Soil Classes and Terrain Attributes

When a variable has a continuous spatial variation, it means that every point is likely to be different from its neighbour and the transition is gradual. Putting similar points into one category, just like putting similar items into the same bucket, does not reflect the continuity of such variables (Qi et al., 2006). Thus, there needs to be an approach that reflects the gradual variation. Such gradual variation can be accommodated through fuzzy logic approach. In fuzzy logic approach a membership of a spatial unit into a given object class is expressed in terms of probability values that range from 0 to 1 (Markus, 1999). Fuzzy logic approach needs to establish a knowledge-base on the behaviour and trend of the spatial variation. When establishing knowledge-base for the soil-landscape continuum, the ranges of the environmental variables in which each soil classes are found are set through empirical knowledge (Cook et al., 1996). By statistically analysing the empirical data, a knowledge-base, i.e. a model, is established. This model is fed into a computer program that is capable of using it for setting membership of a spatial unit, e.g. a grid, into a given soil class (Lagacherie, 2005; Qi et al., 2006).

For digital soil mapping, the fuzzy logic approach uses the principle that a spatial unit, e.g. a pixel, can contain soil which can not be exclusively classified into one class (Qi et al., 2006). In discrete classification a grid either belongs or does not belong to a given soil class. But in fuzzy logic approach there is a third possibility that it '*may'* belong to the soil class. When it '*may'* belong to a class, it means that it '*may'* also belong to one or more other classes. Such a grid is assigned a value between 0 and 1 with regard to its membership to all the soil classes concerned (McBratney and Odeh, 1997).

The idea here is that the value of the membership of each pixel to a given soil class is determined as a function of the values of the terrain attributes for that pixel. A graphical relationship that is similar to one of those shown in figure 4.3 can be established between the probability of the presence of a soil class and each terrain attribute. Such graphical relationships can be established deterministically or empirically based on the statistical distribution of a given terrain attribute values for the given soil class. Curve D in figure 4.3 shows abrupt change in class when the value of the variable X gets out of its range. Such is a case for crisp classification. Curve A shows a one-tailed Z-shaped distribution (skewed to the right) where membership probability decreases with increasing X value. Curve C depicts one-tailed S-shaped (skewed to the left) cases where membership value increases with increasing X until it attains its maximum value 1. Curve B shows a two-tailed bell-shaped case where higher membership values are around the center and decreases towards either direction.

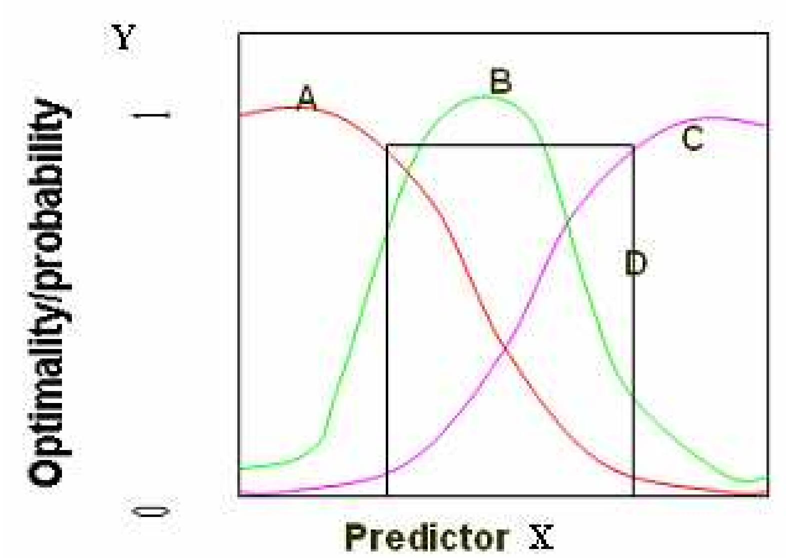



**Figure 4.3** Graphical depiction of the some of the possible relationship between a predictor and the class optimality value

The probability/optimality that a soil class exists in a given location can be related to terrain attributes through numerical models. Since directly building such a non-linear model is not simple, a model that linearises the relationship is built. The best of such models is logit model that relates the natural logarithm of the odds (ratio of the probability of existence to that of non-existence) to the predictor variables. Logit model is preferred because it is less demanding in terms of the behavior of the data sets such as normality, constant moments, etc that are required for its likes (Raimundo et al., 2006 ).

Logit models can be constructed through logistic regression analysis (Menard, 2002). Binary logistic regression is when the dependent variable has just two categories. In cases where the dependent categorical variable has more than two categories multinomial logistic regression is applied. Details of logistic regression (be it binomial or multinomial) will not be treated here.

The mathematical formulation of the relationship between the logit of a category of the dependent variable and its predictors are given as:

$$\text{Logit}_i = \ln(P_i/(1-P_i)) = a + b_1X_11 + b_2X_2 + \ldots + b_nX_n + \varepsilon$$

The equation shows how to calculate the logit of a category, e.g. soil class i, predicted from a number of quantitative factors $X_{1\ldots n}$, e.g. terrain attributes. The 'a' indicates the intercept of the regression curve, the 'b's are the coefficients of each predictor, and $\varepsilon$ represents random and systematic (if any) error.

Multinomial logistic regression analysis provides a number of useful results. First, it enables to identify the most influential predictor variables. Second, it determines the extent of the influence of the predictor variables on the dependent. Third, it helps to construct logit models that could be used to predict the probability of the presence of a given dependent variable in a given area, given the values of its influential predictor variables.

The identification of whether a terrain attribute has significant relation with the distribution of a soil type is expressed by the significance of the logit coefficient of that terrain attribute for the given soil class. The idea of how it is related and to what degree the influences are is not a straight forward issue to interpret. It is the exponent of the coefficients (EXP(B)), often called the odds ratio, that is most suitable for such interpretation. It is suitable because it indicates the factor by which odds ratio of the category increases when a terrain attribute is increased by one unit (Menard, 2002; Peng et al., 2002). If the odds ratio is greater than 1, the probability of occurrence increases due to increase in the values of the predictor variable, and there is positive correlation between the factor (terrain attribute in this case) and the probability that the dependent variable (soil class in this case) exists. On the other hand, EXP(B) below 1 indicates negative correlation between the predictor and the dependent variables. EXP(B) value of 1 indicates that increase by one unit of the terrain attribute does not influence the odds ratio. The farther away the EXP(B) is from 1, the stronger the influence is. However, the magnitude has no direct indication of the change in the probability values (Menard, 2002).

In this research, the multinomial logistic regression (NOMREG) module of the SPSS was employed as the dependent variable had more than two categories. When employing NOMREG, one of the soil classes, Umbrisol, was arbitrarily defined as reference category. The Chi-square based maximum likelihood ratio test was used to evaluate the overall model fit and to estimate the significance of the predictor variables that indicate whether a given terrain attribute is significantly influential in determining the existence of the nominal soil class. The significance of the regression coefficient (B) of each predictor variable for each dependent variable was evaluated using the Wald statistic.

### 4.5.2 Probability Mapping Using Multinomial Logistic Regression Model

To arrive at the prediction function for the probability P, the logit needs to be determined first. The logit is constructed from the output of the logistic regression analysis explained above. Logit is a measure of the probability ratios and can be used to derive the probability models as follows:

$$P_i = \frac{e^{a + b1X1 + b2X2 + \ldots + bnXn + \varepsilon}}{1 + \Sigma_1^{m-1}(e^{a + b1X1 + b2X2 + \ldots + bnXn})^{+\varepsilon}}$$

The equation predicts the probability P that a nominal variable of category i is present given the levels of the independent variables $X_1, X_2, \ldots, X_n$, by dividing the logit of the i to that of the total sum of the logits of all other categories (except the reference category) plus unity (Menard, 2002). The logit of the reference category is not estimated. However, its probability of existence is given as:

$$P_r = \frac{1}{1 + \Sigma_1^{m-1}(e^{a + b1X1 + b2X2 + \ldots + bnXn})^{+\varepsilon}}$$

The values of the a and the b's have to be determined for each soil class based on empirical data. Once the values have been estimated with statistical significance as explained earlier, the two probability models can be integrated into a GIS tool to map the probability that a given soil class i is found at a given pixel based on the values of the terrain attributes X1…n.

In this study, logit models for each soil class were constructed using the terrain attributes that were found significantly influential by the Wald statistic test for that soil class. The logit models were related to the probability models as the above two models. These probability models for each soil class were fed into the raster calculator of ARCGIS.

### 4.5.3 Analysis of Reliability of the Probability Prediction

The ideal way of assessing the accuracy of the prediction would have been by comparing the predicted probability values with the actual probability values. However, the actual probability values do not exist. The reference soil map itself is a vector map created based on discrete classification concept and contains uncertainties. Had the database on which the models were built been soil profiles which are representative of just one soil class, the profiles would have been given probability value of 1 and the deviation of the prediction from those would have easily been calculated as an indicator of the accuracy.

Therefore, two other approaches were used in this research:

- *The rule of thumb or expert knowledge*: Some soil classes develop under restrictively defined landscapes. Using this fact and the expert knowledge of the spatial distribution of soils in the area, the landscape over which each predicted soil type has high probability values were evaluated together with an expert who knows the area and subject well. Besides, the predicted maps were visually compared to the empirical soil map of the area published in Solbakken et al. (2006).
- *Correlation among the probability values*: this is founded on the fact that some soil types develop under similar bio-physical environment. The probability values for such soil types are expected to have strong positive correlation. On the other hand, some soil types develop under completely opposite biophysical environment. The probability values of such soil types are expected to have strong negative correlation. These facts were used and the probability values of the soil classes were correlated amongst each other to check if the theory is maintained by the result. The complete work flow diagram of the method is presented in figure 4.4 below.

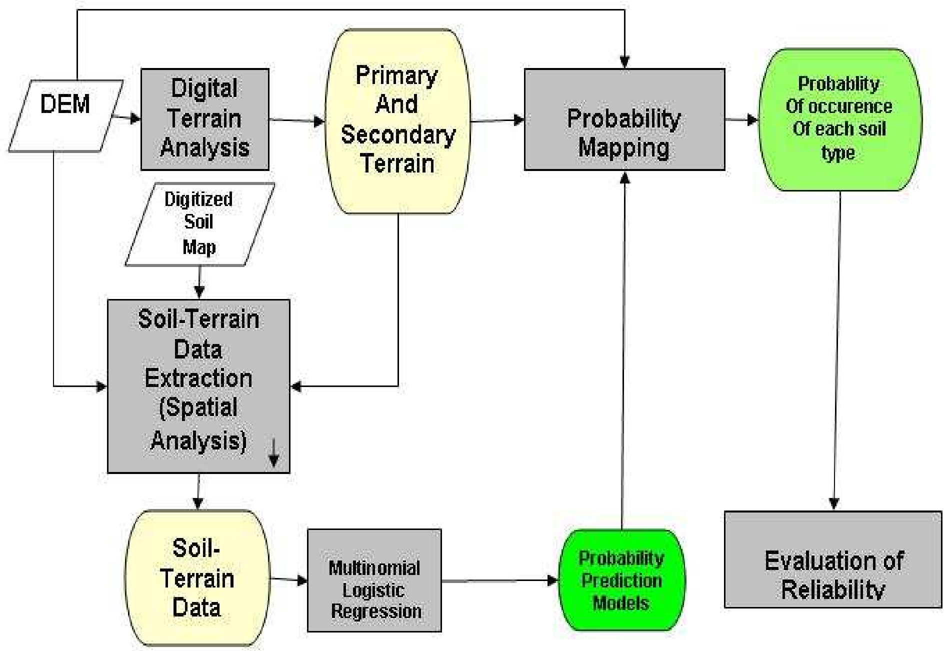



**Figure 4.4** Flowchart showing the procedures followed in the probability mapping using multinomial logistic regression models

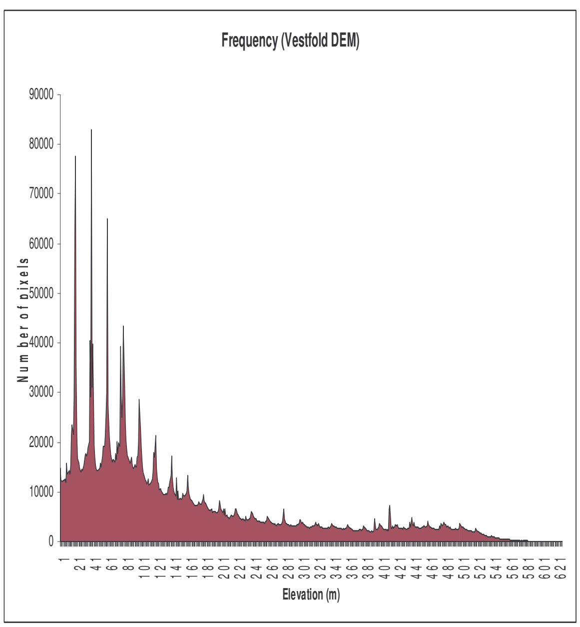
# 5 RESULTS

## 5.1 Quantitative Characteristics of the Terrain

### 5.1.1 The Quality of the Digital Elevation Model

The DEM quality assessment procedures applied on the original DEM has shown a number of constraints to the quality of the DEM. The histograms of the elevation showed high frequencies at some elevation values (figure 5.1 left). These values are multiples of the contour-interval, i.e. 20m. This behavior is much more pronounced in flat areas. The histograms of the aspect also show high frequencies for aspect values in the major eight directions that are multiples of 45 degrees (figure 5.1 right).

The search for outlying elevation values such as depressions and spikes too have identified artificially introduced depressions which are not natural lakes when checked against the land cover map derived from the satellite image. Artificial spike were also identified in the DEM.



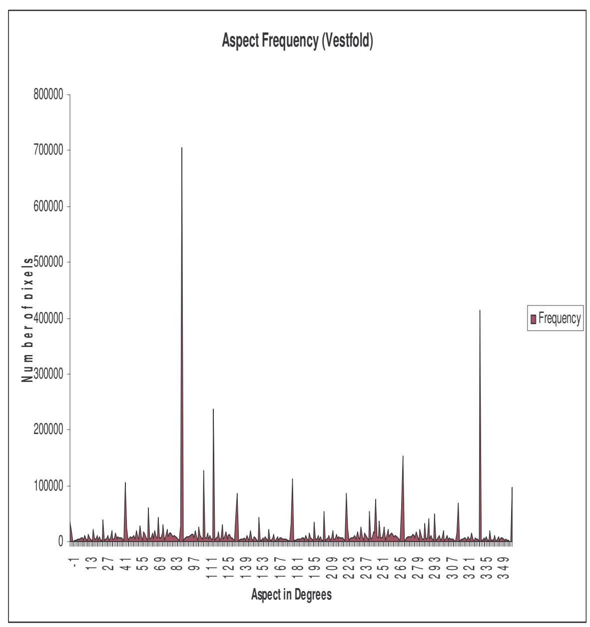




**Figure 5.1** Histograms of the elevation (left) and its aspect (right)

### 5.1.2 Digital Characterisation of the Topography of the Area

The basic terrain attributes used to characterise the topography of the area are elevation, slope, aspect, curvature and the statistical distribution of their values and the general hypsometry. Overview of the landscape can be seen in the 3D shaded relief of the elevation model (figure 5.3). Elevation statistics given in table 5.1 shows that the area is dominated by low altitude areas (positively skewed) and the positive kurtosis indicates that the elevation of the area is *leptokurtic* indicating that the elevation values seem to be peaked around some values and have some extreme tailed high values. Looking at the 3D shows that the extreme high elevation values are located at the northwest of the map; where as, low values are located at the southeast of the map. The statistics of the terrain attributes presented in table 5.2 give overview of the structural characteristics of the topography. It indicates that the mean elevation and slope are low indicating that the area is dominated by low altitude gently sloping areas. Besides, most of the area receives flow from large areas that contributed to the relatively higher level of mean topographic wetness index

Besides, the hypsometric curve of the elevation of the area presented in figure 5.2 together with the hypsometric integral measures the proportion of the area that lies below a given elevation. Both the area and the relief are standardised to values between 0 and 1 as they primarily deal with proportion. The hypsometric curve has a concave shape with hypsometric integral of about 16%. This shows that the majority of the area falls in low altitude relief.

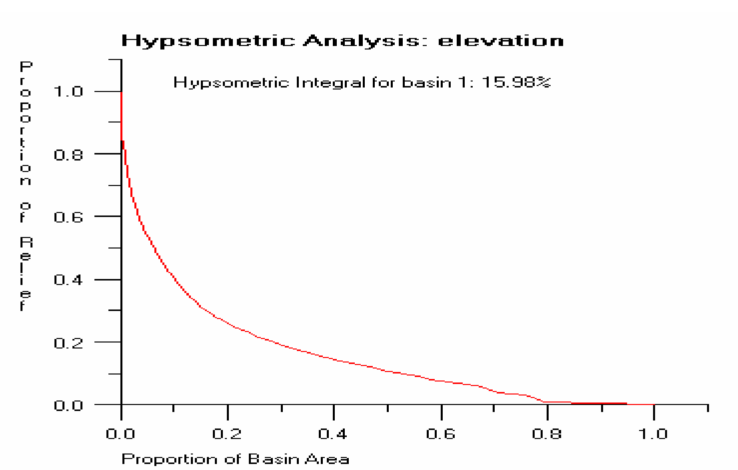



**Figure 5.2** Hypsometric curve of the elevation

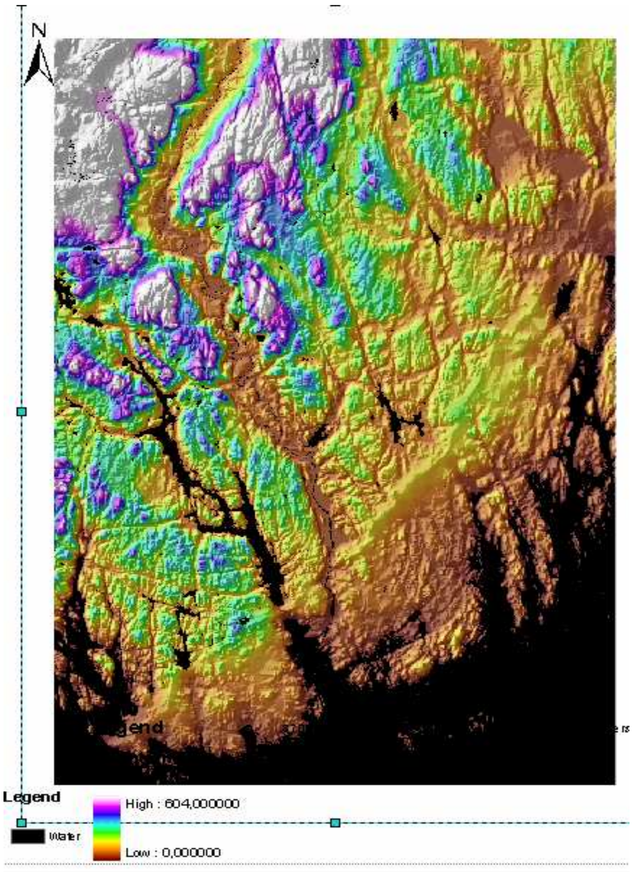



**Figure 5.3** 3D visualisation of the topography of the study area

**Table 5.1** Statistics for the elevation values

| Variable | Values |
|---|---|
| Minimum | 0 |
| Maximum | 604 |
| Mean | 93 |
| Median | 76 |
| First quartile | 19 |
| Third quartile | 172 |
| Standard deviation | 104 |
| Coefficient of variation | 1.12 |
| Skew | 1.40 |
| Kurtosis | 1.07 |
| Critical K-S stat, alpha=.01 | 0.001 |

**Table 5.2** The statistical distributions of each of the terrain attributes

| Layer | MIN | MAX | MEAN | STD |
|---|---|---|---|---|
| Aspect (sin.cos) | -0.50 | 0.50 | -0.05 | 0.33 |
| Down flow length (kilometre) | 0.00 | 2769.81 | 1275.11 | 662.74 |
| Elevation (meter) | 0.00 | 604.00 | 93.67 | 104.11 |
| Mean daily direct radiation (W/m$^2$) | 1151756.50 | 12817120.00 | 9233306.37 | 884174.00 |
| Mean daily duration of direct radiation (hr) | 0.00 | 11.00 | 9.74 | 1.21 |
| Plan curvature (degrees/100m) | -2.50 | 2.50 | 0.03 | 0.41 |
| Profile curvature (degrees/100m) | -3.00 | 3.00 | 0.03 | 0.52 |
| Relative Stream power Index (RSP) | 0.00 | 27030.00 | 26.58 | 129.42 |
| Slope (percent) | 0.00 | 211.50 | 12.22 | 14.75 |
| Specific catchment area (M$^2$/m) | 25.00 | 54310448.00 | 42671.81 | 978953.31 |
| Tangential curvature (degrees/100m) | -1.30 | 1.30 | -0.02 | 0.22 |
| Topographic Sediment transport capacity index (LS) | 0.00 | 955.71 | 4.71 | 9.68 |
| Topographic wetness index | 2.47 | 30.33 | 10.83 | 5.84 |
| Total Curvature (degrees/100m) | -4.50 | 4.50 | 0.00 | 0.80 |
| Upslope slope (percent) | 0.00 | 210.60 | 12.12 | 12.26 |
| Upstream Flow length (kilometre) | 0.00 | 250.00 | 12.58 | 31.83 |

### 5.1.3 Interrelationships among the Terrain Attributes

The Matrix of the Pearson's correlation coefficient among the terrain attributes are presented in table 5.3. The correlation coefficients vary from -0.99 to 0.83. Those greater than +0.4 or less than -0.4 are presented in bold. As per the definition of correlation coefficients, when two variables have positive correlation it indicates that increase in one variable is accompanied by the increase in the other variable proportionate to the correlation coefficient; where as, negative correlation between two variables indicate that increase in one variable is accompanied by the decrease in the other variable proportionate to the correlation coefficient. Besides, it shows that the presence of two highly correlated data in a dataset may not increase the information content of the dataset.

