PERFORMANCE EVALUATION OF CONCEPTUAL HYDROLOGICAL MODELS ON SHAYA WATERSHED, GENALE DAWA RIVER BASIN, SOUTH EASTERN ETHIOPIA

MSc THESIS

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Performance Evaluation of Conceptual Hydrological Models on Shaya Watershed, Genale Dawa River Basin, South Eastern Ethiopia

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POSTGRADUATE PROGRAMS DIRECTORATE

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DEDICATION

This Thesis is dedicated to my father Chimdessa Goshel, my mother Dinkitu Adamu and the entire family members for their love and support in my every walk of life.

STATEMENT OF AUTHOR

By my signature below, I declare and affirm that this thesis is my own work. I have followed all ethical principles of scholarship in the preparation, data collection, data analysis and completion of this thesis. All scholarly matter that is included in the thesis has been given recognition through citation. I affirm that I have cited and referenced all sources used in this document. Every serious effort has been made to avoid any plagiarism in the preparation of this thesis.

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BIOGRAPHICAL SKETCH

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ACRONYMS AND ABBREVIATIONS

AET	Actual Evapotranspiration
BCEOM Le	Bureau Central d'Etudes pour les Equipementsd'Outre-Mer
BCM	Billion Metric Cubic
CI	Confidence Interval
DEM	Digital Elevation Model
FAO	Food and Agricultural Organization of the United Nations
FDC	Flow Duration Curve
GHM	Global Hydrological Model
GIS	Geographic Information System
GLUE	Generalized Likelihood Uncertainty Estimation
HBV	Hydrologiska Byråns Vattenbalansavdelning
LPM	Linear Perturbation Model
m.a.s.l	meter above sea level
MC	Monte Carlo
MoWIE	Ministry of Water Irrigation and Energy
NMA	National Meteorological Agency,
PET	Potential Evapotranspiration,
SD	Standard Deviations
SLM	Simple Linear Model
SMAR	Soil Moisture Accounting and Routing
SNHT	Standard Normal Homogeneity Test
UNESCO	United Nation Educational Scientific and Cultural Organization
UTM	Universal Transverse Mercator
WASMOD-M	Water and Snow balance Modeling system
WaterGAP	Water Global Analysis and Prognosis model
WBM	Water Balance Model

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ABSTRACT

Robust hydrologic models are needed to manage water resources for healthy aquatic ecosystems and reliable water supplies, but there is a lack of comprehensive model comparison studies that quantify differences in stream flow predictions among model applications developed to answer management questions. This study was initiated with the objective to compare and select the best conceptual rainfall-runoff model that can be used in the design, planning, and management of water resources in the watershed and estimation of monthly and annual water balance at the Shaya watershed in Bale mountainous area. Daily rainfall, as well as daily potential evaporation and discharge, for the watershed were collected and prepared as input for the model. In this study GLUE based Monte Carlo was used to assess the uncertainty of the model parameter. The conceptual rainfall runoff models chosen for this study were SMAR and HBV-light. Sensitivity analysis, model calibration and validation were made to evaluate the models. The calibrated SMAR and HBV model performed well for simulation of daily stream flow. The models statistically performance measures, were very good with coefficient of determination (R^2) of 0.95 and 0.81, as well as the Nash-Sutcliffe efficiency (Reff) of 0.91 and 0.75 for both SMAR and HBV respectively. Performance of the model during validation period was with Reff 0.78 and 0.59 for SMAR and HBV respectively. The Mean monthly simulated discharge with the calibrated model were found to be 63.4 mm and 58.6 mm while the mean annual simulated discharge during calibration period found to be 790.29 mm and 721.6 mm for SMAR and HBV respectively. Overall, performance of the model demonstrated good in capturing the patterns and trend of the observed flow series. When we the performance of the two models SMAR gives better result than HBV model for selected watershed. For most parameters good results could be obtained over large ranges whereas a few parameters were well-defined over small ranges. Generally, an indication of the uncertainty in model simulations arising from the uncertainty in the parameterization was given by viewing the monthly simulation periods of discharge.

Keywords: HBV, SMAR and Watershed

1. INTRODUCTION

1.1. Background

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 for models are increasing, the use of these models to simulate a catchment response has become a standard. Rainfall-runoff models are critical for studies which focus on exploiting the untapped potential of surface water (Goswami *et al*., 2006), approximation of watershed yield and climate change impacts on stream flow characteristics (Chiew and Siriwardena, 2005). In general, the purpose of the development of hydrological models is a twofold. The first is to advance our understanding and state of knowledge about the hydrological processes involved in the rainfall-runoff transformation. The second is to provide practical solutions to many of the related environmental and water resources management problems (Mutua and Radwan, 2006).

With the new development of computer aided tools and more detailed information, there is an increasing trend to use distributed or semi-distributed models (Eder *et al*., 2005). They provide more detailed distributed results on a catchment scale approximating heterogeneities of the system. However, uncertainty at high resolution may diminish potential gains in prediction accuracy (Carpenter, 2006). Nevertheless, despite their simplicity, lumped models perform well in many studies (Yang *et al*., 1995; Cameron *et al*., 1999; Uhlenbrook *et al.*, 1999; Yang and Michel, 2000; Asfaw *et al*., 2014). However, they do not need as much data as the distributed models (which are unavailable in many cases), and the complexity and requirements to process them are lower. Furthermore, calibration of the lumped models parameter is much less time consuming and produced higher overall model performance in comparison to the more complex distributed models (Vansteenkiste *et al*., 2014). They are particularly useful in small data-rich catchments and are used in conjunction with field studies (Chiew, 2010). Various studies have been conducted to compare distributed and lumped models (Boyle *et al*., 2001; Koren *et al*., 2004; Zhang *et al*., 2004; Asfaw *et al*, 2014). The suitability of a model depends on the basin and specific regional characteristics.

Challenges remain widespread and reflect severe problems in the management of water resources in many parts of the world (Cosgrove and Rijsberman, 2014). These problems will intensify unless effective and concerted actions are taken. Scarcity and misuse of fresh water pose a serious and growing threat to sustainable development and protection of the environment. So, to mitigate this problem and to make efficient use of available water resources with balanced attention to maximized economic, social, and environmental benefits, it is necessary to have effective integrated water resource planning. Accordingly, the effective integrated water resource planning calls for use of hydrological models. Before using any hydrological model for planning activity for water resources development works in a certain river basin, it is essential first to select and evaluate the hydrological model for the planning of water resource management. However, from a water resource assessment point of view, the primary objective of modeling is often to generate a long representative time series of stream flow volumes for the purpose of planning and management of water resources (Hughes, 1995).

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. Hence, in order to develop any water resource development work the knowledge of stream flow is very important.

1.2. Problem statement

Shaya watershed is one of the watersheds draining in to river basin of Genale Dawa, and it is under threat due to the growing population and increasing demand of water mainly for irrigation as well as, a great demand of water for domestic and livestock consumptions. Even though, there have been little studies about Shaya watershed, so there is need to assess and study the hydrology of the watershed that help in assessing the water resource potential of the watershed.

Hence, assessment of water resource potential with great certainty and understanding the hydrological processes in the catchment has become important to manage and to make optimal use of water resource development alternatives. As hydrological assessment tool, the output of this study can be used to study and design water resources development projects like estimating irrigation potential area within the catchment, assessing the water potential of the catchment, flood forecasting and design of hydraulic structures. Furthermore, the study will help to quantify the total volume of water flowing in the basin stream in different seasons thus supporting to efficient planning and management of the available water resources within the basin.

So, robust hydrologic models are needed to help manage water resources for healthy aquatic ecosystems and reliable water supplies for people. However, there is a lack of comprehensive model comparison studies that quantify differences in stream flow predictions among model applications developed to answer management questions. Conceptual rainfall-runoff models, which simulate the interaction between rainfall and runoff using the water balance theory, are the most commonly used tools to estimate the potential volume of water available within a basin. Among these models HBV and SMAR conceptual hydrological models are widely used in Ethiopia. These models are conceptually simple to simulate stream flow and they require minimum data to run the models.

Each model works within specific spatial (field to basin) and temporal (event based to annual water balances) boundaries and can only simulate specific hydrological processes. It is important to select the 'right' model for the 'right' kind of modeling exercise. Therefore, there is the need to evaluate the models which can be used to estimate these resources and to avoid underestimation of prediction errors, analyzing predictions generated by several alternative models.

1.3. Objectives

The general objective of this study was, therefore, to compare and select the better conceptual rainfall-runoff model that can be used in the design, planning, and management of water resources in Bale mountainous region of the Shaya river watershed with the following specific objectives:

- To compare the Hydrologiska Byråns Vattenbalansavdelning (HBV) and Soil Moisture Accounting and Routing (SMAR) hydrological models on the Shaya watershed.
- To conduct uncertainty analysis of the model parameters.

2. LITERATURE REVIEW

2.1. The Hydrological Cycle

The hydrological cycle is a complex and dynamic system that is strongly interconnected with the energy and biogeochemical cycles (Hagemann, 2011; Pagano and Sorooshian, 2006). It describes the continuous movement and retention of water through and in the Earth's spheres, driven by solar energy and gravitation (Brooks *et al*., 2012).

In this cycle, atmospheric water vapor precipitates on the Earth's surface, eventually flows as runoff to the ocean or inland water sinks while being transferred through the soil, the ground and/or surface water bodies, and finally evaporates again. There by, water fluxes and storage conditions are strongly interconnected and influenced by various climatic and physio-geographic factors. For instance, dependent on temperature, precipitation most commonly occurs as rain or snow, but also includes drizzle, sleet, hail, and in a broader sense fog, dew and frost. Besides temperature, also wind, topography, vegetation and physical obstructions determine the deposition and accumulation of snow and ice. Whether snowmelt and liquid precipitation infiltrate depends on various factors such as the moisture status of the soil, its maximum water-holding capacity, the network and size of pores within the soil matrix, the condition of the soil surface including the vegetation cover, as well as rainfall and snow melt rate. Additionally, human activities influence the hydrological cycle among others by building reservoirs, withdrawal from water storages, or land-use activities that modify vegetation and water bodies, which in turn influences for instance evapotranspiration and the distribution of snow (Brooks *et al.*, 2012).

While its allocation in storage or circulation varies in time, the mass of water remains constant on the global scale. Thus, the components of the hydrological cycle can be estimated for a distinct area by the water balance. Accordingly, input by precipitation P equals the output represented by evapotranspiration (ET) (comprising transpiration, evaporation from interception, bare soil and open water surfaces) and stream flow (Q) (including surface runoff, interflow and base flow) and the change of storages (ΔTWS) such as ice, snow, soil moisture, ground water and surface water bodies as shown in Equation (1) (Schmidt *et al*., 2008).

$$P = ET + Q \pm \Delta TWS \tag{1}$$

where : P = precipitation

ET = evapotranspiration

ΔTWS = change of storages

Q = stream flow

2.2. Hydrologic Modeling

In general, a model is a simplified representation of a real world system, and consists of a set of simultaneous equations or a logical set of operations contained within a computer program (Wheater, 2005). Hydrologic models are simplified, conceptual representations of the different parts of the hydrologic cycle using mathematical representations of the processes involved in the transformation of climate inputs : precipitation, solar energy and wind: through surface and subsurface transfers of water and energy into hydrological outputs (typically, flow in rivers, soil moisture content or water levels in groundwater aquifers (Hughes, 2004).

These models generally came in to use in the 1960s and 1970s when demand for numerical forecasting of water quality was driven by environmental legislations in the United States and United Kingdom. At about this time computers became more widely accessible and powerful enough to significantly assist in modeling processes. There are many hydrological models with unique and common characteristics that are being developed day by day (Wang et al., 1996 and DHI, 2004). The unique and common characteristics of many models make classifications of hydrological models an important issue so that the capabilities and limitations of each model can be identified accurately. Proper classification can be helpful for engineers, experts and researchers to understand the characteristics of models before deciding to employ them for their works. However, the categorizations of hydrological models can be hammered by considerable overlapping characteristics among various classes of models. As a result, even the classification of hydrological models may vary depending on justification (Gosain *et al*., 2009).

Also important in determining the selection of model is whether it is distributed (i.e. capable of predicting multiple points within a river) or lumped. Simple models may only address a single pollutant, whereas a complex model could have multiple runoff and point sources for pollution for more than one chemical, as well as sediment data. It could further divide the channel flow in to strata in which various biotas are modeled in relation to chemical and sediment transport. The ground water component may also be presented in a model (Kim and Kalurachchi, 2008).

Models often address individual steps modularly in the simulation process. Typically sub-routines for surface runoff include components for a land use type, topography, soil type, vegetation cover, precipitation and land management practice (regular agricultural activities e.g. pesticide or fertilizer application).

The predictions of the model are directly compared with measurements for two purposes. First, most water resource models include "free parameters," i.e. variables used in the mathematical formulation for which direct measurements do not exist. These can be estimated by adjusting their values until the resulting model prediction agrees with measurements, a process referred to as model "calibration." Second, the model is operated under the same external conditions as encountered during collection of a set of field data, and the model predictions compared to the field measurements, without any adjustment or "fitting" of the model, to evaluate the performance of the model, a process referred to as model "verification."(Beven, 2012).

Many hydrologic models have been developed to help manage natural resources all over the world. Nevertheless, some models have presented a high complexity regarding data base requirements, as well as, many calibration parameters. This has brought serious difficulties for applying them in watersheds where there is scarcity of data (Beskow et al., 2011).

Most hydrologic models are too complex to be used in areas with limited data (Beskow *et al*., 2009). Under this aspect, a model with a simple approach which makes use of less data may be preferable for better water resource management.

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, 2007).

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 (Beven. 2012).

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 (Beven, 2012). 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 of hydrological models is illustrated in Figure 1.

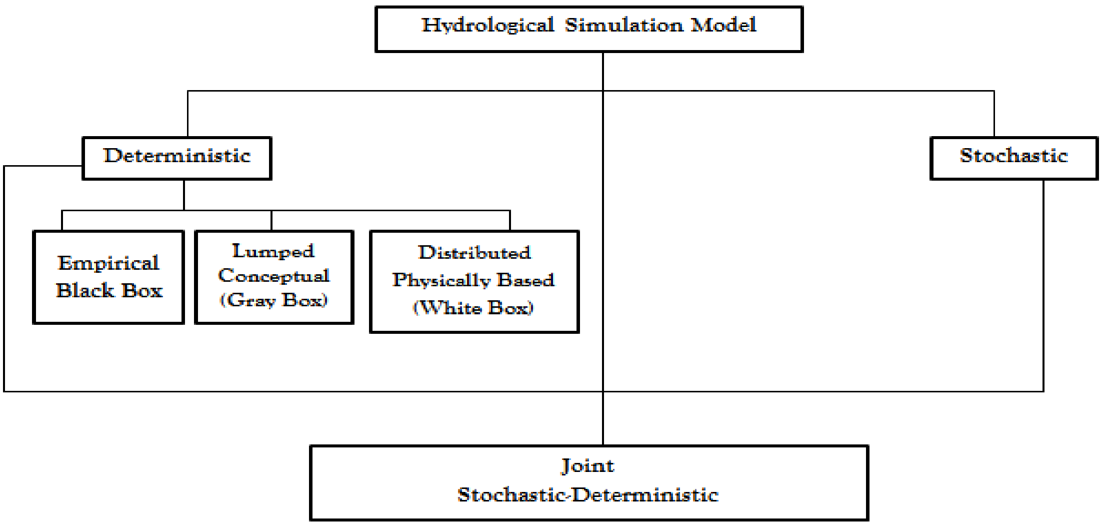

Figure 1.Classification of hydrological models according to process description (source: Refsgaard, 1996)

There is no single way to classify the hydrological models. Based on the criteria of interest to describe and discuss strength, capability and limitations, the hydrological models can be classified in different ways. Based on the description of physical process, the hydrological models can be classified into three groups: Empirical (data driven models), Conceptual, and, Physically based. Based on the spatial representation; lumped, and distributed. Based on the aspect of randomness: Deterministic and Stochastic (Singh and Frevert, 2002; Džubáková, 2010; ESCAP, 2016). Hydrologic models can also be classified as (a) lumped and distributed parameter models, (b) conceptual and hydrodynamic.

In case of empirical (or data driven) hydrological models the mathematical correlations are obtained based on the observed data analysis rather than based on the physical processes in the catchment. The empirical models which also known as "black box" models are again classified into four categories (Refsgaard, 1996; Džubáková, 2010): unit hydrograph based/ linear model; Linear regression and gauge to gauge correlation models; Auto regressive (AR) models (e.g., ARX, ARMAX), and Hydro-informatics based models those based on concept of working neurons (e.g., ANN, WANN, fuzzy logic, and genetic algorithms, OE, Box-Jenkins, and state-space models). In case of the conceptual hydrological models, the physically based system is conceptually represented based on simple principles (e.g., SSARR, TANK model, HBV, XINANJIANG, UBC, NAM, SACRAMENTO, and Symhyd models). Due to representation of the catchment as a series of interconnected storage components and empirical equations for computing the various fluxes the conceptual models are also referred as soil moisture accounting (SMA) models. In case of conceptual models, the parameters are obtained through model calibration. Although the significant hydrograph features can be accurately forecasted by using the conceptual models, they should be applied cautiously especially when they are required to apply for the hydrologic predictions falling outside the range of calibration data (Džubáková, 2010).

Semi-distributed models may adopt a lumped representation for individual sub catchments. Distributed models break space into discrete units, usually square cells (raster's) or triangular irregular networks (TIN) or irregular objects so the parameters, inputs, and outputs vary spatially. There other spatial classification divides models into one-dimensional, two-dimensional and three-dimensional (Moradkhani and Sorooshian, 2008).

2.3. Application of Models for Water Resource Management

Absence of appropriate water management is one of the challenges faced by mankind since history. Many regions are already water scarce currently and projections on future water resources indicate a worsening of the situation. Important to realize is that agriculture is the dominant consumer of water and any changes in water consumptions patterns in this sector will have a substantial impact on total water resources (Shiklomanov and Rodda , 2004)

To feed the growing population requires substantial amounts of water (Seckler *et al*.,1999) estimated that by 2025 cereal production will have to increase by 38% to meet world food demands. The World Water Vision, as outcome from the Second World Water Forum in The Hague in 2000, estimated a similar figure of 40% based on various projections and modeling exercises (Cosgrove and Rijsberman, 2014). Global estimates of water consumption per sector indicate that irrigated agriculture consumes 85% from all the withdrawals and that this consumptive use will increase by 20% in 2025 (Shiklomanov, 1998). Gleick (2000) presented estimates on the amount of water required to produce daily food diets per region.

References given before are related to the global scale, but it is very clear that at smaller scales, such as basins, extreme variations will occur and many basins with tremendous water problems can be found. Despite the fact that the basin is the most appropriate scale to analyze water management issues, in terms of food supply the field scale should be added and, in case of irrigated agriculture, the irrigation system scale as intermediate between basin and field (Droogers *et al.* , 2006).

The most important aspect of applying models however is in the use to explore different scenarios. This can relate to aspects that cannot directly be influenced, such as population growth and climate change. These are often referred to as projections. On the contrary to this are the so-called management scenario's where water managers and policy makers can make decision that will have a direct impact. Examples are changes in reservoir operations, water allocation and agricultural/irrigation practices. In other words: models enable to change focus from a re-active towards a pro-active approach (Droogers *et al*., 2006).

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2.4. 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 in modeling. Accordingly the model user community suggested four criterions for selecting model structures as below (Xu, 2002 and Vaze *et al.*,2012).

a. Consider models which are readily available and whose investment of time and money appeared worthwhile.

b. Decide whether the model under consideration will produce the outputs needed to meet the aims of a particular project.

c. 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.

d. 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.

2.5. Merits of Conceptual Hydrological Model

There are many models to choose from when it comes to hydrological rainfall-runoff modeling. The models can be very advanced with high spatial and temporal resolution and entirely physically based, while other models are much simpler, such as lumped conceptual models.

Today it is common to use physically based distributed models. These models can work with large amounts of different input data resulting in a high complexity in the modeling.

This can be useful when trying to understand different processes. The problem is that it can be difficult to operate such models (both with regards to the data availability, the skills needed to operate the model and the software/hardware configurations).

Distributed physically based models are often based on nonlinear partial differential equations for Darcian flow. These models demand input data such as hydraulic conductivity, different soil properties and overland flow roughness (Beven 1993). All of these inputs can be difficult to acquire especially in the spatially continuous manner typically required by physically based models. It is also difficult to know the uncertainties for this kind of data. These complex models demand extensive calibrations and results can have large uncertainties.

Distributed physically based models are designed so that their parameters should be physically measurable (Beven 1993). This is not the case for conceptual models and is often seen as an advantage of physically based approaches. Still, there often exists incommensurability between what we measure in the field and what a model parameter represents. Many simpler models can give equal performance to more complex models.

Therefore a simple model with high performance is often considered the best model to use. This statement is also supported by for example Jakeman & Hornberger (1993) and Perrin *et al*. (2001). This is particularly true as simple models allow for more transparency into the interaction between various parameters.

Lumped conceptual models are generally easier to operate and do not demand large amounts of input data. Conceptual models mainly represent the transformation from precipitation to runoff. Despite the simplicity of lumped conceptual models they have proved to be efficient and useful when used for e.g. water management. A computation time for these simpler models makes it possible to run the models for several catchments allowing for inter comparison analysis (Perrin *et al*. 2001).

2.6. Model Calibration and Evaluation Methods

In Hydrological Model, especially conceptual ones, parameters do not always correspond to physically measureable properties and thus cannot be determined directly. Therefore, they have to be estimated indirectly, by searching a parameter combination that leads to an optimal match between modeled variables and concurrent observations. This process is calibration. It can either be conducted manual, by 'trial and error', or by using automatic optimization techniques (Fischer, 2013). While manual parameter adjustment is time and cost-consuming and involves subjective judgment, automatic techniques based on mathematical algorithms are capable to solve complex problems fast and objectively (Xu, 2002). Often, calibration is impeded by parameter interactions and multiple parameter sets gain equal acceptable model performance (Beven, 2006). Due to this problem of equifinality, automatic techniques may generate unrealistic solutions and thus still require user expertise to verify the optimized parameter values. Additionally, parameters are usually adjusted within a range of possible values that is based on knowledge of the hydrology in the respective area, literature values or measurements (Fischer, 2013; Xu, 2002).

