JIMMA UNIVERSITY

SCHOOL OF GRADUATE STUDIES

JIMMA INSTITUTE OF TECHNOLOGY

FACULTY OF CIVIL AND ENVIRONMENTAL ENGINEERING

MASTERS OF SCIENCE PROGRAM IN HYDRAULIC ENGINEERING

Stream Flow Modeling and Uncertainty Analysis in Didessa River Basin, Blue Nile, Ethiopia

By

Obsinet Abebe

A Thesis Submitted to School of Graduate Studies of Jimma University in Partial Fulfillment of the Requirement for Degree of Masters of Science in Hydraulic Engineering

April, 2018

Jimma, Ethiopia

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Advisor: Dr. Ing. Tamene Adugna
Co Advisor: Mr. Fayera Gudu (MSc)

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Jimma, Ethiopia

APPROVAL PAGE

This thesis entitled with **"Stream Flow Modeling and Uncertainty Analysis in Didessa River Basin, Blue Nile, Ethiopia"** has been approved by the following: advisors, examiners and department for the proposed work for partial fulfillment of the degree of Master of Science in Hydraulic Engineering.

Submitted by: Obsinet Abebe

Approved by Board of Examiners

As members of the Board of Examiners of the MSc Thesis Open Defense Examination, we Certify that we have read, evaluated the thesis prepared by Obsinet Abebe and examined the candidate. We recommended that the thesis be accepted as fulfilling the requirement for the degree of Master of Science in Hydraulic Engineering.

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DECLARATION

I hereby declare that this thesis titled **"Stream Flow Modeling and Uncertainty Analysis in Didessa River Basin, Blue Nile, Ethiopia"** has been carried out by me under the guidance and supervision of my Advisors Dr.Ing. Tamene Adugna and Mr.Fayera Gudu. This thesis is my original work and has not been submitted and presented in any other university or institutions.

Obsinet Abebe

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This thesis has been submitted for examination with my approval as University supervisor.

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ABSTRACT

To effectively plan for water resources and protect against watershed problems, it is necessary to understand the quantity and quality in space and time through studies. The general objective of this study is to model stream flow of Didessa River using SWAT model and to analyze the related uncertainties. Digital elevation model, Land use classification map, Soil map and the available weather data of 1980 to 2016 were used and the whole Didessa basin was separated into 674 hydrological response units (HRU) in 112 sub-watersheds. The available flow data of 1997-2014 was used for calibration and validation at 2 hydro gauging stations. SUFI-2 and GLUE program of SWAT CUP was used for calibration and uncertainty analysis and performance of the two programs in calibrating SWAT model was also compared.

The SWAT model developed for the river basin evaluated and its performance is certain with the statistical measures, coefficient of determination (R^2) and Nash and Sutcliffe coefficient (NS).The model performance was very good for monthly time steps. The obtained statistical results of (R^2,NS) by SUFI-2 at Dembi were (0.75 ,0.74) and (0.78,0.78) for calibration and validation respectively. The obtained result at Arjo were (0.72,0.71) and (0.73, 0.72) for calibration and validation respectively. The obtained result by GLUE were (0.77 ,0.75) and (0.78,0.77) for calibration and validation at Dembi and (0.73,0.71) and (0.77, 0.72) for calibration and validation at Arjo. The performance of the model for daily time steps were also evaluated. The obtained result of (R^2, NS) value for calibration and validation (0.72,0.69) ;(0.63,0.62) and (0.68,0.66) ;(0.62,0.62) for SUFI-2 and GLUE respectively at Dembi station. The result of uncertainty analysis done by SUFI-2 shows 40-48% and 24-44% percent of observed flow is bracketed by 95PPU for monthly and daily time steps respectively. GLUE uncertainty analysis program brackets 25-34% and 28-29% of observed flow for monthly and daily time steps respectively. GLUE uncertainty program able to obtain high value of R^2 and NS with small percent of p and r-factor which shows good parameter identification, this shows that the overall associated uncertainty come from either conceptual or input or a combination of them but not from parameter identification. So, Both SUFI-2 and GLUE performs well in calibrating SWAT model and they were balanced predictive approach.

The calibrated model can thus use for futuristic prediction and as an input for decision making in developing a better sufficient and integrated water resource management of the river basin.

Key Word*:* Didessa River, Hydrological Modelling, Stream flow, SWAT, SWAT-CUP

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ACRONYMS

ARBIDMP	Abbay River Basin Integrated Development Master Plan
a.m.s.l	above mean sea level
DEM	Digital Elevation Model
DMC	Double Mass Curve
FAO	Food and Agriculture Organization
GIS	Geographic Information Systems
GLUE	Generalized Likelihood Uncertainty Estimation
HRU	Hydrological Response Unit
IAHS	International Association of hydrological science
MERIS	Medium Resolution Imaging Spectrometer
MCMC	Marcov Chain Monte Carlo
MoWIE	Ministry of water resource, irrigation and Energy
NASA	National Aeronautics and Space Administration
NMSA	National Meteorological Service Agency
OWWDSE	Oromia water work design and supervision enterprise
Parasol	Parameter solution
PSO	Particle Swarm Optimization
SUFI-2	Sequential Uncertainty Fitting
SWAT	Soil and Water Assessment Tool
SWAT-CUP	Soil and Water Assessment Tool- Calibration and Uncertainty Programs
95PPU	ninety-five percent prediction uncertainty

1. INTRODUCTION

1.1 Background

Water is a key resource for sustainable economic and social development of the society (Pangare, 2006). It is a basic and an essential element for survival of living things and energetic factor for economic development and supplementing growth of agriculture and industry especially in the perspective of rapidly increasing population and urbanization. Stream flow is the main hydrological component which influences the hydrological characteristics in many ways and shows their importance in balanced agricultural watersheds. Stream flow is the volume of water passing a fixed point over a unit of time. Information on stream flow can be used to predict surface runoff and to know the availability of water resources in space and time. Consistent prediction of surface runoff from rainfall in a catchment is essential for water resource management.

Presently the seasonal variation of a stream flow with increasing demand and competition for water is becoming the great problem. Stream flow can be affected by a number of factors and can vary rapidly as those factors change. Stream flow is affected by both natural and human factors and can respond rapidly to changes in flow parameters (Vishal Singh, 2013). Therefore, the need for water management and protection of water resource is crucial. To effectively plan for water resources and protect against watershed problems, it is necessary to understand the quantity and quality in space and time through studies.

Hydrological modeling is applied as tools for analysis of water resources and is used to simulate river and stream flow. However, the confidence in the model predictions relies on their uncertainties (Gassman et al, 2007). Therefore, measuring the potential water resources through hydrological modeling and understanding the uncertainties within it is of considerable importance in the effective utilization of water resources, the need to improve and augment development and management activities of water resources, and to mitigate for negative impacts of climate change in the future.

A better understanding of hydrological processes in the head water of Blue Nile basin is of considerable importance because of only 5% of Ethiopian surface water (6% of the Nile Basin water resource is being currently utilized by Ethiopia (Arseno and Tamrat, 2005). Thus, in order to utilize these water resources well understanding of the hydrological characteristics to improve and augment development and management activities of these water resource is necessary. Understanding of hydrological process in the head water of Blue Nile Basin is of considerable importance because of international interests to utilize these water resources for socio-economic development of the society of the basin. However, in spite of the national and international importance of the region, relatively few studies have been conducted and there is only a limited understanding of the basin's detailed climatic, hydrological, topographic and hydraulic characteristics (Curtis, 1994; CONWAY, 1997). In monsoonal climate a given rainfall volume at the onset of the monsoon produces a different run-off volume than the same rainfall at the end of the monsoon (Liu, B.Y, 2008). Thus, to enhance the estimates of watershed outflow in the Highlands of Ethiopia with monsoonal climate better understandings of the hydrological processes (i.e. precipitation, evapotranspiration…) is needed.

Didessa River which is the largest tributary of the Blue Nile contributes roughly a quarter of a total flow of Blue Nile as measured at the Sudan border. It is originated from the mountains ranges of Gomma in South Western Ethiopia (Tesfaye M, 2014). Although the sub basin has comparatively sufficient hydrological and meteorological data series, Didessa river basin is one of the less studied area as compared with northern side sub basins the Blue Nile River (Sima, 2011). In addition to this situation, the occurrence of the 2015 flood event at the coffer dam site, calling an urgent discussion and evaluation of the hydrological design of the coffer dam and the relief culvert (OWWDSE, 2016). It additionally requests hydrological study and understand the uncertainties and parameters, which govern the hydrological process of the river basin.

1.2 Statement of the Problem

Although Ethiopia is known by the name Water Tower of North East Africa; most of the famous trans boundary river like Blue Nile doesn't utilized well by Ethiopians. In the Nile basin, water from the Ethiopian highlands particularly from the Blue Nile (known as Abbay in Ethiopia), has a historically benefited downstream people in Sudan and Egypt in different ways: agriculture, livestock, industry and electrical power (Awulachew, 2008).This famous river contributes a very little in the socio-economic development of the people of Ethiopia for the past time.

Nowadays, there is an increasing demand for domestic, irrigation and hydropower development in Ethiopia; because the country is experiencing a number of problems such as rapid population growth, limited water resources, poverty and famine. 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 resource planning and management. Currently there is a great effort towards developments in this river basin to use the domestic, irrigation and hydro-electric power potential of these Blue Nile River water resources. Hence there is currently a water resources development project in the construction and planning phases in the Didessa river basin which is the sub basin of the Blue Nile Basin.

The Didessa river basin has not well studied as compared with the northern sub basins of Blue Nile (Sima, 2011). In addition to this the flood event occurred at Arjo Didessa dam site in 2015 also shows there is a problem of under estimation of flow by designer or the uncertainties in the model. Moreover, models give good result for respective watershed characteristics. Though several methodologies and techniques have been developed to estimate the parameters and assess uncertainties in the hydrological modeling, studies usually use one method without knowing its performance over the other. Therefore, it is necessary to quantify the potential stream flow generated and analyze the uncertainties in the model by using different methods.

1.3 Objective

1.3.1 General Objective

The general objective of this study is stream flow modeling in Didessa river basin by SWAT Model and uncertainty analysis using SWAT CUP.

1.3.2 Specific Objective

- To simulate monthly and annual stream flow of the river basin
- To perform uncertainty analysis by using the methodology in SWAT CUP
- To compare performance of different SWAT CUP approach (SUFI-2 and GLUE) on calibrating SWAT model.
- To summarize the water yield of the sub catchments of the river basins

1.4 Research Questions

- How much amount of monthly and annual stream flow yielded by the river basin?
- What is the prediction uncertainties related to the model?
- Which algorithm of SWAT CUP gives more reasonable and balanced predictive results for Didessa river basin?
- How much amount of water is yielded by each sub catchments?

1.5 Significance of the Study

This stream flow modeling and uncertainty analysis can assist decision makers by providing systematic and consistent information on hydrological characteristics of the Didessa river basin. The importance of this study lies on their capability to simulate the stream flows and water yields of the river basin, which can further used for futuristic predictions; Analysis of uncertainties in the model and identifying the most suitable methods of SWAT CUP (SUFI-2 and GLUE) in calibrating SWAT model. It contributes a better understanding of Didessa river water resources in time and space. Thus, the output of this study may also contribute to fill for the knowledge gap of the river basin and to assure sustainable water resources development activity in the river basin.

2. LITERATURE REVIEW

2.1 Hydrologic Modeling

Hydrology is a science which is concerned with the circulation of water and its constituent through the hydrologic cycle. It deals with precipitation, evaporation, infiltration, ground water flow, runoff, stream flow and the transport of substance dissolved or suspended in the flowing water. Stream can be defined as a flow channel to which the surface runoff from specified basin drains. Stream flow represents runoff phase of hydrologic cycle is the most important basic data for hydrologic cycle (K.Subramanya, 2008). Stream flow is the volume of water passing a fixed point over a unit of time and is usually expressed in cubic meters per second (cumecs).

A hydrologic model involves the application of mathematical expressions that define quantitative relationships between inputs (e.g. flow-forming factors) and outputs (e.g. flow characteristics). The scope of hydrologic modeling and its applications has broadened dramatically over the past decades. It is related to the spatial processes of the hydrologic cycle and is often used to estimate basin water resources as well as for impact assessment or more precisely water resources management. Hydrological modeling is very important for prediction of runoff and soil erosion, and is a major tool for research hydrologists and water resources engineers for planning and management of water resources (Beven K and Binley A, 1992). Hydrological models can be used to estimate river flows at ungauged sites, fill gaps in incomplete data series or predict future runoff and river flows. The need for hydrological models is increasing both in aspects of coverage and functionality (Arnold,et al., 2012).

Hydrological models are tools that describe the physical processes controlling the transformation of precipitation to stream flows. There are different hydrological models designed and applied to simulate the rainfall runoff relationship under different temporal and spatial dimensions. The focus of these models is to found a relationship between various hydrological components such as precipitation, Evapotranspiration, surface runoff, ground water flow and soil water movement. Many of these hydrological models describe the canopy interception, evaporation, transpiration, snowmelt, interflow, overland flow, channel flow, unsaturated subsurface flow and saturated subsurface flow. These models range from simple unit hydrograph-based models to more complex models that are based on the dynamic flow equations.

2.1.1 Classification of Hydrological Model

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. The model processes include all the hydrologic processes that contribute to the system output. Based on the description of those processes, in conjunction with the system characteristics, (Beven, 2000) categorized rainfall-runoff model into lumped or distributed and deterministic or stochastic. Lumped or lumped-parameter models treat an entire watershed as one unit and take no account of the spatial variability in processes, input, boundary conditions, or the hydrologic properties of the watershed (M.Juraj, 2003). In contrast, distributed models ideally account for all spatial variability in the watershed explicitly by solving the governing equations, for instance, for each pixel in a grid (Beven, 2000). Distributed models generally require large amounts of data parameterization in each grid cell. (M.Juraj, 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 (M.Juraj, 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 (Robinson, 2000). They added that models may also be linear or non-linear in either the systems theory or statistical regression sense.

In current years, distributed watershed models are increasingly used to study alternative management strategies in the areas of water resources allocation, flood control, impact of land use change and climate change, and finally environmental pollution control. Distributed hydrological models consider the spatial non-uniformity of hydrological characteristics and processes in the river basin. These models are based on our understanding of the physics of the hydrological processes which control catchment response and use physically based equations to describe these processes. These models can be applied for the study of the effects of land use changes and human intervention on the catchment behavior (Beven K and Binley A, 1992). It is important that these models pass through a careful calibration and uncertainty analysis. Also, 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 (Gassman et al, 2007). 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.

2.2 Hydrological System

Hydrologic system is a system of interrelated components, including the processes of precipitation, evaporation, transpiration, infiltration, groundwater flow, stream flow, etc., in addition to those structures and devices that are used to manage the system. Hydrologic system is subject to different kind of weather pattern and spatial complexity, and is dynamic and random in nature.

2.2.1 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. The detail explanation is given on SWAT theoretical documentation. Schematic representation of Components of the hydrological process shown as fig.2.1 below which is taken from SWAT theoretical documentation (Neitsch et al 2011).