The table shows that all the curvature parameters are strongly correlated negatively or positively. The weakest correlation is observed between tangential and profile curvature indicating the importance of them as indicators of curvature. Elevation, slope and downstream flow length are positively correlated. This shows that elevated parts of the area are steeper in slope and are obviously far from drainage outlets. The topographic wetness index is positively correlated with the upstream flow length and negatively correlated with slope and the topographic erosion index (LS). Topographic erosivity index and relative stream power index have strong positive correlation creating doubt the use of both t the same time. Aspect and specific catchment area are only very weakly related to any of the terrain attributes. For all other correlations one has to look closely to table 5.3.

**Table 5.3** Correlation Coefficients found among the terrain attributes

| Layer | Aspect | Total Curvature | Downstrream Flow length | Mean Daily Radiation Duration | Elevation | Topographic erosion index | Slope | Plan curvature | Profile curvature | Upslope slope | Mean daily radiation | Stream power index | Specific catchment area | Tangential curvature | Upstream Flow length | Wetness Index |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Aspect | 1.00 | | | | | | | | | | | | | | | |
| Total Curvature | -0.01 | 1.00 | | | | | | | | | | | | | | |
| Downstream Flow length | 0.17 | 0.00 | 1.00 | | | | | | | | | | | | | |
| Mean Daily Radiation Duration | -0.19 | 0.35 | -0.35 | 1.00 | | | | | | | | | | | | |
| Elevation | 0.14 | 0.06 | **0.62** | -0.32 | 1.00 | | | | | | | | | | | |
| Topographic erosion index | 0.11 | -0.22 | 0.22 | **-0.51** | 0.27 | 1.00 | | | | | | | | | | |
| Slope | 0.18 | 0.38 | 0.29 | **-0.45** | **0.43** | **0.51** | 1.00 | | | | | | | | | |
| Plan curvature | 0.01 | **0.83** | 0.00 | 0.21 | 0.05 | -0.21 | 0.31 | 1.00 | | | | | | | | |
| Profile curvature | 0.02 | **-0.90** | 0.00 | -0.37 | -0.05 | 0.17 | -0.35 | **-0.50** | 1.00 | | | | | | | |
| Upslope slope | 0.16 | 0.01 | 0.23 | **-0.61** | 0.31 | **0.37** | **0.62** | 0.13 | 0.08 | 1.00 | | | | | | |
| Mean daily radiation | -0.07 | 0.04 | -0.09 | **0.41** | -0.08 | -0.14 | -0.17 | 0.01 | -0.04 | -0.16 | 1.00 | | | | | |
| Stream power index | 0.04 | -0.17 | 0.12 | -0.23 | 0.13 | **0.77** | 0.15 | -0.20 | 0.10 | 0.12 | -0.05 | 1.00 | | | | |
| Specific catchment area | 0.00 | -0.02 | -0.01 | 0.01 | -0.03 | -0.01 | -0.03 | -0.01 | 0.02 | 0.01 | 0.01 | 0.00 | 1.00 | | | |
| Tangential curvature | -0.01 | **-0.82** | 0.00 | -0.21 | -0.05 | 0.21 | -0.31 | **-0.99** | **0.49** | -0.12 | -0.01 | 0.20 | 0.01 | 1.00 | | |
| Upstream Flow length | -0.10 | -0.09 | -0.25 | 0.17 | -0.24 | -0.08 | -0.27 | -0.09 | 0.06 | -0.17 | 0.03 | 0.01 | 0.31 | 0.09 | 1.00 | |
| Wetness Index | -0.24 | 0.09 | **-0.41** | **0.47** | **-0.44** | -0.34 | **-0.53** | 0.05 | -0.11 | -0.35 | 0.11 | -0.10 | 0.12 | -0.05 | **0.58** | 1.00 |

## 5.2 Relationship between Terrain Attributes and Soil Properties

### 5.2.1 Correlation

As stated in the methodology part, the fact that the sample sizes are limited for this analysis does not encourage saying much about the relationships. However, having this fact on the background, the following points can be pointed out about the relationship between terrain attributes and some topsoil properties based on the result in table 5.4. Only those terrain attributes with significant correlations are presented in the table here. The rest are found in appendix 1.

- Clay and $KHNO_3^-$ have high positive correlation with upstream flow length and specific catchment area. They have negative correlation with slope and downstream flow length. These indicate that areas which receive flow over long distance, from large area are more likely to contain more clay and $KHNO_3^-$ compared to their opposites. Besides, the steeper the slope and the farther it is from the catchment outlet, the lower are its clay and $KHNO_3^-$ contents. Although not presented, there is also high positive correlation between soils clay content and its content of $KHNO_3^-$.
- Extractible Nitrogen and Organic carbon positively correlated with topographic wetness index and specific catchment area and negatively correlated with downstream flow length. This means soils of the areas that receive flow from large areas, and consequently have the tendency to get wet, have higher organic matter and nitrogen content. On the other hand, as the place gets far away from drainage outlets, soil organic matter content decreases. Besides, there is naturally high correlation between soil organic carbon content and nitrogen content.
- No significant correlation was found between the terrain attributes and the soils pH levels.

**Table 5.4** Correlation Coefficients and their significance found between terrain attributes and some topsoil properties

| Correlations | | | | | | |
|---|---|---|---|---|---|---|
| Terrain/Soil Attributes | | Clay | Organic Carbon | Kjeldahl's Nitrogen | pHCaCl2 | $KHNO_3$ |
| Slope | Pearson Correlation | **-.40(*)** | 0.08 | -0.05 | -0.27 | **-.41(*)** |
| | Sig. (2-tailed) | 0.03 | 0.67 | 0.81 | 0.23 | 0.04 |
| | N | 29.00 | 29.00 | 29.00 | 21.00 | 27.00 |
| Downstream flow length | Pearson Correlation | **-.60(**)** | **-.40(*)** | **-.48(**)** | 0.32 | -0.13 |
| | Sig. (2-tailed) | 0.00 | 0.04 | 0.01 | 0.16 | 0.52 |
| | N | 29.00 | 29.00 | 29.00 | 21.00 | 27.00 |
| Upstream flow length | Pearson Correlation | **.41(*)** | 0.26 | 0.29 | -0.17 | **.64(**)** |
| | Sig. (2-tailed) | 0.03 | 0.17 | 0.13 | 0.47 | 0.00 |
| | N | 29.00 | 29.00 | 29.00 | 21.00 | 27.00 |
| Topographic Wetness index | Pearson Correlation | -0.04 | **.40(*)** | 0.35 | 0.01 | 0.07 |
| | Sig. (2-tailed) | 0.82 | 0.04 | 0.06 | 0.97 | 0.75 |
| | N | 29.00 | 29.00 | 29.00 | 21.00 | 27.00 |
| Specific catchment area | Pearson Correlation | **.52(**)** | **.50(**)** | **.61(**)** | 0.06 | **.44(*)** |
| | Sig. (2-tailed) | 0.00 | 0.01 | 0.00 | 0.80 | 0.02 |
| | N | 29.00 | 29.00 | 29.00 | 21.00 | 27.00 |
| **. Correlation is significant at the 0.01 level (2-tailed). | | | | | | |
| *. Correlation is significant at the 0.05 level (2-tailed). | | | | | | |

## 5.2.2 Prediction of Soil Properties Using Multiple Linear Regression

The results of multiple linear regression analysis show how much the collection of terrain attributes contribute to the variation of a given soil property. It also enabled to construct a linear regression model that can be used for the prediction of the values of the soil properties. The results are presented and discussed only for clay content, Extractible (Kjeldahl's) nitrogen, and Potassium Nitrate ($KHNO_3^-$). The other soil attributes did not yield significant regression. The results of the regression prediction of these three and their comparison with kriging interpolation are presented case by case in the forthcoming text.

**Clay content**

Regression of soils clay content against the terrain attributes showed that 62 percent (i.e. $R^2$ =0.62) of the spatial distribution of soils clay content can be attributed to terrain parameters. Clay content is significantly related to elevation, downstream flow length, slope and aspect. The result indicated that Clay content seems to increase with decreasing slope and downstream flow length and with increasing upslope flow length. The resulting regression model is given as:

*Clay content = 34.343 - 0.0157 * [downstream flow length] - 1.887 * [slope] - 7.302 * [sin.cos.aspect] ($R^2$ =0.62)*

Interestingly, comparison of the prediction with the validation-based ordinary kriging (table 5.5) showed that the RMSE of the regression model is lower than that of the kriging although the mean value of the error (deviation) is closer to zero in the case of kriging (table 5.5). Besides, as can be seen in figure 5.4, there is high correlation between the observed values and the values predicted by the regression model ($r^2$ = 0.58) as compared to the values interpolated by ordinary kriging ($r^2$ = 0.38). One can see how realistic the prediction by the regression model looks as compared to that of kriging (figure 5.5).

**Table 5.5** Comparison of the prediction performance of the regression model and validation-based ordinary kriging

| | Parameter | Observed value | Predicted (regression) | Error (Regression) | Predicted (Kriging) | Error (Kriging) |
|---|---|---|---|---|---|---|
| Clay | Mean | 9.32 | 7.51 | **7.38** | 7.96 | **6.08** |
| | RMSE | | | **5.97** | | **7.37** |
| KHNO3- | Mean | 69.82 | 70.42 | **0.60** | 60.10 | **-9.72** |
| | RMSE | | | **26.78** | | **46.58** |
| Kjeldahl N | Mean | 0.173 | 0.170 | **-0.003** | 0.162 | **-0.011** |
| | RMSE | | | **0.095** | | **0.096** |

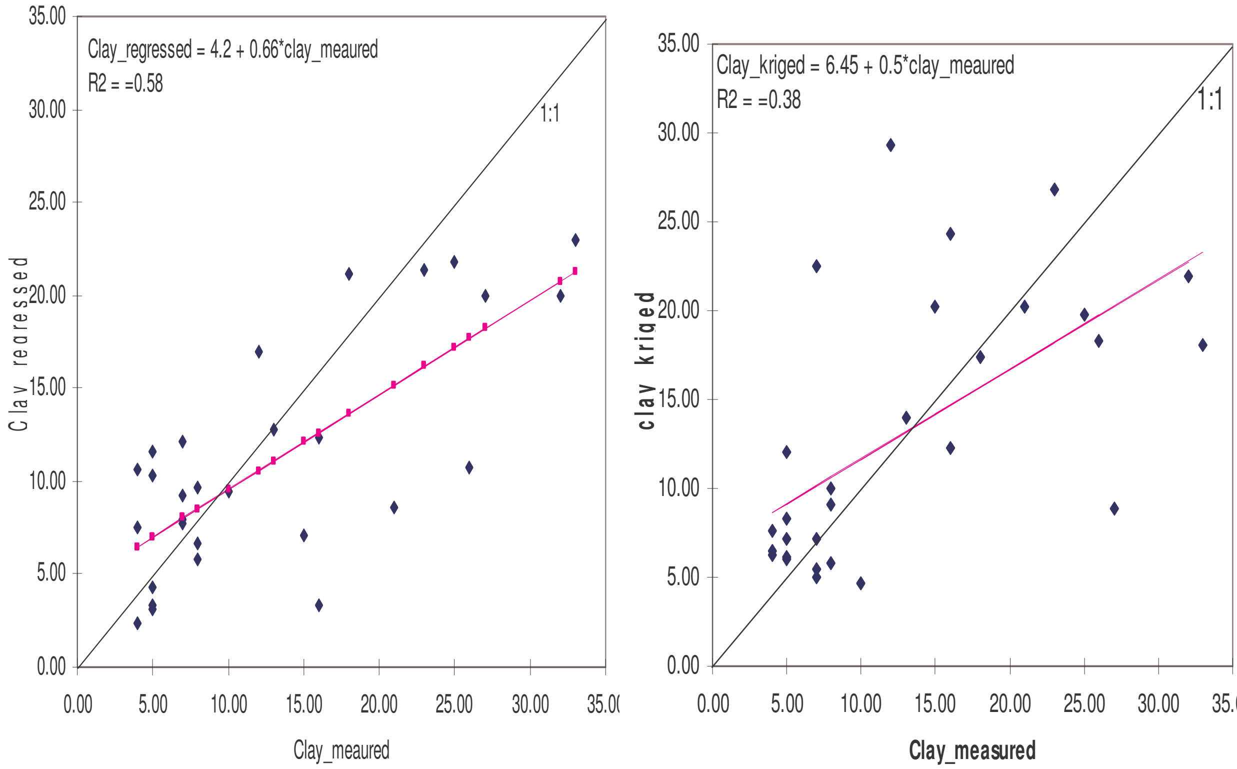



**Figure 5.4** Regression predicted clay content versus observed (left) and Kriged versus observed (right)

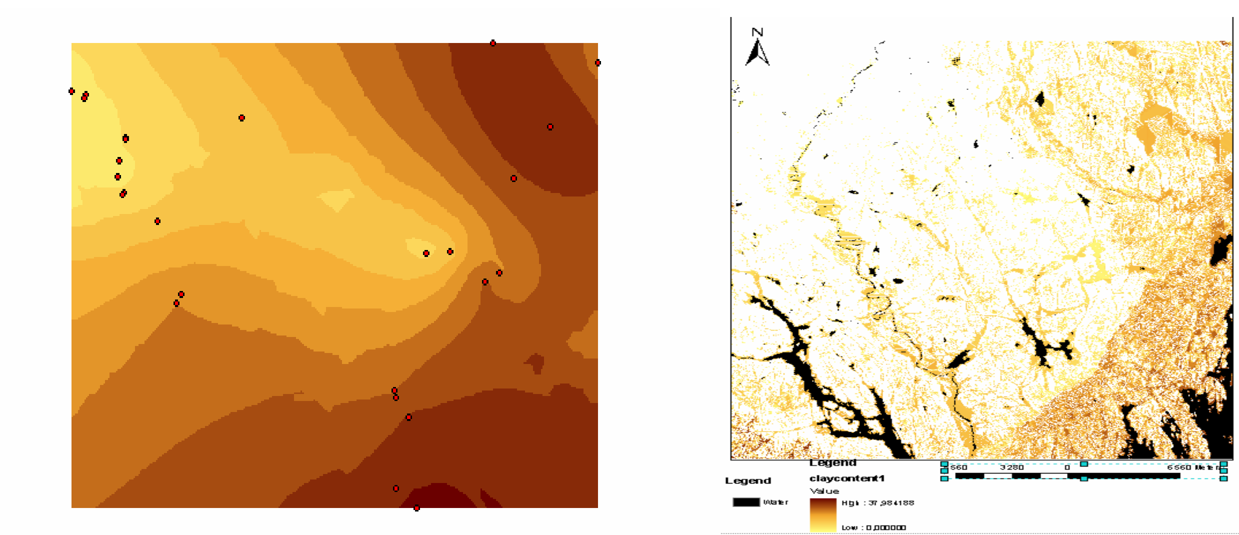



**Figure 5.5** Kriging interpolated clay content together with the data sample points (left) and regression predicted clay map (right). The map covers only part of the study area where profile data were available.

**Potassium Nitrate ($KHNO_3^-$)**

The correlation analysis between potassium nitrate and the terrain attributes showed that negative correlation exists between soils $KHNO_3^-$ content and slope and strong positive correlation between $KHNO_3^-$ and upslope flow length and the topographic wetness index. The regression of $KHNO_3^-$ against the terrain parameters showed the same relationship. It further showed that 62% of the spatial variation of $KHNO_3^-$ can be explained by the terrain attributes. The resulting regression model is given as:

*KHNO3- = 97.387 - 8.329 * [slope] + 1.6 * [mean upstream flow length] + 0.36 * [wetness index]*
*($R^2$ = 0.62)*

Again as in the case of clay, the regression predicted value has much lower RMSE and an error mean very close to zero as compared to ordinary kriging. The graphs in figure 5.6 show that the correlation between the original data and the regression predicted values is much higher *($R^2$ = 0.60)* compared to the kriging interpolated ($R^2$ = 0.03), which indicates almost a failure of the kriging interpolation.

