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PERFORMANCE COMPARISON OF CONCEPTUAL RAINFALL-RUNOFF MODELS ON MUGER CATCHMENT (ABBAY RIVER BASIN)

Master of Science Thesis
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Thesis Submitted to the School of Graduate Studies in Partial Fulfillment of the
Requirements for the Degree of
Master of Science
In
Civil Engineering

By
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DECLARATION

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Dedication

To my father Tufa Tulu

His words of inspiration and encouragement

in pursuit of excellence, is linger on

Abstract

The research is aimed at conducting catchment modeling for better understanding of hydrologic functioning and runoff generation mechanisms of the Muger catchment and selecting the best conceptual rainfall-runoff model that can be used in the design, planning, and management of water resources in Muger sub catchment (Abbay River basin). The conceptual rainfall runoff models chosen for this study are SMAR and HBV-light (Beta Version).

Each of the models was applied to test the catchment, using split record evaluation, involving the calibration and verification periods (about 60% for calibration and 40% for verification). During calibration period of each model, the optimized parameters which give good performance result were determined ($R_{eff}=0.7$) for both models. These optimized parameters are validated. Performance of the model in the validation period indicates that the efficiency is better than calibration period for both models. For the models SMAR and HBV the obtained R_{eff} during validation is 0.70 and 0.71 respectively. Qualitative analysis of models shows that both models have poor performance in producing extreme flows such as floods and low flows. Model parameter transferability test was conducted on the daily time step models showed less performance in Aleltu catchment; whereas the monthly time step model showed high R_{eff} values for both models. The discrepancy occurred between simulated and observed runoff may be due to in adequacy of model structure, human intervention, incorrect estimation of parameters especially in case of manual optimization, if there is an interflow between catchments, the quality of data and the absence of any substantial, consistent, or coherent relationship in the data used to calibrate the models.

Key words: Muger; HBV; SMAR; Rainfall-Runoff

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If I have learned just one thing from this research work, it is that I could not have done it alone. Many peoples and organizations have helped me along the way.

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I feel a deep sense of gratitude for my father and mother who formed part of my vision and taught me the good things that really matter in life, thanks to my brothers and sisters in particular to my sister, Etsegenet, whose strength and courage are the most examples that I will ever have.

Last but not least, I praise the almighty God; the owner of my peace, the grace of my presence, the essence of my existence, my savior and Lord Jesus Christ! "...Who am I, O

LORD God, and what is mine house, that thou hast brought me hitherto?" (1Ch 17: 16) Amen!

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List of symbols

amsl	above mean sea level
ARB	Abbay River Basin
BCEOM	Le Bureau Central d'Etudes pour les Equipements d'Outre-
Mer	
BCM	Billion Metric cubic
DEM	Digital Elevation Model
FDC	Flow Duration Curve
GIS	Geographic Information System
HBV	Hydrologiska Byråns Vattenbalansavdelning means Hydrological Bureau Water balance-section.
MoWR	Ministry of Water Resource
mm	millimetre
NMA	National Meteorological Agency, Ethiopia
Qlowerobs	lower observed discharge
Qmeanobs	mean observed discharge
Qmeansim	mean simulated discharge
Qupperobs	upper observed discharge
SLM	Simple Linear Model
LPM	Linear Perturbation Model
SMAR	Soil Moisture Accounting and Routing
SRTM	Shuttle Radar Topography Mission
UTM	Universal Transverse Mercater

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1 Introduction

1.1 Back Ground

Establishing a rainfall-runoff relationship is the central focus of hydrologic modeling from its simple form of unit hydrograph to rather complex models based on fully dynamic flux equations. As the computing capabilities are increasing, the use of these models to simulate a catchment response has become a standard. Models are generally used as utility in various areas of water resources development, in assessing the available resources, in studying the impacts of human interference in an area such as land use change, deforestation and other hydraulics structures such as dams and reservoirs (Moreda, 1999).

The fact that the world faces a water crisis has become increasingly clear in recent years.

Challenges remain widespread and reflect severe problems in the management of water resources in many parts of the world. These problems will intensify unless effective and concerted actions are taken (WWAP, 2003). However, from a water resource assessment point of view, the primary objective of modelling is often to generate a long representative time series of stream flow volumes for the purpose of planning and management of water resources.

Rainfall-runoff models have been under a continuous state of development. Models used in the earlier days did not integrate the different phases of the hydrological cycle. Instead, they implemented simplified mathematical relationships between precipitation and certain attributes of the final catchment's response. However, estimation of runoff is essential in various kinds of water resources studies. Runoff estimation is normally based on rainfall runoff process. In order to model rainfall-runoff process, a variety of hydrological models have been applied (Hundecha, 2005).

Appropriate assessment of runoff amount is essential for design, planning, and management of river basin projects that deals with conservation and utilization of water for the various purposes. To determine accurately the quantity of surface runoff that takes place in a river basin, understanding of the complex relationships between rainfall and runoff process, which depend upon many geomorphologic and climate factors, is necessary.

1.2 Problem statement

The derivation of relationships between the rainfall over a catchments area and the resulting flow in a river is fundamental problem for the hydrologist (Shaw, 2004). In most countries, there are usually plenty of rainfall records. However, the more elaborate and expensive stream-flow measurements are often required by design engineer for the assessment of water resources or flood hazards. But, river flows are often limited and rarely available for specific sites under investigation. Thus, evaluating river discharges from rainfall has stimulated the imagination (mind's eye) and ingenuity (cleverness) of engineers for many years, and more recently has been the inspiration of many research workers.

"Scarcity and misuse of fresh water pose a serious and growing threat to sustainable development and protection of the environment. Human health and welfare, food security, industrial development and the ecosystems on which they depend, are all at risk, unless water and land resources are managed more effectively in the present decade and beyond than they have been in the past" (ICWE, 1992).

Rainfall-runoff models are useful tools where data are scarce and resources are under development. It is possible to generate runoff discharges from rainfall and meteorological data where river flow is not available (Beven, 2002). However, the main problem in Muger river sub catchments is that most part of the catchment is not gauged. Out of 8188sq.km only 490 sq.km which is about 6% is gauged. Even though

there are rivers which have gauging station, the record length of the stations is not sufficiently long.

Therefore, application of rainfall-runoff models in Muger Sub catchment is important to develop characteristic curves and parameters that are applicable to ungauged part of the catchment of similar characteristics.

1.3 Objective

1.3.1 Main objective

- ❖ The main objective of this study is to conduct catchment modeling for better understanding of hydrologic functioning and runoff generation mechanisms of Muger sub basin.
- ❖ And to compare and select the best conceptual rainfall-runoff model that can be used in the design, planning, and management of water resources in Muger sub catchment (Abbay River basin).

1.3.2 Specific objectives

- ❖ To apply the HBV and SMAR hydrological models to the Muger River sub Basin.
- ❖ To analyze and evaluate the application process and theoretical implications of both models.
- ❖ To compare the results produced by HBV and SMAR in the Muger River Basin.
- ❖ To check the parameters in nearby station (transferability of parameters).

1.4 Study area

The area under study is the Muger River watershed in Abay River basin shown in figure 1-1 having an area of 8,188 km² at the confluence with Abay River, and 490 km² at the gauging station near Chancho.

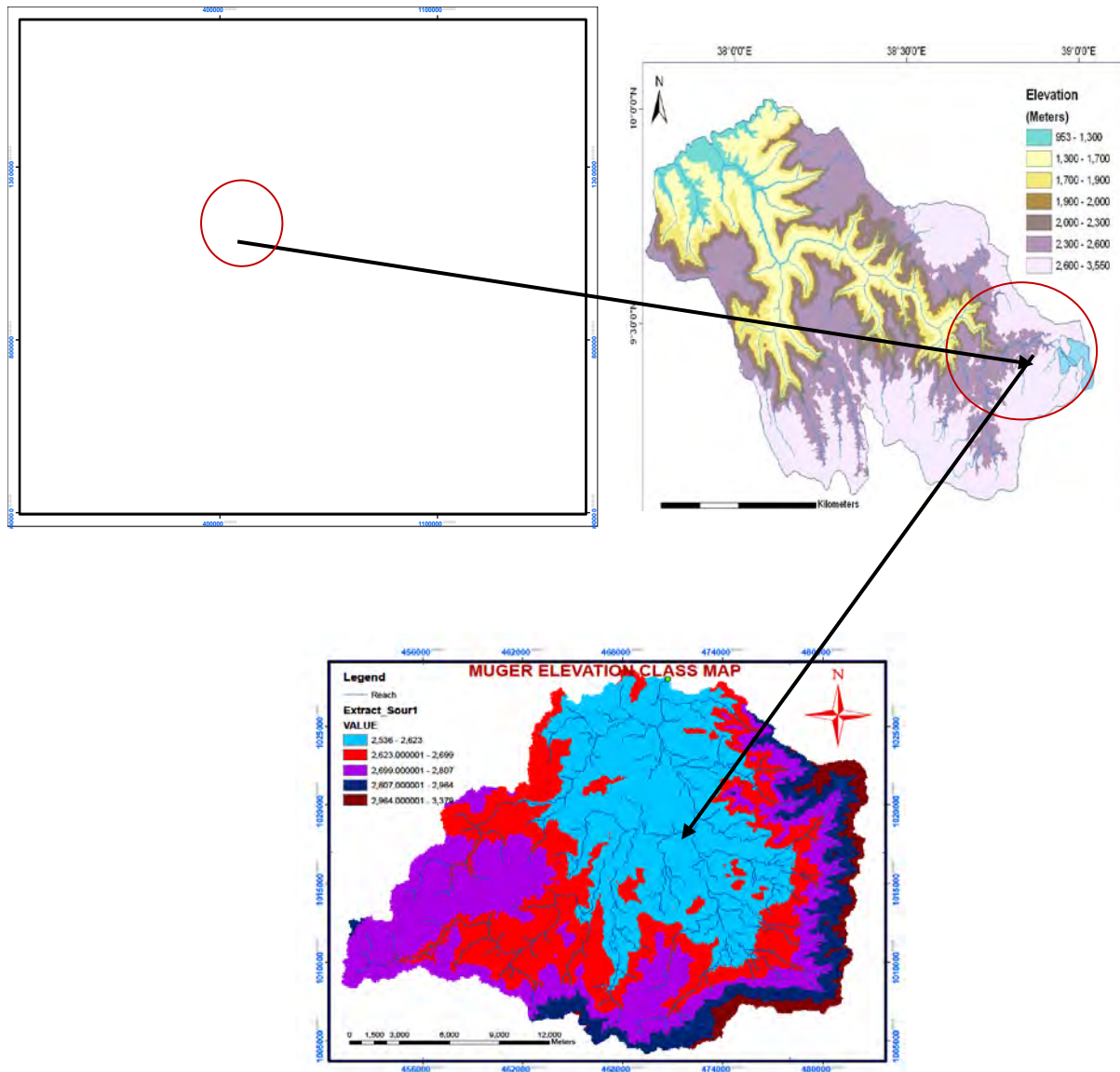


Figure 1-1 *Ethiopia's River Basins with the Abbay River Basin and Muger catchment*

The altitude in Muger sub basin ranges between 953 masl and 3550 masl. The highlands in the eastern and southern part of the sub basin are higher in altitude, greater than 2600 meters up to 3550 meters. The lowlands along the Muger River have lower altitude less than 1700 masl.

The sub basin has an annual rainfall ranging between 833 mm and 1326 mm. Lower annual rainfall from 833 mm up to 1000 mm along the river and lowlands, and higher rainfall greater than 1000 mm is observed in

the highlands. The annual maximum and minimum temperature in the sub basin varies between 16°C - 31.5°C and 13°C -16.5°C respectively.

Potential Evapotranspiration (PET) in the sub basin is between 1215 mm and 1970 mm per year. PET is higher greater than 1800 mm/yr, along the river where there is high temperature. The highlands in the eastern part of the basin show lower PET, less than 1450 mm/yr.

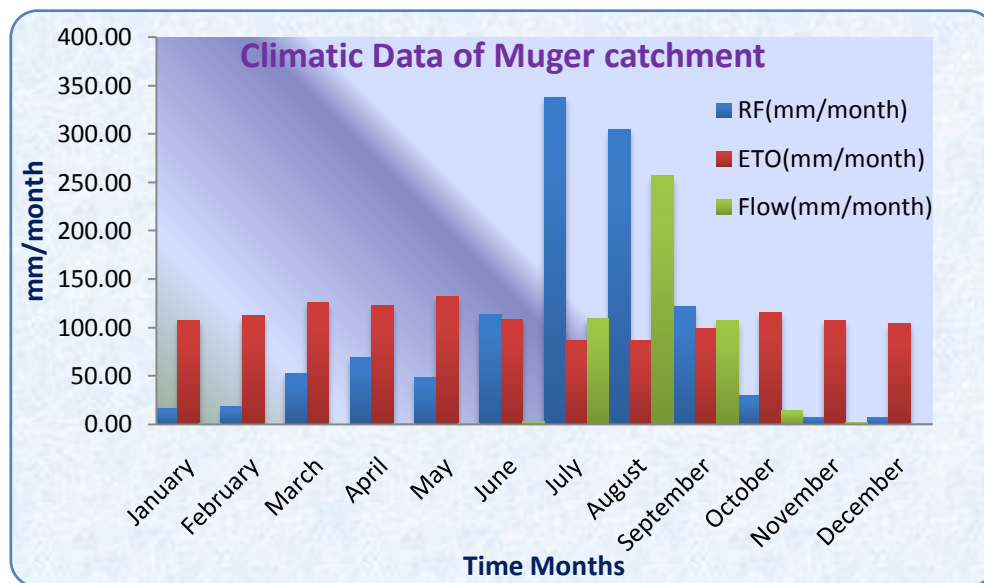


Figure 1-2 Monthly Climatic data in Muger Sub Basin

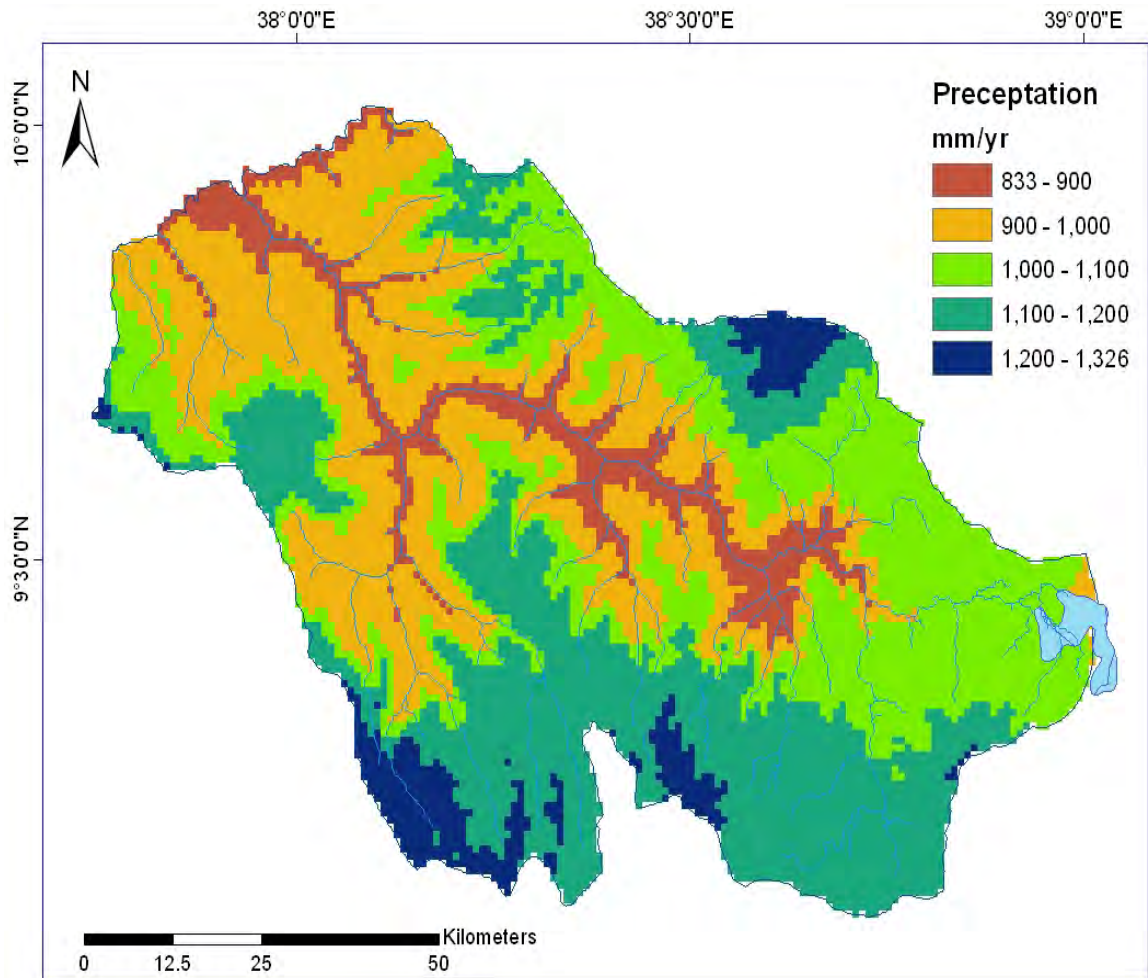


Figure 1-3 Annual Rainfall distribution in Muger Sub Basin

(Source; Characterization and Atlas of the Blue Nile Basin and its Sub basins- Jan-2009)

Major and dominant soil types identified in the sub basin are Leptosols, Luvisols, Vertisols, Fluvisols, and Alisols. The most dominant soil type is Leptosols. The second dominant soil is Luvisols. Small patches of Cambisols, Nitosols and Rigosols are also in some parts of the basin.

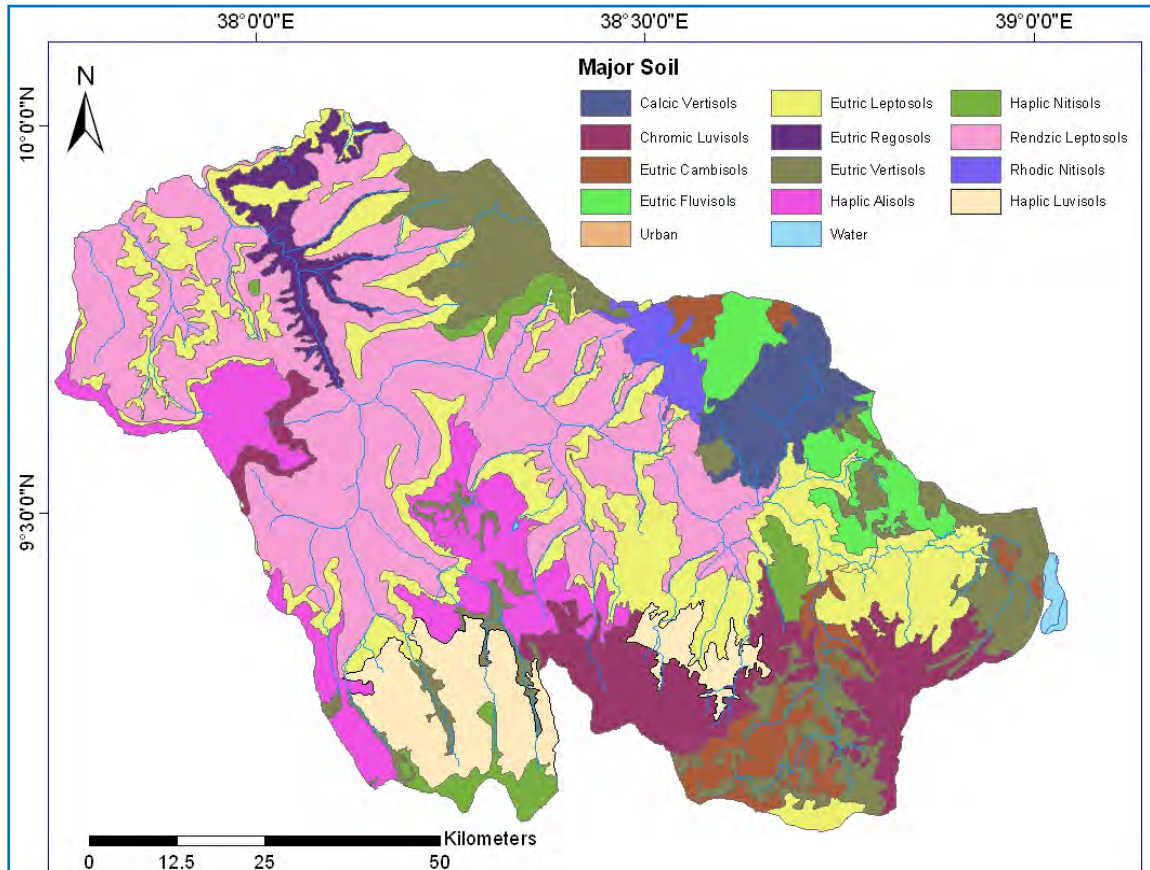
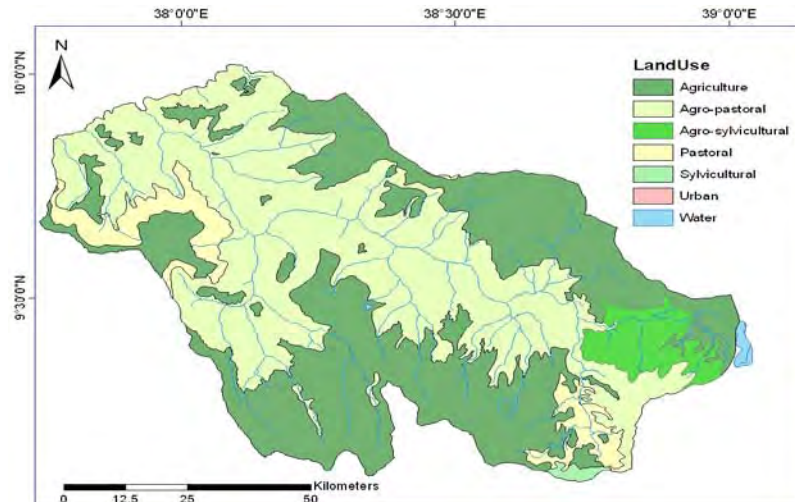


Figure 1-4 Major Soil Types in Muger Sub Basin

The land use in Muger sub basin is dominated by Agro-pastoral and Agriculture. Pastoral land is also observed in some parts of the sub basin. The agro ecological zones are characterized by tepid to cool moist highlands. The north western part of the lowlands is hot to warm moist lowlands.



The geology of the sub basin is mainly dominated by Basalt and Sandstone. There are alluvium deposits in southern and eastern parts of the basin.

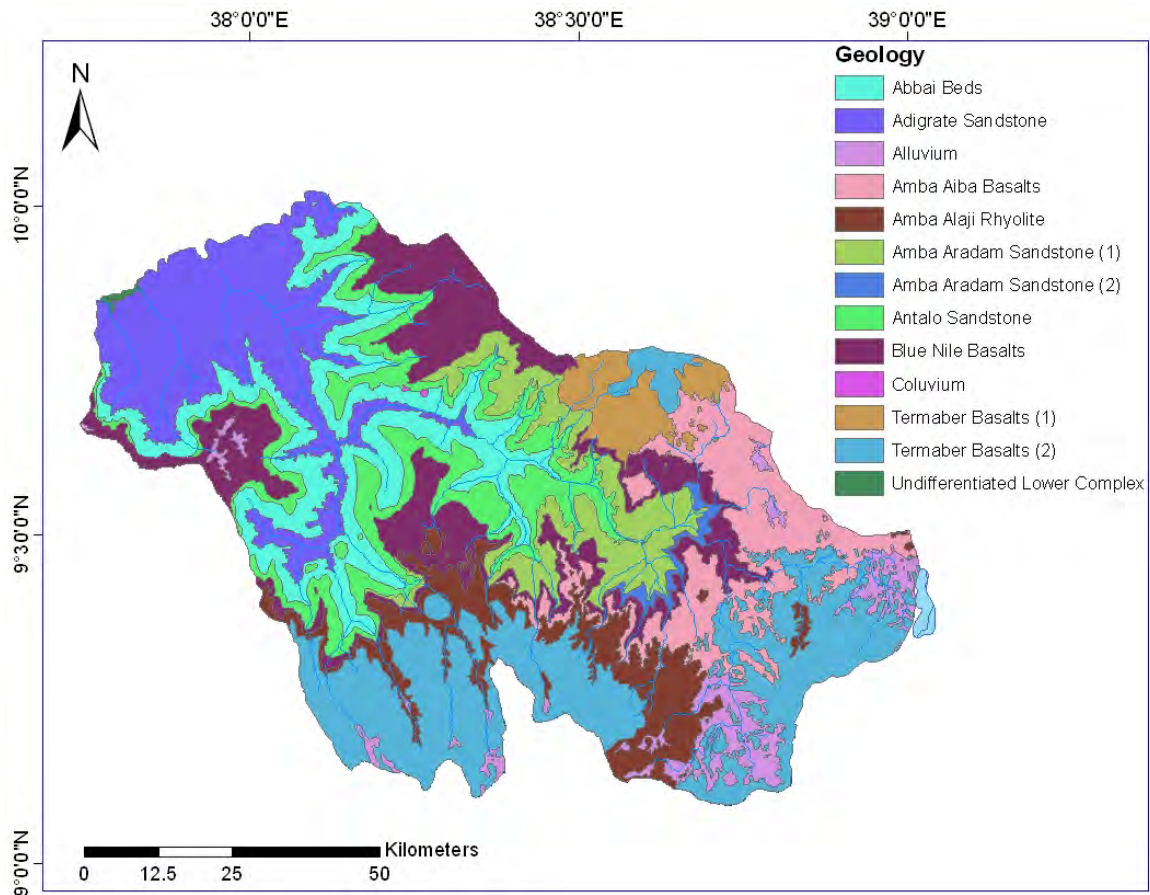
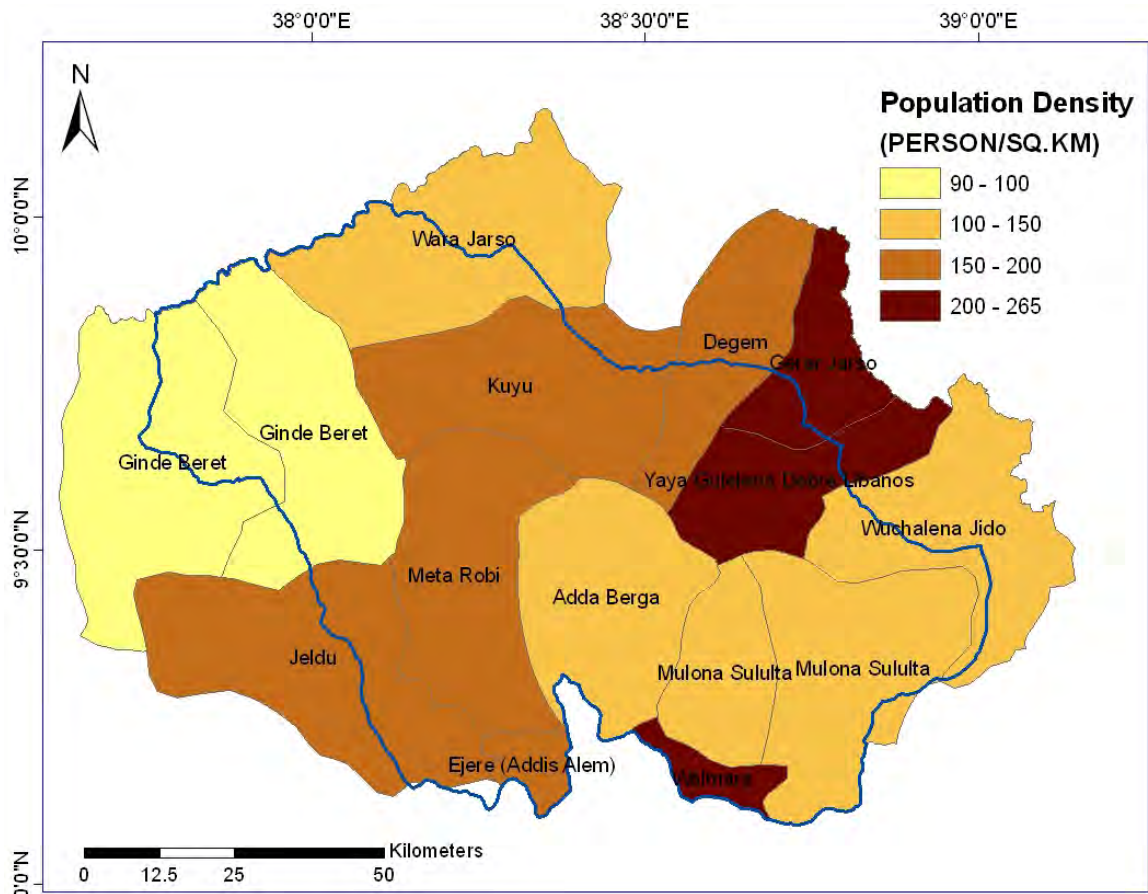


Figure 1-5 Geology of Muger Sub Basin

Muger sub basin covers 15 weredas; Ejersa (Addis Alem), Walmara, Jeldu, Mulo, Sululta, Adda Berga, Meta Robi, Yaya Gulelena Debre Libanos, Wichalena Jido, Ginde Beret, Kuyu, Kutaya, Gerar Jarso, Degem, and Wara Jarso . The total population of the weredas is 2,442,247people.