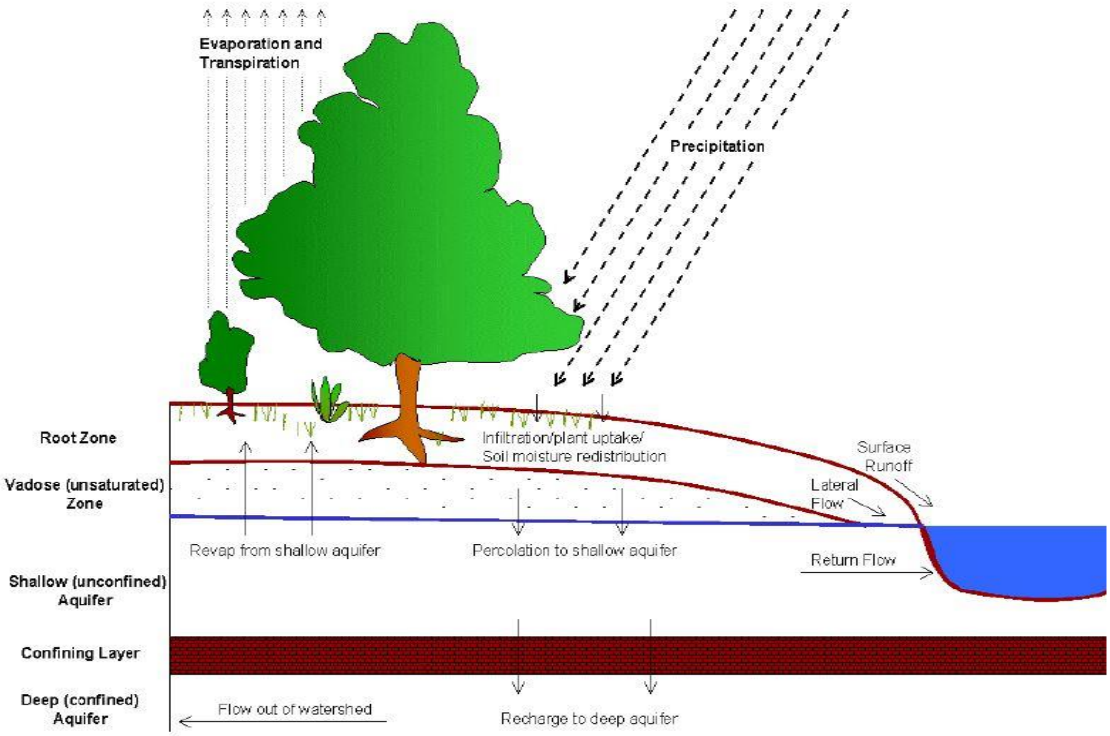


Figure 2.1 Schematic representation of the hydrologic cycle in SWAT (Neitsch et al. 2011)

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 initiative promoted by the International Association of Hydrological Sciences (IAHS) (Abbaspour K.C, 2007). 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 K and Binley A, 1992; V.Gupta, 2006). Reasonable estimates of prediction of uncertainty of hydrologic processes are valuable to water resources and other relevant decision-making processes (V.Gupta, 2006).

The interactions and correlations between parameters can also cause uncertainties (Abbas pour K.,2014). Generally, water resource management projects are planned and designed using scenarios that fall at the conservative end of the range of reasonable 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 (Beven K and Binley A, 1992; V.Gupta, 2006; Abbaspour K.C, 2007; Hongjing Wub, 2014; Abbaspour, K.C, 2014).

2.3.1 Types of Uncertainty

Watershed model suffer from large uncertainties. 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 uncertainties can be divided into: The conceptual model uncertainty (structural uncertainty), input uncertainty and parameter uncertainty.

The conceptual model uncertainty (structural uncertainty) caused in the following situation: Model uncertainties due to simplifications in the conceptual model, Model uncertainties due to processes occurring in the watershed but not included in the SWAT Model, uncertainties due to processes that are included in the model, but their occurrences in the watershed are unknown to the modeler or unaccountable and Uncertainties due to errors in input variables such as rainfall and temperature, as point measurements are used in distributed models (Abbaspour, K.C, 2014).

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. (Abbaspour, K.C, 2014).

2.3.2 Uncertainty Analysis

The deterministic approach to calibration is now outdated and unacceptable. Example of deterministic approach is trial and error. Meaning you keeps adjusting parameter until you get some kind of reasonable match between simulated and observation. In stochastic calibration we recognize the errors and uncertainties in our model. There is an intimate relationship between calibration and uncertainty (Abbaspour, K.C, 2014). Reporting uncertainty is not a luxury in modeling it is a necessity. Without uncertainty analysis of the model calibration is meaningless and misleading (Abbaspour, 2015)

2.4 SWAT Model Review

The Arc SWAT Arc GIS extension is a graphical user interface for the SWAT (Soil and Water Assessment Tool) model (Arnold et al., 1998). SWAT is a river basin, or watershed, scale model developed to predict the impact of land management practices on water, sediment, and agricultural chemical yields in large, complex watersheds with varying soils, land use, and management conditions over long periods of time. The model is physically based and computationally efficient, uses readily available inputs and enables users to study long-term impacts (Neitsch et al., 2011). SWAT can be used to simulate a single watershed or a system of multiple hydrologically connected watersheds. SWAT is currently applied worldwide and considered as 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 decision (Gassman et al., 2007).

Major model components include weather, hydrology, soil temperature and properties, plant growth, nutrients, pesticides, bacteria and pathogens, and land management. In SWAT watershed is divided into multiple sub-watersheds, which are then further subdivided into 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 (Abbaspour K.C, 2007). SWAT model is a popular hydrological modeling which enables the user to achieve a deeper insight into the water related processes of a specific catchment site. Its applicability on both large and small scale offers a huge range of opportunities. Further one can setup a model relatively easily, even though there is not a profound data base provided

2.4.1 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. 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 (Abbaspour, K.C, 2014).

2.4.2 Conceptual basis of SUFI-2 methodology uncertainty analysis

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). The goodness of calibration and prediction uncertainty is judged on the basis of closeness of the *P*-factor to 100% (i.e. all observations bracketed by the prediction uncertainty) and the *R*-factor to 1 (i.e. achievement of rather small uncertainty band) (Abbaspour, K.C, 2014).

2.4.3 Introduction to GLUE

GLUE (Beven K and Binley A, 1992) is an uncertainty analysis technique inspired by Importance sampling and regional sensitivity analysis. 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 number of iterations required to get the best parameter ranges in the simulation result (Abbaspour, K.C, 2014).

2.4.4 *Parameterization*

Parameterization is the subjective and necessary process of selecting model inputs to treat as adjustable in the conditioning process. It is a critical part of any modeling analysis and has received considerable attention in the literature (Romanowicz, 2005).

2.4.5 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, K.C, 2014).

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 (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, K.C, 2014).

2.5 Previous Work Related to this Study

Since its development in 1990s the SWAT model has been widely applied and improved to suit different watershed conditions. Even if SWAT was established for US conditions there have been several successful simulations in different parts of the world.

The application of SWAT model and its parameterization using SWAT CUP (SUFI-2 and GLUE) under GIS platform provides advance option in hydrological modelling. GLUE and SUFI-2 procedures are flexible by allowing for uninformed likelihood measures and objective functions

(Vishal Singh et al., 2013). Hydrological stream flow modeling on Tungabhadra catchment using SWAT CUP have done by using and SUFI-2 and GLUE and both methods gave good results in minimizing the differences between observed and simulated flows. Another similar study in a river basin of eastern India conducted by (Uniyal, 2015) reported that both SUFI-2 and GLUE are the promising techniques for uncertainty analysis of modeling results and there is a need to conduct such types of studies in different catchments under varying agro-climatic conditions for assessing their generic capability.

Many studies have been performed regarding the application of SWAT in Africa. However, there are high levels of uncertainty associated with the model predictions and climate change scenarios that should be evaluated in future studies (Abaho P, 2009). The model has been tested in different tropical watersheds and reported to be able to well explain watershed hydrologic processes. To benefit from its free accessibility and good modeling capability, testing this model for the Ethiopian condition is quite necessary (Lijalem, 2007).

The review of SWAT model applicability to Ethiopian situations at relatively larger watersheds indicated that the model is capable of simulating hydrological processes with a reasonable accuracy (Dilnesaw, 2006). There are also several successful simulations on upper Blue Nile, Ethiopia. Previously (Setegn, 2008) applied SWAT2005 to the Lake Tana basin for modeling of the hydrological water balance. The main objective of the study was to test the performance and feasibility of the SWAT model for prediction of stream flow in the Lake Tana basin. The model was calibrated and validated on four tributaries of Lake Tana; Gumera, Gilgal Abbay, Megech and Ribb rivers using SUFI-2, GLUE and Parasol program. From the review of some literature, it seems the best promising algorithms from uncertainty programs in SWAT CUP (SUFI-2, GLUE, PARASOL, PSO and MCMC) is SUFI-2 and GLUE. Some researcher recommends that using different uncertainty analysis techniques needs to be verified with more applications to different regions.

3. METHODS AND MATERIAL

3.1 Description of the Study Area

The Didessa river basin is geographically located between $07^0$40'N - $10^0$00'N Latitude and $35^0$30'E – $37^0$15'E Longitude in Western part of Ethiopia. Physically; Didessa basin drains 4 zones (Jima, Buno Bedele, East and West Wollega) of Oromia and some part in Kamashi zone of Benishangul-Gumuz. Didessa River, which is the largest tributary of the Blue Nile, contributes roughly a quarter of the total flow of Blue Nile originating from the mountain ranges of Gomma in South Western Ethiopia. The main upper streams namely; Temsa and Yebbu rivers in the South flow eastwards for about 75kms until they are joined by the Eastern tributaries such as Wama, Indris and so on, then after, turning rather sharply to the north until it reaches the Blue Nile(Abbay) River (Tesfaye, 2014).

The total catchment area drained by the river is estimated to be 28,250 km^2. In the North East direction, the main tributary of Didessa River with the largest catchment area is Anger River**.** The general elevation in the basin ranges between 653-meter a.m.s.l. and 3144m a.m.s.l**.** The mean annual rainfall in the study area is about 1818.6mm. The majority of the area is characterized by a humid tropical climate with heavy rainfall and most of the total annual rainfall is received during one rainy season called kiremt (summer). The maximum and minimum temperature varies between 21.3 – 30. 9 ^{0}c and 10.9 - 15.1^{0}c, respectively. Based on the physiography, Didessa river basin can be categorized in to two broad units which are the high land plateau and the associated low lands. The high land plateaus mainly embrace the Jimma-Buno Bedele, East Wollega high lands and highlands of Horo Guduru Wollega, while the associated low lands include the low lands of Didessa valleys of East Wollega. The location map of the study area is displayed as figure 3.1 below.

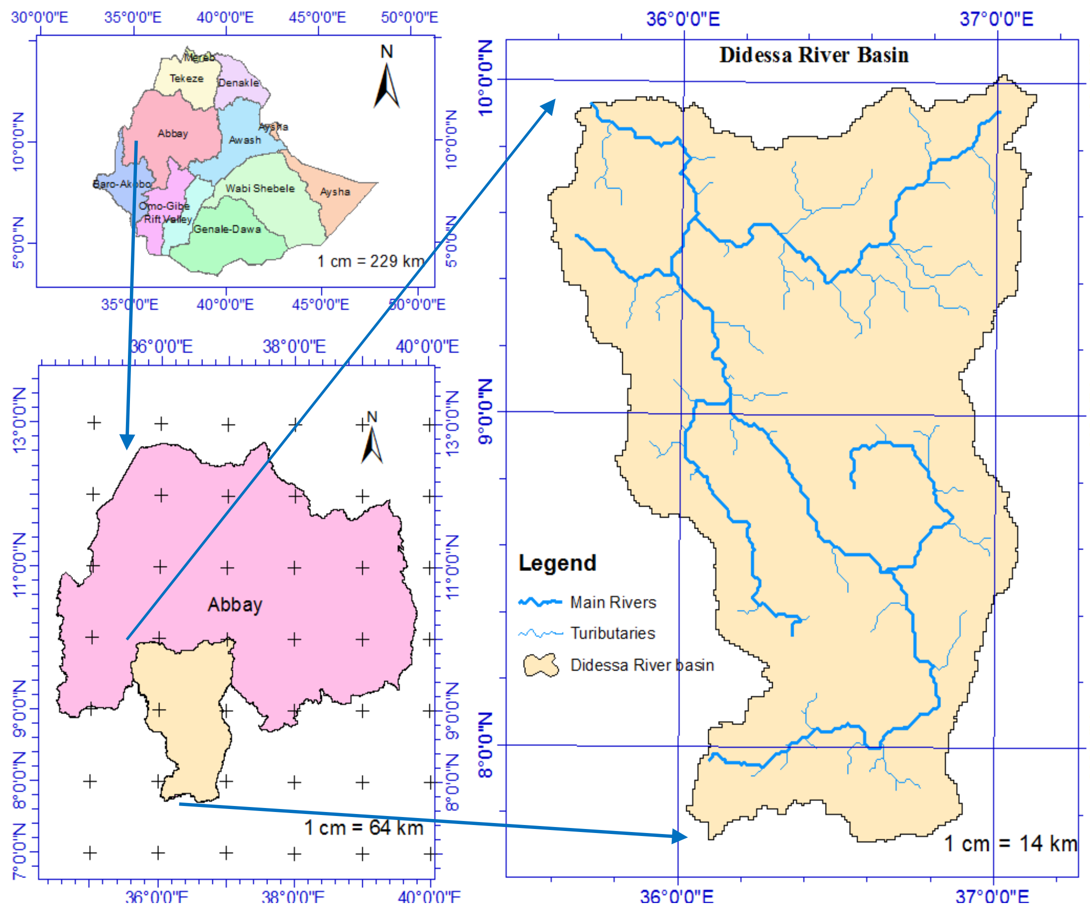


Figure 3.1 Map of Didessa river basin (Study site), Abbay basin, Ethiopia

3.2 Data Collection and Data Source

3.2.1 Meteorological Data

The criterion for the selection of the Metrological data was based on the availability of data, the data quality and possibly whether the station is within the watershed or not? But the distribution of the river watershed depends on the availability of simultaneous long year daily meteorological data to maintain the distribution as far as possible throughout the river basins. All meteorological data (rain fall, temperature, relative humidity, sunshine hour and wind speed) was collected from National Meteorological Agency of Ethiopia (NMSA). These variables served as atmospheric parameters used in driving the hydrologic simulation of the study river. Out of 13 gauged meteorological stations taken from national meteorological agency of Ethiopia, 10 meteorological stations with the least missing data was selected.

