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Creating Initial Digital Soil Properties Map Of Afghanistan

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CREATING INITIAL DIGITAL SOIL PROPERTIES MAP OF AFGHANISTAN

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of

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by

Shams R. Rahmani

In Partial Fulfillment of the

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of

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This thesis is dedicated

to my respected parents and family

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TABLE OF CONTENTS

Page

LIST OF TABLES

LIST OF FIGURES

ABSTRACT

Rahmani, Shams R. M.S., Purdue University, December 2014. Creating Initial Digital Soil Properties Map of Afghanistan. Major Professor: Phillip Owens.

Afghanistan is a country with a population of more than 31 million people and is located in south central Asia. The total arable land in the country is 12%, 5% is irrigated and the remaining 7% is rainfed. Lack of available soil information, poor farming practices, and poor land management planning, severely affect the yield of agricultural products. In order to ensure sustainable agriculture and prevent land degradation problems, understanding the spatial variability of soils is crucial. The overall objective of this research study was to use digital soil mapping techniques to identify the soil resources and to generate a spatially explicit soil map of a 8,358,160 ha pilot study area. The specific objective is to develop a version 1 map of the six Northern provinces of Afghanistan.

Several techniques such as artificial neural networks, multiple regression analysis, and hybrid geostatisitcal approaches are used to create digital soil maps. However, most of these procedures required large amounts of data to create digital soil maps at a useful resolution. Countries like Afghanistan have limited available data and it is difficult to develop the map based on the aforementioned procedures. For this research, we utilized a

knowledge based approach that used fuzzy logic to create a version 1 map with the limited available point data.

The fuzzy logic maps are developed based on the five soil forming factors; therefore knowledge of soil and soil landscape relationships is required. From the ecoregion map of the study area we assumed that climate, organisms and time were constant, and that geology and topography were the driving factors of soil formation. Therefore, the fuzzy property map of the study area was developed from geology and geomorphon composition. In order to capture the variability of the soil, we used terrain attributes that have close relationships with water redistribution. Geomorphons were used to classify the landforms of the study area.

As a part of the fuzzy process, membership curves are required to define soil similarity vectors. Traditionally, the membership curves are manually defined by soil scientists based on their tacit knowledge of the soil and landscape. Even though, the manual method adequately predicts soil properties, it is time consuming and limits the application of fuzzy logic. In order to make fuzzy logic an easy and time effective approach for developing functional property maps, it is essential to use the Automatic Landform Inference Mapping (ALIM) model to automatically generate the accurate membership functions.

The ALIM model developed at Purdue University was used for this research to define the membership functions. To generate the membership functions, the ALIM model combines terrain attributes derived from a digital elevation model with the soil classes. The determined membership values and soil property values were then assigned to the Zhu (1997), equation to predict the soil property maps of the pilot area.

The overall results showed that predicted properties generally followed the landscape patterns, but not in all areas. The accuracy test of Normalized Root Mean Square Prediction Error (RMSPEr) showed that the model prediction was insignificant. Several factors such as too few data points, inaccurate coordinate locations of the data points, and the low 90 m resolution DEM were assumed to be the reason for inaccurate assessment.

Overall, the methods did produce a spatially explicit map that will be useful for developing the next map version. More data and a higher resolution DEM is necessary for improving the soil property predictions of the pilot area.

CHAPTER 1. INTRODUCTION

1.1 Overview of Afghanistan

Afghanistan is a nation with wide ranging geography, climate, population, economy, agriculture, and soils. Soil has a critical role in several vital functions such as crop production, hydrologic cycling, and carbon sequestration, to name a few. Understanding soil variability is necessary for proper land management and improving agriculture practices. Unfortunately, due to 30 years of war and conflict, limited soils information is available, with few detailed soil surveys of Afghanistan.

In order to meet the food demand of the current population, it is necessary to identify the soil resources of the country. This thesis focuses on a technique to identify and map the soil resources of Afghanistan based on a pilot study area.

1.1.1 Geography

Afghanistan is a landlocked mountainous nation located in south central Asia. It is bordered by Tajikistan, Uzbekistan and Turkmenistan in the North, Iran in the West, Pakistan in the South and East, and China to the far Northeast Figure 1.1. Afghanistan has a land area of 650,000 km^2 and extends a maximum of 1239 km from East to West and 563 km from North to South. The highest point of elevation in the country is 7492 m, which is the highest peak of Hindu Kush Mountains. Generally, the average elevation of the country is 1219 m (Wesa, 2002).

Figure 1.1: Location of Afghanistan.(n.p, 2014).

Afghanistan is divided into five main topographic regions (Figure 1.2). (1) Lowland topography is dominant in Southern and Northern provinces. Elevation is less than 600 m and the area is characterized by deserts, sand dunes, salty marsh lands, and playas. (2) Plains have an elevation between 600 to 1500 m. Major features of plains are sand dunes, desert flats, few river valleys and playas. (3) Foothills and valleys have elevations from 1500 to 2100 m and are characterized by flood plains, river terraces and rolling hills. (4) Plateaus and uplands are located in the central mountains. They are characterized by existence of small lakes, limited areas of marshland, and high elevations from 2100 to 2700 m. (5) The elevation of high mountains and peaks ranges from 2700 m to more than 5200 m. These mountains are characterized by steep slopes that are covered with snow throughout the year (Salem and Hole, 1969).

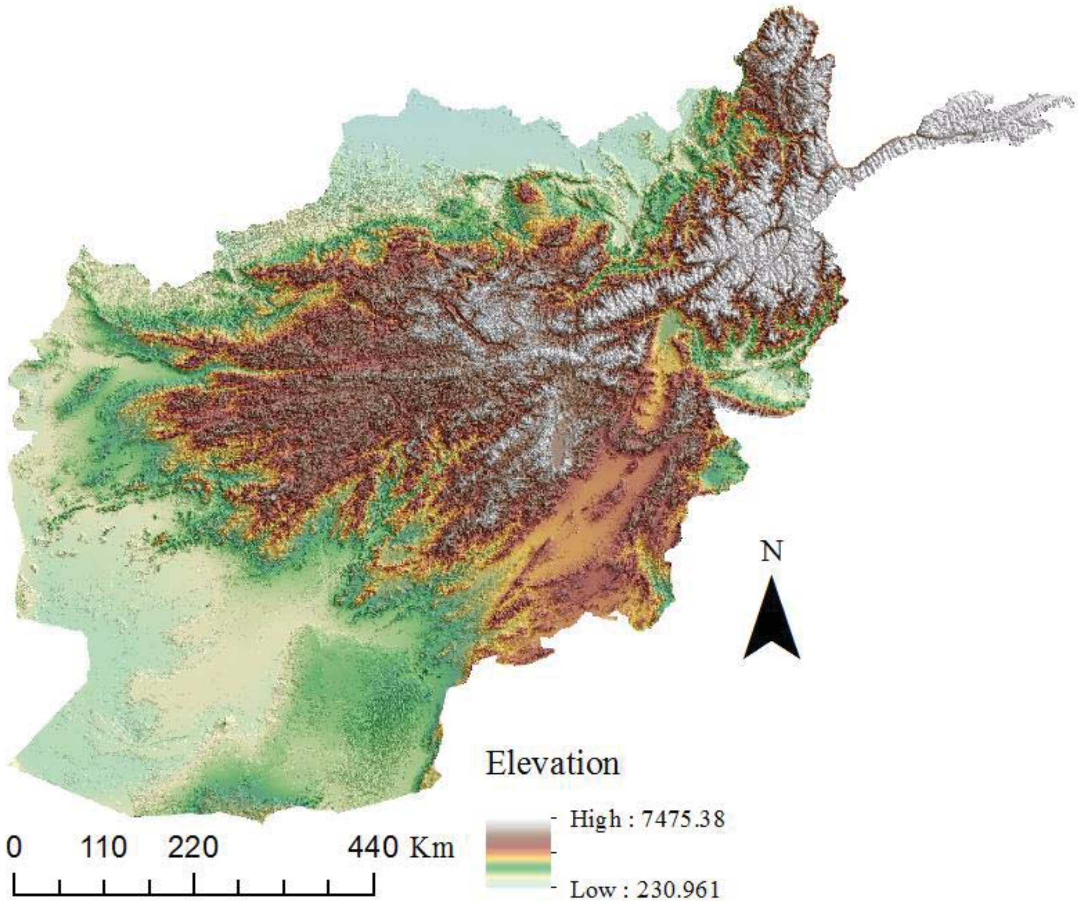

Figure 1.2: SRTM 90 m digital elevation model of Afghanistan (Doebrich and Jeff, 2006).

The climate of Afghanistan is generally described by high evaporation, low relative humidity, strong solar radiation and abundant days without cloud cover (Shroder, 2014). Temperature varies greatly across Afghanistan and generally decreases from the Southwest to the Northeast and decreases from lower elevation to higher elevations (Figure 1.3).

In the lowlands, mean annual summer temperatures exceed 33^{o}C, but mean annual winter temperatures are near 10^{o}C. In the high mountains, mean annual summer temperatures do not exceed 15°C and the mean annual winter temperature is below 0°C (McSweeney et al., 1994).

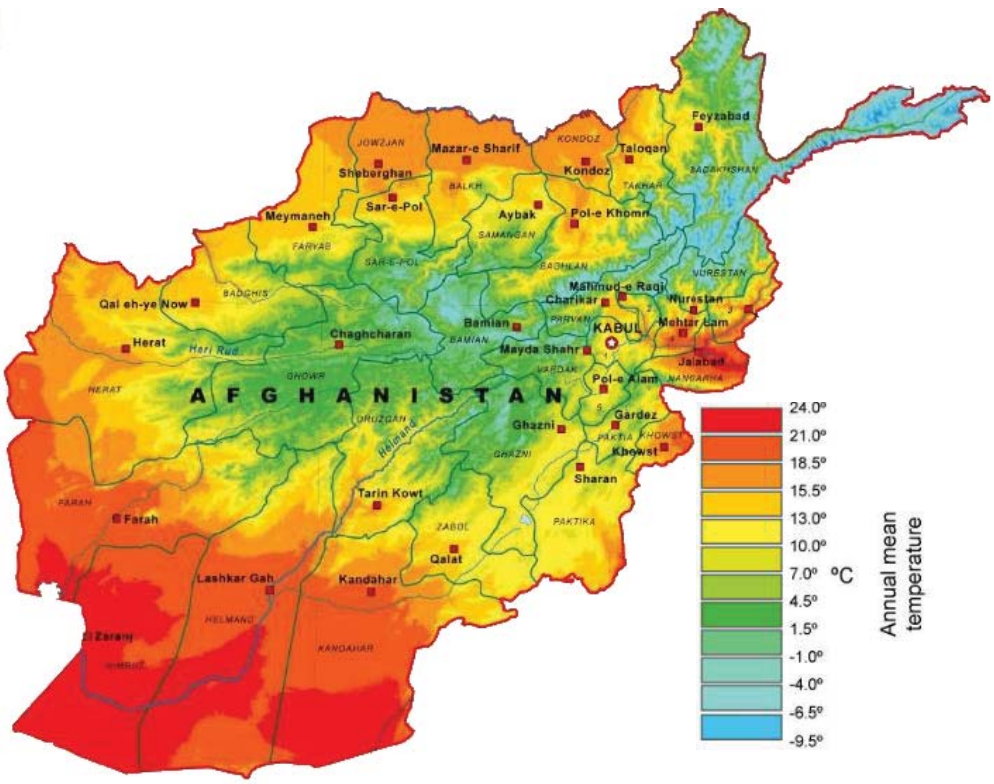

Figure 1.3: Mean annual temperature map of Afghanistan (World Trade Press, 2007).

The geography influences rainfall. Areas with higher potential evaporation also receive the least amount of precipitation. In these locations crops require irrigation (Bhattacharya et al, 2004). Mean annual precipitation in Afghanistan is 327 mm and it ranges from 100 to 400 mm. Most of the precipitation occurs as snow in the mountains and provides irrigation water during the summer for crops grown in the lowlands.