1.5 Structure of the thesis

The thesis is organized as follows: In Chapter 1 back ground, problem statement, objective of the thesis and description of study area is presented. Chapter 2 is a review of the literature on modeling concept and classification in hydrology. This chapter also includes a discussion on CRR models, model structure and data requirements. In Chapter 3, methodology, data collection and data analysis is presented.

In Chapter 4, detail hydrological modeling of SMAR and HBV (calibration and verification) were conducted including sensitivity analysis and Montecarlo simulations. In Chapter 5, comparison of models by using different objective functions and subjective criteria was done. In Chapter 6, a summary and conclusions of the research is presented along with recommendations for conducting further studies.

2 LITERATURE REVIEW

The growth in the speed and capacity of digital computing equipment from the early 1960's was a significant stimulus to the development of various mathematical models for investigating the rainfall-runoff process. Arising from this were models such as: the Stanford Watershed Model IV (Crawford and Linsley, 1966); the Boughton model (Boughton, 1966); the APIC model (Sittner et al., 1969); the Sacramento Soil Moisture Accounting Model (Burnash et al., 1973); the Xinanjiang model (Zhao, 1977, as referenced in Franchini and Pacciani, 1991), and the Tank Model (Sugawara et al., 1984). These models are similar in that they conceptualize the physical (watershed) system into certain abstract constructs (described below) whose physical behaviour is markedly similar to the manner in which watersheds respond to an input stimulus. They are called conceptual rainfall runoff (CRR) models and are very distinct from their counterpart physical models whose modelling approach is based on physically measured properties from the watershed. These CRR models are currently still in use despite continued expansion in computer capabilities that have far surpassed what is required of the models and that have provided fresh encouragement for proponents of physically based, distributed models (see Hornberger and Boyer, 1995). In spite of this, it is unlikely that the popularity of CRR models will wane, for there are many modelling environments for which these models are most suited. Therefore, research on these models needs to continue to address the many shortcomings that still plague application of CRR models.

2.1 Modeling concept and classification

Any conceptualization of a natural process in mathematical or visual form is considered a model. By using models we can understand or explain natural phenomena and in some conditions make predictions either in a deterministic or a probabilistic sense.

Models can be categorized as either formal or material. A formal model is a symbolic representation, usually mathematical of an idealized situation

that has important structural properties of a real system. A material model is a physical representation of a complex system, which is assumed to be simpler than the real system, while having similar properties. Formal models are further subdivided into empirical and theoretical models. In watershed hydrology all formal models are mathematical. Woolhiser and Brakensiek (1982) have presented definitions for these systems as follows:

- ❖ **Empirical models:** These models omit the general physical laws and are in reality a mere representation of the data.
- ❖ **Theoretical models:** Include both a set of general laws and theoretical principles and a set of statements of empirical circumstances. Theoretical models simplify the physical system; in consequence, they are imprecise to a certain degree.

2.2 Hydrologic modeling

2.2.1 Rainfall-runoff Models

Understanding runoff generation has a significant role in catchment hydrology. Some of the tasks envisioned for rainfall runoff models are of a purely hydrological nature, such as real time flood forecasting, design flood estimation, and assessment of the reliability of natural water resources. However, increasingly, outputs of hydrological models are used to investigate wider environmental problems. These include water quality issues in surface and groundwater's, ecological studies, and providing boundary conditions for models dealing with atmospheric general circulation (Todini et al., 1992).

Selecting a model with an appropriate level of model complexity for a particular problem is far from straightforward. An increase in model complexity does not only mean an inevitable increase in data requirements and computational costs, but it also easily results in ill conditioning and non-identifiable parameters. Nevertheless, hydrologists are constantly faced with problems where more detailed knowledge and

quantification of the component processes of the hydrological cycle are essential.

2.2.2 Categories of Hydrological Models

Hydrological modeling is an attempt to determine the operation of the hydrological system in the transformation of rainfall in to runoff. A model relates something unknown (output) to something known (the input). Mathematical model can be classified using different criteria. These focus on the mechanics of the model, how it deals with time, and it addresses randomness and so on. Knowledge of classification is very important in deciding which of the model to use for various applications. For example, if the goal is to create a model for predicting runoff from ungauged watershed, parametric models that require unavailable data for parameter estimation are poor choices. Generally, the classification hydrological models are illustrated in figure 2.1.

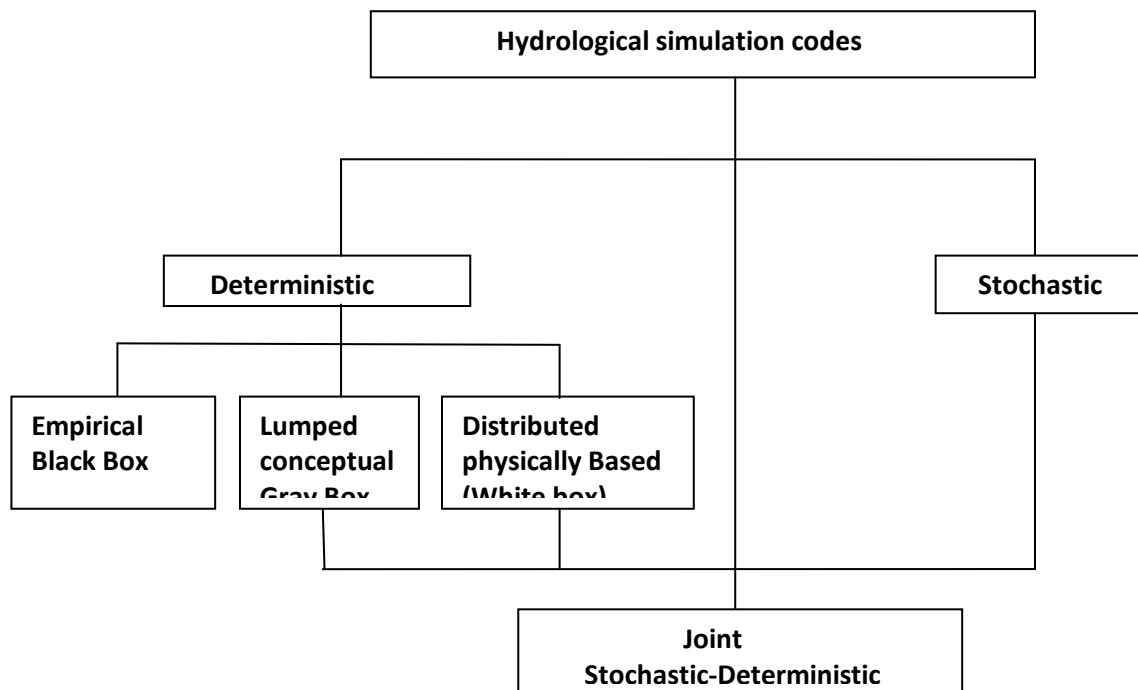


Figure 2-1 Classification of hydrological models according to process description (Refsgaard, 1996)

2.2.2.1 Deterministic Models

A model is to be deterministic if the input data determine the output uniquely as a function of time and not merely as a frequency distribution. A rainfall-discharge model is deterministic because for a given rainfall input, the output of the model is determinate or unique even if it is subject to error in comparison with the actual discharge hydrograph.

The deterministic models can be broadly classified into three categories based on the degree of approximation of the physical processes and their scale of representation by existing physical laws:

- i. System-based (black box) models
- ii. Quasi-physical (lumped) conceptual models
- iii. Physically-based distributed models

a. System-based (block box) models

The simplest black box models (e.g. regression equations) do not attempt to explicitly represent the physical processes. Rather, they employ empirical and mathematical equations to establish relationships between elements of the physical processes from analyses of concurrent input and output time series. The transfer functions are purely derived from the observed datasets and the physical processes are not properly considered. Examples of system-based models include Simple Linear Model (SLM), Linear Perturbation Model (LPM), Transfer Function Models (TF), Seasonally Varying Gain Factor Models (SVGFM) and Neural network model, etc.

b. Quasi-physical (lumped) conceptual models

The conceptual model approach to rainfall-runoff modeling lies intermediate between physically based models and black box models. Generally the term "conceptual" is used to describe models which rely on a simple arrangement of a relatively small number of interlinked conceptual elements, each representing a segment of the land phase of

the hydrological cycle. The most commonly used element in a conceptual model is a storage component. Each such storage usually has one input and one or more outputs and is used to represent basin storage such as surface detention, soil moisture etc. Linear reservoirs and channels are generally used for routing purposes. Conceptual modeling basically consists of a set of rules which govern the moisture flow from one element to another. Conceptual models were initially developed to model small homogeneous areas. However, they have been successfully applied to basins having wide variations in topography and vegetation and areas of the order of thousands of square kilometers. The input data requirements for these models are quite modest and can be easily met. (Blackie et al, 1985) provide excellent discussions on the philosophy and applications of such models.

Conceptual models represent processes in terms of algebraic equations which attempt to approximate the physical processes through differential equations. In terms of description, models are either lumped or distributed depending on whether the spatial distribution of hydrological parameters within the catchment as a homogeneous entity. The lumped model ignores spatial variability of processes, inputs, and parameters and treats the catchments as homogeneous. Examples of lumped conceptual models include Soil moisture accounting (SMAR), ARNO, Stanford watershed model, NAM, Xinanjiang and HBV Models, etc.

c. Physically-based distributed models

The physical processes are explained by nonlinear partial differential equation (PDE) with appropriate numerical methods. The hydrological processes are resolved at finer grid networks and time intervals and require high resolution data and more computing effort and time. The distributed models, attempt to account for the spatial variability in the physical characteristics of a catchment. These models make use of information about topography, soil type and patterns and changes of vegetation.

The distributed physically based models give a detailed and potentially more appropriate description of the hydrological processes in the catchments than do the other model types.

These types of models can in principle be applied to almost any kind of hydrological problem. However, in practice, they will be used complementary to the other model types for cases where the other models are not available. Some examples of typical application are predication of runoff from ungauged catchments, predication of the effects of catchments changes due to human interference in the hydrological cycle and water quality and soil erosion modeling. Examples of physically based distributed models include Mike SHE, SHETRAN (families of SHE model) and TOPKAPI.

2.2.2.2 Stochastic Time-series Models

If a unique input to a particular model produces more than one plausible time series, then the model is said to be stochastic time-series model. Such a time series exhibits random fluctuating properties the causes of which are either unknown or too difficult to discern. The analysis of a stochastic time series is usually carried out on the basis of probability theory and statistics. The time series analysis enables us to predict of the future magnitude of stochastic time series with some degree of accuracy (but never exactly!) over short lead times. Additionally time series analysis allows estimation of the frequency of occurrence of a particular hydrological condition such as the exceedance of the stated peak flow magnitude or the occurrence of certain volume of deficit relative to some demand flow or the failure of the reservoir of the stated size to maintain a given water supply.

Most time series of practical interest arise from a combination of both stochastic and deterministic sources, which is a realistic time series i.e. mixed time series. However, there is no absolute boundary condition which differentiates the two times series.

2.3 Hydrologic Model Selection

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

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

2.4 Selected Conceptual Rainfall Runoff models

2.4.1 HBV light model

The model simulates daily discharge using daily rainfall, temperature and potential evaporation as input. Precipitation is simulated to be either snow or rain depending on whether the temperature is above or below a threshold temperature, **TT** [°C]. All precipitation simulated to be snow, i.e. falling when the temperature is below **TT**, is multiplied by a snowfall correction factor, **SFCF** [-]. Snowmelt is calculated with the degree-day method (Equation 1). Melt water and rainfall is retained within the snowpack until it exceeds a certain fraction, **CWH** [-], of the water equivalent of the snow. Liquid water within the snowpack refreezes according to Equation 2. Rainfall and snowmelt (P) are divided into water

filling the soil box and groundwater recharge depending on the relation between water content of the soil box (**SM** [mm]) and its largest value (**FC** [mm]) (Equation 3). Actual evaporation from the soil box equals the potential evaporation if **SM/FC** is above **LP** [-] while a linear reduction is used when **SM/FC** is below **LP** (Equation 4). Groundwater recharge is added to the upper groundwater box (SUZ [mm]). **PERC** [mm d⁻¹] defines the maximum percolation rate from the upper to the lower groundwater box (SLZ [mm]). Runoff from the groundwater boxes is computed as the sum of two or three linear outflow equations depending on whether SUZ is above a threshold value, **UZL** [mm], or not (Equation 5). This runoff is finally transformed by a triangular weighting function defined by the parameter **MAXBAS** (Equation 6) to give the simulated runoff [mm d⁻¹].

If different elevation zones are used the changes precipitation and temperature with elevation are calculated using the two parameters **PCALT** [%/100 m] and **TCALT** [°C / 100 m] (Equation 7 and 8).

The long-term mean of the potential evaporation, $E_{pot,M}$ for a certain day of the year can be corrected to its value at day t , $E_{pot}(t)$, by using the deviations of the temperature, $T(t)$, from its long-term mean, T_M , and a correction factor, **C_{ET}** [°C⁻¹] (Equation 9).

$$melt = CFMAX(T(t) - TT) \quad (1)$$

$$refreezing = CFR - CFMAX(TT - T(t)) \quad (2)$$

$$\frac{recharge}{P(t)} = \left(\frac{SM(t)}{FC} \right)^{BETA} \quad (3)$$

$$E_{act} = E_{pot} \min\left(\frac{SM(t)}{FC \cdot LP}, 1\right) \quad (4)$$

$$Q_{GW}(t) = K_2 SLZ + K_1 SUZ + K_0 \max(SUZ - UZL, 0) \quad (5)$$

$$Q_{sim}(t) = \sum_{i=1}^{MAXBAS} c(i) Q_{GW}(t-i+1) \quad (6)$$

$$\text{where } c(i) = \int_{i-1}^i \frac{2}{MAXBAS} \left| u - \frac{MAXBAS}{2} \right| \frac{4}{MAXBAS^2} du$$

$$P(h) = P_0 \left(1 + \frac{PCALT(h - h_0)}{10000} \right) \quad (7)$$

$$T(h) = T_0 - \frac{TCALT(h - h_0)}{100} \quad (8)$$

$$E_{pot}(t) = \left(1 + C_{ET}(T(t) - T_M) \right) E_{pot, M} \quad (9)$$

$$\text{but } 0 \leq E_{pot}(t) \leq 2 E_{pot, M}$$

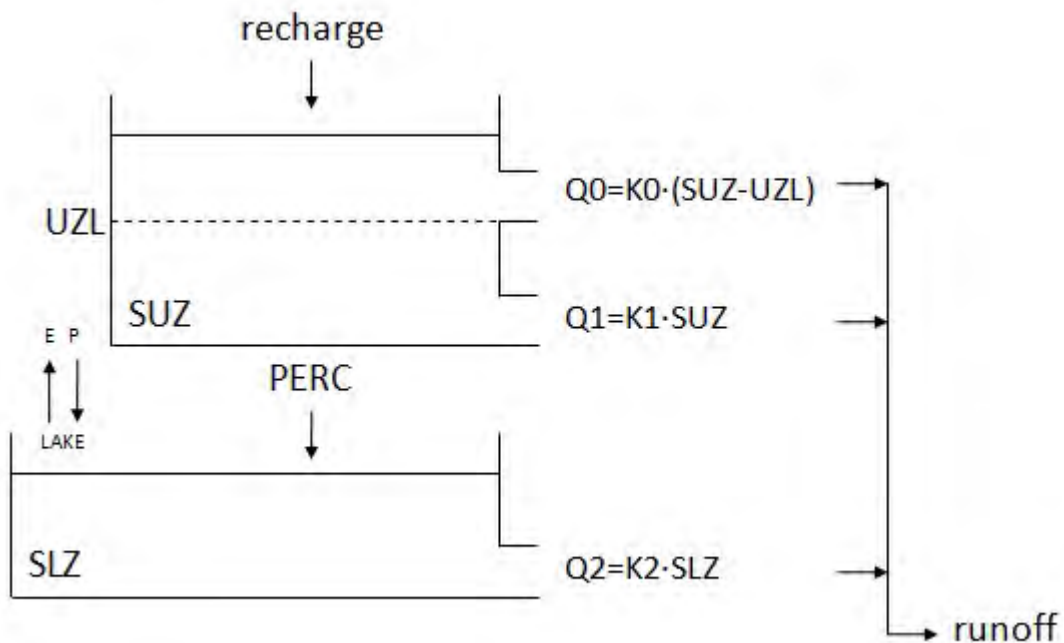


Figure 2-2 HBV Standard Model structure (Model Version using UZL and K0 in SUZ-box)

- Recharge = Input from soil routine [mm/d]
- SUZ = Storage in soil upper zone [mm]
- SLZ = Storage in soil lower zone [mm]
- UZL = Threshold parameter [mm]
- PERC = Maximum percolation to the soil lower zone [mm/d]
- E = Evaporation from the lake
- P = Precipitation into the lake
- K_i = Recession coefficient [1/d]
- Q_i = Runoff component [mm/d]
- runoff = Total amount of generated runoff [mm/d]

NOTE:

- SUZ has no upper limit
- Q_2 can never exceed PERC
- SLZ can never exceed PERC/ K_2

2.4.1.1 Model routines

❖ Soil Moisture Routine

Input to the Model

- Potential evapotranspiration
- Precipitation
- Snowmelt

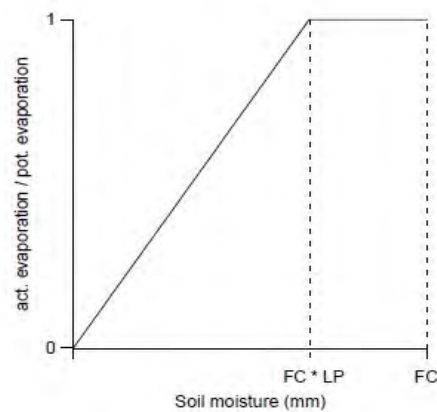
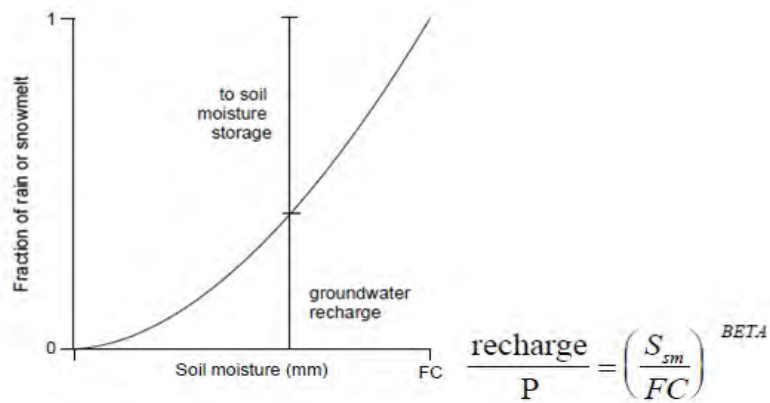
Model output

- Actual evapotranspiration
- Soil moisture
- Groundwater recharge

FC = maximum soil moisture storage (mm)

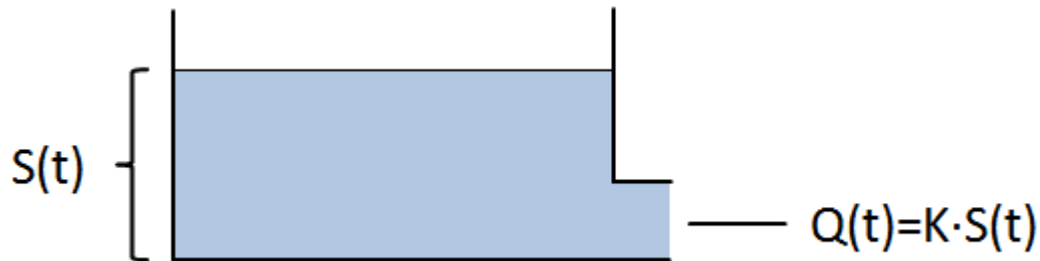
LP = soil moisture value above which ET_{act} reaches ET_{pot} (mm)

BETA= parameter that determines the relative contribution to runoff from rain or snowmelt (-)



❖ Response Function

The model of a single linear reservoir is a simple description of a catchment where the runoff $Q(t)$ at time t is supposed to be proportional to the water storage $S(t)$.



S = storage (mm)

Q = outflow (mm day⁻¹)

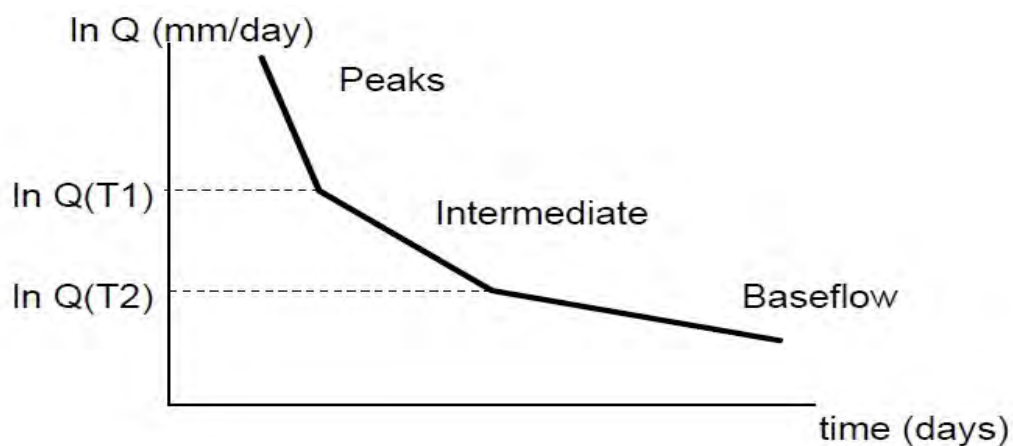
t = time (day)

K = storage (or recession) coefficient (day⁻¹)

(A realization of a single linear reservoir is a box with a porous outlet, thus obtaining Equation (*) from Darcy's law.)

Recession analysis

If $\ln Q$ is plotted against time during a dry period, the slopes of the hydrograph at different runoff values provide good first estimates of the response-function parameter



Slope of the recession:

Peaks: $K_0 + K_1 + K_2$

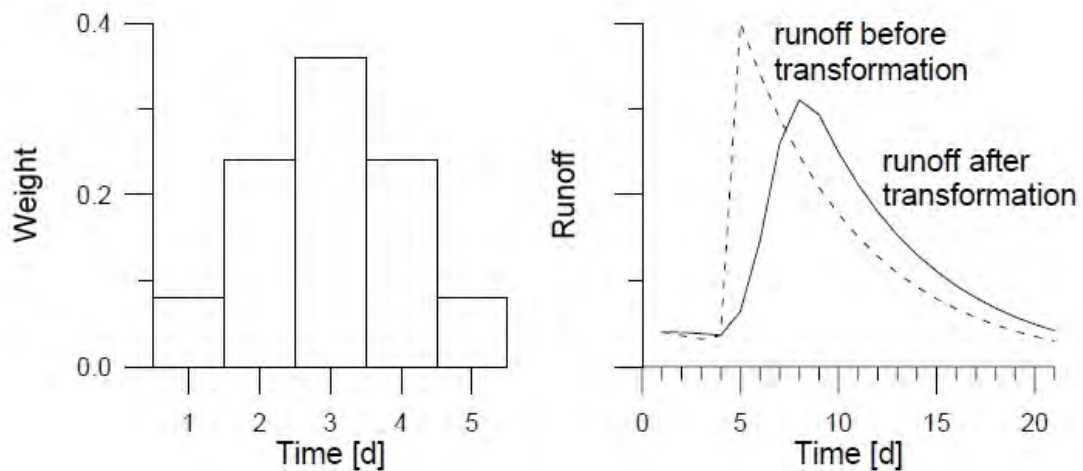
Intermediate: $K_1 + K_2$

Base flow: K_2

Thresholds: $Q(T1): PERC+K1 \cdot UZL$
 $Q(T2): PERC$

❖ Routing Routine

The generated runoff of one time step is distributed on the following days using one free parameter, MAXBAS, which determines the base in a equilateral triangular weighting function.



2.4.1.2 Calibration and Validation of HBV Model

Calibration is a major aspect of hydrological modeling and is aimed at fitting simulated versus measured discharge best. Calibration of the model for the catchment representation was done for the selected catchments. This was followed by a manual trial and error procedure (Bergstrom, 1992) until the result of the calibrated model was considered acceptable. Manual calibration of the model was done by estimating values of the model parameters, running the model and assessing how good the simulations were.

The degree of accuracy of parameter estimates was assessed by applying the model to different data set that was not used for calibration. Validation defines as a process of demonstrating capability of a given

site-specific model to make predictions adequately accurate at other site and/or outside the calibration period.

2.4.2 Soil Moisture Accounting and Routing (SMAR) Model

The Soil Moisture Accounting and Routing (SMAR) Model is a development of the 'Layers conceptual rainfall-runoff model introduced by O'Connell et al. (1970) and modified by Khan (1986). Liang (1992) introduced the concept of separating quick and slow flows in SMAR model and came up with the SMARG model. Tan and O'Connor (1996) and Mingkai (1996) further developed the model. As any lumped conceptual model; it has two major components. The water balance component simulates processes involved in the runoff generation in a simplified manner and the routing component transforms the generated runoff in to discharge at the catchment outlet.

2.4.3 The Water Balance Component

The water balance component simulates processes involved in the runoff generation. The catchment is assumed to be analogous to a vertical stack of horizontal soil layers of total depth Z , which is a model parameter. Except for the lower layer, each layer contains 25 mm depth soil moisture at field capacity. The lower layer may contain less than 25 mm. The evaporation depth at a given time interval is obtained by multiplying the pan or Penman estimated evaporation depth E_p with a conversion parameter T .

If the evaporation is not satisfied by the rainfall R , it will be taken from the soil layers in an exponential manner. Any evaporation from the top layer is assumed to occur at the potential rate, and from the second layer, after exhausting the storage in the first layer, at the potential rate multiplied by a model parameter C whose value is less than unity. On exhaustion of storage in the second layer, any evaporation from the third layer is assumed to occur at the potential rate multiplied by C^2 , and so on.

When the rainfall rate exceeds the evaporation rate, there would be runoff generation and/or moisture replenishment of the soil layers. The first component of the generated runoff is taken as a proportion of rainfall excess $X = R - (T \times E_p)$ and is given by:

$$r_1 = H' \times X \quad \text{if } X > 0 \quad [2-1]$$

$$r_1 = 0 \quad \text{if } X \leq 0 \quad [2-2]$$

The fraction H' is assumed to be proportional to the available water content in the five top layers (Khan, 1986).

$$H' = H \times \frac{W_{act}}{125} \quad \text{for } Z \geq 125 \text{mm} \quad [2-3]$$

$$H' = H \times \frac{W_{act}}{Z} \quad \text{for } Z < 125 \text{mm} \quad [2-4]$$

Where, H = a model parameter to be optimized, and
 W_{act} = actual soil moisture depth in top five layers.

In the original Layers Model (O'Connell et al., 1970), the first component of the generated runoff was simply given as $r_1 = H \times X$.

Of the remaining portion of rainfall excess, anything in excess of actual infiltration rate parameter Y contributes the second component of the generated runoff:

$$r_2 = (1-H') \times X - Y \quad \text{if } (1-H') \times X > Y \quad [2-5]$$

$$r_2 = 0 \quad \text{if } (1-H') \times X \leq Y \quad [2-6]$$

The remainder of excess rainfall at this stage replenishes each layer to its field capacity, from the top layer downwards, until all the rainfall excess is exhausted or until all the layers are at field capacity. Any still remaining surplus of rainfall excess, beyond that required to fill all the layers, contributes a third generated runoff r_3 . In the SMAR model, these three components will form the total generated flow. But, Liang (1992) introduced a sixth parameter G to divide the generated runoff component r_3 into slow and quick responses. The slow response is termed the groundwater component, which is given by:

$$\mathbf{r}_g = \mathbf{G} \times \mathbf{r}_3 \quad [2-7]$$

The remaining fraction of r_3 is supposed to be an inter flow and hence joins the other fast response surface runoff components. Then,

$$\mathbf{r}_s = (\mathbf{1} - \mathbf{G}) \mathbf{r}_3 \quad [2-8]$$

Generally, the water balance component generates the surface runoff r_s and the groundwater runoff r_g for all data points. The routing component converts these generated runoff series into a discharge series at the catchment outlet.

