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Watershed modeling and uncertainty analysis on Gumara watershed

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WTERSHED MODELING AND UNCERTAINTY ANALYSIS ON GUMARA WATERSHED

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By

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Abbreviations and acronyms

AAIT	-Addis Ababa Institute of Technology
ARC SWAT	-SWAT Integrated with Arc GIS
ARS	-Agricultural Research Service
CN II	-Moisture Condition Curve Number
DEM	-Digital Elevation Model
GIS	-Geographic Information Systems
GLUE	-Generalized Likelihood Uncertainty Estimation
HRU	-Hydrological Response Unit
MCMC	-Markov Chain Monte Carlo
MoWE	-Ministry of Water and Energy
MoWR	-Ministry of water resource
NMSA	-National Metrological Services Agency, Ethiopia
ParaSol	-Parameter Solution
PET	-Potential Evapotranspiration
SCS	-Soil Conservation System
SWAT	-Soil and Water Assessment Tool
SWAT-CUP	-Soil and Water Assessment Tool- Calibration and Uncertainty Programs
SUFI-2	-Sequential Uncertainty Fittings version 2
WGEN	-Weather Generator

ABSTRACT

The objective of this thesis work is to model stream flow at the outlet of the gauged Gumara watershed and analyze the associated uncertainty that can affects the accuracy in estimation of the stream flow. Having good certainty on simulated flow helps planners and policy makers to implement appropriate water resource management as Gumara catchment is getting threatened as a result of increasing number of farmers using the river for different purpose, especially for irrigation. The Soil and Water Assessment Tool (SWAT) model was applied to estimate stream flow of the Gumara catchment and associated uncertainty with the simulated outputs. The SWAT model was calibrated for the period of 1995 to 2003 and validated for the period of 2004-2009 based on ten parameters identified during sensitivity analysis. The uncertainty analysis was done by using first SUFI-2 and to check parameter uncertainty using SWAT-CUP, which are both packages of SWAT CUP, were used to establish the uncertainty bounds of the model. The calibration and validation of the model was found satisfactory as performance rating criteria value of coefficient of correlation (R^2) and Nash-Sutcliffe simulation efficiency (E_{NS}) is found to be 0.63 and 0.56 for calibration and 0.71and 0.71 for validation ,respectively. In the same order from the model uncertainties analysis the percentage of the simulated data within the uncertainty bound is only 31% for calibration and 27% for validation, which shows that there is uncertainty in the process. Then using SWAT CUP parameter uncertainty was tested and found with E_{NS} value of 0.68 for calibration and 0.82 for validation. And this shows that the overall associated uncertainty come from either conceptual or input or a combination of them but not from parameter identification. Even though the predicted amount of flow of 1317.33MCM is almost equivalent to the latest study, the uncertainty might come due to either neglected abstractions or poor quality of input data. Therefore, this simulated amount should not be used for any water resource development works unless the correction of these cause of uncertainties are reduced as uncertainty in estimation of simulated flow will lead to wrong water resource management decision.

CHAPTER ONE

1. Introduction

Water is of paramount importance for sustaining life, development and the environment. The availability of water is the key determinant of economic growth and social prosperity. However, water is a finite resource and its use for one purpose reduces its availability for other purposes. Competing water needs trigger conflicts between disparate water users such as the rich and the poor, or between different sectors and regions, such as domestic and agriculture, agriculture and industry, agriculture and fisheries, upstream and downstream, rural and urban areas, and fisheries and flood control. Increased demand for water stemming from population and economic growth and ecosystem services on the one hand, and the problem of water management in flood control situations on the other, have posed significant challenges for the planning and allocation of its uses among competing demands (Syme *et al*.,1999).

Ethiopia has twelve major river basins. Most of them are untapped for modern irrigation and energy development. According to MoWR (2006) water sector strategy report, only 197,225 hectare of the potential irrigable lands are developed, so the existing irrigation development in Ethiopia, as compared to the resources the country has, is negligible. This might be besides financial constraints; the uncertainties of data of the rivers discharge are problem for the development in the sector. Currently, there are great efforts towards developments in some river basins for energy generation and large scale irrigation projects to sell power to neighboring countries and attain food self sufficiency, respectively.

In addition recently, although there is great tendency of utilizing available water resources, the efficiency of using and managing the resource is limited due uncertainties in stream flow and inaccurate model outputs that may come due to model efficiencies, MoWR (2006). Besides using this water resource in a proper management system is not practiced well.

Lake Tana sub basin is part of the Blue Nile basin, which is characterized by increased demand of water for agriculture, industries, domestic, and power generation. As a result the sub-basin requires proper planning and management of water.

Gumara watershed is one of the watersheds draining in to the sub basin of Lake Tana, and this watershed is under great pressure because of growing population and increasing demand of water mainly for irrigation, which is not practiced well now a days in the catchment, and also a great demand of water for domestic and livestock consumption purposes. In addition, the growing uncertainty of surface water availability and increasing levels of water pollution and water diversions threaten to disrupt social and economic development in the area as well as the health of the ecosystem.

Therefore, improvement of techniques to assist in the sustainable management of water resource system of the catchment is a crucial issue as water is a limited resource. Hence, to settle this physical water scarcity, usually attributed to limited access to water resources due to either climatic conditions or unsustainable management of resources, is most often addressed by storage reservoir construction in the specific area.

River discharge is an important issue to be monitored because of its significant influence on agricultural systems and on human lives for water resource exploitation and hazards related to floods and landslides. Hence in order to develop any water resource development work knowing the stream flow with a greater certainty is a must. Even though there have been little studies about Gumara watershed (Dagnenet, 2009; Zelalem, 2009) it can be seen that significant variation in determining the hydrological variables have been detected in assessing the water resource potential of the watershed. Hence, assessment of water resource potential with great certainty and understanding the hydrological processes in the basin has become important to manage and to make optimal use of water resource development alternatives.

Thus, from operational water resources management point of view, hydrological models are developed to guide the formulation of water resource management strategies by understanding spatial and temporal distribution of water resources (Dingman, 2002; Liden and Harlin, 2000). Hence, the same is applied in this study for Gumara watershed.

The objective of this research is therefore applying a physically based semi distributed model i.e. Soil and Water Assessment Tool (SWAT), to understand the rainfall runoff relationship of the watershed and SWAT CUP model to determine associated uncertainty.

1.1 Statement of the problem

Although Ethiopia has the advantage of having the world famous river Blue Nile, it has got little advantage on using the river. Rather Blue Nile River takes so many cubic metric of fertile soil and runoff out of the country. This is due to that the available land and water resources are not practiced and utilized effectively to improve the livelihood and socio-economic condition of the country. Currently, there is an increasing demand for irrigation and hydropower development in Ethiopia and the country is experiencing a number of problems such as rapid population growth, limited water resources, and environmental degradation. So to mitigate this problem and to make efficient use of available water resources with balanced attention to maximized economic, social, and environmental benefits, it is necessary to have effective integrated water planning. Before any planning activity for water resources development works in a certain river basin it is essential first to identify and evaluate the total available water resource of that basin with great certainty.

Gumara watershed is one of the watersheds draining in to the sub basin of Lake Tana, and this watershed is under great pressure because of growing population and increasing demand of water mainly for irrigation, which is not practiced well now a days in the catchment, and also a great demand of water for domestic and livestock consumption purposes. In addition, the growing uncertainty of surface water availability and increasing levels of water pollution and water diversions threaten to disrupt social and economic development in the area as well as the health of the ecosystem. Because of the importance of the Abbay River, many studies had been studied in the past though; there was no much specific study for the development of Gumara watershed exclusively. The reason why this study focuses on Gumara watershed is that, there is adequate meteorological data than other watersheds in the basin for uncertainty study needs enough data.

SMEC, many others (Dagnenet, 2009; Zelalem, 2009) have been conducted in the past to quantify the total available water for development in the Gumara watershed using different approach. However, the results show significant variations. This implies the need for in-depth assessment of water resource potential in the watershed for proper planning and management of water resources.

1.2. Objectives of the study

General objective

The main objective of this study is rainfall-runoff modeling and uncertainty analysis of Gumara watershed using SWAT.

Specific objectives

1. Calibration and verification of SWAT model on Gumara watershed to assess the water resources.
2. To assess the accuracy of the SWAT model through uncertainty analysis of parameters of the model

CHAPTER TWO

2.1 Water resource study of the Blue Nile basin.

Because of the importance of Abbay River, many studies had been carried out in the past, concerning the basin.

Lahmayer (1962) studied on water resources of Gigil Abbay. Although, it was not having adequate data base, the study provided interesting information about Gilgel Abbay and its tributaries, which could be considered as a data base for review and updating in the light of the raw data.

Detailed study on land and water resources development of the Abby basin was undertaken by the United States department of the interior, bureau of reclamation in 1964. When there was a little or no data, very exhaustive analysis of the available data had been carried out to establish hydrological studies. In fact, the pioneering works under taken during that time, has made Abbay basin in Ethiopia, to be proud of possessing a good network of hydrometric stations for making reliable estimates. In this study the Gumara flows near Lake Tana had been estimated for the year 1911 to 1917 and 1932. The mean annual flow was recorded at 793.84Mm^3.

In order to control the flood damages caused by Rib and Gumara rivers, and thereby ensure safe agricultural production, it was felt very important to carry out river engineering works and introduces internal drainage system in the area as early as in 1980 (EWRA,1980). In this study, the then conditions of Gumara and Ribb rivers in the project area were analyzed. On the basis of this, the main features of rivers and Lake Tana flood control, internal drainage system and other infrastructure were worked out. As such, because of inadequate internal drainage, water accumulation increases by surface inflows and intense direct rainfall over the area. This study forms a relevant material for the present study for Gumara watershed development.
The 100 year flood peaks for Gumara and Ribb were estimated to be 420 and 245m^3/sec respectively. The unit hydrographs were constructed using USBR approach. The flood hydrographs convoluted had slightly higher peaks than frequency floods. The flood levels, river cross sections, dyke sections and the like have been designed taking into account the design

flood hydrographs with peaks of 478 and 276m^3/sec for Gumara and Ribb respectively. The need for river mouth training had also been highlighted.

JICA (1997) study gave a very comprehensive analysis of the hydrology of Lake Tana, apportioned evaporation and other losses, and water balance with an objective of developing hydropower. It includes a short study on sedimentation problem as well.The report contains information about climate and hydrology in the south west portion of Abbay basin. It forms a good data base to compensate the lack of data base in that portion of Abbay basin.

Abbey (2008) tried to estimate the hydrological water balance of Lake Tana using HBV model. He found the mean annual flow of the catchment is 1229Mm^3. Similarly, Yohannes (2007) has made remote sensing based assessment of water resource potential for Lake Tana basin. He found that the mean annual flow of Gumara catchment is 1388.84 MCM. In other study (Melkamu, 2005), the annual flow of Gumara-Gelda was found to be 1640.51MCM and Sirak (2008) has conducted a research under the title "Watershed Modeling of Lake Tana Basin Using SWAT" and he has found annual flow amount of 1323.04MCM.
Obviously, there is great variation in the annual flow of simulated by different authors and this might come due to the efficiency of softwares and methods they have used. Therefore, in depth study of determining the certain amount of runoff with up-to-date soft ware is very important.

2.2. Hydrological modeling

2.2.1. General

Hydrology is a science which is concerned with the circulation of water and its constituents through the hydrologic cycle. It deals with precipitation, evaporation, infiltration, groundwater flow, runoff stream flow and the transport of substance dissolved or suspended in the flowing water.

Hydrologic Analysis is a set of technique for simulating components of the hydrologic cycle in which the components are analyses and processed to provide an understanding of the basin hydrology .In water resource analysis that targets to determine available water, hydrologic analysis can be very helpful in terms of providing mechanisms of flow estimation from un-gauged watersheds (Chow *et al*. 1988).

In most hydrologic analysis procedures the following steps are commonly adopted.

- Delineation of catchment morphology from topographies or elevation information
- Analysis of available hydrologic components like evaporation, rainfall etc
- Estimation of missing hydrologic variables using watershed modeling.

2.2.2. Classification of Hydrological Models

There are a number of ways of classifying models. Classifications are generally based on the method of representation of the hydrological cycle or a component of the hydrologic cycle. Owing to the complex nature of rainfall-runoff processes, different hydrologists have different modeling approaches even to the same hydrological system.

Beven (2000) categorized rainfall-runoff models into lumped or distributed and deterministic or stochastic. In lumped models the hydrologic parameters do not vary spatially with in the basin and thus, basin response is evaluated only at the outlet, without explicitly accounting for the response of individual sub-basins (Cunderlik, 2003). He added that the representation of hydrologic processes in lumped hydrologic models is usually very simplified; however they can often lead to satisfactory results, especially if the interest is in the discharge prediction only. The distributed models make predictions that are distributed in space by discretizing the catchment into a large number of elements or grid squares and solving the equations for the state variables associated with every element or grid square (Beven, 2000). Distributed models generally require large amounts of data parameterization in each grid cell. Cunderlik (2003) stated that if governing physical processes are modeled in detail and properly applied; distributed models can provide the highest degree of accuracy.

There is a third type of model in this category called semi-distributed model. In semi-distributed model, the parameters of the model are allowed to vary partially in space by dividing the basin into a number of smaller sub-basins. The main advantage of semi-distributed models is that their structure is more physically based than the structure of lumped models, and that they are less demanding an input data than fully distributed models (Cunderlik, 2003). Deterministic models permit only one outcome from a simulation with one set of inputs and parameter values while stochastic models allow for some randomness or uncertainty in the possible outcomes due to uncertainty in input variables, boundary conditions or model parameters (Beven, 2000).

Conceptual and physically based models are the other forms of model classification. Conceptual models are based on limited representation of the physical processes acting to produce the hydrological outputs, for instance the representation of a drainage basin by a cascade of stores, while physically based models are based more solidly on understanding of the relevant physical processes (Ward & Robinson, 2000). They added that models may also be linear or non-linear in either the systems theory or statistical regression sense. To make clear, the different types of classification of model are presented in below figure 2.1.

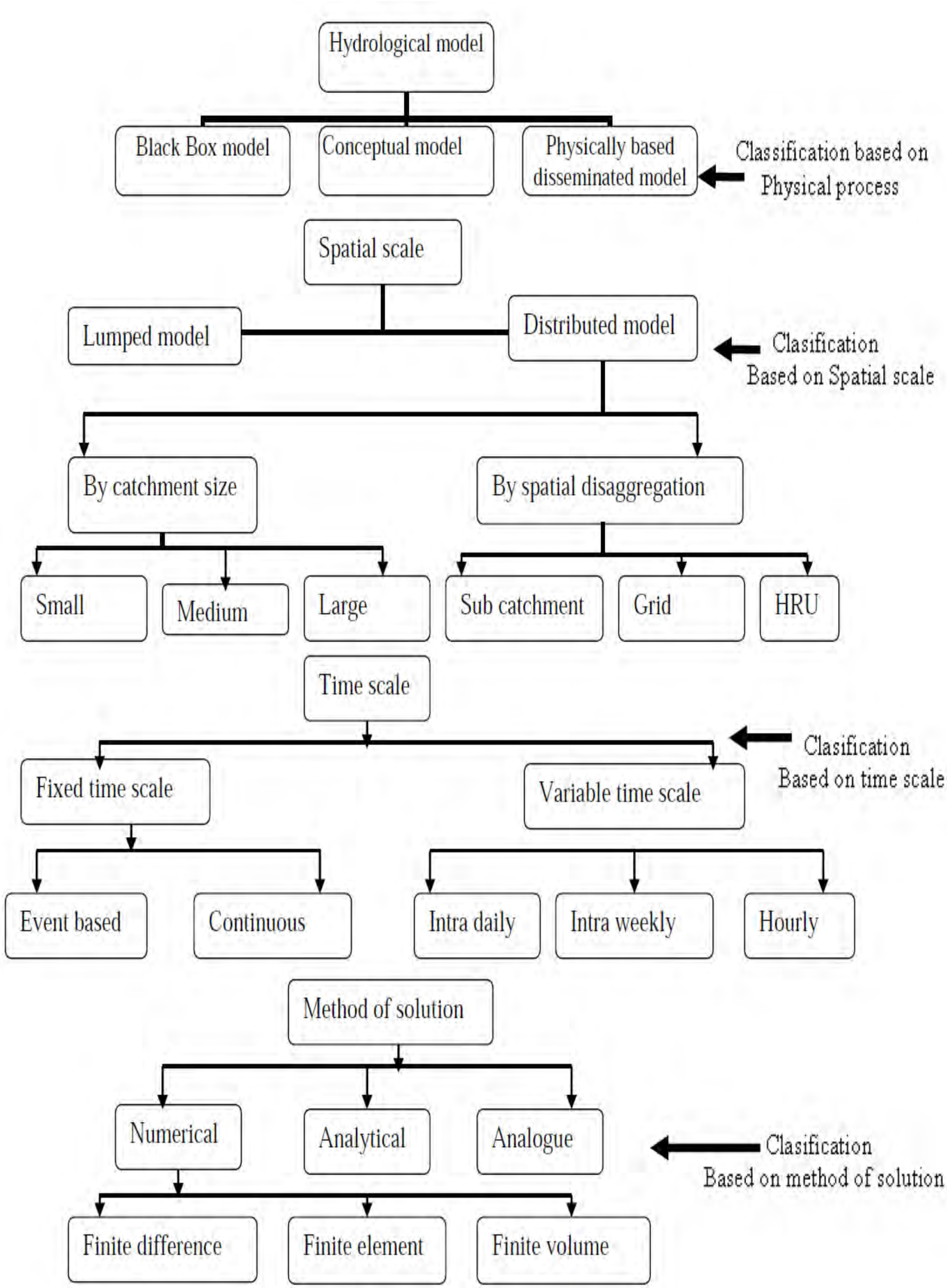

Figure 2.1 Simplified flow chart of hydrological model classification (Source: Semu. 2007)

2.2.3. Model selection

There are a range of possible model structures within each class of models. Hence, choosing a particular model structure for a particular application is one of the challenges of the model user community. Beven (2000) suggested four criterions for selecting model structures as below.

1. Consider models which are readily available and whose investment of time and money appeared worthwhile.
2. Decide whether the model under consideration will produce the outputs needed to meet the aims of a particular project.
3. Prepare a list of assumptions made by the model and check the assumptions likely to be limiting in terms of what is known about the response of the catchment. This assessment will generally be a relative one, or at best a screen to reject those models that are obviously based on incorrect representations of the catchment processes.
4. Make a list of the inputs required by the model and decide whether all the information required by the model can be provided within the time and cost constraints of the project.

2.2.3.1 Distributed models

Distributed watershed models, are increasingly being used to support decisions about alternative management strategies in the areas of land use change, climate change, water allocation, and pollution control. For this reason it is important that these models pass through a careful calibration and uncertainty analysis. Furthermore, as calibration model parameters are always conditional in nature the meaning of a calibrated model, its domain of use, and its uncertainty should be clear to both the analyst and the decision maker.

Large-scale distributed models are particularly difficult to calibrate and to interpret the calibration because of large model uncertainty, input uncertainty, and parameter non-uniqueness. To perform calibration and uncertainty analysis, in recent years many procedures have become available. As only one technique cannot be applied to all situations and different projects can benefit from different procedures. In this research two programs to the hydrologic simulator Soil and Water Assessment Tools (SWAT) (Arnold *et al*., 1998) under the same platform, SWAT-CUP (SWAT Calibration Uncertainty Procedures) were used for uncertainty analysis. These procedures include: Generalized Likelihood Uncertainty Estimation (GLUE) (Beven and Binley, 1992), Parameter Solution (ParaSol) (van Griensven and Meixner, 2006), and Sequential Uncertainty FItting (SUFI-2) (Abbaspour, *et al*., 2007).

2.2.4. SWAT model review

SWAT is a basin-scale, continuous-time model that operates on a daily time step and is designed to predict the impact of management on water, sediment, and agricultural chemical yields in ungauged watersheds. The model is physically based, computationally efficient, and capable of continuous simulation over long time periods. Major model components include weather, hydrology, soil temperature and properties, plant growth, nutrients, pesticides, bacteria and pathogens, and land management. In SWAT, a watershed is divided into multiple sub-watersheds, which are then further subdivided into hydrologic response units (HRUs) that consist of homogeneous land use, management, and soil characteristics. The HRUs represent percentages of the sub-watershed area and are not identified spatially within a SWAT simulation. Alternatively, a watershed can be subdivided into only sub-watersheds that are characterized by dominant land use, soil type, and management (Philip, 2007)

2.2.4.1 Climatic Inputs and HRU Hydrologic Balance

Climatic inputs used in SWAT include daily precipitation, maximum and minimum temperature, solar radiation data, relative humidity, and wind speed data, which can be input from measured records and/or generated. Relative humidity is required if the Penman-Monteith (Monteith, 1965) or Priestly-Taylor (Priestly and Taylor, 1972) evapotranspiration (ET) routines are used; wind speed is only necessary if the Penman-Monteith method is used. Measured or generated sub-daily precipitation inputs are required if the Green-Ampt infiltration method (Green and Ampt, 1911) is selected. The average air temperature is used to determine if precipitation should be simulated as snowfall. The maximum and minimum temperature inputs are used in the calculation of daily soil and water temperatures. Generated weather inputs are calculated from tables consisting of 13 monthly climatic variables, which are derived from long-term measured weather records. Customized climatic input data options include:

1. simulation of up to ten elevation bands to account for orographic precipitation and/or for snowmelt calculations,
2. adjustments to climate inputs to simulate climate change, and
3. forecasting of future weather patterns, which is a new feature in SWAT 2005.

The overall hydrologic balance is simulated for each HRU, including canopy interception of precipitation, partitioning of precipitation, snowmelt water, and irrigation water between surface runoff and infiltration, redistribution of water within the soil profile, evapo-transpiration, lateral subsurface flow from the soil profile, and return flow from shallow aquifers. Estimation of areal snow coverage, snowpack temperature, and snowmelt water is based on the approach described by Fontaine *et al*. (2002). Three options exist in SWAT for estimating surface runoff from HRUs, which are combinations of daily or sub-hourly rainfall and the USDA Natural Resources Conservation Service (NRCS) curve number (CN) method (USDA-NRCS, 2004) or the Green-Ampt method. Canopy interception is implicit in the CN method, while explicit canopy interception is simulated for the Green- Ampt method.

A storage routing technique is used to calculate redistribution of water between layers in the soil profile. Bypass flow can be simulated, as described by Arnold *et al*. (2005), for soils characterized by cracking, such as Vertisols. SWAT2005 also provides a new option to simulate perched water tables in HRUs that have seasonal high water tables. Three methods for estimating potential ET are provided: Penman-Monteith, Priestly-Taylor, and Hargreaves (Hargreaves *et al*., 1985). ET values estimated external to SWAT can also be input for a simulation run. The Penman-Monteith option must be used for climate change scenarios that account for changing atmospheric CO2 levels. Recharge below the soil profile is partitioned between shallow and deep aquifers. Return flow to the stream system and evapotranspiration from deep-rooted plants (termed “revap”) can occur from the shallow aquifer. Water that recharges the deep aquifer is assumed lost from the system.

2.2.4.2 Comparisons of SWAT with other models

Borah and Bera (2003, 2004) compared SWAT with several other watershed-scale models. In the 2003 study, they reported that the Dynamic Watershed Simulation Model (DWSM) (Borah *et al*., 2004), Hydrologic Simulation Program - Fortran (HSPF) model (Bingner *et al*., 1997), SWAT, and other models have hydrology, sediment, and chemical routines applicable to watershed-scale catchments and concluded that SWAT is a promising model for continuous simulations in predominantly agricultural watersheds. In the 2004 study, they found that SWAT and HSPF could predict yearly flow volumes and pollutant losses, were adequate for monthly predictions except for months having extreme storm events and hydrologic conditions, and were poor in simulating daily extreme flow events.

In contrast, DWSM reasonably predicted distributed flow hydrographs and concentration or discharge graphs of sediment and chemicals at small time intervals. Shepherd *et al.* (1999) evaluated 14_models and found SWAT to be the most suitable for estimating phosphorus loss from a lowland watershed in the U.K.

Van Liew et al. (2003a) compared the stream flow predictions of SWAT and HSPF on eight nested agricultural watersheds within the Little Washita River basin in southwestern Oklahoma. They concluded that SWAT was more consistent than HSPF in estimating stream flow for different climatic conditions and may thus be better suited for investigating the long-term impacts of climate variability on surface water resources. Saleh and Du (2004) found that the average daily flow, sediment loads, and nutrient loads simulated by SWAT were closer than HSPF to measured values collected at five sites during both the calibration and verification periods for the upper North Bosque River watershed in Texas. Singh et al. (2005) found that SWAT flow predictions were slightly better than corresponding HSPF estimates for the 5,568 km^2 Iroquois River watershed in eastern Illinois and western Indiana, primarily due to better simulation of low flows by SWAT. Nasr et al. (2007) found that HSPF predicted mean daily discharge most accurately, while SWAT simulated daily total phosphorus loads the best, in a comparison of three models for three Irish watersheds that ranged in size from 15 to 96 km^2.

El-Nasr *et al*. (2005) found that both SWAT and the MIKE-SHE model (Refsgaard and Storm, 1995) simulated the hydrology of Belgium's Jeker River basin in an acceptable way. However, MIKE-SHE predicted the overall variation of river flow slightly better. Srinivasan *et al*. (2005) found that SWAT estimated flow more accurately than the Soil Moisture Distribution and Routing (SMDR) model (Cornell, 2003) for 39.5 ha FD-36 experimental watershed in east central Pennsylvania, and that SWAT was also more accurate on a seasonal basis. SWAT estimates were also found to be similar to measured dissolved and total P for the same watershed, and 73% of the 22 fields in the watershed were categorized similarly on the basis of the SWAT analysis as compared to the Pennsylvania P index (Veith *et al*., 2005).