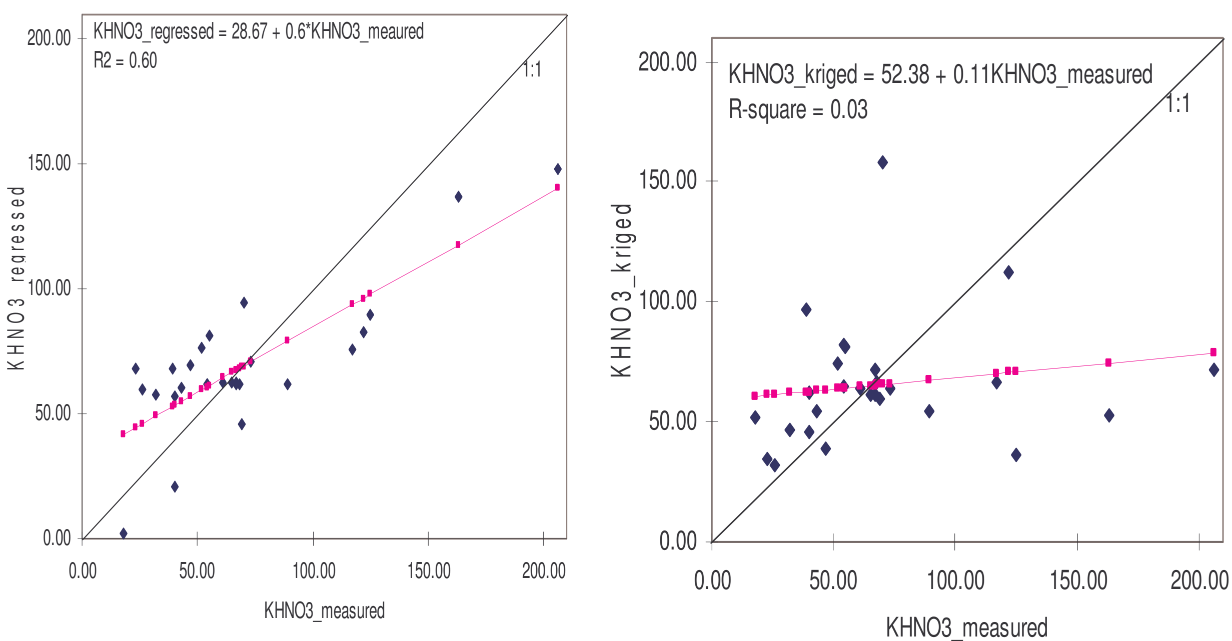



**Figure 5.6** Regression predicted versus observed (left) and Kriged versus observed (right) KHNO3- data

**Extractible (Kjeldahl's) Nitrogen**

The result of the multiple linear regressions showed that nitrogen is related to elevation, downstream flow length, the topographic wetness index, slope and aspect. It further indicated that topographic attributes account for about 67 percent ($R^2 = 0.67$) of the spatial variation of soils extractible nitrogen content. The resulting regression model is given as:

*Kjeldahl_N = 0.361 - 0.000101 * [downstream. Flow length] + 0.002 * [wetness index] - 0.007 * [tangent curve] + 0.022 * [ LS] - 0.096 * [si.ncos.aspect] + 0.002 * [elevation] - 0.069 * [slope]*

($R^2 = 0.67$)

The regression prediction predicted the mean value better with error mean much closer to zero and with a slightly lower RMSE compared to the kriging interpolation (table 5.5). The graphs in figure 5.7 depict how much each predictive approach reproduced the original data. It also confirms that the regression prediction performs better ($R^2 = 0.40$) compared to the interpolation by kriging ($R^2 = 0.31$).

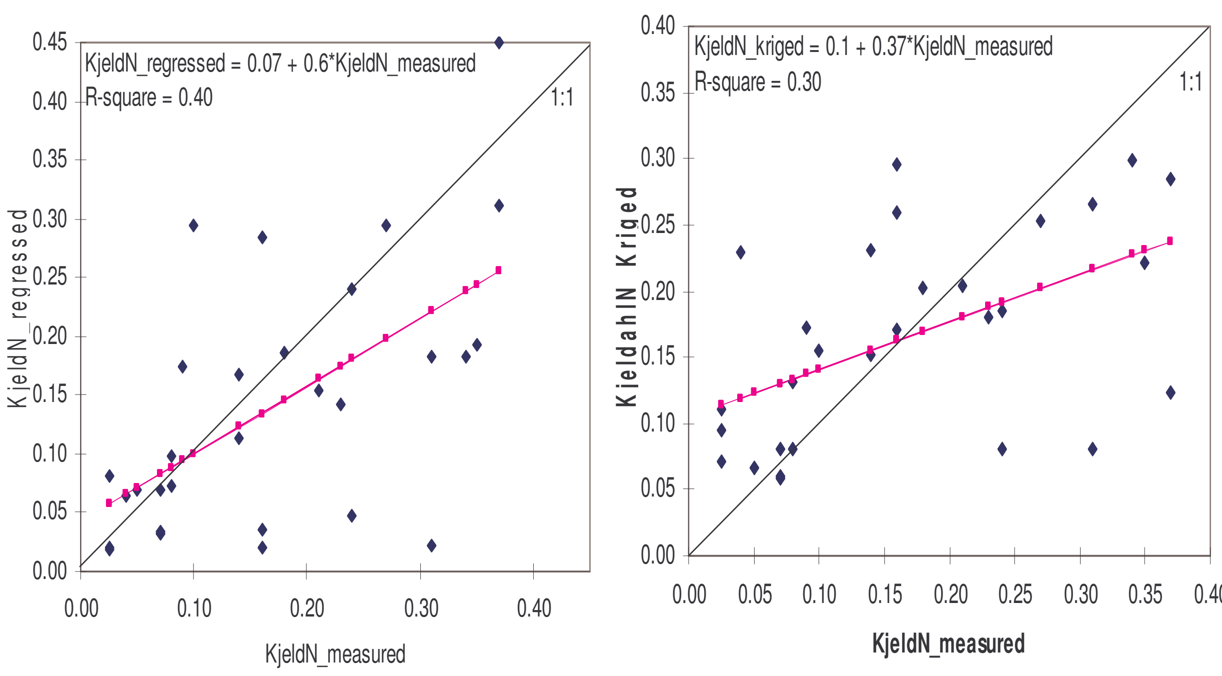



**Figure 5.7** Regression predicted versus observed (left) and Kriged versus observed (right) N data

## 5.3 Digital Mapping of Soil Classes as Discrete Objects Using Terrain Classification Algorithms

### 5.3.1 Analysis Of Variance

Analysis of variance among the soil classes showed that there is significant variation among the soil classes on all terrain attributes. The F-values of all the terrain attributes indicate that the null hypothesis is rejected (table 5.6). Accordingly, there is significant difference between the soil classes in all terrain attributes. Hoverer, pair-wise comparison between two soil classes based on each terrain attribute, although not presented due to its length, showed different picture. Some terrain attributes are capable of distinguishing some soil classes while they are incapable of doing the same between some other soil classes. The result in general showed that all the terrain attributes are important in distinguishing soil classes but not all terrain attributes are important for all soil classes.

The ANOVA result shows that based on their significance and their capability to separate soil classes (look at the F-values in table 5.6), the terrain attributes can be arranged as follows from the most significant to the least significant: elevation, downstream flow length, mean duration of daily direct radiation, slope, upslope slope, wetness index, and flow length, Sediment Transport Index (LS), profile curvature, aspect, etc. The terrain attribute with the least significance, i.e. with the smallest F value, was found to be plan curvature. This shows that, first and foremost, the soil classes are spatially distributed based on elevation, then distance from drainage outlet, followed by slope, etc.

**Table 5.6** ANOVA result of the soil classes against the terrain attributes

| Attribute (factor) | Sum of Squares | degrees of freedom | Mean Square | F | Sig. |
|---|---|---|---|---|---|
| Elevation | 11591085,83 | 13,00 | 891621,99 | 1461,54 | 0,00 |
| Downstream Flow Length | 217390769,21 | 13,00 | 16722366,86 | 284,71 | 0,00 |
| Mean daily duration of direct radiation | 2096,43 | 13,00 | 161,26 | 272,96 | 0,00 |
| Slope | 63300,18 | 13,00 | 4869,24 | 133,38 | 0,00 |
| Upslope slope | 86467,71 | 13,00 | 6651,36 | 86,14 | 0,00 |
| Topographic wetness index | 35097,87 | 13,00 | 2699,84 | 65,06 | 0,00 |
| Topographic Sediment transport capacity index (LS) | 11530,66 | 13,00 | 886,97 | 62,18 | 0,00 |
| Profile curvature | 33,84 | 13,00 | 2,60 | 34,66 | 0,00 |
| Aspect(sin.cos) | 52,07 | 13,00 | 4,01 | 33,23 | 0,00 |
| Relative Stream power Index (RSP) | 648995,39 | 13,00 | 49922,72 | 23,81 | 0,00 |
| Total curvature | 51,86 | 13,00 | 3,99 | 23,79 | 0,00 |
| Mean daily direct radiation | 667941478839501,00 | 13,00 | 51380113756884,70 | 16,05 | 0,00 |
| Upstream Flow length | 166149,49 | 13,00 | 12780,73 | 11,10 | 0,00 |
| Specific catchment area | 4124914809726,60 | 13,00 | 317301139209,74 | 8,17 | 0,00 |
| Tangential curvature | 0,85 | 13,00 | 0,07 | 5,10 | 0,00 |
| Plan curvature | 2,66 | 13,00 | 0,20 | 5,09 | 0,00 |

### 5.3.2 Object-Oriented Supervised Terrain Classification Approach to Digital Soil Mapping

There are three important analysis results of this approach that needs to be presented here: First, *the segmentation of homogeneous terrain attributes:* Segmenting terrain-objects at appropriate level was not found to be an easy task and required multiple try as it is solely based on trial and error. The final result which gave maximum classification accuracy was conducted at scale value of 20 using all the terrain attributes with shape factor of 0.1 shared between smoothness and compactness equally. This segmented the 2933694 pixels (1401columns by 2094 rows) into 327238 terrain objects, decreasing the units to be classified by almost 90 percent.

Second, *the features used for the classification*: The identification of the best combination of features was based on how well the features separated the soil classes. The separation distance, which indicates how well classes are distinct, increased with the number of features until the optimum number was reached, then it started to decrease (figure 5.8). The final combination with relatively best result was obtained by inserting 47 features which were optimized by the program to 21 features with best minimum separation distance of 1.7. These features included the mean, standard deviation and mean difference to the scene mean of: elevation, slope, downstream flow length, aspect, specific catchment area, upstream flow length, and wetness index.  The result still agrees with the result of the ANOVA presented earlier in table 5.6 with minor differences.

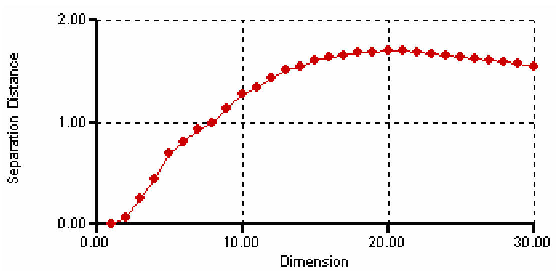



**Figure 5.8** Separation distance between sample soil classes as plotted against the number of features (dimension)

Third, *the classification result and its accuracy*: The classification result (figure 5.9) and its accuracies, presented in table 5.7, were obtained after so many trials. It was learnt that the approach seems to be working for the mapping of some soil types while it fails for others. In the end, the overall accuracy could not go beyond 30 percent (table 5.7). Umbrisols, Cambisols, Luvisols and Albeluvisols have relatively higher level of prediction accuracy, with Umbrisols getting the highest accuracy.  Where as, the other soils have very low prediction accuracy indicating almost failure of the method. The accuracy decreased as the scale factor increased or decreased from the optimum scale factor of 20.

The area coverage of the different soil classes in the whole study area is also presented in the bar chart of figure 5.11. This helps to compare the area coverage of the soils in the reference map with that in the prediction map. Besides, the accuracies were related to the area coverage. Accordingly, both producer and user accuracies correlated with the area coverage of the soils (table 5.8). The correlation is even stronger with the prediction map. This indicates that the more widespread soils in the area have better accuracies as can actually be seen in table 5.6. Besides, there is strong correlation between the soils area coverage in the reference map and in the prediction map. This indicates that the method almost kept the area proportion of the soil classes during the prediction. There is good correlation between the user and producer accuracies indicating comparable errors of omission and commission.

**Table 5.7** Accuracy of the Object-oriented classification

| Class | Producer accuracy | User accuracy |
|---|---|---|
| Umbrisol | 76.09 | 44.33 |
| Luvisol | 31.82 | 12.97 |
| Cambisol | 31.69 | 31.95 |
| Albeluvisol | 14.26 | 28.64 |
| Anthropic Regosol | 1.64 | 4.31 |
| Podzol | 1.53 | 4.71 |
| Histosol | 0.97 | 8.28 |
| Leptosol | 0.94 | 0.91 |
| Phaeozem | 0.57 | 4.68 |
| Gleysol | 0.52 | 6.99 |
| Anthrosol | 0.50 | 0.46 |
| Arenosol | 0.49 | 3.81 |
| Fluvisol | 0.33 | 3.48 |
| Regosol | 0.00 | 0.00 |
| Overall Accuracy | | 30.90 |

**Table 5.8** Relationship of the prediction accuracies to other parameters

| correlation statistics | Observed area cover | predicted area cover | producer accuracy | User accuracy |
|---|---|---|---|---|
| Observed area cover | 1 | | | |
| predicted area cover | 0.78 | 1 | | |
| producer accuracy | 0.37 | 0.57 | 1 | |
| User accuracy | 0.36 | 0.46 | 0.88 | 1 |

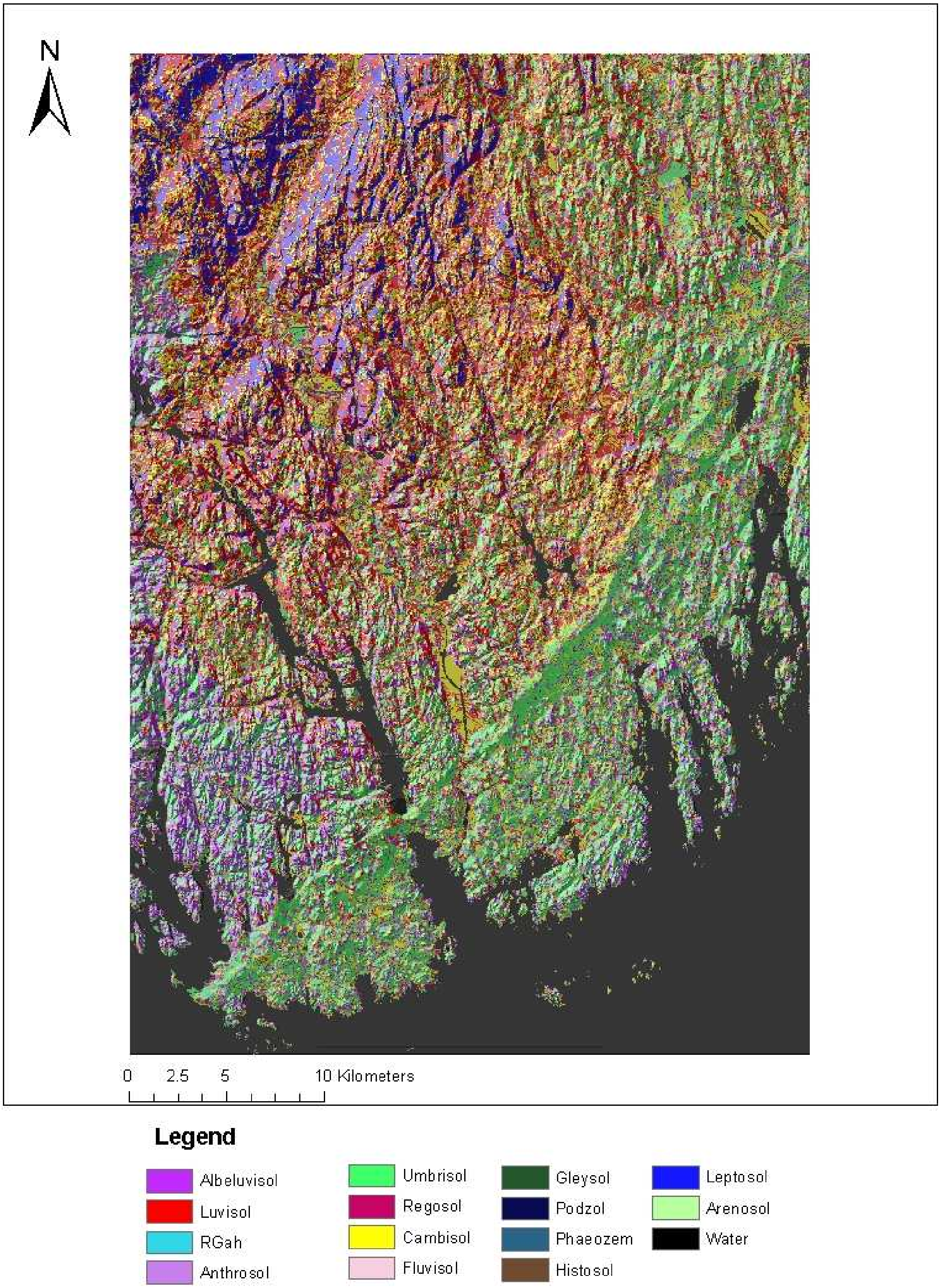



**Figure 5.9** Map of the soil classes as predicted by object-oriented terrain classification

### 5.3.3 Pixel-Based Supervised Terrain Classification Approach to Digital Soil Mapping

The result of the ordinary pixel-based supervised classification is presented in figure 5.10. The figure shows the spatial distribution of each soil type as predicted by supervised classification of terrain pixels. The accuracies of the prediction are also presented in table 5.9. The overall accuracy could not go beyond 14 percent. That is by far very low in absolute sense and compared to the result of the object-oriented classification. Again, the same soil classes tend to have higher user accuracy as in the case of object-oriented classification. However, the producer accuracy has different trend. There seems to be very low correlation between producer and user accuracy. There is also loose connection between the area cover of a soil type and its accuracy of prediction. The prediction map shows that Podzols (36%) are the most wide-spread soil type followed by Umbrisols (20%). This is contrary to the original soil map and to the object-oriented prediction.

**Table 5.9** Pixel-based prediction accuracies

| Class | Producer accuracy | User Accuracy | |
|---|---|---|---|
| Podzol | 39.16 | 4.58 | |
| Umbrisol | 31.26 | 34.76 | |
| Regosol | 29.73 | 0.69 | |
| Arenosol | 22.98 | 4.06 | |
| Cambisol | 14.47 | 41.56 | |
| Fluvisol | 4.18 | 6.18 | |
| Histosol | 3.74 | 5.29 | |
| Gleysol | 2.25 | 9.38 | |
| Luvisol | 2.15 | 20.24 | |
| Anthropic Regosol | 2.15 | 4.33 | |
| Phaeozem | 2.11 | 1.94 | |
| Anthrosol | 0.38 | 1.65 | |
| Leptosol | 0.16 | 1.31 | |
| Albeluvisol | 0.06 | 20.53 | |
| Overall Accuracy | | | 13.58 |

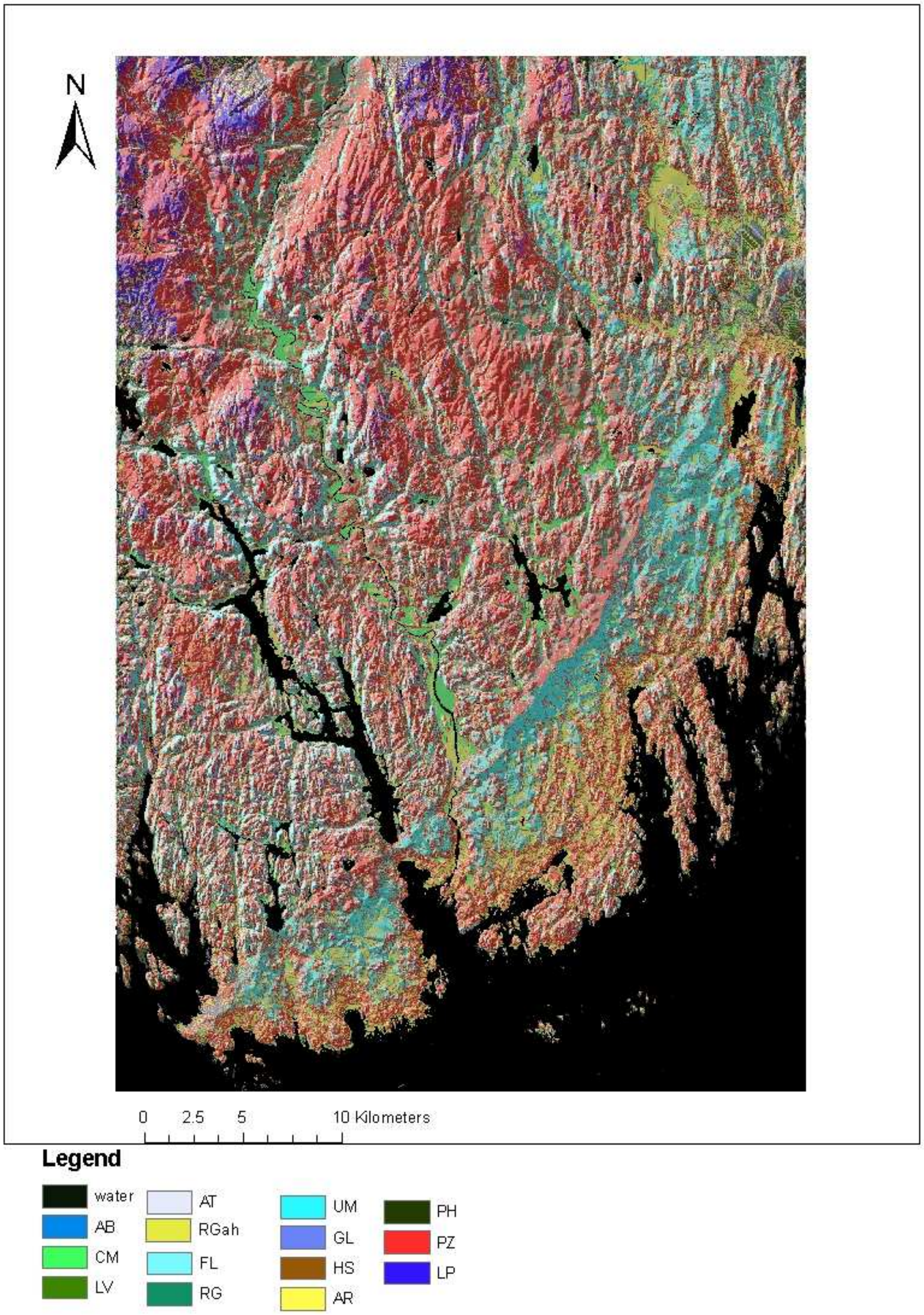



**Figure 5.10** Map of the soil classes as predicted by pixel-based supervised classification

## 5.4 Digital Mapping of Soil Classes as Fuzzy Variables

### 5.4.1 Multinomial Logistic Regression

The overall multinomial logistic model was found to be significantly fit at $p<0.05$. Table 5.10 further shows that the most significant terrain attributes in influencing the spatial distribution of the soil classes were found to be elevation, downstream flow length, mean daily duration of radiation, mean upslope slope, slope aspect, etc (See appendix 2 for the raw result of the analysis). In fact, with the exception of plan curvature all of them were found to be significantly influential.