Table 3.1 Summary of rainfall stations used with years of record

S/N	Station name	Lat.(^{0})	Long. (^{0})	Elevation	Year of data	Missed (%)	Remark
1	Limu Genet	8.0667	36.95	1766	1980-2016	9	Filled
2	Gatira	7.9833	36.2	2358	1980-2016	12	Filled
3	Bedele	8.45	36.38	2011	1980-2016	13	Filled
4	Nekemte	9.08	36.45	2080	1980-2016	10	Filled
5	Gida Ayana	9.8667	36.6167	1850	1980-2016	17	Filled
6	Shambu	9.5712	37.1212	2460	1980-2016	15	Filled
7	Arjo	8.75	36.5	2565	1980-2016	38	Filled
8	Didessa	9.3833	36.1	1310	1980-2016	13	Filled
9	Gimbi	9.1667	35.7833	1970	1980-2016	19	Filled
10	Nedjo	9.5	35.45	1860	1980-2016	21	Filled

The map which shows the meteorological stations locations used in this study overlapped with the study area by Thiessen polygon is displayed below as figure.3.2

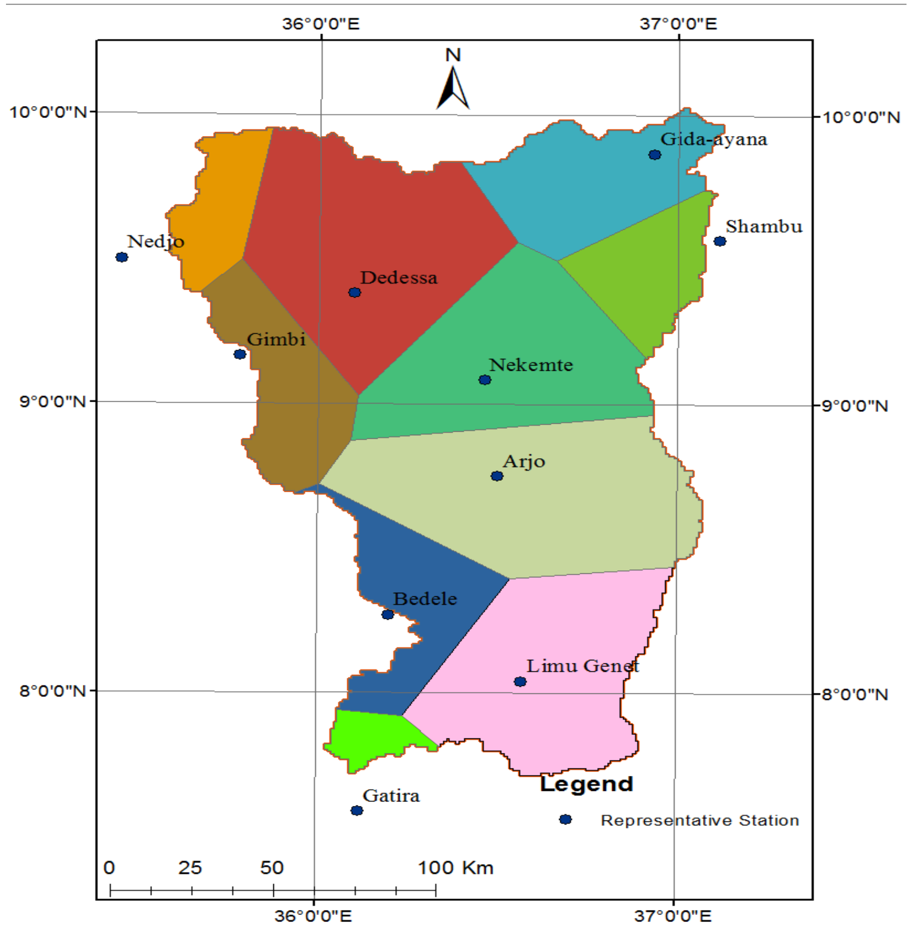


Figure 3.2 Map of weather gauging location and Thiessen Polygon

3.2.2 Flow Data

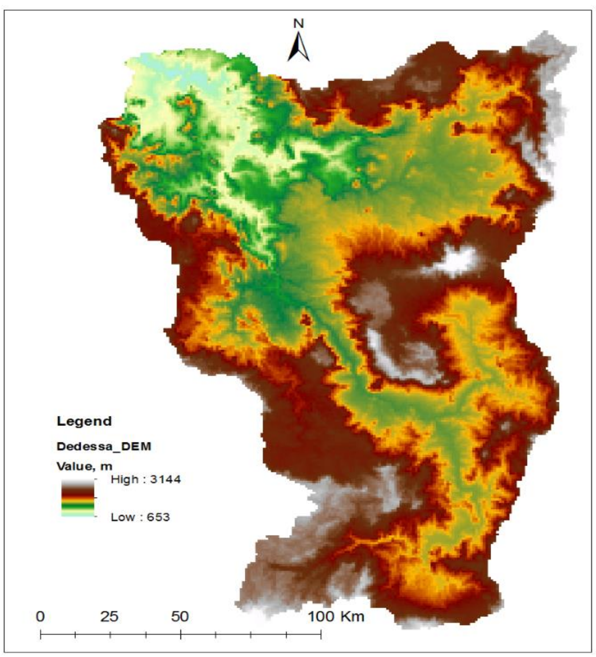
Flow measurements were obtained from the Ministry of Water Resource, Irrigation and Energy of Ethiopia. The relevant gauging station of Didessa river basin is located near Dembi (Toba), Arjo Didessa near Arjo, Dabana near Abasena, Wama near Nekemte and Angar near Nekemte. Out of this the hydro-gauging stations which have consistent long year flow data Didessa near Dembi having the flow data from 1997-2014, and Didessa near Arjo having the flow data 1997-2014 are employed for calibration and validation to find sensitive parameters and its approximate value.

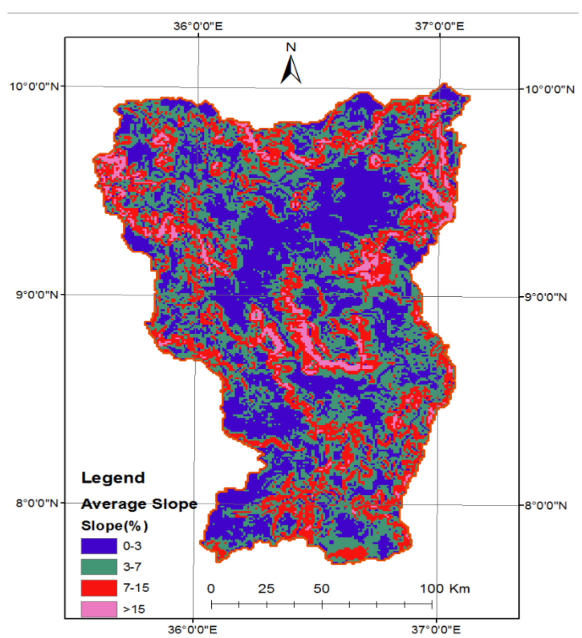
3.2.3 Spatial Data

Different spatial data describing physical characteristics of the watershed needed for the model development. The spatial data used in this study were:

3.2.3.1 Digital Elevation Model

A (30 X 30) DEM is used to delineate the watershed, to calculate Sub-basin parameters such as slope, slope length, and to define stream network characteristics. The digital elevation model ASTER GDEM was obtained from NASA (National Aeronautics and Space Administration) (2015). It is a product of the Ministry of Economy, Trade and Industry of Japan and the NASA. The grid resolution lies at 30 m (see figure 3.3). It is necessary for the stream network processing in SWAT. The calculations establishing the river system are included in the Arc SWAT procedure facilitating the application. Further the sub basins are generated. In total there were 112 sub basins established for Didessa River catchment area. The topography of the study area ranges from low to high land area. Accordingly, the highest elevation range as high as up to 3144m a.m.s.l. and low up to 653m a.m.s.l. Its topographic feature extends from flat to a number of mountain ranges. The mountains ranges distributed throughout the study area. The average slope which is necessary for the HRU generation later on were also derived from DEM. The DEM and the map which shows the spatial distribution of multiple slopes over the study area is displayed below as figure 4.3 (a) and (b)





(a) (b)

Figure 3.3 (a) DEM (b) Average slopes of the study area

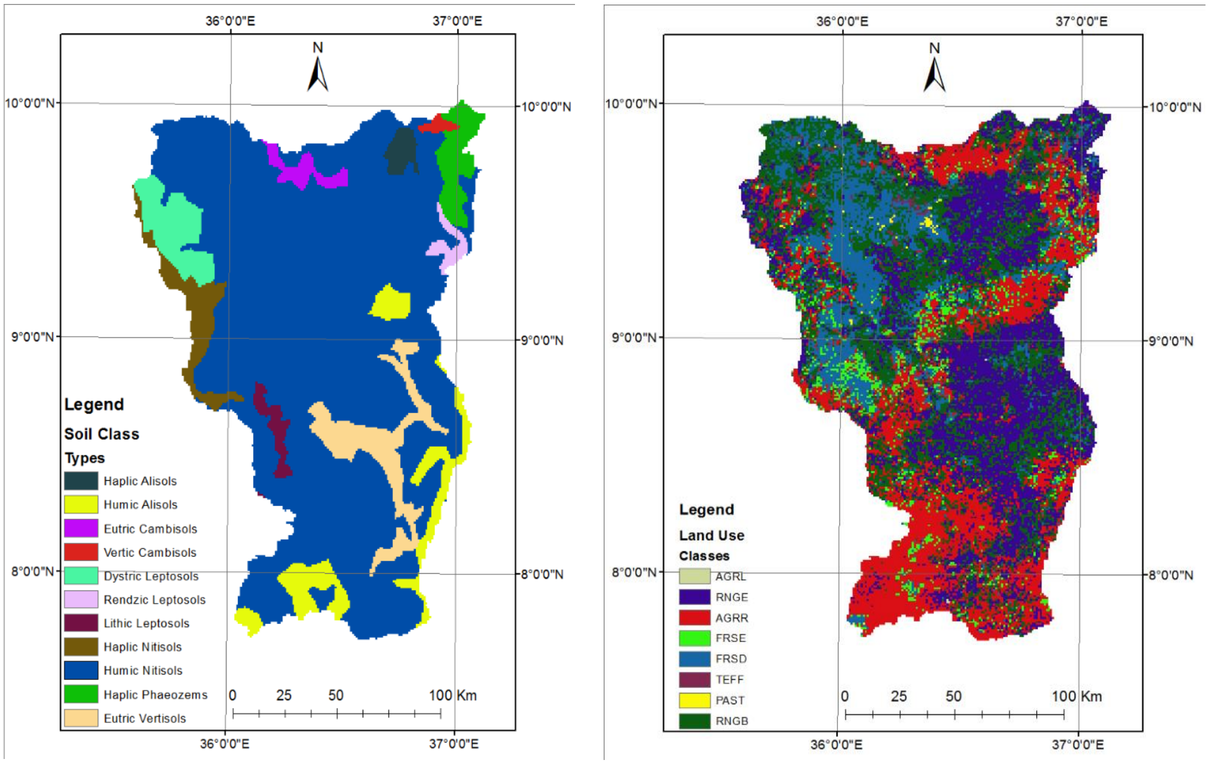
3.2.3.2 Soil Classification Data

Soil classification map gives information of hydrological soil type classification which considers the physical properties of soils including texture, infiltration capacity, and particle size and soil structure. These data were obtained from various sources. The soil map obtained from Ministry of Water Resources, Irrigation and Energy of Ethiopia. However, several properties like moisture bulk density, saturated hydraulic conductivity, percent clay content, percent silt content and percentage sand content of the soil which are required by SWAT model were not incorporated. Due to these deficient information additional data were corroborated from another source like ‘Soil geo-database of Ethiopia’ prepared by (Belete B. et al.,2013). The map which shows the spatial distribution of major soil types over the study area is given below as figure 3.4 a.

3.2.3.3 Land Use/Cover Data

Land use map gives the spatial extent and classification of the various land use/ land cover classes of the study area. The source of land use map of the study is the MERIS (Medium Resolution Imaging Spectrometer) based Glob-Cover 2009 land cover map. It is used after clipping it for my study area and modified to correspond with the SWAT predefined land uses classification. It contains a raster version of the Glob-Cover land cover map produced for the year 2009.

The majority of the basin is used for agricultural purpose particularly, in the southern region of the basin. The central eastern part is covered by range of grass land mixed with range brush; whereas north western part of the basin is dominated by Deciduous forest mixed with Range Brush. This may be due to rapid intensive need for agriculture, the topographic and soil suitability. Deforestation for bush land and forest area for agricultural purpose in addition to that used on cultivation purpose have expected to exert its own effect on quantity and variability of stream flow. The map which shows the spatial distribution of major Land use over the study area is given below as figure 3.4 b.



(a) (b)

Figure 3.4 (a) soil classification map (b) LUC map

3.3 Method of Filling of Missed Data

The goal of any missing data filling technique is creation of complete data set, which may then be analyzed using complete data inferential methods. A variety of methods exist in the literature for filling missing hydrological data, ranging from simple to the complex. For longer and continuous data establishment, correlation method with the neighboring stations having longer data can be used. The estimation of missing meteorological data can be done through within station, between stations or regression-based methods (Allen, 2001). Short gaps can be filled by simple within station method such as, interpolation between available data or moving averages.

XLSTAT software is used for filling of missing temperature and rainfall data. XLSTAT started in 1995 in order to make accessible to anyone a powerful, complete and user-friendly data analysis and statistical solution. The accessibility comes from the compatibility of XLSTAT with all the Microsoft Excel versions that are used nowadays (starting from Excel 97 up to Excel 2016), from the interface that is available in several languages and downloaded from the XLSTAT website www.xlstat.com.

The power of XLSTAT comes from both the C++ programming language, and from the algorithms that are used. The algorithms are the result of many years of research of thousands of statisticians, mathematicians, computer scientists throughout the world. Each development of a new functionality in XLSTAT is preceded by an in-depth research phase that sometimes includes exchanges with the leading specialists of the methods of interest. Last, the usability comes from the user-friendly interface, which after a few minutes of trying it out, facilitates the use of some statistical methods that might require hours of training with other software. Most XLSTAT functions include options to handle missing data. However, only few approaches are available. This tool allows you to complete or clean your dataset using advanced missing value treatment methods.

Different methods are available depending on your needs and data:

- ❖ For quantitative data, XLSTAT allows you to:
  - Remove observations with missing value.
  - Use a mean imputation method.
  - Use a nearest neighbor approach.
  - Use the NIPALS algorithm.
  - Use an MCMC multiple imputation algorithm.
- ❖ For qualitative data, XLSTAT allows you to:
  - Remove the observations with missing value.
  - Use a mode imputation method.
  - Use a nearest neighbor approach.

XLSTAT proposes a multiple imputation algorithm based on the Markov Chain Monte Carlo (MCMC) approach also called fully conditional specification (Van Buulen, 2007). Hence missing data of meteorological data are filled by Using a correlation between nearest neighbor approach.

3.4 Data Quality Testing

Data quality refers to the level of quality of data. Data is considered of high quality if it correctly represents the real-world concept to which it refers. Conventional definition of data quality is about Accurateness, Completeness, Uniqueness, Timeliness and Consistency of data

3.4.1 Consistency test

Sometimes a significant change may occur in and around a particular rain gauge stations. Such change occurring in a particular year will start affecting the rain gauge data, being reported from a particular station. In order to detect such inconsistency and to correct and adjust the reported rainfall values, a technique called double mass curve method is generally adopted. In this method a group of 5 to 10 neighboring stations are chosen in the vicinity of doubtful station. The mean daily rainfall values are serially arranged in reverse chronological order to determine relative consistency; one compares the observations from a certain station with the mean of observations from several nearby stations. This mean is called the 'base' or 'pattern'. Data of each station are arranged in descending order. The curve plot of sum of cumulative rainfall collected at a gauge where measurement condition may have changed significantly against the average of the cumulative rainfall for the same period of record collected at several gauges in the same region data are consistent, the plot will be straight line. On the other hand, inconsistent data will exhibit a change in slope or break at the point where the inconsistency occurred.

The cumulative precipitation values of doubtful station, X say ΣPx, and cumulative values of group average say ΣPav are then plotted on a graph paper. Px' (corrected precipitation) and given by the following formula.

$$Px' = Px\frac{M'}{M} \quad \text{--(3.1)}$$

Where, Px'= corrected precipitation at station x

Px= original recorded precipitation at station x

M'= corrected slope of double mass curve

M= original slope of double mass curve

Typical graph is shown below in figure 3.5 is a DMC of 5 stations, which shows the consistency of the data.