Grizzetti *et al*. (2005) reported that both SWAT and a statistical approach based on the SPARROW model (Smith et al., 1997) resulted in similar total oxidized nitrogen loads for two monitoring sites within the 1,380 km2 Great Ouse watershed in the U.K. They also state that the statistical reliability of the two approaches was similar, and that the statistical model should be viewed primarily as a screening tool while SWAT is more useful for scenarios.

Srivastava et al. (2006) found that an artificial neural network (ANN) model was more accurate than SWAT for stream flow simulations of a small watershed in southeast Pennsylvania.

2.2.4.3 SWAT strengths, weaknesses, and research needs

The worldwide application of SWAT reveals that it is a versatile model that can be used to integrate multiple environmental processes, which support more effective watershed management and the development of better-informed policy decisions. The model will continue to evolve as users determine needed improvements that: (1) will enable more accurate simulation of currently supported processes, (2) incorporate advancements in scientific knowledge, or (3) provide new functionality that will expand the SWAT simulation domain. This process is aided by the open-source status of the SWAT code and ongoing encouragement of collaborating scientists to pursue needed model development. The model has also been included in the Collaborative Software Development Laboratory that facilitates development by multiple scientists (CoLab, 2006).

The foundational strength of SWAT is the combination of upland and channel processes that are incorporated into one simulation package. However, every one of these processes is a simplification of reality and thus subject to the need for improvement. To some degree, the strengths that facilitate widespread use of SWAT also represent weaknesses that need further refinement, such as simplified representations of HRUs. There are also problems in depicting some processes accurately due to a lack of sufficient monitoring data, inadequate data needed to characterize input parameters, or insufficient scientific understanding. The strengths and weaknesses of five components has discussed in this workshop, including possible courses of action for improving current routines in the model (CoLab, 2006).

2.2.5 Model parameterization

A soil unit appearing in various locations in a watershed, under different land uses and/or climate zones may have the same or different parameters. Probably it should have different parameters. The same argument could be made with all other distributed parameters. How far should one go with this differentiation? On the one hand we could have thousands of parameters to calibrate, and on other we may not have enough spatial resolution in the model to see the difference between different regions. This balance is not easy to determine and the choice of parameterization will affect the calibration results. Detailed information on spatial parameters is indispensable for building a correct watershed model. A combination of measured data and spatial analysis techniques using pedotransfer functions, geostatistical analysis, and remote sensing data would be the way forward (Abbaspour *et al*., 2009).

2.3. Uncertainty in water resource management

Uncertainty estimation in hydrological surface and subsurface modeling is receiving increasing attention from researchers and practitioners. In fact, the scientific literature has recently proposed numerous contributions about this issue. Uncertainty assessment is also one of the main goals of the Prediction in Gauged and Ungauged Basins (PUB) initiative promoted by the International Association of Hydrological Sciences. This intense scientific activity about uncertainty analysis has resulted in many different philosophies and approaches for quantifying the reliability of hydrological models. The transfer of know-how about uncertainty assessment among scientists and from scientists to end-users is still difficult, notwithstanding the extensive research activity mentioned above (Abbaspour *et al*., 2009).

Many researchers agree that one of the reasons preventing efficient communication about uncertainty assessment in hydrology is the lack of a coherent terminology and a systematic approach, which would allow us to classify in a clear way the practical problems to solve and, consequently, the methods that can be used. Even the term "uncertainty" itself is sometimes used without referring to a precise scientific definition of its meaning. Different sources of uncertainty are recognized and tools have been developed to describe and quantify each source, or to control and reduce uncertainty. As can be expected, there is not yet a single framework that covers all methods (Abbaspour *et al*., 2009).

Uncertainty within model output is a major concern, particularly when modeling results are used to set policy. Because of uncertainties associated with input, model structure, parameter, and output, the model predictions are not a certain value, and should be represented with a confidence range (Beven and Binley, 1992, Gupta *et al*., 1998; Beven and Freer, 2001; Beven, 2006; VanGriensven, 2008). Reasonable estimates of prediction of uncertainty of hydrologic processes are valuable to water resources and other relevant decision making processes (Liu and Gupta, 2007). Usually, water management projects are planned and designed using scenarios that fall at the conservative end of the range of plausible outcomes. Over estimation of uncertainty can result in over design of mitigation measures, while under estimation of uncertainty can lead to inadequate preparation for potential situations. In order to successfully apply hydrological models in practical water resources investigations, careful calibration and prediction uncertainty analysis are required (Duan *et al*., 1992; Beven and Binley, 1992; Vrugt *et al*., 2003; Yang *et al*., 2008; Van Griensven *et al*., 2008).

In order to check the applicability of the model in the target region a comprehensive uncertainty analysis is performed as validation data are rare in tropical Ethiopia. Both, the spatial resolution of input data as well as the model parameters have a significant impact on the model performance. Calibration improves the overall model performance but leads to a hidden uncertainty within the modelling system as model calibration also calibrates data errors and incorrect model assumptions (Abbaspour *et al*., 2009).

2.3.1 Types of uncertainty

2.3.1.1 Conceptual model uncertainty

Simply speaking, model uncertainty arises from incomplete understanding of the system being modeled and/or the inability to accurately reproduce hydrological processes with mathematical and statistical techniques. These are cause of model uncertainty

i) Model uncertainties due to simplifications in the conceptual model. For example, the assumptions in the universal soil loss equation for estimating sediment loss, or the assumptions in calculating flow velocity in a river. Figures 2.2a and 2.2b. show some graphical illustrations.

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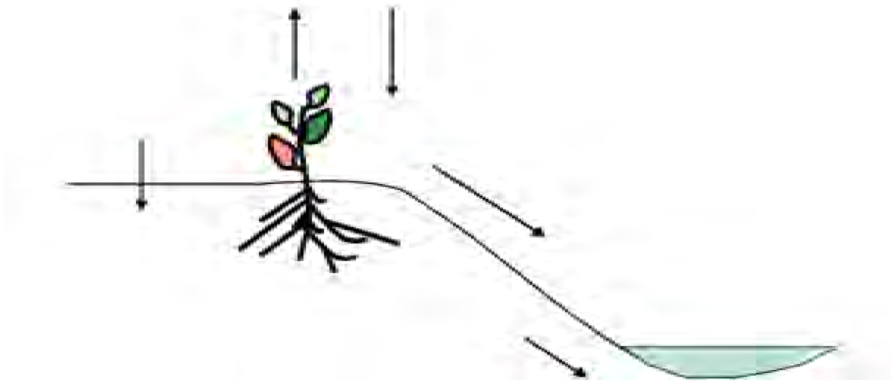

Fig 2.2a. A simplified conceptual model of hydrology in a watershed where revap is ignored. (Source: SWATCUP manual,2009)

Fig. 2.2b. A natural process near the source of Yellow River in China playing havoc with river loading based on the USLE.(Source: SWATCUP manual,2009)

ii) Model uncertainties due to processes occurring in the watershed but not included in the SWAT model. For example, wind erosion (Fig. 2.3a), erosions caused by landslides (Fig.

2.3b), and the “second-storm effect” effecting the mobilization of particulates from soil surface.

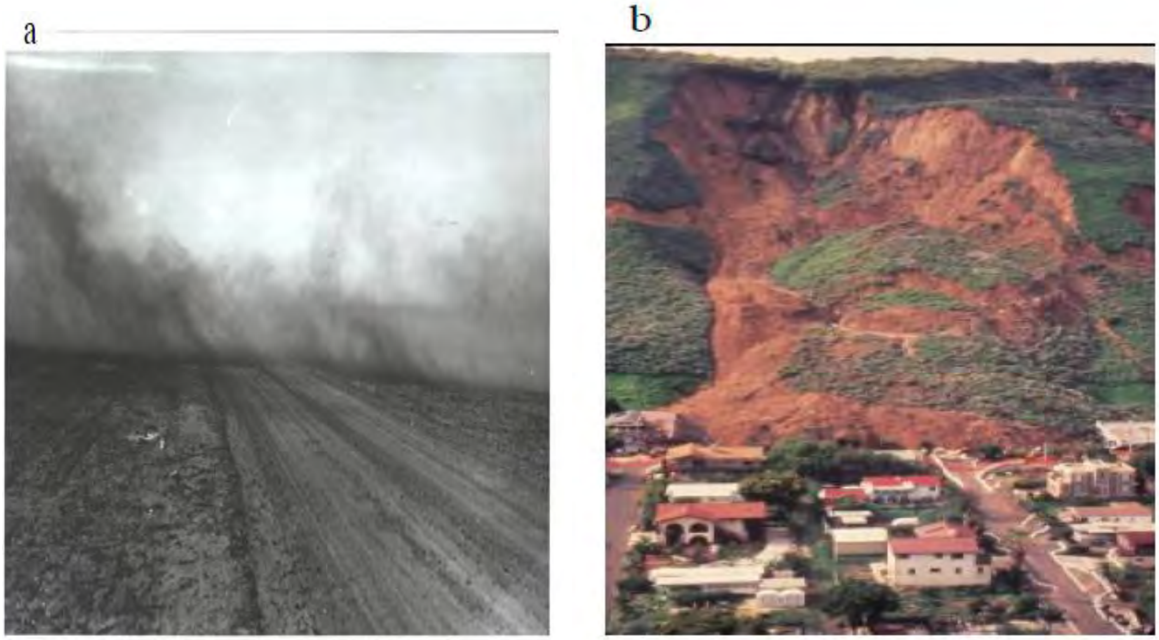

Figure 2.3. Natural processes not included in most watershed models but with a large impact on hydrology and water quality of a watershed, albeit for a short period (Source: SWATCUP manual,2009)

iii) Model uncertainties due to processes that are included in the model, but their occurrences in the watershed are unknown to the modeler or unaccountable; for example, various forms of reservoirs, water transfer, irrigation, or farm management affecting water quality. For example: agricultural management practices such as water withdrawal and animal husbandry can affect water quantity and quality. These, may not always be known to the modeller. And also water control and water diversions may change the flow in ways that are unknown to the modeller and, hence, cannot be accounted for in the model (Abbaspour *et al*., 2009).

iv) Model uncertainties due to processes unknown to the modeler and not included in the model either! These include dumping of waste material and chemicals in the rivers, or processes that may last for a number of years and drastically change the hydrology or water quality such as large-scale constructions of roads, dams, bridges, tunnels, and the likes, that is, large construction projects such as roads, dams, tunnels, bridges, etc. can change river flow and water quality for a number of years. This may not be known or accountable by the modeller or the model (Abbaspour *et al*., 2009).

2.3.1.2 Input uncertainty

In addition to model uncertainty, there are uncertainties due to errors in input variables such as rainfall and temperature, as point measurements are used in distributed models. It is quite difficult to account for input uncertainty. Some researchers propose treating inputs as random variable, which allows fitting them to get better simulations. As model outputs are very sensitive to input data, especially rainfall, care must be taken in such approaches. In mountainous regions, input uncertainty could be very large.

2.3.1.3 Parameter uncertainty

Parameter uncertainty results from incomplete knowledge of parameter values, ranges, physical meaning, and temporal and spatial variability. But parameter uncertainty also reflects the incomplete model representation of hydrological processes (model uncertainty) and inadequacies of parameter estimation techniques in light of uncertain, and often limited, measured data.

Even though measuring uncertainties is difficult, packages like SWAT-CUP can help decrease modeler uncertainty by removing some probable sources of modeling and calibration errors. It is highly desirable to separate quantitatively the effect of different uncertainties on model outputs, but this is very difficult to do. The combined effect, however, should always be quantified on model out puts (Abbaspour *et al*., 2009).

2.3.2 Uncertainty analysis

Most important issue with calibration of watershed models is that of uncertainty in the predictions. Watershed models suffer from large model uncertainties. These can be divided into: conceptual model uncertainty, input uncertainty, and parameter uncertainty.

1. Conceptual model uncertainty (or structural uncertainty)
2. Input uncertainty is as a result of errors in input data such as rainfall, and more importantly, extension of point data to large areas in distributed models.
3. Parameter uncertainty

Another uncertainty worth mentioning is that of "modeler uncertainty". It has been shown before that the experience of modelers could make a big difference in model calibration. The packages like SWAT-CUP can help decrease modeler uncertainty by removing some probable sources of modeling and calibration errors. On a final note, it is highly desirable to separate quantitatively the effect of different uncertainties on model outputs, but this is very difficult to do. The combined effect, however, should always be quantified on model outputs (Abbaspour *et al*., 2009).

2.3.2.1 SWAT-CUP

SWAT-CUP is an interface that was developed for SWAT. Using this generic interface, any calibration/uncertainty or sensitivity program can easily be linked to SWAT. This is demonstrated by the program links GLUE, Parasol, SUFI2, and MCMC procedures to SWAT. In this particular study it was preferred to use sequential uncertainty fittings (SUFI2) first and also GLUE (Generalized Likelihood uncertainty estimation) to check the parameter uncertainty independently. It is automated model calibration requires that the uncertain model parameters are systematically changed, the model is run, and the required outputs (corresponding to measured data) are extracted from the model output files. The main function of an interface is to provide a link between the input/output of a calibration program and the model.

A) Conceptual Basis of the SUFI-2 uncertainty analysis routine

In SUFI-2, parameter uncertainty accounts for all sources of uncertainties such as uncertainty in driving variables (e.g., rainfall), conceptual model, parameters, and measured data. The degree to which all uncertainties are accounted for is quantified by a measure referred to as the P-factor, which is the percentage of measured data bracketed by the 95% prediction uncertainty (95PPU). As all the processes and model inputs such as rainfall and temperature distributions are correctly manifested in the model output (which is measured with some error)-the degree to which we cannot account for the measurements - the model is in error; hence uncertain in its prediction. Therefore, the percentage of data captured (bracketed) by the prediction uncertainty is a good measure to assess the strength of our uncertainty analysis. The 95PPU is calculated at the 2.5% and 97.5% levels of the cumulative distribution of an output variable obtained through Latin hypercube sampling, disallowing 5% of the very bad simulations. As all forms of uncertainties are reflected in the measured variables (e.g., discharge), the parameter uncertainties generating the 95PPU account for all uncertainties. Breaking down the total uncertainty into its various components is highly interesting, but quite difficult to do (Abbaspour *et al.*, 2009).

Another measure quantifying the strength of a calibration/uncertainty analysis is the R-factor, which is the average thickness of the 95PPU band divided by the standard deviation of the measured data. SUFI-2, hence seeks to bracket most of the measured data with the smallest possible uncertainty band. The concept behind the uncertainty analysis of the SUFI-2 algorithm is depicted graphically in Figure 2.4. This Figure illustrates that a single parameter value (shown by a point) leads to a single model response (Fig. 2.4a), while propagation of the uncertainty in a parameter (shown by a line) leads to the 95PPU illustrated by the shaded region in Figure 2.4b. As parameter uncertainty increases, the output uncertainty also increases (not necessarily linearly) (Fig. 2.4c). Hence, SUFI-2 starts by assuming a large parameter uncertainty (within a physically meaningful range), so that the measured data initially falls within the 95PPU, then decreases this uncertainty in steps while monitoring the P-factor and the R-factor. In each step, previous parameter ranges are updated by calculating the sensitivity matrix (equivalent to Jacobian), and equivalent of a Hessian matrix, followed by the calculation of covariance matrix, 95% confidence intervals of the parameters, and correlation matrix. Parameters are then updated in such a way that the new ranges are always smaller than the previous ranges, and are centered on the best simulation (Abbaspour *et al.*, 2009).

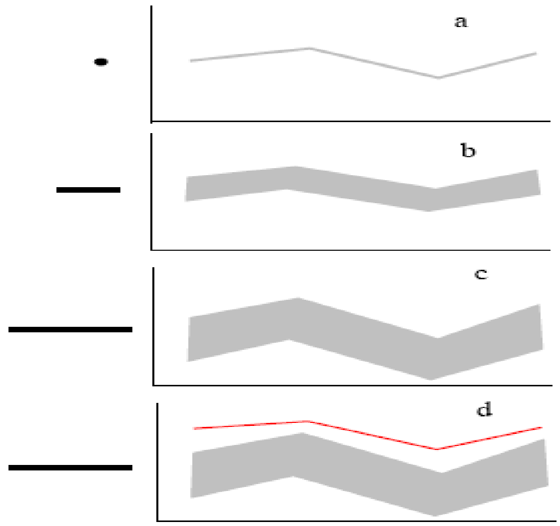

Figure 2.4. A conceptual illustration of the relationship between parameter uncertainty and prediction uncertainty (Source: SWAT CUP user manual, 2009)

The goodness of fit and the degree to which the calibrated model accounts for the uncertainties are assessed by the above two measures. Theoretically, the value for P-factor ranges between 0 and 100%, while that of R-factor ranges between 0 and infinity. A P-factor of 1 and R-factor of zero is a simulation that exactly corresponds to measured data. The degree to which we are away from these numbers can be used to judge the strength of our calibration. A larger P-factor can be achieved at the expense of a larger R-factor. Hence, often a balance must be reached between the two. When acceptable values of R-factor and P-factor are reached, then the parameter uncertainties are the desired parameter ranges. Further goodness of fit can be quantified by the R^2 and/or Nash-Sutcliff (E_{NS}) coefficient between the observations and the final "best" simulation. It should be noted that we do not seek the "best simulation" as in such a stochastic procedure the "best solution" is actually the final parameter ranges. If initially we set parameter ranges equal to the maximum physically meaningful ranges and still cannot find a 95PPU that brackets any or most of the data, for example, if the situation in Figure 2.5d occurs, then the problem is not one of parameter calibration and the conceptual model must be re-examined.

B) Introduction to the program GLUE

The Generalized Likelihood Uncertainty Estimation (GLUE) (Beven and Binley, 1992) was introduced partly to allow for the possible non-uniqueness (or equifinality) of parameter sets during the estimation of model parameters in over-parameterized models. The procedure is simple and requires few assumptions when used in practical applications. GLUE assumes that, in the case of large over-parameterized models, there is no unique set of parameters, which optimizes goodness-of fit-criteria. The technique is based on the estimation of the weights or probabilities associated with different parameter sets, based on the use of a subjective likelihood measure to derive a posterior probability function, which is subsequently used to derive the predictive probability of the output variables. In Romanowicz et al., (1994) a statistically motivated, more formal equivalent of GLUE is developed, where the likelihood function is explicitly derived based on the error between the observed outputs and those simulated by the model. This formal approach is equivalent to a Bayesian statistical estimation: it requires assumptions about the statistical structure of the errors. GLUE is usually applied by directly likelihood weighting the outputs of multiple model realizations (deterministic or stochastic, defined by sets of parameter values within one or more model structures) to form a predictive distribution of a variable of interest.

Prediction uncertainties are then related to variation in model outputs, without necessarily adding an additional explicit error component. There is thus an interesting question as to whether an appropriate choice of likelihood measure can produce similar results from the two approaches.

There are a number of possible measures of model performance that can be used in this kind of analysis. The only formal requirements for use in a GLUE analysis are that the likelihood measure should increase monotonously with increasing performance and be zero for models considered as unacceptable or non-behavioral. Application-oriented measures are easily used in this framework. Measures based on formal statistical assumptions, when applied to all model realizations (rather than simply in the region of an "optimal" model) should give results similar to a Bayesian approach when used within a GLUE framework (Romanowicz et al., 1994), but the assumptions made (additive Gaussian errors in the simplest cases) are not always easily justified in the case of nonlinear environmental models with poorly known boundary conditions.

A GLUE analysis consists of the following three steps:

1) After the definition of the "generalized likelihood measure" $L(\theta)$, a large number of parameter sets are randomly sampled from the prior distribution and each parameter set is assessed as either "behavioral" or "non-behavioral" through a comparison of the "likelihood measure" with the given threshold value.

2) Each behavioral parameter is given a "likelihood weight" according to:

$$w_i = \frac{L(\theta_i)}{\sum_{k=1}^{N} L(\theta_k)} \qquad \text{---Eq(2.1)}$$

where N is the number of behavioral parameter sets.

3) Finally, the prediction uncertainty is described as prediction quantile from the cumulative distribution realized from the weighted behavioral parameter sets. In literature, the most frequently used likelihood measure for GLUE is the *Nash- Sutcliffe* coefficient (*NS*), which is also used in the GLUE06 program:

$$NS = 1 - \frac{\sum_{t_i=1}^{n} (y_{t_i}^{M}(\boldsymbol{\theta}) - y_{t_i})^2}{\sum_{t_i=1}^{n} (y_{t_i} - \bar{y})^2} \qquad \text{---Eq(2.2)}$$

where n is the number of the observed data points, and *ti y* and *M* (**θ**) *ti y* represents the observation and model simulation with parameter θ at time *ti*, respectively, and *y* is the average value of the observations.

2.3.2.2 Performance measuring unit for uncertainty

A) P factor

The degree to which all uncertainties are accounted for is quantified by a measure referred to as the P-factor, which is the percentage of measured data bracketed by the 95% prediction uncertainty (95PPU). As all the processes and model inputs such as rainfall and temperature distributions are correctly manifested in the model output (which is measured with some error) - the degree to which we cannot account for the measurements - the model is in error; hence uncertain in its prediction. Therefore, the percentage of data captured (bracketed) by the prediction uncertainty is a good measure to assess the strength of our uncertainty analysis. The 95PPU is calculated at the 2.5% and 97.5% levels of the cumulative distribution of an output variable obtained through Latin hypercube sampling, disallowing 5% of the very bad simulations. As all forms of uncertainties are reflected in the measured variables (e.g., discharge), the parameter uncertainties generating the 95PPU account for all uncertainties. Breaking down the total uncertainty into its various components is highly interesting, but quite difficult to do, and as far as the author is aware, no reliable procedure yet exists (Abbaspour *et al*., 2009)

B) R factor

R factor is the average thickness of the 95PPU band divided by the standard deviation of the measured data. SUFI-2, hence seeks to bracket most of the measured data with the smallest possible uncertainty band.

The goodness of fit and the degree to which the calibrated model accounts for the uncertainties are assessed by the above two measures. Theoretically, the value for P factor ranges between 0 and 100%, while that of R-factor ranges between 0 and infinity. A P-factor of 1 and R-factor of zero is a simulation that exactly corresponds to measured data. The degree to which we are away from these numbers can be used to judge the strength of our calibration. A larger P-factor can be achieved at the expense of a larger R-factor.

Hence, often a balance must be reached between the two. When acceptable values of R factor and P-factor are reached, then the parameter uncertainties are the desired parameter ranges. Further goodness of fit can be quantified by the R^2(coefficient of correlation) and/or Nash-Sutcliff (E_{NS}) coefficient between the observations and the final "best" simulation. It should be noted that we do not seek the "best simulation" as in such a stochastic procedure the "best solution" is actually the final parameter ranges (Abbaspour *et al*., 2009).

CHAPTER THREE

3.0 MATERIALS AND METHODS

3.1 Description of the study area

3.1.1 Location and accessibility

Gumara watershed, drained by Gumara River, is located in south Gonder zone of the Amhara National Regional State, at 624 KM North of Addis Ababa. This watershed is part of the Abay Basin and more particularly part of Lake Tana sub-basin which is situated on the North Eastern side of Lake Tana. It drains Dera, Farta, Fogera and some part of Estie Wereda. The geographical location of the watershed is between 11^0 34‟41.41‟‟‟N and11^0 56‟ .36.95‟‟‟N latitude to 37^0 29‟30.48‟‟‟E and 38^0 10‟58.01‟‟‟E longitude.

The main asphalted road from Bahir Dar to Gonder crosses the study area. The area is also accessed by other gravel roads which connect Wereta, Amed Ber, Debre Tabor, Gassay, Mekane Eyesus, Arb Gebeya, Anbesame and Wanzaye.