1.1.2 Population

In 2013, Afghanistan had a population of 31 million people including 2.7 million Afghan refugees in Pakistan and Iran. Urban populations make up 23.5% of the total population. The population density of Afghanistan is 47 persons per km^2. Afghan national demographic composition is complex and is composed of a multi-ethnic and multi-lingual society. According to the World Factbook of Central Intelligence Agency (CIA), Pashtun is the largest ethnicity in the country, followed by Tajiks, Hazars, Aimaks, Turken, Baloch, Pashai, Nuristani, Gujjar, Arab, Brahui, and Pamiri (Breu et al, 2014).

Both Pashto and Dari languages were named as official languages in the 1964 Constitution. Beside these two official languages, more than 18 other languages are spoken in the country, including Uzbaki, Balochi, Turkmani, Pashayi, Nuristani, Kyrgyz, Brahui, and Pamiri.

1.1.3 Economy

Since Afghanistan is a rural country, agriculture, livestock and irrigation are the three major sectors for enhancing the economy of the country. Almost 80% of the population and half of the country's Gross Domestic Product (GDP) are supported by agriculture. From an economic stand point, Afghanistan had a growing and well-functioning economy during the late 1970s. Afghanistan exported raisins, cotton, animal fibers, carpets, and skin garments commodities to Central Asia and India. Additionally, during that time Afghans were also self-sufficient in meat and milk production (Ward et al, 2008).

The Soviet Union invasion, between 1979 – 1985, greatly affected Afghanistan's economy. This civil unrest destroyed the infrastructure and limited land-use due to minefields. As a war tactic to remove the Mujahideen, the Soviets burned most of the orchards and made fields unmanageable with underground mines. During the invasion, many Afghans left the country and migrated to Pakistan, Iran, and other countries. Mass emigration led to the loss of the irrigation systems because of lack of maintenance (De Beurs and Henebry, 2008).

Establishment of the transitional government in 2001 had a great impact on Afghan economic revitalization and development. International cooperation, reconstruction of infrastructures, improving the agriculture sector, and increasing international markets for Afghan dry and fresh fruits are the main factors of economic growth. The World Factbook reported that in 2013 the GDP was 45.3 billion ($US) (Breu et al., 2014).

1.1.4 Agriculture

About 8 million hectares (ha), or 12%, of the total land is suitable for agriculture practices. Of this, 5% is irrigated and the remaining 7% is rainfed (Pedersen, 2006). Table 1.1 shows the land cover and land use of Afghanistan. The average size of an Afghan farm is 5 hectares. Due to the large areas of rangelands, improved livestock practices would serve as the best alternative for improving the livelihood of farmers and rural settlers (Hildreth, 1957).

Table 1.1: Land cover and land use in Afghanistan (Pedersen, 2006).

Land cover/use	Area (ha)	Area%
Urban	29,494	0.05
Orchard	94,217	0.10
Agriculture land Irrigated	3,207,790	5.0
Intensive	1,559,654	2.4
Intermittent	1,648,136	2.6
Agriculture land rainfed	4,517,714	7.0
Forest	1,337,582	2.1
Rangelands	29,176,732	45.2
Barren Lands	24,076,016	37.3
Marshlands	417,563	0.60
Water bodies	248,187	0.40
Snow covered areas	1,463,101	2.30
Total	64,559,396	100

The main source of water for irrigated agriculture is provided by existing basins and rivers. Afghanistan has five main rivers which are: the Amu Darya, the Kabul, the Helmand, the Harirod-Murghab and the Northern Rivers (Figure 1.4). The Amu Darya Rive has a 86,000 km^2 catchment area, and feeds the northeastern part of Afghanistan. This river drains into the Aral Sea. The Kabul River also known as the Indus River, flows from west to the east and has a 143,000 km^2 catchment area. This river mostly covers the eastern and southeastern parts of the country. The Helmand River, with a 166,000 km^2 catchment area, flows from east to the west. This river supplies water for south and southwestern Afghanistan. The catchment area for the Harirod-Murghab River is 131,000 km^2. The Harirod-Murghab provides irrigation water for the western part of the country and leaves Afghanistan and flows into the Tejen Oasis of Turkmenistan. The Northern River is a combination of several smaller rivers, the Kashan, the Kushk and the Gularn. The catchment area for the Northern River is 116,000 km^2 (Shobair and Alim, 2004).

Generally, the agriculture and the economy of both Pakistan and Iran are dependent on rivers that flow out of Afghanistan. Throughout the year, water fluctuation creates political problems between Afghanistan and Pakistan and Iran. The Helmand River originates in the Paghman Mountains around Kabul, and creates disagreements between the Afghan and Iran governments. The water of this river is used for irrigation purposes in both countries. The main issue was created by the construction of the Helmand hydroelectricity dam by the Afghan government on the Helmand River. The Iranian government made allegations that building the Helmand dam and overuse of Helmand water by Afghans adversely affected the Sistan Wetlands of Iran. A similar problem exists with Pakistan over the Kabul or Indus river. In Pakistan, the Kabul River is used for both electricity and agriculture production; therefore, it has a vital role in the Pakistan economy. The use of the Kabul River water for irrigation or power production inside Afghanistan creates a concern for Pakistan regarding the decrease in water.

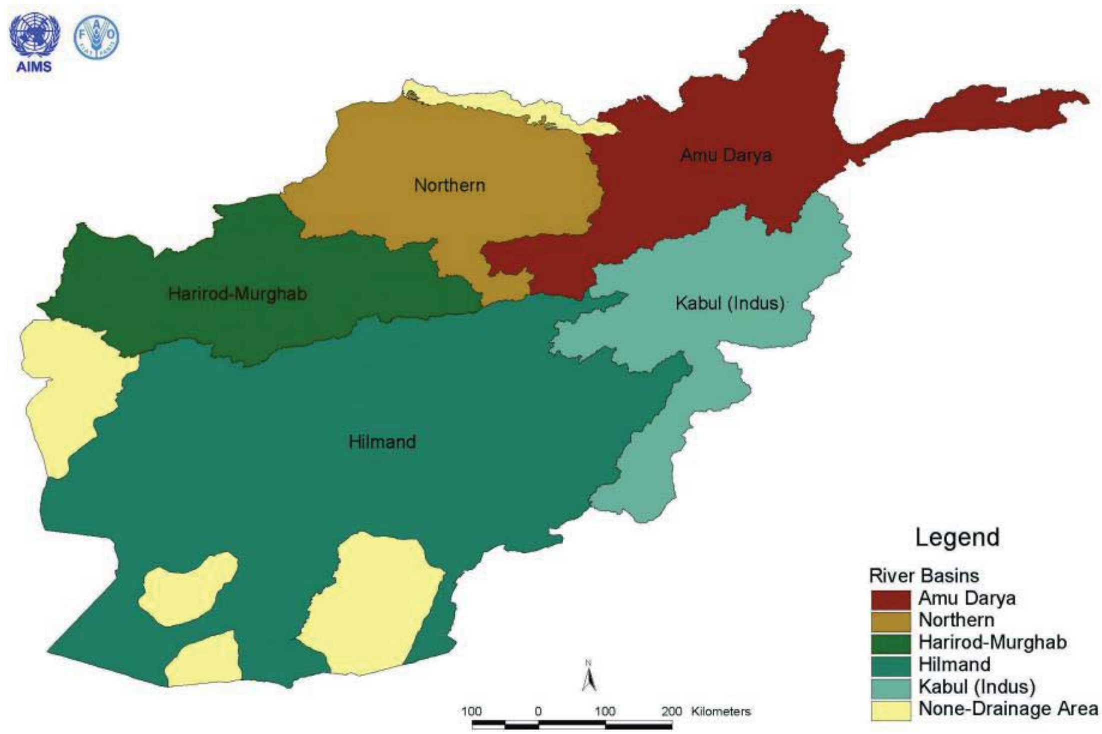

Figure 1.4: The five major river basins of Afghanistan (FAO/AIMS, 2003)

The northern and western parts of the country have the best suited arable lands for both annual and perennial crop production (Hildreth, 1957). These areas along with the southwest have access to the river basins for irrigation. Wheat, corn or maize, rice, and barely are the major cereal crops grown by Afghan farmers. The northern part of the country has numerous rivers including the Amu River, where 40 to 55 % of irrigated and rainfed wheat production fields areas are located (ICARDA/USAID, 2002). Presently, Afghanistan is not self-sufficient and must rely on imports of wheat and flour from neighboring countries. From 2002 to 2004, Afghanistan imported 600,000 tons of wheat flour from Pakistan (Chabot and Dorosh, 2007).

Natural resource degradation is a big concern in Afghanistan and has direct impacts on agricultural production. Soil erosion due to over grazing, deforestation, and desertification increases the stress on the land. From 1977 to 2002, Afghan forests were reduced by 52 percent (Pedersen, 2006). Naturally low soil fertility, existence of saline and sodic soils, high alkalinity, lack of water, soil compaction from use of heavy equipment, pest and diseases attack, lack of farmer’s understanding regarding soil management, and the harsh and dry climate affect Afghan agricultural production.

A combination of several agriculture practices can reduce the agricultural problems in Afghanistan. Conservation tillage, increasing soil organic matter, composting, crop rotation, mulching, and cover crops are the easiest means to improve soil conditions and boost crop production. Management practices are often soil and landscape specific. Understanding soil resources is crucial for designing best management practices. The soil information must be spatially explicit and delivered in a format that allows for easy application.

Digital Soil Mapping (DSM) is an efficient, consistent, and low cost method for predicting soil properties. Digital soil maps will help create products that can be used to identify problems and determine potential solutions (Lomurut, 2014). As an example, DSM would predict low soil organic matter content and soil erosion on sloping landforms, which can then be managed by conservation practices.

1.1.5 Soil

Soil in Afghanistan can be considered “pedologically young” because of the arid and semiarid climate conditions. Because of the high content of calcareous material, the pH of Afghan soils is usually greater than 7 and considered as alkaline in terms of reaction (FAO/UNDP, 1972). More than 50% of the soils have a pH between 8 and 8.5, about 35% of the soils have a pH between 8.5 and 9 and only 10% of the soils have a pH of 9 and above (FAO/UNDP, 1972). The soils, in general, have low fertility and low organic matter content (usually less than 2%). Generally, Afghanistan has the following soil orders Aridisols, Entisols, Inceptisols, Alfisols and Mollisols (Shroder, 2014).

One of the first studies conducted on Afghan soils was done by the Institute of Applied Botany of Leningrad. In 1924 and 1926 – 1927 the institute sent scientists to Afghanistan for soil evaluation. They made general observations of the soils and took soil samples for physical and chemical analysis. A general soil map was developed with the following four soil groups: 1) Soils in low river valleys classified as heavy loam. 2) Soils of the foothills in northern Afghanistan identified as loess-like loam. 3) Soils on slopes were classified as medium loams and 4) The irrigated cultivated soils of the oases (urban centers) (Hildreth, 1957).

Salem and Hole (1969), conducted research on Afghan soil properties and classification. This research studied eight pedons and found that most of the soils in these areas were classified as Aridisols and Entisols.

In 2001, the Natural Resource Conservation Service of the United States Department of Agriculture (NRCS/USDA) developed a soil regions map for Afghanistan.

This map was based on soil Great Groups, moisture regimes and temperature regimes and identified 25 different soil regions in the country (Shroder, 2014).

The Salem and Hole (1969), and NRCS/USDA investigations developed soil maps and provided general information about Afghan soil. More effort is required to conduct detailed soil surveys and generate more accurate and high resolution soil maps of Afghanistan.

1.2 Statement of the Problem

Soil is a key component of the earth system. Improvement or destruction of soil has an effect on both the geosphere and biospheres. Soil information is not only required for predicting yield, sustainable agricultural production, and land use analysis, but also, for environment protection and natural resource management.

Large numbers of field observations are required for traditional soil surveys. Recently, with advanced technology it is possible to provide essential and accurate information in a limited timeframe and without significant expenses (Stoorvogel et al, 2009). Recently, digital soil mapping has become the leading alternative for traditional soil surveys due to the cost and time required.