2.4.3.1 The Routing Component

The water balance component removes most of the non-linear effect of the processes involved in the rainfall-runoff transformation. However, the routing component transforms the generated runoff in to discharge at the catchment outlet. The attenuation and diffusion (translation) effect of the catchment is accounted by routing the generated runoff through linear time-invariant storage systems. For the Nash (1960) cascade of N equal linear reservoirs; the unit impulse response is a gamma distribution of parameters N and NK , where K is the system storage coefficient:

$$\mathbf{h}(t) = \frac{1}{K\Gamma(N)} \left(\frac{t}{K}\right)^{N-1} e^{-t/K} \quad [2-9]$$

Where $\Gamma(N)$ is the gamma function defined by the improper integral of;

$$\Gamma(N) = \int_0^{\infty} e^{-y} y^{N-1} dy \quad [2-10]$$

The unit step response of the storage system is

$$\mathbf{S}(t) = \int_0^t \mathbf{h}(\tau) d\tau \quad [2-11]$$

The unit pulse response of the system for a pulse of duration Δt is

$$\mathbf{h}(\Delta t, t) = \frac{1}{\Delta t} [\mathbf{S}(t) - \mathbf{S}(t - \Delta t)] \quad [2-12]$$

Hydro-meteorological data are either sampled or averaged at a fixed time interval. When both the input and the output are expressed in blocks of duration Δt , the corresponding pulse response is given by;

$$\mathbf{h}_j = \frac{1}{\Delta t} \int_{j-\Delta t}^{j\Delta t} \mathbf{h}(\Delta t, t) dt, \quad \mathbf{j} = \mathbf{1, 2, 3, \dots, m} \quad \mathbf{[2-13]}$$

Where j is the number of ordinates of the pulse response blocks and m is the memory length of the system.

Then surface generated runoff series $r_{t,s}$ can be transformed into the corresponding discharge series $Q_{t,s}$ using the convolution summation relation;

$$Q_{t,s} = \sum_{j=1}^m \mathbf{h}_j r_{t-j+1,s} \quad \mathbf{[2-14]}$$

The groundwater generated runoff $r_{t,g}$ will be routed through a simple linear reservoir having a storage coefficient parameter K_g . The groundwater component discharge $Q_{t,g}$ will be obtained by the same convolution summation.

$$Q_{t,g} = qQ_{t-1,g} + (1-q)r_{g,t}, \quad \text{where, } q = e^{-T/K_g} \quad \mathbf{[2-15]}$$

This indicates final estimated total discharge at the catchment outlet.

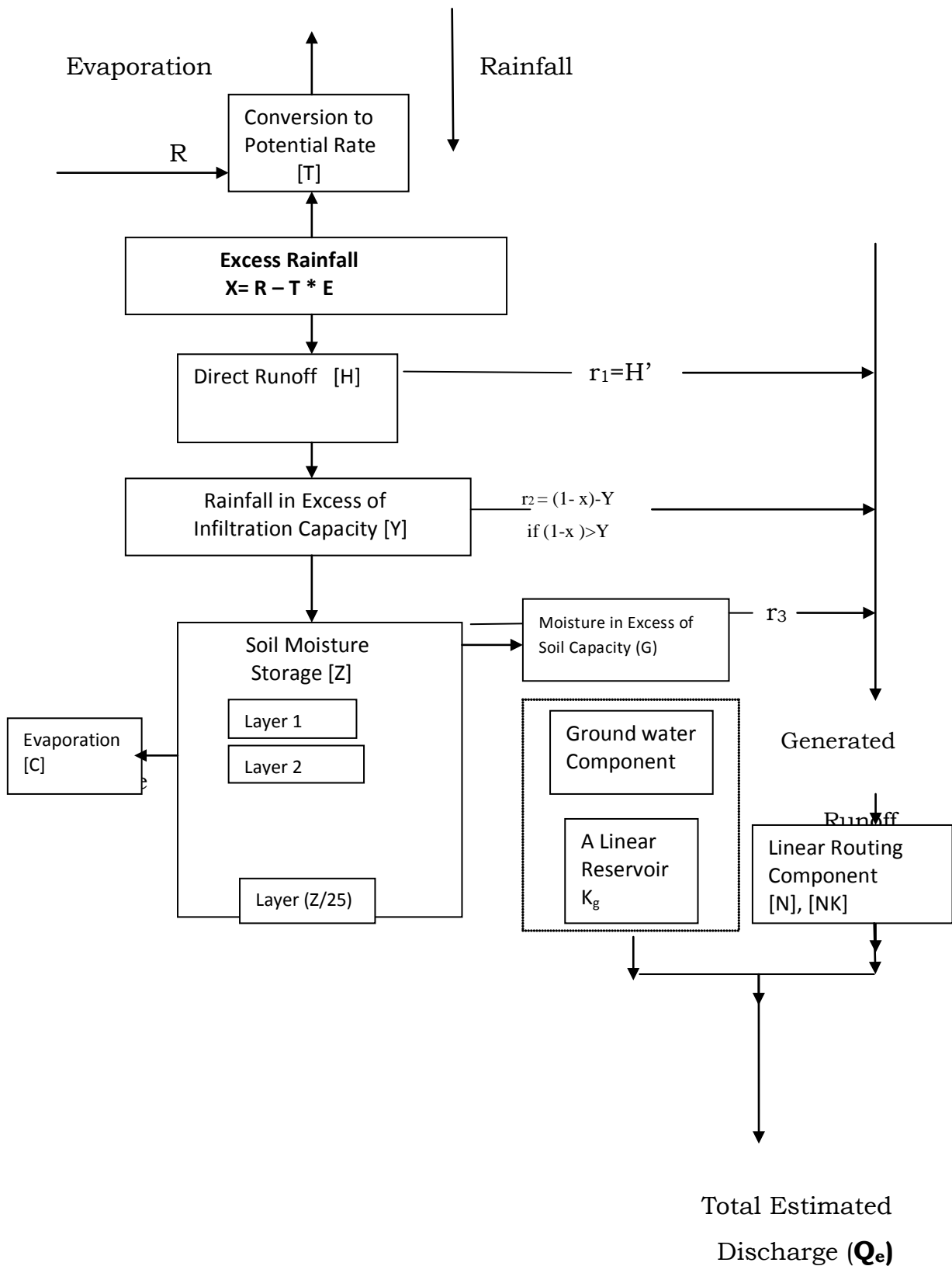


Figure 2-3 Schematic diagram of SMARG model (after incorporating the Liang (1992) groundwater modification on SMAR model)

2.5 Other studies on Abbay basin by HBV and SMAR Models

❖ COMPARISON AND SELECTION OF CONCEPTUAL RAINFALL-RUNOFF MODELS FOR SELECTED CATCHMENTS IN ABBAY RIVER BASIN

Comparison of different models on selected catchments which have different hydrological regimes in Abay river basin was conducted. Both SMAR and HBV were applied to three catchments namely Dedesa, Gilgel Abay and Neshe. The performance of the models shows that SMAR ranks first when as compared to HBV, in Dedesa and Gilgel Abay but HBV perform best in Neshe catchment during calibration. The hydrograph shows that, the SMAR, ARNO and HBV models are completely underestimate the annual maximum flow except the HEC-HMS model simulates well i.e. it overestimate and underestimate in a regular way in Gilgel Abbay catchment.(Kebede, 2009)

❖ Catchment Modeling and Preliminary Application of Isotopes for Model Validation in Upper Blue Nile Basin, Lake Tana, Ethiopia

Despite uncertainties emanating from raingauge network density, spatial location of raingauges, and spatial and temporal variation of rainfall at the point measurement stations used for regionalization of rainfall performance of the HBV model in UGASC and KSC was found to range from satisfactory ($Reff > 0.6$) to good ($Reff > 0.75$) during calibration and validation.

Improvement of model performance was noted as a result of increasing the time step length from daily to 15 days.

In UGASC the simulated discharge corresponded to the observed river flow with $Reff > 0.78$. As shown in the plots of simulated and observed discharge hydrographs, simulation of the rising and the recession limbs of hydrograph of Gilgel Abay River were more or less well performed by the model. Rising and recession curves of the simulated runoff somehow coincided with hydrograph of the observed Koga River flow. (Ashenafi S. 2007)

3 Methodology and data analysis

3.1 General

Hydrological modelling to a large extent depends on hydrometeorological (precipitation, temperature and potential evapotranspiration) and hydrological (river discharge and lake water level) data. Reliability of the collected raw hydrometeorological and hydrological data significantly affects quality of the model input data and, consequently, the model simulation. This chapter sequentially presents, rough data screening of raw hydrometeorological and hydrological data, completion of identified missing data, estimation of a real rainfall and temperature for the study area (catchment and sub-catchments), and analysis done to check consistency and homogeneity of the estimated a real data sets.

Seasonal Diagram

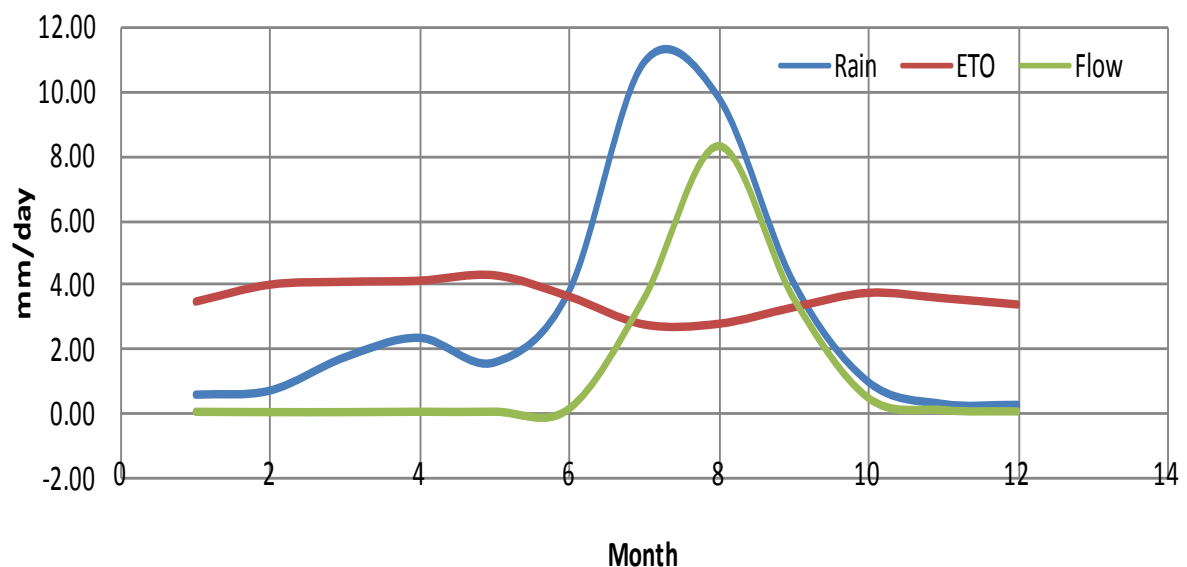


Figure 3-1 Monthly Mean Areal Rainfall, Discharge and Evapotranspiration on the Muger catchment

Table 3-1 Monthly Mean Areal rainfall, discharge and evapotranspiration

Month	RF(mm/month)	ETO(mm/month)	Flow(mm/month)
January	17.09	107.61	0.92
February	19.24	112.66	0.57
March	53.35	126.02	0.59
April	69.82	122.98	0.95
May	48.31	132.08	1.02
June	113.60	108.74	3.73
July	338.55	86.43	109.70
August	305.00	87.00	256.96
September	122.18	98.95	107.37
October	29.72	115.78	14.59
November	7.82	107.27	2.52
December	7.22	104.98	1.31
Total Annual	1131.9	1310.5	500.2

3.2 Data collection

3.2.1 Hydrological data

The office responsible for collecting and disseminating hydrological data is the Hydrology Department in the Ministry of Water Resources (MoWR). Daily data of 20 years of Muger river at two gauging stations (Muger Near Chanco and Aleltu at Muketuri) were collected. The records of discharge used for this study is fourteen years daily data from 1992-2005 for Muger near Chanco, and eleven years data for Aleltu sub-catchment at Muketuri from 1992-2002.

3.2.2 Hydrometriological data

The only source of raw hydrometeorological data in Ethiopia is the National Meteorological services Agency (NMA) of Ethiopia. A request for monthly rainfall and temperature data of 30 years period, and daily: rainfall, temperature, relative humidity, sunshine hours, and wind speed data of 25 years period was made to the agency.

Following the approval of the agency's higher officials daily data of 10 years period of four Fitcha, Shola Gebeya, Addis Ababa Observatory and Chancho) stations was collected together with the available monthly data of up to 30 years except for Chancho which the record begins in 2000.

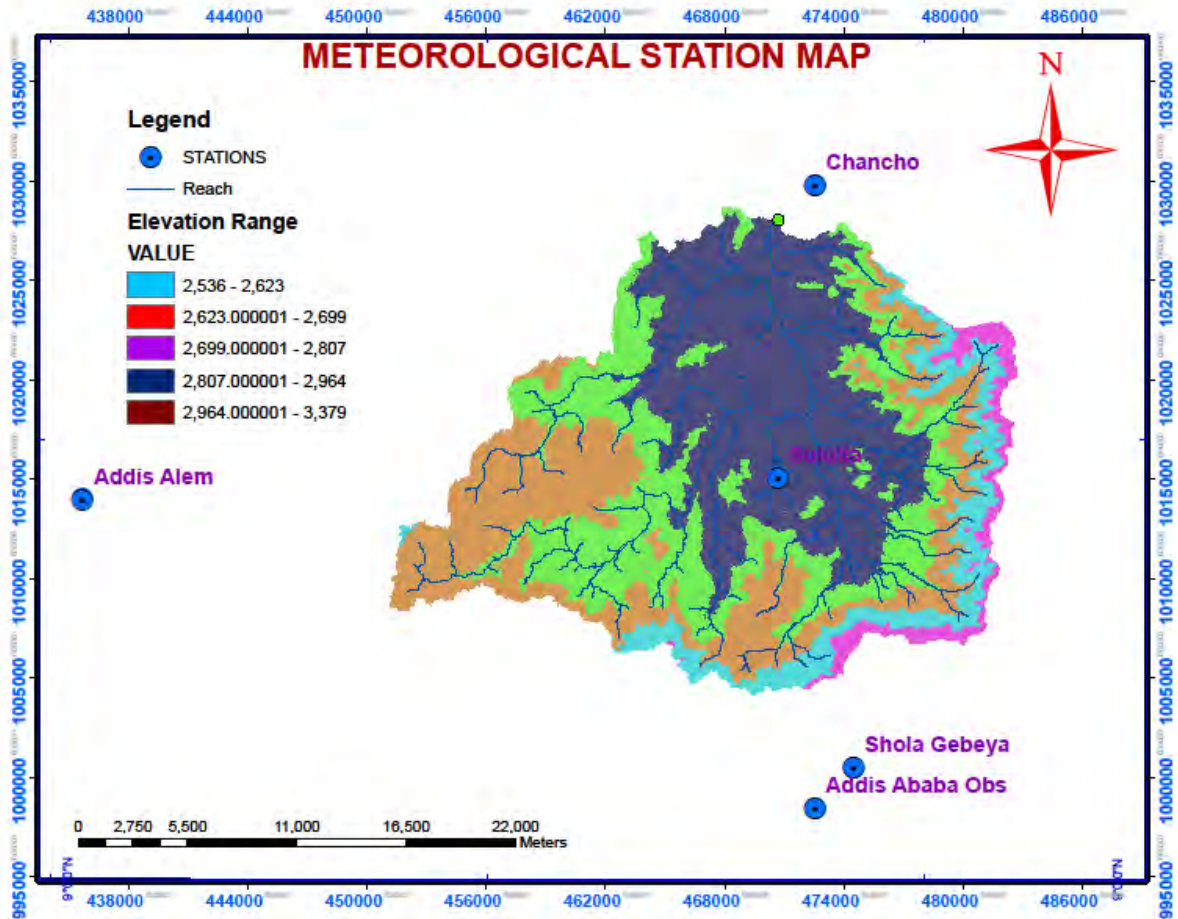


Figure 3-2 Meteorological Station Map

Table 3-2 Summary information for the data used for the study

Station Name	Latitude	Longitude	Altitude	Record	
				Period	Length
Fitche	9.800	38.700	2750	1992-2004	13
Addis Ababa Observatory	9.033	38.750	2408	1992-2004	13
Shola Gebeya	9.167	39.333	2500	1992-2004	13
DebreBirihan	9.633	39.583	2750	1992-2004	13
Chancho	9.317	38.750	1972	2000-2004	5
Sululta	9.183	38.733	2610	2000-2004	5

3.2.3 Topographic data

A 30m by 30m grid SRTM format Digital Elevation Model (DEM) covering the entire country was acquired from the MoWR; and that covering the study area was clipped there from.

The Soil, Land Cover, and Land Use data for the entire Abbay River Basin were also obtained from the Ministry of Water Resources. The original source of the data is the Abbay River Basin Integrated Master Plan Project for which the Ministry of Water Resources was the client.

3.3 Data analysis

Hydrological modelling to a large extent depends on hydrometeorological (precipitation, temperature and potential evapotranspiration) and hydrological (river discharge and lake water level) data. Reliability of the collected raw hydrometeorological and hydrological data significantly affects quality of the model input data and, consequently, the model simulation. This sub chapter sequentially presents, rough data screening of raw hydrometeorological and hydrological data, completion of identified missing data, estimation of a real rainfall and temperature for the study area (catchment and sub catchments), and analysis done to check consistency and homogeneity of the estimated a real data sets.

3.3.1 Hydrometeorological data analysis

Missing data is common problem in hydrology. To perform hydrological analysis and simulation using data of long time series, filling in missing data is very vital. The missing data can be completed by using meteorological and/or hydrological stations located in the nearby area, provided that the stations are located in a hydrologically homogenous region.

Filling in missing runoff data

The initial step taken during the river discharge data screening as suggested by Gordon et al. (1992) was quick visual scan of the data time series to detect gross errors such as erroneous peak flow, missed recordings, and flows of constant rate. It helped to detect the year with magnitude change in the data (1995), long periods of missing records, and short-term missing data.

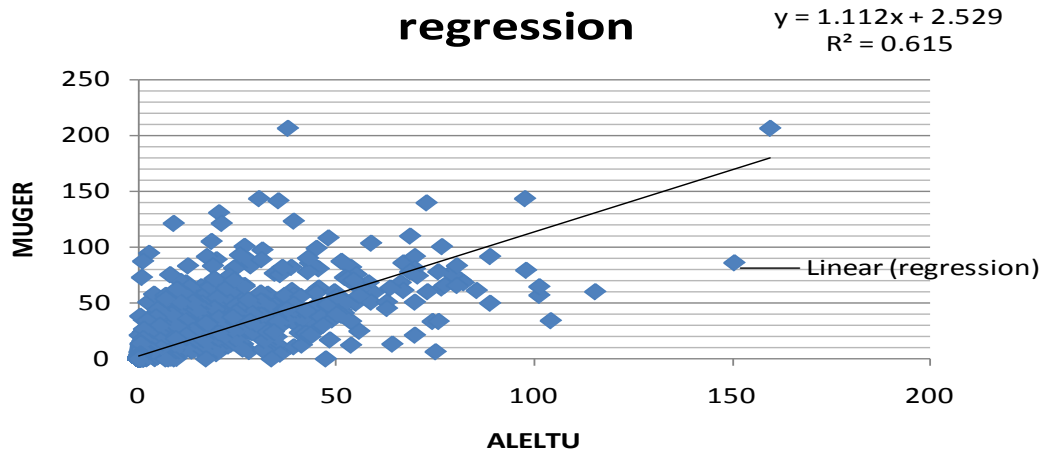
Runoff records of the selected catchments were completed by correlating their long term flow rate records with other hydrological stations which have similar characteristics. The flow of Muger River is correlated to Aleleltu River which has similar characteristic having correlation coefficient of 0.615.

The equation developed by regression analysis is as follows.

$$Q_m = 1.111Q_A + 2.529$$

Where Q_m - flow of Muger River

Q_A -flow of Aleltu



Filling in Missing Rainfall Data

In order to fill the missing rainfall data, joint application of the regression analysis and spatial interpolation techniques are used to complete short and long period breaks in data series for a given meteorological station.

Measured precipitation data are important to many problems in hydrologic analysis and design. Because of the cost associated with data collection, it is very important to have complete records at every station. Obviously, conditions sometimes prevent this. For gages that require periodic observation, the failure of the observer to make the necessary visit to the gage may result in missing data. Vandalism of recording gages is another problem that results in incomplete data records, and instrument failure because of mechanical or electrical malfunctioning can result in missing data. Any such causes of instrument failure reduce the length and information content of the precipitation record.

A number of methods have been proposed for estimating missing rainfall data. The station-average method is the simplest method. The normal-ratio and quadrant methods provide a weighted mean, with the former basing the weights on the mean annual rainfall at each gage and the latter having weights that depend on the distance between the gages

where recorded data are available and the point where a value is required. The isohyetal method is the fourth alternative.

For this study normal ratio method is used method, because normal-ratio method is conceptually simple, but it differs from the station-average method in that the average annual catch is used to derive weights for the rainfall depths at the individual stations. The general formula for computing is;

$$\hat{P} = \sum_{i=1}^n W_i P_i$$

in which w_i is the weight for the rainfall depth P_i at gage i . The weight for station i is computed by

$$W_i = \frac{A_x}{n A_i}$$

Test for consistency of record

Estimating missing data is one problem that hydrologists need to address. A second problem occurs when the catch at rain gages is inconsistent over a period of time and adjustment of the measured data is necessary to provide a consistent record. A consistent record is one where the characteristics of the record have not changed with time. Adjusting for gage consistency involves the estimation of an effect rather than a missing value. An inconsistent record may result from any one of a number of events; specifically, adjustment may be necessary due to changes in observation procedures, changes in exposure of the gage, changes in land use that make it impractical to maintain the gage at the old location, and where vandalism frequently occurs.

Double-mass-curve analysis is the method that is used to check for an inconsistency in a gaged record. A double-mass curve is a graph of the cumulative catch at the rain gage of interest versus the cumulative catch of one or more gages in the region that has been subjected to similar hydrometeorological occurrences and is known to be consistent. If a rainfall record is a consistent estimator of the hydrometeorological occurrences over the period of record, the double-mass curve will have a

constant slope. A change in the slope of the double mass curve would suggest that an external factor has caused changes in the character of the measured values. If a change in slope is evident, then the record needs to be adjusted, with either the early or later period of record adjusted. Conceptually, adjustment is nothing more than changing the values so that the slope of the resulting double-mass curve is a straight line. The rainfall records of the station X are adjusted by multiplying the recorded values of rainfall by the ratio of slopes of the straight lines before and after change in environment.

$$Y_2 = \frac{S_2}{S_1} Y_1$$

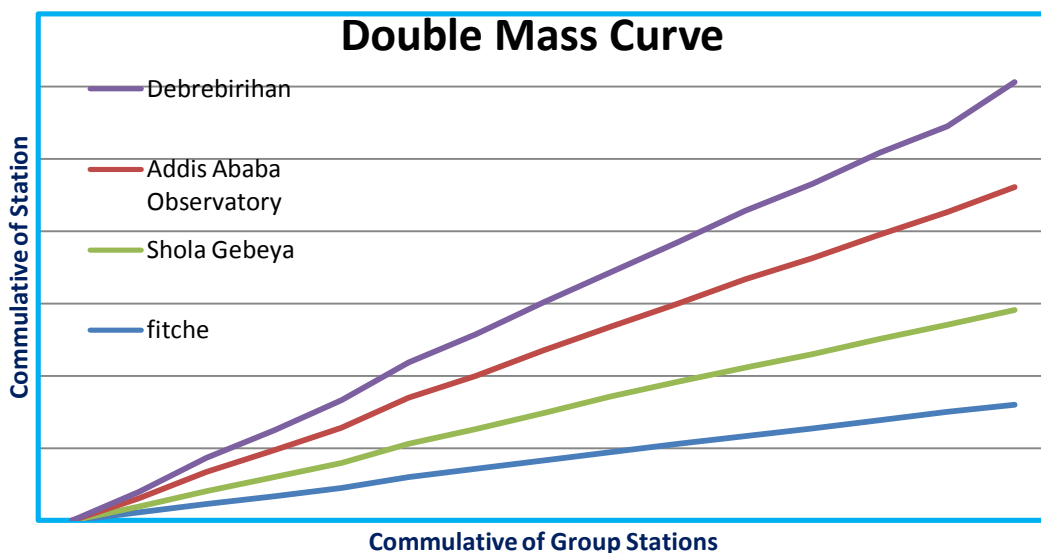
Where: Y_2 = corrected precipitation at station x

Y_1 = original recorded precipitation at station x

S_2 = slope of double mass curve to be corrected

S_1 = original slope of double mass curve

In order to check the consistency of all the rainfall stations the double mass curve is used. According to the double mass curves, all the stations were found to be consistent. The double mass curves for all stations are attached in appendix.



Filling in missing air temperature data

Missing air temperature data of the meteorological stations were completed by following the same steps and procedures followed to fill in

missing rainfall data. After all meteorological and hydrological input data were filled and their consistency checked, the data is prepared as the standard format for each type of selected models.

Areal rainfall

Point rainfall—it is the rainfall at a single station. For small areas less than 50 km², point rainfall may be taken as the average depth over the area. In large areas, there is network of rain-gauge stations; the average depth of rainfall over the area is determined by one of the following three methods: These methods are the Arithmetic mean, the Thiessen polygon and the Isohyetal method etc. However, the Thiessen polygon was used for this study for its sound theoretical basis and availability of computational tools. But the method is dependent on a good network of representative rain gauges.

To determine the mean areal rainfall, the rainfall amount of each station is multiplied by the area of its polygon and the sum of these products is divided by the total area of the catchment. If P_1, P_2, \dots, P_n are the rainfall magnitudes recorded by the stations 1, 2, ..., n respectively areas of Thiessen Polygon, then the average rainfall over the catchment P is given by.

$$P_{\text{avg}} = \frac{P_1A_1 + P_2A_2 + \dots + P_nA_n}{A_1 + A_2 + A_3 + \dots + A_n}$$

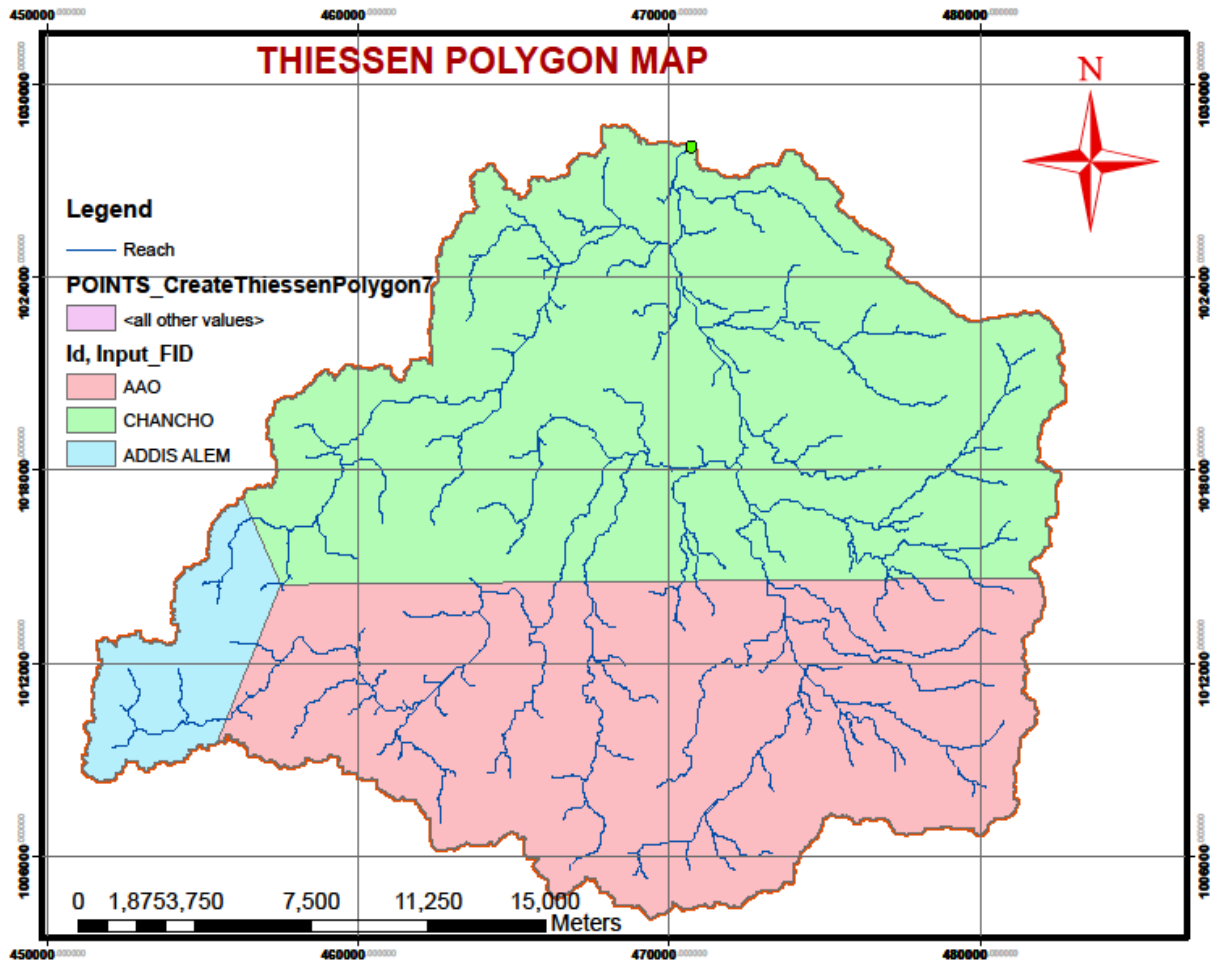


Figure 3-3 Thiessen polygons for estimating areal rainfall

Potential Evapotranspiration

There are number of methods to estimate potential evapotranspiration. However, the methods vary based on climatic variables required for calculation. The temperature based method uses only temperature and sometimes day length; the radiation based method uses net radiation and air temperature and some other formula like Penman requires a combination of the above net radiation, air temperature, wind speed, and relative humidity. The FAO Penman_Monteith method is recommended as the sole ETO method for determining reference evapotranspiration when the standard meteorological variables including air temperature, relative humidity and sunshine hours are available (Allen et al., 1998 cited in Kedir A., 2007).

$$ET_o = \frac{0.408\Delta(R_n - G) + \gamma \frac{900}{T + 273} u_2 (e_s - e_a)}{\Delta + \gamma(1 + 0.34u_2)}$$

Where,

ET _o = reference Evapotranspiration	(mm day ⁻¹)
R _n = net radiation at the crop surface	(MJ m ⁻² day ⁻¹)
G = Soil heat flux density	(MJ m ⁻² day ⁻¹)
T = air temperature at 2m height	(°C)
U ₂ = wind speed at 2m height	(ms ⁻¹)
e _s = saturation vapour pressure	(kPa)
e _a = actual vapour pressure	(kPa)
e _s -e _a =saturation vapour pressure deficit	(kPa)
Δ = slope vapour pressure curve	(kPa°C ⁻¹)

Potential evapotranspiration for the study area was computed by FAO Penman-Monteith method for Addis Ababa Observatory and Fitch stations which have the required meteorological variables. The long term potential evapotranspiration was computed for the two stations to be used as input for the two conceptual hydrological models.