The main Gumara River covers a total length of about 72 km up to the gauge station. It has diverse altitudinal difference which ranges from 1790 m to 3600 meters above sea level. The catchment has area coverage of 1350.25Km^2 (Dagnenet, 2009)

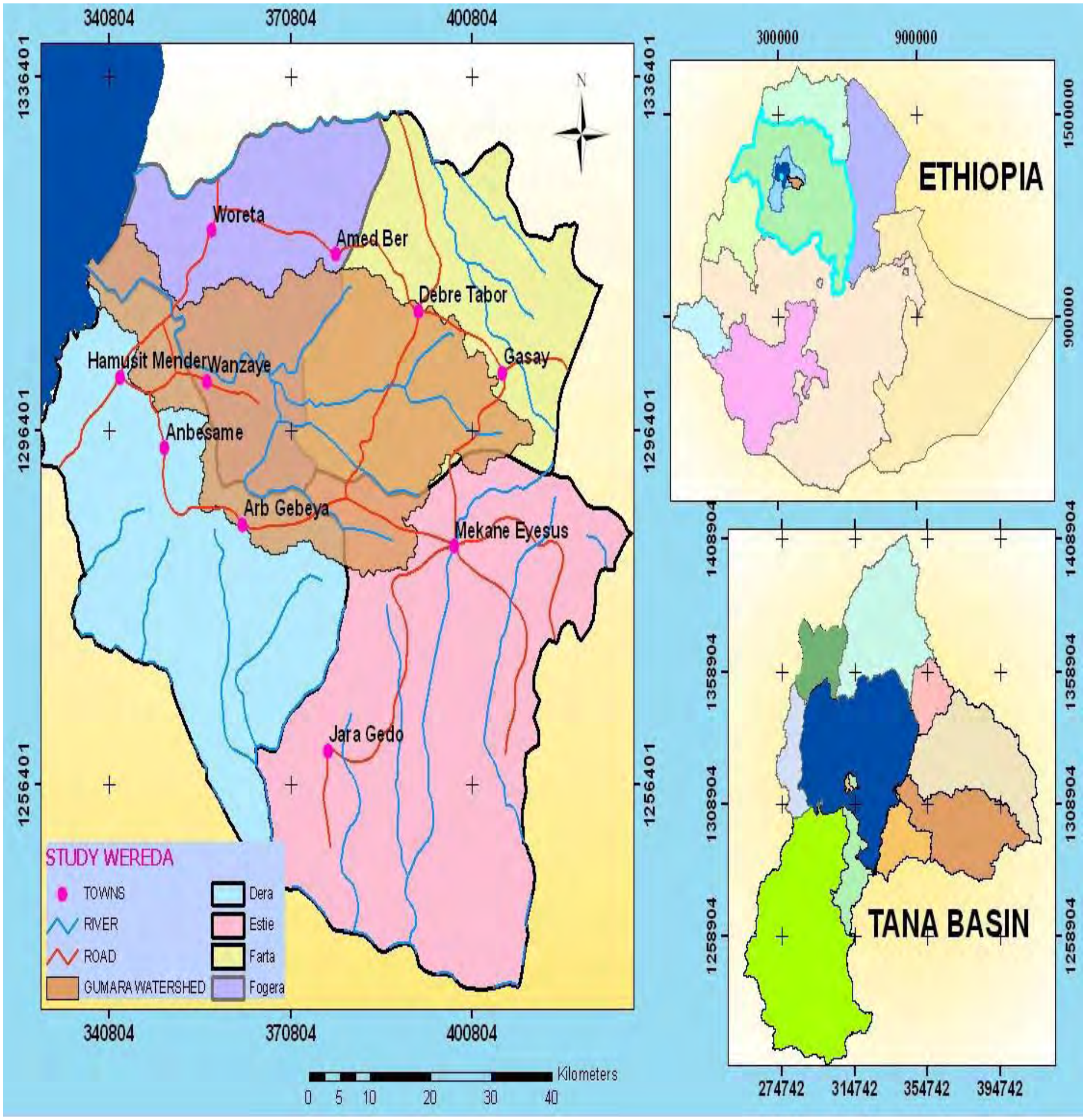

Figure 3.1. Location map of the study area. (Source: Dagnenet, 2009)

3.1.2 Topography

Gumara watershed consists of rugged and undulating topographies which vary from 1790 masl up to 3700 masl. The area has a steep slope (greater than 25%) in the high mountainous region in the east which rises above 2000 masl elevation, and of lower slope (below 3%) towards Lake Tana, the area that ranges from 1700 - 1900 masl altitude. The lower down plain reaches, near the confluence of Gumera with Lake Tana, is subject to inundation in wet seasons. This is because of the flat slopes, further worsened by back water effects of the Lake which is at higher levels during the floods (Zelalem, 2009). The maps in Figure 3.2 ,3.3 and 3.4 shows the elevation, topographic variation in 3D and slope variation of the watershed respectively.

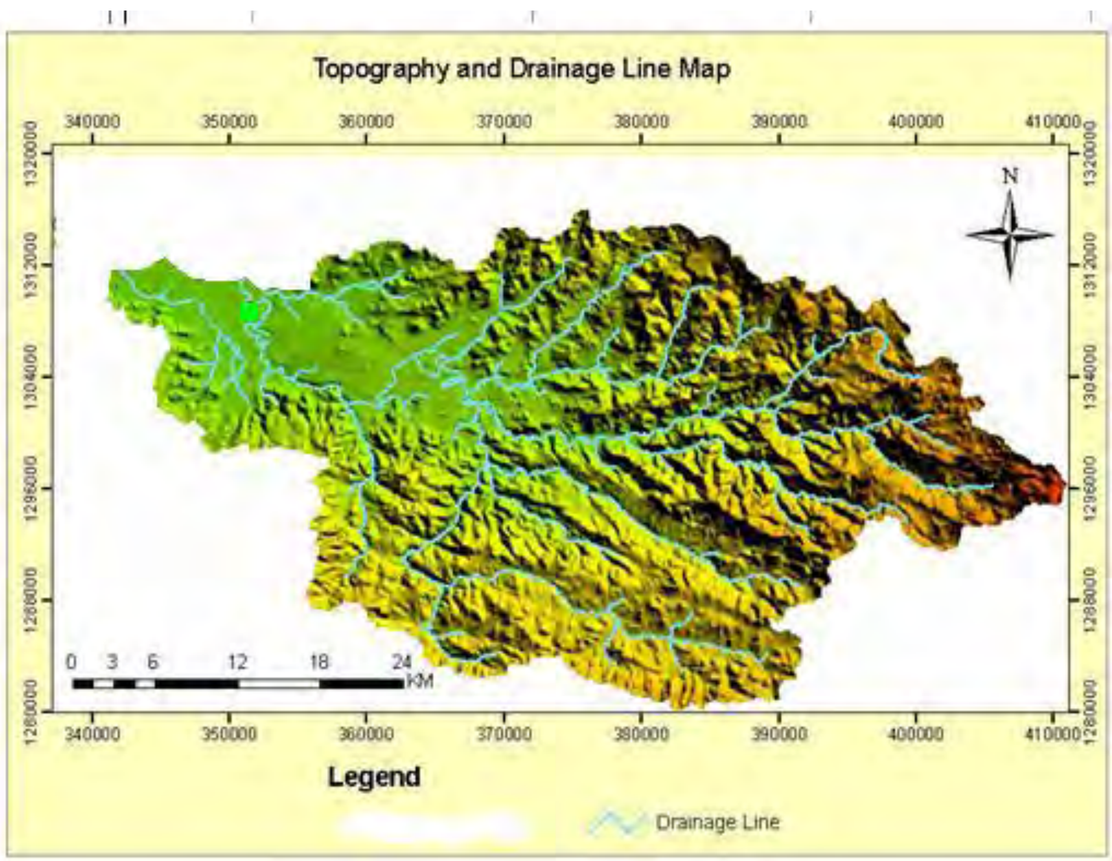

Figure 3.2. Topography of Gumara watershed (source: Zelalem, 2009)

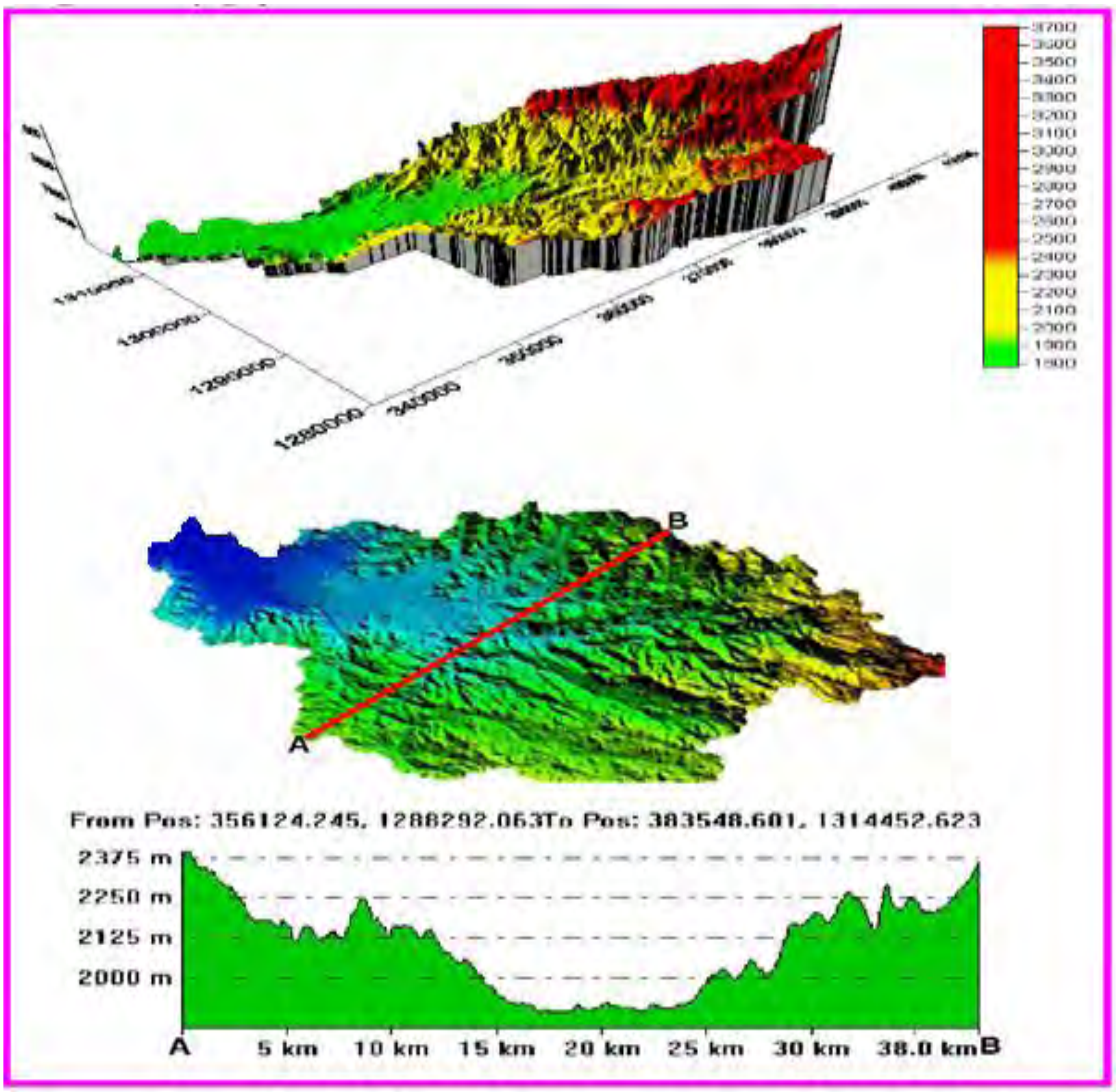

Figure 3.3 Topographic variations in 3D and cross-sectional view.(source:Zelalem,2009)

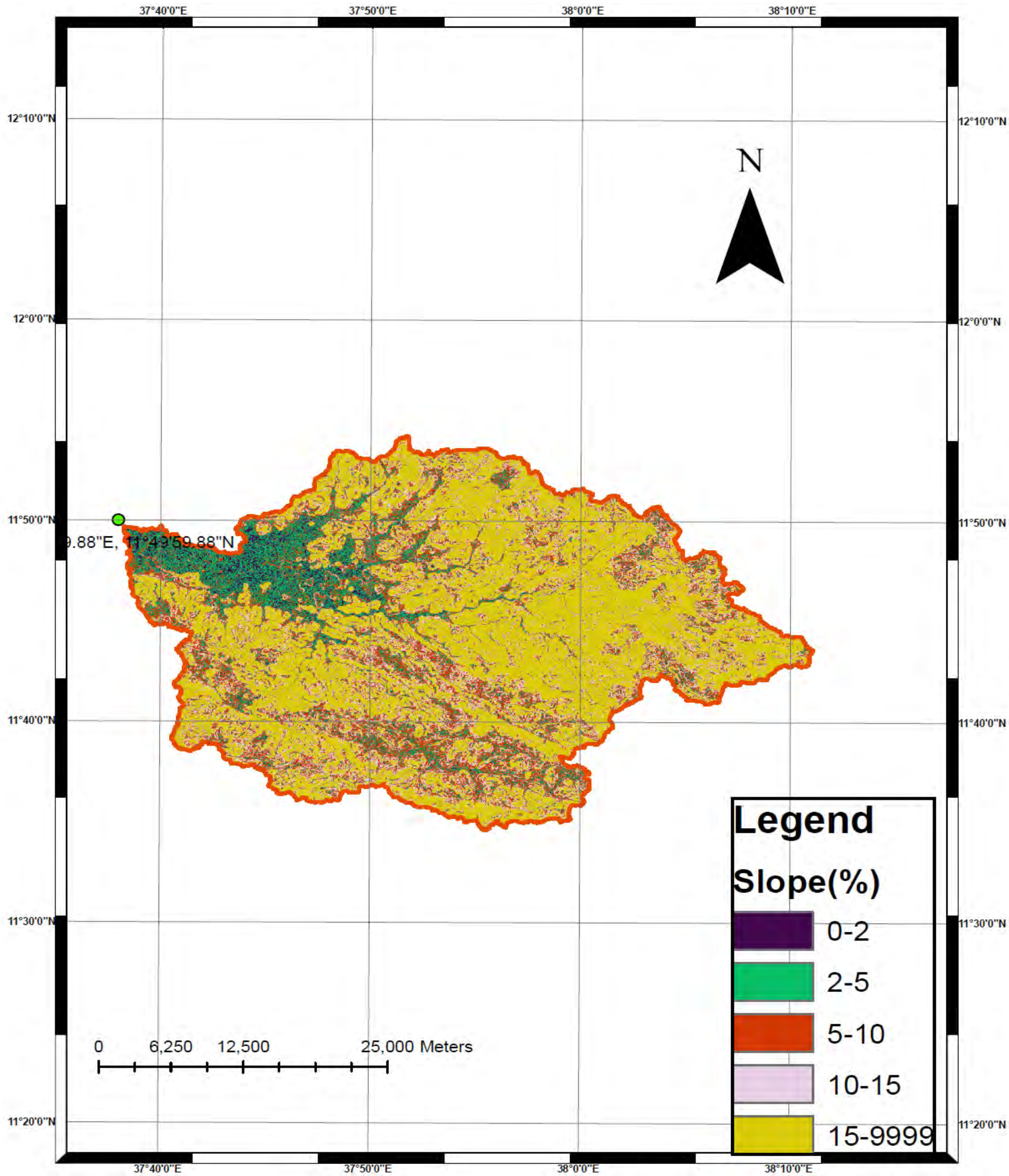

Figure 3.4.Slope of Gumera watershed.

3.1.3 Climate

3.1.3.1 Rainfall

Gumara watershed has one rainy season mainly centered on the months of June to September. April and May are an intermediate season where minor rains often occur. The annual rainfall is relatively higher in the watershed ranging between 1145 mm and 1523 mm; the eastern plain having lower annual rainfall, 1145-1300 mm, and the mountainous areas having higher annual rainfall, greater than 1300 mm (Blue Nile Basin Atlas, 2009). The detail is presented in figure 3.5.

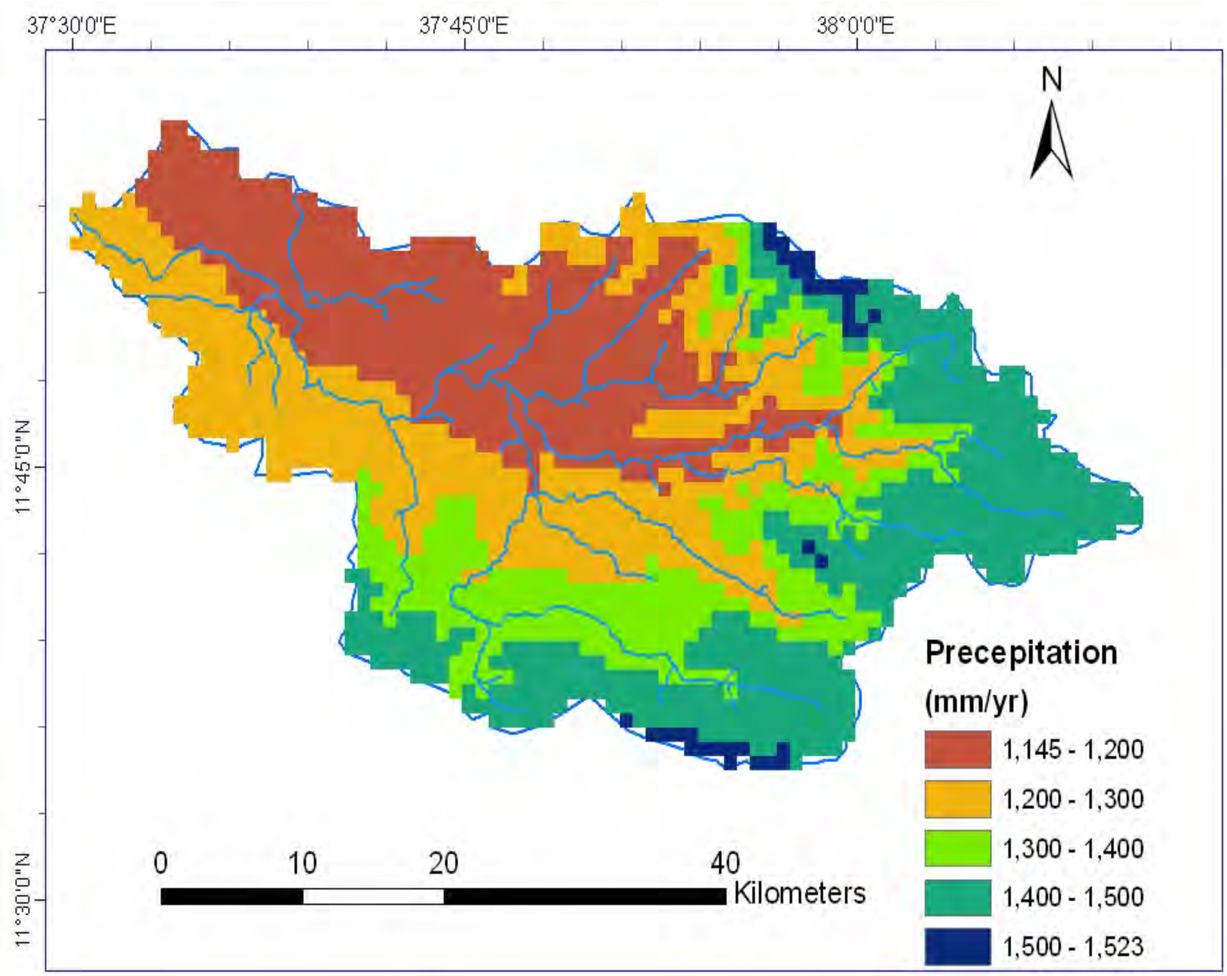

Figure 3.5.Rainfall distribution in Gumara watershed (source: Blue Nile basin atlas, 2009)

In addition the long term average monthly rainfall is presented in figure 3.6.

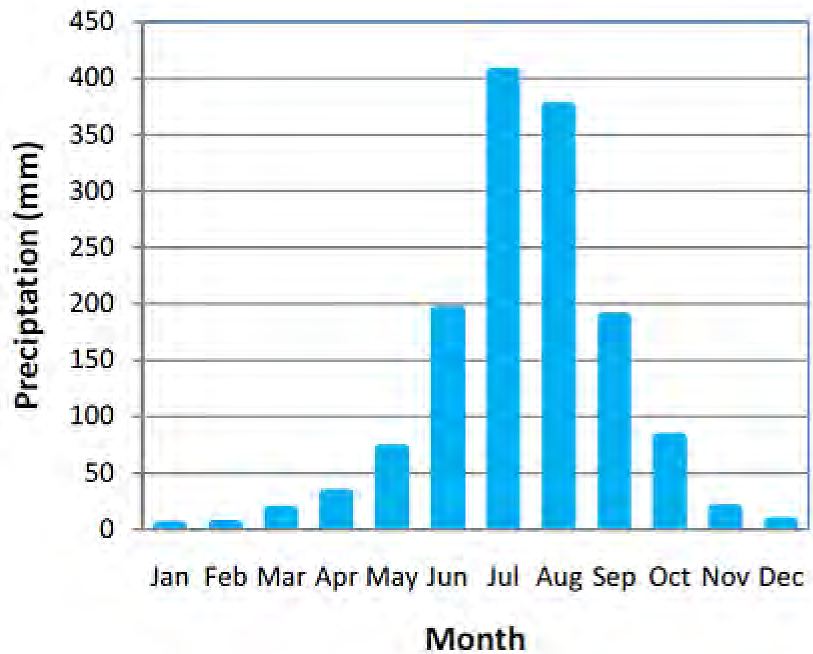

Figure 3.6 Long-term monthly precipitation distribution of Gumara river catchment

3.1.3.2 Temperature

The maximum and minimum monthly temperature in the watershed varies between 23^0C-29.9^0C and 7^0C-14^0C respectively. Annual maximum and minimum temperature variesbetween 16^0C-27^0C and 2^0C-12^0C (Blue Nile basin atlas, 2009). A map which shows maximum and minimum temperature is shown in figure 3.7 and 3.8 respectively.

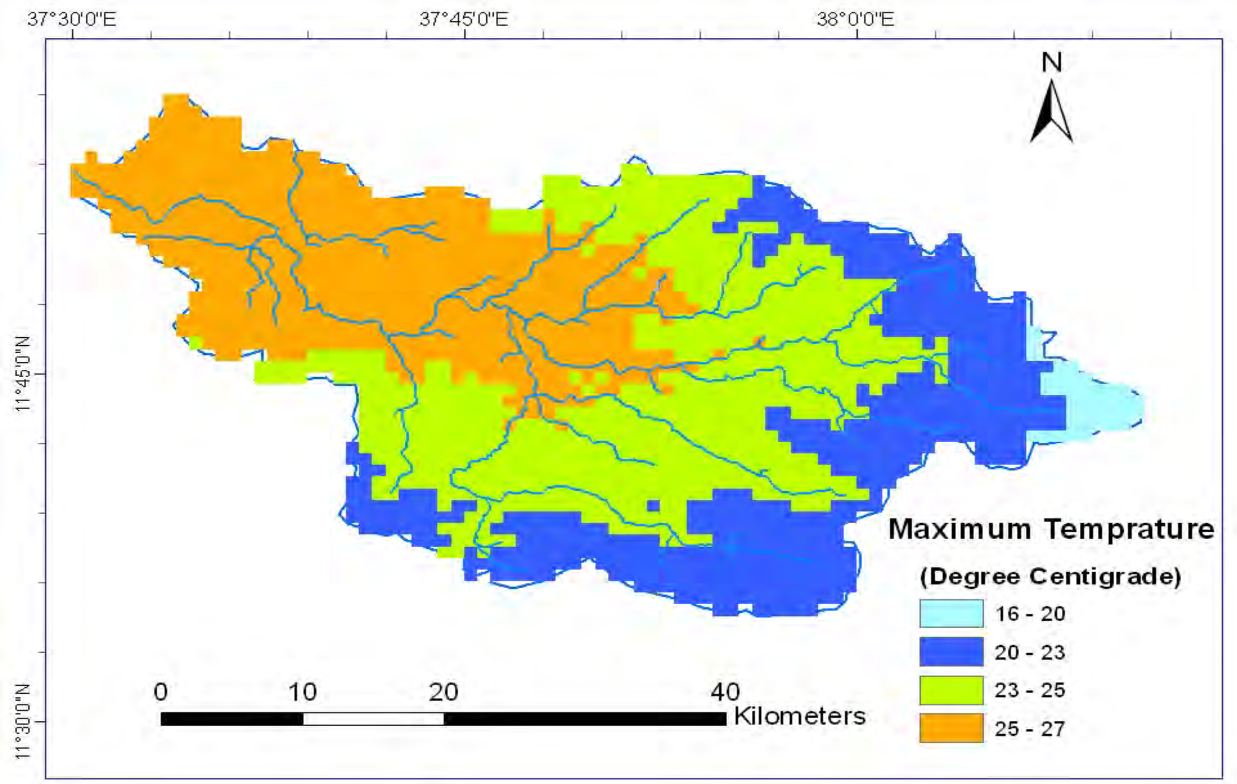

Figure 3.7. Maximum temperature in Gumara watershed (source: Blue Nile basin atlas, 2009)

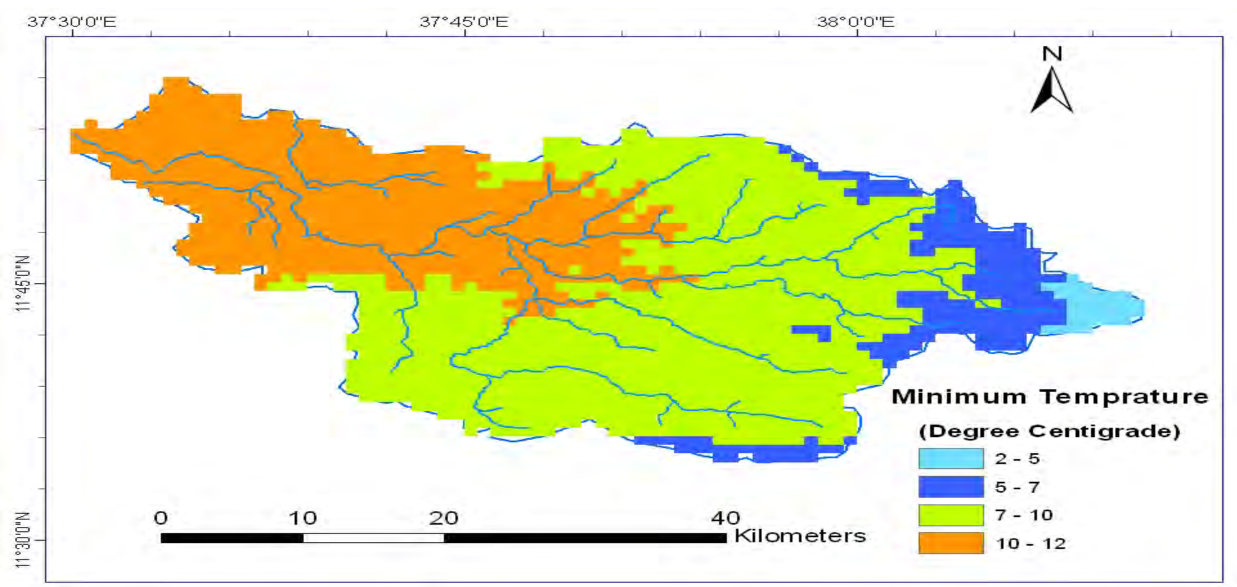

Figure 3.8 Minimum temperature in Gumera watershed (source: Blue Nile basin atlas, 2009)

3.1.3.3 Potential evapotranspiration

Potential Evapotranspiration (PET) is high in the downstream part of the watershed, ranging between 1600 mm and 1800 mm per year. Upstream of the watershed the PET is lower, below 1600 up to 1200mm at the source of the Gumara watershed (Blue Nile basin atlas.2009).

