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Assessment of land degradation processes in the northwestern Ethiopian Highlands

Doctoral Thesis

To obtain the academic degree of Dr. nat. techn.

At the University of Natural Resources and Life Sciences, Vienna

Submitted by:

Hailu Kendie Addis

Vienna, October 2016

Declaration

I, hereby declare to the University of Natural Resources and Applied Life Sciences, Vienna that this is my original thesis work and all sources of materials used are duly acknowledged. This work has not been submitted to any other educational institutions for achieving any academic degree awards.

Name: Hailu Kendie Addis

Signature:____________________

Place and time: Vienna, October 2016

Acknowledgement

This study is the result of the cumulative efforts of a team of researchers; hence, I would like to thank all the scientists that contributed to the success of this thesis. First and foremost, I express my appreciation for the guidance and patience provided by my supervisor Ao. Univ. Prof. Dipl.-Ing. Dr. nat. techn. Andreas Klik. He is a model advisor and taught me many things. Without his help and support, this thesis could never have been completed. I like to thank my committee member, Dr. Stefan Strohmeier, for his guidance during the development of the research and for his valuable comments on earlier draft of the document as well as for providing so much support for completing the thesis work.

I would like to express my appreciation to graduate students at BOKU University of Natural Resources and Life Sciences, Vienna, who participated in the fieldwork of the cooperative project ***"Unlocking the potential of rainfed agriculture in Ethiopia for improved rural livelihoods"*** coordinated by the International Center of Agriculture Research in the Dry Areas (ICARDA), BOKU University of Natural Resources and Life Sciences, Vienna and Amhara Regional Agricultural Research Institute (ARARI), and financed by Austrian Development Agency (ADA) as well as the Consultative Group for International Agricultural Research (CGIAR) Water Land and Ecosystems (WLE) project. I am also grateful to the local community and development agents for their support during the fieldwork.

I would also like to recognize the contribution by the staff of Gondar Agricultural Research Center, Soil and Water Management Research Directorate and Gondar Soil Laboratory Office for their technical and logistical support. That includes: Muuz G/Tsadik, Baye Ayalew, Anteneh Abewa, Tadess Demesie, Nigus Demelash, Dr. Abereham Abeyu, Atikilt Abera, and Dr. Menale Wondie. Since this cumulative thesis consists of three peer-reviewed publications, I thankfully acknowledge the anonymous reviewers for taking the time and effort necessary to provide such insightful guidance and very important comments.

Hailu Kendie Addis: Watershed based land degradation modeling and soil property assessment

Abstract

Soil erosion in the northwestern Amhara region, Ethiopia has been a subject of anxiety, resulting in a major environmental threat to the sustainability and productive capacity of agricultural areas. In the present thesis, selected soil properties, hydrological and sediment dynamics were assessed for a watershed, while predicting the spatial distribution of soil properties was also done. The 53.7 km^2 Gumara-Maksegnit watershed was divided into a 500 m by 500 m grid to sample bulk density (ρd), pH, soil organic carbon (SOC), total nitrogen (TN), available phosphorus (AP) and texture of topsoil (roughly 10 to 25 cm depth). Such properties were investigated with respect to the two main land-uses (forest and agriculture) and three different slope steepness classes, 0–10 (%), 10–30 (%), >30 (%). The result indicated higher SOC, TN, silt and sand content in forest soils compared to agricultural soils, while ρd is lower in the forest soil. Overall an increase of SOC, TN, silt and sand content from gentle to steep slopes have been observed for both land-uses. In contrast, clay content and ρd seem to increase from steep to gentle slopes on agricultural areas, which might be due to accumulation of particularly fine soil particles eroded from the steep areas.

In the second part, the performance of ordinary kriging (OK), inverse distance weighting (IDW) and radial basis functions (RBF) for predicting the spatial distribution of soil texture, pH, soil organic carbon (SOC) and available phosphorus (AP) were done. The performance of each interpolation method was assessed quantitatively in terms of Nash-Sutcliffe efficiency (E), coefficient of determination (R^2) and index of agreement (d). The interpolated maps generated based on the highest value of E displayed OK was best performed for SOC and sand. RBF was most suitable for mapping of AP and clay, while IDW gave better result when applied to pH. Overall, the cross-validation statistics for each interpolation method showed there was no single method that significantly outperformed the others. Therefore, one of the interpolation methods could be applied for surfaces map generation in future studies of similar regions.

In the third part, the Soil and Water Assessment Tool (SWAT) model was used to model hydrology and sediment dynamics of the watershed. Spatially distributed stone bund impacts were applied in the model through modification of the surface runoff ratio and adjustment of a support practice factor simulating the trapped amounts of water and sediment at the SWC structure and watershed level. The resulting Nash-Sutcliffe efficiency (NSE) for daily streamflow simulation was 0.56 for the calibration and 0.48 for the validation period, suggesting satisfactory model performance. In contrast, the daily sediment simulation resulted in unsatisfactory model performance, with the NSE value of 0.07 for the calibration and –1.76 for the validation period and this could be as a result of high intensity and short duration rainfall events in the watershed. Meanwhile, the calibrated model indicated 21.08 Mg ha^{-1} average annual sediment yield, which is far beyond potential soil regeneration rate.

Key words: Agricultural watershed, erosion, Ethiopian Highlands, interpolation, landuse, radial basis functions, semivariogram, slope steepness, soil and water conservation, soil properties, watershed hydrology.

Hailu Kendie Addis: Watershed based land degradation modeling and soil property assessment

Abstrakt

Die Folgen von Bodenerosion im Nordwesten Amhara's in Äthiopien sind erheblich und beeinflussen die Nachhaltigkeit der Umwelt sowie die Produktivität der landwirtschaftlich genutzten Flächen maßgeblich. Die vorliegende Arbeit erörtert verschiedene Bodeneignschaften, sowie hydrologische und bodendynamische Prozesse auf Einzugsgebietsebene als auch die räumliche Verteilung diverser bodenspezifischer Merkmale. das 53.7 km^2 große Gumara-Maksegnit Einzugsgebiet wurde in 500m Raster unterteilt und entnommene Bodenproben hinsichtlich ihrer Trockendichte (ρd), pH, organischem Kohlenstoff (SOC), Gesamttickstock (TN), verfügbarem Phosphor (AP) und der oberflächennahen Bodentextur (ca. 10 bis 25cm Tiefe) untersucht. Die Bodeneigenschaften wurden in Zuordnung zu den zwei dominierenden Landnutzungen (Wald und landwirtschaftliche Flächen), sowie drei Geländeneigungsklassen, 0-10 (%), 10-30 (%), >30 (%), untersucht. Die Ergebnisse deuten auf erhöhte Werte von SOC, TN, Schluff und Sand, und niedrigere ρd Werte in Waldböden im Vergleich zu landwirtschaftlichen Böden hin. Generell wurden ansteigende Werte von SOC, TN, Schluff und Sand mit steigenden Geländeneigungen bei beiden Landnutzungen festgestellt. Im Gegensatz dazu scheint Ton und ρd mit abnehmender Hangneigung auf landwirtschaftlichen Flächen zuzunehmen, was mit der Deposition erodierter Feinpartikel von steileren Regionen zusammenhängt.

Im zweiten Teil der Arbeit wurden die räumlichen Interpolationsmethoden Ordinary Kriging (OK), Inverse Distance Weighting (IDW) und Radial Bias Functions (RBF) verwendet, um die punktförmig erhobenen Daten von Bodentextur, pH, organischen Kohlenstoff (SOC) und verfügbaren Phosphor (AP) räumlich zu verteilen. Die Güte aller Interpolationsmethoden wurde quantitativ anhand der Nash-Sutcliffe Effizienz (NSE), dem Bestimmtheitsmaß (R^2) und dem Index of Agreement (d) überprüft. Die Interpolationsergebnisse weisen OK als die beste Interpolationsmethode für SOC und Sand aus. RBF scheint die beste Methode bezüglich der Kartierung von Ton zu sein, und IDW

führte zu den besten Ergebnissen für pH Interpolation. Generell deuten durchgeführte Kreuzvalidierungen darauf hin, dass keine der Interpolationsmethoden durchwegs signifikant beste Ergebnisse erzielte. Demzufolge könnte sich jede der gewählten Methoden für die Kartierung vergleichbarer Regionen eignen.

Im dritten Teil der Arbeit wird das Soil and Water Assessment Tool (SWAT) Modell verwendet, um Abfluss- und Erosionsprozesse in dem Einzugsgebiet zu simulieren. Dieses hydrologisches Modell wurde eingesetzt,, um die Effekte ‚stone bunds' als Bodenschutzmaßnahmen und Maßnahmen zur Speicherung von Wasser und Sediment abzuschätzen und somit einen ‚support practice factors' abzuleiten. Die resultierende Nash-Sutcliffe Effizienz (NSE), gemessen an tagesbasierten Abflussdaten, erreichte 0.56 für die Kalibrierungsperiode und 0.48 für die Validierungsperiode, was einer zufriedenstellenden Modellgüte entspricht. Im Gegensatz dazu resultierte die tagesbasierte Simulation des Sedimentaustrags mit nicht zufriedenstellender Modellgüte und einer NSE von 0.07 für die Kalibrierung sowie -1.76 für die Validierung. Dieser Umstand kann durch die kurzen und intensiven Regenfälle im Einzugsgebiet verursacht sein. Das kalibrierte Modell simulierte 21.08 Mg ha^{-1} durchschnittlichen Sedimentaustrag pro Jahr und somit eine Bodenabtragsrate weit jenseits der potenziellen Bodenerneuerung.

Schlüsselwörter: Landwirtschaftliches Einzugsgebiet, Äthiopisches Hochland, Interpolation, Landnutzung, Radial Bias Functions, Semivariogramm, Geländeneigung, Boden- und Wasserschutz, Bodeneigenschaften, Einzugsgebietshydrologie.

Contents

1. Introduction

Accelerated soil erosion, mainly caused by water, is a widespread problem affecting environmental quality, agricultural productivity and food security in many countries of the world (Lal, 2001; Morgan, 2009). The excessive rate of soil erosion in Ethiopia is caused by a combination of physical factors such as erosive tropical rains, rugged terrain and steep slopes and the accumulated human pressure on the environment (Nyssen et al., 2004). Soil erosion affects several soil functions (food and other biomass production, water storing, filtering and transformation, habitat and gene pool, physical and cultural environment for mankind, and source of raw materials) and hence soil quality (Poesen, 2011).

Early study documented that innumerable example of horrible consequences of soil erosion in the northern Ethiopian highlands (Meshesha et al., 2012). Therefore, adoption of recommended soil and water conservation measures (SWC) is a survival for populations living in the highlands of Ethiopia. A successful implementation of land management practices which ultimately minimizes soil degradation can be achieved through active involvement of communities and awareness sharing (Tesfahunegn et al., 2011). Development of effective erosion control plans and sustainable agricultural production requires understanding the spatial soil variability, hydrological processes as well as erosion dynamics of the study area.

Spatial soil variability is inherent in nature due to different soil forming factors (Wei et al., 2008) in which climate, time, topography, living organisms, and parent materiel have been indicated as the main drivers of soil genesis (Jenny, 1994). The described soil forming factors interact across different spatial and temporal scales (Iqbal et al., 2005). Insight into the variability of the soils affected by different soil forming factors is essential for evaluating the impacts of future landuse and climate changes on the soil status (Kosmas et al., 2000), and consequentially, for understanding the entire ecosystem response (Townsend et al., 1995). Typically, spatial soil variability and hydrological processes depend on the specific soil studied but, such information for soil of the study watershed is lacking and hence, need to be assessed.

Meanwhile, many rainfall–runoff–soil erosion and sediment transport processes models (Agricultural Policy/Environmental eXtender (APEX), Soil and Water Assessment Tool (SWAT), Water Erosion Prediction Project (WEPP), USLE, etc.) with a broad spectrum of concepts were classified as spatially lumped, spatially distributed, empirical, regression, semi-distributed eco-hydrological model and factorial scoring models (de Vente et al., 2013). The Soil and Water Assessment Tool (SWAT) is a semi-distributed eco-hydrological model and one of the most widely used watershed models, which was developed by the United States Department of Agriculture-Agricultural Research Service (USDA-ARS) (Arnold et al., 1998) and can be used to predict agricultural land management impacts on the hydrological regime of a watershed through simulation of variable soil, land use and management conditions over long periods (Gassman et al., 2007; Gassman and Wang, 2015). In Ethiopia, SWAT has been used in a number of studies to predict streamflow and sediment yield with different outcomes and recommendations concerning the usability of the model for remote landscapes (Setegn et al., 2010; Betrie et al., 2011; Mengistu and Sorteberg, 2012; Wosenie et al., 2014; Schmidt and Zemadim, 2015; Yesuf et al., 2015).

This thesis was part of a multidisciplinary research project that was conducted within the Gumara-Maksegnit watershed which is part of the Blue Nile River Basin in the Amhara region of Ethiopia. Integrated watershed research was performed, including several soil variability, hydrology and agro-environmental related analyses, to gain a deeper insight into the spatial distribution of a soil as well as a watershed scale hydrology and land degradation issues and evaluate various soil and water conservation interventions. The spatial assessment of surface runoff and sediment yield within Gumara-Maksegnit watershed using SWAT is a key component of the overall research project.

2. Hypotheses and objectives

This thesis follows the motivation to contribute research results to the scientific community with the objective of a watershed scale land degradation processes, soil properties measurement as well as predicting the spatial distribution of selected soil properties. The following main hypotheses were assumed:

- Variation in landuse/land cover change can affect the soil physical and chemical properties.
- The spatial distribution of selected soil properties can change across a watershed.
- Increase in slope will result in a decrease in soil nutrients.
- Spatially distributed stone bund structures can increase the trapped amounts of water and sediment at the SWC structure level.
- Different soil properties measured at different slope steepness classes can have a correlation
- Different interpolation methods can result in a different surfaces map of a soil property.

The hypotheses resulted in the following main research objectives:

- Assessing the impacts of landuse and slope steepness on selected soil properties.
- Analyzing the performance of frequently used spatial interpolation techniques (IDW, OK and RBF) for predicting topsoil pH, soil organic carbon (SOC), available phosphorus (AP) and texture.
- Determining the optimum spatial interpolation method for mapping of selected soil properties in the study sub-watersheds.
- Assessing the applicability of SWAT for simulating the key watershed processes of a remote and mountainous agricultural watershed.
- Evaluating the impact of spatially distributed soil and water conservation (SWC) structures on surface runoff and soil erosion.

3. Structure of the study

This doctoral thesis consists of three independent chapters. The three chapters reported here were performed in the context of a multidisciplinary research project that includes linking selected soil properties to landuse and hillslope, predicting the spatial distribution of selected soil properties as well as hydrological processes and sediment dynamics of the Gumara-Maksegnit watershed. In chapter 5, intensive soil sampling was undertaken to investigate the general links of landuse and topography related to selected soil properties. Soil sampling points for the study watershed were selected using a well-organized regular sampling interval in a GIS environment, coupled with a systematic selection of the most representative soil-landscape features. Meanwhile, a detailed soil samples were also measured at the sub-watershed scale for predicting the spatial distribution of selected soil properties (In chapter 6). The measured soil datasets through the course of this study were further used as an input for the semi-distributed eco-hydrological model (SWAT) in chapter 7. Over a period of three consecutive years, the hydrological processes as well as sediment dynamics of the Gumara-Maksegnit watershed were measured and this data is presented in chapter 7.

4. Dissemination

Since this is a cumulative doctoral thesis, the central parts of the study were subject to scientific publications in peer-reviewed journals (Thomson Reuters/Science Citation Index (SCI) Web of Science List). Therefore, the international communities will have access to read and shear our experience and applied the procedures in future studies of similar regions. Details are listed in Tables 4-1 and 4-2.

Table 4-1. List of scientific publications in journals that are under Thomson Reuters/Science Citation Index (SCI) Web of Science List.

Chapter of this study	SCI-Journal	Impact factor (2015)	Title
5	Soil and Water Research	0.67	Linking Selected Soil Properties to Land Use and Hillslope – A Watershed Case Study in the Ethiopian Highland[1]
6	Applied Engineering in Agriculture	0.57	Performance of Frequently Used Interpolation Methods to Predict Spatial Distribution of Selected Soil Properties in an Agricultural Watershed, Ethiopia[2]
7	International Journal of Agricultural and Biological Engineering	1.01	Modeling Streamflow and Sediment using SWAT in the Ethiopian Highlands[3]

Table 4-2. List of presentation on international scientific conference.

Chapter of this study	Conference	Date and City	Title and type of presentation
5	TropiLakes2015	Sep 23 to 29, 2015 Bahir Dar, Ethiopia	Variation of Selected Soil Properties in Relation to Land Use Types and Slope Steepness in a Mountainous Watershed, Ethiopia
6	Sustainable Land and Watershed Management (SLWM): Experience and Lessons	May 26 to 27, 2014 Mekelle, Ethiopia	Comparing the performance of spatial interpolation techniques in mountainous terrain for mapping soil properties, Ethiopia.
7	Annual SWAT Conference	July 17 to 19, 2013 Toulouse, France	Using SWAT model to evaluate the impact of community-based soil and water conservation interventions for an Ethiopian watershed.

[1]Addis, HK., Klik, A., Oweis T., Strohmeier, S., 2016. Soil and Water Research, 11: 163-171. doi: 10.17221/117/2015-SWR

[2]Addis, HK., Klik, A., Strohmeier, S., 2016. Applied Engineering in Agriculture (in press, doi: 10.13031/aea.32.11447).

[3]Addis, HK., Strohmeier, S., Ziadat, F., Melaku, N.D., Klik, A.,2016. International Journal of Agricultural and Biological Engineering, 9(5): 51-66. doi: 10.3965/j.ijabe.20160905.2483

5. Linking Selected Soil Properties to Land Use and Hillslope – A Watershed Case Study in the Ethiopian Highland[4]

Abstract

Deforestation of native forests for crop production in the Gumara-Maksegnit watershed, located in the Lake Tana basin, Ethiopia, dramatically increases the vulnerability of the soil for rainfall driven erosion. Hence, the central task of the study is to investigate the general links of land-use and topography related to selected soil properties. The 53.7 km^2 watershed was divided into a 500 m by 500 m square grid to sample bulk density (ρd), pH, soil organic carbon (SOC), total nitrogen (TN), available phosphorus (AP) and texture of topsoil. Such properties were investigated with respect to the two main land-uses (forest and agriculture) and three different slope steepness classes, 0–10 (%), 10–30 (%), >30 (%). Descriptive statistics and correlation analyses were undertaken to explore potential dependencies of the obtained soil parameters according to land-use and slope steepness. The study indicates higher SOC, TN, silt and sand content in forest soils compared to agricultural soils, while ρd is lower in the forest soil. Overall an increase of SOC, TN, silt and sand content from gentle to steep slopes have been observed for both land-uses. In contrast, clay content and ρd seem to increase from steep to gentle slopes on agricultural areas, which might be due to accumulation of particularly fine soil particles eroded from the steep areas. Basic correlations valid for both land-uses and slope steepness classes have not been detected. Nevertheless, the study suggests slope steepness as a tool to assess the potential drivers of soil depletion in the Ethiopian Highlands.

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[4]Addis, H., Klik, A., Oweis T., and Strohmeier, S., 2016. Soil and Water Research, 11: 163-171. doi: 10.17221/117/2015-SWR

5.1 INTRODUCTION

Soil variability is inherent in nature due to different soil forming factors (Wei et al., 2008); in which climate, time, topography, living organisms, and parent materiel have been indicated as the main drivers of soil genesis (Jenny, 1941). The effects of vegetation on soil formation are related to the impacts on microclimate, soil erosion, microbial activity, organic matter accumulation, clay minerals, infiltration, and nutrient cycling (Foth, 1984). Meanwhile, hillslope orientation and slope steepness affect the soil profile development, especially in areas where rainfall and runoff enforce the detachment and the translocation of soil (Foth, 1984). The described soil forming factors interact across different spatial and temporal scales (Iqbal et al., 2005). Insight into the variability of the soils affected by different soil forming factors is essential for evaluating the impacts of future land use and climate changes on the soil status (Kosmas et al., 2000), and consequentially, for understanding the entire ecosystem response (Townsend et al., 1995).