We are not aware of any efforts to create a digital soil map for Afghanistan. The main hypothesis of this study is that soil properties can be predicted, and a digital soil map can be developed, using topographic information, terrain analysis, and environmental conditions.

1.3 Objectives

The overall purpose of this research project was to develop a method to create a soil map of the country based on a pilot study area. The specific objective was to use

Fuzzy Logic, a knowledge-based inference approach, and Automated Landform Inference Mapping (ALIAM) model for prediction and development of a digital soil map of soil properties for a pilot study area in the north part of Afghanistan.

1.4 Limitation of the Study

Developing accurate digital soil maps requires data points and a high resolution Digital Elevation Model (DEM). For this research, availability of analyzed point data was scarce and only a 90 meter resolution DEM was available. This 90 meter DEM has low resolution and noise problems. Several sources have been contacted for providing analyzed point data and a higher resolution DEM, but without result. Therefore the map produced by this study is a first generation digital soil map that provides general soil classes for the study area.

CHAPTER 2. SOIL SURVEY AND MAPPING

Soil has a vital role in several life sustaining environmental process such as providing a medium for plant growth, cleaning and storing water, supporting buildings, and biogeochemical cycling. The soil system is an irreplaceable natural resource which is limited in quantity and, if mismanaged, is easily degradable in quality. Soil sustain life for organisms such as plants, animals, and microorganisms. Human life is directly affected by how society treats the soil. Proper soil management is crucial to sustaining this natural resource (White, 2009).

Improper use can degrade and reduce the soil’s ability to perform its proper function. Soil degradation and erosion negatively affects crop yield, soil quality and productivity, which relates to erosion and sedimentation, emission of trace gases, and creates water quality problems (Lal, 2001). In particular to current climate change issues, carbon sequestration and enhancement of soil carbon pools of degraded land not only decreases fossil fuel emissions but also increases crop yield (Lal, 2004).

It is estimated that by 2050, the world population will reach 9 billion. This rapid increase in population presents numerous challenges to scientists in various fields. Land management is crucial for an increased demand of food, energy and water.

Understanding soil properties allows scientists in all disciplines to extrapolate research from small plots to larger areas, which is essential for better land management for society. Soil mapping is a vital tool for spatially representing and understanding soil properties and related soil functions.

Governments and policy makers recognize the value of soil and soil mapping for the fulfillment of societal needs. Many governments support development of these maps to understand the relationship between the soil and the environment. In 1896, soil surveys were authorized in the United States to determine, classify and develop maps of soil types and their properties for the prediction of the soil's behavior and proper use (Soil Survey Division Staff, 1993). Additionally, for regional and local planning, there is a need to know the location, formation and potential use of various soils (Thuy, 2013). However, traditional soil surveys are expensive, time-consuming and often not at a scale useful for land management.

Soil survey information is a basic infrastructure need for nations. All land-use is dependent on the soil and landscapes. Some examples are: A farmer and rancher could predict the suitability of their land for crop types and forages for livestock, and they also will understand the management options for their soils. An engineer would use the provided information of a soil survey for construction projects. Even a homeowner can use the information for improving their garden or yard (Soil Survey Division Staff, 1993).

In the United States, published soil surveys of each county contain the following components (Soil Survey Division Staff, 1993):

1) Geographical information of the county
2) Soil map with the associated soil types and characteristics
3) Aerial photographs

4) Tables that present information about total area, comparison of various crop productions, and land use planning of each soil type
5) Tables of physical, chemical and engineering properties of soil.

In the traditional soil survey, soils are examined by well-trained experts. The soil scientists develop mental models of how soil patterns occur on landscapes and use these mental models to delineate polygons on the landscape. The resulting maps are relatively accurate and reliable for the intended scales. In a soil survey, the mapping units are chosen according to the properties of a landscape, which generally relate to the land's capabilities and its response to management (Bayramin, 1998).

For most of the earth, and even for developed countries, there are no large scale and scientifically based datasets to use in association with soil survey maps. Development of such a database is important and would serve many different applications and research studies. Financial resources, technical capacity, and political issues often limit development of soil databases. Since there are often no available databases and not enough data for data driven map products, tacit knowledge and soil pattern development must be used to develop soil maps.

2.1 Soil Properties of Afghanistan

Afghanistan has an arid and semi-arid climate, therefore vegetation is sparsely distributed. The dry and warm climatic condition of the country slows soil development processes and limits the organic matter content of the soils.

The dominant parent materials of Afghan soils are limestone, sandstone, and metamorphic rocks. Aridisols, Entisols, and Alfisol are the most dominant soil orders of the arid and semi-arid regions (Shroder, 2014).

Due to low precipitation and high evapotranspiration, there is commonly a great accumulation of soluble salts which is generally reported in the soils of arid and semi-arid regions. In the rare periods of high rainfall intensity, the bare surface results in high soil erosion rates in these regions (Balba, 1995).

Only a few studies have been conducted by scientists concerning Afghan soils. Morrison-Knudsen Afghanistan Inc was the first company that took steps towards conducting soil surveys of the country. In 1946, the Morrison-Knudsen company conducted extensive studies on the Hilmand River Valley soils. Mr. Frenk O. Youngs was responsible for this project and he completed the soil survey and soil classification of more than 222,577 ha in Helmand, Arghstan, Tarnak and the Dori River valleys.

The Morrison-Knudsen company also made a detailed soil survey of more than 4,046 ha in the Balikat Flat of Nangarhar Province. The soil survey maps from this company contain information about soil chemical and physical properties, slope, and land capability classes (Hildreth, 1957). The extensive research of the Morrison-Knudsen company found that most Afghan soils are naturally supplied with calcium carbonate, resulting in high soil pH. They also concluded that crop yield in the Nad-i-Ali District of Hilmand Province is highly dependent on availability of water.

The Afghan Department of Agriculture hired Dr. George Hauser from 1949 – 1953 for investigation of Afghan soils. During his investigation his work focused on the following issues (Hildreth, 1957):

1) Determining the main soil types of different parts of the country.
2) Developing methods for dealing with new land for cultivation.

3) Identifying alkali salts in Afghan soils and development of management methods for their improvement.
4) Describing soil profiles and sampling Baghlan sugar beet, Kunduz cotton, and Khanabad rice soils.
5) Determining fertilizer and manure application rates for various crops.

Dr. Hauser found that application of phosphorus (P) fertilizer is required for obtaining higher yield in the Kataghan area of Afghanistan.

In 1985, Geokart classified Afghan soils based on the Russian soil classification system. Sierozems (alkali desert soils), Saline, Brown Forest Soil and Takyrs (dry lake basins) classes were noted. Salem and Hole (1969), investigated eight soil profiles in different zones and concluded that five were Aridisols, two were alluvial Entisols, and one was a Mollisol (Shroder, 2014).

Recently, the USDA developed a soil region map for Afghanistan. The map was developed from topographic data rather than field soil data; therefore it is theoretical and has some inaccuracies (Shroder, 2014). The map, which was based on soil Great Groups and soil moisture and temperature regimes, identified 25 different soil regions in the country.

The Japan International Research Center for Agriculture Science (JIRCAS) analyzed the properties of paddy soils of 20 villages in the Nangarhar Province of Afghanistan. The sandy loam and loam textured soils were dominantly alkaline. In this research, the Olsen-P method was used for testing of available phosphorus, and it was reported to be constant (20.7 mg/kg P_2O_5). Diethylene triamine pentaacetic acid- triethanolamine (DTPA-TEA) extraction was used for determination of available micronutrients.

On average, baseline iron (Fe), manganese (Mn), cupper (Cu) and zinc (Zn) were reported at 35.9, 9.6, 4.75 and 0.33 mg/kg respectively. Nitrogen (N), P and Zn were reported as deficient in paddy soils (Masunaga et al, 2014).

This research found that the due to the alkaline nature of the soil, overall fertility was low for the paddy soil properties when compared to tropical Asia paddy soil properties. They concluded that distribution of various types of parent materials such as limestone, dolomite and lava caused the differences in the properties of paddy soils (Masunaga et al, 2014).

2.2 Spatial Variability of Soil Properties

Understanding soil forming factors in a given location is the first and foremost tool for predicting soil properties. According to Jenny (1941), soil is a function of climate, organisms, relief, parent material and time. Therefore, understanding these soil forming factors are necessary for mapping soils for soil survey. For the modern soil survey, in addition to understanding the five state factors, field soil samples should to be collected and then supported by remote sensing technologies (Soil Survey Division Staff, 1993).

Understanding spatial variability of soil properties is the key for many uses but is particularly important for precision agriculture (Kravchenko and Bullock, 1999). Soil variability is a result from the interaction of several processes which occur within a landscape. Yield potential, chemical applications and transport, and hydrologic responses are affected by spatial distribution of soil properties (Cambardella et al, 1994).

Variability of soil properties is caused by both vertical and horizontal relationships of soil horizons to soil forming factors but soil scientists have traditionally focused on their vertical relationships (Moore et al., 1993). The variability of soil properties is spatially and temporally dependent. Generally, samples that are collected near each other are generally more alike than those that are collected far apart from each other. For prediction of soil spatial variability, geostatistical analyses have been used as opposed to parametric statistics. This is because in parametric statistics observations are assumed to be independent of the distribution in distance (Cambardella et al, 1994). Most of the published literature contains information about spatial variability of one or a few parameters, and few of them contain information about spatial variability of comprehensive parameters of soil.

Soil physical properties such as texture, structure, and organic matter content have a strong correlation with parent material and topography. Chemical properties of the surface soil are more susceptible to change by soil management and tillage operations (Trangmar et al, 1985). Therefore, soil survey maps are primarily developed based on physical and chemical properties of the whole soil (Wollenhaupt et al, 1997).

Texture, depth to bedrock, type of clay, and cation exchange capacity are static properties and don’t change rapidly in a time interval of several seasons. Temperature and precipitation fluctuations are considered as the main factor of temporal variation. Dynamic properties such as soil moisture content, surface soil structure, organic matter, NO_3 – N and nutrient holding capacity are greatly affected by temporal variations and management. Therefore, dynamic properties should be sampled at the proper time and the current and historical land use noted (Wollenhaupt et al, 1997).

2.3 Digital Soil Mapping (DSM)

The goal of soil mapping is to obtain spatial information for both physical and chemical properties of soils and to deliver that information in an understandable format.

As mentioned previously, traditional soil survey is a manual process for the investigation of the spatial distribution of soil types utilizing field observations and aerial imagery interpretations. In the soil survey, which is based on soil-landscape models, soil formation is interpreted as the result of various environmental factors over time (Zhu et al., 2001).

In traditional soil survey, the following steps are used to developed a soil map (Thuy, 2013).

1) Planning the project
2) Preparing for the fieldwork
3) Interpreting the photo- interpretation and pre-processing of the auxiliary data
4) Analyzing the collected field data
5) Inputting and organizing the data
6) Presenting and application of the final soil mapping products.

Project planning is one of the most important steps in a traditional soil survey, because it consists of sample planning, developing the classification system, and data organization. Literature review and reconnaissance surveys are the main parts of fieldwork preparation. The final product of traditional soil survey depicts the distribution of soils as polygons and the associated properties of the map units are described in an accompanying by a soil survey report.

Traditional soil survey methods face the following two limitations. First, soil survey relies on polygon based mapping processes which ignore spatial variation within the delineation of a discrete polygon. Second, a manually developed map is expensive, time consuming and contains errors (Zhu et al, 2007).

Scientists are now using highly advanced technologies for obtaining better spatial representation and improved accuracy in maps. Geographic information systems (GIS) have wide applications for developing thematic maps of the entered data. The layers or database of GIS typically are DEMs, legacy soil surveys, or spatial data-including remotely sensed data (Bayramin, 1998).