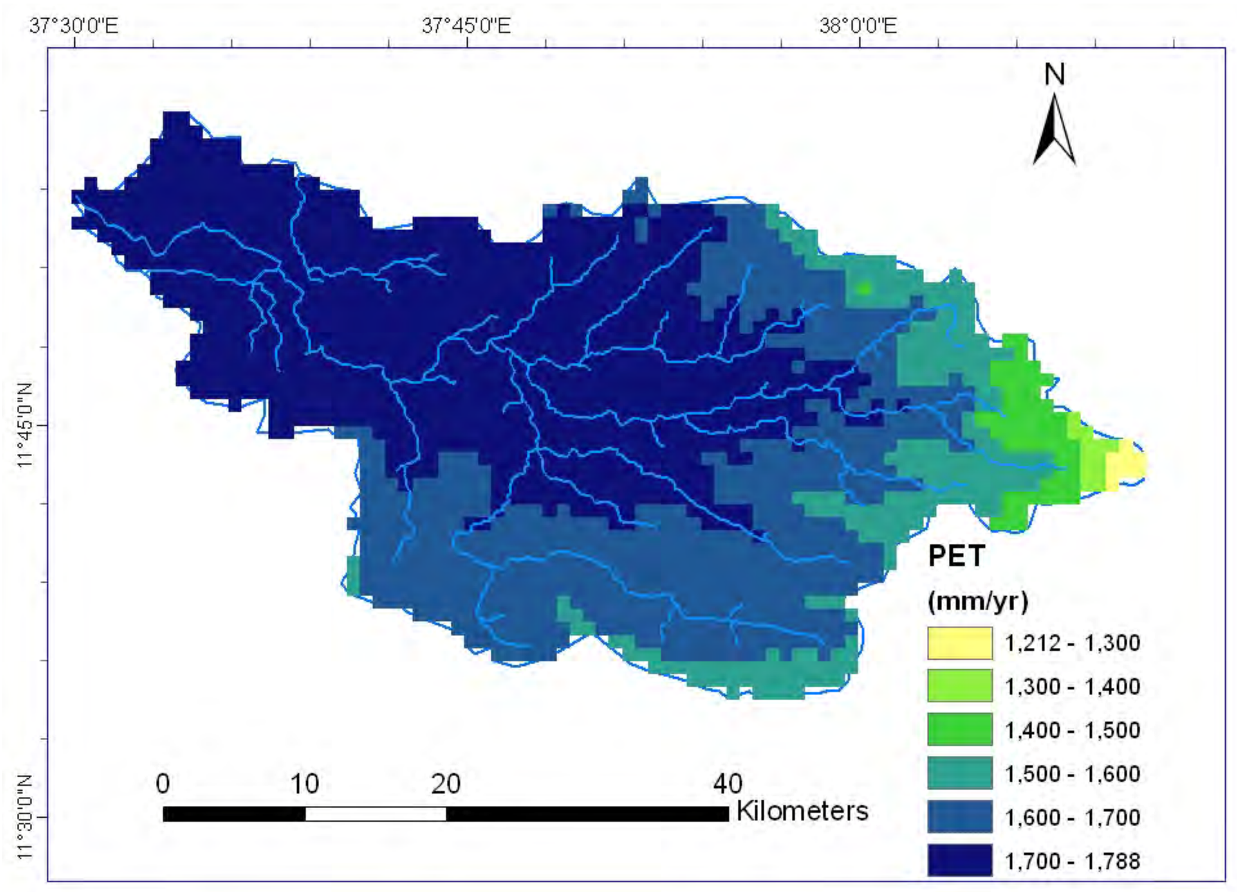

Figure 3.9 potential evapotranspiration in Gumera watershed (source: Blue Nile basin atlas, 2009)

3.1.4 Land use

The Land cover of an area is governed by its geographic, climatic and ecological conditions. The study area has not pronounced natural forest coverage. Most indigenous vegetation cover are observed around churches .The eastern extreme high land area near mount Guna has very small coverage as it has been seen in the map. However, the land coverage at the moment is dramatically decreasing due to fast population growth and the demand for utilization of the land for agricultural practices. Due to this fact more than 95% of the area is employed for agricultural activities. Currently even scatter shrubs and grass lands are being cleared and the land is utilized for food security purpose. Base on the type of covering material of the area with their present services, major land use/land cover units of the study are described. The description is based on previous reports and slight modification of the changes as a result of natural observation during the field visit.

1. Intensively cultivated with moderately deep rooted crops of cereal type like maize, sorghum, millet, teff, barley, wheat etc.
2. Moderately cultivated with shallow to deep rooted crops like onion, beans peas as well as some prevailing grass and shrubs.
3. Afro-alpine heath vegetation.

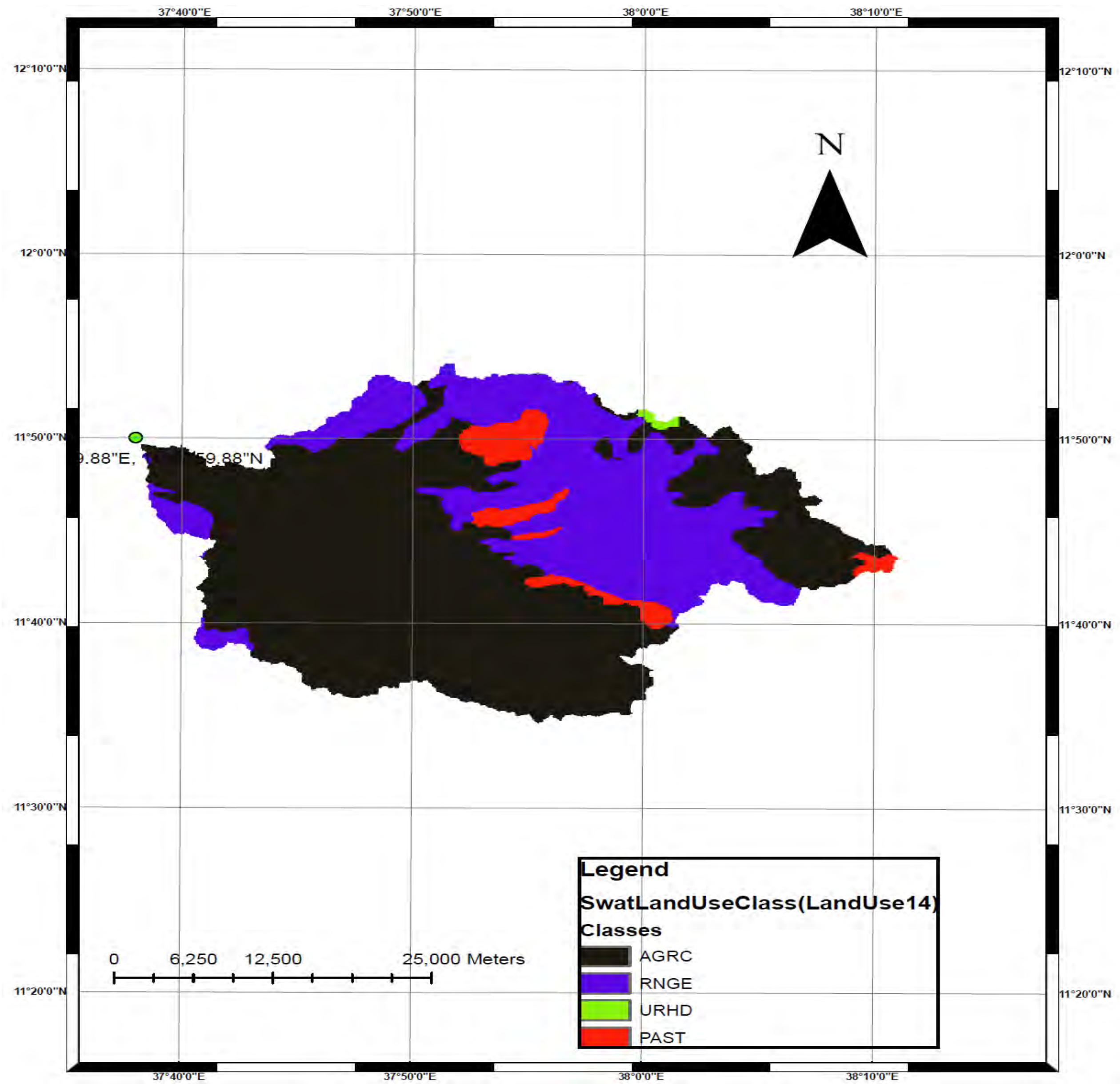

Figure 3.10. Land use/land cover map of Gumara watershed**.**

3.1.5 Soil

The lowland flat plains of the watershed are dominated with Vertisols and Fluvisols which have a dominant textural class of sandy clay and sandy loam, respectively. Shallow Leptisols are the dominant soil types found in the mountain and hills of the watershed. The watershed is characterized by four major dominant soil groups: Chromic Luvisols, Eutric Fluvisols, Haplic Luvisols and Eutric Leptosols Euric vertisols and urban land.

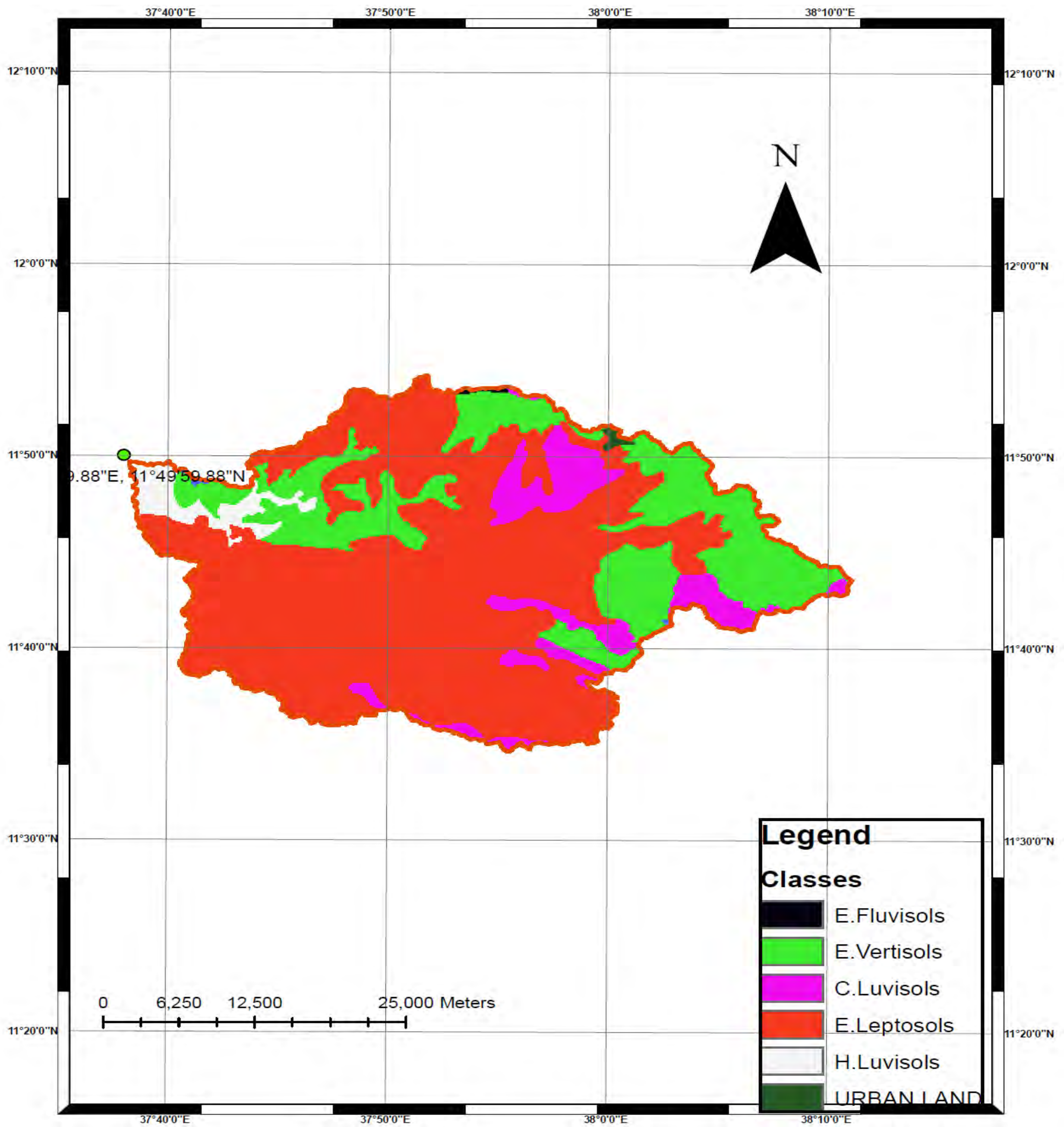

Figure 3.11. Soil types of Gumara watershed

3.2. Methodology

3.2.1 Hydrological modeling

A physically based hydrological model was developed for Gumara watershed to assess the water resource potential of Gumara watershed and associated model uncertainty analysis of the catchment. Soil and Water Assessment tool (SWAT) was selected as the best modeling tool owing to many reasons. First and for most it is a public domain model and it is used for free. Secondly in countries like Ethiopia, there is a shortage of long term observational data series to use sophisticated models; however, SWAT is computationally efficient and requires minimum data. Besides SWAT was checked in the highlands of Ethiopia and gave satisfactory results (Setegne, 2007). SWAT model was developed to predict the impact of land management practices on water, sediment, and agricultural chemical yields. However, this study concentrated on the hydrological aspect of the watershed. The description of the model, model inputs and model setup are discussed in detail in the subsequent sections.

3.2.1.1 SWAT model

The Soil and Water Assessment Tool (SWAT) model (Arnold et al., 1998; Arnold and Fohrer, 2005) has proven to be an effective tool for assessing water resource and non point source pollution problems for a wide range of scales and environmental conditions across the globe.

SWAT is a basin scale, continuous time model that operates on a daily time step and is designed to predict the impact of management on water, sediment, and agricultural chemical yields in un-gauged watersheds. The model is physically based, computationally efficient, and capable of continuous simulation over long time periods. Major model components include weather, hydrology, soil temperature and properties, plant growth, nutrients, pesticides, bacteria and pathogens, and land management.

I) Sub watershed discretization and determination of HRUs.

The sub watershed discretization was carried out to divide the watershed into sub basins based on topographic features of the watershed. This technique helped to preserve the natural flow paths, boundaries, and channels required for realistic routing of water, sediment and chemicals. The GIS interfaces developed for SWAT use the sub watershed discretization to divide a watershed.

The number of sub basins chosen to model the watershed depends on the size of the watershed, the spatial detail of available input data and the amount of detail required to meet the goals of the project. When subdividing the watershed, keep in mind that topographic attributes (slope, slope length, channel length, channel width, etc.) are calculated or summarized at the sub basin level. The sub basin delineation detailed enough to capture significant topographic variability within the watershed.

Once the sub basin delineation has been completed, the sub basins were portioned into multiple hydrologic response units (HRUs). HRUs are used in most SWAT runs since they simplify a run by lumping all similar soil and land use areas into a single response unit.

3.2.2 Hydrologic water balance.

Water balance is the driving force behind everything that happens in the watershed. In SWAT simulation of hydrology of the watershed can be separated in to two major divisions. The first division is the land phase of hydrologic cycle controls the amount of water, sediment, nutrient and pesticide loadings in to the main channel in each sub basin. The second division is the routing phase of hydrological cycle which can be defined as the movement of water, sediments, and the likes through the channel network of the watershed to the outlet. As far as this research work is concerned the hydrologic cycle mainly focused on only on the movement of water, which is the runoff generation.

It might be vital to discuss the most important hydrological cycle components and their estimation by SWAT model for this study; for further detailed explanation the author recommends referring the SWAT2005 theoretical documentation. The representation of this process is shown in figure 3.11.

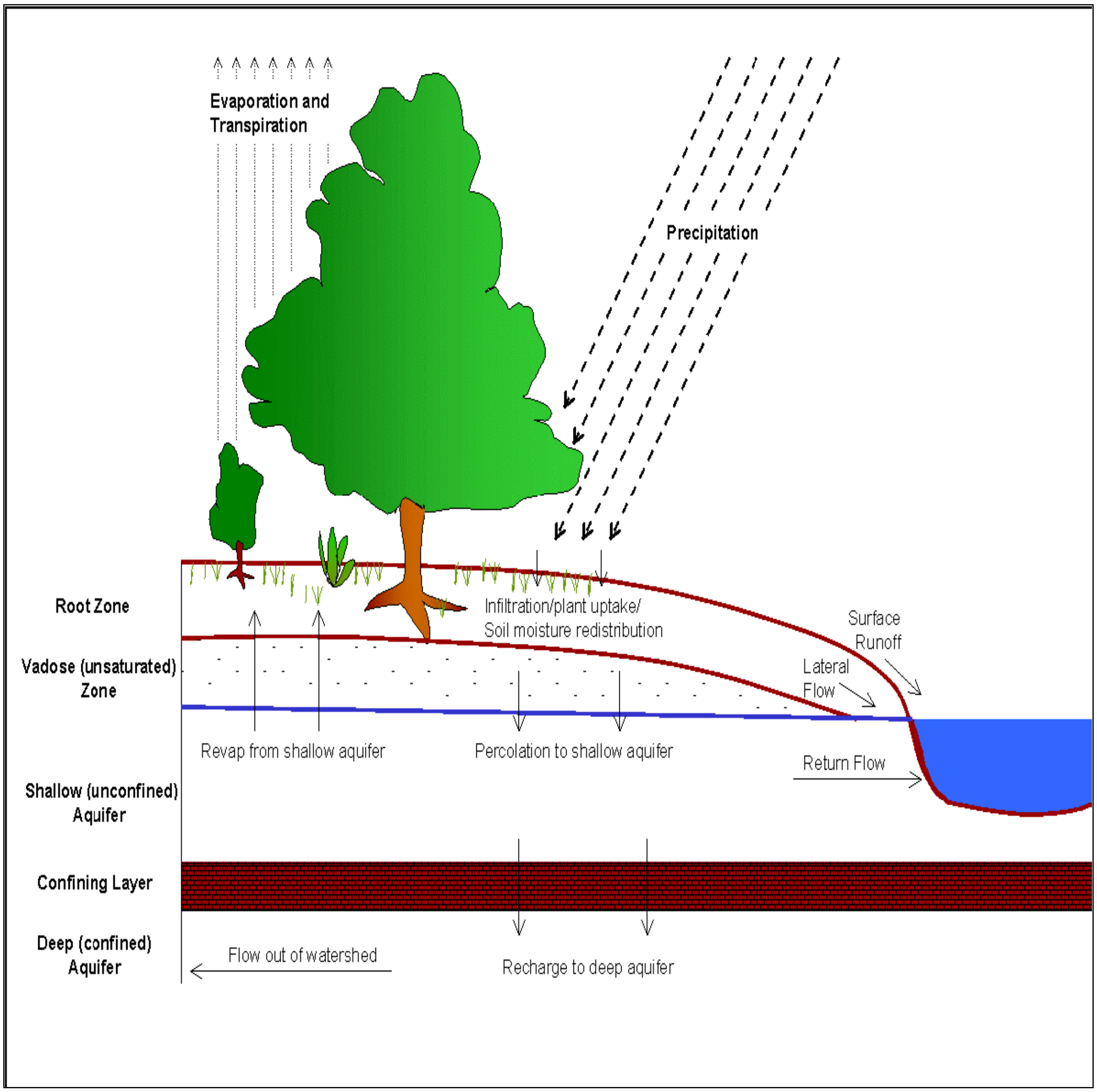

Figure 3.12 Schematic representation of Hydrologic cycle used in SWAT Model (source: SWAT2005 theoretical documentation)

The hydrologic cycle simulated by SWAT is based on the following water balance equation.

$$SW_t = SW_o + [\sum_{i=1}^{t} (R_{day} - Q_{surf} - E_a - W_{seep} - Q_{gw})] \text{--------------Eq. (4.1)}$$

Where;

SW_t = the final water content (mm H_2O)

SW_o = the initial soil water content on day i (mm H_2O)

t = time, days

R_{day} = is the amount of precipitation on day i (mm H_2O)

Q_{surf} = is the amount of surface runoff on day i (mm H_2O)

E_a = is the amount of evapotranspiration on day i (mm H_2O)

W_{seep} = is the amount of water entering the vadose zone from the Soil profile on day i (mm H_2O)

Q_{gw} = is the amount of ground water flow on day i (mm H_2O)

The subdivision of the watershed enables the model to reflect differences in evapo-transpiration for various crops and soils. Runoff is predicted separately for each HRU (Hydrologic response unit) and routed to obtain the total runoff for the watershed. This increases accuracy and gives a much better physical description of the water balance.

3.2.3 SWAT input data

3.2.3.1 Digital elevation model (DEM)

A Digital Elevation Model (DEM) was used to model the geography of the study area. A DEM is a grid of square cells where each cell represents the elevation value at that location. The size of each cell determines the resolution of the DEM. Larger the cell coarser the resolution. For large areas coarser resolutions are preferred over finer resolutions due to lower computational times and availability issues. The elevation value for each cell is an average over all the elevations inside the cell. The assumption here is that for the extent of the study area this approximation is not a cause of a significant error. The user ultimately needs to make a decision regarding the resolution to be adopted for the DEM for the study area under consideration. In this study, a 90meter by 90meter DEM was used.

Stream flow, DEM (digital elevation model) which is 90 by 90 meter resolution was collected from the federal ministry of water resources. The digital elevation model (DEM) data was used to delineate the sub-watersheds in the Arc SWAT interface.

The DEM data was shown in Figure 3.12. Before the DEM data was loaded in to Arc SWAT interface, it was projected into projected coordinate system. The projection of the DEM data was done using the Arc tool box operation in Arc GIS.

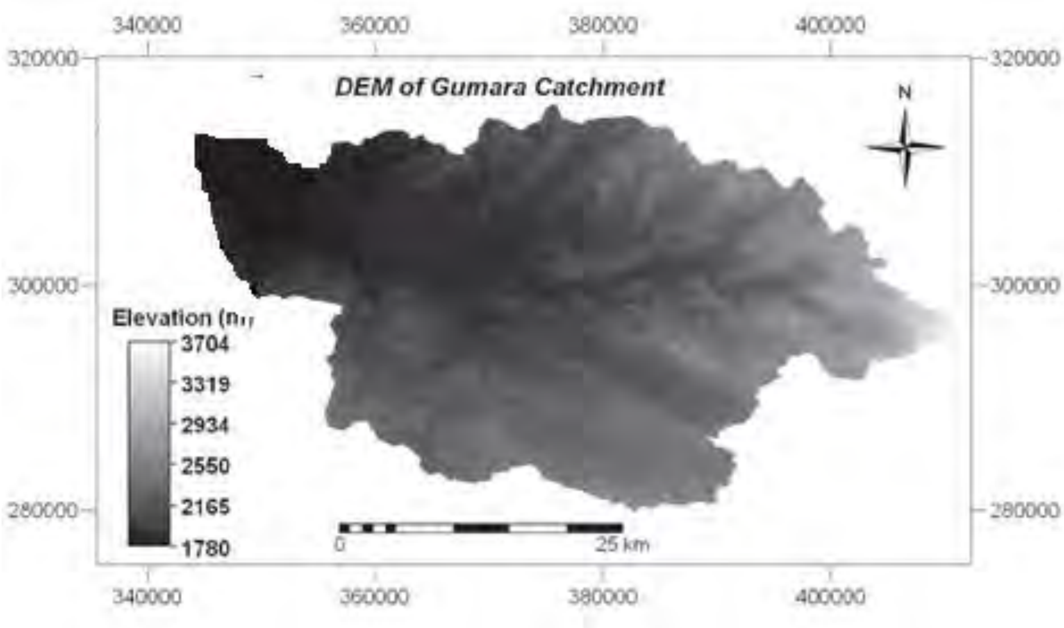

Figure 3.13. DEM of Gumara watershed

3.2.3.2 Land use/Land cover

The land use/land cover data of the study area was collected from MoWE GIS department which was obtained in shape file format. The land use/cover data was reclassified according to the SWAT land use/cover type.

A look up table that identifies the 4-letter SWAT code for the different categories of land cover/land use were prepared so as to relate the grid values to SWAT land cover/land use classes. SWAT calculated the area covered by each land use. The different land use/cover types are presented in Figure 4.1.

3.2.3.3 Soil data

Soil data was also collected from the Ethiopian MoWE GIS department .However, this data (Figure 5.2) was only in shape file format and the characteristics of the soils needed by the SWAT couldn‟t be found. The soil data used for this study was rather collected from the soil map of Ethiopia which is found in the Ministry of water resource.

3.2.3.4 Meteorological data

Meteorological data is needed by the SWAT model to simulate the hydrological conditions of the basin. The meteorological data required for this study were collected from the Ethiopian National Meteorological Services Agency (NMSA). The meteorological data collected were precipitation, maximum and minimum temperature, relative humidity, and wind speed and sunshine hours. Data from three stations (Debretabor, Bahirdar and Woreta), was represented based on Thissen polygon method which are within and around the study area, were collected. However, most of the stations have short length of record periods. Two of the stations i.e. Bahirdar and Debretabor, have records within the range of 1995-2009 but most of them have missing data especially during 2005 and 2009 where locally collected data were not delivered to the national office of meteorological agency. In some periods there is a record for precipitation but there will be a missing data for temperature, and vice versa. As the SWAT model requires data of the same periods of record, the weather data used for the study was set from 1995-2009. The consistency graph for precipitation is presented in appendix F.