Recently, the reduction of the soil quality and thus crop productivity become severe in some regions of the Ethiopian Highlands (Habtamu et al., 2014). Some of the factors causing considerable nutrient depletion in agricultural lands are related to the cultivation of the steep and fragile soils, limited recycling of dung and crop residues, deforestation and overgrazing (Habtamu et al., 2014), poor soil management and soil erosion by water (Kosmas et al., 2000; Amare et al., 2013). Particularly, soil erosion by water, leaching of nutrients due to intensive rainfall events, organic matter depletion as a result of continuous removal of crop residues and use of cow dung for different purposes were detected as the driving factors for poor soil productivity in the Ethiopian Highlands.

As a matter of fact, the study site covers only smaller parts of the Ethiopian Highlands, at which large areas of the landscape are still not explored in detail; however, the opportunity of linking soil specific case study results with other aspects of watershed research may support integrated watershed assessment. The specific task of this research is to assess the impact of land use and slope steepness on selected soil properties. Nevertheless, general outcomes and linkages may be used as starting point for advanced soil quality assessment even at field level to aim for sustainable land management for the fragile Ethiopian Highland ecosystem.

5.2 MATERIALS AND METHODS

5.2.1 Description of the study area

The study was conducted in the Gumara-Maksegnit watershed (53.7 km^2) located in the northwestern Amhara region, Ethiopia between 12° 24’ and 12° 31’ North, and between 37° 33’ and 37° 37’ East (Figure 5-1). The soil types are predominately Cambisol and Leptosol in the upper and central part of the watershed, and Vertisol in the lower catchment near the outlet. The mean annual rainfall is 1170 mm at which more than 90 (%) of the rainfall occurs during the three month periods, June to August. Average daily maximum and minimum temperatures are 28.5 ^{0}C and 13.6 ^{0}C, respectively. The elevation of the study watershed varies from 1920 m at the outlet to 2850 m in the northern mountains. The majority of the study watershed is mountainous and consists of dissected terrain with steep slopes (Addis et al., 2015).

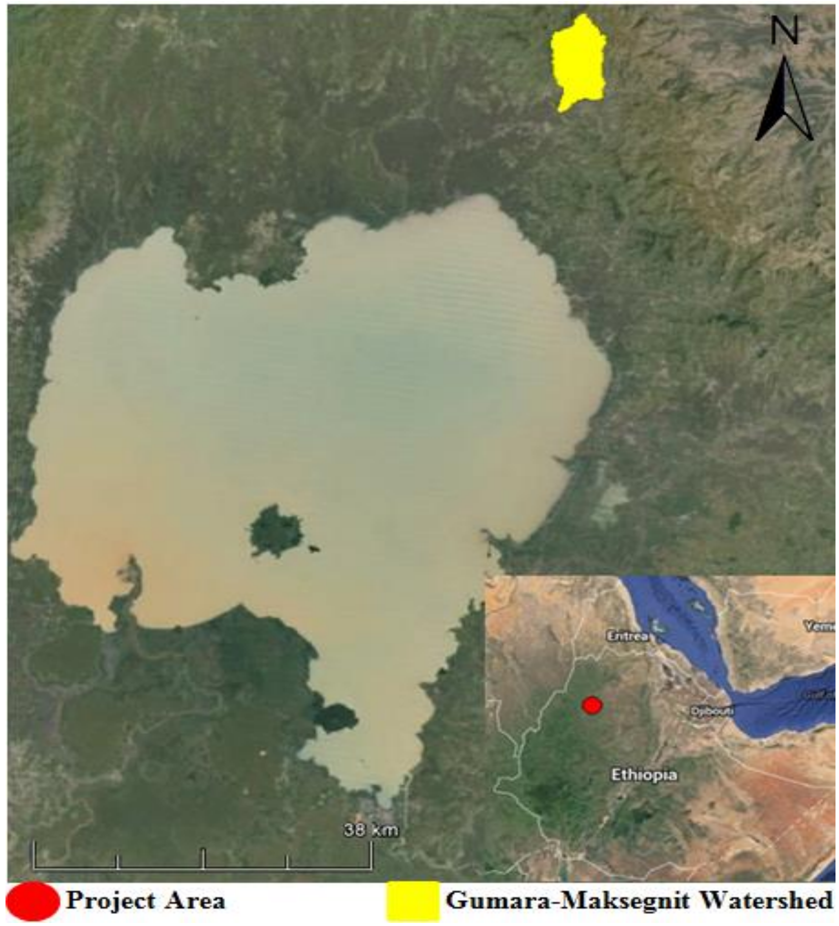

Figure 5-1. Overview of the project watershed area in the northwest Amhara region, Ethiopia

The 53.7 km^2 watershed was divided into a 500 m by 500 m square grid. Approximately, at the center of each grid soil samples of about 2 kg were collected from the surface soil horizon (0–25 cm) for chemical and physical analyses. Composite soil samples from agricultural and forest land use systems under three slope steepness classes: 0–10 (%) (18.77 km^2) (Gentle slope), 10–30 (%) (17.66 km^2) (Moderate slope) and greater than 30(%) (17.26 km^2) (Steep slope) were collected using bucket auger and core cylinder equipment resulting in 230 sampling points (Figure 5-2a). A few soil samples were collected outside the periphery of the study watershed, however, in this study such soil samples were not considered during the analyses. Meanwhile, the land use types of the

Gumara-Maksegnit watershed are mainly agricultural land 63.5 (%) followed by forest 24.3 (%) and grassland 12.2 (%) (Figure 5-2b). Although there exist a consensus regarding the soil characteristics of grassland are largely different from arable land, neither the soil sampling intensity nor the relative distribution of soil samples on the grassland of the study watershed is optimal for the statistical analyses; therefore, this research only analyzed soil samples collected on agricultural and forest land use systems, which were located at three different slope steepness classes.

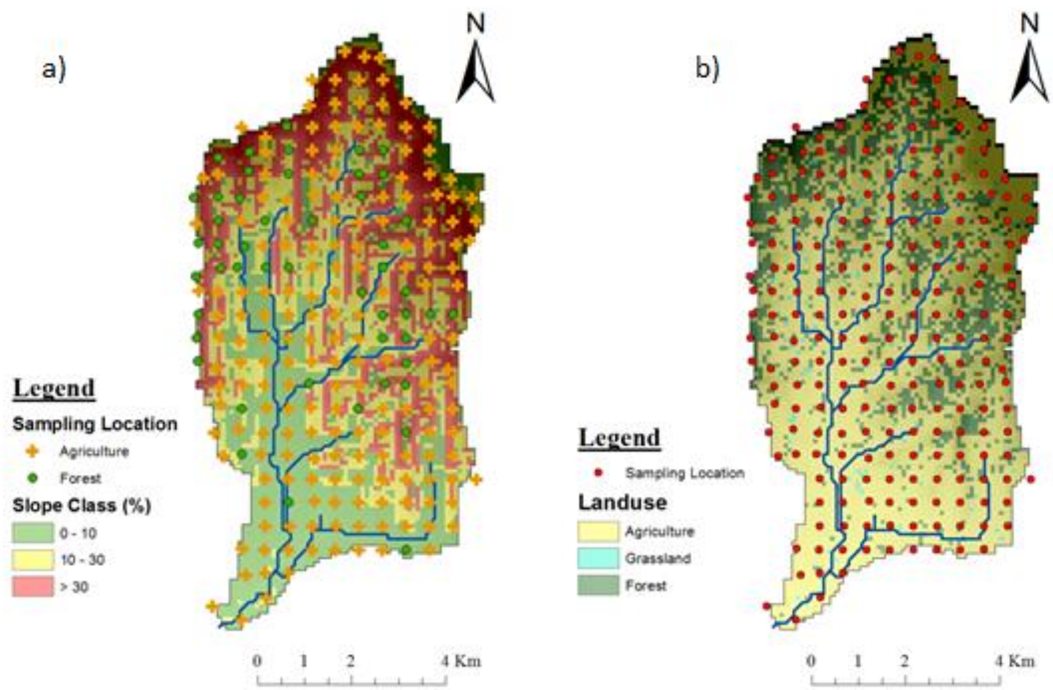

Figure 5-2. Distribution of soil sampling points; (a) Under different slope steepness classes and (b) Under different land use systems

5.2.2 Statistical analyses

The selected soil attributes were subject to descriptive statistics which includes mean, standard deviation (sd), and coefficient of variation (CV) using R software (R Development Core Team, 2013). Two-way analysis of variance (ANOVA) was executed to evaluate the effects of land use and slope steepness on the observed soil properties. The least significant difference ($LSD_{0.05}$) was used for determination of statistical significance ($P<0.05$).

5.3 RESULTS AND DISCUSSIONS

5.3.1 Soil textural classes

Five different soil textural classes were determined within the Gumara-Maksegnit watershed: sandy clay loam, sandy loam, clay loam, loam, and clay. Descriptive statistics were derived based on the mean values gained from the soil textural analyses, classified for the different land use and slope steepness classes (Table 5-1). The resulting soil textures seem significantly dependent on land use and slope steepness (Table 5-2), which was also indicated by Wei et al. (2008). In this study, the average silt, sand and clay contents in different land uses and slope steepness classes vary between 28.4 % and 37.1 %, 29.3 % and 41.7 %, and 21.2 % and 42.3 %, respectively (Table 5-2). Generally, higher silt and sand contents were found in forested areas compared to agricultural lands. This contradicts to the studies conducted by Wei et al. (2008), and Ezeaku and Eze (2014) where land uses do not affect particularly the silt fraction. Compared to the other slope steepness classes, clay contents tend to be higher on the gentle slopes of both land uses. The increasing clay content with decreasing slope steepness might be a result of the long-term soil erosion and accumulation processes, as reported by several studies (Ogban and Babalola, 2009; Obalum et al., 2011). As a standardized measure of variance, the coefficient of variation (CV) was used to describe the shape of the frequency distribution of the observations. Based on the CV values, silt, sand and clay contents may be generally considered as moderately variable (CV ranges from 14 % to 37 %). Silt content at gentle slopes of the forest is least variable (CV less than 14 %), while clay content at gentle slopes of agricultural areas has largest variation (CV equals to 38 %).

5.3.2 Bulk density

The descriptive statistical summary of bulk densities for both land uses and slope classes is presented in Table 5-1. Mean bulk density varies from 1.4 ± 0.24 g/cm^3 to 1.3 ± 0.09 g/cm^3 at gentle slope, from 1.2 ± 0.02 g/cm^3 to 1.2 ± 0.04 g/cm^3 at moderately slope, and from 1.2 ± 0.02 g/cm^3 to 1.1 ± 0.04 g/cm^3 at steep slope classes. Mean bulk density on forested areas is significantly lower compared to agricultural areas (Figure 5-3a). This could be associated to low rooting density and higher organic matter accumulation (Barker and Pilbeam, 2007), well-developed fine to medium granular structure and high organic matter contents in forested soils (Cardelli et al., 2012). On agricultural areas, bulk density seems to be significantly affected by the slope steepness. In contrast, there is no statistical significant difference between the mean values measured in the forest with respect to the different slope steepness classes. However, bulk density measured at gentle slope seems higher than the other slope classes (Table 5-2). Significant changes of bulk density on agricultural areas might be – amongst other impacts – related to the agricultural practices applied. Similarly, Emadi et al. (2008) documented compaction of topsoil layer due to intensive cultivation.

5.3.3 Soil pH

The descriptive statistical summary of measured pH indicates a mean value of 6.7 ± 0.03 (Table 5-1). Variation in pH, with respect to the interaction of land uses and slope classes is mostly non-significant, which was also shown by Worku (2014). However, focusing only on agricultural soil, pH might change slightly for different slope classes (Table 5-2). The highest pH value was obtained on agricultural soil, similar to the results reported by Bewket and Stroosnijder (2003).

Several studies also indicate that forest soils are often more acidic than agricultural soils (Barker and Pilbeam, 2007; Binkley and Fisher, 2012). Soils in high altitudes often related to steeper slopes – tend to lower pH value, which likely indicates the washing out of solutes and very high leaching of bases and clay particles from these areas as a result of intensive rainfall in the watershed. Some of the factors which are responsible for the reduction of pH at steep slope classes of forested soils might be associated with dense vegetation cover and slow decomposition leading to plenty of organic matter accumulation, eventually reducing soil pH. Similarly, Dlapa et al. (2011) stated that pH has a close relationship with soil organic carbon (SOC) as pH is commonly decreased with increasing SOC. Meanwhile, higher pH on agricultural areas could probably due to the long-term cultivation practices (Dlapa et al., 2011). Generally, the observed soil pH is the least variable (CV less than 7 %) compared to the other soil properties. Similarly, Abu and Malgwi (2011) indicates low coefficients of variation for pH compared to other soil properties.

5.3.4 Effects of land use and slope on soil chemical properties

The nutrient supplying power of the soil is determined by the chemical properties of the soil which are also the most important factors that affect soil fertility (Habtamu et al., 2014). In this research, the most essential chemical properties of the soil such as soil organic carbon (SOC), total nitrogen (TN) and available phosphorous (AP) were analyzed and displayed in Tables 5-1 and 5-2. The results revealed that for both land use types significantly higher SOC was observed at the steeper slopes, particularly steep slopes of the forested areas, this might be due to the different litter decomposition rate (Tsui et al., 2004), types of vegetative cover (Grigal and Ohmann, 1992) and the intensity of human interaction (Reynolds et al., 2007). In this study, SOC is generally low on agricultural areas with high clay content. Low SOC on cultivated areas may be attributed to unfavorable soil conditions due to the utilizations of crop residues and animal fodder as a fuel, continuous farming and soil erosion impacts mentioned in the literature (Craswell and Lefroy, 2001; Emadodin et al., 2009).

Comparison of the topsoil TN grouped for agriculture and forest suggests that overall TN on forested areas is significantly higher compared to the agricultural lands (Table 5-2). This may be explained by the higher soil organic matter (SOM) in the forest soils. Such results were in agreement with Díaz-Raviña et al. (2005) who described the changes in SOM could lead to changes in TN as more than 95 % of soil N comes from SOM. Similarly, Belachew and Abera (2010) indicated that the contribution of SOM to TN is significantly high. On the other hand, performed ANOVA suggests that AP does not significantly change between both land uses and slope steepness classes. The AP content in the watershed ranges from 1.2 to 77.2 (ppm), with an arithmetic mean of 12.40 (ppm). The coefficient of variation, standard deviation, and basic statistical parameters of AP for both land uses and slope steepness show that AP has relatively large variance (CV equals 101 %). This may be related to the heterogeneity of the land use patterns, overlaid with random application of inorganic fertilizer and also severe but variable erosion occurrence within the watershed. Similarly, Addis et al. (2015) documented highest CV for AP.

Table 5-1. Overview of the descriptive statistics of the selected soil properties classified based on land use and slope steepness

Soil properties	Agriculture									Forest								
	0–10(%)			10–30(%)			>30(%)			0–10(%)			10–30(%)			>30(%)		
	Mean	sd	CV	Mean	sd	CV	Mean	sd	CV	Mean	sd	CV	Mean	sd	CV	Mean	sd	CV
ρd (g/cm^3)	1.4	0.19	0.1	1.2	0.16	0.1	1.2	0.15	0.1	1.3	0.24	0.2	1.2	0.15	0.1	1.1	0.2	0.1
pH	7	0.44	0.1	6.7	0.4	0.1	6.6	0.35	0.1	6.7	0.33	0.1	6.7	0.21	0	6.6	0.2	0
Silt (%)	28.4	8.17	0.3	35.3	5.64	0.2	36.1	6.26	0.2	30.3	9.98	0.3	38	7.6	0.2	37.1	4.9	0.1
Sand (%)	29.3	8.75	0.3	39.6	7.36	0.2	39.9	8.56	0.2	31.6	6.22	0.2	39.9	10.5	0.3	41.7	7.8	0.2
Clay (%)	42.3	14	0.3	25.1	8.89	0.4	24	8.64	0.4	38.1	14.7	0.4	22	4.47	0.2	21.2	4.4	0.2
SOC (%)	1	0.57	0.6	1.7	1.01	0.6	2	1.09	0.6	1.1	0.54	0.5	1.8	0.87	0.5	2.1	1.1	0.5
TN (%)	0.2	0.16	1	0.2	0.13	0.5	0.3	0.12	0.5	0.3	0.12	0.5	0.3	0.06	0.2	0.3	0.1	0.4
AP (ppm)	12.8	12.8	1	16.7	15.8	1	12.6	15.4	1.2	16.6	25.5	1.1	8.4	4.95	0.6	10.4	12	1.1

ρd–bulk density; SOC–soil organic carbon; TN–total nitrogen; AP–available phosphorous; sd–standard deviation; CV–coefficient of variation

Table 5-2. Interaction effects of observed soil properties at different land uses and slope steepness classes

Soil properties	Agriculture					Forest					Overall sample	
	0–10(%)	10–30(%)	>30(%)	LSD	mean	0–10(%)	10–30(%)	>30(%)	LSD	mean	LSD	CV
ρd	1.4	1.2	1.2	0.06***	1.3	1.3	1.1	1.1	ns	1.2	0.05***	0.2
pH	7	6.7	6.5	0.15*	6.7	6.7	6.7	6.6	ns	6.7	ns	0.1
Silt	28.4	35.3	36.1	2.52***	33.3	30.3	38	37.1	6.12*	35.2	2.38**	0.2
Sand	29.3	39.6	39.9	3.04***	36.3	31.6	39.9	41.7	7.47*	37.7	3.01*	0.3
Clay	42.3	25.1	24	4.06***	30.4	38.1	22	21.2	5.79***	27.1	4.09**	0.4
SOC	1	1.7	1.9	0.34***	1.4	1.1	1.8	2.1	0.81*	1.7	0.31*	0.6
TN	0.2	0.2	0.3	0.05***	0.2	0.2	0.3	0.3	0.08*	0.2	0.04*	0.6
AP	12.8	16.7	12.6	ns	14	16.6	8.4	10.4	ns	11.8	ns	1.0

*, **, *** Significant at $p \leq 0.05$, 0.01 and, 0.001, respectively; ns–not significant; LSD–least significant difference

5.3.5 Correlation among the soil attributes

Correlation of the eight soil attributes related to the different land uses and slope steepness classes were evaluated based on the correlation coefficient and the corresponding significance level (Tables 5-3 and 5-4). The correlation analysis indicates that bulk density (ρd) seems significantly positively correlated with pH and significantly negatively correlated with SOC and silt, while clay is significantly positively correlated with pH. These findings follow the general principle that bulk density mostly increases with decreasing soil SOC (Cardelli et al., 2012) and pH commonly increases with decreasing SOC (Dlapa et al., 2011). AP was found to be significantly negatively correlated to bulk density and clay content, while significantly positively correlated with TN. Observed TN is significantly negatively correlated with pH and clay content, while significantly positively correlated with SOC. Focusing on single pairwise correlations, some of the observed soil properties seem significantly linked with the others. However, there is no clear indication that any of the measured soil properties is correlated with the other variables across the combined classes – slope steepness classes and land uses allowing generalized statements. Nevertheless, potential trends for the correlation of different soil properties for individual combinations of land uses and slope steepness classes are evident, which may enable the link of specific soil properties for certain areas considering a proper level of uncertainty.