Catchment Data Analysis

Catchment topography, soil and land cover patterns govern spatial distribution of soil water (Wooldridge and Kalma, 2001). Subsequently, in response to watershed climate, topography, and land cover conditions runoff production behavior within a catchment fluctuates (Chang, 2003; Schmocker-Fackel et al., 2007). Boundary and the stream networks were delineated from a 30x30 m² grid cell digital elevation model (DEM) using hydrologic functions of ArcGIS.

Elevation and Slope

Elevation information of Muger was obtained from DEM using ArcGIS. The lowest elevation of Muger is 2535 m amsl at its outlet (gauging station) and its peak reaches an elevation of 3524 m amsl in the south eastern most part of the catchment.

Land surface slope of Muger catchment was computed (in degrees) using ArcGIS. To get insight on variation of catchment responses owing to slope difference between the watersheds, slope of each watershed was reclassified to gentle (0 – 6), steep (7 – 14) and excessive (> 14) slope classes as defined by Scott and Hofer (1995), see Fig.3-4 below.

The excessive slope area of the watersheds lies in the south and decreases northwards.

A considerable part of Muger has gentle slopes, since the ground slope is responsible for controlling the infiltration process.

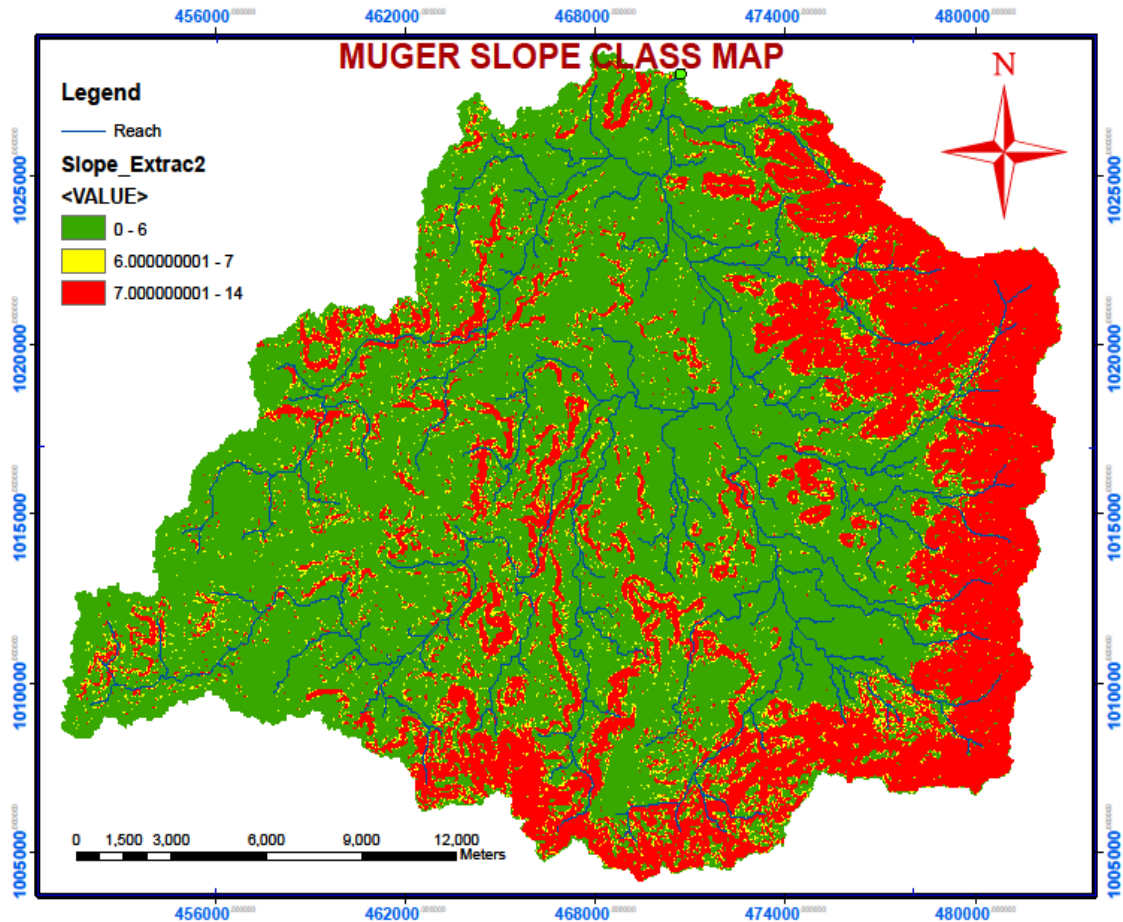


Figure 3-4 Slope Classification of Muger Catchment

Land use and Land cover

As discussed in BCEOM (1999) land use refers to the economic use of the land and because of the multi uses of the lands identifying and separating those economic activities is quite difficult. The study area is divided into agricultural, agro-pastoral, urban and agro-sylvicultural land use units; among these agricultural land use dominates covering (Fig. 3-5).

Areas identified in this land use are dominantly cultivated for the production of grains.

The Agro-pastoral land use includes moderately cultivated areas where grazing activities are as equal important as cultivation. Constituents of the Agro- sylvicultural land use unit are moderately cultivated areas

mixed with significant forest/ woodland, or forest/woodland areas with extensive cultivation.

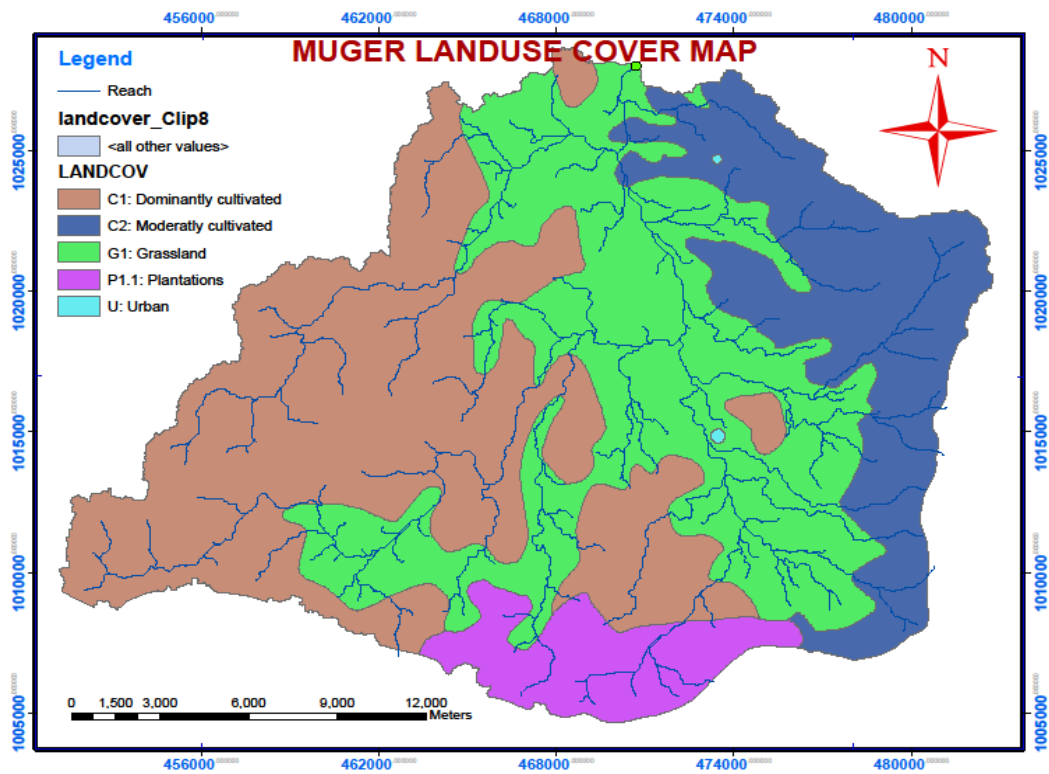
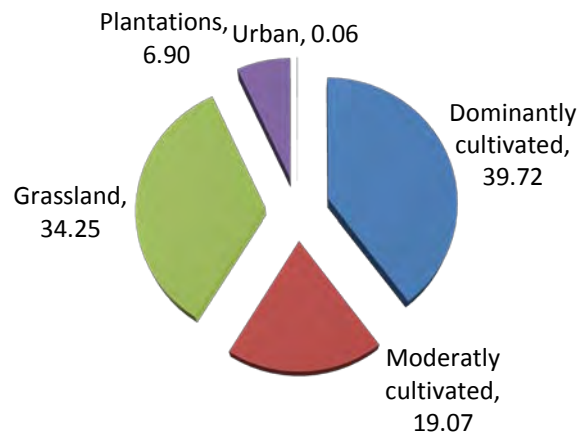


Figure 3-5 Land use land Cover map of Muger Catchment

Summary of Model input

SMAR Model

While the models are set up, each model requires the standard data in order to run the models. The SMAR model needs daily rainfall, daily evaporation and daily discharge to run the models and calculate the discharge at the catchment outlets.

HBV Model

The HBV model used in this study needs daily data of rainfall, temperature, discharge and potential Evapotranspiration.

Semi-Distributed Representation

For the semi-distributed catchment representation of the study area catchment input data shown in Table 3-3 was used. Elevation of precipitation measurements and elevation of temperature measurements are the same as those given in Table 3.4.

Table 3-3 Model input catchment data for semi-distributed representation of the study area

<i>Elevation Zone</i>	<i>Mean Elevation</i>	<i>Cultivated Land</i>	<i>Grass Land</i>	<i>Plantation</i>
Zone-1	2579.5	11.2200	25.7919	0.0030
Zone-2	2661	19.7121	7.3080	1.1489
Zone-3	2753	21.8397	1.0191	3.1898
Zone-4	2885.5	4.2977	0.1874	2.2670
Zone-5	3171.5	1.7222	X	0.2931

PCALT

The catchment is divided into different elevation zones. For each zone the precipitation will be corrected according to the its increase with elevation above sea level per 100 m, parameter PCALT. PCALT, the rainfall correction rate of the HBV model was calculated based on long term mean annual total rainfall and elevation data given in Table 4.5. Fitch

and Shola Gebeya stations were used to calculate PCALT value for Muger. The PCALT values obtained were equal to 7.1% per 100 m.

TCALT

Following the above steps used for PCALT, reference elevation for temperature and temperature correction lapse rate (TCALT) were estimated as give in Table 3-4. Fitch and Addis Ababa Observatory stations were used to calculate TCALT value for Both MUNC and ANC.

Table 3-4 Catchment level rainfall and temperature model input values

Catchment name	PCALT [m a.m.s.l] [% per 100 m]	TCALT [m a.m.s.l] [% per 100 m]	Reference elevations [m a.m.s.l]	
			Rainfall	Temperature
MUNC	7.1	0.86	2625	2579
ANC	7.1	0.86	2625	2579

3.4 Comparison of Models

3.4.1 Comparison criteria

The performance of a model must be evaluated on the extent of its accuracy, consistency and adaptability (Goswami et al., 2005). A forecast efficiency criterion is therefore necessary to judge the performance of the model. Assessing performance of a hydrologic model (Krause et al., 2005) requires subjective and/or objective estimates of the closeness of the simulated behavior of the model to observations.

Performance of the HBV and SMAR models was evaluated in a subjective way by following the basic approach of assessing model efficiency by visual inspection. It enabled examining systematic behavior, over- or under prediction, and dynamic behavior, timing, rising limb, and recession curve, of the simulated and observed hydrographs visually during calibration and validation of the model.

Objective assessment of the model was done by mathematical estimation of the error; it was used as the main criteria for accepting the parameter

estimates while calibrating the model manually and also while testing transferability of parameter set values. The error between simulated and observed runoff was quantified using the four efficiency criteria given in Table 4-5.

Each of the efficiency criteria (in Table 4-5) has its own limitation to be the absolute objective function. Therefore, because decisions on the goodness of the estimated model parameters was to a great extent based on measurement of the model performance, collective use of the four efficiency criteria was considered with special emphasis on Reff and meandiff values. Short description and limitation of each efficiency criteria is summarized from Krause et al. (2005) as follows.

Nash and Sutcliffe Efficiency Criteria (R^2): proposed by Nash and Sutcliffe (1970) its value lies between 1.0 (perfect fit) and efficiency of lower than zero indicates that the mean value of the observed time series would have been a better predictor than the model. The largest disadvantage of this efficiency criterion is that larger values in a time series are strongly overestimated whereas lower values are of minor importance. For the quantification of runoff predictions this leads to an overestimation of the model performance during peak flows and an underestimation during low flow conditions

Coefficient of Determination (r^2): estimates how much of the observed dispersion is explained by the prediction. Its value range lies between 0 and 1 and a value of zero means no correlation at all whereas a value of 1 means that the dispersion of the prediction is equal to that of the observation. Similar to Reff, r^2 is not very sensitive to systematic model over- or under prediction especially during low flow periods. A model which systematically over- or under predicts all the time will still result in good r^2 values close to 1.0 even if all predictions were wrong.

Efficiency using Logarithmic Value (logReff): is modification of Reff calculated by taking logarithmic values of the observed and simulated

runoff. Logarithmic transformation of the runoff values flattens the peaks and keeps the low flows more or less at the same level. As a result the influence of the low flow values is increased in comparison to the flood peaks resulting in an increase in sensitivity of $\log R_{\text{eff}}$ to systematic model over- or under-prediction.

Mean Difference (meandiff): measures long-term annual difference between the observed and simulated runoff; meandiff values equal to zero were considered perfect.

In summary, performance of both models in simulating the observed discharge was assessed during calibration, verification and transferability test of the model.

Inspecting simulated and observed runoff graphs visually assessing accumulated difference between simulated and observed runoff and comparing the R_{eff} , $\log R_{\text{eff}}$, r^2 and meandiff values (the main objective functions used for deciding goodness of fit during calibration were R_{eff} and mean diff).

Table 3-5 Efficiency Criteria for evaluating model performance

Objective function	Definition	Value for 'perfect' fit
Efficiency (<i>Reff</i>)	$1 - \frac{\sum (Q_{obs} - Q_{sim})^2}{\sum (Q_{obs} - \overline{Q_{obs}})^2}$	1
Efficiency using ln(Q) (<i>logReff</i>)	$1 - \frac{\sum (\ln Q_{obs} - \ln Q_{sim})^2}{\sum (\ln Q_{obs} - \overline{\ln Q_{obs}})^2}$	1
Coefficient of determination (<i>r2</i>)	$\frac{(\sum (Q_{obs} - \overline{Q_{obs}})(Q_{sim} - \overline{Q_{sim}}))^2}{\sum (Q_{obs} - \overline{Q_{obs}})^2 \sum (Q_{sim} - \overline{Q_{sim}})^2}$	1
Mean difference (<i>meandiff</i>)	$\frac{\sum (Q_{obs} - Q_{sim})}{No\ of\ days} \ 365$	0

4 Hydrological Modeling

4.1 Calibration

Model calibration entails the modification of parameter values and comparison of predicted output of interest to measured data until a defined objective function is achieved (James and Burges, 1982). The calibration and verification of the models are implemented by splitting the concurrent rainfall, evapotranspiration and flow data series into calibration and verification periods (about two-thirds for calibration and one-third for verification) and the first year for warm up period.

SMAR MODEL

The Shuffled Complex Evolution optimization algorithm is used for estimating the parameters of the SMAR model for the water balance component (T, H, Y, Z and C) and for the routing component (G, N, NK and Kg). The memory lengths (the duration of the pulse response) of the catchments were determined recursively from the modeling experiments.

The Shuffled Complex Evolution method of optimization is done by the process of allowing all parameters to optimize at the same time. The optimal values of the parameters are shown in the table 4.1.

Table 4-1 The nine optimized parameters of SMAR model for Muger catchment

Parameters	Lower Limit	Starting Value	Upper Limit	Optimized Value
T	0.5	0.75	1	0.76
H	0	0.95	1	0.09
Y	10	75	100	28.66
Z	25	100	125	125.00
C	0.5	0.87	1	0.55
G	0	0.75	1	0.96
N	1	5	10	10.00
NK	1	5	10	1.24
Kg	1	150	200	11.72

The appropriate shape of the ordinates of the pulse response function of the SMAR model is obtained for the memory length of 5 days for Muger catchment is shown as figure 4-1.

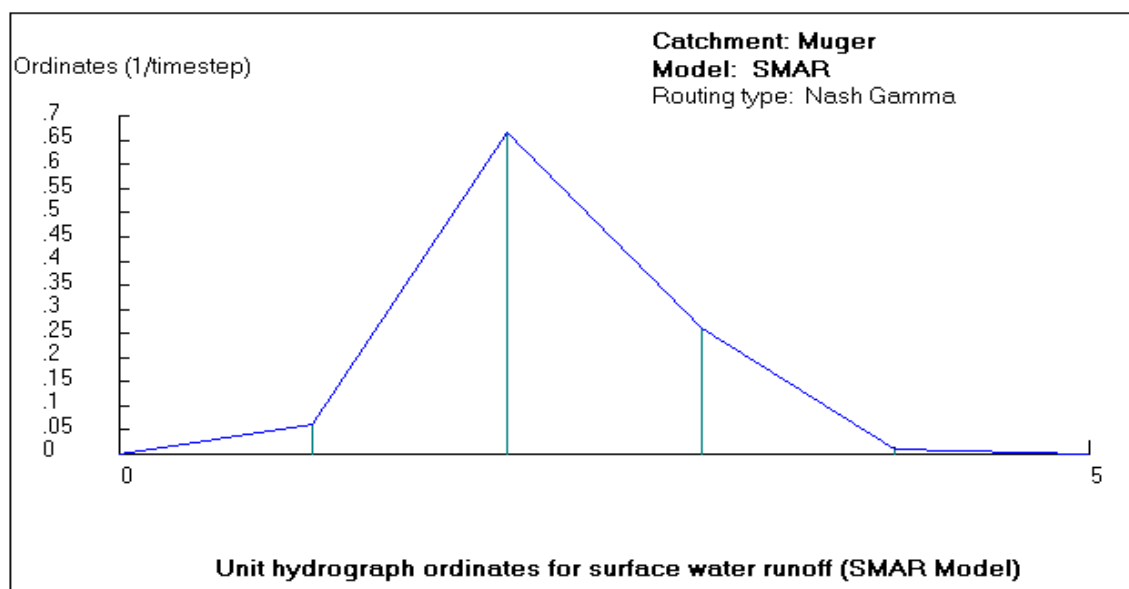


Figure 4-1 Unit hydrograph ordinates for surface water runoff (SMAR Model)

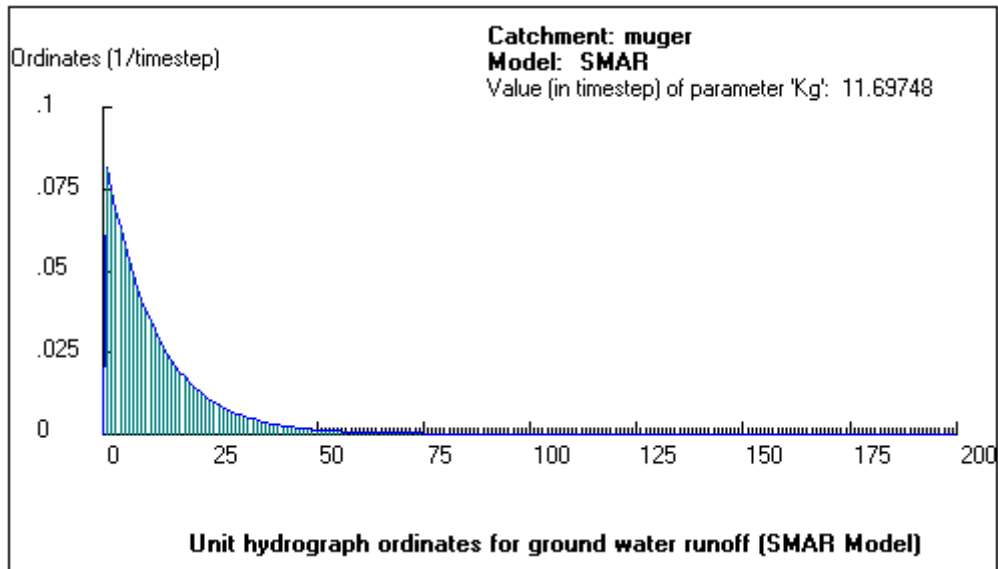


Figure 4-2 Unit hydrograph ordinates for Ground water runoff (SMAR Model)

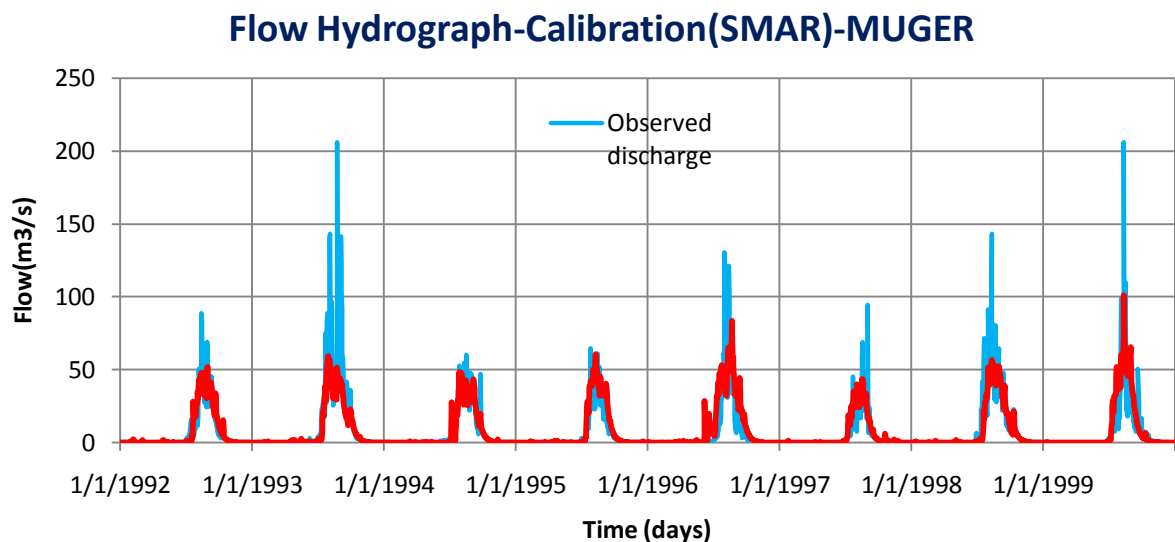


Figure 4-3 Calibration of observed and simulated flow hydrograph of Muger River gauged Period (1992-1999)-SMAR

HBV

Manual adjustment of the calibration parameters (listed in Table 4.2) resulted in set of parameters that minimized the difference between observed and simulated discharge (measured by the model performance criteria in section 4-4) for Muger catchment. Before starting hand tuning model parameters the range in which the calibration parameters would

give a better simulation was identified by Monte Carlo Simulation (detail discussion is given in Chapter 4-3).

The input data used for calibration of the HBV model in Muger were of the periods 1992-1999. The optimal calibration parameters attained together with the model efficiency values obtained are presented in table 4-2 and 5-1 respectively.

Table 4-2 The optimized parameters of HBV model for Muger catchment

Parameters	Lower Limit	Upper Limit	Optimized Value		
			Vegetation Zone 1	Vegetation Zone 2	Vegetation Zone 3
FC	50	1500	193.39	270.83	350
LP	0.3	1	0.62	0.84	0.74
BETA	1	6	5.92	5.84	1.08
PERC	0	6	1.19		
UZL	0	100	81.90		
K0	0.05	0.5	0.35		
K1	0.01	0.3	0.15		
K2	0.001	0.1	0.05		
MAXBAS	1	5	1.64		
Cet	0	0.3	0.12		

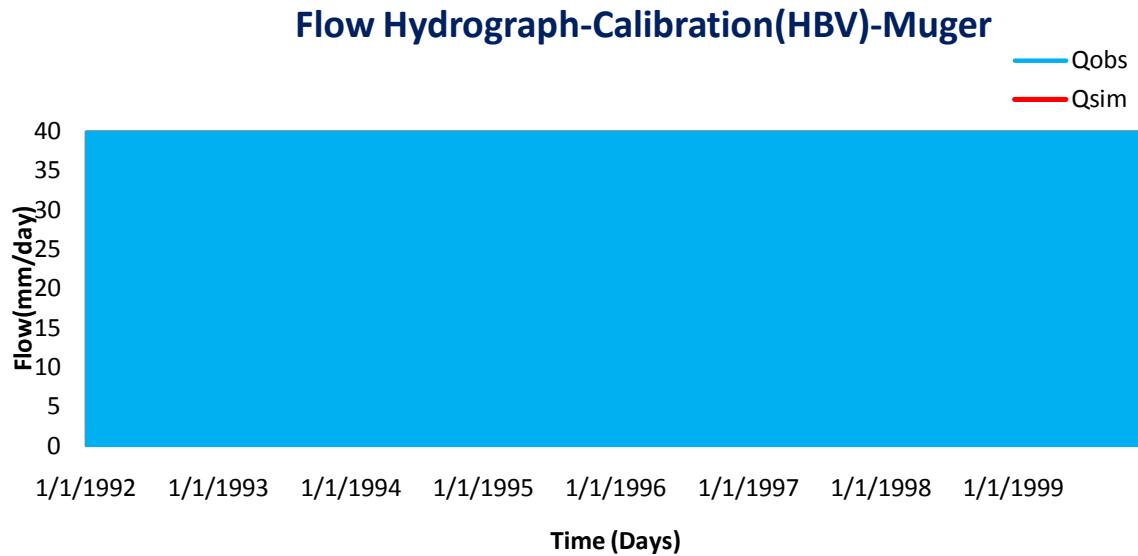


Figure 4-4 Calibration of observed and simulated flow hydrograph of Muger River gauged Period (1992-2000)-HBV model

4.2 Verification

Due to the complexity of the real world, representing the real world system by a model approach may not be accurate. Models therefore are uncertain and models cannot be stated reliable when only one field station is simulated. As such, it may occur that under different hydrologic stress conditions the model does not accurately represent the real world system behavior despite the fact that optimal and calibrated model parameter are used.

Validation is a process of demonstrating that a given site-specific model is capable of making accurate predictions for periods outside a calibration period (Refsgaard and Knudsen, 1996).

Simple model structures, calibrated over a certain period, are influenced by the rainfall-runoff sequence specific to that period (Lee et al., 2005) therefore in order to prove validity of a model; the model should be tested against a second, independent set of stress conditions.

Validation was done for the Muger catchment with data from 2000 to 2004. The objective functions available in HBV-96 and SMAR models

were used for testing the validity of the modeling on Muger catchment. The objective functions used to measure the reliability of the model are the mean difference, coefficient of determination and the Nash-Sutcliffe coefficient (Reff).

Performance of the model in the validation period, as measured by splitting-record technique, indicated that better simulation efficiency than in the calibration period for both models. For both models SMAR and HBV the obtained Reff is 0.7 and 0.71 respectively. Even though the HBV model showed overestimation of the observed discharge by around 60 mm/year the performances in simulating low flows was very good (logreff = 0.85). The SMAR model also showed underestimation of the observed flow by 62mm/year it performs best in estimating low flow (logReff=0.83).