Filling in missing weather data

The ability of SWAT to reproduce observed stream hydrographs is greatly improved by the use of measured precipitation data. In this study, the weather information used was considered for a period of 1995-2009. Missing weather data are left as it was in name.dbf format and a negative (-99.0) inserted for missing data. This value tells SWAT to generate weather data for that day. Daily values for weather are generated from average monthly values. The model generates a set of weather data for each sub basin. The method used for weather generator has been mentioned in methodology section.

The same weather generator technique has been applied for filling in maximum, minimum temperature, wind speed, relative humidity and solar radiation.

3.2.3.5 Hydrological data

The hydrological data was required for performing sensitivity analysis, calibration and uncertainty analysis and validation of the model. Daily stream flow data within Gumara was collected from Ministry of Water Resources (MoWR) hydrology department. The hydrological data collected was daily flow for Gumara river. The data collected has missing discharge data at some days. Even though, long record of time series data are available, concurrent data set for all the stations from a period of 1995-2003 has been used for model calibration and from 2004-2009 used for model validation. Hence, the hydrological data of the river was used for sensitivity analysis, calibration and validation. The observed average monthly discharge hydrograph is presented in figure 3.13.In addition the consistency graph of flow data is presented in appendix G.

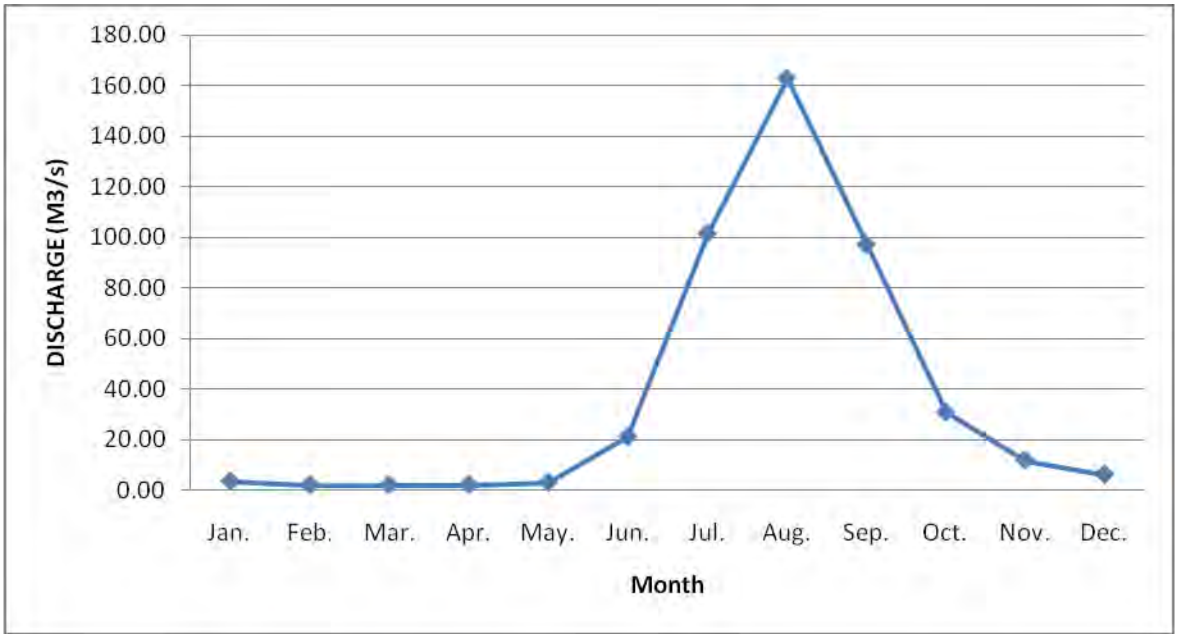

Figure 3.14. Observed average monthly discharge hydrograph of Gumara watershed.

3.2.4 SWAT model setup

3.2.4.1 Watershed delineation

SWAT uses digital elevation model (DEM) data to automatically delineate the watershed into several hierologically connected sub-watersheds. The watershed delineation operation uses and expands Arc GIS and Spatial Analyst extension functions to perform watershed delineation. The first step in the watershed delineation was loading the properly projected DEM. Next, a polyline stream network dataset was burnt-in to force SWAT sub-basin reaches to follow known stream reaches. Burning-in a stream network improves hydrological segmentation, and sub-watershed delineation. After the DEM grid was loaded and the stream networks superimposed, the DEM map grid was processed to remove the non-draining zones. The initial stream network and sub-basin outlets were defined based on drainage area threshold approach. The threshold area defines the minimum drainage area required to form the origin of a stream. The interface lists a minimum, maximum and suggested threshold area. The smaller the threshold area, the more detailed the drainage network delineated by the interface but the slower the processing time and the larger memory space required. In this study, defining of the threshold drainage area was done by successive re-run of the stream and outlet definition routine from the suggested to the minimum area until known smaller streams were created. The watershed delineation activity was finalized by calculating the geomorphic sub-basin parameter.

3.2.4.2 Hydrologic response unit analysis

Hydrologic response units (HRUs) are lumped land areas within the sub-basin that are comprised of unique land cover, soil and management combinations. HRUs enable the model to reflect differences in evapo-transpiration and other hydrologic conditions for different land covers and soils. The runoff is estimated separately for each HRU and routed to obtain the total runoff for the watershed. This increases the accuracy in flow prediction and provides a much better physical description of the water balance.

The land use and the soil data in a projected shape file format were loaded into the Arc SWAT interface to determine the area and hydrologic parameters of each land-soil category simulated within each sub-watershed. The land cover classes were defined using the look up table. A look-up table that identifies the 4-letter SWAT code for the different categories of land cover/land use was prepared so as to relate the grid values to SWAT land cover/land use classes. After the land use SWAT code assigned to all map categories, calculation of the area covered by each land use and reclassification were done. As of the land use, the soil layer in the map was linked to the user soil database information by loading the soil look-up table and reclassification applied. The land slope classes were also integrated in defining the hydrologic response units. The DEM data used during the watershed delineation was also used for slope classification. The multiple slope discretization operation was preferred over the single slope discretization as the sub-basins have a wide range of slopes between them. Based on the suggested min, max, mean and median slope statistics of the watershed, five slope classes (0-2, 2-5, 5-10, 10-15 and >15 %) were applied and slope grids reclassified. After the reclassification of the land use, soil and slope grids overlay operation was performed.

The last step in the HRU analysis was the HRU definition. The HRU distribution in this study was determined by assigning multiple HRU to each sub-watershed. In multiple HRU definition, a threshold level was used to eliminate minor land uses, soils or slope classes in each sub-basin. Land uses, soils or slope classes which cover less than the threshold level are eliminated. After the elimination process, the area of the remaining land use, soil, or slope class was reapportioned so that 100% of the land area in the sub-basin is modeled. The threshold levels set is a function of the project goal and amount of detail required. In the SWAT user manual it is suggested that it is better to use a larger number of sub-basins than larger number of HRUs in a sub-basin; a maximum of 10 HRUs in a sub-basin is recommended. Hence, taking the recommendations in to consideration, 20%, 10%, and 20% threshold levels for the land use, soil and slope classes were applied, respectively so as to encompass most of spatial details. In this study 110 HRUs were used

3.2.4.3 Weather generator.

SWAT includes the WXGEN weather generator model (Sharpley and Williams, 1990) to generate climatic data or to fill in gaps in measured records. The occurrence of rain on a given day has a major impact on relative humidity, temperature and solar radiation for the day. The weather generator first independently generates precipitation for the day. Once the total amount of rainfall for the day is generated, the distribution of rainfall within the day is computed if the Green & Ampt method is used for infiltration, maximum temperature, minimum temperature, solar radiation and relative humidity are then generated based on the presence or absence of rain for the day. Finally, wind speed is generated independently.

In order to prepare the weather generator the monthly average value of minimum and maximum temperature, wind speed, humidity and sunshine hours were determined using PCPSTAT program and the rest solar radiation value were determined using CROPWAT model.

Finally, a statistical weather generator file WXGEN for Bahirdar and Debretabor stations was prepared for fifteen years to generate climatic data and fill in gaps in the measured records of climatic data.

The daily precipitation generator is a Markov chain-skewed (Nicks, 1974) or Markov chain-exponential model (Williams, 1995). A first-order Markov chain is used to define the day as wet or dry. When a wet day is generated, a skewed distribution or exponential distribution is used to generate the precipitation amount. In this research work a skewed distribution has been used.

I) Occurrence of wet or dry day

According to SWAT 2005 theoretical documentation (Neitsch S.L, *et al.*, 2005) with the first-order Markov-chain model, the probability of rain on a given day is conditioned on the wet or dry status of the previous day. A wet day is defined as a day with 0.1 mm of rain or more.

Wet-Dry probabilities and monthly statistics value of rainfall, Maximum, Minimum Temperature, solar radiation, wind speed and relative humidity for principal stations in the study area have been computed based on the formula presented in Appendix B-1.

The weather generator stochastically determines the occurrence of rainfall in a particular day. The probability of a wet day on day i given a wet day on day i – 1, Pi (W/W), and the probability of a wet day on day i given a dry day on day i – 1, Pi (W/D), for each month of the year. From these inputs the remaining transition probabilities can be derived:

$$P_i(D/W) = 1 - P_i(W/W) \quad \text{--Eq. (3.1)}$$

$$P_i(D/D) = 1 - P_i(W/D) \quad \text{--Eq. (3.2)}$$

Where Pi (D/W) is the probability of a dry day on day i given a wet day on day i – 1 and Pi (D/D) is the probability of a dry day on day i given a dry day on day i – 1.

To define a day as wet or dry, SWAT generates a random number between 0.0 and 1.0. This random number is compared to the appropriate wet-dry probability, Pi (W/W) or Pi (W/D). If the random number is equal to or less than the wet-dry probability, the day is defined as wet. If the random number is greater than the wet-dry probability, the day is defined as dry.

Skewed probability distribution function has been used for the study area to describe the distribution of rainfall amount.

3.2.4.4 Flow simulation

Surface runoff occurs whenever the rate of water application to the ground surface exceeds the rate of infiltration. SWAT provides two methods for estimating surface runoff: the SCS curve number procedure (SCS, 1972) and the Green & Ampt infiltration method (1911). For these research work SCS curve number method has been used.

The SCS curve number used (SCS, 1972) has the following computational formula (Neitsch S.L, *et al*., 2005):

$$Q_{surf} = \frac{(R_d - I_a)^2}{(R_d - I_a + S)} \text{---Eq (3.3)}$$

Where;

Q_{surf} = the accumulated runoff or rainfall excess (mmH_2O)

R_{day} = the rainfall depth for the day (mm mmH_2O)

I_a = the initial abstractions which includes surface storage, interception and infiltration prior to runoff (mm H_2O)

S = the retention parameter (mm).

The retention parameter varies spatially due to changes in soils, land use, management and slope and temporally due to changes in soil water content. The retention parameter is defined as:

$$S = 25.49\left(\frac{1000}{CN} - 10\right) \text{---Eq. (3.4)}$$

Where: CN is the curve number for the day.

The initial abstraction, Ia, is commonly approximated as 0.2S Abbaspour (2009). and Eq. (3.4) becomes,

$$Q_{surf} = \frac{(R_{day} - 0.2S)^2}{(R_{day} + 0.8S)} \text{--Eq. (3.5)}$$

Runoff will only occur when $R_{day} > Ia$.

For the definition of the soil hydrologic groups, the model used the U.S. Natural Resource Conservation Service (NRCS) classification, which classifies soils into four hydrologic groups (A, B, C, & D) based on infiltration characteristics of the soils. Group A, B, C and D soils have high, moderate, slow, and very low infiltration rates with low, moderate, high, and very high runoff potential, respectively.

i) Peak runoff rate

The peak discharge or the peak surface runoff rate is the maximum volume flow rate passing a particular location during a storm event. SWAT calculates the peak runoff rate with a modified rational method. In rational method it is assumed that a rainfall of intensity i begins at time t = 0 and continues indefinitely, the rate of runoff will increase until the time of concentration, $t = t_{conc}$ (Neitsch S.L, *et al.*, 2005). The modified rational method is mathematically expressed as (SCS, 1972).

$$q_{peak} = \frac{\alpha_{tc} * Q_{surf} * Area}{3.6 * t_{conc.}} \text{--Eq. (3.6)}$$

Where:

q_{peak} is the peak runoff rate (m^3/s),

α_{ct} is the fraction of daily rainfall that occurs during the time of concentration, Q_{surf} is the surface runoff (mm), Area is the sub-basin area (km²),

t_{conc} is the time of concentration (hr), and 3.6 is a conversion factor

According to SCS method, SWAT estimates the value of α using the following equation

$$\alpha_{tc} = 1 - \exp[2 * t_{conc} * \ln(1 - \alpha_{0.5})] \text{---Eq. (3.7)}$$

Where:

t_{conc} is the time of concentration (hr), and

$\alpha_{0.5}$ is the fraction of daily rain falling in the half-hour highest intensity rainfall.

ii) Time of concentration

The time of concentration, t_{conc}, is a time within which the entire sub basin area is discharging at the outlet point. It is calculated by summing up both the overland flow time of the furthest point in the sub basin to reach a stream channel (t_{ov}) and the upstream channel flow time needed to reach the outlet point (t_{ch}):

$$t_{conc} = t_{ov} + t_{ch} \text{---Eq. (3.8)}$$

The overland flow time (t_{ov}) was computed as:

$$t_{ov} = \frac{Lslp}{3600 * V_{ov}} \text{--Eq. (3.9)}$$

Where:

L_{slp} is the average sub basin slope length (m),

V_{ov} is the overland flow velocity (m/s), and 3600 is a unit conversion factor.

The overland flow velocity for a unit width along the slope is calculated by using the Manning‟s equation:

$$V_{ov} = \frac{q_{ov}^{0.4} * Slp^{0.3}}{n^{0.6}} \text{--Eq. (3.10)}$$

Where:

q_{ov} is the average overland flow rate (m3/s),

Slp is the average slope of the sub basin (m/m),

n is Manning‟s roughness coefficient of the sub basin

According to the method (SCS, 1972) an average flow rate of 6.35 Km/hr (Neitsch S.L, *et al.*, 2005) and substituting the equation of V_{ov} into t_{ov}, the simplified equation of the overland flow becomes:

$$t_{ov} = \frac{L_{slp}^{0.6} * n^{0.6}}{16 * slp^{0.3}} \text{---Eq. (3.11)}$$

Channel flow time was computed as:

$$t_{ch} \frac{L_c}{3.6 * V_c} \text{--Eq. (3.12)}$$

Where: L_c is the average flow channel length (km),

V_c is the average flow velocity (m/s), and 3.6 is a unit conversion factor.

The average flow channel length was calculated as:

$$L_c = \sqrt{L * L_{cen}} \text{---Eq. (3.13)}$$

Where:

L is the channel length from the furthest point to the sub basin outlet (km),

L_{cen} is the distance along the channel to the sub basin centroid (km).

According to the method (SCS, 1972), assuming L_{cen} = 0.5L, and using the Manning"s equation for V_c for a trapezoidal channel with side slope of 2:1 and bottom width to depth ratio of 10:1, channel flow time becomes:

$$t_{ch} = \frac{0.62 * L * n^{0.75}}{Area^{0.125} * Slp_{ch}^{0.375}} \text{--Eq. (3.14)}$$

Where:

t_{ch} is the time of concentration for channel flow (hr),

L is channel length from the most distant point to the sub basin outlet (km),

n is Manning"s roughness coefficient for the channel,

Area is the sub basin area (km2), and

Slp_{ch} is the channel slope (m/m).

iii) Surface runoff lag

In large sub basins with a time of concentration greater than 1 day, only a portion of the surface runoff will reach the main channel on the day it is generated. SWAT incorporates a surface runoff storage feature to lag a part of the surface runoff release to the main channel.

Once surface runoff was calculated, the amount of surface runoff released to the main channel was calculated as:

$$Q_{surf} = (Q'_{surf} + Q_{surf,i-1}) * (1 - Exp[\frac{-surlag}{t_{conc}}]) \text{------------------------------------Eq. (3.15)}$$

Where:

Q_{surf} is amount of surface runoff discharged to main channel in a day (mm),

Q'_{surf} is amount of surface runoff generated in a sub basin in a day (mm),

Qstor,i-1 is the surface runoff stored or lagged from the previous day (mm),

Surlag is the surface runoff lag coefficient, and

t_{conc} is the time of concentration for the sub basin (hrs)

Iv) Routing method

The routing phase is the second division of hydrological cycle which can be defined as the movement of water, sediments, and the like through the channel network of the watershed to the outlet. Water is routed through the channel network using the variable storage routing method or the Muskingum River routing method.

The variable storage routing method was developed by Williams (1969) and used in the HYMO (Williams and Hann, 1973) and ROTO (Arnold et al., 1995) model has been used in this research work.

For a given reach segment, storage routing is based on the continuity equation:

$$\Delta V_{stored} = V_{in} - V_{out} \text{ --Eq. (3.16)}$$

Where:

V_{in} is the volume of inflow during the time step (m^3 water),

V_{out} is the volume of outflow during the time step (m^3 water), and

$\Delta V_{storage}$ is the change in volume of storage during the time step (m^3 water).

This equation can also be detailed as follows:

$$V_{storage,2} - V_{stored,1} = \Delta t * (\frac{q_{in,1} + q_{in,2}}{2}) - \Delta t * (\frac{q_{out,1} + q_{out,2}}{2}) \quad \text{------------------------Eq. (3.17)}$$

Where: Δt is the length of the time step (s),

q_{in}, 1 is the inflow rate at the beginning of the time step (m^3/s),

q_{in}, 2 is the inflow rate at the end of the time step (m^3/s),

q_{out}, 1 is the outflow rate at the beginning of the time step (m^3/s),

q_{out}, 2 is the outflow rate at the end of the time step (m^3/s),

Vstorage, 1 is the storage volume at the beginning of the time step (m^3 water),and

Vstorage, 2 is the storage volume at the end of the time step (m^3 water).

Travel time was computed by dividing the volume of water in the channel by the flow rate.

$$TT = \frac{V_{storage}}{q_{out}} = \frac{V_{storage,1}}{q_{out,1}} = \frac{V_{storage,2}}{q_{out,2}} \quad \text{---Eq. (3.18)}$$

Where:

TT	is the travel time (s),
$V_{storage}$	is the storage volume (m^3 water), and
q_{out}	is the discharge rate (m^3/s)

3.2.4.5 Potential evapotranspiration

Potential evapotranspiration (PET) was a concept originally introduced by Thornthwaite (1948) as part of a climate classification scheme. He defined PET is the rate at which evapotranspiration would occur from a large area uniformly covered with growing vegetation that has access to an unlimited supply of soil water and that was not exposed to advection or heat storage effects. Because of the evapotranspiration rate is strongly influenced by a number of vegetative surface characteristics, Penman (1956) redefined PET as “the amount of water transpired by a short green crop, completely shading the ground, of uniform height and never short of water”. Penman used grass as his reference crop, but later researchers (Jensen, et al., 1990) have suggested that alfalfa at a height of 30 to 50 cm may be a more appropriate choice.

Numerous methods have been developed to estimate PET. Three of these methods have been incorporated into SWAT: the Penman-Monteith method (Monteith, 1965; Allen, 1986; Allen et al., 1989), the Priestley-Taylor method (Priestley and Taylor, 1972) and the Hargreaves method (Hargreaves et al., 1985). The model will also read in daily PET values if the user prefers to apply a different potential evapotranspiration method.

The three PET methods included in SWAT vary in the amount of required inputs. The Penman-Monteith method requires solar radiation, air temperature, relative humidity and wind speed. The Priestley-Taylor method requires solar radiation, air temperature and relative humidity. The Hargreaves method requires air temperature only. In this study Penman-Monteith Method is used by default.

i) Penman-monteith method

The Penman-Monteith equation combines components that account for energy needed to sustain evaporation, the strength of the mechanism required to remove the water vapor and aerodynamic and surface resistance terms.

The penman-Monteith equation is (Penman, 1956)

$$\lambda E = \frac{\Delta.(H_{net} - G) + \rho_{air}.C_p.[e^o{}_z - e_z]/r_a}{\Delta + \gamma.(1 + r_c / r_a)} \quad \text{---Eq. (3.19)}$$

Where λE is the latent heat flux density (MJ m-2 d-1),

E is the depth rate evaporation (mm d-1), Δ is the slope of the saturation vapor pressure-temperature curve, de/dT (kPa °C-1), Hnet is the net radiation (MJ m-2 d-1), G is the heat flux density to the ground (MJ m-2 d-1), ρ_{air} is the air density (kg m-3), cp is the specific heat at constant pressure (MJ kg-1 °C-1), is the saturation vapor pressure of air at height z (kPa), e^o_z e_z is the water vapor pressure of air at height z (kPa), γ is the psychrometric constant (kPa °C-1), r_c is the plant canopy resistance (s m-1), and r_a is the diffusion resistance of the air layer (aerodynamic resistance) (s m-1).

For well-watered plants under neutral atmospheric stability and assuming logarithmic wind profiles, the Penman-Monteith equation may be written (Jensen et al., 1990):

$$\lambda E_t = \frac{\Delta.(H_{net} - G) + \gamma.K_1.(0.622.\lambda.\rho_{air} / P).[e^o{}_z - e_z] / r_a}{\Delta + \gamma.(1 + r_c / r_a)}$$ ------------------------Eq. (3.20)

Where λ is the latent heat of vaporization (MJ kg-1), Et is the maximum transpiration rate (mm d-1), K1 is a dimension coefficient needed to ensure the two terms in the numerator have the same units (for uz in m s-1, K_1 = 8.64 x 104), and P is the atmospheric pressure (kPa).

3.2.4.6 Groundwater system

Groundwater balance in SWAT model is calculated by assuming two layers of aquifers. SWAT partitions groundwater into a shallow, unconfined aquifer and a deep-confined aquifer and it simulates two aquifers in each sub basin. The shallow aquifer is an unconfined aquifer that contributes to flow in the main channel or reach of the sub basin. The deep aquifer is a confined aquifer. Water that enters the deep aquifer is assumed to contribute to stream flow somewhere outside of the watershed (Arnold et al., 1993).

Groundwater flow contribution to total stream flow is simulated by creating shallow aquifer storage (Arnold et al, 1993). Percolate from the bottom of the root zone is recharge to the shallow aquifer. A recession constant, derived from daily stream flow records, is used to lag flow from the aquifer to the stream. Other components of groundwater system include evaporation, pumping withdrawals, and seepage to the deep aquifer.

i) Shallow aquifer

The water balance for a shallow aquifer in SWAT was calculated with:

$$aq_{sh,i} = aq_{sh,i-1} + w_{rchrg} - Q_{gw} - w_{revap} - w_{deep} - w_{pump,sh} \text{------------------------------Eq. (3.21)}$$

where $aq_{sh,i}$ is the amount of water stored in the shallow aquifer on day i (mm), $aq_{sh,i-1}$ is the amount of water stored in the shallow aquifer on day i-1 (mm), w_{rchrg} is the amount of recharge entering the aquifer on day i (mm), Q_{gw} is the groundwater flow, or base flow, into the main channel on day i (mm), w_{revap} is the amount of water moving into the soil zone in response to water deficiencies on day i (mm), w_{deep} is the amount of water percolating from the shallow aquifer into the deep aquifer on day i (mm), and $w_{pump,sh}$ is the amount of water removed from the shallow aquifer by pumping on day i (mm).

ii) Deep aquifer

The water balance for the deep aquifer in SWAT was computed as:

$$aq_{dp,i} = aq_{dp,i-1} + w_{deep} - w_{pump,dp} \text{ ---Eq. (3.22)}$$

where aq_{dp}, i is the amount of water stored in the deep aquifer on day i (mm), $aq_{dp,\, i-1}$ is the amount of water stored in the deep aquifer on day i-1 (mm), w_{deep} is the amount of water percolating from the shallow aquifer into the deep aquifer on day i (mm), and $w_{pump,dp}$ is the amount of water removed from the deep aquifer by pumping on day i (mm). If the deep aquifer is specified as the source of irrigation water or water removed for use outside the watershed, the model will allow an amount of water up to the total volume of the deep aquifer to be removed on any given day

After preparing weather generator and the identified soil type was incorporated into the model, the model was run by incorporating the different look up tables mentioned previously.

3.2.4.7 Sensitivity Analysis

SWAT is a complex model with many parameters that makes manual calibration difficult. Hence, sensitivity analysis was performed to limit the number of optimized parameters to obtain a good fit between the simulated and measured data. Sensitivity analysis helps to determine the relative ranking of which parameters most affect the output variance due to input variability (van Griensven et al., 2002) which reduces uncertainty and provides parameter estimation guidance for the calibration step of the model. SWAT model has an embedded tool to perform sensitivity analysis and provides recommended ranges of parameter changes. SWAT2005 uses a combination of Latine Hypercube Sampling and One-At-a-Time sensitivity analysis methods (LH-OAT method) (van Griensven, 2005). The concept of the Latin-Hypercube Simulation is based on the Monte Carlo Simulation to allow a robust analysis but uses a stratified sampling approach that allows efficient estimation of the output statistics while the One-Factor-At-a-Time is an integration of a local to a global sensitivity method (van Griensven, 2005). In local methods, each run has only one parameter changed.

Therefore sensitivity analysis as an instrument for the assessment of the input parameters with respect to their impact on model output is useful not only for model development, but also for model validation and reduction of uncertainty (Hamby, 1994 cited in Lenhart *et al.* 2002)

Using the built in tool in SWAT model auto sensitivity analysis has been performed for stream flow in the basin and the result is found in modeling section of this report.

3.2.4.8 Calibration and Validation of Model

a) Calibration

Physically based semi distributed model SWAT generally have a large number of parameters which are not directly measurable and must therefore be estimated through model calibration, i.e. by fitting the simulated outputs of the model to the observed outputs of the watershed by adjusting the model parameters. A measure of the fit between the simulated and observed outputs is called calibration. The goal of calibration is to find those values for the model parameters that minimize (Maximize) the specified calibration criterion.