Basin-scale hydrological model are traditionally calibrated against observed river discharge, as these point-measurements integrate over processes in the whole upstream basin (Döll *et al.*, 2016). In contrast, Global Hydrological Model (GHMs) have rarely been calibrated, with a few exceptions such as Water Global Analysis and Prognosis model (WaterGAP) and Water and Snow balance Modeling system (WASMOD-M). For them, one or two parameters are adjusted by evaluation of simulated against observed river discharge. Calibration in a broader sense also includes tuning of adjustment factors in order to reduce the bias between model output and observations, which for example is performed for WaterGAP and Water Balance Model (WBM) (Döll *et al.*, 2016 and Sood and Smakhtin, 2015).

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 (Refsgard and Storm, 1990).

The calibrated model's performance and suitability is evaluated in a validation process, by comparing the model's output with independent information, either from data of the same catchment not utilized for calibration (split sample test) or data from another basin (proxy basin test). While simple split sample testing examines the transferability of the model under stationary conditions, differential split sample testing checks for the model's validity under transient conditions by dividing the time series e.g. in a wet and dry period. Similar, the proxy basin test, which verifies spatial transferability, can be combined with differential split sample testing (proxy basin differential split sample test) (Xu, 2002).

To assess model performance objectively during both, calibration and validation, statistics that estimate the error between simulated and observed variables are used (Legates and McCabe, 1999). In the course of this, errors of the observational data are usually neglected and measurements are assumed to represent the ground-truth (Döll *et al.*, 2016 and Moriasi *et al.*, 2007).

In general, GHMs are calibrated and evaluated either on the eco region, climate or continental scale, or, similar to traditional Hydrological Model, against discharge observations from large river basins, whereby the number of considered basins varies depending on the study (Sood and Smakhtin, 2015). Although most GHMs run on daily time steps, calibration and evaluation is conducted on monthly or long-term annual scales.

The model performance (including sensitivity analysis, calibration, and validation) evaluated using indicators: Nash-Sutcliffe efficiency (ENS); -∞ to 1.0 (perfect fit) (Nash and Sutcliffe, 1970), coefficient of determination (R); 0 (no correlation) to ±1.0(perfect linear relationship), percent bias (PBIAS, %); 0 (optimal value) to ±100 (volume difference tendency against observed counterparts) (Moriasi et al., 2007), and root mean squared error (RMSE); 0 (perfect fit) to ∞ (only used for model sensitivity analysis) from Equation (2-5). For all cases of model simulation performance evaluation, the statistics computed for comparisons of observed and simulated stream flow are for the periods of model simulation (for direct runoff), not the total storm event duration.

$$E_{NS} = 1 - \frac{\sum_{i=1}^{n}(O_i - S_i)^2}{\sum_{i=1}^{n}(O_i - \bar{O}_i)^2} \tag{2}$$

$$R^2 = \left[\frac{\sum_{i=1}^{n}(O_i - \bar{O})(S_i - \bar{S})}{\sqrt{\sum_{i=1}^{n}(O_i - \bar{O})^2}\sqrt{\sum_{i=1}^{n}(S_i - \bar{S})^2}} \right]^2 \tag{3}$$

$$PBIAS = \frac{\sum_{i=1}^{n}(O_i - S_i)}{\sum_{i=1}^{n} O_i} * 100 \quad (4)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(O_i - S_i)^2}{n}} \quad (5)$$

$$Mean\ Difference\ (D) = \frac{\sum(O_i - S_i)}{No\ of\ days} 365 \quad (6)$$

where: O_i and S_i are the observed and simulated stream flow respectively and $\bar{O}$ and$\bar{S}$ are the averages of observed and simulated stream flow, respectively

2.7. Conceptual Rainfall Runoff Models

2.7.1. HBV light model

HBV model simulates daily discharge using daily rainfall, temperature and potential evaporation as input (Seibert, 2005). 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 bellow TT, is multiplied by a snowfall correction factor, SFCF [-]. Snowmelt is calculated with the degree-day method (Equation 7). 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 8. 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 9). 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 10). 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 11). This runoff is finally transformed by a triangular weighting function defined by the parameter MAXBAS (Equation 12) 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 [ºC / 100 m] (Equation13 and 14). The long-term mean of the potential evaporation, Epot, M for a certain day of the year can be corrected to its value at day t , Epot (t), by using the deviations of the temperature, T(t), from its long-term mean, TM , and a correction factor, CET [°C^{-1}] (Equation 10).

$$melt = CFMAX(T(t) - TT) \tag{7}$$

$$refreezing = CFR\ CFMAX(TT - T(t) \tag{8}$$

$$\frac{recharge}{P(t)} = \left(\frac{SM(t)}{FC}\right)^{BETA} \tag{9}$$

$$\mathrm{E_{act}} = \mathrm{E_{pot}} \min\left(\frac{SM(t)}{FC.LP}, 1\right) \tag{10}$$

$$\mathrm{QGW(t) = K2SLZ + K1SUZ + Komax(SUZ - UZL, 0)} \tag{11}$$

$$Qsim(t) = \sum_{I=1}^{MAXBAS} c\ (\mathrm{i}) Q_{GW}(\mathrm{t - i + 1}) \tag{12}$$

where$C(i) = \int_{i-1}^{t} \frac{2}{MAXBAS} - \left| U - \frac{MAXBAS}{2} \right| \frac{4}{MAXBAS^2}$ du

$$P(h) = P_O\left(1 + \frac{PCALT(h - h_o)}{10000}\right) \tag{13}$$

$$T(h) = T_O - \frac{TCALT(h - h_o)}{100} \tag{14}$$

$$E_{pot}(\mathrm{t}) = \left(1 + C_{ET}(\mathrm{T(t)} - T_M)\right) * E_{Pot,M} \tag{15}$$

where:

• 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]

• Qi = Runoff component

•E = Evaporation from the lake

• P = Precipitation into the lake

• Ki = Recession coefficient [1/d]

• PERC = Maximum percolation to the soil lower zone [mm/d] [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 $PERC/K_2$

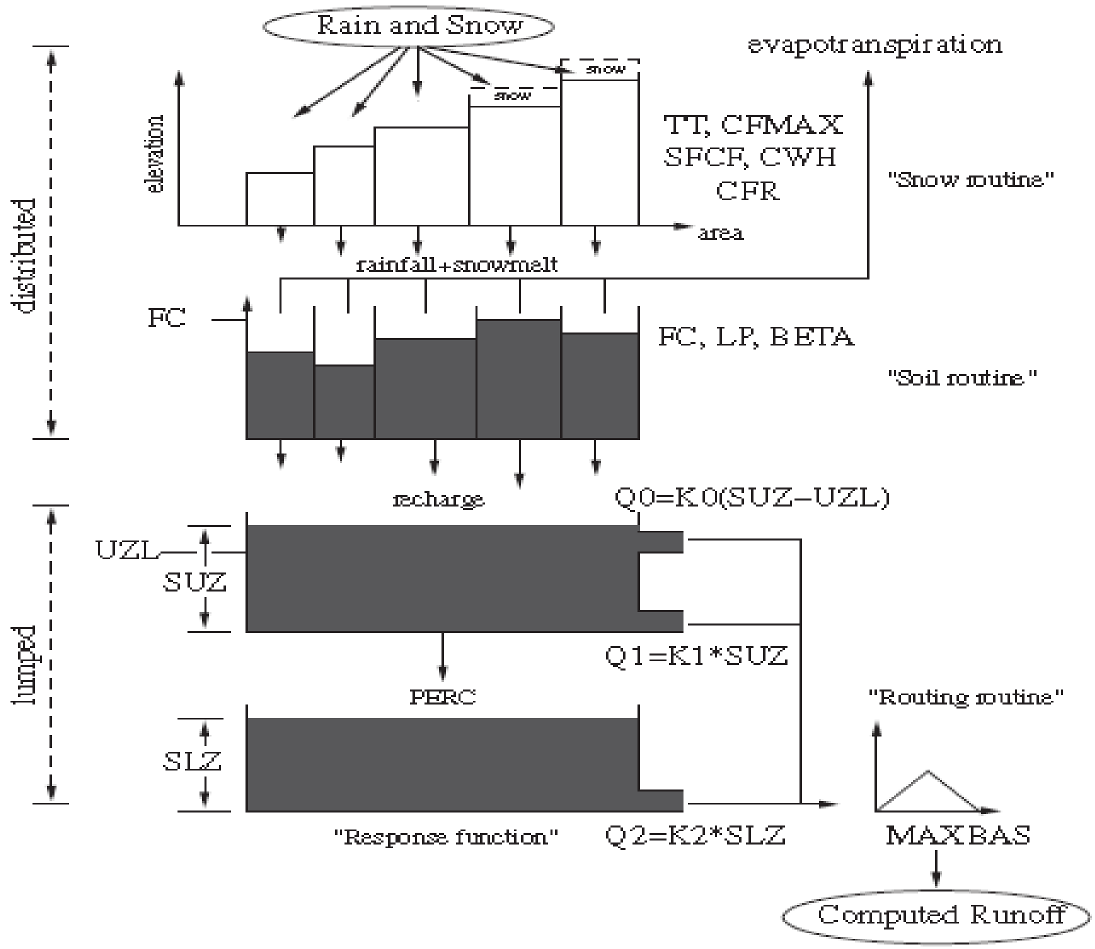

Figure 2. HBV model structure (reproduced from Seibert (2000)).

2.7.2. 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) and Liang, (1992) introduced the concept of separating quick and slow flows in SMAR model and came up with the SMAR 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 (Podger, 2004). SMAR model simulates daily and monthly discharge using daily rainfall, evaporation and watershed area as input.

2.7.2.1. 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 Ep with a conversion parameter T (Podger ,2004).

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*Ep) and is given by:

$$r_1 = H' * X \text{ if } X > 0 \tag{16}$$

$$r_1 = 0 \text{ if } X \leq 0 \tag{17}$$

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

$$H' = \frac{H * Wact}{125} \text{ for } Z \geq 125 \tag{18}$$

$$H' = \frac{H * Wact}{Z} \text{ for } Z < 125 \tag{19}$$

where, H = a model parameter to be optimized, and Wact = 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 $r_1 = H * X$.

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

$$r2 = (1 - H') * X - Y \text{ if } (1 - H') * X > Y \tag{20}$$

$$r2 = 0 \text{ if } (1 - H') * X \leq Y \tag{21}$$

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 r3 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 r3 into slow and quick responses. The slow response is termed the groundwater component, which is given by:

$$rg = G * r3 \tag{22}$$

The remaining fraction of r3 is supposed to be an inter flow and hence joins the other fast response surface runoff components. Then,

$$rs = (1 - G) * r3 \tag{23}$$

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

2.7.2.2. The routing component

The water balance component removes most of the non-linear effect of the processes involved in the rainfall-runoff transformation (Podger ,2004). 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 and HRS, 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:

$$h(t) = \frac{1}{KT(N)}\left(\frac{t}{k}\right)^{N-1} e^{-t/t} \tag{24}$$

where Γ (N) is the gamma function defined by the improper integral of;

$$\tau(N) = \int_0^\infty e^y y^{N-1}\, dy \tag{25}$$

The unit step response of the storage system is

$$S(t) = \int_0^t h(\tau)\, d\tau \tag{26}$$

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

$$h(\Delta t, t) = \frac{1}{\Delta t}[S(t) - S(t - \Delta t)] \tag{27}$$

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;

$$hj = \frac{i}{\Delta t}\int_{j-\Delta t}^{j\Delta t} h(\Delta t, t)\, dt \qquad j = 1,2,3, \dots \dots \dots \dots . . m \tag{28}$$

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 rt,s can be transformed into the corresponding discharge series Qt,s using the convolution summation relation;

$$Qt, s = \sum_{j=1}^{m} hjr\, t - j + 1, s \tag{29}$$

The groundwater generated runoff rt,g will be routed through a simple linear reservoir having a storage coefficient parameter Kg. The groundwater component discharge Qt,g will be obtained by the same convolution summation.

$$\mathrm{Qt, g = qQt - 1, g(1 - q)rg, t, where, q = e^{-\frac{T}{kg}}} \tag{30}$$

This indicates final estimated total discharge at the catchment outlet.

Calibration procedure-algorithm involves provision of five automatic optimization procedures/methods. These methods are the Simplex search algorithm, the Rosenbrock direct search method, the Particle Swarm Optimization method, the Simulated Annealing method, and the Shuffled Complex Evolution algorithm. These may be used either individually or sequentially for model calibration (Podger ,2004).

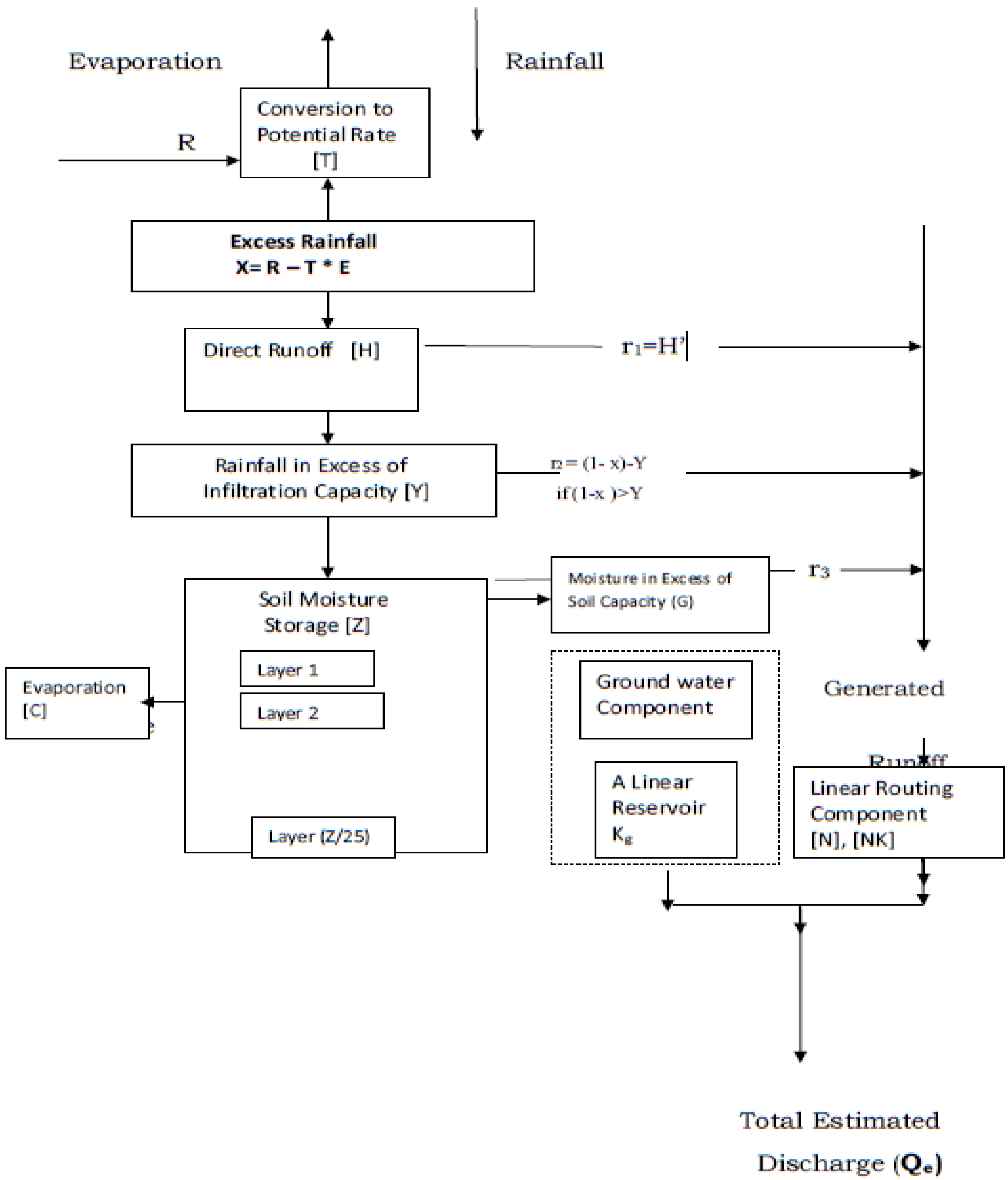

Figure 3.Schematic diagram of SMAR model (Podger, 2004).

2.8. Other Studies Using HBV and SMAR Models in Ethiopia

One of the previous studies conducted in testing the applicability of HBV model in the Baro Akobo basin was done by (Asfaw *et al*., 2014). In this study conceptual model HBV model together with WaSiM distributed physically based models were applied to simulate the flow conditions for a reference period (1990– 1997) and a future period (2011–2050). According to the findings of the study the results indicated that the WaSiM-ETH model captured the peak discharge better than the HBV-Light model. The coefficient of determination of the resulting regression function indicates an acceptable model performance. The analysis indicates that there was not a large difference in performance between the two models

The other study was done by Kebede, (2009) the research was undertaken for comparison of different models on selected catchments which have different hydrological regimes in Abay river basin. Both SMAR and HBV were applied to three catchments namely Dedesa, Gilgel Abay and Neshe. Accordingly, the performance of the SMAR model 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 completely underestimate the annual maximum flow except the HEC-HMS model simulates well.

Further study was done by Kumela, (2011) for comparison of models on Muger catchments in Abay river basin. The models were 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 (Reff = 0.7) for both models SMAR and HBV the obtained Reff during validation is 0.70 and 0.71 respectively.

Dessalegn et al, (2017) was study different flood forecasting methods and evaluate for their potential of stream flow forecasting using Galway River Flow Forecasting and Modeling System (GFFMS) in Lake Tana basin, upper Blue Nile basin, Ethiopia. The areal rainfall and temperature data were used for the model input. Three forecast updating methods, i.e., autoregressive (AR), linear transfer function (LTF) and neuron network updating (NNU) methods were compared for stream flow forecasting, at one to six days lead time. The most sensitive parameters were fine-tuned first and modeled for a calibration period of 1994-2004 for three selected watersheds of the Tana basin. The results indicate that with the exception of the simple linear model, an acceptable result could be obtained using models embedded in the software. Artificial neural network model performed well for Gilgel Abay (NSE = 0.87) and Gumara (NSE = 0.9) watersheds but for Megech watershed, SMAR model (NSE = 0.78) gave a better forecast result. In capturing the peak flows LTF and NNU in forecast updating mode performed better for Gilgel Abay and Megech watersheds, respectively. The results of this study implied that GFFMS can be used as a useful tool to forecast peak stream flows for flood early warning in the upper Blue Nile basin.

2.9. Sources of Uncertainty in Rainfall-Runoff Models

The uncertainties in rainfall-runoff modeling stem mainly from the three important sources (Louck *et al*., 2005):

Observational uncertainty: Uncertainty related to the observation used for rainfall runoff modeling can be classified as observational uncertainty. The observation is the measurement of the input (e.g., precipitation and temperature) and output (e.g., stream flow) fluxes of the hydrological systems and sometimes of its states (e.g., soil moisture content, groundwater levels). The observational or data uncertainty usually consists of two components: a) measurement errors due to both instrumental and human errors b) error due to inadequate representativeness of a data sample due to scale incompatibility or difference in time and space between the variable measured by the instrument and the corresponding model variable. The latter is sometimes called sampling uncertainty (Abebe, 2004). These two error components have very different characteristics which may vary from variable to variable; hence, statistics of both errors should be considered and adequately specified.

Model uncertainty: A model is a simplified representation of the real world. The complex real processes are greatly simplified while deriving the basic concepts and equations of the model. Conceptualization with inappropriate approximations and ignored or misrepresented processes can result in large error in the conceptual structure of the model. Model errors can also arise from the mathematical implementation (e.g., spatial and temporal discretization) that transforms a conceptual model into a numerical model (Louck *et al*., 2005).

Parameter uncertainty: The uncertainty in the model parameters results from an inability to accurately quantify the input parameters of a model (Louck *et al*., 2005). The parameters of the model may not have direct physical meaning. Furthermore, those parameters that have a physical meaning cannot be directly measured or it is too costly to measure them in the field. In such case their values are generally estimated by indirect means (e.g., expert judgment, model calibration) Expert judgment is normally subjective and hence uncertain. The parameters obtained from the calibration process are also not free from uncertainty for various reasons including data uncertainty (data used to calibrate the model contains errors), model uncertainty (the model structure used to calibrate the model is not adequate), lack of sufficient data etc.

2.9.1. Uncertainty analysis in rainfall-runoff modeling

Model complexity is measured according Shrestha, (2009) by its number of parameters and requirements of input data. As the model complexity increases, in principle, structure uncertainty decreases due to detailed representation of the physical process. However, with the increasing complexity of model, the number of the input and parameters also increases and if such complex models with many parameters and data inputs are not parameterized properly or lack quality input data, there is a high probability that uncertainty associated with input data or parameter estimation will increase. Due to the inherent trade-off between model structure uncertainty and input/parameter uncertainty, for every model and the associated data set there exists the optimal level of model complexity where the total uncertainty is minimum.

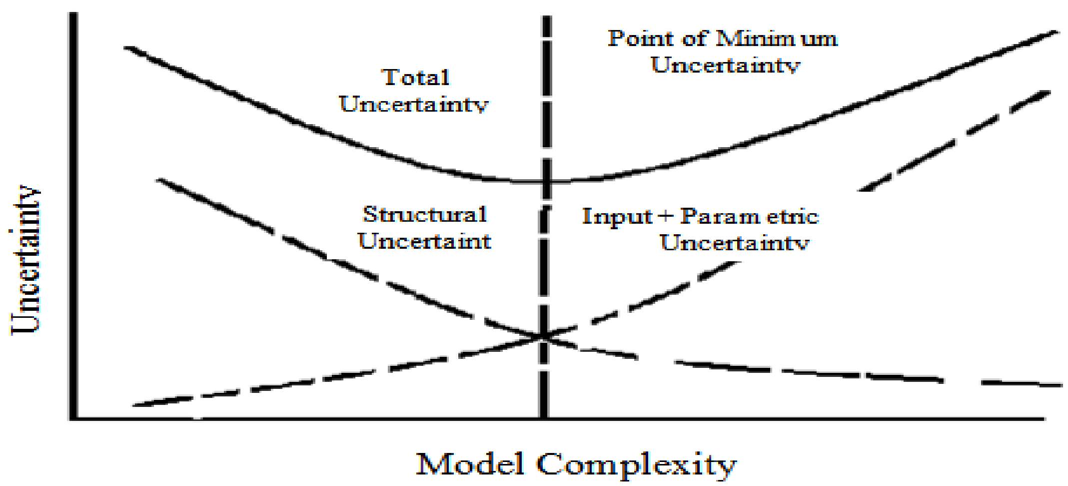

Figure 4. An illustration of relationship between different sources of uncertainty and the combined effect on total model uncertainty

The relationship between model uncertainty and model complexity is important to consider during model development. Increasingly complex models have reduced model framework/theory uncertainty as more scientific understandings are incorporated into the model. However, as models become more complex by including additional physical, chemical, or biological processes, their performance can degrade because they require more input variables, leading to greater data uncertainty (EPA, 2009). An NRC Committee (2007) recommended that models used in the regulatory process should be no more complicated than is necessary to inform regulatory decision and that it is often preferable to omit capabilities that do not substantially improve model performance.