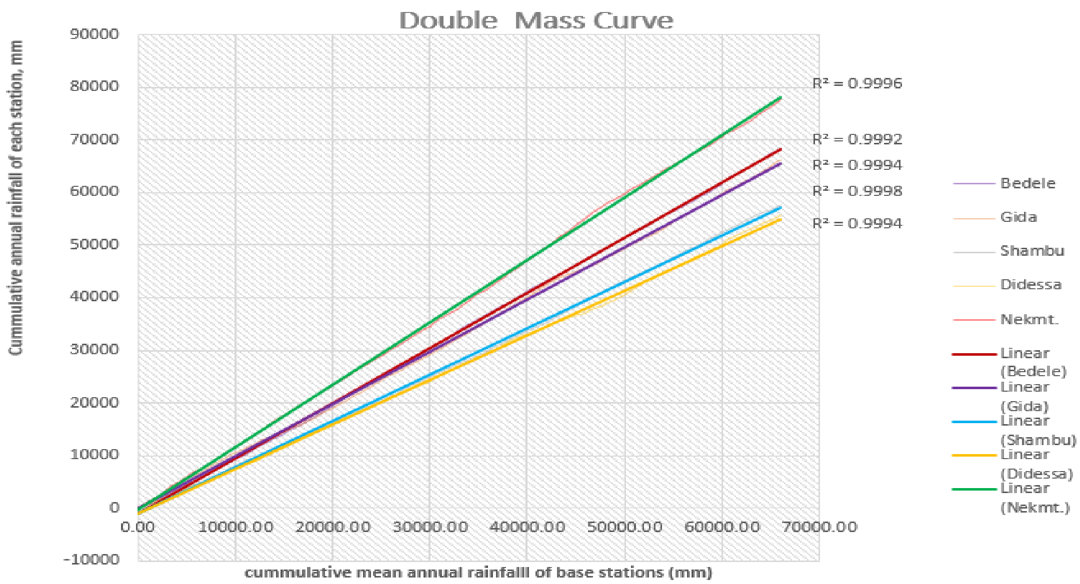


Figure 3.5 Consistency tests of precipitation data for Bedele, Nekemte, Gida, Shambu and Didessa stations.

3.5 Data Process

As additional contribution to SWAT simulations in Ethiopia, in this study the SWAT model is applied to a sub basin of Blue Nile Basin, namely Didessa river basin. SUFI-2 and program of SWAT CUP were selected for calibration and uncertainty analysis. The thesis work has the following components: Data collection; data preparation; Model setup, Sensitivity analysis, calibrating and validating the model, Model result interpretation and comparison. The Arc SWAT 2012 of SWAT model interface with Arc GIS 10.1 of ESRI product was used for processing the analysis.

3.6 SWAT Model

Soil and water assessment tool (SWAT) is a physically based, continuous-time, long-term simulation, lumped parameter, deterministic and originated from agricultural method. The SWAT model uses physically based inputs such as weather variables, soil properties and topography, vegetation and land management practices occurring in the catchment. The physical processes associated with water flow, sediment transport, crop growth, nutrient cycling, etc. are directly modeled by SWAT (Arnold et al., 2012). However, this study focused on the hydrological aspect of the watershed.

Soil and Water Assessment tool (SWAT) was selected as the best modeling tool due to many advantages: It is a public domain model and it is used for free; It is physically based and distributed and uses readily available inputs; it is user friendly, and it is computationally efficient to operate on large basins in a reasonable time. In countries like Ethiopia, where there is a shortage of long term observational data series to use sophisticated models. SWAT is preferred because it is computationally efficient and requires minimum data. SWAT model predicts the hydrology at each HRU using the water balance equations:

$$SW_t = SW_o + \sum_{i=1}^{t} (R_{day} - Q_{surf} - E_a - W_{seep} - Q_{gw}) \quad \text{--------------------------------(3.2)}$$

Where; SW_t = the final water content (mm H2O)

SW_o = the initial soil water content on day i (mm H2O)

t = time, days

R_{day} = is the amount of precipitation on day i (mm H2O)

Q_{surf} = is the amount of surface runoff on day i (mm H2O)

E_a = is the amount of evapotranspiration on day i (mm H2O)

W_{seep} = is the amount of water entering the vadose zone from the Soil profile on Day i (mm H2O)

Q_{gw} = is the amount of ground water flow on day i (mm H2O)

A detail description of the model components can be found from SWAT theoretical documentation (Neitsch et al, 2011;Arnold et al, 2012). This research work is concerned the hydrologic cycle mostly focused on the movement of water.

3.6.1 Model Set-up

To simulate the various hydrological components, SWAT model set-up is needed and SWAT 2012 integrated with ARC-GIS 10.1 is used in this study. The model setup includes watershed delineation, HRU definition, write input table and model simulation

3.6.1.1 Watershed Delineation

SWAT uses digital elevation model (DEM) data to automatically delineate the watershed into several hydrologically connected sub-watersheds. The watershed delineation operation uses and expands Arc GIS and Spatial Analyst extension functions to perform watershed delineation. The watershed delineation process comprises the following steps: DEM setup, stream definition, outlet and inlet definition, watershed outlets selection and definition and calculation of sub-basin parameters.

Firstly, soil map, land use land cover map and the DEM were projected into the same projection called UTM Zone 37N, which is projection parameters for Ethiopia. The catchment and sub basins delineation were carried out based on an automatic delineation procedure using a Digital Elevation Model (DEM) to define the location of the stream network. 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 all known smaller streams were created.

3.6.1.2 HRU Definition

The sub watershed discretization was carried out to divide the watershed into sub basins based on topographic features of the watershed. 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 GIS interfaces developed for SWAT use the sub watershed discretization to divide a watershed. Sub basin discretization was made based on slope, soil and land use percentage thresholds. 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, four slope classes (0-3, 3-7, 7-15, 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. HRUs are used in most SWAT runs since they simplify a run by taking all similar soil and land use areas into a single response unit. 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%, 20%, and 15% threshold levels for the land use, soil and slope classes were applied, respectively so as to include most of spatial details. In this study according to the result of the delineated study area the watershed of the Didessa River basin was divided into 112 sub basins based on the defined stream networks and each sub basin is then sub divided into a total of 674 hydrologic response units (HRUs).

3.6.1.3 Writing Input Tables

The write input tables menu contains items that allow building database files containing the information needed to generate default input for SWAT. Weather data to be used in a watershed simulation was imported once the HRU distribution has been defined. The weather data has been loaded using the weather stations command in the write input tables menu item. Using the file browser, the locations of the weather generator stations prepared in the text format was selected. In this study all the weather stations or the weather data definitions locations were prepared in text format and loaded.

After the database set up was completed the weather gages selected was added to the monitoring point layer. The Write commands become enabled after weather data were successfully loaded. These commands were enabled in sequence and processed only once for a project. Before the SWAT run, the initial watershed input values were defined. These values were set automatically based on the watershed delineation and land use/soil/slope characterization. The write all command option has been selected to build the initial values.

3.6.1.4 Model Simulation Run

After watershed delineation and HRU analysis having successfully loaded prepared weather generator data and arranged data of meteorological stations, the model was able to run for the year 1980-2016.The first three years (1980-1982) is taken for warm up period. The simulation able to produce the necessary output information on streamflow on a daily, monthly and yearly basis. Surface run-off in SWAT can be computed using a modification of the SCS curve number (USDA Soil Conservation Service1972) or the Green and Ampt infiltration method (Neitsch S.L., 2005). Even though the later method is better in estimating runoff volume accurately, its sub-daily time step data requirement makes it difficult to be used for this study. SWAT simulates surface runoff volumes and peak runoff rates for each HRU. In this study, the SCS curve number method was used to estimate surface runoff. The model was developed to provide a consistent basis for estimating the amounts of runoff under varying land use and soil types SCS curve number method calculates the runoff as follows;

$$Q_{SURF} == \frac{(R_{day} - I_a)^2}{(R_{day} - I_a + S)} \quad \text{--(3.3)}$$

Where, Q_{surf} = Accumulated runoff (mm)

R_{day} = Rainfall depth on the day (mm)

I_a= initial abstraction (mm) which includes surface storage, interception and infiltration prior to runoff. It is usually approximated as 0.2S.

S = retention parameter (mm) Retention parameter

where, Q_{surf} is the accumulated runoff or rainfall excess (mm), Rday is the rainfall depth for the day (mm), S is the retention parameter (mm).

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

$$S = 25.4\left(\frac{1000}{CN} - 10\right) \quad \text{--(3.4)}$$

where CN is the curve number for the day. Run-off will occur when $R_{day} > 0.2S$.

CN is curve number for the day and it depends on soil permeability, land use and antecedent soil water. Runoff occurs if and only if $R_{day} > I_a$. Assuming the approximate value of the initial abstraction as 20% of the retention parameter, Equation 3.2 is rewritten as

$$Qsurf = \frac{(Rday - 0.2S)^2}{(Rday + 0.8S)} \quad \text{--(3.5)}$$

3.7 Parameter Sensitivity Analysis

Sensitivity analysis is the process of identifying the model parameters that exert the highest influence on model calibration or on model predictions. Model sensitivity is defined as the change in model output per change in parameter input. An important aim of the parameter sensitivity analysis is to allow the possible reduction in the number of parameters that must be estimated, thereby reducing the computational time required for model calibration. As watershed processes are influenced by a large number of parameters, sensitivity analysis was performed using the Sequential Uncertainty Fitting (SUFI-2) algorithm to identify the key parameters that affect stream flow for calibration. The global sensitivity analysis approach which considers the sensitivity of one parameter in relation to other parameters under consideration was used to determine the sensitive parameters in this study. Firstly, the parameters those were sensitive for Blue Nile (Abbay) basin were arranged from articles published, since Didessa river basin is found in Abbay basin. The global sensitivity analysis approach which considers the sensitivity of one parameter in relation to other parameters under consideration was used to determine the sensitive parameters in this study.

Twenty six parameters considered for sensitivity analysis were: ALPHA_BF (Base flow alpha factor [days]), GWQMN (Threshold water depth in the shallow aquifer for flow [mm]), GW_REVAP (Groundwater "revap" coefficient), REVAPMN (Threshold water depth in the shallow aquifer for "revap" [mm]), ESCO (Soil evaporation compensation factor), SLSUBBSN (Average slope length [m]), CH_K2(Channel effective hydraulic conductivity [mm/hr.]), CN2 (Initial SCS CN II value), SOL_AWC (Available water capacity [mm WATER/mm soil]), SURLAG(Surface runoff lag time [days]),GW_DELAY (Groundwater delay [days]) RCHRG_DP (Deep aquifer percolation fraction), GW_SPYLD(Specific yield of the shallow aquifer (m3/m3)), CANMX (Maximum canopy storage [mm]), SOL_K(Saturated hydraulic conductivity [mm/hr.]) , SOL_ALB (Moist soil albedo), EPCO (Plant uptake compensation factor), CH_N (Manning's n value for main channel), SHALLST(Initial depth of water in the shallow aquifer(mm)), DEEPST(Initial depth of water in the deep aquifer (mm)), LAT_TTIME(Lateral flow travel time) , USLE_P (USLE equation support par). Out of these parameters 18 most sensitive parameter to the model output was selected for calibration. The most sensitive parameters and their best fit value is presented in section 4 as a part of the result.

3.8 Model Calibration and Validation

Physically based semi distributed model SWAT generally has 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. Model calibration is a means of adjusting or fine modification model parameters to match with the observed data as much as possible, with limited range of deviation accepted. Similarly, model validation is testing of calibrated model results with independent data set without any further adjustment at different spatial and temporal scales (Arnold et al., 2012).

Calibration and validation of SWAT model have done by using SWAT CUP. For this study the selected methodology of SWAT CUP approach is SUFI-2 and GLUE. The calibration is firstly done by SUFI-2 and then by GLUE algorithm under the same frame work. The two methods then compared with each other based on the result of the objective function.

Generally, after collection and preparation of all necessary data used to run the model the work flow followed were displayed below as a flow chart which is given in a more simplified form.

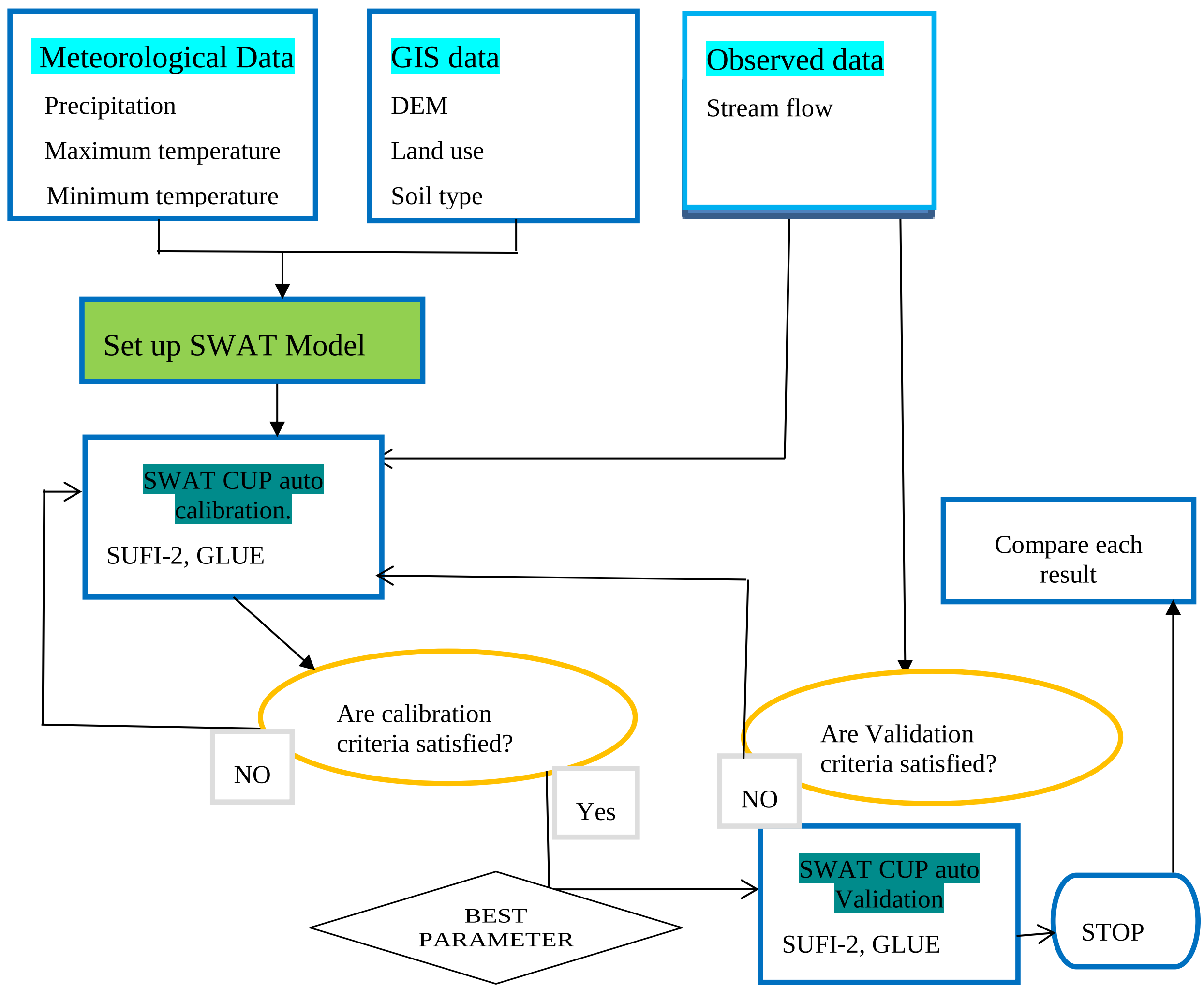


Figure 3.5 The work flow of the study

3.8.1 Model Performance Evaluation

The performance of SWAT was evaluated using statistical measures to determine the quality and reliability of predictions when compared to observed values. The performance of the model is demonstrated by 4 objective functions: correlation coefficient (R^2) and the Nash-Sutcliffe (1970) simulation efficiency (NS) values, p-factor and r-factor.

