EFFECT OF WATERSHED SUBDIVISION AND ANTECEDENT MOISTURE CONDITION ON HEC-HMS MODEL PERFORMANCE IN THE MAHA OYA BASIN, SRI LANKA

Muhammad Kamran

(15579 F)

Degree of Master of Science in

Water Resources Engineering and Management

Department of Civil Engineering

University of Moratuwa

Sri Lanka

Febryary 2017

EFFECT OF WATERSHED SUBDIVISION AND ANTECEDENT MOISTURE CONDITION ON HEC-HMS MODEL PERFORMANCE IN THE MAHA OYA BASIN, SRI LANKA

Muhammad Kamran

(15579 F)

Thesis Submitted in Partial Fulfillment of the Requirements for the Degree of Master of Science in Water Resources Engineering and Management

Supervised by

Dr. R. L. H. L. Rajapakse

UNESCO Madanjeet Singh Center for South Asia Water Management (UMCSAWM)

Department of Civil Engineering

University of Moratuwa

Sri Lanka

February 2017

DECLARATION

I declare that this is my own work and this thesis does not incorporate without acknowledgement any material previously submitted for a Degree or Diploma in any other University or institute of higher learning and to the best of my knowledge and belief it does not contain any material previously published or written by another person except where the acknowledgement is made in the text.

Also, I hereby grant to University of Moratuwa the non-exclusive right to reproduce and distribute my thesis/dissertation, in whole or in part in print, electronic or other medium. I retain the right to use this content in whole or part in future works (such as articles or books).

…………………………..   …………………..

Muhammad Kamran   Date

The above candidate has carried out research for the Master's thesis under my supervision.

………………………………   ……………………..

Dr. R. L. H. L. Rajapakse   Date

ACKNOWLEDGEMENTS

First and above all, I praise Allah, the almighty for providing me this opportunity and granting me the capability to proceed successfully.

Furthermore, I would like to express the deepest appreciation to my research supervisor Dr. R. L. H. Lalith Rajapakse for his research guidance and for his warm and constant encouragement during my research tenure. Without his dedicated supervision and continued guidance, this thesis would not have been a success. I am deeply grateful to him for his valuable time and support, encouragement and professional advice that I received through out in the research and writing of this thesis.

I will never hesitate to convey my thanks to the Center Chairman Professor N. T. S. Wijesekera who always helped me by extending all necessary help to carry out my research. He was kind enough to provide guidance and support even with his tight schedules. His sincere and consistent encouragement is greatly appreciated.

I would like to extend my utmost appreciation to Dr. T. M. N Wijayaratna, Head/Hydraulic and Water Resources Engineering Group of the Department of Civil Engineering for extending help and support and professional advice for my research.

I would also like to thank Mr. H. W. Kumarasinghe and all staff at UMCSAWM, who encouraged, inspired, supported, assisted, and sacrificed their time and efforts to help my pursuit of a Master's degree.

I am indebted to many of my colleagues with whom I worked together and who supported me despite their own work and those who helped me in achieving the success in research and writing of the thesis and all the other persons that supported me, directly or indirectly in many ways during my stay here.

I would especially like to thank Late Shri Madanjeet Singh, SAF (India) and the University of Moratuwa for giving me this opportunity to study towards a Master's Degree in Water Resource Engineering and Management, at the UNESCO Madanjeet Singh Centre for South Asia Water Management (UMCSAWM), Department of Civil Engineering, University of Moratuwa, Sri Lanka. Last and most importantly, I would like to thank my family, and friends for giving me the strength to finish this thesis.

ABSTRACT

Effect of Watershed Subdivision and Antecedent Moisture Condition on HEC-HMS Model Performance in the Maha Oya Basin, Sri Lanka

Rainfall-Runoff models such as Hydrologic Modeling System (HEC-HMS) are used for predicting the hydrologic response of watersheds. Due to the effect of discretization, the model accuracy increases with number and watershed sub-divisions and the inferred level of soil saturation in the model. Therefore, an important issue that must be addressed by all users of these models is the determining of an appropriate level of watershed subdivision and Antecedent Moisture Condition (AMC) for runoff simulation.

The present research study was conducted in an attempt to find appropriate answers for the above two modelling issues. As a case study, the Badalgama watershed is selected as study area in the Maha Oya Basin in Sri Lanka. Spatial extent of Badalgama watershed is 1272 km^2 with an upstream river length of 96 km. Four rainfall stations and one river gauge station are selected in Badalgama watershed. Daily rainfall and streamflow data were used for calibration period from 2005 ~ 2008 and for validation period from 2010 ~ 2013.

River basin was divided into 3, 6, 9, and 16 number of subdivisions based on critical threshold area method using ArcGIS 10.5. Nash–Sutcliffe (NASH) and Mean Ratio of Absolute Error (MRAE) objective functions were selected as the evaluation criteria of the model. HEC-HMS modeling was carried out for different subdivisions and varying AMC conditions.

The result shows that with MRAE objective function, the accuracy of the model increased by 4.5% up to six subdivisions and with NASH, the accuracy increased by 4.2% with respect to the same lumped model. The accuracy of the model found to decrease for the model with six subdivisions to sixteen sub-divisions. The accuracy of the model with Antecedent Moisture Condition with AMC-III was found to increase by 12.04% as compared to AMC-II.

With the above findings, it is concluded that subdivision of watershed for modeling results in no more than modest improvements in prediction of low flow and medium flow simulation. As the result shows in the AMC analysis AMC-III produced improved accuracy of 12.04% in calibration period and 6.60% for validation period as compared to AMC-II. The event-wise estimation of AMC led to further increase in model accuracy.

In this research, the recession method was considered for the base flow simulation which led to a mass balance error exceeding 20%. Therefore, it is recommended apply linear reservoir method as base flow simulation method to further improve the modelling accuracy by conserving the water balance.

Keywords: Antecedent Moisture Condition, Hydrological modeling, Sensitivity analysis, Watershed subdivision

TABLE OF CONTENTS

LIST OF APPENDIX

LIST OF FIGURES

LIST OF TABLES

1.0 INTRODUCTION

1.1 Background of the study

Sri Lanka is an island situated near the southern tip of India, located between latitude 6° N and 10° N and longitude 80° E and 82° E. Rainfall in Sri Lanka has multiple origins with monsoonal, convectional and expressional sources while monsoonal rain accounts for a major share of the annual rainfall. The mean annual rainfall varies from under 900 mm in the driest parts (south-eastern and north-western) to over 5000 mm (in the central hill slopes).

Wijesekera, Imbulana, and Neupane (2005) stated that Sri Lanka is a humid tropical island, situated in the path of two monsoons, the south-west and the north-east monsoons. In spite of this fact, Sri Lanka has greater part of the country experiencing extended dry spells lasting several months due to spatial variability of rainfall leading to vast areas of water deficit in the country. The wet zone in the west of the country is the only water surplus area in the country. Critical deficit exists in the northern, north-western, north-eastern, and south-eastern parts. In the dry zone which surrounds 75 % of the land area, the availability of surface water is frequently affected by the failure of the north-east monsoon. Due to poor aquifer conditions, groundwater too is limited in the dry zone.

The rainfall-runoff hydrologic models are used as a tool in solving water resource issues especially in ungauged basins. To solve hydrological problems, there are two major types of hydrologic modeling which are often involved (i.e. lumped and distributed). The watershed is treated to be homogenous with its representative parameters (land use, soil type, etc.) in a lumped hydrologic model. However, with the large watershed sizes, the homogeneity can be affected because larger watersheds are more likely to have variable conditions within the watershed (Cleveland, Luong, and Thompson, 2009a). Due to such large watershed sizes, the rainfall runoff modeling treating the entire basin as a single lumped model might lead to poor simulation results. Watershed subdivision is usually used in semi-distributed hydrologic models to capture spatial heterogeneities of distributed land cover and soil data sets and to characterize distributed inputs in different areas within the watershed.

In a previous study, Zhang, W.J.Wang, W.Q.Wang, Li, and Wang (2013) have done work in Clear Creek watershed in Lowa, United States to investigate the effect of watershed scale on HEC-HMS calibrated parameters. Authors concluded that the value of key calibrated parameters are sensitive to watershed partition scheme and watershed partition affected hydrologic process due to parameter changes. Kanchanamala, Herath, and Nandalal (2016) stated that the impact with catchment scale on rainfall runoff modeling would increase the model performance by increasing the number of sub-basins and also suggested that a modeler needs to consider along with the stream network, the other catchment properties such as soil properties, land cover, land use, slope, etc., when dividing a catchment into sub-catchments. Ghosh and Hellweger (2012) described about effects of sub-catchments and that sub-watershed size affects the determination of peak flow magnitude and that the effect varies for different storm types. Similarly Ao et al. (2003) described that with higher subdivision level during the wet period, the discharges are generally increased while that decreases in the dry period. But in case of annual runoff simulation, the difference between total runoff is said to be negligible.

For antecedent soil moisture (AMC), Wei and Zhang (2011) had carried out research work to investigate the effect of AMC on runoff modeling. The authors worked on Rangeland Hydrology and Erosion Model (RHEM) model and concluded that model sensitivity analysis showed an average of 0.05 mm change in runoff generation for each 1% change in soil moisture, indicating an approximate 0.15 mm average variation in runoff accounted for by the 3% standard deviation of measured AMC.

Several authors have used a variety of well-established hydrological models to investigate the effects of sub-watershed size on hydrological model output and these studies include the SWAT model (Kumar and Merwade, 2009), SWMM (Ghosh and Hellweger, 2012) and HEC-HMS (Cleveland, Luong, and Thompson, 2009).

This present study was conducted based on the hydrologic modeling system and model developed by the Hydrologic Engineering Center (HEC-HMS), which has a large number of parameters that can be individually calibrated. This study was focused to check the effect of watershed sub-division on the HEC–HMS model performance and also the effects of antecedent soil moisture.

For this research, Badalgama watershed study area is selected in the Maha Oya basin. The Maha Oya (river) originates in the Kandy district of Sri Lanka and travels about 130 km passing four districts to reach the sea at Kochchikade in Sri Lanka. It holds the 3rd largest average annual runoff among the 103 of distinct river basins in Sri Lanka.

1.2 Hydrological modeling in Sri Lanka

Sampath, Weerakoon and Herath (2014) have applied HEC-HMS model for runoff simulation in the tropical catchment of Deduru Oya river basin in Sri Lanka. Authors used daily rainfall data and five layered soil moisture accounting loss method, Clark unit hydrograph transformation method, and recession based flow method in HEC-HMS model. The results depicted that the capability of HEC-HMS to reproduce stream flows in the basin by Nash Sutcliffe efficiencies of 0.80 and concluded that the calibrated model is capable of capturing the seasonal characteristics of stream flow satisfactorily.

Kanchanamala, Herath and Nandalal (2016) reported a similar work in Kalu Ganga basin, Sri Lanka with lumped and distributed models using a selection of loss methods, transform methods and base flow methods with eighteen different combinations and three configurations. Authors concluded based on the results that the most appropriate set of parameter combination for Kalu Ganga upper catchment was the deficit constant method as loss method, Snyder unit hydrograph method as transform method and the recession method as base flow method gave satisfactorily result with Nash of 0.761.

Ratnayake, Sachindra and Nandalal (2010) have carried out a study for flood prediction in the Nilwala basin using HEC-HMS with Clark's, Snyder's and SCS transformation methods and also used HEC-RAS hydraulic model. Out of the three transformation methods, Snyder's method had performed better with Nash-Sutcliff efficiencies greater than 70% and 50% in calibration and verification, respectively.

Halwatura and Najim (2013) have conducted a study for runoff simulation in a tropical catchment in Sri Lanka using HEC-HMS. Authors selected three methods; the Soil Conservation Services (SCS) Curve Number and the deficit constant as loss methods and the Snyder's unit hydrograph method and the Clark's unit hydrograph method selected as the transformation methods while objective functions were the coefficient performance for the error series A (CP_A) and RE%. According to the results, the most reliable CP_A value obtained from the calibration process was closer to the zero (both with Clark unit hydrograph method and Snyder unit hydrograph method).

1.3 Why hydrological models are needed?

Hydrologic models are generally designed to meet two primary objectives. One objective of the catchment modeling is the generation of artificial segment of hydrologic data for facility design or for use in forecasting. Another objective of the catchment modeling is to gain a better mastery and comprehension of the hydrologic situation in a catchment.

Vorosmarty et al. (1989) described that mathematical models have taken over the most important tasks in problem solving in hydrology. Similarly, Moradkhani and Sorooshian (2008) stated that hydrology modeling is a simplified representation of a real world system and nowadays considered an essential tool for water resource management. The best hydrologic model is the one which gives results close to reality with the use of the least number of parameters and model complexity.

1.4 Challenges of water situation in Sri Lanka

1.4.1 Impact of climate change

According to National Climate Change Adaptation Strategy for Sri Lanka (2016), the sectors most affected by climate change are agriculture, water resources and public health. The Second National Communication warns that observable shifts in weather patterns coupled with a continuous rise of ambient temperature across the country and increasing variability of rainfall are projected to have large-scale effects on agricultural productivity, food and water security.

1.4.2 Water demand for agriculture sector

In Sri Lanka, all the three main crops (Tea, Rubber and Coconut) are almost totally fed by rain. Only 16 % of Sri Lanka’s GDP depends on agriculture and forestry, which includes the use of underground water. Total water withdrawals have been estimated at 10 km^3 in 1996. Most of the water withdrawals are used for growing rice with ~85%

of the irrigated area and 44% of the population being in the dry zone. A huge irrigation infrastructure has to be maintained for just one crop, which is essential for food security in the country as it is the main diet. The irrigation efficiency at present is about 20%, which could double by 2025. By any measure, water use in agriculture is a very inefficient practice with poor returns (Gunatilaka, 2008).

1.4.3 Water demand for water supply sector

In Sri Lanka, the average per capita water availability is 2500 $m^3\ yr^{-1}$. The district level water availability for per capita is highly variable, with effective steps needed for water conservation and management if severe scarcities are to be avoided in many parts of the country. As Gunatilaka (2008) stated, the per capita availability of 1750 $m^3\ yr^{-1}$ is the water-stress threshold for a country.

1.5 Problem statement

For water resource management, medium flow and low flow conditions are highly important and therefore with the large scale of a watershed, the accuracy level of medium and low flow simulation could decline and therefore it is important to subdivide the watershed to achieve and appropriate the level of accuracy.

In Kelani river basin, the resulting flood level was much higher than the expected due to 2016 (May, June) storm events. This is unprecedented and the reason may be due to saturated moisture level in the soil layer. Therefore, the AMC is an important parameter to be investigated to check the accuracy and possible further improvement of the basin model.

Therefore, identification of the most appropriate level of sub-divisions and antecedent soil moisture condition is of utmost importance in hydrologic modelling.

1.6 Objectives

1.6.1 Overall objective

To develop a rainfall runoff model and identify the effect of watershed subdivision and antecedent moisture condition on HEC-HMS model performance in Badalgama sub-watershed of Maha Oya Basin, Sri Lanka.

1.6.2 Specific objectives

1. To develop a rainfall runoff model for Maha Oya basin using HEC-HMS.
2. To identify parameter sensitivity and response to governing parameters.
3. To validate and calibrate the developed model for different watershed subdivisions.
4. Comparison of model performance with respect to different watershed subdivision.
5. To assess the effect of antecedent moisture condition on HEC-HMS calibrated parameters and model performance.
6. Deriving recommendations for better water resource management.

1.7 Limitations and scope of the research

The rainfall input consists of measurements for only four rainfall stations within the watershed. The use of these few rainfall stations to represent conditions over an entire watershed provides for only a rough estimate of the observed conditions. The rainfall input into watershed models is often the largest source of error in the modeling process because point measurements fail to accurately represent the watershed rainfall. The delineation of watershed subdivisions is carried out based on stream network and slope and other watershed characteristics are not considered in this research. Evaporation and canopy is ignored for the simplicity of the approach. Due to constraints in the data set, only eight-year data was used in this research. Antecedent moisture conditions model in HEC-HMS analysis was run only for that particular values associated with AMC-II and AMC-III conditions to check the performance of model (using the respective Curve Number, CN related to watershed characteristics).

The scope of the research is targeted for better water resource management by proposing the appropriate level of subdivisions while antecedent moisture model is considered for flood disaster management.

2.0 LITERATURE REVEIW

2.1 General detail of hydrological model

Application of mathematical models in water resource planning and forecasting has become increasingly popular during the last decade in Sri Lanka and elsewhere in the world, with the introduction of microcomputers. Dharmasena (1997) described that numerical models can be used for the simulation of river flows in planning of water resource projects and real-time flood forecasting.

The term Hydrological model is commonly used for all the models describing the hydrological cycle or its major parts. It is very difficult to construct general models that treat the whole hydrological cycle in any given catchment in the world due to variations in climate, topography, land types, and land-use as well as various man-made intrusions with the system. Models developed in a certain climatic or geologic region often have difficulties when used in a different setting (Lundin et al., 2000).

2.2 Types of hydrological modeling

Hydrologic models are simplified, conceptual representations of a part of the hydrologic or water cycle. There are two major types of hydrologic models that can be distinguished based on their characteristics.

2.2.1 Stochastic models

These models are black box systems based on data and they use mathematical and statistical concepts to link a certain input (for instance rainfall) to the model output (for instance runoff). Commonly used techniques in this type of models are regression, transfer functions, neural networks and system identification, and these models are known as stochastic hydrologic models. Stochastic models use a random variable to represent process uncertainty and generate different results from one set of input data and parameter values (Pechlivanidis, Jackson, Mcintyre, and Wheater, 2011).

2.2.2 Process-based models

These models are known as deterministic hydrologic models and these models try to represent the physical processes observed in the real world. Typically, such models give a representation of surface runoff, subsurface flow, evapotranspiration, and channel flow, but they can be far more complicated. Stochastic rainfall could be used as an input to a deterministic rainfall model (Pechlivanidis et al., 2011).

2.2.3 Lumped hydrologic models

Lumped models can be made to behave more like distributed parameter models by adopting a detailed database and dividing a watershed into very small sub watersheds. Lumping method averages the total rainfall, its distribution over space, soil characteristics, overland flow conditions, etc. for the entire watershed, ignoring all flow-routing mechanisms that exist within it. Lumped models treat the catchment as a single unit, with state variables that represent averages over the catchment area (Beven, 2008).

2.2.4 Semi-distributed hydrologic models

A semi-distributed model represent the important features of catchment, while at the same time requiring less data and lower computational costs than distributed model (Orellana, Pechlivanidis, McIntyre, Wheater, and Wagener, 2008).

2.2.5 Distributed hydrologic models

United States Army Corps of Engineers (USACE) examined the application of the distributed model by using HEC-HMS Model. Based on statistical and graphical data it has been found that the HEC-HMS distributed approach simulated streamflow is better than lumped modeling approach (Bhattacharjya, 2011). All distributed models use average variables and parameters at element or grid scales, and often parameters are averaged over many grid squares, mainly due to data availability (Beven, 2012). A catchments having heterogeneity of rainfall distribution the distributed rainfall runoff model may offer better approach for flood hydrograph simulation (Abushandi and Merkel, 2013).

2.3 Classification of hydrological modeling

Rainfall runoff models can be classified as continuous simulation models or event based models. Continuous simulation typically would take into account a time series of rainfall, which may incorporate more than one storm events, while event-based models take into account only one storm event.

Hydrological models may be classified into those of small catchments (up to 100 km^2), medium-size catchments (100 ~ 1000 km^2), and large catchments (greater than 1000 km^2). For averaged reasonable process scale, the classification might be based on homogeneity (Wagener, Sivapalan, Troch, and Woods, 2007).

Pechlivanidis, Jackson, Mcintyre, and Wheater (2011) stated that the time scale may be defined by the time intervals used for input and internal computations, or by those used for output and calibration of the model.

2.4 HEC-HMS Background

The Army Corps of Engineers Hydrologic Engineering Center (HEC) created the Hydrologic Modeling System (HEC-HMS) as a flexible runoff modeling software package. It replaced the popular HEC-1 program and also it is capable of modeling a wide range of watersheds by offering several different mathematical models, and in nature all of which are deterministic. HEC-HMS improvements over HEC-1 include a graphical user interface that allows for convenient editing and also result viewing (Viessman, Lewis, and Knapp, 2002). According to Li, Coe, Ramankutty, and de Jong (2007) HEC-HMS is a valuable tool for forecasting and quantifying the effects of different inputs for a watershed. Hydrological models, like HEC-HMS are vast range and also economical.

According to the HEC-HMS manual of the, HEC-HMS has three basic model components as:

1. Basin model
2. Meteorological model and
3. Control specification

Basin model represents the physical characteristics of the hydrologic elements of a watershed and also it converts atmospheric conditions into streamflow at specific locations of the watershed. Meteorological model is for preparing meteorological boundary conditions to sub-basins. HEC-HMS supports to seven evapotranspiration method and eight different precipitation methods. Control specifications used to control the simulation time span (Scharffenberg, 2016).

Precipitation loss method, transform method, base flow method are main components of the basin model. There are 11 different precipitation loss methods in HEC-HMS model and the purpose of precipitation loss methods is to simulate the actual surface runoff, reducing the infiltration. Infiltration, surface runoff and sub-surface processes acting together in the real world. There are 7 different transform methods in HEC-HMS and transform method is created to perform actual surface runoff calculations. Base flow method is created to simulate subsurface processes and 6 different methods have provided in the software (Scharffenberg, 2016).

Short wave radiation method, Precipitation method, Evapotranspiration method and snow melt methods are main components of meteorological model. Suns' incoming radiation is represented by shortwave radiation method. Snowfall or precipitation is represented by the precipitation method and there are 8 and 2 different method for precipitation and snow respectively in the software by the evapotranspiration method potential evapotranspiration over the land surface is represented by using the air temperature, snowmelt method determines whether the precipitation is rain or snow (Scharffenberg, 2016).

2.4.1 Continues and event base simulation

A single-event hydrologic modelling should be used for simulating storm and frontal rainfall induced floods. Continuous modelling approach should be then employed for simulating snowmelt and mixed rainfall-snowmelt flooding, as well as for simulating the prolonged periods of summer low flows (Munz, 2017).

Halwatura and Najim (2013) described that infiltration methods, Loss methods and base flow methods in HEC-HMS need to be selected according to the simulation type. Considering loss methods, deficit and constant method and soil moisture accounting method has created for continuous simulations while all other methods can be used for event based simulations. In case of infiltration losses, Green and Ampt method for event based simulations are used because it assumes uniform initial soil moisture content in the soil layer.

Continuous simulations show rainfall events and their cumulative effects over lengthy periods of time. Atmospheric data, soil texture classifications, and soil properties are needed for continuous simulations and suggested that five layer method is suitable for continuous model simulations (DeSilva, Weerakoon, and Herath, 2014).

2.5 Antecedent moisture condition

The USDA (1972) stated that Soil Conservation Services Curve Number (SCS-CN) method is widely used to compute direct surface runoff (or rainfall-excess) from rainfall events using curve number derived from watershed characteristics and 5-day antecedent rainfall. The intrinsic curve number variability face in real-World application of SCS-CN methodology is mostly assigned to the spatial and temporal variability of rainfall, quality of measured rainfall-runoff data, and the variability of antecedent rainfall and associated soil moisture amount (Ponce and Hawkins, 1996).

Antecedent moisture conditions AMC-I (Dry), AMC-II (Normal), and AMC-III (Wet) are statically related to 90%, 50%, and 10% of cumulative probability of the exceedance of runoff depth, respectively, for a given rainfall (Jain, Mishra, and Singh, 2006).

2.5.1 Importance of soil moisture on runoff

Soil moisture data for rainfall runoff model, considered is preliminary application for improvement of calibration and verification (Wooldridge, Kalma, and Walker, 2003). Goodrich et al. (1994) stated that soil moisture play an important role on runoff, infiltration, and evapotranspiration .The relative importance of the effect of antecedent soil moisture on runoff response is different in various environments (Brocca, Melone, Moramarco, and Singh, 2009).

The role of antecedent conditions on runoff represents an important consideration in flood modeling, particularly in arid areas in which there is a large difference in terms of catchment discharge properties between dry and wet periods, as well as for catchments with large storages such as those with large reservoirs or multiple smaller on-farm dams or storm water detention basins (Pathiraja, Westra, and Sharma, 2012).

2.5.2 CN variability with antecedent moisture condition

Curve numbers vary with storm events according to Soil Conservation Service (2007) CN variability through the use of Antecedent Moisture Condition (AMC).Soil Conservation Service (2007) provides a table of values used to reclassify CNs from desire AMC-II or median condition to AMC-I and AMC-III because AMC accounted for in the SCS CN method by first computing the median CN for a soil type and hydrologic treatment and then recalculating CN for the desire AMC. The reclassification value are shown in the Figure 2-1.

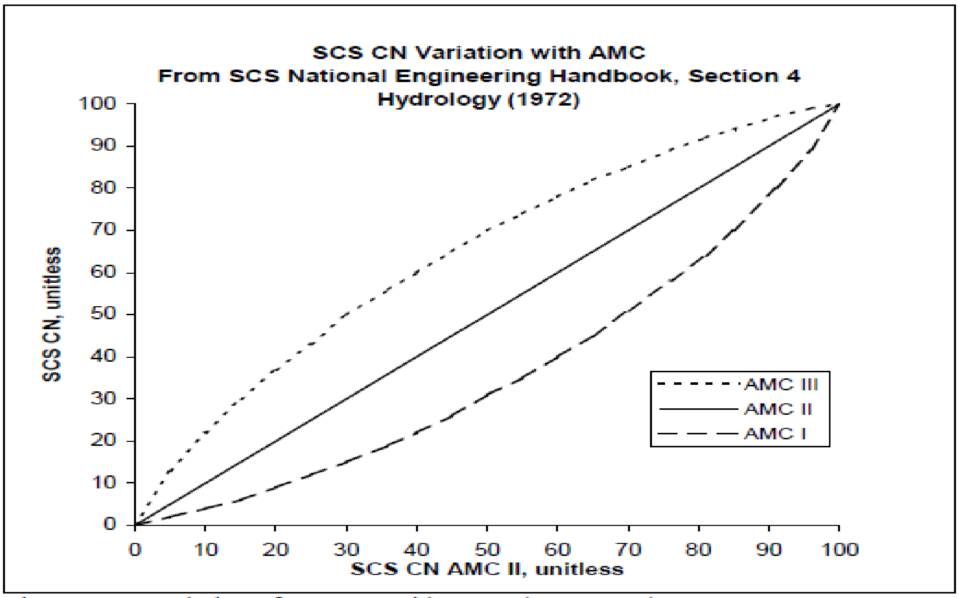


Figure 2-1: Variation of SCS CN with AMC
Source: (SCS, 1972)

The AMC dependent CN value given by NEH-4 (USDA, 1972) in tabular form can be fairly represented by mathematical expression given by different researchers Sobhani (1975) later Hawkins, Hjelmfelt, and Zevenbergen (1985); Chow, Maidment, and

Larry (1988) also proposed algebraic expression for the same CN-conversion. Recently, Neitsch et al. (2002) provided an entirely different form and these are being used in SWAT Model. The accuracy of runoff computation mostly depends on the correction of CN-values so it is necessary to compare these conversion formulae and discuss their justifiability. The popular AMC-dependent CN-conversion formulae are presented in Table 2-1.

Table 2-1: Variation of SCS CN with AMC
Source: (SCS, 1972)

Method	**AMC-I**	**AMC-III**
Sobhani (1975)	$CN_I = \frac{CN_{II}}{2.281 - 0.01334CN_{II}}$	$CN_{III} = \frac{CN_{II}}{0.4036+0.005964CN_{II}}$
Hawkins et al. (1985)	$CN_I = \frac{CN_{II}}{2.281 - 0.0128CN_{II}}$	$CN_{III} = \frac{CN_{II}}{0.427+0.00573CN_{II}}$
Chow et al. (1988)	$CN_I = \frac{4.2CN_{II}}{10 - 0.058CN_{II}}$	$CN_{III} = \frac{23CN_{II}}{10+0.13CN_{II}}$
Neitsch et al. (2002)	$CN_I = CN_{II} - \frac{20(100-CN_{II})}{\{100-CN_{II} + \exp[2.533-0.0636(100-CN_{II})]\}}$	$CN_{III} = CN_{II}\exp\{0.00673(100-CN_{II})\}$

2.5.3 Major weaknesses in AMC

Antecedent moisture content (AMC) authorizes by NEH-4 suffers from major weakness (Moatamednia, Nohegar, Malekian, and Zarchi, 2015)

1) The relationship between AMC and antecedent rainfall holds for discrete classes, rather than continuous (Hawkins, 1978).
2) The use of 5-day antecedent rainfall is not based on physical reality ,but on subjective judgment.

2.6 Scale effect in modeling

With large catchment scales, the runoff generation becomes quite insensitive to rainfall intensity changes recorded at individual gauges and the catchment scale runoff response appears to be governed by macro scale catchment characteristics (Amorocho, Dougal, Mcfall, and Jones, 1962). Similarly, Minshall (1962) stated that the impact of catchment scale on hydrologic response and its importance in rainfall runoff modeling has been identified since early 1960's.

Bingner, Arnold, and Srinivasan (1997) applied the SWAT to the Goodwin Creek watershed in northern Mississippi. The authors' objective was to determine the degree of watershed subdivision for achievement of appropriate results in the prediction of watershed runoff and sediment yield and the authors concluded that model predicted runoff volume was not completely dependent on the degree of watershed subdivision, however the model predicted sediment yield did depend on the subdivision of watershed.

Jha (2002) applied SWAT model in his study to four Iowa watersheds to examine the relation between watershed subdivision and water quality model results. The author reported that streamflow was not significantly affected by a decrease in sub-watershed scale, where model predicted results stabilized with about ten subdivisions but the model predicted sediment yields were more dependent on sub-watershed scale.

Tripathi, Raghuwanshi, and Rao (2006) used SWAT to investigate the effect of watershed subdivision upon various components on water balance on a distributed scale and found clear variation of evapotranspiration, percolation, and soil water content with the subdivision pattern even though the influence on annual runoff was slightly only changed.

Casey, Stagge, Moglen, and McCuen (2015) have conducted a study on effect of watershed subdivision on peak discharge in rainfall runoff modeling using WinTR-20 model and concluded that peak discharge was more sensitive to subdivision. The peak discharge was found to be the most sensitive parameter to series subdivision, which produced greater than 25% increase in peak flow by act of subdivision alone regardless of the area ratio and also presents some guidelines to aid the engineers in the rational application of subdivision.

2.6.1 Issue of scale in hydrologic modeling

Dooge (1982) stated the issue of hydrologic parameterization at different scales and also made point that linking the case at field scales (10~100 ha) and also for catchment scales (10~100 km^2) which is an unresolved problem. Klemes (1983) stated that occurrence of a hydrological process is a wide range of scale which spans up to about eighth order of magnitude in span and time because in the hydrological cycle, the precipitation is an important component ranging from 1 m (cumulus convection) to 1000 km (frontal system). Further, a hydrological process have a similar length scale as precipitation but have delayed time scale problems may arise when large scale models are used to make small scale prediction and vice versa, and scale refers to a characteristics time or length of a process (Bloschl and Sivapalan, 1995).

2.7 Objective function

Hydrologic simulation models are calibrated by comparing observed data with data generated by the models. The comparison is made in an optimization procedure using an objective function adopted for that purpose and a set of data which is a subset of all data available or observable. Objective function is the function used to match the model result with the reality. The objective function depends on the modeling objective such as modeling for flood control, water resource planning and management, etc. The objective function used differed from researcher to researcher even with the same objective. Green and Stephenson (2009) described that since 1965, a number of goodness of-fit criteria for assessing the accuracy of model output have been proposed and any one criterion, however, may give more weight to certain aspect of disagreements between simulated output and observed data than another. There are many types of objective functions which can be used to measure the goodness of fit of a simulation.

Green and Stephenson (2009) discussed such 21 objective functions and the recommended objective functions are listed below.

i. Percent Error in Peak (PEP)

$$PEP=\frac{Q_{op}-Q_{cp}}{Q_{op}} \text{ X } 100 \quad \textbf{(2-1)}$$

ii. Percent Error in Volume (PEV)

$$PEV=\frac{V_o-\mathbf{V_c}}{V_o} \text{ X } 100 \quad \textbf{(2-2)}$$

iii. Sum of Square Residual (SSR)

$$SSR=\sum(\mathbf{Q_{obs}}-\mathbf{Q_{cal}})^2 \quad \textbf{(2-3)}$$

iv. Sum of Absolute Residuals (SAR)

$$SAR=\sum ABS(\mathbf{Q_{\mathit{obs}}}-\mathbf{Q_{cal}}) \quad \textbf{(2-4)}$$

v. Coefficient of Efficiency (CE) or Nash-Sutcliff

$$NSE=1-\left(\sum_{i=1}^{N}(S_i-O_i)^2/\sum_{i=1}^{N}(O_i-O_{mean})^2\right) \quad \textbf{(2-5)}$$

2.7.1 Nash-Sutcliffe efficiency

The Nash–Sutcliffe efficiency (E) is a widely used and potentially reliable statistic for assessing the goodness of fit of hydrologic models. Moriasi et al. (2007) and Ritter and Muñoz-Carpena (2013) commonly accepted that if the NSE is greater than 0.65, the hydrologic model is acceptable and if NSE value less is than 0.65, it will give unsatisfactory results. Nash can be used for peak flow estimation but sometimes overestimation of the model performance during peak flow and under estimation during low flow condition (Krause, Boyle, and Base, 2005) could occur. The NSE is given by,

$$NSE=1-\left(\sum_{i=1}^{N}(S_i-O_i)^2/\sum_{i=1}^{N}(O_i-O_{mean})^2\right) \quad \textbf{(2-6)}$$

where S = model simulated output; O = observed hydrologic variable; O_{mean} = mean of the observations that the NSE uses as a benchmark against which performance of the hydrologic model is compared; and N = total number of observations. The NSE values range from negative infinity to 1, where 1 shows a perfect model. If NSE is zero, then it implies that the observed mean is as good a predictor as the model, and if NSE is less than zero, then the model is a worse predictor than Q_{mean}.

2.7.2 Coefficient of determination (R^2)

Coefficient of determination (R^2) is the weak form-based objective function, such as it is used to estimate the statistical properties of model residuals (i.e. deviations) between the model predictions and observed data (Guinot, Cappelaere, Delenne, and Ruelland, 2011). The equation of R^2 is,

$$R^2=\frac{\left(\sum_1^n (Obs_i-\overline{obs})(sim_i-\overline{sim})\right)^2}{\sum_1^n (obs_i-\overline{obs})^2 \sum_1^n (sim_i-\overline{sim})^2} \quad \textbf{(2-7)}$$

where obs_i is the observed flow, $\overline{obs}$ is the mean of the observed flow while sim_i is the simulated flow and $\overline{sim}$ is the mean of the simulated flow.

2.7.3 Mean absolute error (MAE)

Willmott et al. (1985) stated that the mean absolute error indicates the average magnitude of the model error (accuracy) as follows.

$$MAE=\frac{1}{n}\sum_1^n |obs_i-sim_i| \quad \textbf{(2-8)}$$

where obs_i is observed flow and sim_i is from the n simulated flows.

2.7.4 Mean squared error (MSE)

Green and Stephenson (1986) stated that mean squared error is most widely proposed in model calibration. The distance-based objective function, such as mean squared error (MSE), is defined as the distance (similar to the spatial distance) between model predictions and observed data which is most widely proposed in the model calibration and for emphasizing special runoff component specially (flood and base flow). The distances between the model predictions and observed data are often multiplied with user-defined weights in the distance-based objective function.

$$MSE=\frac{1}{n}\sum_1^n (obs_i-sim_i)^2 \quad \textbf{(2-9)}$$

where obs_i is observed flow and sim_i is from the n simulated flows.

2.7.5 Ratio of Absolute Error to Mean

World Meteorological Organization (1975) in its publication compares conceptual models used for operational hydrological forecasting and recommends several objective functions. One of them are Ratio of Absolute Error to Mean (RAEM) which is given below.

$$RAEM=\frac{\sum|Q_{obs}-Q_{cal}|}{n\overline{Q_{obs}}} \quad \textbf{(2-10)}$$

where Q_{obs} is the observed streamflow, Q_{cal} is the calculated streamflow and n is the number of observations used for comparison.

2.7.6 Mean Ratio of Absolute Error (MRAE)

Wijesekera and Abeynayake (2003) defined that Mean Ratio of Absolute Error (MRAE) is the difference between calculated and observed flow with respect to that particular observation.

$$MRAE=\frac{1}{n}\left[\sum\frac{|Q_{obs}-Q_{Cal}|}{Q_{obs}}\right] \quad \textbf{(2-11)}$$

where Q_{obs} is the observed streamflow, Q_{cal} is the calculated streamflow, and n is the number of observations used for comparison.

2.8 Characteristics of objective functions

Legates and Mccabe (1999) described that the NSE/MSE have drawback to square the difference between model predictions and observations so the authors proposed new objective function where the user can choose the power of error by themselves. Gupta, Kling, Yilmaz, and Martinez (2009) described that NSE is calculated by subtracting the ratio between the MSE and the variance of the observation from one, thus the NSE ranges from minus infinity to one in the theory and it is dimensionless.

Krause et al. (2005) described that MAE can balance consideration of the high flow and low flow. Wu and Liu (2014) indicated that MAE emphasizes neither high nor low value. World Meteorological Organization (1982) described that REAM objective function depends on the characteristics of the observed flow series and when there are big and small peaks, the error values may not enable for easy comparison and mean of observed flow does not reflect the real mean value of the flow series. Wijesekera and Abeynayake (2003) described that mean ratio of absolute error (MRAE) is the difference between calculated and observed flow with respect to that particular observation and it compares the errors with respect to each observed flow. Therefore, this gives better representation of comparison when contrasting data is presented in the observed data set.

2.9 Identification of hydrological model

2.9.1 Calibration of hydrological model

Model calibration is a fundamental step in developing a reliable model because it provides assurance that the model produces accurate results. It is mentioned that more refined calibration has been done for the transmissivities in a catchment where more than 100 different values were assessed through the calibration (Refsgaard, 1997). For closed simulation of hydrological behavior of the catchment model, calibration is the process of selecting suitable value of model parameter (Moore and Doherty, 2005).

Lim, Engel, Muthukrishnan, and Harbor (2006) discussed the importance of calibration in simulating hydrologic and water quality impacts of land use changes with the L-THIA model in the Little Eagle Creek watershed (70.5 km^2) near Indianapolis, Indiana and developed a simple method to calibrate the L-THIA model.

2.9.2 Manual calibration

Manual calibration is generally the process of finding an acceptable parameter set by trial and error. In this process, experts are directly involved and use their expertise to search the parameter space. This close cooperation makes the manual calibration process extremely determined and also expert dependent yet very reliable, informative and precise. Manual calibration process is a time consuming and the whole procedure could provide limited or no information from the previous parameter adjustment (Sorooshian and Gupta, 1995a).

Boyle, Gupta, and Sorooshian (2000) described that in the past decades, the manual calibration has been commonly used for the calibration in watershed modeling and with the development of computer resources and availability of optimization algorithms, this rigorous human model interactive process has been made ancient.

2.9.3 Automatic calibration

Automatic calibration refers to a calibration process in which an algorithm is the parameter space that finds the best parameter set. The automatic process gives more reliable result and reduces the need for expertise with the particular model. In general, an automatic calibration process has three main parts: A criteria for comparison of model simulated result with observed data, optimization algorithm, and the terminal criteria (Sorooshian & Gupta, 1995b). The aim of automatic calibration is to maintain the consistent performance by excluding the human judgment involved in the manual approach by developing an objective policy for parameter estimation (Boyle et al., 2000).

2.9.4 Verification of hydrological model

Verification (also known as validation) takes place after calibration to test if the model performs well on a separate portion of data, which is not used in calibration. Sorooshian and Gupta (1995a) stated that when degree of polarity is considered unsatisfactory, the modeler has to examine the model structure and calibration procedure for valid or unsuitable assumptions and then revise accordingly.

Gupta, Beven, and Wagener (2005) described that the purpose of model validation is to validate the model's strength and capability to describe the catchment's hydrological response and further detect and discard any bias in the calibration period.

2.10 Sensitivity analysis

There are two types of sensitivity analysis: local sensitivity analysis, and global sensitivity analysis. The former type of analysis aims to assess the impact of change in the parameter values within the local region of insignificance on the model output. According to Wagener and Kollat (2007), the global sensitivity analysis explores the full parameter space within the range of physical parameter range.

Sensitivity of the model to a parameter is determined using the percentage difference between the output values of the objective function for simulations performed immediately before and immediately after changing the value of a parameter (Silva et al., 2015). Sensitivity analysis is helpful to identify and rank parameters that have significant impact on specific model outputs of interest (Zhou and Lin, 2017).

3.0 MATERIALS AND METHODOLOGIES

3.1 General

Badalgama Watershed which lies in Maha Oya Basin is selected as study area. There are four rainfall stations and one stream gauging station located in this watershed. Rainfall data and streamflow data were collected from Meteorological Department and Irrigation Department, respectively, and consequently data checking and consistency tests were performed to check the reliability and accuracy of the data.

3.2 Study area

The Maha Oya is a major stream in the Sabaragamuwa Province of Sri Lanka. It measures approximately 134 km (83 mi) in length. It runs across four provinces and five districts. Maha Oya has 14 water supply networks to serve the need of water and more than 1 million people live by the river. Its catchment area receives approximately 3644 million cubic meters (MCM) of rain per year, and approximately 34% of the water reaches the sea. Up to Badalgama area is selected for study purpose. Badalgama watershed is a sub watershed of Maha Oya Basin and drainage area is 1271 km^2.

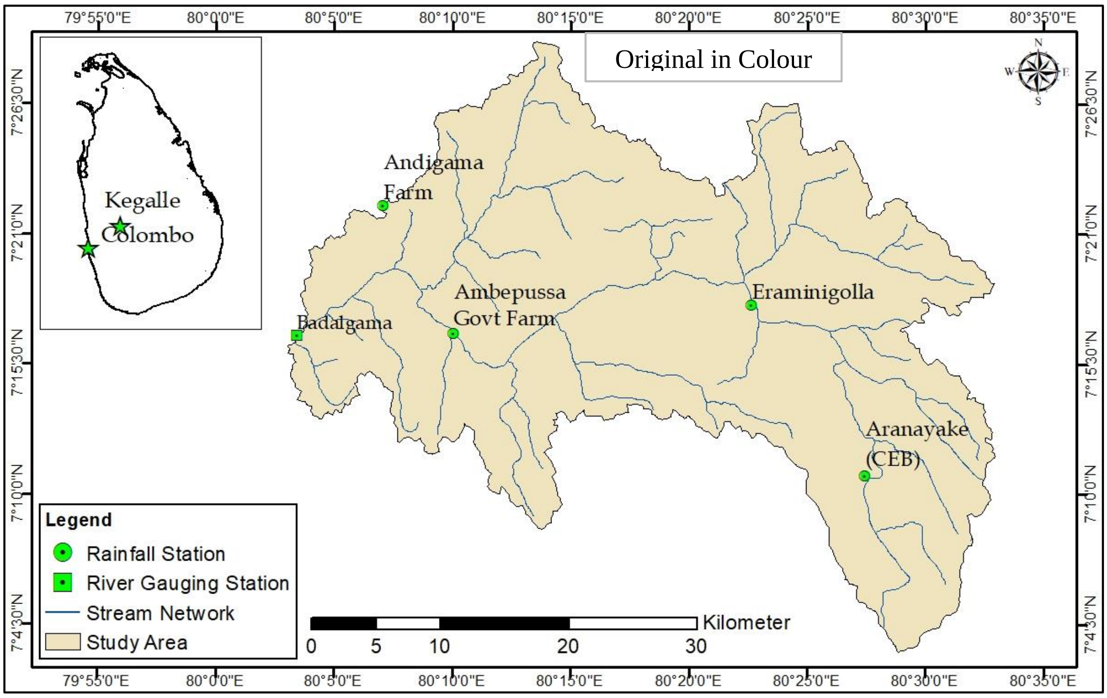


Figure 3-1: Study area of Badalgama watershed

3.3 Data and data sources

There is only one river gauging station in Badalgama watershed and the four rain gauging stations located within the study area are namely, Ambepussa Government Farm, Andigama Farm, Arayanake, and Eraminigolla. The location of the river gauging/rain gauging stations in Badalgama watershed are given in Table 3-1. The details of respective data sources and data resolution are given in Table 3-2.

Table 3-1: Location of gauging stations in Badalgama watershed

Gauging station	Location
Badalgama river gauging station	7° 19' 30" N 79° 58' 50" E
Ambepussa Gov. Farm rain gauge	7° 16' 48" N 80° 10' 12" E
Andigama Farm rain gauge	7° 22' 12" N 80° 7' 12" E
Eraminigolla rain gauge	7° 17' 60" N 80° 22' 48" E
Arayanake rain gauge	7° 10' 48"N 80°27' 36" E

Table 3-2: Data sources and resolutions

Data type	Temporal resolution	Data period	Data source
Rainfall	Daily	January 2005 to December 2013	Department of Meteorology, Colombo
Streamflow	Daily		Dept. of Irrigation, Colombo
Land use	1:50,000	N/A	Dept. of Survey, Colombo
Soil type	1:50,000		Dept. of Survey, Colombo
Topography	1:50,000		Department of Survey, Colombo

For study purposes, the land uses are classified into seven classes as given in Table 3-3. It is observed that about 55.81% of the study area is under plantations while the area under homesteads/garden is about 20.22%. For this study, it is considered that 50% of the homestead area is impervious, and rock area and built up area are also considered as impervious areas.

Table 3-3: Land use classification for Badalgama watershed

Land use type	Area (km^2)	Percent of total area (%)
Agriculture	194.92	15.32
Built-up area	17.26	1.36
Homestead	257.18	20.22
Forest	33.14	2.61
Plantation	709.93	55.81
Water bodies	9.01	0.71
Scrub area	49.70	3.91

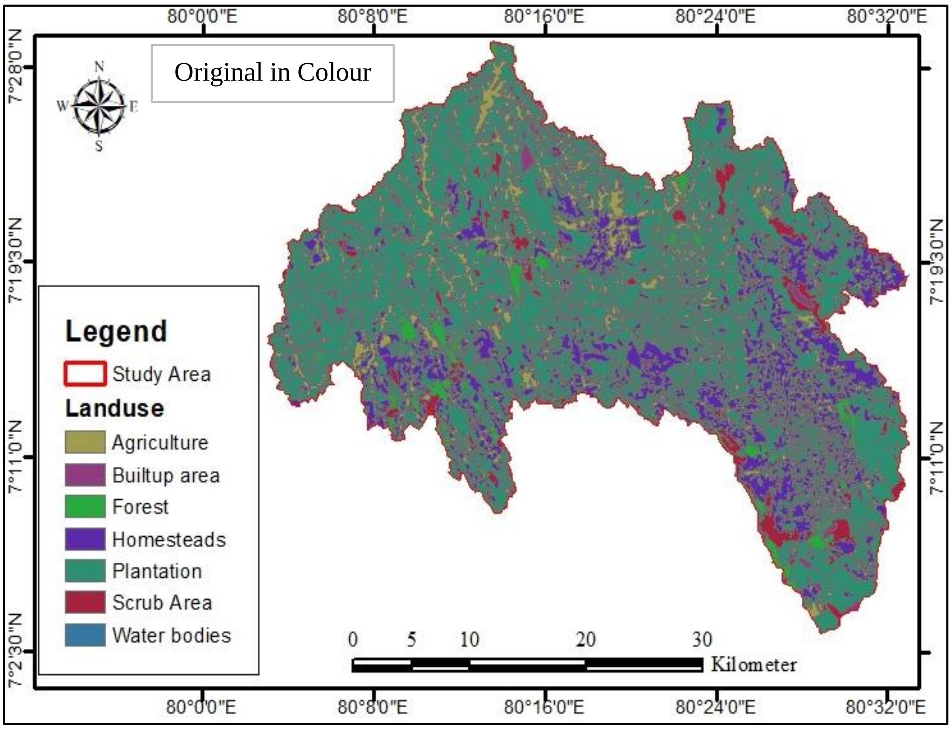


Figure 3-2: Land use classification for Badalgama watershed

3.4 Data checking

3.4.1 Details of missing data

For the present study purpose, precipitation data from four rainfall stations and one river gauging station in Badalgama watershed have been collected for the period from 01-October-2005 to 30-September-2013. It was observed that in the data set for year 2009, there is nine month period of missing data. Therefore, following the preliminary data analysis and data checking, this year was removed from the data set. The details of missing data are given in Table 3-4.

Table 3-4: Details of missing data

<table>
<tr><th>Ambepussa Govt. Farm</th><th>Andigama Farm</th><th>Aranayake (CEB)</th><th>Eraminigolla</th></tr>
<tr><td>Nov-05</td><td>Mar-14</td><td rowspan="3">Oct-11</td><td>Nov-10</td></tr>
<tr><td>Jul-11</td><td rowspan="2">Aug-14</td><td>Dec-10</td></tr>
<tr><td>Oct-11</td><td>Feb-11</td></tr>
<tr><td>Nov-11</td><td rowspan="3">Sep-14</td><td rowspan="3">Dec-12</td><td>Dec-11</td></tr>
<tr><td>Jan-12</td><td rowspan="2">Dec-12</td></tr>
<tr><td>Dec-12</td></tr>
</table>

3.4.2 Thiessen rainfall

Rainfall data recorded at each station is given a weightage based on the area closest to or covered by the station, following the Thiessen weighted mean method. The rainfall is never uniform over the entire area of the basin or catchment, but varies in intensity and duration from place to place. Thus, the rainfall recorded by each rain gauge station should be weighted according to the area coverage of the station. Thiessen polygons were created based on spatial distribution of rainfall gauging stations and the assigned weights in Badalgama sub-basin in Maha Oya river basin are given in Table 3-5.