Once the existence of uncertainty in a rainfall-runoff model is acknowledged, it should be managed by a proper uncertainty analysis process to reduce the impact of uncertainty. Pappenberger *et al.* (2006) provide a decision tree to find the appropriate method for a given situation. The uncertainty analysis process in rainfall runoff models varies mainly in the following ways: (i) the type of rainfall-runoff models used; (ii) the source of uncertainty to be treated; (iii) the representation of uncertainty; (iv) the purpose of the uncertainty analysis; and (v) the availability of resources. Uncertainty analysis is a well-accepted procedure and has comparatively long history in physically based and conceptual modeling (Gupta *et al.*, 2005). With increasing application of data-driven techniques in rainfall-runoff modeling, there is also growing interest to quantify the uncertainty of the predictions made by the data-driven models. The uncertainty methods used in such models are obviously different from those used in physically based and conceptual models.

Regarding to the sources of uncertainty, Monte Carlo (MC) type methods are widely used for parameter uncertainty, Bayesian methods and/or data assimilation can be used for input uncertainty and Bayesian model averaging method is suitable for structure uncertainty. Uncertainty analysis method also depends on whether the uncertainty is represented as randomness or fuzziness. Similarly, uncertainty analysis methods for real time forecasting purpose would be different than those used in design purpose (design discharge for structures built in the rivers). In the former case the running time of the model is crucial and hence computationally expensive MC based methods are impractical. Availability of resources such as computational power also determines the selection of different methods used for uncertainty analysis. Uncertainty analysis methods in all of the above cases should involve: Identification and quantification of the sources of uncertainty; Reduction of uncertainty; Propagation of uncertainty through the model; Quantification of uncertainty in the model outputs; and, Application of the uncertain information in decision making process. However, the practice of uncertainty analysis and use of the results of such analysis in decision making is not widespread (Shrestha, 2009).

2.9.2. Uncertainty estimation using GLUE

The generalized likelihood uncertainty estimation (GLUE) procedure (Beven and Binley, 1992) is an extension of Monte Carlo random sampling that incorporates the goodness-of-fit of each simulation (Hassan *et al*., 2008) , and has been widely used to quantify uncertainty based on model calibration results (Huang *et al*., 2014) . The GLUE procedure comprehensively estimates the likelihood of all possible outcomes for a specific distribution of inputs, and practically determines behavioral parameter sets of a model (Chu *et al*., 2010 and Huang *et al*., 2014). Based on the results of the GLUE procedure in assessments of multiple possibilities for generating simulations, a set of parameter sets, which lead to acceptable model realizations rather than only one "optional" calibrated parameter set, is determined. This determination refers to "equifinality" for model uncertainty analysis (Beven and Freer, 2001). It is noted that most relevant hydrological and groundwater studies have tended to use GLUE for their uncertainty analysis, such as Chu *et al*. (2010) and Mirzaei *et al.* (2015) in hydrological modeling; Hassan *et al*. (2008), Jackson *et al*. (2016), and Marchant *et al*. (2016) in groundwater modeling; and Wang *et al*. (2012) and Huang *et al*. (2014) in wetland modeling.

Working with (complex) models with many parameters introduces the problem of equifinality. This is the effect that multiple parameter sets give approximately the same results. The question is therefore whether one should look for the "best" parameter set. The philosophy of the Generalized Likelihood Uncertainty Estimation (GLUE) is that instead of finding one optimal parameter set, multiple behavioral parameter sets are accepted as a possible realization of the hydrology in a catchment. By selecting one or multiple likelihood measures (e.g. Nash-Sutcliff, or Relative Volume error), the parameter sets are analysed on their performance. Only the parameter sets that meet the constraints of the Likelihood measure are selected as "behavioral sets" (Beven and Binley, 1992).

The steps of a GLUE analysis are generally as follows (Gupta *et al.*, 2005):

- Define the parameters that are to be evaluated (i.e. which are assumed to be unknown a priori).
- Select a performance measure (Objective Function). Some of objective function for performance measure area NSE, RMSE and R^2, for NSE the objective function calculated as follows:

$$\text{Nash stcliffe efficency (NSE)} = \quad 1 - \frac{\sum_{i=1}^{n}(O_i - S_i)^2}{\sum_{i=1}^{n}(O_i - \bar{O}_i)^2} \tag{31}$$

where: O_i and S_i are the observed and simulated stream flow respectively and $\bar{O}_i$ is the averages of observed stream flow, respectively

- Perform a Monte-Carlo simulation on the selected unknown parameters with a sufficient amount of samples. For every run, a set of parameters is randomly selected from a pre-defined uniform distribution of each parameter.

  The MC simulation is performed by running the hydrological model M multiple times either changing the input data x or the parameters vectors or even the structure of the model, or a combination of them. In this paper we assume that the model structure and the input data are certain (correct), so mathematically this can be expressed as:

$$\hat{y}_{t,i} = M(x, \theta_i); t = 1,2, \dots, n; \;\; i = 1,2, \dots, s \tag{32}$$

where θ_i is the set of parameters sampled for the i^{th} run of the MC simulation, $\hat{y}_{t,i}$is the model output of the t^{th} time step for the i^{th} run, n is the number of time steps and s is the number of simulations.

- Analyze the performance of all selected parameter sets for the selected performance measure using the selected objective function.
- Select 'behavioral' parameter (High objective function) sets. These are parameter sets which give a performance above a user-defined threshold. This is one of the subjective steps in the GLUE analysis

- Rescale the performance measure of each behavioral parameter set into a likelihood (zero likelihood where the parameter is equal to the performance measure threshold value) so that the sum of all likelihood values equals one.

According to equation (33), the likelihood values L_t can be calculated for each objective function value F_t with the following equation:

$$L_t = \frac{F_{max} - F_t}{F_{max} - F_{min}} \tag{33}$$

where, F_{max} is the maximal objective function value from all parameter sets, F_{min} is the minimal objective function value from all parameter sets and F_t is the objective function value for which the likelihood L_t is calculated.

By applying the GLUE analysis an estimate for the model parameter uncertainty is given. The number of approved parameter sets can then be seen as a value for the uncertainty.

The uncertainty of the simulated runoff caused by parameter uncertainty has to be studied in more detail. However, the tentative results indicated that simulated runoff during a certain period may vary considerably for parameter sets which gave almost similar good fits during calibration.

3. MATERIALS AND METHODS

3.1. Description of the Study Area

The Shaya river watershed is located in Bale Zone, Oromia Regional State South-eastern part of Ethiopia. The watershed is situated in Genale-Dawa river basin at the upper most parts of the Weyib basin. Geographically, the Shaya watershed area is situated at $6^{0}52^{'}00^{''}$ - $7^{0}15^{'}00^{''}$ North Latitude and $39^{0}46^{'}00^{''}$- $40^{0}02^{'}02^{''}$ East Longitude, with an elevation ranges of 2,357– 4,342 meter above sea level (m.a.s.l). The area covers about 465 km^{2} of land.

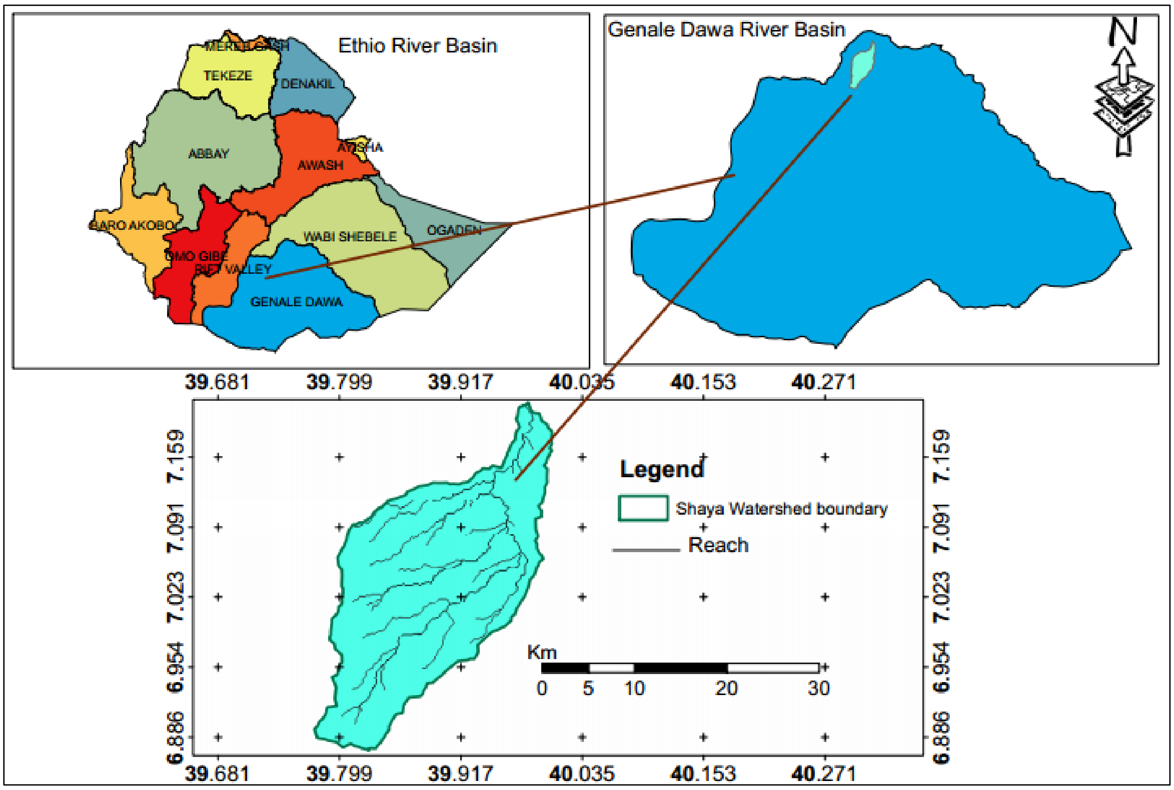

Figure 5. Location map of the study watershed.

3.1.1. Topography

There is high elevation change between the upstream and downstream of the watershed which is 4343 and 2357 m.a.s.l. at the upstream and downstream edge of the watershed, respectively. The upper most parts of the watershed topographically are the steepest parts up to 77% maximum slope range while the middle and the downstream parts have flat to gentle slope which is very suitable for agriculture. The altitude decreases from south to north in the watershed (Alemayehu , 2012).

3.1.2. Climate

The climate of Shaya watershed is in the range of frost (Wurch) at the upper most part near Sanetti Mountains to humid highlands of Bale Mountains. Rainfall during the year occurs in distinctly different seasons. The rainfall pattern is bimodal type, which divide the year into two main seasons: a main rainy season Kiremt (June to October) and short rainy season Belg (March to May). The bimodal type of rainfall pattern is generally characterized by a double peak rainfall pattern with a small peak in April and maximum peak in August (MoWIE, 2007). Based on meteorological data from Robe, Goba, Agarfa, Dinsho and Sinana stations the average annual rainfall amount is 1015.28 mm and generally, the temperature and rainfall pattern in all stations follows similar trend as shown in Appendix Figure 1 and 2. The annual maximum and minimum temperature of the watershed area is about 19.7 ºC and 6.1 ºC, respectively (Figure 6).

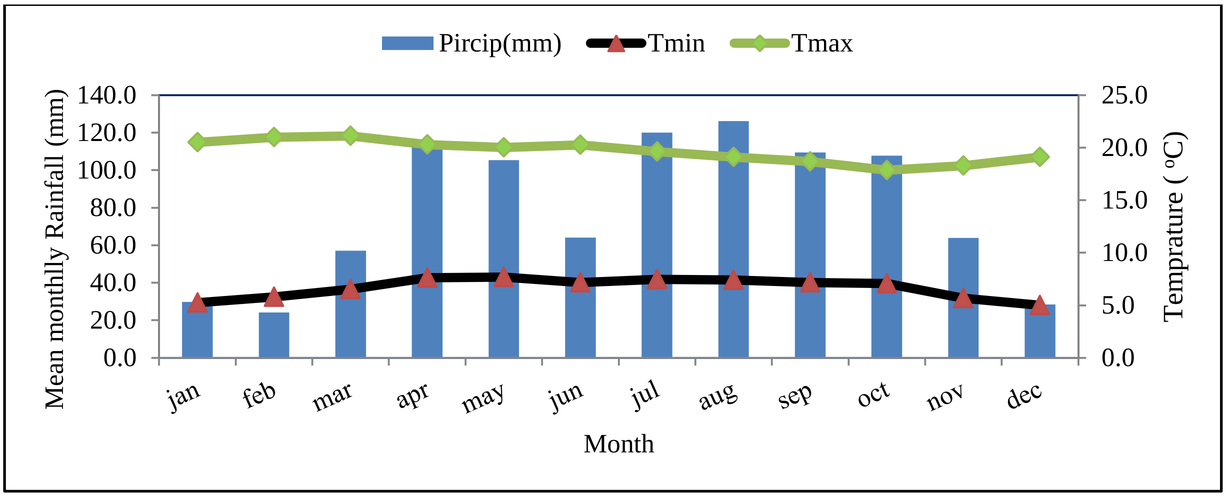

Figure 6. Mean monthly rainfall and maximum and minimum temperature of the study watershed.

3.1.3. Soil

Soils in the study watershed are classified on the basis of the revised FAO/UNESCO-ISWC (1998) classification system. The soil data was extracted from the 1:250,000 scale of soil map developed by MoWIE (2007).

There are three major Soil groups in the Shaya watershed, the Cambisol, Luvisol and Regosol of which again classified into six soil units, the Dystric Cambisols (15.46%), Eutric Cambisols (26.27%), Chromic Cambisols (22.02%), Haplic Luvisols (5.88%), Vertic Luvisols (26.59%) and Eutric Regosols (3.78%). The Eutric Regosols and Dystric Cambisols are found in the upper most edge, Chromic Cambisols is found down from the earlier two, Eutric cambisols and Vertic Luvisol are found in the middle part and Haplic Luvisols is found at the downstream part of the watershed.

3.1.4. Land use and/or land cover

The land cover in the Shaya watershed is represented by cultivated lands, natural vegetation and settlement. Each of these cover types are tremendously influenced by properties of land form, soils and climate as elsewhere in Ethiopia. The natural vegetation cover especially the forest land is encroached by cultivated fields as a result of high population growth followed by peoples for food and export crops in order to alleviate the prevailing food and employment insecurity (MoWIE, 2007).

The land use/land cover (LULC) of the study area includes the Afro-alpine and Sub-afro-alpine vegetation (35.36%); pasture land (21.3%), forest (5.25%), range land (11.0%), agricultural land (22.17%) and settlements (4.91%). Afro-alpine is the LULC types that occur in the upper most parts of the watershed and includes short shrubs, heath and giant Lobelia, sedentary grazing with barley, onions and honey as main crop/product (MoWIE, 2007). The pasture type of LULC is distributed in different parts of the watershed. Agricultural land is also the LULC type which is distributed from the middle to downstream parts of the watershed. It is the land cover under the intensive and moderate crop cultivation for the production of annual crop (wheat and barley crops are grown widely).

3.2. Data Collection

3.2.1. Meteorological data

Meteorological data was collected from National Meteorological Service Agency (NMSA) of Ethiopia for Robe, Dinsho, Agarfa, Bale Goba and Sinana stations. Meteorological data from these five station and their recording periods are listed below in the Table (1).

All weather stations provided precipitation and maximum and minimum temperature while solar radiation, wind speed and relative humidity were obtained from Robe, Sinana and Agarfa weather stations with varying recording periods. Due to proximity to the watershed boundary weather data from Sinana meteorological station have not been used.

Table 1. Inventory of meteorological stations

Station	Altitude (m)	Data recording period				
		Rainfall	Temperature (Max and Min)	Sunshine	Wind Speed	Humidity
Robe	2464	1985-2015	1985-2015	1995-2014	1990-2015	1996-2015
Sinana	2410	1980-2015	1981-2015	1989-2015	1989-2014	1998-2011
Agarfa	2360	1990-2015	1986-2015	1993-2013	1983-2010	1983-2003
Dinsho	3072	1989-2009	1990-2015	-	-	-
Goba	2545	1990-2012	1980-2015	-	-	-

3.2.2. Hydrological data

Daily river discharge data of the Shaya watershed for about 20 years (1995-2015) were obtained from the Hydrology Department of the Ministry of Water Irrigation and Electricity (MoWIE). It was used for performing sensitivity analysis, calibration and validation of the models. Shaya is the only river watershed which has a gauging station on its outlet other than the neighboring watersheds.

3.3. Data Pre-Processing and Quality Checking

3.3.1. Filling in missing rainfall data

A number of methods have been proposed for estimating missing rainfall data (Garg, 2005 and Raghunath, 2006). For this study normal ratio method was used, because normal-ratio method is conceptually simple, this method is used if the annual precipitations vary considerably by more than 10 %, by weighing the precipitation at the neighboring stations by the ratios of normal annual precipitations.

The general formula is given below:

$$P_x = \frac{N_x}{M}\left[\frac{P_1}{N_1} + \frac{P_2}{N_2} + \cdots + \frac{P_m}{N_m}\right] \tag{34}$$

where:

N_x = Annual-average precipitation at the gage with missing values

N_1 , N_2 , …, Nm = Annual average precipitation at neighboring gages

3.3.2. Test for consistency of record

Double mass curve was used to check the consistency of rainfall record of the stations. It is the method used to check for an inconsistency in a rain gauged record. A double-mass curve is a graph of the cumulative rainfall at the rain gauge of interest versus the cumulative rainfall of one or more gauges in the region that has been subjected to similar hydro meteorological occurrences and is known to be consistent (Raghunath, 2006). If a rainfall record is a consistent estimator of the hydro meteorological 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.

$$Y = \frac{S_1}{S_2} * Y_1 \tag{35}$$

where: Y= corrected precipitation at station x

Y_1=original recorded precipitation at station Y_1

S_1= corrected slope of double mass curve

S_2= original slope of double mass curve

3.3.3. Homogeneity test

To determine the homogeneity and independency of the rainfall data series, the Standard Normal Homogeneity Test Method (SNHT) was used at 5% significance level using **XLSTAT** Software (Version 2016**).**

3.4. Model Used and Input Data

The conceptual rainfall runoff models chosen for this study are SMAR and HBV-light. Data requirement for both Models are, rainfall data, in mm/day entered using the models data storage format, observed flow in mm/day and entered the Model data storage and Evapotranspiration; Evapotranspiration is calculated using FAO Penman-Monteith equation. This equation is derived from the original Penman- Monteith equation and the equations of the aerodynamic and surface resistance (Allen *et al*.,1998). The catchment area (in km^2) of watershed was used for SMAR Model.

3.5. Watershed Delineation

DEM with 30m resolution was used to delineate the watershed by the help of spatial analysis toolbox in Arc GIS 10.1. To delineate the watershed the hydrological gauge station located at the downstream of the watershed was used as an outlet. The following procedures were used to delineate the watershed of the study area.

Preparation: DEM layer was added to the Arc map then using spatial analysis toolbox the following steps was done.

Step 1: The flow direction and flow accumulation hydrology layers were created from DEM.

Step 2: Pour point layer (shape file) was created using outlet point.

(These instructions was based on the document *http://courses.washington.edu/geog460/readings/ArcMAP/Make%20a%20shapefile/*)

Step 3: Pour point (outlet) was specified in the pour point shape file.

Step 4: Finally the watershed was delineated using Watershed tool.

3.6. Data Analysis

3.6.1. Areal rainfall

To identify the representative rainfall stations, which contributes for the watershed Thiessen polygon method was used. The method is dependent on a good network of representative rain gauges. To determine the mean areal rainfall, the rainfall amount of each station was multiplied by the area of its polygon and the sum of these products where divided by the total area of the catchment. If P_1, $P_2 \ldots P_n$ are the rainfall magnitudes recorded by the stations 1, 2….n respectively areas of Thiessen Polygon, then the average rainfall over the catchment P_{ave} is given by:

$$P_{ave} = \frac{P_1A_1 + P_2A_2 + \cdots + P_nA_n}{A_1 + A_2 + A_3 + \cdots + A_n} \quad (36)$$

where $\mathbf{P_{ave}}$ = Average rainfall over the catchment

P_1, $P_{2\ldots}.P_n$= Rainfall amount of each station

A_1, $A_{2\ldots}.A_n$= The area of its polygon of each station

Table 2. Location of rainfall station and their respective area for Shaya watershed

No Station	Station	Area(km^2)	Location(in degree)	
			Longitude	**Latitude**
1	Robe	158	40.05	7.13
2	Gobba	87	39.95	6.85
3	Dinsho	207	39.75	7.05
4	Agarfa	13	39.85	7.25

3.6.2. Sensitivity analysis

Sensitivity analysis was conducted to quantify the impact of input parameters on the model results/output and to limit the number of optimized parameters to obtain a good fit between the simulated and measured data. Sensitivity analysis helps to determine the relative ranking of which parameters most affect the output due to input variability (van Griensven *et al*., 2002). In this study, the sensitivity analysis was performed to select the most sensitive parameters, of the model parameters for calibration and parameter uncertainty analysis.

3.6.3. Model calibration and validation

Calibration is the process of finding the optimum set of parameters that would help the model to reproduce the observed data within the desired accuracy. Calibration of HBV and SMAR model was done separately for Shaya river watershed.

The calibration of the selected sensitive parameters was undertaken in different steps. The automatic calibration method was the first step to reach at some level of agreement with the observed stream flow and also to minimize the potential range that bound the value of each parameter. Then manual calibration (trial-and-error) was used. The Objective function (Nash-Sutcliffe efficiency, Mean Difference (mm/year), and Coefficient of determination) were used in this study with an objective of minimizing the differences between the simulated and measured time series. The calibration period was 15 years of data (1996-2010).