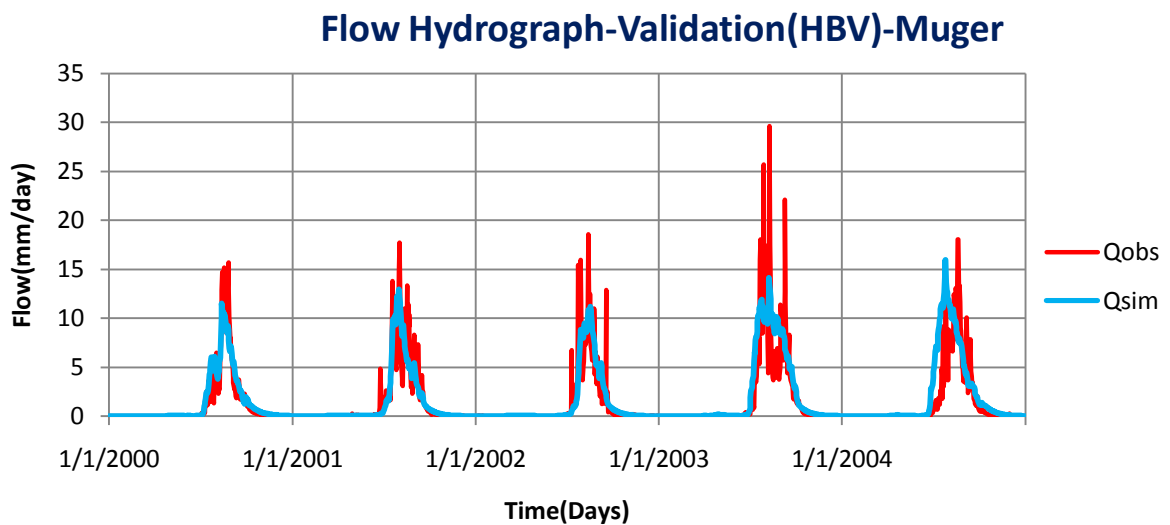


Figure 4-5 Hydrograph of Muger River gauged Period (2000-2004) By HBV Model during Validation.

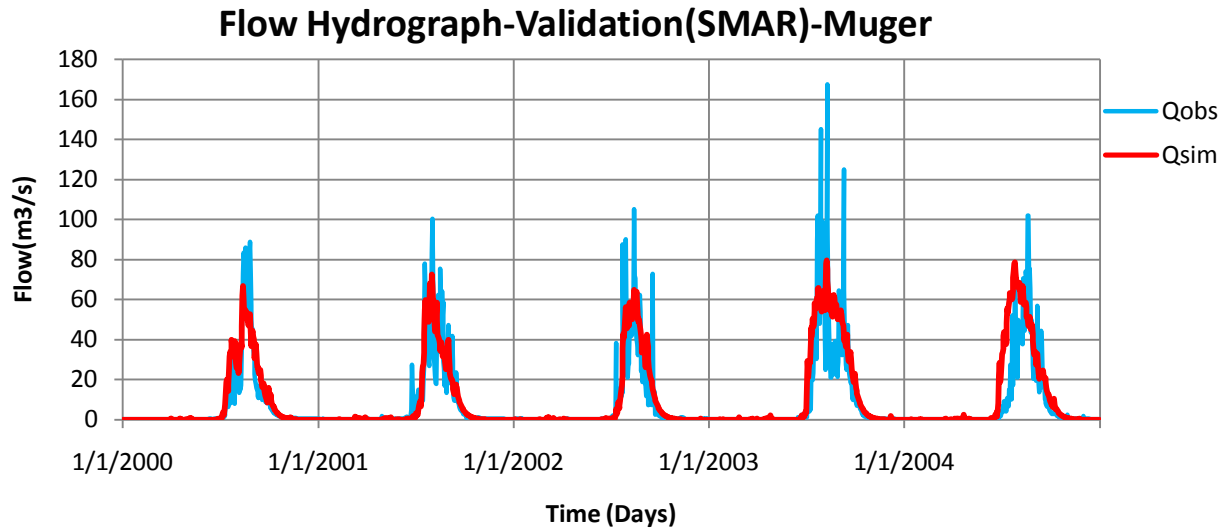


Figure 4-6 Hydrograph of Muger River gauged Period (2000-2004) By SMAR Model during Validation.

From the shape of hydrograph of Muger it was noticed that systematic and dynamic errors emanating from unknown catchment response pattern unaccounted by structure of the HBV and SMAR models were very less. This was further asserted by calibrating and validating the model in an increased simulation time step (of 30 days). In Table 4-3 it can be seen that the river discharge is well simulated by the selected time step. The Reff values attained for both HBV and SMAR are greater than 0.80 during calibration and validation. Compared to the performance of the models calibrated on daily time step, this has shown low annual mean difference between the observed and the simulated discharge; the meandiff value shows that the underestimated river discharge has decreased from 26 mm/year (daily time step) to 4.7 mm/year in by HBV model during calibration. By SMAR model subsequent to increasing the modeling time step, the overestimation of 46 mm/year observed in the daily time step model was decreased to overestimation of 0.24 mm/year.

Table 4-3 Model efficiency values achieved during calibration and validation of the increased time step models (monthly)

Objective Functions	Calibration		Validation	
	HBV	SMAR	HBV	SMAR
Reff	0.89	0.89	0.87	0.89
logReff	0.87	0.88	0.89	0.82
Meandiff(mm/year)	4.7	0.24	-56	46
Coefficient of determination(R^2)	0.95	0.95	0.94	0.95

Increasing the time step showed increases the performances of the HBV model in low flow simulation of Muger during validation. Compared to results of the daily time step of SMAR model, efficiency of the models measured by logReff has declined in validation and increased in calibration.

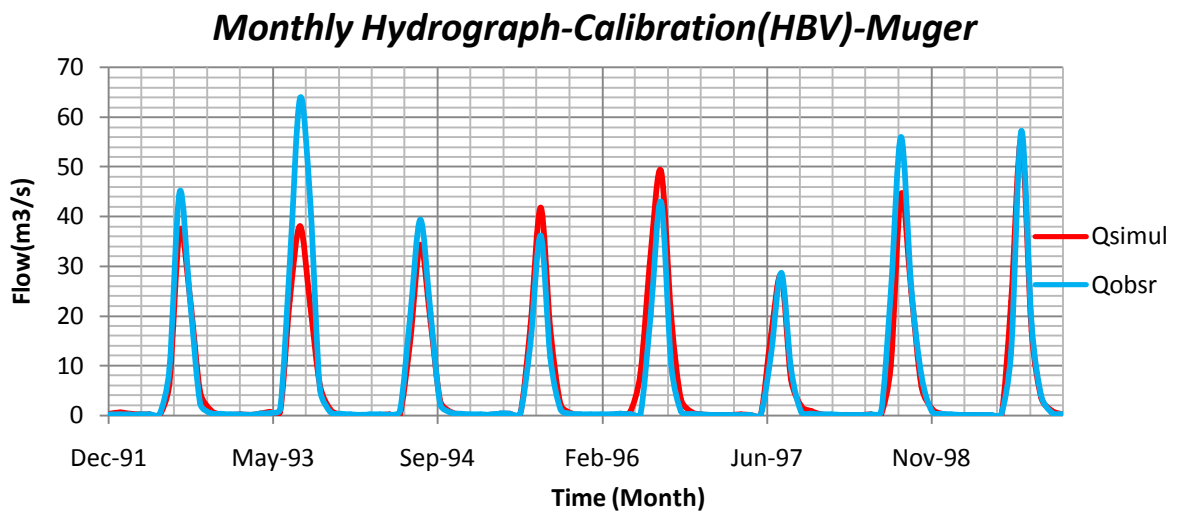


Figure 4-7 Hydrograph of Muger River gauged Period (1992-1999) By HBV Model during Calibration for increased time step

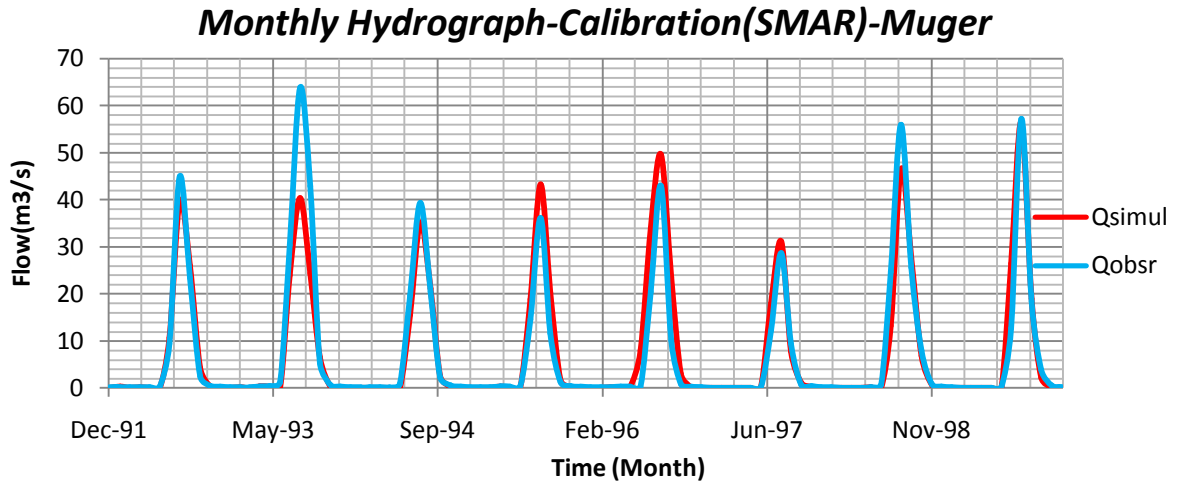


Figure 4-8 Hydrograph of Muger River gauged Period (1992-1999) By SMAR Model during Calibration for increased time step

As a result of increasing the modeling time step erratic behavior of the observed discharge during the rainy season (mainly) was avoided. Peak of the averaged observed discharge was seen to stand above the simulated ones except in the years 1997 (HBV) and 1994 for SMAR model when they were almost equal. The rising and recession limbs of the simulated flows fit with the averaged observed ones but in some occasions they rise quicker and/or fall delayed. The former was the model's reflection of increased rainfall input due to averaging the rainfall records which couldn't be better simulated (to the level attempted) by the model parameters governing the rising limb.

4.3 Sensitivity Analysis and Monte Carlo Simulations

4.3.1 Sensitivity analysis

SMAR

Sensitivity analysis involves investigating the behavior of the performance of a model in respect of one or more parameters which might be highly sensitive or insensitive to changes in values. A parameter which is insensitive to changes in values, may be kept at a fixed value while carrying out optimization to reduce the effective number of parameters to be optimized, thereby ensuring better convergence to optimum value of the objective function. Effect of changes on hydrometeorological conditions of the catchment on the model performance may be investigated by considering different scenarios involving sensitive parameters. In this case, unlike the equifinality study, only the parameter, whose sensitivity is to be studied, is to be allowed to vary by specifying different lower and upper limits and the starting value. All other parameters are to be kept fixed by specifying equal value for the lower limit, the upper limit and the starting number. When the program is run, the values of performance evaluation criterion (Nash Sutcliffe efficiency index in this version of the program) are evaluated for the specified number of model runs with different value of the parameter in each run. From the results, the sensitivity of the parameter in terms of change in its value and the corresponding change in the value of the performance evaluation index can be assessed. If dependence of two or more parameters in respect of sensitivity is to be investigated, these parameters only are to be allowed to vary by keeping the remaining parameters at fixed values.

Hence sensitivity analysis was performed on the SMAR model to determine which input parameters have the greatest influence on simulation results. Input parameters considered include T, H, Y, Z, C, G, N, NK and Kg. The sensitivity analysis was performed for each calibration event by varying each of the above parameters by plus or minus 2, 4, 6, 8

and 10%, in separate simulations, and then calculating the percent change in output parameters. The surface condition constant and H, N and NK were observed to have negligible influence on simulation results, whereas G, T and Z are found to be relatively sensitive.

The generated outflow is more dependent on the weighting parameter (G), determining the amount of generated 'groundwater' used as input to the 'groundwater' routing element. A parameter (less than unity) that converts the given evaporation series to the model-estimated potential evaporation series is the second governing parameter. The combined water storage depth capacity of the layers (mm) is also the governing component in generating the flow.

Generally ground water component, evapotranspiration and soil moisture storage depth are govern the flow generation mechanism in Muger catchment.

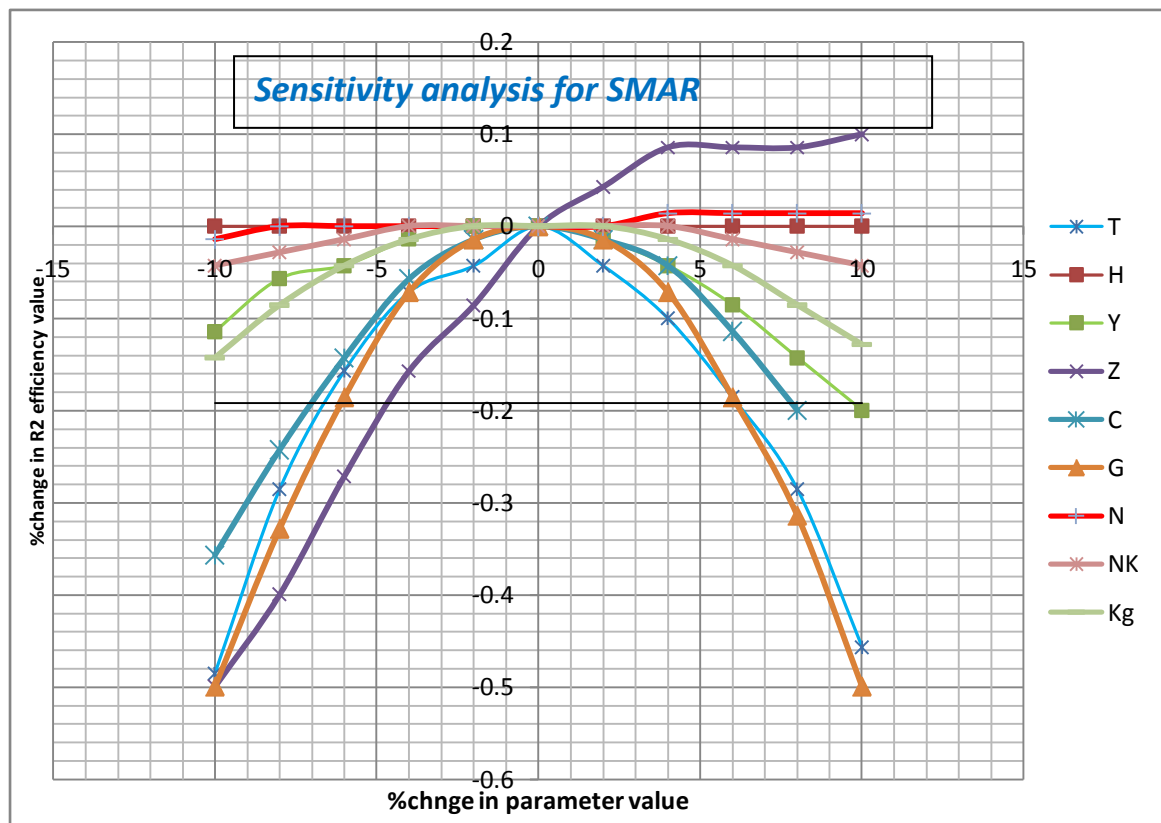


Figure 4-9 Result of sensitivity analysis of SMAR model

Table 4-4 Error analysis for SMAR model

% CHANGE Of parameters	% change in R ²								
	T	H	Y(mm/Time step)	Z (mm)	C	G	N	NK	Kg
10	-0.456	0.000	-0.200	0.100		-0.499	0.014	-0.043	-0.128
8	-0.285	0.000	-0.143	0.086	-0.200	-0.314	0.014	-0.029	-0.086
6	-0.185	0.000	-0.086	0.086	-0.114	-0.185	0.014	-0.014	-0.043
4	-0.100	0.000	-0.043	0.086	-0.043	-0.071	0.014	0.000	-0.014
2	-0.043	0.000	-0.014	0.043	-0.014	-0.014	0.000	0.000	0.000
0	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
-2	-0.043	0.000	0.000	-0.086	-0.014	-0.014	0.000	0.000	0.000
-4	-0.071	0.000	-0.014	-0.157	-0.057	-0.071	0.000	0.000	-0.014
-6	-0.157	0.000	-0.043	-0.271	-0.143	-0.185	0.000	-0.014	-0.043
-8	-0.285	0.000	-0.057	-0.399	-0.243	-0.328	0.000	-0.029	-0.086
-10	-0.48502	0	-0.1141227	-0.49929	-0.35663	-0.49929	-0.01427	-0.0428	-0.14265

HBV

Sensitivity analysis enables identifying the most important calibration parameters, detect parameter interactions, test model conceptualization, improve the model and provide a basis for an uncertainty analysis of the model (Krause and Base, 2006; Siebert and Uhlenbrook, 2005).

In this study sensitivity analysis was carried out to identify the sensitive model parameters and associate them with the catchment runoff generation characteristics.

Initial Monte Carlo simulations were done by assigning range of possible values of each parameter based on range of calibrated values from other applications of the HBV model (e.g. Uhlenbrook et al., 1999). After identifying the range of values for which the simulation showed better efficiency, by modifying ranges of possible values different parameter set values were produced by running 500,000 Monte Carlo simulations.

The highest Reff values obtained from these simulations for Muger Catchment were 0.71 resulted meandiff of 10 mm/year. Several simulations with Reff values comparable to the highest values were obtained. In MC 44 simulations resulted in $Reff > 0.71$ while 226,489 and 111,960 simulations yielded $0.7 > Reff > 0.65$ and $0.65 > Reff > 0.6$

respectively. Simulations with $Reff > 0.71$ were considered as “good” while simulations with $0.65 < Reff < 0.7$ were regarded as “satisfactory”. In general, outputs of the simulations showed that most parameters give good/ satisfactory model efficiency in a very wide range of values in sub-catchment. Thus, parameters are considered sensitive if they enable achieving good/satisfactory model performance in a range of values below the full scale of the standardized range. Parameters are defined “more sensitive” if their values result in acceptable performance only over a small range in the standardized range (e.g. in Fig 10-4, range of value for which FC shows good model efficiency is to be from 0.01 – 0.32 so it is more sensitive; whereas LP_1 can give good model performance over the whole range, hence it is not sensitive.)

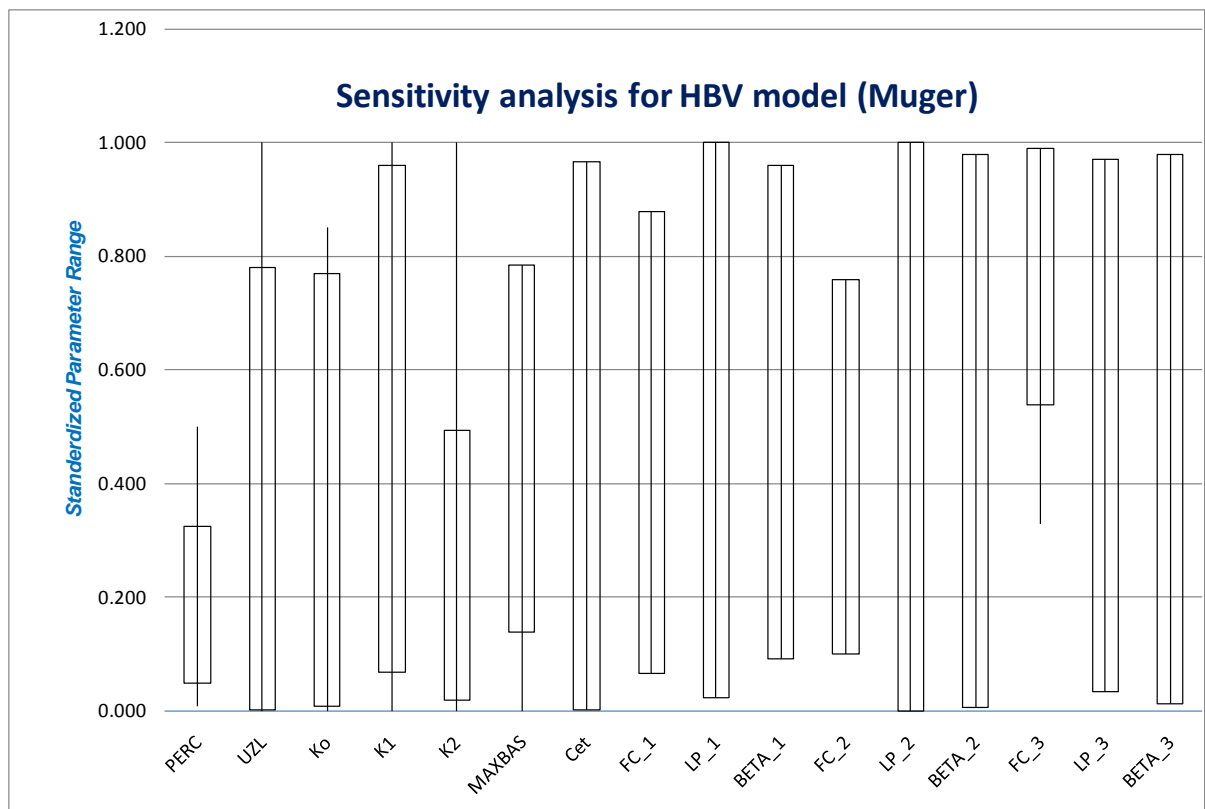


Figure 4-10 Result of sensitivity analysis of HBV model

The semi-distributed catchment representation models of Muger Catchment were sensitive to PERC, K2, and MAXBAS.

According to the structure of the HBV model those parameters govern the soil and evaporation routine, groundwater and response routine and routing routine. Among these, parameters those which were sensitive to values of relatively small range were identified as more sensitive parameters, these include PERC, K2, FC_3, FC_2, MAXBAS and K0.

The most sensitive parameters are the response routing (PERC) and K2 which govern subsurface and base flow contributions in Muger sub catchment. The second sensitive parameters are the soil moisture routing which are FC_3 and FC_2 that determines amount of water storage in the sub-catchments. In general, the stream flow of Muger River can be categorized as flow controlled by soil moisture rather than storm.

4.3.2 Uncertainty Analysis

Because of measurement errors in input and response and errors in model structure, predictions of hydrologic models are inevitably affected by uncertainty. Hydrologic models play an important role in supporting environmental decisions, e.g., by assessing water availability, exploring vulnerability to environmental change, or predicting the effect of management measures in the watershed. Therefore, to be able to support environmental decisions under consideration of prediction uncertainty, careful analysis and quantification of uncertainty are crucial in hydrologic modeling.

Usually the HBV model is calibrated by seeking one optimal parameter set that represents the catchment. It is known that, it is hardly possible to find a unique parameter set. This is because of errors in both the model structure and the observed variables and because of interactions between the different model parameters. Therefore, there may be many sets of parameters which give similar good results during a calibration period, but their predictions may differ when simulating runoff in the future. In this study a Monte Carlo procedure was used to assess the uncertainty of the simulated flow estimation and to describe differences

in this uncertainty for different parameter sets. For 95% confidence the upper and lower bound of simulated hydrograph is shown in table 4-11.

The procedure of montecarlo procedure is as follows;

- About 500,000 random parameter sets is produced
- For each parameter set flow is generated
- From generated flow only with $Reff > 0.6$ is considered for further analysis.
- At last monthly upper and lower limit of flow is calculated and plotted in figure 4-11 with 95% confidence limit.

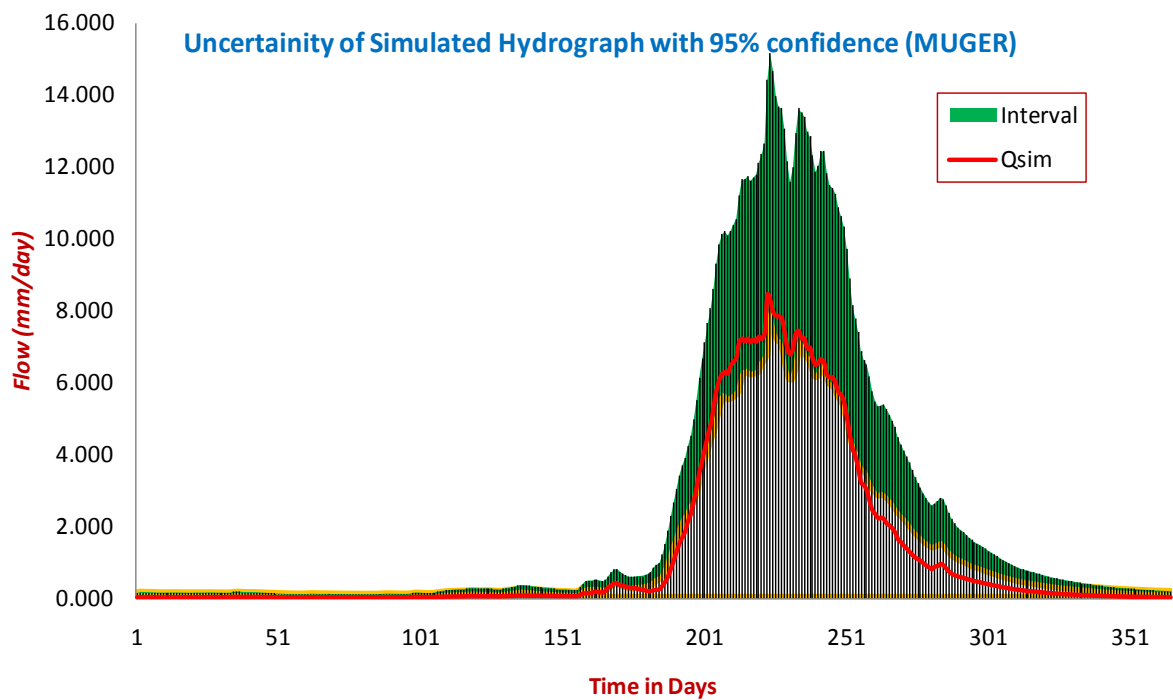


Figure 4-11 Plots of 95% prediction uncertainty bands associated with parameter uncertainty (Green shaded Area) for calibration period Hydrograph.

As it is shown in figure above some part of the simulated hydrograph lays outside the uncertainty range. In this study only parameter uncertainty is considered. But other sources of uncertainty have significant effect on the simulated output, these uncertainty sources are like input uncertainty, model structure uncertainty and it can be also due to compound uncertainty. Therefore the result of simulated flow is less reliable.

5 Results and discussion

Each of the models is applied to Muger catchment, using split-record evaluation, involving the use of calibration and verification periods (about two-thirds for calibration and one-third for verification).

Thus, the above variables (section 4-4) were used for each selected models for the selected catchments to compare and select the appropriate model. The statistical comparisons and visual comparisons of observed and simulated values were conducted to evaluate the performance of the selected models. Table 5-1 gives a summary of statistics of simulations by the selected models for both calibration and validation periods.

Table 5-1 *Calibration and verification results HBV and SMAR models*

Models		Reff(R ²)	Coefficient of Determination(r ²)	logReff	Mean Difference (meandiff) mm/year
	Calibration				
HBV		0.70	0.70	0.82	26
SMAR		0.70	0.70	0.84	-46
	Verification				
HBV		0.71	0.73	0.85	-60
SMAR		0.70	0.73	0.83	62

Results indicate that in general both models, with optimization, will successfully simulate runoff in the Muger Catchment during calibration and both reaches an efficiency of about 70% for 1992 to 1999. The result during validation shows that the efficiency is better as compared to that of calibration period. The highest result attained was Reff=0.71 by HBV model followed by SMAR (Reff=0.7).

5.1 Result Analysis using Flow Duration Curves

The comparison of observed and simulated flow duration curves is probably the most effective test of model performance. Flow duration curves are useful in providing an indication of the distribution of daily flows, as might be required for licensing abstractions or effluents, and other design applications. However, they cannot show whether a particular flow estimate is simulated on the same day on which it is recorded, as might be required for operational matters such as flow forecasting; for this it is necessary to compare observed and simulated by daily flow hydrographs. The flow duration curves which represent the lower, median and upper observed discharge and median simulated discharge of the Muger catchment is illustrated as Figure 5.1.