Table 3-5: Thiessen weight of rain gauging stations for Badalgama watershed

Rainfall station	Area (km^2)	Total Area (km^2)	Thiessen Weight
Ambepussa Govt. Farm	341.5	1272	0.27
Aranayake (CEB)	264.45	1272	0.20
Eraminigolla	473.87	1272	0.38
Andigama Farm	192.05	1272	0.15

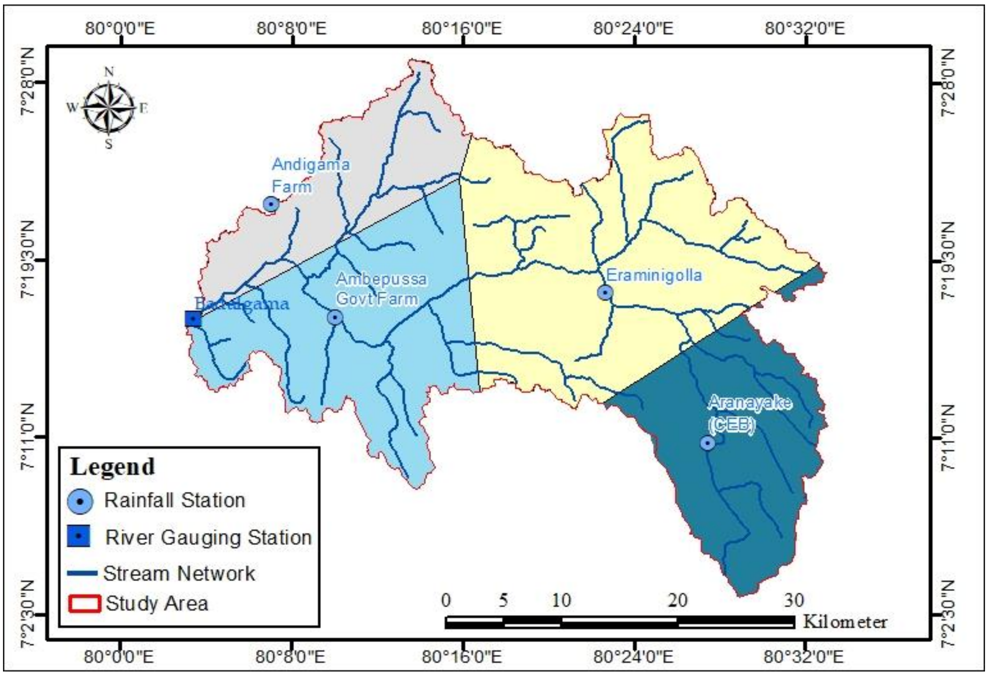


Figure 3-3: Thiessen polygons for Badalgama Watershed

3.4.3 Visual data checking

3.4.3.1 Visual data checking without filling missing data

Visual data checking has been performed first without filling the missing data in the data set and later checked by filling the missing data to fully visualize the catchment streamflow response to rainfall. Visual checks were also performed to find if there are inconsistencies in the data set. Streamflow responses to rainfall were plotted for each rainfall gauging station for each year and the representation of streamflow responses of streamflow at Badalgama river gauging station to rainfall at each rain gauging station for the year 2005 and 2011 are shown in the Figure 3- 4 and Figure 3-5.

The inconsistencies observed are highlighted in red and it can be observed that in the red box of Figure 3- 4 that Badalgama streamflow does not respond adequately to the rainfall at Ambepussa Govt Farm rainfall station for August-2005 and December-2005. The rainfall at other rainfall stations where streamflow does not respond similarly in 2005 are marked with red boxes as shown in Figure 3- 4. In year 2011, the streamflow does not respond well to rainfall at Ambepussa Govt. Farm rainfall station in December-2011 which is marked again with a red box. Similarly, for other rainfall stations where streamflow does not respond acceptably in 2011 are marked also with red boxes.

3.4.3.2 Visual data checking after filling missing data

Visual data checking has been performed once again after filling in the missing data. Streamflow response of Badalgama river gauging station with rainfall for each rain gauging station in year 2005 and 2011 is shown in the Figure 3-6 and Figure 3-7, respectively. The streamflow at Badalgama does not respond to the rainfall at Ambepussa Govt. Farm rainfall station for March-2005, August-2005 and December-2005 which are marked with red boxes and also for other rainfall stations where streamflow does not respond adequately in 2005 are similarly marked with red boxes.

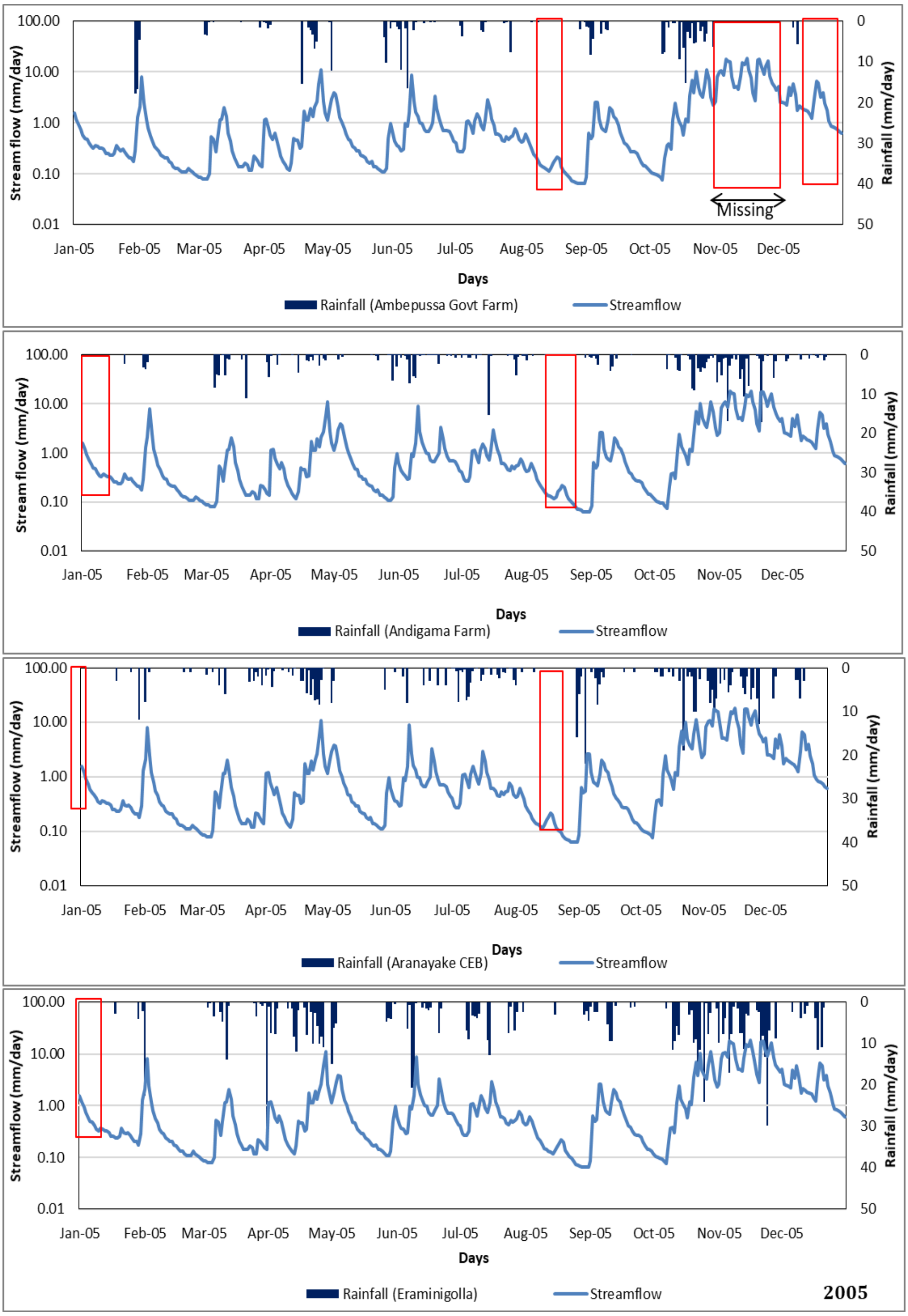


Figure 3- 4: Streamflow response to rainfall without filling missing data in 2005

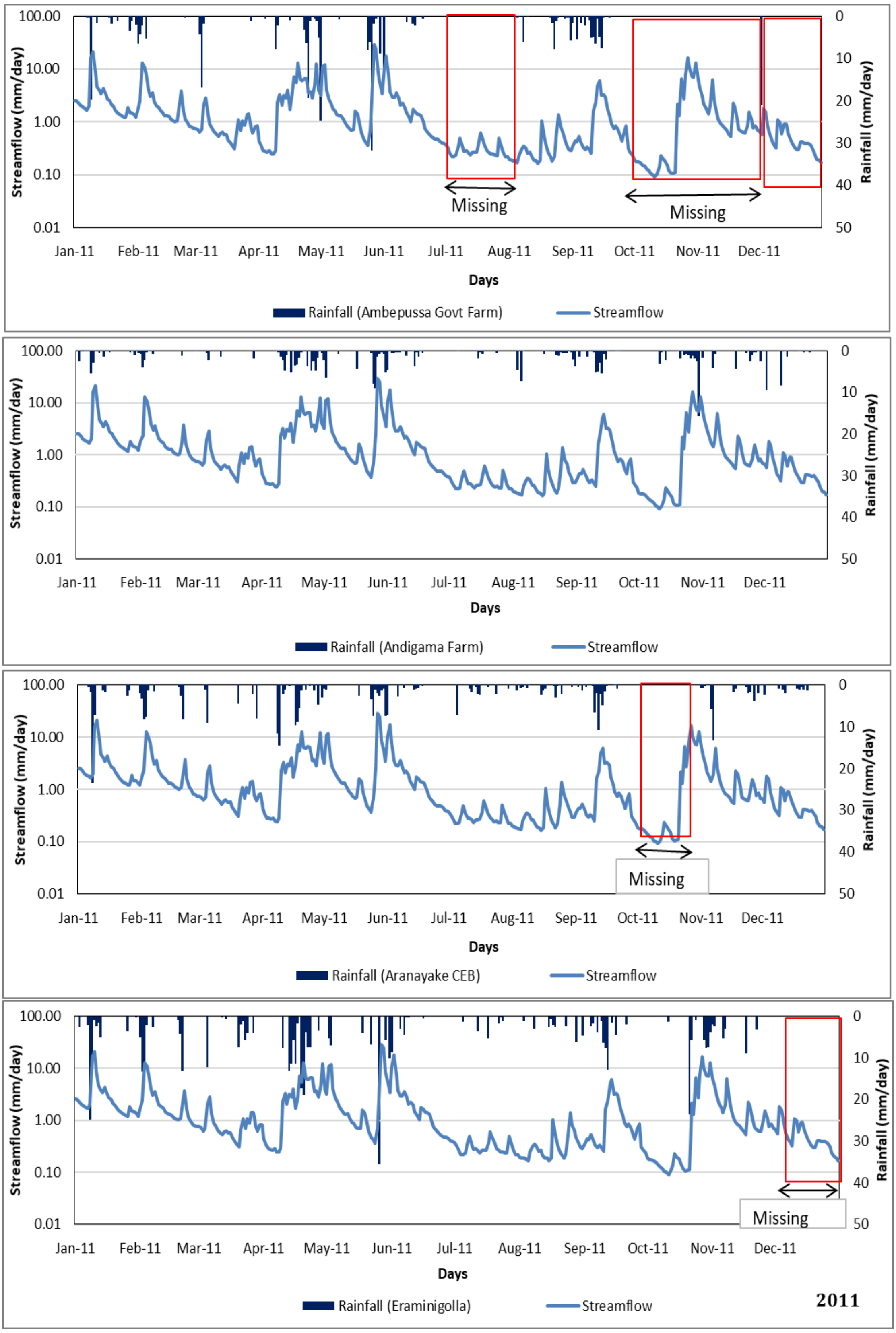


Figure 3-5: Streamflow response to rainfall without filling missing data in 2011

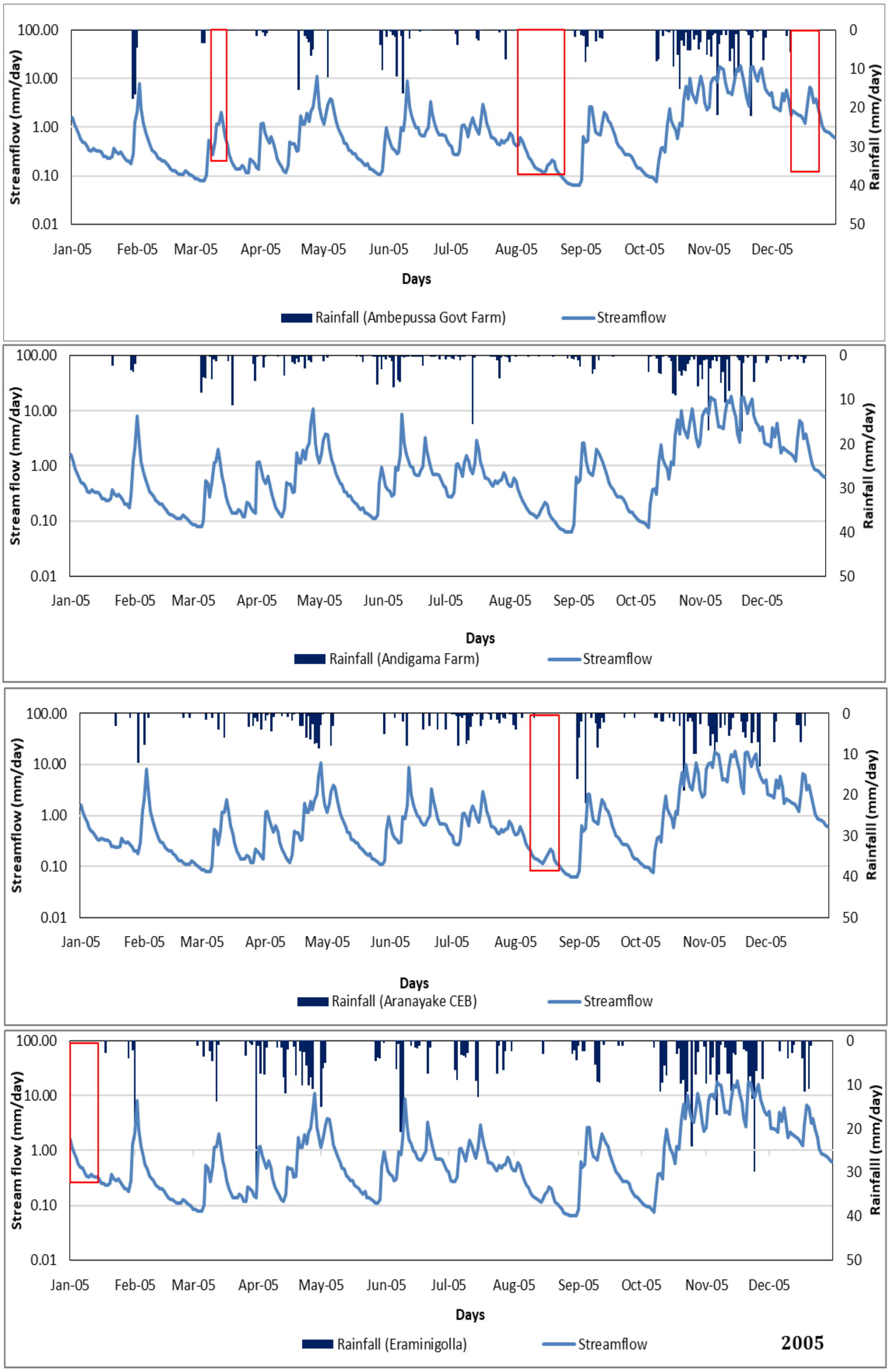


Figure 3-6: Streamflow response to rainfall after filling missing data in 2005

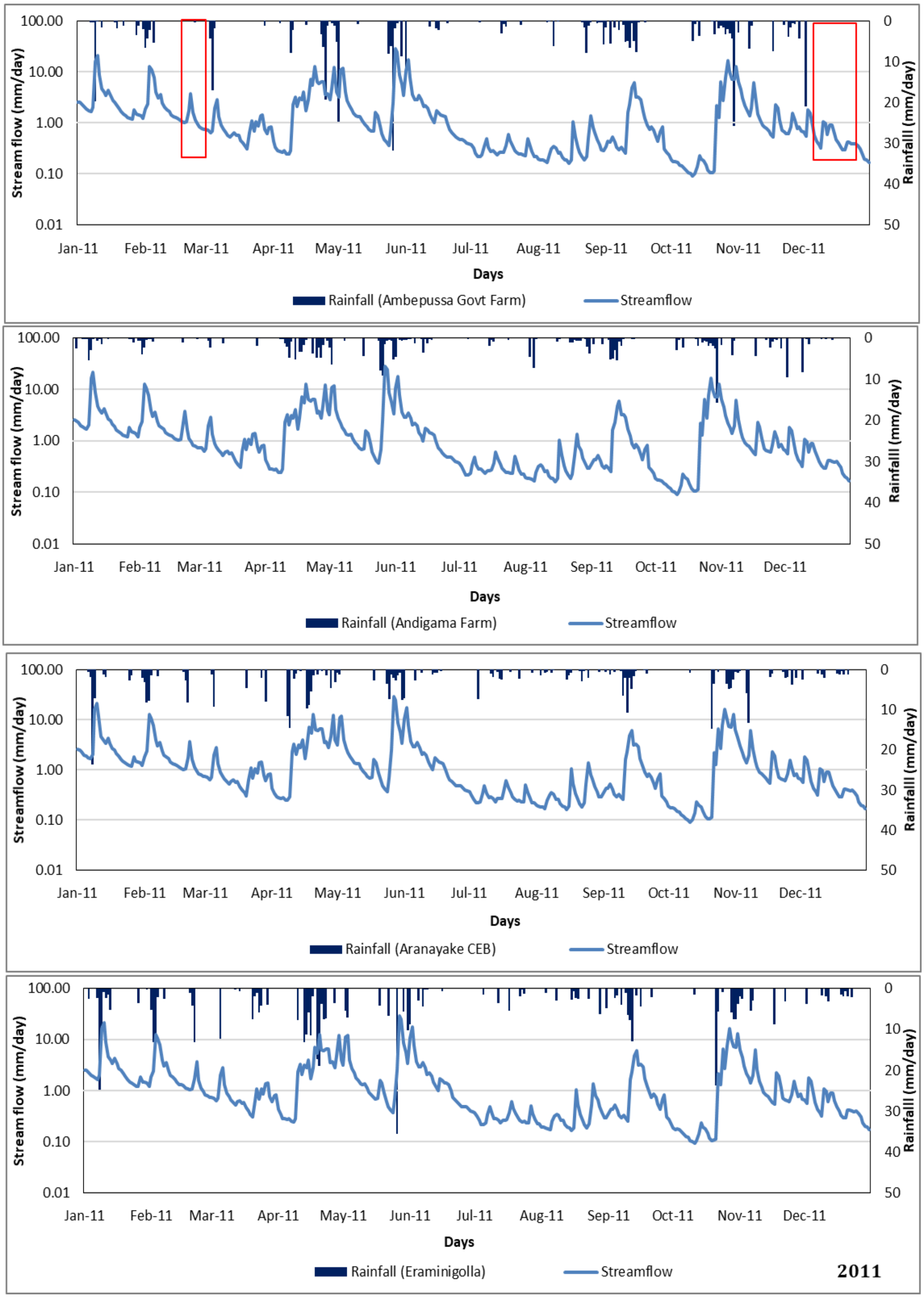


Figure 3-7: Streamflow response to rainfall after filling missing data for 2011

3.5 Filling in of missing data

Statistical analysis is likely to be biased when more than 10% of data are missing and the amount of missing data is not the single criterion by which a researcher assesses the missing data problem (Dong and Peng, 2013). Therefore, the data set for year 2009 was removed from the data series because for year 2009, more than 10 % of data were missing in Eraminigolla Station. Moeletsi, Shabalala, Nysschen, and Walker (2016) stated in their study that missing values can be filled in either directly using the values at neighboring stations or adjusted by a factor from the ratio of long-term means between the two stations.

In this study for filling in missing data, a factor is calculated by using slope of cumulative data series for the two nearest rainfall stations. To calculate the slope, single mass curve is plotted for each year of rainfall station by skipping the month with missing data for each rainfall station if one rainfall station has missing value for that particular month. For year 2005, single mass curve shown in the Figure 3-8 was used as a specimen calculation while for other years, single mass curves without filling missing data and with filling in missing data is given in Appendix B.

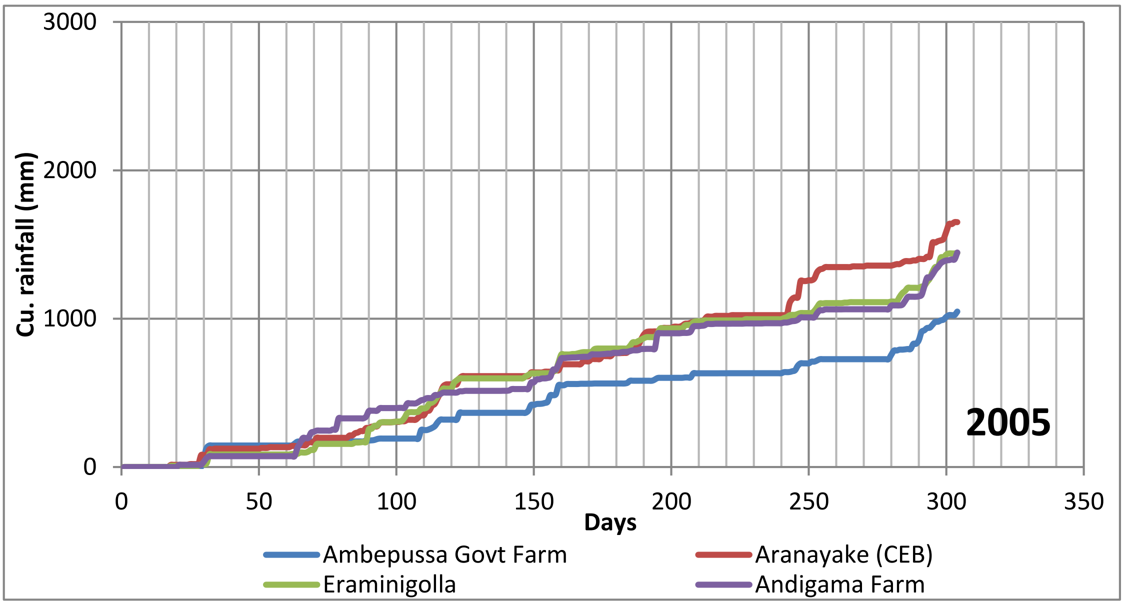


Figure 3-8: Single mass curve without filling missing data

After plotting the single mass curves, the missing data was filled in by multiplying the value at the closest rainfall station by the calculated slope factor. Following formula is used for replacing the missing values.

$$\text{Precipitation of Station B} = \frac{\text{Slope of station B}}{\text{Slope of station A}} \text{X Precipitation of Station A}$$

Table 3-6: Slope factor estimated for rainfall stations in 2005

Rainfall station	Slope factor
Andigama Farm to Ambepussa Govt Farm	0.725
Ambepussa Govt Farm to Andigama Farm	1.380
Eraminigola to Aranayake (CEB)	1.144
Aranayake (CEB) to Eraminigola	0.874

All the missing data were thus filled with above slope method and the estimated slope factors are given in the Table 3-6. After filling in the missing data, the single mass curves were again plotted to check the consistency of the data series. For year 2005, similarly plotted single mass curves are shown in the Figure 3-9.

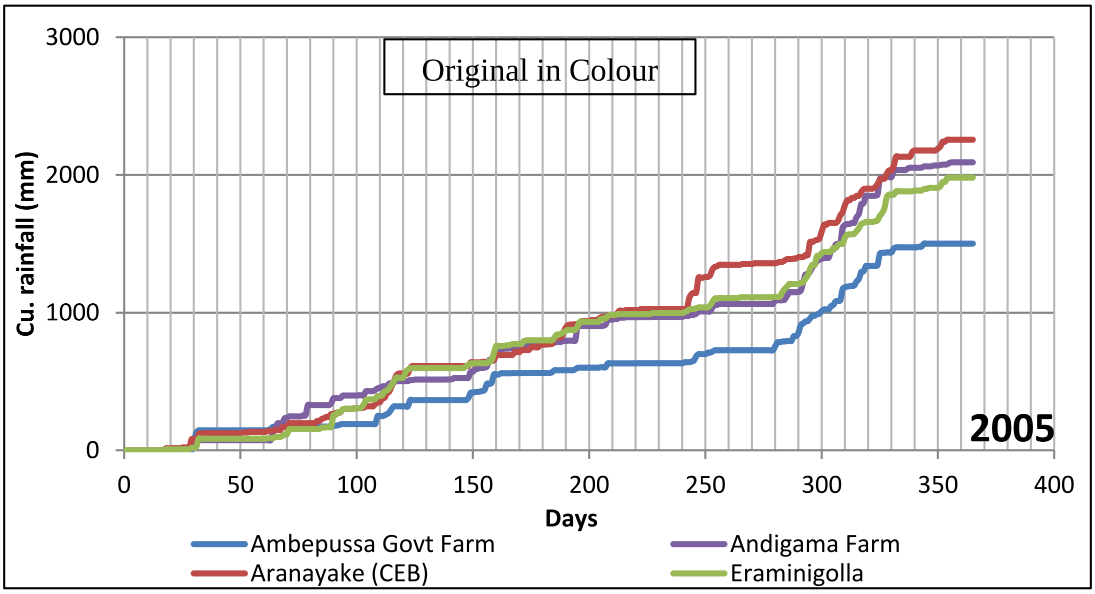


Figure 3-9: Single mass curves after filling in the missing data

3.5.1 Annual water balance

Water balance can be used to describe the flow of water in and out of a system. Annual water balance analysis was carried out for Badalgama watershed from year 2005 to 2013 in order to compare the annual rainfall and streamflow. Annual water balance of Badalgama watershed is shown in Figure 3-10 and Table 3-7. Table 3-7 shows that in 2008, the rainfall is high while the stream flow is low, thus the difference in this year is relatively higher as compared to that of the other years. Contrastingly in 2011, the difference is low. The graphical representation of annual water balance is presented in Figure 3-10.

Table 3-7: Annual water balance in Badalgama watershed

Year	Rainfall (mm)	Streamflow (mm)	Difference (mm)
2005	1914	661.43	1252.57
2006	2431	1304.20	1126.34
2007	1835	597.36	1237.92
2008	2305	974.56	1330.07
2010	2439	1278.24	1160.30
2011	1549	721.66	827.34
2012	1876	639.86	1235.79
2013	1956	829.66	1126.29
Average	**2037.95**	**875.87**	**1162.08**

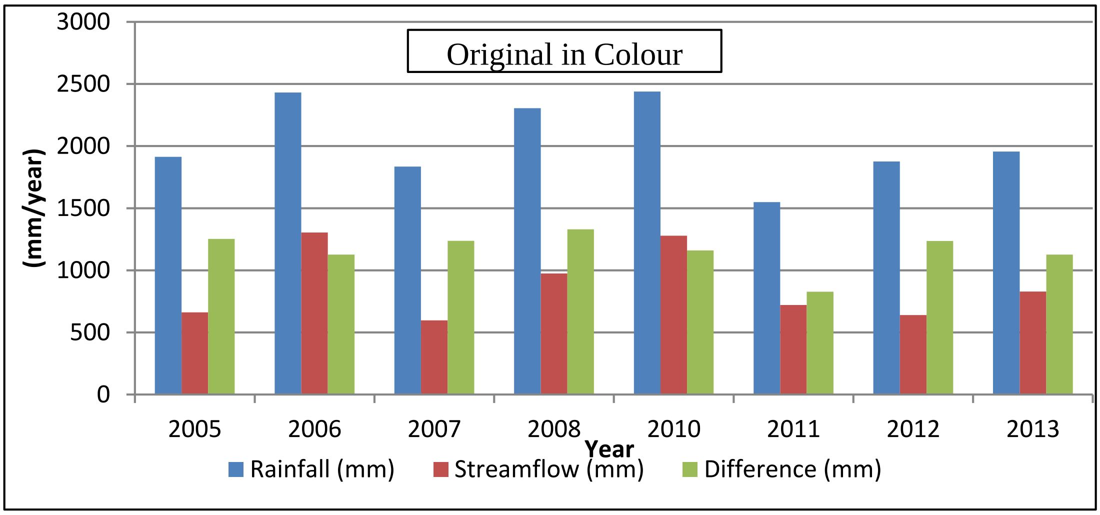


Figure 3-10: Annual water balance for Badalgama watershed

3.5.2 Variation of annual runoff coefficients

Annual runoff coefficient in the basin varies from 0.34 to 0.52. It can be observed that in 2006, the runoff coefficient is high as compared to other years where as it is low in year 2007 and 2012. In 2008, the evaporation has been very low compared to the other years. The reason is that the streamflow does not respond adequately to the rainfall in this year and also in 2005 leading a low streamflow. Therefore, the rainfall runoff coefficient is low in this year and in 2010 where an increased evaporation can be seen as shown in Table 3-8.

Table 3-8: Variation of annual runoff coefficient of Badalgama watershed

Year	Rainfall (mm)	Streamflow (mm)	Runoff Coefficient	Pan Evap.	Pan coefficient	Actual Evap.
2005	1914	661.43	0.35	1157.88	0.80	926.30
2006	2431	1304.20	0.54	1232.32	0.80	985.86
2007	1835	597.36	0.33	1235.36	0.80	988.29
2008	2305	974.56	0.42	1091.73	0.80	873.38
2010	2439	1278.24	0.52	1339.08	0.80	1071.26
2011	1549	721.66	0.47	1262.11	0.80	1009.69
2012	1876	639.86	0.34	1315.91	0.80	1052.73
2013	1956	829.66	0.42	1191.19	0.80	952.95
Avg.	**2037.95**	**875.87**	**0.42**	**1228.20**	**0.80**	**982.56**

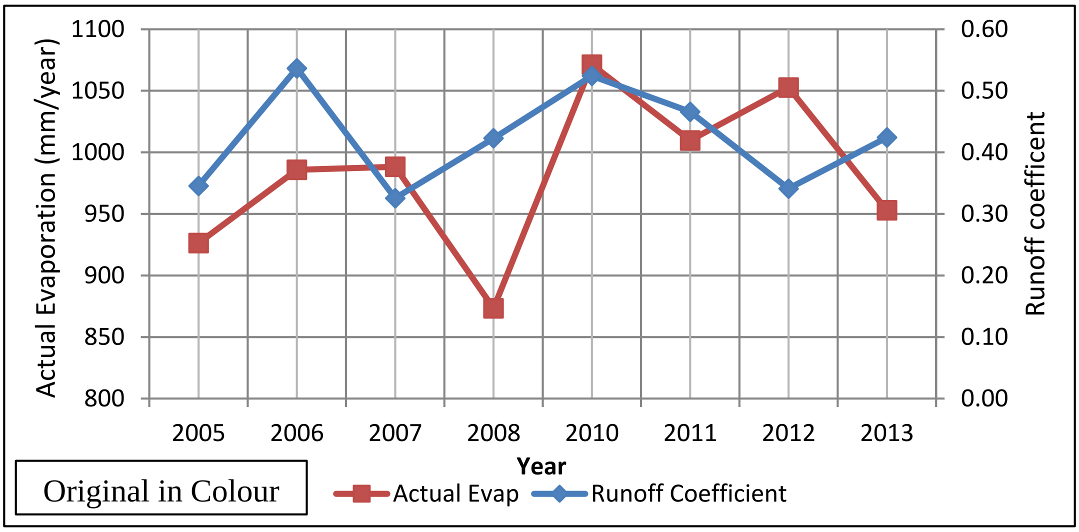


Figure 3-11: Variation of annual runoff coefficient of Badalgama watershed

3.5.3 Variation of annual rainfall and streamflow

Annual rainfall value increases from 2005 to 2006 and 2007 to 2010 while it decreases from 2006 to 2007 and 2010 to 2011. The streamflow also increased responding to the rainfall increases in these years. But in 2011 to 2012, the streamflow value decreases by 81 mm and rainfall increased by 327 mm which is unexpected and this is encircled in Figure 3-12. From year 2012 to 2013, the rainfall increases and the stream flow also increases in tandem with the above variation in rainfall.

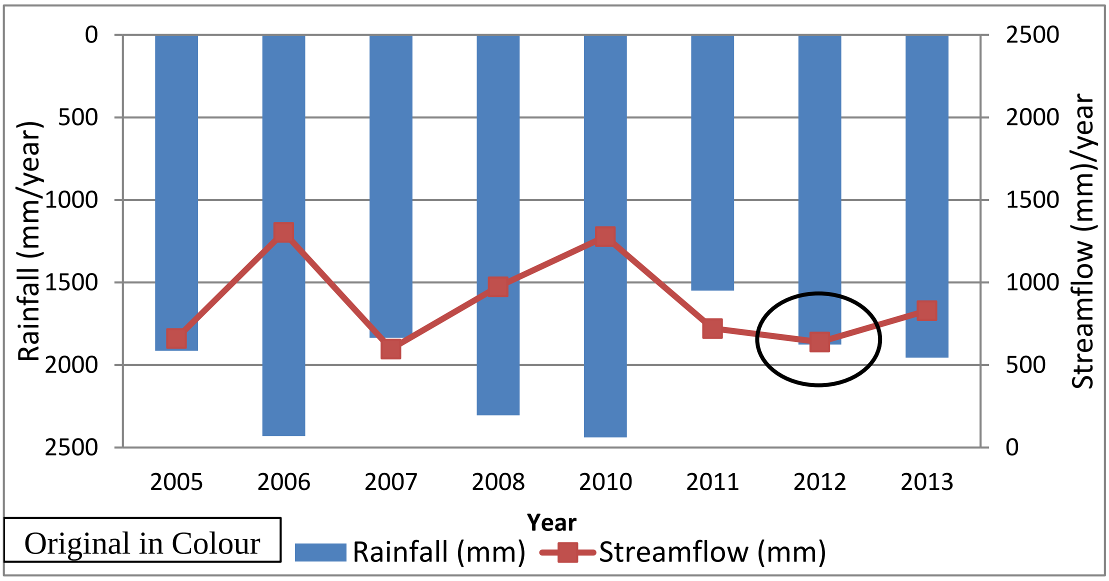


Figure 3-12: Variation of annual rainfall and streamflow for Badalgama watershed

3.5.4 Comparison of annual rainfall

Annual rainfall from January 2005 to December 2013 for each rain gauging station are given in Table 3-9 and it is plotted in Figure 3-13. There is a considerable rise in rainfall in 2010 at Eraminigolla rainfall gauging station while there is a considerable decrease in annual rainfall in Andigama Farm rainfall gauging station in 2013. Among all the rainfall gauging stations, Andigama rainfall station has the lowest rainfall value and Eraminigolla rainfall station has the highest value as compared to the other rainfall gauging stations as shown in Table 3-9.

Table 3-9: Comparison of annual rainfall

Year	Rainfall (mm) (Ambepussa Govt Farm)	Rainfall (mm) (Andigama Farm)	Rainfall (mm) (Aranayake (CEB))	Rainfall (mm) (Eraminigolla)
2005	404	316	451	743
2006	746	392	478	815
2007	500	263	330	743
2008	653	395	426	830
2010	605	345	512	976
2011	408	255	357	530
2012	657	302	328	589
2013	554	250	459	693

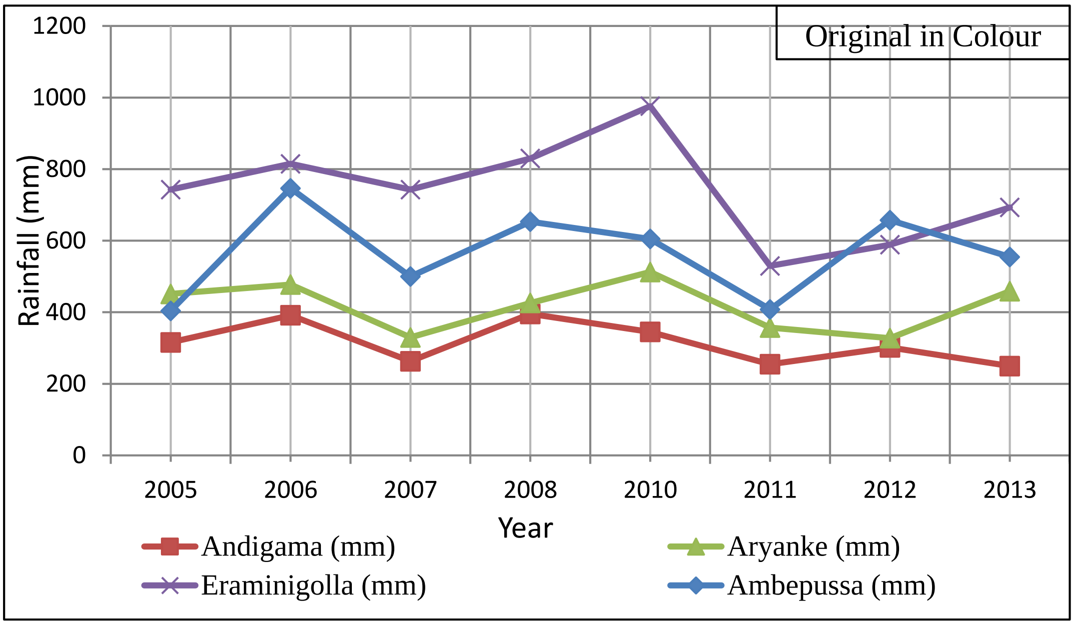


Figure 3-13: Comparison of annual rainfall

3.5.5 Double mass curve

The double-mass curve can be used to identify and adjust inconsistent precipitation data. The graph of the cumulative data of one variable versus the cumulative data of a related other variable is a straight line so long as the relation between the variables is a fixed ratio. Merriam (1937) stated that this method was first used to analyze the consistency of precipitation data in Susquehanna watershed in the United States. Searcy and Hardison (1960) described that the double mass curve is a plot of cumulative values of one variable against the accumulation of another quantity during the same time period and also described that the theory behind the double mass curve is that by plotting the accumulation of two quantities, the data will plot as a straight line and the slope of this line will represent the constant of proportionality between the two quantities.

Mu, Zhang, Gao and Wang (2010) described that double mass curve is a simple, visual and practical method, and it is widely used in the study of the consistency and long-term trend test of hydro meteorological data. For the study purpose, the double mass curve is plotted for each rainfall station to check the consistency of the data sets at each rainfall station as shown in Figure 3-14.

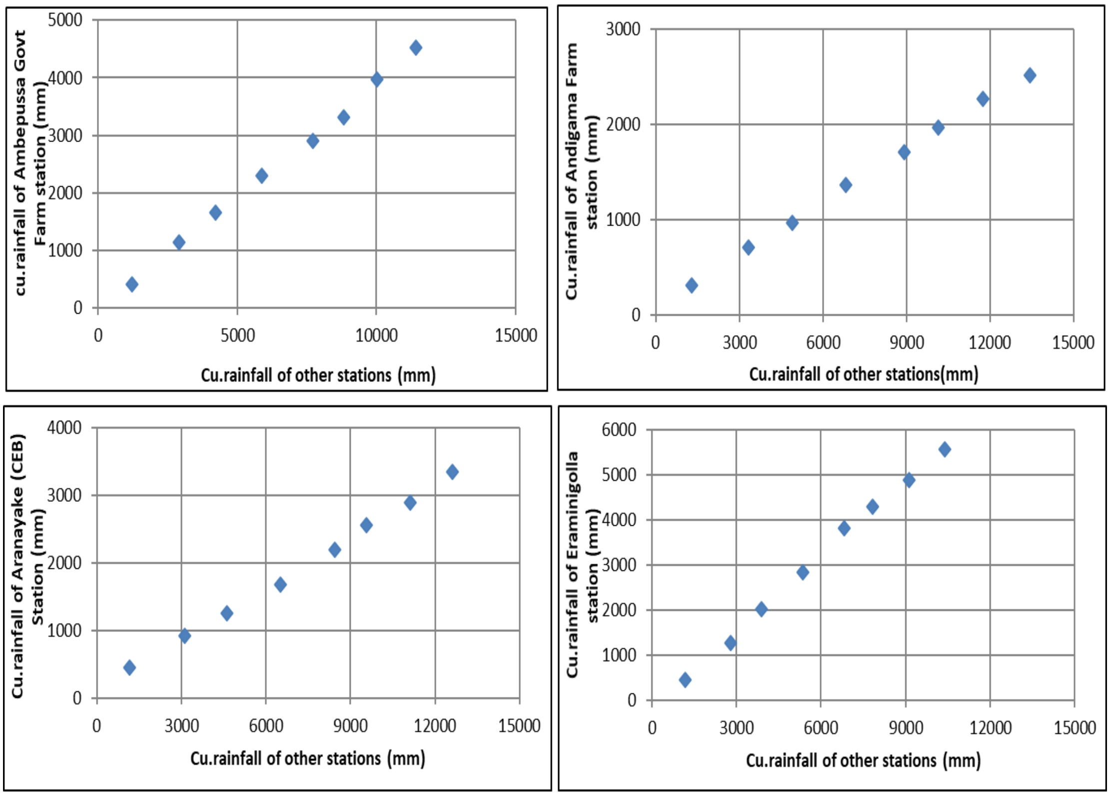


Figure 3-14: Double mass curves for each rainfall gauging station

3.6 Research methodology

The research methodology used for this research is shown in Figure 3-15. After identifying the research problem and objective and specific objectives, a literature survey was carried out to recognize the present status of research in the field of hydrological modelling and to identify a suitable hydrologic model and different objective function for the purpose of the present study. After reviewing the hydrological models which were applied in various river basins under different circumstances, the HEC-HMS model (Hydrologic Modeling System of Hydrologic Engineering Center) is selected for the analysis purposes of the present research study. The fact that this software is available in the public domain for free download, its capacity to analyze parameter sensitivity, its improved hydrologic computations in simple, efficient and useful manner in terms of runoff simulations were also considered in model selection.

Model development is carried out by considering three main components, namely the Basin model, Precipitation model and Control specification. There are several sub models in the basin model itself for rainfall loss, direct runoff, baseflow and channel routing and the selection of sub models are done by considering several criteria. The model is developed only up to Badalgama river gauging station for lumped and different subdivision layout. Model development, calculation of initial parameters and selection of objective functions is described in the analysis section.

Four-year data from January 2005 to December 2008 were used for model calibration and four-year data from 01-January-2010 to 31-December-2013 were used for model verification. The model performances have been evaluated for the minimum value of Mean Ratio of Absolute Error (MRAE) as the objective function. In addition, Nash-Sutcliff coefficient values were also checked for comparison and observation. Objective function values corresponding to model calibration and verification and other graphical presentations are given in the analysis section for all selected model layouts.

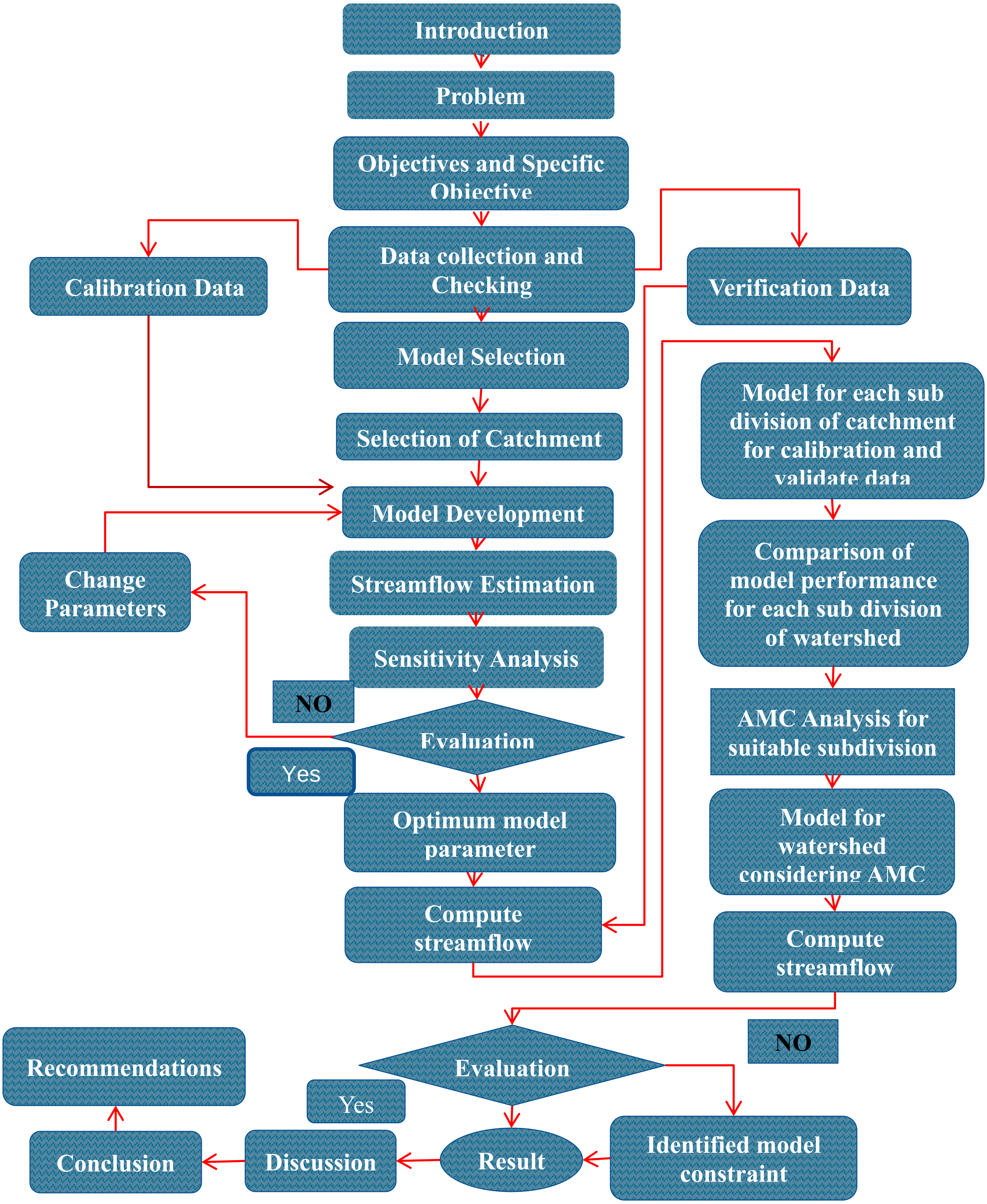


Figure 3-15: Methodology flow chart

3.6.1 Development of the basin model

For study purpose, a lumped model has been developed for river flow at Badalgama gauging station where daily streamflow data is available.

3.6.2 Development of the precipitation loss model

In HEC–HMS, there are eleven methods available for estimation of precipitation loss. Initially soil moisture accounting method is selected. Initial parameters were selected based on previous research by De Silva, Weerakoon, and Herath (2014) in Kelani Basin in Sri Lanka. The following model parameters given in the Table 3-10 are used initially for the loss model.

Table 3-10: Parameters for loss model

Serial number	Parameter	Initial Value
1	Ratio to peak	0.164
2	Recession constant	0.923
3	Time of concentration	57
4	G1 percolation	0.35
5	Max infiltration	4.75
6	Soil storage	276
7	Tension storage	21
8	Soil percolation	0.456
9	Impervious	19

3.6.3 Development of transform model

Transform (direct runoff) model is selected to represent the study by considering the following criteria; (1) Number of parameters (2) Use of empirical equations (3) Appropriateness of assumptions. Clark unit hydrograph model is selected in this model. The parameter, time of concentration is calculated using different equations developed by different researchers. The length of the longest channel path for Badalgama water course is 83.24 km and the slope of the channel is 0.0075 km/km. Time of Concentration is given in the Table 3-11 and lag time is calculated using the equation $T_L = 0.6 \times T_C$.

Table 3-11: Time of concentration and lag time calculation

Methods	Time of concentration (hours)	Lag time (0.6xTc) (hours)
Bransbey Willium Method	26.54	15.92
Dooge Method	15.90	9.54
Picking Method	8.75	5.25
Ven te Chow Method	13.20	7.92
Pickering Method	13.14	7.88

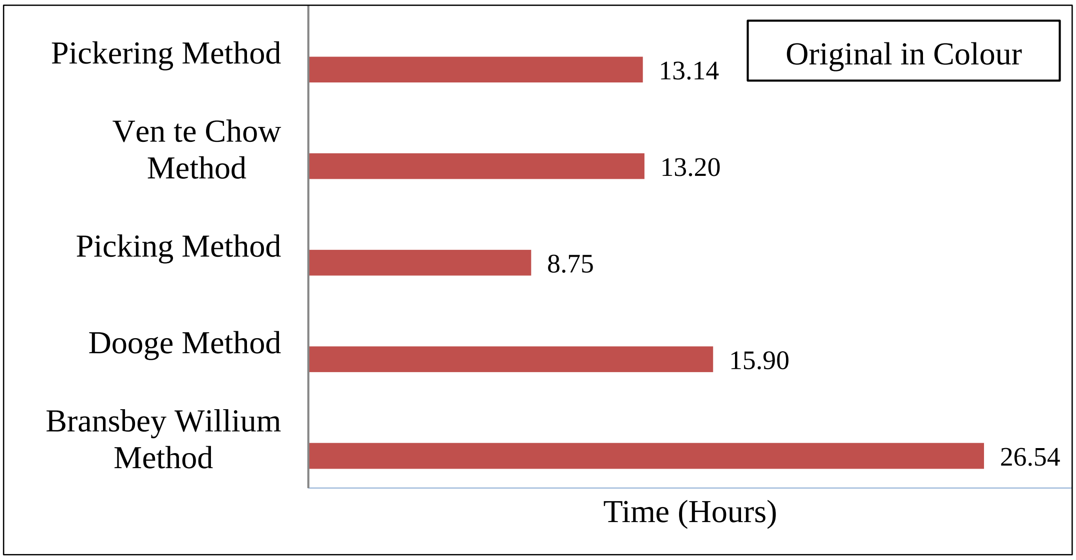


Figure 3-16: Time of concentration

3.6.4 Development of baseflow model

In HEC-HMS, there are four models given for baseflow estimation and out of these, the recession baseflow model is selected by considering the number of parameters and initial flow which is the flow at the beginning of the simulation. In this method, it is considered that the inflection point on the receding limb of a hydrograph marks where the surface flow has stopped contributing to runoff. After this point, the receding limb represents the contributions from both interflow and groundwater flow.

3.6.5 Development of precipitation model

Thiessen (gauge weight) method for precipitation was used in the precipitation model. Thiessen polygons for Badalgama watershed were created using Arc GIS and Thiessen weights for each sub basin were calculated as shown in Table 3-12.