Correlation coefficient (R^2) and Nash and Sutcliffe simulation efficiency (NS) were used to evaluate the model performance during calibration and validation processes. The coefficient of determination ($R^{2)}$ value is an indicator of strength of relationship between the observed and simulated values. It describes the proportion of variance of the measured data. It has to be treated carefully due to its over sensitivity to outliers. Further it is insensitive to proportional differences (Legates and McCabe Jr, 2010). For the calculation, the following equation is used.

$$R^2 = \frac{\left[\sum_{i=1}^{n}(Q_{m.i}-\overline{Q_m})(Q_{s,i}-\overline{Q_s})\right]^2}{\sum_{i=1}^{n}(Q_{m,i}-\overline{Q_m})^2(Q_{s,i}-\overline{Q_s})^2} \quad \text{-----(3.6)}$$

Where, Q is a variable (e.g., discharge), and *m* and *s* stand for measured and simulated, *i* is the *i* th measured or simulated data. R^2 lies within the bounds of 0 and 1. A value of 0 indicates that there is no relationship between observed and measured data, 1 signifies a perfect linear relation. Hence, the closer R^2 is to 1, the less is the error variance (Moriasi et al. 2007).

The Nash-Sutcliffe simulation efficiency (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, NS is 1. If the NS is between 0 and 1, it indicates deviations between measured and predicted values. If 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).

$$\mathrm{NS} = 1 - \frac{\sum_{i=1}^{n}(Qi^m - Qi^s)^2}{\sum_{i=1}^{n}(Qi^m - \overline{Q^m})^2} \quad \text{-----(3.7)}$$

Where,

Qi^m= observed discharge at time step i

Qi^s = Simulated discharge at time step i

$\overline{Q^m}$= mean of observed discharge

SWAT developers in Santhi et al., (2001) assumed an acceptable calibration for hydrology at R^2 >0.6 and NS > 0.5. These values were also considered in this study as adequate statistical values for acceptable calibration.

3.8.2 Uncertainty Analysis Methods

Understanding, quantifying and reduction of uncertainty are the three critical aspects to be considered in order to adequately address uncertainty in hydrologic modeling. The problem of uncertainty can be simplified by considering these uncertainties separately based on certain assumptions. model calibration does not guarantee reliability of model predictions. The parameter values gotten during calibration and the subsequent predictions made using the calibrated model are only as accurate 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 for the reason that it is too unlikely to find error-free observational data (e.g. stream flow, topography and etc.) and because no simulation model is an entirely true reflection of the physical process being modeled.

For this study the uncertainty analysis was done firstly using SUFI-2 methodology of SWAT cup and Secondly done using GLUE methodology in SWAT CUP. The two algorithms have been applied successfully in former applications to the Blue Nile Basin (e.g. in Setegn (2008). The two-uncertainty analysis method was compared with each other by the same objective function. In SUFI-2, parameter uncertainty accounts for all sources of uncertainties such as uncertainty in driving variables, conceptual model, parameters and measured data.

GLUE is an uncertainty analysis technique inspired by importance sampling and regional sensitivity analysis. 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 (Beven K and Binley A, 1992).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). 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 (Abbaspour, 2007).

The prediction uncertainties in the two methods was evaluated by using the same objective functions p-factor and r-factor. r-factor is another measure quantify the strength of uncertainty analysis which is the average thickness of the 95PPU band divided by the standard deviation of the measured data. The goodness of calibration and prediction uncertainty is judged on the basis of the *P* and the *R*-factor. A p- factor ranges from 0-100% and r- factor from 0-∞. The p-factor of 1 and r-factor of 0 is a simulation that exactly much the observed data. A detail of the parameter uncertainty analysis technique by SUFI-2 and GLUE can be found in SWAT-CUP 2012 - A user manual (Abbaspour et al., 2014).

4. RESULTS AND DISCUSIONS

4.1 SWAT Hydrological Model Results

According to the result of the delineated study area the watershed of the Didessa River basin was divided into 112 sub basins based on the defined stream networks and each sub basin is then sub divided into a total of 674 hydrologic response units (HRUs) based on 20%, 20%, and 15% threshold levels for the land use, soil and slope classes. The delineated map of the study area and its sub basin is shown below as figure 4.1

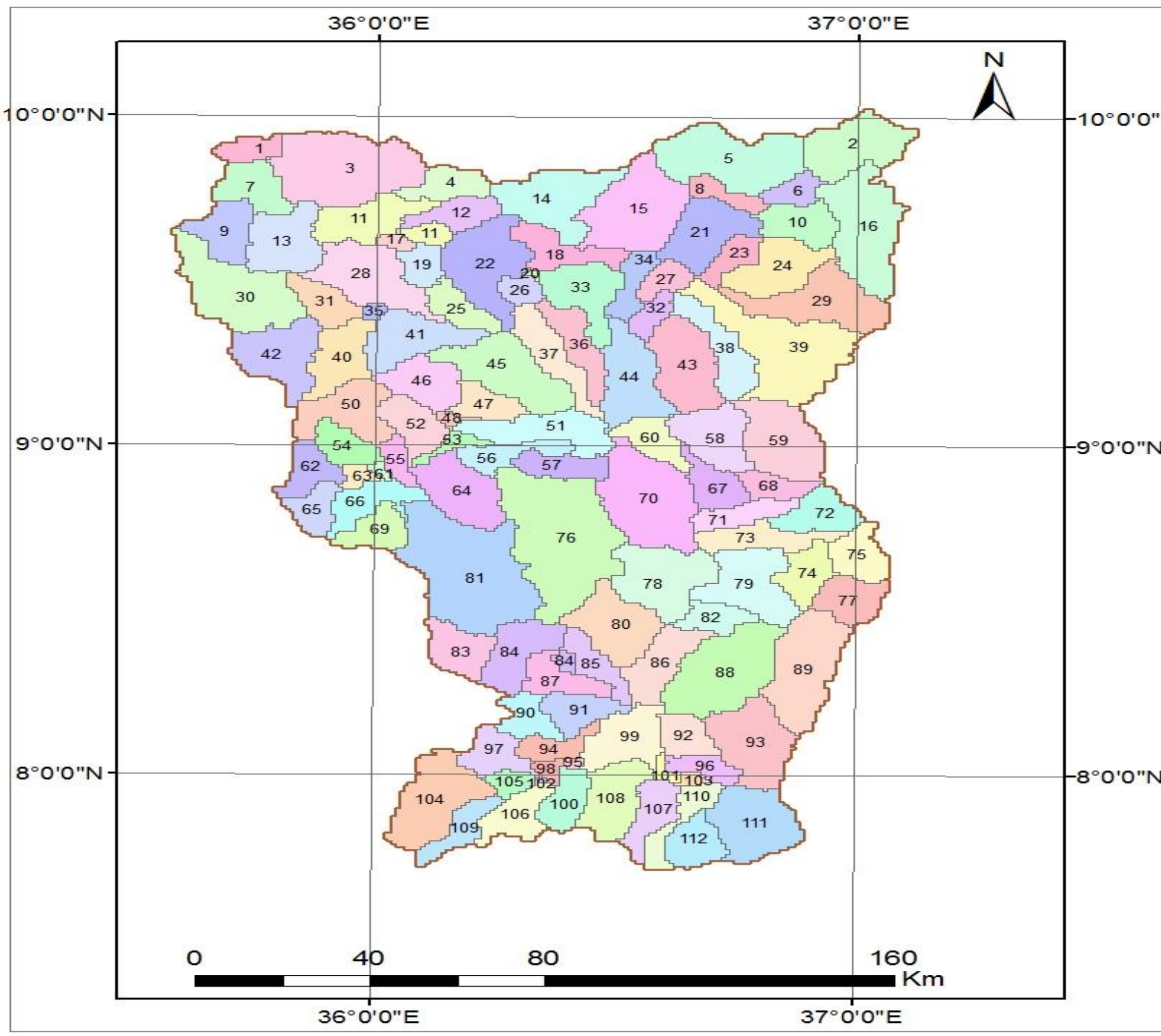


Figure 4.1 The map of delineated watersheds and sub basins

4.1.1 Land Use

The delineated watershed is found to composed of five land use types: range-grasses, agricultural land-row crops, forest-deciduous, range-brush and forest-evergreen. Agricultural land-row crops and range- brush covers the largest area while forest- ever green covers the smallest area of the watershed. The summarization of the land use classification of the Didessa river basin is given in table 4.1 below.

Table 4.1 Land use classification of watershed of Didessa river basin.

S/N	Land use	SWAT land use class	Area in(ha)	% of total area
1	Range-Brush	RNGB	872503.1231	30.88
2	Agricultural land Row crops	AGRR	2098443.2799	30.06
3	Range-Grasses	RNGE	777029.6491	27.50
4	Forest-Deciduous	FRSD	311838.8986	11.04
5	Forest-Evergreen	FRSE	14516.3642	0.51
Total			2,825,099.2	99.99%

4.1.2 Soil Types

Eleven soil types were identified and distributed in different amounts in sub watershed. The major soil types of the area were humic-nitisols which cover 78. 43% of the total watershed. The other soil types distributed in sub watershed are displayed in table 4.2. The major texture of the soil of the area were loam which covers about 81.6%. The others are clay (13.8%), sandy loam (0. 05%).

Table 4.2 Soil types of Didessa river basin

Serial No.	Soil type	Area in (ha)	Total area in percentage
1	Humic Nitisols	2215683.2111	78.43
2	Eutric Vertisols	133274.7728	4.72
3	Humic Alisols	127455.2387	4.51
4	Dystric Leptosols	96648.7630	3.42
5	Haplic Nitisols	87400.8471	3.09
6	Haplic Phaeozems	70846.6444	2.51
7	Rendzic Leptosols	29646.1696	1.05
8	Lithic Leptosols	29181.8692	1.03
9	Haplic Alisols	16464.6897	0.58
10	Eutric Cambisols	13830.9590	0.49
11	Vertic Cambisols	4666.0477	0.17
Total		2825099.2124	100%

4.1.3 Slopes

The area was found to have multiple types of slopes and the dominant one is 3-7 % which covers about the 40.4% of the total area and slope of 0-3% is the next dominant type of slope with total area coverage of 36.94% of the whole watershed area. The types of slopes which were found from SWAT analysis is presented in table 4.3

Table 4.3 Multiple Slopes of Didessa river basin.

Serial No.	Slopes	Area in (ha)	Total area in percentage
1	0-3	1043560.4976	36.94
2	3-7	1141443.9991	40.40
3	7-15	584302.2271	20.68
4	>15	55792.4886	1.97
Total		2825099.2124	100%

4.1.4 SWAT Model Run

After watershed delineation and HRU analysis having successfully loaded weather generator data and arranged data of meteorological stations, the model was able to simulate for the year 1980-2016. The result from the simulation cannot be directly used for further analysis. Instead, the performance of the model to sufficiently predict the constituent stream flow should be evaluated through model calibration and validation.

4.2 Parameters Sensitivity Analysis

Sensitivity analysis was done for the SWAT model to guide calibration process. It was carried out to find the order of sensitivity of stream flow to the input parameters. There are a few methods available in assessing a sensitivity of input parameters in hydrological models. In SWAT model, input parameters can be either manually adjusted in the SWAT model or can be accessed in the SWAT-CUP.

In this study the parameters those govern stream flow is identified and selected through detail literature review. Twenty-six parameters previously mentioned were considered for sensitivity analysis and eighteen most sensitive parameters were selected for calibration based on relative sensitivity. The selected parameters were calibrated using the observed daily and monthly flow. The global sensitivity analysis process was carried out by the methodologies in SWAT CUP for the period of 1997-2006 for Didessa at Dembi and Arjo.

The most sensitive parameters controlling the surface runoff in the river basin were found to be the curve number (CN2), the soil available water capacity (SOL_AWC), the soil evaporation compensation factor (ESCO), and Saturated hydraulic conductivity (R_SOL_K). with respect to the base flow, the threshold water depth in the shallow aquifer for flow (GWQMN), Deep aquifer percolation fraction (RCHRG_DP), Baseflow alpha factor for bank storage (ALPHA_BNK) and Groundwater delay(V_GW_DELAY).

Dotty plots command show the dotty plots of all parameters. These are plots of parameter values vs objective function. The main purpose of these graphs is to show the distribution of the sampling points as well as to give an idea of parameter sensitivity. Dotty plots for Dembi watershed is shown as an example in Figure 4.2. The x-axis ranges of calibration parameters where, the Y-axis is objective function (Nash-Sutcliffe Efficiency).

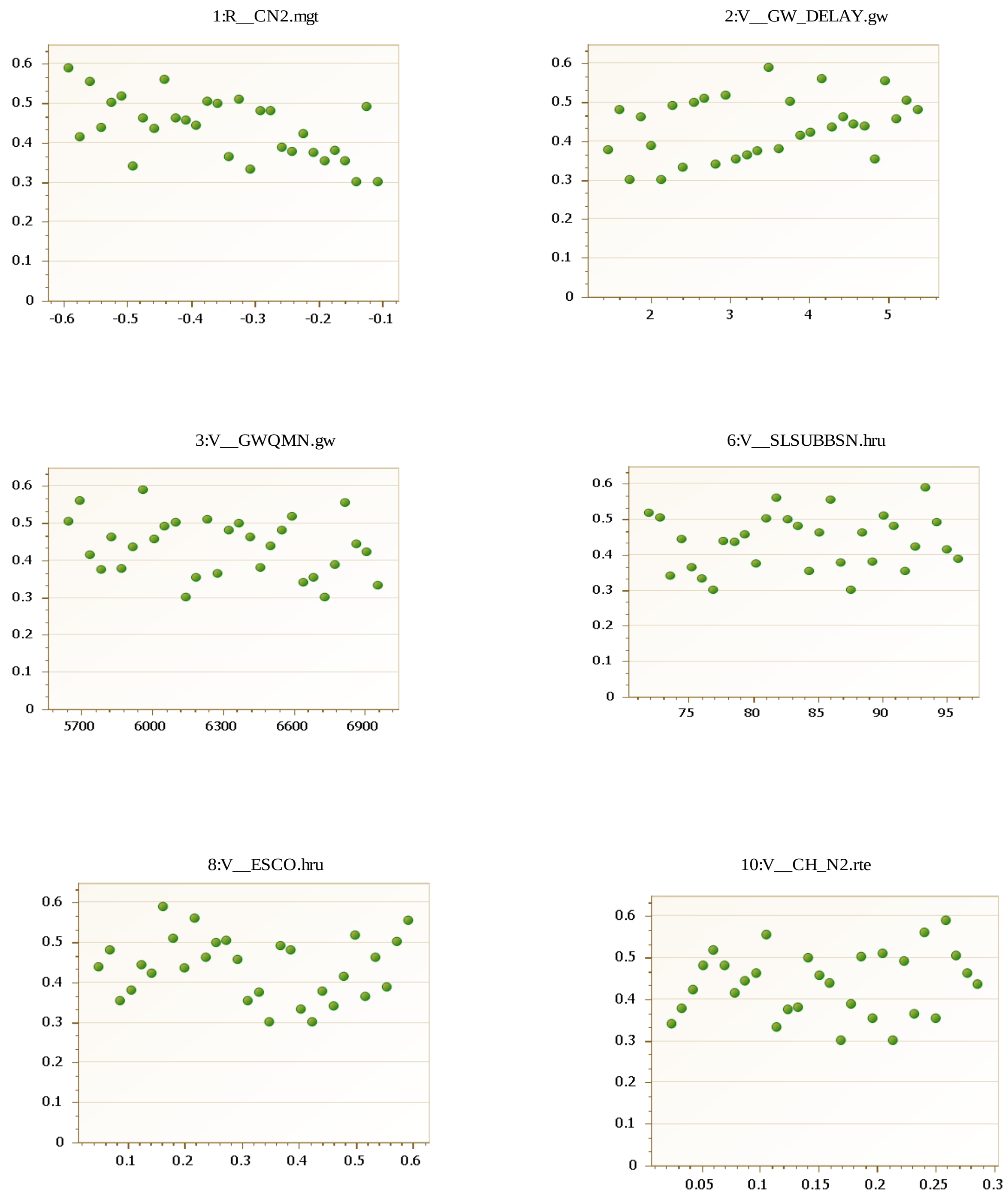


Figure 4.2 Plots showing most identified sensitive parameters during monthly calibratio

4.3 Model Calibration and Validation

After the sensitive parameters identification calibration followed by validation were performed. Flow was the first and the only output calibrated for this study. The stream flow comparison has been done between the observed and simulated discharge values on daily and monthly time steps at 2 known hydro gauging stations. The initial simulation was run for the years 1980–2016 on daily and monthly basis. Manipulation of the parameter values were carried out within the allowable ranges recommended by SWAT developers. Numerous simulations have been run and applied to achieve the best model efficiency between the observed and simulated flows.