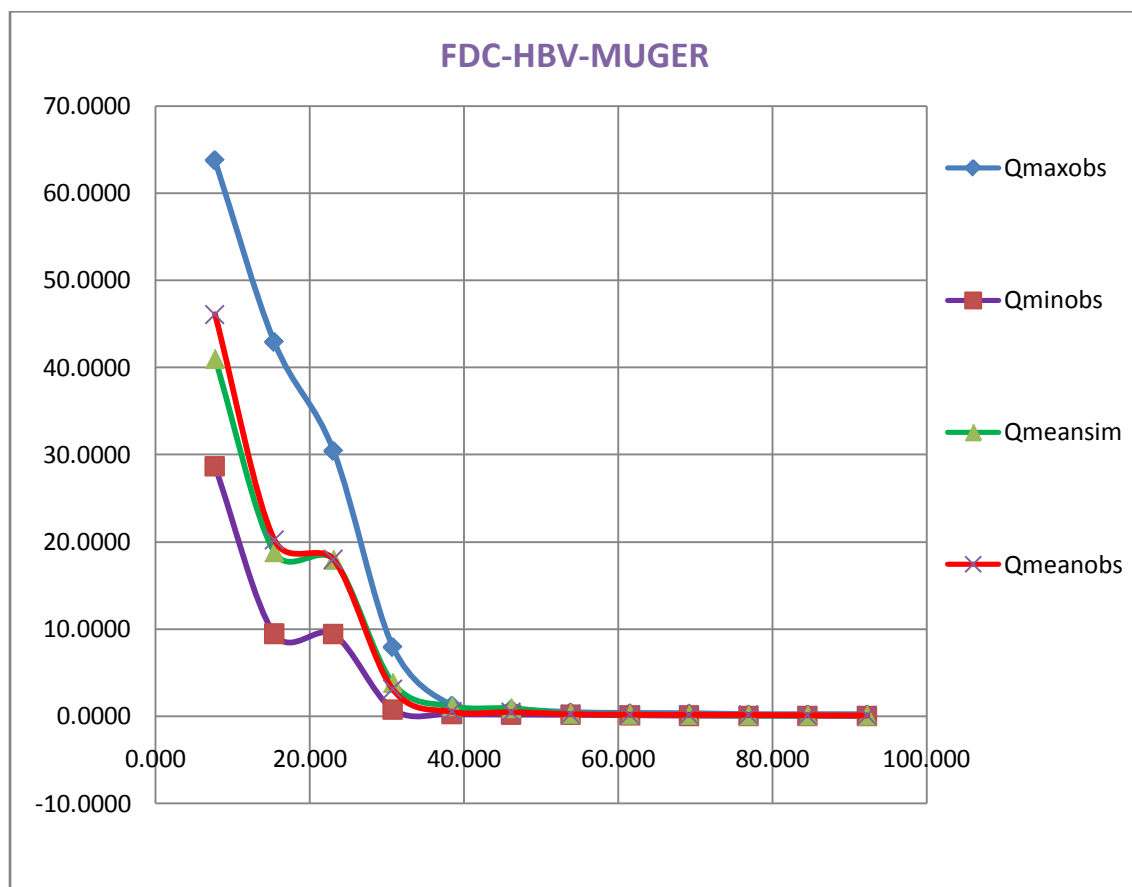


Figure 5-1 The observed and its 95% confidence limits with simulated FDC of MUGER by HBV model

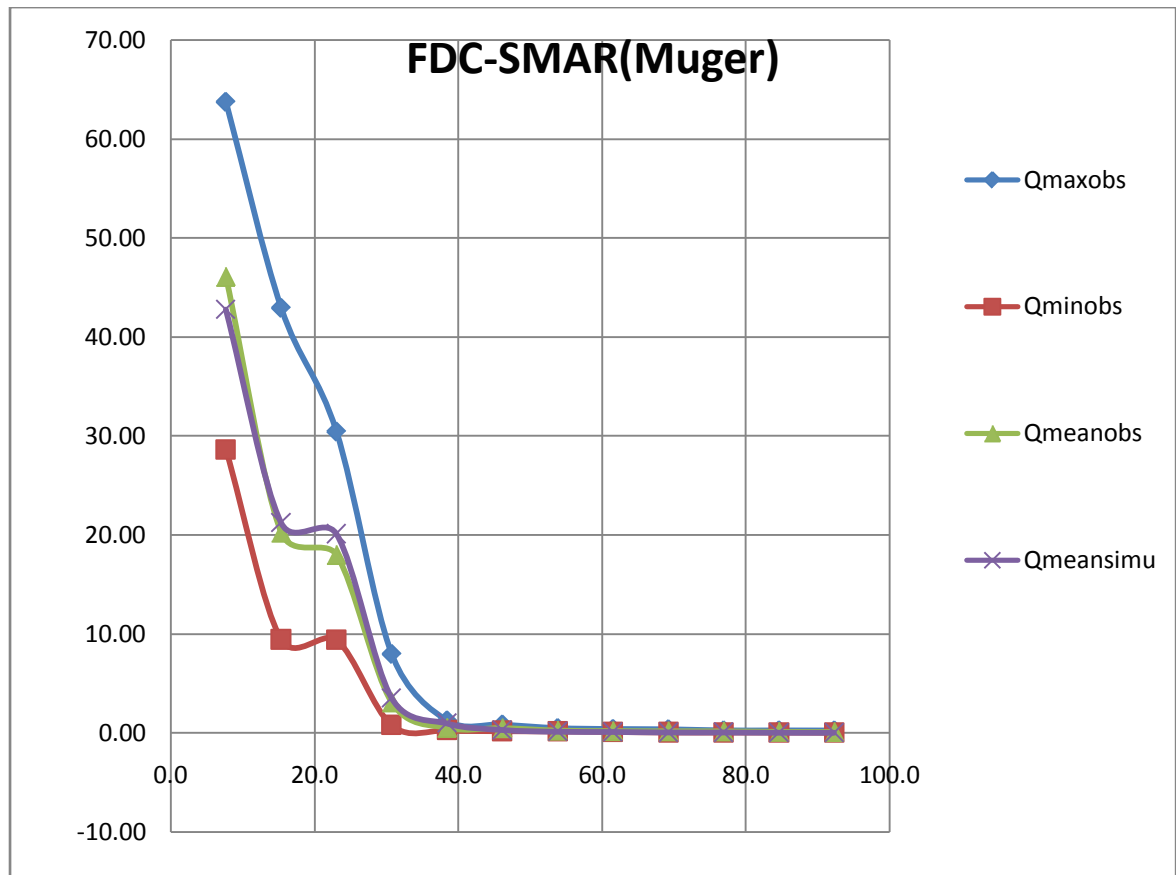


Figure 5-2 The observed and its 95% confidence limits with simulated FDC of MUGER by SMAR model

From figure 5-1 and 5-2 one clearly understand that, the shape of the flow duration curve in high flow region indicates the type of flood regime is likely to have, whereas, the shape of the low- flow region characterizes the ability of the basin to sustain low-flows during dry seasons. A very steep curve (high flow for short periods) shows rain caused floods on watersheds. However, a very flat FDC indicates that moderate flows are sustained throughout the year due to natural or artificial stream flow regulation, or to a large groundwater capacity which sustains the base flow to the stream.

The flow duration curves confirm that models SMAR and HBV have a tendency to underestimate the higher flows and underestimate the lower flows, and that the intermediate flows can be nearly equally estimated in both models in Muger catchment. However, in many cases, the models

actually underestimate the very low flows: the simulated flow duration curves are often characterized by a distinct and abrupt bend somewhere in the middle of the curve, caused by the flow receding too quickly.

5.2 Transferability of Model Parameters

Most part of the Muger catchment is ungauged transferability of the model parameters obtained for the sub-catchment was tested before applying either of them to the entire area. Aleltu River which has similar hydrological characteristics is selected to check the transferability of parameters shown in Table 5-2 and corresponding hydrographs are shown in Fig. 5-4 and 5-5.

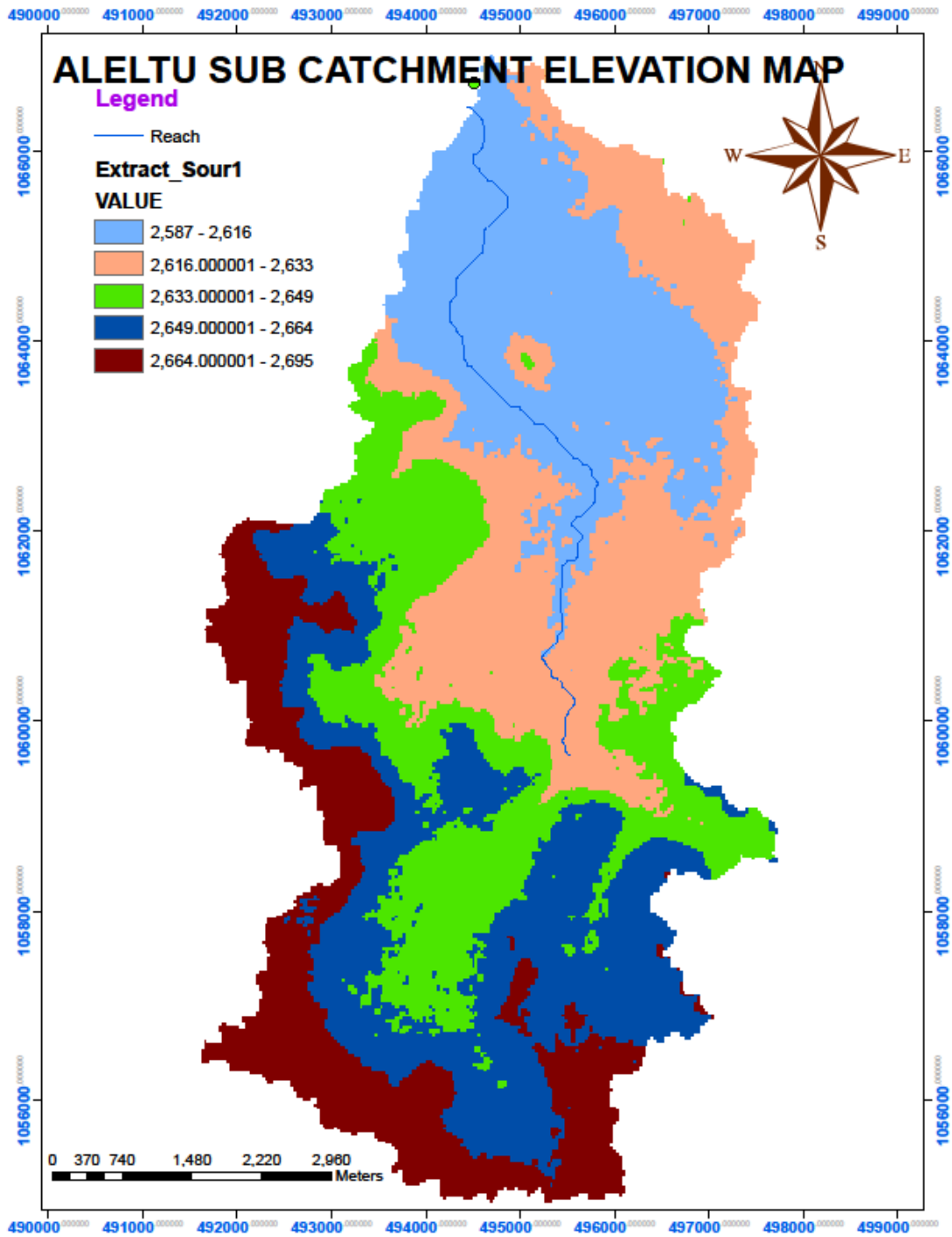


Figure 5-3 Elevation map of Muger Sub-catchment

Table 5-2 Model efficiency values obtained from daily model transferability test

Catchment	Model	Reff	logReff	R ²	meandiff	parameter transferred
Muger	SMAR	0.53	0.71	0.65		Muger-Aleltu
	HBV	0.51	0.6	0.45	-131	Muger-Aleltu

The table shows that the sets of parameters optimized by SMAR model on Muger catchment selected yielded satisfactory performance on Aleltu sub-catchment they were transferred to (Reff > 0.53). However, from visual inspection of simulated (Qtrn - with transferred parameters and Qsim with its calibrated parameters) and observed (Qobs) flow hydrographs of Aleltu, undestimation of the peaks was observed. The efficiency of HBV model is 0.5, which is relatively good but inaccuracies such as overestimation (during the rise and recession), delay of the rising limb (e.g., 2000/01) and underestimation of the peaks (e.g., 1999 and 2000) were noticed.

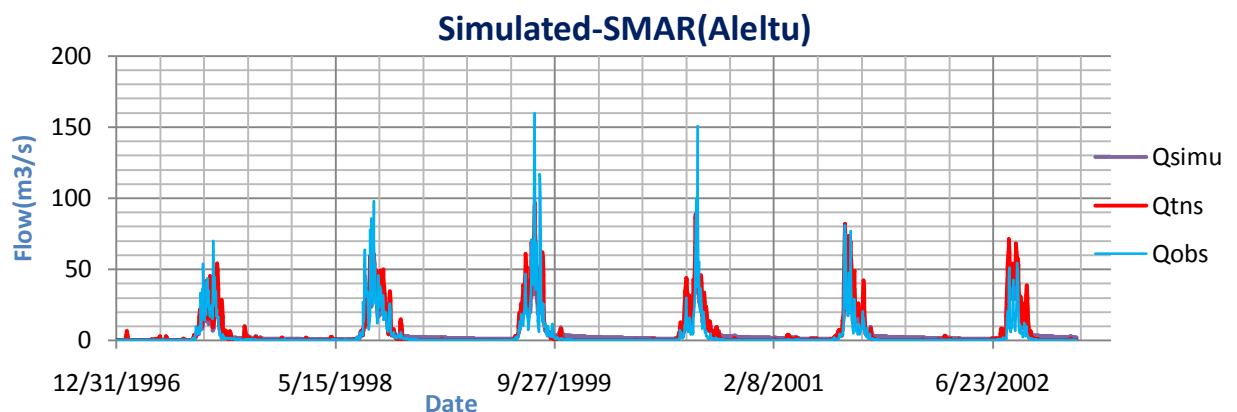


Figure 5-4 Simulated (with and without transferring parameters) and observed flows by SMAR Model.

The model evaluation, both graphically and statistically, shows good agreement between the observed and simulated stream flow after the

model parameters are transferred. Similarly parameters optimized by HBV model was transferred to Aleltu Sub catchment yielded an efficiency of R_{eff} of 0.51 which is nearly equal to that of by SMAR model. From visual inspection a dalliance of rising and recession limb is observed. The model underestimates the peak flood but it overestimates the total water yield of the catchment (Figure 5-4).

Although some peaks are not captured adequately, in general, the model can be said to have an acceptable performance and that the hydrological processes and streamflow dynamics have been simulated realistically.

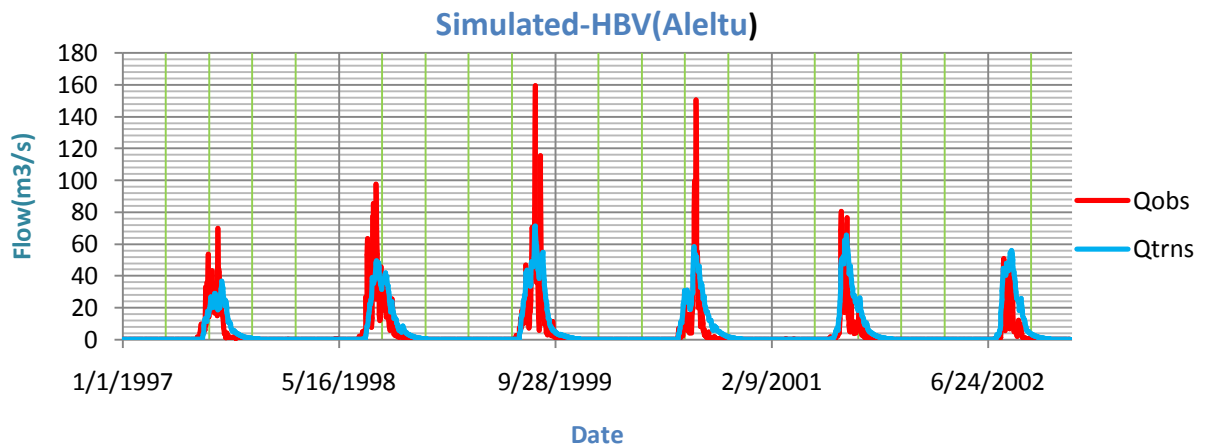


Figure 5-5 Simulated (with transferring parameters) and observed flows of SMAR Model.

Investigation done to test transferability of the obtained best model parameter sets to Aleltu sub catchment showed change in hydrologic behavior of the respective subcatchment the parameter set values were applied to. For it would be hasty to conclude unfeasibility of the parameter transfer only based on test of the daily models, by taking importance of incorporating comparison of results at different time scales into consideration transferability of the monthly time step model parameter value sets were also tested (Hartmann and Bardossy, 2005). Parameter transferability test of the increased time step showed good performance (see Table 5-3) by both models with R_{eff} of 0.74 and 0.67 by

SMAR and HBV, respectively; the resulted other efficiency criteria is presented in table 5-3.

Table 5-3 Model efficiency values obtained from model transferability test of the increased time step model (monthly time step)

Catcment	Model	Reff	logReff	R ²	meandiff	parameter transferred
Muger	SMAR	0.74	0.69	0.94	-123	Muger-Aleltu
	HBV	0.67	0.87	0.91	-137	Muger-Aleltu

The objective functions used for evaluating performance of the HBV and SMAR models showed better model performance. By subjective evaluation of Fig. 5-6 and 5-7, hydrographs of the simulated discharge Qtrn (using transferred model parameter set values) overestimated the peak flow of Aleltu by both models.

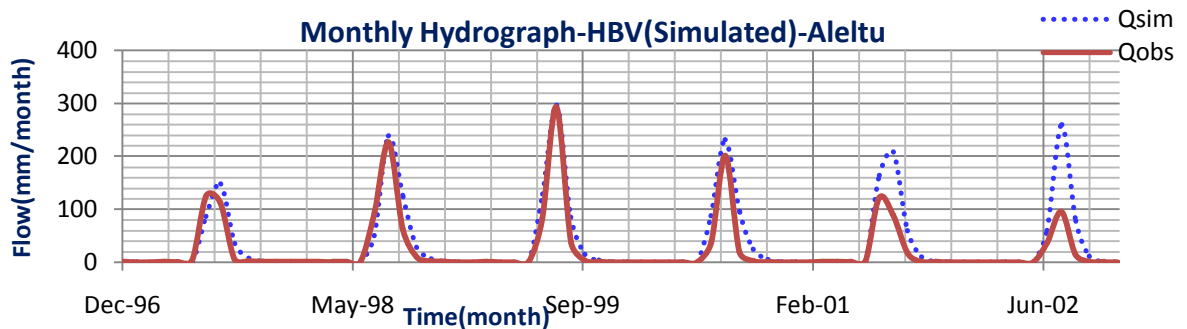


Figure 5-6 Simulated and observed flow hydrographs for increased time step (monthly) by HBV model

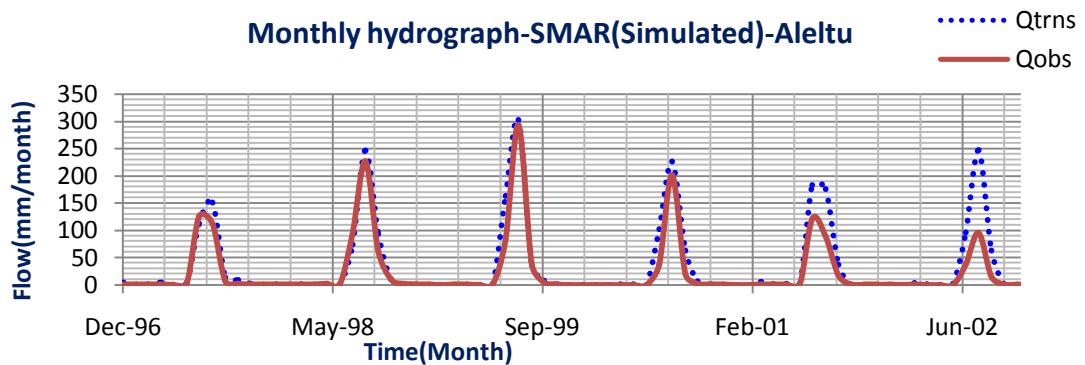


Figure 5-7 Simulated and observed flow hydrographs for increased time step (monthly) by SMAR model

5.3 Direct Runoff and Ground water Flow

Direct runoff (DR), and Ground water flow components quantified by the HBV model showed that surface runoff make the highest contribution of outflows of Muger catchment. In Fig. 5-8 it can be seen that with a varying magnitude the direct runoff contributes to the catchment outflow between June and October. Furthermore, the rainfall occurring in April and May seem to contribute to outflow of the catchment after infiltration and initiating interflow and/or base flow than turning to direct runoff. This can be valid at the scale of the whole sub-catchments; however, at a scale lower than sub-catchment level (e.g. at elevation zones) this might not always hold true

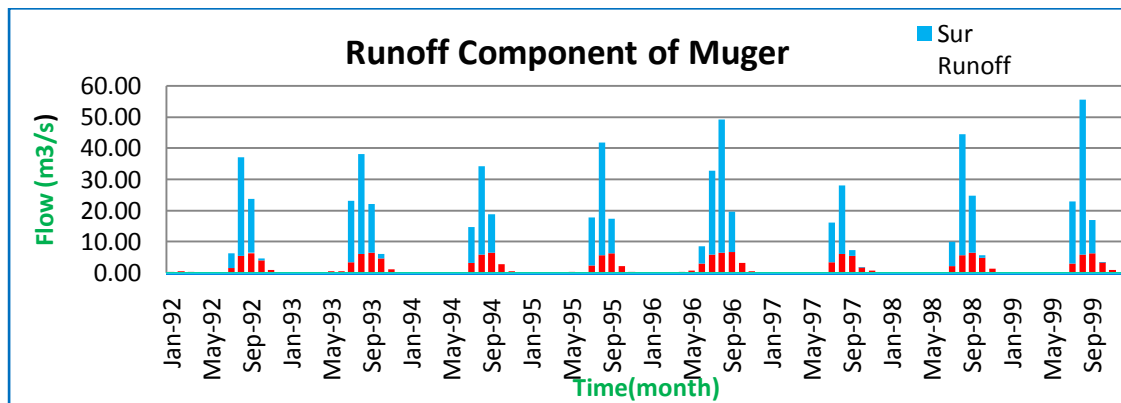


Figure 5-8 Contribution of direct runoff, Ground Water flow to the flow hydrograph (HBV Model)

From the result of the SMAR model it is observed that surface runoff flow contributes the highest flow at the outlet of the catchment. In Fig. 5-9 it can be seen that with a varying magnitude the direct runoff contributes to the catchment outflow between June and October.

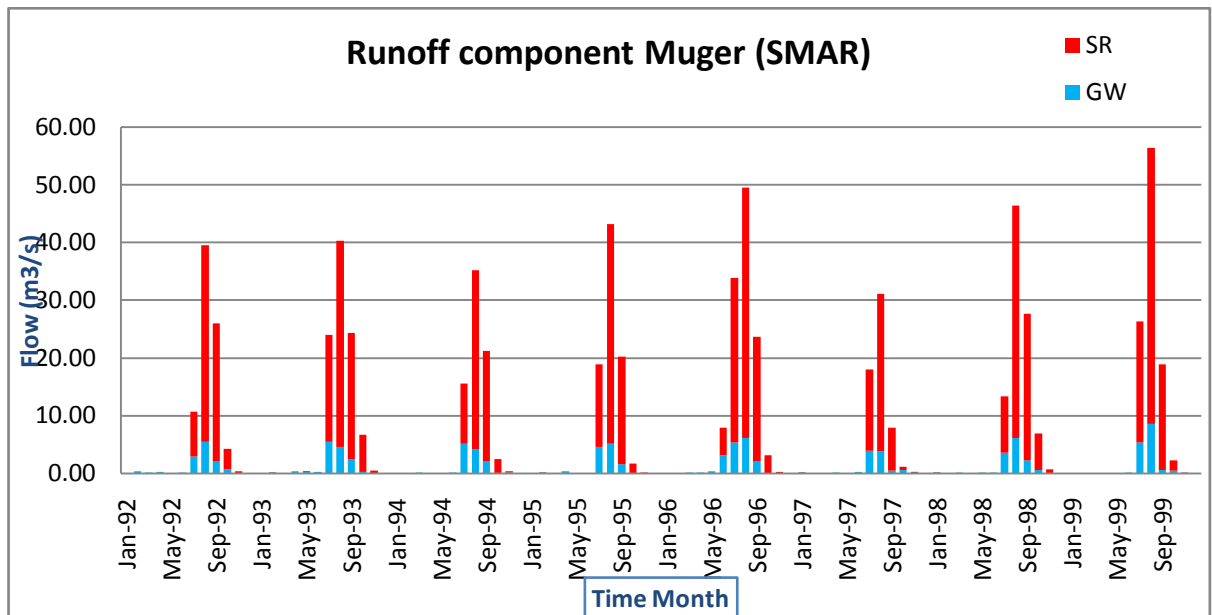


Figure 5-9 Contribution of direct runoff, Ground Water flow to the flow hydrograph (SMAR Model)

On a yearly basis, values acquired from HBV Model indicate that the proportion of direct surface runoff and Base flow are 74% and 26% of the annual flow.

Similar computation by SMAR model shows 83% and 17% share of the annual total leaves the sub-catchment by direct surface runoff, Ground water flow(interflow and base flow) respectively. The difference in percentage of direct runoff component of Muger by HBV and SMAR models are due to the difference in the structure of the models in transferring rainfall to runoff.

5.4 Scatter diagram

It is observed that from the scatter diagram of observed vs. simulated more values appeared to above the 45° line in calibration periods which shows the model overestimate the simulated flows.

From Figure 5-9, it is observed that SMAR and HBV underestimate the low flows and peak flow indicates both models miss the two extreme flows. The scatter diagrams of SMAR and HBV models for calibration periods for Muger catchment are shown in figure 5-9 and 5-10. Though, the scatter diagram for verification period is depicted in Appendix-C,

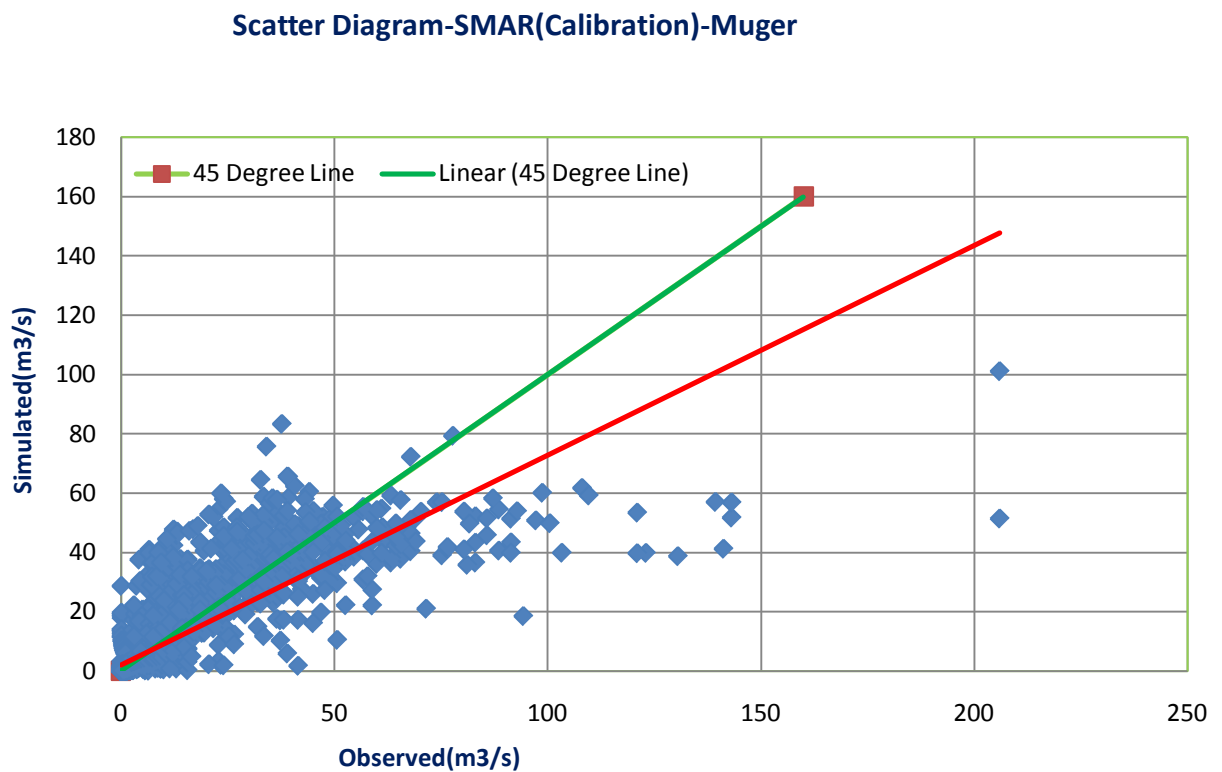


Figure 5-10 Simulated vs. observed scatter diagrams for SMAR Model

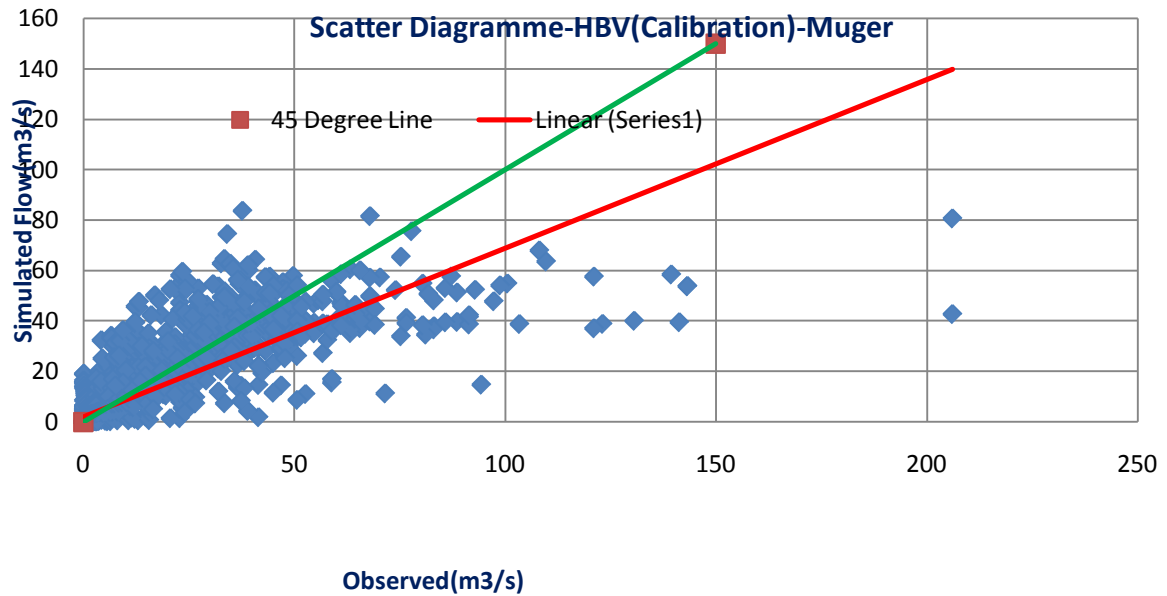


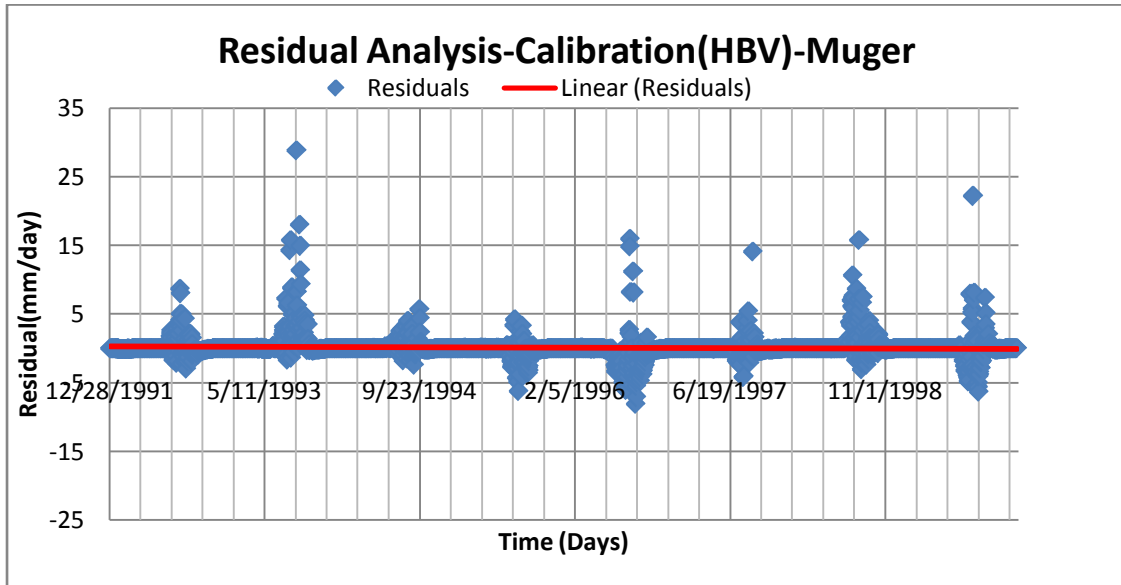
Figure 5-11 Simulated vs. observed scatter diagrams for HBV Model