Table 3-12: Thiessen weight of rainfall stations

Rainfall Stations	Thiessen Weight
Ambepussa Govt Farm	0.27
Aranayake (CEB)	0.20
Eraminigolla	0.38
Andigama Farm	0.15

In precipitation model, the daily Thiessen rainfall data were used as input to the model for each rain gauging station. Time series discharge data of Badalgama river gauging station was the inputs for model calibration.

3.6.6 Control specification

Starting date and end date for model calibration was taken as 30-December -2004 to 31-December-2008 while the simulation time interval is set to 1 day.

3.6.7 Model calibration

Model calibration has been carried out based on data from year 2005 ~ 2008. After the selection of the components for model development, the model calibration was undertaken to increase the efficiency of the model that depends upon the parameters. First, manual calibration was done and after that optimized calibration was done using the automatic calibration function in HEC-HMS. For matching the results, Nash-

Sutcliff coefficient and Mean Ratio of Absolute Error (MRAE) were selected as the objective functions. The optimum parameters were obtained by changing the initial values of the parameters until the objective function change was negligible.

3.7 Development of model considering antecedent moisture condition

3.7.1 Calculation of model parameters

For HEC-HMS model development, the following parameters are needed.

1) Calculation of curve number
2) AMC-I, AMC-II and AMC-III
3) Potential maximum retention
4) Initial abstraction

1) Calculation of curve number

In order to apply the SCS curve number procedure in Badalgama watershed, watershed soils has been classified into appropriate hydrological soil groups was undertaken according to the methodology used by the Soil Conservation Services (Soil Conservation Service, 2007b). The description of soil group is described which are following.

Group A: These soils have low runoff potential and high infiltration rates even when thoroughly wetted.

Group B: These soils have moderate infiltration rates when thoroughly wetted and consist chiefly of moderately deep to deep, moderately well to well drained soils with moderately fine to moderately coarse textures.

Group C: These soils have low infiltration rates when thoroughly wetted and consist chiefly of soils with a layer that delays downward movement of water and soils with moderately fine to fine texture.

Group D: These soils have high runoff potential. They have very low infiltration rates when thoroughly wetted and consist mostly of clay soils with a high swelling potential. Soils with a permanent high water table, soils with a clay pan or clay layer at or near the surface.

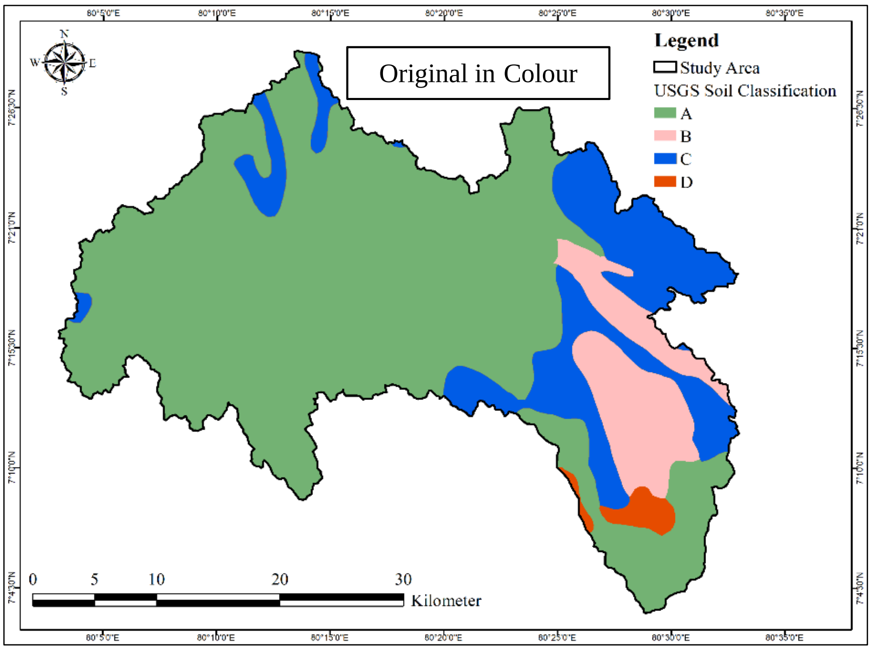


Figure 3-17: Soil classification

Table 3-13: CN value for land use classes

Land use type	Hydrological soil group			
	A	B	C	D
Forest	48	67	77	83
Forest (open)	68	79	86	89
Settlement	48	66	78	83
Agriculture	67	78	85	89
Scrub	48	67	77	83
Barren land	64	75	83	85
Water bodies	90	94	98	100

1-A) Weighted curve number

Curve number is assigned for different land use types; the following equation is used for weighted curve number.

$$\text{Weighted curve number} = \frac{\sum CN_1 * A_1 + CN_2 * A_2 + CN_n * A_n}{\sum A} \quad \textbf{3-1}$$

Table 3-14: Curve number for Badalgama watershed

Land use type	**Area (km^2)**	**Area (%)**	**Total curve number**
Agriculture	194.92	15.30	66.39
Built up area	17.26	1.40	
Homestead	257.18	20.20	
Forest	33.14	2.60	
Plantation	709.93	55.80	
Water bodies	9.01	0.70	
Scrub area	49.70	3.90	

2) Calculation of AMC-I, AMC-II and AMC-III

The **AMC-II is calculated using** the CN **characteristics of Badalgama watershed which is 66.39** as **given in the** Table 3-14. **Hawkins formula is used for the calculation of AMC-I and AMC-III. Limitation of AMC-I and AMC-II is given in the** Table 3-15. **After calculation of Antecedent Moisture Conditions, potential maximum retention and initial abstraction is calculated as shown in the** Table 3-16. **AMC values is calculated for the data 2010 ~ 2013 of lumped model. The purpose of AMC calculation in watershed** is **to know that which AMC conditions is prevalent. The summary of AMC of lumped model is given in the** Table 3-17.

Table 3-15: Limitation of AMC value SCS
Source: (NEH-4, 1964)

Total Five-day Antecedent Rainfall (cm)		
AMC	Dormant season	Growing season
I	Less than 1.3	Less than 3.6
II	1.3 to 2.8	3.6 to 5.3
III	Over 2.8	Over 5.3

Table 3-16: Calculations of Antecedent moisture conditions value

AMC-I			AMC-II			AMC-III		
AMC-I (CNI)	S	IA	AMC-II (CNII)	S	IA	AMC-III (CNIII)	S	IA
46.4	293.3	58.7	66.4	128.6	25.7	82.2	54.9	10.98

Table 3-17: Summary of AMC lumped model

Summary	
AMC	**Lumped Model**
AMC-I	366
AMC-II	65
AMC III	145

3.7.2 Development of HEC-HMS model for AMC

Soil Conservation Services (SCS) curve number as loss method is selected for the development of the model of Antecedent Moisture Conditions (AMC). Loss parameters used in this research are given in Table 3-16**.** Snyder Unit hydrograph is selected as the transform method. There are two parameters in Snyder Unit hydrograph, namely: 1. Standard lag value and the optimum value has been achieved 0.5 hr. 2. peak coefficient and optimum value has been achieved 0.5 hr. Base flow recession method is selected and there are three parameters, namely, 1. Initial discharge (m^3/sec), 2. Recession constant 3. Ratio to peak, for these parameters optimum value is achieved at 54.5, 0.999 and 0.06, respectively.

In control specification, start and ending time of 00:00 and time interval of 1 day were selected. For the precipitation gauge, rainfall data is selected from 01-December-2010 to 09-December-2010 for calibration and 09-January-2011 to 17-January-2011 is selected for validation period. This data set lies mostly in AMC-III and AMC-I data were used for part of this study focused on flood management. Starting and ending time in precipitation gauge for calibration period is selected according to data period.

4.0 RESULTS AND DISCUSSION

4.1 General

Watershed subdivision has been carried out according to threshold area approach. Calibration period was selected from 01-January-2005 to 31-December-2008 and validation period was selected from 01-January-2010 to 31-December-2013. The MRAE and Nash-Sutcliff objective functions were checked but main focus was on MRAE for water resource management. Water balance and accuracy for high, medium and low flow were also checked in this study. In Antecedent Moisture Condition (AMC) section, AMC values and other parameters for HEC-HMS analysis were calculated for 2010~2013. Nash objective function was selected for disaster management in the AMC section aforementioned.

4.2 Calibration for Badalgama lumped model

4.2.1 Statistical goodness of fit measures for initial parameters

Badalgama lumped model was calibrated by matching the simulated streamflow series with the observed flow at Badalgama river gauging station. Performance of the model was checked by Nash-Sutcliff, Mean Ratio of Absolute Error (MRAE) and percentage of annual mass balance error of Badalgama lumped model. The error values at each region of flow are given in the Table 4-1.

The results show satisfactory model performance in hydrograph matching. Nash-Sutcliff value is 0.80 and however, the model did not produce satisfactory results when MARE was selected as objective function for water resource management. Overall 0.82 MRAE is achieved by initial parameters, while Nash Sutcliff and MRAE achieved for high flow region are 0.61 and 0.36, respectively. In medium flow region, Nash-Sutcliff value was very low as -0.152 and MRAE was 0.60. Nash and MRAE in the low flow region is -0.46 and 1.92, respectively.

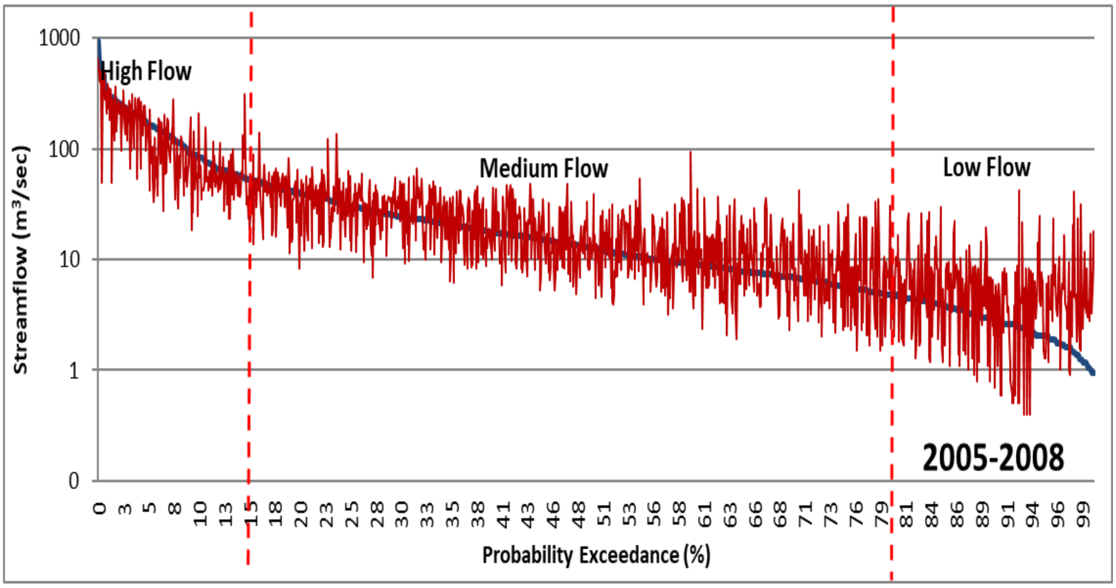


Figure 4-1: Flow duration curve for initial parameters

Table 4-1: Calibration result for initial parameters

<table>
<tr><th rowspan="2">Flow Condition</th><th colspan="2">Objective Function</th><th colspan="4">Mean Annual Mass Balance Error (%)</th></tr>
<tr><th>Nash</th><th>MRAE</th><th>2005</th><th>2006</th><th>2007</th><th>2008</th></tr>
<tr><td>Overall</td><td>0.80</td><td>0.82</td><td rowspan="4">41.00</td><td rowspan="4">36.10</td><td rowspan="4">38.00</td><td rowspan="4">36.30</td></tr>
<tr><td>High</td><td>0.61</td><td>0.36</td></tr>
<tr><td>Medium</td><td>-0.15</td><td>0.60</td></tr>
<tr><td>Low</td><td>-0.46</td><td>1.92</td></tr>
</table>

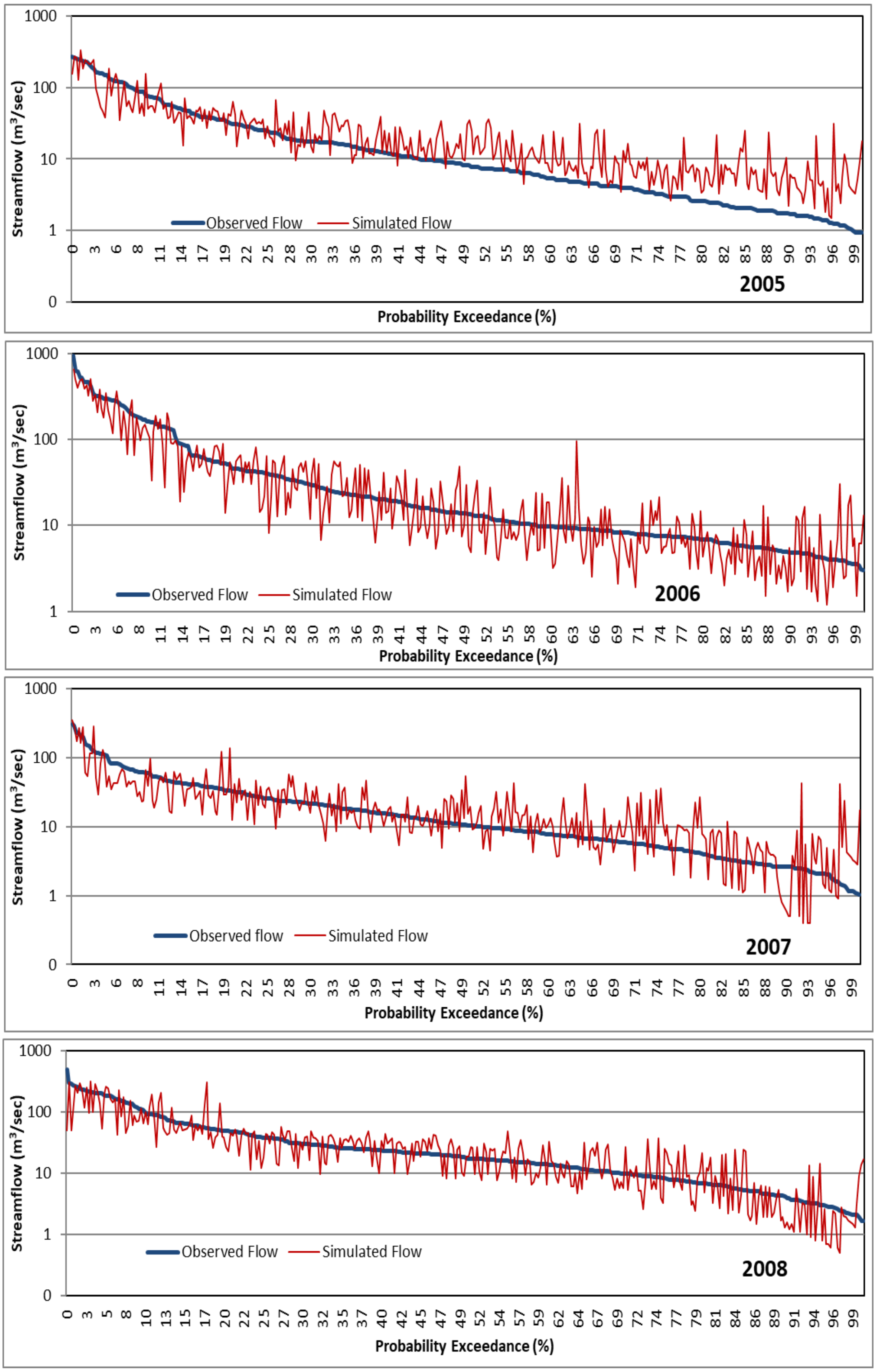


Figure 4-2: Flow duration curve of initial parameters in calibration period

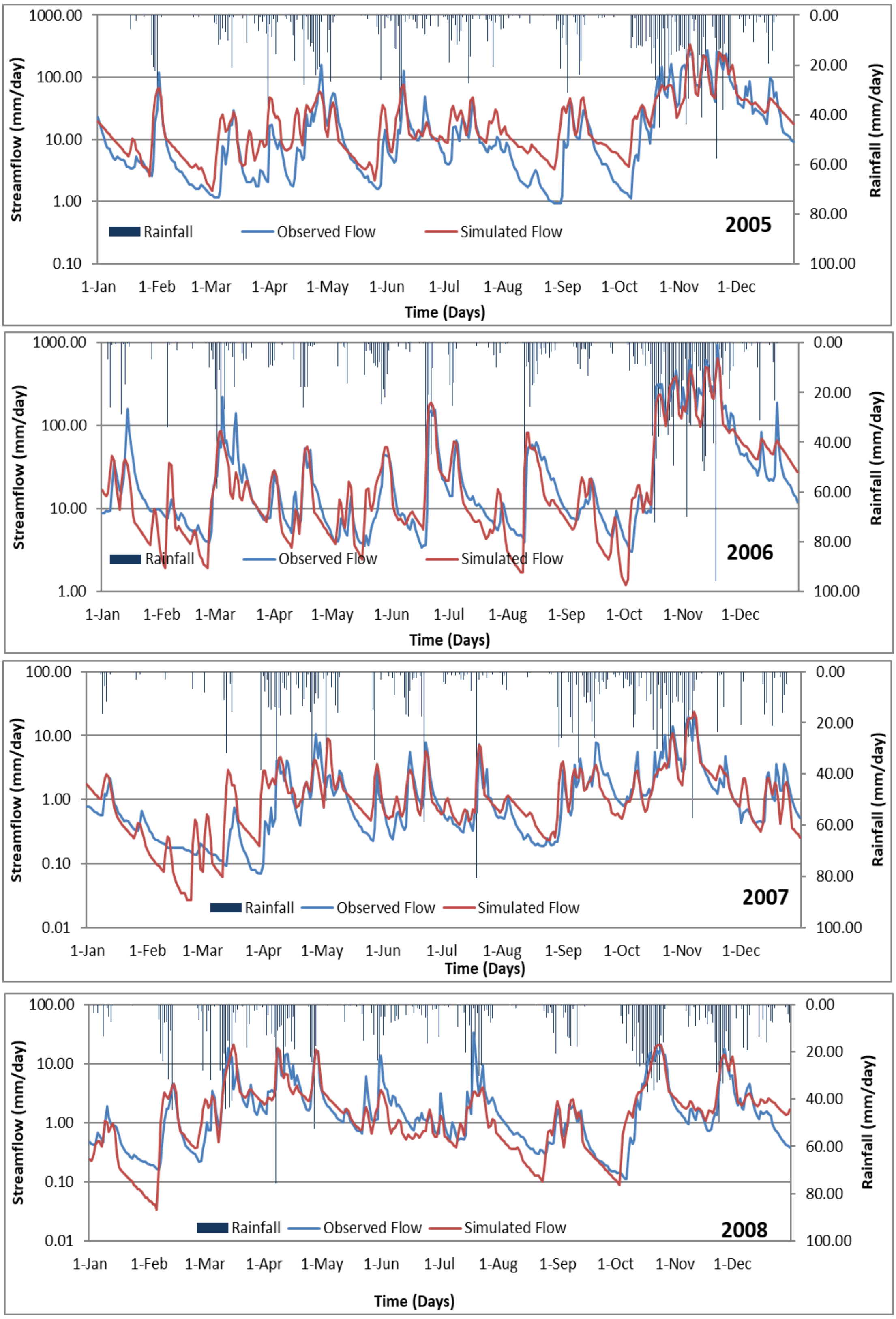


Figure 4-3: Hydrograph result of initial parameters in calibration period

4.3 Parameters sensitivity analysis

In this study, initial parameter estimation process was accomplished based on literature support. Initial parameters were selected based on research done by (De Silva et al., 2014) in Kelani Basin in Sri Lanka. After performing manual and automatic adjustment of the parameters, sensitivity analysis of the parameters was performed to check the responsive behavior of the parameters.

In this study, the sensitivity analysis has been performed to determine the appropriate range of parameters for model calibration. Initially, the model was run with the initially estimated parameters. Thereafter, out of the various soil moisture accounting parameters, Clark unit hydrograph parameters and recession for base flow parameters, one parameter at a time was varied and analyzed from -50% to 50% with increments of 10%, keeping all other parameters constant. Greater percentage change in the simulated volumes represents greater variable sensitivity. Figure 4-4 shows that soil percolation is most sensitive parameter and tension storage is least sensitive parameter.

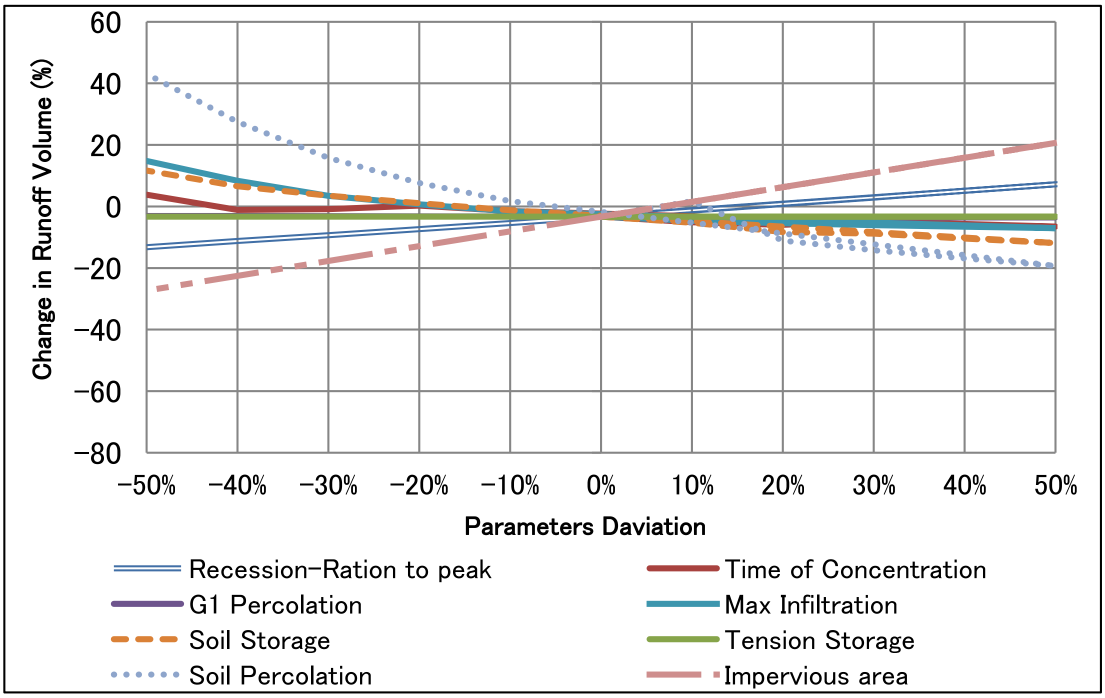


Figure 4-4: Parameters sensitivity analysis

4.4 Optimization of parameters

After performing the sensitivity analysis, manual calibration has been carried out by changing most sensitive parameters. In manual calibration, MRAE achieved was 0.464 and Nash was 0.683. Later, further optimization has been attempted by changing each parameter one by one. For further refinement of the parameters, the parameters were divided into groups like surface flow parameters, baseflow parameters and precipitation loss parameters. The MRAE objective function is selected which provides an average indicator for the matching of each and every point of the two hydrographs relative to the observed value at that particular time point. For parameter optimization, the automatic optimization has been used in HEC-HMS.

Table 4-2: Manual calibrated parameters values

Serial number	Parameters	Initial Values	Optimum values
1	Recession-Ration to peak	0.164	0.164
2	Recession-constant	0.923	0.923
3	Time of concentration	57.000	85.000
4	GW1 Percolation	0.350	0.320
5	Max infiltration	4.750	3.800
6	Soil storage	276.000	150.000
7	Tension storage	21.000	21.000
8	Soil percolation	0.456	0.436
9	Impervious	19.000	9.550

Table 4-3: Initial parameter values

Surface flow Parameters	**Initial Values**	**Loss Parameters**	**Initial Values**	**Base flow Parameters**	**Initial Values**
Soil storage	150.000	Soil percolation	0.436	Recession constant	0.923
Impervious area	9.550	Maximum infiltration	3.800	Ratio to peak	0.164
Time of concentration	85.000	Tension storage	21.000		
Storage coefficient	35.400	GW1 storage	138.000		
		GW1 storage coefficient	10.000		
		GW1 Percolation	0.320		

Parameter classification has been done by considering overflow, loss parameters and base flow parameters for best matching fit. After parameter classification, automatic calibration has been carried out in HEC-HMS by keeping all the parameters unlocked and the result was checked with the value of the chosen objective function. In this way, MRAE value of 0.591 and Nash value of 0.686 were achieved later on by changing the parameters group wise, for example by changing the surface flow parameters and locking other parameters and vice versa. The results thus obtained are shown in the Table 4-4 to Table 4-7.

After performing automatic calibration, again manual calibration has been carried out by changing parameters which is most sensitive and minimum MREA value close to zero was obtained. In automatic calibration, the optimum value has been checked by performing global optimization. The global optimizations have been performed by changing two parameters at the same time and by changing up to minimum and maximum values over the entire range. The results obtained are shown in the Figure 4-8.

Table 4-4: Result by changing overall flow parameters

Surface Flow	Initial Value	Optimum Value	Nash	MRAE
Soil storage	150.0	150.0	0.683	0.464
Time of concentration	85.0	85.0		
Storage coefficient	35.40	35.40		

Table 4-5: Result by changing loss parameters

Loss parameter	Initial Value	Optimum Value	Nash	MRAE
Soil percolation	0.44	0.43	0.69	0.48
Maximum infiltration	3.80	3.53		
Tension storage	21.00	21.20		
GW1 storage	138.00	138.20		
GW1 storage coefficient	10.00	10.20		
GW1 Percolation	0.32	0.52		

Table 4-6: Result by changing base flow parameters

Base flow parameter	Initial value	Optimum value	Nash	MRAE
Recession constant	0.92	0.94	0.68	0.48
Ratio to peak	0.16	0.13		

Table 4-7: Result by changing surface flow parameters

Surface flow parameter	**Initial value**	**Optimum value**	**Nash**	**MRAE**
Soil storage	150.00	152.58	0.68	0.46
Time of concentration	85.00	78.40	0.70	0.47
Storage coefficient	35.40	10.28	0.74	0.55
Soil percolation	0.44	0.42	0.68	0.48
Maximum infiltration	3.80	3.25	0.69	0.49
Tension storage	21.00	30.11	0.68	0.47
GW1 storage	138.00	40.07	0.69	0.47
GW1 storage coefficient	10.00	10.20	0.68	0.46
GW1 percolation	0.32	0.06	0.68	0.46
Recession constant	0.923	0.94	0.69	0.54
Ratio to peak	0.164	0.23	0.69	0.53

Table 4-8: Optimized parameter value

Parameter	Initial Value	Optimized Value
Initial discharge	21.0	10.0
Ratio to peak	0.164	0.164
Recession constant	0.923	0.923
Time of concentration	85.0	79.0
Soil storage	150.0	445.0
Max infiltration	3.80	4.50
Storage coefficient	35.40	59.0
Soil percolation (mm/hr)	0.440	0.320
Impervious	9.550	9.550
Soil (%)	90.0	90.0
Groundwater 1 (%)	80.0	80.0
Groundwater 2 (%)	90.0	90.0
Tension storage (mm)	21.0	21.0
Groundwater 1 storage	138.0	70.0
GW1 percolation (mm/hr)	0.320	0.30
GW1 coefficient (hr)	10.0	10.0
GW2 storage (mm)	300.0	10.0
GW2 percolation (mm/hr)	0.30	0.30
GW2 coefficient (hr)	70.0	30.0

Table 4-9: Global optimization for soil storage and ratio to peak parameters

Ratio to peak → / Soil storage ↓	0.000	0.040	0.080	0.120	0.164	0.370	0.580	0.790	1.000
21.000	3.120	3.440	3.970	4.500	5.020	7.180	8.740	9.780	10.310
111.300	0.680	0.490	0.470	0.510	0.560	0.890	1.200	1.460	1.620
222.500	0.640	0.480	0.430	0.410	0.420	0.620	0.850	1.050	1.170
333.800	0.640	0.480	0.440	0.400	0.400	0.550	0.760	0.940	1.050
445.000	0.640	0.500	0.440	0.410	0.390	0.530	0.730	0.890	1.00
708.800	0.650	0.510	0.450	0.420	0.410	0.530	0.710	0.870	0.97
972.500	0.650	0.530	0.460	0.440	0.440	0.550	0.730	0.880	0.970
1236.300	0.660	0.540	0.470	0.450	0.450	0.570	0.740	0.900	1.000
1500.00	0.670	0.540	0.470	0.460	0.460	0.590	0.760	0.930	1.020

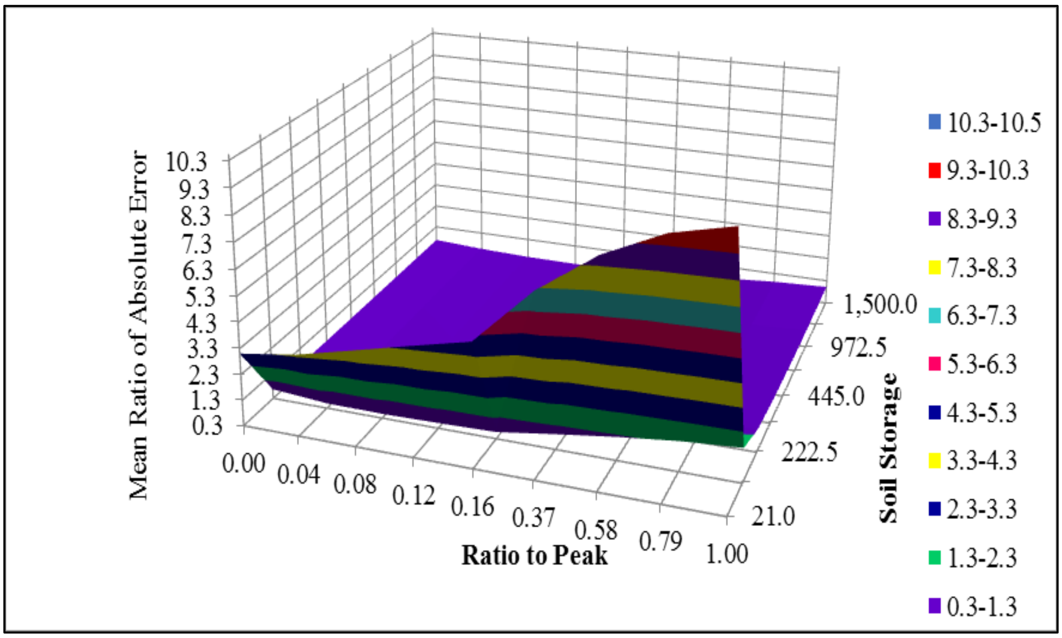


Figure 4-5: Global optimization for soil percolation and soil storage

Table 4-10: Global optimization for soil storage and ratio to peak parameter

Soil Percolation	→							
Soil Storage ↓		0.00	0.11	0.21	0.32	166.88	333.44	500.0
	21.00	5.02	5.02	5.02	5.02	5.02	5.02	5.02
	162.33	5.00	1.98	0.84	0.52	0.53	0.53	0.53
	303.67	4.97	1.98	0.70	0.42	0.53	0.53	0.53
	445.00	4.94	1.99	0.68	0.41	0.53	0.53	0.53
	796.67	4.86	2.04	0.73	0.43	0.53	0.53	0.53
	1148.33	4.80	2.08	0.77	0.46	0.53	0.53	0.53
	1500.00	4.75	2.11	0.81	0.49	0.53	0.53	0.53

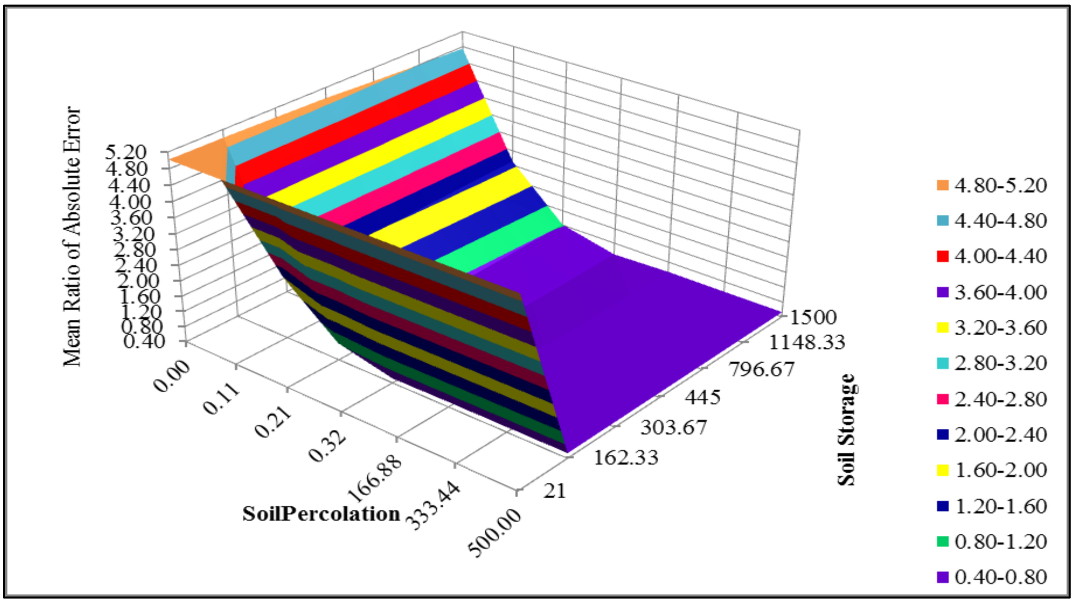


Figure 4-6: Global optimization for soil storage and ratio to peak parameter

4.5 Lumped model result for optimum parameters in calibration period

4.5.1 Annual water balance

Water balance for Badalgama watershed has been done as indicated in Table 4-11. Water balance results reflect good performance with optimum parameters during the calibration period with MRAE and Nash–Sutcliffe efficiency value of 0.393 and 0.641, respectively.

Table 4-11: Annual water balance of lumped model in calibration period

Year	Thiessen Rainfall (mm)	Simulated Streamflow (mm)	Observed Streamflow (mm)	Observed Water Balance (mm)	Simulated Water Balance (mm)	Annual Water Balance Difference
2005	1914	417	661	1253	1497	-245
2006	2431	968	1304	1126	1463	-337
2007	1835	426	597	1238	1409	-171
2008	2305	643	974	1331	1661	-331

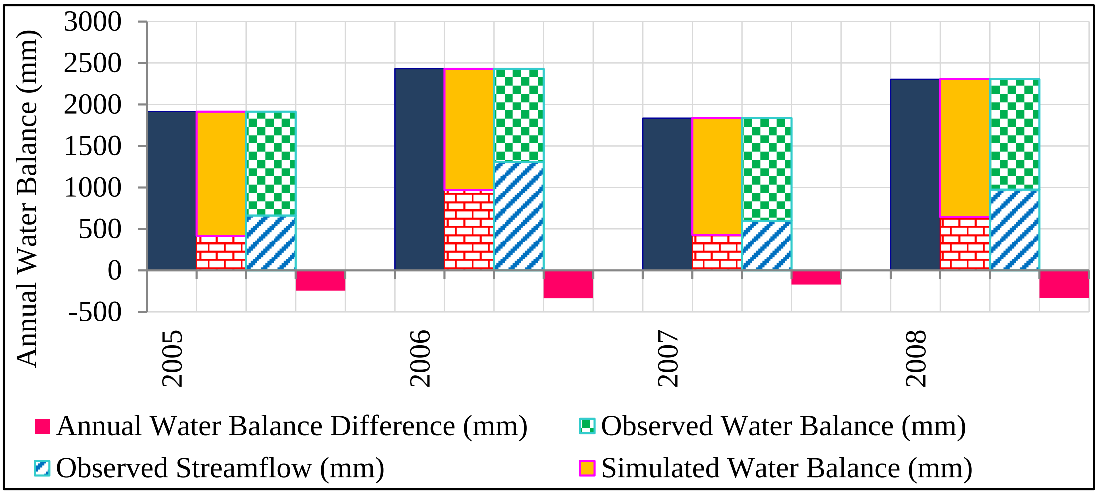


Figure 4-7: Annual water balance of lumped model in calibration period

4.5.2 Flow duration curve in calibration period

For detailed analysis of the behavior of the model parameters, flow duration curves have been divided into three regions, as high flow, intermediate flow and low flow. High flow is taken as stream flow which occurred for less than 15% of the time and low flow which is more than 80% of the time and the balance was identified as intermediate flow. The Nash and MRAE efficiency was computed for high, medium and low flow to identify the performance of optimum model parameters. The performance of model parameters is given in Table 4-12 for different flow regions.

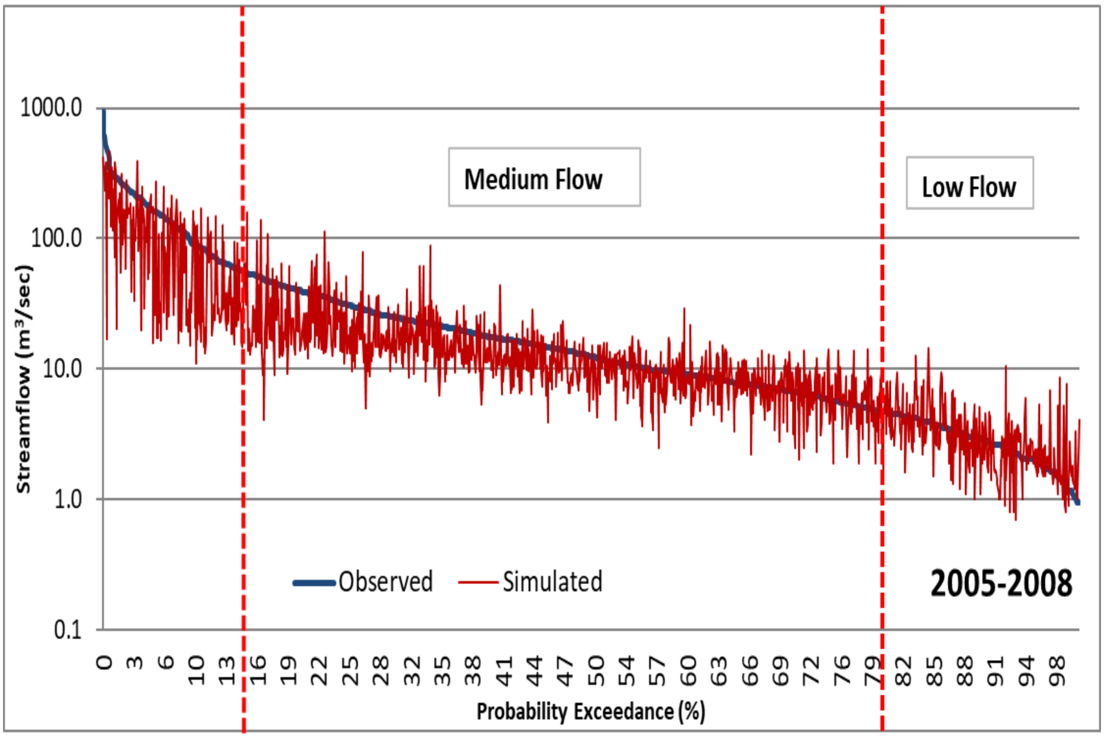


Figure 4-8: Flow duration curve in calibration period Badalgama watershed

Table 4-12: Model performance for calibration for different flow condition

Flow Condition	Objective Function	
	Nash	MRAE
Overall	0.641	0.393
High	0.276	0.359
Medium	0.684	0.390
Low	0.399	0.430

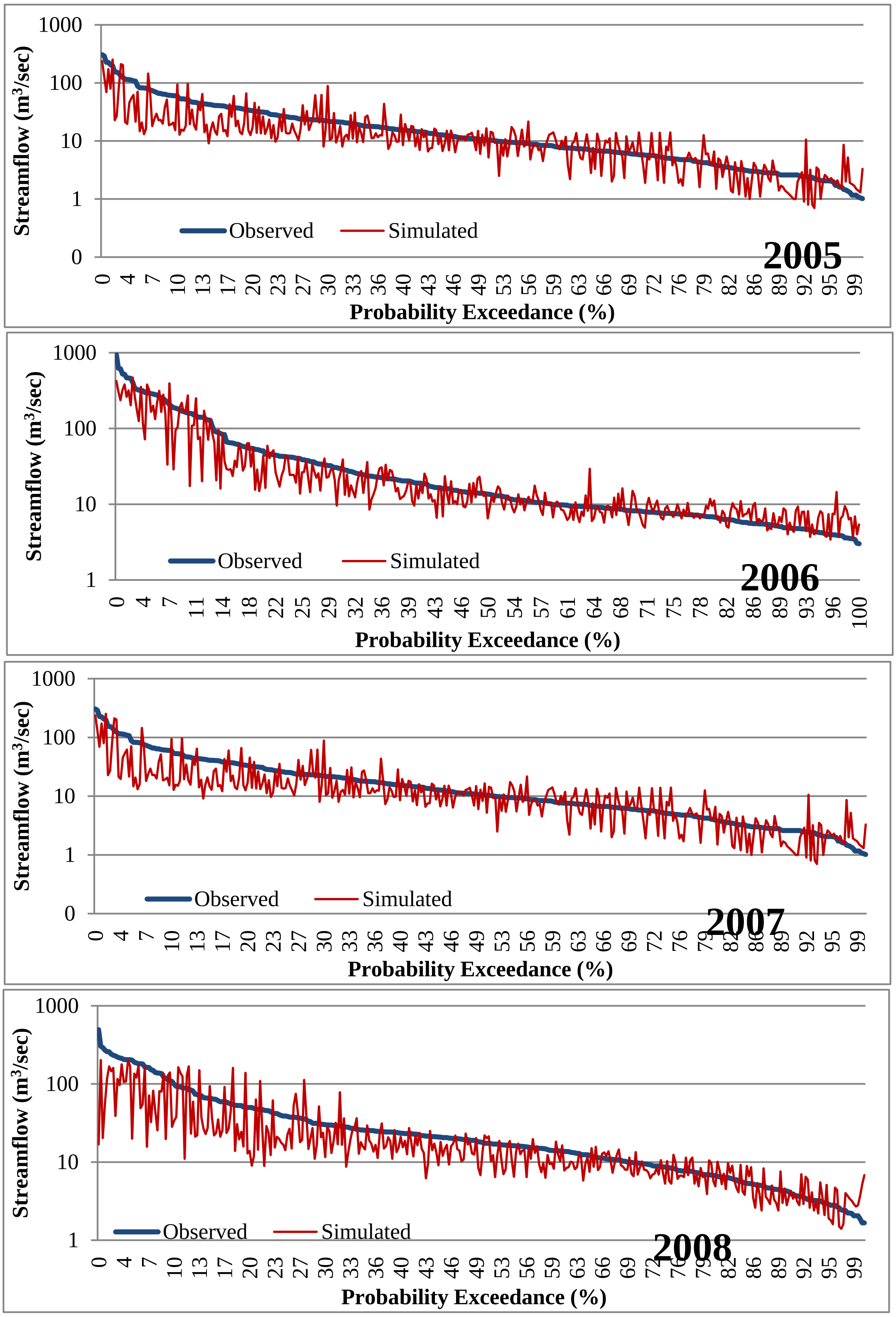


Figure 4-9: Flow duration curve for each year in calibration period

4.5.3 Outflow hydrograph

The outflow hydrograph of observed and simulated streamflow corresponding to daily Thiessen rainfall for calibration period is shown in the Figure 4-10. The overall performance of the model with mean annual mass balance error and other indicators are given in the Table 4-13.

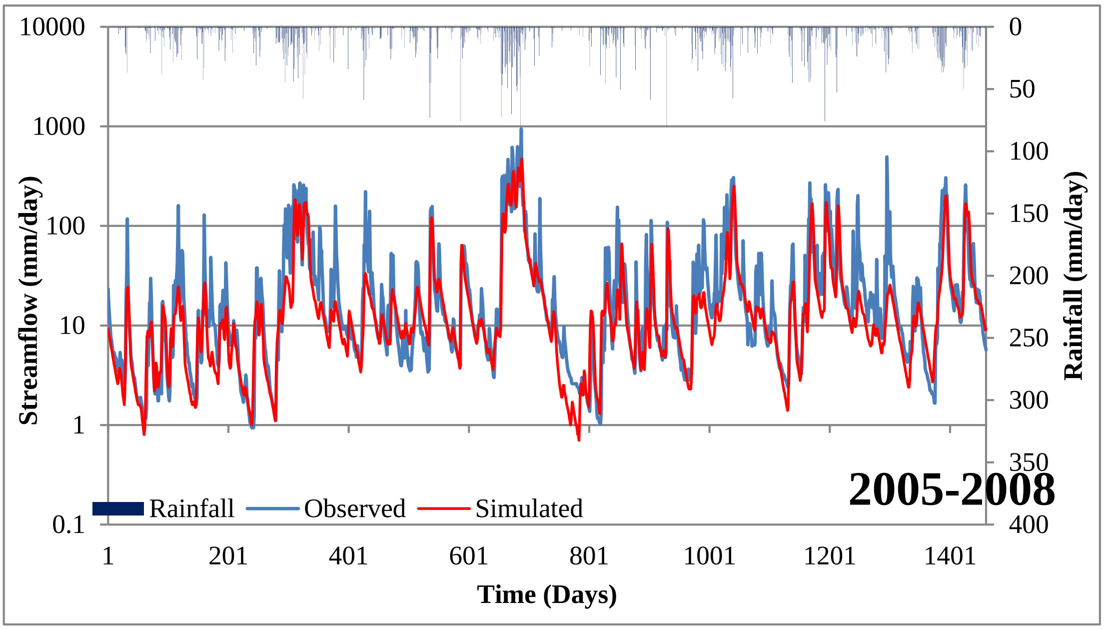


Figure 4-10: Hydrograph for calibration period

Table 4-13: Model performance for lumped model in calibration period

Flow Condition	Objective Function		Mean Annual Mass Balance Error (%)			
	Nash	MRAE	2005	2006	2007	2008
Overall	0.641	0.393	34.740	36.000	26.500	32.700
High	0.276	0.359				
Medium	0.684	0.390				
Low	0.399	0.430				

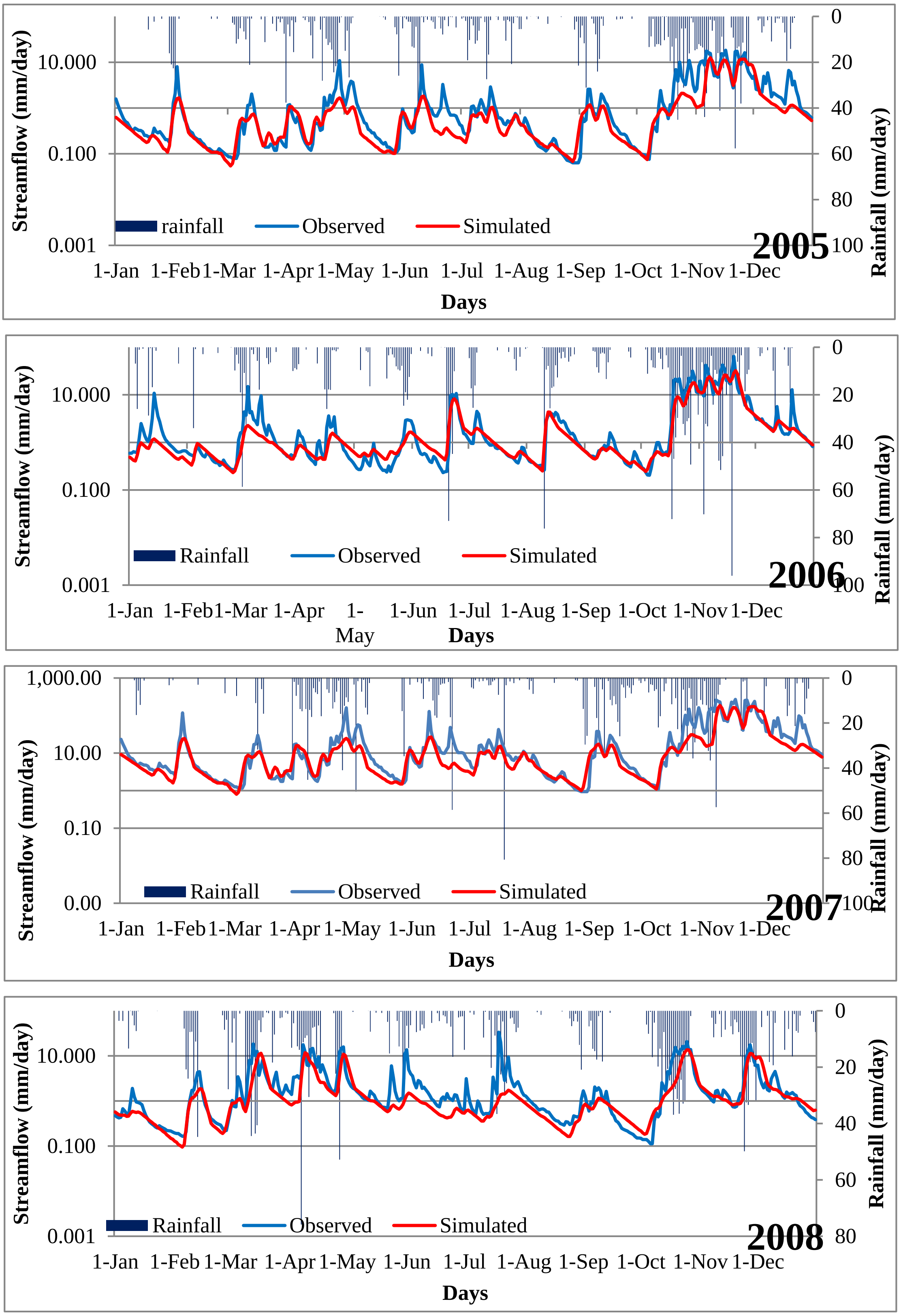


Figure 4-11: Hydrograph of lumped model in calibration period

4.6 Lumped model result for optimum parameters in validation period

4.6.1 Annual water balance

Water balance for Badalgama watershed is indicated in Table 4-14. Water balance performance reflects substantial improvement with percentage difference of 2.89% for validation period.