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 is the step where the capabilities of the calibrated model in simulating acceptable results could be confirmed (Henriksen *et al.,* 2003). In this study, the validation of the model was performed to test if the calibrated parameter set would behave consistently for the watershed using different observed datasets in another period than the calibration period (2011-2015). In this case, the stream flow data set was the only observed data used for model validation.

3.6.4. Model evaluation criteria and comparison

In this study the models have been evaluated using their performance. The performance of a model must be evaluated on the extent of its accuracy, consistency and adaptability (Goswami *et al.,* 2005). 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 both HBV and SMAR models was evaluated in a subjective way by following the basic approach of assessing model efficiency by visual inspection. This 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 (Nash-Sutcliffe efficiency, Mean Difference (mm/year), and Coefficient of determination) of the model was done by mathematical estimation of the error; it is 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 following efficiency criteria given in Table (3).

The coefficient of determination, *R*, known as the square of the sample correlation coefficient, ranges from 0 to 1 and describes the amount of observed variance explained by the model. A value of 0 implies no correlation, while a value of 1 suggests that the model can explain all of the observed variance. The Nash-Sutcliffe coefficient of efficiency, Reff, measures the model's ability to predict variables different from the mean and gives the proportion of the initial variance accounted for by the model.

Table 3. Efficiency criteria for evaluating model performance

Objective function	**Value for Perfect fit**
Nash-satcliffe efficiency(Reff)	1
Mean difference(meandiff)	0
Coefficient of determination (R^2)	1

3.6.5. Water balance estimation

Water balance was estimated using the model for Shaya watershed on monthly and annual basis for calibration period (1996-2010). The water balance was estimated based on the models equations of water balance components using daily inflows and outflows data for the assessment of water balance based the two models.

The water balance of a watershed is a deterministic relationship between the various components of the water balance, which are random variables in time and space whose probability distributions are generally unknown. In a water tight (no water leaks or gains) watershed, the independent input variable is precipitation, and the dependent output variables are evapotranspiration, stream flow, soil storage change, and groundwater storage. The volumetric water balance per unit area can therefore be expressed as:

$$P - ET - SS - GS = Q \tag{37}$$

where P is the precipitation, ET is the actual evapotranspiration, SS is the soil water storage, GS is the groundwater storage, and Q is the stream flow (Eagleson, 1982).

All the terms except P are dependent on the soil moisture redistribution, which is generally not measured. Assuming the storage change to be negligible over an integration interval spanning a full year, substituting the expected values gives the following average annual water balance equation (Milly, 1994 and Everson, 2001):

$$\mathrm{P - ET = Q} \tag{38}$$

Equation (38) was used to estimate annual water balance of the Shaya watershed using both models.

3.6.6. Uncertainty analysis of the model parameters

The accuracy and reliability of stream flow prediction depends on various factors, including, input data, model parameters and model structure, and model errors are largely due to the inherent uncertainties of these factors. Typically, a decision maker requires not only deterministic simulations but uncertainty estimates as well, which are represented by the model prediction interval (Shrestha and Solomatine, 2008). Integrating the simulations and uncertainty estimates can enhance the capability of simulated data for to act as a warning system, and contribute to water resource management policy in the future.

In this case, GLUE method was applied to obtain the parameter uncertainty. Four thousand (4000) random parameter sets, with uniform distribution for each parameter were generated using Monte Carlo. Monte Carlo method in context to the uncertainty analysis of rainfall runoff model involves in generating uniform random parameters values from the known upper and lower limit of the parameter. Only those parameters are considered which are more sensitive and other parameters are kept constant. After generating the uniform random numbers of the parameters, possible combination of all parameters where formed. Each parameter set is fed into the rainfall runoff model and model efficiency is calculated. Most sensitive parameters were selected for this analysis to simulation time.

The sensitivity of the model parameters again checked by plotting behavioral parameters of objective function versus range of parameters value then most sensitive parameters selected for further analysis (parameter uncertainty).

For SMAR the selected parameters were Evaporation Conversion Parameter (T), Proportion direct runoff (H), Ground Water runoff coefficient (G), Storage loss coefficient (Kg) and UH. Linear routing component (Nk) while the selected parameters for HBV models was Shape coefficient (BETA), Recession coefficient (K_1), Storage coefficient (K_0), Threshold for reduction of evaporation (LP) and Triangular weighing function (MAXBAS).

The result is a table of 4000 parameter sets each with 4000 objective function values. However, the actual amount of parameter sets to be used to obtain the final probability Q (Flow) distribution should be lower, since not every parameter set gives reasonable Q (Flow). The probability distribution of different amount of parameter sets was obtained by applying the likelihood function and rescaling procedure. In this case, 331 and 664 for SMAR and HBV respectively parameter sets were found to be reasonable or behavioral.

Flow was simulated at 95^{th} ,5^{th} ,75^{th} and 25^{th} Percentile (90% and 50% confidence interval) for model parameters and compared with observed discharge.

4. RESULTS AND DISCUSSION

4.1. Watershed Delineation

DEM with 30m resolution was used to delineate the watershed by the help of spatial analysis tool in Arc GIS 10.1. To delineate the watershed the hydrological gauge station located at the downstream of the watershed was used as an outlet and the watershed area was 465 km^2 as shown in Figure 7.

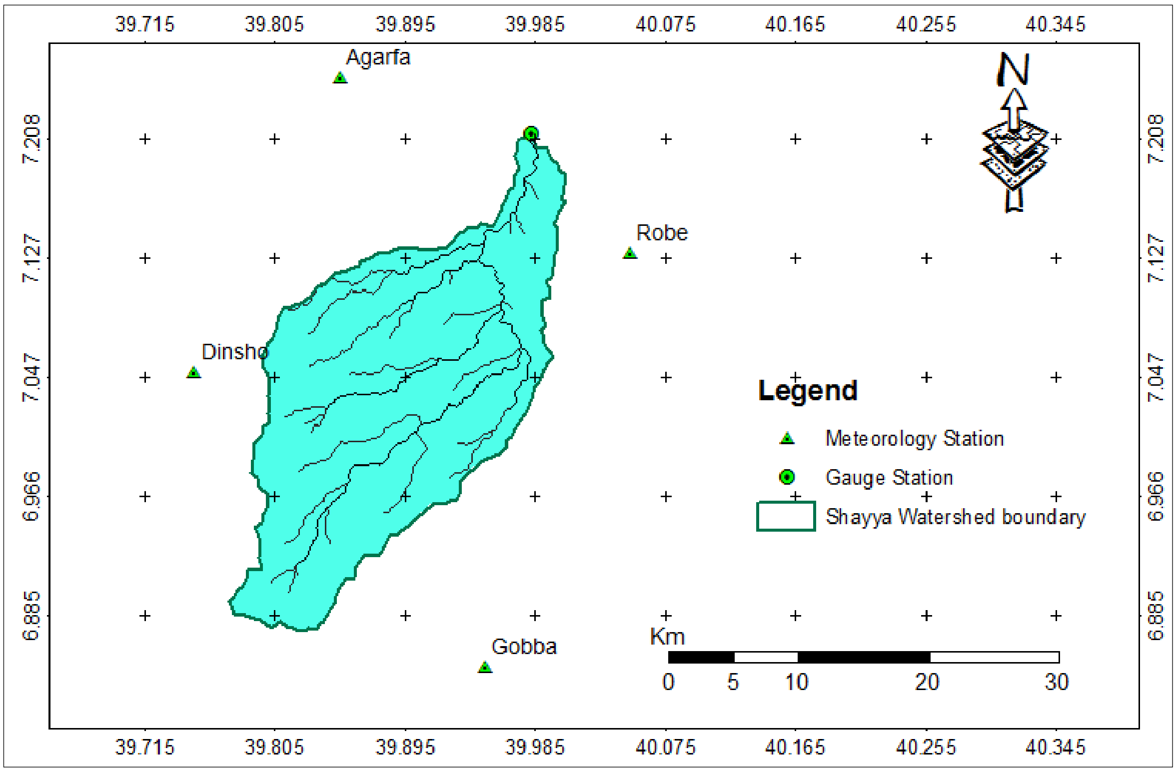

Figure 7. Map of Shaya watershed and location of hydrological and rainfall station.

4.2. Consistency and Homogeneity of Rainfall Data

The double mass curve for the plot of the cumulative annual rainfall data of the base station with the cumulative average annual rainfall data of neighborhood stations are presented in Figure (8). Accordingly, the graph of the double mass curve plot was found to be almost linear for all the considered stations with a coefficient of determination (R^2) ranging from 0.995 to 0.998.This implies that the rainfall data was consistent over the considered period of time.

and it was resulted rainfall record at Robe, Dinsho, Gobba and Agarfa, station were consistent, with no break having value of R^2 = 0.995, 0.998, 0.998 and 0.997 respectively.

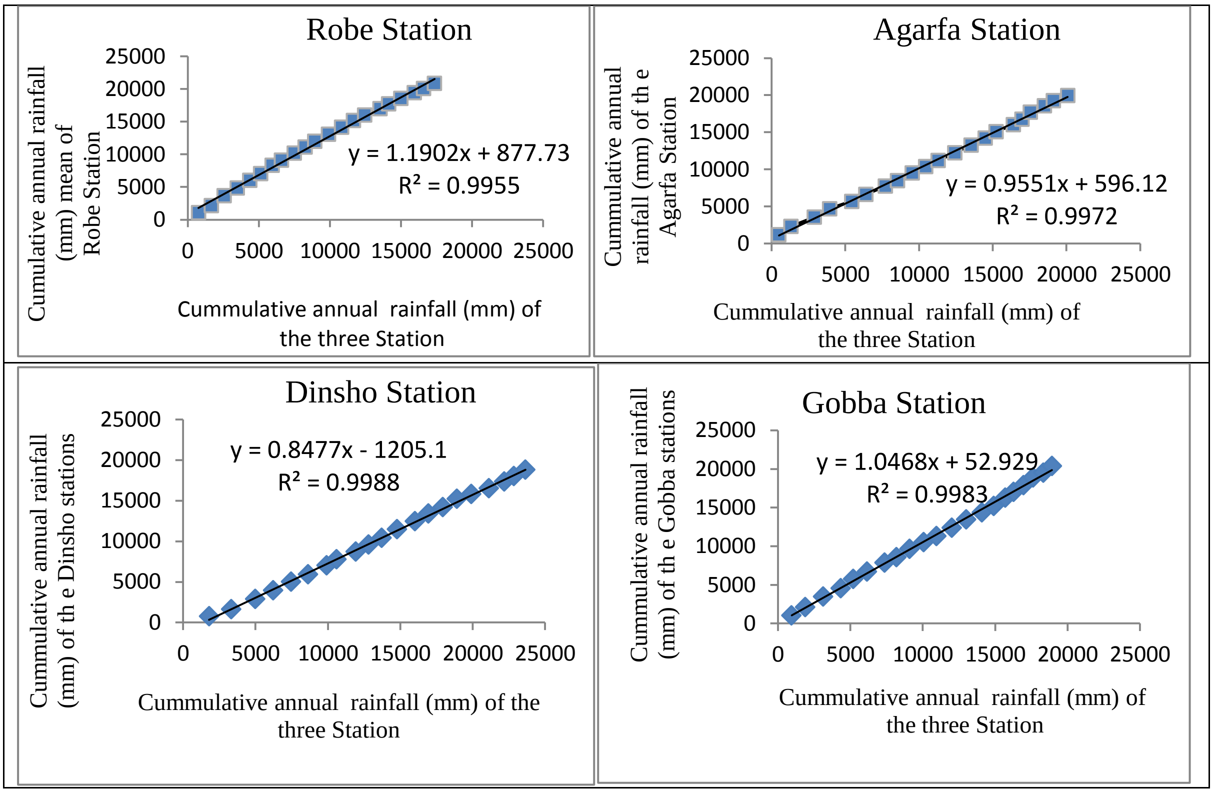

Figure 8. Double mass curve of rainfall stations nearby the watershed.

The result of XLSTAT (Version 2016) of homogeneity test shows that computed P-value was greater than alpha value and it was homogenous (Table 4). Accordingly, rainfall data of all the station were resulted homogeneous since the p-value was greater than alpha value for all rainfall stations. The P-value has been computed using 10000 Monte Carlo simulations at 95% confidence interval.

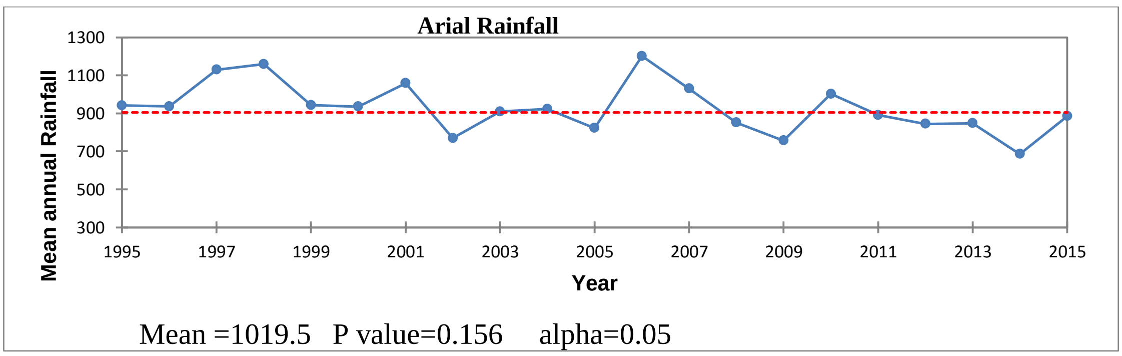

Figure 9. Homogeneity test for areal rainfall of the Shaya watershed.

Table 4. Summery statistics of the XLSTAT using method of SNHT for the stations considered

Statistics	ARF	Robe	Gobba	Dinsho	Agarfa
P-value	0.156	0.885	0.395	0.6	0.454
Alpha	0.05	0.05	0.05	0.05	0.05

where: ARF = Aerial rainfall

Based on the analysis made as indicated in Table 4, the computed p-values for stations of Robe, Gobba, Dinsho and Agarfa were found to be greater than the significance level (alpha = 0.05), this indicating that the data is homogenous, independent and identically distributed. The homogeneity test results of each station are presented in Appendix Figure 7 and 8.

4.2.1. Areal rainfall

To determine the mean areal rainfall of the Shaya watershed, Thiessen polygon method was used. The mean annual and monthly rainfall of the watershed was 1015.28 and 84.6mm respectively.

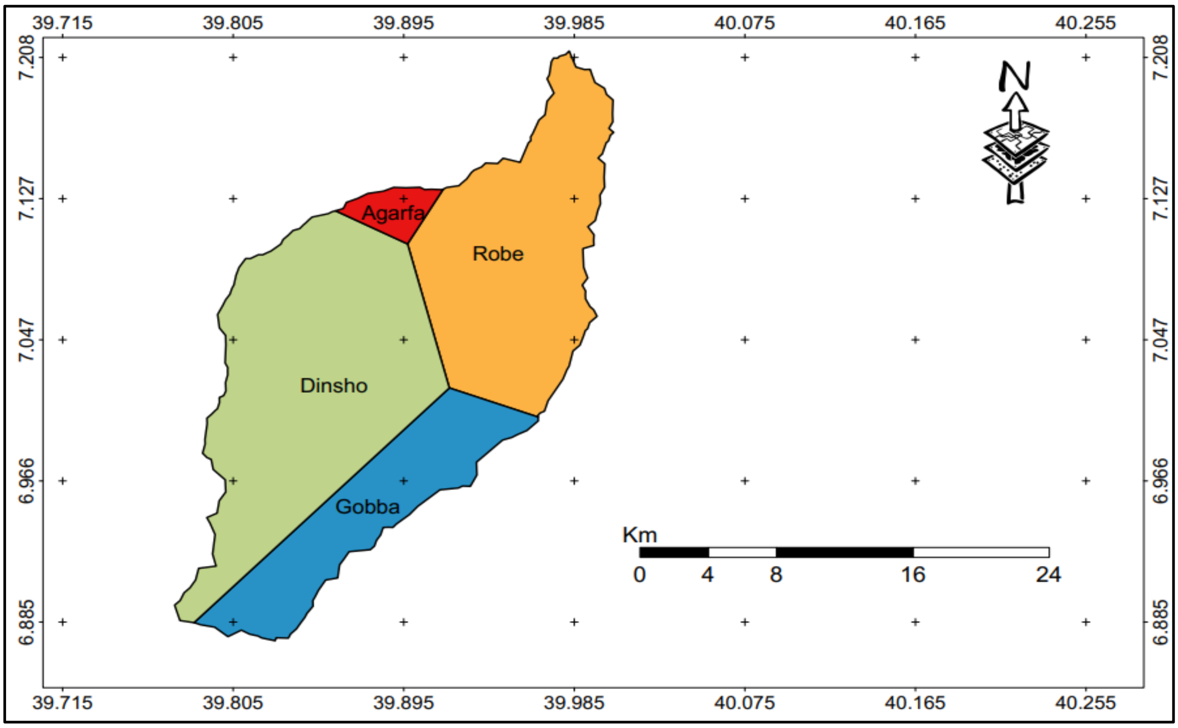

Figure 10. Thiessen polygons for estimating areal rainfall of Shaya watershed.

4.3. Sensitivity Analysis of Parameters

4.3.1. SMAR model

The 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 5, 10, 15, 20 and 25 %, in separate simulations, and then calculating the percent change in output parameters. The Evaporation Conversion Parameter (T) were observed to have highly influence on simulation results followed by Proportion direct runoff (H) and Ground Water runoff coefficient (G) respectively, whereas Storage loss coefficient (Kg), UH. linear routing component (Nk) and UH. Linear routing (N) are found to less sensitive effect on the model output and while parameter, Ground water evaporation rate (C), Infiltration Rate (Y) and Soil Moisture total storage depth (Z) are no effects on the model output. A parameter (less than unity) that converts the given evaporation series to the model-estimated potential evaporation series was the governing parameter for the watershed. The generated outflow was secondly dependent on the weighting parameter (G), determining the amount of generated 'groundwater' used as input to the 'groundwater' routing element. Generally, ground water component (G), evapotranspiration (T) and direct runoff (H) are governing the flow generation mechanism in Shaya watershed using SMAR model. The sensitivity index of the SMAR model parameter was shown in Table 6.

Table 5. SMAR model parameter

	Parameter	Unit	Description
Water Balance Component	C	[-]	The soil evaporation decay coefficient
	H	[-]	Proportion direct runoff coefficient
	T	[-]	Evaporation conversion coefficient
	Y	[mmd^{-1}]	Infiltration Rate
	Z	[mms]	Soil moisture total storage depth
Routing Component	Nk=(N*K)	[days]	UH. linear routing component
	Kg	[days]	Storage loss
	N	[-]	UH. linear routing coefficient
	G	[-]	Ground water runoff coefficient

Table 6. Relative sensitivity index of the SMAR model parameter

Parameter	Relative Sensitivity Coefficient	Rank
T	0.4881	1
H	0.0180	2
G	0.0083	3
Kg	0.0019	4
Nk	0.0005	5
N	0.00009	6
C	0.0000	7
Y	0.0000	7
Z	0.0000	7

4.3.2. HBV model

Sensitivity analysis for HBV model was conducted and some parameters were found highly sensitive, some low sensitive and the rests where found non-sensitive - meaning model efficiency would be constant whether the parameter value had increased or decreased. Highly sensitive parameters was Triangular weighing function (MAXBAS), Shape coefficient (BETA), Recession coefficient (Ko, K1), and SM threshold for reduction of evaporation (LP). Low sensitive parameter had been maximum soil moisture storage (FC), threshold parameter (UZL); maximal flow from upper to lower GW-box (PERC) and non-sensitive parameters was Recession coefficient (K2).The sensitivity index of the HBV model parameter is shown in Table 8.

Table 7. HBV-Light model parameter

	ID	Unit	Description
	FC	[mm]	Maximum soil moisture storage
Soil Moisture Routine	BETA	[-]	Parameter that determines the relative contribution to runoff from rain or snow melt (Shape coefficient)
	LP	[-]	SM threshold for reduction of Evaporation (Coefficient)
Routing Routine:	MAXBAS	[day]	Triangular weighing function
Response Routine	Ko	[1/day]	Storage coefficient
	UZL	[mm]	Threshold parameter
	PERC	[mm/day]	Defines max percolation rate from the upper to the lower ground box
	K1	[1/day]	Recession coefficient

K2	[1/day]	Recession coefficient

Table 8. Relative sensitivity index of the HBV model parameter

Parameter	Relative Sensitivity Coefficient	Rank
MAXBAS	0.8160	1
BETA	0.5900	2
Ko	0.5100	3
K1	0.5200	4
LP	0.3180	5
PERC	0.0160	6
FC	0.0120	7
UZL	0.0056	8
K2	0.00012	9

The model has 14 parameters to be calibrated. In this study, the snow routine was not used due to the absence of snow in the area. From the soil moisture routine, FC was used to determine the amount of water that goes to the root zone and groundwater as recharge and parameters, BETA determines the relative contribution to runoff from rain and LP is a parameter used to determine the relation between actual and potential evaporation. The response routine works with 3 parameters. PERC controls the maximum percolation rate from the upper to the lower groundwater zone. UZL is a parameter used to compute runoff from the groundwater zone as the sum of linear outflow equations using storage coefficient (Ki) depending on whether the upper groundwater zone is above a threshold parameter UZL. Lastly, the routing routine has one parameter, MAXBAS, which is used to transform runoff to simulated runoff using a triangular weighting function.

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 MAXBAS, BETA, K0, K1, and LP. The most sensitive parameters are the Routing Routine (MAXBAS) which is used to transform runoff to simulated runoff using a triangular weighting function, K0 and K1 which govern subsurface and base flow contributions in Shaya watershed. In general, the stream flow of Shaya River can be categorized as flow controlled by Routing Routine (MAXBAS) rather than storm.

4.4. Model Calibration and Validation

4.4.1. Model calibration

4.4.1.1. SMAR model calibration

Calibration of SMAR model was done to the final manual adjustment of some of the parameters, after performing the automatic calibration, guided by the visual comparison. The Genetic optimization algorithm was 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 Genetic Algorithm method of optimization was done by the process of allowing all parameters to optimize at the same time. Then finally manual adjustment of the parameters where done. The optimal values of the parameter are shown in the table below Table (9).