Digital soil mapping (DSM) is a computer modeling system which derives spatial information of soil through combination of soil information and related environmental covariates (Hartemink et al, 2008). Dobos et al (2006), indicated that DSM techniques can be used for predicting soil properties in an unobserved area of a landscape. To make a soil map, soil variability (spatial or temporal) should be systematic. If the variability is random and not systematic, then soil scientists can only describe the soils and can't make a reliable map (Bayramin, 1998).

For deriving spatial distribution of soil information, several mathematical techniques are used, for example; fuzzy logic, artificial neural networks, multiple regression analysis, and hybrid geostatistical methods (Florinsky, 2012). Mertens et al (2002), developed a soil texture map by using a Classification and Regression Tree (CART) model. The basic inputs of this model were topographical maps, geological maps and texture and profile data (Mertens et al., 2002). In South-Eastern Australia, McKenzie and Ryan (1999), studied the relationship between the depth of the soil profile and the total P and the total carbon (C) by utilizing regression trees and generalized linear models. A random forest model was developed by Wiesmeier et al (2011), and showed that land use has high correlation with soil organic carbon (SOC), total C, total N and sulphur (S).

Models like SoLIM (Soil-Land Inference Model) have been developed to generate digital soil maps based on soil and landscape relationships. Milne (1947), reported that soils are closely related to the landscape position. Milne (1947), introduced the concept of catena. A catena of soils has the same age and formed from the same parent material under identical climate conditions but only varies in topography. The reason for a catena was determined to be the redistribution of water which is controlled by relief of the area (Milne, 1947). Areas with convex slope shed the water but concave areas will collect the water. During the runoff from the convex slope, eroded material from hilly parts are moved downward to the footslope (Lindstrom et al, 1992).

Milne's (1947) model has broad application and encompasses and integrates processes of water movement, erosion, transportation, deposition and pedogenic process (Bayramin, 1998). Each of the processes stated above directly affects soil formation, therefore understanding soil and landscape relationships are essential for spatial information and soil mapping.

In a given location, both soil moisture and temperature affect soil formation and development processes (Ronald, 1985.). The soil moisture regime is related to the average water content of the soil. Horizons with a tension of 1500 kPa or more are considered dry horizons with tension between zero and less than 1500 KPa are considered moist (USDA, 1999).

Given the qualitative models of Milne (1947) and Jenny (1941), differences in soil moisture conditions are described based on topography of the landscape position and these principles can be used for digital soil mapping purposes. The same amount of precipitation in an area with various topographic settings will result in different local moisture conditions, which results in pedogenesis. For instance, if an area annually receives 46 cm of precipitation, soils on side slopes will have less chance of infiltration, thus it will be considered a locally arid soil. On the other hand, soils of depressional areas will receive the same amount of precipitation (46 cm/year) and runoff from the surrounding higher topographies, therefore it will be considered a locally humid soil (Jenny, 1941). Landscape position also affects soil erosion rates. Areas with greater slope compared to depressions have lower water permeability and water-tables but have higher runoff and soil erosion potential.

McSweeney et al (1994), developed soil-landscape model by using field data and spatial analysis. The following are the four correlative stages of this model.

The primary stage is integration of available data sets for understanding physiography and soil patterns of the study area. Available data of geology, climate, vegetation, topography, remote sensed data and other essential data are used for the purpose of integration.

In the second stage, primary and secondary attributes of landscape that come from the DEM are used for determination of geomorphometric characterization of the landscape. The primary attributes (flow direction, slope, aspect and plan and profile curvatures) are directly derived from the DEM, but secondary attributes come from combination of the primary attributes.

The third stage of the model is legend development of the soil horizon which will serve as a representation of the other horizons in the landscape. Field investigation and sampling is necessary for the third stage. In the fourth stage, both laboratory and statistical analysis are run on the collected data to refine the stratigraphy of horizons and their correlation to geomorphometric landscape patterns.

Hudson (1992), stated that the soil-landscape paradigm serves as the base of soil survey. He summarized the paradigm of soil-landscape as follows.

1) All five soil forming factors interact within a like soil-landscape and develop the same soil in that soil-landscape.
2) If two soil-landscapes have more different conterminous areas, there will be an abrupt and striking discontinuity among them. Conversely, discontinuities will not as dramatic between the two soil-landscapes with similar conterminous areas.
3) Similar landscapes will have similar soils, and unlike landscapes will have different soils.
4) There is a spatial relationship that exists between adjacent areas of various soil-landscapes. For instance, on a landscape one area is always located either above or below another.
5) Identification of soil and landscape relationships makes it easy to understand and infer the soils of the area.

Digital Terrain Models (DTMs) are used for the purpose of analyzing and modeling landscape relationships with its various components (Florinsky et al, 2002). DTMs are built based on quantitative data of topography. Moore et al (1993), made conclusions based on the soil development and water movement, which was supported by a strong correlation between soil and terrain attributes.

According to the catena concept of Milne (1947) soil formation and properties vary on different slope positions. Ruhe (1960) modified the hillslope model of Wood (1942), and King (1953). The modified model presents the different elements of hillslope such as summit, shoulder, backslope, footslope, and toeslope (Bayramin, 1998).

Recently, scientists use SoLIM and other knowledge based techniques such as fuzzy logic to develop digital soil maps based on soil and landscape relationships and overcome the aforementioned limitations of traditional soil survey (Menezes et al, 2013). SoLIM is a new approach for representing the soil forming factors equation (Figure 2.1).

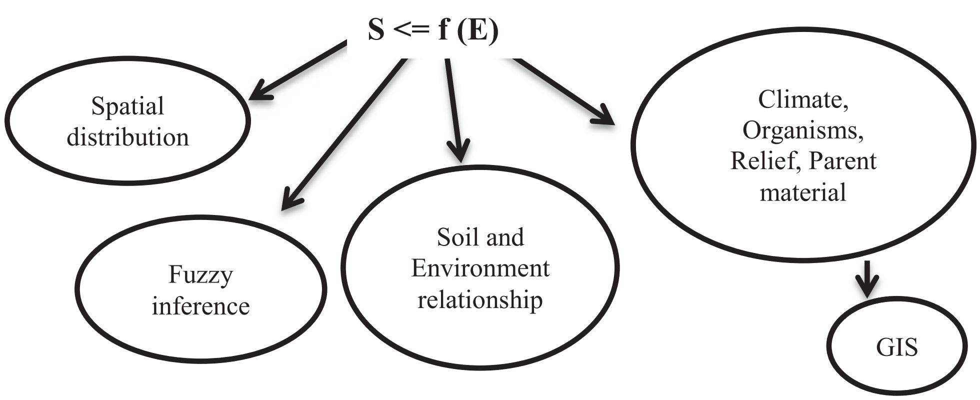

Figure 2.1: Schematic of SoLIM implementation on the soil forming equation (Zhu et al, 1997).

The process of developing a soil map by SoLIM and fuzzy logic has been demonstrated to be more accurate, efficient and cost effective compared to traditional soil survey (Zhu et al, 2007). In addition, soil and landscape relationships are documented and can be updated in future soil surveys. The limitation of SoLIM is that SoLIM is highly dependent on the quality of both Digital Elevation Model (DEM) and Geographic Information System (GIS) used (Zhu et al, 2007).

According to SoLIM, ArcSIE and other stated landscape models, it is possible to predict the soil from the landscape position and environment relationships. However, most of the time landscape models are unsuccessful in predicting the soil because the landscape was studied as two dimensional or studied in less detail. A successful and useful model is the one which represents the actual conditions in the field. Therefore, for better understanding of morphology and ongoing processes of the landscape, the model should represent a three dimensional view of the landscape (Hall and Olson, 1991).

Developing soil maps by utilizing SoLIM requires fuzzy membership values, also known as soil similarity vectors. The membership values ranges from 0 to 1 and are used for assigning the numbers to the soil types of each pixel. Membership with a value of 1 indicates that observation is exactly matched and similar to the class centroid. If the observation does not match, the number will be assigned based on the closeness to the centroid (Ren, 2012).

For the SoLIM model, the bell shaped membership curves are manually generated by the users. However, the Purdue University developed ALIM model, which is used for this research, automatically generates the membership curves by fitting probability density functions.

2.3.1 Mapping with limited data

Countries such as Afghanistan have limited data to create a useful soil map. On the other hand, there is a tremendous need to produce a map now as the country is growing and expanding rapidly. Most of the DSM procedures such as geostatistical based approaches require a tremendous amount of data to create maps at a useful resolution. In lieu of data, knowledge and information can be substituted by local scientists familiar with a particular region. The ideal soils and properties serve as the centroids and probability memberships based on terrain can be utilized for continuous predictions.

This research will utilize a method which is a hybrid of that approach where the sparse data points will be linked to particular geologic and topographic combinations to identify soil property values to set the centroid points. With these types of information, Version 1 continuous soil maps can be created for land assessment and management.

CHAPTER 3. MATERIALS AND METHODS

3.1 Study Area

The study area covers six Northern provinces of Afghanistan which include Faryab, Sari-Pul, Jawzjan, Balkh, Samangan, and Kunduz (Figure 3.1). Afghanistan is located in South Central Asia and lies between latitude of 33^{o} 00' and longitude of 65^{o} 00'. Thes aforementioned provinces are categorized as highly productive agricultural provinces of the country. The area of each province is provided with the available soil point data in Table 3.1.

Figure 3.1: The powder blue color represents the pilot study area which covers 83,581.60 Km^2.

Table 3.1: Approximate area and number of point data of each province.

Province	Area (Km^2)	Number of Point data
Faryab	20,797.6	66
Sari-Pul	16,360	8.0
Jawzjan	10,326	10
Balkh	16,840	46
Samangan	11,218	9.0
Kunduz	8,040	1.0
Total	**83,581.60**	**140**

3.2 Data

As mentioned in Chapter 1, one of the main limitations of this study is the scarcity of available soil point data. The soil point data used for this study was sent from Afghanistan and was not collected based upon a pre-planned sampling procedure which creates biased samples. Most of the samples were collected from one single location located on the low relief area Figure 3.2. The soil samples were analyzed for several soil properties such as organic matter content (OM), pH, electrical conductivity (EC), calcium carbonate ($CaCO_3$), nitrogen (N), phosphorus (P), potassium (K) and soil texture.

Soil texture is important and affects many attributes such as soil water holding capacity, cation exchange capacity (CEC), bulk density (Bd) and structural stability. However, it was observed that there was no large variation among the texture classes in the study area. Sandy loam and sandy clay loam were the two dominant texture classes in the pilot area and had little variability within the data. Therefore, for this study we only focused on OM, pH, EC and $CaCO_3$ since these were the available soil properties provided with the data. Currently we want to use these properties to test the procedure and develop a research methodology for the future works.

The methods used to analyze these properties include the Walkley-Black method was used for OM determination; pH measured by glass electrode method; electrical conductivity was determined by saturated paste extract method; and Carbonate Bomb method was used to measure the $CaCO_3$ level. There was no further information provided regarding the methods for soil analysis.

The location of the point data was determined by Global Positioning System (GPS). Some of the data points had incorrect coordinates, and eight points did not have the associated soil property data. Therefore, those points that had incorrect or missing information were removed and not included in this study. Other data types such as; DEM, soil maps, and environmental covariates were also used which will be discussed in the following sections.