5.5 Residual analysis

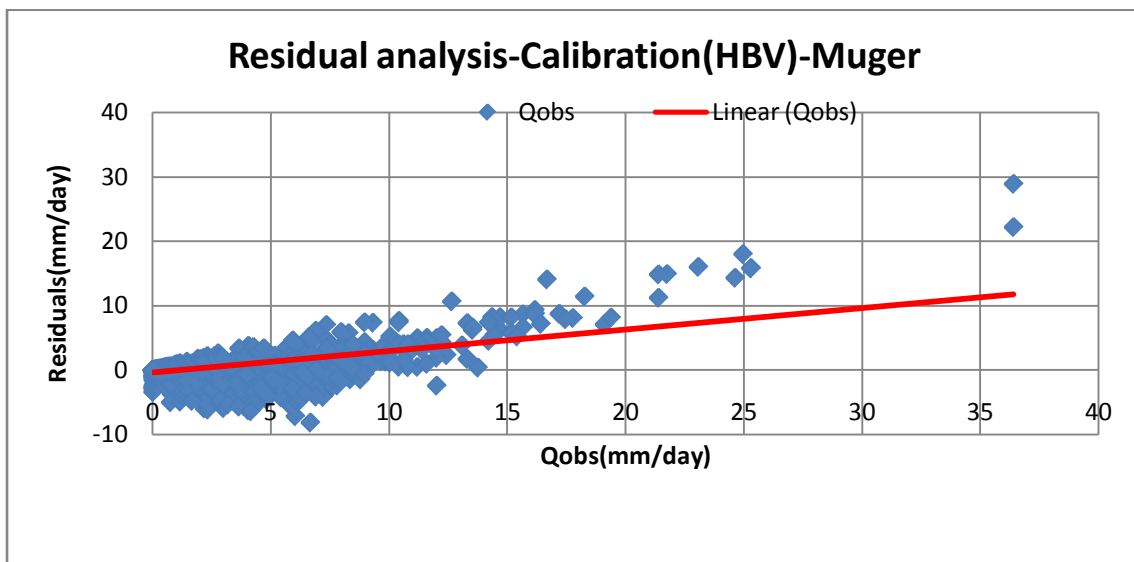
Evaluation of models is also done by way of residual analysis. In typical residual analysis several assumptions are made about the independence and normality of residuals. In an ideal situation the fit between observed and simulated values is expected to be 1:1 mapping, but in reality this is not possible.

The residuals were calculated by subtracting the simulated from observed streamflow. The slope for the residuals against time was tested against a zero-slope hypothesis both for the calibration and validation periods (Fig 5-11). In the validation period, the residues showed a slight increasing trend while in the calibration there was no indication of trend against time for both models SMAR and HBV. The residuals against observed stream flow showed a high dependency on discharge in the calibration period while a greater dependency was observed in the validation period. This is because peak flows in the validation period are higher than in the calibration period for both models. Thus, with the underestimation of peak flows, the residuals are much larger giving the seemingly increased dependency of residuals on streamflow in the validation period. This slight dependency could be due to the

underestimation of peaks occurring in the 2003. Both models SMAR and HBV were not able to capture these peaks adequately in which case they had some leverage on the residual's trend. The residuals exhibits seasonality, more systematic relationship of residuals was obtained with observed discharge indicating that the model output is inadequately represented by the model.

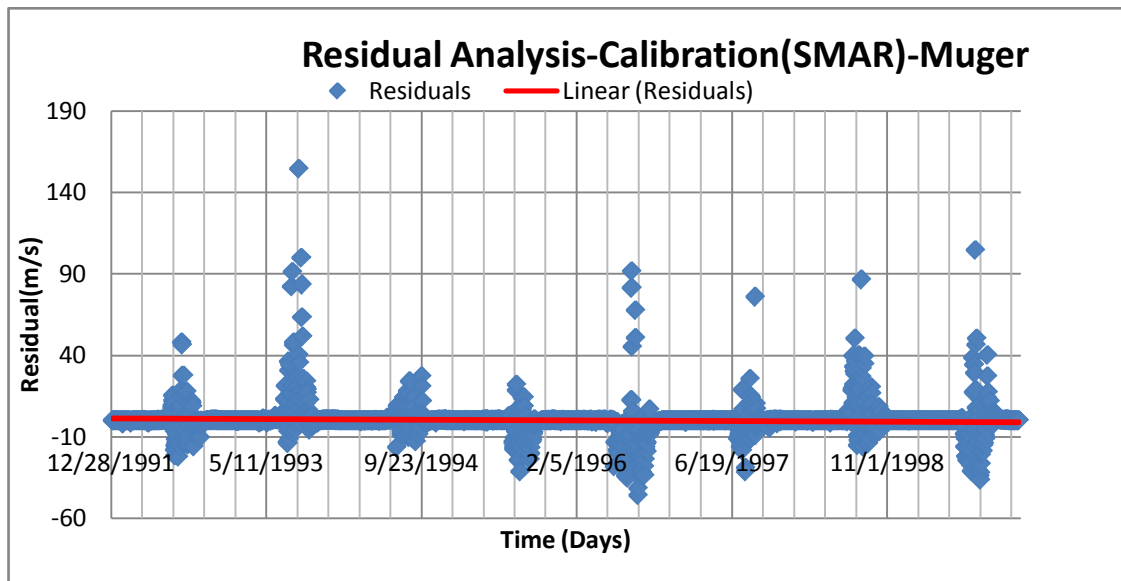


(a)

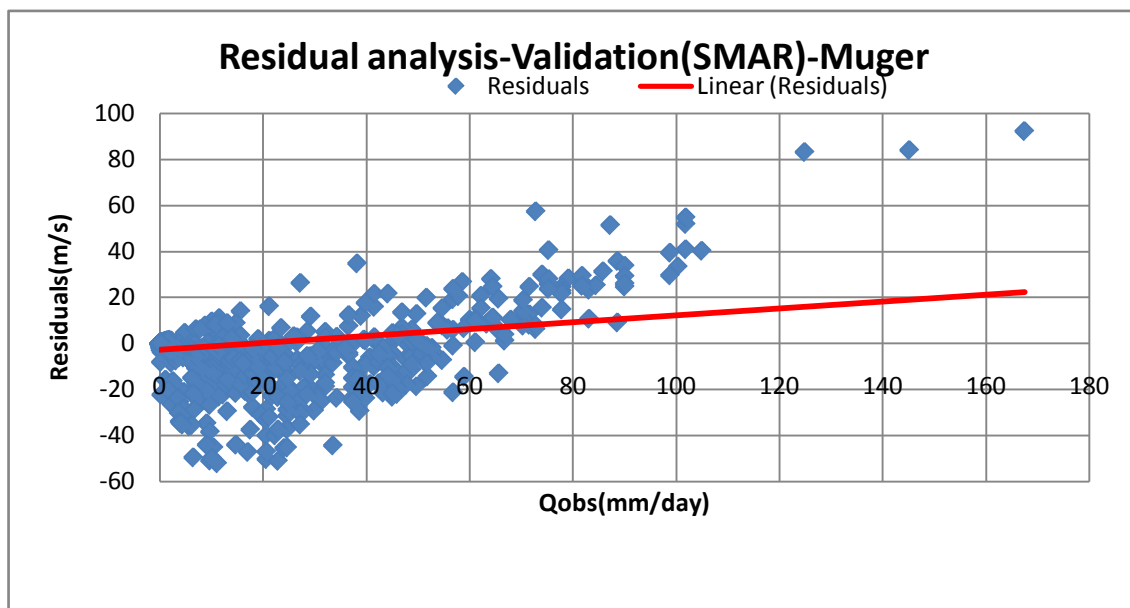


(b)

Figure 5-12 Residual plots against time (a) and observed (b) stream flow for the calibration by HBV model



(a)



(b)

Figure 5-13 Residual plots against time (a) and observed (b) streamflow for the calibration by SMAR model

6 Summary, Conclusions and Recommendations

6.1 Summary and conclusion

The objectives of this study were to conduct catchment modeling and to compare and select the best conceptual rainfall-runoff model that can be used in the design, planning, and management of water resources in Muger catchment. Two conceptual rainfall-runoff models namely SMAR and HBV were selected and tested for the hydrological characteristics of Muger catchment.

Each of the models was applied to test the catchment, using split record evaluation, involving the calibration and verification periods (about 60% for calibration and 40% for verification).

During calibration period of each model, the optimized parameters which give good performance result that is 0.7 for both models were determined. These optimized parameters are validated; the validation result indicated that an efficiency value of 0.7 and 0.71 for SMAR and HBV respectively were obtained. Automatic calibration was applied for the SMAR model. However, manual calibration was applied for HBV-light model.

Even if the models have been calibrated, discrepancies between computed and observed hydrographs have occurred. This might be due to input data, that are not representative in a special situation, or that the models structure may not be a perfect description of the nature of the catchment.

Generally speaking, the results show that both models can reproduce historical daily runoff series with an acceptable accuracy. The values of R_{eff} , $\log R_{eff}$ and $meandiff$ in indicate that both selected models produced good results for calibration and better result during validation periods. The SMAR model has the highest R_{eff} value followed by HBV value in Muger sub basin during calibration and vice-versa during validation.

From the result analysis of each candidate models, it was concluded that both the right kind and right duration of data are needed for a good calibration. Besides ensuring that the data are error free, one has also to be careful about the duration of the calibration period.

The hydrograph shows that, the SMAR and HBV models are completely underestimate the peak flow.

For simulation of the flow duration curve, the underestimation of very low flows for models suggests that the models are not simulating the slow release of water during dry periods. The overestimation or underestimation of the higher flows for the same models reflects the poor simulation of flood peaks, for the daily flows. In particular, the quality of the flow duration curves for model reflects the quality of the simulated daily flows.

The slope for the residuals against time was tested against a zero-slope hypothesis both for the calibration and validation periods. In the validation period, the residuals showed a slight increasing trend while in the calibration there was no indication of trend against time for both models SMAR and HBV. The residuals against observed stream flow showed a high dependency on discharge in the calibration period while a greater dependency was observed in the validation period. This is because peak flows in the validation period are higher than in the calibration period.

From this study it confirms that both conceptual models underestimate the low flow due to the concept that conceptual model is lumped as it does not consider the deep percolation and ground flow and soil moisture analysis as that of distributed model.

The model is not robust if there is large value missing data in the observed series, and could probably benefit from applying input data where gaps in the series have been filled. The simulation also revealed that the areal representation of precipitation input, besides the data

quality of the precipitation values, is crucial to the satisfactory running of the model.

6.2 Recommendations

From this study it is recommended to identify the characteristics of catchment reasonably in order to apply the appropriate models and to transfer flow to the ungauged catchment with the suitable methods.

Both selected conceptual models are tested with good data quality in Muger catchment to drive homogeneous response units that could be applied to generate the flow in ungauged catchments.

Further, to arrive at parameters which are representative for the various hydrometeorological extremes which the catchment is likely to face, both the right kind and right duration of data which lead to sufficient activation of the model parameters are necessary.

The challenge of having adequate and good quality data may be a far away dream in the developing countries. In this research it was quite a daunting task to collect data especially from home institutions and when it was made available, the quality was always questionable. A thorough process of quality control is more likely to leave the user with half the data required. As such, other types/sources of data such as remotely sensed data (e.g. for rainfall) could be explored to provide a wider coverage of rainfall distribution and complement the already existing records.

Areal rainfall estimated by Thiessen polygon method was used for this study. To reduce uncertainty of the model resulting from low quality, in future studies radar rainfall data should be used in addition to point measurements on the ground.

The limitations of conceptual models lie mainly in the lack of direct interpretation of some of their parameters in terms of catchments

characteristics. This will incur serious limit on the application of such models to ungauged catchments. On the other hand, when long records of rainfall and runoff are available, conceptual models can be successfully calibrated and used both for simulation and for real time flood forecasting.

The modules of the conceptual models that failed to reproduce different flow regimes (low and high flows) should be investigated and improved in future.

It has been established that changes in land cover have contributed more to increased runoff than climate change. Both these changes have occurred together to have an even greater impact than if each were acting alone. Thus mitigation measures with regard to problems of environmental degradation should take into account.

References

1. Abdo, K. (2008). Assessment of Climate Change impacts on the Hydrology of Gilgel Abbay Catchment in the Tana Sub Basin, Ethiopia.
2. Ashenafi, S. (2007). Catchment Modeling and Preliminary Application of Isotopes for Model in Upper Blue Nile Basin, Lake Tana, Ethiopia, M.Sc. Thesis degree at the UNESCO-IHE Institute for Water Education, Delft, the Netherlands.
3. Aster D. and Seleshi B. (2009). Characterization and Atlas of the Blue Nile Basin and its Sub basins, International Water Management Institute.
4. Belay, Z. (2008). GIS Based Hydrological Modeling for Woldiya Watershed and Hydraulic Modeling of Upper Shelle Reach, MSc Thesis, Arbaminch, Ethiopia.
5. Bergstrom, S. (1992). The HBV model - its structure and applications. In: Seibert, J., 2002. HBV light user's manual, Uppsala University.
6. Beven, K.J (2002). Rainfall-runoff modelling Lancaster University, UK
7. Genene, A. (2006). Inter comparison of the performance of different rainfall runoff hydrological model In Abaya- chamo river basin a case study of Bilate and Kulfo catchments MSc Thesis, Arbaminch, Ethiopia.
8. Hayalsew, Y. W. (2005). Water shed Modeling and management aspects of the Gilgel Abbay Sub basin, master thesis, Arbaminch University, Ethiopia.
9. Houghton-Carr, H. (1999). Assessment criteria for simple conceptual daily rainfall runoff models, Institute of Hydrology, Crowmarsh Gifford, Wallingford, Oxfordshire OX10 8BB, UK.
10. Hundecha, Y (2005). Regionalization of Parameters of a Conceptual Rainfall- Runoff Model University of Stuttgart Germany.
11. Jain, S. (1994). Calibration of conceptual models for rainfall-runoff simulation, National Institute of Hydrology, Roorkee, India.

12. Kebede, S. (2009). Comparison and Selection of Conceptual Rainfall-Runoff Models for selected Catchments in Abbay River Basin, Arbaminch University, Ethiopia.
13. Lauren Donnelly. (1990). Comparison of Rainfall-Runoff modeling techniques in small forested catchment, University of Alberta,.
14. Moreda, F. (1999) Conceptual Rainfall-Runoff Models for Different Time Steps with Special Consideration for Semi-arid and Arid Catchments Laboratory of Hydrology and Inter-University Program in Water Resources Engineering Vrije Universiteit, Brussels.
15. Muluneh, B. (2008) Evaluation of Impact of Climate Change on Water Resource Availability in the Catchments of Blue Nile Basin, Arbaminch University, Ethiopia.
16. Refsgaard, J.C. and B. Storm (1996). Construction, calibration and validation of hydrological models, in: Bayesian estimation of parameters in a regional hydrological model, In: Engeland, K. and L. Gottschalk (2002), Hydrology and Earth System Sciences 6(5), 883–898.
17. Seibert, J. (1997). Estimation of parameter uncertainty in the HBV model. In: Uhlenbrook, S., J. Seibert, Ch. Leibundgut and A. Rodhe (1999), Prediction of conceptual rainfall-runoff models caused by problems in identifying model parameters and structures, Hydrological Sciences, 44 (5): 779-797.
18. Seibert, J. (2002). HBV light user's manual, Uppsala University.
19. Sieber, A. and S. Uhlenbrook (2005). Sensitivity analysis of a distributed catchment model to verify the model structure, Journal of Hydrology 310: 216-235.
20. Sirak T. (2008). Watershed Modelling of Lake Tana Basin Using SWAT, Arbaminch, Ethiopia.

Appendices

Appendix A. 1: Monthly Mean Rainfall (mm) of Muger catchment

YEAR	January	February	March	April	May	June	July	August	September	October	November	December
1992	31.00	47.05	26.30	51.78	32.60	57.18	256.73	295.08	132.88	52.35	4.25	6.38
1993	11.05	55.15	9.23	122.85	81.13	83.18	349.41	272.23	155.00	35.93	0.00	1.40
1994	0.40	0.53	70.80	49.48	39.20	101.60	296.45	244.10	124.00	0.26	19.23	0.00
1995	0.00	37.93	39.90	116.50	43.45	50.08	340.76	295.68	96.90	1.35	0.00	22.24
1996	27.68	4.88	96.73	64.65	109.95	193.53	321.23	326.08	142.83	2.20	6.65	0.45
1997	35.10	1.03	45.90	73.40	26.78	115.60	276.63	221.18	58.88	85.80	35.03	0.90
1998	24.50	15.55	39.18	49.68	73.10	63.03	305.08	326.35	150.03	58.50	0.05	0.00
1999	13.45	0.08	20.33	8.53	15.08	90.85	361.01	399.33	69.20	65.78	3.55	0.38
2000	0.00	0.00	20.04	67.96	47.88	81.74	305.70	322.20	137.40	31.02	25.02	7.92
2001	2.86	15.00	121.98	27.06	94.76	119.50	391.80	245.62	64.40	4.68	0.86	3.96
2002	24.24	24.52	100.40	46.52	37.96	122.16	321.06	327.56	101.84	1.52	0.00	24.66
2003	24.74	40.04	60.16	117.88	6.22	159.22	418.34	386.60	215.74	0.72	2.60	22.96
2004	27.12	8.36	42.64	111.36	19.90	239.14	456.92	303.04	139.22	46.22	4.46	2.68
2005	46.88	31.65	66.48	103.01	127.83	175.26	366.55	351.87	198.25	6.17	3.01	0.00
Mean	19.22	20.12	54.29	72.19	53.99	118.00	340.55	308.35	127.61	28.04	7.48	6.71

Appendix A 2: Monthly Mean Evapotranspiration (mm/month) of Muger catchment

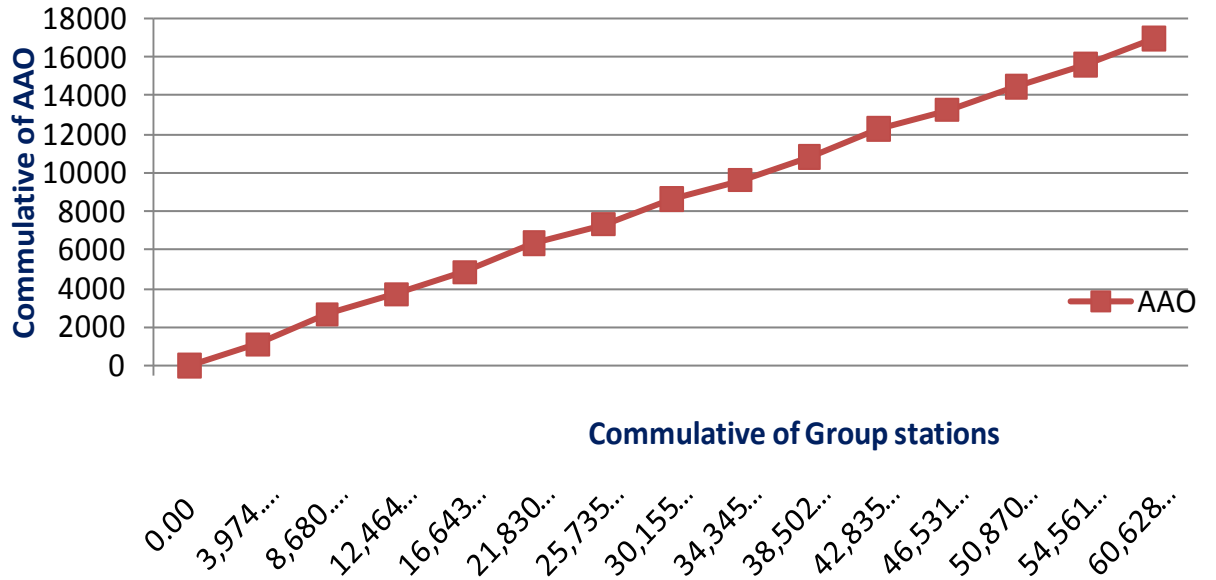
YEAR	January	February	March	April	May	June	July	August	September	October	November	December
1992	103.44	101.40	129.69	124.79	134.76	129.77	85.46	80.08	96.24	110.53	99.26	103.21
1993	102.97	98.09	138.67	107.67	119.48	104.56	86.34	89.57	88.83	114.03	109.09	109.62
1994	115.66	115.58	125.28	124.72	140.20	101.79	81.51	83.76	98.84	124.73	106.79	110.38
1995	114.13	108.52	129.60	109.43	128.78	117.63	82.96	88.57	100.96	119.95	109.42	101.89
1996	104.04	115.83	117.55	118.82	122.56	98.53	86.22	87.88	99.02	119.24	107.42	104.80
1997	103.83	118.02	130.34	120.99	142.32	116.13	86.51	91.09	113.66	115.49	102.26	107.47
1998	109.65	107.82	125.12	133.67	126.03	113.97	82.72	86.80	96.80	105.58	107.42	105.90
1999	108.73	116.27	125.06	131.39	138.24	113.31	82.18	90.43	101.23	105.99	107.56	105.57
2000	113.55	122.19	140.89	121.01	127.73	106.56	87.47	83.82	92.83	113.83	106.55	106.29
2001	106.24	114.22	100.43	136.71	121.02	97.96	83.83	84.53	101.76	116.92	110.68	109.24
2002	106.95	118.59	121.72	138.44	131.46	106.31	111.76	90.43	104.93	127.50	114.14	95.70
2003	106.90	114.55	129.69	119.67	147.34	105.56	80.08	85.68	93.29	123.23	108.45	103.21
2004	102.88	113.55	124.20	111.46	137.09	101.54	86.58	88.41	97.94	108.18	105.47	101.47
2005	101.35	114.03	125.92	120.06	117.75	104.63	83.15	94.37	99.54	116.23	105.52	107.42
Mean	107.16	112.76	126.01	122.77	131.05	108.44	86.19	87.53	98.99	115.81	107.14	105.15

Appendix A. 3: Monthly Mean Flow (mm/month) of Muger catchment

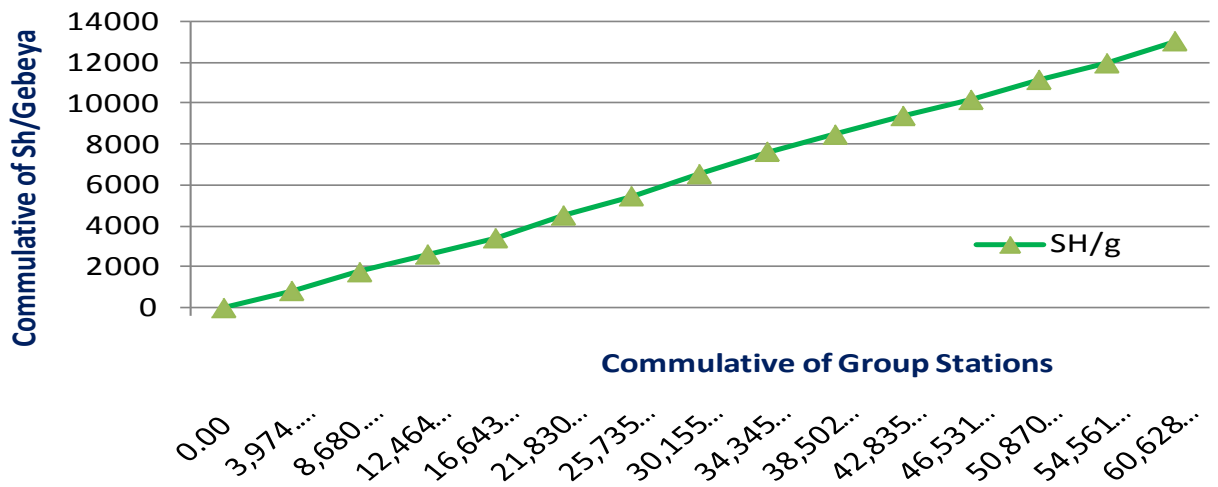
YEAR	January	February	March	April	May	June	July	August	September	October	November	December
1992	1.319	1.222	0.756	0.855	1.058	1.662	51.543	246.207	124.531	13.395	2.706	1.532
1993	1.110	0.836	0.620	1.920	2.578	6.617	166.706	349.159	227.549	29.141	4.024	1.923
1994	1.284	0.559	0.768	1.015	0.881	4.800	107.436	215.295	108.662	12.486	2.824	1.644
1995	0.884	0.960	0.844	2.003	1.804	1.910	79.740	197.876	61.662	6.992	2.050	1.467
1996	0.932	1.050	1.253	1.514	1.412	1.577	111.705	235.341	53.386	4.996	1.434	0.897
1997	0.596	0.327	0.313	0.597	0.349	0.991	67.155	156.886	50.098	4.246	2.088	1.035
1998	1.091	0.499	0.434	0.378	1.092	3.749	135.350	306.292	136.049	43.590	4.392	1.566
1999	0.994	0.271	0.392	0.274	0.313	1.546	69.392	313.205	97.284	21.426	2.987	1.256
2000	0.711	0.267	0.175	0.363	0.734	1.159	53.594	282.231	79.126	15.308	2.968	1.450
2001	0.871	0.387	0.970	0.952	1.786	18.077	161.270	229.782	80.433	5.789	1.678	1.003
2002	0.898	0.401	0.598	0.565	0.380	0.988	112.023	242.653	70.167	2.370	2.043	1.100
2003	0.681	0.301	0.418	0.771	0.416	3.079	209.523	273.570	202.597	20.565	1.573	0.921
2004	0.566	0.299	0.179	1.167	0.507	2.339	100.712	292.041	104.212	9.319	2.017	1.190
2005	74.545	57.811	63.239	68.604	102.972	106.862	510.747	928.992	532.049	156.838	92.759	83.077
Mean	6.177	4.657	5.069	5.784	8.306	11.097	138.350	304.967	137.700	24.747	8.967	7.147