The SWAT model was calibrated and validated for flow in Gumara river flow on a monthly basis for flow in Gumara gauged watershed. Before the calibration exercise was implanted, 26 hydrological parameters were tested for sensitivity analysis for the simulation of the stream flow in the study area. Out of these 26 sensitive parameters the first 10 parameters were taken for calibration for the year 1995-2003.The details of all hydrological parameters are found in the ArcSWAT interface for SWAT user"s manual (Neitsch, *et al*., 2004; Winchell *et al*., 2007). Auto-calibration methods were implemented for minimizing the difference between measured and predicted flow. Parameters that are mostly used for SWAT model runoff generation is presented in table 3.1.

Table 3.1 Most common parameters used in SWAT model for runoff generation

S.No.	Parameter	legend
1	ALPHA_BF	Base flow alpha factor [days]
2	GWQMN	Threshold water depth in the shallow aquifer for flow [mm]
3	GW_REVAP	Groundwater "revap" coefficient
4	REVAPMN	Threshold water depth in the shallow aquifer for "revap" [mm]
5	ESCO	Soil evaporation compensation factor
6	SLOPE	Average slope steepness [m/m]
7	SLSUBBSN	Average slope length [m]
8	TLAPS	Temperature lapse rate [°C/km]
9	CH_K2	Channel effective hydraulic conductivity [mm/hr]
10	CN2	Initial SCS CN II value
11	SOL_AWC	Available water capacity [mm WATER/mm soil]
12	SURLAG	Surface runoff lag time [days]
13	GW_DELAY	Groundwater delay [days]
14	RCHRG_DP	Deep aquifer percolation fraction
15	CANMX	Maximum canopy storage [mm]
16	SOL_K	Saturated hydraulic conductivity [mm/hr]
17	SOL_Z	Soil depth [mm]
18	SOL_ALB	Moist soil albedo
19	EPCO	Plant uptake compensation factor
20	CH_N	Manning's n value for main channel
21	BLAI	Maximum potential leaf area index
22	BIOMIX	Biological mixing efficiency

b) Validation

In order to utilize the calibrated model for estimating the effectiveness of future potential management practices, the model tested against an independent set of measured data. This testing of a model on an independent set of data set is commonly referred to as model validation. As the model predictive capability was demonstrated as being reasonable in both the calibration and validation phases, the model was used for future predictions under different management scenarios.

Validation for the year 2004-2009 was done on daily average monthly basis.

3.2.4.9 Evaluation of Model Performance

The performance of SWAT was evaluated using statistical measures to determine the quality and reliability of predictions when compared to observed values. Coefficient of determination (R^2) and Nash-Sutcliffe simulation efficiency (E_{NS}) were the goodness of fit measures used to evaluate model prediction. The R^2 value is an indicator of strength of relationship between the observed and simulated values. The Nash-Sutcliffe simulation efficiency (E_{NS}) indicates how well the plot of observed versus simulated value fits the 1:1 line. If the measured value is the same as all predictions, E_{NS} is 1. If the E_{NS} is between 0 and 1, it indicates deviations between measured and predicted values. If E_{NS} is negative, predictions are very poor, and the average value of output is a better estimate than the model prediction (Nash and Sutcliffe, 1970). The R^2 and E_{NS} values are explained in equations 4.25 and 4.26 respectively. The performance of a model must be evaluated on the extent of its accuracy, consistency and adaptability (Goswami et al., 2005)

A forecast efficiency criterion is therefore necessary to judge the performance of the model. Assessing performance of a hydrologic model (Krause et al., 2005) requires subjective and/or objective estimates of the closeness of the simulated behavior of the model to observations.

Correlation coefficient (R^2) and Nash and Sutcliffe simulation efficiency (E_{NS}) (Nash and Suttcliffe ,1970) were used to evaluate the model,s performance during calibration and validation processes. And the result is presented in chapter five of this report.

SWAT developers in Santhi et.al, (2001) assumed an acceptable calibration for hydrology at $r^2 > 0.6$ and $E_{NS} > 0.5$ these values were also considered in this study as adequate statistical values for acceptable calibration. The detailed description of R^2 and E_{NS} is presented below.

The r^2 coefficient and E_{NS} simulation efficiency measure how well trends in the measured data are reproduced by the simulated results over a specified time period and for a specified time step. The range of values for r^2 is 1.0 (best) to 0.0.

The r^2 coefficient for n time steps is calculated as:

$$r^2 = \frac{\left[\sum_{i=1}^{n}(q_{si} - \overline{q}_s)(q_{oi} - \overline{q}_o)\right]^2}{\sum_{i=1}^{n}(q_{si} - \overline{q}_s)^2 \sum_{i=1}^{n}(q_{oi} - \overline{q}_o)^2} \text{ --Eq. (3.25)}$$

Where:

q_{si} is the simulated value

q_{oi} is the measured values

$\overline{q}_s$ is the average simulated value

$\overline{q}_o$ is the average measured value

The E_{NS} simulation efficiency for n time steps is calculated as:

$$E_{NS} = 1 - \frac{\sum_{i=1}^{n}(q_{oi} - q_{si})^2}{\sum_{i=1}^{n}(q_{oi} - \overline{q}_o)^2} \text{ --Eq. (3.26)}$$

Where:

q_{si} is the simulated value

q_{oi} is the measured value

The statistical index of modeling efficiency (E_{NS}) values range from 1.0(best) to negative infinity.

Another performance parameters used in this study were the percent difference (D) and observation standard deviation ratio (RSR).

The percent difference for a quantity (D) over a specified period with total days is calculated from measured and simulated values of the quantity in each model time step as:

$$D = 100 \cdot \left[\frac{\left(\sum_{i=1}^{n} q_{oi} - \sum_{i=1}^{n} q_{si} \right)}{\sum_{i=1}^{n} q_{oi}} \right] \text{--Eq. (3.28)}$$

Where:

q_{si} is the simulated value

q_{oi} is the measured value

A value close to 0% is best for D. A negative value indicates model over estimation and a positive value indicate model under estimation.

RMSE Observation standard deviation ratio (RSR) also another performance rating can be described as follows:

RSR standardizes RMSE using the observations standard deviation, and it combines both an error index and the additional information recommended by Legates and (McCabe 1999, Cited in D.N Moriasi, 2007). RSR is calculated as the ratio of the RMSE and standard deviation of measured data, as shown in equation Eq. (3.29)

$$RSR = \frac{[\sum_{i=1}^{n}(Q_{obs} - Q_{sim})^2]^{1/2}}{[\sum_{i=1}^{n}(Q_{obs} - \overline{Q}_{obs})^2]^{1/2}} \text{ ---Eq. (3.29)}$$

Where: Q_{obs} is the observed flow.

Q_{sim} is the simulated flow.

$\overline{Q}_{obs}$ is mean observed flow.

RSR incorporates the benefits of error index statistics and includes a scaling / normalization factor, so that the resulting statistic and reported values can apply to various constituents. RSR varies from the optimal value of 0, which indicates zero RMSE or residual variation and therefore perfect model simulation, to a large positive value. The lower RSR, the lower the RMSE, and the better the model simulation performance.

Note: E_{NS}= 1- $(RSR)^2$

The general summery of all the performance criteria is presented in table 3.2.

Table 3.2 General Performance ratings for recommended statistics for a monthly time step. (D. N Moriasi, et al. 2007) and Santhi et.al, (2001) for R^2.

Performance rating	For stream Flow			
	RSR	E_{NS}	% D	R^2
Very good	0.0<=RSR<=0.5	0.75<NSE<=1	D <=±10	
Good	0.5<RSR<=0.6	0.65<NSE<=0.75	±10 <=D < ±15	
Satisfactory	0.6<RSR<=0.7	0.5<NSE<=0.65	±15<=D<± 25	>0.6
Unsatisfactory	RSR>=0.7	NSE<=0.5	D >= ± 25	<0.6

3.2.4.10. Uncertainty analysis

As distributed hydrological modeling is subject to large uncertainties, the definition and quantification of model uncertainty has become the subject of considerable research in recent years. To fulfill this demand, researchers have developed various uncertainty analysis techniques for watershed models. These include Bayesian inference methods, such as: the Markov chain Monte Carlo (MCMC) method, generalized likelihood uncertainty estimation (GLUE), parameter solution (Parasol), and sequential uncertainty fitting (SUFI-2). As no single calibration program can meet the objectives of different modelling needs, GLUE, Parasol, SUFI-2, and MCMC were interfaced with SWAT into a single package, referred to as SWAT-CUP (SWAT Calibration Uncertainty Programs).

In addition, model calibration does not guarantee reliability of model predictions. The parameter values obtained during calibration and the subsequent predictions made using the calibrated model are only as realistic as the validity of the model assumptions for the study watershed and the quality and quantity of actual watershed data used for calibration and simulation. Therefore, even after calibration, there is potentially a great deal of uncertainty in results that arises simply because it is too unlikely to find error-free observational data (e.g. precipitation, stream flow, topography) and because no simulation model is an entirely true reflection of the physical process being modeled. This study used first SUFI-2 for overall uncertainty analysis and GLUE for parameter uncertainty analysis to investigate uncertainties involved with predicting stream flow for the study watershed.

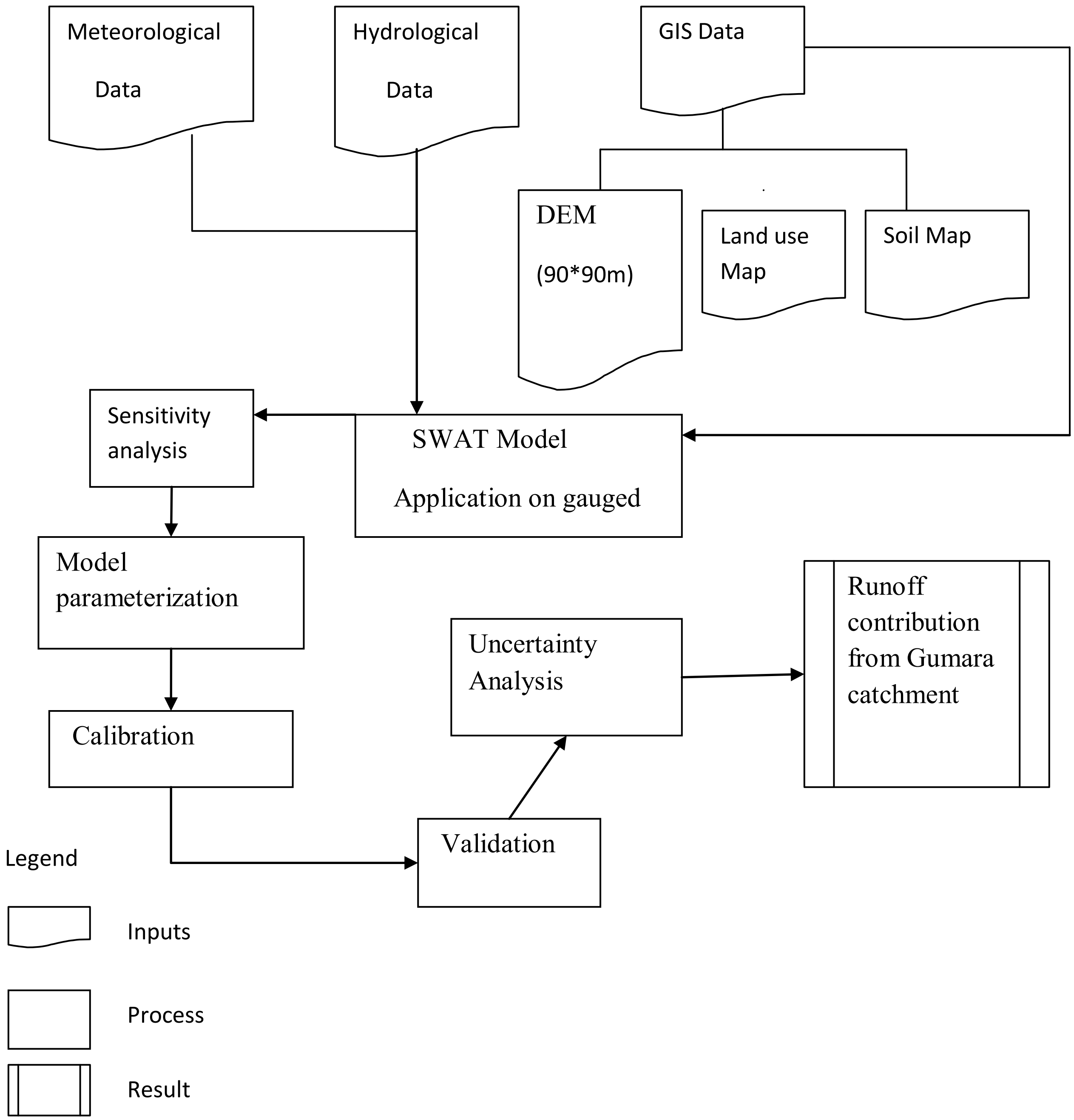

Figure 3.15. Simplified flow chart of the Methodology adopted in the research

CHAPTER FOUR

4. Results and Discussion

4.1. SWAT Hydrological Model

This chapter covers the findings of the study obtained from the SWAT model analysis.

4.1.1. Land use

As shown in table 4.1 and figure 4.1 the watershed were found to composed of four land use types: Agricultural land, Range land, Pastoral land and Residential land. Agricultural lands close grown (AGRC) and residential high density (URHD) covering the largest (63.80%) and smallest (0.23%) portion of it respectively. The land uses of the area were defined according to SWAT"s system of nomenclature.

Table 4.1. Land use classification of Gumera catchment using SWAT Model.

No.	Land use	SWAT Land use Class	Area (Km^2)	% of Total Area
1	Agriculture	AGRC	819	63.8
2	Range land	RNGE	400	31.39
3	Pastoral	PAST	55.36	4.28
4	Residential	URHD	3	0.23
Total			1273.36	100

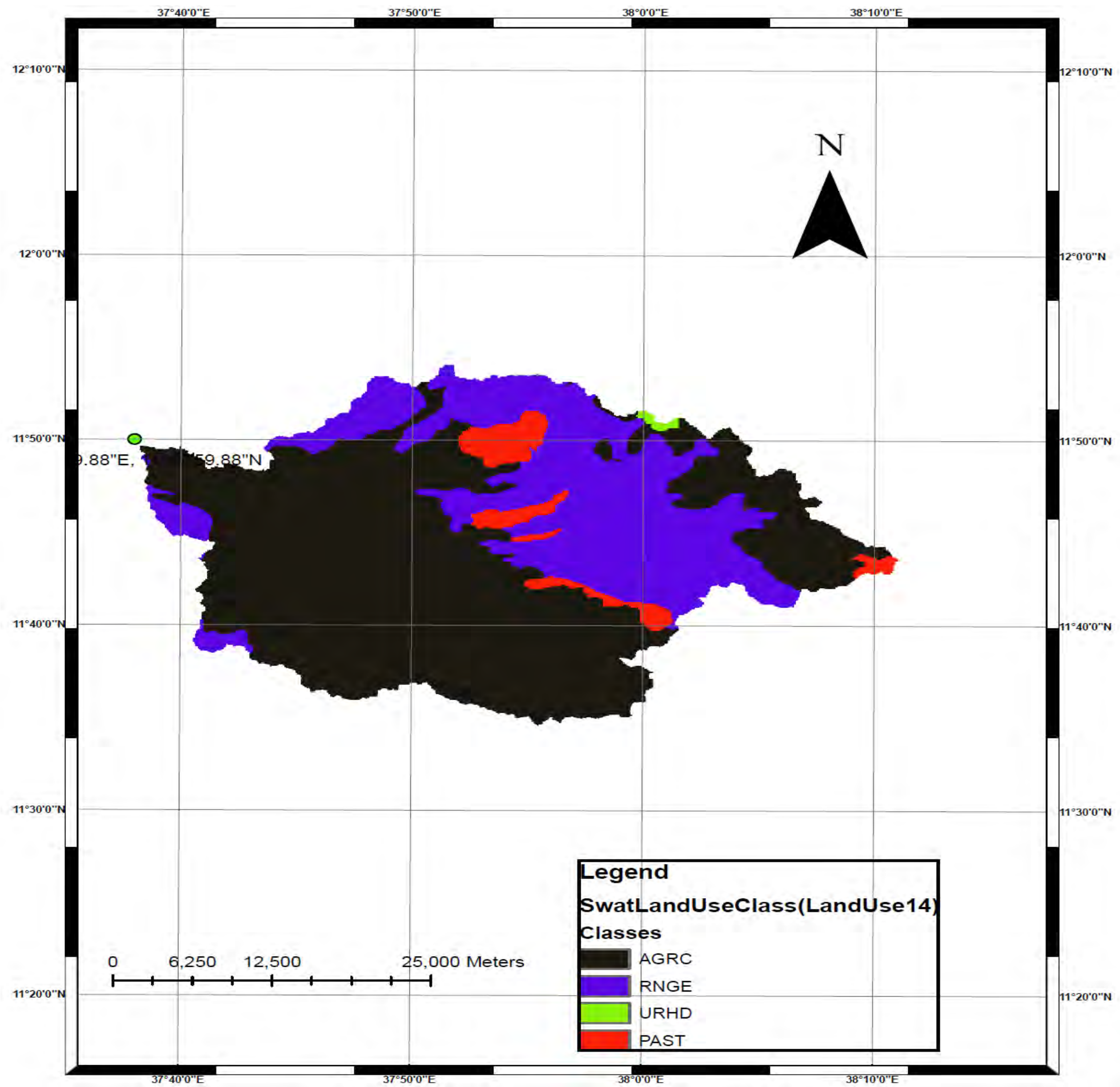

Figure 4.1.Landuse map of Gumara watershed

4.1.2 Soil

Six soil types were identified in the sub watershed and the details are shown in table 4.2 and figure 4.2. The Eutric Leptosols and Eutric Vertisols are the major soil types covering 63.48% and 24.30% of the overall sub watershed area, respectively. The smallest portion of the area is covered with Eutric Fluvisols (0.13%) and Urban Land (0.25%).

Table 4.2. Soil type of Gumera catchment as per FAO-UNESCO soil classification system

No.	Soil Type	Soil Classes defined In SWAT	Area (Km^2)	Total Area(%)
1	Halpic Luvisols	LVh	38	3.01
2	Chromic Luvisols	LVx	113	8.83
3	Eutric Leptosol	LPe	812	63.48
4	Eutric Vertisols	VRe	310	24.30
5	Eutric Fluvisols	FLe	1.96	0.13
6	Urban land		2.4	0.25
Total			1277.36	

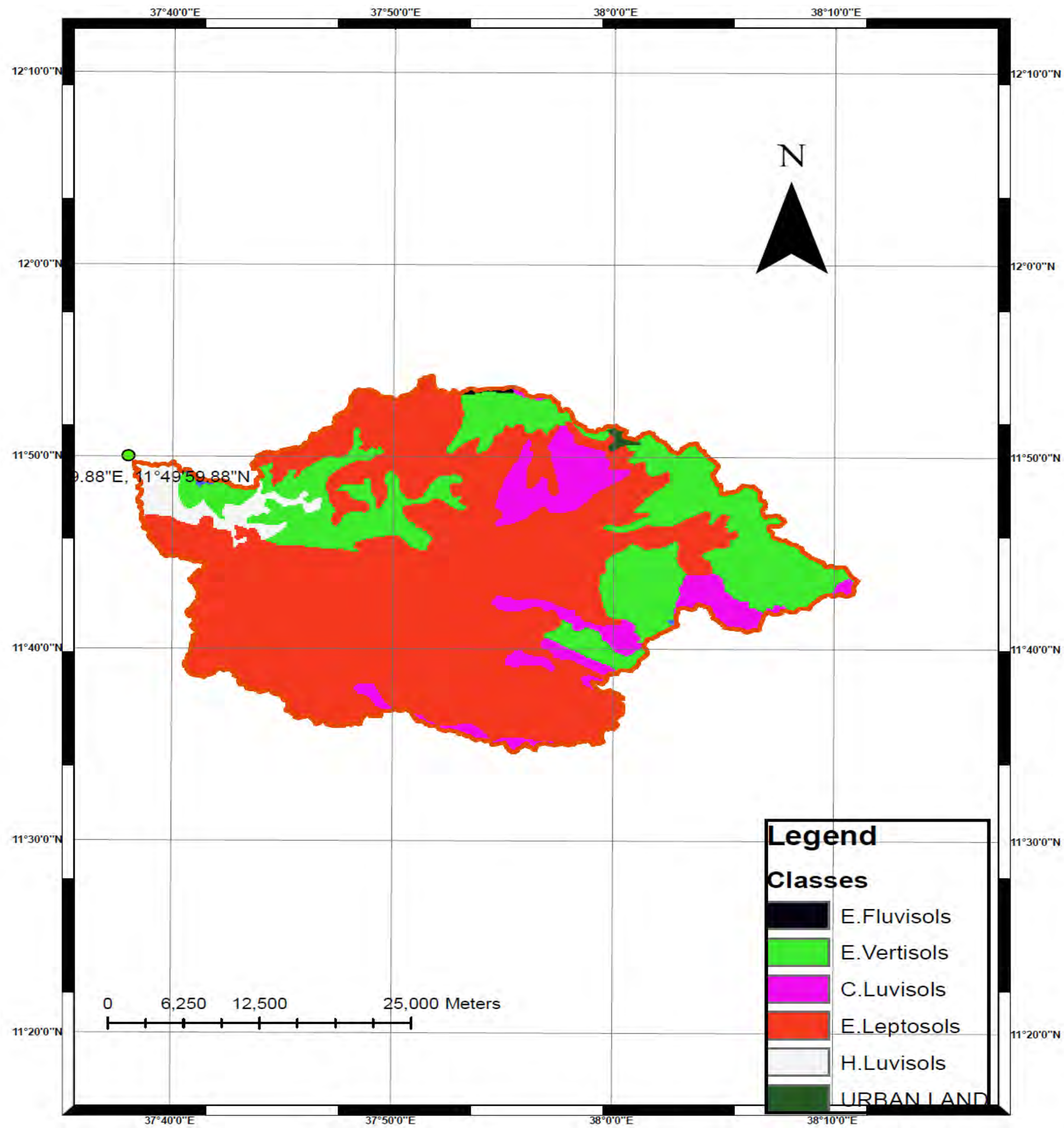

Figure 4.2.Soil map of Gumara watershed.

4.1. 3.Slope

The area was found to have multiple types of slopes and the dominant one is steep slope of 15%-over which covers about the 48.24% of the total area and slope of 5-10% is the next dominant type of slope with total area coverage of 19.34% of the whole watershed area. The common types of slopes which were found from SWAT analysis of the software is presented in table 4.3 and figure 4.3. This shows that the area is steeper in nature which might lead to erosive action of water erosion since most the area is used for agricultural cultivation purpose.

Table 4.3.Multiple Slope of the Gumara watershed

No.	Slope (%)	Area (Km^2)	% of Total Area
1	0-2	46.36	3.64
2	2-5	140	10.95
3	5-10	247	19.34
4	10-15	224	17.53
5	15-over	620	48.24

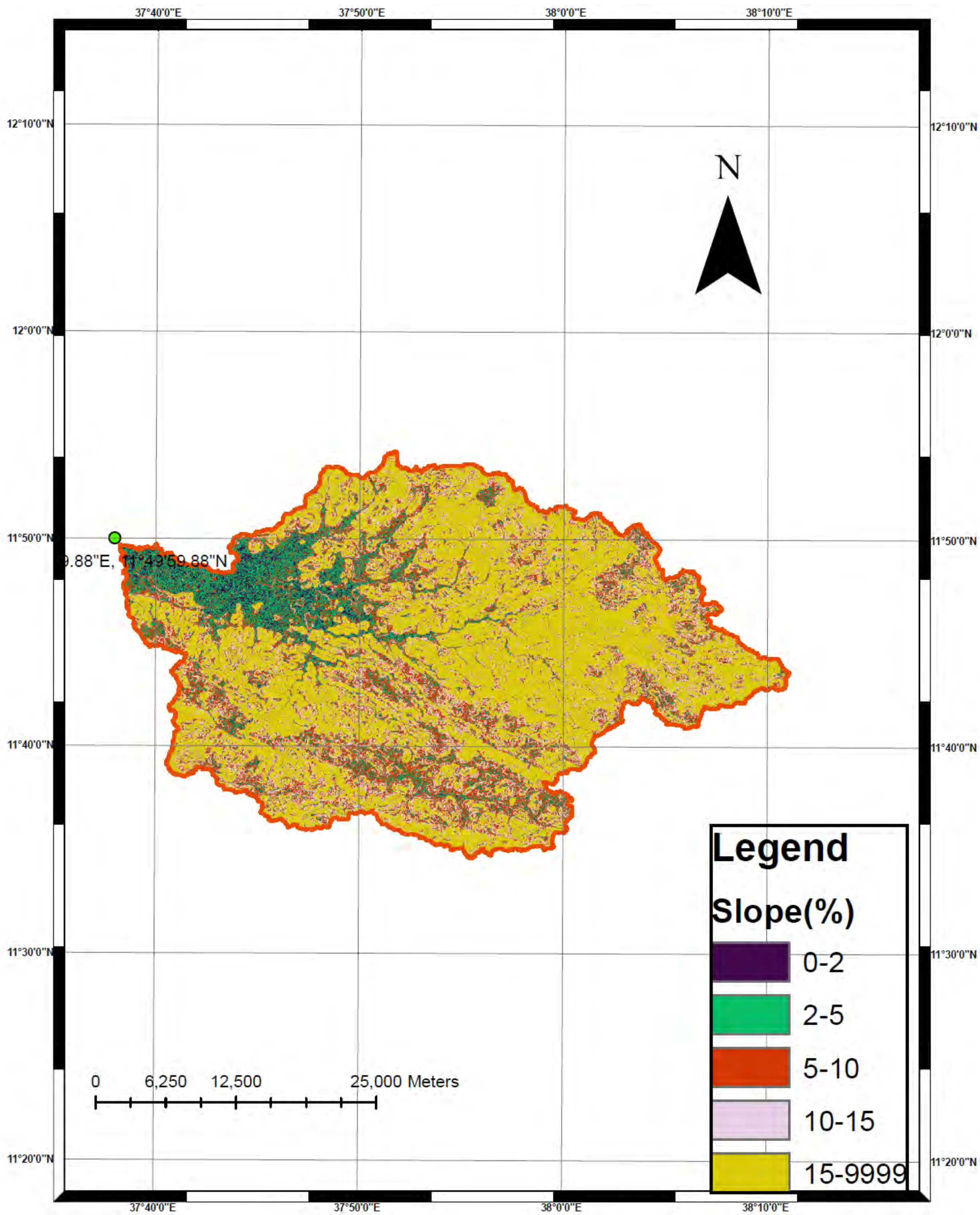

Figure 4.3.Slope map of Gumara watershed.