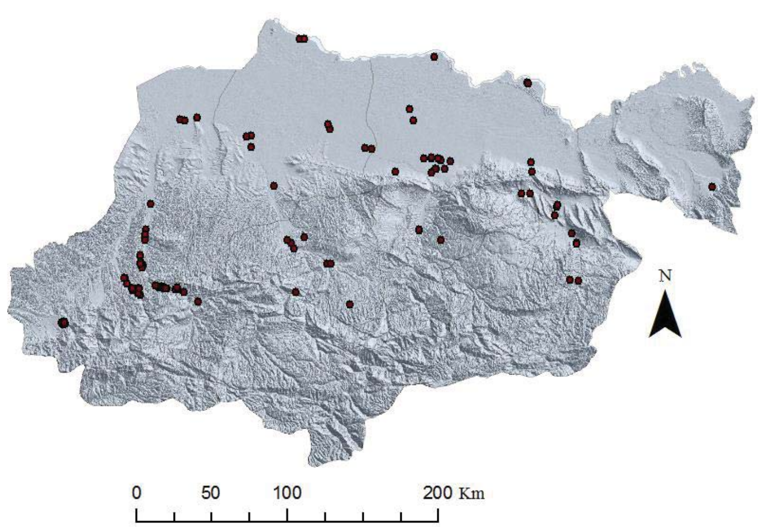

Figure 3.2: Location of the collected samples for the study area

3.3 Digital Elevation Model

Understanding soil forming factors is the first step in identifying the soil type in a given location. In order to understand the topography of the study area, a 90 meter resolution DEM was downloaded from United States Geologic Survey (USGS) web page. The 90 meter Shuttle Radar Topography Mission (SRTM) – DEM was obtained from the National Aeronautics and Space Administration (NASA) Jet Propulsion Laboratory. Downloaded DEM was used in QGIS, ArcMap, SAGA GIS and GRASS GIS for generation of different terrain attributes.

3.4 Geology Map

For this study, the USGS developed geology map of Afghanistan was used as a surrogate for parent material. This digital geologic and mineral resource map presents information about minerals, oil, gas, coal, water and earthquake hazard, was developed by a joint collaboration between USGS and the Afghanistan Geodesy and Cartography Head Office. This map was compiled by Wahl and Doebrich (2006) and provides full coverage of the country.

All 32 series of this map are available for download from http://pubs.usgs.gov/of/2005 website (Doebrich and Jeff, 2006). More than 100 geologic classes were presented in the geologic map of the country, but only six of them are located in the study area (Table 3.2).

Table 3.2: Six main geologic classes of the study area.

Value	Name of the geologic unit
1	Brown clay, siltstone, sandstone, conglomerate, limestone
2	Clay, shale, siltstone, sandstone, limestone, marl, gypsum, conglomerate (North Afghanistan - Katavaz Basin); sandstone, siltstone, conglomerate and gravelstone, acid and mafic volcanic rocks (Gerirud Basin)
3	Limestone, marl
4	Red clay, siltstone, sandstone, conglomerate, limestone
5	Sandstone, siltstone, clay, conglomerate, coal (North Afghanistan); Limestone, marl, sandstone, shale, siltstone (Middle Afghanistan); sandstone, shale, siltstone, acid volcanic rocks (Kishmaran Tectonic Zone)
6	Shingly and detrital sediments, gravel, sand, clay, clay sand, loam, loess, travertine

3.5 Ecoregions

An ecoregion or a bioregion is a geographical area which presents information about flora and fauna of that area that is largely related to temperature and moisture. Ecoregion maps shows climate and vegetation relationships which is helpful for obtaining information about the climate and organisms represent by the 5 state factor model which also relates to land-use dynamics and soil formation (Gallant et al, 2004).

The USGS developed ecoregion map of Afghanistan was used for the interpretation of climate, organisms and vegetation of the study area. The ecoregion of the study area was not extremely diverse, therefore for this study, the climate and organism factors of soil formation were considered constant to simplify the method for soil mapping.

3.6 ALIM

The ALIM model, developed at Purdue University, develops maps of soil properties by integration of the fuzzy logic inference map and automatic classification of landforms. For the process of the ALIM model, soil knowledge is necessary. In order to define the membership rules for the fuzzy model process, ALIM combines developed terrain attributes of DEM such as slope, aspect and TWI with classified landforms (Ashtekar, 2014).

ALIM is primarily based on the principle of water distribution and topography acting on a particular geology on the landscape and assumes:

1) Soil difference is caused by the topography of the landscape, because topography affects water movement and distribution over geologic time.
2) ‘Topographic landforms can act as functional soil classes’ (Ashtekar, 2014).

The following are the steps that were used for developing predictive soil properties map of our study area:

1) Classifying landforms by automated algorithms, for this purpose Geomorphon was used (model will be described later in the chapter)
2) Developing soil class maps from geology and Geomorphon combinations
3) Extracting each of the terrain attributes and soil properties values to the soil classes
4) Calculating and determining the membership functions by ALIM model
5) ‘Developing continuous prediction of soil properties’ (Ashtekar, 2014).

3.7 Environmental Covariates

Environmental covariates, also known as predictor variables, are necessary attributes for predicting soil properties in the area of interest. A strong correlation exists among terrain attributes and soil properties (Behrens et al, 2005).

For this study, both primary and secondary attributes were developed. Primary attributes are directly calculated from the DEM and includes slope, aspect, catchment area and plan and profile curvature, these attributes have been successfully used for numerous studies to predict soil properties (McBratney et al, 2003). Secondary attributes, also known as compound attributes, are derived from the combination of two or more primary attributes and characterized landscape processes (Wilson and Gallant, 2000). In this research, the focus centered on those terrain attributes which have close relationship with water distribution.

3.7.1 Aspect

Aspect is defined as the mean orientation of neighborhood around a given pixel (Behrens et al, 2010). Aspect expresses the soil formation and development in north and south facing slopes within a landscape. Lower organic matter content and microbial activity was observed in north-facing slopes in Italy (Sidari et al, 2008). Weathering and soil formation rate is higher in south-facing compared to north-facing slope (Rech et al, 2001).

In a previous study conducted in a Mediterranean region, south-facing slopes had higher $CaCO_3$, pH and available P but north-facing had higher amounts of organic matter, Na, K and chlorine (Cl), and available N (Kutiel, 1992). An aspect map of the study area

(Figure 3.3) was developed in Grass GIS. The lower and higher values of aspect map indicate the degree of steepness of facing slope.

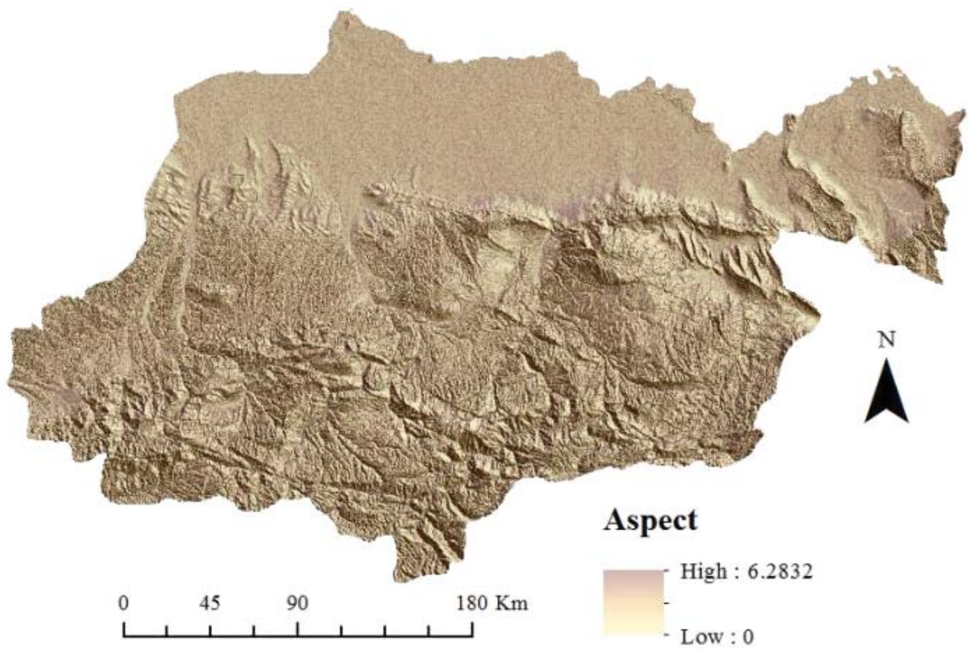

Figure 3.3: Aspect map of the study area.

3.7.2 Topographic Wetness Index (TWI)

The terrain attribute, TWI, also termed Compound Topographic Index (CTI), is one of the most important terrain attributes used for determination of water and sediment movement direction in a given landscape. TWI is defined by the following formula.

$$TWI = \ln (Aq/\tan \beta). \qquad (1)$$

'Where Aq is the upslope contributing area expressed as m^2 per unit width and β is the slope angle' (McKenzie and Ryan, 1999). Drainage depressions areas are represented with a higher value of TWI, whereas steep slope areas (hills, ridges, crests and plateaus) are represented by a lower value of TWI (Yang et al, 2005).

Both slope and wetness index are strongly correlated to the land surface, and accounts for about one-half of the variability of surface horizon thickness, pH, extractable P, OM content, and silt and sand (Dobos et al, 2000).

TWI was developed (Figure 3.4) by utilizing the System for Automated Geoscientific Analysis (SAGA) wetness index commends inside the QGIS-Chugiak 2.4.0, previously known as Quantum GIS. QGIS contains both GRASS GIS and SAGA commands and can run several terrain attributes at the same time on a large DEM. The slope map (Figure 3.5) was developed based on radians inside SAGA-GIS.

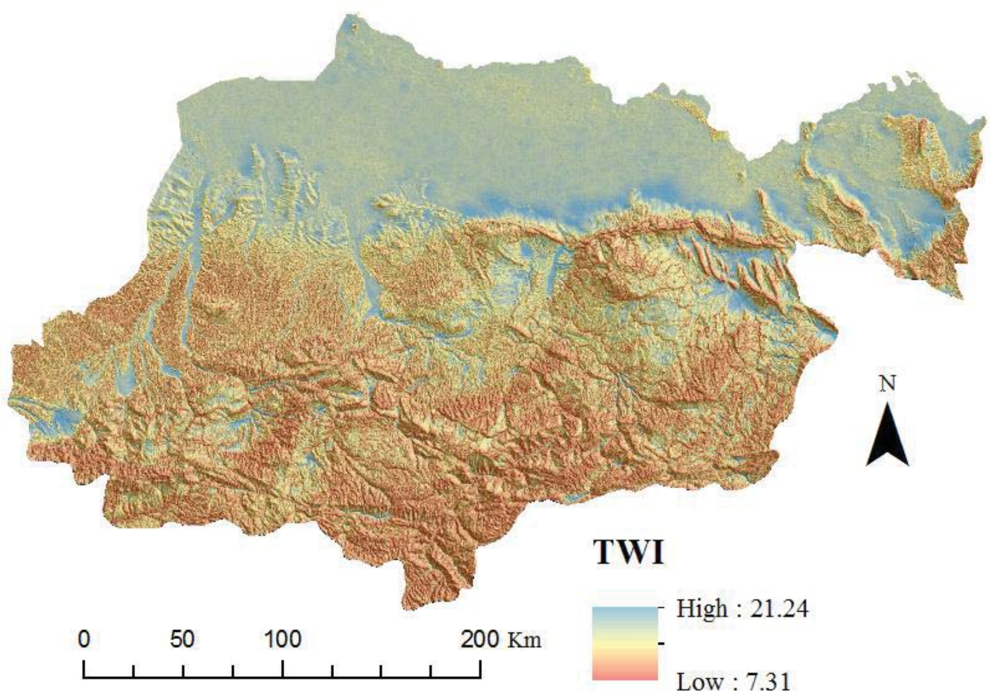

Figure 3.4: TWI wetness map of the study area

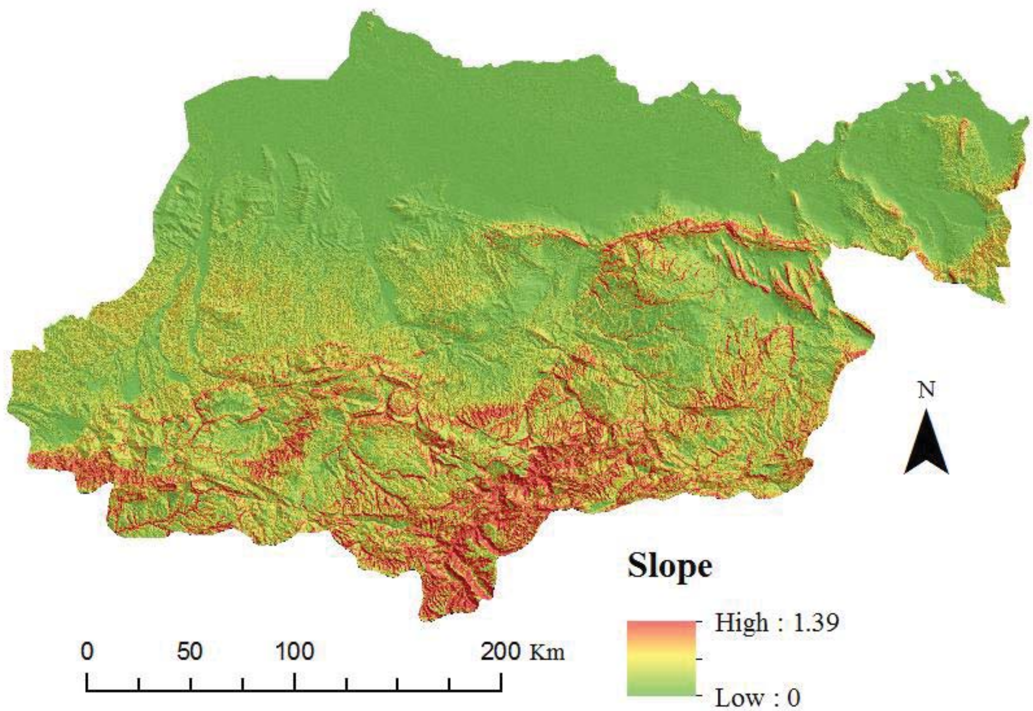

Figure 3.5: SAGA GIS developed slope map of the study area in radians.