Table 4-14: Annual water balance of lumped model in validation period

Year	Thiessen Rainfall (mm)	Simulated Streamflow (mm)	Observed Streamflow (mm)	Observed Water Balance (mm)	Simulated Water Balance (mm)	Annual Water Balance Difference (mm)
2010	2360	1274	1278	1081	1086	-4
2011	1550	601	722	828	949	-121
2012	1876	695	830	1046	1181	-135
2013	1956	772	640	1316	1183	133

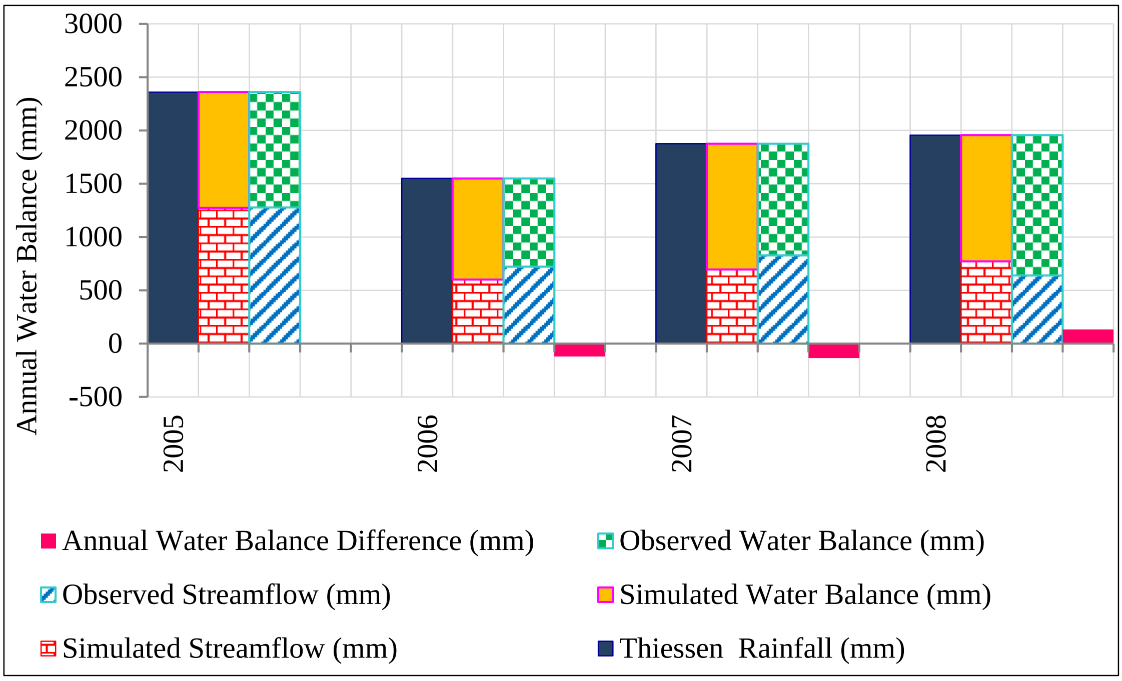


Figure 4-12: Annual water balance for validation period of lumped model

4.6.2 Flow duration curve for validation period

For detailed analysis of the behavior of the model parameters, flow duration curve was divided into three regions as high flow, intermediate flow and low flow. High flow region was taken as stream flows which occurred for less than 15% of the time and medium flows were taken as stream flows which occurred greater than 15% of the time and less than 80% while low flows were taken as which occurred more than 80% of the time. The Nash and MRAE efficiency were computed for high, medium and low flow to identify the performance of the model. The performance of model parameters is given in the Table 4-15 and Figure 4-13. The result shows that the performance of Nash in low flow is not satisfactory.

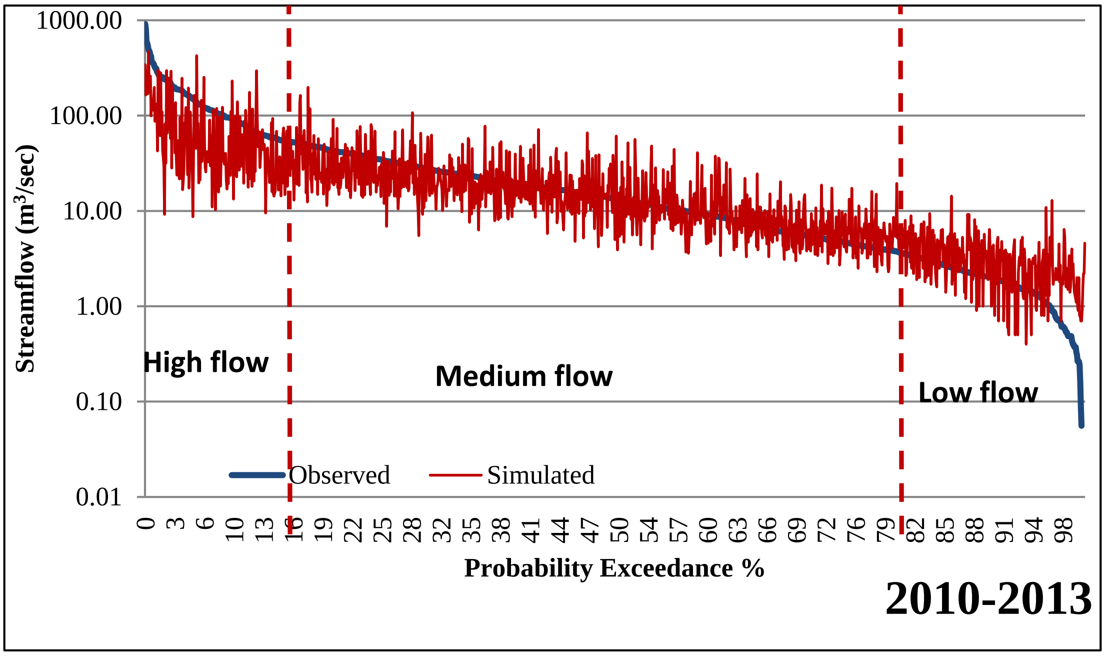


Figure 4-13: Flow duration curve of lumped model in validation period

Table 4-15: Performance for lumped model for validation period

Flow Condition	Objective Function		Mean Annual Mass Balance Error (%)			
	Nash	MRAE	2010	2011	2012	2013
Overall	0.480	0.640	35.762	36.054	43.258	36.650
High	0.500	0.480				
Medium	0.490	0.650				
Low	0.380	0.740				

4.6.3 Outflow hydrograph

The outflow hydrograph of observed and simulated streamflow corresponding to daily Thiessen rainfall of validation period is shown in the Table 4-14. The overall performance of the model with mean annual mass balance error and other indicators are given in the Table 4-15.

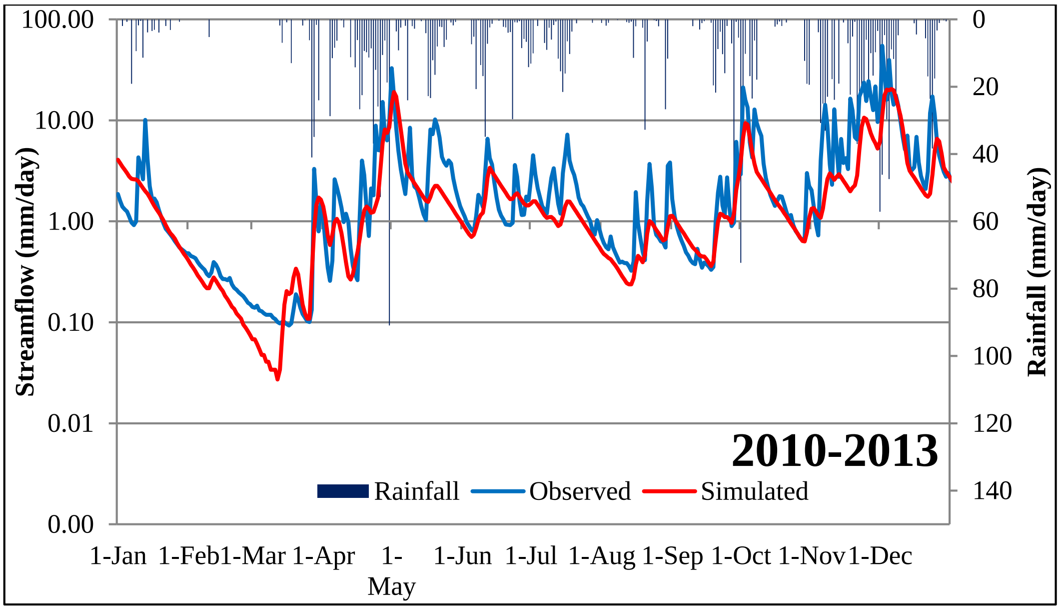


Figure 4-14: Hydrograph of lumped model in validation period

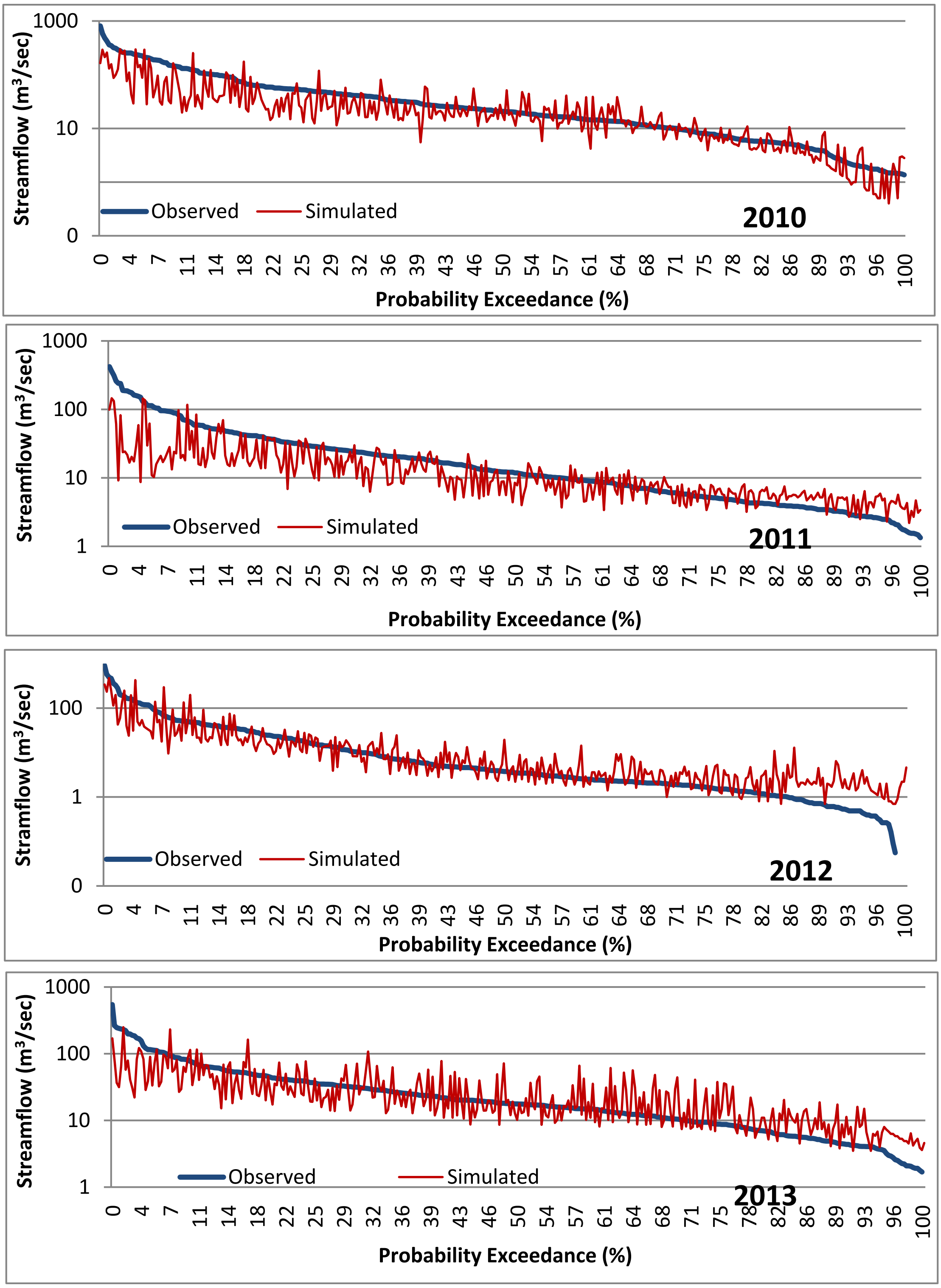


Figure 4-15: Flow duration curve at each year of lumped model for validation period

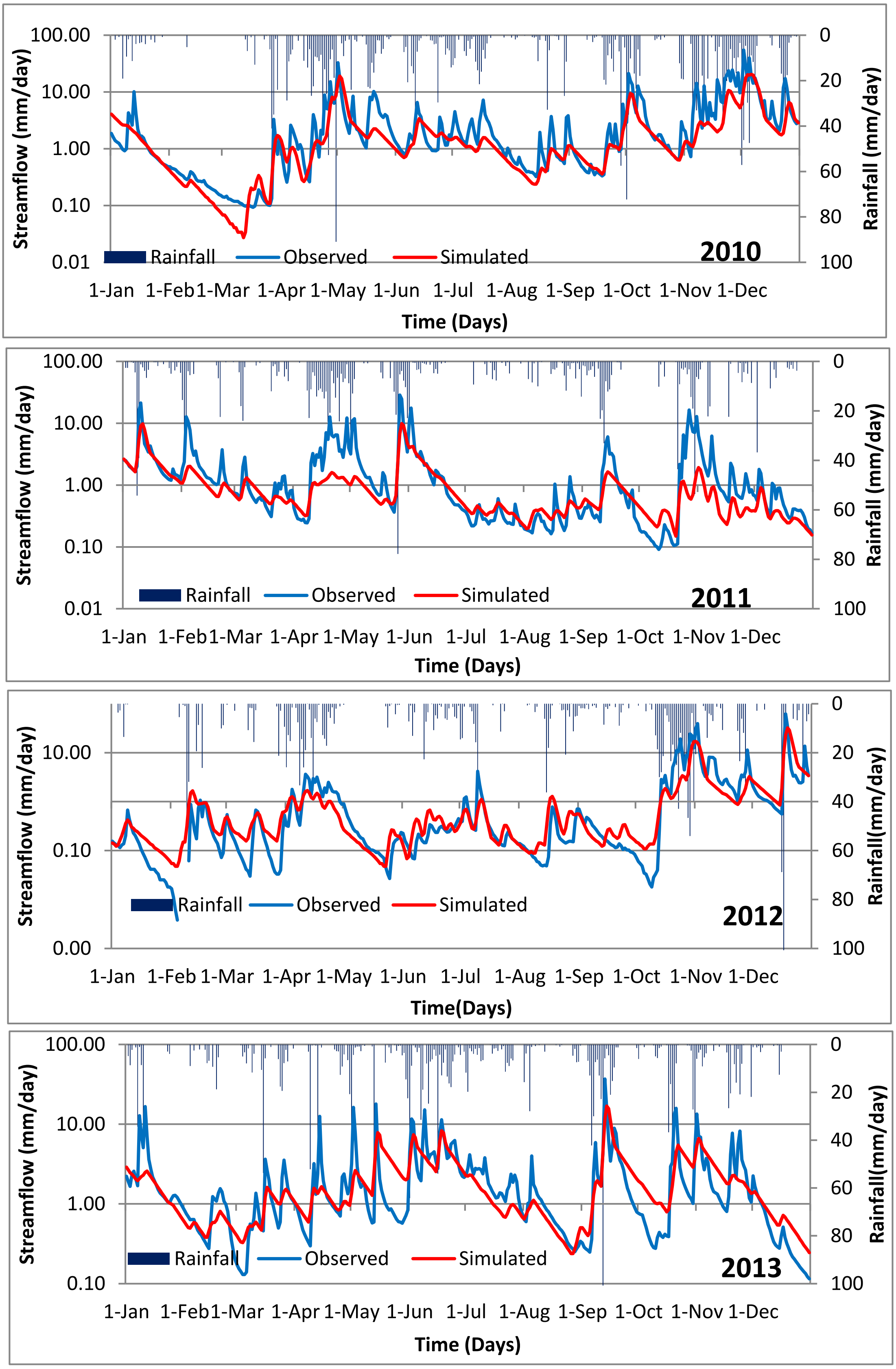


Figure 4-16: Hydrograph of lumped model for validation period

4.7 Distributed model

In this research, manual and automated tools in Arc GIS 10.2 were used to construct lumped catchment and subdivision of the watershed. The critical threshold approach for stream generation is chosen based on analyst's expertise and judgment. According to Kumar and Merwade (2009a), the threshold is the minimum upstream drainage area for a channel to originate and can be specified by a percentage of total watershed area. For this study, a 30 m resolution Digital Elevation Model (DEM) is used and critical threshold area is verified accordingly.

4.7.1 Three subdivision model result in calibration period

Three sub divisions were made based on critical threshold approach for stream generation as shown in Table 4-17. Thiessen polygons were used for weights of rainfall gauging stations of every watershed subdivision.

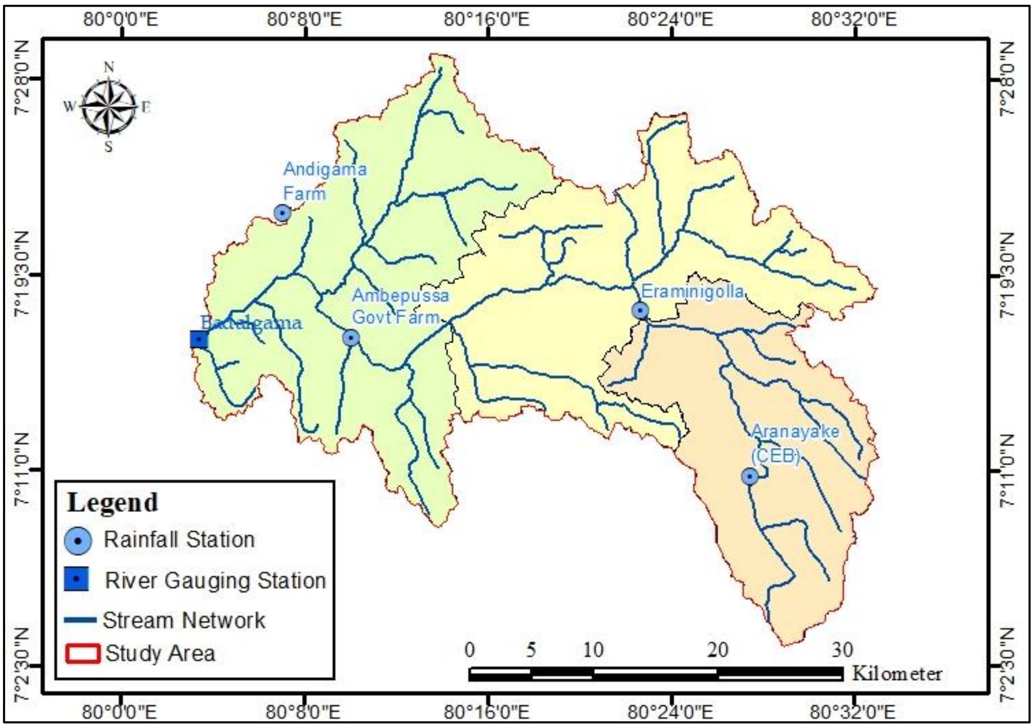


Figure 4-17: Three subdivisions of Badalgama watershed

Table 4-16: Rainfall gauge weight for three subdivisions

Subdivisions		Sub division1	Sub division 2	Sub division 3
Area (km^2)		500.240	430.780	340.110
Rainfall station	Ambepussa Govt Farm	0.570	0.130	
	Andigama Farm	0.380		
	Eraminigolla	0.050	0.840	0.260
	Aranayake (CEB)		0.028	0.740

4.7.1.1 Annual water balance

Comparison of calculated and simulated streamflow water balance has been performed for Badalgama watershed as indicated in Figure 4-18. Water balance comparison reflects an acceptable performance during the calibration period with MRAE and Nash-Sutcliffe efficiency value of 0.385 and 0.685, respectively with the optimum parameters. With this result, it shows that the percentage difference in water balance is 18.32 % which is also in acceptable range. Optimum parameters are given in the comparison section.

Table 4-17: Annual water balance for three subdivisions in calibration period

Year	Thiessen Rainfall (mm)	Simulated Streamflow (mm)	Observed Streamflow (mm)	Observed Water Balance (mm)	Simulated Water Balance (mm)	Annual Water Balance Difference (mm)
2005	1914	442	661	1253	1472	-220
2006	2431	913	1304	1126	1517	-391
2007	1835	420	597	1238	1415	-177
2008	2305	652	974	1331	1652	-322

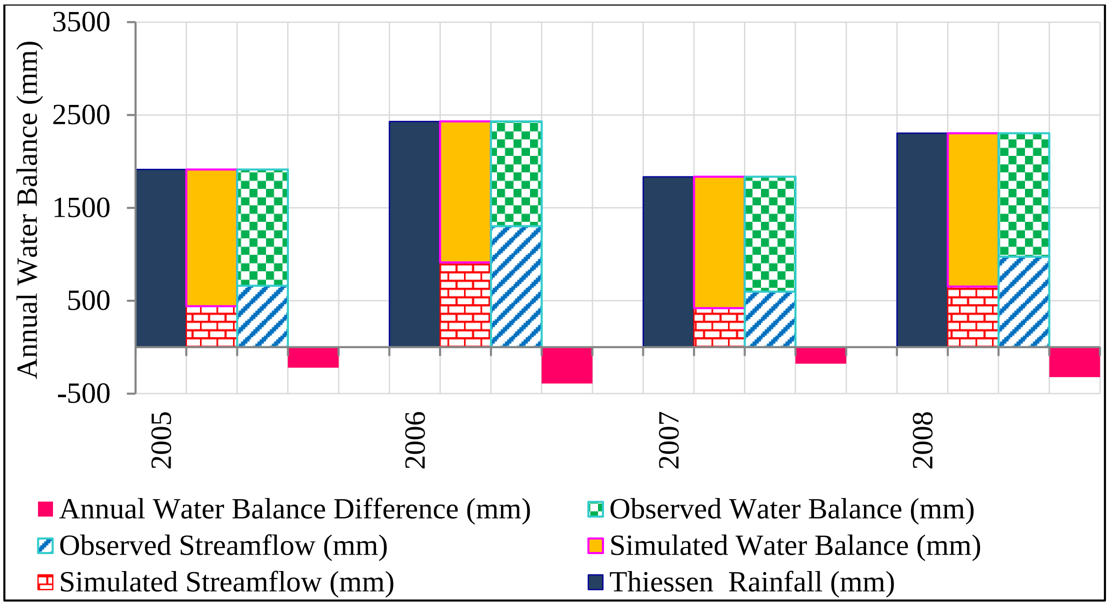


Figure 4-18: Annual water balance for three subdivisions in calibration period

4.7.1.2 Flow duration curve

For detailed analysis of the behavior of the model parameters, flow duration curves were divided into three regions as high flow, intermediate flow and low flow. High flows were taken as stream flows which occurred for less than 15% of the time and low flows were the flows which persisted for more than 80% of the time. The Nash and MRAE efficiency were computed for high, medium and low flow regions to identify the performance of optimum model parameters. The performance of model parameters is given in the Table 4-18. The result in the Table 4-18 showed that for the calibration period, high flow gives better performance for MRAE and however the performance under Nash-Sutcliffe objective function was found to be unsatisfactory.

Table 4-18: Result for three subdivisions in calibration period

Flow condition	**Objective function**	
	Nash	MRAE
Overall	0.641	0.393
High	0.276	0.359
Medium	0.684	0.390
Low	0.399	0.430

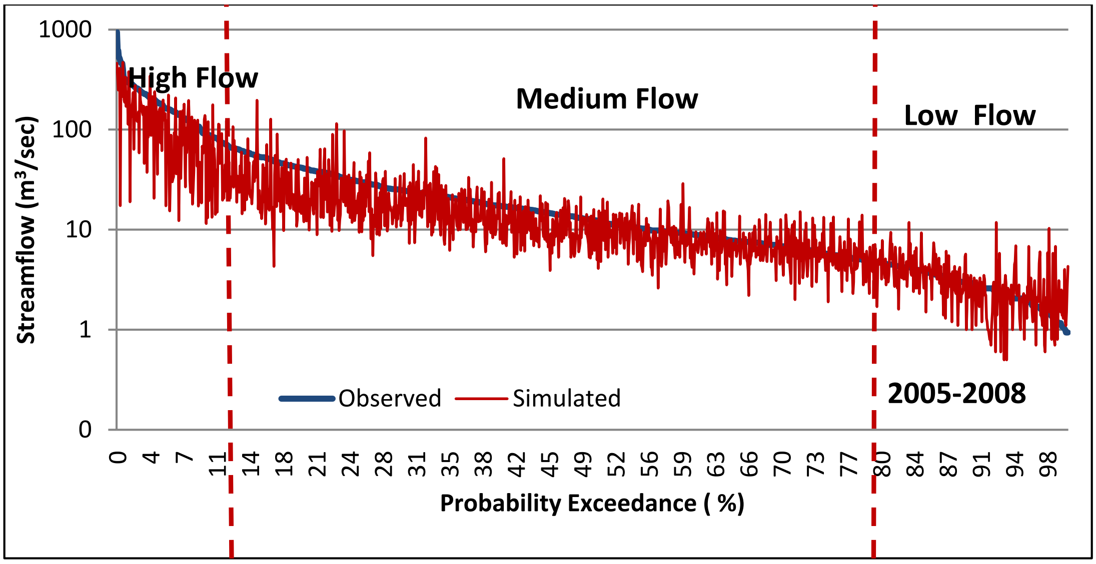


Figure 4-19: Flow duration curve for three subdivision model in calibration period

4.7.1.3 Outflow hydrograph

The outflow hydrograph of observed and simulated streamflow corresponding to daily Thiessen rainfall for calibration period is given in the Figure 4-21. The overall performance of the model with mean annual mass balance error are given in the Table 4-18.

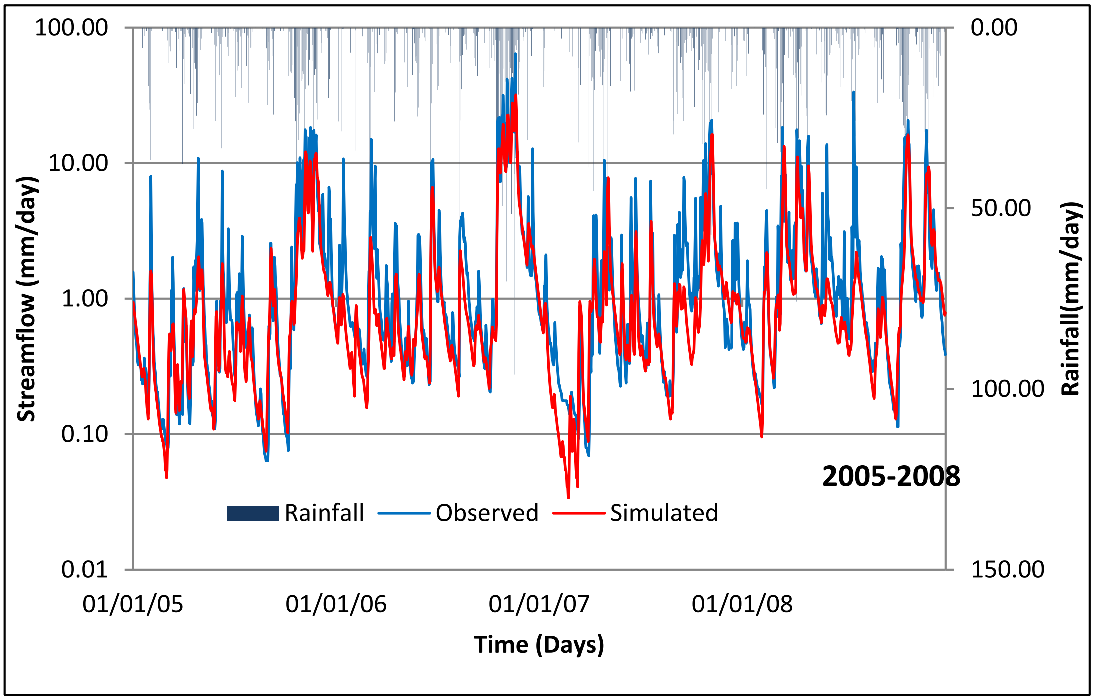


Figure 4-20: Hydrograph for three subdivision model in calibration period

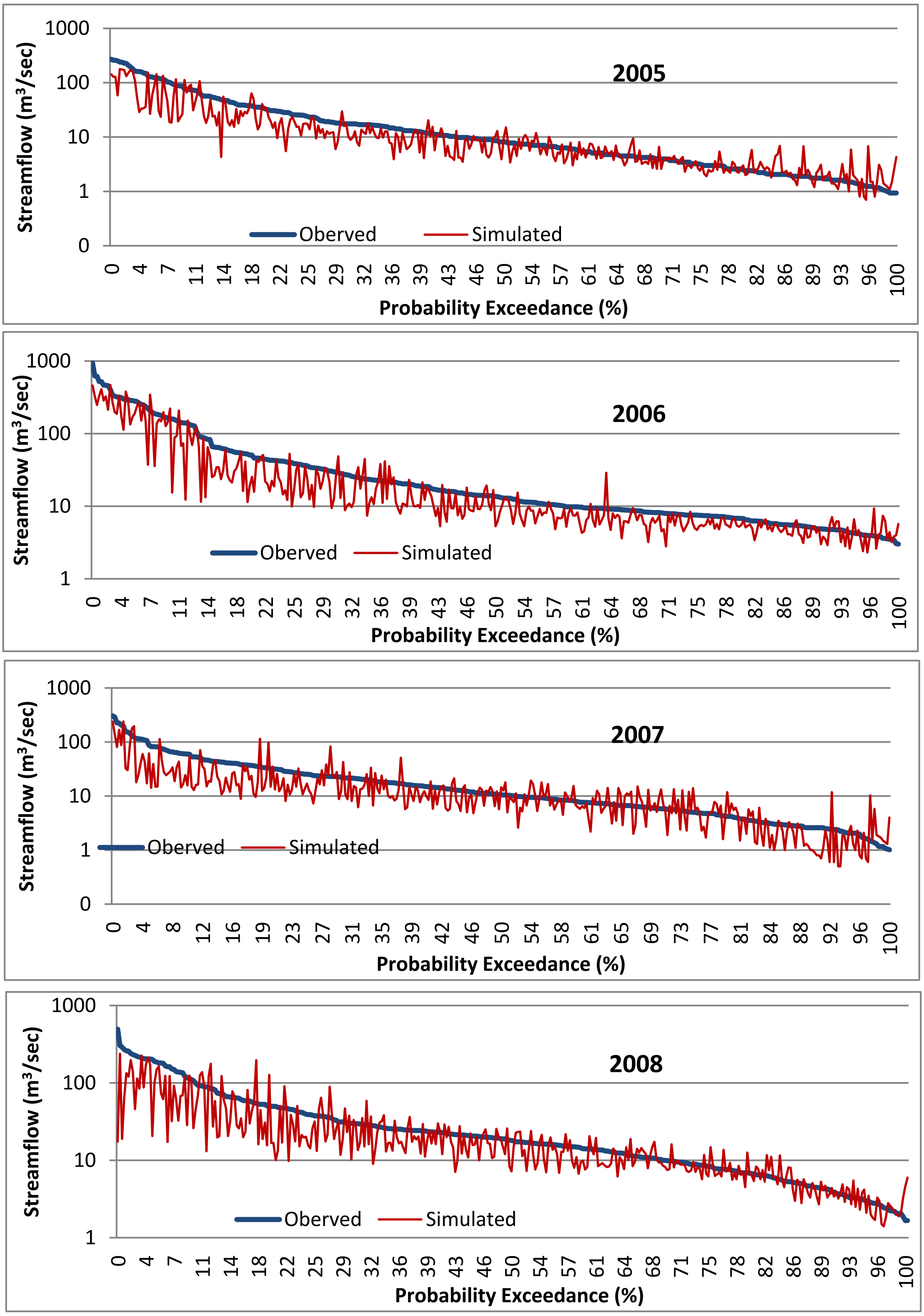


Figure 4-21: Flow duration curve **for three sub divisions** model in **calibration period**

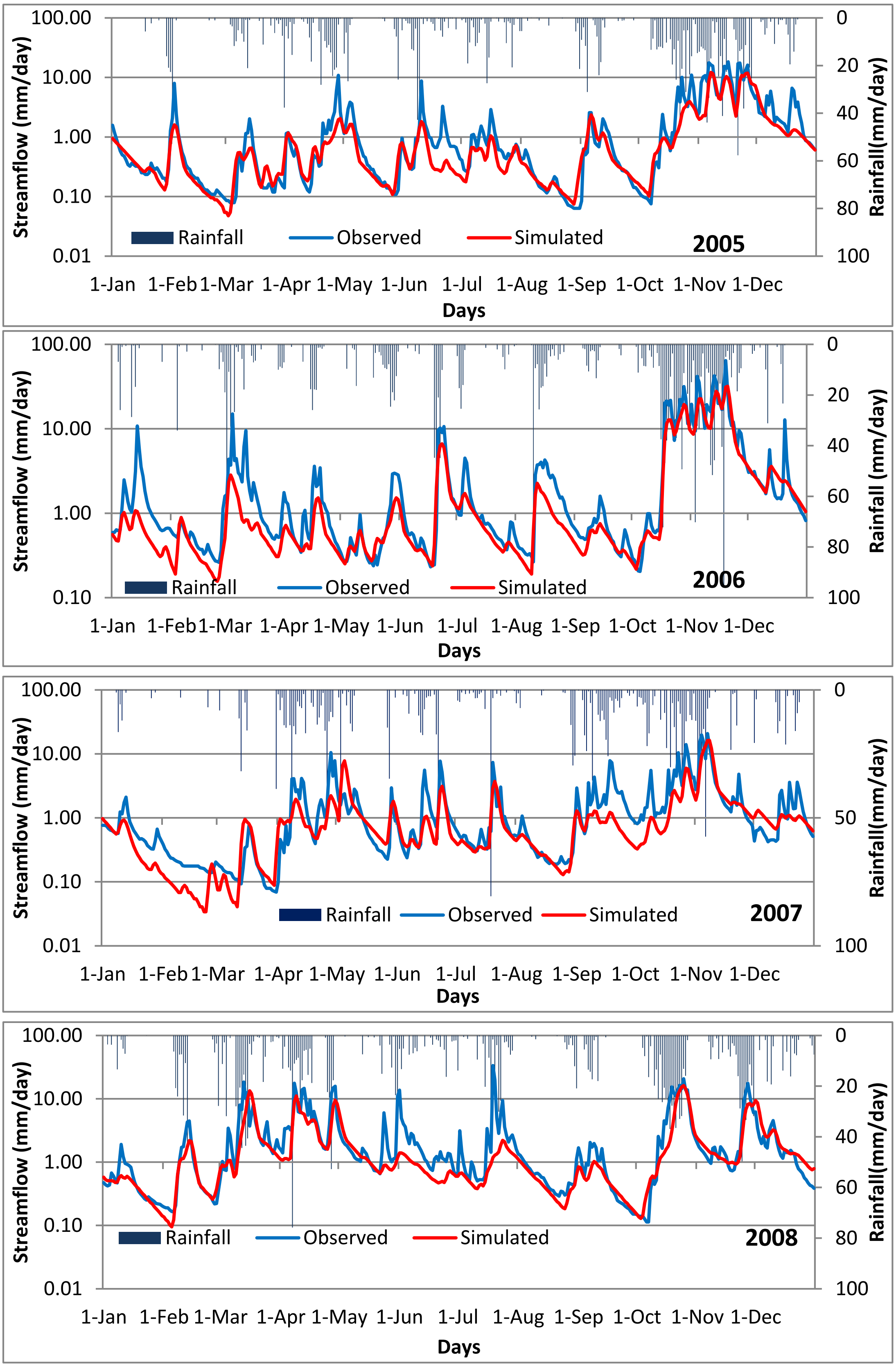


Figure 4-22: Hydrograph for three subdivision model in calibration period

4.7.2 Three subdivision model results in validation period

4.7.2.1 Annual water balance

Comparison of observed and simulated water balance for Badalgama watershed is indicated in Table 4-19 and water Balance performance reflects good results with percentage difference of 20.16% for validation periods which is aceptable.

Table 4-19: Annual water balance for three subdivision model in validation period

Year	Thiessen Rainfall (mm)	Simulated Streamflow (mm)	Observed Streamflow (mm)	Observed Water Balance (mm)	Simulated Water Balance (mm)	Annual Water Balance Difference (mm)
2010	2360	836	1278	1081	1524	-442
2011	1550	377	722	828	1173	-345
2012	1876	497	830	1046	1379	-333
2013	1956	680	640	1316	1276	41

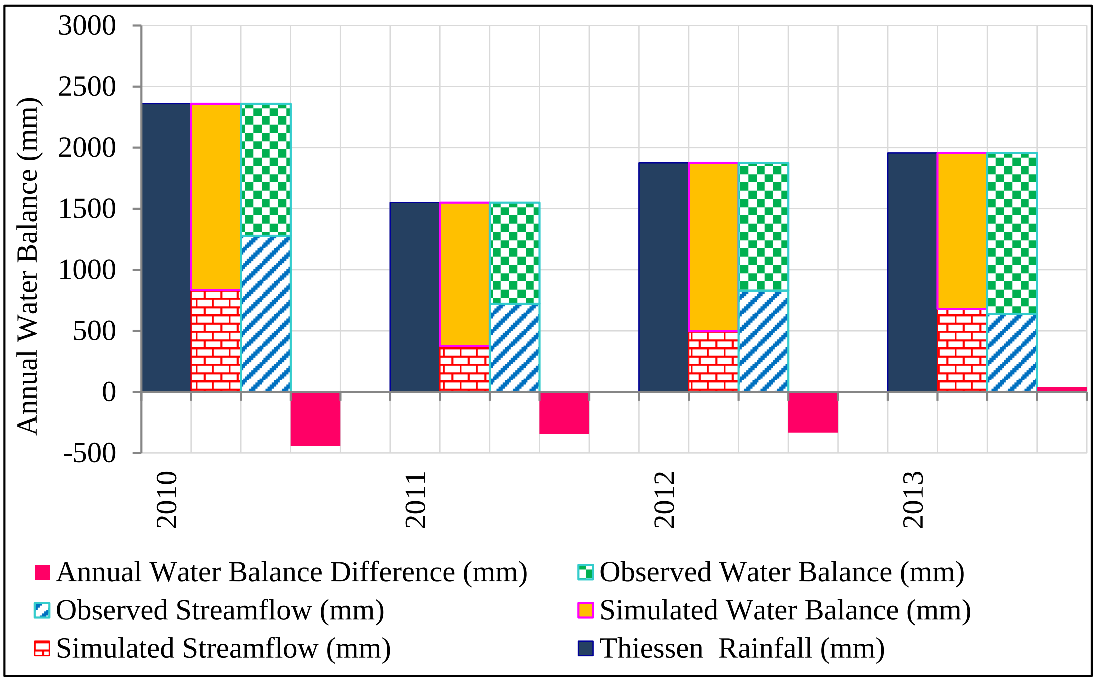


Figure 4-23: Annual water balance for three subdivision model in validation period

4.7.2.2 Flow duration curve result

The details of flow duration curve are given in 4.5.2 section, while the graphical representation is given in the Figure 4-25.

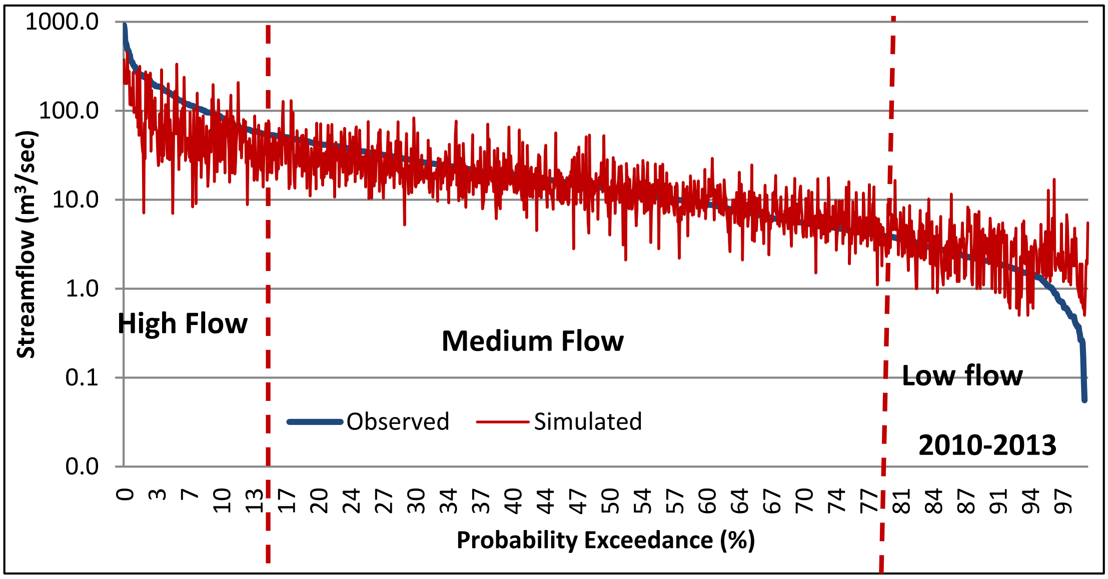


Figure 4-24: Flow duration curve for three sub divisions model in validation period

4.7.2.3 Outflow hydrograph

The outflow hydrograph of observed and simulated streamflow corresponding to daily Thiessen rainfall for validation period is given in the Figure 4-25. Other performance detail is described in comparison section.

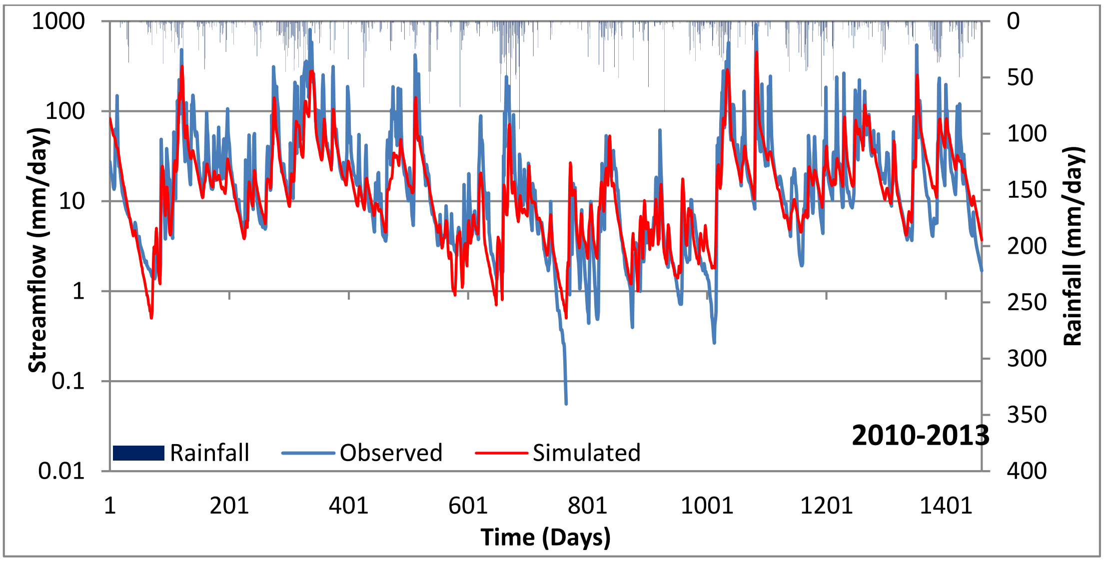


Figure 4-25: Hydrograph for three subdivision model in validation period

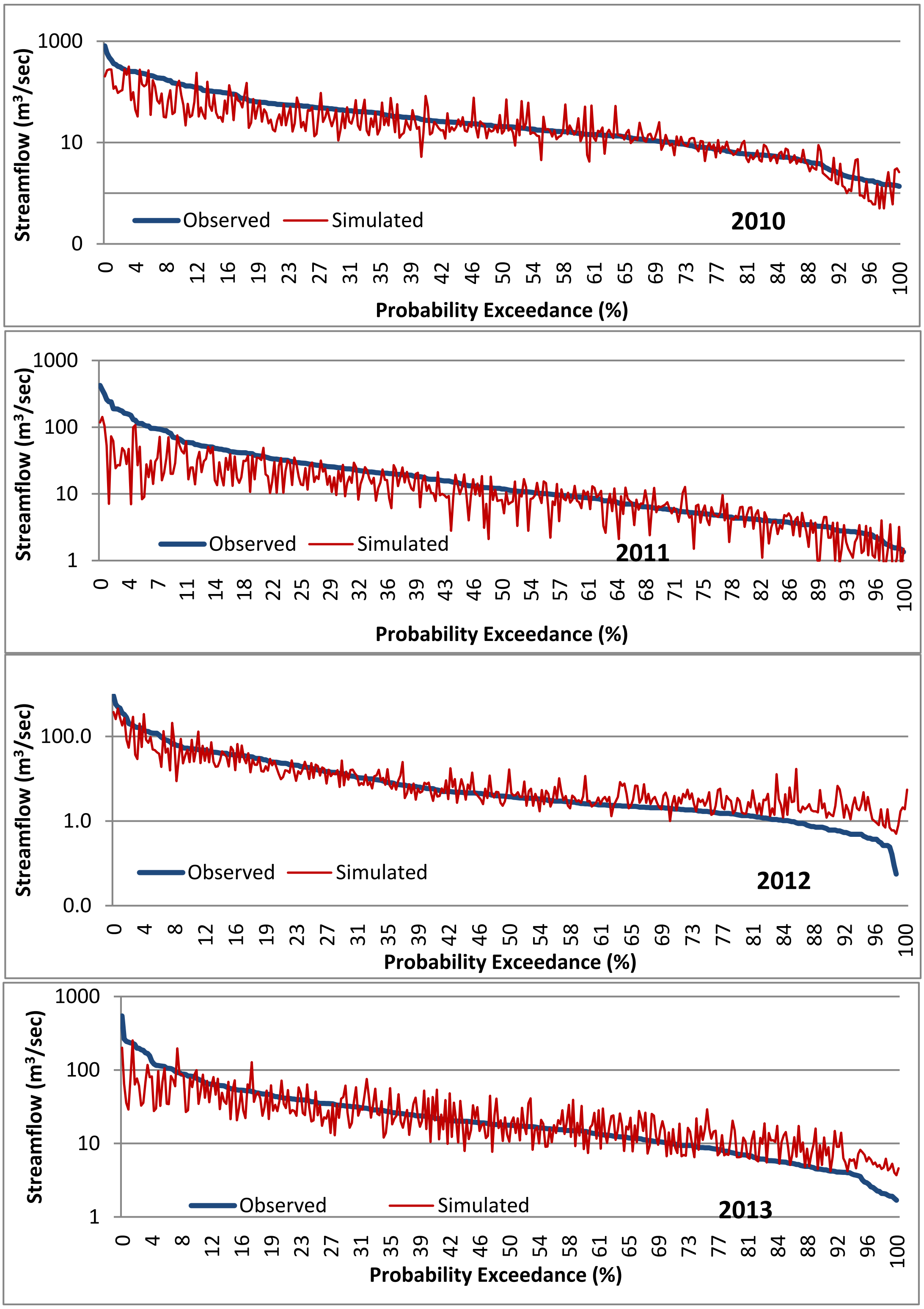


Figure 4-26: Flow duration curve for three subdivision model in validation period

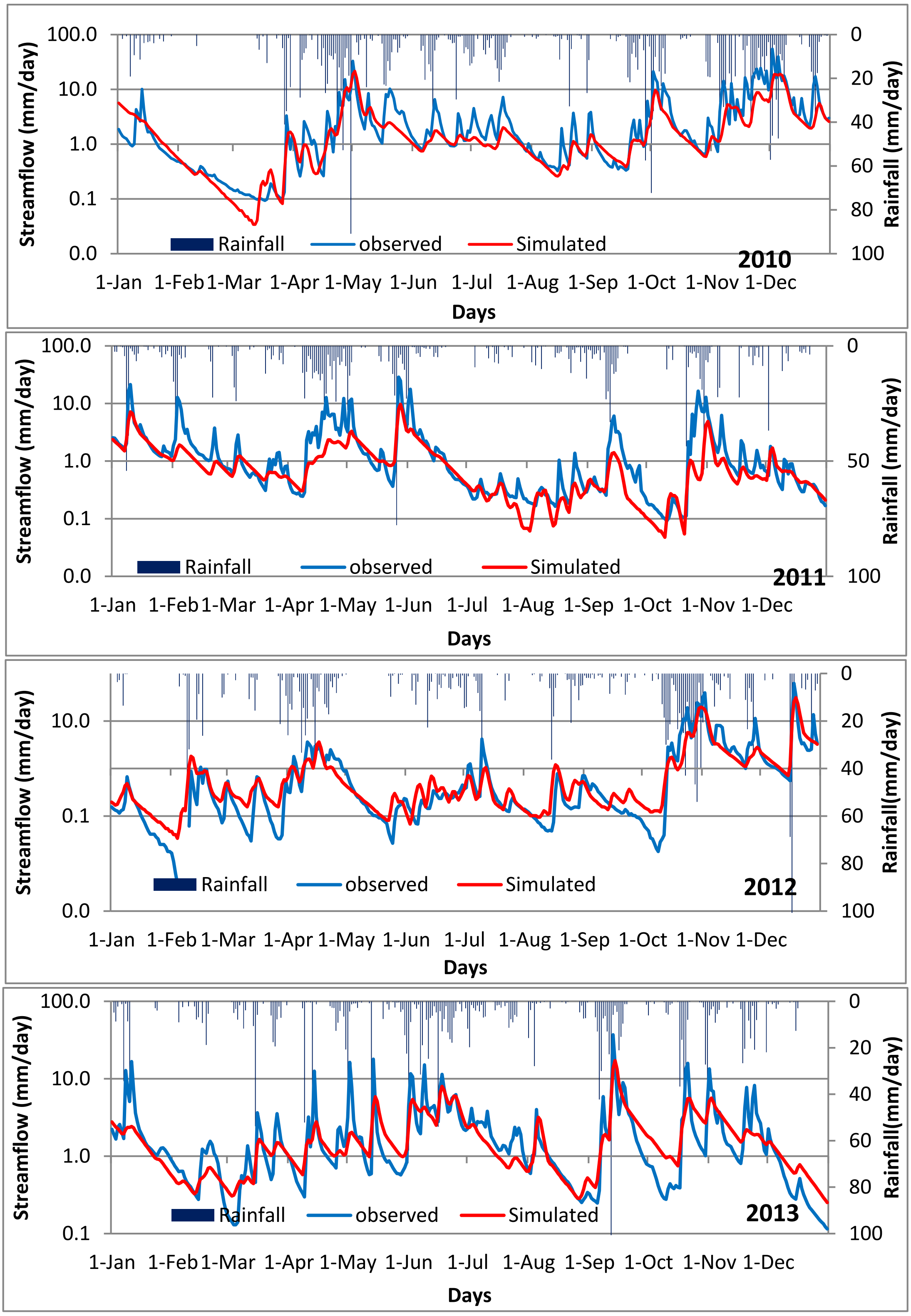


Figure 4-27: Hydrograph for three subdivision model in validation period

4.7.3 Six subdivisions model result in calibration period

Six sub divisions within Badalgama watershed were delineated based on critical threshold area method as shown in the Figure 4-28. Thiessen polygons were used for assigning weightages of rainfall gauging stations at every watershed subdivision. Schematic diagram in HEC-HMS is shown in Figure 4-29.