On the other hand, almost all soil classes were found to be influenced by at least two terrain attributes. The extent of the influence is presented in table 5.11. The magnitudes in the table indicate the factor by which the odds ratios of the soil classes change if the value of a given terrain attribute is increased by a unit. Besides, values greater than 1 indicate that increase in the values of the terrain attribute results in the increase in the odds ratios of that soil class, although the magnitude has no direct meaning for the values of the probabilities. On the other hand, values less than 1 show the opposite of this. The further the values are from 1, the stronger the change in the odds ratios that is caused by increase in one unit of the predictor. This will be discussed in detail later as it needs cautionary explanation. The terrain attributes which were found significantly influential in the spatial distribution of each soil class and the type and extent of the influences are presented in table 5.10.

**Table 5.10** The significance of each terrain attribute in the overall model

| Likelihood Ratio Tests | | | | |
|---|---|---|---|---|
| | Model fitting criteria | Likelihood Ratio Tests | | |
| Effect | -2 Log Likelihood of Reduced Model | Chi-Square | degree of freedom | Sig. |
| Elevation | 223469.33 | 18769.14 | 13.00 | 0.00 |
| Downstream flow length | 215214.89 | 10514.70 | 13.00 | 0.00 |
| Mean daily duration of radiation | 206495.91 | 1795.72 | 13.00 | 0.00 |
| Mean upslope slope | 205509.50 | 809.32 | 13.00 | 0.00 |
| slope | 205030.49 | 330.30 | 13.00 | 0.00 |
| Aspect (sin.cos) | 204857.72 | 157.53 | 13.00 | 0.00 |

| | | | | |
|---|---|---|---|---|
| Received Mean daily direct radiation | 204836.65 | 136.46 | 13.00 | 0.00 |
| Upstream flow length | 204802.35 | 102.16 | 13.00 | 0.00 |
| Specific catchment area | 204786.02 | 85.83 | 13.00 | 0.00 |
| Wetness Index | 204773.80 | 73.61 | 13.00 | 0.00 |
| Erosion Index (LS) | 204754.32 | 54.13 | 13.00 | 0.00 |
| Relative Stream Power Index | 204754.30 | 54.11 | 13.00 | 0.00 |
| Tangent Curvature | 204732.28 | 32.10 | 13.00 | 0.00 |
| Total Curveture | 204729.45 | 29.26 | 13.00 | 0.01 |
| Profile curvature | 204725.98 | 25.79 | 13.00 | 0.02 |
| Plan Curvature | 204 667.44 | 16.54 | 13.00 | 0.22 |

**Table 5.11** The influence of each terrain attribute on each soil class as expressed in odd ratios

| **Parameter Estimates** | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Predictor** | **EXP(B) of Soil class** | | | | | | | | | | | | |
| | AB | AR | AT | CM | FL | GL | HS | LP | LV | PH | PZ | RG | Rgah |
| Aspect (sin.cos) | 1.39 | | 0.27 | 1.35 | | | | | 1.17 | 0.48 | | | 1.90 |
| Total Curvature | | 0.13 | | | | | | | | | | | |
| Downstream Flow Length | 1.01 | 1.01 | 1.01 | 1.01 | 1.01 | 1.01 | 1.01 | 0.99 | 1.01 | 0.99 | 0.99 | 1.01 | 0.99 |
| Elevation | 0.99 | 0.91 | 0.98 | 0.95 | 0.98 | 0.99 | 1.01 | 1.05 | 0.98 | 1.02 | 1.00 | 1.01 | 0.97 |
| Topographic erosion index (LS) | | | | | 1.12 | 1.12 | | | | | | | |
| slope | 0.93 | 1.05 | | | 0.86 | 0.86 | 0.85 | | 0.92 | | | 0.85 | |
| Profile curvature | | 0.10 | | | | | | | | | | | |
| Mean Upslope slope | 0.99 | 0.96 | | 0.96 | 0.99 | | 1.02 | | | | 0.97 | | 0.99 |
| Relative stream power index | | 1.00 | | | 0.99 | 0.99 | | | | | | | |
| Specific catchment area | | 0.99 | | 0.99 | | | | | 0.99 | | 0.99 | | 0.99 |
| Tangential curvature | | 0.03 | | | | | | | | | | | |
| Upstream flow length | | 1.01 | | 1.01 | 1.00 | | | | | | 1.01 | | 1.01 |
| Wetness index | | 0.99 | 0.95 | | | | | | 0.98 | 1.04 | 0.96 | | |
| Mean duration of direct radiation | | 0.72 | 3.21 | 0.62 | 0.37 | 0.81 | 0.59 | | | 0.50 | 0.75 | 1.74 | 0.70 |
| Mean direct shortwave radiation | 1.00 | | | 1.00 | 1.00 | 1.00 | 1.00 | | 1.00 | 1.00 | 1.00 | | |

a. The reference category is: UM

The other outcome of the analysis is the possibility of constructing logit models for each soil class except for the reference soil class. Each model enables to predict the probability that a given soil class exists in a given area given the values of the terrain attributes which are found to be significantly influential in the spatial distribution of that soil class. More correctly, the models linearly relate terrain attributes to the logit of the soil classes. The coefficient B shows the linear change in the logit of the soil class when a terrain attribute is increased by a unit value. Since it is linearly related to the logit, it is used to construct the logit model for each soil class in analogy with a multiple linear regression. One can look at the models presented in table 5.12 to know how the logit of each soil class is related to a particular terrain attribute.

**Table 5.12** The logit models of the soil classes as expressed by the terrain attributes. (Note that the units are as expressed in table 4.1)

| *ln(p/1-p) of Soil class* | *Logit model* |
|---|---|
| Albeluvisol | 0.325 * [aspectsincos] + 0.31 * [curve_total] + 0.002 * [downstr._flow_length] - 0.011 * [elavation] + 0.75 * [profilecurve] - 0.012 * [upslope_slope] - 0.066 * [slope] |
| Anthropic Regosol | 7.723 + 0.639 * [aspectsincos] - 0.001 * [downstr._flow_length] - 0.034 * [elavation] - 0.014 * [upslope_slope] - 0.040 * [slope] + 0.006 * [upstr._flow_length] - 0.362 * [mean_radiation_duration] |
| Anthrosol | - 15.12 - 1.32 * [aspectsincos] + 0.001 * [mean_radiation_duration] - 0.024 * [elavation] - 0.091 * [slope] - 0.045 * [wetness_index] + 1.146 * [mean_radiation_duration] |
| Arenosol | 5.81 + 0.002 * [downstr._flow_length] - 0.098 * [elavation] - 0.72 * [profilecurv] - 0.04 * [upslope_slope] - 0.03 * [slope] + 0.007 * [upstr._flow_length] - 0.014 * [wetness_index] - 0.323 * [mean_radiation_duration] |
| Cambisol | 6.8 + 0.296 * [aspectsincos] + 0.002 * [downstr._flow_length] - 0.048 * [elavation] - 0.434 * [profilecurv] - 0.038 * [upslope_slope] - 0.047 * [slope] + 0.006 * [upstr._flow_length] - 0.473 * [mean_radiation_duration] |
| Fluvisol | 9.42 + 1.04 * [curve_total] + 0.001 * [downstr._flow_length] - 0.018 * [elavation] + 0.111 * [ls] + 1.6 * [profilecurv] - 0.008 * [upslope_slope] - 0.008 * [rsp] - 0.182 * [slope] + 0.004 * [upstr._flow_length] - 0.999 * [mean_radiation_duration] |
| Gleysol | 2.88 + 0.745 * [curve_total] + 0.001 * [downstr._flow_length] - 0.009 * [elavation] + 0.124 * [ls] + 2.178 * [profilecurv] - 0.015 * [rsp] - 0.256 * [slope] - 0.222[mean_radiation_duration] |
| Hsitosol | 5.008 + 1.209 * [curve_total] + 0.001 * [downstr._flow_length] + 0.006 * [elavation] + 2.334 * [profilecurv] + 0.023 * [upslope_slope] - 0.207 * [slope] + 0.021 * [wetness_index] - 0.544 * [mean_radiation_duration] |
| Leptosol | - 0.004 * [downstr._flow_length] + 0.050 * [elavation] |
| Luvisol | 2.730 + 0.152 * [aspectsincos] + 0.496 * [curve_total] + 0.001 * [downstr._flow_length] - 0.022 * [elavation] + 1.264 * [profilecurv] - 0.081 * [slope] - 0.016 * [wetness_index] |
| Phaeozem | 10.332 - 0.706 * [aspectsincos] - 0.004 * [downstr._flow_length] + 0.024 * [elavation] - 0.135 * [slope] - 0.712 * [mean_radiation_duration] |
| Podzol | 4.632 - 0.001 * [downstr._flow_length] + 0.004 * [elavation] - 0.032 * [upslope_slope] + 0.010 * [upstr._flow_length] - 0.040 * [wetness_index] - 0.285 * [mean_radiation_duration] |
| Regosol | -9.309 + 0.001 * [downstr._flow_length] + 2.324 * [profilecurv] - 0.148 * [slope] + 0.543 * [mean_radiation_duration] |

### 5.4.2 Digital Soil Mapping Using Multinomial Logistic Regression

The resulting prediction map of each soil class, presented in figures 5.11 to 5.17, show the probabilities that a given soil class is located in a given pixel with values between 0 and 1, where 0 is absolutely no chance and 1 indicates sure existence of the soil. The high values are shown in red in all of the maps. With the exception of Anthrosols and Regosols the maximum probability values of all the other soil classes were above 0.5. The maps were found to be very reliable when evaluated using the two approaches explained in the methodology part of this thesis. When the maps were evaluated based on the generic definition of the soil classes and comparison with the (Solbakken et al., 2006) high probability areas for a soil class more or less coincided with areas covered with that soil class.

Besides, the probability maps were investigated through 3D visualization and correlations studies with other terrain attributes. These five groups listed below fit well with the theory of the spatial distribution of soil classes and correlated visually well with the empirical soil map.

1. Soils with high probability on the hills and mountains and steep areas: These are Leptosols dowelling the hill tops and Umbrisols and Podzols dowelling steep areas.
2. Soils with high probabilities in the valleys and very gentle slopes: these are cambisols, Fluvisols, Luvisols, and Albeluvisols.
3. Soils with high probabilities at the depressions and beach playas: These are Gleysols and Arenosols
4. Soils that that have high probabilities in valleys: these are Histosols and luvisols
5. Soils with unreliable topographic relations: Anthrosols, regosols and anthropic regosols.

**Probability correlation:** The basic guideline here was that soils that are known to develop in similar environment are expected to have higher positive correlation in their probabilities while those develop under opposite environment are expected to have higher negative correlation.

The result, which further strengthened the reliability of the probability mapping, is presented in table 5.13. Very high correlation values are presented in bold. Based on the result, some groups which have high positive correlation among themselves could be identified:

1. Histosol, Fluvisol and Gleysol group: The FAO definition and characterization of the environment of this group shows some common feature. The first two develop in areas where there is accumulation of organic matter which requires the presence of wetness.

The presence of wetness links these two to Gleysol as Gleysols are created due to poor drainage.

2. Luvisol, Albeluvisol, Cambisol and Regosol group: These soils have common features. These soil classes are known to dwell flat and gently sloping areas with pedogenically favorable conditions.
3. The third group comprises of Podzol and Umbrisol which have very high positive correlation. These two soil classes are found basically under the same physical environment that is subjected to bleaching and eluviation, but they differ in that the second contains high organic matter.
4. Anthrosol and Anthropic regosol correlated well indicating the spatial correlation of human activities that lead to the formation of these soil classes.
5. Leptosol correlates poorly or negatively with all of the soil classes as it dwells topographically well distinguished environment, the hilltops.
6. Phaeozem also correlated poorly with any soil class indicating that it too occupied a unique environment in this study area.

**Table 5.13** Correlation among the probabilities of the soil classes

| Layer | AB | AR | AT | CM | FL | GL | HS | LP | LV | PH | PZ | RG | Rgah | UM |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| AB | 1.00 | | | | | | | | | | | | | |
| AR | -0.38 | 1.00 | | | | | | | | | | | | |
| AT | -0.24 | **0.54** | 1.00 | | | | | | | | | | | |
| CM | 0.05 | **0.52** | 0.13 | 1.00 | | | | | | | | | | |
| FL | 0.12 | -0.07 | -0.12 | 0.23 | 1.00 | | | | | | | | | |
| GL | 0.26 | 0.06 | 0.22 | 0.22 | **0.33** | 1.00 | | | | | | | | |
| HS | 0.31 | -0.28 | -0.21 | -0.19 | **0.30** | **0.44** | 1.00 | | | | | | | |
| LP | -0.35 | -0.40 | -0.35 | -0.57 | -0.25 | -0.46 | -0.14 | 1.00 | | | | | | |
| LV | **0.39** | 0.16 | **0.36** | **0.45** | 0.19 | **0.57** | 0.01 | -0.71 | 1.00 | | | | | |
| PH | -0.20 | -0.12 | 0.05 | -0.24 | -0.03 | -0.06 | -0.01 | -0.03 | -0.17 | 1.00 | | | | |
| PZ | 0.13 | -0.35 | -0.23 | -0.26 | -0.06 | -0.30 | -0.08 | -0.06 | -0.17 | 0.00 | 1.00 | | | |
| RG | **0.41** | -0.18 | 0.07 | -0.13 | 0.06 | **0.52** | **0.40** | -0.23 | **0.36** | -0.04 | -0.04 | 1.00 | | |
| Rgah | -0.41 | 0.52 | **0.53** | 0.17 | -0.07 | -0.02 | -0.29 | -0.43 | 0.15 | 0.16 | -0.14 | -0.17 | 1.00 | |
| UM | 0.30 | -0.37 | -0.24 | -0.23 | -0.08 | -0.26 | -0.03 | -0.08 | -0.08 | -0.10 | **0.80** | 0.00 | -0.26 | 1.00 |