3.8 Geomorphon

Geomorphon is a new approach for landform analysis. For the first time, Stepinski and Jasiewicz (2011), developed the Geomorphon for the purpose of landform classification and mapping based on the landform pattern recognition. This method classifies 498 unique land patterns by using local ternary pattern which were made of a 3x3 window. Values of 1, 0, and -1 were assigned to each of the eight neighborhood cells, to determine the elevation of each to their central cell (Figure 3.6). Cells having higher elevations were indicated by 1, and the same elevations cells were indicated by 0, and cells with lower elevations assigned -1.

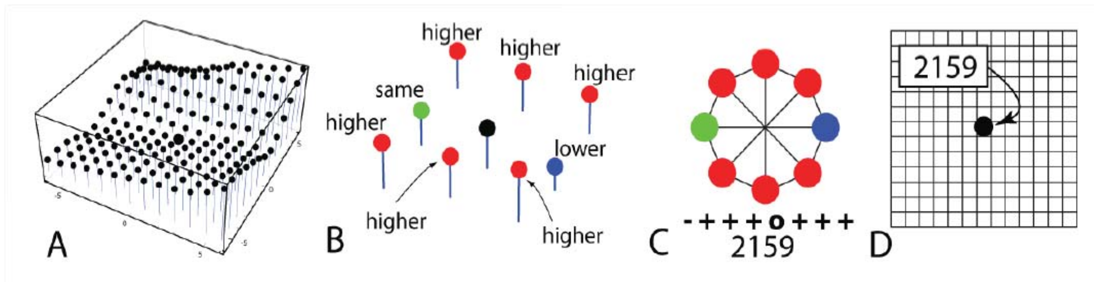

Figure 3.6: Local Ternary Pattern (LTP) concept for classification of landfrom elements. (A): DEM around the cell. (B) Relative elevation of the neighborhood cells to the cell of interest. (C) Three forms of LTP. (D) Assigned LTP to a cell of a raster (Jasiewicz and Stepinski, 2013).

Geomorphon classes were reduced to the following 10 most common and frequent landforms (Figure 3.7), which are used for mapping landscapes. Geomorphon is not based on neighborhood cell but it is based on look up distance. A look up distance detects the elevation changes by looking 8 directions within the set up radius.

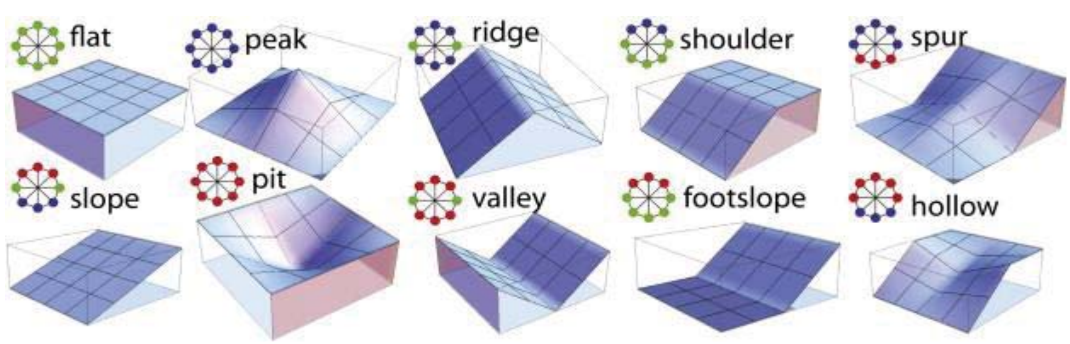

Figure 3.7: 3D form of the ten landform components (Jasiewicz and Stepinski, 2013).

In order to run the Geomorphon, the original DEM was converted to ascii files inside the ArcGIS and then exported to GRASS GIS. In GRASS GIS, before running Geomorphon, the fill and depression command was run on the DEM to produce continuous flow and eliminate the lowest points in a depression.

In order to determine the greatest landscape changes, a lookup radius of 10, 20, 30, 40, 50, 60, 70, and 80 cells were run for Geomorphon. According to the Stepinski and Jasiewicz (2011), larger lookup distances capture more landforms. Within our evaluation comparing multiple lookup distance, a lookup distance of 80 cells were selected for the Geomorphon of the study area (Figure 3.8).

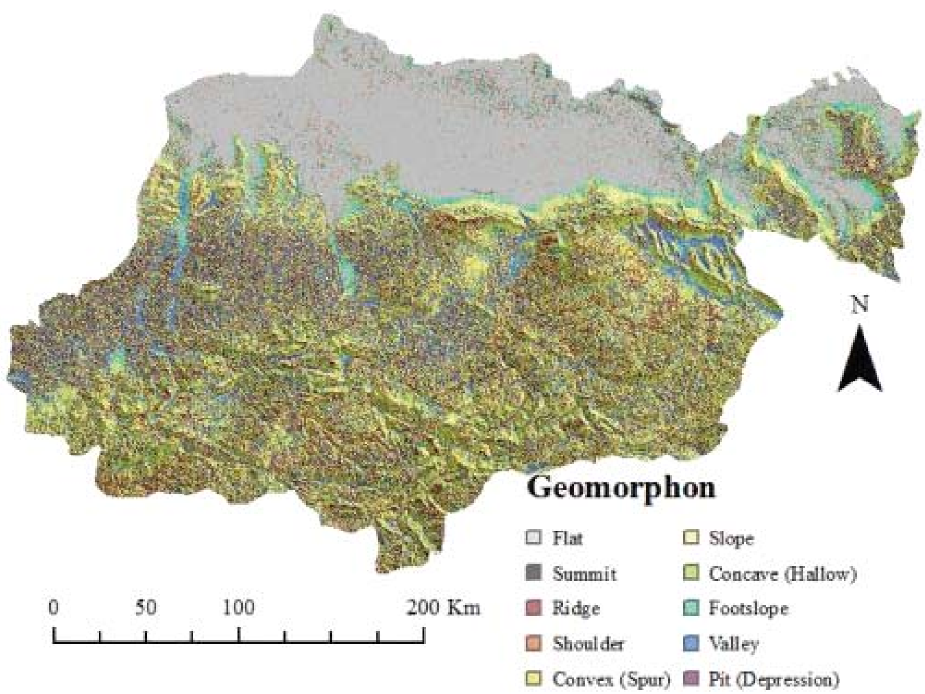

Figure 3.8: Geomorphon map of the study area.

Geomorphon was reclassified (Table 3.3) in GRASS GIS to prevent form duplicates during the combination with geology

Table 3.3: Landform of the reclassified Geomorphon.

Original Geomorphon	Landform	Reclassified Geomorphon	Grid cells
1	Flat	**11**	221,016
2	Summit (peak)	**23**	346,104
3	Ridge	**35**	135,644
4	Shoulder	**47**	141,588
5	Spur (convex)	**59**	140,576
6	Slope	**61**	209,111
7	Hollow (concave)	**73**	121,184
8	Footslope	**85**	332,711
9	Valley	**97**	142,647
10	Depression (pit)	**109**	357,218

3.9 Soil Class Map

Since ecoregion of the study area was not diverse, we assumed that all soil forming factors were constant except geology and topography. A soil class map was developed based on geology and Geomorphon combinations. Raster calculator in ArcMap was used to combine the six geology classes and ten Geomorphon landforms. This combination resulted in 21 soil classes in the study area (Table 3.4).

Table 3.4: Soil classes from the geology and Geomorphon combinations.

Soil Class	Geomorphon landforms	Geology class
1	Ridge	Brown clay, siltstone, sandstone, conglomerate, limestone
2	Flat	Shingly and detrital sediments, gravel, sand, clay, clay sand, loam, loess, travertine
3	Hollow (concave)	Brown clay, siltstone, sandstone, conglomerate, limestone
4	Hollow (concave)	Clay, shale, siltstone, sandstone, limestone, marl, gypsum, conglomerate (North Afghanistan - Katavaz Basin); sandstone, siltstone, conglomerate and gravelstone, acid and mafic volcanic rocks (Gerirud Basin)
5	Valley	Brown clay, siltstone, sandstone, conglomerate, limestone
6	Summit (peak)	Red clay, siltstone, sandstone, conglomerate, limestone
7	Depression (pit)	Brown clay, siltstone, sandstone, conglomerate, limestone
8	Spur (convex)	Limestone, marl
9	Slope	Limestone, marl
10	Shoulder	Shingly and detrital sediments, gravel, sand, clay, clay sand, loam, loess, travertine
11	Slope	Red clay, siltstone, sandstone, conglomerate, limestone

Table 3.4 Continued

12	Valley	Limestone, marl
13	Depression (pit)	Limestone, marl
14	Spur (convex)	Shingly and detrital sediments, gravel, sand, clay, clay sand, loam, loess, travertine
15	Slope	Shingly and detrital sediments, gravel, sand, clay, clay sand, loam, loess, travertine
16	Hollow (concave)	Sandstone, siltstone, clay, conglomerate, coal (North Afghanistan); Limestone, marl, sandstone, shale, siltstone (Middle Afghanistan); sandstone, shale, siltstone, acid volcanic rocks (Kishmaran Tectonic Zone)
17	Hollow (concave)	Shingly and detrital sediments, gravel, sand, clay, clay sand, loam, loess, travertine
18	Valley	Red clay, siltstone, sandstone, conglomerate, limestone
19	Footslope	Shingly and detrital sediments, gravel, sand, clay, clay sand, loam, loess, travertine
20	Valley	Shingly and detrital sediments, gravel, sand, clay, clay sand, loam, loess, travertine
21	Depression (pit)	Shingly and detrital sediments, gravel, sand, clay, clay sand, loam, loess, travertine

3.9.1 Fuzzy membership curves

Membership curves were developed to define the similarity vectors which were required for fuzzy soil property predictions. Traditionally, the soil scientists define the membership curves based on their expert knowledge regarding soil and landscape relationships, and using the available soil information and maps. However for this study, the Purdue developed model ALIM was used to define the membership curves. The Y-axis of a membership curves shows the membership values (ranges from 0 to 1), and the X-axis shows the range of terrain attributes values.

In a standard method, the bell shape curves which are used to determine the membership curves, shows that terrain attributes are normally distributed within each soil class. However, properties usually do not follow the normal distribution; therefore, the ALIM model was used to generate several probability density functions for each of the terrain attributes within a soil class. The built-in function of Matlab was used to generate these probability density functions. For this study, exponential, weibull, normal and lognormal distributions were generated.