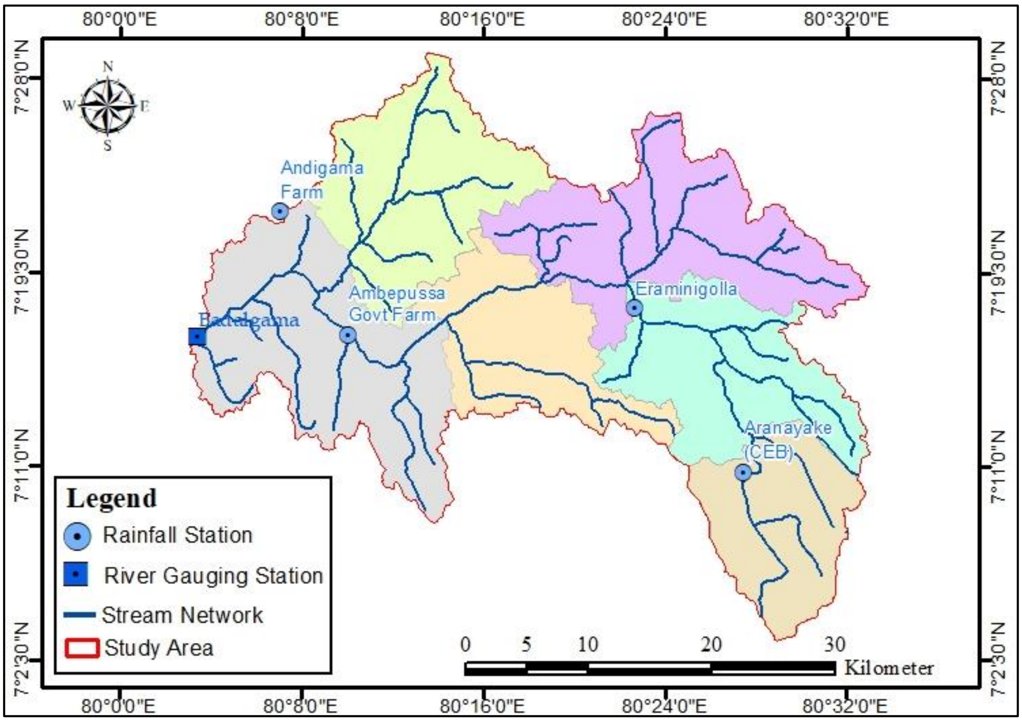


Figure 4-28: Six sub divisions of Badalgama watershed

Table 4-20: Thiessen weight for six sub divisions

Sub-divisions		Sub-division 1	Sub - division 2	Sub - division 3	Sub-division 4	Sub - division 5	Sub - division 6
	Area (km²)	284.70	215.79	167.97	253.46	197.81	151.64
Rainfall Stations	Ambepussa Govt Farm	0.78	0.29	0.34	0.00		
	Andigama Farm	0.22	0.60				
	Eraminigolla		0.11	0.62	0.98	0.49	
	Aranayake (CEB)			0.04	0.02	0.51	1.00

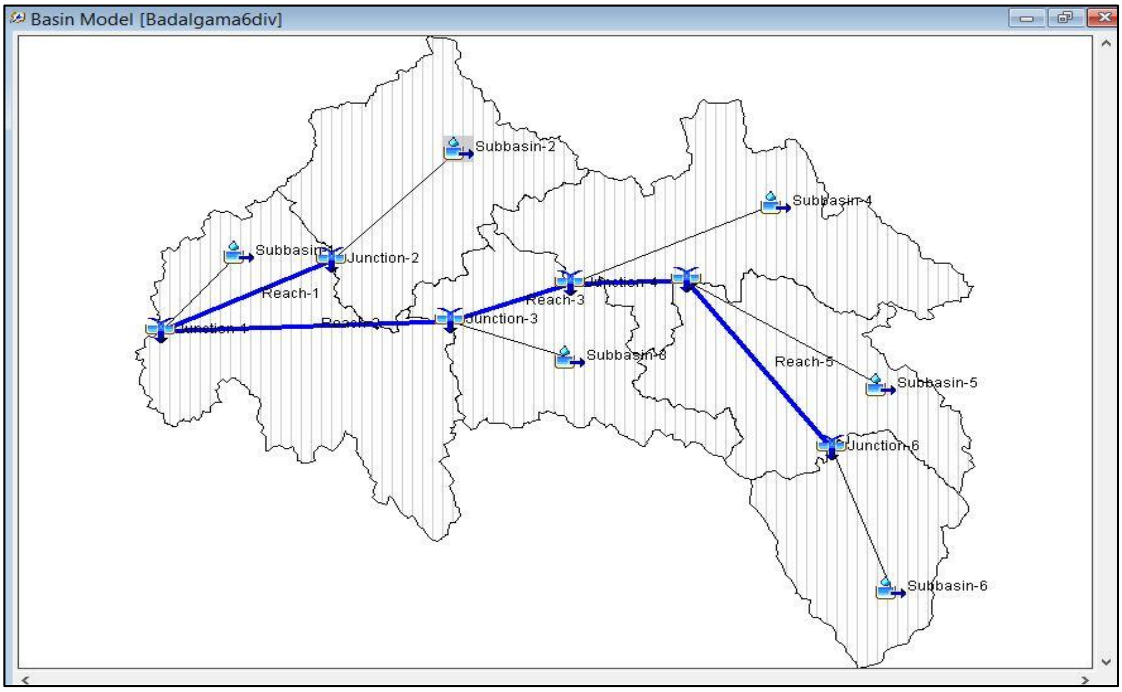


Figure 4-29: Schematic diagram for six sub division model in HEC-HMS

4.7.3.1 Annual water balance

Comparison of observed and simulated water balance in Badalgama watershed is indicated in Table 4-21. Results reflect the acceptable performance during the calibration period with MRAE of 0.375 and Nash–Sutcliffe efficiency of 0.669 with the optimum parameters.

Table 4-21: Annual water balance for six subdivision model in calibration period

Year	Thiessen Rainfall (mm)	Simulated Streamflow (mm)	Observed Streamflow (mm)	Observed Water Balance (mm)	Simulated Water Balance (mm)	Annual Water Balance Difference (mm)
2005	1914	436	661	1253	1478	-226
2006	2431	911	1304	1126	1520	-393
2007	1835	421	597	1238	1414	-176
2008	2305	659	974	1331	1646	-316

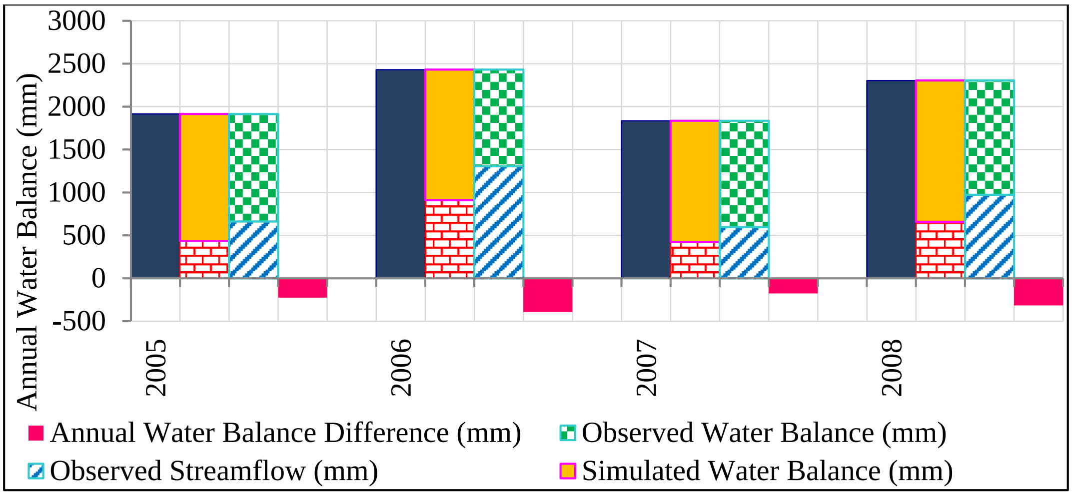


Figure 4-30: Annual water balance for six subdivision model in calibration period

4.7.3.2 Flow duration curve

For detailed analysis of flow duration curve, see the flow duration curve in Section 4.5.2. Performance details of six subdivisions are shown in Figure 4-31.

Table 4-22: Flow duration curve result for different flow conditions

Flow Condition	Objective Function	
	NASH	MRAE
Overall	0.669	0.375
High	0.405	0.353
Medium	0.707	0.383
Low	0.453	0.368

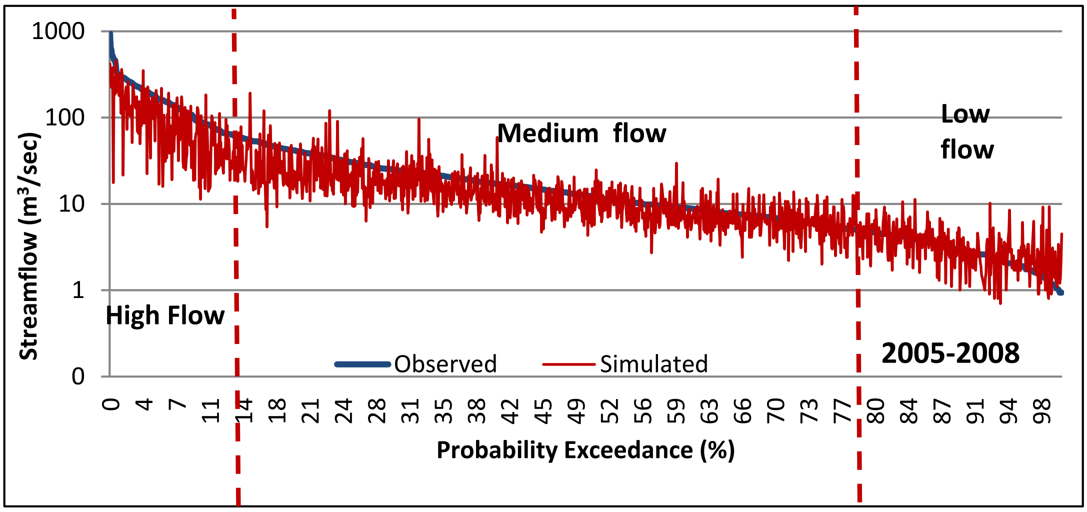


Figure 4-31: Flow duration curve for six sub division model in calibration period

4.7.3.3 Outflow hydrograph

The outflow hydrograph of observed and simulated streamflow corresponding to daily Thiessen rainfall for validation period are shown in Figure 4-32. Performance detail is described in Table 4-23.

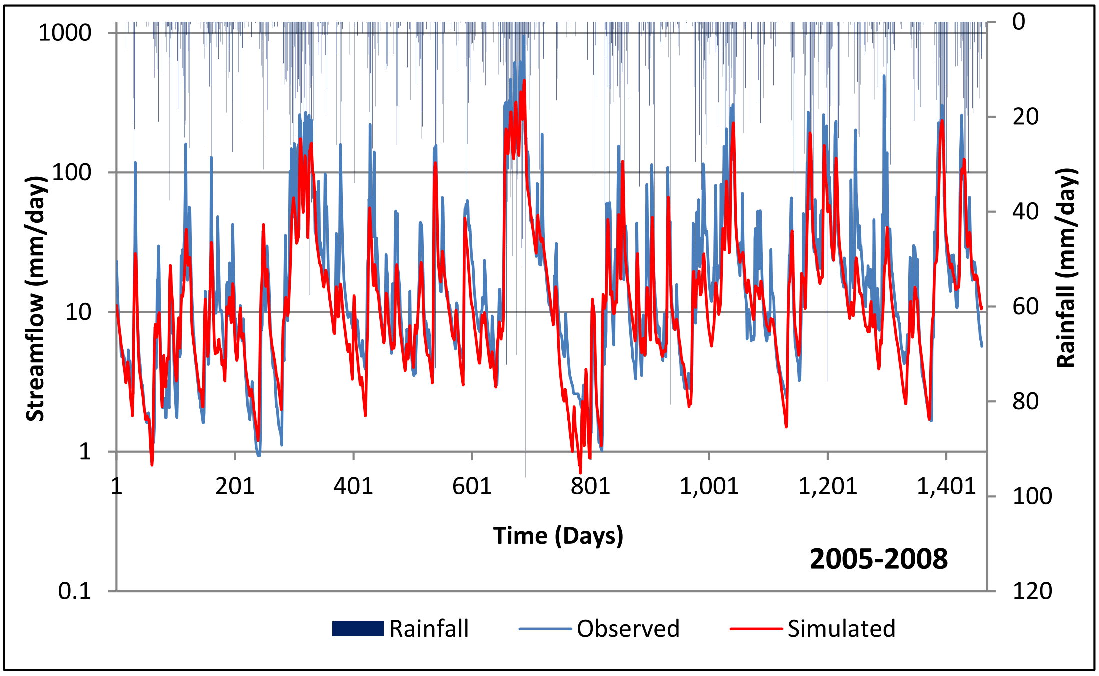


Figure 4-32: Hydrograph for six sub division model in calibration period

Table 4-23: Model performance for six sub division model in calibration period

Flow Condition	**Objective Function**		**Mean Annual Mass Balance Error (%)**			
	Nash	MRAE	2005	2006	2007	2008
Overall	0.669	0.375	29.073	26.92	35.9	32
High	0.405	0.353				
Medium	0.707	0.383				
Low	0.453	0.368				

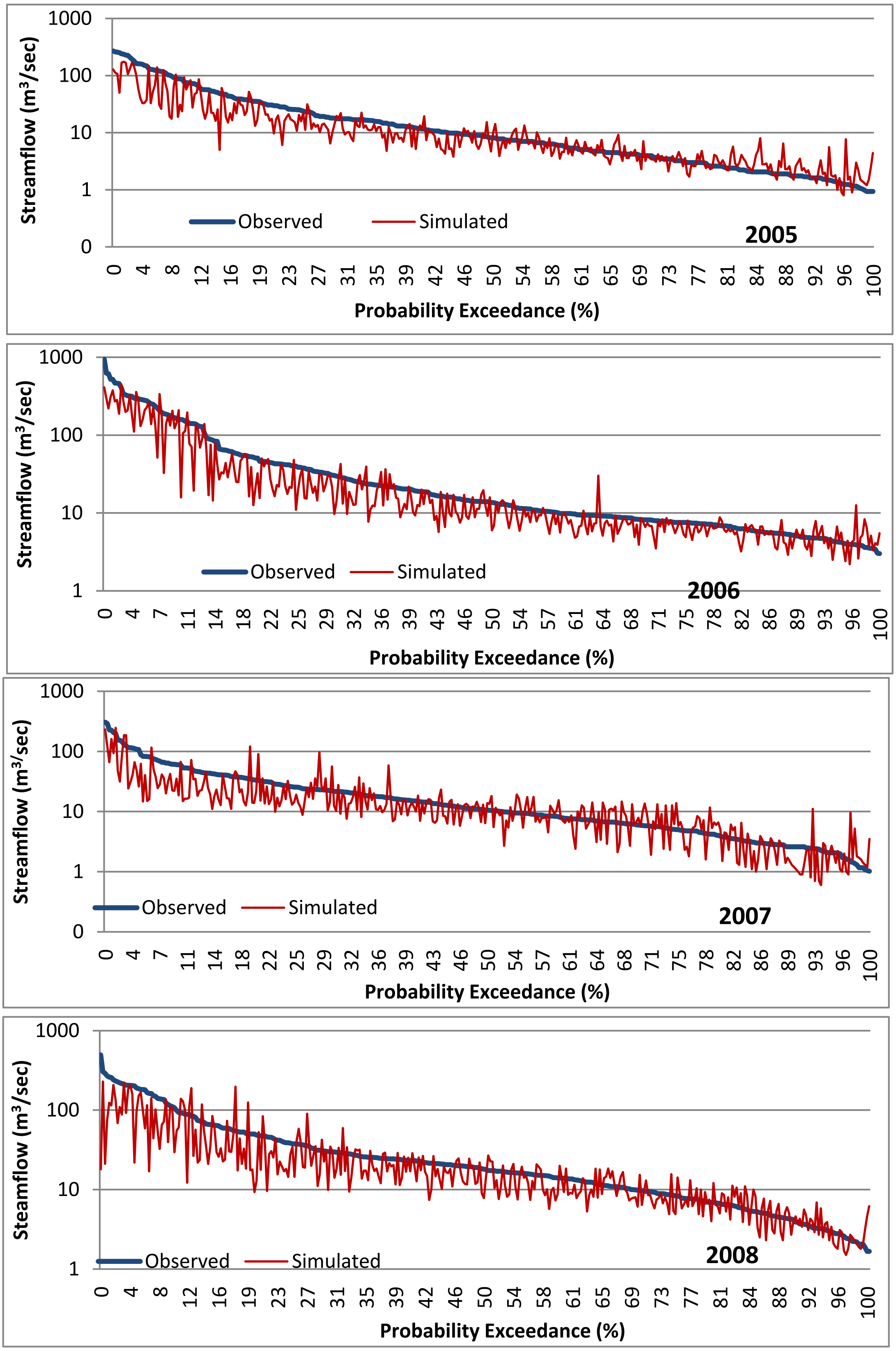


Figure 4-33: Flow duration curve for six subdivision model in calibration period

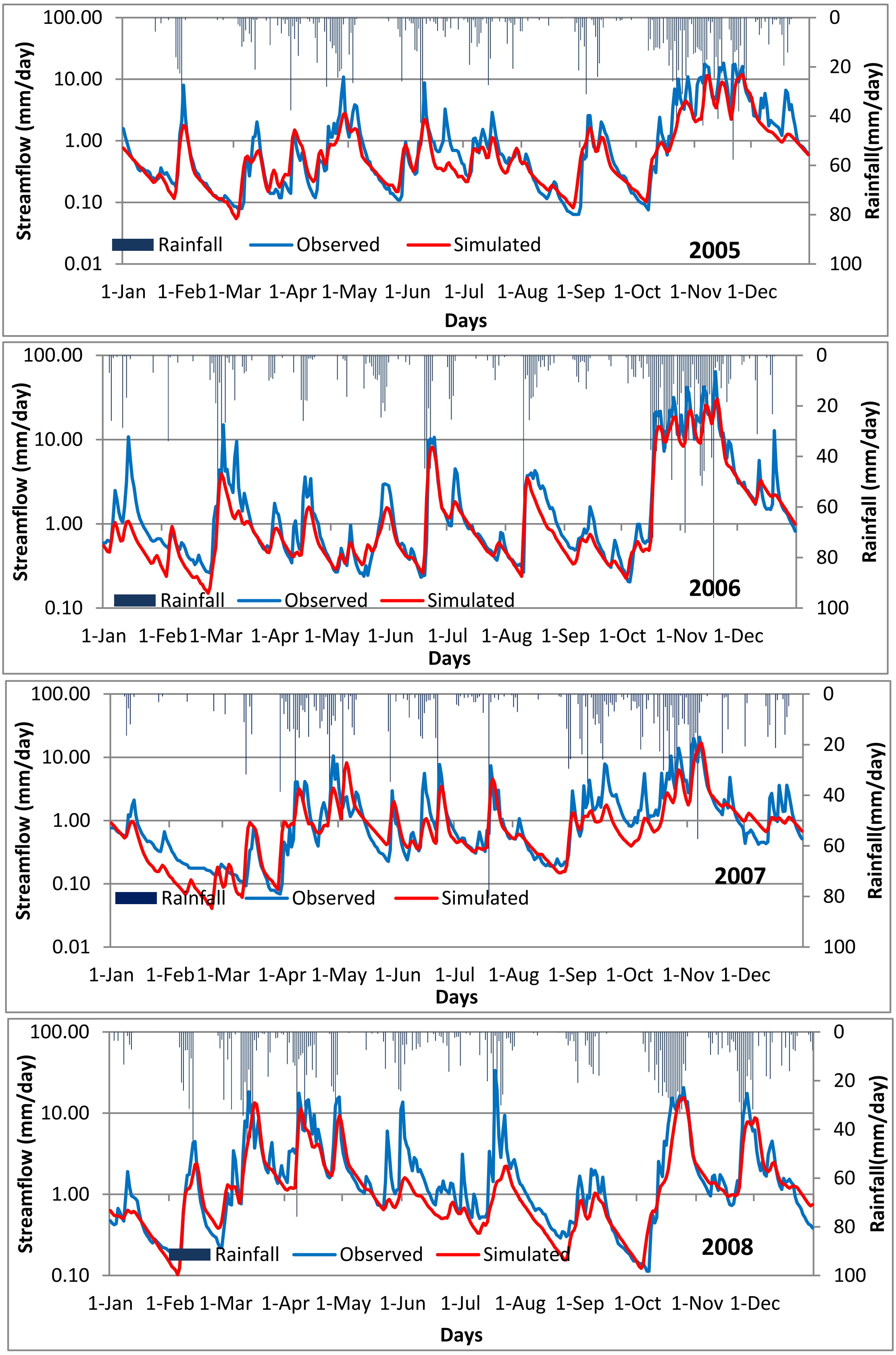


Figure 4-34: Hydrograph for six subdivision model in calibration period

4.7.4 Six subdivisions model result in validation period

4.7.4.1 Annual water balance

Comparison of observed and simulated water balance in Badalgama watershed is given in the Table 4-24 and Figure 4-35. The percentage difference is found to be 2.89% which is acceptable.

Table 4-24: Annual water balance for six subdivision model in validation period

Year	Thiessen Rainfall (mm)	Observed Streamflow (mm)	Simulated Streamflow (mm)	Observed Water Balance (mm)	Simulated Water Balance (mm)	Annual Water Balance Difference (mm)
2010	2360	1274	1278	1086	1081	4
2011	1550	601	722	949	828	121
2012	1876	695	830	1181	1046	135
2013	1956	772	640	1183	1316	-133

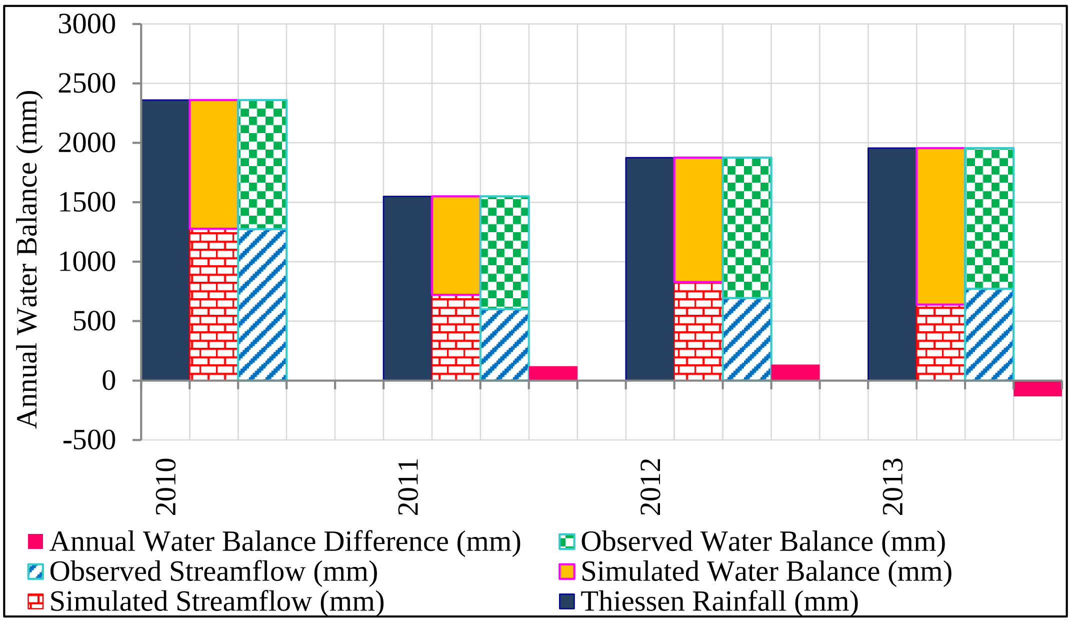


Figure 4-35: Annual water balance for six subdivision model in validation period

4.7.4.2 Flow duration curve

The details of flow duration curve are given in Section 4.5.2 and the graphical representation for six subdivision model is given in Figure 4-36.

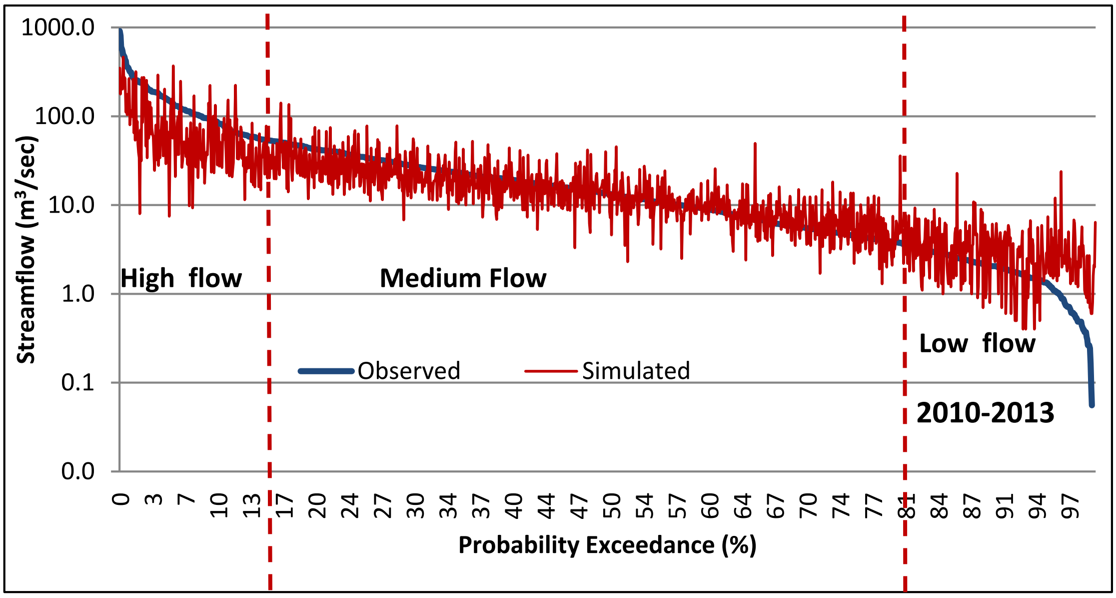


Figure 4-36: Flow duration curve for six subdivision model in validation period

Table 4-25: Performance for the model of six subdivisions in validation period

Flow Condition	**Objective Function**		**Mean annual mass balance error (%)**			
	Nash	MRAE	2010	2011	2012	2013
Overall	0.530	0.610	34.342	31.034	42.218	33.418
High	0.600	0.430				
Medium	0.530	0.690				
Low	0.450	0.500				

4.7.4.3 Outflow hydrograph for validation of six subdivision

Hydrograph for the model with six subdivisions for validation period is show in the Figure 4-37 and performance of the model is given in the Table 4-25.

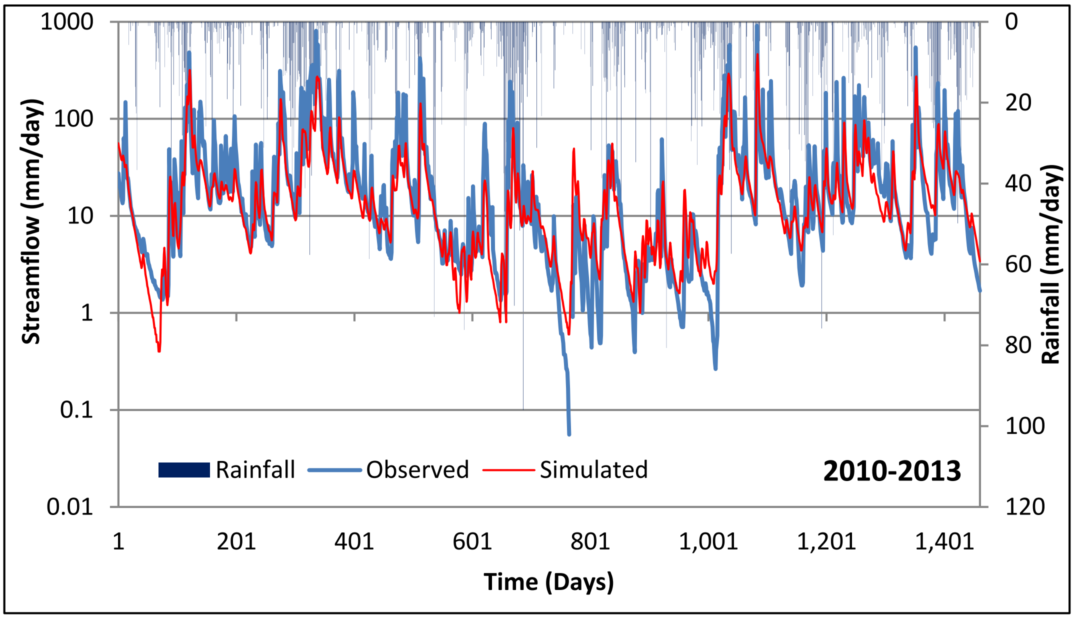


Figure 4-37: Hydrograph for the model of six subdivisions in validation period

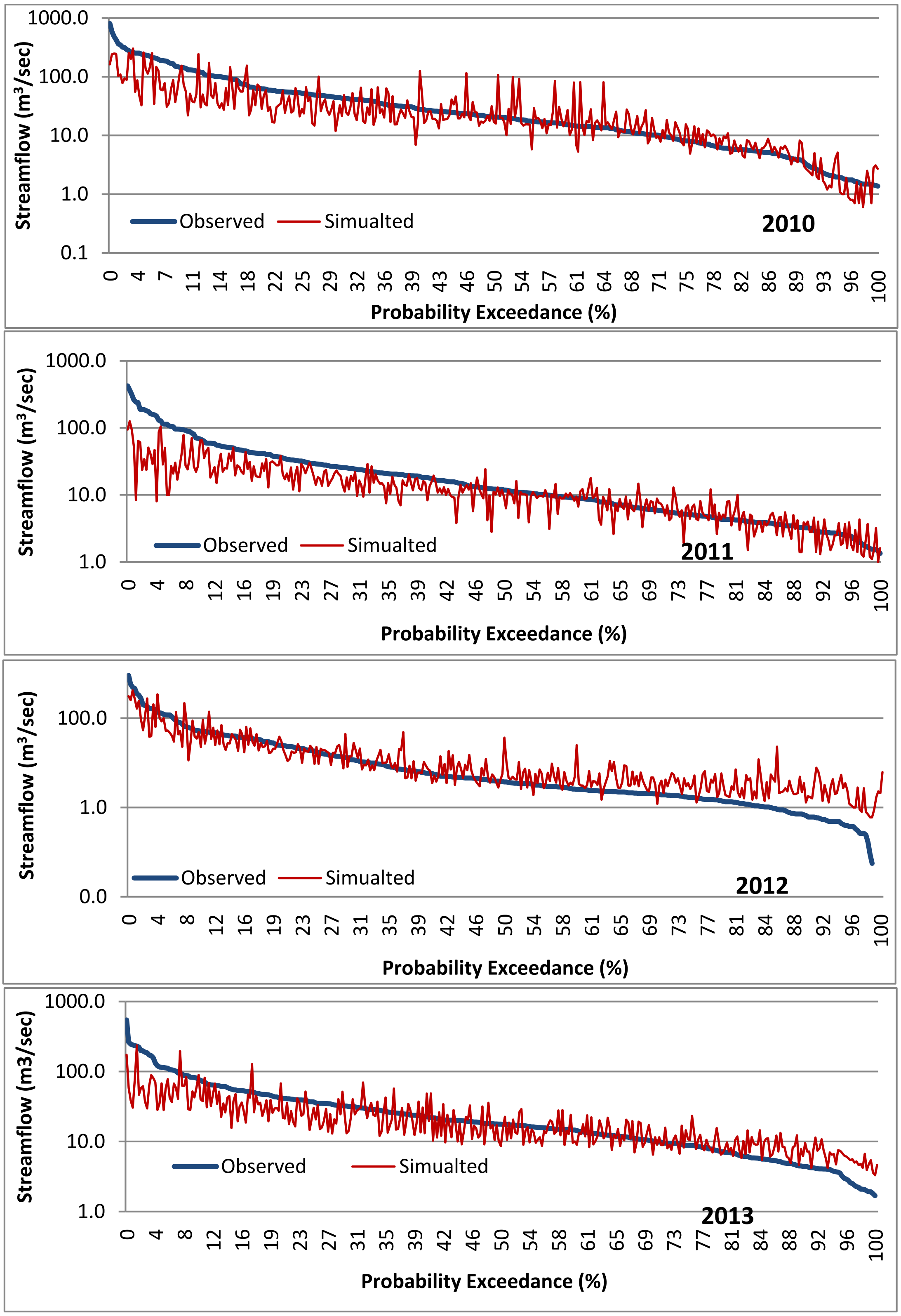


Figure 4-38: Flow duration curve for six subdivision model in validation period

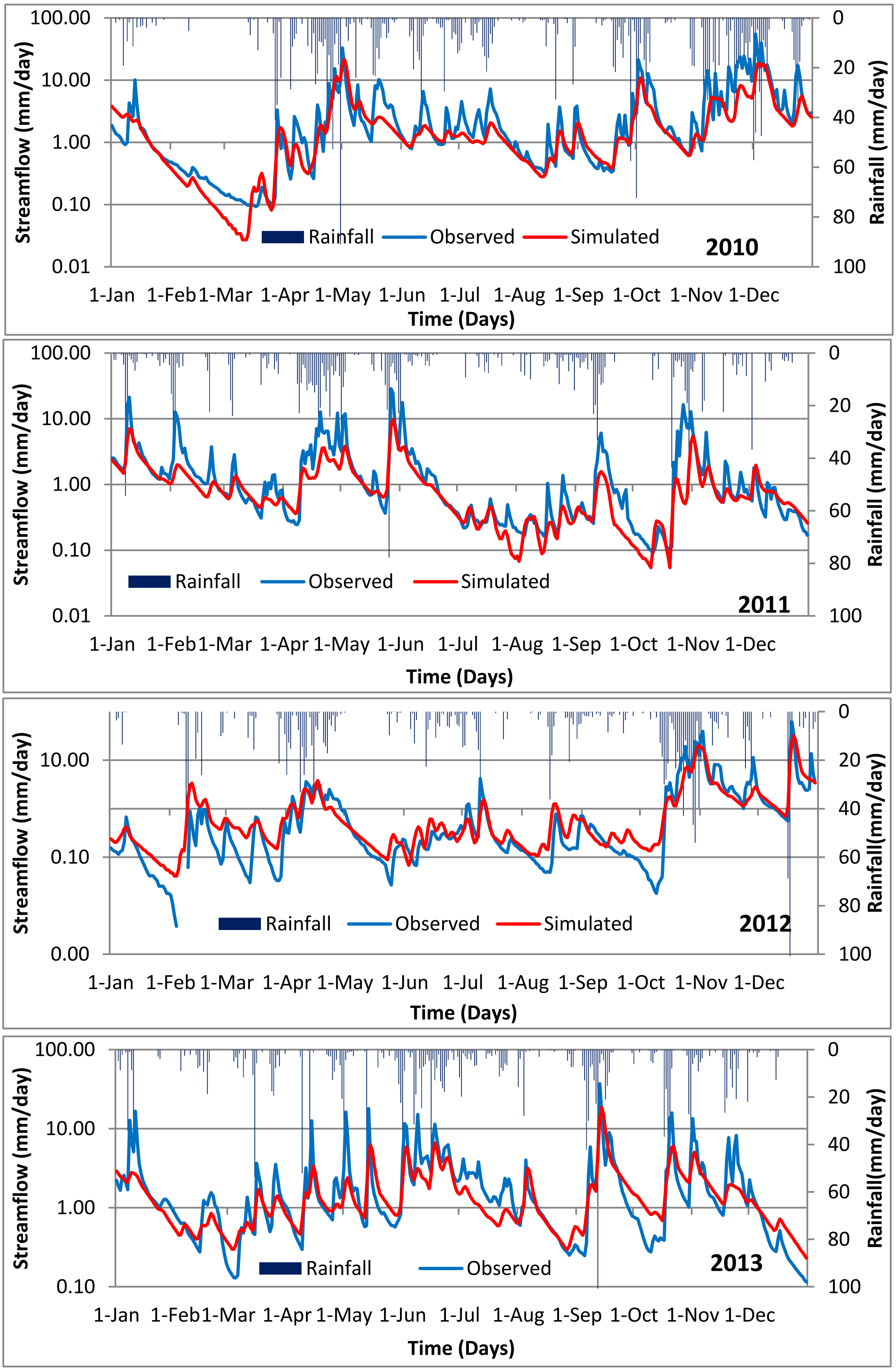


Figure 4-39: Hydrograph for six subdivision model in validation period

4.7.5 Nine subdivision model result in calibration period

Nine sub divisions within Badalgama watershed were delineated based on critical threshold area as shown in Table 4-40. Thiessen polygons were used for assigning weights for rainfall gauging station in every watershed subdivision. Schematic diagram in HEC-HMS is shown in the Figure 4-41.

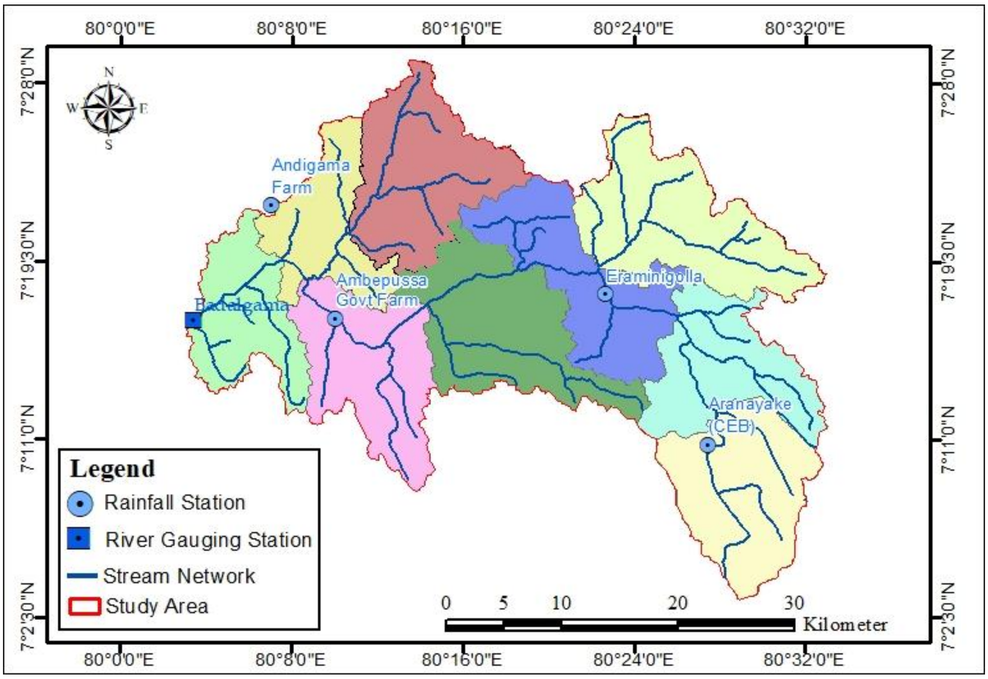


Figure 4-40: Delineation of nine subdivisions for Badalgama watershed

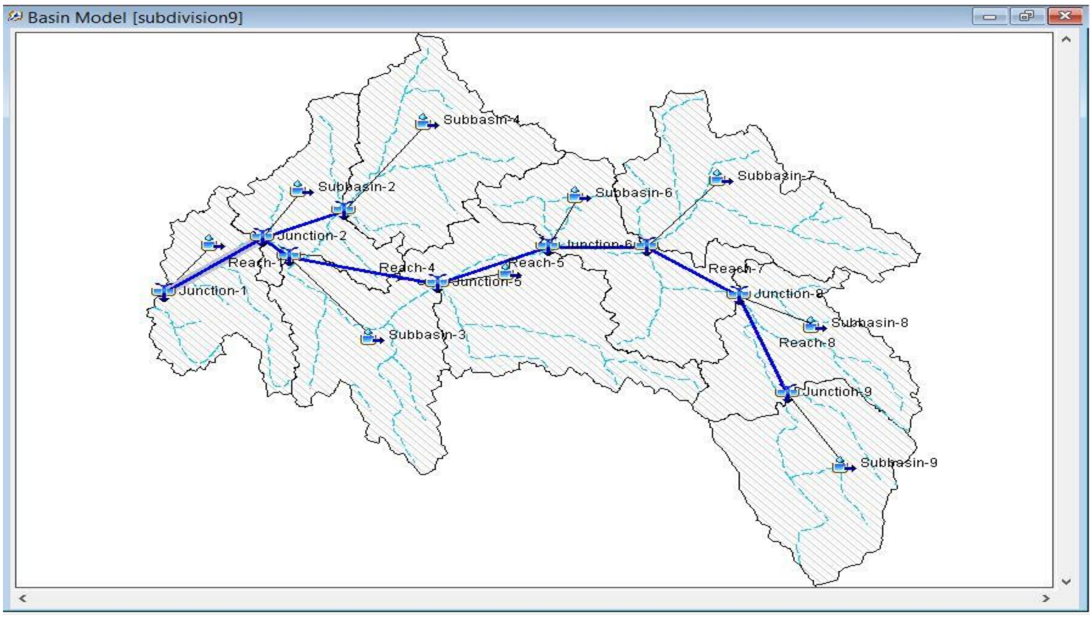


Figure 4-41: Schematic diagram of nine subdivisions in HEC HMS

4.7.5.1 Annual water balance

Comparison of observed and simulated water balance in Badalgama watershed is indicated in the Table 4-26 and water balance comparison reflects inferior model performance as compared to six subdivision model during the calibration with MRAE and Nash–Sutcliffe efficiency values of 0.384 and 0.656, respectively with the optimum parameters. The percentage difference for annual water balance is 18.3% which is acceptable.

Table 4-26: Annual water balance for nine subdivisions model in calibration period

Year	Thiessen Rainfall (mm)	Simulated Streamflow (mm)	Observed Streamflow (mm)	Observed Water Balance (mm)	Simulated Water Balance (mm)	Annual Water Balance Difference (mm)
2005	1914	442	661	1253	1472	-220
2006	2431	913	1304	1126	1517	-391
2007	1835	420	597	1238	1415	-177

2008	2305	652	974	1331	1652	-322

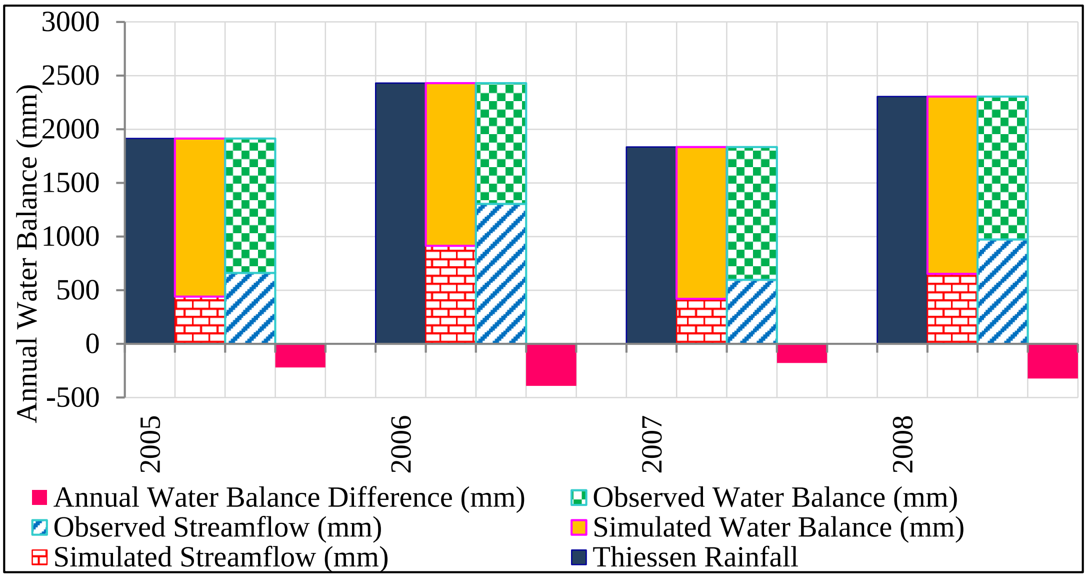


Figure 4-42: Annual water balance for nine subdivision model in calibration period

4.7.5.2 Flow duration curve

The details of flow duration curve are given in Section 4.5.2 and the graphical representation for nine subdivisions is given in Figure 4-43.

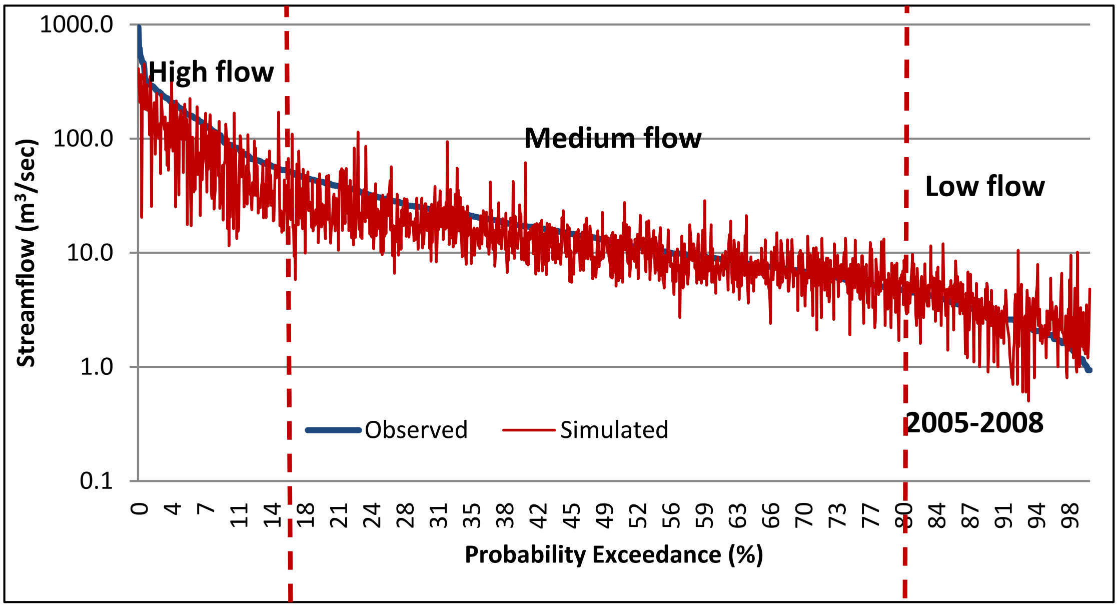


Figure 4-43: Flow duration curve for nine sub division model in calibration period

Table 4-27: Performance of nine sub division model at different flow conditions in calibration period

Flow Condition	Objective Function	
	Nash	MRAE
Overall	0.656	0.384
High	0.375	0.366
Medium	0.692	0.398
Low	0.448	0.351

4.7.5.3 Outflow hydrograph

Hydrograph for the model of nine subdivision for calibration periods is in Figure 4-44 and the performance of the model is given in Table 4-256.