Table 9. The nine optimized parameters of SMAR model for Shaya watershed

Parameter	Min	Max	Calibrated Value
Ground water evaporation rate (**C**)	0	1	0.12
Ground water runoff coefficient (**G**)	0	1	0.52
Proportion direct runoff (**H**)	0	1	0.08
Storage loss coefficient (**KG**)	0	1	0.24
UH. linear routing (**N**)	1	6	1.93
UH. linear routing component NK=(**N*K**)	0.01	1	0.024
Evaporation conversion parameter (**T**)	0	1	0.012
Infiltration rate (**Y**)	0	5000	295.22
Soil moisture total storage depth (**Z**)	0	5000	760.69

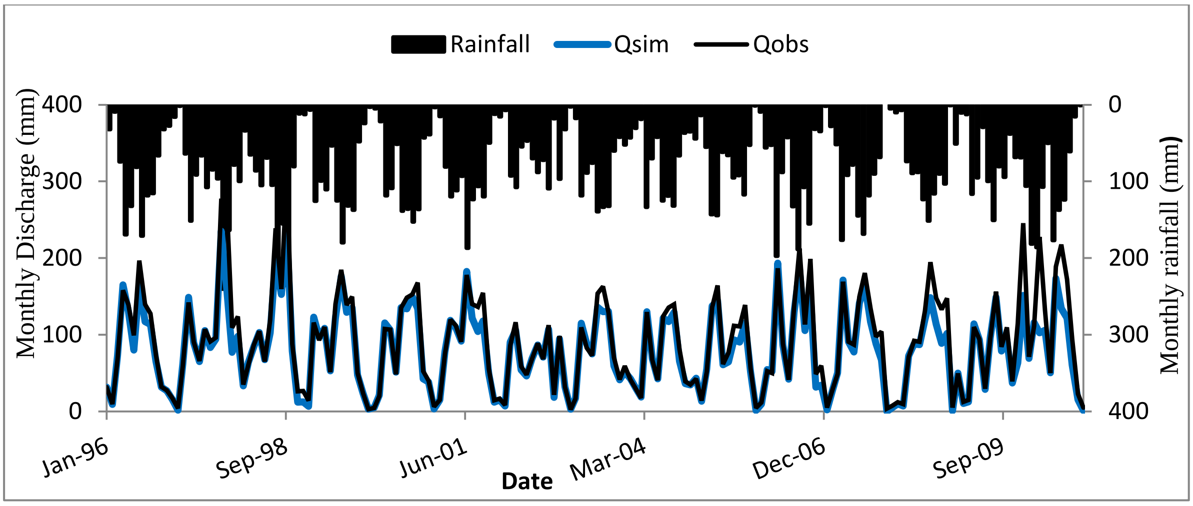

Figure 11. Monthly calibration of observed and simulated flow hydrograph of Shaya watershed for the period (1996-2010) using SMAR model

4.5.1.2. HBV model calibration

Automatic and Manual adjustment of the calibration parameters resulted in set of parameters that minimized the difference between observed and simulated discharge measured by the model performance criteria for Shaya watershed. Before starting hand tuning model parameters the range in which the calibration parameters would give a better simulation was identified by Monte Carlo Simulation. The input data used for calibration of the HBV model in Shaya watershed were of the periods 1996-2010. The optimal calibration parameters attained together with the model efficiency values obtained are presented in Table (10) below.

Table 10. The optimized parameters of HBV model for Shaya watershed

Parameters	**Lower Limit**	**Upper Limit**	**Optimized Value**
FC	50	500	85
LP	0.3	1	1
BETA	0.1	6	0.12
PERC	0	6	0
UZL	0	100	0
K0	0.05	1	0.99
K1	0.01	1	0.99
K2	1	0.1	0.1
MAXBAS	0	5	1.55

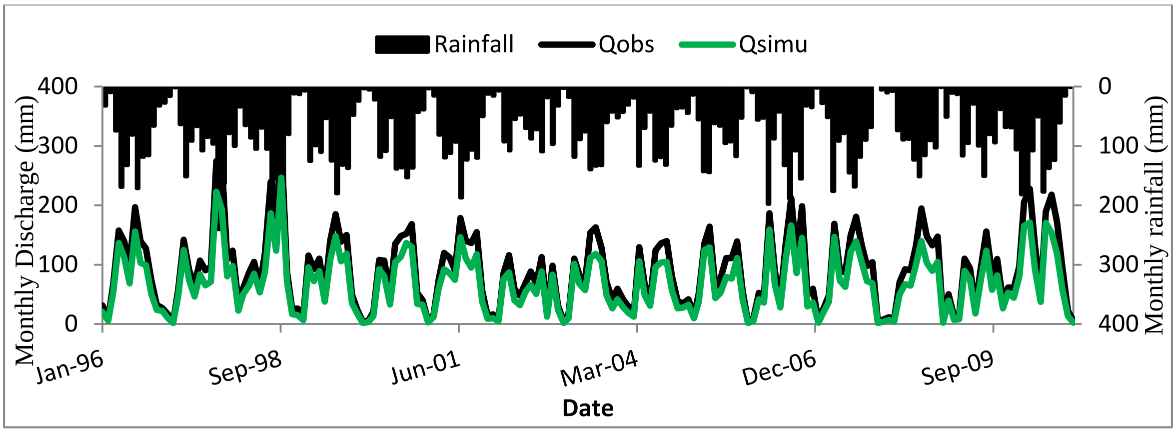

Figure 12. Monthly calibration of observed and simulated flow hydrograph of Shaya river watershed for the period (1996-2010) using HBV model.

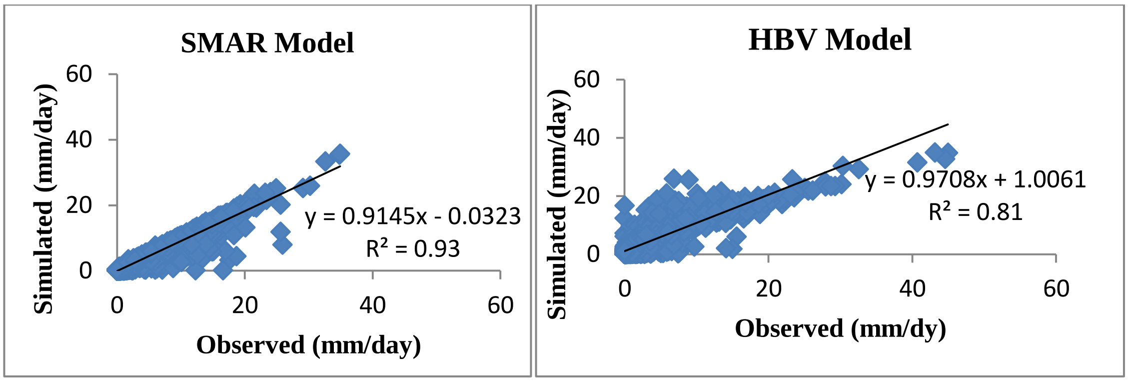

Figure 13. Scatter plot of observed and simulated daily flow for the calibration period (1996-2010) for both model.

4.4.2. Model validation

Validation was done for the Shaya watershed with data from 2011 to 2015. The objective functions available in HBV and SMAR models were used for testing the validity of the modeling on Shaya watershed. Accordingly, the performance of the model in the validation period, as measured by splitting-record technique, indicated the better simulation efficiency for both models.

For both SMAR and HBV models the obtained Reff is 0.78 and 0.59 respectively. Even though, both SMAR and HBV model showed underestimation of the observed discharge by around 4.6 and 11 mm/year respectively (Table 11).

The R^2 values of both models calculation for the watershed indicate that the observed and simulated runoff is well correlated. Observed and simulated runoff values were relatively less correlated for HBV model (R^2 = 0.81) and highly correlated for Shaya watershed (R^2 = 0.93) using SMAR model during validation period (Figure 13).

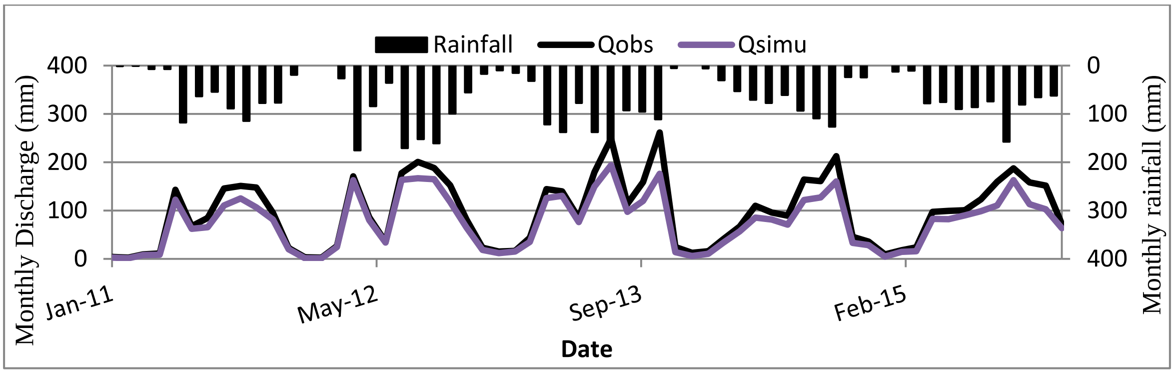

Figure 14. Comparison of observed and simulated hydrograph of Shaya watershed for the period (2011-2015) by SMAR model during validation

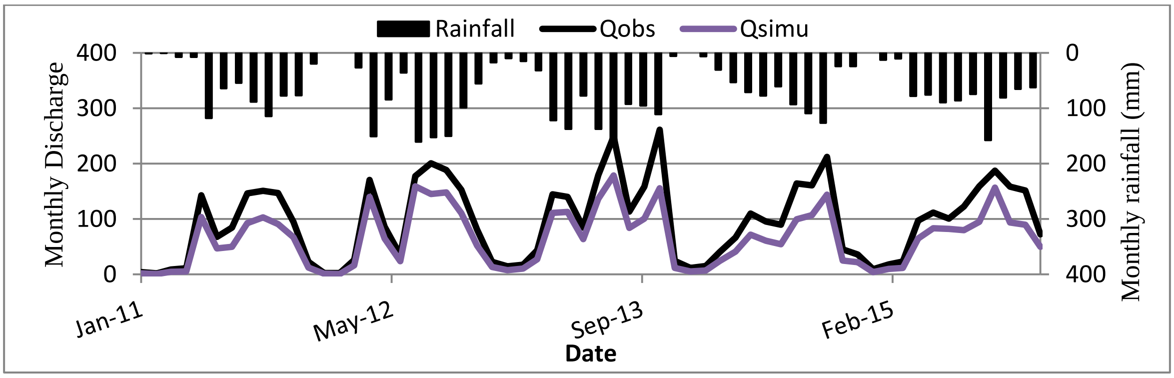

Figure 15. Comparison of observed and simulated hydrograph of Shaya watershed for the period (2011-2015) by HBV model during validation

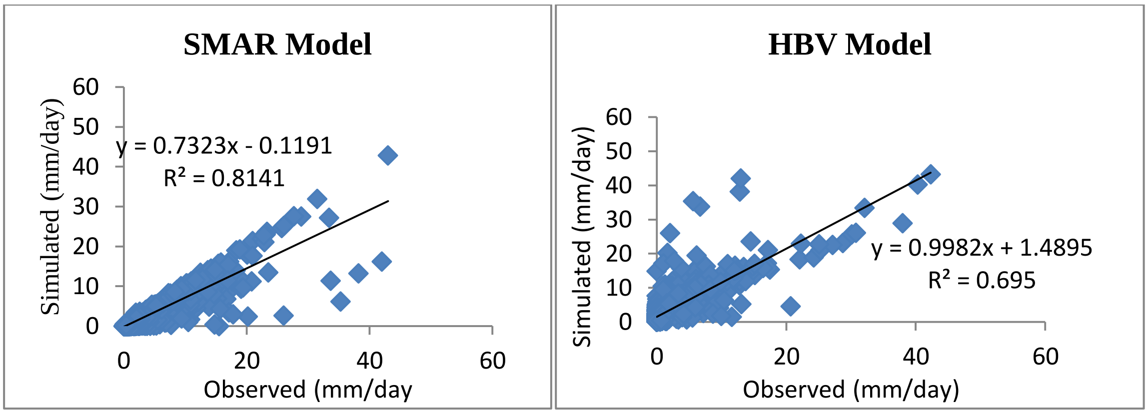

Figure 16. Scatter plot of observed and simulated daily flow for the validation period (2011-2015) for both model.

4.5. Model Evaluation and Comparisons

Statistical and visual comparisons of observed and simulated values were conducted to evaluate the performance of SMAR and HBV models on Shaya watershed. The evaluated performance statistics for the calibration and validation period are presented in Table (11). For visual comparisons, observed and simulated runoff graphs are presented in the appendix figure 11 and 12 only the statistical evaluations are discussed here.

The calibration results of HBV and SMAR are good for the objective function of Nash-Sutcliffe efficiency, Mean Difference (mm/year), and Coefficient of determination. Since the calibration results statistics value is greater than 50 percent it can be accepted as good result (Moriasi *et al*., 2007 and Bressiani *et al*., 2015). But when compared to each other SMAR model scored the best result for all objective functions for both calibration and validation periods.

The value of Nash–Sutcliffe coefficient (Reff) in Table (11) indicates that both models are performed quite well at Shaya watershed and it was 0.91 and 0.75 for calibration period and 0.78 to 0.59 for validation period. For the validation period, the performances of both models were somewhat reduced.

General observation of the calibration and verification result shows that both conceptual rainfall-runoff models exhibit better results in calibration than in verification period. Overall, the result shows that both models perform well to reproduce historical records.

The performance evaluation criteria used were the overall agreement between the observed and predicted hydrographs and the models' ability to predict the time and magnitude of peak discharges and runoff volume (Meselhe *et al*., 2004). The results indicated that the SMAR model captured the peak discharge better than the HBV-Light model as indicated in Figure 17.

The correlation coefficients obtained are 0.95 and 0.81 for calibration 0.81 and 0.69 for validation for SMAR and HBV model respectively. SMAR emerged as the best fit model for Shaya watershed. The results supports the findings of Sileshi, (2010) used the three conceptual models to examine the Awash basin and reported that the SMAR model performance was good.

Table 11. Daily models performance evaluation result for calibration (1996-2010) and validation period (2011-2015)

Variable	**Objective Function**	**HBV Model**	**SMAR Model**
Calibration	Nash-Sutcliffe efficiency	0.75	0.91
	Mean difference(mm/year)	11.00	4.90
	Coefficient of determination (R^2)	0.81	0.95
Validation	Nash-Sutcliffe efficiency	0.59	0.78
	Mean difference (mm/year)	20.30	17.80
	Coefficient of determination (R^2)	0.69	0.81

As indicated in Table (11) the performance of the models calibrated on daily time step, this has shown low mean annual difference between the observed and the simulated discharge the mean difference (mean diff) value was 11 mm/year and 4.90 mm/year during calibration and 20.30 mm/year and 17.80 mm/year at validation for HBV and SMAR models. This show that the result is within acceptable range as Donigaian, (2000) stated as the range less than 10 it is very good, between 10 - 15 it is good and when the range 15-25 it is fair.

Comparisons of mean monthly runoff hydrograph values simulated by SMAR and HBV models with the observed values are depicted in Figure 17. There is a good agreement in the mean monthly observed runoff with both model simulations. The mean monthly runoff simulations of both models were underestimated for Shaya watershed. The main purpose of comparing the observed runoff with model simulated value was to check the capability of the models in reproducing the historical records at acceptable accuracy for Shaya watershed in order to make sure that the simulations perform well.

HBV simulated runoff was more underestimated than SMAR simulated runoff. Generally, the result demonstrates that both models were able to reproduce the observed flow of monthly runoff hydrograph for the watershed as indicated in Figure (17) and has two peaks which show the area has two seasons (bimodal).

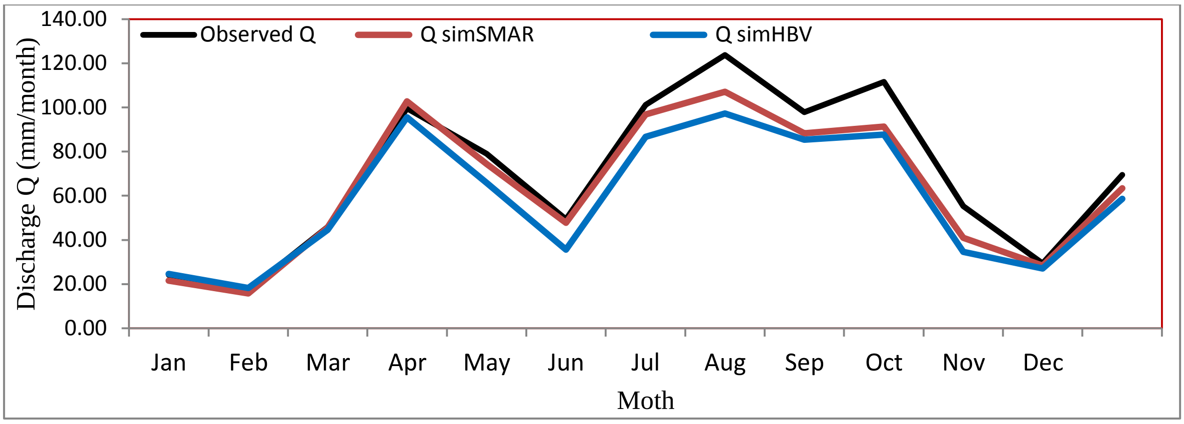

Figure 17. Comparison monthly simulated discharge of HBV and SMAR model for the whole period with respect to measured discharge.

Figure 18 also compares the measured mean monthly discharge (mm/month) over the calibration period with the SMAR and HBV-Light model results, and the coefficient of determination of the resulting regression function indicates an acceptable model performance. The R^2 values of both models calculation for watershed show that the observed and calculated runoff is well correlated

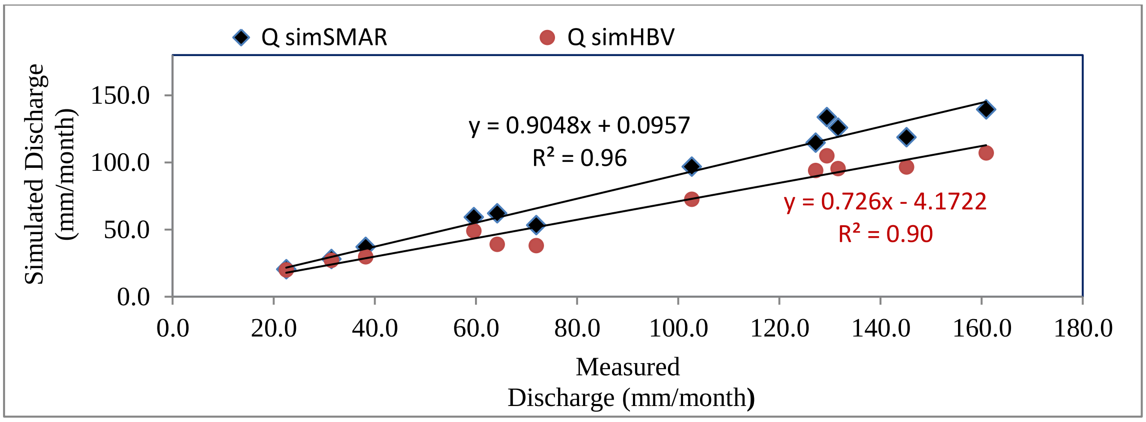

Figure 18. Monthly correlation plots of HBV (Red) and SMAR (Black) for the whole period.

A similar study by Kumela, (2011), conducted on Muger Sub Catchment in Ethiopia, demonstrated the lower performances of the HBV model as compared to the SMAR conceptual rainfall runoff models, which is comparable to the result obtained for this study.

However, the overall results reflected that the SMAR model simulation of the stream flow was better than that of HBV. The low quality data, low data availability and the model parameter might be possible obstacles for higher efficiency achievement during model validation. Overall, the good agreement between the observed and simulated flow demonstrated by the two models indicates, that the models can allow hydrological simulation in the study catchment.

The best agreement between the observed (69.53 mm/month) and simulated (63.40 mm/month) flow of long-term mean was found better for the SMAR model for Shaya watershed, while HBV model is not well reproducing the high flows and medium flow regimes. These differences may probably be attributed to rainfall events concentrated in few days, which produce exceptionally high flows and due to model parameter.

Both of the models do a fair job of simulating the discharge of Shaya watershed. However, it is noted that the SMAR model simulated a higher discharge compared to the HBV model. The models underestimated the high flows, while the low flows are well predicted.

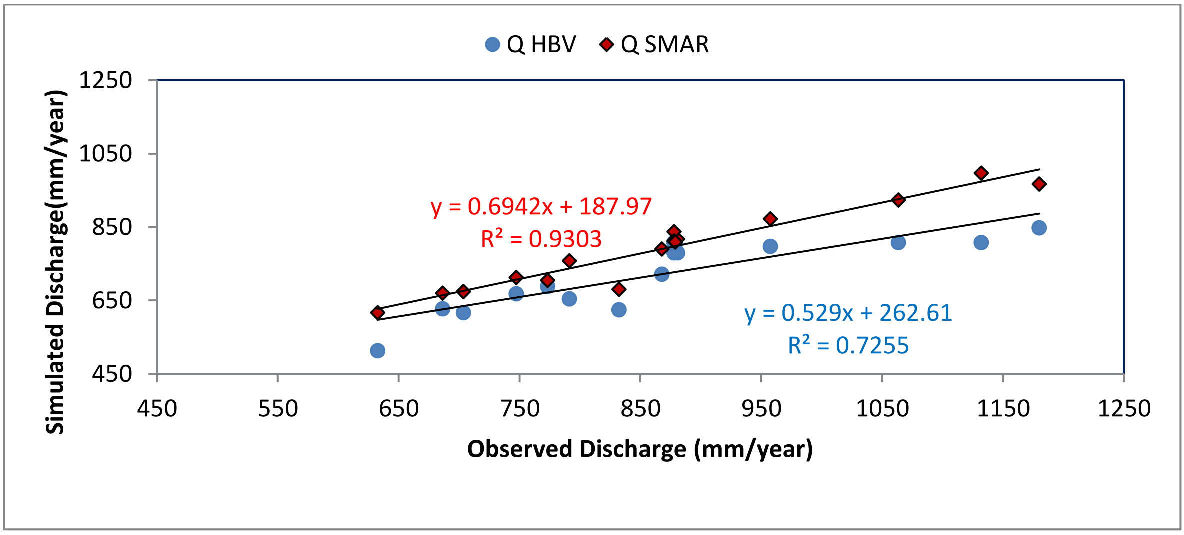

Figure 19.Annual correlation plots of HBV(Blue) and SMAR(Red) for the (1996-2010) period.