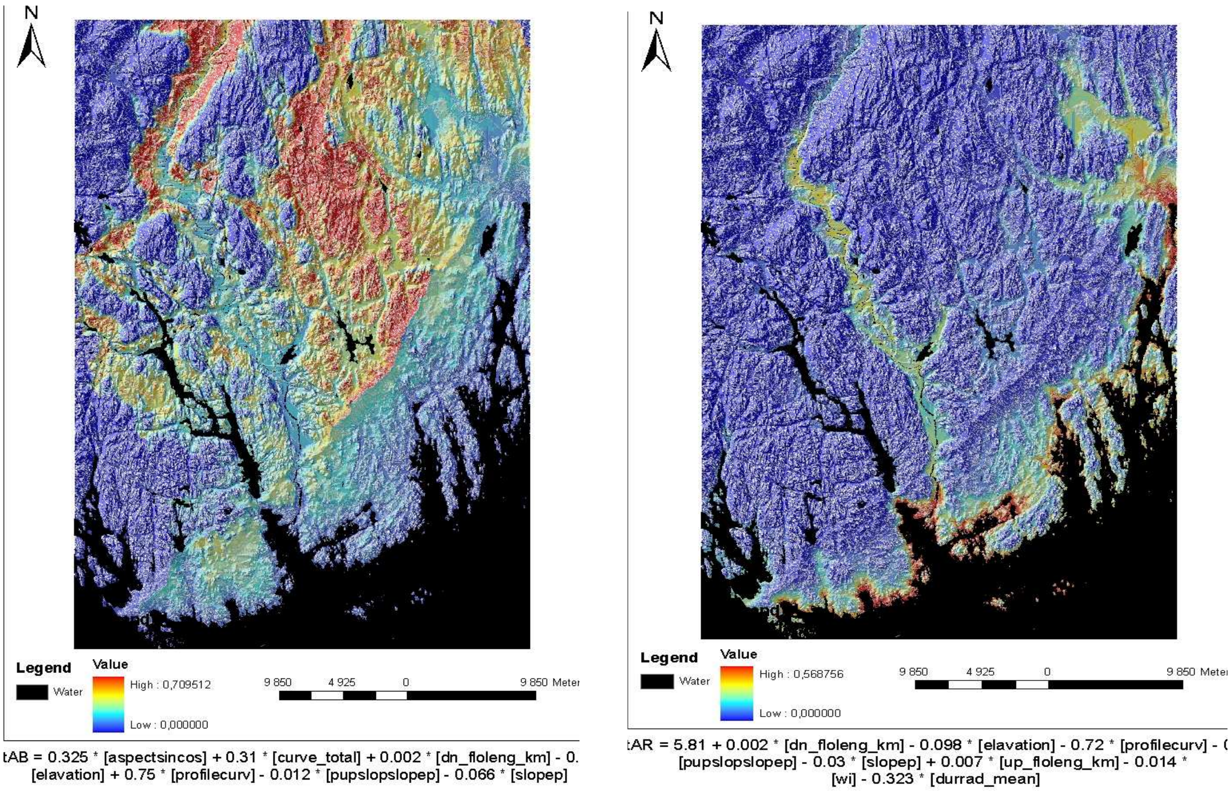



**Figure 5.11** Probability Distribution of Albeluvisol (left) and Arenosol (right)

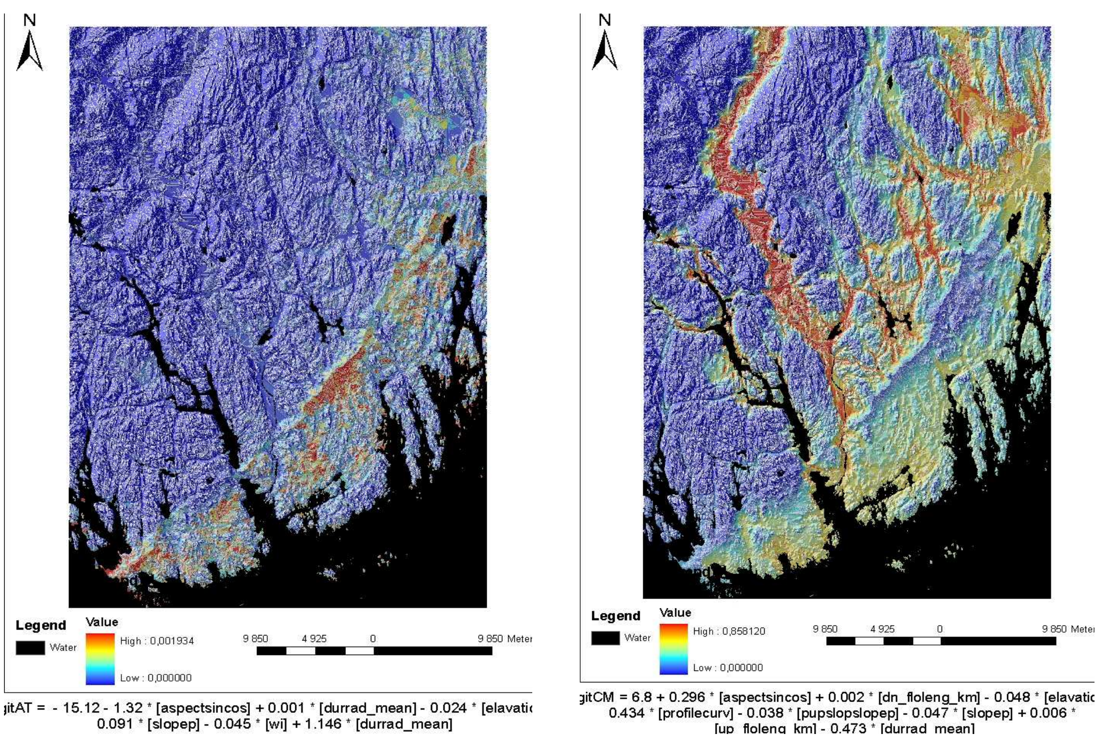



**Figure 5.12** Probability Distribution of Anthrosol (left) and Cambisol (right)

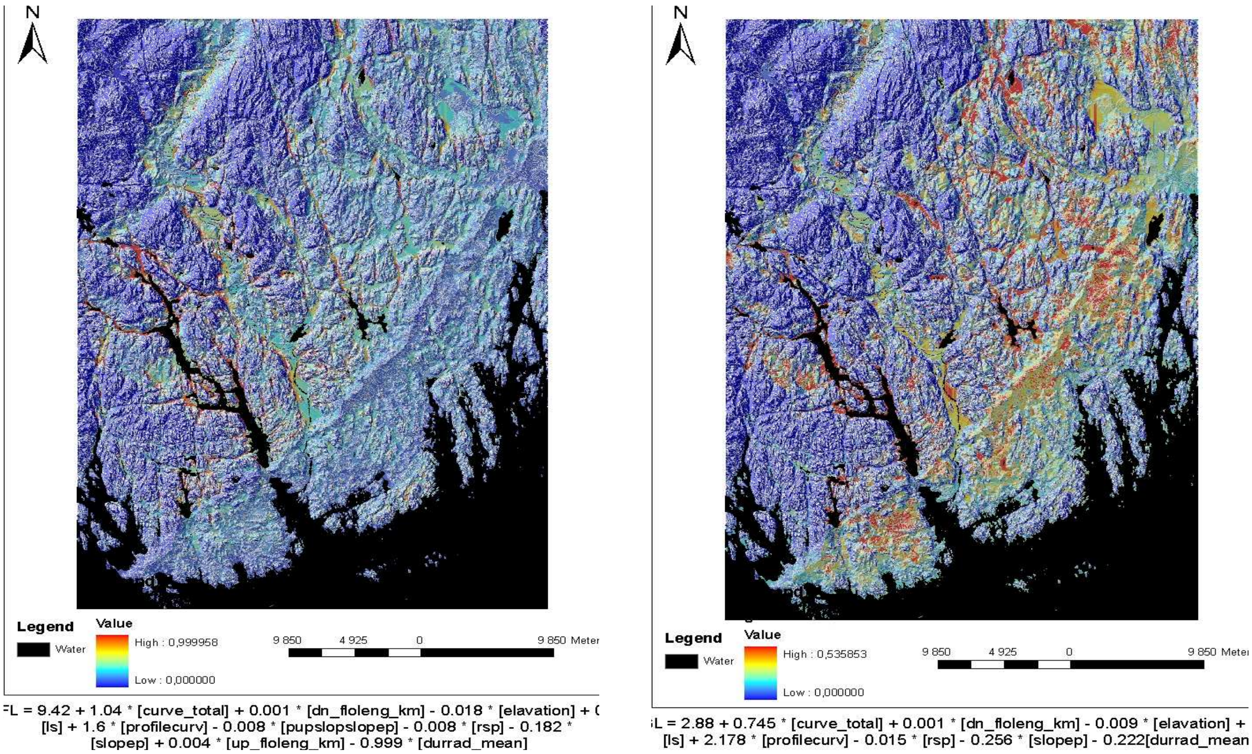



**Figure 5.13** Probability Distribution of Fluvisol (left) and Gleysol (right)

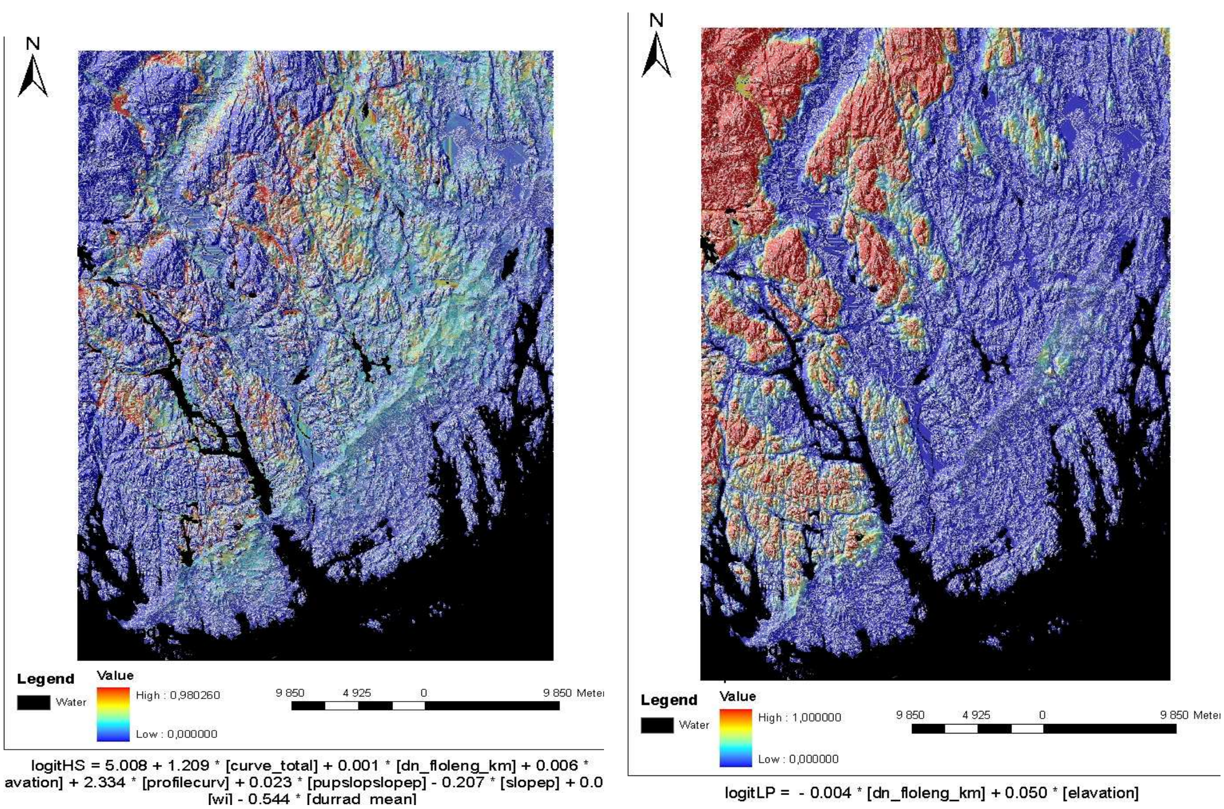



**Figure 5.14** Probability Distribution of Histosol (left) and Leptosol (right)

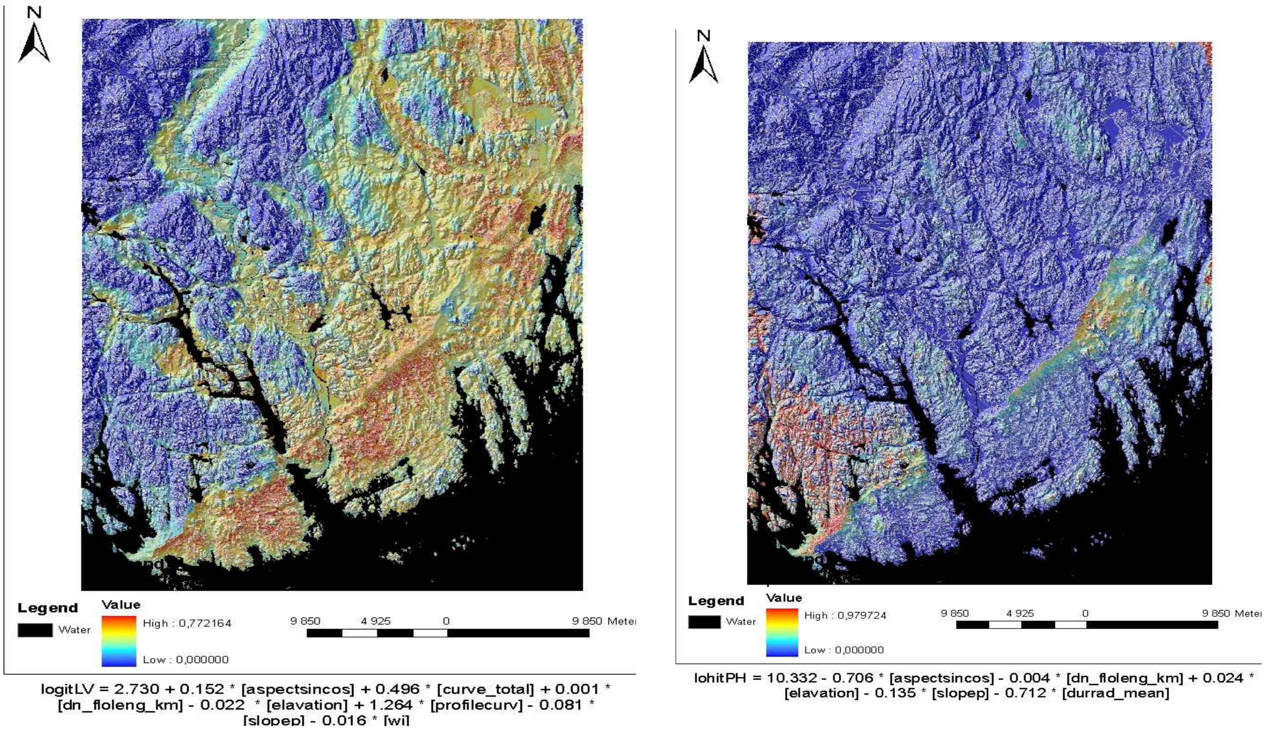



**Figure 5.15** Probability Distribution of Luvisol (left) and Phaeozem (right)

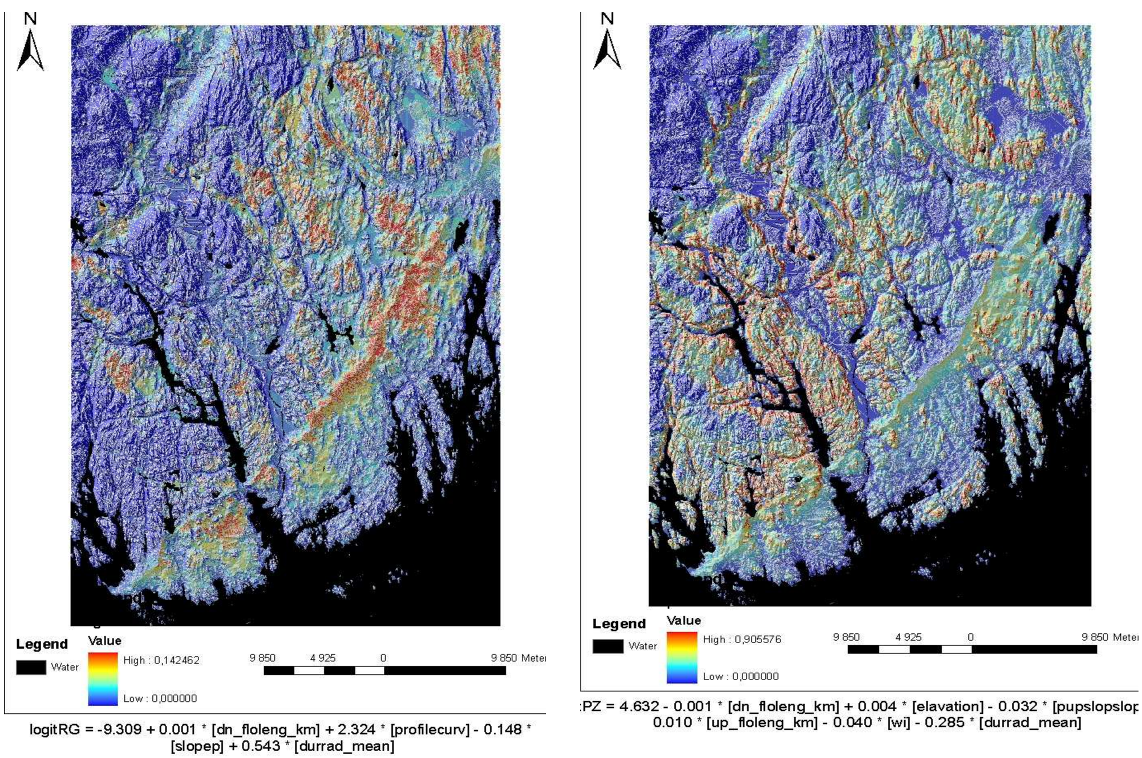



**Figure 5.16** Probability Distribution of Regosol (left) and Podzol (right)

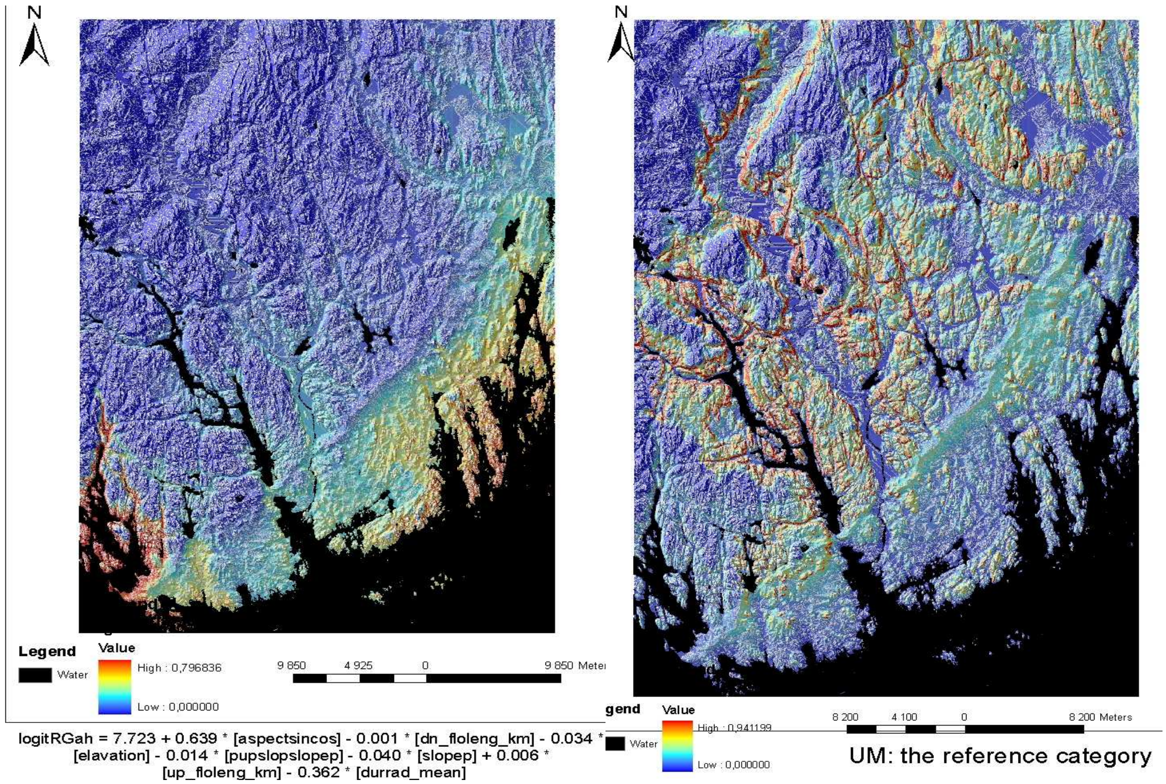



**Figure 5.17** Probability Distribution of Anthropic Regosol (left) and Umbrisol (right)

# 6 DISCUSSION

## 6.1 Reflections on the Results

### 6.1.1 Digital Terrain Analysis

Before proceeding to any discussion with other results, it is noteworthy to briefly discuss digital representation of the terrain, the major uncertainties identified and the remedial procedures applied. As presented in the result, statistics of terrain attributes, hypsometry, the correlation matrix of the terrain attributes, and last but not least, 3D visualization were used to present the characteristics of the topography digitally. They were all used because they present different feature of the topography.

As can be seen from the statistics of the terrain attributes and the hypsometric curve and its integral, the area is dominated by low altitude, gently slopped terrain. Hypsometry is generally used as a measure of geomorphic development. Concave hypsometric curves as in the case of this study indicate peneplained, i.e. geomorphologically and tectonically more stabilized, landscapes (Hurtrez et al., 1999). Besides, hypsometric integral increases with tectonic activities such as uplifting and is highly sensitive to land surface processes such as erosion and deposition. The geology of the study area also shows that there is no dramatically active tectonic and geomorphological processes taking place since the last ice age (Solbakken et al., 2006; Sorensen, 1988). Therefore, it makes sense that, although there are relatively slow geomorphological processes such as erosion and deposition in the area, the landscape seems tectonically stabilized.