Table 5-3. Matrix of the correlation coefficients among the measured soil properties in all the slope positions at agricultural land use

Slope position	Variables	ρd	pH	Silt	Sand	Clay	SOC	TN	AP
>30(%) with n=65	ρd								
	pH	0.51**							
	Silt	-0.39**	-0.45**						
	Sand	-0.25	-0.16	0.37**					
	Clay	0.39**	0.36**	-0.82**	-0.84**				
	SOC	-0.26*	-0.43**	0.17	-0.1	-0.03			
	TN	-0.02	-0.27*	-0.05	0.02	0.02	0.36**		
	AP	-0.15	-0.01	0.3*	0.18	-0.28*	0.14	0.28*	
10–30(%)with n= 67	ρd								
	pH	0.44**							
	Silt	-0.26*	-0.3*						
	Sand	0.003	-0.16	-0.08					
	Clay	0.16	0.32**	-0.57**	-0.77**				
	SOC	-0.26*	-0.3*	0.24*	0.15	-0.28*			
	TN	-0.25*	-0.43**	0.52**	0.16	-0.46**	0.38**		
	AP	0.02	0.06	0.32**	-0.09	-0.13	0.19	0.12	
0–10(%) with n= 49	ρd								
	pH	0.01							
	Silt	-0.1	0.07						
	Sand	0.06	0.45**	-0.35*					
	Clay	0.01	-0.49**	-0.37**	-0.74**				
	SOC	-0.09	-0.11	-0.06	0.17	-0.12			
	TN	-0.38**	-0.22	0.23	0.06	-0.23	0.34*		
	AP	-0.24	-0.09	0.11	0.11	-0.19	0.04	0.43**	

*, **, *** Correlation is significant at $p \leq 0.05$, 0.01 and 0.001 (two-tailed), respectively; n–number of samples

Table 5-4. Matrix of the correlation coefficients among the measured soil properties in all the slope positions at forest land use

Slope position	Variables	ρd	pH	Silt	Sand	Clay	SOC	TN	AP
>30(%) with n=7	ρd								
	pH	0.85*							
	Silt	-0.9**	-0.71						
	Sand	-0.72	-0.67	0.62					
	Clay	0.92**	0.77*	-0.94**	-0.85*				
	SOC	-0.55	-0.81*	0.38	0.51	-0.48			
	TN	-0.79*	-0.98**	0.58	0.63	-0.66	0.8*		
	AP	0.21	0.05	-0.29	0.16	0.13	0.29	-0.07	
10–30(%) with n=17	ρd								
	pH	-0.25							
	Silt	-0.35	-0.16						
	Sand	0.23	0.28	-0.93**					
	Clay	0.04	-0.39	0.48	-0.77**				
	SOC	-0.15	0.19	-0.2	0.23	-0.2			
	TN	-0.27	-0.26	0.15	-0.14	0.09	0.42		
	AP	-0.49*	-0.12	0.1	-0.19	0.27	-0.04	0.11	
0–10(%) with n=25	ρd								
	pH	0.01							
	Silt	-0.2	-0.02						
	Sand	0.17	0.13	-0.85**					
	Clay	-0.07	-0.2	0.39	-0.81**				
	SOC	-0.51**	-0.07	0.42*	-0.26	-0.009			
	TN	-0.29	-0.2	-0.12	0.2	-0.22	-0.001		
	AP	-0.35	-0.03	0.05	0.003	-0.06	0.11	0.48*	

*, **, *** Correlation is significant at $p \leq 0.05$, 0.01 and 0.001 (two-tailed), respectively; n–number of samples

Slope steepness has been indicated as the main abiotic factor that controls the soil genesis on a local scale (Buol et al., 1997). The steeper the slopes, the higher the runoff as well as the greater the relocation of soil materials downslope through rainfall driven erosion. In the study watershed, slope has a significant effect on the majority of obtained soil properties and there were a number of soil properties which have also been found to be strongly correlated to slope steepness. The highest positive correlations with slope were found, in descending order, for sand, SOC, silt and TN. The highest negative correlations with slope were found, in ascending order, for AP, pH, bulk density and clay content. The box plot diagrams (Figures 5-3 and 5-4) give insight into the distribution of the different soil properties. Particularly, larger variances of SOC, TN and AP might indicate different impacts of human interferences, such as local fertilization and individual agricultural management, overlaid with variable hillslope processes – for example surface runoff induced soil erosion and translocation of soil materials. This may inhibit a clear statement on parameter dependency, even though general trends and interactions seem detectable based on the box plots (Figures 5-3 and 5-4).

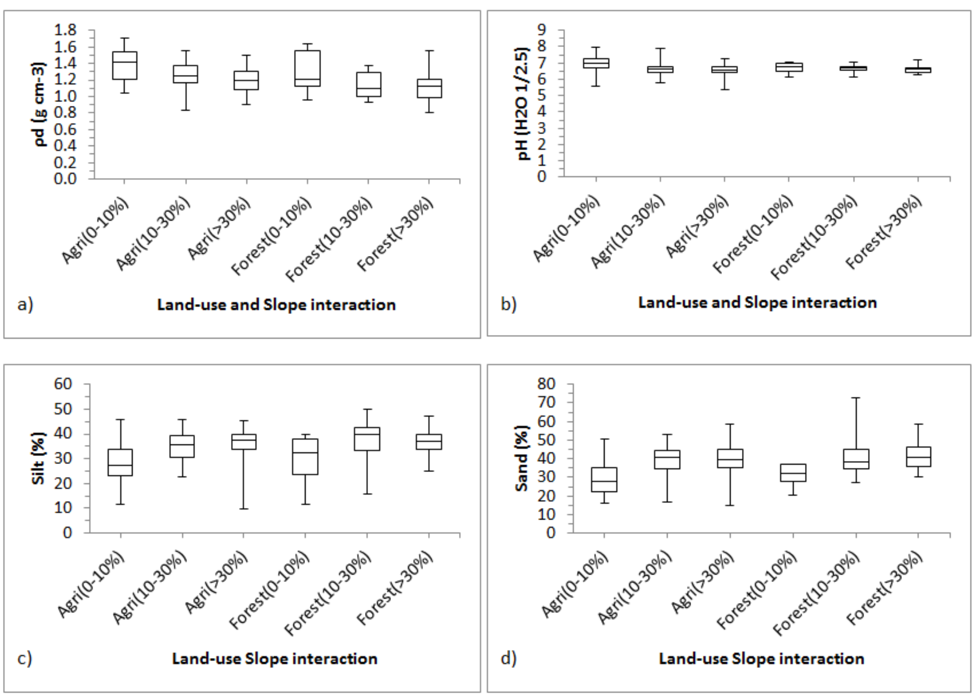

Figure 5-3. Distribution (box plots with 25th, mean, and 75th percentile) across the different land uses and slope steepness classes; (a) ρd (g/cm^3), (b) pH, (c) Silt (%) and (d) Sand (%)

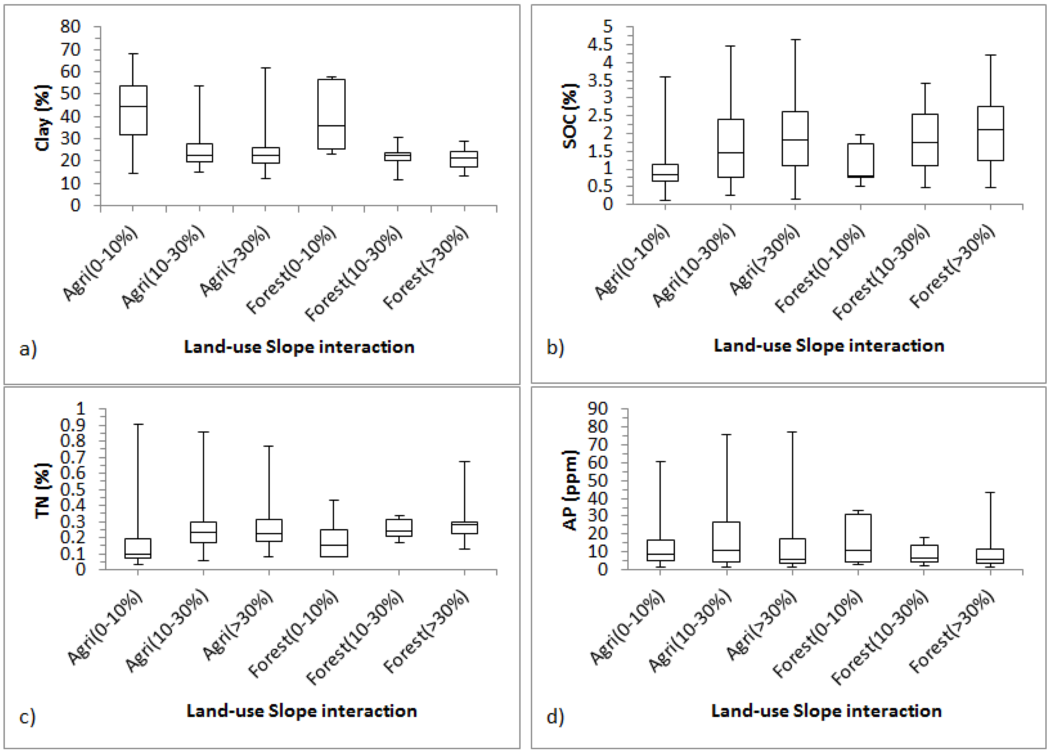

Figure 5-4. Distribution (box plots with 25th, mean, and 75th percentile) across the different land uses and slope steepness classes; (a) Clay (%), (b)SOC (%), (c) TN (%) and (d) AP (ppm)

5.4 CONCLUSIONS

This study aims for the investigation of potential interactions and linkages between selected soil properties across the different land uses as well as topographic conditions (three slope steepness classes; 0-10%, 10-30%, >30%), sampled within mountainous watershed in the Ethiopian Highland. The study showed that forested areas of the Gumara-Maksegnit watershed tend to have higher soil nutrients (SOC and TN) as well as higher silt and sand contents compared to agricultural lands, while bulk density is lower in the forest. However, some of the investigated soil properties do not indicate any dependency (such as AP). Concerning SOC, TN, silt and sand content an overall increase from gentle to steep slope classes have been observed for both land uses. The study also points out high levels of clay content and bulk density occurred on the gentle slope of agricultural lands. Higher clay content on flat agricultural areas might be due to the deposition of clay particles eroded from uphill slopes. Generally, the obtained results suggest certain potential for using slope steepness classification as a tool for soil property definition in the Ethiopian Highlands. Based on the applied correlation statistics some of the soil properties are significantly linked (correlated) to the others, which may support the allocation of the most endangered regions concerning land degradation. However, basic linkages valid for all land uses and slope steepness classes have not been detected. Nevertheless, significant parameter correlations considering specific land use and slope steepness may help to delimit required soil sampling for future research. In fact, soil property pattern assessed in the present study may be used as a basis for specific task related to research at field level - to assess the potential drivers of soil depletion and to come up with proper interventions to counteract ongoing land degradation in the Ethiopian Highlands.

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6. Performance of Frequently Used Interpolation Methods to Predict Spatial Distribution of Selected Soil Properties in an Agricultural Watershed, Ethiopia[5]

Abstract

Soil map of a watershed provide a wealth of knowledge and can be vital for implementing site specific soil managements. Hence, watershed based soil assessment was conducted to select an optimum spatial interpolation method, while aiming for sustainable soil managements. Intensive soil sampling was undertaken to investigate the performance of ordinary kriging (OK), inverse distance weighting (IDW) and radial basis functions (RBF) for predicting the spatial distribution of soil texture, pH, soil organic carbon (SOC) and available phosphorus (AP). The 72ha study area was divided into a 100m by 100m grid and approximately at the center of each grid, topsoil samples (roughly from 10–25cm depth) were collected over 75 locations across the entire watershed. The exponential and Gaussian models were best fitted in the semivariogram of measured soil. The performance of each interpolation method was assessed quantitatively in terms of Nash-Sutcliffe efficiency (E), coefficient of determination (R^2) and index of agreement (d). The interpolated maps generated based on the highest value of E displayed OK was best performed for SOC and sand. RBF was most suitable for mapping of AP and clay, while IDW gave better result when applied to pH. The highest value of R^2, E and d (0.51, 0.51, and 0.83, respectively) resulted from the spatial interpolation of AP. Overall, the cross-validation statistics for each interpolation method showed there was no single method that significantly outperformed the others. Therefore, one of the interpolation methods could probable be applied for surfaces map generation in future studies of similar regions.

[5]Addis, H.K., Klik, A., and Strohmeier, S., 2016. Applied Engineering in Agriculture (in press, doi: 10.13031/aea.32.11447).

6.1 INTRODUCTION

Soils continually undergo development and vary over a wide range of spatial and temporal scales. Spatial scales reach from the micro-environment (a small area of a few square meters) to the watershed and beyond, while temporal scales extend from seconds to centuries and longer (Addis et al., 2015). Therefore, any effort to enhance soil productivity in different types of cropping method may not yield appropriate results without a careful understanding of soil variability. The spatial variability of soil is often measured using a number of interpolation methods. Selecting an ideal spatial interpolation method for map generation is crucial in surface analysis (Zandi et al., 2011).

The goal of spatial interpolation is to estimate the magnitude of the variable (Z_0) at location X_0, Y_0 using surrounding points with known X and Y coordinates and magnitude of variable (Z) (Meijerink et al., 1994). However, spatial interpolation and interpretation is predominantly human dependent, and therefore subjective (Furrer and Genton, 1999). The spatial interpolation methods, including geostatistics, have been developed for and applied in various disciplines (Zhou et al., 2007). Numerous factors including sampling density, sample volume, spacing, sampling design and variation in the data affect the predictive ability of a spatial interpolation method (Li and Heap, 2008). These factors make it difficult to select an appropriate spatial interpolation method for a given input dataset (Burrough and McDonnell, 1998).

The precision of various spatial interpolation techniques for predicting unmeasured values have been documented by a number of researchers (Weber and Englund, 1992; Nalder and Wein, 1998; Kravchenko and Bullock, 1999). Nevertheless, there have been many conflicting findings regarding the relative performance of different spatial interpolation methods and the use of basic statistics to predetermine both interpolation techniques and their parameters (Robinson and Metternicht, 2005).

Spatial interpolation techniques are developed for specific data types or a particular variable (Li and Heap, 2008). Most of the methods perform at an acceptable level for estimating soil attributes in gentle terrain, whereas few perform well in rugged terrain (Pandey and Pandey, 2010; Yao et al., 2013). Three of the most popular interpolation methods, IDW, RBF and ordinary kriging have been commonly used in agricultural research (Zandi et al., 2011). Several studies; however, have found that IDW to be more accurate than kriging for mapping of soil organic matter (SOM) and soil NO_3 levels (Gotway et al., 1996) and for mapping of P and K levels (Wollenhaupt et al. 1994). Similarly, research conducted by Robinson and Metternicht (2005) reported that IDW predicted the subsoil pH with greater accuracy than kriging and spline. However, kriging has been the preferred method for predicting agricultural yield data (Birrell et al., 1996; Batchelor et al., 2002; Whelan et al., 2002), topsoil pH (Robinson and Metternicht, 2005) and for mapping of soil Zn (Leenaers et al., 1990). In contrast, research conducted by Zandi et al. (2011) showed that RBF outperformed OK and IDW for interpolating topsoil pH and this study tried to test the validity of such methods at a sub-watershed scale.

Surface soil map generation for an agricultural watershed provide a wealth of information and can be an important tool for implementing various site specific soil managements but such information for soil of the study agricultural sub-watersheds is lacking and hence, need to be assessed. Considering these different and conflicting findings, the objectives of this research were to i) analyze the performance of frequently used spatial interpolation techniques (IDW, OK and RBF) for predicting topsoil pH, soil organic carbon (SOC), available phosphorus (AP) and texture; and, ii) determine the optimum spatial interpolation method for mapping of selected soil properties in the study sub-watersheds.

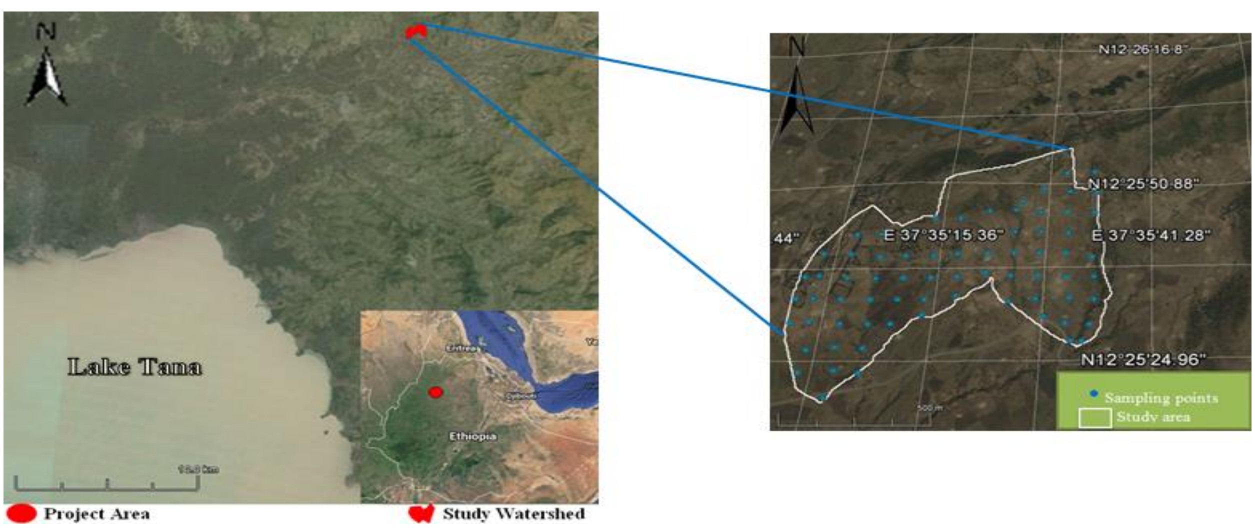

Figure 6-1. Location of the study sub-watersheds and the distribution of observed soil samples.

6.2 MATERIALS AND METHODS

6.2.1 Study Area Description

The study was carried out in the Ayeye and Aba-Kaloye sub-watersheds ($37^0$35'15"E, $12^0$25'50"N), which are located near Lake Tana basin in the northwestern Amhara region, Ethiopia (Figure 6-1). The two sub-watersheds have a total area of 72ha and the elevation ranges from 1,997m to 2,532m, while the hillslopes range from nearly flat (<2%) to extremely steep (> 50%). The climate of the area is characterized by intense rainfall events occurring mainly between June and August and a dry period between November and April; average annual rainfall is 1170mm (Addis et al., 2015). The study area, which is part of the northern highlands of Ethiopia, belongs to the Trap Series of Tertiary volcanic eruptions (Mohr, 1963). In the study sub-watersheds, some of the factors causing considerable nutrient depletion in agricultural lands are related to soil erosion by water, the cultivation of the steep and fragile soils, limited recycling of cow dung and crop residue, deforestation, and overgrazing.

6.2.2 Soil Sampling Method

The study sub-watersheds were under agricultural land-use system (crop production) with varying landscape features, including elevation, slope steepness and aspect, soil categories and land management. The soil sampling sites were selected using a well-organized regular sampling interval in a GIS environment, coupled with a systematic selection of the most representative soil-landscape features as it was described by Buttafuoco et al. (2012). Garmin explorer GPS accuracy: (± 3m) was used for locating the geographic coordinates of the sampling points in the field so that, topsoil samples of around 2kg were removed for analysis (Addis et al., 2015). During this study, sometimes the center of the square grid may not be a representative location, thus in such cases sampling point was shifted to the area which describe the grid well (Addis and Klik, 2015). The systematic method is the most commonly used technique and provide more accurate results than random sampling pattern (Wang and Qi, 1998; Kavianpoor et al., 2012) and is an appropriate method when no other information is available regarding the soil variability prior to sampling. Therefore, the 72ha study area was divided into a 100m by 100m square grid using ArcGIS and a total of 75 soil samples across the entire sub-watersheds were collected from the topsoil horizon (roughly 10–25cm depth) with the best available tool (bucket auger) for analyses. The pH value of the soil was measured with a pH meter in the supernatant suspension of 1:2.5 ratios (sample to water mixture). Soil texture was measured following the procedure as described by Gee and Or

(2002), and organic carbon was determined by wet oxidation method as described by De Vos et al. (2007). Available phosphorus (AP) was extracted using sodium bicarbonate solution at pH 8.5 following the procedure described by Olsen (1954). In this study, classical statistical analyses were used to describe soil properties and geostatistical analyses were used to select an optimum spatial interpolation method.