Figure 19 also compares the measured annual discharge (mm/year) over the calibration period with the SMAR and HBV-Light model results, and the coefficient of determination of the resulting regression function indicates an acceptable model performance. The analysis indicates that there was not a large difference in performance between the two models so both models simulate the discharge. But comparatively SMAR model perform well relative to the HBV model.

The result of the comparative studies by Kumela, (2011) showed that HBV and SMAR model performance good at Muger Sub Catchment. Taye *et al*. (2011) used two lumped conceptual models (VHM and NAM) in Lake Tana, Blue Nile basin, and confirmed that both model performances were satisfying. Jean, (2014) also used two conceptual models (HBV and TOPMODEL) in Ungagged Peat land Basins, at Canada, and confirmed that HBV is a reliable tool for rainfall-runoff simulation and performances were satisfying.

Generally, both models evaluated in this study are suitable for simulations of annual discharge at Shaya watershed because they produced comparable results. According to this study, the SMAR model is most suitable for discharge simulations in similar regions such as the Genale Dawa River basin. The annual water balance components of both model results are presented in Appendix Table 1 and 2.

4.6. Model Parameters Uncertainty Analysis

4.6.1. SMAR model parameters distribution

A uniform distribution was assumed for the selected parameters set for both SMAR and HBV model. GLUE methodology was applied in order to find the behavioral (Reff > 0.75) parameter sets.

The plot showed that, the value of objective function versus the value of model parameters (i.e upper and lower range of the parameters value) so that most sensitive parameters and the range of high objective function identified (Figure 20 and 22). For T and H the objective function Reff (NSE) value results reach 0.97 for high parameter values between 0 to 0.1 for T and 0.5 to 1 for H. However, most of T, H, G, Kg and Nk parameter value results have an objective function F threshold of > 0.75 (Reff) (Figure 20). According to the results it was determined that T values between 0.2 and 0.8 are most likely to have low objective function Reff values. In the case of H the value range is 0.5 to 1 for low Reff. On the other hand, objective function Reff value results are relatively evenly distributed for all G, Kg and Nk parameters range (Figure 20). This means that parameter G, Kg and Nk is less sensitive, therefore for constant T and H values; any parameter combination can result in high or low Reff values.

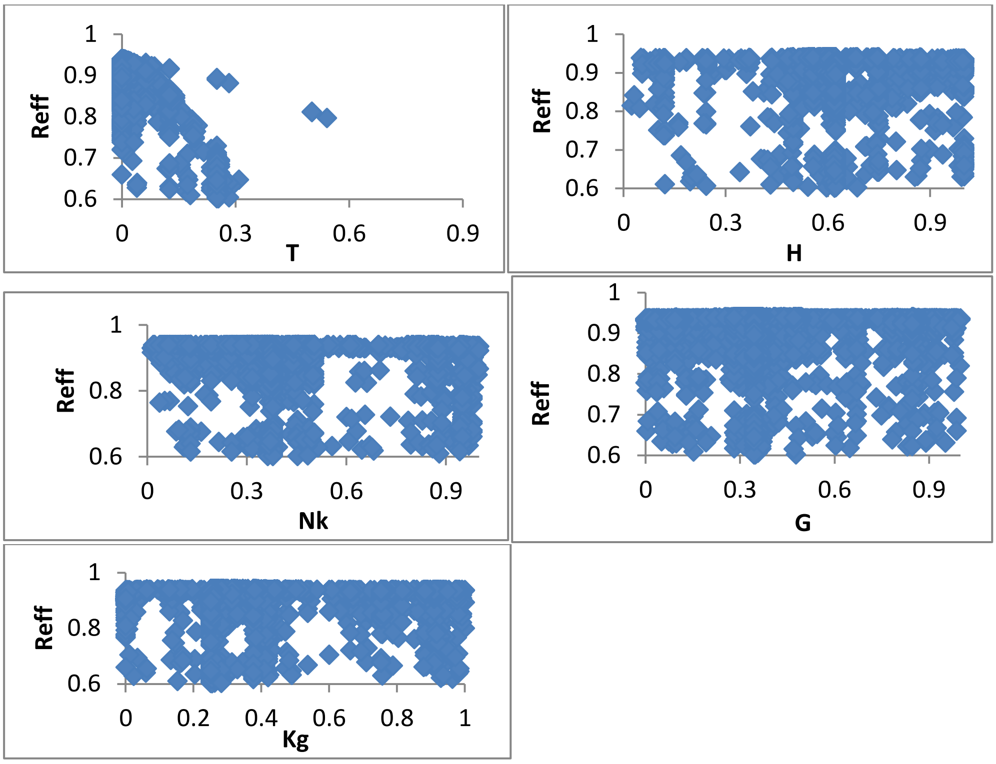

Figure 20. Scatter plot of objective functions results for most sensitive SMAR model parameters.

From the scatter plot (Figure 20) the objective function used was Nash-satcliffe efficiency (Reff) the plot were Reff versus range of model parameters for behavioral parameters(Reff > 0.75) .

Following the methodology in section 3.5.6, the likelihood values were resampled in accordance to an objective function Reff value limit. In this case, 331 resample likelihood values were found to be the behavioral amount according to graphical inspection between Q observed values and simulated higher and lower bounds for a 90% confidence level.

As can be seen in Figure 21, the 5th percentile line is skewed to the Q observed values. Normally higher values of T and H result in lower Q simulated values. The model is not taken into account higher parameter values that in theory should be included. Therefore, the simulated uncertainty bounds are overestimated explaining the reason of the skew.

Even though, the shape of the Q observed curve is identical to the Q simulated curves (Figure 21), there are two Q observed values that remain outside the 50% confidence interval. This means that the uncertainty is underrepresented. However, measurement uncertainty can affect the Q observed values, predominantly in dry months like February and November. Furthermore, despite the fact, that the model structure is assumed to be adequate for the watershed conditions, according to these results inadequate model structure can be possible.

Overall, the obtained parameter uncertainty should not be rejected, keeping in mind that other uncertainties (structural, measurement) are affecting the results.

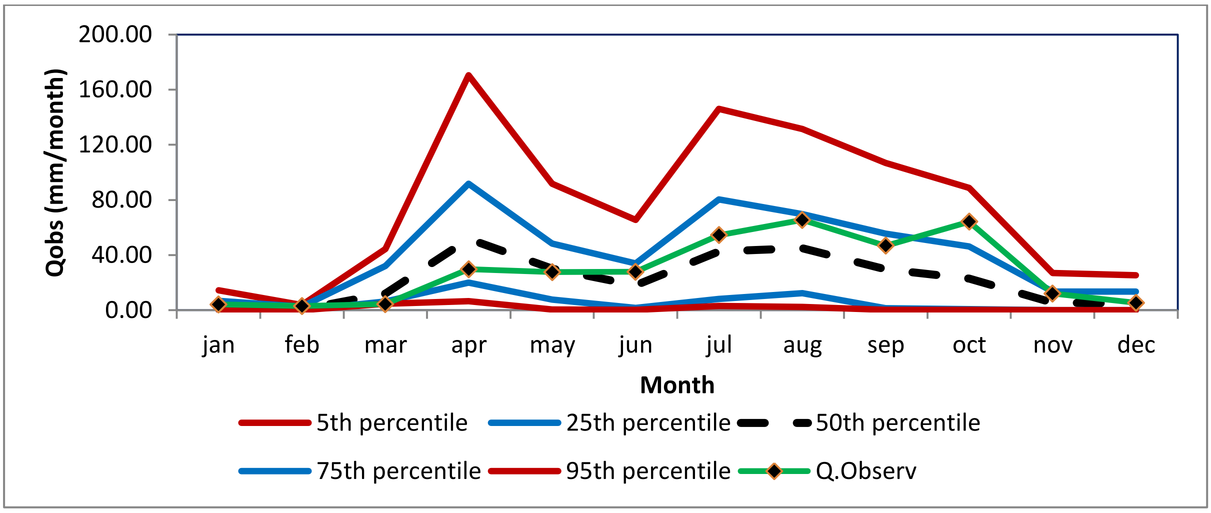

Figure 21. Simulated discharge values for a (95^{th} ,5^{th} ,75^{th} and 25^{th} Percentile) 90% and 50% confidence interval and observed discharge values (SMAR parameter uncertainty).

4.6.2. HBV model parameters distribution

From the result some of BETA and MAXBAS has the objective function Reff (NSE) value results reach 0.85 for high parameter values between 0.1 to 0.2 for BETA and 1 to 1.6 for MAXBAS. However as some of SMAR model parameters , most of K1, K0 and LP parameter value results have an objective function F threshold of 0.75 (Reff) (Figure 22). According to the results it was determined that BETA values between 0.4 and 1.9 are most likely to have low objective function Reff values. In the case of MAXBAS the value range is 1.6 to 2 for low objective function Reff. On the other hand, objective function Reff value results are relatively evenly distributed for all K0 and LP parameters range (Figure 22). This means that parameter K0 and LP is less sensitive, therefore for constant BETA and MAXBAS values; any parameter combination can result in high or low Reff values.

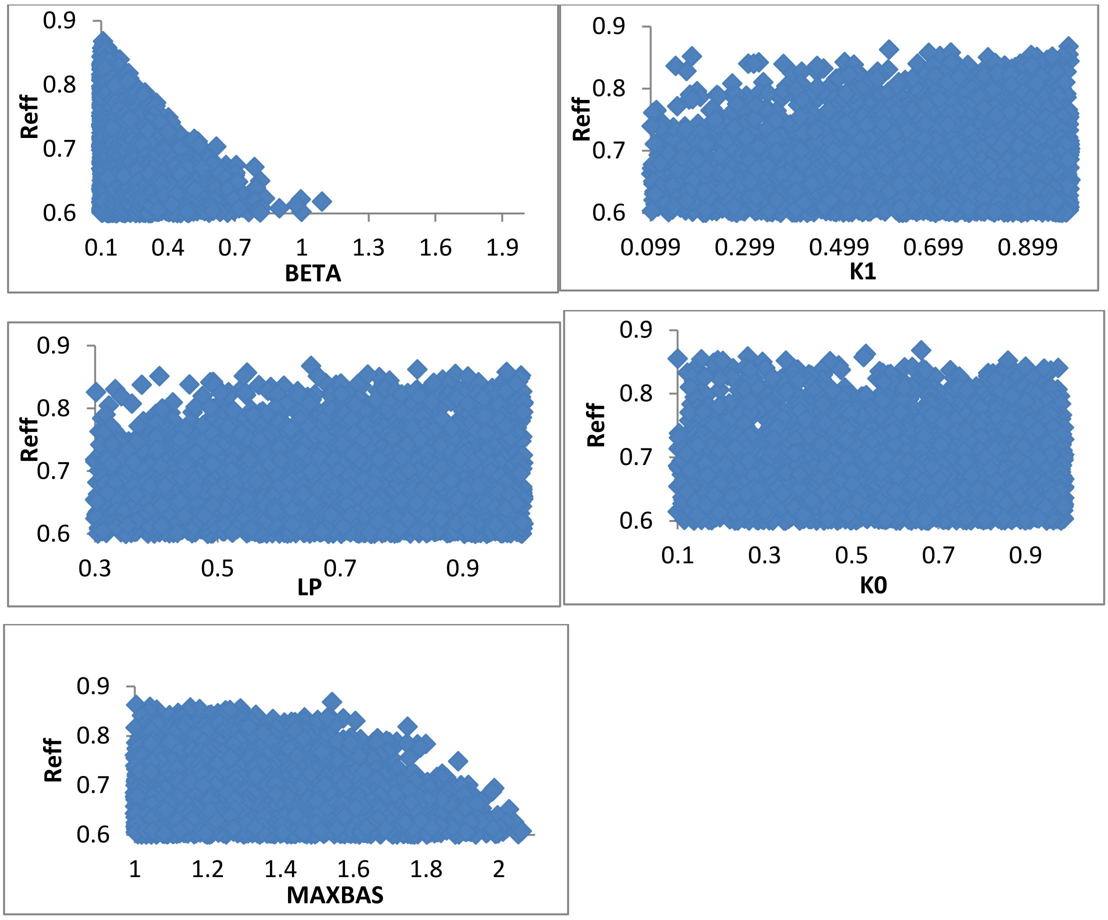

Figure 22. Scatter plot of objective functions results for most sensitive HBV model parameters.

Following the methodology 664 resample likelihood values were found to be the behavioral amount according to graphical inspection between Q observed values and simulated higher and lower bounds for a 90% confidence level.

As can be seen in Figure 23, the 5th and 75th percentile line is skewed to the Q observed values. Normally higher values of BETA and MAXBAS result in under estimation of Q simulated values. Therefore, the simulated uncertainty bounds are overestimated and underestimated explaining the reason of the skew.

The shape of the *Q* observed curve is identical to the *Q* simulated curves (Figure 23), there are five *Q* observed values that remain outside the 50% confidence interval. This means that the uncertainty is underrepresented. However, input (data) uncertainty can affect the *Q* observed.

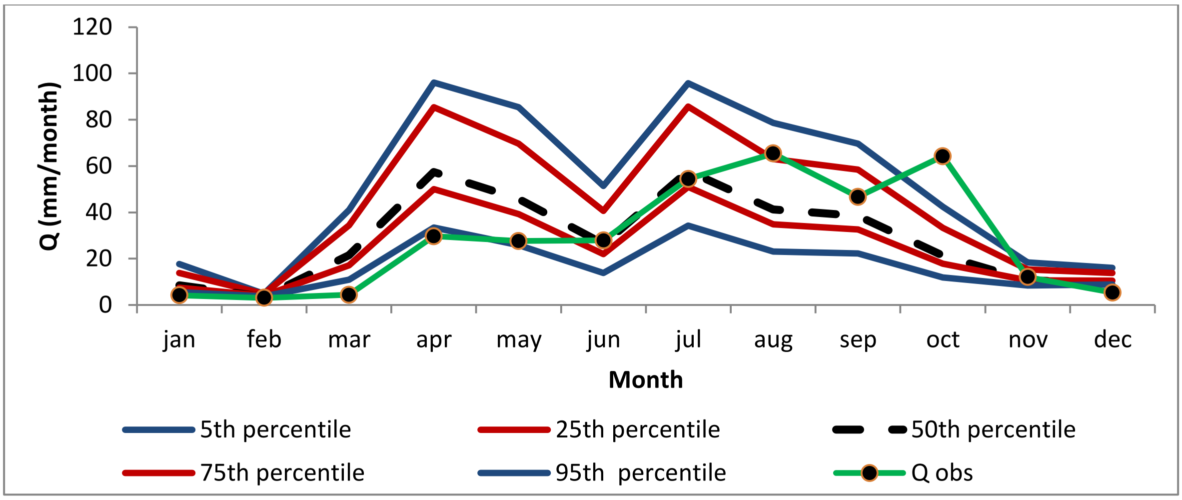

Figure 23. Simulated discharge values for a (95th ,5th ,75th and 25th Percentile) 90% and 50% confidence interval and observed discharge values (HBV parameter uncertainty).

A further application using actual observations of historical stream flow data from Shaya watershed showed that despite good agreement between the observed time series and the simulated predictions, some of the high flows fall outside of the estimated prediction uncertainty intervals. This supports the findings of other studies (Thiemann *et al*., 2001; Wagener *et al*., 2003; Gupta *et al*., 2003 ; Vrugt *et al*., 2003 and Moradkhani *et al*., 2005) that the role of other sources of uncertainty (model structural error and input measurement errors) must also be considered to improve accuracy in the model predictions.

5. SUMMARY, CONCLUSION AND RECOMMENDATIONS

5.1. Summary and Conclusions

Hydrological models are one of the most useful tools for understanding and managing watersheds. The objectives of this study were to conduct watershed modeling and compare and select the best conceptual rainfall-runoff model that can be used in the design, planning, and management of water resources in Shaya watershed. Two conceptual rainfall-runoff models namely SMAR and HBV were selected and tested for the hydrological characteristics of Shaya watershed. The performance and applicability of both SMAR and HBV model was successfully evaluated through sensitivity analysis, model calibration and validation. Automatic and manual calibration was applied for both models during calibration period. During calibration period of the models, the optimized parameters which give good performance result that is Reff > 0.7 for both models were determined. These optimized parameters where validated, and the result indicated that an efficiency value of 0.78 and 0.59 for SMAR and HBV respectively were obtained. 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.

Over all the results show that both models can reproduce historical daily runoff series with an acceptable accuracy. The values of Reff, NSE and mean difference indicate that both selected models produced good results for calibration and better result during validation periods. The SMAR model has the highest Reff value followed by HBV value in Shaya watershed during calibration and validation. From the result analysis of both models, it can be 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 underestimating the peak flow. The overestimation or underestimation of the higher flows for the models reflects the poor simulation of flood peaks, for the daily flows. 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

Intercomparision of the models based on the statistical and graphical performance indicators showed that the SMAR achieved better performances than the HBV model. Generally, the two models were capable of simulating the dominant hydrological processes. According to this study, the SMAR model is most suitable for discharge simulations in data-sparse regions such as the Genale Dawa basin even if it is a conceptual model. However, great caution is required for application of the models in water resource management related.

The Generalized Likelihood Uncertainty Estimation (GLUE) was applied to determine the model parameter uncertainty. Four thousand parameter sets for both SMAR and HBV were randomly generated, assuming uniform distribution for each parameter. Finally, 331 and 664 parameter sets were selected as behavioral for SMAR and HBV model respectively. It was determined that for both model the selected behavioral data sets the model parameter uncertainty is higher for different confidence intervals. Parameter uncertainties were combined and the highest runoff variability in the Shaya watershed was found to be in April and the lowest in February for different confidence intervals for both models.

From the analysis it can be concluded that model SMAR is relatively better since the observed discharge is within 95% confidence interval obtained by the MC simulation. It can be said that in general SMAR models reproduce the MC simulations uncertainty bounds reasonably well except for some peaks. Although some errors can be noticed, the predicted uncertainty bounds follow the general trend of the MC uncertainty bounds. Noticeably, HBV model fails to capture the observed flow during some peak events. Note however, that the results of the SMAR model and the MC simulations are visually closer to the observed data.

It was found that including model parameter uncertainty in the simulated monthly water balance, decreases reliability between 5% and 10% .Therefore it is important to include Input uncertainty for reliability studies to obtain more dependable results. Thus, further study in the Shaya watershed and Genale Dawa basin in general with updated data and a variety of models is required. In addition, possible adaptation options for the watershed impacts must be studied.

5.2. Recommendations

- The SMAR model performed well in simulating monthly and daily flow of the Shaya watershed. Therefore, the calibrated parameter values can be considered for further hydrologic simulation of the watershed and the model can be taken as a potential tool for simulation of the hydrology of unguaged watershed in mountainous areas of Ethiopia which behave hydro meteorologically similar with Shaya watershed.

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

- Uncertainty assessments of model predictions are crucial for a sound use of models in water resources management in practice. Model predictions without uncertainty assessments correspond to only presenting a (minor) part of the available information.

- Further studies on the uncertainties of predicting the flow should be practiced using other methods.

- Further research on trends in all water balance components is needed by incorporating the climate and land use change. However, in water balance components, the land use and climate change for the Shaya watershed was not considered. Therefore, detail research works which incorporate the land use and climate change, ground water, is recommended to understand the interaction of surface and sub-surface condition and river water balance.