When one looks at the list of the terrain attributes analyzed, one might wonder if each of these contains unique information. The correlation matrix tried to resolve this puzzle. As presented in the result, some terrain attributes are highly correlated. There are many causes for these: first, some terrain attributes correlate because they are simply different ways of expressing the same parameter. E.g. the high positive correlation between the topographic erosion index (LS) and the topographic stream power index alarms the reevaluation of the need for the use of both of them. They seem to be redundancy of the same index as their values correlate and they are both related to erosion. Second, some terrain attributes correlated due to their inherent mathematical definition which explains the natural relationship between the parameters. For example, the positive correlation between plan curvature and tangential curvature is just due to their definition that tangential curvature is a product of plan curvature and the sine of the slope (Gallant and Wilson, 2000). Third, some terrain attributes correlate because they fulfill the natural logic of increasing one may result in the decrease or increase of the other.  The strong correlation between upslope flow length and specific catchment area is obviously due to the fact that when flow comes from a very long distance it is likely that large areas contribute to such flows increasing flow accumulation and contributing area per pixel. Besides, one can also notice the obviously justifiable negative correlations of the topographic wetness index with attributes such as elevation, slope and downstream flow length and its positive correlation with upslope flow length. Fourth, some correlations between the terrain attributes are just unique to the study area and do not show any repeatability in another landscapes. These are important in expressing the nature of the landscape. For instance, the correlation between elevation and slope in this area is just due to the nature of the landscape such that high elevation areas are more rugged than low elevation areas. The opposite would have been true had the area been dominated by table plateaus.

All those information discussed so far might tempt one to believe that digital terrain modeling is without flaws. However, as the saying goes, the devil is in detail. One has to be aware of the different sources of uncertainty. The errors that accompany the original DEM, the errors that are introduced through DEM improvement processes, the errors that are introduced due to the algorithms used to derive each terrain attributes, etc are all there to have impact.

The unrealistic high frequencies of elevation values at multiples of 20m, the interval of the source contour, are just indicators of the poor performance of the interpolation algorithm used to derive the DEM from the original data (Wilson and Gallant, 2000a).  These repetitive high frequencies were observed to be more pronounced in flat areas because, in flat areas, the contours are spatially very scattered and the interpolated values during DEM creation naturally tend to be pulled together around the values of the contour. The poor performance of the aspect calculation algorithm that looks to limited search  directions has also been depicted in the histogram of the aspect where unrealistic high frequencies were observed at multiples of 45 degrees (Wilson and Gallant, 2000a).

Artificial depressions are errors introduced due to a number of reasons  such as data errors, interpolation, and the limitations by horizontal and vertical resolutions that are unable to incorporate the reality of ridges and streamlines (Creed-I.F and Lindsay-J.B, 2005). Their removal is necessary for subsequent analyses in hydro-geomorphic applications (Creed-I.F and Lindsay-J.B, 2005; Wilson et al., 2000). The removal of depression is actually helpful in routing flows so that attributes such as flow direction, flow length, contributing area, etc are realistically estimated. One has to be aware of the fact that the remedial measures are not only solutions but they also introduce other sources of uncertainties. To remove depressions, natural and artificial ones have to be differentiated first. But as admitted by (Wang and Liu, 2006) this is a tedious and complicated process that at the end may not even have great advantages over simply removing entire depression.

The measures used in this thesis to remove artificial depressions (Darboux and Planchon, 2002; Planchon, 2001) involves enforced flow on flat areas in addition to the removal of depression and spikes.  The consequences of such depression removal procedures are variable and deserve separate study. A study conducted by (Creed-I.F and Lindsay-J.B, 2005) revealed that such procedures alter spatial and statistical distribution of terrain attributes. They state that the degree to which each terrain attribute is affected is controlled by the number of neighbors used in the processing of the terrain attribute. Removal of depressions and spikes and the enforcement of flow on flat areas can create other artificial features in flat areas.

In any case, in this study it was observed that without the removal of depressions and spikes and without enforced flow on flat areas, flow related terrain attributes and compound attributes such as wetness index could not have been realistically estimated. Other than the blockage of flows in depressed areas, spikes create unrealistically very high slopes which have adverse effects on the estimation of other terrain attributes. Besides, flat areas will have absolutely zero values of slope and undefined flow direction creating difficulty when parameters which involve division by these attributes are estimated. Therefore, the remedial procedures had enormous advantages.

### 6.1.2 Digital Terrain Analysis and Soil Properties

The interpretation of the results of the relationship between the terrain attributes and the topsoil properties needs caution due to a number of reasons. First, the sample size was not large enough to enable to say much about the correlation with confidence. Second, the samples were not collected with the intention of such analysis, and therefore their spatial distribution was not taken into consideration. However, soil properties, although not exactly the ones attempted in this study, have been predicted from terrain attributes by many researchers (Bell et al., 2000; Chamran et al., 2002; Florinsky et al., 2002; McBratney et al., 1995) with highly reliable results. Having these facts on the background, it is worthwhile to comment on the correlations observed in this research.

The correlations of clay content with some terrain attributes in table 5.4 are very well in agreement with theory of soil particle redistribution and erosion-deposition process (Brady and Weil, 2002). The attributes influence soils clay content through their influence on the movement of water and particles. $KHNO_3^-$ also follows the pattern of clay as there is high correlation between clay content and $KHNO_3^-$ content. Therefore, it is no surprise that most of the correlation and regression behavior of $KHNO_3^-$ is related to that of clay.

The prediction of clay and $KHNO_3^-$ is more reliable compared to that of the extractible nitrogen. Clay and $KHNO_3^-$ are highly related to parent material, topography and pedogenic processes. Where as nitrogen is more related to climate, vegetation, and other properties such as clay content, organic matter content, etc. It is even temporally very dynamic depending on the local land use and season. Therefore, the role of topography is less pronounced or less stable in such properties as nitrogen content compared to the other two. This fact has been evidenced in the bivariate correlation matrix as well. Besides, nitrogen is highly related to the organic carbon content of soils with which the terrain attributes of this area had very weak correlation. The weak correlation with organic carbon content can be linked to the fact that it is more of the presence of organic materials that dictate soils content of organic carbon than the topography.  The lack of correlation with pH can be ascribed to the fact that soils pH is highly influenced by climate and parent material than topography. Therefore, significant variation of pH at toposcale might not be encountered, in addition to the limitations of the sample size.

Nonetheless, the prediction of the soil properties through multiple regression using terrain attributes have shown its superiority to the most commonly used interpolation technique, i.e. ordinary kriging. Kriging estimates variable values at unknown places based on the values of the surrounding points and the distance between the unknown point and the points surrounding it (Bishop and McBratney, 2001; Goovaerts, 1999), regardless of the local terrain and other characteristics. It is solely based on distance and relies on the concept that 'near things are more alike than distance things' of Tobler (Sui, 2004). On the other hand, the regression prediction estimated the unknown values based on the local terrain characteristics and using the relationship between terrain attributes and the soil property in question. Of course, the values at the known points influence the setting up of the relationship, i.e. model building. In reality two very close points can have very different values in a given soil property (.e.g. clay content) due to abrupt changes in local terrain characteristics. Where kriging considers such pixels as near pixels and relates their values, regression considers their local slope, aspect, curvature or any other relevant terrain attribute to estimate their values. That is why regression-prediction appears more realistic on the map (e.g. figure 5.5) and its errors are lower (table 5.5).

One drawback that was observed from the results of the prediction of the soil properties is that they fail in very steep and high altitude areas. This is simply due to the fact that the samples used for the regression model building did not contain representatives of such areas. Therefore, that led to a kind of model extrapolation, i.e. model use out of its domain area. It would have been best to include samples from all types of landscape and/or stratify the area so that different models are built for different strata. Regionalization is stressed by Florinsky et al, (2002) in their attempt to predict soil properties using terrain attributes. Their studies revealed that the relationship between soil properties and terrain attributes is dependent upon spatial and temporal scale and depth of the soil where the soil properties are measured. Such dependences have not been explored in this study simply because it was not the goal of the research. However, one should be reminded of those facts.

### 6.1.3 Digital Terrain Analysis and Soil Classes

One of the two conceptually different approaches to digital soil mapping followed in this thesis was crisp (discrete) classification, the other being continuous (fuzzy logic) approach. Before progressing to the spatial prediction of soils using crisp approach, analysis of variance was conducted. This step was crucial because: first, it confirmed the theory that soil classes are different in the type of terrain attribute they develop on; Second, it helped to figure out which terrain attributes are more important in distinguishing soil classes. Without having empirical evidence that the dependent attribute is really dependent on the predictor variables, there would not have been any need of attempting the prediction.

When one looks at the list in the ANOVA result of table 5.6, it becomes clear that the attributes are so arranged due to their direct or indirect roles in pedogenic processes. Those on the top of the list (i.e. elevation, flow length, mean duration of daily radiation, wetness index, slope, aspect, etc) are known to dictate the spatial distribution of temperature, radiation, moisture and solid materials (Hugget and Cheesman, 2002; Wilson and Gallant, 2000a). These are crucial factors of soil formation processes (Schaetzl and Anderson, 2005). Therefore, the ANOVA result complies with the theory of pedogenesis.

ANOVA tests whether the mean values of each terrain attribute is significantly different from one soil class to the other (Anderson, 2001) . Crisp (discriminant) classification is based on the same idea (McCloy, 2006). It first defines means of each variable (e.g. terrain attribute) for each class (e.g. soil class) based on the samples and includes the unknown pixels or objects based on their proximity to the mean centers.

The two discriminant classification approaches used in this thesis, i.e. object-oriented and pixel-based, are similar in concept but employ different procedures. The better performance of the Object-oriented approach can be ascribed to the following reasons. First and foremost, the approach classifies objects (adjacent pixels of similar terrain characteristics) rather than individual pixels. Terrain objects are thus adjacent pixels which are not significantly different in their values of the terrain attributes at that scale. It is a long established concept that the boundaries of soil units tend to follow that of topographic units (Park et al., 2001; Thompson et al., 2006). It is based on that concept that the famous soil-landscape model was developed and has long been used in qualitative soil mapping. Therefore, classification of terrain objects means classification of soil mapping units into soil classes. Pixels do not complement with such concept.

Secondly, object-oriented approach provides extra features that are only related to objects or classes that can be used in discriminating classes. These features can be the shape of the objects of a given class, contextual features such as neighborhood, and geometry. Such features are impossible to utilize in pixel-based classification as all pixels have the same shape and geometry. The most important of these object and class related features in the case of soil mapping has been found to be topological information such as relative distance to neighboring class. This is because as explained in soil catena concept (Schaetzl and Anderson, 2005), soil classes tend to have a certain pattern of spatial distribution. Some soil classes tend to be accompanied with a certain soil class.

Thirdly, Object-oriented approach in eCgnition offers the possibility of navigating through different scales of object aggregation until the most appropriate level with high classification accuracy is obtained. This helps to arrive at the aggregation level which best coincides with the spatial extent of soil units. On the other hand, the only scale parameter in pixel-based approach is the pixel resolution, which is fixed level of generalization. It has not come with a surprise that the object-oriented approach performed better because of the aforementioned reasons and other empirical researches conducted on other geographical objects such as land cover (Mas et al., 2006; Whiteside and Ahmad, 2005) that comply with the findings of this thesis.

In this research, regarding the segmentation (terrain object delineation) it has been learnt that increasing the scale value to more than 50 showed that some soil units completely disappear because their spatial extent is less than the object size. In such cases, collecting sample objects for each class would be difficult, if not impossible, because objects that coincide with a single class become hard to pass by. It was also learnt that increasing the shape parameter during segmentation results in more geometrically similar terrain objects, which do not seem to be natural, and leads to decreased classification accuracy. Although it needs further research, it seems that DEMs with high spatial resolution are needed to navigate further between the scale values without facing difficulty in identifying sample objects.

The classification algorithm used in eCgnition is the Nearest Neighbor Classifier. In eCgnition this approach is used based on fuzzification and defuzzification concepts (Baatz et al., 2000). (Baatz et al., 2000) First multidimensional fuzzy membership values are assigned to the object for all classes based on its distance from the mean center of sample objects in the multidimensional feature space, i.e. fuzzification. Then the object is assigned to the class for which it has the highest membership value (the nearest neighbor), i.e. defuzzification. This approach is different from the maximum likelihood classifier approach used in the pixel-based classification where pixels are assigned membership values of either 0 (not belong to the class) or 1 (belong to the class). This might also have consequences in the classification accuracy and deserves separate research.

There were very high discrepancies among the accuracies of the soil classes. This applies to both the object-oriented and pixel-based approaches. This was expected right from the beginning and has a number of causative reasons:

- First, the spatial distributions of all soil types are not influenced by topography to the same extent. Some soil classes are highly dictated by topography; where as, others are dictated less by topography and more by parent material or climate or organisms. Therefore, even if all the data, methodology and other things were perfect, variation in accuracy among the soil classes can be expected.
- Second, the area coverage of the soil classes in the study area varies greatly. This increases the chances of being accurate for the most abundant and decreases that of the least abundant.
- Third, the sizes of soil units for the soil classes also vary greatly. Some soil classes, especially those in the topographically more uniform areas, have large soil units; while, those found on the topographically more rugged areas have small soil units. The larger the

soil unit, the better is the chance to coincide with terrain objects. It is even difficult to collect sample objects for the small soil units because they may not totally cover a terrain object at some scales, and they are divided into different kinds of terrain objects at smaller scale values.

- Fourth, the number and the spatial distribution of the sample objects is one of the crucial reasons why the accuracies vary a lot. Attempt was made to keep the number of the sample objects in proportion with the area share of the soil classes. That could reduce the statistical strengths of the least abundant soil classes. Besides, the spatial distribution of the samples is the most difficult one to deal with. Attempt was made to evenly distribute them across the entire area. However, even distribution does not guarantee the representation of the various terrain types. Even the reference soil map from which the samples were collected did not cover high elevation and steep slope areas. One would therefore expect the bias of the samples and thence of the accuracies.
- Fifth, it is known that all those predictions were based on the terrain attributes which were directly or indirectly derived from the elevation data (DEM). The DEM contains uncertainties that are most likely to vary from steep areas to flat areas depending on the source of the original data and the procedures applied on them. If the uncertainty varies with terrain type, it means it varies with soil type. Therefore, the terrain attributes of the soil classes which developed in the areas of high DEM uncertainty have not been well represented or measured, leading to decreased prediction accuracy for such soil classes.

The logistic regression analysis employed in this research came up with a number of useful results. First, it showed which terrain attributes are generally influential in the spatial distribution of soils. The reason as to why some terrain attributes are very influential has been discussed earlier and is related to their influence in the spatial distribution of radiation, temperature and moisture. The only insignificant attribute is the plan curvature, which is the curvature of aspect. This attribute also had the lowest F value in the analysis of variance. The influence of the curvature of aspect is more represented by tangential curvature which measures aspect curvature and combines that with the local slope (Gallant and Wilson, 2000).

Second, the result enabled to identify which terrain attributes influence the continuous spatial variation of each soil class and to what degree. The extent of the influence is measured through the odds ratios, i.e. EXP(B), of the terrain attributes for each soil class. One has to be cautious in comparing the EXP(B) of one terrain attribute to the other because they are simply not on the same scale. Notice that some terrain attributes have odds ratios, i.e. EXP(B), far away from 1 (e.g. aspect, curvature) while others have either 1 or close to it (e.g. elevation, flow length, etc) for most soil classes. Such differences are created due to two possible reasons: First, due to the fact that one terrain attribute actually has greater or less effect on the soil class than the other. Second, the unit value of one terrain attribute is practically of larger order than that of the other. For example, a unit of elevation is a meter which does not dramatically change the probability of any soil class. Where as, a unit of aspect, in this case expressed as the product of the sine and cosine of the aspect in degrees, is a unitless 1 which is of course very big because the entire 360 degrees is distributed from -1 to 1. Therefore, one has to be reminded of the unit values when looking at the odds ratios of each terrain attribute. This was the reason why terrain attributes with small measurement units were converted to a unit that can reduce the magnitude. For example, the unit of flow length was converted from meter to kilometer to cope with this situation, because a one unit change in the predictor has to be meaningful (Peng et al., 2002). However, what is more important is whether the odds ratio is greater than 1 which corresponds to the positive correlation of the linear regression, or less than 1 which corresponds to the negative correlation of the linear regression.

Third, it helped to construct prediction models which enabled to predict the spatial distribution of the probability of finding each soil type in the study area. Accordingly some soil classes were found to have high probability values in the area while others have very low due to a number of possible reasons. First, based on the sample data used for the model construction, it has been found out that the terrain is more suitable for the development of some soil classes, while it is less so for others. This applies to the very low maximum probability values predicted for the almost non-present soil class in the study area, i.e. Regosol. Second, the results of multinomial logistic regression is known to be biased by the proportion of the samples, although not as strongly as its comparatives such as linear regression (Peng et al., 2002; Raimundo et al., 2006 ). Since the proportion of the samples in this research was not even, it may have had impact on the result. Third, the spatial distribution of some soil classes is less dictated by topography than other bio-physical factors, making their prediction from terrain attributes difficult. Typical examples of such soil classes are Anthrosols and Anthropic Regosols, a subclass of Regosol included for its unique genesis.

Another important point that has to be made clear with regard to this analysis is the problem created due to the fact that the sample soil class data that was used for the analysis was obtained as vector map of the soil classes. Each polygon of a soil class is in principle assigned probability value of 1 for that soil class and 0 for the other soil classes. The problem is that this probability values are not based on actual observed values, since the polygons were assigned to the soil classes based on the observations made at a point within the polygon. The point might contain exclusively a given soil class, but it is unlikely that the entire polygon is exclusively of that soil class. Therefore, the problem with this analysis is that the assumed empirical data is not actually observed data but combination of observed and inferred data. Had the whole data set been soil class data from point observation, they would have been considered free of uncertainties and the uncertainties of the prediction would have been straight forward to estimate. The error estimation could have been done by subtracting the predicted probabilities of the observed points from 1 (the observed probability value).

Nonetheless, the two approaches used to evaluate the reliability of the predictions worked fine as they enabled to relate the prediction with the theories of pedogenesis and with the actual spatial distribution of the soil classes in the study area. The generic characteristics of each soil class with regard to the type of landscape, geology and climate they are likely to develop on was the foundation of the evaluation. Besides, the similarity and differences between the soil classes led to the quantitative evaluation of the probability correlations. They both confirmed the reliability of the method.

## 6.2 General Remarks

It has thoroughly been discussed that digital terrain analysis has great potential in digital soil mapping. First, three out of five topsoil properties correlated well with some terrain attributes and their spatial distributions were predicted with very reliable accuracy. Besides, soil classes that cover large proportion of the study area and that are highly related to topography were reliably predicted as discrete objects or as fuzzy variables. These, at least, indicate that the methods tried in this research have future in the field of digital soil mapping. Therefore, the application could go beyond academic curiosity to practical soil survey projects. However, there are a number of considerations and further investigations that needed to be taken into account depending on the specific area of application.

When predicting soil properties using terrain analysis, it should be noted that the prediction is dependent on the influence of topography in the specific soil property. That influence varies with the depth of the soil, spatial scale, temporal scale (Florinsky et al., 2002), and possibly other factors such as the type of parent material and the climatic condition.  Besides, the reliability of the prediction is dependent upon the quality of the data.

To use digital terrain analysis for prediction of soil properties with limited uncertainty requires caution. First, the sample data that is used for the model building should be large enough to reduce biasness and spatially well distributed to represent the entire area. Very often, there is such a strong spatial variation that a single model may not be valid for the entire area. In such cases, it is advised that the area be regionalised or stratified so that one model is built for every soil property for each stratum (Florinsky et al., 2002). Here stratification does not only mean horizontal stratification but vertically based on soil depth or horizon as well. Through spatial distribution of sampling and stratification, model extrapolation and bias can be avoided.

The advantage with such digital analysis is also that it can be kept in a database and can be reused every time additional data is obtained.  One has to always bear in mind, though, that additional information on the other soil forming factors improves the prediction and it is advised to include in the model building where such data are available.