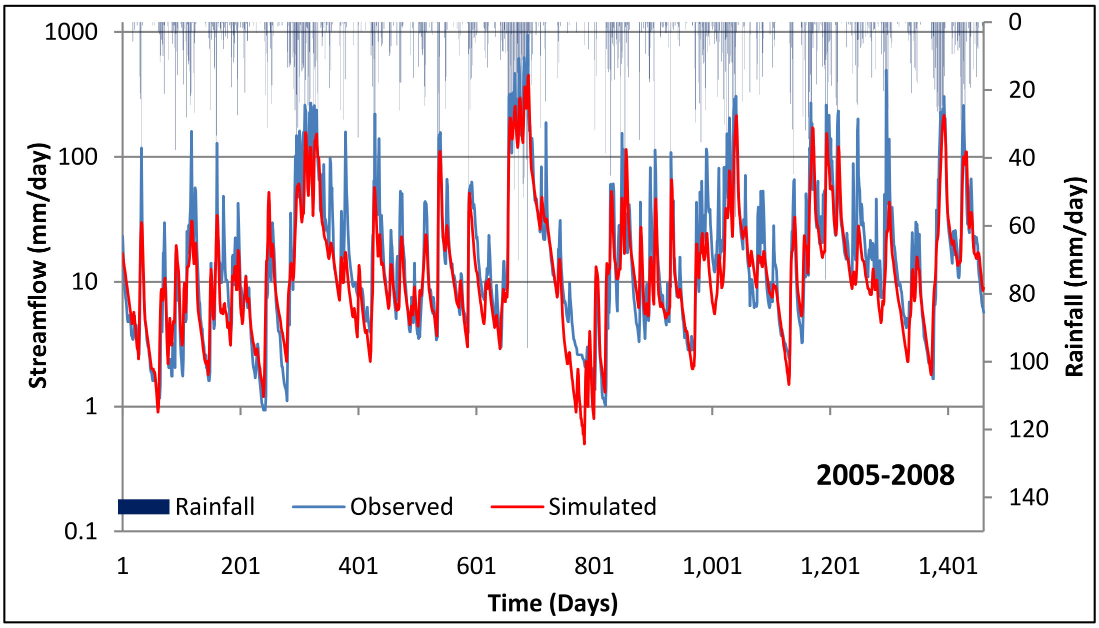


Figure 4-44: Hydrograph for nine sub division model in calibration period

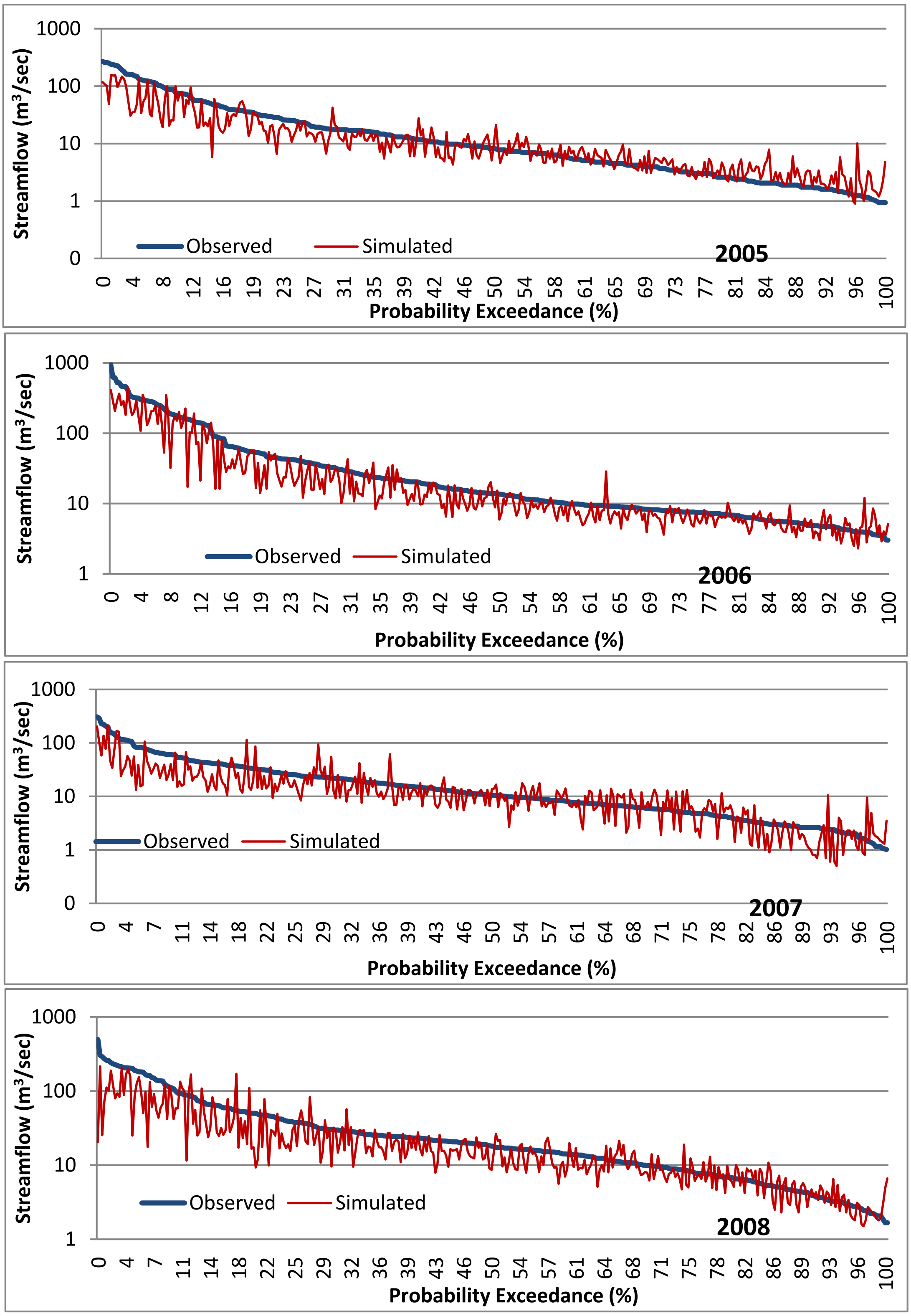


Figure 4-45: Flow duration curve for nine sub divisions model in calibration period

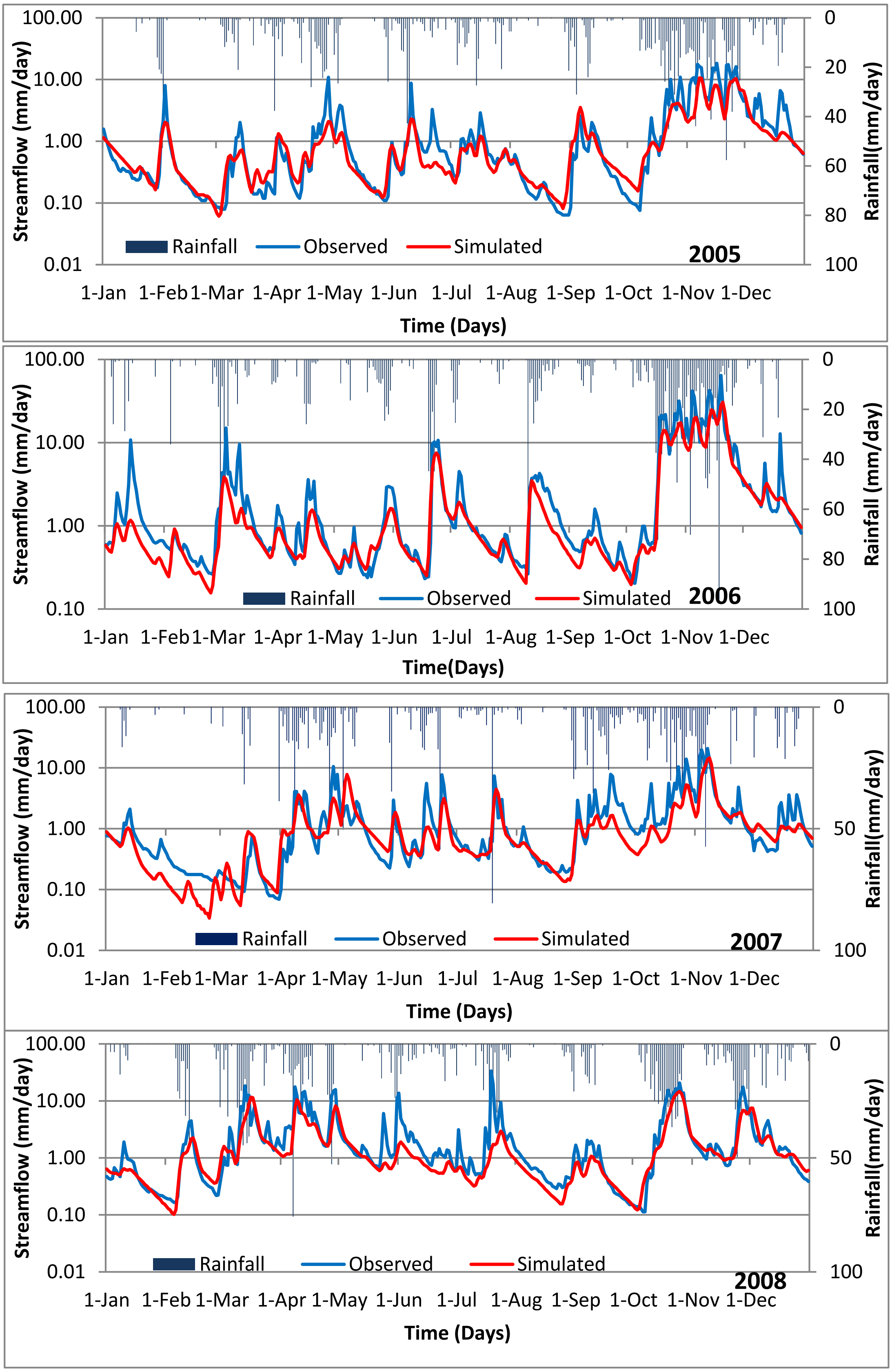


Figure 4-46: Hydrograph for nine sub division model in calibration period

4.7.6 Nine subdivisions model result in validation period

4.7.6.1 Annual water balance

Comparison of simulated and observed water balance in Badalgama watershed is given in Table 4-28. The percentage difference is 21.0% which is acceptable.

Table 4-28: Annual water balance for nine sub division model in validation period

Year	Thiessen Rainfall (mm)	Simulated Streamflow (mm)	Observed Streamflow (mm)	Observed Water Balance (mm)	Simulated Water Balance (mm)	Annual Water Balance Difference (mm)
2010	2360	809	1278	1081	1550	-469
2011	1550	382	722	828	1168	-340
2012	1876	522	830	1046	1353	-307
2013	1956	587	640	1316	1369	-53

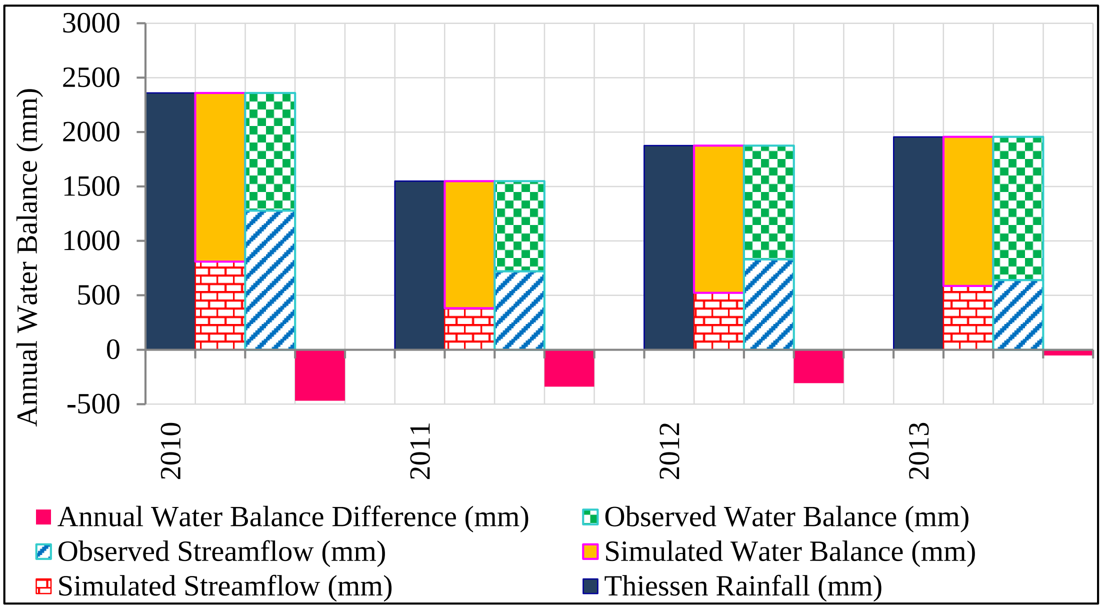


Figure 4-47: Annual water balance for nine sub division model in validation period

4.7.6.2 Flow duration curve result

The details of flow duration curve are given in Section 4.5.2 and the graphical representation is given in the Figure 4-48.

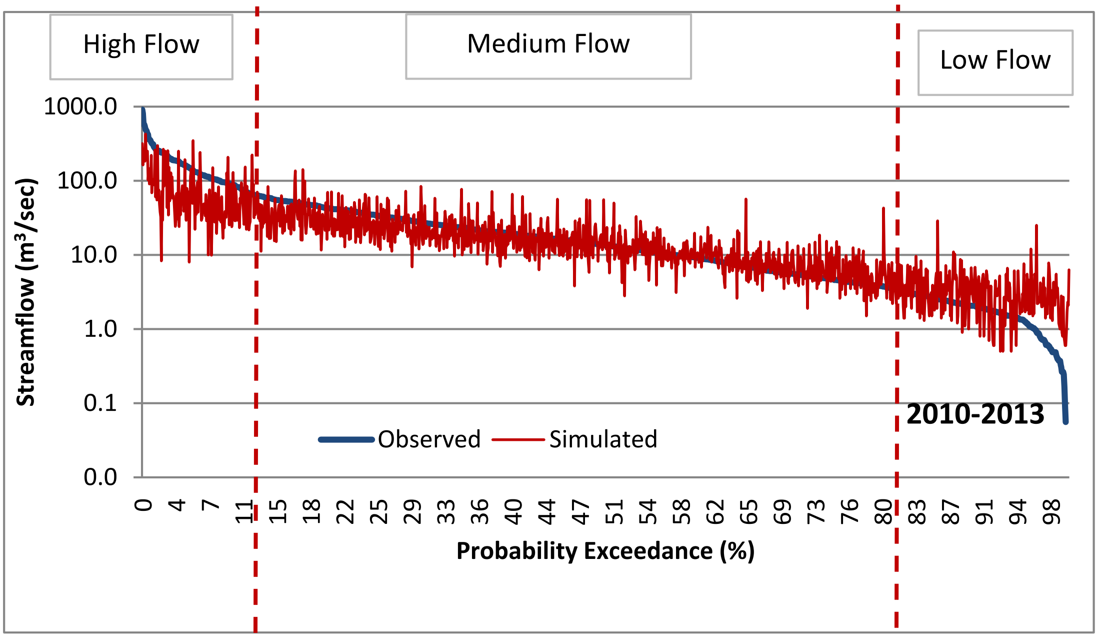


Figure 4-48: Flow duration curve for nine sub division model in validation period

Table 4-29: Performance of nine sub division model in validation period

Flow Condition	**Objective Function**	
	Nash	MRAE
Overall	0.50	0.65
High	0.57	0.48
Medium	0.50	0.73
Low	0.42	0.50

4.7.6.3 Outflow hydrograph

Hydrograph of nine subdivision model for calibration periods is shown in the Figure 4-49 and performance of the model is given in the Table 4-28.

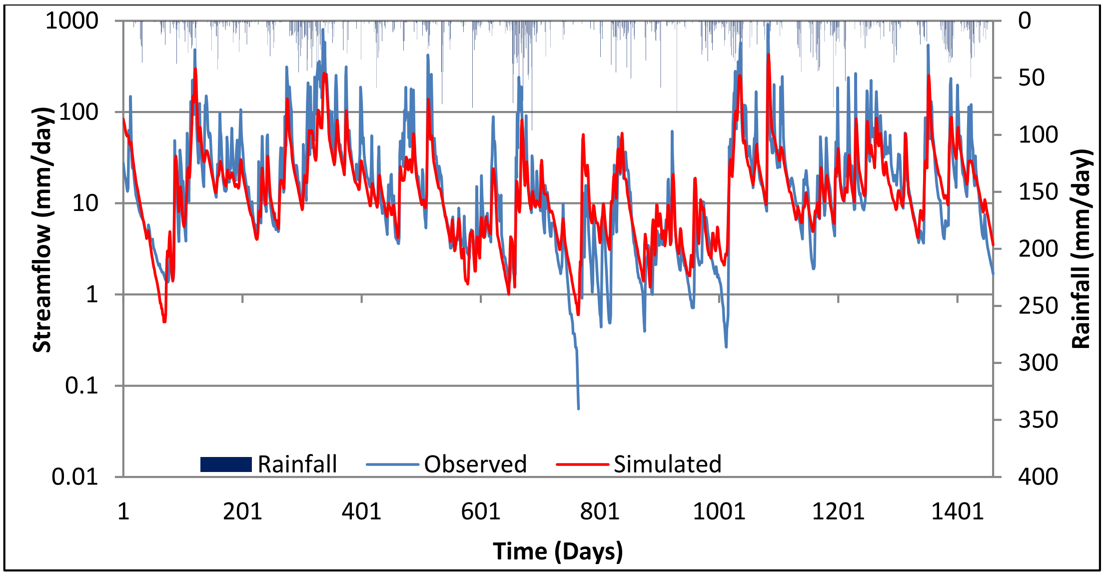


Figure 4-49: Hydrograph for the model of nine subdivisions in validation period

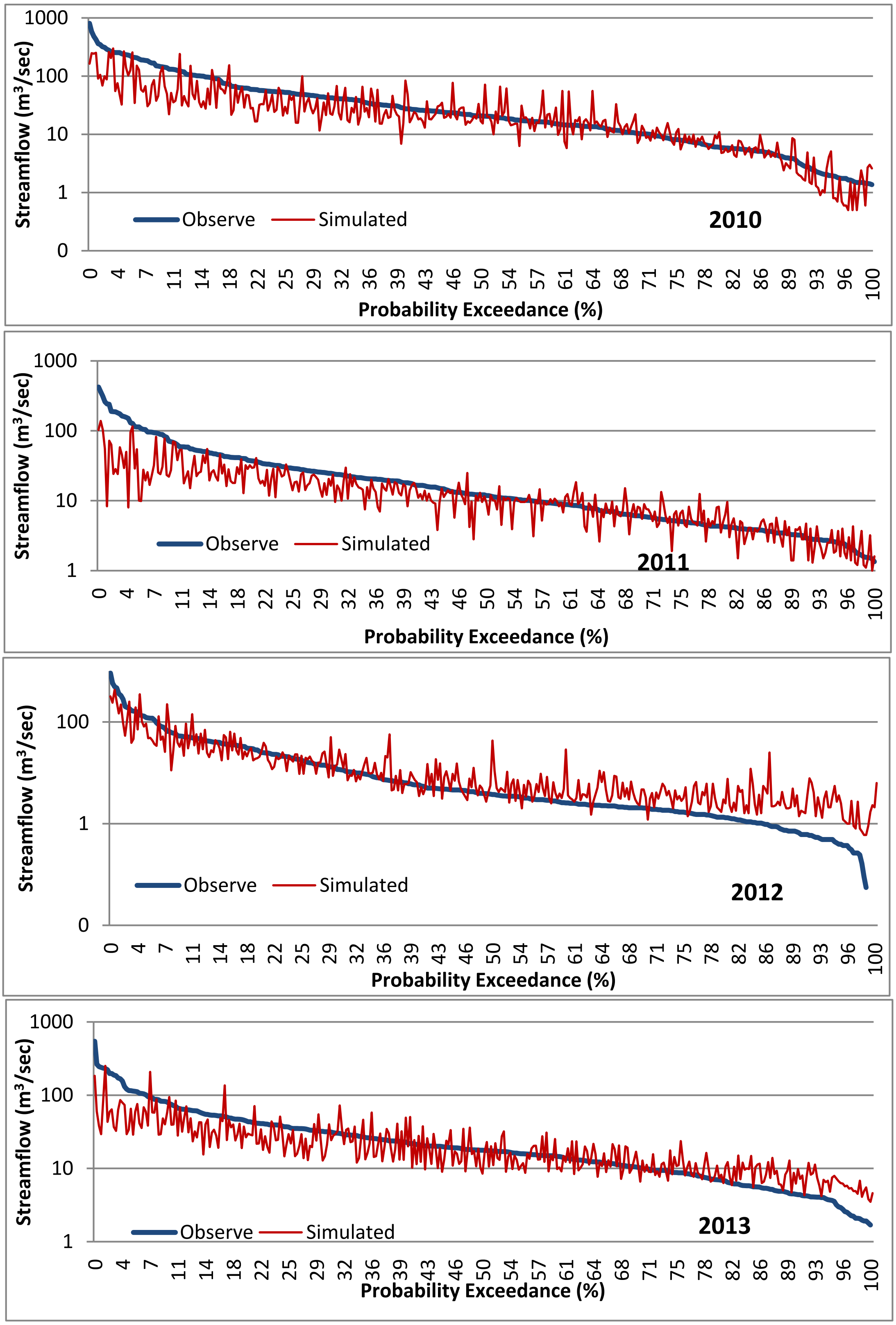


Figure 4-50: Flow duration curve for nine sub division model in validation period

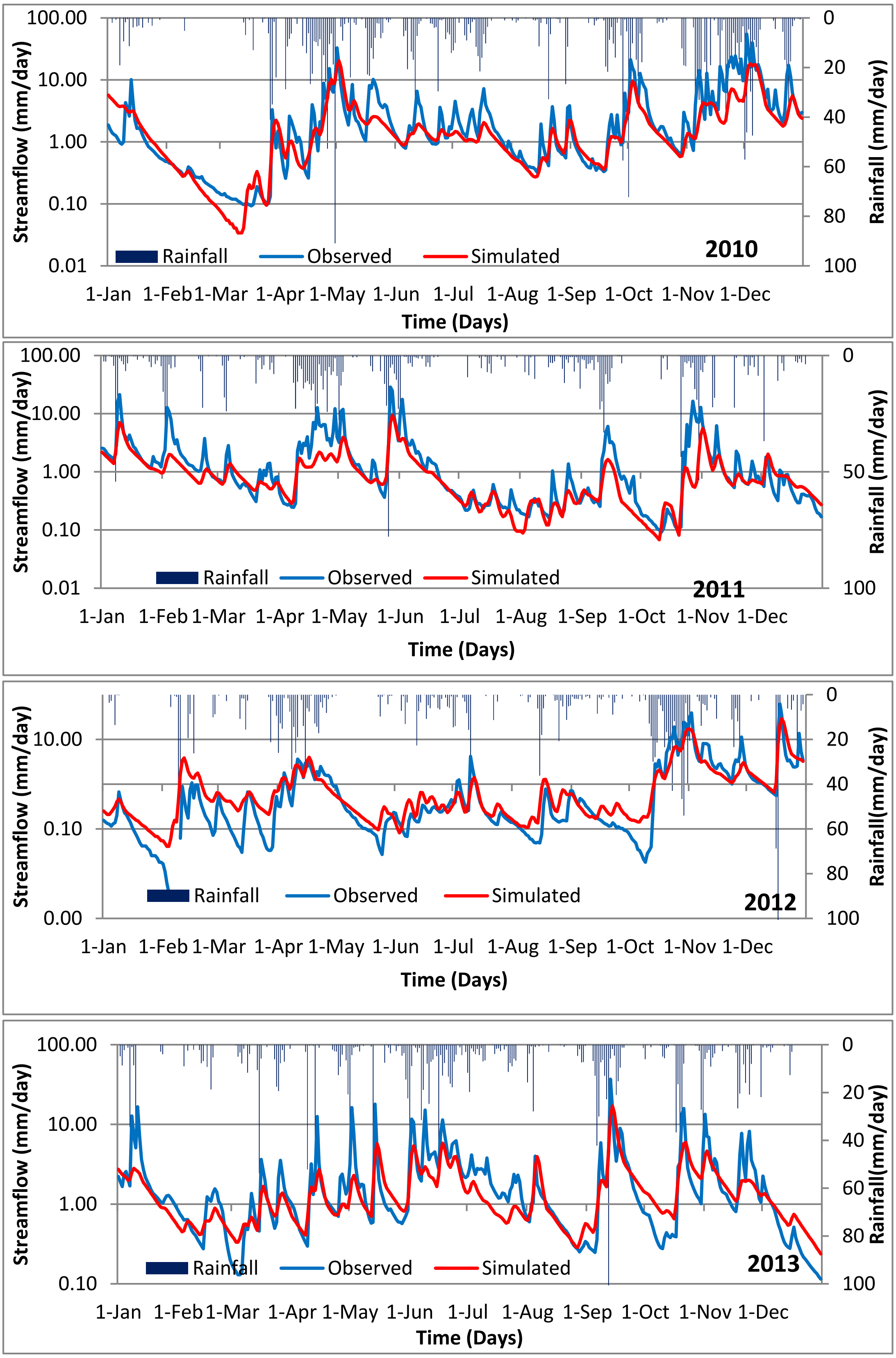


Figure 4-51: Hydrograph for nine sub division model in validation period

4.7.7 Sixteen subdivisions model result in calibration period

Thiessen polygons were used for assigning weightages of rainfall gauging stations of each watershed subdivision. Schematic diagram in HEC-HMS is shown in Figure 4-53. Sixteen sub divisions within Badalgama watershed were delineated based on critical threshold area method as shown in the Figure 4-52.

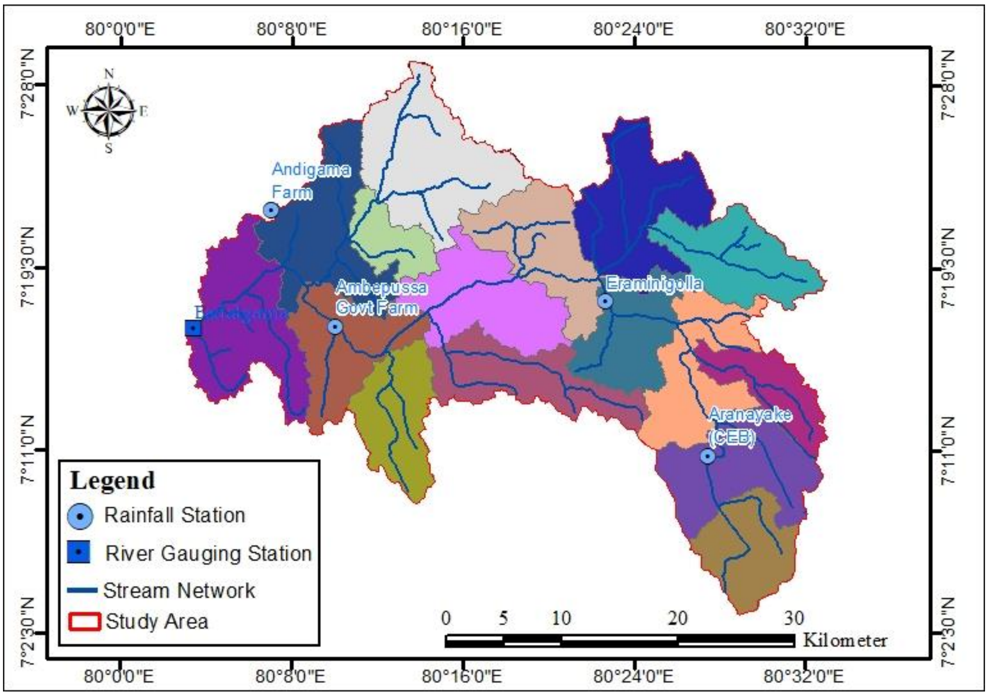


Figure 4-52: Sixteen subdivisions in Badalgama watershed

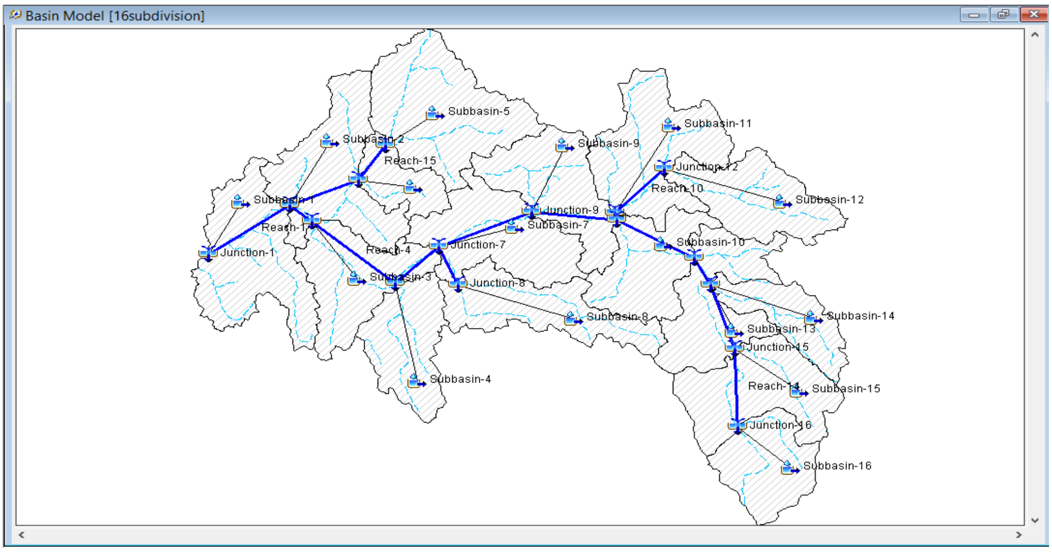


Figure 4-53: HEC-HMS schematic diagram of sixteen subdivision model in Badalgama watershed

4.7.7.1 Annual water balance

Comparison of observed and simulated water balance in Badalgama watershed is given in Figure 4-35 and Figure 4-54.The percentage difference is 19% which is acceptable.

Table 4-30: Annual water balance for sixteen sub division model in calibration period

Year	Thiessen Rainfall (mm)	Simulated Streamflow (mm)	Observed Streamflow (mm)	Observed Water Balance (mm)	Simulated Water Balance (mm)	Annual Water Balance Difference (mm)
2005	1914	441	661	1253	1473	-220
2006	2431	878	1304	1126	1552	-426
2007	1835	410	597	1238	1426	-188
2008	2305	622	974	1331	1683	-352

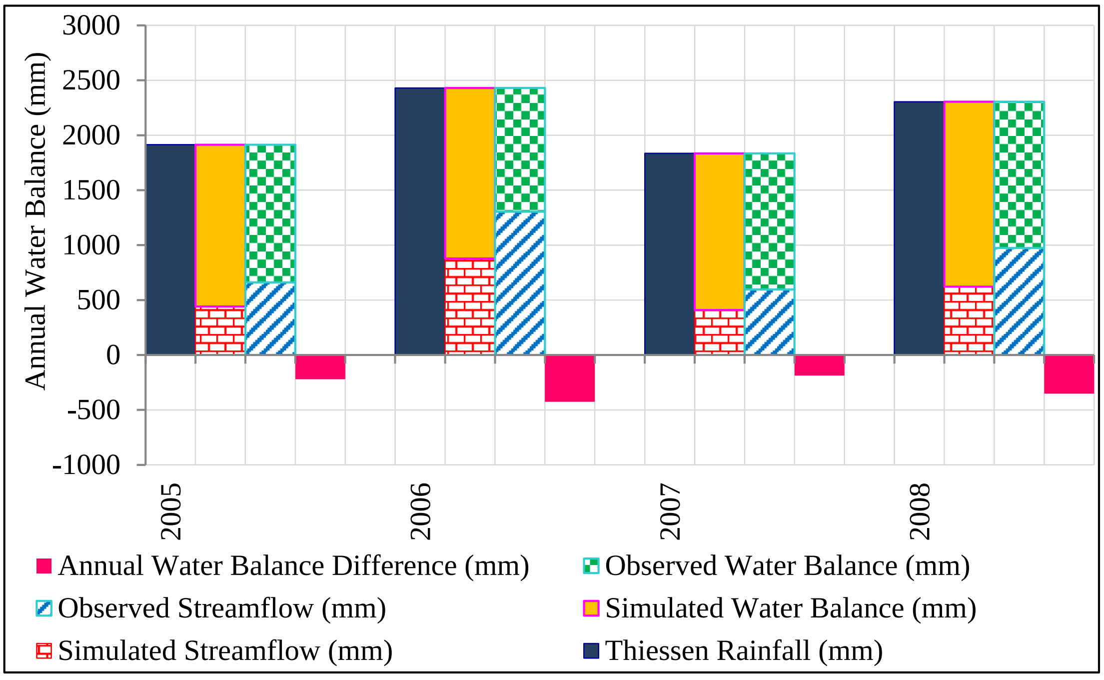


Figure 4-54: Annual water balance for sixteen sub division model in calibration period

4.7.7.2 Flow duration curve result

The details of flow duration curve are given in Section 4.5.2 and the graphical representation is given in the Figure 4-55.

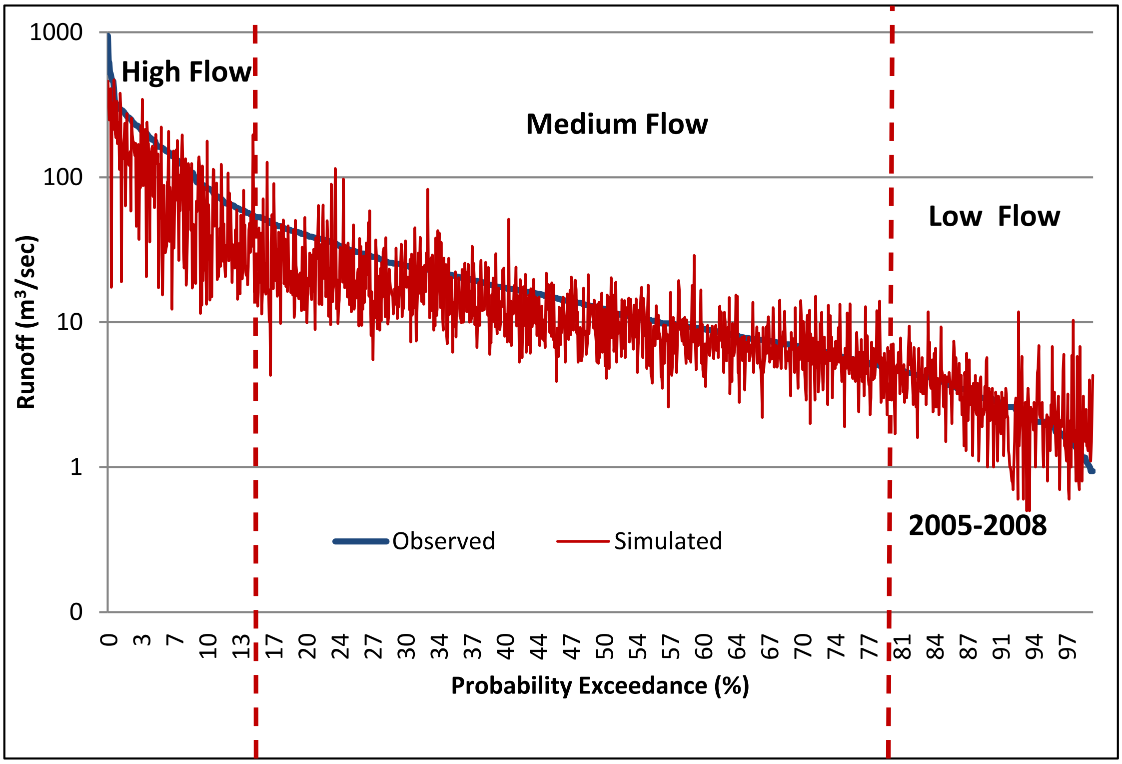


Figure 4-55: Flow duration curve for sixteen sub division model in calibration period

Table 4-31: Performance of sixteen sub division model in calibration period

Summary for Flow	**Objective Function**	
	Nash	MRAE
Overall	0.630	0.411
High	0.333	0.439
Medium	0.668	0.414
Low	0.407	0.380

4.7.7.3 Outflow hydrograph

Hydrograph for the model of sixteen subdivisions in calibration period is shown in Figure 4-56 and performance of the model is given in the Table 4-31.

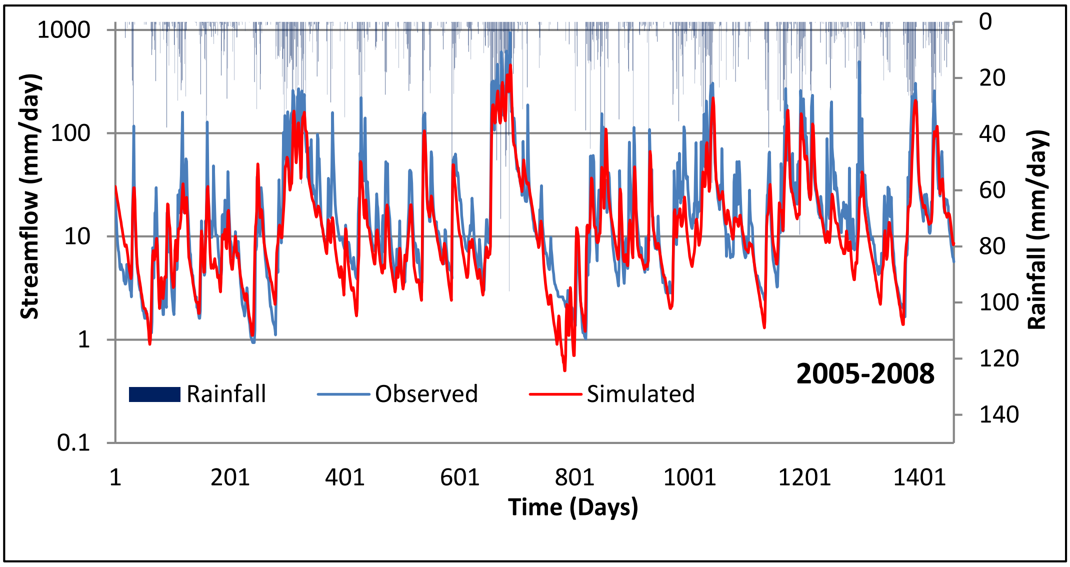


Figure 4-56: Hydrograph of sixteen sub division model in calibration period

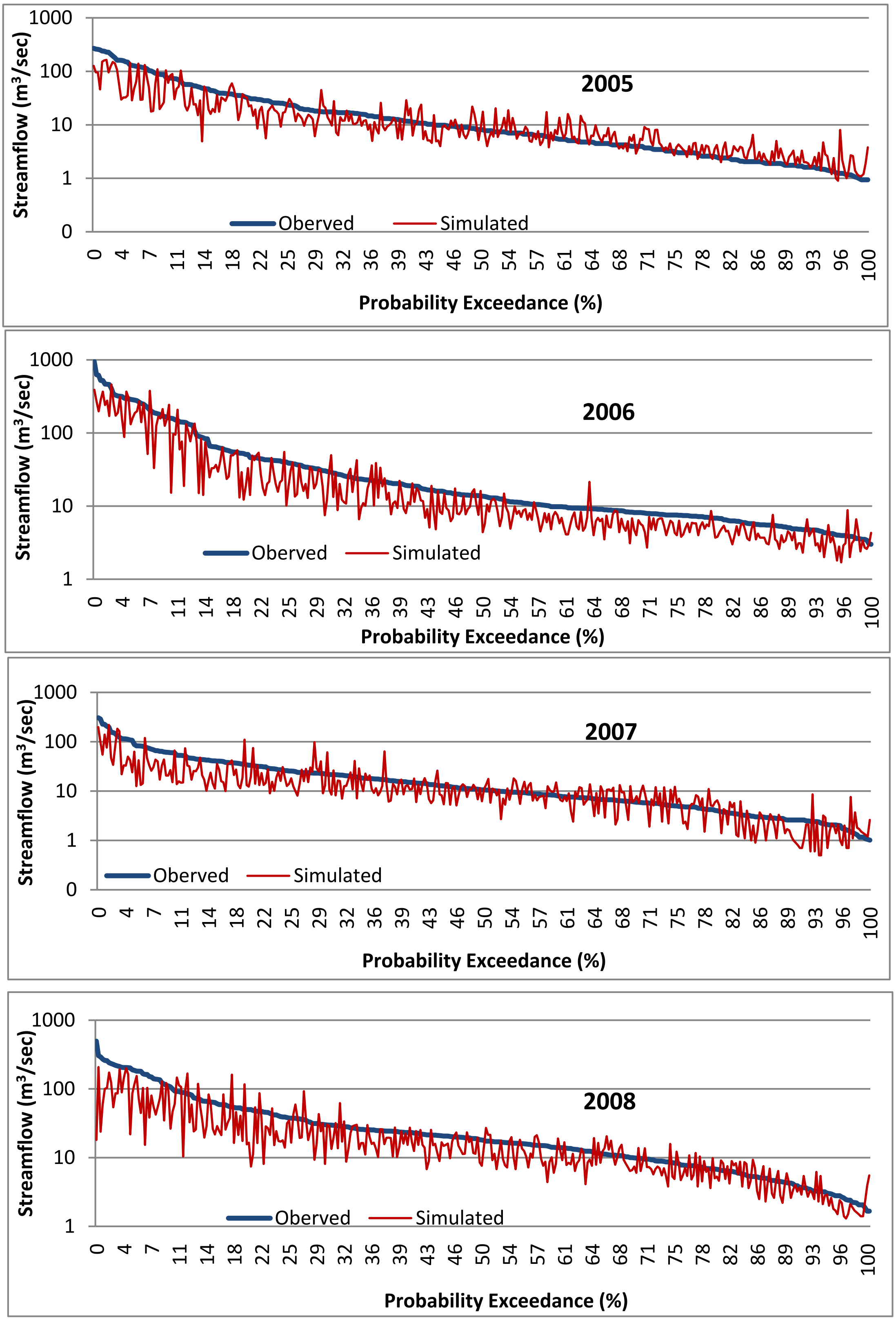


Figure 4-57: Flow duration curve for sixteen sub division model in calibration period

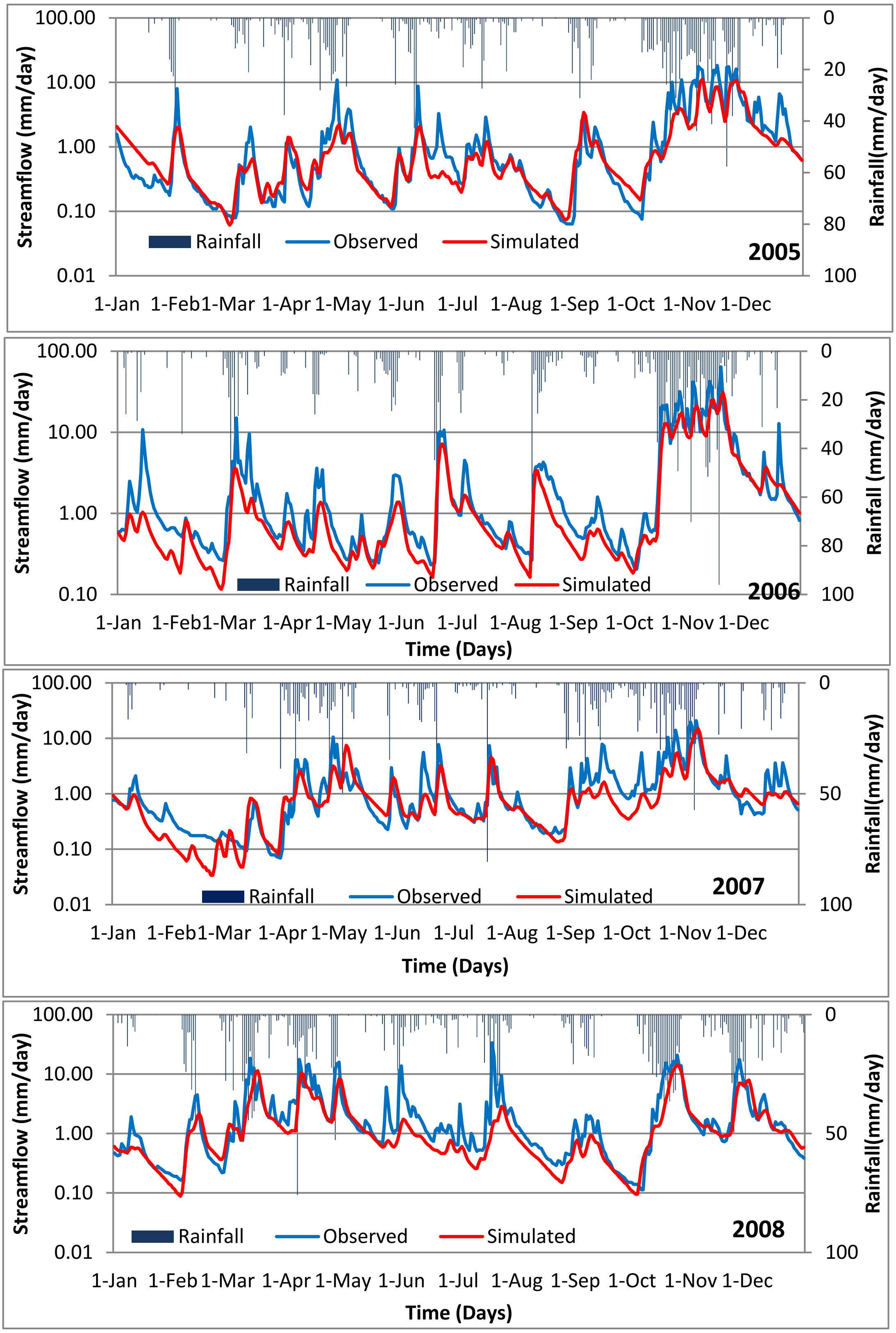


Figure 4-58: Hydrograph for sixteen sub division model in calibration period

4.7.8 Sixteen subdivisions model result in validation period

4.7.8.1 Annual water balance

Comparison of observed and simulated water balance in Badalgama watershed is given in Table 4-32. The percentage difference is 21.0 % which shows an inferior model performance as compared to other subdivision models.

Table 4-32: Annual water balance for sixteen sub division model in validation period

Year	Thiessen Rainfall (mm)	Simulated Streamflow (mm)	Observed Streamflow (mm)	Observed Water Balance (mm)	Simulated Water Balance (mm)	Annual Water Balance Difference (mm)
2010	2360	807	1278	1081	1552	-471
2011	1550	382	722	828	1168	-340
2012	1876	528	830	1046	1347	-301
2013	1956	602	640	1316	1354	-38

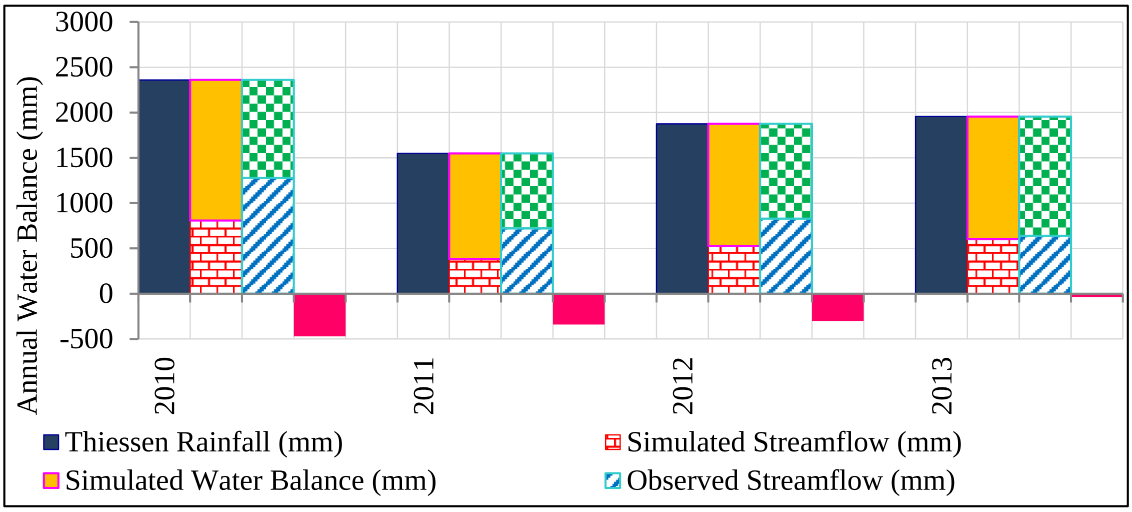


Figure 4-59: Annual water balance for sixteen sub division model in validation period

4.7.8.2 Flow duration curve result

The details of flow duration curve are given in Section 4.5.2 and the graphical representation is given in Figure 4-60.

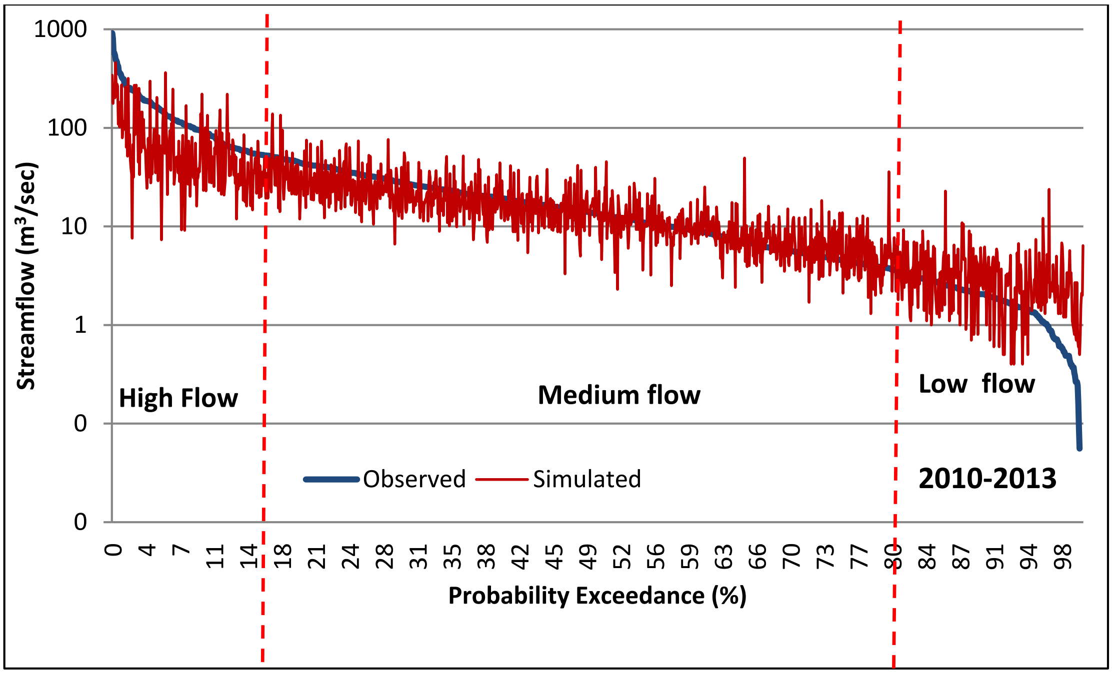


Figure 4-60: Flow duration curve for sixteen sub division model in validation period

Table 4-33: Performance of sixteen sub division model at different flow conditions in validation period

Flow Condition	**Objective Function**	
	NASH	MRAE
Overall	0.52	0.61
High	0.60	0.44
Medium	0.53	0.68
Low	0.44	0.50

4.7.8.3 Outflow hydrograph

Hydrograph for model of sixteen subdivisions in validation periods is shown in Figure 4-61.