4.3.1 Model Calibration

Calibration was done based on monthly and daily basis to observe the performance of the model based on a monthly and daily time step at two selected hydro gauging stations of the river basin Dembi and Arjo for the year 1997-2006. Five objective functions have been used for evaluation of model performance, namely R^2, NS, p-factor, r-factor and br^2. The correlation coefficient (R^2) and Nash-Sutcliffe (1970) simulation efficiency (NS) are used as the main objective function for the model following the SUFI-2 approach between the observed and predicted stream flow. According to the model performance evaluation given by (Moriasi, et.,al 2007):NS>0.65 is very good, NS between 0.5 and 0.65 is adequate, NS >0.5 is satisfactory and NS<0.5 is unsatisfactory both for calibration and validation. Based on the values of correlation coefficient (R^2) and the Nash-Sutcliffe (1970) simulation efficiency (NS), the model performance was very good based on monthly time step and good based on daily time steps. The calibration results of SUFI-2 program is summarized below in a table 4.5

Table 4.4 Calibration statistics by SUFI-2

S/N	Objective function	Monthly calibrations		Daily calibrations	
		Dembi	Arjo	Dembi	Arjo
1	p-factor	0.40	0.48	0.42	0.27
2	r-factor	0.38	0.66	0.54	0.56
3	R^2	0.75	0.72	0.72	0.70
4	NS	0.74	0.71	0.69	0.53

The daily calibration predicts uncertainty over monthly calibration. The simulated flow based on daily time step shows a relatively good agreement with the observed stream flow data. The difficulties were due to the increase in variation of the observed flow with large amount of data. The model over predicts the stream flow for some years and it takes more time to adjust the parameters and more iteration numbers. Manipulation of the parameters were carried out within the allowable ranges recommended by SWAT developers.

4.3.2 Model Validation

Validation proves the performance of the model for simulated flows in periods different than the calibration periods, but without additional adjustment in the calibrated parameters. So, validation was performed for 8 and 7 years 2007-2014 and 2008-2014 at Arjo and Dembi. For validation period, the model performs very well based on monthly time steps and performs well for daily time steps. That means the capability of this simulation is very good enough to utilize the calibrated model for estimating the flow for future effective potential water resource management practices. The obtained result for validation period is summarized in table 4.6 below.

Table 4.5 Validation statistics by SUFI-2

S/N	Objective function	Monthly time steps		Daily time steps	
		Dembi	Arjo	Dembi	Arjo
1	p-factor	0.43	0.40	0.44	0.24
2	r-factor	0.33	0.74	0.51	0.64
3	R^2	0.78	0.73	0.63	0.7
4	NS	0.78	0.72	0.62	0.59

Even if there are some uncertainties in predicting stream flows the results we got from the validation shows the calibrated model performed well for validation period. As a result, the overall performance of the model is acceptable and it is better to consider the uncertainties independently. A typical graph shown as figure 4.4 and 4.5 below is the time series graph of observed and simulated daily stream flow at Didessa near Arjo station for calibration and validation period respectively.

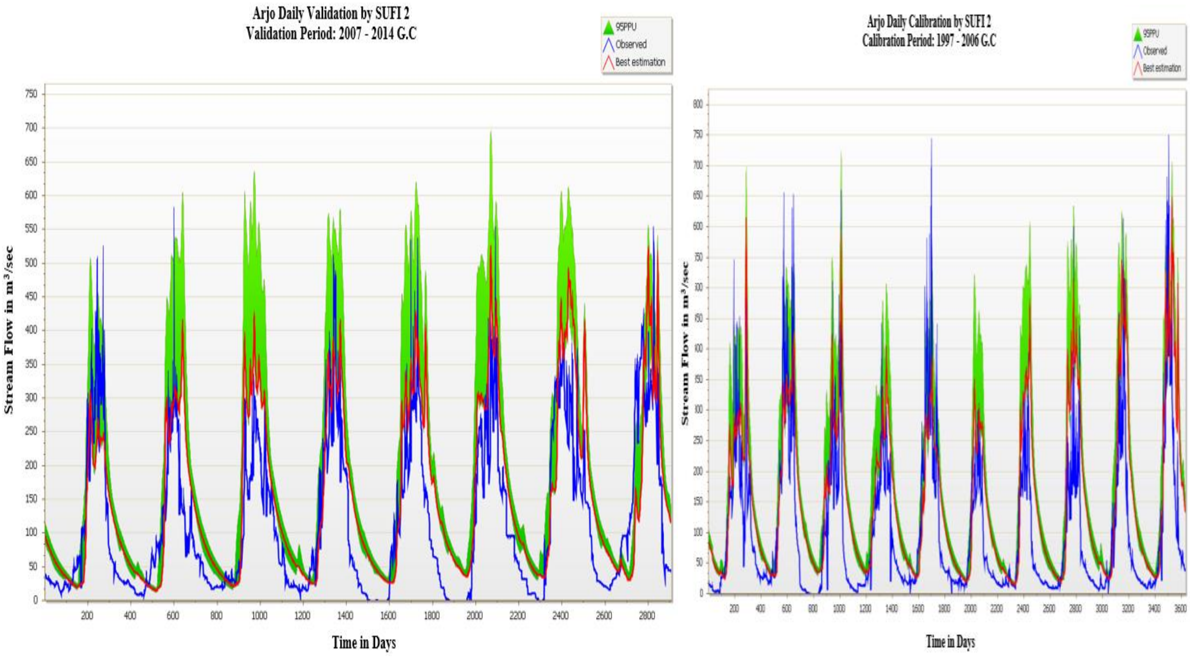


Figure 4.3 SUFI-2 output of Observed and Simulated daily stream flow graph of Didessa at Arjo for calibration period 1997-2006 and validation period 2007-2014

4.3.3 Optimum Value of Parameters and Best Simulation

After calibration best parameters are found Best_par.txt in Sufi-2. These file shows the" best parameter" values as well as their ranges. These are the parameters, which gave the best objective function values in the current iteration. The fitted value of these best parameters can really give the best simulation of stream flow. The Optimum value of sensitive parameters at final stage of daily calibration is displayed below as table 4.8 and 4.9 below for monthly and daily basis for Didessa at Dembi.

Table 4.6 The optimum value of sensitive parameters at Dembi on monthly basis.

Parameter Name	Fitted Value	Min value	Max value	rank
R_CN2.mgt	-0.575	-0.6	-0.1	3
V_GW_DELAY.gw	5.1572	1.4	5.44	4
V_GWQMN.gw	6611.959961	5625	6977	11
V_SHALLST.gw	255.690002	35	796	5
V_SLSUBBSN.hru	87.124001	71.5	96.300003	7
V_ESCO.hru	0.068	0.04	0.6	1
V_EPCO.hru	0.2125	0.15	0.4	12
V_CH_N2.rte	0.2279	0.02	0.29	2
V_CH_K2.rte	20.5142	4.52	27.700001	8
V_ALPHA_BNK.rte	0.7375	0.61	0.76	6
R_SOL_K(..).sol	51.451	31.5	59.599998	10
R_SOL_BD(..).sol	2.8875	2.25	3.5	9

Table 4.7 The best fitted value of sensitive parameters for Didessa river at Dembi for daily basis at final stage of calibration.

Parameter Name	Fitted Value	Min value	Max value	Rank
R_CN2.mgt	0.054	-0.239	0.187	2
V_ALPHA_BF.gw	0.668	0.545	0.673	13
V_RCHRG_DP.gw	0.130	0.124	0.177	10
V_DEEPST.gw	2478.815	1002.500	3230.900	12
V_SLSUBBSN.hru	92.270	71.500	96.300	6
V_ESCO.hru	0.089	0.040	0.600	1
V_LAT_TTIME.hru	20.020	13.600	23.290	11
R_SURLAG.bsn	9.281	5.400	16.900	7
R_USLE_P.mgt	0.231	0.100	0.240	5
V_CH_K2.rte	7.824	0.520	19.370	4
V_ALPHA_BNK.rte	0.677	0.640	0.750	9
R_SOL_AWC(..).sol	0.432	0.340	0.660	3
R_SOL_K(..).sol	40.126	28.500	41.600	14
R_SOL_BD(..).sol	2.169	2.150	2.650	8

Best simulation results of stream flow are summarized below in table 4.7 below and displayed with observed flow for comparison

Table 4.8 Summary of total monthly observed and simulated flows

Station	Year	observed Q in m^3/sec	Simulated Q in m^3/sec	Mean monthly observed (m^3/sec)	Mean monthly simulated (m^3/sec)
Dembi	1997-2006	4886.4	5405.46	42.2	45.14
Dembi	2008-2014	3664.03	3800.498		
Arjo	1997-2006	14215.64	15785.36	117.35	128.7
Arjo	2007-2014	1158.3	12087.71		

The average mean monthly observed and simulated flow for Didessa at Dembi is 42.2 m^3/sec and 45.14 m^3/sec respectively. The average mean monthly observed and simulated flow for Didessa at Arjo is 117.35m^3/sec and 128.04 m^3/sec respectively.

4.4 Uncertainty Analysis

Calibration of hydrological model is a challenging task because of the possible uncertainties that may occur as discussed in section 2.2. Carrying out uncertainty analysis for the prediction of the hydrological model is vital 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 uncertainties such as uncertainty in driving variables (e.g. rainfall), conceptual model, parameters and measured data (Abbaspour, K.C, 2014). For this study the uncertainty analysis is firstly done by SUFI 2 methods in SWAT CUP to check for overall model performance.

Parameter uncertainty is calculated from all the input and output source uncertainties such as the uncertainty in the input rainfall data, the land use and soil type, parameters, and observed data, in SUFI-2. The agreement between the simulated and observed flow based on monthly time step were very good, for daily calibrations performance was good. Even if the result shows there is some amount of uncertainties in model prediction, the performance of the model is proved as good for validation period with acceptable amount of uncertainty. The obtained result of p-factor and r-factor is for monthly time steps is 0.40,0.38 and 0.48,0.66 for Dembi and Arjo respectively. For daily calibration the obtained value was 0.42,0.54 and 0.27,0.56 for Dembi and Arjo respectively.

This difference between monthly and daily time steps may be due to the difference between the way the daily flow data is collected and the way the model predicts the daily stream flow in addition to the overall uncertainty related to large amount of daily data and variations of daily stream flow. The model uncertainties may occur due to Poor quality of the input data, some errors in data input sources, some errors during data preparation and due to parameter uncertainties. The graph which shows 95PPU, monthly observed and simulated stream flow of Didessa river is displayed below to visually inspect the observed stream flow bracketed by 95PPU by SUFI-2 uncertainty prediction for calibration period 1997-2006

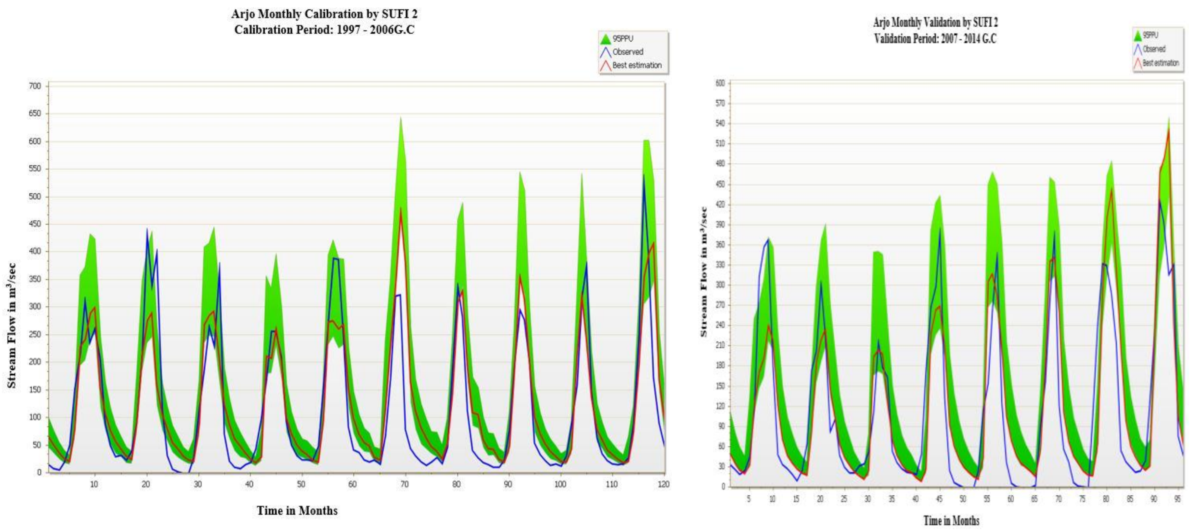


Figure 4.4 SUFI-2 output of Observed and simulated monthly stream flow with 95PPU graph of Didessa at Arjo for calibration period 1997-2006 and validation period 2007-2014

4.4.1 Parameter Uncertainty

For this study the model parameter uncertainties were minimized through parametrization to achieve a very good agreement between observed and simulated flow. At initial stage of calibration, the obtained value of R^2 and NS was below the standard which shows bad simulation and it was improved by adjusting the parameters and calibrating the model many times. In this study to check parameter uncertainty independently, the uncertainty method in SWAT-CUP, GLUE program was used by using the same range of parameter and the same number of simulation used in SUFI-2 for GLUE program.

Table 4.9 Calibration statistics of SUFI-2 and GLUE at Arjo

S/N	Objective function	SUFI-2 Cal.	GLUE cal.	SUFI-2 val.	GLUE val.
1	p-factor	0.48	0.34	0.40	0.26
2	r-factor	0.66	0.53	0.74	0.59
3	R^2	0.72	0.76	0.73	0.77
4	NS	0.71	0.72	0.72	0.72

The calculated p- factor were 0.48 and 0.40 and only 0.34 and 0.26 for calibration and validation by SUFI-2 and GLUE respectively. However, it was able to achieve the obtained value of objective function achieved after several iterations at once by GLUE. The obtained value of R^2 and NS value (which is the most frequently used likelihood measure for GLUE in literature), (SWAT CUP manual, 2012) and also assigned as an objective function in the model program running process) of 0.76 and 0.72 for calibration and 0.77 and 0.72 for validation which represents there is a good parameter identification.