As shown in this thesis, the prediction of soil classes from terrain attributes can be approached in two ways, i.e. discrete and fuzzy approach. However, the question here is, beyond academic exercise, can such approaches be used for practical soil survey? The object-oriented approach seems to be promising for practical application for soils that are largely abundant in the area of concern. If one wants to employ the approach for soil survey projects, there has to be stratification of the area based on other auxiliary information such as geology so that representatives of all terrain types and possibly all soil classes are included. Then after, sample data (ground truth) can randomly be collected from each stratum. Without such stratification, the samples become biased and the accuracy of the prediction becomes low. Additional auxiliary data such as on geology, land use and land cover are also important both in the stratification and classification. However, the most important thing that needs further exploration before practical application is the role of spatial scale, sample size, area coverage of each class, and levels of generalisation (pixel resolution) in the soil-terrain relations.

On the other hand the probability mapping using logistic regression seems even more promising in practical works. It worked fine with all soil classes that are known to be influenced by topography. During practical application, the following points should be taken into account:

- First, it should be known that the predictive models may not be robust enough to be valid for all kinds of landscape. Therefore, there needs to be stratification of the landscape based on, for example geology and topography, so that a model is built for each soil class in each stratum.
- Then, for each stratum, samples for the model building can be collected. Such samples need to be spatially well distributed to avoid over representation of some areas and under-representation of others.
- It is difficult to judge any prediction without accuracy report. To estimate accuracies of such approach, the data on soil classes are better based on profile points, and classification of each profile to a given soil class should be dead sure in which case the actual probability is assumed to be 1 and can later be used as a reference for accuracy estimation.
- Last but not least, it should be known that although logistic regression has good reputation in social and medical sciences, it is relatively fresh in geosciences.

Therefore, its reliability should be studied in relation to the behaviour of geo-spatial data.

The remarks so far are concerned with the use of digital terrain analysis in the prediction of soils and their properties. The level of uncertainties might be high in such cases where only one environmental predictor variable, i.e. topography, is used to predict a complex dependent variable, i.e. soil. Thus, such prediction results can be used as a guide for further surveys of soil. In such cases, for instance, the predicted probability maps can be used to get overview of where to expect certain soil class. With that expectation, sample observations can be made to validate the prediction. Therefore, the approaches should not only be seen as ends by themselves. They can be used as steps in the lengthy procedures of acquiring soil information.

The diagram of figure 6.1 models the over all procedure that can be followed during practical application of digital terrain analysis for digital soil mapping. The transition from reality to data is the one that needs the most attention. The whole approach is sought for in order to reduce the time and financial costs incurred to acquire data. The quality of both terrain and soil data with regard to accuracy, representativeness, distribution, etc are crucial. It is not just soil and terrain data that can be included at this stage, any other auxiliary data that is needed for the prediction are basically included here. Although both analysis and modelling are dependent on the quality of the data, the methods and procedures used during the analysis and modelling are also vital. This step involves the derivation of the terrain attributes, studying the spatial distribution and characteristics of both the soil and the terrain data, and modelling the relationship between terrain and soil. The output is, therefore, a model (models for that matter) that can be used for the prediction of soil types or their properties. Such models can be partially explicit as the logit models of this study or more of implicit models that are hidden in the background of all automated terrain classification algorithms. The predicted result is only meaningful when validated through one of many different means. For example, validation data may be collected after the prediction is carried out, or training data and validation data may be kept apart right from the beginning. Such validation data can be used to estimate the accuracy or the reliability of the prediction. The cylinders and the grey colours used at all steps in figure 6.1, except the reality, is to indicate that some of the processes are of grey-box nature what happens there is not explicit. Besides, the reality gets blurred at all those steps because of the involvement of uncertainties that are created at the particular step or propagated from the previous steps.

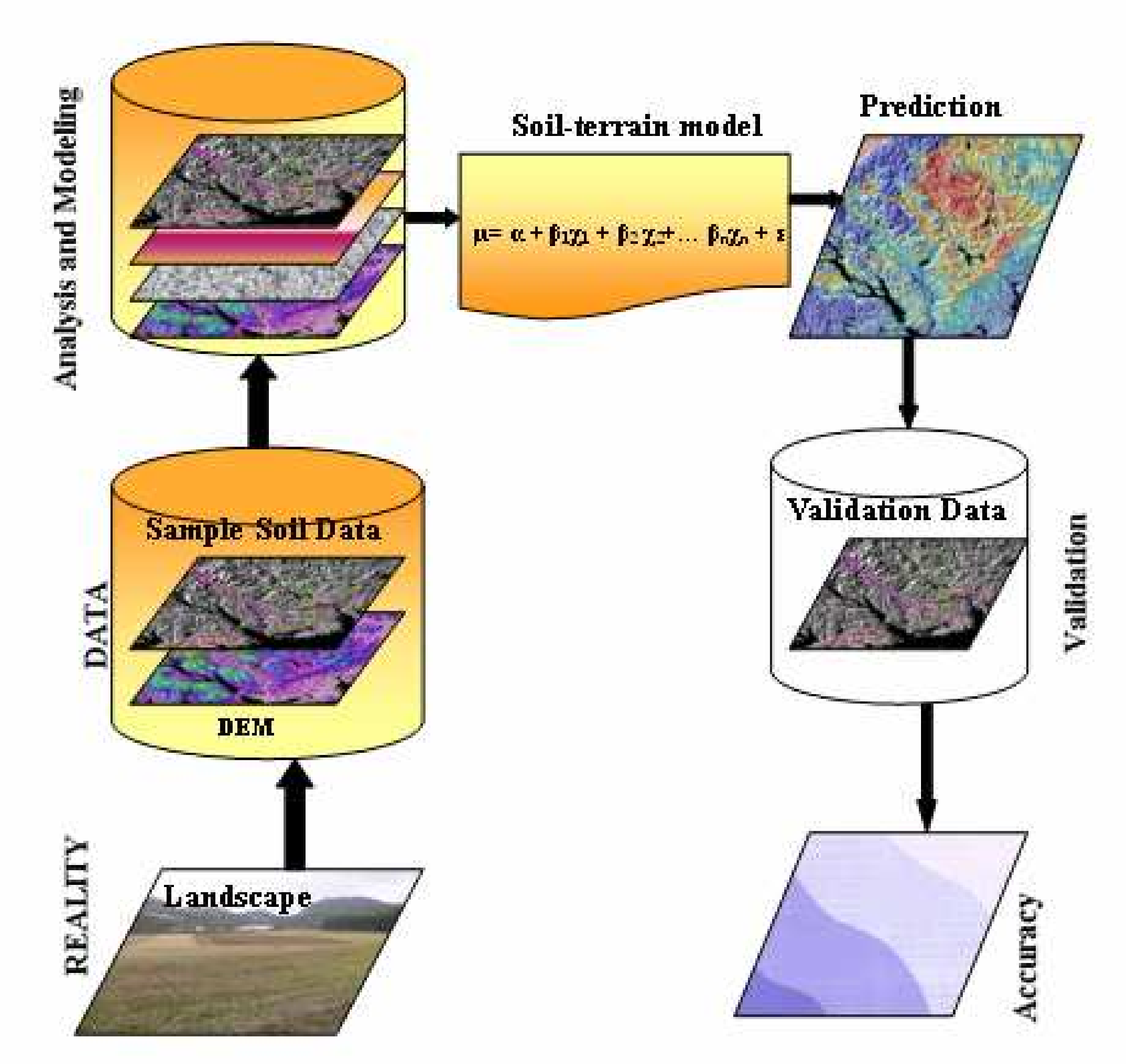



**Figure 6.1** A diagram modelling the work flow that might be followed during digital soil mapping

# 7 CONCLUSIONS

This research has been a methodological research that explored the capabilities of digital terrain analysis in digital soil mapping. The following conclusions are made based on the outcome of this research and might only hold for this study area:

There is good correlation between some topsoil properties (clay, KHNO3- and Kjeldhal's nitrogen) and some terrain attributes although the sample size might not enable to make strong conclusion. The correlation is so strong that around 60% of the spatial variation of topsoil clay content, KHNO3 content and extractible nitrogen content could be ascribed to terrain. Besides, the prediction of the soil properties from the terrain attributes using GIS-integrated multiple linear regression model performs much better than ordinary kriging interpolation.

In the discrete conceptualisation of soil classes, the soil classes are significantly different in all the terrain attributes. The most influential terrain attributes as obtained from the analysis of variance and the logistic regression analysis are elevation, Flow length, Slope, Mean Daily duration of Radiation, aspect, topographic Wetness index and so on. The reason behind this is that these terrain attributes influence the distribution of moisture, temperature, radiation and flux of material which in turn dictate pedogenesis.

Object-oriented terrain classification predicted discrete soil units with better accuracies as compared to the ordinary pixel-based supervised classification although they both ended up with low overall classification accuracy. It can genuinely be said that pixel-based classification failed to predict any soil class with reliable accuracy. The reason for this is that soil units are more related to terrain objects than square grids. The accuracy of the prediction of the soil classes are highly influenced by the segmentation scale, spatial coverage of the soil classes, the spatial distribution of the samples and the representation of all terrain types in the sampling.

Digital terrain analysis can effectively be used to make fuzzy digital maps of soils. In this regard, probability prediction using logit models of logistic regression are robust in terms of their reliability and flexibility to certain data constraints. Therefore, they produce reliable results of prediction for most soil classes except for those which are influenced more by other factors such as human activity than topography. However, the prediction could even be improved if the sample qualities, size and spatial distribution improved.

In general, the capabilities of digital terrain analysis in the prediction of the spatial distribution of soils seem to be limited to soils and soil properties which are considerably influenced by topography and those with considerable spatial coverage at least in the case of object-oriented classification.

As the approaches were found to be promising, future researches are recommended in the following areas:

- ★ Ways to combine kriging and regression (regression Kriging) in the prediction of soil properties
- ★ Probability mapping using multinomial logistic regression integrated into GIS with attention to sampling strategy, error estimation, etc
- ★ In the Object-oriented approach detail investigation is needed about the influence of resolution, scale, sample spatial distribution, etc on the accuracy
- ★ Use of Additional data such as geology, vegetation cover, land use, etc for the digital soil mapping
- ★ Extrapolation of the approaches

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# 9 APPENDICES

**Appendix 1** The correlation coefficients between terrain attributes and some topsoil properties

| | | Clay | Organic carbon | Kjeldahl Nitrogen | KHNO3 | phCaCl2 |
|---|---|---|---|---|---|---|
| Aspect | Pearson Correlation | -0.159 | 0.012 | 0.013 | -0.216 | 0.137 |
| | Sig. (2-tailed) | 0.410 | 0.951 | 0.945 | 0.280 | 0.553 |
| | N | 29 | 29 | 29 | 27 | 21 |
| Total Curvature | Pearson Correlation | -0.005 | -0.051 | 0.010 | 0.165 | -0.090 |
| | Sig. (2-tailed) | 0.981 | 0.791 | 0.960 | 0.412 | 0.697 |
| | N | 29 | 29 | 29 | 27 | 21 |
| Downstream Flow length | Pearson Correlation | **-0.598** | **-0.377** | **-0.480** | -0.129 | 0.315 |
| | Sig. (2-tailed) | 0.001 | 0.044 | 0.008 | 0.521 | 0.164 |
| | N | 29 | 29 | 29 | 27 | 21 |
| Mean daily duration of direct radiation | Pearson Correlation | 0.272 | 0.116 | 0.197 | 0.288 | -0.202 |
| | Sig. (2-tailed) | 0.153 | 0.549 | 0.306 | 0.146 | 0.380 |
| | N | 29 | 29 | 29 | 27 | 21 |
| Elevation | Pearson Correlation | -0.200 | 0.221 | 0.205 | -0.091 | -0.164 |
| | Sig. (2-tailed) | 0.298 | 0.249 | 0.287 | 0.651 | 0.477 |
| | N | 29 | 29 | 29 | 27 | 21 |
| Topographic erosion index (LS) | Pearson Correlation | -0.200 | 0.161 | 0.005 | -0.288 | -0.158 |
| | Sig. (2-tailed) | 0.298 | 0.403 | 0.981 | 0.145 | 0.494 |
| | N | 29 | 29 | 29 | 27 | 21 |
| Slope | Pearson Correlation | **-0.387** | 0.107 | -0.021 | **-0.401** | -0.252 |
| | Sig. (2-tailed) | 0.038 | 0.582 | 0.914 | 0.038 | 0.271 |
| | N | 29 | 29 | 29 | 27 | 21 |
| Plan Curvature | Pearson Correlation | 0.139 | 0.114 | 0.215 | 0.293 | 0.005 |
| | Sig. (2-tailed) | 0.473 | 0.556 | 0.264 | 0.138 | 0.983 |
| | N | 29 | 29 | 29 | 27 | 21 |
| Profile curvature | Pearson Correlation | 0.123 | 0.178 | 0.163 | -0.017 | 0.160 |
| | Sig. (2-tailed) | 0.524 | 0.355 | 0.398 | 0.933 | 0.489 |
| | N | 29 | 29 | 29 | 27 | 21 |
| Upslope slope | Pearson Correlation | -0.263 | -0.248 | -0.224 | -0.102 | -0.062 |
| | Sig. (2-tailed) | 0.168 | 0.194 | 0.243 | 0.613 | 0.789 |
| | N | 29 | 29 | 29 | 27 | 21 |
| Mean Daily received direct radiation | Pearson Correlation | -0.044 | -0.023 | -0.056 | -0.069 | -0.201 |
| | Sig. (2-tailed) | 0.821 | 0.906 | 0.772 | 0.732 | 0.383 |
| | N | 29 | 29 | 29 | 27 | 21 |
| Relative stream Power index | Pearson | - | 0.176 | 0.025 | -0.265 | -0.139 |

| | | | | | | |
|---|---|---|---|---|---|---|
| | Correlation | 0.186 | | | | |
| | Sig. (2-tailed) | 0.333 | 0.362 | 0.897 | 0.182 | 0.549 |
| | N | 29 | 29 | 29 | 27 | 21 |
| Specific catchment area | Pearson Correlation | **0.410** | 0.298 | 0.308 | **0.631** | -0.062 |
| | Sig. (2-tailed) | 0.027 | 0.116 | 0.104 | 0.000 | 0.789 |
| | N | 29 | 29 | 29 | 27 | 21 |
| Tangential curvature | Pearson Correlation | - 0.138 | -0.115 | -0.215 | -0.293 | -0.004 |
| | Sig. (2-tailed) | 0.474 | 0.553 | 0.263 | 0.138 | 0.985 |
| | N | 29 | 29 | 29 | 27 | 21 |
| Mean Upstream flow length | Pearson Correlation | 0.428 | 0.275 | 0.302 | **0.649** | -0.072 |
| | Sig. (2-tailed) | 0.021 | 0.149 | 0.112 | 0.000 | 0.756 |
| | N | 29 | 29 | 29 | 27 | 21 |
| Wetness index | Pearson Correlation | 0.071 | -0.319 | -0.240 | 0.181 | -0.096 |
| | Sig. (2-tailed) | 0.713 | 0.092 | 0.209 | 0.365 | 0.678 |
| | N | 29 | 29 | 29 | 27 | 21 |
| **. Correlation is significant at the 0.01 level (2-tailed). | | | | | | |
| *. Correlation is significant at the 0.05 level (2-tailed). | | | | | | |