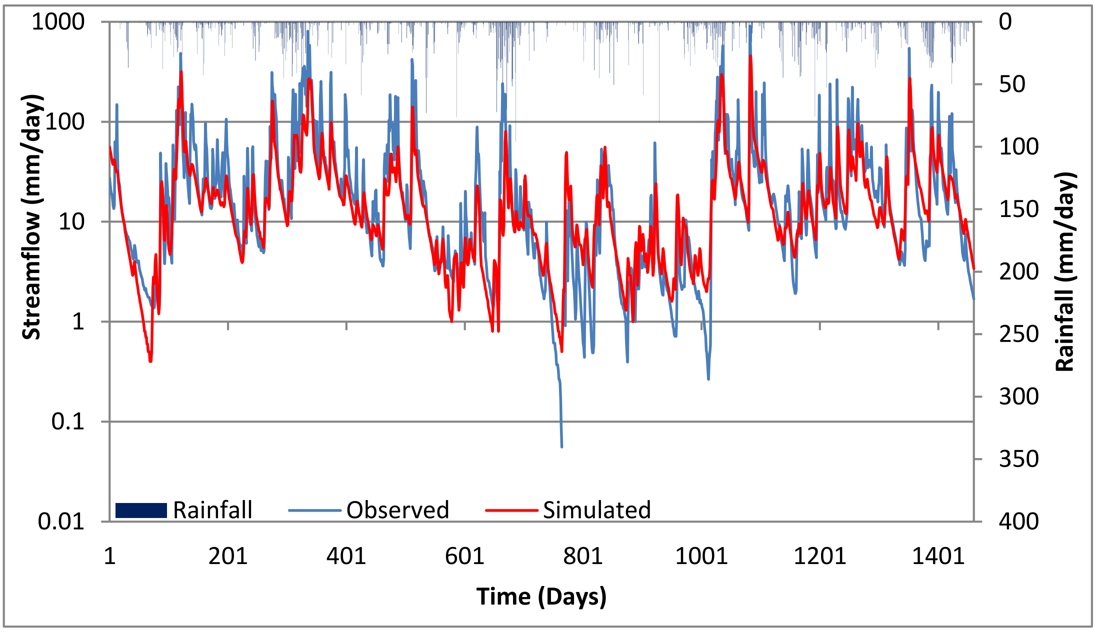


Figure 4-61: Hydrograph for the model of sixteen sub divisions in validation period

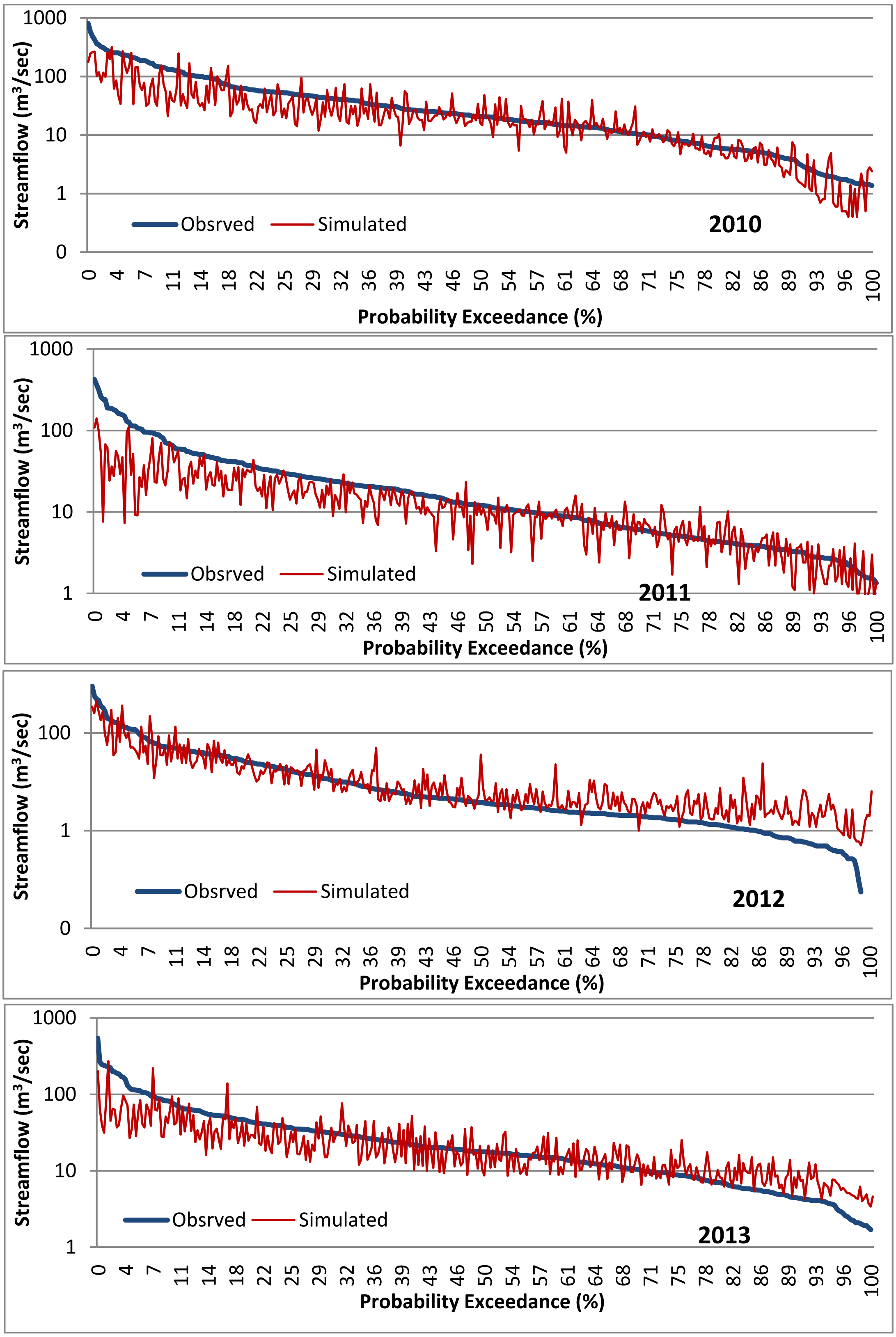


Figure 4-62: Flow duration curve for sixteen sub division model in validation period

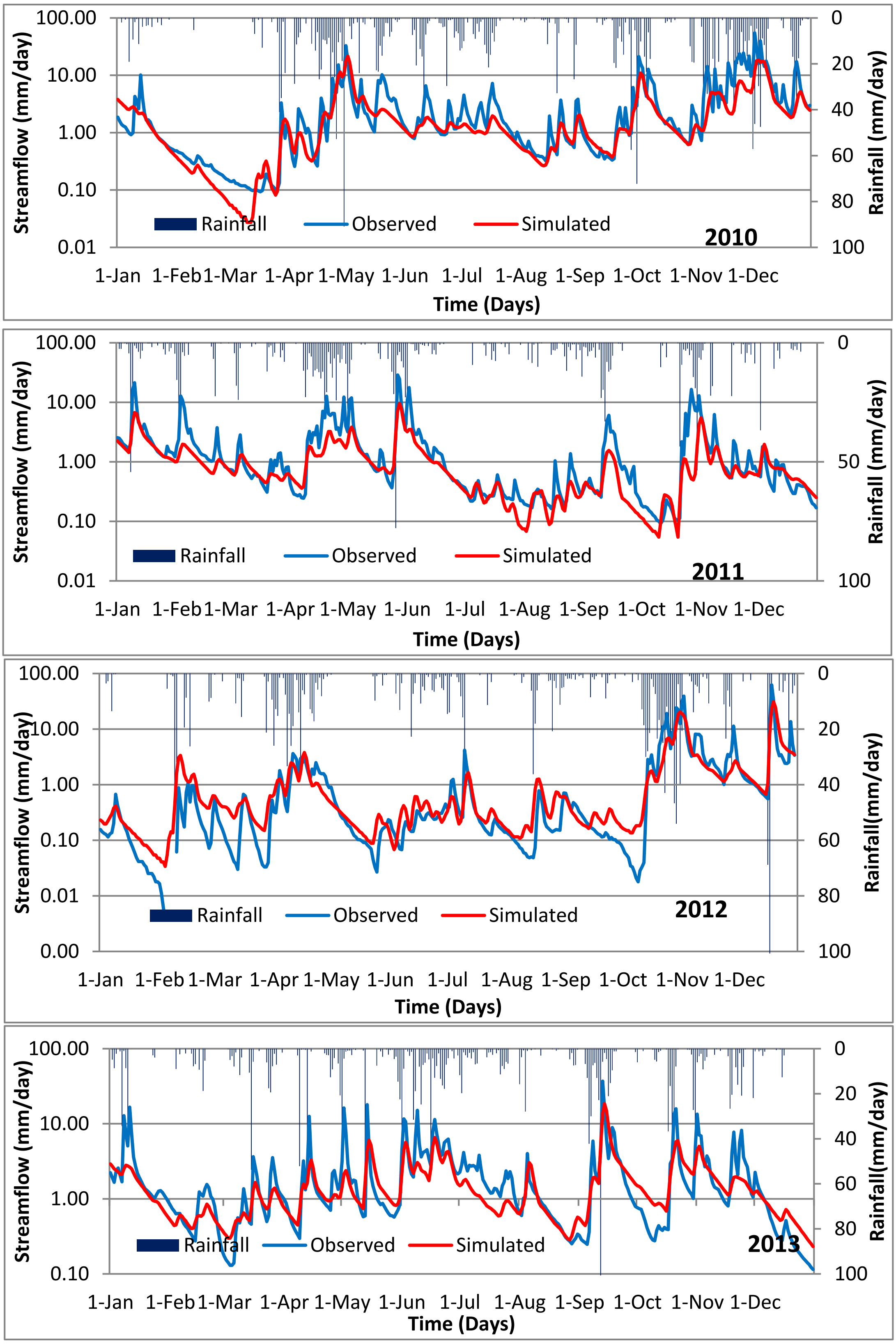


Figure 4-63: Hydrograph for sixteen sub division model in validation period

4.8 Comparison of model calibration results

The evaluation of hydrological model behavior and performance is commonly made and described through comparisons of simulated and observed value in reference to selected objective functions. Usually the comparisons are made between simulated and measured streamflow at the catchment outlet. For the present comparison, statistical performance indicators are used for model evaluation accordingly.

4.8.1 Flow comparisons

For the evaluation of model performance, flow at the catchment outlet (MCM) is compared under different flow conditions.

Table 4-34: Performance comparison for high flow in calibration period

High Flow Condition			
Model	**Observed Discharge (MCM)**	**Simulated Discharge (MCM)**	**Error (MCM)**
Lumped Model	225.25	130.41	42.10
Subdivision 3 model	225.25	136.22	39.52
Subdivision 6 model	225.25	151.36	32.80
Subdivision 9 model	225.25	156.60	30.48
Subdivision 16 model	225.25	165.42	26.56

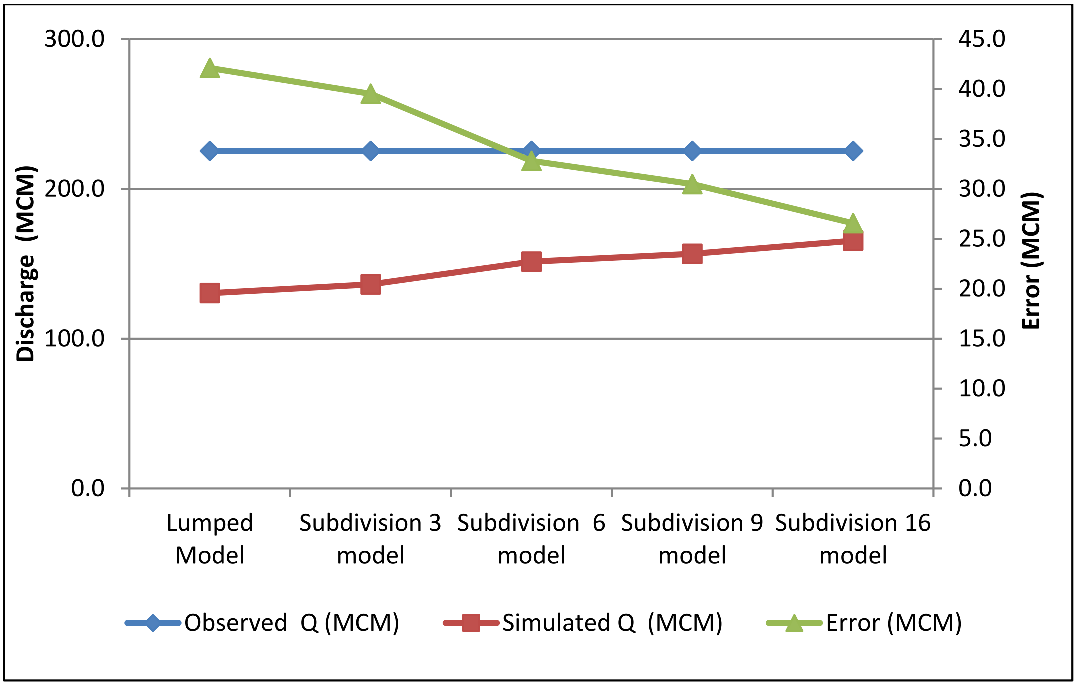


Figure 4-64: Performance comparison for high flow in calibration period

Table 4-35: Performance comparison for medium flow in calibration period

Medium flow			
Model	**Observed Discharge (MCM)**	**Simulated Discharge (MCM)**	**Error (MCM)**
Lumped Model	3215.50	2306.23	28.28
Subdivision 3 model	3215.50	2240.00	30.34
Subdivision 6 model	3215.50	2257.58	29.79
Subdivision 9 model	3215.50	2227.40	30.73
Subdivision 16 model	3215.50	2174.00	32.39

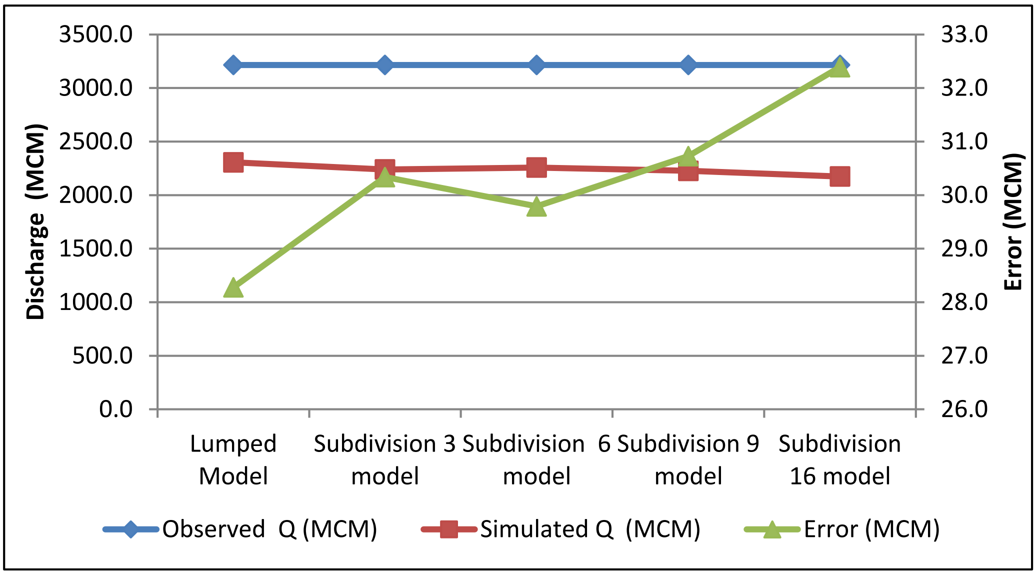


Figure 4-65: Performance comparison for medium flow in calibration period

Table 4-36: Performance comparison for low flow in calibration period

Low Flow Condition			
Model	**Observed Discharge (MCM)**	**Simulated Discharge (MCM)**	**Error (MCM)**
Lumped Model	1059.13	685.49	35.28
Subdivision 3 model	1059.13	714.66	32.52
Subdivision 6 model	1059.13	698.10	34.09
Subdivision 9 model	1059.13	673.79	36.38
Subdivision 16 model	1059.13	651.28	38.51

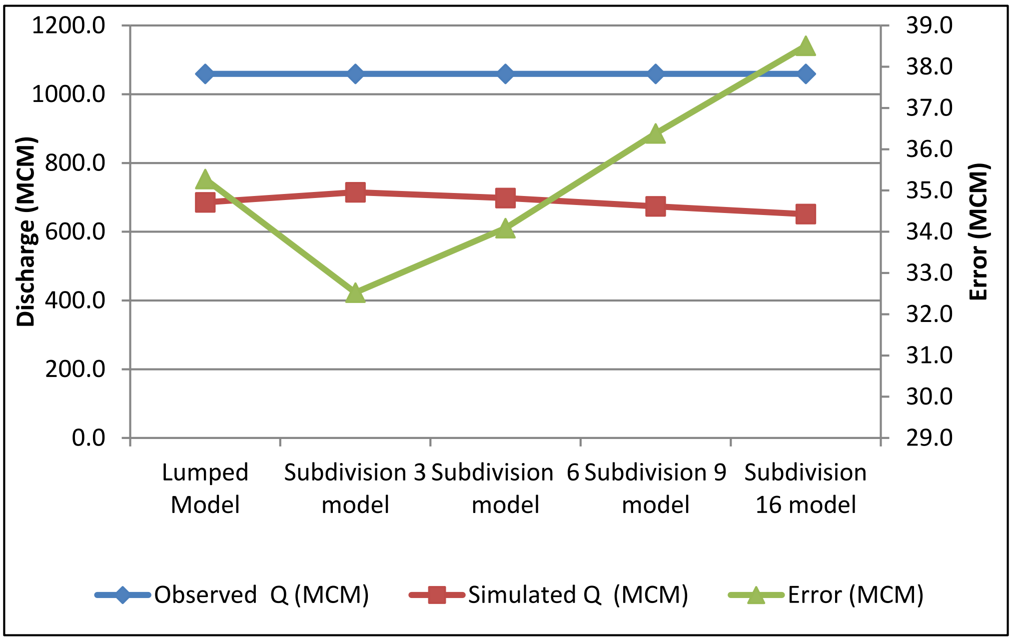


Figure 4-66: Performance for low flow in calibration period

The model of subdivision sixteen gives best performance for high flow as compared to other models as shown in the Table 4-34 and Figure 4-64. In the lumped model, the error is 42.10 MCM but for high flow, this error decreases when the scale goes higher.

For the comparison of medium flow, the lumped model gives best performance for medium flow as compared to other models as shown in the Table 4-35 and Figure 4-65. In overall with objective function, the model with six subdivisions gives good performance as compared to models with other subdivisions. In the lumped model, the error is 28.28 MCM and for six subdivisions the error is 29.79 MCM.

For the comparison of low flow, the model with three subdivisions gives the best performance as compared to other models as shown in the Table 4-36 and Figure 4-66. For low flow comparison in lumped model, the error is 35.28 MCM and for six subdivisions the error is 32. 52 MCM. The accuracy for sixteen subdivisions is decrease with the error 38.51 MCM.

4.9 Comparison of model in validation period

4.9.1 Flow comparisons

For the evaluation of model performance, the observed and simulated flows (MCM) were compared under different flow conditions in validation period.

Table 4-37: Performance comparison for high flow in validation period

High flow			
Model	**Observed Q (MCM)**	**Simulated Q (MCM)**	**% Error (MCM)**
Lumped Model	580.38	433.10	25.38
Subdivision 3 model	580.38	478.95	17.48
Subdivision 6 model	580.38	459.62	20.81
Subdivision 9 model	580.38	486.01	16.26
Subdivision 16 model	580.38	457.92	21.10

For the comparison of high flow as shown in the Table 4-37 and Figure 4-67, the model with nine subdivisions gives best performance for high flow as compared to other models. In the lumped model, the error is 25.38 MCM and for nine subdivisions it was 16.26 MCM but for high flow, this error is decreased when it goes up to nine subdivisions while for sixteen subdivisions the error was 21.10 MCM.

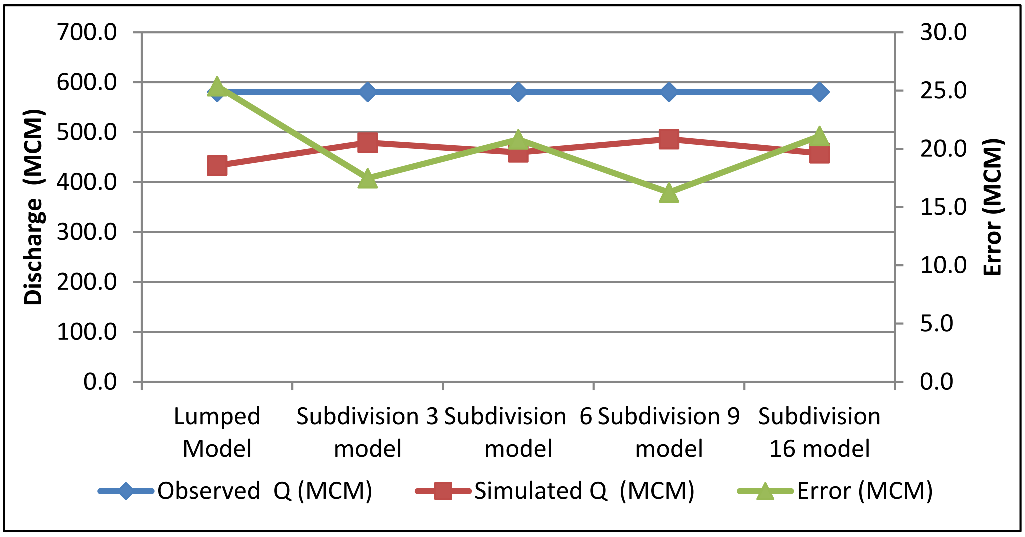


Figure 4-67: Performance comparison for high flow in validation period

Table 4-38: Performance comparison for medium flow in validation period

Medium flow			
Model	**Observed Discharge (MCM)**	**Simulated Discharge (MCM)**	**Error (MCM)**
Lumped Model	2942.98	1794.88	39.01
Subdivision 3 model	2942.98	1796.36	38.96
Subdivision 6 model	2942.98	1853.09	37.03
Subdivision 9 model	2942.98	1797.59	38.92
Subdivision 16 model	2942.98	1831.61	37.76

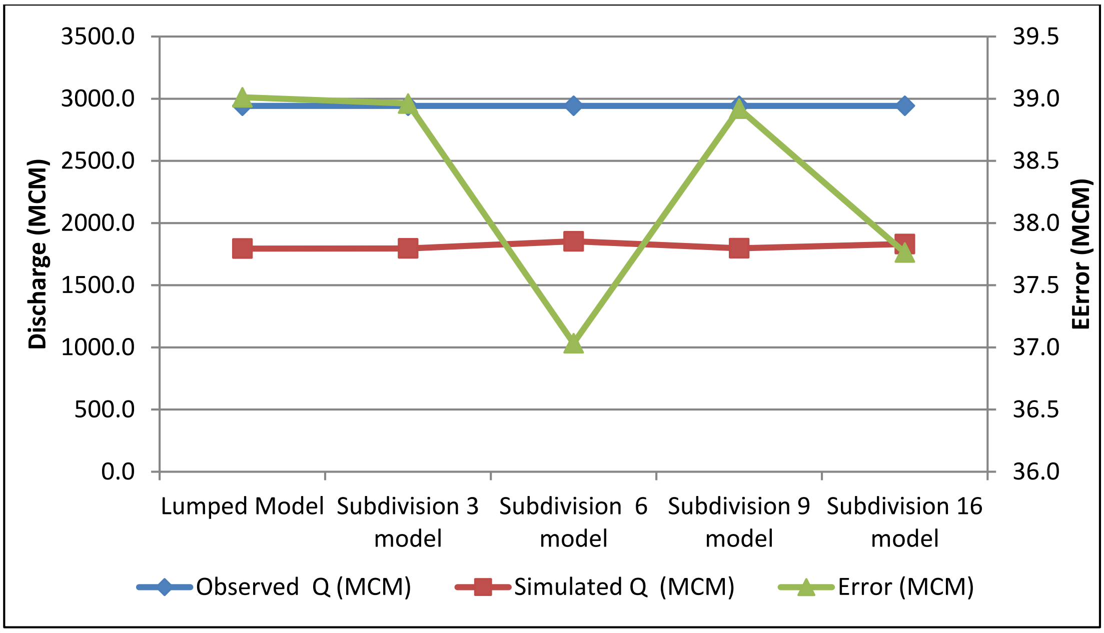


Figure 4-68: Performance comparison for medium flow in validation period

Table 4-39: Performance comparison for low flow in validation period

Low flow			
Model	**Observed Discharge (MCM)**	**Simulated Discharge (MCM)**	**Error (MCM)**
Lumped Model	889.67	801.58	9.90
Subdivision 3 model	889.67	765.39	13.97
Subdivision 6 model	889.67	642.31	25.29
Subdivision 9 model	889.67	642.31	27.80
Subdivision 16 model	889.67	660.55	25.75

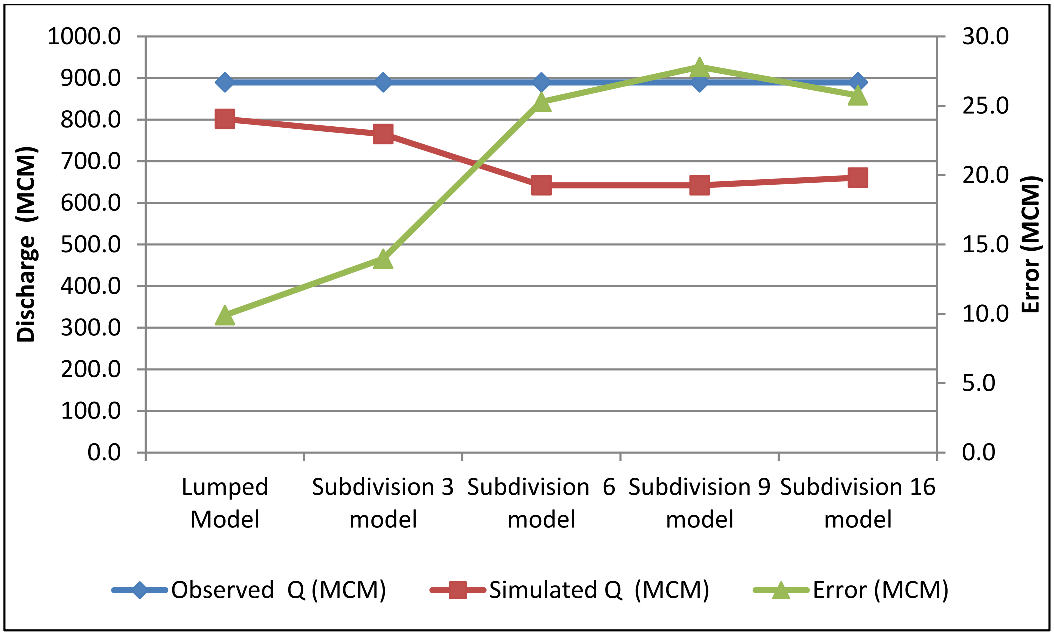


Figure 4-69: Performance comparison for low flow in validation period

For the comparison of medium flow, six subdivision model gives the best performance as compared to other models as shown in the Table 4-38 and Figure 4-68. In the lumped model, the error was 39.01 MCM and for six subdivisions, the error was 37.03 MCM for medium flow.

For the comparison of low flow, the lumped model gives the best performance as compared to the other models as shown in the Table 4-39 and Figure 4-69. In the lumped model, the error was 9.90 MCM and error for nine subdivisions was 27.78 MCM which showed a higher error under low flow condition.

4.10 Comparison of error in annual mass balance

4.10.1 Comparison of error in annual mass balance during calibration

Annual mass balance errors are compared in Badalgama lumped model and for different subdivisions during calibration period. Variation of annual mass balance errors are shown in Table 4-40. Maximum mass balance error occurred in 2006 year which is 27.45 and mass balance error is lesser in subdivision six model as compared to models with other subdivisions.

4.10.2 Comparison of error in annual mass balance during validation

Annual mass balance errors were compared in Badalgama lumped model and for different subdivisions during validation period. Variation of annual mass balance errors are shown in Figure 4-70. Maximum mass balance error was observed in 2006 year which is 30.47 as shown in Table 4-41 and the mass balance error was lesse in six subdivision model as compared to other models.

Table 4-40: Comparison of annual mass balance error (%) in calibration period

Year	Annual Mass Balance Error (%)				
	Lumped Model	Subdivision 3 model	Subdivision 6 model	Subdivision 9 model	Subdivision 16 model
2005	16.35	14.94	16.00	15.39	14.95
2006	23.00	25.76	25.79	26.20	27.45
2007	12.14	12.53	11.61	12.62	13.17
2008	19.91	19.47	18.52	19.73	20.94

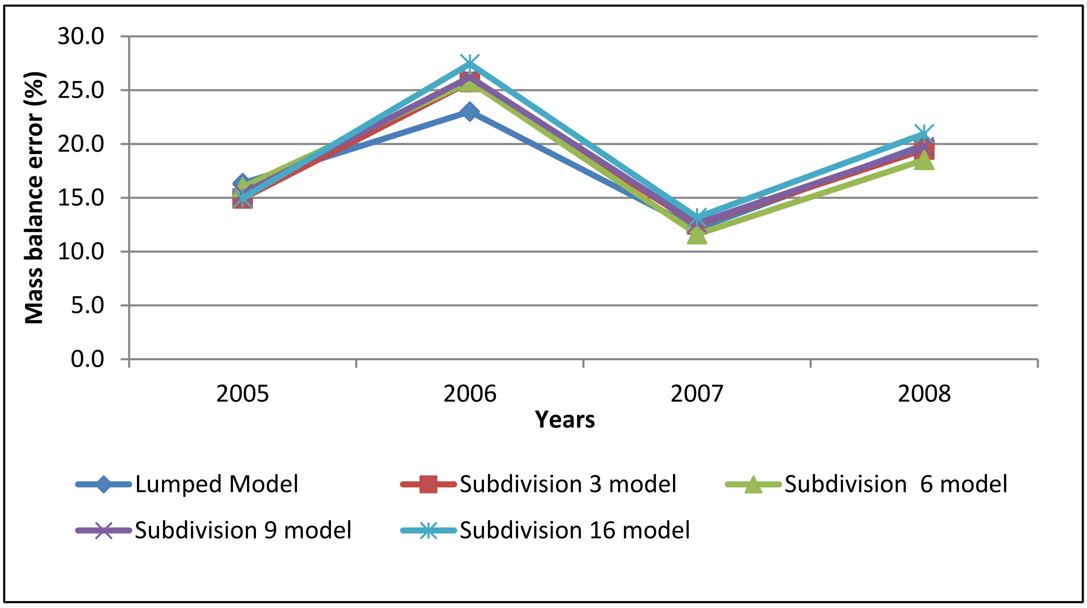


Figure 4-70: Comparison of annual mass balance error (%) for calibration period

Table 4-41: Comparison of annual mass balance error (%) in validation period

Year	Annual Mass Balance Error (%)				
	Lumped Model	**Subdivision 3 model**	**Subdivision 6 model**	**Subdivision 9 model**	**Subdivision 16 model**
2010	30.47	29.02	29.71	30.25	30.33
2011	29.17	29.38	18.21	29.09	29.11
2012	24.90	24.14	12.20	22.71	22.36
2013	5.64	3.08	12.37	3.88	2.82

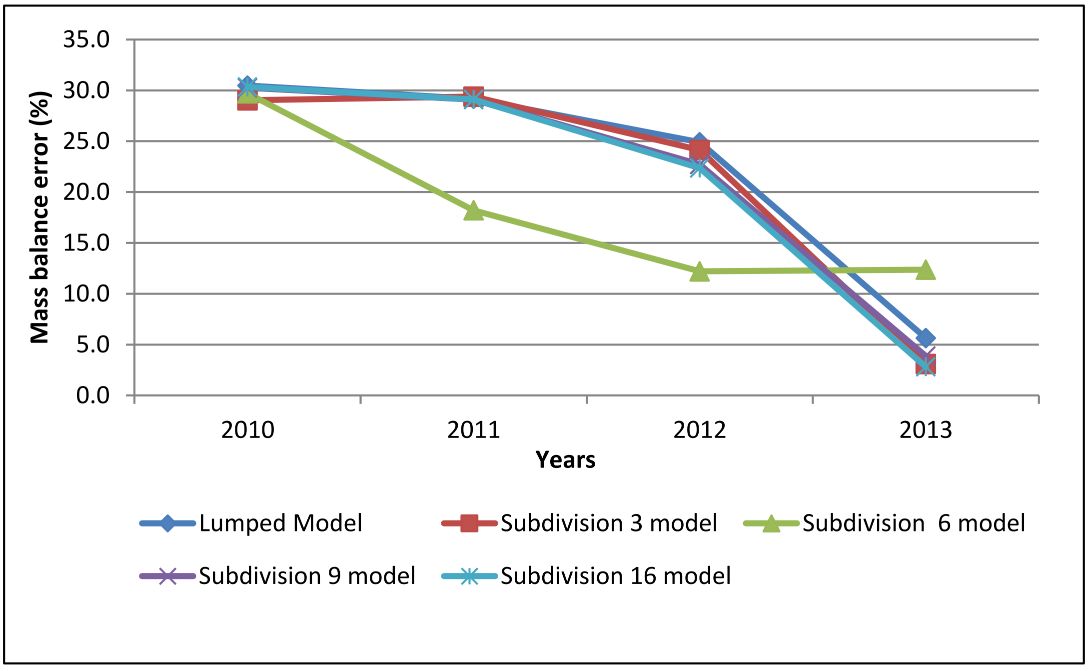


Figure 4-71: Comparison of annual mass balance error (%) in validation period

4.10.3 Statistical performance in calibration and validation period

Comparisons of statistical performance was done for lumped model of Badalgama watershed and compared with model with subdivisions 3, subdivisions 6, subdivisions 9 and subdivisions 16, as given in Table 4-42.

Table 4-42: Statistical performance comparison in calibration period

Model	**Nash-Sutcliff**	**MRAE**	**Annual Mass Balance Error (%)**	**Flow Condition**					
				High		**Medium**		**Low**	
				NASH-Sutcliff	**MRAE**	**NASH-Sutcliff**	**MRAE**	**NASH-Sutcliff**	**MRAE**
Lumped Model	0.64	0.39	17.85	0.28	0.36	0.68	0.39	0.40	0.43
3 Sub division Model	0.69	0.39	18.18	0.32	0.36	0.73	0.39	0.36	0.44
6 Sub division Model	0.67	0.38	17.98	0.41	0.35	0.71	0.38	0.45	0.37
9 Sub division Model	0.66	0.38	18.49	0.38	0.37	0.69	0.40	0.40	0.35
16 Sub division Model	0.63	0.41	19.13	0.33	0.44	0.67	0.41	0.41	0.38

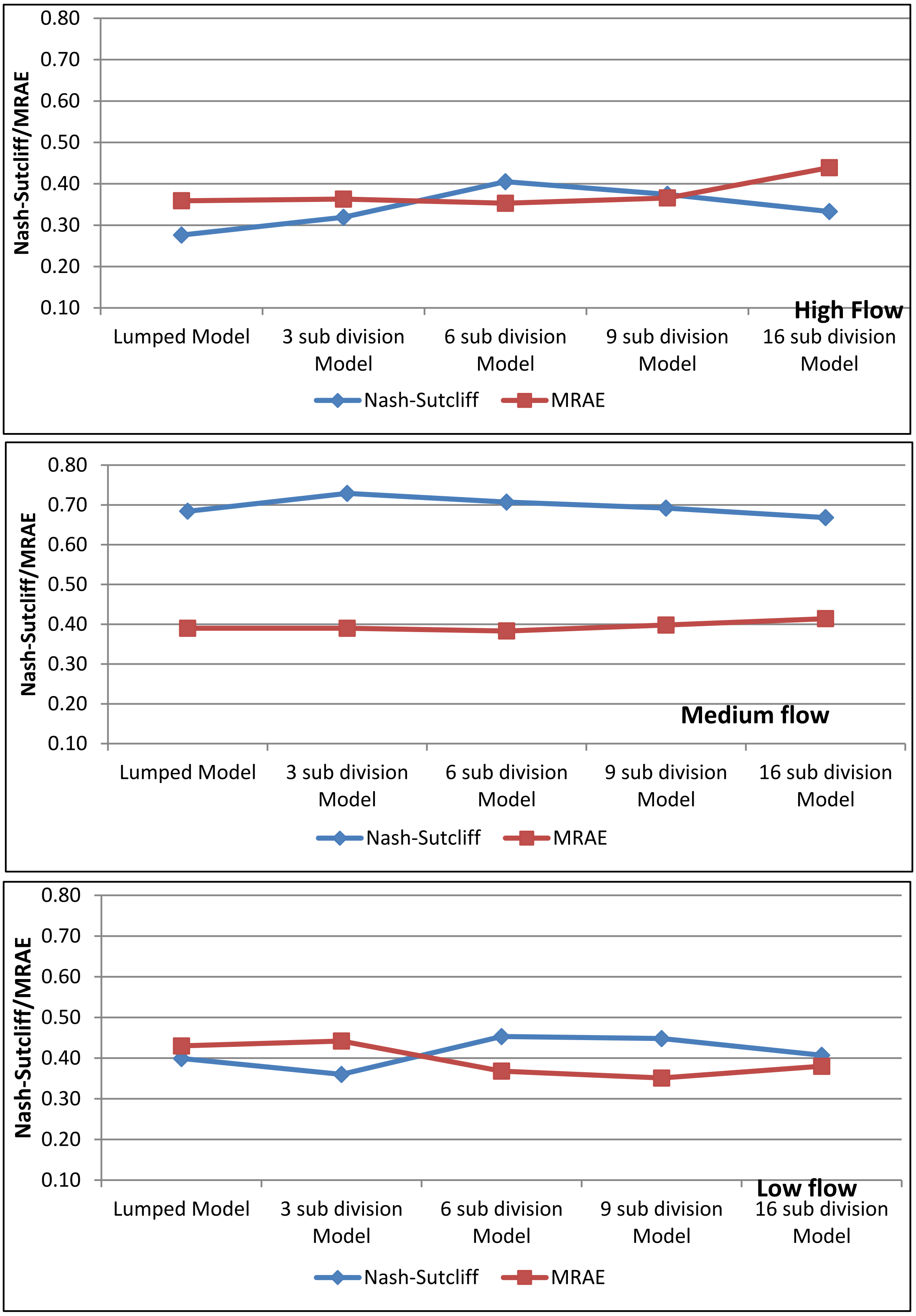


Figure 4-72: Performance comparisons of statically in calibration period

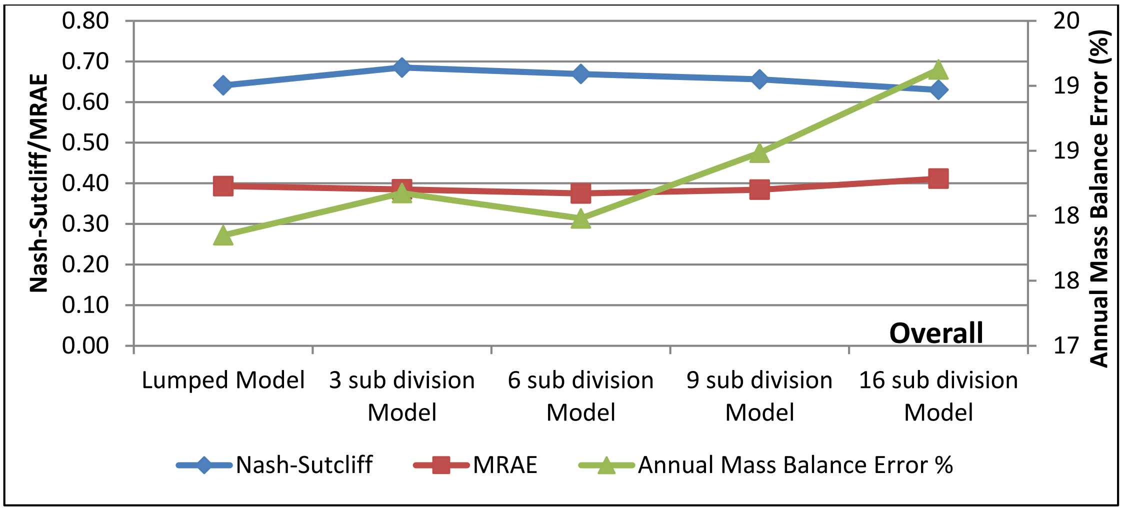


Figure 4-73: Overall comparison of statically performance in calibration period

Table 4-43: Overall comparison of statically performance in validation period

Model	**Nash-Sutcliff**	**MRAE**	**Annual Mass Balance Error (%)**	**Flow Condition**					
				High		**Medium**		**Low**	
				Nash-Sutcliff	**MRAE**	**Nash-Sutcliff**	**MRAE**	**Nash-Sutcliff**	**MRAE**
Lumped Model	0.48	0.64	22.55	0.50	0.48	0.49	0.65	0.38	0.74
3 Sub division Model	0.54	0.58	21.45	0.59	0.48	0.55	0.61	0.47	0.59
6 Sub division Model	0.53	0.61	18.12	0.60	0.44	0.53	0.69	0.45	0.50
9 Sub division Model	0.50	0.65	21.49	0.57	0.48	0.50	0.73	0.42	0.50
16 Sub division Model	0.53	0.61	21.16	0.60	0.44	0.53	0.68	0.44	0.50

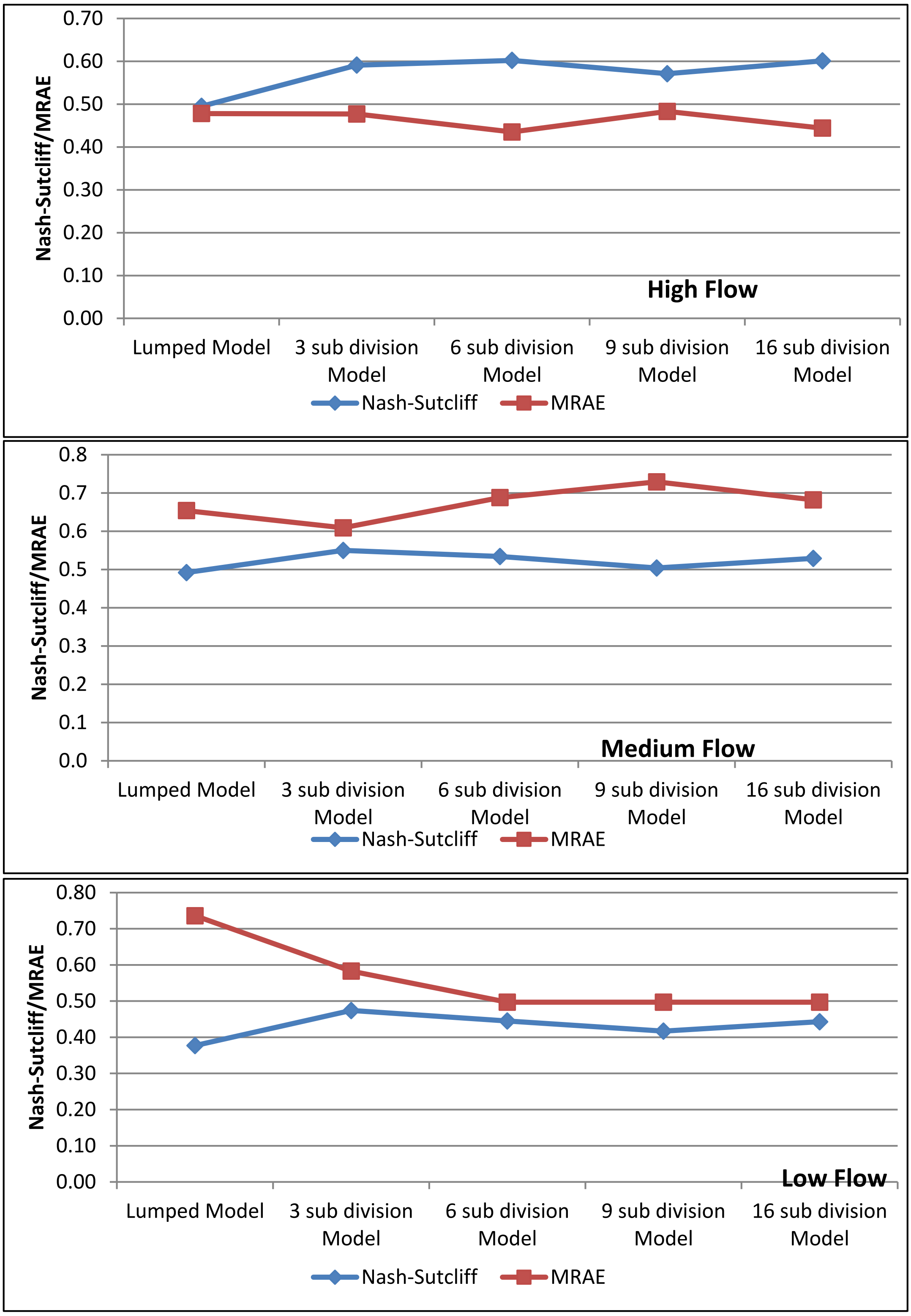


Figure 4-74: Statically performance comparison in validation

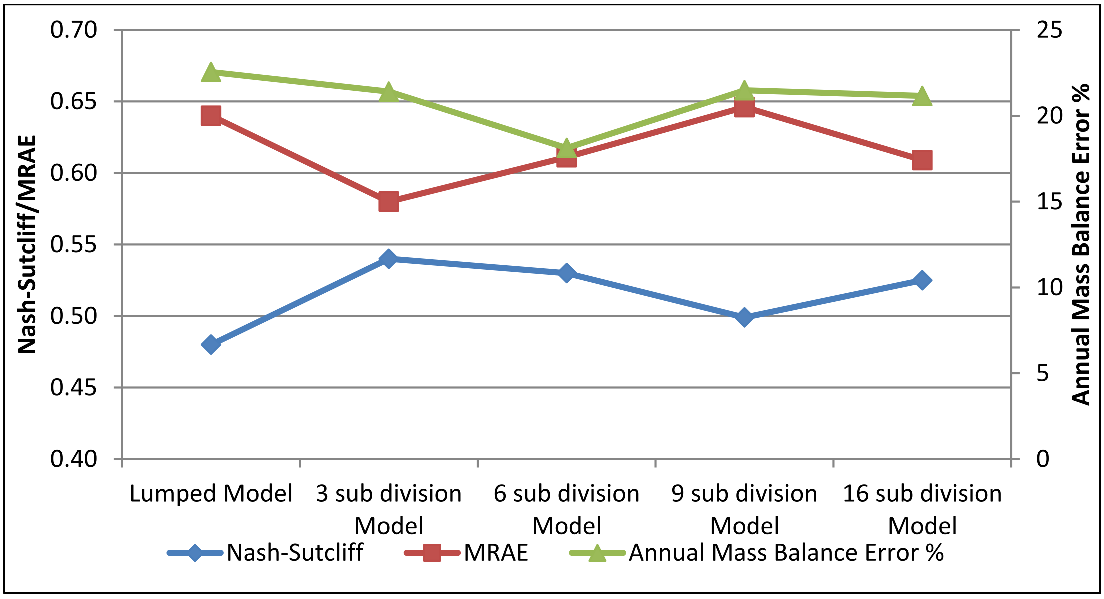


Figure 4-75: Overall comparisons of statically performance in Validation

For calibration period and validation period, the overall performance is shown in Table 4-42 and Figure 4-73 and in Table 4-43 and Figure 4-75, respectively. Among 3, 6, 9, and 16 subdivisions, for the 6 subdivision model (with MRAE 0.375), the accuracy increased by 4.687% as compared to lumped model (with MRAE 0.393) during calibration period and during the validation period, the accuracy increased in six subdivision model (with 4.636%) as shown in the Table 4-43. According to overall performance among models with 3, 6, 9, and 16 subdivisions, the accuracy of the 6 subdivision model (with Nash 0.641) increased by 4.185% as compared to lumped model (with Nash 0.669) in calibration period and in validation period, a 9.434% increase in accuracy was found.

In 6 sub division model, the flow was divided into three regimes as high flow, medium flow and low flow. For the model with six subdivisions, the simulated high flow and medium flow showed an increased accuracy by 1.671% and 1.795%, respectively and with MRAE of 0.353 and 0.383, respectively for calibration period but the accuracy for low flow was even higher which is increased by 22.507% as compared to the lumped model. During validation period, the overall performance of 6 sub division model simulated high flow with an increased accuracy (by 8.996%) with MRAE of 0.435 but the accuracy of simulated medium and low flow decreased (by -5.119%) with respect to the low flow of the lumped model (with MRAE of 0.736).

4.10.4 Comparisons of model parameters for Badalgama watershed

A detailed comparison of model parameters is given in Appendix C.

4.11 Result for the model of Antecedent Moisture Condition

The AMC value is calculated for the rainfall data from 01-January-2010 to 31-December-2013 for lumped model and subdivision 6 model, because subdivision 6 model produced the best results as compared to the models with other sub divisions. The purpose of the calculation of AMC in each subdivision of the model with six subdivision was to know that which AMC conditions was actually prevalent under the observed rainfall conditions. The summary of AMC of each sub division and lumped model is given in the Table 4-44. Subsequently, the statistical T-test was carried out to check the significant differences between lumped model and each subdivision as shown in the Appendix D. Accordingly, it was found that there was no significant different between AMC of lumped model and model with 6 subdivisions.

Table 4-44:Summary of AMC for six subdivisions and lumped model

Summary							
AMC	**Sub-div 1**	**Sub-div 2**	**Sub-div 3**	**Sub-div 4**	**Sub-div 5**	**Sub-div 5**	**Lumped**
AMC-I	376	376	373	382	367	361	366
AMC -II	53	53	63	69	78	79	65
AMC -III	147	147	140	125	131	136	145

4.11.1 Result for calibration period

Calibration period was selected from 01-December-2010 to 09-December-2010 because peak value of streamflow lies in this period. For evaluation of the model, the Nash-Sutcliffe indicator was selected for targeting flood management purposes. The performance of the model is given in Table 4-45.