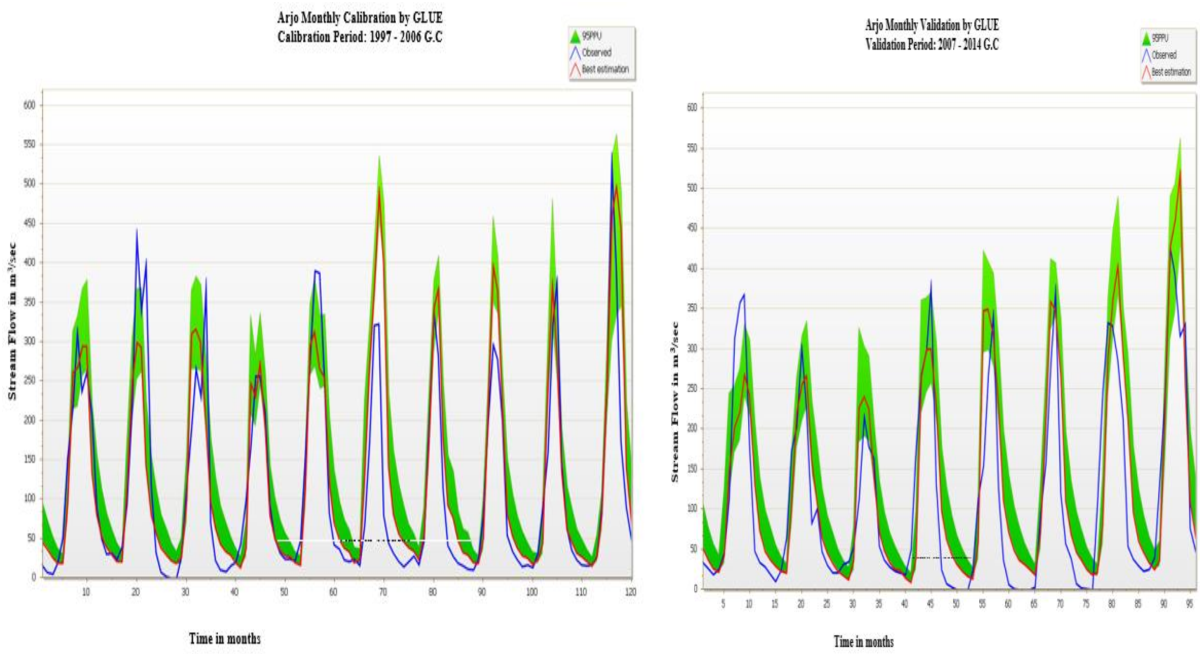


Figure 4.5 GLUE output of 95PPU, Observed and simulated monthly stream flow graph of Didessa at Arjo for calibration period 1997-2006 and validation period 2007-2014

4.5 Comparison of SUFI 2 and GLUE

The calibration of the model was also done by GLUE. The efficiency of the model and the two-uncertainty analysis method of SWAT CUP, SUFI-2 and GLUE was compared based on the previously mentioned objective functions. Based on the quantities of the four objective functions, namely P-factor, R-factor, coefficient of determination R^2 and Nash–Sutcliffe coefficients (NS) the results show very good correlation during monthly calibration time steps, whereas daily calibration exhibits relatively good agreement between the observed and simulated flows for both SUFI 2 and GLUE technique. The result is displayed in table 4.10.

Table 4.10 Statistical results of calibration and validation by SUFI-2 and GLUE for Didessa at Dembi for calibration period 1997-2006 and validation period 2008-2014.

S/N	Objective function	SUFI-2 Cal.	GLUE cal.	SUFI-2 val.	GLUE val.
1	p-factor	0.40	0.25	0.43	0.33
2	r-factor	0.38	0.38	0.33	0.32
3	R^2	0.75	0.77	0.78	0.78
4	NS	0.74	0.75	0.78	0.77

The strength of the model calibration and uncertainty procedure has been analyzed using the r-factor and p-factor. The obtained value of p-factor and r-factor is 0.40 and 0.38 for SUFI-2 and 0.25 and 0.38 for GLUE. The results show 40% of observed flow is bracketed by 95PPU by

SUFI-2 and only 25% of observed flow is bracketed by 95%PPU by GLUE for calibration period of 1997-2006 with r-factor of 0.38 for both. For validation period of 2008-2014 the obtained value of p-factor and r-factor is for SUFI-2, 0.43 and 0.33; for GLUE,0.33 and 0.32. The result shows 43% of observed flow is bracketed by 95PPU by SUFI-2 and only 33% of observed flow is bracketed by 95%PPU by GLUE with the great value of NS 0.78 and 0.77 respectively. The result shows model performance capacity is very good enough even if there is a problem of prediction uncertainty.

The time series graph observed and simulated flow for the calibration period of 1997-2006 and validation period 2008-2014 were plotted for visual comparison to explore the similarity within the peak values resulting from both procedures is displayed below as figure 4.5 and figure 4.6. The result shows there is no significant difference between output graph by the two methods. Both method was good predictive approach even if there is slight difference in prediction uncertainties.

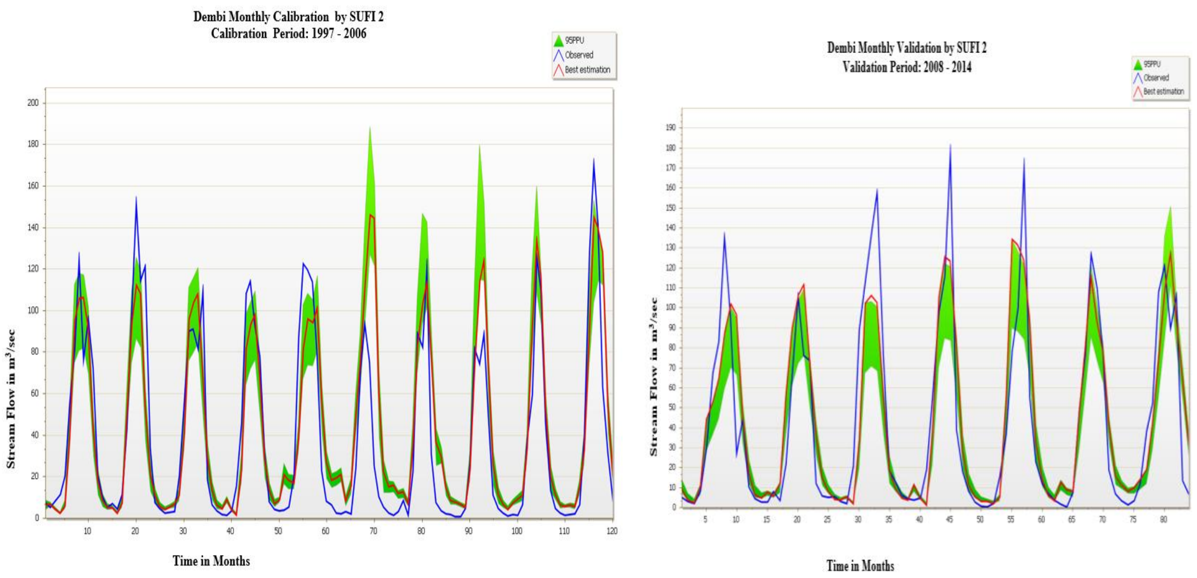


Figure 4.6 SUFI-2 output graph of observed and simulated stream flow with 95PPU for Didessa at Dembi for calibration and validation period.

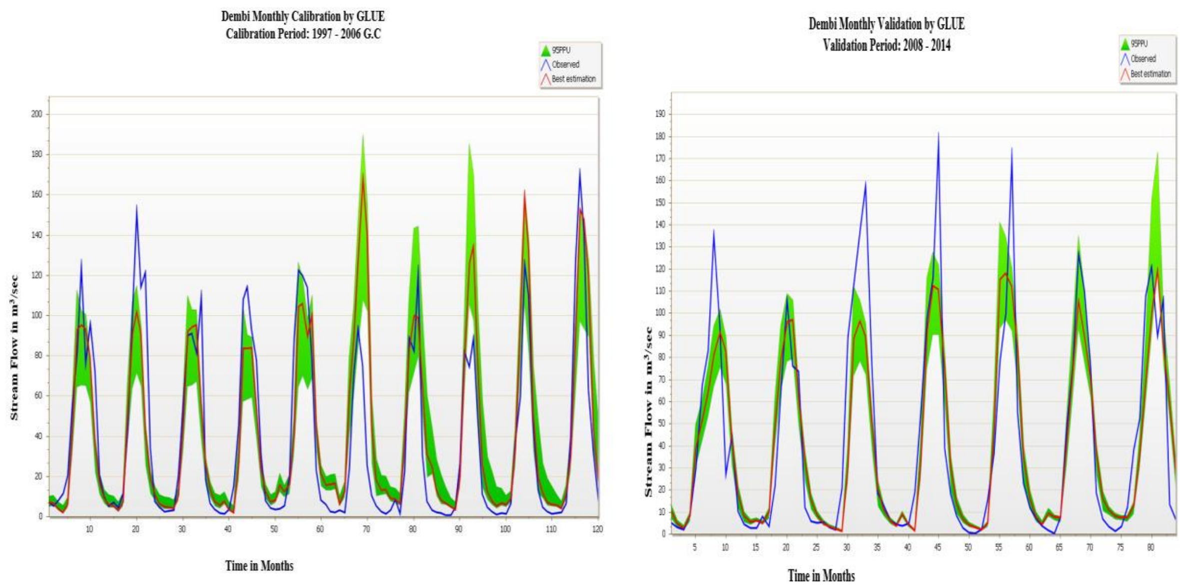


Figure 4.7 GLUE output graph of observed and simulated stream flow with 95PPU of Didessa at Dembi for calibration and validation period.

The performance evaluation of the model by SUFI-2 and GLUE is also done based on daily time steps to evaluate the performance of the daily simulation. The stream flow is predicted by SUFI-2 and GLUE for two periods of 10 years (1997-2006) and 7 years (2008-2014) and compared with the observed stream flow for Didessa at Dembi. The obtained result shows there is good agreement between observed and predicted flows based on the objective functions. The uncertainty analysis capacity of the two methods is compared based on p-factor and r-factor which is 0.42 and 0.54 for SUFI-2 and 0.28 and 0.51 for GLUE for calibration period. The results show 42% of observed flow is bracketed by 95PPU by SUFI-2 and only 28% of observed flow is bracketed by 95%PPU by GLUE for calibration period of 1997-2006.

The value of p-factor and r-factor for validation period 0f 2008-2014 were 0.44 and 0.51 for SUFI-2, and 0.29 and 0.45 for GLUE. This means 44% of observed flow is bracketed by 95PPU by SUFI-2 and only 28% of observed flow is bracketed by 95%PPU by GLUE.

Table 4.11 Statistical results of daily calibration and validation by SUFI-2 and GLUE for Didessa at Dembi

S/N	Objective function	SUFI-2 Cal.	GLUE cal.	SUFI-2 val.	GLUE val.
1	p-factor	0.42	0.28	0.44	0.29
2	r-factor	0.54	0.51	0.51	0.45
3	R^2	0.72	0.68	0.63	0.62
4	NS	0.69	0.66	0.62	0.62

The time-series data of the observed and simulated flows on daily time steps which is the output of SUFI-2 and GLUE program for the calibration period of 1997-2006 for visual comparison of the peak and base flows is displayed below as figure 4.7.

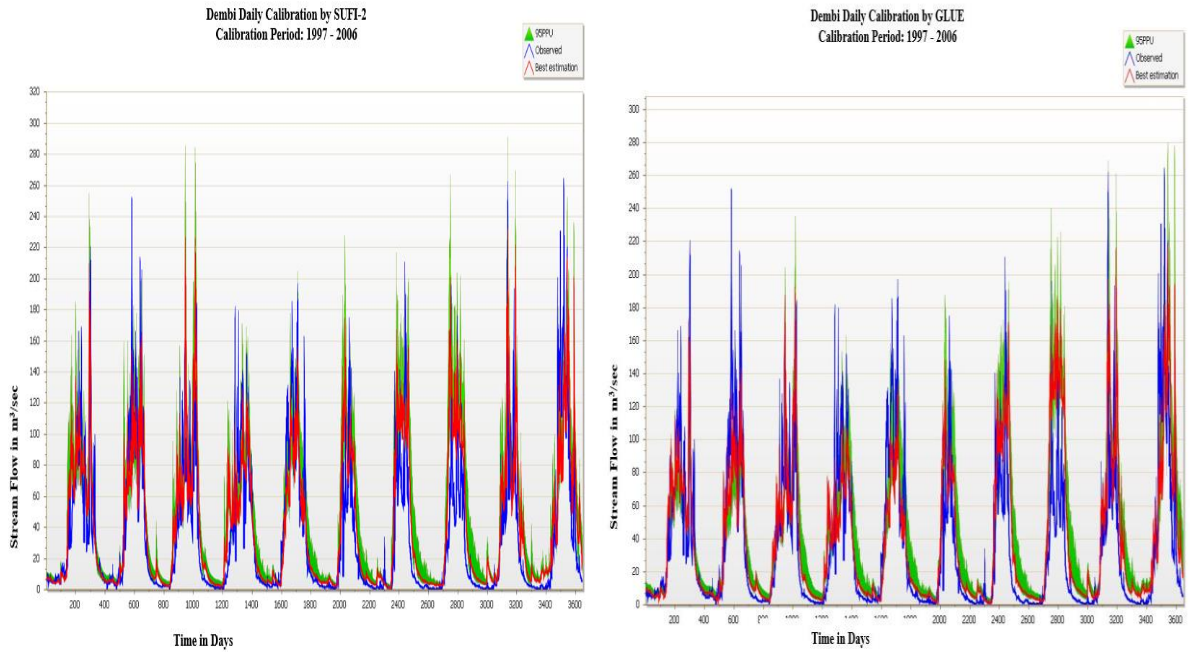


Figure 4.8 Observed and Simulated daily stream flow and 95PPU graph of Didessa at Dembi for Calibration period by SUFI-2 and GLUE

The time-series graph of the observed and simulated flows on daily time steps by SUFI-2 and GLUE for Validation period of 2008-2014 is displayed for visual comparison of the peak and base flows below. The result was not unique from that of the calibration period.