4.1.4 Sensitivity analysis

The sensitivity analysis was carried out for a period of nine years, which included the calibration period (from January 1st, 1995 to December 31st, 2003). As shown in table 4.4, the first ten parameters showed a relatively high sensitivity, being the alpha factor (ALPHA_BF) the most sensitive of all. The most sensitive parameters controlling the surface runoff in the sub watershed were found to be the curve number (CN2), the soil available water capacity (SOL_AWC), maximum canopy storage (CANMX) and soil depth (SOL_Z) and the soil evaporation compensation factor (ESCO). With respect to the base flow, the threshold water depth in the shallow aquifer for flow (GWQMN), and the ground water recession factor (ALPHA_Bf) have the highest influence in controlling the base flow for all catchments. The ten relative sensitivity of all the twenty seven parameters are presented in the table 4.4 and the whole twenty six sensitive parameter is presented on the appendix E.

Table 4.4. Results of sensitivity analysis prior to uncertainty analysis.

No	Parameters	Description of the parameters	Sensitivity rank
1	ALPHA_BF	Base flow alpha factor [days]	1
2	CN2	Initial SCS CN II value	2
3	Gwqmn	Threshold water depth in the shallow aquifer for flow [mm]	3
4	ESCO	Soil evaporation compensation factor	4
5	Sol_Z	Soil depth [mm]	5
6	Sol_Awc	Available water capacity [mm WATER/mm soil]	6
7	Sol_Z	Soil depth [mm]	7
8	Revapmn	Threshold water depth in the shallow aquifer for "revap" [mm]	8
9	Canmx	Maximum canopy storage [mm]	9
10	Gw_Revapmn	Groundwater "revap" coefficient	10

4.1.5 Flow Calibration

After the sensitive parameters identification, calibration followed by validation was executed for the significant parameters. The calibration of the model was executed to evaluate the performance of the model simulation using automatic calibration tools embedded in SWAT in addition to manual calibration technique for all catchments.

Flow calibration was also performed for a period of nine years from January 1st, 1995 to December 31st, 2003 for monthly peak surface runoff using the sensitive parameters identified. However, flow was simulated for seven years from January 1st, 1997 to December 31st, 2003, as the first two years were considered as a *warm up* periods. As discussed in Chapter 4, the flow was calibrated using automatic calibration method by using the observed flow gauged at the outlet of the sub watershed.

First of all, the surface runoff component of the gauged flow was balanced with that of the simulated flow. Here the model was adjusted to calculate the potential evapotranspiration of this sub watershed by using the Hargreaves Method. Afterwards the adjusted flow was further calibrated temporally by making delicate adjustments to ensure best fitting of the simulated flow curves with the gauged flow curves. Manipulation of the parameter values were carried out within the allowable ranges recommended by SWAT developers.

As a result, the number of performance optimization parameters modified during the calibration was kept to a minimum relative to the total number of SWAT parameters available for calibration. The performance test result of the model is presented in the table 4.5.

Table 4.5: Calibration statistics of the monthly peak simulated and gauged flows at the Outlet of Gumara watershed

Period (monthly)	Total flow(M^3/S)		RSR	R^2	E_{NS}	D
	Observed	simulated				
1997-2003	2950.68	3858.74	0.66	0.63	0.56	-30.77

The calibration results in table 4.5 shows that there is a satisfactory agreement between the simulated and gauged monthly flows. This is demonstrated by the correlation coefficient (R^2=0.63) and the Nash-Suttcliffe (1970) simulation efficiency (ENS=0.56) values for the whole watershed. The results fulfilled the requirements suggested by D. N Moriasi, et al. (2007) in table 3.2. for R^2 >0.6 and ENS > 0.5.

D value which is negative value (-30.77) is very far from zero which is unsatisfactory performance. In addition negative value indicates model over estimation but RSE value of 0.66 lies under satisfactory range as suggested by D. N Moriasi, et al. (2007) in table 3.2.

Generally, the overall performance of the prediction capacity of the model is under satisfactory range rather than lied under very good to good performance range for best result. This shows that there is some uncertainty on prediction of the simulated flow. The calibration graph of the watershed is shown in figure 4.5.

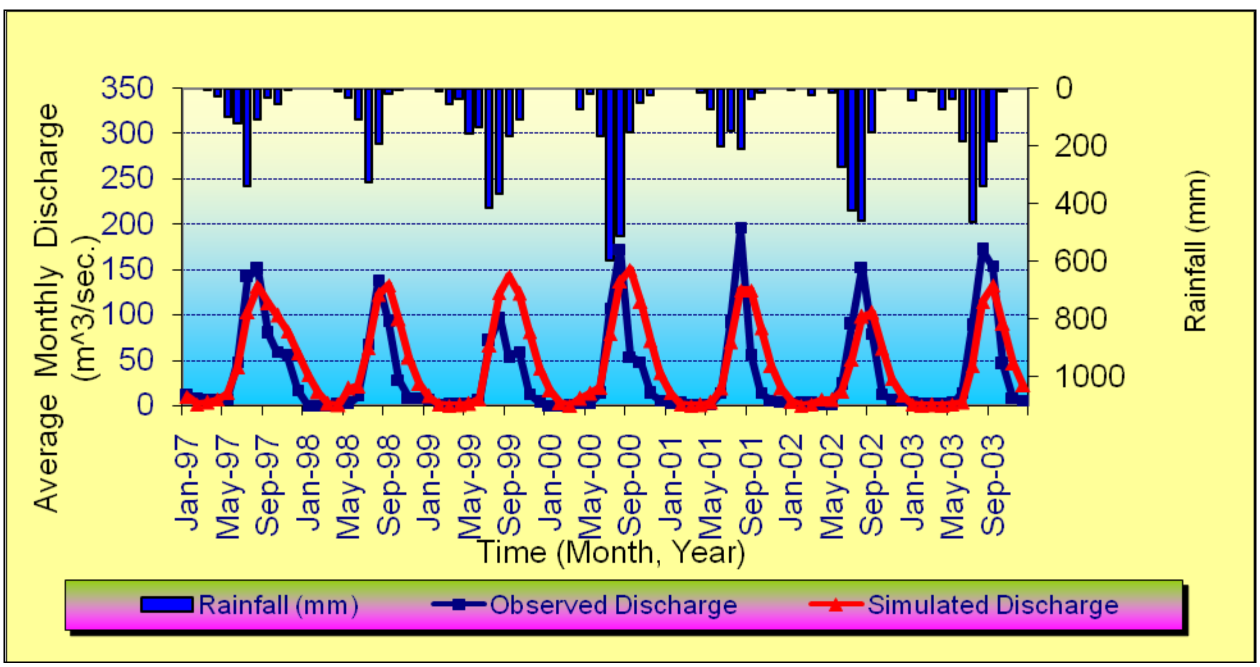

Figure 4.4. Calibration of observed and simulated flow hydrograph of Gumera river. Period (1197-2003).

4.1.6 Flow validation

Validation proves the performance of the model for simulated flows in periods different than the calibration periods, but without any further adjustment in the calibrated parameters. Consequently, validation was performed for six years period from January 1st, 2004 to December 31st, 2009. The performance test result of the validation value is presented in table 4.6.

Table 4.6. Validation statistics of the monthly peak simulated and gauged flows at the Outlet of Gumara watershed

Period (monthly)	Total flow(M^3/S)		RSR	R^2	E_{NS}	D
	Observed	simulated				
2004-2009	3468.01	3310	0.54	0.71	0.71	2.58

As shown in table 4.6. performance value of RSR, R^2, E_{NS} lies under good performance and D value of 2.58 shows very good performance. That means despite there is only satisfactory prediction performance values were recorded under calibration, the capability of this prediction is very good enough to utilize the calibrated model for estimating the flow for the future effective potential management practices. The validation graph is presented in figure 4.6.

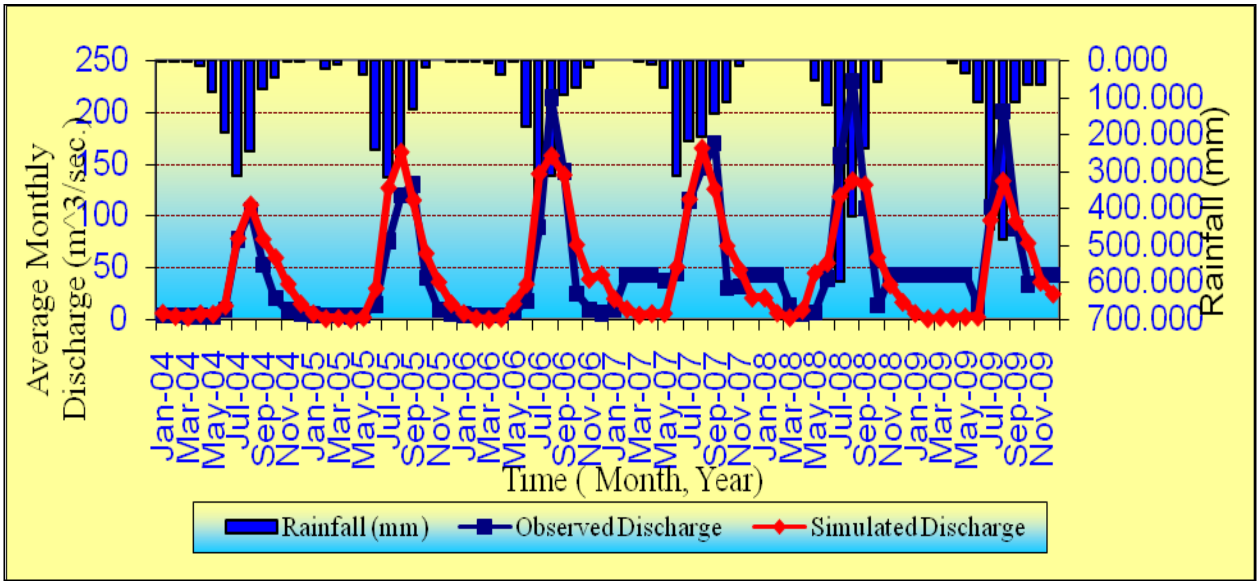

Figure 4.5. Validation of observed and simulated flow hydrograph of Gumara river. Period (2004-2009)

Generally, the overall average value of the basin values is summarized in table 5.7.

Table 4.7. Average annual basin values of Gumara watershed

No	Parameter	predicted Value
1	Precipitation(mm)	1497.5
2	Surface runoff Q(mm)	345.65
3	Lateral soil Q (mm)	97.3
4	Groundwater (mm)	287
5	Re-evaporation(mm)	6.76
6	Transmission loss(mm)	8.65
7	Deep aquifer recharge (mm)	15.46
8	Total aquifer recharge (mm)	309.26
9	Total water yield (mm)	721.3
10	Percolation out of soil(mm)	301.04
11	Evapotranspiration (mm)	741.9
12	Potential evapotranspiration(mm)	1190
13	Minimum elevation(m)	1793
14	Maximum elevation(m)	3712
15	Mean elevation(m)	2270.46
16	Watershed area(km^2)	1277.37
17	Peak flow (MCM)	1317.33

Note: Total water yield = (Surface runoff) + (Lateral flow) + (Ground water flow) – (Transmission losses)

The Gumara watershed, as part of the Abbay river basin has been studied by different consultants since 1964. So far estimation of flow coming towards the out let, where MoWR planned to build reservoir for irrigation purpose, is 1317.33MCM as shown in table 4.7. The finding of this research is somewhat near to a value predicted by Sirak (2008) using a similar model (1323.03MCM).

4.1.7 Uncertainty analysis

SWAT was calibrated based on the daily average value of monthly measured flow, at the outlets for each catchment using the automatic calibration method embedded in Arc Swat. A split sample procedure 60 and 40 percent was used for calibration and validation respectively. For most of the selected catchments data from the period of 1995–2003 were used for calibration, and data from 2004–2009 were used to validate the model. It should be noted that a watershed model can never be fully calibrated and validated. Calibration of models at a watershed scale is a challenging task because of the possible uncertainties that may exist as discussed in section 2 and 3 in detailed. Sources of uncertainties in distributed models are due to inputs such as rainfall and temperature. Rainfall and temperature data are measured at local stations and regionalization of these data may introduce large errors. In SWAT, climate data for every subbasin is furnished by the station nearest to the centroid of the subbasin. Direct accounting of rainfall or temperature distribution error is quite difficult as information from many stations would be required.

Therefore, carrying out uncertainty analysis for the prediction of the hydrological model is crucial to decide the calibrated parameters to transfer to other homogenous catchments and also using for further predictions. In SUFI-2, parameter uncertainty accounts for all sources of uncertainty, e.g., input uncertainty, conceptual model uncertainty, and parameter uncertainty, because disaggregation of the error into its source components is difficult, particularly in cases common to hydrology where the model is nonlinear and different sources of error may interact to produce the measured deviation (Gupta et al., 2005 cited SWAT-CUP User Manual).

After calibration of flow of the catchment the value of the uncertainty is determined using SUFI-2 (Sequential Uncertainty Fitting, ver. 2, Abbaspour et al., 2009) interface and the following result was obtained. As shown in table 4.8 and also figure 4.6 for calibration and figure 4.7 for validation.

Table 4.8. Performance index of Gumara watershed after uncertainty analysis using SUFI-2

	P factor	R factor	D factor	R^2	E_{NS}
Calibration (1995-2003)	0.31	0.54	0.26	0.72	0.70
Validation(2004-2009)	0.27	0.25	0.43	0.85	0.83

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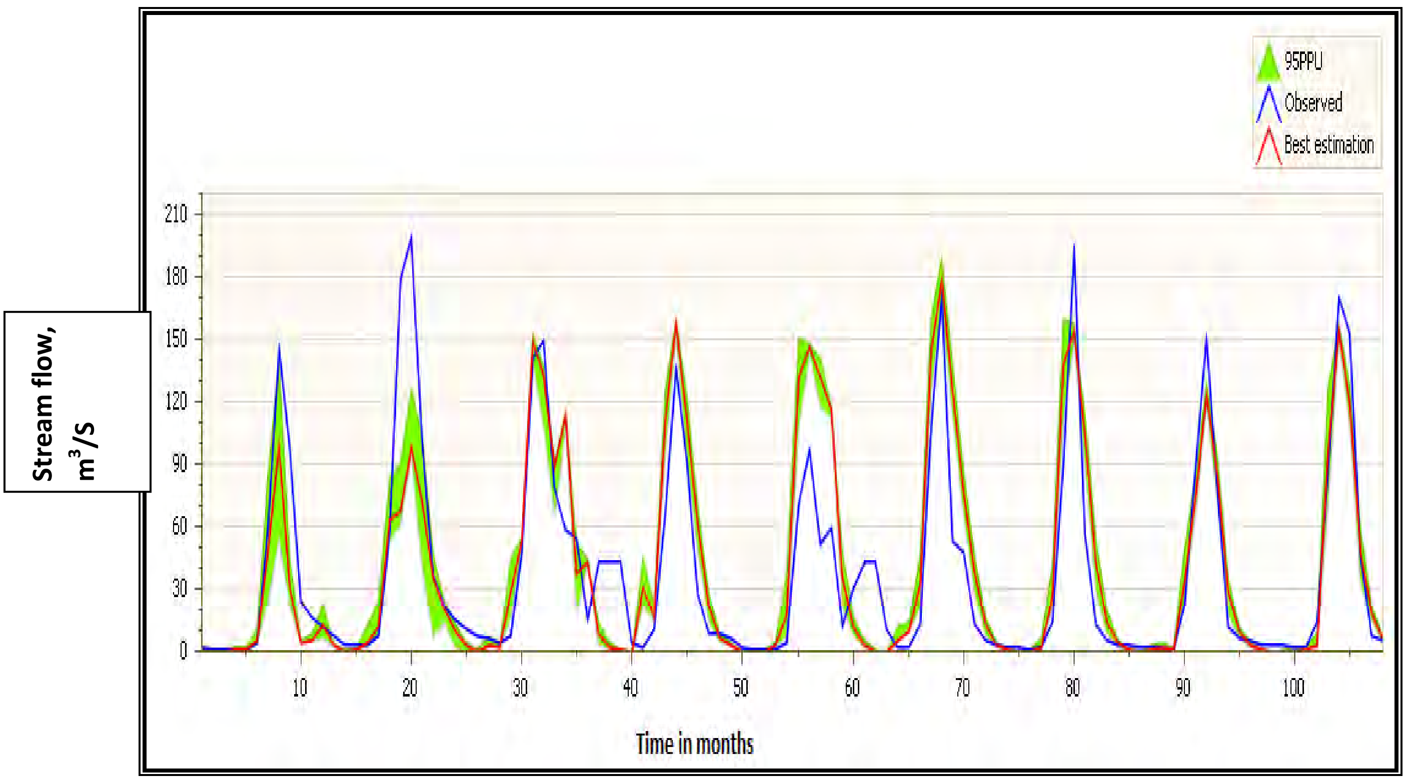

Figure 4.6. The 95% prediction uncertainty (95PPU) for Gumara river for calibration.

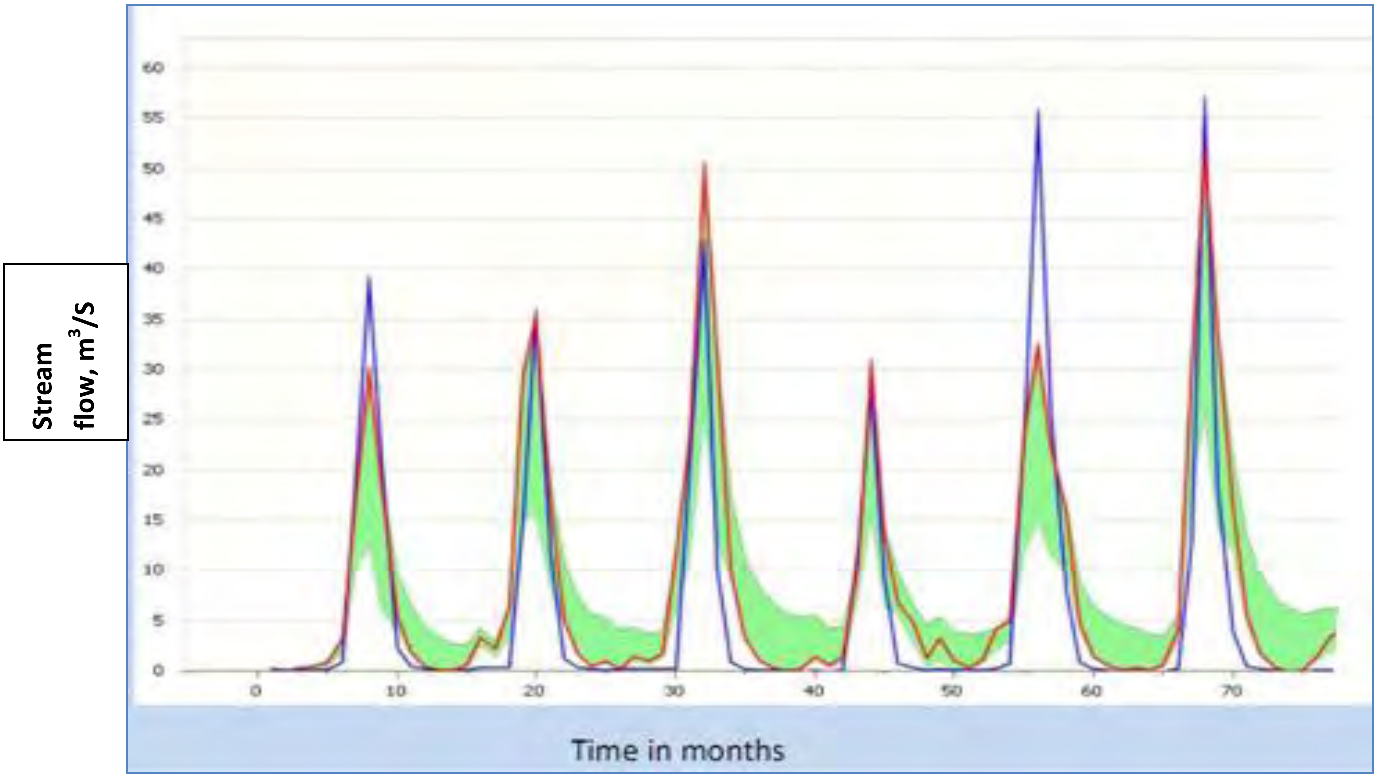

Figure 4.7. The 95% prediction uncertainty (95PPU) for Gumara river for validation.

P-factor shows the percentage of observations covered by the 95PPU and as a result the value of p factor in the above table 4.8. Shows that only 31% of the observation data matches with the simulated data. In addition, the small *P*-factor and relatively large R-factor values for these stations represent there is some uncertainties. In addition, D factor of 0.26 also shows small relative width of 95% probability band which represents to greater uncertainties.

This shows that there is great uncertainty in the estimation of the flow as the acceptable range of percentage value was found to be very far from 100%. Whereas, even though, there is not good value of P factor and D factor, the E_{NS} value of 0.70 is very much better than the calibration value of E_{NS} before uncertainty analysis value of 0.56 and also the validation value 0.83 is also an improvement from the value of 0.71 which shows that there is some improvement in E_{NS} value of prediction.

Therefore, as a result of smaller values of p and R factor for calibration as well as for validation value the improved performance Nash Sutcliff value of the calibration as well as validation after uncertainty analysis represents that there is some overall uncertainty over the flow simulated.

Hence, calibration and validation results of the watershed could be qualified as „poor" in this study. As a result further using of the calibrated flow leads to relatively significant error. This uncertainty may appear due to poor quality of the input data as well as large conceptual model errors in the watershed model.

4.1.7.1 Parameter Uncertainty Analysis

Even though there is overall great uncertainty, to check parameter uncertainty independently SWAT CUP interface GLUE (generalized likelihood uncertainty estimation) method of uncertainty analysis was implemented and the following results were obtained as shown in table 4.9.

Table 4.9 Performance index of Gumara watershed after GLUE analysis

	P factor	**R factor**	**D factor**	**R^2**	**E_{NS}**
Calibration (1995-2003)	**0.27**	**0.21**	**0.26**	**0.70**	**0.68**
Validation(2004-2009)	**0.41**	**0.23**	**0.43**	**0.84**	**0.82**

As table 4.9. shows there is small values of P and R factor but the E_{NS} value (which is in literature, the most frequently used likelihood measure for GLUE(SWAT CUP manual,2009) and also assigned as an objective function in the model program running process) of 0.68 and 0.82 for calibration and validation respectively represents there good parameter identification.

4.1.7.2 Sensitivity analysis after uncertainty analysis

The sensitivity ranges of parameters that were found under auto calibration and sensitivity analysis in chapter Four has got reshuffled after uncertainty analysis, as t-stat provides a measure of sensitivity (larger absolute values are more sensitive) and P-values determined the significance of the sensitivity (a value close to zero has more significance), the sensitivity value of the parameters is shown in the below table 4.10

Table 4.10. Results of sensitivity analysis using GLUE after uncertainty analysis

Parameter Name	t-Stat	P-Value	Sensitivity rank
Canmx	-0.10	0.92	9
ALPHA_BF	0.53	0.60	8
Gwqmn	-0.54	0.59	7
SOL_Z	0.67	0.51	6
Esco	-0.78	0.44	5
Revapmn	0.83	0.41	4
SOL_AWC	-1.22	0.23	3
CN2	-1.71	0.09	2
GW_Revap	-1.78	0.08	1

As shown in table 4.10. the most sensitive parameter is ground water re-evaporation (Gw_Revap). But the most sensitive parameter in the case of sensitivity analysis prior to uncertainty analysis was Alpha- Bf. Therefore, there is contradiction between the results before and after uncertainty and this represents that there is great uncertainty in estimation of simulated flow as sensitivity affects calibration and calibration again determined simulation amount of flow. In addition the very good values of ENS value under GLUE test shows parameter uncertainty is insignificant for Glue measures the overall parameter uncertainty than the explicit individual parameter values.. As the most sensitive parameter is more liable to uncertainty, GW_Revap is the most liable parameter to uncertainty than other parameters.

CHAPTER FIVE

5.0 Summary, Conclusion and recommendation

5.1 Summary

In this study runoff contribution was estimated from Gumara catchment using semi distributed model known as SWAT, in combination with the GIS interface ArcSWAT was successfully applied to quantify flow amount for the Gumara catchment in order to manage the available water resource properly with good water management strategy at a detailed sub basin level and monthly basis with uncertainty analysis using SWAT CUP.