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7. APPENDICES

7.1. Appendix Tabels

Table 1. Annual (1995-2015) of rainfall all station

Year	Robe	Gobba	Agarfa	Dinsh
1995	763.0	939.8	759.6	1296.8
1996	895.5	888.7	596.6	1174.1
1997	1392.3	1233.9	811.5	1453.5
1998	929.6	1224.0	1737.0	1334.6
1999	1123.8	859.7	1374.7	1201.8
2000	773.8	938.0	1432.4	1150.4
2001	1238.2	1230.6	1327.9	1051.7
2002	648.9	801.5	1220.7	907.7
2003	891.4	921.3	806.3	875.5
2004	793.4	973.9	1004.5	895.7
2005	987.9	892.5	1044.0	1002.9
2006	972.0	1381.9	780.3	1144.3
2007	1135.0	1118.6	1108.1	1013.4
2008	830.0	839.7	958.3	598.8
2009	797.5	617.2	896.8	987.0
2010	1067.1	768.63	1168.7	1372.5
2011	622.5	866.6	789.9	998.9
2012	1079.9	1048.6	987.2	1205.8
2013	1009.5	945.1	994.1	1096.8
2014	1019.9	855.5	637.3	1035.2
2015	895.2	996.3	928.1	1064.4
Mean	946.0	968.6	1017.3	1088.6

Table 2. Comparison of the both model based on their relative error

Year	SMAR			HBV		
	Q Simulated	Q Observed	Relative error (%)	Q Simulated	Q Observed	Relative error (%)
Jan	21.54	24.15	-10.8	24.55	24.15	1.6
Feb	15.77	17.31	-8.9	18.18	17.31	5.1
Mar	45.54	45.85	-0.7	44.55	45.85	-2.8
Apr	102.77	99.54	3.2	95.45	99.54	-4.1
May	74.46	79.00	-5.7	65.82	79.00	-16.7
Jun	47.69	49.38	-3.4	35.55	49.38	-28.0
Jul	96.77	101.23	-4.4	86.73	101.23	-14.3
Aug	107.15	123.77	-13.4	97.27	123.77	-21.4
Sep	88.23	97.85	-9.8	85.36	97.85	-12.8
Oct	91.31	111.62	-18.2	87.73	111.62	-21.4
Nov	40.92	55.31	-26.0	34.64	55.31	-37.4
Dec	28.38	29.38	-3.4	27.0	29.38	-8.1
Mean	63.40	69.50	-8.85	58.6	69.5	-15.8

Table 3. Uncertainty analysis statistics for selected input parameter for SMAR model

Parameter	Range	CI(95%)	Mean	SD	SE
C	0-1	±0.0079	0.497	0.286	0.004
G	0-1	±0.0079	0.499	0.288	0.004
H	0-1	±0.008	0.497	0.29	0.0041
KG	0-1	±0.008	0.5	0.29	0.0041
N	1-6	±0.0399	3.5	1.44	0.0203
NK	0.0-1	±0.0079	0.5	0.285	0.004
T	0-1	±0.008	0.502	0.2893	0.004
Y	0-5000	±39.71	2476.05	1432.56	20.25
Z	**0-5000**	**±40.1083**	**2495.6**	**1446.67**	**20.459**

CI (95%) =95%confidence Interval; SD=Standard deviations and SE=Standard error of the mean

Table 4. Uncertainty analysis statistics for selected input parameter for HBV model

Parameter	Range	Mean	SE	SD	CI (95%)
PERC	0-4	2.04	0.035	1.135	±0.0704
UZL	0-70	35.8	0.655	20.72	±1.28
K0	0.1-0.99	0.538	0.0081	0.258	±0.016
K1	0.01-0.99	0.499	0.0089	0.282	±0.0175
K2	0.00001-0.1	0.495	0.0088	0.278	±0.017
MAXBAS	1-2.5	1.758	0.0138	0.438	±0.027
FC	9-550	276.01	4.93	155.9	±9.678
LP	0.3-1	0.649	0.0065	0.2	±0.0128
BETA	0.1-5	3.03	0.037	1.17	±0.072

CI (95%) =95%confidence Interval; SD=Standard deviations and SE=Standard error of the mean

Table 5. Error analysis for SMAR model parameters

% Change of Parameters	SMAR Model Parameters								
	C	G	H	Kg	N	Nk	T	Y	Z
-25	0.000	0.000709	0.003072	0.000141	0.000046	0.000065	-0.006102	0.000	0.000
-20	0.000	0.000524	0.002409	0.000107	0.000047	0.000065	-0.006102	0.000	0.000
-15	0.000	0.000333	0.001762	0.000075	0.000049	0.000052	-0.004849	0.000	0.000
-10	0.000	0.000205	0.001240	0.000060	0.000051	0.000052	-0.003558	0.000	0.000
-5	0.000	0.000144	0.000976	0.000054	0.000052	0.000051	-0.002232	0.000	0.000
0	0.000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000	0.000
5	0.000	0.000000	0.000219	6.71E-05	5.57E-05	4.84E-05	0.002131	0.000	0.000
10	0.000	-2.9E-05	0.000180	8.44E-05	5.71E-05	5.62E-05	0.004173	0.000	0.000
15	0.000	-3.7E-05	0.000110	0.000111	6.51E-05	7.06E-05	0.005020	0.000	0.000
20	0.000	-2.1E-05	0.000000	0.000135	6.51E-05	6.99E-05	0.007181	0.000	0.000
25	0.000	2.01E-05	0.000178	0.000176	6.51E-05	0.000164	0.007836	0.000	0.000

Table 6. Error analysis for HBV model parameters

% Change of Parameters	HBV Model Parameters								
	FC	LP	BETA	PERC	UZL	Ko	K1	K2	MAXBAS
-25	-0.0015	0.0398	-0.0304	-0.0020	-0.0014	0.0383	0.039	0.0003	-0.0804
-20	-0.0012	0.0291	-0.0241	-0.0016	-0.0011	0.0304	0.031	0.0002	-0.0688
-15	0.0009	-0.0201	0.0180	0.0012	0.0008	-0.0226	-0.0231	-0.0002	0.0543
-10	0.0006	-0.0125	0.0119	0.0008	0.0006	-0.015	-0.0153	-1E-04	0.0376
-5	0.0003	-0.0028	0.0060	0.0004	0.0003	-0.0074	-0.0076	0.0000	0.0194
0	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
5	0.0003	-0.0027	0.0058	0.0004	0.0003	-0.0074	-0.0075	-1E-04	0.0201
10	0.0005	-0.0052	0.0116	0.0008	0.0005	-0.0146	-0.0149	-1E-04	0.0408
15	0.0007	-0.0076	0.0174	0.0012	0.0008	-0.0217	-0.0222	-0.0002	0.0619
20	0.0010	-0.0089	0.0231	0.0017	0.0011	-0.0287	-0.0294	-0.0002	0.0830
25	0.0012	-0.0121	0.0286	0.0022	0.0021	-0.0356	-0.0364	-0.0003	0.1042

7.2. Appendix Figures

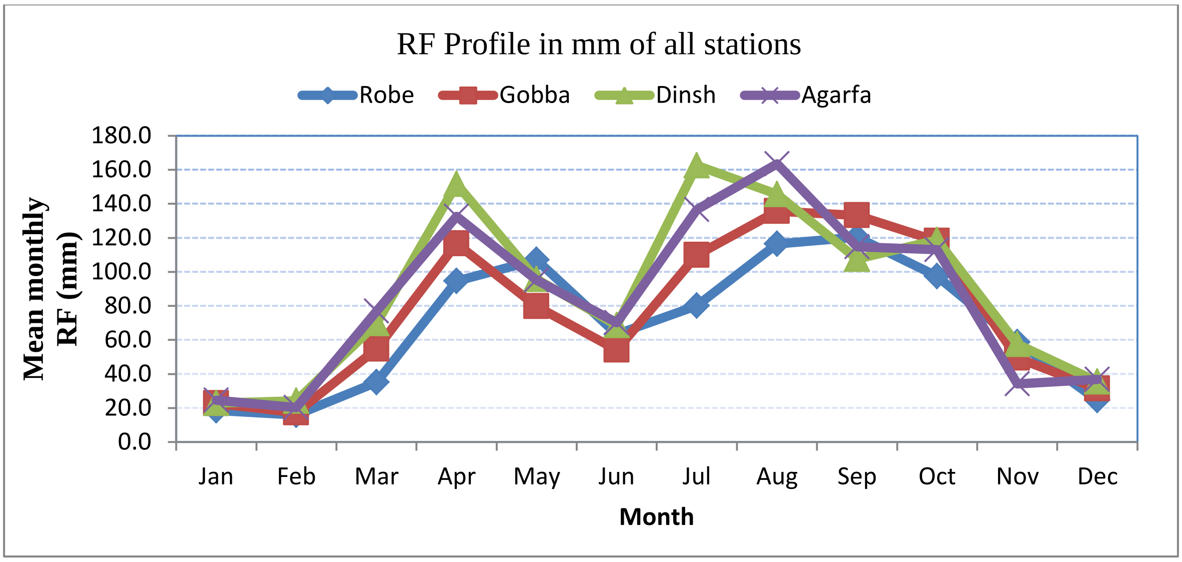

Figure 1. Average monthly rainfall distributions in Shaya river watershed.

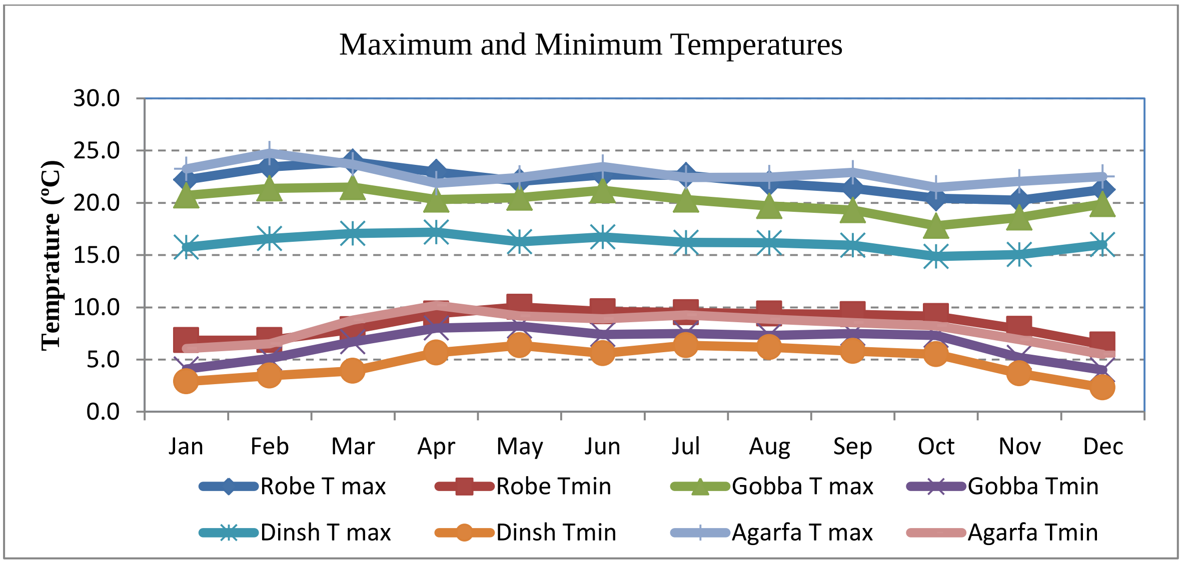

Figure 2. Mean monthly minimum and maximum temperature profile.

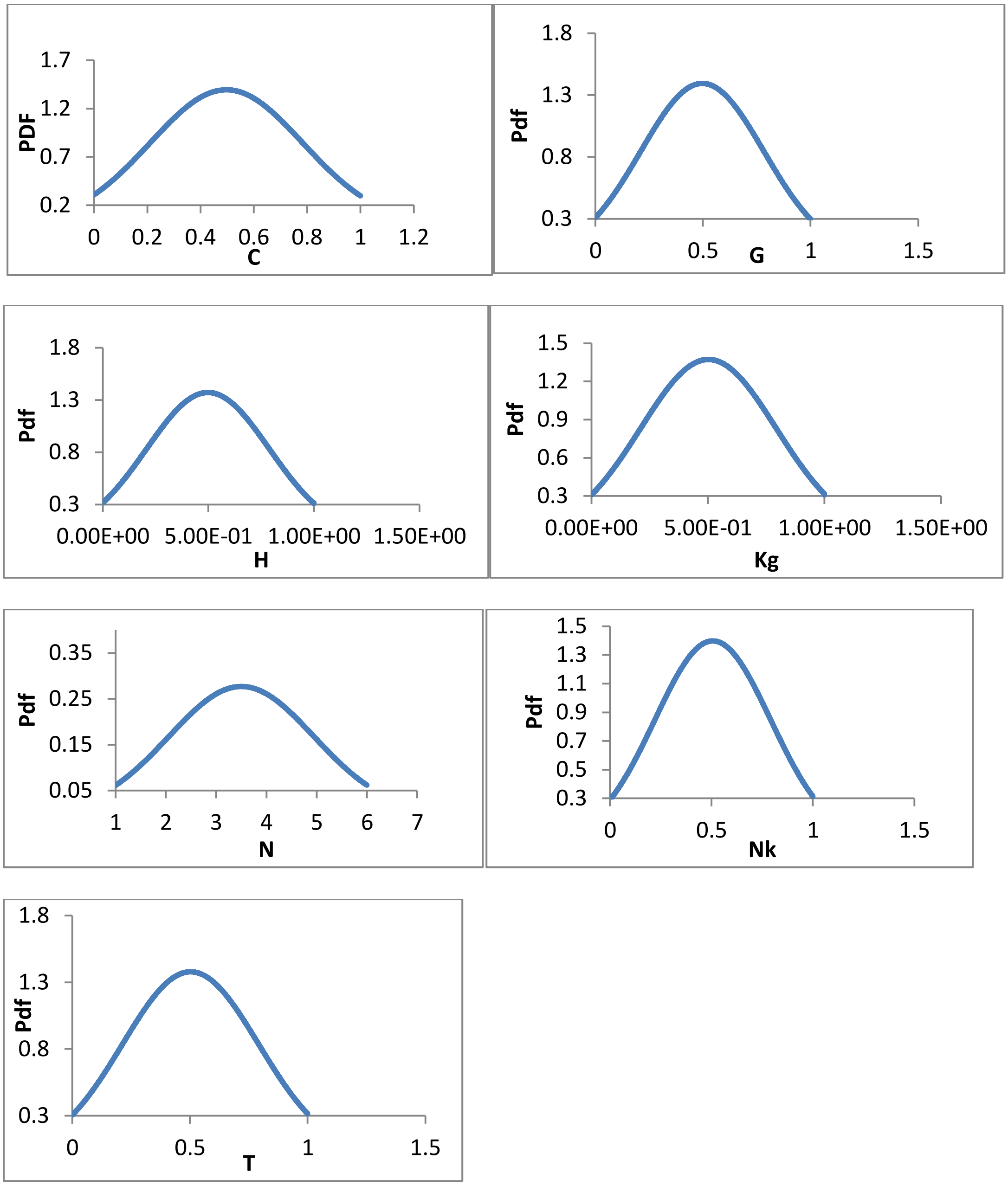

Figure 3. Probabilty distribution funcation (pdf) of the selleceted SMAR model parameters.

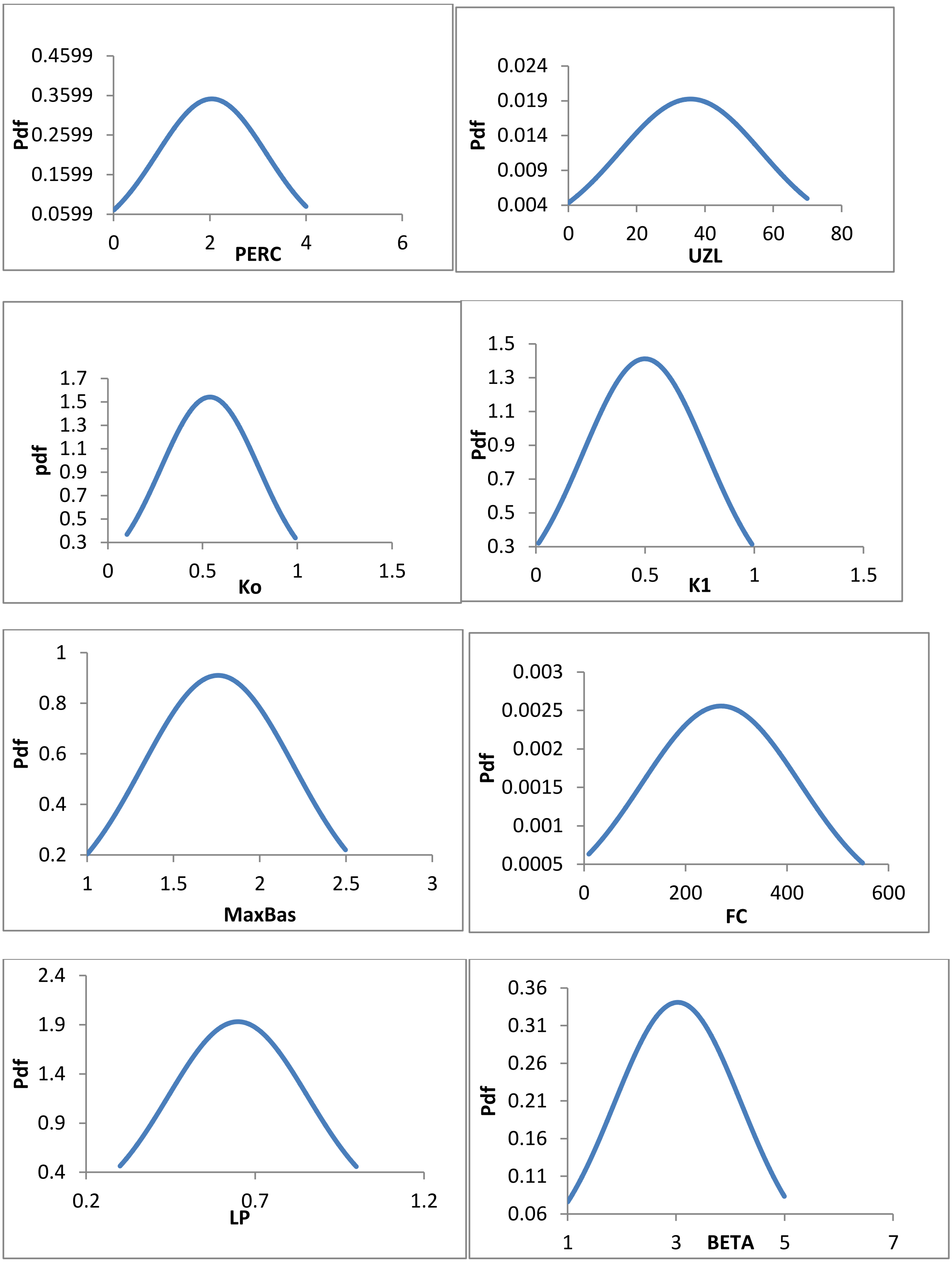

Figure 4. Probability distribution funcation (pdf) of thes HBV model parameters.

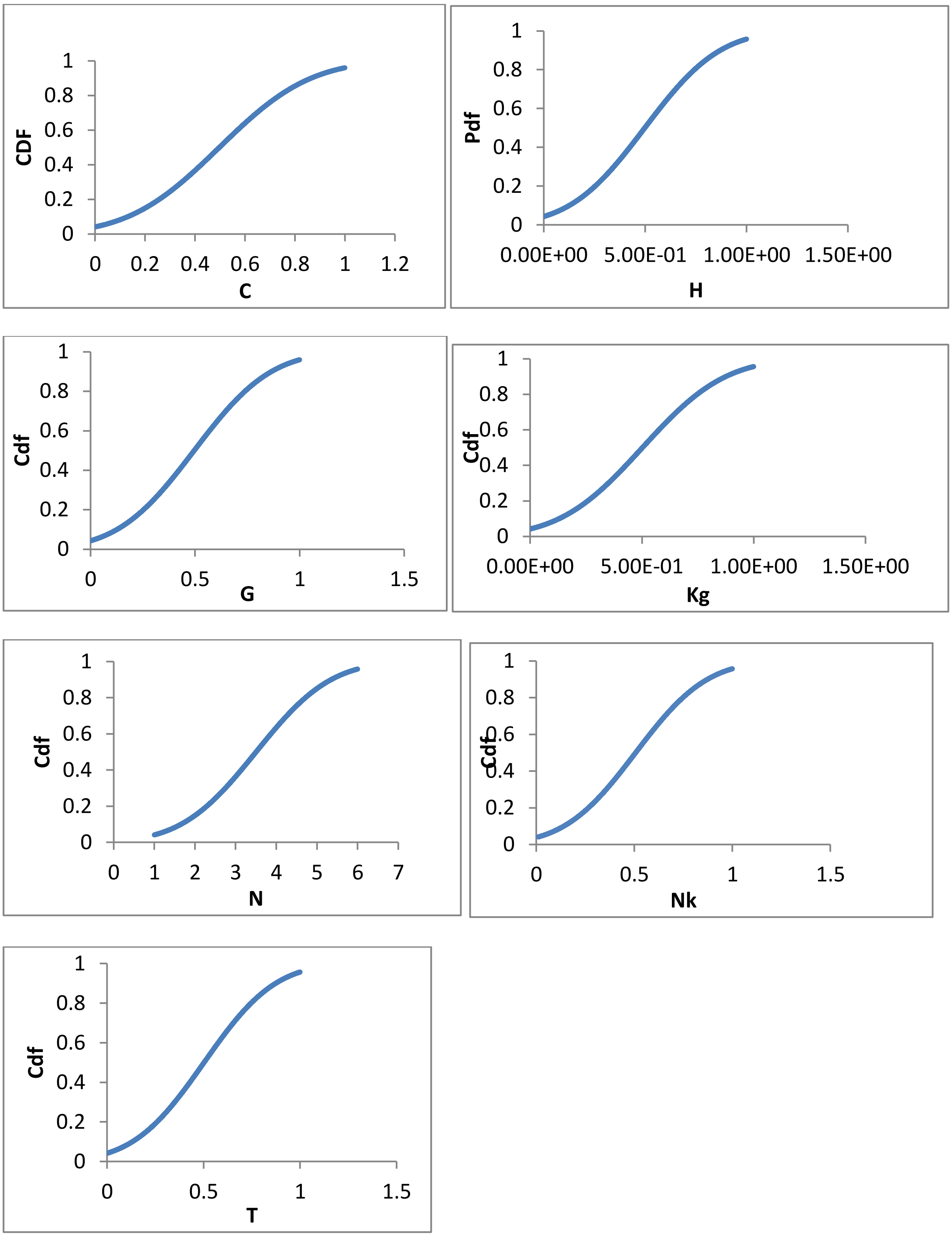

Figure 5. Cumulative probabilty distribution (cdf) of the selleceted SMAR model parameters.