6.2.3 Spatial Interpolation Techniques

Frequently used spatial interpolation techniques (OK, RBF and IDW) were selected to predict the spatial continuous surfaces of soil properties in the study sub-watersheds. Naturally, the selected interpolation techniques are commonly described as weighted average methods, and they all share the same basic mathematical formulation (Webster and Oliver, 2001; Li and Heap, 2008) and calculated as:

$$\check{z}(x_0) = \sum_{i=0}^{n} \lambda_i \, z(x_i) \qquad [6\text{-}1]$$

Where n represents the number of sampled points used for the prediction, $\check{z}$ is the predicted value of an attribute at the point of interest x_0, z is the observed value at the sampled point x_i, and λ_i is the weight assigned to the sampled point (Webster and Oliver, 2001).

6.2.3.1 Kriging

Kriging is a statistical procedure for interpolating values at unmeasured locations between locations with sampled data (Nielsen and Wendroth, 2003). Kriging analysis is applicable for environmental disciplines such as agricultural yield mapping (Blackmore, 1999), spatial continuous soil surface generation (Goovaerts, 1999), spatial variability assessment of rainfall (Naoum and Tsanis, 2004) and air pollution modelling (Wong et al., 2004). Ordinary kriging is a type of kriging that considers the mean is constant but unknown across the spatial domain of interest (Li and Heap, 2008). Kriging utilizes the spatial variance structure available in a semivariogram and provides a best linear unbiased estimate of an unmeasured value calculated from weighted values measured in a local neighborhood (Nielsen and Wendroth, 2003). Semivariance (γ) is an important concept in geostatistics (Webster and Oliver, 2001) and can be estimated from the observed values as follows:

$$\gamma(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} [z(x_i) - z(x_i + h)]^2 \qquad [6\text{-}2]$$

Where h is the distance between point x_i and x_0 and $\gamma(h)$ is commonly referred to as semivariogram (Webster and Oliver, 2001), $N(h)$ is the number of data pairs within a given class of distance and direction.

A plot of $\gamma(h)$ against h is known as the experimental semivariogram, which displays several important features (e.g. nugget, sill and range) (Burrough and McDonnell, 1998). If the ratio of nugget to sill is close to 1, it reflects a weak degree of spatial dependency (Cambardella et al., 1994). The “range” is a value of distance at which the “sill” is reached (Li and Heap, 2008) and the range provides information about the size of a search window used in the spatial interpolation methods (Burrough and McDonnell, 1998). GS+ was used to obtain the semivariogram model of each observed soil properties (Robertson, 2008) and model with the least reduced sum of squares (RSS) was further examined to find the number of neighbors that returned the best cross-validation result (Robinson and Metternicht, 2005).

6.2.3.2 Inverse Distance Weighted (IDW)

Inverse Distance Weighted (IDW) is a deterministic method that uses a weighted average of nearby locations, with closer points to the center of the cell being estimated having greater weight in the averaging process (Zeiler, 2010). The most important factor that affects the accuracy of IDW is the value of the weighting (the power) parameter (Isaaks and Srivastava, 1989). IDW is commonly used for estimating soil properties or (attributes) (Leenaers et al., 1990; Wollenhaupt et al., 1994; Gotway et al., 1996) using the following formula:

$$z(x_0) = \frac{\sum_{i=1}^{n} z(x_i) d_{ij}^{-r}}{\sum_{i=1}^{n} d_{ij}^{-r}} \quad [6\text{-}3]$$

Where x_0 is the estimation point and x_i are the data points within a chosen neighborhood. The weights (r) are related to distance by d_{ij}, which is the distance between the estimation point and the data points.

One of the concerns with the IDW method is that higher or lower values of the site under consideration will be overlooked if they are not sampled (EPA, 2012) so if the peaks and valleys of the data are not represented in the sample, this technique may be wildly inaccurate in some locations. Since IDW is a deterministic technique, it does not take into account the spatial structure of the sample points. Thus, the results can be influenced by sampling density and sampling interval. In addition, if the sampling of input points is sparse or uneven, the results may not sufficiently represent the desired surface (Watson and Philip, 1985).

6.2.3.3 Radial Basis Functions (RBF)

Radial Basis Functions (RBF) is a family of five deterministic exact interpolation techniques: thin-plate spline, spline with tension, completely regularized spline, multi-quadratic function and inverse multi-quadratic function (Zeiler, 2010). The differences among RBFs are small, so the generated surfaces are almost similar (Burrough and McDonnell, 1998). Unlike IDW (which is also an exact interpolator), RBF can predict values above the maximum or below the minimum of the measured values (Zeiler, 2010). RBFs are used to produce smooth surfaces from a large number of sample points. The functions produce good results for gently varying surfaces such as elevation. However, the techniques are inappropriate when large changes in the surface values occur within short distances and/or when you suspect the sample data is prone to measurement error or uncertainty (Zeiler, 2010).

6.2.4 Model Evaluation Techniques

Spatial interpolation methods are increasingly used in a wide range of disciplines despite increasing concern about their accuracy and precision (Hartkamp et al., 1999; Huo et al., 2012). The concern about their accuracy and precision is because they were developed either for specific disciplines or even for specific variables based on the data properties modelled and each method has its own specific assumptions and features (global versus local, exact versus inexact, deterministic versus stochastic, and gradual versus abrupt) (Li and Heap, 2008). Therefore, several error measurement methods have been used to assess the accuracy and precision of the interpolation methods (Li and Heap, 2008, 2011).

In this study, cross-validation with a single variogram was used to assess the performance of each spatial interpolation method. Cross-validation is an appropriate method to evaluate models when two independent datasets (calibration and validation) cannot be built because of the reduced number of data points (jack-knifing) (Guisan and Zimmermann, 2000). The model is fit to a portion of the data, and then the attained equation is applied to the remaining data points to determine their estimated values (Davis, 1987; Li and Heap, 2008). The estimated values from cross-validation were used to calculate an error estimator (Willmott, 1982). The performance of each interpolation method was assessed quantitatively in terms of mean error (ME), mean squared error (MSE), root mean squared error (RMSE), Nash-Sutcliffe efficiency (E), coefficient of determination (R^2) and index of agreement (d).

6.2.4.1 Nash-Sutcliffe Efficiency (E)

The Nash-Sutcliffe efficiency (E) is a normalized statistic that explains the relative magnitude of the residual variance ("noise") associated with the observed data variance (Nash and Sutcliffe, 1970; Moriasi et al., 2007). The efficiency E documented by Nash and Sutcliffe, (1970) is defined as follows:

$$E = 1 - \frac{\sum_{i=1}^{n}(E_i - O_i)^2}{\sum_{i=1}^{n}(O_i - \bar{O})^2} \qquad [6\text{-}4]$$

Where n is the number of observations or samples, O_i is the observed value of sample *i*, E_i is the estimated value of sample *i*, and $\bar{O}$ is the mean of observed values.

The range of E lies between −∞ and 1.0 with E = 1 describing a perfect fit. Values between 0.0 and 1.0 are generally viewed as acceptable levels of performance, whereas values < 0.0 indicate that the mean observed value is a better predictor than the estimated value (unacceptable performance) (Moriasi et al., 2007). The key weakness of the Nash-Sutcliffe efficiency is the fact that larger values in a dataset are strongly overestimated whereas lower values are neglected (Legates and McCabe, 1999).

6.2.4.2 Coefficient of Determination (R^2)

The coefficient of determination, R^2, is the squared value of the coefficient of correlation (Krause et al., 2005). It is defined as follows:

$$R^2 = \left[\frac{\sum_{i=1}^{n}(O_i - \bar{O})\,(E_i - \bar{E})}{\sqrt{\sum_{i=1}^{n}(O_i - \bar{O})^2}\sqrt{\sum_{i=1}^{n}(E_i - \bar{E})^2}}\right]^2 \qquad [6\text{-}5]$$

Where n is the number of observations or samples, O_i is the observed value of sample *i*, E_i is the estimated value of sample *i*, $\bar{O}$ is the mean of observed values and $\bar{E}$ is the mean of estimated values.

The range of R^2 lies between 0 and 1, and describes how much of the observed value is explained by the predicted value (Krause et al., 2005). A value of 1 means the predicted value is equal to the observed value, where a value of zero means there is no correlation between the predicted and observed values.

6.2.4.3 Index of Agreement (d)

The index of agreement, d, as reported by Willmott (1981) is a standardized measure of the degree of model accuracy. The range of d is the same as R^2 ranging from 1 (perfect fit) to 0 (no correlation) (Moriasi et al., 2007). The index of agreement is described as follows:

$$d = \frac{\sum_{i=1}^{n}(E_i - O_i)^2}{\sum_{i=1}^{n}(|\check{E}_i| + |\check{O}_i|)^2} \qquad [6\text{-}6]$$

Where n is the number of observations or samples, O_i is the observed value of sample *i*, E_i is the estimated value of sample *i*, $\bar{O}$ is the mean of observed values, $\check{O}_i$ is the difference between the observed value for sample *i* and the mean observed value (O_i–$\bar{O}$), and $\check{E}_i$ is the difference between the estimated value of sample *i* and the mean observed value (E_i–$\bar{O}$).

Krause et al. (2005) have reported relatively high value of d (more than 0.65) even for poor model fits. It has also been found that d is overly sensitive to extreme values due to the squared differences (Legates and McCabe, 1999).

Table 6-1. Descriptive statistics summary for soil physical and chemical properties of the study sub-watersheds.

Soil attributes	No. of samples	Minimum	Maximum	Range	Mean	SD[b]	se (mean)[b]	CV[b]	Skewness	Kurtosis
SOC (%)[a]	75	0.13	5.22	5.09	1.81	0.97	0.11	0.53	0.67	0.81
AP (ppm) [a]	75	0.32	155.92	155.60	22.98	38.95	4.50	1.69	2.32	4.92
pH	75	5.68	7.37	1.69	6.57	0.34	0.04	0.05	0.18	-0.15
Clay (%)	75	10	58	48	29.19	10.22	1.18	0.35	0.17	-0.22
Silt (%)	75	18	62	44	35.64	6.51	0.75	0.18	0.49	2.96
Sand (%)	75	16	62	46	35.17	10.55	1.22	0.30	0.73	-0.17

[a]SOC is soil organic carbon and AP is available phosphorous.

[b]SD is standard deviation, se (mean) is standard error of mean and CV is coefficient of variation.

6.3 RESULTS AND DISCUSSION

According to laboratory measurements soil texture was rather heterogeneous across the study area, primarily clay loams, loams and sandy loams with the clay contents ranging from 10% to 58%, and sand contents from 16% to 62%. The descriptive statistical summary of the measured soil physical and chemical properties of the study sub-watersheds is presented in Table 6-1. Variability of soil properties can be described by the minimum and maximum values, SD, and CV. Among these values, the CV is the most selective factor as it is a useful statistic for comparing the degree of variation from one data series to another, even if the means are drastically different from each other (Wei et al., 2008). According to the soil variability guidelines provided by Wilding (1985), the property shows low variability when CV is less than or equals to 0.15, moderate variability when the CV is between 0.15 to 0.35, and the most variable when the CV is greater than 0.35. Based on these guidelines, AP, SOC and clay contents were the most variable soil properties, while silt and sand contents had moderate variability, and pH was the least variable (Table 6-1). A similar study by Sun et al., (2003) and Addis et al. (2015) documented that AP showed the highest variation, while pH had the least, based on the CVs. The range of SOC increased from 0.13% at the outlet to greater than 3.2% at upper catchment areas. A lognormal ordinary kriging was used for AP as the coefficient of skewness is greater than 1 (Table 6-1).

Table 6-2. Coefficients of the theoretical semivariogram statistic produced for different ordinary kriging models of the selected soil properties.

Variable	Model type	Nugget [Co]	Sill [Co+C]	Range Ao (m)	RSS[a]	$R^{2[a]}$	nugget/sill ratio [Co /(Co+C)]
SOC	Linear	0.32	1.07	497.85	1.21	0.92	0.30
	Spherical	0.35	1.06	282	8.72E-03	0.97	0.33
	Exponential	0.23	1.88	711	0.01	0.94	0.12
	Gaussian	**0.18**	**1.01**	**503**	**8.01E-03**	**0.97**	**0.18**
Lognormal AP	Linear	1.64	3.17	497.85	5.35	0.65	0.52
	Spherical	0.001	2.85	246	0.11	0.93	0.00
	Exponential	0.001	3.03	119	0.17	0.9	0.00
	Gaussian	**0.22**	**2.86**	**118**	**0.09**	**0.94**	**0.08**
pH	Linear	0.09	0.41	497.85	2.04E-03	0.79	0.22
	Spherical	0.09	0.37	1979	1.06E-04	0.79	0.24
	Exponential	0.09	0.37	1097	1.13E-04	0.77	0.24
	Gaussian	**0.09**	**0.39**	**1104**	**9.11E-05**	**0.92**	**0.23**
Clay	Linear	0.0063	0.011	497.85	7.91E-07	0.93	0.57
	Spherical	0.006	0.014	1074	6.50E-07	0.94	0.43
	Exponential	**0.0059**	**0.02**	**1110**	**5.58E-07**	**0.95**	**0.30**
	Gaussian	0.0071	0.014	541	1.35E-06	0.88	0.51
Silt	Linear	0.0035	0.005	497.85	4.90E-06	0.85	0.70
	Spherical	0.0035	0.007	1634	1.64E-07	0.86	0.50
	Exponential	**0.0034**	**0.007**	**749**	**1.30E-07**	**0.89**	**0.49**
	Gaussian	0.0039	0.008	824	2.80E-07	0.75	0.49
Sand	Linear	0.0073	0.012	497.85	1.39E-06	0.86	0.61
	Spherical	0.007	0.014	1037	1.19E-06	0.88	0.50
	Exponential	**0.0069**	**0.02**	**1067**	**1.07E-06**	**0.89**	**0.35**
	Gaussian	0.0082	0.017	651	2.24E-06	0.77	0.48

[a] RSS is residual sum squares and R^2 is coefficient of determination. Bolded values were chosen as the best model.

6.3.1 Comparison of the Interpolation Methods

The spatial variability of selected soil properties was assumed to be identical in different directions and the isotropic experimental semivariogram for each observed soil variable was calculated using Eq. [6-2]. The results of the experimental semivariograms show that the exponential and Gaussian models were best fitted and the model with the least RSS value was chosen (Table 6-2). Selecting an appropriate spatial interpolation method for a given input dataset is difficult, as they are data-specific or even variable-specific. Therefore, the choice of spatial interpolation techniques is subjective (Furrer and Genton, 1999). This study did not overlook the possibility of anisotropy and directional semivariograms have been examined but the directional semivariograms do not properly describe the spatial variability of measured soil properties and the spatial structures of the directional semivariograms for each soil property were very week; thus, the study end up using an isotropic semivariogram. The isotropic semivariograms for the selected soil properties are shown in Figures 6-2a to 6-2f. The semivariograms of clay, silt and sand contents were best-fitted with the exponential function and each of their R^2 is greater than 0.89, which suggested that clay, silt, and sand contents had stronger spatial structure.

Typically, the nugget to sill ratio or relative nugget effect [Co/(Co+C)] reflects the spatial autocorrelation (Li and Reynolds, 1995). The relative nugget effect was calculated for each observed soil properties and used to assess the degree of spatial dependence and correlation related with each soil variables (Jabro et al., 2010). The relative nugget effect of each observed soil properties were then classified into one of the three classes to describe the spatial dependence (Cambardella et al., 1994). If the relative nugget effect was less than or equal to 0.25, the soil property was categorized as strongly spatially dependent; if the relative nugget effect was greater than 0.25 and less than 0.75, the soil property was categorized as moderately spatially dependent; and if the relative nugget effect was greater than 0.75, the soil property was categorized as weakly spatially dependent (Cambardella et al., 1994; Jabro et al., 2010). The relative nugget effect of clay, silt, and sand for the best fitted model ranged from 0.30 to 0.49, indicating moderately spatially dependent.

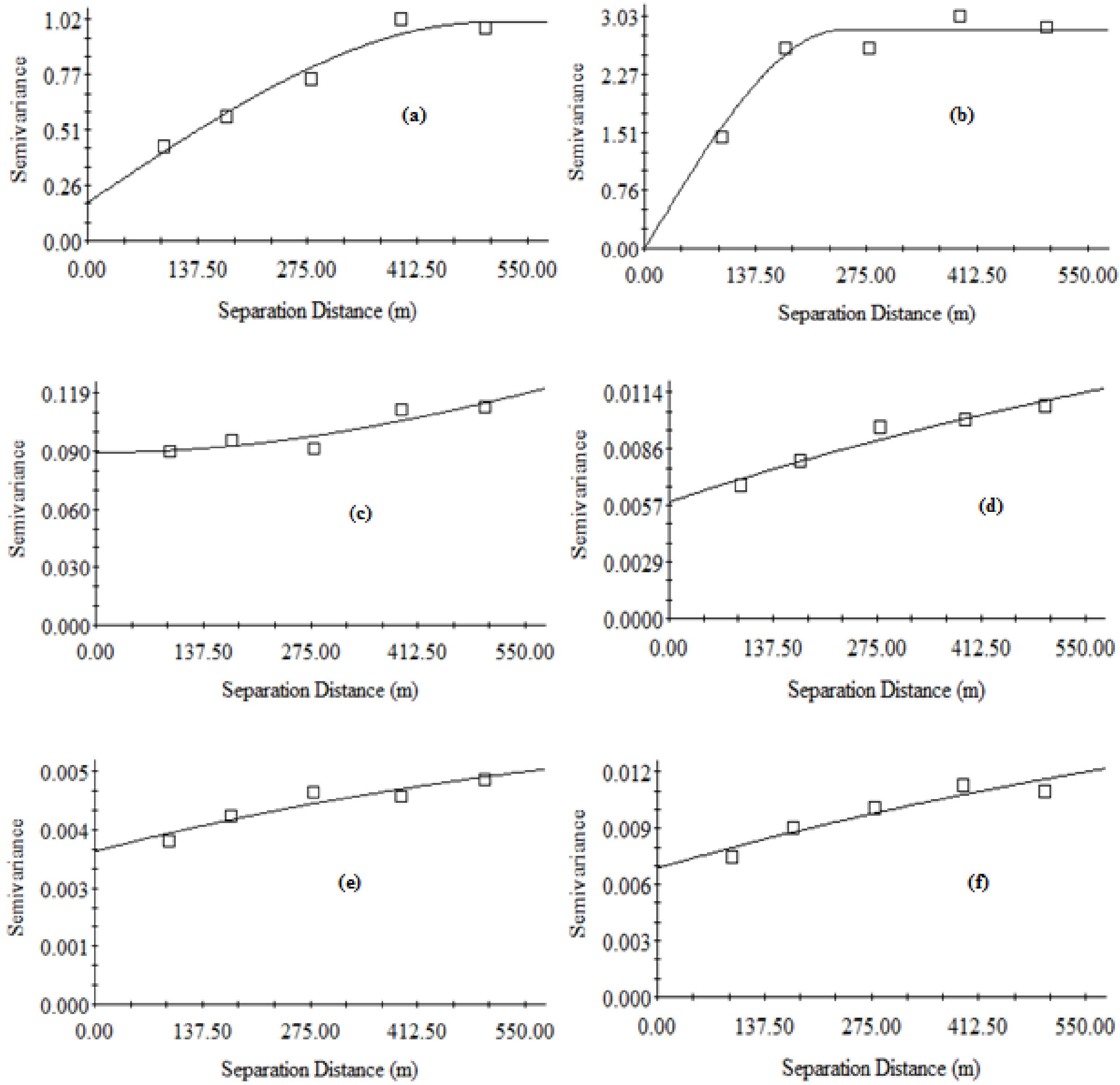

Figure 6-2. Fitted semivariogram for the selected soil property of (a) SOC using the Gaussian model, (b) AP using the Gaussian model, (c) pH using the Gaussian model, (d) clay using exponential model, (e) silt using exponential model and (f) sand using exponential model.