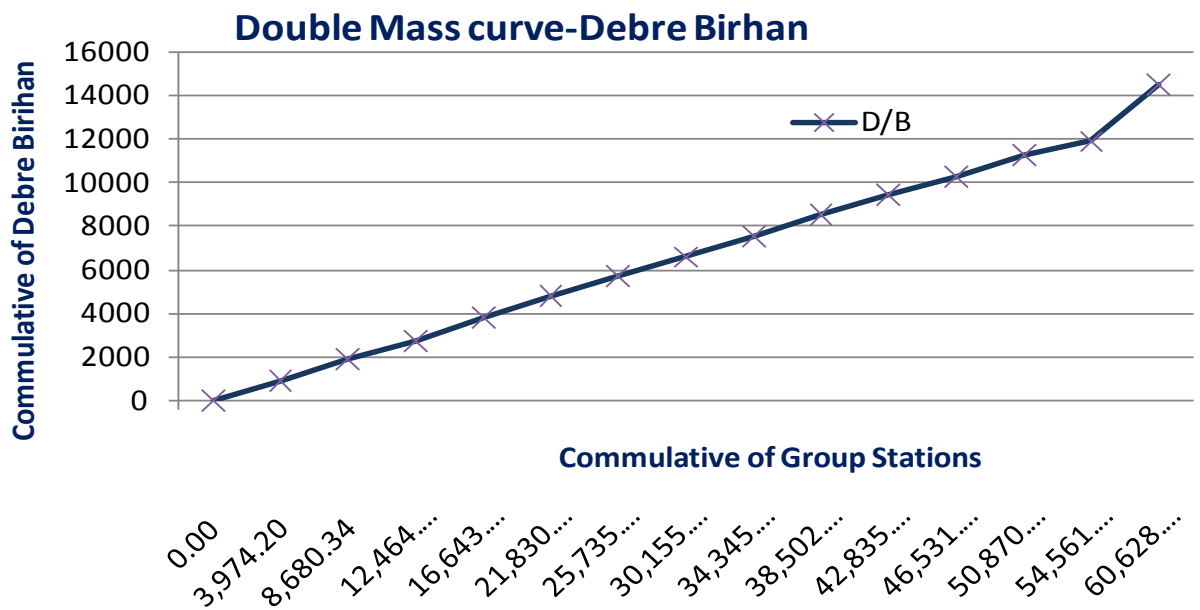
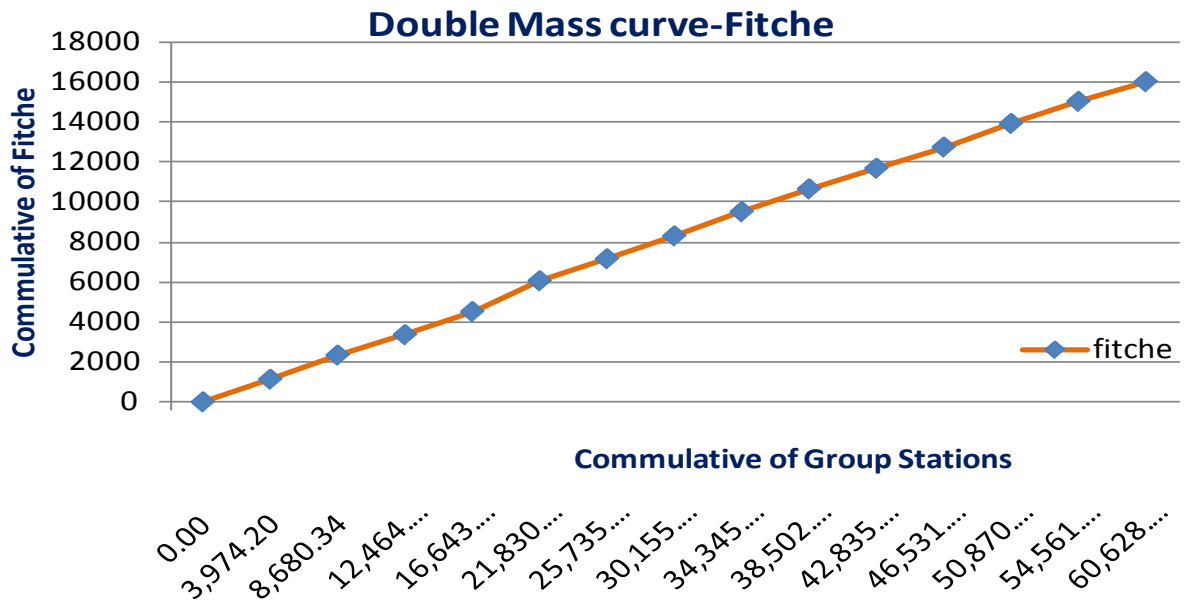
Appendix-B- Double mass curve analysis of rainfall data

Double Mass curve-Addis Ababa Observatory

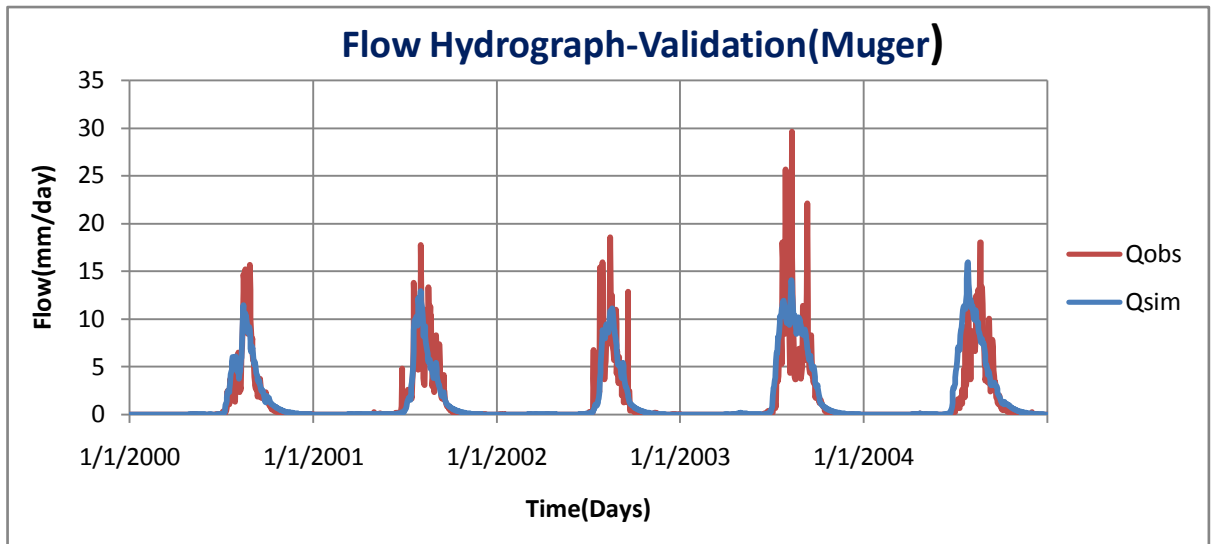
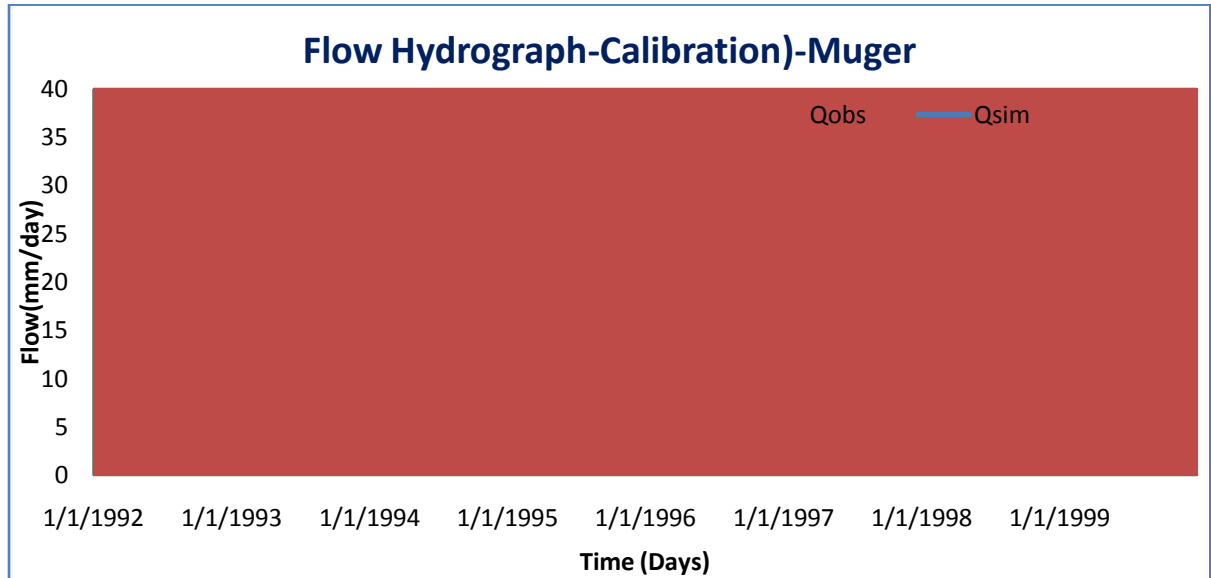


Double Mass curve-Shola Gebeya

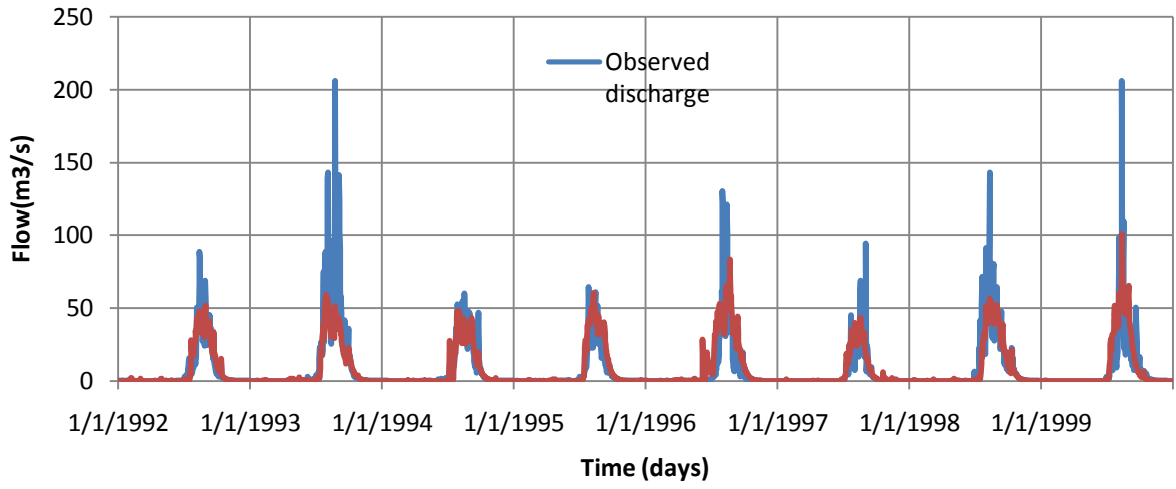




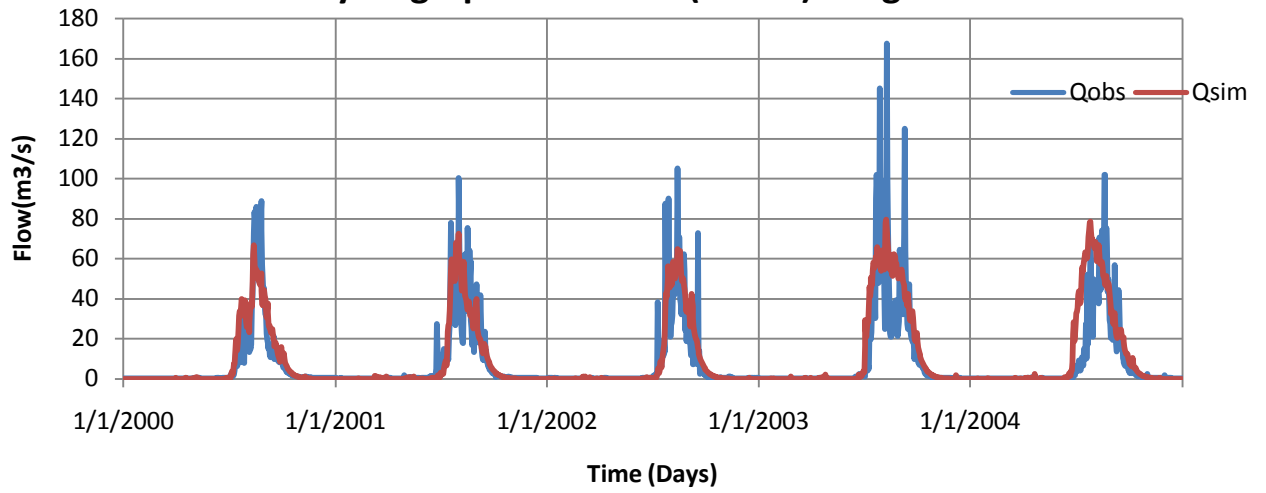
Appendix C- The hydrograph result in calibration and verification periods in Muger catchment (Daily Time Step)



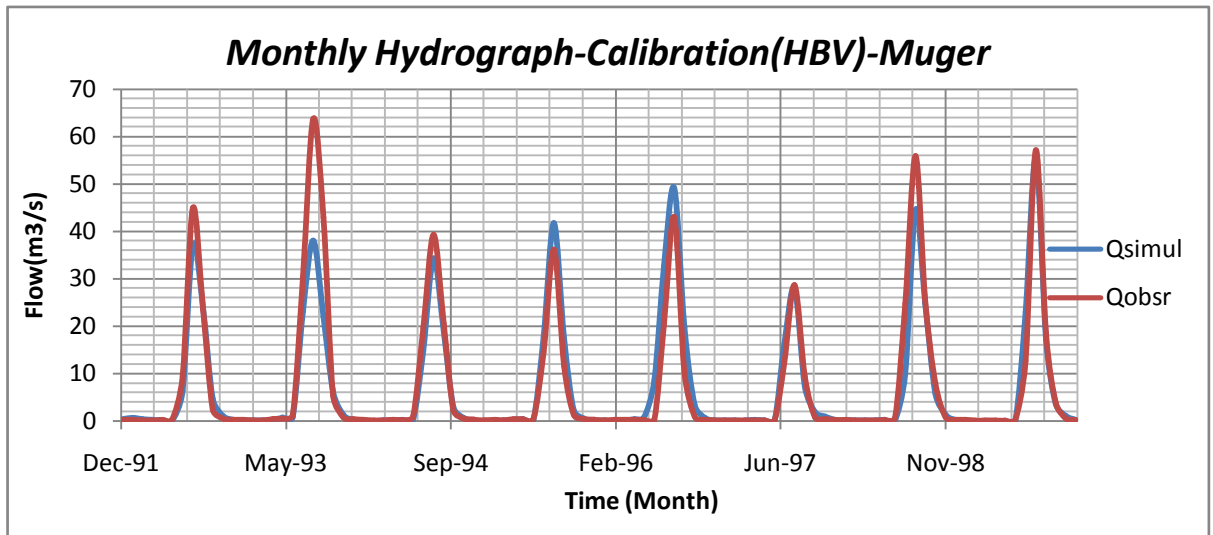
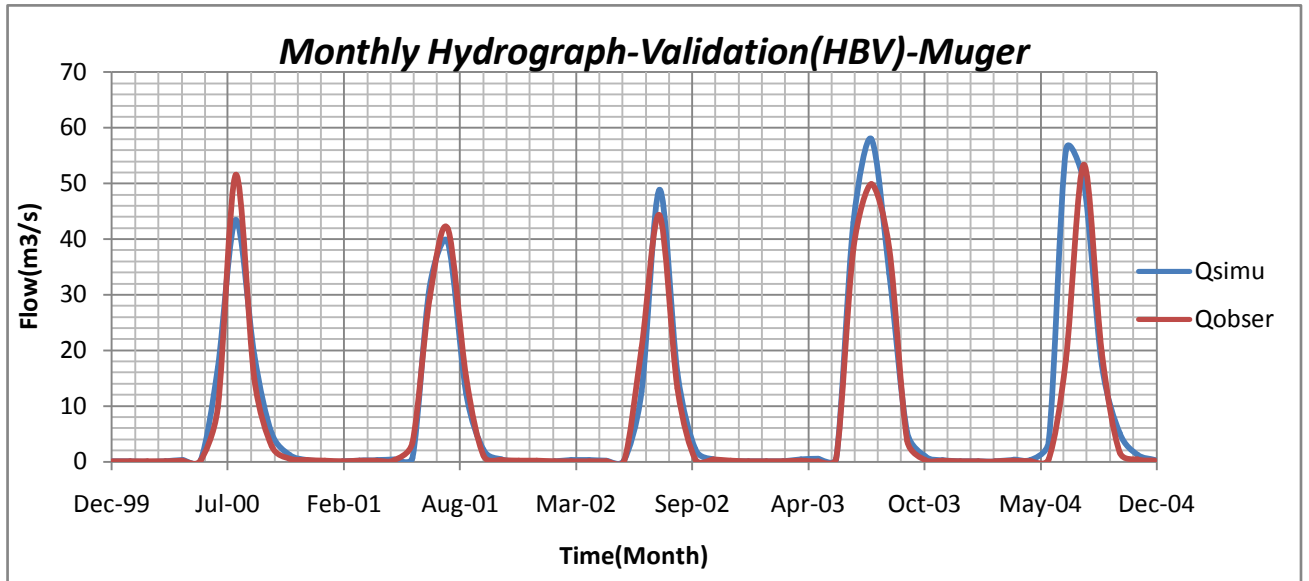
Flow Hydrograph-Calibration(SMAR)-MUGER

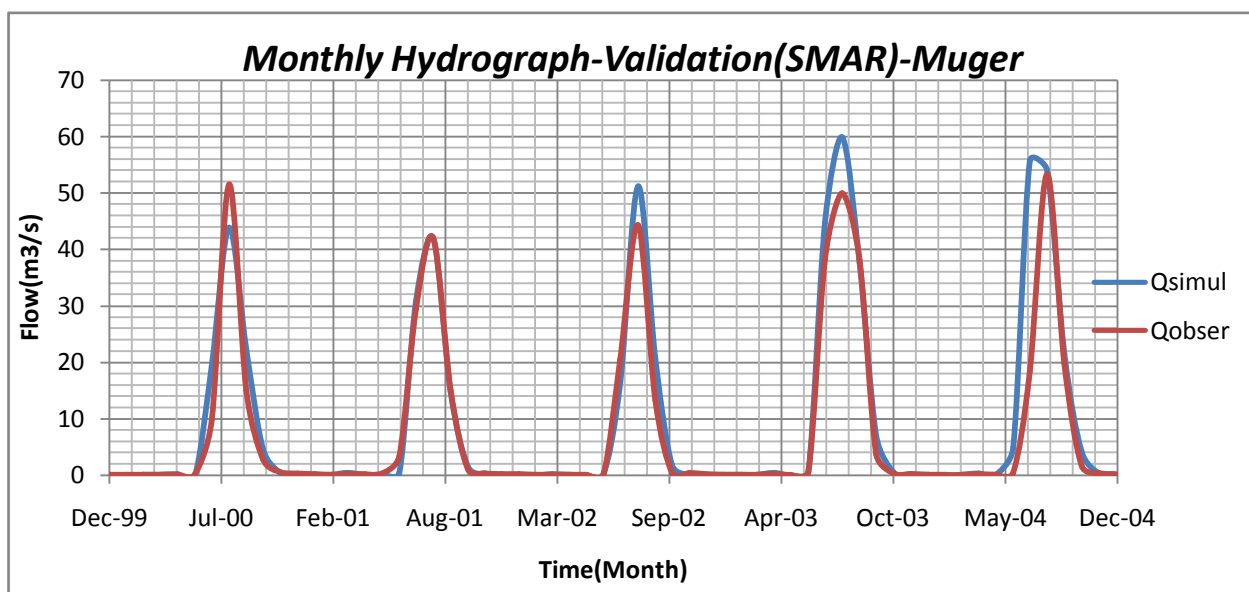
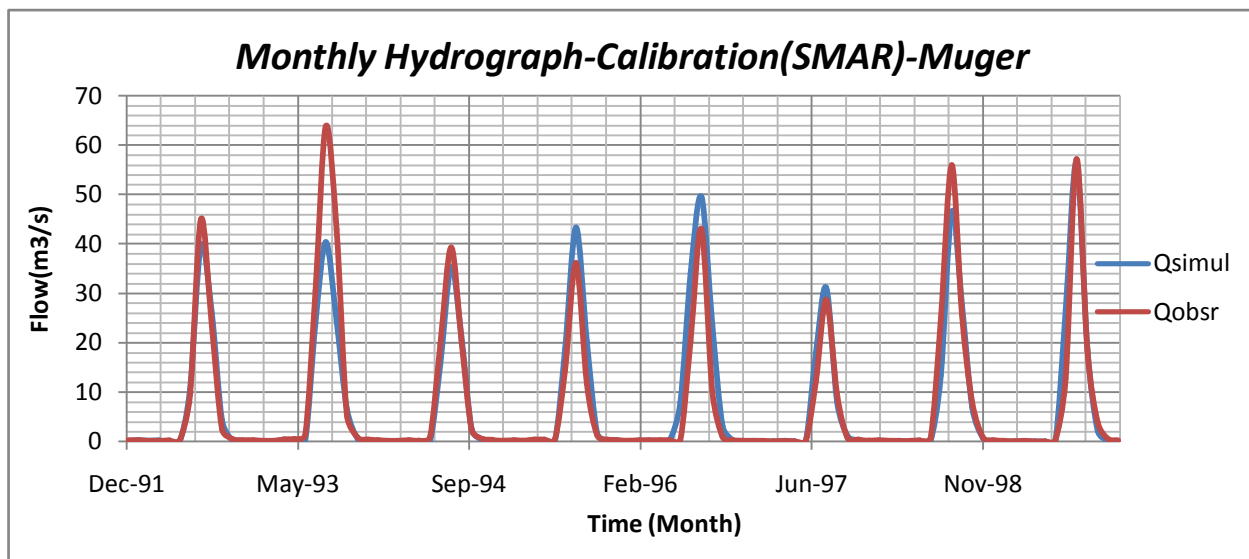


Flow Hydrograph-Validation(SMAR)-Muger

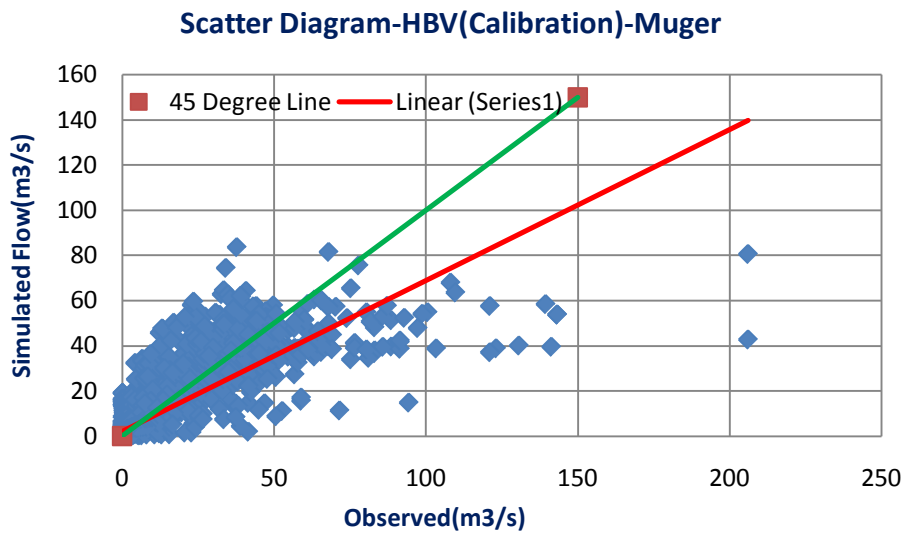
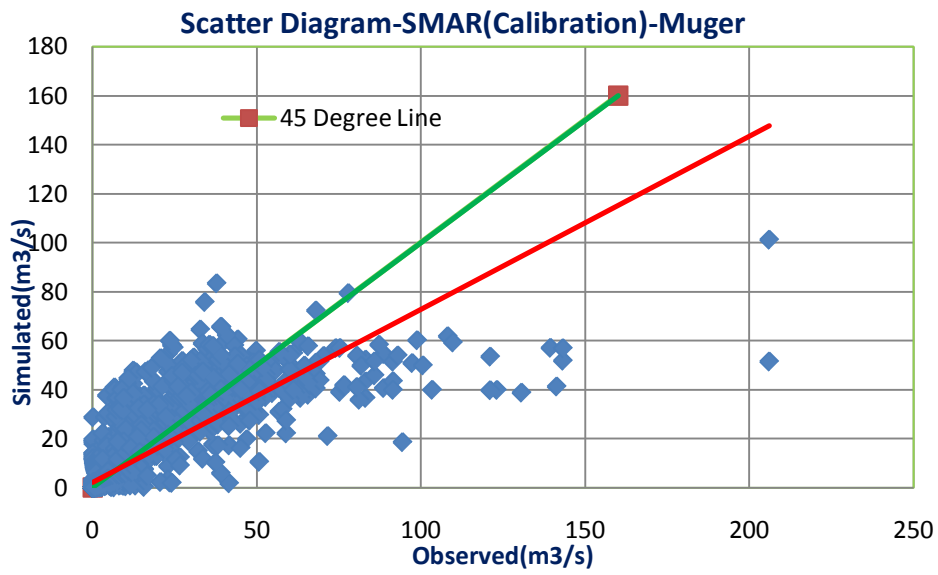


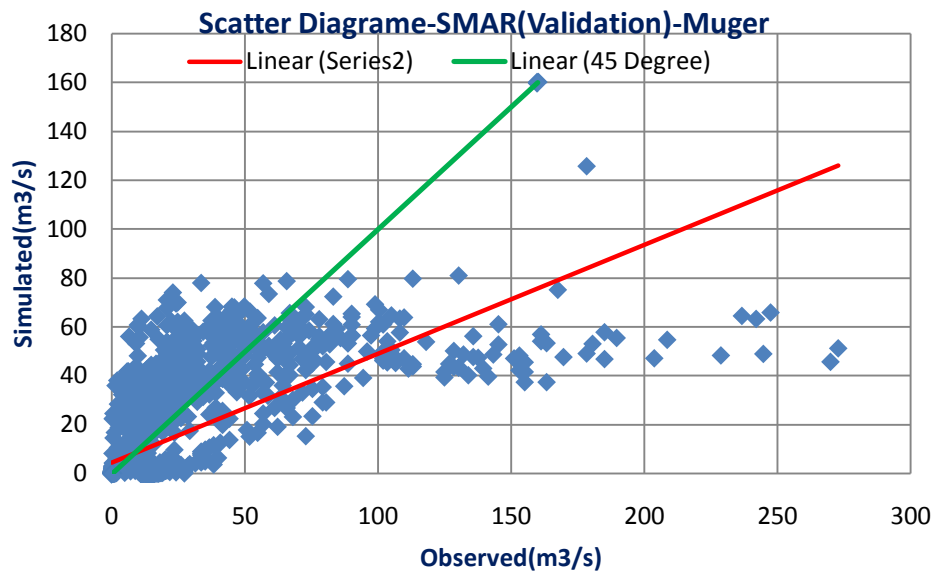
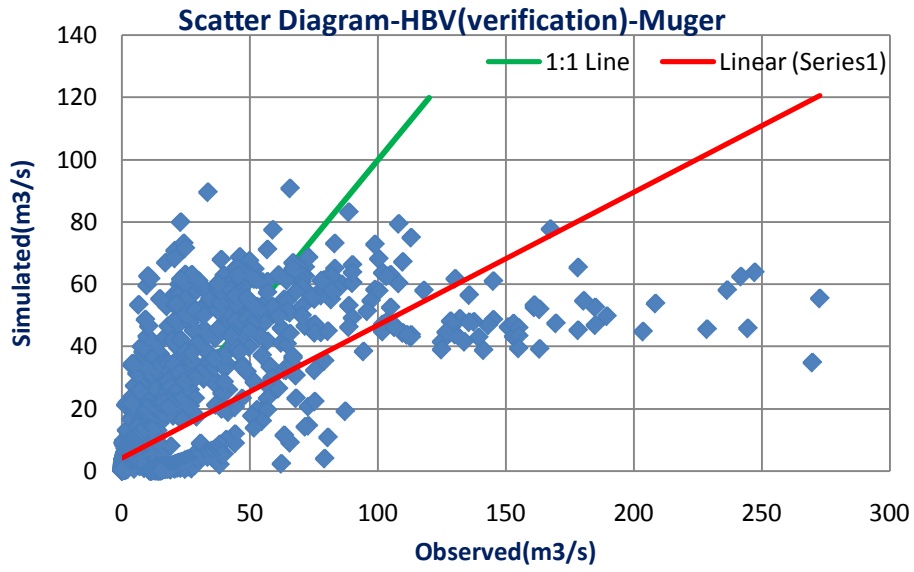
Appendix D- The hydrograph result in calibration and verification periods in Muger catchment (Monthly Time Step)





Appendix E- Simulated vs. observed scatter diagrams for Muger catchment





Appendix F- Residual diagrams during calibration and validation periods for HBV and SMAR