In order to determine the best final fitted distribution membership function, the Pearson's linear correlation test among the fitted distributions.

$$r = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})}\sqrt{\sum_{i=1}^{n}(y_i - \bar{y})}} \qquad (2)$$

Where, $x_{i,}\, y_i$ are the values of paired observation, $\bar{x}, \bar{y}$ are the mean of observations and n is the sum of paired observations (Ashtekar, 2014). The probability density function was rescaled for the chosen fitted distribution from 0 to 1, and used as the membership function.

3.9.2 Fuzzy maps and soil property predictions

After developing membership curves in each class, the membership values of each of the terrain attributes were determined for each grid cell. It means that each grid cell will have a set of membership values which resulted from the combinations of 3 terrain attributes and 21 classes. The overall membership of each class from 3 terrain attributes was then determined based on Liebig's law of minimum, which expresses that limited resource affect the crop yield. In case of this study, the lowest resource negatively affects soil development. Therefore, among the 3 terrain attributes, the lowest membership was used for overall membership of the soil class. After setting the overall membership, individual grid cell has a set of membership values in which one belongs to each individual class (Ashtekar, 2014)

Continuous soil properties can be predicted from the developed fuzzy class maps. In fuzzy logic, assigning the property value to a grid cell, represents its' membership in all classes. The result is that, the grid cells which relate to the same class have different property values (Ashtekar, 2014). Equation 3 was used to calculate and derive the soil property values.

$$D_{ij} = \frac{\sum_{k=1}^{n} S_{ij}^{k} * D^{k}}{\sum_{k=1}^{n} S_{ij}^{k}} \qquad (3)$$

In equation 3, D_{ij} is the value of property at site (i, j), n is the sum of all classes, S_{ij}^{k} is the similarity value of soil at site (i, j) and soil class k and D^{k} shows the soil property of soil class k (Zhu, 1997).

In this method, only one representative sample is required for property prediction. Therefore, the average property value of several samples related to the same class was taken.

3.10 Validation

Accuracy test was conducted for organic matter content (OM), pH, $CaCO_3$ and EC. The accuracy test for these properties was based on Mean Absolute Prediction Error (MAPE), Root Mean Square Prediction Error (RMSPE) and Normalized standard deviation of Root Mean Square Prediction Error (RMSPEr). Prediction is considered satisfactory accurate when RMSPEr is close to 0.4 or 40%. Values more than 0.7 or 70% shows unsatisfactory prediction (Hengl et al, 2004).

$$MAPE = \frac{1}{t}.\sum_{j=1}^{1} |\{\hat{z}(Sj) - z^{*}\ (Sj)\}| \qquad (4)$$

$$RMSPE = \sqrt{\frac{1}{t}.\sum_{j=1}^{1}[\ \hat{z}(Sj) - z^{*}(Sj)]^{2}} \qquad (5)$$

$$RMSPEr = \frac{RMSPE}{s_z} \qquad (6)$$

In the above equations, t is the sum of all validation points, $\hat{z}$(Sj) is the predicted value of the model, z* (Sj) is the observed value and sz is the standard deviation of observed values.

CHAPTER 4. RESULTS AND DISCUSSION

4.1 Soil Property Mapping

The soil property maps of the study area were developed based on Fuzzy Logic, a knowledge based inference approach and Purdue developed ALIM model. To predict soil properties by fuzzy logic, development of soil classes and defining the membership values are required.

Soil fuzzy classes for the study area were derived from geology and Geomorphon combination. Gemorophon was used to classify the landforms that related to pedogenic processes. The outcome of Geomorphon classifications are presented in Figure 3.8. According to the number of grid cells of Table 3.3, flat was the most dominant and shoulder was the least dominant landforms in the study area.

Geology is an important factor of soil formation because it contains the physical soil properties based on its unique relationship to soil textures and many other physical and chemical properties. The USGS developed a digital geologic and mineral resource map of Afghanistan that was used as a surrogate of parent material. Six different geology classes presented in Table 3.2 were located in the research area. The combination of geology classes and Geomorphon derived landforms resulted in 21 different soil classes which are presented at Table 3.4.

The Purdue developed model (ALIM), was then used to define the membership or soil similarity value of terrain attributes within a soil class. The ALIM model generates several probability density functions for terrain attributes. The built-in function of the Matlab was used to generate the fitted distribution curves. The best fitted density function is then determined by the highest value of Pearson's linear correlation coefficient and used as the final membership curve. Once the membership values were determined by ALIM, then the soil properties maps were predicted by Zhu (1997), equation as stated in the "Fuzzy maps and soil property predictions" section of chapter 3.

Generally, the soil properties followed the landforms but in some cases, this did not occur. For example, according to the Figure 4.1 organic matter content was higher in soil class 15 which had a slope landform and it was lower in soil class 19 which had a footslope landform.

Several contributing factors such as limited point data, accurate point locations, sample biases and low 90 m resolution DEM might be the reasons for this variation. The research area was extremely large area for the 140 data points which were used for developing the property maps. Since the data points were not collected on a preplanning procedure, sample biases and inaccuracy of the points locations can be expected. On the other hand, a 90 m low resolution DEM cannot accurately represent and relate to the smaller area represented by the point data.

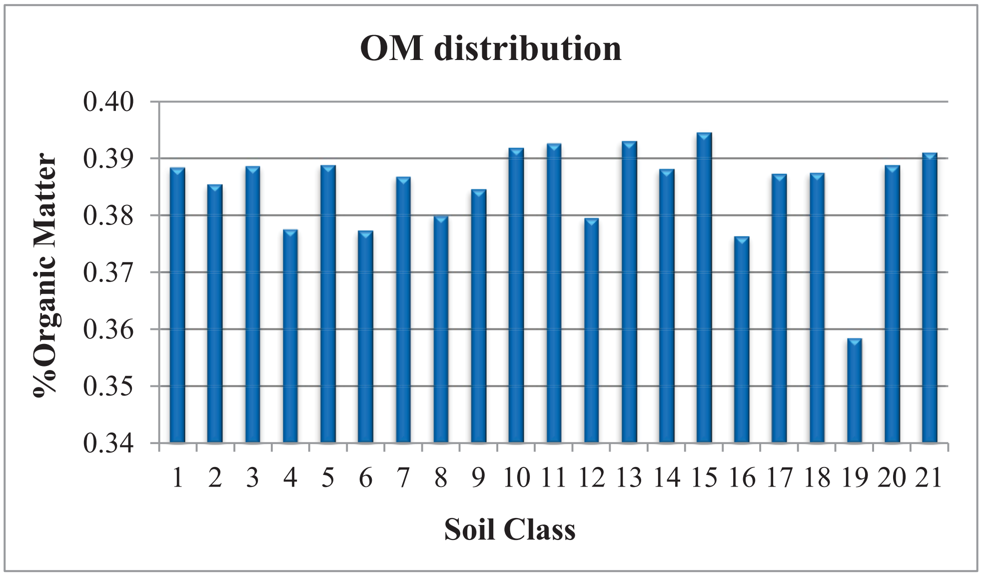

Figure 4.1: Organic matter distribution within each soil class.

Figure 4.2 through 4.5 shows the predicted soil properties maps for the ALIM model.

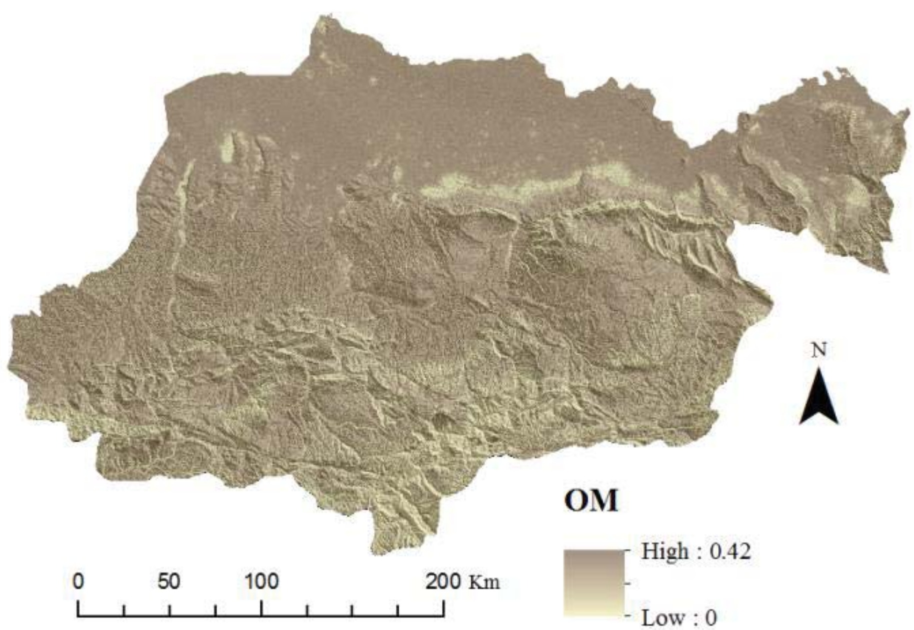

Figure 4.2: Predicted organic matter map of the research area.

According to Figure 4.2, overall organic matter content followed the landform and is higher in the depression area compare to the highlands.

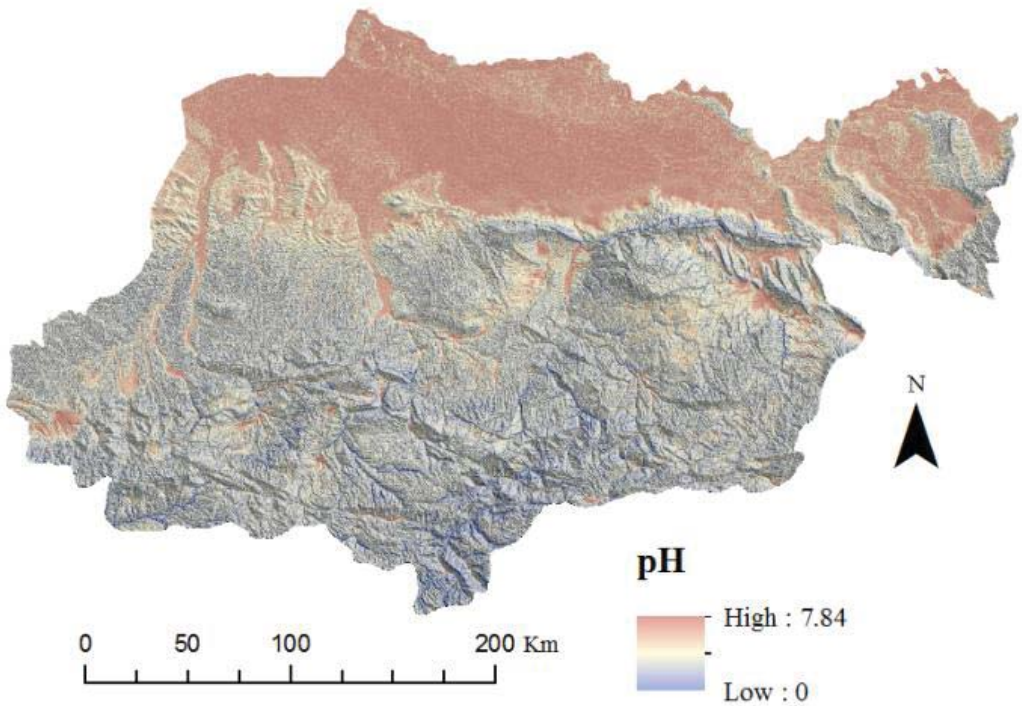

Figure 4.3: The ALIM model developed pH map for the study area

The predicted value of pH followed the terrain patterns in which the higher values are in the lowland were predicted and lower pH was predicted in the upland area (Figure 4.3). The pH values are supported by the calcium carbonate developed map (Figure 4.4).