The semivariograms of SOC, AP and pH were well fitted to the Gaussian model and each of their R^2 is greater than or equal to 0.92, which suggest that SOC, AP, and pH had stronger spatial structure. The spatial analysis of SOC, AP and pH shows a clear structure with a strong to moderate relative nugget effect (0.18 to 0.52) (Table 6-2). A similar study by Cambardella et al. (1994) documented that pH and silt had strong spatial dependence. The ranges of spatial dependencies were large and differ between 118m for AP to 1110m for clay indicating that the optimum sampling interval varies greatly among different soil properties. The choice of a suitable sampling interval depends on the scale of the variation that the research wishes to resolve e.g. plot, field, catchment, administrative region and so on scale (Oliver and Webster, 2015). Ideally a large number of data locations generated from a very small sampling interval can be best but this increases the cost of collecting the data. As a rule of thumb, the sampling interval of less than half the range of the semivariogram can be used to guide the optimum sampling interval (Oliver, 2010; Oliver and Webster, 2015). Therefore, a 100m by 100m sampling interval could illustrate the variability of measured soil properties in the study area because all of the ranges of the observed soil properties except AP were greater than 200m (Table 6-2).

The quantitative summary of the performance of each interpolation method is shown in Table 6-3. In this study, 5 to 25 neighboring points were considered for each interpolation method as the numbers of neighboring points have a strong effect on the accuracy of the interpolation methods (Robinson and Metternicht, 2005; Li and Heap, 2008). Meanwhile, a power of 1, 2, and 3 were tested and the best weighting parameter for IDW was found to be a power of two. With regards to RBF, the five kernel functions were tested although the best kernel function was found to be completely regularized spline. Ordinary kriging for observed soil property and lognormal ordinary kriging for available phosphorous were also tested.

The ME, MSE and RMSE were calculated as measures of accuracy and the E, R^2 and d were determined as measures of effectiveness for each observed soil property (Table 6-3). The lowest RMSE for clay, silt and sand contents were found with a neighborhood of 15, 5 and 16 points, respectively. The lowest RMSE for SOC, AP and pH were found with a neighborhood of 5, 8 and 15 points, respectively. The predictions of the selected soil properties except AP were relatively unbiased as the ME was almost equals to 0 (Table 6-3).

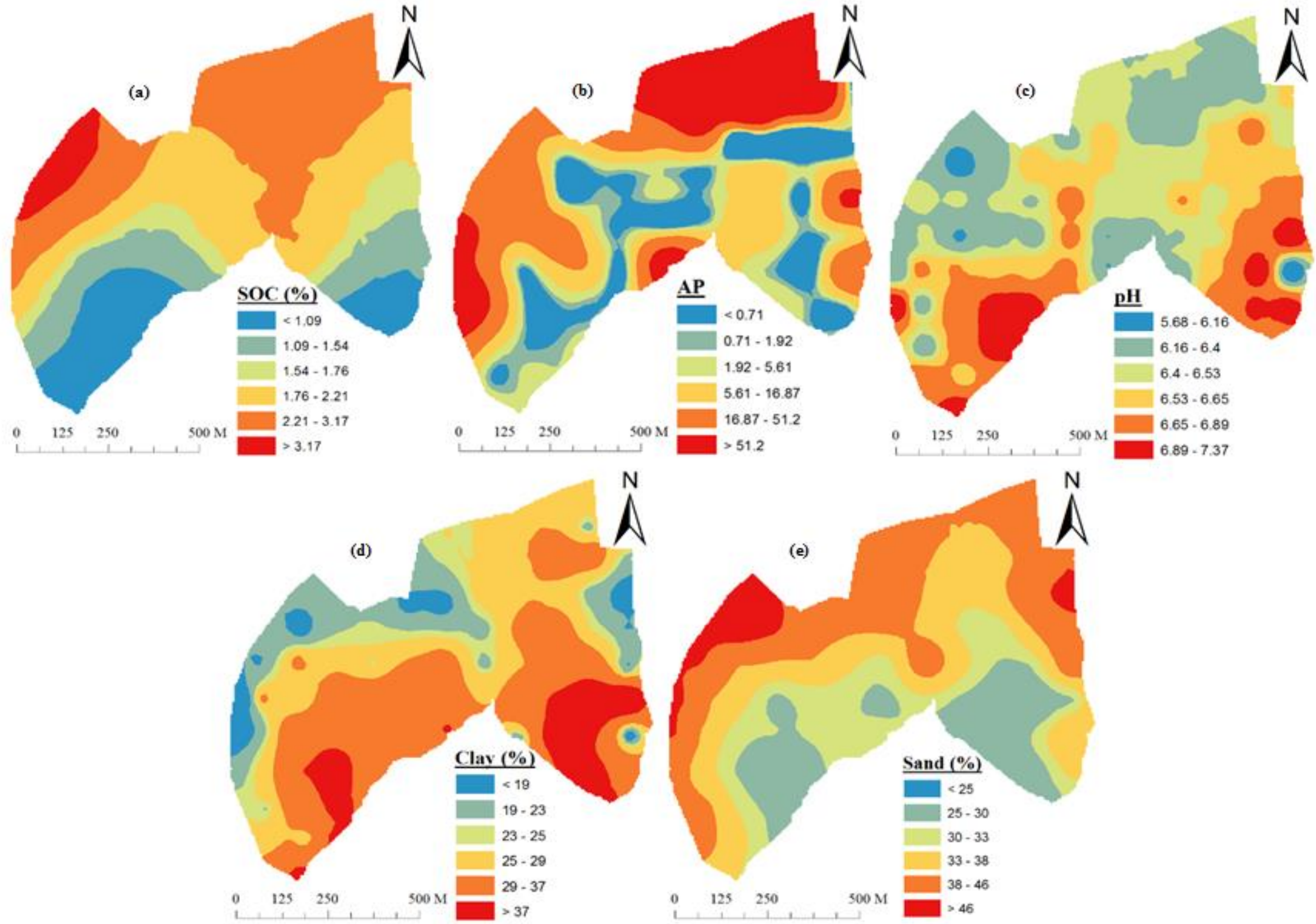

Figure 6-3. Best interpolated soil map of (a) SOC using ordinary kriging, (b) AP using RBF, (c) pH using IDW, (d) clay using RBF and (e) sand using ordinary kriging.

The interpolated maps generated based on the highest value of the E resulted from the cross-validation of the selected soil properties can be seen in Figure 6-3. Interpolation of SOC using the Gaussian model with the highest Nash-Sutcliffe efficiency value of 0.44 is shown in Figure 6-3A. The study area had SOC ranging from 0.13% to 5.22% and the highest SOC (> 3.17%) was occurred in northwest of Aba-Kaloye sub-watershed. The lowest SOC (0.13% to 1.54%) values occur on the central to the outlets of the sub-watersheds which were intensively cultivated. Interpolation of AP using RBF with the highest Nash-Sutcliffe efficiency value of 0.51 is shown in Figure 6-3B. AP content in the central part of the study area was less than the mean value (22.98 ppm), and area where AP content was twice the mean value was observed in northeast of Ayeye sub-watershed (Figure 6-3B). Interpolation of pH over the study sub-watersheds using IDW technique with E equals to 0.45 is shown in Figure 6-3C. These results disagreed with those found by Laslett et al. (1987) and Robinson and Metternicht (2005) where topsoil pH was better estimated by using OK than by using IDW. The observed soil pH data had a value ranged from 5.68 to 7.37 which suggests the area is very good for crop production. The area where pH was lower than the mean value (6.57) was observed in northwest of Aba-Kaloye sub-watershed, and area where pH was greater than the mean value was found around the outlets of the sub-watersheds (Figure 6-3C). Meanwhile, RBF proved to be the better method for interpolating clay content of the study sub-watersheds with the Nash-Sutcliffe efficiency value of 0.17 (Figure 6-3D). The area where clay contents was lower than the mean value (29.19%) was observed in northwest of Aba-Kaloye sub-watershed, and area where clay contents was greater than the mean value was found at the outlets of the sub-watersheds (Figure 6-3D). Exponential ordinary kriging proved to be the best method for interpolating sand contents with E equals to 0.17 (Figure 6-3E). The Nash-Sutcliffe efficiency for all measured soil properties except silt showed a positive value (Table 6-3). Silt was the only measured soil property for which the resulting Nash-Sutcliffe efficiency of each interpolation method had a negative value (less than –0.34), that suggested the prediction would have been more reliable if the sample mean had been used instead. The study showed the potential of various spatial interpolation methods as a tool for spatial continuous surfaces map generation but also the need for further studies. Overall, the cross-validation statistics for all of the spatial interpolation methods showed there was no single interpolation method that significantly outperformed the others which agreed with previous studies (Robinson and Metternicht, 2005; Karydas et al., 2009). Therefore, one of the interpolation methods could probable be applied for spatial continuous surfaces map generation of the measured soil properties in future studies of similar regions.

Table 6-3. Quantitative summary of the performance of the three interpolation methods for the study sub-watersheds.

	Interpolation methods																	
	OK[a]						IDW[a]						RBF[a]					
Variable	ME[b]	RMSE[b]	MSE[b]	d[b]	E[b]	R^2	ME	RMSE	MSE	d	E	R^2	ME	RMSE	MSE	d	E	R^2
SOC	0	0.72	0.51	0.78	0.44	0.44	-0.01	0.73	0.53	0.75	0.43	0.43	0	0.72	0.52	0.76	0.44	0.44
AP	1.48	32.35	1046.8	0.67	0.30	0.30	0.09	31.04	963.69	0.72	0.36	0.36	0.01	27.2	739.67	0.83	0.51	0.51
pH	0	0.32	0.1	0.58	0.16	0.17	0	0.3	0.1	0.65	0.18	0.19	0	0.33	0.11	0.59	0.17	0.17
Clay	0.06	9.34	87.17	0.58	0.15	0.17	0.04	9.28	86.09	0.61	0.16	0.17	0.04	9.23	85.21	0.62	0.17	0.18
Silt	0.03	7.49	56.17	0.33	-0.34	0	0.07	7.58	57.48	0.32	-0.37	0	0	7.49	56.15	0.33	-0.34	0
Sand	-0.08	9.51	90.44	0.64	0.17	0.18	-0.44	10.08	101.66	0.54	0.11	0.13	-0.09	9.99	99.89	0.57	0.14	0.16

[a] OK is ordinary kriging, IDW is inverse distance weight and RBF is radial base function.

[b] ME is mean error, RMSE is root mean square error, MSE is mean square error, d is index of agreement and E is Nash-Sutcliffe efficiency.

The spatial interpolation techniques used for each soil properties indicated that values of R^2 range from 0.00 to 0.51. The highest value of R^2, E and d (0.51, 0.51, and 0.83, respectively) resulted from the spatial interpolation of AP using RBF (Table 6-3). A comparison of E with R^2 displays the fact that the two criteria had a strong positive correlation with the correlation coefficient (r) equals to 0.92. The correlation between E and d was also significantly positively correlated (r = 0.98). Similarly, the correlation between R^2 and d was also significantly positively correlated (r = 0.96).

6.4 CONCLUSIONS

This study aims to analyze the performance of frequently used spatial interpolation techniques (IDW, OK and RBF) and determine the optimum spatial interpolation method for mapping of selected soil properties, which were sampled in mountainous agricultural sub-watersheds, Ethiopia. The descriptive analyses revealed that AP, SOC and clay contents were the most variable soil properties, with CV greater than 0.35 while, silt and sand contents were moderately variable, with CV vary from 0.18 to 0.30. Cross-validation was used to get the best agreement between the observed data and the predicted values of selected spatial interpolation methods. This study considered 5 to 25 neighboring points for each interpolation method. Meanwhile, the five kernel functions and a power of 1, 2, and 3 were tested for RBF and IDW, respectively. The best kernel function for RBF was found to be completely regularized spline, while the best weighting parameter for IDW was found to be a power of two.

The predictions of the selected soil properties except AP were relatively unbiased as the mean errors were almost equals to 0 and the Nash-Sutcliffe efficiency for each soil property except silt showed a positive value ($E \geq 0.17$). When comparing the resulting values of the efficiency criteria, for each interpolation technique, the OK method was best performed for SOC and sand contents. RBF method was produced more accurate maps for AP and clay contents, while IDW performed best for interpolating topsoil pH. The surface maps for the selected soil properties indicated that values of R^2 range from 0.00 to 0.51. The highest value of R^2, E and d (0.51, 0.51, and 0.83, respectively) resulted from the spatial interpolation of AP using RBF. Overall, the results of the cross-validation statistics for each spatial interpolation method showed that there was no single interpolation method that can be considered significantly outperformed the others; hence, one of the interpolation method could be applied for surface map generation of a soil property in future studies of similar regions.

General, the study shows the potential of various spatial interpolation methods as a tool for surface map generation but also the need for further studies. Therefore, future research in the area should consider the different approaches which include various spatial interpolation methods, land management practices, landuse and topographic conditions to improve the performance of each spatial interpolation method. Finally, environmental models which use soil map as an input might consider the influence of the soil map produced by different spatial interpolation techniques.

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7. Modeling Streamflow and Sediment using SWAT in the Ethiopian Highlands[6]

Abstract

The coincidence of intensive rainfall events at the beginning of the rainy season and the unprotected soil conditions after exhaustive dry spells expose the Ethiopian Highlands to severe soil erosion. Soil and water conservation measures (SWC) have been applied to counteract land degradation in the endangered areas, but SWC efficiency may vary related to the heterogeneity of the landscape. The Soil and Water Assessment Tool (SWAT) model was used to model hydrology and sediment dynamics of a 53.7 km^2 watershed, located in the Lake Tana basin, Ethiopia. Spatially distributed stone bund impacts were applied in the model through modification of the surface runoff ratio and adjustment of a support practice factor simulating the trapped amounts of water and sediment at the SWC structure and watershed level. The resulting Nash-Sutcliffe efficiency (NSE) for daily streamflow simulation was 0.56 for the calibration and 0.48 for the validation period, suggesting satisfactory model performance. In contrast, the daily sediment simulation resulted in unsatisfactory model performance, with the NSE value of 0.07 for the calibration and –1.76 for the validation period and this could be as a result of high intensity and short duration rainfall events in the watershed. Meanwhile, insufficient sediment yield prediction may result to some extent from daily based data processing, whereas the driving runoff events and thus sediment loads occur on sub-daily time scales, probably linked with abrupt gully breaks and development. The calibrated model indicated 21.08 Mg ha^{-1}average annual sediment yield, which is far beyond potential soil regeneration rate. Despite the given limits of model calibration, SWAT may support the scaling up and out of experimentally proven SWC interventions to encourage sustainable agriculture in the Ethiopian Highlands.

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[6] Addis, H.K., Strohmeier, S., Ziadat, F., Melaku, N.D., and Klik, A., 2016. International Journal of Agricultural and Biological Engineering, 9(5): 51-66.

7.1 INTRODUCTION

The rise of the human civilizations is directly linked with the cultivation of the land and thus, inevitably, with land degradation[1]. Human interventions, such as deforestation for agricultural food production, the cultivation of marginal lands, overgrazing and the exploitation of soil fertility accelerate soil erosion[2] and subsequent soil depletion is accompanied with reduced crop productivity[3]. Ongoing land degradation endangers the agricultural productivity in many areas around the globe[4], and undoubtedly, the Ethiopian Highlands are among the most affected. Various impacts and consequences of the severe land degradation in the Ethiopian Highlands have been reported by Hurni[5]. The extensive famines in 1973 and 1984, as an alarming consequence of droughts and low crop productivity, initiated governmental rethinking concerning rural land management[6]. The Ethiopian government responded with large scale rehabilitation measures and the establishment of various soil and water conservation (SWC) interventions across the country to counteract the ongoing soil depletion[6,7].

From the beginning of agricultural activities different SWC techniques have been developed[8] mainly to retain soil fertility and thus crop productivity. Various SWC techniques and their variable impacts have been intensively discussed in the literature[7,9]. In particular for the Ethiopian Highlands SWC management through stone bunds was found as sound practice for soil erosion control[10]. Stone bunds are elevated structures intersecting a hillslope in specific intervals[7], resulting in decreased surface runoff and sediment yield through slope length reduction and the creation of a small retention area[11]. However, SWC interventions are often uniformly applied across landscapes but may only be reasonable for certain field conditions. In fact, field conditions are often highly variable in the Ethiopian Highlands[12]. Therefore, site specific assessment of the most influential watershed processes may be crucial for the development of efficient conservation measures.

At present, many models with a broad spectrum of concepts, which were classified as spatially lumped, spatially distributed, empirical, regression, semi-distributed eco-hydrological model and factorial scoring models, are in use for modelling the rainfall–runoff–soil erosion and sediment transport processes at different scales[13]. The Soil and Water Assessment Tool (SWAT) is a semi-distributed eco-hydrological model. SWAT is one of the most widely used watershed models, which was developed by the United States Department of Agriculture-Agricultural Research

Service (USDA-ARS)[14] and can be used to predict agricultural land management impacts on the hydrological regime of a watershed through simulation of variable soil, land use and management conditions over long periods[14,15]. In Ethiopia, SWAT has been used in a number of studies to predict streamflow and sediment yield[16–21] with different outcomes and recommendations concerning the usability of the semi-distributed eco-hydrological model for remote landscapes. In fact, large areas of the Ethiopian Highlands are still under investigated and therefore proper model input and particularly calibration data (such as streamflow and sediment yield) are scarce, which might impede proper model calibration and validation in many cases. Various studies[13,22] have shown that advanced erosion models suffer from the lack of available input data especially for large scale application. Conclusively, there remains extensive need to evaluate semi-distributed eco-hydrological watershed modeling in the Ethiopian Highlands.

The study reported here was performed in the context of a multidisciplinary international research project that is being conducted within the Gumara-Maksegnit watershed which is located in the Lake Tana basin in the Amhara region of Ethiopia. Integrated watershed research is being conducted, including several soil, crop, hydrology and agro-environmental related analyses, to gain a deeper insight into watershed scale hydrology and land degradation issues, evaluate various soil and water conservation interventions and to aim for an improved livelihood of stakeholders living in the watershed. The spatial assessment of surface runoff and sediment yield within Gumara-Maksegnit study site using SWAT is a key component of the overall research project. The model case study was conducted: (1) to assess the applicability of SWAT for simulating the key watershed processes of a remote and mountainous agricultural watershed, and (2) to evaluate the impact of spatially distributed soil and water conservation (SWC) structures on surface runoff and soil erosion. Eventually, the study aims for the establishment of a well-calibrated semi-distributed eco-hydrological model as a tool for evaluating multiple land management practices suitable for reduction of sediment transport, which can be scaled up to assess proper SWC strategies and to counteract ongoing land degradation at a broader scale.

Figure 7-1. Overview of the project watershed area in the northwest Amhara region, Ethiopia

7.2 MATERIALS AND METHODS

7.2.1 Description of the study watershed

The Gumara-Maksegnit watershed, is located in the Amhara region in northwest Ethiopia between 37°33′00″–37°37′00″E and 12°24′00″–12°31′00″N (Figure 7-1). The confined watershed area is 53.7 km^2 based on an ArcGIS watershed delineation using a 90 m grid Digital Elevation Model (DEM) produced by SRTM (*Shuttle Radar Topography Mission*)[23]. The watershed elevation ranges from 1,920 m (outlet) to 2,850 m above sea level in the north, while the hillslopes range from nearly flat (< 2%) to extremely steep (> 70%) (Figure 7-2a). The northern part of the watershed, Denkez Mountain Ridge, borders to Tekezi Basin, while the Gumara-Maksegnit watershed is part of the Blue Nile River Basin. The watershed geology is dominated by a Trap Series of Tertiary volcanic eruptions[24], which are commonly described by their degree of oxidation as exemplified by the frequent dominance of ferric over ferrous iron and by the abundant water content[24]. The main soils are Cambisol and Leptosol in the upper and central part of the watershed and Vertisol in the lower part near the outlet. The Gumara-Maksegnit River is the main stream of the study watershed, which part of the Lake Tana drainage basin. Lake Tana is the origin of the Blue Nile River and the largest lake in Ethiopia. The Gumara-Maksegnit River discharges continuously throughout the year and is characterized by several flood events during the rainy season versus drastically decreased flow during the dry season. The climate of the Gumara-Maksegnit watershed is characterized by the 'Woina Dega' zone (cool semi-humid) between 1,920 m to 2,400 m above sea level, and the 'Dega' zone (cool) above 2,400 m. The majority of the watershed area is located within the cool semi-humid zone at an elevation of 1,920 m to 2,400 m above sea level. The climate is dominated by distinct wet and dry periods. The wet season typically occurs from June to September and the dry season occurs from November to April, while May and October are transition months. The mean annual rainfall in the watershed is 1,200 mm of which more than 90% occurs during the rainy season (June to September). The average monthly maximum and minimum temperatures recorded from 1997 to 2013 were 31.8°C for March and 10.8°C for January.