Extensive calibration and validation as well as sensitivity and uncertainty analyses were performed to increase the reliability of the model outputs. The model was calibrated against river discharge. SUFI-2 and GLUE which are component of SWAT CUP were used to calculate 95% prediction uncertainty band for the outputs to characterize model uncertainty.

Based on SWAT watershed delineation at outlet of the catchment, the catchment area was found to be 1277.37 KM^2. Accordingly the mean annual inflow is estimated to be 1317.33 MCM.

Hence, estimation of runoff has become important for future Developments. The performance rating criteria shows that the model in all catchments were satisfactory and within an acceptable performance. The result of sensitivity analysis also shows that Alpha_Bf is the most sensitive parameter in all catchments.

5.2. Conclusion

The aim of the research is to determine the flow at the out let of Gumara watershed to use it for planning purpose using SWAT model to a great certainty by using SWAT CUP model. As the performance rating and sensitivity value is different from the results prior to uncertainty analysis, there is uncertainty in estimation of simulated runoff. These uncertainties may come either due to conceptual model uncertainty or input uncertainty or parameter uncertainty or combination of them. These uncertainties may come due the following reasons:

- Constructed small diversion structures which were constructed by CARE nongovernmental organization, small local roads and tunnels available can affect the local hydrology for many years. Because these structures regulate the runoff of the river Gumara and also delaying the runoff and significantly contributing to higher evaporation losses. This is an important and often neglected source of uncertainty in large-scale hydrological modeling. As the extent of management in water resources development increases, hydrological modeling will become more and more difficult and will depend on the availability of detailed knowledge of the management operations.

- A larger uncertainty band for the watershed might be due to higher conceptual model uncertainty as water management projects (not included in the model) could alter natural hydrology as discussed previously. Such as the irrigation practice there by local farmers, which mostly have local importance, are currently also not accounted in the model irrigation. Ignoring this would have created some uncertainty which leads to an incorrect picture of water balance in this watershed.
- over- or under-estimation of precipitation;
- difficulties in simulating the outflow from wetland (the river drains to marshy area during rainy season around local area known as „Esat aheyya" and most of remains their as the level is lower in elevation)
- the effect of smaller lakes, reservoirs, wetlands, and irrigation projects that were not included;
- simplifications by using dominant soil types and land cover classes in the sub basins; and
- various water use abstractions, which were not included
- due to poor performance of the software they used

As the value of E_{NS} during Glue analysis is very good, parameter uncertainty is insignificant. Therefore, the greater uncertainty contribution may come either from inputs or structural/conceptual/model uncertainties or a combination of both of them. In many cases, it is likely that conceptual model uncertainty may dominate the overall magnitude of uncertainty. However, there are currently no general procedures for decision-making in the presence of conceptual model uncertainty, other than to examine alternative conceptual models as distinct cases. As a consequence of these conceptual model simplifications, there are a number of site-specific conditions under which the codes may provide inaccurate, potentially non conservative results. These conditions include: the presence of significant preferential flow in the near surface, significant temporal variation in net infiltration and water content,

Therefore, as a result of this uncertainty the modeling result will not be used directly to water resource planning works as it will lead to misleading conclusion.

After modeling the gauged watershed, calibrated parameters should not be transferred to ungauged watershed like Wanzaye Catchment by lumping the parameters having the same hydrologic response unit (HRUs) as there is some uncertainty in the Gumara catchment simulation.(i.e. lacks exactness).

The previous studies in the basin were hampered to account spatial and temporal variation of inputs and this study is an attempt of applying semi distributed model, which accounts spatial and temporal variation of inputs in the basin. This study has paramount importance as it is new and original contribution using SWAT semi distributed modeling approach, to mainly estimate runoff from gauged part of the catchments and to study the water resource potential of the catchment.

Certainly when the model has, as in this case, produced encouraging results in the prediction of uncertainty percentiles, the results might still be useful in decision making during water resource decision making process.

5.3 Recommendation

Based on the results obtained, the researcher reaches the following conclusion:

- SWAT model calibrated using observed flow data at gauging station but with significant uncertainty. In order to improve the model performance, the weather stations should be improved both in quality and quantity. Hence, it is highly recommended to establish a good network of both hydrometric and meteorological stations. Because, to decrease model uncertainty, a better description of the climate data, water management, and water use would be essential. Hence the reliability of the water resources decreases as the uncertainties increase

- The study aims to estimate the runoff contribution from Gumara catchment based on a semi distributed modelling approach. However, in water balance components, the sub-surface condition for the Gumara watershed was not considered. Therefore, detail research work, which incorporates ground water, is recommended to understand the interaction of surface and sub-surface condition and River water balance.
- To minimize uncertainty the input data should be investigated thoroughly especially the weather data.
- The focus on parametric uncertainty in model calibration and uncertainty methodologies does not address over all model predictive uncertainty which encompasses uncertainty introduced by data errors (in input and output observation),model structural errors and uncertainties introduced by the likelihood measure or objective function used to develop a model. Therefore, further studies on the uncertainties of predicting the flow should be practiced using other methods such as Montecarlo sensitivity analysis method.
- Due to the existence of high topographic variations between low land and high land areas, the meteorological stations existing in and around the study area are not sufficient. Therefore at least one or two first order meteorological stations which will measure all meteorological parameters should be established to supplement the only pre-existing first order Debretabor rain gauge station.
- Local irrigation activity has already been practiced using dewatering pump from Gumara River. Such practice will possibly restrain the river flow provided the numbers of beneficiaries are increasing from time to time. Therefore for future study is a paramount activity.
- In the attempt of estimating the watershed inflow much of the exercise has been made numerically. Observed data has been modeled with the simulated data and the techniques of best fit have been used to estimate the catchment inflow. This approach has to be supported with field level data collections especially regarding the physical features of each sub basins. In the future much has to be done in this regard and an attempt has to be made to the level of physical modeling at higher research level. The inflow estimated during this research work is limited largely to office level works with three times field work and in using it the reliability in this regard has to be given due consideration.

- Further research should be carried out on the study area by improving the rainfall pattern using other technique like satellite data.
- The uncertainty in discharge measurement should be minimized by improving data recording system, as this would be a reason why some parts of the hydrograph were over predicted or under predicted
- While there will always be uncertainty in the information that is used to manage water resources, an improved understanding of the sources and magnitude or extent of that uncertainty, should contribute to improved management practices. On the one hand, resources could be directed at reducing the uncertainty (improved monitoring, estimation methods, training, etc.), while on the other hand the uncertainty can be accounted for as part of risk management within decision making processes. It is therefore important to improve (i) our understanding and quantitative knowledge of the various sources of uncertainty, (ii) the way in which this is communicated to water resource managers and other stakeholders and (iii) the way in which uncertainty is incorporated into water resource management decision making.
- In the end the researcher fills that the following recommendation are important for future development of the Gumara watershed.

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7. APPENDICES

Appendix-A Location of Meteorological station in the study area.

Station Name	X-Co-ordinate	Y-Co-ordinate	Elevation
Debretabor	394353	1313350	2690

Appendix-B Weather generator (WGEN) parameters used by the SWAT Model

Table B-1

Legend of the parameters used in the weather generation		
	Symbol	Description
A	TMPMX	Average or mean daily maximum air temperature for month (ºC).
B	TMPMN	Average or mean daily minimum air temperature for month (ºC).
C	TMPSTDMX	Standard deviation for daily maximum air temperature in month (ºC).
D	TMPSTDMN	Standard deviation for daily minimum air temperature in month (ºC).
E	PCPMM	Average or mean total monthly precipitation (mm H2O).
F	PCPSTD	Standard deviation for daily precipitation in month (mm H2O/day).
G	PCPSKW	Skew coefficient for daily precipitation in month.
H	PR_W1	Probability of a wet day following a dry day in the month.
I	PR_W2	Probability of a wet day following a wet day in the month.
J	PCPD	Average number of days of precipitation in month.
K	SOLARAV	Average daily solar radiation for month (MJ/m2/day).
L	DEWPT	Average daily dew point temperature in month (ºC).
M	WNDAV	Average daily wind speed in month (m/s).

TMPMX (mon): Average or mean daily maximum air temperature for month (ºC).

Calculated based on the following formula:

$$\mu mx_{mon} = \frac{\sum_{d=1}^{N} T_{mx,mon}}{N}$$

Where μmax_{mon} is the mean daily maximum temperature for the month (^{0}C), *Tmx,mon* is the daily maximum temperature on record *d* in month *mon* (^{0}C), and *N* is the total number of daily maximum temperature records for month *mon*.

TMPMN(mon): Average or mean daily minimum air temperature for month (ºC).

Calculated based on following formula:

$$\mu mn_{mon} = \frac{\sum_{d=1}^{N} T_{mn,mon}}{N}$$

Where μmn_{mon} is the mean daily minimum temperature for the month (^{0}C), $T_{mn,mon}$ is the daily minimum temperature on record *d* in month *mon* (^{0}C), and *N* is the total number of daily minimum temperature records for month *mon*.

TMPSTDMX(mon): Standard deviation for daily maximum air temperature in month (ºC)

Calculated based on following formula:

$$\sigma mx_{mon} = \sqrt{\frac{\sum_{d=1}^{N} (T_{mx,mon} - \mu mx_{mon})^2}{N-1}}$$

Where σmx_{mon} is the standard deviation for daily maximum temperature in month *mon* (ºC), $T_{mx,mon}$ is the daily maximum temperature on record *d* in month *mon* (^{0}C), $\mu_{mx,\ mon}$ is the average daily maximum temperature for the month (^{0}C), and *N* is the total number of daily maximum temperature records for month *mon*.

TMPSTDMN(mon): Standard deviation for daily minimum air temperature in month (ºC).

Calculated based on following formula:

$$\sigma mn_{mon} = \sqrt{\frac{\sum_{d=1}^{N}(T_{mn,mon} - \mu mn_{mon})^2}{N-1}}$$

Where σmn_{mon} is the standard deviation for daily minimum temperature in month *mon* (ºC), *Tmn,mon* is the daily minimum temperature on record *d* in month *mon* (^{0}C), *µmnmon* is the average daily minimum temperature for the month ^{0}C), and *N* is the total number of daily minimum temperature records for month *mon*.

PCPMM(mon): Average or mean total monthly precipitation (mm H2O).

Calculated based on the following formula:

$$\overline{R}_{mon} = \frac{\sum_{d=1}^{N} R_{day,mon}}{yrs}$$

where $\overline{R}_{mon}$ is the mean monthly precipitation (mm H2O), $R_{day,mon}$ is the daily precipitations for record *d* in month *mon* (mm H2O), *N* is the total number of records in month *mon* used to calculate the average, and *yrs* is the number of years of daily precipitation records used in calculation.

PCPSTD(mon): Standard deviation for daily precipitation in month (mm H2O/day).

Calculated based on following formula:

$$\sigma_{mon} = \sqrt{\frac{\sum_{d=1}^{N}(R_{day,mon} - \overline{R}_{mon})^2}{N-1}}$$

Where σ_{mon} is the standard deviation for daily precipitation in month *mon* (mm H2O), $\overline{R}_{mon}$ is the mean monthly precipitation (mm H2O), $R_{day,mon}$ is the daily precipiation for record *d* in month *mon* (mm H2O), *N* is the total number of records in month *mon* used to calculate the average, and *yrs* is the number of years of daily precipitation records used in calculation.

PCPSKW(mon): Skew coefficient for daily precipitation in month.

Calculated based on following formula:

$$g_{mon} = \frac{N \cdot \sum_{d=1}^{N} (R_{day,mon} - \overline{R}_{mon})^3}{(N-1) \cdot (N-2) \cdot (\sigma_{mon})^3}$$

Where g_{mon} is the skew coefficient for precipitation in the month, *N* is the total number of daily precipitation records for month *mon*, $R_{day,mon}$ is the amount of precipitation for record *d* in month *mon* (mm H2O), $\overline{R}_{mon}$ is the average precipitation for the month (mm H2O), and σ_{mon} is the standard deviation for daily precipitation in month *mon* (mm H2O).

PR_W(1,mon) : Probability of a wet day following a dry day in the month.

Calculated based on following formula:

$$P_i(W/D) = \frac{days_{W/D,i}}{days_{dry,i}}$$

Where *Pi(W/D)* is the probability of a wet day following a dry day in month *i*, $days_{W/D,i}$ is the number of times a wet day followed a dry day in month *i* for the entire period of record, and $days_{dry,i}$ is the number of dry days in month *i* during the entire period of record. A dry day is a day with 0 mm of precipitation. A wet day is a day with > 0 mm precipitation

PR_W(2,mon) : Probability of a wet day following a wet day in the month.

Calculated based on following formula:

$$P_i(W/W) = \frac{days_{W/W,i}}{days_{wet,i}}$$

Where *Pi(W/W)* is the probability of a wet day following a wet day in month *i*, $days_{W/W,i}$ *i* is the number of times a wet day followed a wet day in month *i* for the entire period of record, and

$days_{wet,i}$ is the number of wet days in month i during the entire period of record. A dry day is a day with 0 mm of precipitation. A wet day is a day with > 0 mm precipitation.

PCPD(mon): Average number of days of precipitation in month.

Calculated based on following formula:

$$\bar{d}_{wet,i} = \frac{days_{wet,i}}{yrs}$$

Where $\bar{d}_{wet,i}$, is the average number of days of precipitation in month i, $days_{wet,i}$ is the number of wet days in month i during the entire period of record, and yrs is the number of years of record.

SOLARAV(mon): Average daily solar radiation for month (MJ/m2/day).

Calculated based on following formula:

$$\mu rad_{mon} = \frac{\sum_{d=1}^{N} H_{day,mon}}{N}$$

Where μrad_{mon} is the mean daily solar radiation for the month (MJ/m^2/day), $H_{day,mon}$ is the total solar radiation reaching the earth‟s surface for day d in month mon (MJ/m^2/day), and N is the total number of daily solar radiation records for month mon.

DEWPT(mon): Average daily dew point temperature in month (ºC).

Calculated based on following formula:

$$\mu dew_{mon} = \frac{\sum_{d=1}^{N} T_{dew,mon}}{N}$$

Where μdew_{mon} is the mean daily dew point temperature for the month (ºC), $Tdew,mon$ is the dew point temperature for day d in month mon (ºC), and N is the total number of daily dew point records for month mon.

WNDAV(mon): Average daily wind speed in month (m/s).

Calculated based on following formula:

$$\mu wnd_{mon} = \frac{\sum_{d=1}^{N} \mu_{wnd,mon}}{N}$$

Where μwnd_{mon} is the mean daily wind speed for the month (m/s), $\mu_{wnd,mon}$ is the average wind speed for day d in month *mon* (m/s), and N is the total number of daily wind speed records for month *mon*.

Table- B-2

	PR_W1_12	PR_W2_1	PR_W2_2	PR_W2_3	PR_W2_4	PR_W2_5	PR_W2_6	PR_W2_7	PR_W2_8
debretabor	0.05	0.67	0.64	0.60	0.68	0.66	0.80	0.94	0.93
bahirdar	0.03	0.38	0.39	0.59	0.60	0.63	0.76	0.92	0.90

STATION	WLATITUDE	WLONGITUDE	WELEV	RAIN_YRS	TMPMX1	TMPMX2	TMPMX3
Debrtabor	11.53	38.02	2742.00	15.00	21.60	23.88	23.81
Bahirdar	11.60	37.42	1770.00	16.00	26.77	28.41	29.39

Station	TMPMX4	TMPMX5	TMPMX6	TMPMX7	TMPMX8	TMPMX9	TMPMX10	TMPMX11
Debretabor	22.83	23.93	21.88	18.44	18.99	19.20	13.31	14.05
Bahirdar	29.95	29.30	27.05	24.36	24.39	25.63	26.59	26.76

Station	TMPMX12	TMPMN1	TMPMN2	TMPMN3	TMPMN4	TMPMN5	TMPMN6	TMPMN7
Debretabor	5.83	7.14	8.90	8.88	9.82	10.83	10.48	10.11
Bahirdar	26.74	9.11	10.98	13.28	15.27	15.48	14.88	14.49

Station	TMPMN8	TMPMN9	TMPMN10	TMPMN11	TMPMN12	TMPSTDMX1	TMPSTDMX2	TMPSTDMX3
Debretabor	10.04	7.66	1.39	0.51	-6.70	1.13	1.26	1.53
Bahirdar	14.36	13.78	13.73	11.82	9.67	1.55	1.81	1.74

Station	TMPSTD MX4	TMPSTD MX5	TMPSTD MX6	TMPSTD MX7	TMPSTD MX8	TMPSTD MX9	TMPSTD MX10
Debretabor	2.02	2.34	2.24	1.73	1.48	1.33	1.36
Bahirdar	1.99	1.92	1.69	1.50	1.43	1.28	1.18

Station	TMPSTD MX11	TMPSTD MX12	TMPSTD MN1	TMPSTD MN2	TMPSTD MN3	TMPSTD MN4	TMPSTD MN5	TMPSTD MN6
Debretabor	1.16	0.96	1.29	1.35	1.48	1.54	1.37	1.30
Bahirdar	1.05	1.16	2.18	2.35	2.70	2.45	1.83	1.25

Station	TMPSTD MN7	TMPSTD MN8	TMPSTD MN9	TMPSTD MN10	TMPSTD MN11	TMPSTD MN12	PCPMM1	PCPMM2
Debretabor	1.35	1.19	1.08	1.32	1.34	1.27	20.15	13.48
Bahirdar	1.03	1.06	1.13	1.53	2.11	2.29	2.52	3.29

Station	PCPMM3	PCPMM4	PCPMM5	PCPMM6	PCPMM7	PCPMM8	PCPMM9	PCPMM10
Debretabor	37.36	58.35	99.78	181.35	394.34	372.59	195.24	96.68
Bahirdar	20.45	33.06	75.29	204.67	420.88	378.74	192.26	94.93

Station	PCPMM11	PCPMM12	PCPSTD1	PCPSTD2	PCPSTD3	PCPSTD4	PCPSTD5	PCPSTD6
Debretabor	35.38	42.45	3.21	1.58	3.55	4.32	7.48	8.99
Bahirdar	13.51	3.11	0.62	1.09	3.11	3.70	6.65	11.23

Station	PCPSTD7	PCPSTD8	PCPSTD9	PCPSTD10	PCPSTD11	PCPSTD12	PCPSKW1	PCPSKW2
Debretabor	11.24	11.07	8.60	7.77	3.01	4.03	11.77	5.13
Bashirdar	16.18	15.04	10.00	7.13	2.33	0.79	9.10	14.38

Station	PCPSKW3	PCPSKW4	PCPSKW5	PCPSKW6	PCPSKW7	PCPSKW8	PCPSKW9	PCPSKW10
Debretabor	6.39	3.71	4.25	4.56	1.57	1.71	2.33	7.09
Bahirdar	13.29	5.78	5.05	2.70	2.33	2.63	2.77	3.29

Stations	PCPSKW11	PCPSKW12	PR_W1_1	PR_W1_2	PR_W1_3	PR_W1_4	PR_W1_5	PR_W1_6
Debretabor	3.77	9.29	0.04	0.05	0.11	0.16	0.23	0.59
Bahirdar	7.16	9.79	0.01	0.03	0.08	0.10	0.20	0.48

Stations	PR_W1_7	PR_W1_8	PR_W1_9	PR_W1_10	PR_W1_11	PR_W1_12	PR_W2_1	PR_W2_2
Debretabor	0.93	0.76	0.52	0.17	0.07	0.05	0.67	0.64
Bahirdar	0.81	0.83	0.58	0.22	0.05	0.03	0.38	0.39

Stations	PR_W2_3	PR_W2_4	PR_W2_5	PR_W2_6	PR_W2_7	PR_W2_8	PR_W2_9	PR_W2_10
Debretabor	0.60	0.68	0.66	0.80	0.94	0.93	0.80	0.79
Bahirdar	0.59	0.60	0.63	0.76	0.92	0.90	0.78	0.58

Stations	PR_W2_11	PR_W2_12	PCPD1	PCPD2	PCPD3	PCPD4	PCPD5	PCPD6
Debretabor	0.72	0.83	3.87	3.67	7.33	10.67	13.33	23.13
Bahirdar	0.33	0.18	0.81	1.13	5.31	6.19	11.56	20.81

Stations	PCPD7	PCPD8	PCPD9	PCPD10	PCPD11	PCPD12	RAINHHMX1	RAINHHMX2
Debretabor	30.00	29.33	23.00	15.33	7.00	8.20	0.00	0.00
Bahirdar	29.38	28.38	22.94	11.50	2.63	1.1	0.00	0.00

Stations	RAINHH MX3	RAINHH MX4	RAINHH MX5	RAINHH MX6	RAINHH MX7	RAINHH MX8	RAINHH MX9	RAINHH MX10
Debretabor	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Bahirdar	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Stations	RAINHH MX11	RAINHH MX12	SOLARAV1	SOLARAV2	SOLARAV3	SOLARAV4	SOLARAV5	SOLARAV6
Debretabor	0.00	0.00	11.90	12.40	14.20	12.90	13.40	11.30
Bahirdar	0.00	0.00	21.14	21.49	21.62	21.38	21.28	20.64

Stations	SOLARAV7	SOLARAV8	SOLARAV9	SOLARAV10	SOLARAV11	SOLARAV12	DEWPT1	DEWPT2
Debretabor	10.70	12.20	12.40	12.00	11.50	12.20	4.10	4.69
Bahirdar	20.09	20.09	20.71	20.83	20.93	20.71	9.88	9.24

Stations	DEWPT3	DEWPT4	DEWPT5	DEWPT6	DEWPT7	DEWPT8	DEWPT9	DEWPT10
Debretabor	6.09	6.66	9.17	11.28	11.28	11.18	9.28	1.71
Bahirdar	9.94	10.88	12.77	15.24	15.55	15.87	15.34	13.93

Stations	DEWPT11	DEWPT12	WNDAV1	WNDAV2	WNDAV3	WNDAV4	WNDAV5	WNDAV6
Debretabor	0.39	-7.36	0.75	0.77	0.84	0.47	0.92	0.82
Bahirdar	11.87	10.32	0.46	0.53	0.63	0.70	0.65	0.70

Stations	WNDAV7	WNDAV8	WNDAV9	WNDAV10	WNDAV11	WNDAV12
Debretabor	0.77	0.83	0.75	0.58	0.61	0.72
Bahirdar	0.59	0.60	0.60	0.60	0.51	0.46

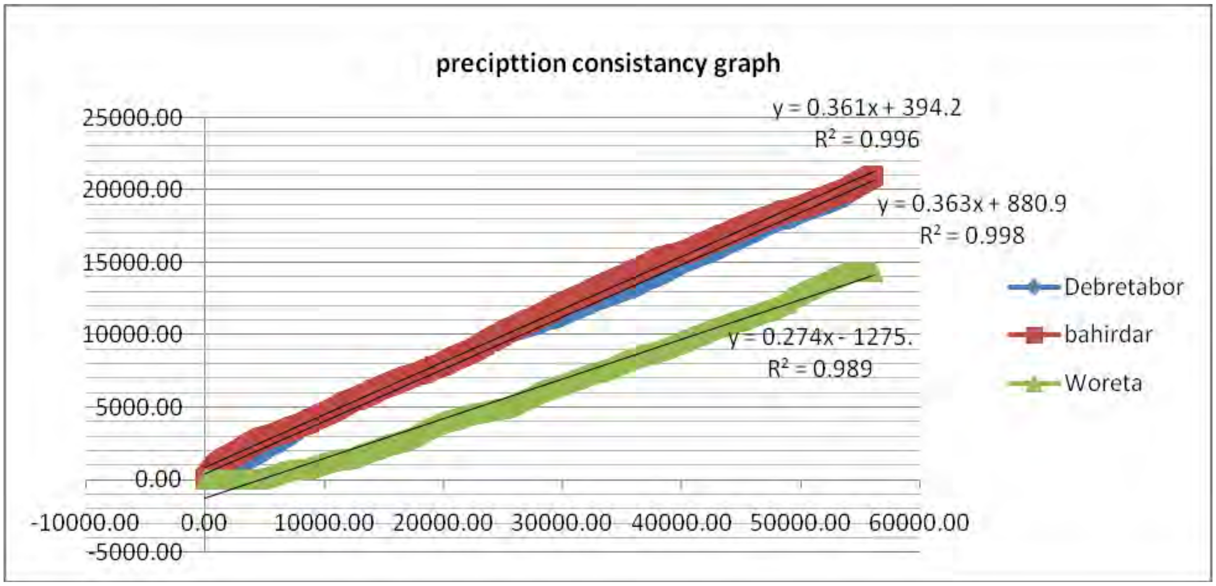
Appendix-C Summary of Meteorological data collected from NMA

Station Name	Daily meteorological data collected									
	Precipitation (mm)		Temperature (O_C)		Relative Humidity (%)		Sunshine Duration		Wind speed (m/s)	
	From	To	From	To	From	To	From	To	From	To
Bahirdar	1995	2009	1995	2009	1995	2009	1995	2009	1995	2009
Debretabor	1995	2009	1995	2009	1995	2008	1995	2008	1995	2009
Addiszemen	1995	2008	2000	2006	-	-	-	-	-	-

Appendix -E

No	parameter	Sensitivity rank
1	Alpha_Bf	1
2	Cn2	2
3	Gwqmn	3
4	Esco	4
5	Blai	5
6	Sol_Awc	6
7	Sol_Z	7
8	Revapmn	8
9	Canmx	9
10	Gw_Revap	10
11	Ch_K2	11
12	Epco	12
13	Ch_N2	13
14	Slope	14
15	Sol_K	15
16	Gw_Delay	16
17	Sol_Alb	17
18	Surlag	18
19	Biomix	19
20	Timp	20
21	Slsubbsn	21
22	Smtmp	22
23	Sftmp	23
24	Smfmn	23
25	Smfmx	23
26	Smfmx	23

Appendix F Preciptation consistancy graph



Appendix G : flow data consistency graph