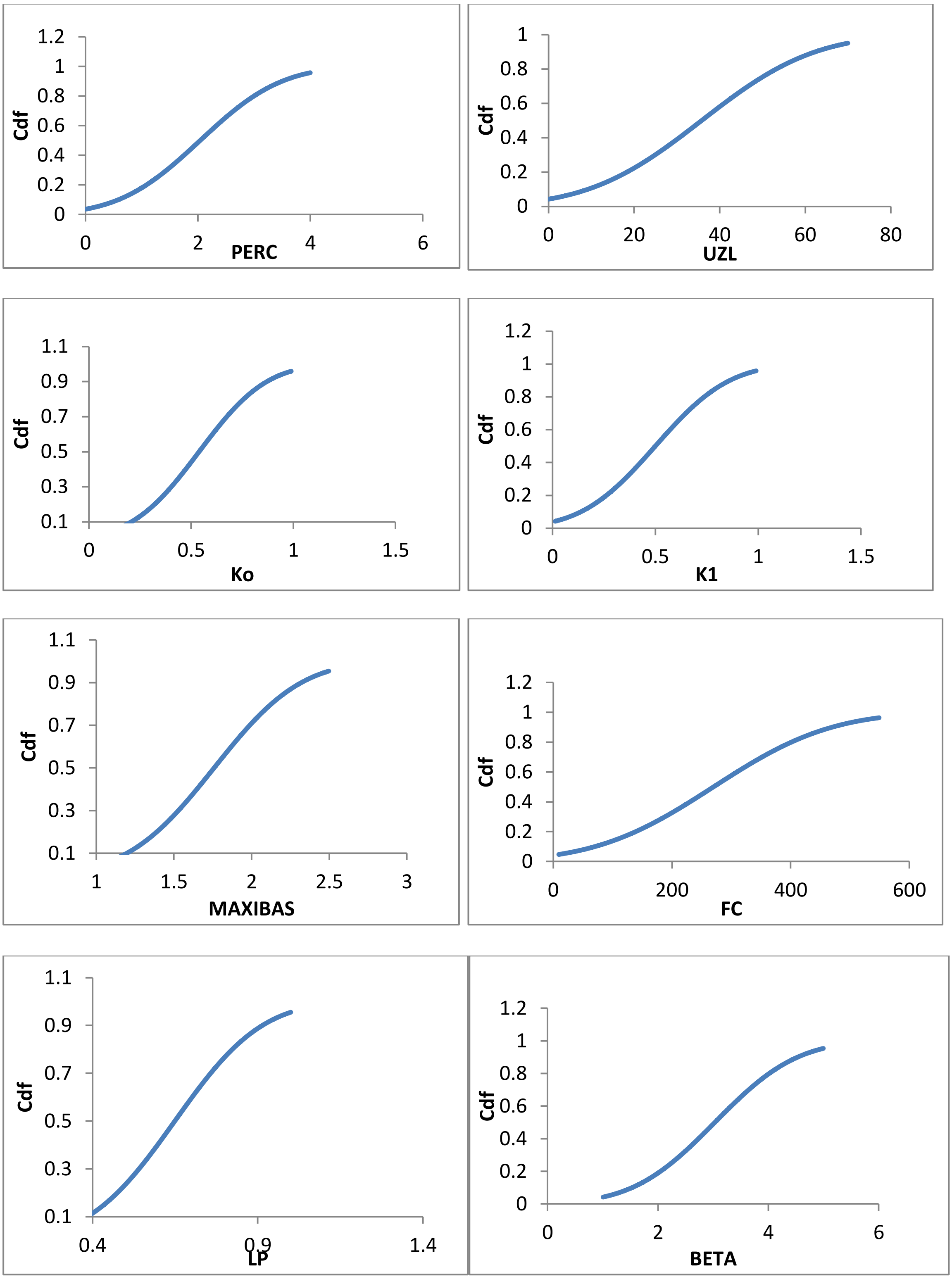

Figure 6. Cumulative probabilty distribution (cdf) of the selleceted HBV model parameters.

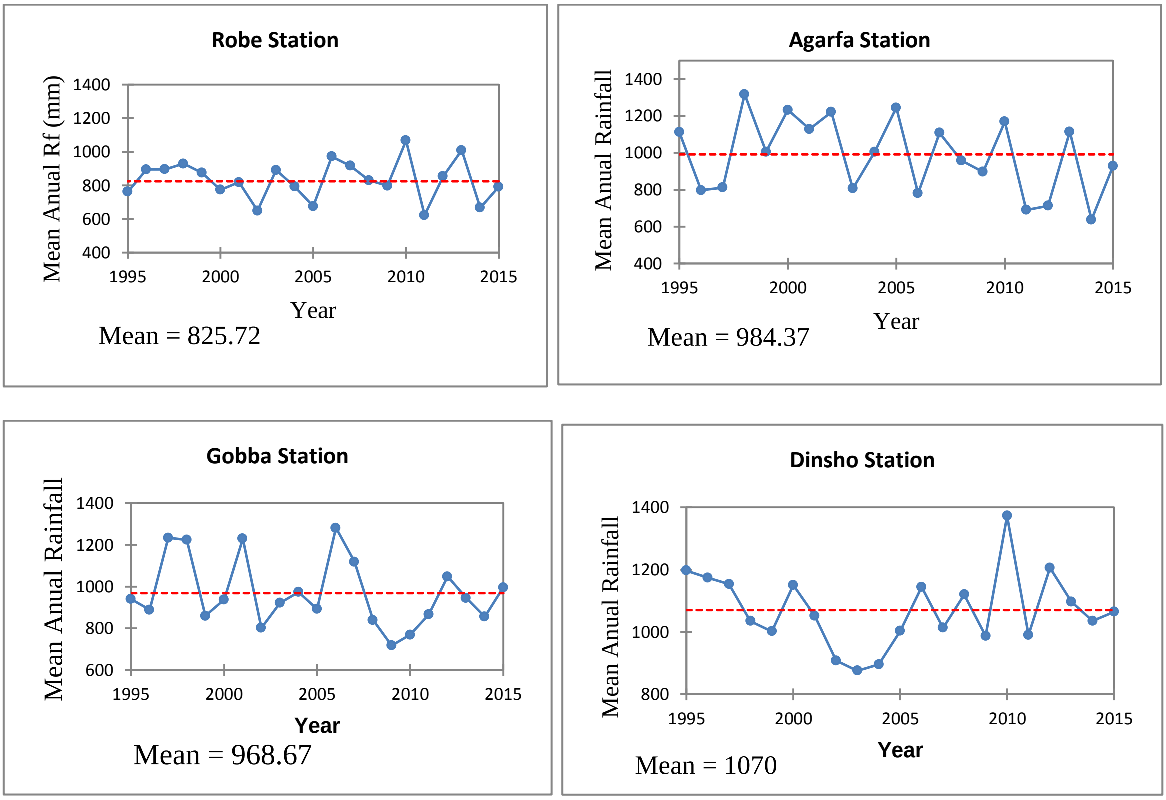

Figure 7. Homogeneity test of rainfall station using their annual data using standard normal homogeneity test (SNHT)

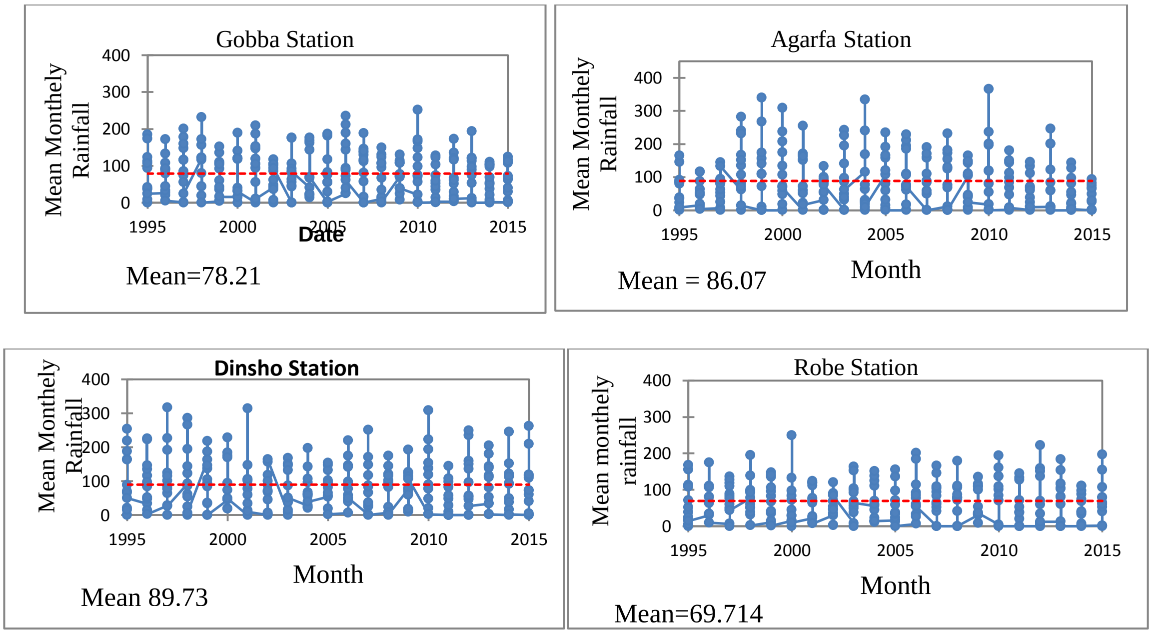

Figure 8. Homogeneity test of rainfall station using their monthly data using standard normal homogeneity test (SNHT)

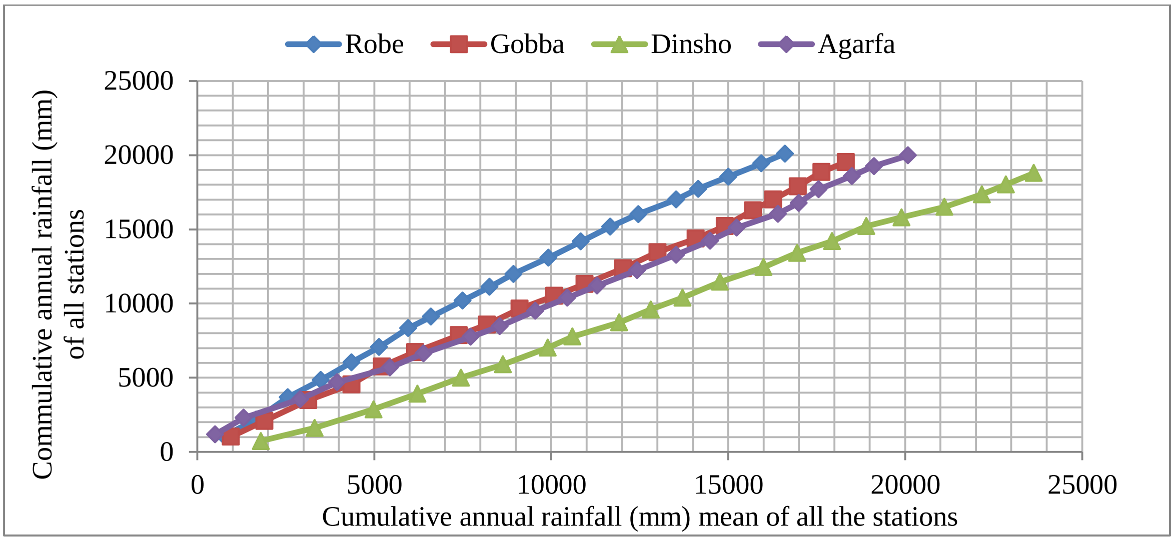

Figure 9. Double mass curve of all the rainfall station

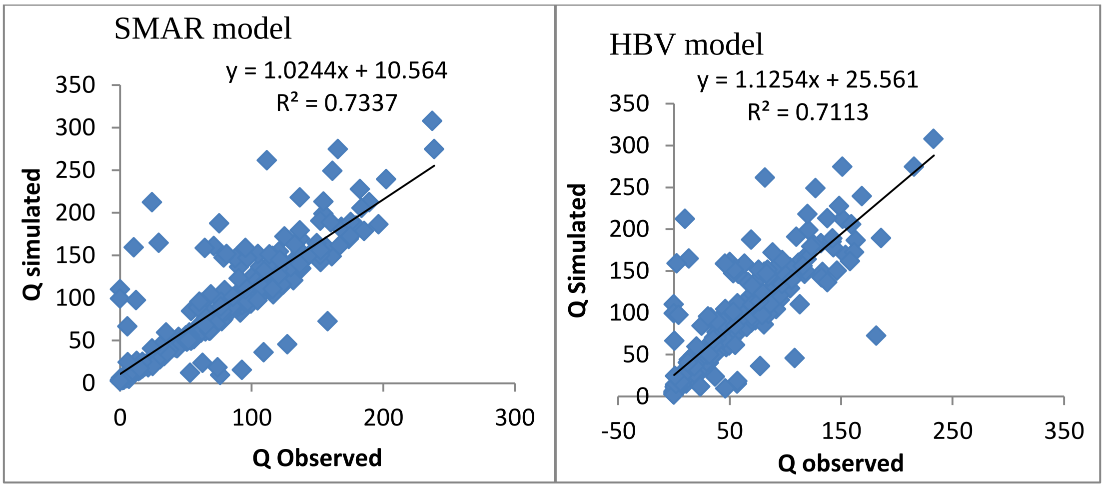

Figure 10. Scatter plot diagram of simulated vs observed discharge using SMAR and HBV model for the whole period (1996-2015)

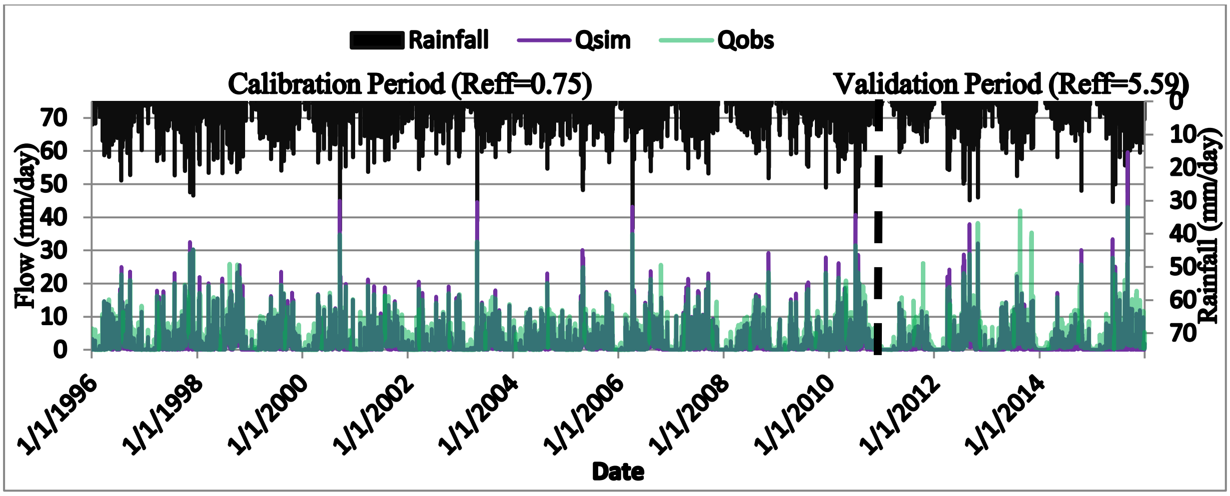

Figure 11. Comparison of calibration (1996-2010) and validation (2011-2015) result of HBV model for daily observed and simulated discharge.

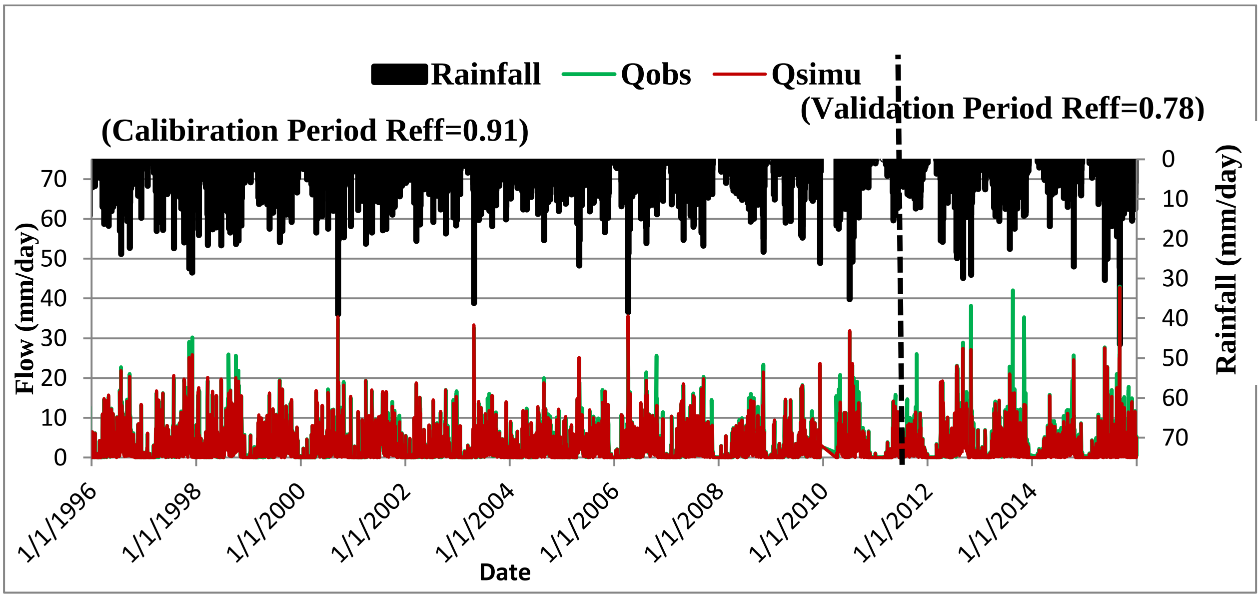

Figure 12. Comparison of calibration (1996-2010) and validation (2011-2015) result of SMAR model for daily observed and simulated discharge.

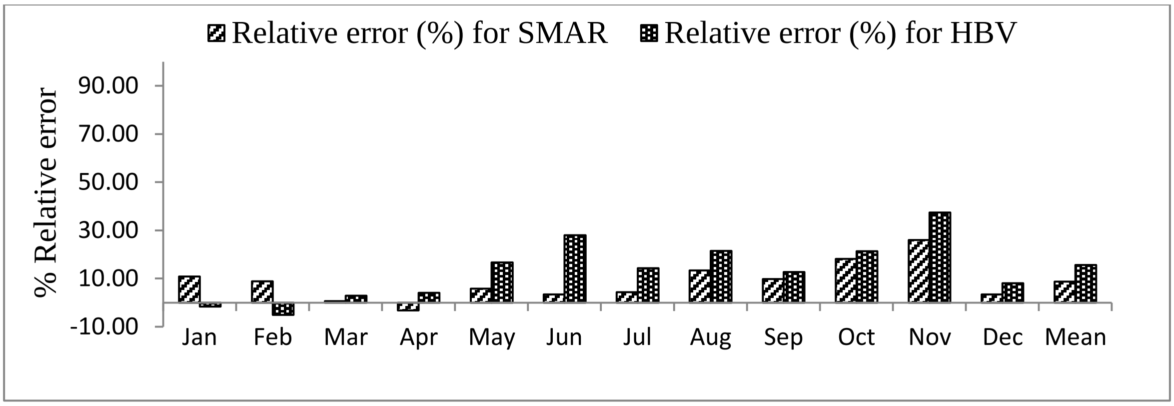

Figure 13. Relative error percent (%) of monthly simulated discharge for both models

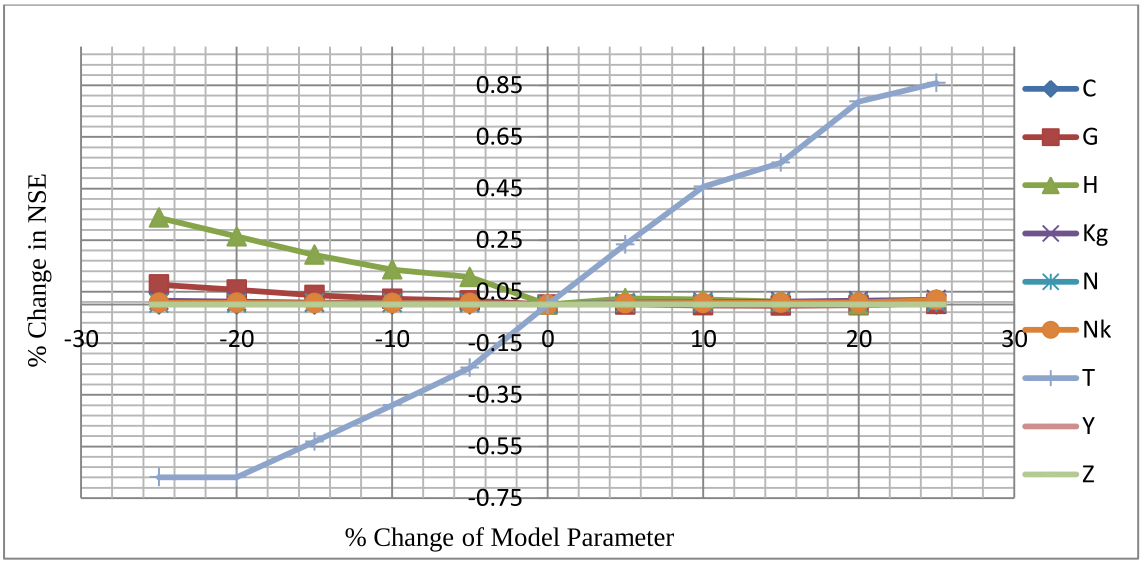

Figure 14. Result of sensitivity analysis of SMAR model.

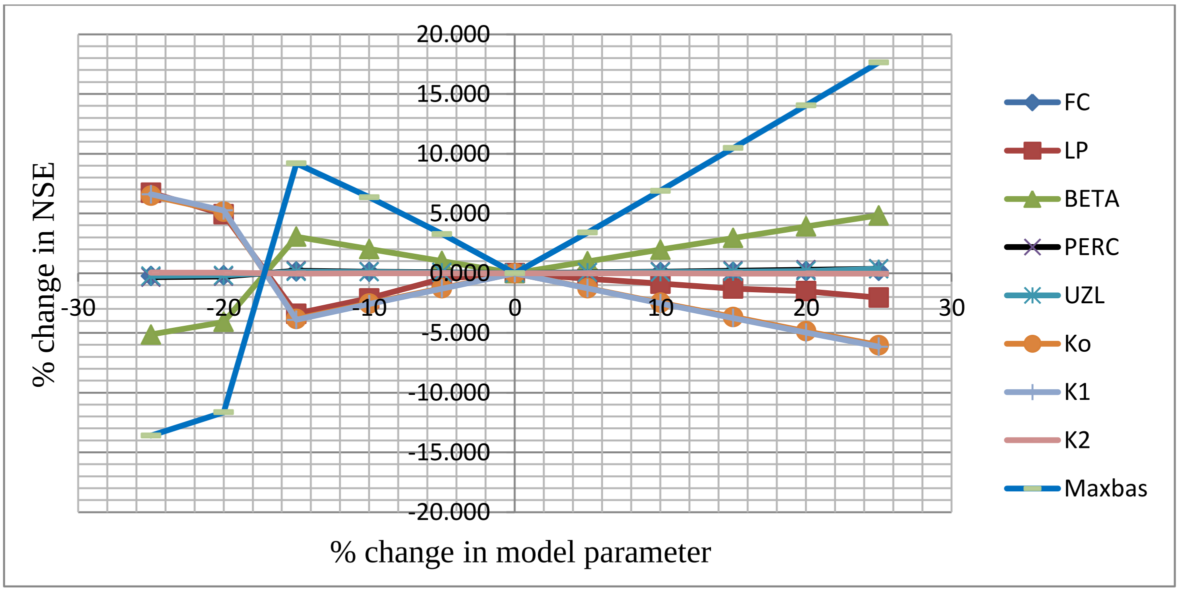

Figure 15. Result of sensitivity analysis of HBV model.