7.2.2 SWAT model

The SWAT model is a semi-distributed eco-hydrological continuous event watershed-scale model usable to evaluate the impact of different land management practices on surface and subsurface water movement, sediment, and agricultural chemical yields in complex watersheds with different soil, land-use and management conditions[25]. ArcSWAT, as an ArcGIS interface[26], uses GIS spatial algorithms to spatially link multiple model input data, such as watershed topography (DEM), soil, land use, land management and climatic data. During watershed delineation, the entire watershed is divided into different sub-basins. Then, each sub-basin is discretized into a series of Hydrologic Response Units (HRUs) as the smallest computation unit of a SWAT model, which are characterized by homogeneous soil, land use and slope combinations. Daily climate input data for defined locations (mostly related to ground weather stations) are spatially related to the different sub-basins of the model using a 'nearest neighbor' GIS algorithm. Different model outputs, such as surface runoff, sediment yield, soil moisture, nutrient dynamics, crop growth etc., are simulated for each HRU, aggregated and processed to sub-basin level results on a daily time step resolution.

SWAT provides different runoff routing techniques for both surface runoff and streamflow. In this study, surface runoff was computed using the USDA (United States Department of Agriculture) NRCS (Natural Resources Conservation Service) approach[27], while channel routing was processed by Muskingum routing method[28]. The NRCS method was chosen to enable user friendly and comprehensive consideration of soil and water conservation (SWC) impacts. A number of methods with varying data requirements for evapotranspiration (ET) estimation are incorporated in SWAT: for this study the Hargreaves formula[29] was used. In SWAT, up-land soil erosion is computed based on the Modified Universal Soil Loss Equation (MUSLE)[29], which allows the consideration of a support practice factor representing supposed SWC effects on sediment loss.

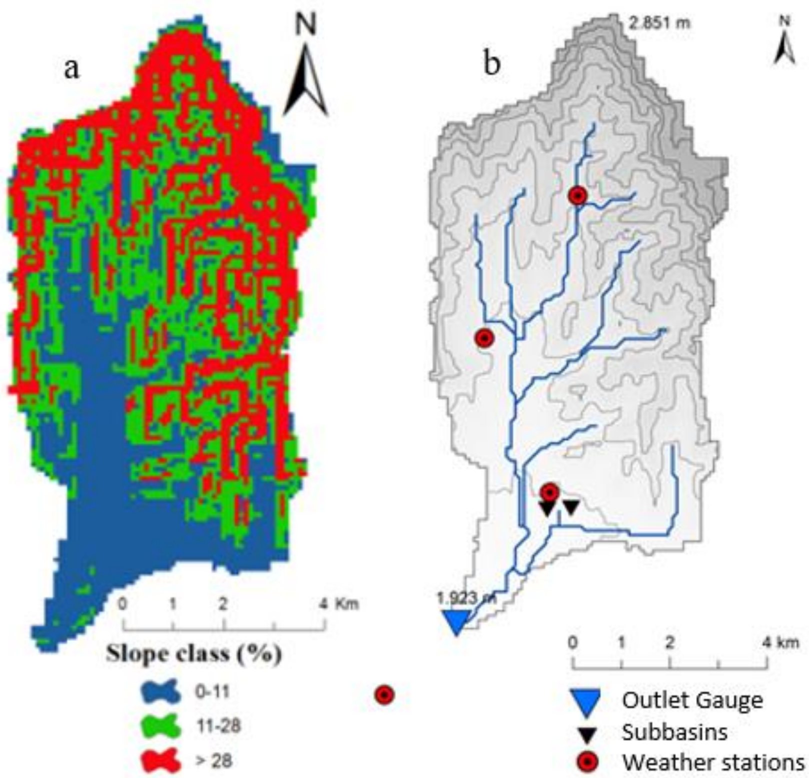


Figure 7-2. Gumara-Maksegnit watershed maps showing (a) slope classes, and (b) elevation data and location of weather stations and subbasins included in stone bund experiment assessment discussed in Section 2.3.5.

7.2.3 Input data

SWAT input data in developing countries (such as Ethiopia) are usually not readily available and are often difficult to collect, and data availability is even more limited for good quality calibration and validation data. Amongst the acquisition of various remote sensing sources for DEM and land use input preparation, comprehensible field sampling and hydrological monitoring were a central task of the Gumara-Maksegnit watershed study.

7.2.4 DEM (Digital Elevation Model)

For this study, the 90 m grid cell DEM, produced by SRTM (*Shuttle Radar Topography Mission*)[23] was used to obtain the topographic characteristics of Gumara-Maksegnit watershed. Then, the watershed had been divided into three slope steepness classes, namely: 0°–11° (18.77 km^2), 11°–28° (17.66 km^2) and greater than 28° (17.26 km^2) (Figure 7-2a).

7.2.5 Climate

Climate input data required by SWAT includes daily precipitation, maximum and minimum temperature, relative humidity, half hour rainfall, wind speed and solar radiation. Required daily precipitation and maximum/minimum air temperature data was collected at four different weather stations located within (three stations) and slightly outside (one station) the watershed (Figure 7-2b). Daily solar radiation, relative humidity, and wind speed data were recorded at a different metrological station slightly outside the study watershed (Figure 7-2b). The SWAT weather generator[30] was used for simulating missing daily weather data. The daily climatic data (from January, 1, 1997 to December, 31, 2013) recorded at the weather station, which was located slightly outside the watershed (Figure 7-2b) was used to create the monthly weather statistics using the weather generator.

7.2.6 Land use

Land cover map for this research was produced on the pixel based supervised classification of 10 m spot satellite image (Figure 7-3a). The study watershed has three major land-use classes (Figure 7-3b) and is mainly covered by agricultural land (63.5%) followed by mixed forest (24.3%), and grazing land (12.2%). The agricultural land was further subdivided into six major agricultural crops: tef (*Eragrostis Tef*) (30.0%), sorghum (13.2%), barley (6.9%), fava bean (5.6%), winter wheat (4.3%) and chickpea (3.5%). Tef is a minor cereal crop on a global scale, but a major food grain and lovegrass (lovegrass is commonly used as livestock fodder) in Ethiopia and Eritrea and this annual crop can be grown under a wide range of conditions[31]. Tef and sorghum are the main staple crops, whereas chickpea is grown in the lower regions and cannot be grown in the higher altitude.

7.2.7 Soil

SWAT requires multiple soil physical and chemical attributes for various soil depths such as soil texture, bulk density, stone content, organic carbon, hydraulic conductivity, soil erodibility, etc.,[32]. At least one software package is available which can be used to calculate the spatial distribution of various soil properties for environmental modeling using selected input parameters[33]. Nevertheless, good quality field sampling data may be used preferentially. In this study, an intensive field sampling campaign was carried out to determine various soil properties in a 500 m by 500 m grid over the entire watershed. A total of 234 soil samples were collected using a bucket auger. At each location approximately 2 kg bulk soil samples from different soil layers (0–25), (25–60) and (60–100 cm) were taken for physical and chemical analysis. Undisturbed soil core cylinder samples were taken from the topsoil layer to determine bulk density following previously developed procedures[34]. Soil texture was measured based on an earlier published method[35], and organic carbon was determined by a wet oxidation method[36]. Available water content and hydraulic conductivity for each layer as well as bulk density for the second and third layer were assessed using a pedotransfer function developed by Saxton and Rawls[37]. Nevertheless, the most important soil data impacts were manually determined based on the previously described intensive field sampling results. The soil map that describes the distribution of different soil textural classes of the study watershed is presented in Figure 7-3c.

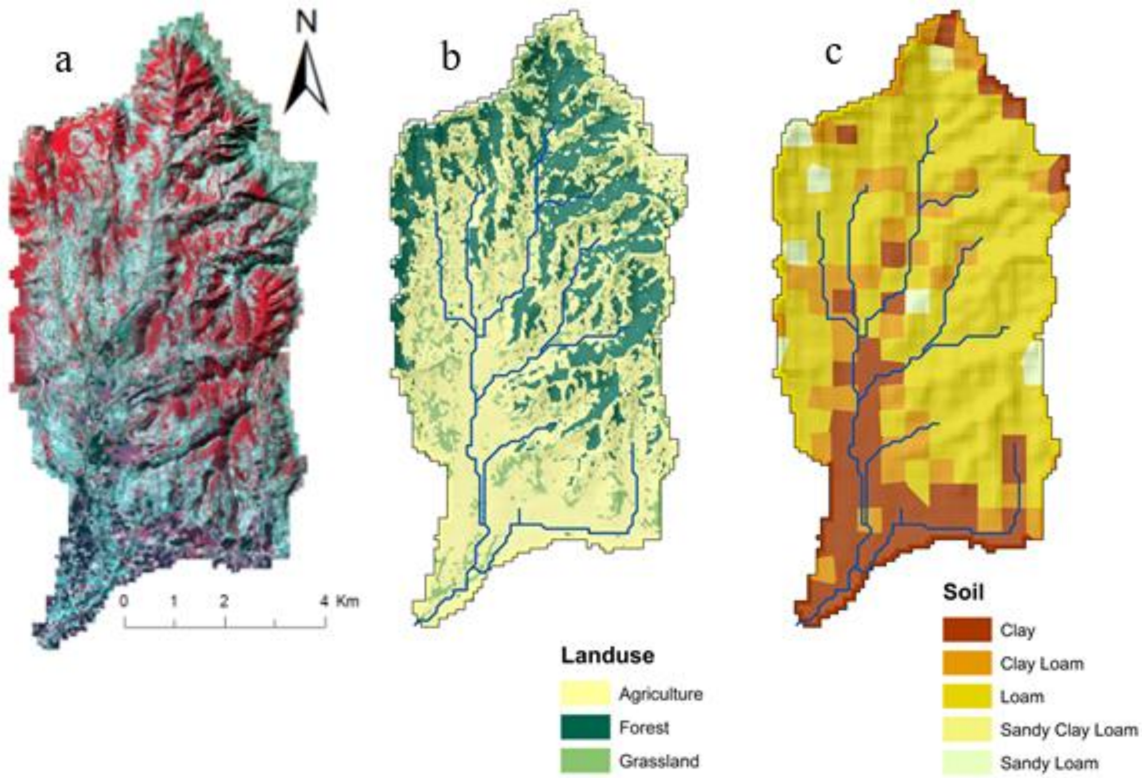
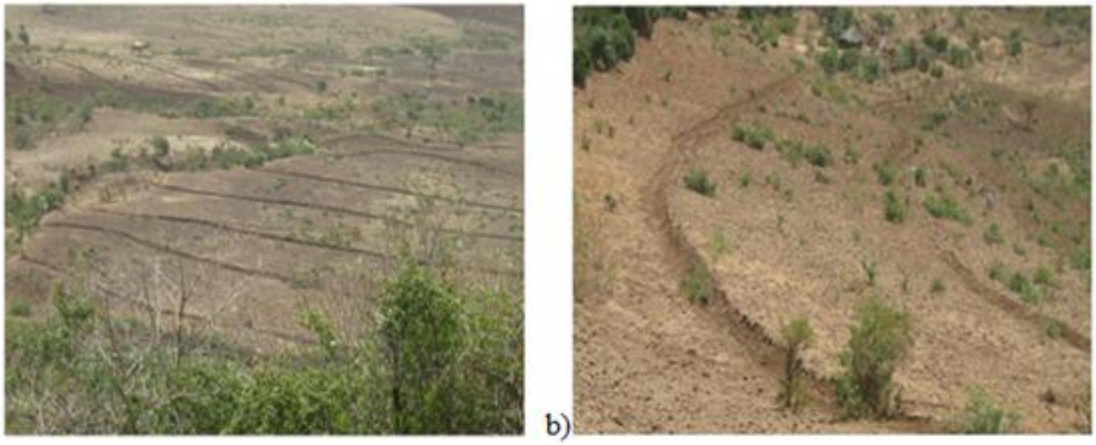


Figure 7-3. The Gumara-Maksegnit watershed: (a) spot satellite image, (b) three major land cover categories, and (c) soil textural class maps

7.2.8 Soil and Water Conservation (SWC) Interventions

Different SWC practices have been applied in the Gumara-Maksegnit watershed such as stone bunds, micro water harvesting ponds, trenches and semi-circular stone bunds (Figure 7-4). However, linear (slightly graded) stone bunds are the predominant practice, which affect large agricultural areas in the central and the lower part of the watershed. Locally installed harvesting ponds (four structures applied within the watershed), trenches and semi-circular stone bunds may have a positive effect on runoff and soil erosion at the field level, but based on their local or minor areal extent these structures have limited effect on watershed level hydrology or sediment dynamics. Thus, stone bunds were the only SWC interventions considered during watershed modeling and approximately 50% of the study watershed is presently treated with the stone bunds. As described by Bosshart[11], SWC impacts of stone bunds are mainly related to the reduction of surface runoff and sediment yield by intersecting hillslope lengths in specific intervals and the ponding effects that occur at each structure. In the course of the Gumara-Maksegnit watershed study, different plot level as well as sub-basin level experiments were carried out[38] to investigate the effects of stone bunds on surface runoff and soil loss, and moreover, to enable the implementation of SWC impacted in SWAT modeling. SWAT provides various options to consider SWC impacts[32] including: (1) surface runoff may be modified through the adjustment of the runoff ratio (Curve Number) and/or the consideration of a micro-pond (pothole) at the related HRU level, which will also impact soil erosion, and (2) impacts on sediment yield levels via adjustment of the support practice factor (P-factor) and/or the slope length factor (LS) of the MUSLE[39]. The ideal factors that describe the effect of stone bunds are the USLE support practice factor (P-factor), the Curve Number and average slope length (SLSUBBSN). In this study, the SLSSUBSN value was modified by editing the HRU (.hru) input table, whereas the P-factor and Curve Number values were modified by editing Management (.mgt) input table.

The 53.7 km^2 Gumara-Maksegnit watershed was discretized into 15 sub-basins and 2799 HRUs for the SWAT simulations. The high number of HRUs for the study watershed occurred as a result of the 234 user defined soil name, the 3 slope classes and the 9 landuse type interactions. However, a coarse DEM mesh used as an input for this study was one of the limitations. The study watershed is composed of rugged topography with different management practices; thus, the 234 soil sampling points are considered totally different and the study did not set a threshold that eliminates minor soil types. Therefore, every HRU for the study watershed corresponds an average area of 1.9 ha. Similarly, Zabaleta[40] used 165 HRUs for a 4.8 km^2 watershed in Spain, which averaged about 2.9 ha per HRU.



a) b)

Figure 7-4. Stone bund treated fields (a) and the small channel above the stone bund (b)

The impact of stone bund SWC structures was simulated through reduction of the Curve Number (CN_2) for surface runoff ratio modification as well as the adjustment of the support practice factor (P-factor) to account for the amount of trapped sediments at the stone bunds. The effect of stone bunds on runoff and soil erosion was initially assessed during the erosion plot experimental campaigns in 2012 and 2013, based on the comparison of treated and untreated sub-basins located in the watershed (this activity is still ongoing). Based on the plot experiments carried out in 2013[41], stone bund structures were found to reduce surface runoff by approximately 60 to 80% and sediment yield between 40 to 80%. This is consistent with other plot experimental findings reported by Adimassu[42], where stone bunds reduced sediment yield by roughly 50% compared to untreated plots. However, plot experiments tend to reflect optimized stone bund conditions for just a very limited area. In fact, the stone bund plot experiments carried out in Gumara-Maksegnit do not account for cumulative hillslope lengths or the overall length of the stone bund walls and thus how much total area those affect, which may lead to considerably lower SWC impacts at a farm or sub-basin level. For the sub-basin level experiment, (Figure 7-2b), where the area of each sub-basin is approximately 30 ha, the difference of measured surface runoff between treated and untreated sub-basins was around 30%. However, the measured sediment yield declined by only approximately 10% during the 2012 rainy season, which is not consistent with the results reported by Gebremichael[43]. These results include a large range of uncertainty particularly for sediment yield, but also due to only a few synchronically recorded rainfall events in the treated and untreated sub-basins (Figure 7-2b). Moreover, the comparability of different sub-basins is limited as a result of the inherent landscape and rainfall related variability, even though the sub-basins border each other and the soil, slope, and landuse conditions are generally homogenous. However, the current

SWC impact research is ultimately designed to provide comprehensive SWC assessment and conclusive modeling parameters. Hence, as an early stage assessment, the CN_2 was reduced for agricultural HRUs in the treated areas with the target to achieve overall surface runoff reduction of about 30% on treated HRU's compared to untreated conditions. The P-factor was set equal to 0.85, because: (1) the CN_2 reductions already leads to reduced soil erosion on the treated areas, and (2) as a compromise between plot and sub-basin level sediment yield ratio outcomes. A small range of variability was assigned to the defined CN_2 and P-factor parameter sets during the calibration procedure, which allowed additional minor adjustments during the automated model optimization. These assumptions result in the stone bunds essentially replicating the effects of terraces[16], in terms of how the average slope length (SLSUBBSN) is modified to represent terrace effects in cropped landscapes.

7.2.9 Calibration and validation data

Different calibration approaches can be used in SWAT with respect to frequency and quantity of observation data available for model calibration. Nevertheless, the most powerful calibration is usually achieved through following a specific calibration order as suggested by Arnold[44]. In particular, streamflow data at the sub-basin or watershed level are required to perform accurate model hydrologic balance and streamflow calibration, followed by calibration of different pollutants such as sediment load, nutrient yields and other water quality variables. The calibration procedure is typically based on initial sensitivity analysis results (using a set of sensitive parameters) and is executed either manually or automatically[44,45]. Calibrations can be performed manually, which can be important for clearly understanding some processes[44]. However, automated calibration is more efficient for some applications[46], especially for complex hydrologic models. Different datasets may be required to evaluate model performance for different environmental conditions[45]. However, the number of attributes and the observation period required for proper consideration of the driving watershed processes may vary from site to site. Long term and good quality data is especially rare for the Ethiopian Highlands. In the present study, the entire simulation period is limited to field observation data from 2011 to 2012 (calibration) and 2013 (validation). The calibration/validation model run was performed with a warm-up period of seven years to minimize the effect of non-equilibrium initial conditions such as soil moisture or residue cover[47]. In this research, daily streamflow and sediment yield recorded at the outlet of the watershed were used for both calibration and validation of the model.