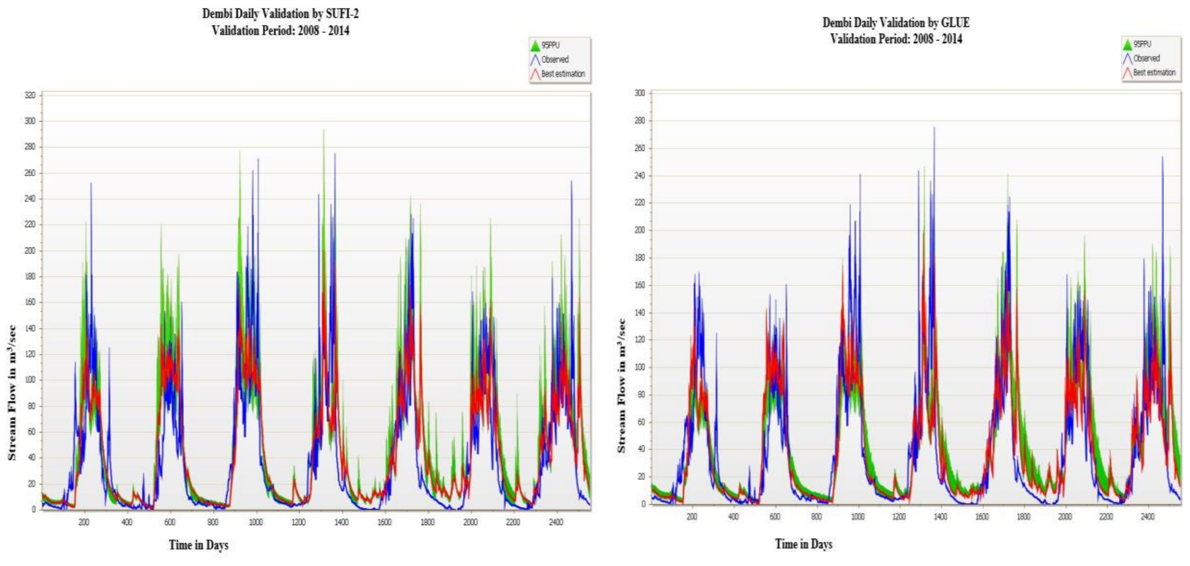


Figure 4.9 Observed and Simulated daily stream flow and 95PPU graph of Didessa at Dembi for validation period by SUFI-2 and GLUE

4.6 Stream Flow and Water Yield of the River Basin.

Having reliable information of the stream flow and water yield may help us to understand the basin characteristics for future possible watershed management and flood controlling measures of the river-basin. Average monthly basin rainfall, Evapo-transpiration, surface flow, Potential Evapo-transpiration and average basin water yield is obtained From Arc SWAT output. From this out put one can understand hydrological characteristics of the basin in terms of months with high and minimum surface and base flow. To easily understand the output hydrological property, it is better to divide output results into two seasons which are wet and dry has been used in this study. From the calculated average basin values, the result was summarized in a monthly and seasonal basis as comparatively dry (Nov–Feb), wet (Jun-Sept), intermediate (March–May). By observing long term average monthly stream flow, it was understood that the lowest stream flow occurs in February and highest in August. Season of heavy rainfall is known by high surface runoff and high-water yield. The average simulated monthly maximum basin water yield occurs in September is 209.83mm which occurs after maximum average monthly rainfall of July and August, which is (333.67 mm and 322.07 mm). The mean annual flow of the river basin is estimated to be 16,959.18 and 57,290.32 in CM at Dembi and Arjo respectively.

4.6.1 Summary of water yield of the sub catchments

The obtained optimum parameters during calibration were edited for the basin by using manual calibration helper and the simulation is re run. Then outputs of the SWAT hydrological model for Didessa Sub-river basin on the water yield of the major tributaries have also been evaluated. The five known tributaries of Didessa River are Anger, Dabana, Wama, Dembi and Uke. In terms of size of the catchment area and contribution to the total runoff of Didessa River, Anger Sub watershed stands first among the tributary watersheds of the sub-basin with area 4819km^2. The mean annual rainfall in Anger Sub-watershed is about 1817.29 mm, and the average annual water yield is about 996.67mm.

The other important sub-watershed in Didessa river basin is Dabana Sub-watershed, with a catchment area 2769km^2, the mean annual precipitation in this watershed is 1440mm with the average annual water yield is 613.45mm.

Wama is also among the top important sub-watersheds in terms of share in Didessa river basins with area 1934 km^2 and the mean annual precipitation and water yield 1994.7mm and 1145.7mm respectively.

The sub-watershed with smallest catchment area 384.3 km^2, Uke having mean annual precipitation 2117.9 and water yield 1276.5 mm is also among the known tributaries of the river basin.

The mean annual rainfall in Dembi Sub-watershed, the reach of Didessa River upstream of its confluence with Wama River, is about 1961.3mm and the mean annual water yield is 1167.8 mm, it drains an area of 2052 km2. It is an important sub-catchment where the dam and reservoir for Arjo-Didessa Irrigation Development Project, a project to develop about 80,000 ha of land through irrigation is being constructed.

5. CONCLUSION AND RECOMMENDATION

5.1 Conclusion

The Arc SWAT interface of SWAT model has been used successfully for modelling stream flows of the Didessa River basin. SWAT CUP advance calibration and uncertainty analysis tool has been used for automatic calibration of stream flows provides an effective graphical interface for visualization of outputs, including simulated data, observed data, best-fit model results and 95PPU for all variables used in model calibration.

SUFI-2 and GLUE procedures shows better correlation and agreement between the simulated and observed monthly average stream flows. The obtained results by SUFI-2 at Dembi and Arjo is (R^2, NS) value (0.75, 0.74); (0.72,0.71) for calibration period and (0.78 ,0.78) and (0.73, 0.72) for validation. The obtained result by GLUE is (R^2,NS) value (0.77,0.75) and (0.73,0.71) for calibration and (0.78,0.77) and (0.77,0.72) for validation. The calibration and validation based on daily time steps done at Dembi stations was used to evaluate the model performance based on daily time steps. The obtained result was (R^2,NS) value for calibration and validation (0.72,0.69);(0.63,0.62) and (0.68,0.66);(0.62,0.62) for SUFI-2 and GLUE respectively. Overall, calibration and validation of the hydrological model SWAT on the Didessa river basin yielded good for both daily and monthly time steps. It can be noticed that the performance is lower for daily calibration compared to monthly calibration.

The result of uncertainty analysis done by SUFI-2 shows 40-48% and 24-44% percent of observed flow is bracketed by 95PPU for monthly and daily time steps respectively. GLUE brackets 25-34% and 28-29% of observed flow for monthly and daily time steps respectively. GLUE program able to obtain high value of R^2 and NS with small percent of p and r-factor which shows that the overall associated uncertainty come from either conceptual or input or a combination of them but not from parameter identification. Both SUFI-2 and GLUE performs very well in calibrating SWAT model and they are balanced predictive approach.

A SWAT model produces a very well simulation results of the stream flow of the river basin; So, this stream flow model can be applied for futuristic prediction and for planning of water resource management of the river basin.

5.2 Recommendation

This study aimed in the stream flow modeling of Didessa River basin flow based on a semi distributed modelling approach. The model outputs were influenced by some level of uncertainty. Hence, the results of this study should be taken with slight care by considering the level of prediction uncertainties obtained. The focus on parametric uncertainty in model calibration uncertainty methodologies does not address over all uncertainty in hydrologic modelling; therefore, to minimize the overall uncertainty: The input data (i. e meteorological and river flow data) should be investigated thoroughly and the quality of the way of collecting the data should be improved. The responsible body should take care of those data for the future study.

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APPENDIX

Table A-1 Mean Annual rainfall

Year	Limugenet	Gatira	Bedele	Arjo	Shambu	Gidayana	Nekemt	Didessa	Gimbi	Nedjo
1980	1903.7	1779.9	1777.8	1933.5	1522.1	2029.3	2084.7	1426.9	1906.0	1554.9
1981	1793.4	1603.9	1660.3	1808.3	1402.8	1796.3	1911.7	1306.8	1313.9	1794.6
1982	1870.0	1812.9	1761.2	1910.9	1462.3	1571.0	2002.5	1360.1	2053.7	1639.4
1983	1995.0	1938.1	1793.2	1945.5	1499.9	1958.9	2013.9	1358.1	1942.2	1699.7
1984	1770.5	1740.7	1510.3	1825.3	1389.5	1694.2	1683.7	1300.6	1617.3	1492.0
1985	2049.9	1867.0	1824.9	2021.0	1582.7	1714.7	1921.2	1460.2	1486.9	1622.6
1986	1911.9	1695.2	1392.7	1726.6	1295.8	1760.3	1436.1	1206.3	1521.7	1433.8
1987	1742.0	2263.9	1991.8	2030.8	1443.6	1815.3	2139.5	1447.9	1829.8	1719.9
1988	1964.6	2473.9	2001.5	2106.2	1698.6	1838.8	2324.9	1557.7	1980.3	1847.4
1989	1726.9	2084.8	1810.3	1854.5	1688.9	1882.2	2229.1	1902.3	2216.3	1788.2
1990	1881.9	1793.1	1711.5	1571.4	1772.3	1733.3	1974.7	1284.4	1606.4	1578.3
1991	1787.7	1732.2	1712.5	1558.8	1548.1	1395.1	1889.2	1304.0	1936.1	1527.6
1992	2037.3	1978.0	1909.2	2073.2	1833.1	1885.7	2218.6	1087.2	2238.5	1790.4
1993	2095.1	2016.4	1740.9	2087.6	1604.3	1879.2	2189.8	1474.2	1756.8	1752.7
1994	1659.7	1689.1	1526.2	1779.7	1354.4	1559.3	2144.5	1274.5	1602.4	1504.7
1995	1460.6	1657.3	1838.8	1745.4	1330.9	1543.4	2058.9	1261.7	1375.8	1467.0
1996	2005.1	1933.9	1735.0	1996.0	1542.1	1975.2	2262.7	1409.3	1576.0	1471.9
1997	2183.4	2056.4	2001.6	2144.2	1648.1	2119.0	2274.0	1483.1	1857.0	1614.8
1998	1840.0	1842.8	1942.5	2080.4	1624.2	2080.9	2165.5	1454.3	1903.2	1578.6
1999	1598.8	1941.6	2322.5	2022.3	1567.6	1909.8	2187.6	1465.8	1980.7	1765.1
2000	1665.8	1850.5	1827.8	1960.2	1520.5	1764.7	2032.5	1390.6	2028.7	1328.5
2001	1947.8	1789.1	1657.5	1776.5	1378.0	1680.0	1896.8	1291.6	1603.6	1134.5
2002	1657.3	1594.8	1521.7	1677.8	1266.7	1512.8	1786.9	1207.7	1651.0	1433.7
2003	1807.2	1777.5	1713.6	1860.6	1439.2	1538.3	1971.7	1329.4	1946.3	1527.6
2004	1941.0	1932.3	1830.5	1936.2	1491.1	1724.4	1831.7	1389.6	1873.3	1598.9
2005	1981.8	1798.7	1822.4	1950.8	1503.5	1733.4	2248.7	1397.9	1880.1	1503.2
2006	2155.5	2173.7	1974.0	2139.9	1664.6	1921.2	2139.4	1541.6	1962.7	1822.9
2007	2074.5	1975.1	1929.4	2008.3	1544.6	1796.6	2173.0	1451.5	1884.5	1736.0
2008	2256.9	2109.2	2114.2	2245.4	1753.6	1932.5	2441.3	1605.4	2059.5	1888.6
2009	1914.5	1891.2	1786.1	1857.3	1447.6	1543.0	2022.8	1347.7	1682.0	1606.9
2010	2405.2	2130.3	1951.7	2098.6	1699.6	1941.5	2482.1	1586.8	1899.0	1861.9
2011	2586.1	1896.1	1827.5	2449.7	1565.1	1797.2	2010.4	1477.5	1550.1	1758.0
2012	1881.5	1886.7	1790.2	1901.1	1489.5	1729.8	2109.3	1401.8	1817.3	1690.8
2013	2152.9	1970.6	1868.1	1921.4	1542.3	1783.9	1965.3	1441.2	1918.4	1713.8
2014	2362.9	2529.9	2440.7	2396.4	2052.3	2367.7	2527.1	1947.2	2530.5	2133.5
2015	2330.9	2092.4	1808.6	2334.4	1377.5	1911.4	2667.7	1567.1	2028.7	1869.0
2016	1933.2	2094.0	1624.6	2240.2	1685.9	1916.5	2070.1	1486.9	2354.1	1799.1

Table A-2 Average Basin Values

Mon	Rain (MM)	Snow Fall (MM)	SURF Q (MM)	LAT Q (MM)	Water Yield (MM)	ET (MM)	Sed. Yield (MM)	PET (MM)
1	12.92	0.00	0.21	0.19	19.75	23.52	0.01	122.09
2	18.88	0.00	0.27	0.14	4.86	25.01	0.01	124.84
3	54.53	0.00	1.05	0.26	4.01	60.26	0.04	130.43
4	94.12	0.00	2.56	0.50	5.83	78.32	0.08	127.42
5	220.91	0.00	14.11	1.45	24.55	95.48	0.29	124.27
6	307.07	0.00	31.60	2.45	76.06	97.13	0.54	105.55
7	330.06	0.00	41.87	3.12	150.61	74.44	0.67	85.60
8	319.70	0.00	38.32	3.26	200.16	71.67	0.62	88.76
9	273.88	0.00	29.54	2.90	207.26	82.89	0.56	114.88
10	131.40	0.00	12.77	1.73	178.70	67.29	0.29	120.70
11	38.02	0.00	1.70	0.71	108.64	45.95	0.07	114.07
12	17.11	0.00	0.56	0.36	57.48	31.62	0.02	119.63

Table A-3 Definition of Weather Generator statistic and probability value Symbol

Symbol	Symbol description
TMPMX	Average or mean daily maximum air temperature for month (^{0}c)
TMPMN	Average or mean daily maximum air temperature for (^{0}c)
TMPSTDMX	Standard deviation for daily maximum air temperature month (^{0}c)
TMPSTDMN	Standard deviation for daily minimum air temperature (^{0}c)
Month PCPMM	Average or mean total monthly precipitation (H_2O)
PR_W1	Probability of a wet day following a dry day in month
PR_W2	Probability of a wet day following a wet day in month
PCPD	Average number of days of precipitation in month
SOLARAV	Average daily solar radiation for month (MJ/m2/day)
DEWPT	Average daily dew point temperature in month (^{0}c)
WNDAV	Average daily wind speed in month (m/s)

Table A-4 : Weather generator statistic and probability value of Nekemte station

SYMBOL	JAN	FEB	MAR	APRIL	MAY	JUNE	JULY	AUG	SEPTEM	OCT	NOV	DEC
TMPMX	25.9	27.3	27.4	26.8	24.5	22.1	20.7	20.9	22.3	23.7	24.3	25.0
TMPMN	12.2	13.1	13.8	14.1	13.5	12.6	12.4	12.6	12.5	12.6	12.5	11.7
TMPSTDMX	1.4	1.6	1.8	2.0	2.1	1.5	1.6	1.7	1.5	1.4	1.3	1.1
TMPSTDMN	1.4	1.6	1.7	1.5	1.4	1.1	1.1	1.0	1.0	1.1	1.1	2.3
PCPMM	12.7	16.1	56.6	97.1	252.6	364.0	387.9	384.3	305.6	155.2	45.3	17.0
PCPSTD	1.4	1.7	4.0	5.9	10.1	10.6	11.8	11.6	9.0	7.6	4.0	2.3
PCPSKW	6.2	6.1	4.7	3.5	3.0	2.8	2.4	2.6	1.9	2.8	5.4	8.7
PR_W1	0.7	0.8	0.8	0.9	0.9	0.9	0.9	0.9	0.9	0.8	0.7	0.8
PR_W2	0.1	0.1	0.2	0.2	0.5	0.9	0.8	0.8	0.7	0.3	0.2	0.1
PCPD	9.1	10.3	18.3	19.8	25.7	28.7	29.8	30.0	27.8	21.9	14.5	10.1
RAINHHMX	1.3	1.4	6.4	6.4	9.2	9.9	9.8	11.3	9.9	8.1	2.5	1.9
SOLARAV	20.5	21.9	21.2	21.2	21.2	15.3	14.5	14.1	16.2	19.4	20.4	19.8
DEWPT	12.0	11.5	12.7	14.0	14.4	14.5	14.2	14.5	14.9	14.1	13.2	12.1
WNDAV	1.0	1.0	1.1	1.1	1.0	0.9	0.9	0.8	0.9	0.8	0.8	0.8