**Appendix 2** Multinomial logistic regression output

| WRB_code(a) | | B | Std. Error | Wald | degree of freedom | Sig. | Exp(B) | 95% Confidence Interval for Exp(B) | |
|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | | Lower Bound | Upper Bound |
| **AB** | **Intercept** | .021 | .489 | .002 | 1 | .966 | | | |
| | **Aspect (sin.cos)** | .325 | .070 | 21.841 | 1 | .000 | 1.385 | 1.208 | 1.587 |
| | **Total Curvature** | .309 | .121 | 6.511 | 1 | .011 | 1.362 | 1.074 | 1.726 |
| | **Downstream flow length** | .002 | .000 | 560.688 | 1 | .000 | 1.002 | 1.002 | 1.002 |
| | **Elavation** | -.011 | .001 | 114.311 | 1 | .000 | .989 | .987 | .991 |
| | **Topographic erosivity index (LS)** | .007 | .012 | .335 | 1 | .563 | 1.007 | .983 | 1.032 |
| | **Profile curvature** | .750 | .175 | 18.340 | 1 | .000 | 2.118 | 1.502 | 2.986 |
| | **Upslope slope** | -.012 | .003 | 14.329 | 1 | .000 | .988 | .982 | .994 |
| | **Relative stream power index** | -.001 | .001 | 1.345 | 1 | .246 | .999 | .998 | 1.001 |
| | **slope** | -.066 | .006 | 114.726 | 1 | .000 | .936 | .925 | .947 |
| | **Specific catchment area** | .000 | .000 | 2.316 | 1 | .128 | 1.000 | 1.000 | 1.000 |
| | **Upstream Flow length** | .003 | .002 | 2.222 | 1 | .136 | 1.003 | .999 | 1.006 |
| | **Wetness index** | -.005 | .006 | .816 | 1 | .366 | .995 | .984 | 1.006 |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | **Mean daily duration of direct radiation** | .017 | .040 | .185 | 1 | .667 | 1.017 | .940 | 1.101 |
| | **Mean daily direct radiation** | .000 | .000 | 5.286 | 1 | .021 | 1.000 | 1.000 | 1.000 |
| **AR** | **Intercept** | 5.810 | .591 | 96.481 | 1 | .000 | | | |
| | **Aspect (sin.cos)** | .100 | .086 | 1.332 | 1 | .248 | 1.105 | .933 | 1.309 |
| | **Total Curvature** | .061 | .171 | .125 | 1 | .724 | 1.062 | .759 | 1.487 |
| | **Downstream flow length** | .002 | .000 | 241.502 | 1 | .000 | 1.002 | 1.002 | 1.002 |
| | **Elavation** | -.098 | .002 | 3476.578 | 1 | .000 | .907 | .904 | .909 |
| | **Topographic erosivity index (LS)** | .002 | .022 | .007 | 1 | .931 | 1.002 | .960 | 1.045 |
| | **Profile curvature** | -.720 | .242 | 8.864 | 1 | .003 | .487 | .303 | .782 |
| | **Upslope slope** | -.040 | .004 | 100.343 | 1 | .000 | .961 | .953 | .968 |
| | **Relative stream power index** | -.002 | .002 | 2.161 | 1 | .142 | .998 | .994 | 1.001 |
| | **slope** | -.030 | .009 | 11.047 | 1 | .001 | .971 | .954 | .988 |
| | **Specific catchment area** | .000 | .000 | 18.956 | 1 | .000 | 1.000 | 1.000 | 1.000 |
| | **Upstream Flow length** | .007 | .002 | 12.952 | 1 | .000 | 1.007 | 1.003 | 1.010 |
| | **Wetness index** | -.014 | .006 | 4.402 | 1 | .036 | .986 | .974 | .999 |
| | **Mean daily duration of direct radiation** | -.323 | .047 | 47.192 | 1 | .000 | .724 | .660 | .794 |
| | **Mean daily direct radiation** | .000 | .000 | 1.257 | 1 | .262 | 1.000 | 1.000 | 1.000 |
| **AT** | **Intercept** | -15.117 | 2.616 | 33.404 | 1 | .000 | | | |
| | **Aspect (sin.cos)** | -1.318 | .322 | 16.704 | 1 | .000 | .268 | .142 | .504 |
| | **Total Curvature** | .310 | .714 | .188 | 1 | .665 | 1.363 | .336 | 5.521 |
| | **Downstream flow length** | .001 | .000 | 4.462 | 1 | .035 | 1.001 | 1.000 | 1.001 |
| | **Elavation** | -.024 | .005 | 26.959 | 1 | .000 | .976 | .967 | .985 |
| | **Topographic erosivity index (LS)** | .084 | .104 | .645 | 1 | .422 | 1.087 | .886 | 1.334 |
| | **Profile curvature** | 1.547 | 1.058 | 2.140 | 1 | .143 | 4.700 | .591 | 37.362 |
| | **Upslope slope** | .019 | .014 | 1.682 | 1 | .195 | 1.019 | .991 | 1.048 |
| | **Relative stream power index** | -.005 | .008 | .419 | 1 | .517 | .995 | .979 | 1.011 |
| | **slope** | -.091 | .040 | 5.095 | 1 | .024 | .913 | .844 | .988 |
| | **Specific catchment area** | .000 | .000 | .760 | 1 | .383 | 1.000 | 1.000 | 1.000 |
| | **Upstream Flow length** | .007 | .005 | 2.348 | 1 | .125 | 1.007 | .998 | 1.017 |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | **Wetness index** | -.045 | .022 | 4.073 | 1 | .044 | .956 | .915 | .999 |
| | **Mean daily duration of direct radiation** | 1.146 | .211 | 29.477 | 1 | .000 | 3.147 | 2.080 | 4.760 |
| | **Mean daily direct radiation** | .000 | .000 | 1.741 | 1 | .187 | 1.000 | 1.000 | 1.000 |
| | **Intercept** | 6.808 | .499 | 185.933 | 1 | .000 | | | |
| | **Aspect (sin.cos)** | .296 | .072 | 16.943 | 1 | .000 | 1.344 | 1.168 | 1.548 |
| | **Total Curvature** | .038 | .127 | .091 | 1 | .763 | 1.039 | .810 | 1.332 |
| | **Downstream flow length** | .002 | .000 | 614.634 | 1 | .000 | 1.002 | 1.002 | 1.003 |
| | **Elavation** | -.048 | .001 | 2018.033 | 1 | .000 | .953 | .951 | .955 |
| | **Topographic erosivity index (LS)** | -.015 | .013 | 1.289 | 1 | .256 | .985 | .959 | 1.011 |
| | **Profile curvature** | -.434 | .183 | 5.625 | 1 | .018 | .648 | .453 | .927 |
| | **Upslope slope** | -.038 | .003 | 131.964 | 1 | .000 | .962 | .956 | .969 |
| **CM** | **Relative stream power index** | -.001 | .001 | .526 | 1 | .468 | .999 | .998 | 1.001 |
| | **slope** | -.047 | .006 | 52.113 | 1 | .000 | .954 | .942 | .967 |
| | **Specific catchment area** | .000 | .000 | 16.959 | 1 | .000 | 1.000 | 1.000 | 1.000 |
| | **Upstream Flow length** | .006 | .002 | 13.172 | 1 | .000 | 1.006 | 1.003 | 1.010 |
| | **Wetness index** | -.008 | .006 | 2.090 | 1 | .148 | .992 | .980 | 1.003 |
| | **Mean daily duration of direct radiation** | -.473 | .041 | 132.482 | 1 | .000 | .623 | .575 | .675 |
| | **Mean daily direct radiation** | .000 | .000 | 34.478 | 1 | .000 | 1.000 | 1.000 | 1.000 |
| **FL** | **Intercept** | 9.418 | .618 | 232.199 | 1 | .000 | | | |
| | **Aspect (sin.cos)** | .100 | .097 | 1.054 | 1 | .305 | 1.105 | .913 | 1.336 |
| | **Total Curvature** | 1.040 | .186 | 31.188 | 1 | .000 | 2.830 | 1.965 | 4.078 |
| | **Downstream flow length** | .001 | .000 | 106.500 | 1 | .000 | 1.001 | 1.001 | 1.002 |
| | **Elavation** | -.018 | .001 | 177.408 | 1 | .000 | .982 | .979 | .984 |
| | **Topographic erosivity index (LS)** | .111 | .022 | 26.143 | 1 | .000 | 1.117 | 1.071 | 1.165 |
| | **Profile curvature** | 1.600 | .266 | 36.168 | 1 | .000 | 4.953 | 2.940 | 8.343 |
| | **Upslope slope** | -.008 | .004 | 4.574 | 1 | .032 | .992 | .984 | .999 |
| | **Relative stream power index** | -.008 | .002 | 23.633 | 1 | .000 | .992 | .988 | .995 |
| | **slope** | -.182 | .011 | 297.214 | 1 | .000 | .834 | .817 | .851 |
| | **Specific catchment area** | .000 | .000 | 1.082 | 1 | .298 | 1.000 | 1.000 | 1.000 |
| | **Upstream Flow length** | .004 | .002 | 4.199 | 1 | .040 | 1.004 | 1.000 | 1.008 |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | **Wetness index** | .003 | .007 | .186 | 1 | .667 | 1.003 | .989 | 1.018 |
| | **Mean daily duration of direct radiation** | -.999 | .049 | 419.800 | 1 | .000 | .368 | .335 | .405 |
| | **Mean daily direct radiation** | .000 | .000 | 4.852 | 1 | .028 | 1.000 | 1.000 | 1.000 |
| **GL** | **Intercept** | 2.877 | .738 | 15.209 | 1 | .000 | | | |
| | **Aspect (sin.cos)** | .169 | .106 | 2.539 | 1 | .111 | 1.184 | .962 | 1.458 |
| | **Total Curvature** | .745 | .246 | 9.161 | 1 | .002 | 2.107 | 1.300 | 3.414 |
| | **Downstream flow length** | .001 | .000 | 46.574 | 1 | .000 | 1.001 | 1.001 | 1.001 |
| | **Elavation** | -.009 | .002 | 33.066 | 1 | .000 | .991 | .988 | .994 |
| | **Topographic erosivity index (LS)** | .124 | .045 | 7.500 | 1 | .006 | 1.132 | 1.036 | 1.236 |
| | **Profile curvature** | 2.178 | .357 | 37.266 | 1 | .000 | 8.830 | 4.388 | 17.770 |
| | **Upslope slope** | -.006 | .005 | 1.407 | 1 | .236 | .994 | .985 | 1.004 |
| | **Relative stream power index** | -.015 | .004 | 12.933 | 1 | .000 | .985 | .977 | .993 |
| | **slope** | -.256 | .016 | 257.052 | 1 | .000 | .774 | .750 | .799 |
| | **Specific catchment area** | .000 | .000 | 2.489 | 1 | .115 | 1.000 | 1.000 | 1.000 |
| | **Upstream Flow length** | .002 | .002 | .920 | 1 | .338 | 1.002 | .998 | 1.006 |
| | **Wetness index** | -.003 | .008 | .175 | 1 | .676 | .997 | .982 | 1.012 |
| | **Mean daily duration of direct radiation** | -.222 | .060 | 13.674 | 1 | .000 | .801 | .712 | .901 |
| | **Mean daily direct radiation** | .000 | .000 | 16.017 | 1 | .000 | 1.000 | 1.000 | 1.000 |
| **HS** | **Intercept** | 5.008 | .683 | 53.691 | 1 | .000 | | | |
| | **Aspect (sin.cos)** | .073 | .105 | .486 | 1 | .486 | 1.076 | .876 | 1.322 |
| | **Total Curvature** | 1.209 | .212 | 32.389 | 1 | .000 | 3.349 | 2.209 | 5.078 |
| | **Downstream flow length** | .001 | .000 | 18.392 | 1 | .000 | 1.001 | 1.000 | 1.001 |
| | **Elavation** | .006 | .001 | 15.123 | 1 | .000 | 1.006 | 1.003 | 1.009 |
| | **Topographic erosivity index (LS)** | -.026 | .026 | .977 | 1 | .323 | .974 | .926 | 1.026 |
| | **Profile curvature** | 2.334 | .308 | 57.246 | 1 | .000 | 10.316 | 5.636 | 18.881 |
| | **Upslope slope** | .023 | .004 | 33.415 | 1 | .000 | 1.023 | 1.015 | 1.031 |
| | **Relative stream power index** | .000 | .001 | .010 | 1 | .920 | 1.000 | .998 | 1.003 |
| | **slope** | -.207 | .013 | 244.074 | 1 | .000 | .813 | .792 | .834 |
| | **Specific catchment area** | .000 | .000 | .034 | 1 | .853 | 1.000 | 1.000 | 1.000 |
| | **Upstream Flow length** | -.003 | .002 | 1.629 | 1 | .202 | .997 | .993 | 1.002 |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | **Wetness index** | .021 | .008 | 7.062 | 1 | .008 | 1.021 | 1.006 | 1.037 |
| | **Mean daily duration of direct radiation** | -.544 | .054 | 101.060 | 1 | .000 | .581 | .522 | .646 |
| | **Mean daily direct radiation** | .000 | .000 | 16.484 | 1 | .000 | 1.000 | 1.000 | 1.000 |
| **LP** | **Intercept** | -4.569 | 5.105 | .801 | 1 | .371 | | | |
| | **Aspect (sin.cos)** | .569 | .391 | 2.114 | 1 | .146 | 1.766 | .820 | 3.802 |
| | **Total Curvature** | .610 | .711 | .736 | 1 | .391 | 1.841 | .457 | 7.420 |
| | **Downstream flow length** | -.004 | .001 | 47.803 | 1 | .000 | .996 | .995 | .997 |
| | **Elavation** | .050 | .007 | 48.469 | 1 | .000 | 1.051 | 1.036 | 1.066 |
| | **Topographic erosivity index (LS)** | .023 | .040 | .351 | 1 | .553 | 1.024 | .947 | 1.106 |
| | **Profile curvature** | 1.190 | 1.068 | 1.243 | 1 | .265 | 3.288 | .406 | 26.657 |
| | **Upslope slope** | .010 | .027 | .135 | 1 | .713 | 1.010 | .959 | 1.064 |
| | **Relative stream power index** | .001 | .002 | .144 | 1 | .704 | 1.001 | .997 | 1.005 |
| | **slope** | -.075 | .040 | 3.499 | 1 | .061 | .928 | .858 | 1.004 |
| | **Specific catchment area** | .000 | .000 | .408 | 1 | .523 | 1.000 | 1.000 | 1.000 |
| | **Upstream Flow length** | .014 | .010 | 2.120 | 1 | .145 | 1.014 | .995 | 1.033 |
| | **Wetness index** | -.046 | .031 | 2.148 | 1 | .143 | .955 | .899 | 1.016 |
| | **Mean daily duration of direct radiation** | -.202 | .275 | .543 | 1 | .461 | .817 | .477 | 1.400 |
| | **Mean daily direct radiation** | .000 | .000 | 1.566 | 1 | .211 | 1.000 | 1.000 | 1.000 |
| **LV** | **Intercept** | 2.730 | .522 | 27.371 | 1 | .000 | | | |
| | **Aspect (sin.cos)** | .152 | .074 | 4.152 | 1 | .042 | 1.164 | 1.006 | 1.346 |
| | **Total Curvature** | .496 | .133 | 13.865 | 1 | .000 | 1.642 | 1.265 | 2.131 |
| | **Downstream flow length** | .001 | .000 | 63.224 | 1 | .000 | 1.001 | 1.001 | 1.001 |
| | **Elevation** | -.022 | .001 | 408.716 | 1 | .000 | .978 | .976 | .980 |
| | **Topographic erosivity index (LS)** | .009 | .013 | .438 | 1 | .508 | 1.009 | .983 | 1.036 |
| | **Profile curvature** | 1.264 | .193 | 43.063 | 1 | .000 | 3.539 | 2.426 | 5.161 |
| | **Upslope slope** | .000 | .003 | .000 | 1 | .986 | 1.000 | .993 | 1.007 |
| | **Relative stream power index** | .000 | .001 | .109 | 1 | .742 | 1.000 | .998 | 1.001 |
| | **slope** | -.081 | .007 | 143.832 | 1 | .000 | .922 | .910 | .934 |
| | **Specific catchment area** | .000 | .000 | 9.499 | 1 | .002 | 1.000 | 1.000 | 1.000 |
| | **Upstream Flow length** | .003 | .002 | 3.139 | 1 | .076 | 1.003 | 1.000 | 1.007 |

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|---|---|---|---|---|---|---|---|---|---|
| | **Wetness index** | -.016 | .006 | 6.954 | 1 | .008 | .984 | .973 | .996 |
| | **Mean daily duration of direct radiation** | -.013 | .043 | .096 | 1 | .756 | .987 | .907 | 1.074 |
| | **Mean daily direct radiation** | .000 | .000 | 10.912 | 1 | .001 | 1.000 | 1.000 | 1.000 |
| **PH** | **Intercept** | 10.332 | 2.052 | 25.349 | 1 | .000 | | | |
| | **Aspect (sin.cos)** | -.706 | .293 | 5.815 | 1 | .016 | .493 | .278 | .876 |
| | **Total Curvature** | .193 | .435 | .196 | 1 | .658 | 1.213 | .517 | 2.845 |
| | **Downstream flow length** | -.004 | .000 | 93.943 | 1 | .000 | .996 | .996 | .997 |
| | **Elavation** | .024 | .004 | 34.758 | 1 | .000 | 1.025 | 1.016 | 1.033 |
| | **Topographic erosivity index (LS)** | .054 | .035 | 2.487 | 1 | .115 | 1.056 | .987 | 1.130 |
| | **Profile curvature** | .660 | .648 | 1.039 | 1 | .308 | 1.936 | .544 | 6.889 |
| | **Upslope slope** | .010 | .012 | .692 | 1 | .406 | 1.010 | .987 | 1.034 |
| | **Relative stream power index** | -.001 | .002 | .318 | 1 | .573 | .999 | .994 | 1.003 |
| | **slope** | -.135 | .028 | 23.847 | 1 | .000 | .873 | .827 | .922 |
| | **Specific catchment area** | .000 | .000 | 1.920 | 1 | .166 | 1.000 | 1.000 | 1.000 |
| | **Upstream Flow length** | .010 | .006 | 2.518 | 1 | .113 | 1.010 | .998 | 1.022 |
| | **Wetness index** | .039 | .022 | 3.188 | 1 | .074 | 1.039 | .996 | 1.084 |
| | **Mean daily duration of direct radiation** | -.712 | .152 | 21.942 | 1 | .000 | .491 | .364 | .661 |
| | **Mean daily direct radiation** | .000 | .000 | 32.723 | 1 | .000 | 1.000 | 1.000 | 1.000 |
| **PZ** | **Intercept** | 4.632 | .780 | 35.233 | 1 | .000 | | | |
| | **Aspect (sin.cos)** | .051 | .111 | .213 | 1 | .645 | 1.053 | .847 | 1.308 |
| | **Total Curvature** | .047 | .191 | .062 | 1 | .804 | 1.049 | .721 | 1.524 |
| | **Downstream flow length** | -.001 | .000 | 30.955 | 1 | .000 | .999 | .999 | .999 |
| | **Elavation** | .004 | .002 | 4.987 | 1 | .026 | 1.004 | 1.000 | 1.007 |
| | **Topographic erosivity index (LS)** | -.014 | .022 | .406 | 1 | .524 | .986 | .945 | 1.029 |
| | **Profile curvature** | .243 | .275 | .779 | 1 | .377 | 1.275 | .743 | 2.188 |
| | **Upslope slope** | -.032 | .006 | 26.687 | 1 | .000 | .969 | .957 | .981 |
| | **Relative stream power index** | -.001 | .002 | .115 | 1 | .734 | .999 | .997 | 1.002 |
| | **slope** | -.008 | .010 | .634 | 1 | .426 | .992 | .972 | 1.012 |
| | **Specific catchment area** | .000 | .000 | 5.718 | 1 | .017 | 1.000 | 1.000 | 1.000 |
| | **Upstream Flow length** | .010 | .003 | 14.282 | 1 | .000 | 1.010 | 1.005 | 1.015 |

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|---|---|---|---|---|---|---|---|---|---|
| | **Wetness index** | -.040 | .009 | 18.397 | 1 | .000 | .960 | .943 | .978 |
| | **Mean daily duration of direct radiation** | -.285 | .063 | 20.320 | 1 | .000 | .752 | .664 | .851 |
| | **Mean daily direct radiation** | .000 | .000 | 25.785 | 1 | .000 | 1.000 | 1.000 | 1.000 |
| **RG** | **Intercept** | -9.309 | 1.583 | 34.588 | 1 | .000 | | | |
| | **Aspect (sin.cos)** | -.073 | .194 | .141 | 1 | .707 | .930 | .635 | 1.361 |
| | **Total Curvature** | .668 | .449 | 2.213 | 1 | .137 | 1.951 | .809 | 4.703 |
| | **Downstream flow length** | .001 | .000 | 20.259 | 1 | .000 | 1.001 | 1.001 | 1.001 |
| | **Elavation** | .005 | .003 | 3.423 | 1 | .064 | 1.005 | 1.000 | 1.011 |
| | **Topographic erosivity index (LS)** | .047 | .073 | .418 | 1 | .518 | 1.048 | .909 | 1.209 |
| | **Profile curvature** | 2.324 | .667 | 12.139 | 1 | .000 | 10.211 | 2.763 | 37.734 |
| | **Upslope slope** | -.005 | .011 | .179 | 1 | .672 | .995 | .973 | 1.018 |
| | **Relative stream power index** | -.004 | .005 | .590 | 1 | .443 | .996 | .986 | 1.006 |
| | **slope** | -.148 | .028 | 27.208 | 1 | .000 | .862 | .815 | .912 |
| | **Specific catchment area** | .000 | .000 | 1.483 | 1 | .223 | 1.000 | 1.000 | 1.000 |
| | **Upstream Flow length** | .005 | .005 | .798 | 1 | .372 | 1.005 | .994 | 1.015 |
| | **Wetness index** | -.008 | .015 | .270 | 1 | .604 | .992 | .965 | 1.021 |
| | **Mean daily duration of direct radiation** | .543 | .127 | 18.167 | 1 | .000 | 1.721 | 1.341 | 2.209 |
| | **Mean daily direct radiation** | .000 | .000 | .569 | 1 | .450 | 1.000 | 1.000 | 1.000 |
| **RGah** | **Intercept** | 7.723 | .605 | 162.774 | 1 | .000 | | | |
| | **Aspect (sin.cos)** | .639 | .089 | 51.974 | 1 | .000 | 1.894 | 1.592 | 2.253 |
| | **Total Curvature** | .167 | .159 | 1.103 | 1 | .294 | 1.182 | .865 | 1.614 |
| | **Downstream flow length** | -.001 | .000 | 21.844 | 1 | .000 | .999 | .999 | 1.000 |
| | **Elavation** | -.034 | .001 | 634.469 | 1 | .000 | .967 | .964 | .969 |
| | **Topographic erosivity index (LS)** | -.014 | .015 | .891 | 1 | .345 | .986 | .958 | 1.015 |
| | **Profile curvature** | .367 | .229 | 2.572 | 1 | .109 | 1.443 | .922 | 2.259 |
| | **Upslope slope** | -.014 | .004 | 12.378 | 1 | .000 | .986 | .979 | .994 |
| | **Relative stream power index** | .001 | .001 | .596 | 1 | .440 | 1.001 | .999 | 1.002 |
| | **slope** | -.040 | .008 | 26.583 | 1 | .000 | .961 | .946 | .975 |
| | **Specific catchment area** | .000 | .000 | 11.950 | 1 | .001 | 1.000 | 1.000 | 1.000 |
| | **Upstream Flow length** | .006 | .002 | 10.953 | 1 | .001 | 1.006 | 1.003 | 1.010 |

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|---|---|---|---|---|---|---|---|---|---|
| | **Wetness index** | -.011 | .007 | 2.545 | 1 | .111 | .989 | .976 | 1.003 |
| | **Mean daily duration of direct radiation** | -.362 | .049 | 54.634 | 1 | .000 | .696 | .632 | .766 |
| | **Mean daily direct radiation** | .000 | .000 | 1.852 | 1 | .174 | 1.000 | 1.000 | 1.000 |
| a The reference category is: UM. | | | | | | | | | |