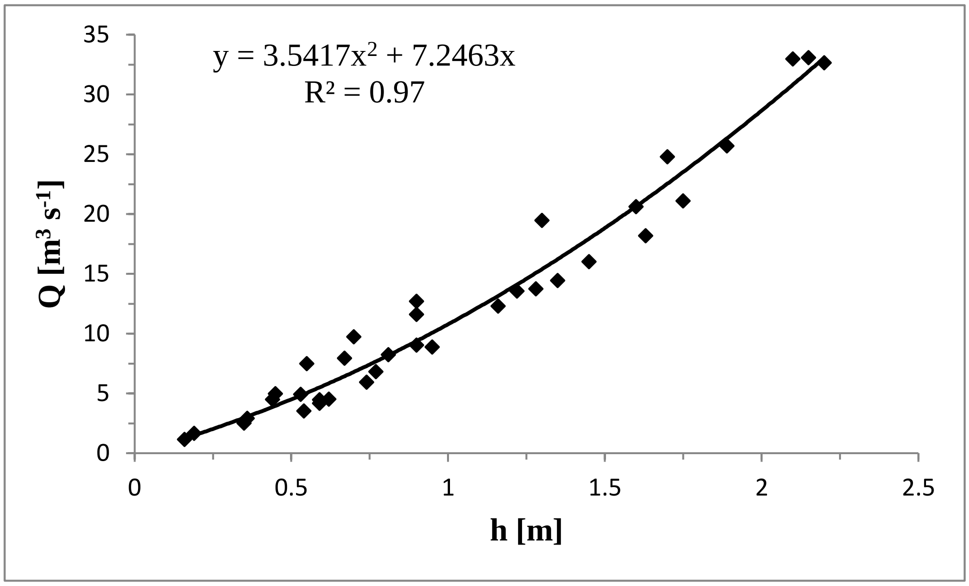


Figure 7-5. Established rating curve at the outlet of Gumara-Maksegnit Watershed[48]

Streamflow was obtained by converting quasi-continuous water level (m) records (using pressure transducer) into flow (m s^{-1}) based on an experimentally developed water level and discharge rating curve[48] (Figure 7-5). The respective rating curve was established based on water level and manual flow velocity measurements using a one-dimensional flow velocity device analyzing several runoff events. The outlet of the watershed was constructed as a fixed cross section, which was built from stones, concrete and gabions to ensure an explicit and constant relationship between water level and discharge. Hysteresis effects related to the different stages of a peak wave (arriving and leaving) were found to have negligible impact on the calculation of the daily discharge, considering various sources of uncertainty (such as measurement errors and gaps). Moreover, a turbidity sensor was installed at the side wall of the fixed cross section to gain insight into sediment dynamics of the main stream. The turbidity meter was calibrated in the laboratory using on-site sediments to assess the fraction of suspended soil (g l^{-1}) in water related to indirect light signal measurement. However, considerable data uncertainty has to be taken into account and the derived sediment concentrations may be used to describe general sediment dynamics solely. According to this, quasi-continuous turbidity readings were controlled and adjusted based on manual bottle sampling throughout the runoff monitoring period. Streamflow and sediment yield, which were derived through multiplying sediment concentration with the according flow volume, were compiled on a daily basis usable for SWAT calibration. Figure 7-6 shows the derived hydrograph for the main outlet during approximately the four month rainy season in 2013. However, several unmeasured sediment concentration and streamflow data, mainly due to sensor failures or power supply errors, reveal the challenging monitoring conditions that exist at the site.

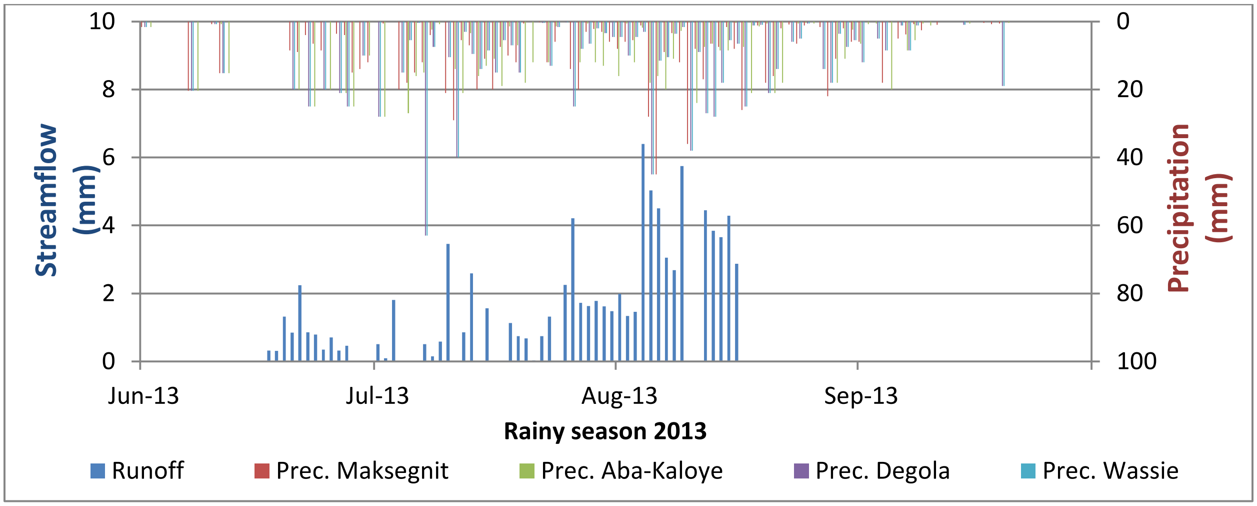


Figure 7-6. Hydrograph at the main outlet and precipitation data of the four rain gauge stations in Gumara-Maksegnit watershed

7.2.10 Model efficiency assessment

Efficiency criteria are defined as a mathematical measure of how well a model simulation matches corresponding observed data[45]. SWAT calibration procedures, including the SWAT-CUP calibration tool, provide multiple model efficiency criteria to be used as an objective function for model calibration and validation[49]. The ‘Sequential Uncertainty Fitting 2’ (SUFI-2) procedure, available within SWAT-CUP software, was used to perform model sensitivity analysis, calibration and validation procedures[49] through iterative variation of user defined parameter sets. The SUFI-2 algorithm accounts for various sources of uncertainty such as input data uncertainty, conceptual model uncertainty and parameter uncertainty[50]. In the present study, the goodness of the model fit related to streamflow and sediment yield was assessed based on root mean squared error (RMSE), Nash–Sutcliffe efficiency (NSE), percent bias (PBIAS) and coefficient of determination (R^2). However, during the SWAT-CUP calibration multiple simulations are executed accounting for the user-adjusted set of parameters and related parameter ranges. This procedure can result in a very large set of simulations, depending on the number of parameters selected for calibration, the user-adjusted range for parameter variation and the selected calibration methodology (including the number of iterations, parameter range discretization etc.).

7.2.10.1 Root mean square error (RMSE)

The root mean square error (RMSE) has been used as a standard statistical metric to measure model prediction error in meteorology, air quality, and climate research studies; a smaller RMSE value indicates better model performance[51]. Although RMSE is sensitive to outliers as it places a lot of weight on large errors, it has been developed to confirm the reliability of models[52]. The RMSE does not provide information about the relative size of the average difference and the nature of differences comprising them[53]. The RMSE is calculated with the following equation:

$$RMSE = \left[\frac{1}{n}\sum_{i=1}^{n}(E_i - O_i)^2\right]^{1/2} \qquad [7\text{-}1]$$

7.2.10.2 Nash-Sutcliffe Efficiency (NSE)

The Nash-Sutcliffe efficiency is a normalized statistic that determines the relative magnitude of the residual variance (“noise”) compared with the measured data variance (“information”)[54]. The Nash-Sutcliffe efficiency is calculated as:

$$NSE = 1 - \frac{\sum_{i=1}^{n}(E_i - O_i)^2}{\sum_{i=1}^{n}(O_i - \bar{O})^2} \qquad [7\text{-}2]$$

The range of E lies between $-\infty$ and 1.0 with E = 1 describing a perfect fit. Values between 0.0 and 1.0 are generally viewed as acceptable levels of performance, whereas values < 0.0 indicate that the mean observed value is a better predictor than the model[55].

7.2.10.3 Percent bias (PBIAS)

Percent bias (PBIAS) is defined as the average tendency of the observed data compared with their simulated counterparts[56]. The negative values of PBIAS indicate model overestimation bias, and positive values indicate model underestimation bias. The optimal value of PBIAS is 0.0, with low-magnitude values indicating accurate model simulation[45]. PBIAS is calculated with the following equation:

$$\text{PBIAS} = \left[\frac{\sum_{i=1}^{n}(O_i - E_i) * 100}{\sum_{i=1}^{n}(O_i)}\right] \qquad [7\text{-}3]$$

7.2.10.4 Coefficient of determination (R^2)

The coefficient of determination R^2 is defined as the squared value of the coefficient of correlation[57]. It is calculated as follows:

$$R^2 = \left[\frac{\sum_{i=1}^{n}(O_i - \bar{O})\,(E_i - \bar{E})}{\sqrt{\sum_{i=1}^{n}(O_i - \bar{O})^2}\sqrt{\sum_{i=1}^{n}(E_i - \bar{E})^2}}\right]^2 \qquad [7\text{-}4]$$

Where n: Number of observations or samples; O_i: Observed value; E_i: Estimated values; Ō: Mean of observed values; Ē: Mean of estimated values; i: counter for individual observed and predicted values.

The range of R^2 lies between 0 and 1, and describes how much of the observed value is explained by the predicted value[55]. A value of 1 means the predicted value is equal to the observed value, where a value of zero means there is no correlation between the predicted and observed values.

7.3 RESULTS AND DISCUSSION

In the Ethiopian Highlands, erratic and intensive rainfalls during the rainy season generate several peak runoff events (Figure 7-6), exposing steep sloped areas to potentially severe soil erosion. In SWAT, rainfall erosive impacts are estimated mainly as a function of the intensity and duration of rainfall events. The hydrograph at the outlet of the study watershed is dominated by the short period peak flows, occurring several times weekly whereas mean base flow was observed between 1 and 2 $m^3\ s^{-1}$ during rainy season of the calibration periods. Intense rainfall events correspond to peak flows on daily time scale which states that rainwater is routed through the watershed in sub-daily time intervals. This refers to the steep sloped and the rugged mountainous watershed as well as the convective rainfall characteristics in the Ethiopian Highlands. At the outlet, peak discharges of about 30 $m^3\ s^{-1}$ have been observed during the 2012 rainy season whereas extreme floods are expected to exceed this amount several times. In contrast, the SWAT model derives maximum mean daily discharges of less than 10 $m^3\ s^{-1}$ for the whole calibration period of the 2011 rainy season. This may be due to the daily based runoff computation which can't adequately account for intense storms of short duration. Rainfall records for the Aba-Kaloye weather station (2011-2013); located in the lower central part of the watershed, suggest that more than 50% of the annual maximum daily rainfall occurs within 30 minute time periods during intense storms (Table 7-1). Considering the relatively small watershed area, Gumara-Maksegnit flood events are characterized by relatively short time periods (sub-daily) and distinct peak flows. Based on a simulation of the whole period of available climate input data (1997-2013), the calibrated model estimates 352 mm of average annual surface runoff, whereas recharge to the deep aquifer is approximately 19 mm, and entirely, more than 31% (373 mm) of rainwater balance is used for evapotranspiration. This low amount of ET in the study watershed was found to be attributable to land use/land cover change, mainly from expanding agricultural activities, as it was described by Alemu[60]. Generally, from field observation more water is drained out of the watershed as a result of the minimum soil conservation coverage, landuse change and the steep slope nature of the study watershed. In contrast, a similar studies by Yesuf[58] and Gebremicael[59] showed that 48% and 53% of the precipitation was converted to ET, respectively.

Table 7-1. Annual maximum series rainfall in units of millimeters for Aba-Kaloye weather station

Year	15m[1*]	30m	1h	3h	6h	12h	24h	48h	72h[2*]
2011	20.2	38.6	42.6	47.4	54.6	68.2	74.6	94.4	119.2
2012	16.8	29.6	37.2	40.4	42.8	54.6	58.8	69.6	83.6
2013	15.6	27.8	31.4	36.6	40.2	49.6	52.4	64	79.2

Durations in the table range from 15-minutes (15m[1*]) to 72 hours (72h[2*]).

7.3.1 Model sensitivity analysis

Sensitivity analysis supports the determination of the driving watershed processes and thus the identification of the most sensitive parameters through the assessment of the rate of change of model outputs with respect to defined changes of model inputs[44]. Fourteen hydrological (Table 7-2) and eight sediment-related (Table 7-3) parameters were selected for the subsequent SWAT calibration on the bases of the sensitivity analysis. In this study, the CN_2 and channel cover factor were found to be the most sensitive parameters with respect to streamflow and sediment yield, respectively.

Table 7-2. List of model parameters sensitive to streamflow and fitted values in order of ranking

Parameter name	Description	Adjusted or fitted parameter value	Ranking
r__CN2.mgt*	Curve number	-0.13	1
r__RCHRG_DP.gw**	Deep aquifer percolation fraction	0.3	2
r__GWQMN.gw	Threshold depth of water in the shallow aquifer required for return flow to occur (mm H_2O)	-0.13	3
v__ALPHA_BF.gw	Base flow alpha factor (days)	0.019	4
r__GW_REVAP.gw	Groundwater "revap" coefficient	0.4	5
v__GW_DELAY.gw	Groundwater delay time (days)	110	6
v__CH_K2.rte	Effective hydraulic conductivity in main channel alluvium (mm/hr)	82.49	7
v__CH_N2.rte	Manning's "n" value for the main channel	-0.00783	8
v__ESCO.hru	Plant uptake compensation factor	0.63	9
r__SOL_K(1).sol	Saturated hydraulic conductivity	-0.52	10
r__REVAPMN.gw	Threshold depth of water in the shallow aquifer percolation to the deep aquifer to occur (mm H_2O)	-0.2	11
r__SLSUBBSN.hru	Average slope length (m)	0.01	12
v__SURLAG.bsn	Surface runoff lag coefficient	0.3	13
r__SOL_AWC(1).sol	Soil available water storage capacity	0.28	14

*The qualifier (r__) refers to relative change in the parameter where the value from the SWAT database is multiplied by 1 plus the fitted value, while (v__) means the existing parameter value from the SWAT database is to be replaced by the fitted value.

**The extension (e.g., .gw) refers to the SWAT input file where the respective parameter is located.

Table 7-3. Model parameters sensitive to sediment yield and fitted values in order of ranking

Parameter name	Description	Fitted parameter value	Ranking
v__CH_COV2.rte*	Channel cover factor	0.8	1
v__CH_COV1.rte	Channel erodibility factor	0.15	2
v__SPCON.bsn**	Linear parameter for calculating the maximum amount of sediment that can be reentrained during channel sediment routing	0.009	3
v__PRF.bsn	Peak rate adjustment factor for sediment routing in the main channel	1.4	4
v__HRU_SLP.hru	Average slope steepness (m/m)	0.18	5
v__SPEXP.bsn	Exponent parameter for calculating sediment reentrained in channel sediment routing	1.35	6
r__USLE_P.mgt	USLE equation support practice factor	-0.01	7
v__RSDIN.hru	Initial residue cover (kg/ha)	3400	8

*1The qualifier (v__) means the existing parameter value from the SWAT database is to be replaced by the fitted value, while (r__) refers to relative change in the parameter where the value from the SWAT database is multiplied by 1 plus the fitted value.

**The extension (e.g., .bsn) refers to the SWAT file type where the parameter occurs.

7.3.2 Model calibration and validation

The automated calibration (SWAT-CUP) for streamflow (Figure 7-**7**, top) leads to adequate daily calibration results, and validation (Figure 7-**7**, bottom) indicates satisfactory model fit according to the assessment criteria suggested by Moriasi[45,61]. For the calibration period NSE = 0.56, PBIAS = 6%, R^2= 67 and RMSE = 0.62, while for the validation period NSE = 0.48, PBIAS = 18%, R^2= 53 and RMSE = 3.4. Meanwhile, the measured peak flows on the same day often over-predicted for the calibration period and under-predicted for the validation period (Figure 7-7). Some of the previously published SWAT studies for smaller watersheds in the northeast and northwest of Ethiopia tend to show weaker hydrologic results[18,21], which is an indication that it may be difficult to accurately represent processes and thus obtain better results for smaller watersheds. Nevertheless, obvious correspondence of the hydrographs of observed and simulated streamflow (Figure 7-**7**) for both, the calibration and validation period, indicates that SWAT is capable to simulate the hydrological regime of Gumara-Maksegnit watershed.

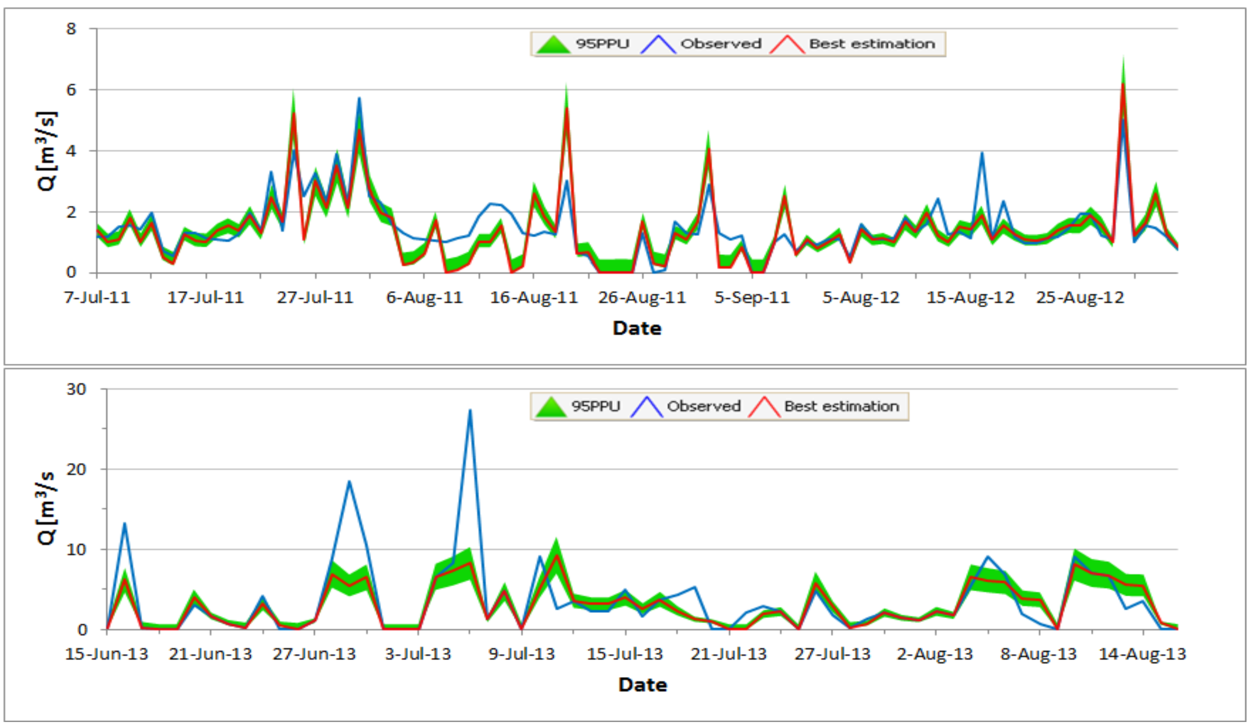


Figure 7-7. Observed and simulated daily streamflow hydrograph at the outlet of Gumara-Maksegnit watershed, calibration (top) and validation (bottom)

In contrast, the sediment simulation results were unsatisfactory, especially during the validation period, which is shown by the low or even negative NSE values (i.e. 0.07 for the calibration period and –1.76 for the validation period). The low sediment yield fit is not surprising, particularly in highly erosive regions, where abrupt gully development may affect daily loads significantly. However, Betrie[16] reported that the fit between the model daily sediment predictions and the observed concentrations showed good agreement as indicated by very good values of the NSE = 0.88 for the calibration period and NSE = 0.83 for the validation period at El Diem gauging station. During the calibration of streamflow about 39% of the data and during the validation period about 31% of the data were bracketed by 95PPU, while during daily sediment yield simulation around 18% of the data were bracketed for the calibration period and 13% of the data were bracketed for the validation period by 95PPU. The calculated *R-factor*[49] for the daily streamflow were 0.51 for the calibration periods and 0.49 for the validation period, whereas the *R-factor*[49] for the daily sediment yield were 0.23 for the calibration periods and 0.18 for the validation period. The daily sediment data show exceptionally large prediction uncertainties as compared to stream flow prediction. These model uncertainties might be as a result of some errors in the data input sources, data preparation and parameterization[62]. Moreover, the uncertainties might also be as a result of human and instrumental errors during data processing[63]**.** Even though kinematic wave runoff routing is used in the model, peaks of erosional forces of the channel runoff might be underestimated, especially in gully regions of changing flow directions because of gully meanders and/or locally changed flow conditions. Some of the potential reasons for such unsatisfactory sediment yield simulations could probably be, the length of overall measured data, which is quite short, strong hydrological heterogeneity and poor monitoring data as well as the use of USLE (or similar) equations in areas where rainfall happens under the form of short intense rainfall events. Nevertheless, calibration (and validation) of sediment yield on a monthly basis may give much better results, but due to plenty of gaps within the observed data, monthly balancing is not possible for this study. The trends as well as the order of magnitudes of sediment yield seem to be achieved through modeling, and therefore, the model may be able to describe long-term soil erosion characteristics, even if the event based predictions are uncertain. In this study, sediment concentration was also manually sampled at three stages of various flood events. Although selectively sampled sediment data may not be suitable for daily based model calibration, sediment data was used to establish a relation between runoff and sediment concentration (Figure 7-8).