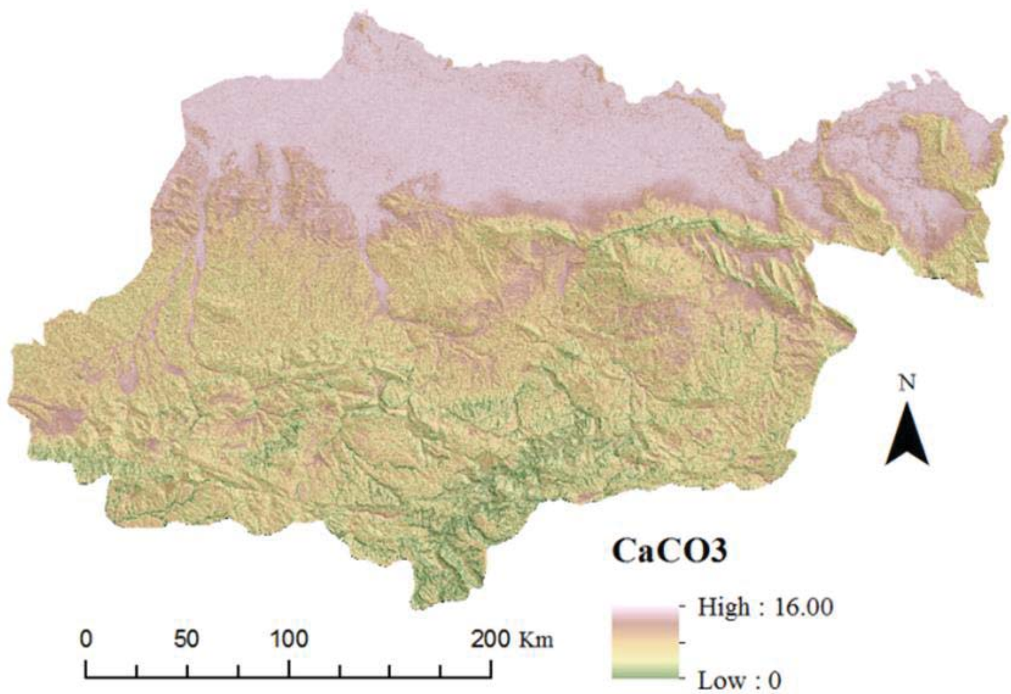

Figure 4.4: The calcium carbonate ($CaCO_3$) developed map for the ALIM model

Since limestone was the dominant parent material of the study area, the higher calcium carbonate content and higher pH values were observed in the data and predicted by ALIM. Additionally, the climate is arid and semi-arid which would limit the leaching of the carbonates and lead to the calcareous soils. According to Figure 4.4, the calcium carbonate percentage was highest in the lowland and flat areas when compared to the steep sloping area.

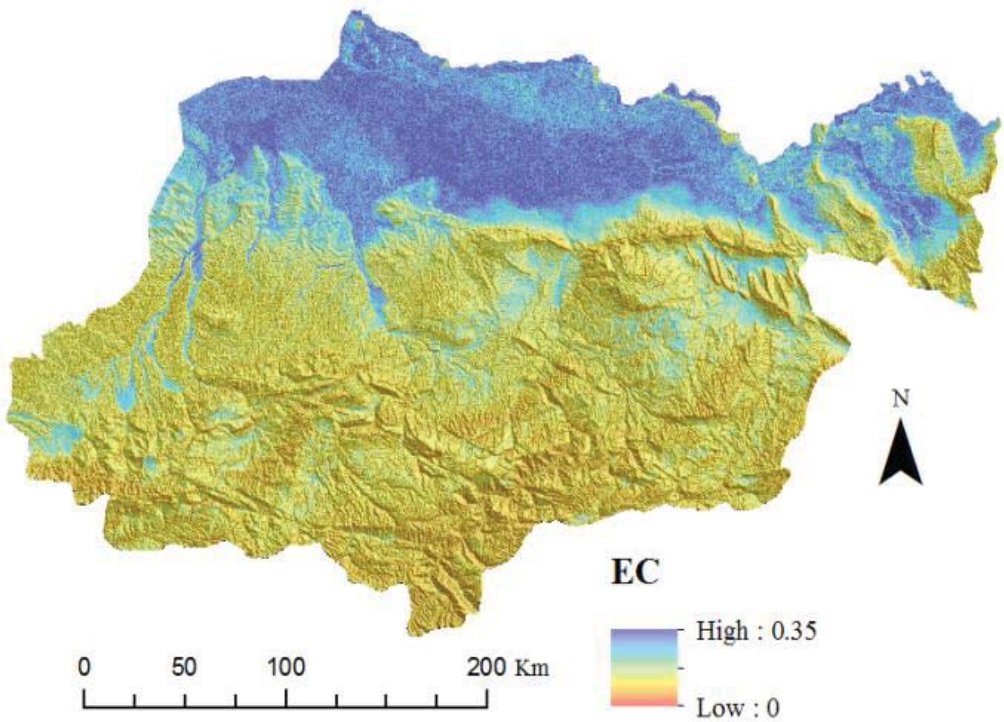

Figure 4.5: The electrical conductivity (EC) predicted map for the study area.

According to Figure 4.5, EC also followed the land pattern. The EC predictions were higher in the lowland areas compare to the steep sloping areas. This trend is similar to the carbonate prediction which would be expected.

4.2 Combination of all Properties within the Study Area

The following table presents information about the mean, standard deviation and the range value of each soil property for all 21 soil classes.

Table 4.1: Mean, standard deviation, and range value of all four predicated soil properties.

	Mean	**Standard deviation**	**Range**	
			Low	High
%OM	0.39	0.01	0.36	0.39
pH	7.7	0.06	7.57	7.8
%$CaCO_3$	15.21	0.49	13.97	15.8
EC (mS/cm)	0.28	0.03	0.21	0.34

In table 4.1, the ranged values of organic matter and $CaCO_3$ are based on percentage and EC is based on mS/cm.

From Table 4.1, the data suggests that the organic matter content of the research area is low (0.36 – 0.39 %). Several factors can explain this low organic matter percentage. The dry and warm climatic conditions, the rate of organic matter decomposition is higher than accumulation. Additionally, as reported by most researchers Afghan farmers are use poor farming practices, which cause organic matter depletion, which may be influenced by the fact that the point data was biased and sampled on farms.

According to the geologic setting of the area of interest, limestone covers most of the area and serves as the dominant parent material in the research area. Therefore high $CaCO_3$ and pH values were observed in the data and predicted in the digital soil map Figure 4.4 and 4.3 for all areas within the study area. However, $CaCO_3$ was highest in the lowland and flat areas compare to the steep sloping areas.

We expected higher EC value in the study area. However, most of the sampled areas were located close to streams and rivers; therefore, the accumulated salts were likely washed out during the rainy seasons and moved into the adjacent rivers. These areas on the floodplains are likely the lowest EC values within the study area.

4.3 Validation

Validation of the predicted soil properties was assessed by Mean Absloute Prediction Error (MAPE), Root Mean Square Prediction Error (RMSPE) and Normalized Root Mean Square Prediction Error (RMSPEr). According to Hengl et al (2004), soil property prediction is significant if RMSPEr is between 0.4 – 0.7. Values greater than 0.7, are considered insignificant predictions and reflects that the model is not sufficient. The results of soil properties validation for the soil classes are presented in Table 4.2.

Table 4.2: Results of soil properties validation for all soil classes.

	OM	pH	$CaCO_3$	EC
MAPE	0.14	0.39	1.90	0.11
RMSPE	0.20	0.72	2.64	0.15
RMSPEr	0.99	0.98	0.96	0.91

According to the values of Normalized Root Mean Square Prediction Error (RMSPEr) which were greater than 0.7 for all soil properties, it can be concluded that the prediction of ALIM model was insignificant. Few data points, sample bias, low soil property values, inaccurate point locations, low DEM resolution and derived terrain attribute Geomorphon could be the reasons for insignificant prediction.

For developing the soil property maps of the study area, we used 140 point data which is a small number and it was not collected and analyzed based on the pre-planned sampling procedure, so sample biases can be expected. We observed that some of the pedons had missing and incorrect coordinate locations. In order to get the accurate and accepted values of RMSPEr, the variability range of the soil property were sufficient; however the variability ranges of the predicted soil properties were very low. Additionally, we assume that the low resolution DEM which we used for our study may cause inaccurate predictions. This 90 m DEM is an average elevation and the points represent a smaller area, therefore the relationship may not be detected or realistic.

Derived terrain attributes and developed Geomorphon are the other reason of inaccuracy of the model. They are not developed for soil mapping purposes, but in this case they are serving as surrogates of water redistribution. Since Milne (1934) observed that the catena was related to the topography and soils varied among the catena, a greater DEM resolution is needed to capture the catena process. The 90 m DEM likely did not have the resolution necessary for this fine resolution difference.

CHAPTER 5. CONCLUSIONS

Understanding spatial variability of soil properties is needed for sustainable agriculture and land management planning. Soil mapping is crucial for identifying the spatial variability of soil properties. However, traditional soil mapping which is based on morphological differences is expensive and time consuming and also contains errors. Additionally, traditional soil mapping is based on discontinuous polygon and does not represent continuous soil variability of the landscape. The polygon developed maps of the traditional method are less useful, because they are mapping morphologic and taxonomic differences; whereas, people need soil properties maps for functional homogeneity for land-use decisions.

As opposed to traditional soil mapping, digital soil mapping (DSM) techniques are cost and time effective and display continuous soil variability across the landscape. However, most of the digital soil mapping techniques for developing accurate maps requires many soil samples which are difficult to be collected in developing countries because of political limits, war and money. As mentioned in chapter 2, countries like Afghanistan have limited data and it is difficult to develop useful soil maps. This research attempted to use pedological principles combined with new technology to develop a map detailed enough for management decisions.

In order to develop a first generation digital soil map for Afghanistan with limited data points, we used fuzzy logic, knowledge based approach and the Purdue University developed ALIM model. Predicted soil property maps in this method were generated by a hybrid approach, where soil point data was linked to particular geology and Geomorphon combinations.

Developing DSM by fuzzy logic requires membership curves or soil similarity vectors, which has been manually generated by users as a bell shaped curves. However, ALIM automatically generate these membership curves by fitting probability density functions to the terrain attributes within a soil class. Visually, the ALIM developed soil maps of the study area displays that all four soil properties (OM, pH, $CaCO_3$ and EC) are following the topography of the landscape.

The higher value of Normalized Root Mean Square Prediction Error (RMSPEr) shows that overall; the prediction of fuzzy logic and ALIM model was insignificant for all four soil properties. It does not mean that using this method is not recommended. The following factors were expected to be the reasons of insignificant predictions.

1) As mentioned in chapter 3, point data which was not collected based upon a pre-planned sampling procedure, therefore sample bias was expected. The soil property values of the study area were analyzed and were lower than the actual values found in the area, for example, most of the research showed that the pH of Afghan soil on the average base is 8.4 (Masunaga et al, 2014). Though, the used point data for this research had a pH value lower than 8.4. In addition, to the low analyzed values, some of the pedons had missing property values.

2) Some of the pedons had missing and inaccurate GPS locations. Even though we did not include the missing coordinates and tried to correct the inaccuracy in GPS, there are still some errors.
3) The 90 m low resolution DEM represents average elevation and cannot capture the small area represented by the point data. Therefore, the relationship may not be realistic or captured in the model.
4) The terrain attributes which were derived from the low resolution DEM, were not developed for soil mapping purposes, but it have been used successfully in other studies (Ashtekar et al, 2014).
5) Geomorphon used for this study was also not developed for the purpose of soil landform classification. Since there is no automated soil landform classification method, we used Geomorphon. Prediction of ALIM might be improved if soil specific terrain attributes and landform classifications were developed.

The research of this study does not mean the ALIM model for soil mapping is not useful. More extensive research is required to be conducted on the highly variable soils to test the ability of the ALIM model for predicting soil properties. Higher resolution DEM, unbiased data and targeted samples could improve the model. Additionally, locations can be highlighted where more data is needed to improve the soil map for later versions. In lieu of data, tacit knowledge from experts could be used to determine soil class centroid values.

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