Based on the manual bottle sampling upper and lower boundaries of the expected sediment yield for certain discharge was defined. Though it is commonly accepted that observed data are inherently uncertain[45], simulated sediment yield was compared to the expected sediment yield (Figure 7-9), and the observed sediment yield ranged from 2.9 to 27.6 Mg ha^{-1}, whereas the calibrated model predicted 10.0 Mg ha^{-1} sediment yield for the observed period and 21.08 Mg ha^{-1} annually. Similarly, Setegn[19] used SWAT to simulate the sediment yield simulations for the Anjeni, a small watershed in the northern highlands of Ethiopia, using different slope classifications and the results showed a very high spatial variability for the obtained annual sediment yields, which ranged from 0 to more than 65 Mg ha^{-1}.

Although stone bunds reduce the slope length, and decrease overland flow and sheet erosion, the calibrated model still predicted average annual sediment yields which were higher than the potential soil regeneration rate. This indicates a need for expanding SWC practices in the Gumara-Maksegnit watershed to further mitigate soil erosion problems.

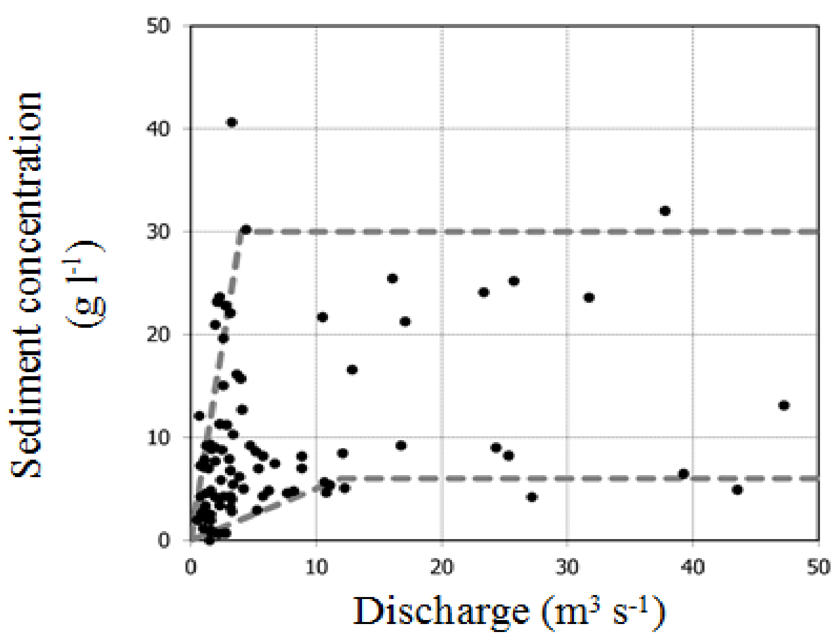


Figure 7-8. Scatterplot of discharge and sediment concentration of the manual bottle sampling at the main outlet, where dashed lines indicate the lower and upper defined limit of the expected relation between discharge and sediment concentration

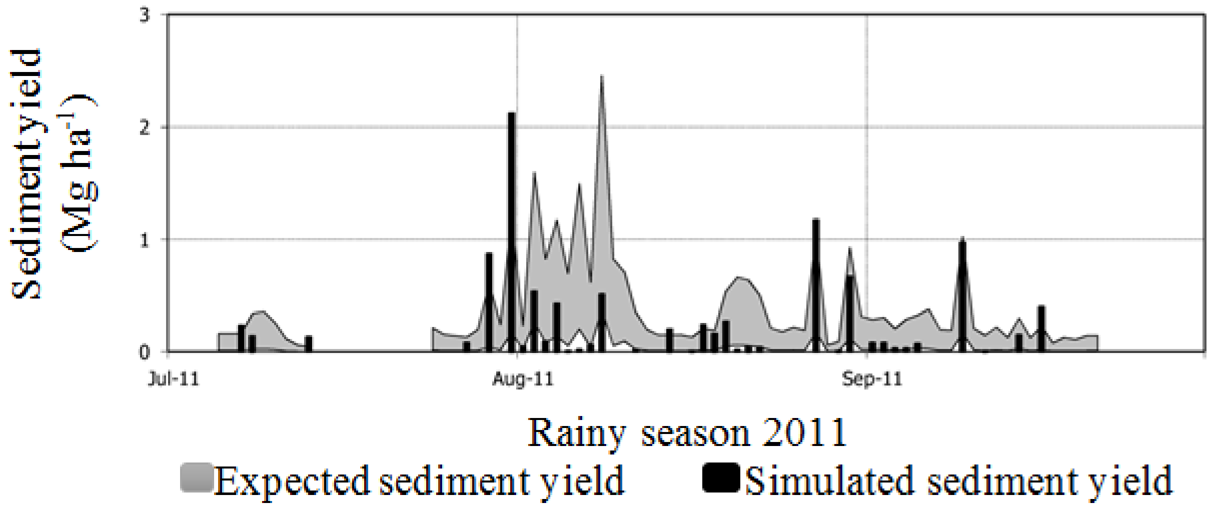


Figure 7-9. Comparison of the observed range of daily sediment yield (manual bottle sampling) and the simulated daily sediment yield at the main outlet of the watershed

Compared to other studies from the literature, Gumara-Maksegnit watershed study may provide conclusive results, for example, SWAT was applied for streamflow simulation of Gedeb catchment, located at the upper Blue Nile River basin[12], which resulted in unsatisfactory model performance for both calibration and validation period. However, Koch[12] pointed out various reasons for unsatisfactory model results, which seem also valid for the Gumara-Maksegnit case study; i.e., poor monitoring data, strong hydrological heterogeneity and a difficult and remote terrain. In contrast, Setegn[19] reported very good SWAT model performance (NSE equal to 0.81 during calibration) for monthly based sediment yield of Anjeni-gauged watershed. This may indicate a well performing model on one hand, but on the other hand the reasonable calibration result also demonstrates typical increasing accuracy of sediment yield prediction for monthly based assessment. Typically, model simulations show a much better fit as the comparison time scale increases[14,64,65]. There are also a number of previous SWAT studies in Ethiopia, which documented satisfactory streamflow results including studies that report daily comparisons within the Lake Tana drainage area[17,20]. However, these are for larger systems with longer overall observed data versus the smaller Gumara-Maksegnit watershed analyzed in this study with quite short measured data.

Generally, this study documented insufficiencies for matching daily based sediment yield simulation with observed data; this might be a result of poor monitoring data (e.g. short observation period, uncertain data inherent of the measurement technique, occasional data gaps, etc.). Moreover, missing records inhibit the model assessment on a larger time scale (such as monthly or yearly), which typically increases the goodness of the model fit. Hence, especially remote watershed modeling suffers from lack of continuous and good quality data, which has to be considered for semi-distributed eco-hydrological based modeling approaches for such areas.

7.4 CONCLUSIONS

In this research, SWAT watershed modeling was performed to describe the driving hydrological and sediment transport related processes of a 53.7 km^2 watershed in the Ethiopian Highlands. The collected model input data, either from remote earth observation or direct field sampling, are supposed to match SWAT requirements, but limited monitoring data, strong hydrological heterogeneity and poor monitoring data as well as the use of USLE (or similar) equations in areas where rainfall happens under the form of short intense rainfall events are inevitably connected with a large model uncertainty. Another source of uncertainty is the simulated stone bund impacts applied through the surface runoff ratio (Curve Number) and support practice factor (P-factor) modification. However, model calibration executed through the SWAT-CUP software resulted in satisfactory model performance regarding streamflow. However, poor agreement between daily observed and simulated sediment yield resulted as indicated by the NSE =0.07 for the calibration period and –1.76 for the validation period. Nevertheless, overall sediment dynamics and the order of magnitude of various erosion events may be achieved through SWAT simulation. Because of acceptable streamflow simulation (NSE = 0.56 for the calibration period and 0.48 for the validation period), but considerable imprecise daily sediment yield prediction at the same time, it is possible that fluctuating sediment processes are influenced by abrupt gully bank breaks and gully network development. Highly variable sediment transport in the main stream may be also a result of distinct sub-daily runoff characteristics of the Gumara-Maksegnit River, and therefore, daily based rainfall and streamflow processing may be limited to describe variable sub-daily peak wave characteristics, inherently linked with variable sediment yield characteristics.

Based on the calibrated SWAT model, the long-term average annual runoff at the main outlet was predicted to be 352 mm, while approximately one third of annual rainfall amount (373 mm) becomes evapotranspiration. The model predicts 21.08 Mg ha^{-1} as an average annual sediment yield, which is still alarming and far beyond the potential soil regeneration rate, especially for the situation of largely applied SWC structures (mainly stone bunds) within the watershed. Thus, rethinking of performed land management strategies and intensification of SWC interventions may be needed to achieve sustainable agriculture. The Ethiopian Highlands are a fragile ecoregion worthy of protection and physically-based modeling may be one method to guide scaling up of efficient measures to counteract ongoing land degradation. Eventually, advanced SWC impact assessment may be needed to satisfyingly consider the interaction between various SWC structures and heterogenic landscape conditions to support proper decision making in the future.

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8. Final conclusion

In the present thesis, the linkages between selected soil properties across the different land uses as well as slope steepness classes were assessed in chapter 5 and the result showed that forested areas of the Gumara-Maksegnit watershed tend to have higher soil nutrients (SOC and TN) as well as higher silt and sand contents compared to agricultural lands, while bulk density is lower in the forest. The study also points out high levels of clay content and bulk density occurred on the gentle slope of agricultural lands. Higher clay content on flat agricultural areas might be due to the deposition of clay particles eroded from uphill slopes. The correlation statistics for some of the soil properties are significantly linked (correlated) to the others, which may support the allocation of the most endangered regions concerning land degradation. However, basic linkages valid for all land uses and slope steepness classes have not been detected. Meanwhile, the performance of three interpolation techniques for predicting the spatial distribution of selected soil properties at a sub-watershed scale were discussed in chapter 6 and the study revealed that AP, SOC and clay contents were the most variable soil properties, with CV greater than 0.35 while, silt and sand contents were moderately variable, with CV vary from 0.18 to 0.30. Cross-validation was used to get the best agreement between the observed data and the predicted values of selected soil properties. This study considered 5 to 25 neighboring points for each interpolation method. Meanwhile, the five kernel functions and a power of 1, 2, and 3 were tested for RBF and IDW, respectively. The best kernel function for RBF was found to be completely regularized spline, while the best weighting parameter for IDW was found to be a power of two.

The predictions of the selected soil properties except AP were relatively unbiased as the mean errors were almost equals to 0 and the Nash-Sutcliffe efficiency for each soil property except silt showed a positive value ($E \geq 0.17$). When comparing the resulting values of the efficiency criteria, for each interpolation technique, the OK method was best performed for SOC and sand contents. RBF method was produced more accurate maps for AP and clay contents, while IDW performed best for interpolating topsoil pH. Overall, the results of the cross-validation statistics for each spatial interpolation method showed that there was no single interpolation method that can be considered significantly outperformed the others; hence, one of the interpolation method could be applied for surface map generation of a soil property in future studies of similar regions.

The results of chapter 7 showed that the SWAT model calibration executed through the SWAT-CUP software resulted in satisfactory model performance regarding streamflow. However, poor agreement between daily observed and simulated sediment yield resulted as indicated by the NSE =0.07 for the calibration period and –1.76 for the validation period. Because of acceptable streamflow simulation (NSE = 0.56 for the calibration period and 0.48 for the validation period), but considerable imprecise daily sediment yield prediction at the same time, it is possible that fluctuating sediment processes are influenced by abrupt gully bank breaks and gully network development. Highly variable sediment transport in the main stream may be also a result of distinct sub-daily runoff characteristics of the Gumara-Maksegnit River, and therefore, daily based rainfall and streamflow processing may be limited to describe variable sub-daily peak wave characteristics, inherently linked with variable sediment yield characteristics. Based on the calibrated SWAT model, the long-term average annual runoff at the main outlet was predicted to be 352 mm, while approximately one third of annual rainfall amount (373 mm) becomes evapotranspiration. The model predicts 21.08 Mg ha^{-1} as an average annual sediment yield, which is still alarming and far beyond the potential soil regeneration rate, especially for the situation of largely applied SWC structures (mainly stone bunds) within the watershed. Thus, rethinking of performed land management strategies and intensification of SWC interventions may be needed to achieve sustainable agriculture. In general, this study had verified that different approaches which include spatial soil variability, erosion dynamics, land management, landuse as well as topographic conditions might help to gain a deeper insight into watershed scale hydrology, land degradation issues and evaluate various soil and water conservation interventions.

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10. Index of tables

11. Index of figures

12. Curriculum Vitae

Hailu Kendie Addis

M.Sc. in Tropical Land Resource Management

PERSONAL INFORMATION		Nationality Place of Birth Date of Birth Sex Marital status	Ethiopian S/Gondar January,10, 1982 Male Married
EDUCATION		BOKU - University of Natural Resources and Applied Life Sciences **PhD Candidate in Environment, Hydrology and Rural Water Management**	Austria 10-2012
		Mekelle University **M.Sc., Tropical Land Resource Management**	Mekelle 7-2009
		Debub University Wondo Genet College of Forestry **B.Sc., Forestry**	Wondo Genet 7-2003
PRACTICA	**Student Counsel and Senate Member**	Debub University Wondo Genet College of Forestry Observing, assisting and supporting freshman and senior student.	Wondo Genet 9- 2002 to 7-2003
	Software Skill and Experience	ArcGIS Map Based Analysis Software	Austria
		Soil and Water Assessment Tool (SWAT)	Jordan
		Calibration and Validation Tool (SWAT_CUP)	Jordan
		JMP Statistical Analysis Software	Mekelle
		HYDRUS 1D model for saturated and unsaturated flow	Austria
		ERDAS IMAGIN Land Use Land Cover Change Analysis Tool	Bahir Dar

RESEARCH		Mekelle University, Gondar Agricultural Research Center and Austria, Vienna	Mekelle, Gondar and Austria, Vienna
	Researcher	Characterization and mapping of land resource of the Gumara-Maksegnit watersheds (DEM, soil, land use/cover, land suitability and soil erosion hotspots) Baseline survey (PRA) for the watersheds and identify the technology needs Studying the causes of gully formation classification and management requirements of the Amhara region Assessment of current land use and potential soil and water conservation measures in the Gumara-Maksegnit watershed, Ethiopia, on surface runoff and sediment yield	Gondar Agricultural Research Center 4-2009 till now
		Working under the supervision of Prof. Andreas Klik, BOKU University for conduction experiment on "Assessment of the Impact of Rainwater Harvesting and Soil Conservation Structures on Surface Runoff and Sediment Yield from an Agricultural Watershed in Ethiopia"	Austria and Ethiopia 10-2011 to present
		I was working in Gondar Agricultural Research Center as a Soil and Water Conservation Researcher	Gondar 5-2009 to 10-2011
		Worked under supervision of Prof. Metiku Haile, for experimenting "Effect of Carbon to Nitrogen ratio on Vermicomposting of Rice husk, Cow dung, with Biosolid''.	Mekelle 9-2007 to 7-2009
	Experience	Employees of Mertul Mariam Agricultural Technical Vocational Educational Training College as an instructor	Mertul Mariam 10-2003 to 11-2005
		Employees of Fogera Woreda Environmental Protection and Land Administration Office as Environmental Protection Expert	Fogera Woreda 12-2005 to 4-2009
		Now I am working as a PhD Candidate at BOKU University conducting research around leak Tana basin.	Gondar 5-2009 to present
		Working as a Soil and Water Research Directorate Director	Gondar 10-2009 to 10-2011

FOCAL PERSON	ICARDA (International Center for Agricultural Research in the Dry Areas) and NIDP (Nile Irrigation and Drainage Project) supported projects in Gondar Agricultural Research Center.	Gondar 12-2009 to 09-2011
SPECIAL TRAINING	➢ Integrated Training and Capitalizing on Experience given by National Center of Competence in Research North-South University of Bern Switzerland ➢ Scientific Writing and Publication given by National Center of Competence in Research North-South University of Bern Switzerland ➢ Exercises Communication with the Media given by National Center of Competence in Research North-South University of Bern Switzerland ➢ Integrated Watershed Management given by International Center for Agricultural Research in the Dry Areas (ICARDA)	Bahir Dar
	➢ Soil and Water Assessment Tool and SWAT-CUP for Integrated Watershed Management sponsored by International Center for Agricultural Research in the Dry Areas (ICARDA)	Jordan
	➢ Soil Conservation-A Challenge for the Future	Czech Republic
	➢ Possible impacts of climate change on water resources	Austria
TEACHING	Mertul Mariam ATVET College	Mertul Mariam
	Soil Science and Soil and Water Conservation methods.	10-2003 to 11-2005
FOREIGN LANGUAGE	English (fluent: speak, write, read, translate)	

13. List of publications

Scientific Publications in *Peer-Reviewed* Journals

Addis, H.K., A. Klik, and S. Strohmeier **2015.** Spatial Variability of Selected Soil Attributes under Agricultural Land Use System in a Mountainous Watershed, Ethiopia. International Journal of Geosciences, 6: 605–613. http://dx.doi.org/10.4236/ijg.2015.66047

Addis, H.K., and A. Klik **2015.** Predicting the spatial distribution of soil erodibility factor using USLE nomograph in an agricultural watershed, Ethiopia. International Soil and Water Conservation Research, 3(4): 282–290. http://dx.doi.org/10.1016/j.iswcr.2015.11.002

Addis, H.K., A. Belayneh, G. Muuz, and A. Baye 2015. Gully Morphology and Rehabilitation Measures in Different Agroecological Environments of Northwestern Ethiopia. Applied and Environmental Soil Science. http://dx.doi.org/10.1155/2015/789479.

Published Contributions to Scientific Conferences

Addis, H.K., S. Strohmeier, R. Srinivasan, F. Ziadat, and A. Klik **2013.** Using SWAT model to evaluate the impact of community-based soil and water conservation interventions for an Ethiopian watershed. *In*: SWAT, Conference Proceedings (Oral presentation). SWAT, Toulouse, France, July 17-19, 2013.

Addis, H.K., A. Klik, T. Oweis, and S. Strohmeier **2015.** Variation of Selected Soil Properties in Relation to Land Use Types and Slope Steepness in a Mountainous Watershed, Ethiopia. *In*: TropiLakes2015, Conference Proceedings (Oral presentation). TropiLakes2015, Bahir Dar, Ethiopia, September 23-29, 2015.

Addis, H.K., O. Wendroth, A. Klik, F. Ziadat, and S. Strohmeier **2014.**The spatial variability of measured soil properties in a mountainous agricultural watershed with different land-use and management practices, Ethiopia. *In*: Sustainable Land and Watershed Management (SLWM): Experience and Lessons, Conference Proceedings (Oral presentation). Mekelle, Ethiopia, May 26-27, 2014.

Addis, H.K., O. Wendroth, A. Klik, F. Ziadat, and S. Strohmeier **2014.** Comparing the performance of spatial interpolation techniques in mountainous terrain for mapping soil properties, Ethiopia. *In*: Sustainable Land and Watershed Management (SLWM): Experience and Lessons, Conference Proceedings (Poster). Mekelle, Ethiopia, May 26-27, 2014.