Table 4-45: Performance of the model for different AMC conditiond in calibration period

AMC	Nash
AMC-III	0.708
AMC-II	0.416
AMC-I	-0.16

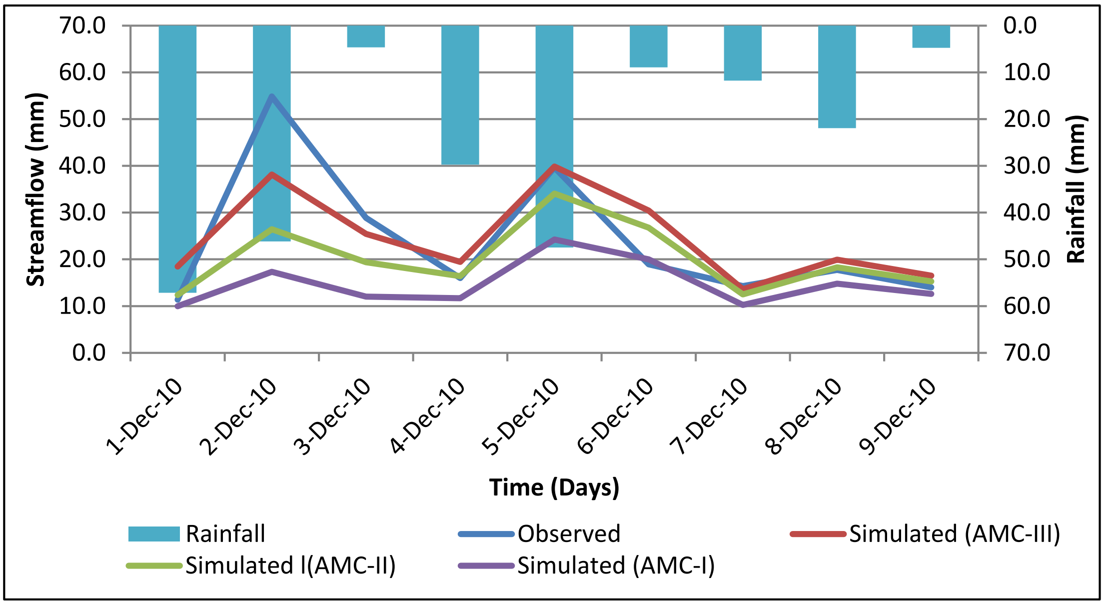


Figure 4-76: Performance for the model of different AMC condition in calibration period

4.11.2 Result for validation period

For validation of the model, data from 09-January-2011 to 17-January-2011 was selected and Nash-Sutcliffe coefficient values achieved for AMC-III, AMC-II and AMC-I were 0.573, 0.290 and 0.240, respectively.

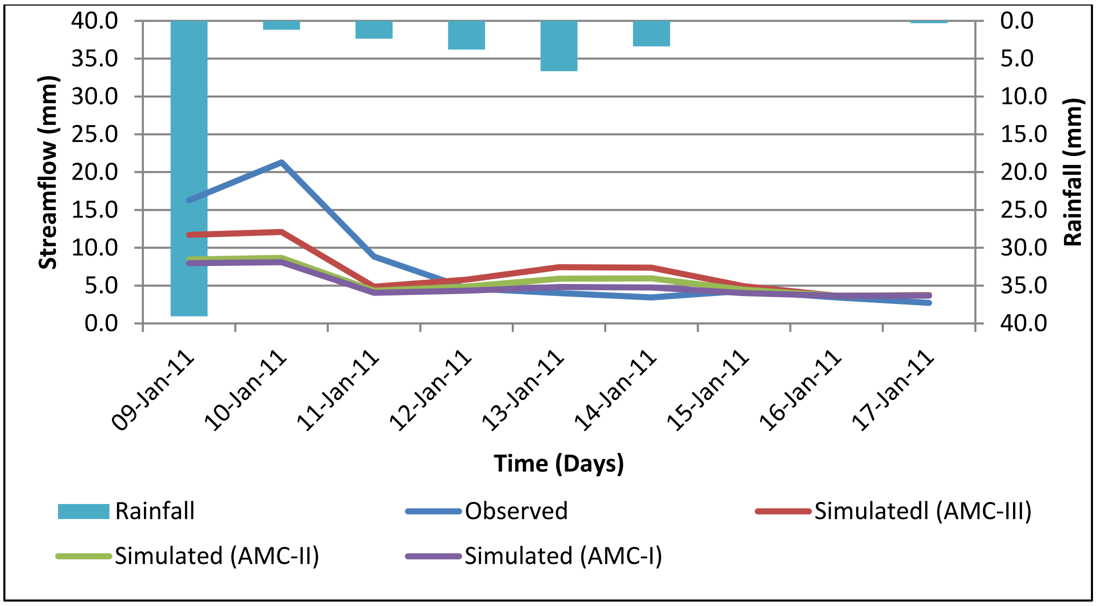


Figure 4-77: Performance for the model for different AMC condition in validation period

4.12 Discussion of the Results

4.12.1 Data and data period

In the selection of data periods, initially the availability of nine-years of data at Badalgama river gauging stations was considered. There are two river gauging stations in Badalgama watershed. First river gauging station is situated near Andigama Farm and other is Badalgama River gauging station. The gauging station near Andigama farm is not functioning. Hence, data availability and data reliability of recent data for Badalgama River gauging station was deemed more acceptable as compared to the old data and therefore nine-year data was considered from 2005-2013. But in 2009, rainfall data of nine months was missing, and therefore this year's data was not considered reliable for modeling according to literature. Calibration period was selected from 01-January-2005 to 31-December-2008 and validation period was selected from 01-January 2010 to 31-December-2013. It was observed that dry periods and wet periods are representatively covered within this data set and it was assumed that the resultant runoff data were independent of the data period.

4.12.2 Existence of data errors

In year 2009, there is nine month missing data period so that this year's data were excluded in the data periods selected for modeling. Further in year 2012, the rainfall was found to be increasing but the streamflow series was decreasing indicating that streamflow had not responded well to the variations in rainfall in this year.

4.12.3 Selection of model parameters and objective function

Initially, the model parameters were selected based on literature available for the HEC-HMS models already developed in Sri Lanka. Objective function was also selected based on literature sources which were discussed in detail in the Literature survey section of the report. For water resource management, MRAE was the main focus while Nash-Sutcliff coefficient was also checked for model accuracy. For the AMC, part of the study using HEC-HMS model, the Nash-Sutcliff was selected targeting flood management purposes.

4.12.4 Model development and sensitivity analysis

Initially, the model development using the initial parameters showed that Nash-Sutcliff value was 0.80 while the MRAE was 0.82 which was not acceptable. Subsequently, automatic model calibration was performed to identify the effect of sensitive parameters and then by looking at those parameters, sensitivity analysis was performed which indicated that among the eight model parameters, soil percolation was the most sensitive parameter which has the highest percentage change of the runoff value (43.09%) with a 66.67% change in parameters and tension storage was the least sensitive parameters with runoff change of 3.31% with a similar 66.67% change in the parameter.

4.12.5 Subdivisions of the watershed

Watershed sub divisions has been carried out based on the findings of the literature survey. Most of the researchers have used critical threshold area method for this as shown in Appendix E. The threshold was the minimum upstream drainage area for a channel to originate and can be specified by a percentage of total watershed area.

4.12.6 Evaluation criteria of model in calibration period

For the models with 3, 6, 9 and 16 subdivisions, the runoff modeling was done using HEC-HMS and the calibrated model accuracy increased up to 6 sub divisions with MRAE for calibration of 0.385, 0.375, 0.384 and 0.411, respectively while accuracy marginally decreased with Nash objective function with the values of 0.685, 0.669,0.656 and 0.630, respectively as shown in Table 4-46. The overall performance among models with 3, 6, 9, and 16 subdivisions, for the 6 subdivision model (with MRAE 0.375), the model accuracy increased by 4.687% as compares to lumped model (with MRAE 0.393) for the calibration period. Similarly considering the overall performance among models with 3, 6, 9 and 16 subdivisions, for the model with 6 subdivisions (with Nash 0.641), the model accuracy increased by 4.185% as compared to lumped model (with Nash 0.669) for the calibration period. The annual mass balance error in the lumped model was 17.850 but in case of the distributed model with 6 subdivisions, the annual mass balance error was 17.980 which was only marginally higher (and yet lower than the others).

Table 4-46: Model performance for calibration period

Model	Nash-Sutcliff	MRAE	Annual Mass Balance Error (%)
Lumped Model	0.641	0.393	17.850
3 Sub division Model	0.685	0.385	18.175
6 Sub division Model	0.669	0.375	17.980
9 Sub division Model	0.656	0.384	18.485
16 Sub division Model	0.630	0.411	19.125

4.12.7 Evaluation criteria of model in validation period

For validation period, the model accuracy increased for 3 subdivision model and then decreased up to 9 subdivisions while for 16 sub divisions, the accuracy again slighlty increased with reference MRAE. For 3, 6, 9 and 16 subdivision models, the HEC-HMS model accuracy decreased up to 9 subdivisions and increased for 16 subdivisions with Nash values of 0.540, 0.530, 0.499 and 0.525, respectively. Considering the overall performance among 3, 6, 9, and 16 subdivision models, for the 6 subdivision model , the accuracy increased by 4.636% with MRAE and with Nash objective function, the accuracy increased by 9.434%, compared to the lumped model. Accuracy for annual mass balance error in lumped model is 22.545% and among the distributed models, the model with 6 subdivisions produced the best results in terms of annual mass balance error which was 18.122% as shown in the Table 4-47.

Table 4-47: Model performance in validation period

Model	Nash-Sutcliff	MRAE	Annual Mass Balance Error %
Lumped Model	0.480	0.640	22.545
3 Sub division Model	0.540	0.580	21.405
6 Sub division Model	0.530	0.611	18.122
9 Sub division Model	0.499	0.646	21.485
16 Sub division Model	0.525	0.609	21.155

4.12.8 Matching of the flow duration curve

Among the all subdivision models, the model with 6 subdivisions produced the best results with MRAE and Nash objective functions. For the model with six subdivisions, the flow regime was divided into three regions as high flow, medium flow and low flow following the flow duration curve at probability exceedance of 15%, 15% ~ 80% and 80% ~ 100%, respectively. In the model with 6 subdivisions, the simulated high flow and medium flow accuracy increased (by 1.671% and 1.795%, respectively) with MRAE of 0.353 and 0.383, respectively, in calibration period but accuracy for low flow was high in 9 subdivision model which increased by 22.507%. But the overall performance accuracy of the 9 subdivision model was lower by 2.28% with an MRAE of 0.384. In the 6 sub division model, the estimated medium and low flow accuracy decreased (by -5.119%) with respect to lumped model (with NASH of 0.736). The model performance in low and medium regions were very important to analyze and assess water resource management alternatives as this study was more focused on continuous simulation and it was necessary to predict streamflow in medium and low flow regions for water resource management rather than predicting flood peaks.

As shown in the Table 4-48, the overall performance of the model was accptable with both objective functions but for focusing on water resource management, the medium and low flow regions were essentially important. The medium flow range which was greater than 15% exceedance probability showed an MRAE value of 0.383 which indicated that the model was matching simulated medium flows with observed flows very well and in this case, the objective function Nash value also produced a good response with a Nash value of 0.707 which indicated that model was satisfactorily matching peak values as well. The flows corresponding to 15% and 80% exceedance probability were 55.5 m^3/sec and 4.8 m^3/sec, respectively.

Table 4-48: Performance for different flow region in calibration period of six subdivision model

Type of flow	Nash	MRAE
Overall	0.669	0.375
High	0.405	0.353
Medium	0.707	0.383
Low	0.453	0.368

4.12.9 Comparison of flow residuals

Variation of flow residual through the calibration period for lumped model and sub division 6 model are shown in the Figure 4-78. It can be observed that there are higher residuals in year 2005 and 2006 and the highest flow residuals are marked with circles as shown in Figure 4-78 and Figure 4-79. From Figure 4-78, it can be inferred that the residual were higher in 2006 and therefore, the mass balance error was also greater than 20% for each model in 2006.

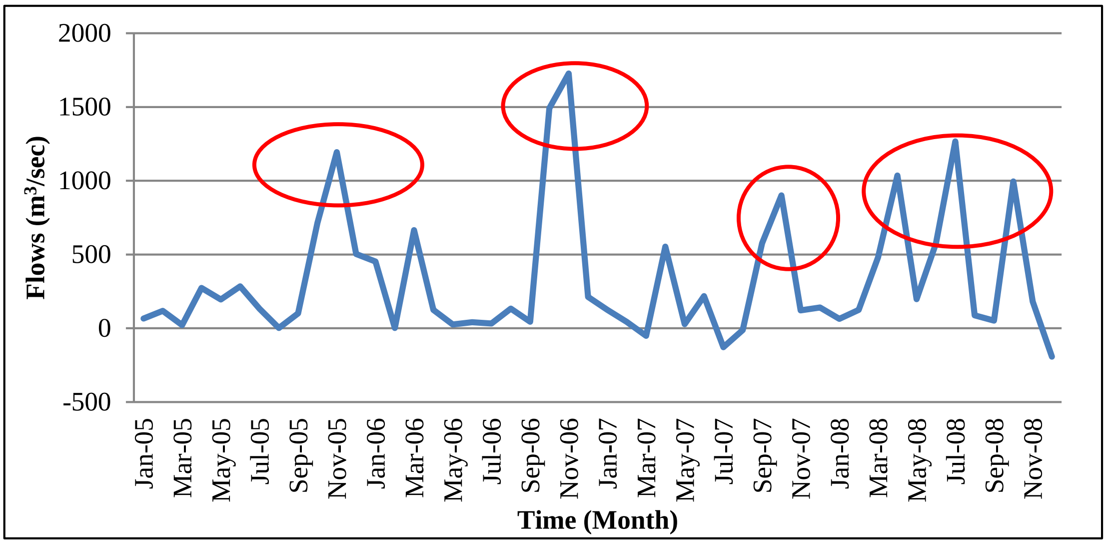


Figure 4-78: Variation of streamflow residuals of lumped model in calibration period

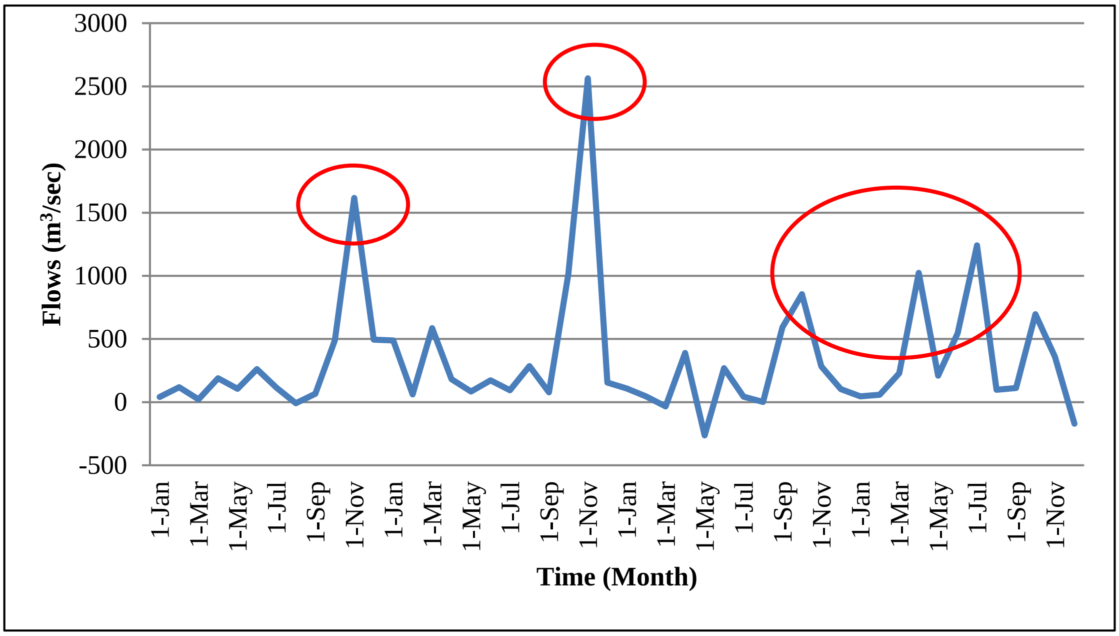


Figure 4-79: Variation of streamflow residuals of six subdivision model in calibration period

4.12.10 Data and data period for Antecedent Moisture Conditions

For the study of effect of Antecedent Moisture Condition (AMC), rainfall data from 01-January-2010 to 31-December-2013 were selected and it was noted that AMC-I was more prevalent in this data set due to the occurrence of higher number of zero rainfall values. The AMC-III was the second most prevalent condition while AMC-II was the least prevalent. For the analysis, only AMC-III data was selected for targeting peak flood management alternatives. This was due to the fact that when AMC-III condition occurs, the soil is fully saturated with an even higher chance of flood occurrences with this condition.

4.12.11 Evaluation criteria for AMC calculations

The initial AMC calculations were performed using literature support. Different researchers have defined AMC in different ways to carry out their studies related to AMC as shown in the Appendix F.

In Appendix F, the results shows the ranks given to each research work carried out in related to AMC by different researchers. After scrutinizing the findings of the literature survey, it was noted that Hawkins et al. (1985) shows the best results which was ranked number 1with an RMSE value of 13.5 and found to be the method with the least error as compared to other research. Therefore, Hawkins equation was selected for the calculation of AMC-III and AMC-I in the present study.

4.12.12 Evaluation of AMC model

1) From the analysis results, it was found that the AMC-III condition produces better model results when compared to the others.
2) a) Accuracy of model results increased by 12.04% with a Nash value of 0.709 for AMC-III as compared to AMC-II with a Nash value of only 0.416 for calibration period.

   b) Accuracy increased by 6.60% with a Nash value of 0.573 for AMC-III as compared to AMC-II with a Nash value of only 0.29 for validation period.

5.0 CONCLUSIONS AND RECOMMENDATIONS

5.1 Conclusion

1. The HEC-HMS model simulations with 3, 6, 9 and 16 watershed subdivisions in Badalgama watershed were used to study the effect of watershed subdivision and antecedent moisture content on model performance. The model with 6 subdivisions produced and improved accuracy of 4.687% in calibration period and 4.636% for validation periods with respect to lumped model. Based on the findings of the present research, it can be concluded that the subdivision of watersheds for modeling results in no more than modest improvements in prediction of low flows and medium flows.
2. It can be emphasized that the improvements generally disappear when the number of subdivisions reaches a relatively small number, something between six and nine sub-watersheds.
3. Further, the watershed subdivision multiplies the number of model parameters to be estimated and discriminating parameter values between subdivisions is difficult to justify from a technical perspective. Among all parameters, the soil percolation is the most sensitive parameter which has a 43.09% change in runoff with 66.67% change in parameter value and the tension storage is the least sensitive parameter with only a 3.31% runoff change with a similar 66.67% change in the parameter value.
4. Higher number of subdivision, as implemented in HEC-HMS, was difficult and time-consuming and the only minute improvement achieved in model results is not worth considering the level of effort required to develop the models.
5. As the result shows in the AMC analysis, the AMC-III condition gives more reliable results with model result improvements of 12.04% in calibration period and 6.60% for validation period as compared to AMC-II for the modelling of peak discharge targeting flood management alternatives.
6. The modeler calculates AMC-II condition by using watershed characteristics. This often leads to produce inaccurate model simulation results when soil is fully saturated during the rainy periods and AMC-III can produce better results under such circumstances.

5.2 Recommendations

1. In this research the recession method was considered for base flow estimation, and that let to mass balance error exceeding 20% therefore it is recommended that for improved accuracy to considered linear reservoir method as base flow to conserve the water balance.
2. In this research stream network is considered for watershed subdivisions therefore for further accuracy it is recommended that land use, and slope should have considered.
3. Modeler should consider AMC-III also for the design of structure under saturated soil conditions.

LIST OF REFERENCES

Abushandi, E., & Merkel, B. (2013). Modelling Rainfall Runoff Relations Using HEC-HMS and IHACRES for a Single Rain Event in an Arid Region of Jordan. *Water Resources Management*, *27*(7), 2391–2409.

Amorocho, J., Dougal, M. D., Mcfall, R. L., & Jones, B. A. (1962). Discussion of Predicting Storm Runoff on Small Experimental Watersheds by Neal E. Minshall. *Transactions of the American Society of Civil Engineers*, *127*(1), 646–656.

Ao, T., Yoshitani, J., Takeuchi, K., Fukami, K., Mutsuura, T., & Ishidaira, H. (2003). Effects of sub-basin scale on runoff simulation in distributed hydrological model: BTOPMC. In *Weather Radar Information and Distributed Hydrological Modelling (Proceedings of symposium HS03 held during IUGG2003 at Sapporo, July 2003)* (Vol. 282, pp. 1–7). IAHS Publ.

Beven, K. (2008). From: Rainfall-Runoff Modelling: The Primer.

Beven, K. (2012). *Rainfall-Runoff Modelling: The Primer*. Chichester, UK: John Wiley & Sons, Ltd.

Bhattacharjya, R. K. (2011). Rainfall-Runoff Modeling: Distributed Models. *Encyclopedia of Hydrological Sciences*, 270–275.

Bingner, R. ., Arnold, J. ., & Srinivasan, R. (1997). Effect of watershed subdivision on simulation runoff and fine sediment yield - ScienceBase-Catalog, *40(5)*(Transaction of the ASAE), 1329– 1335.

Bloschl, G., & Sivapalan, M. (1995). Scale issues in hydrological modelling: A review. *Hydrological Processes*, *9*(3–4), 251–290.

Boyle, D. P., Gupta, H. V, & Sorooshian, S. (2000). Toward improved calibration of hydrologic models: Combining the strengths of manual and automatic methods. *Water Resources Research*, *36*(12), 3663–3674.

Brocca, L., Melone, F., Moramarco, T., & Singh, V. P. (2009). Assimilation of Observed Soil Moisture Data in Storm Rainfall-Runoff Modeling. *Journal of Hydrologic Engineering*, *14*(2), 153–165.

Casey, M. J., Stagge, J. H., Moglen, G. E., & McCuen, R. H. (2015). Effects of Watershed Subdivision on Peak Discharge in Rainfall-Runoff Modeling in the WinTR-20 Model. *Journal of Hydrologic Engineering*, *20*(10), 04015020–.

Chow, V., Maidment, D., & Larry, M. (1988). *Applied Hydrology*.

Cleveland, T., Luong, T., & Thompson, D. (2009a). Water Subdivision for Modeling. In *World Environmental and Water Resources Congress 2009* (pp. 1–10). Reston, VA: American Society of Civil Engineers.

Cleveland, T., Luong, T., & Thompson, D. (2009b). Water Subdivision for Modeling. In *World Environmental and Water Resources Congress 2009* (pp. 1–10). Reston, VA: American Society of Civil Engineers.

De Silva, M. G., de Aguiar Netto, A. de O., de Jesus Neves, R. J., do Vasco, A. N., Almeida, C., & Faccioli, G. G. (2015). Sensitivity Analysis and Calibration of Hydrological Modeling of the Watershed Northeast Brazil. *Journal of Environmental Protection*, *6*(08), 837.

De Silva, M. M. G. T., Weerakoon, S. B., & Herath, S. (2014). Modeling of Event and Continuous Flow Hydrographs with HEC–HMS: Case Study in the Kelani River Basin, Sri Lanka. *Journal of Hydrologic Engineering*, *19*(4), 800–806.

Dharmasena, G. T. (1997). Application of mathematical models for flood forecasting in Sri Lanka. *ResearchGate*, (239).

Dong, Y., & Peng, C. Y. J. (2013, May). Principled missing data methods for researchers. *SpringerPlus*.

Dooge, J. C. I. (1982). Parameterization of hydrologic processes. *Cambridge University Press, New York, N.Y.*, pp : 243-288.

Ghosh, I., & Hellweger, F. L. (2012). Effects of Spatial Resolution in Urban Hydrologic Simulations. *Journal of Hydrologic Engineering*, *17*(January), 129–137.

Goodrich, D. C., Schmugge, T. J., Jackson, T. J., Unkrich, C. L., Keefer, T. O., Parry, R., Amer, S. A. (1994). Runoff simulation sensitivity to remotely sensed initial soil water content. *Water Resources Research*, *30*(5), 1393–1405.

Green, A., & Stephenson, D. (1986). Criteria for comparison of single event models. *Hydrological Sciences -Journal -Des Sciences Hydrologiques*, *313*(9).

Green, I. R. A., & Stephenson, D. (2009). Criteria for comparison of single event models. *Hydrological Sciences Journal*, *31*(3), 395–411.

Guinot, V., Cappelaere, B., Delenne, C., & Ruelland, D. (2011). Towards improved criteria for hydrological model calibration: theoretical analysis of distance- and weak form-based functions. *Journal of Hydrology*, *401*(1–2), 1–13.

Gunatilaka, A. (2008). Water security and related issues in Sri Lanka : The need for integrated water resource management (IWRM). *Journal of the National Science Foundation of Sri Lanka*, *36 Special*(3), 3–15.

Gupta, H. V., Beven, K., & Wagener, T. (2005). Model Calibration and Uncertainty Estimation. *Encyclopedia of Hydrological Sciences*, *11(131)*, 1–17.

Gupta, H. V., Kling, H., Yilmaz, K. K., & Martinez, G. F. (2009). Decomposition of the mean squared error and NSE performance criteria: Implications for improving hydrological modelling. *Journal of Hydrology*, *377*(1–2), 80–91. 3

Halwatura, D., & Najim, M. M. M. (2013). Application of the HEC-HMS model for runoff simulation in a tropical catchment. *Environmental Modelling and Software*, *46*, 155–162.

Hawkins, R. H. (1978). Runoff Curve Numbers With Varying Site Moisture. *ASCE J Irrig Drain Div*.

Hawkins, R. H., Hjelmfelt, A. T., & Zevenbergen, A. W. (1985). Runoff Probability, Storm Depth, and Curve Numbers. *Journal of Irrigation and Drainage Engineering*, *111*(4), 330–340.

Jain, M. K., Mishra, S. K., & Singh, V. P. (2006). Evaluation of AMC-dependent SCS-CN-based models using watershed characteristics. *Water Resources Management*, *20*(4), 531–552.

Jha, M. K. (2002). Level of watershed subdivision for water quality modeling. *Master's Thesis, Iowa State University*.

Kanchanamala, D. P. H. M., Herath, H. M. H. K., & Nandalal, K. D. W. (2016). Impact of Catchment Scale on Rainfall Runoff Modeling: Kalu Ganga River Catchment upto Ratnapura. *Engineer: Journal of the Institution of Engineers, Sri Lanka*, *49*(2), 1.

Klemes, V. (1983). Conceptualization and scale in hydrology. *Journal of Hydrology*, *65*(1–3), 1–23.

Krause, P., Boyle, D. P., & Base, F. (2005). Comparison of different efficiency criteria for hydrological model assessment. *Advances in Geosciences*, *5*, 89–97.

Kumar, S., & Merwade, V. (2009a). Impact of watershed subdivision and soil data resolution on swat model calibration and parameter uncertainty. *Journal of the American Water Resources Association*, *45*(5), 1179–1196.

Kumar, S., & Merwade, V. (2009b). Impact of Watershed Subdivision and Soil Data Resolution on SWAT Model Calibration and Parameter Uncertainty. *JAWRA Journal of the American Water Resources Association*, *45*(5), 1179–1196.

Legates, D. R., & Mccabe, G. J. (1999). Evaluating the use of "goodness-of-fit" Measures in hydrologic and hydroclimatic model validation. *Water Resources Research*, *35*(1), 233–241.

Li, K. Y., Coe, M. T., Ramankutty, N., & deJong, R. (2007). Modeling the hydrological impact of land-use change in West Africa. *Journal of Hydrology*, *337*(3–4), 258–268.

Lim, K. J., Engel, B. A., Muthukrishnan, S., & Harbor, J. (2006). Effects of initial abstraction and urbanization on estimated runoff using CN technology. *Journal of the American Water Resources Association*, *42*(3), 629–643.

Lundin, L.-C., Linner, H., Hultman, B., Levlin, E., Eriksson, E., & Johansson, S. (2000). *Sustainable Water Manangement in the Baltic Sea Basin - Water Use and Management* (2nd ed.). Sweden: A Baltic University Programme Publication.

Merriam, C. F. (1937). A comprehensive study of the rainfall on the Susquehanna Valley. *Eos, Transactions American Geophysical Union*, *18*(2), 471–476.

Minshall, N. E. (1962). Predicting Storm Runoff on Small Experimental Watersheds. *Transactions of the American Society of Civil Engineers*, *127*(1), 625–645.

Moatamednia, M., Nohegar, A., Malekian, A., & Zarchi, K. K. (2015). Performance of Different Models for Curve Number Estimation (Case study : Bar Watershed in Khorasan Razavi Province , Iran). *Ecopersia*, *3*(3), 1031–1049.

Moeletsi, M. E., Shabalala, Z. P., Nysschen, G. De, & Walker, S. (2016). Evaluation of an inverse distance weighting method for patching daily and dekadal rainfall over the Free State Province, South Africa. *Water SA*, *42*(3), 466–474.

Moore, C., & Doherty, J. (2005). Role of the calibration process in reducing model predictive error. *Water Resources Research*, *41*(5), 1–14.

Moradkhani, H. and Sorooshian, S. (2008). General Review of Rainfall-Runoff Modeling: Model Calibration, Data Assimilation, and Uncertainty Analysis, in Hydrological Modeling and Water Cycle, Coupling of the Atmospheric and Hydrological Models. *Springer, Water Science and Technology Library, Volume 63, Part 1, 1-24, DOI: 10.1007/978-3-540-77843-1-1.*, 291p.

Moriasi, D. N., Arnold, J. G., Liew, M. W. Van, Bingner, R. L., Harmel, R. D., Veith, T. L., … Moriasi, D. N. (2007). Model Evaluation Guidelines For Systematic Quantification Of Accuracy In Watershed Simulations. *Transactions of the ASABE*, *50*(3), 885–900.

Mu, X. M., Zhang, X. Q., Gao, P., & Wang, F. (2010). Theory Of Double Mass Curves And Its Applications In Hydrology And Meteorology. *Journal China Hydrology*, *30*(4), 47–51.

Munz, E. D. (2017). Psychotherapie in der Psychiatrie. *Nervenheilkunde*, *36*(10), 800–805.

National Climate Change Adaptation Strategy for Sri Lanka 2011 to 2016. (2016).

Neitsch S.L., Arnold J.G., Kiniry J.R., Williams J.R., King K.W. (2002). Soil and water assessment tool (SWAT): theoretical documentation, version 2000. Texas Water Resources Institute, College Station, TX, TWRI Report TR-191.

Orellana, B., Pechlivanidis, I. G., McIntyre, N., Wheater, H. S., & Wagener, T. (2008). A toolbox for the identification of parsimonious semi-distributed rainfall-runoff models: Application to the Upper Lee catchment. In *iEMSs 2008: Integrating Sciences and Information Technology for Environmental Assessment and Decision Making* (Vol. 1, pp. 670–677).

Pathiraja, S., Westra, S., & Sharma, A. (2012). Why continuous simulation? the role of antecedent moisture in design flood estimation. *Water Resources Research*, *48*(6), 1–15.

Pechlivanidis, I. G., Jackson, B. M., Mcintyre, N. R., & Wheater, H. S. (2011). Catchment Scale Hydrological Modelling: A Review Of Model Types, Calibration Approaches And Uncertainty Analysis Methods In The Context Of Recent Developments In Technology And Applications. *Global NEST Journal*, *13*(3), 193–214.

Perrin, C., Michel, C., & Andreassian, V. (2001). Does a large number of parameters enhance model performance? Comparative assessment of common catchment model structures on 429 catchments. *Journal of Hydrology*, *242*(3–4), 275–301.

Ponce, V. M., & Hawkins, R. H. (1996). Runoff Curve Number: Has It Reached Maturity? *Journal of Hydrologic Engineering*, *1*(1), 11–19.

Ratnayake, U., Sachindra, D. A., & Nandalal, K. D. W. (2010). Rainfall Forecasting for Flood Prediction in the Nilwala Basin, (December), 13–14.

Refsgaard, J. C. (1997). Parameterisation, calibration and validation of distributed hydrological models. *Journal of Hydrology*, *198*(1–4), 69–97.

Ritter, A., & Muñoz-Carpena, R. (2013). Performance evaluation of hydrological models: Statistical significance for reducing subjectivity in goodness-of-fit assessments. *Journal of Hydrology*, *480*, 33–45.

Sampath, D. S., Weerakoon, S. B., & Herath, S. (2014). Runoff Simulation in the Deduru Oya River Basin, Sri Lanka. In *Conference on Sri Lanka–Japan Collaborative Research 2014 (SLJCR 2014), At University of Peradeniya, Peradeniya, Sri Lanka* (p. 3).

Scharffenberg, W. (2016). Hydrologic Modeling System HEC-HMS User's Manual CPD-74A.

Searcy, J. ., & Hardison, C. . (1960). . Double Mass Curves. U.S. Geological Survey. *Water-Supply Paper*, *1541–B.*, pp1541–B.

Sobhani, G. (1975). *A Review of Selected Small Watershed Design Methods for Possible Adoption to Iranian Conditions M.S. thesis*. Utah State Univ., Logan, Utah.

Soil Conservation Service. (2007a). *National engineering handbook. Supplement A,Section 4*. Soil Conservation Service, USDA, Washington, D.C.

Soil Conservation Service. (2007b). *National engineering handbook*. (V. McKeever, W. Owen, & R. Rallison, Eds.).

Sorooshian, S., & Gupta, V. . (1995a). *Model Calibration, Computer models of watershed hydrology. Water Resources Publications, USA.*

Sorooshian, S., & Gupta, V. K. (1995b). Model Calibration, Computer models of watershed hydrology. *Water Resources Publications, USA.*

Tripathi, M. P., Raghuwanshi, N. S., & Rao, G. P. (2006). Effect of watershed subdivision on simulation of water balance components. *Hydrological Processes*, *20*(5), 1137–1156.

USDA, S. C. S. (1972). National Engineering Handbook. *Soil Conservation, Hydrology*, 10.1-10.24. Retrieved from

Van Liew, M. W., & Veith, T. L. (2010). Guidelines for Using the Sensitivity Analysis and Auto-calibration Tools for Multi-gage or Multi-step Calibration in SWAT, 1–30.

Viessman, W., Lewis, G. L., & Knapp, J. W. (2002). Introduction to hydrology. *Introduction to Hydrology*, 780.

Vorosmarty, C. J., Moore III, B., Grace, A. L., Gildea, M. P., Melillo, J. M., Peterson, B. J., … Steudler, P. A. (1989). Continental scale models of water balance and fluvial transport: An application to South America. *Global Biogeochem. Cycles*, *3*(3), 241–265.

Wagener, T., & Kollat, J. (2007). Numerical and visual evaluation of hydrological and environmental models using the Monte Carlo analysis toolbox. *Environmental Modelling and Software*, *22*(7), 1021–1033.

Wagener, T., Sivapalan, M., Troch, P., & Woods, R. (2007). Catchment Classification and Hydrologic Similarity. *Geography Compass*, *1*(4), 901–931.

Wei, H., & Zhang, Y. (2011). Effects of antecedent soil moisture on runoff modeling in small semiarid watersheds of southeastern Arizona. *Hydrol. Earth Syst. Sci.*, *15*(10), 3171–3179.

Wijesekera, N. T. S., Imbulana, K. A. U. & Neupane, B. (2005). Surface water resources, Proceedings Workshop on Sri Lanka National Water Development Report. *World Water Assessment Programme. Paris, France*.

Wijesekera, N. T. S., & Abeynayake, J. (2003). Watershed similarity conditions for peak flow transition. A study of river basins in the wet zone of Sri Lanka,. *Engineer Journal of the Institution of Engineers, Sri Lank*.

Willmott, C. J., Ackleson, S. G., Davis, R. E., Feddema, J. J., Klink, K. M., Legates, D. R., … Rowe, C. M. (1985). STATISTICS FOR THE EVALUATION AND COMPARISON OF MODELS. *Journal of Geophysical Research-Oceans*, *90*(NC5), 8995–9005.

Wooldridge, S. A., Kalma, J. D., & Walker, J. P. (2003). Importance of soil moisture measurements for inferring parameters in hydrologic models of low-yielding ephemeral catchments. *Environmental Modelling and Software*, *18*(1), 35–48.

World Meteorological Organization. (1975). Geneva; Switzerland. https://doi.org/(Operational hydrology report no.7/WMO-No 429).

World Meteorological Organization. (1982). WMO project for the intercomparison of conceptual models of snowmelt runoff. In *Hydrological Aspects of Alpine and High-Mountain Areas* (pp. 193–202).

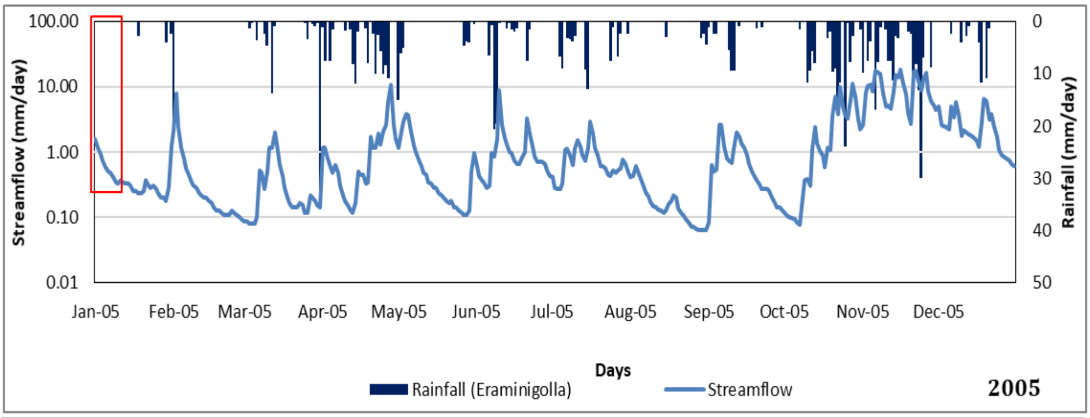
Wu, Y., & Liu, S. (2014). A suggestion for computing objective function in model calibration. *Ecological Informatics*, *24*, 107–111.

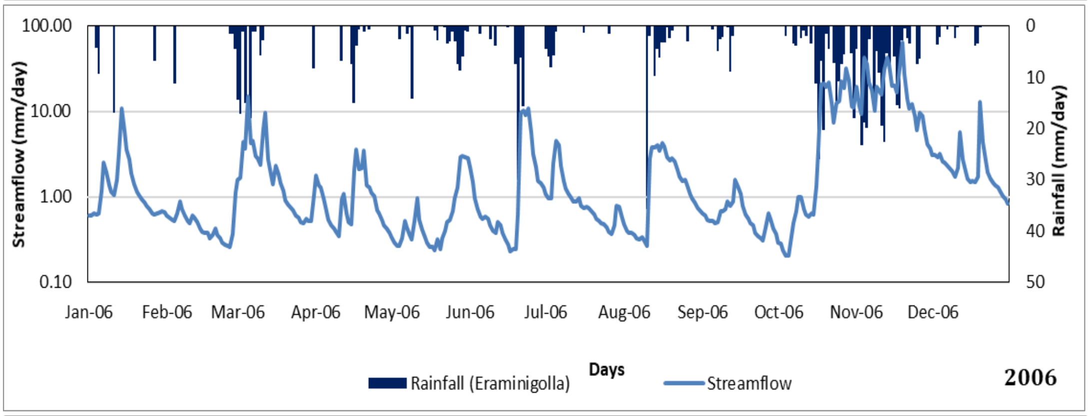
Zhang, H. L., Wang, Y. J., Wang, Y. Q., Li, D. X., & Wang, X. K. (2013). The effect of watershed scale on HEC-HMS calibrated parameters: A case study in the Clear Creek watershed in Iowa, US. *Hydrology and Earth System Sciences*, *17*(7), 2735–2745.

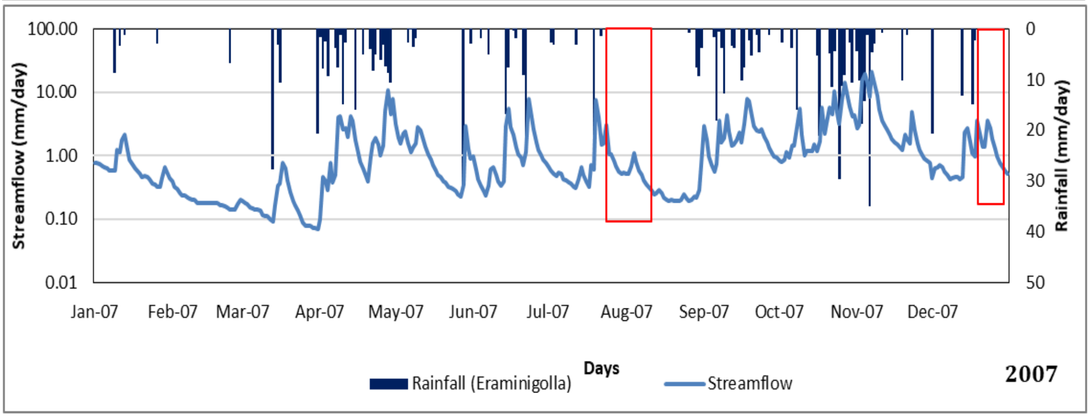
Zhou, X., & Lin, H. (2017). Sensitivity Analysis. In *Encyclopedia of GIS* (1 edition, pp. 1884–1887). Chichester; New York: Wiley.

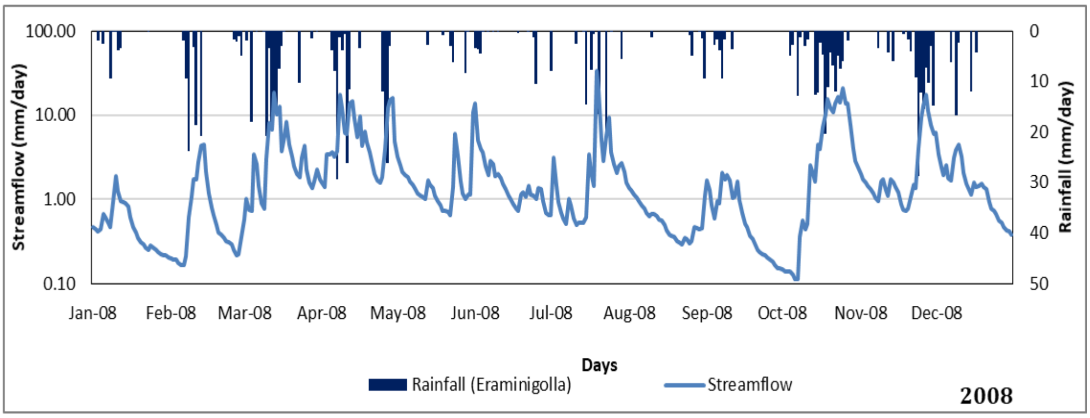
Appendix A: Visual checking of data without filling missing data in calibration and validation period

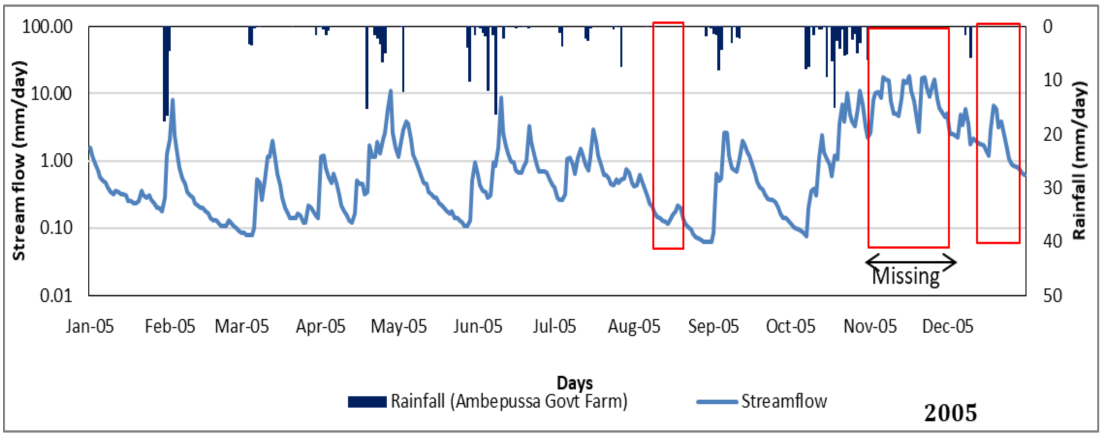
Visual checking without filling missing data in calibration period

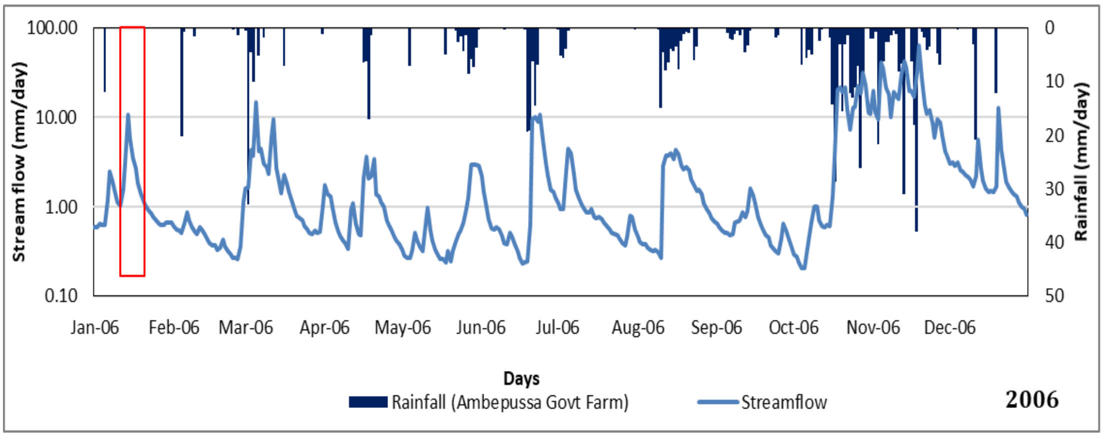


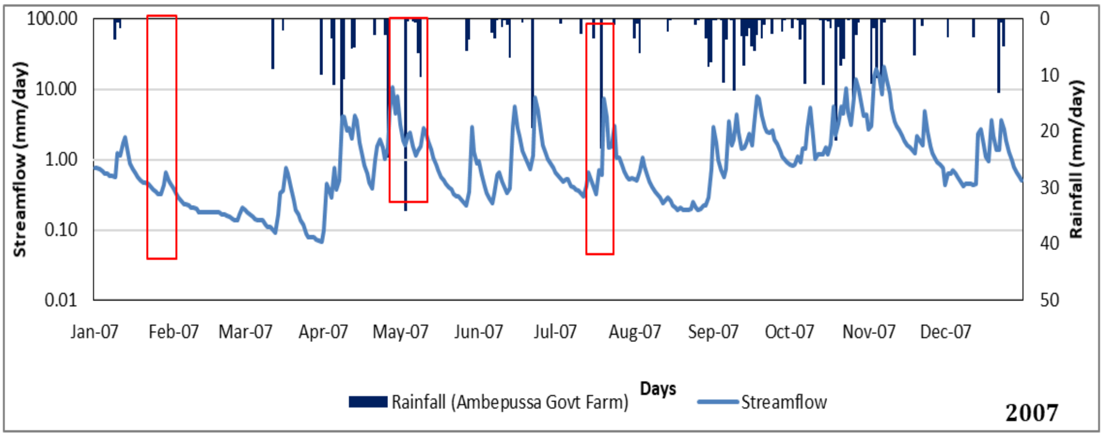


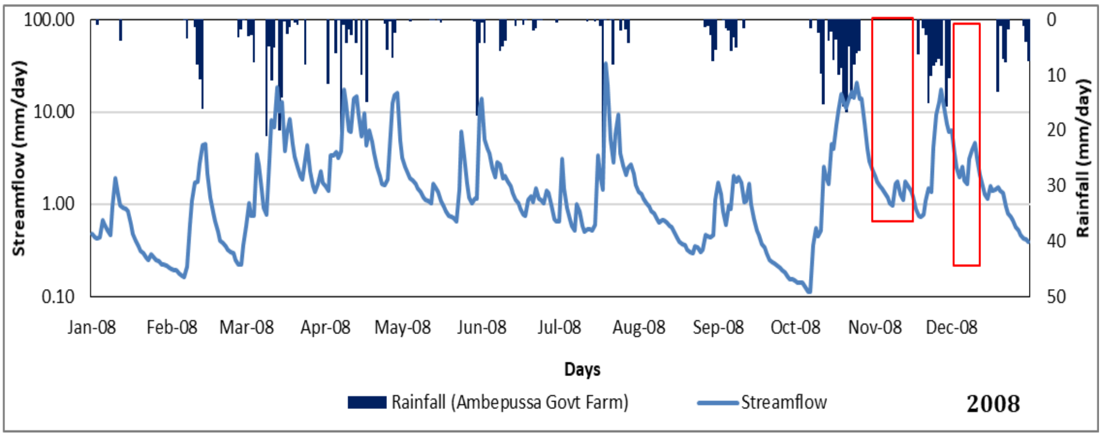


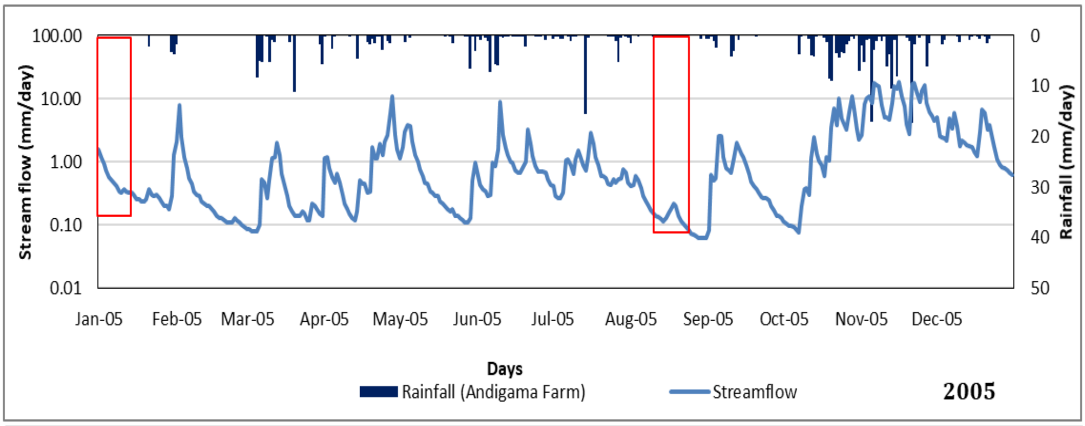


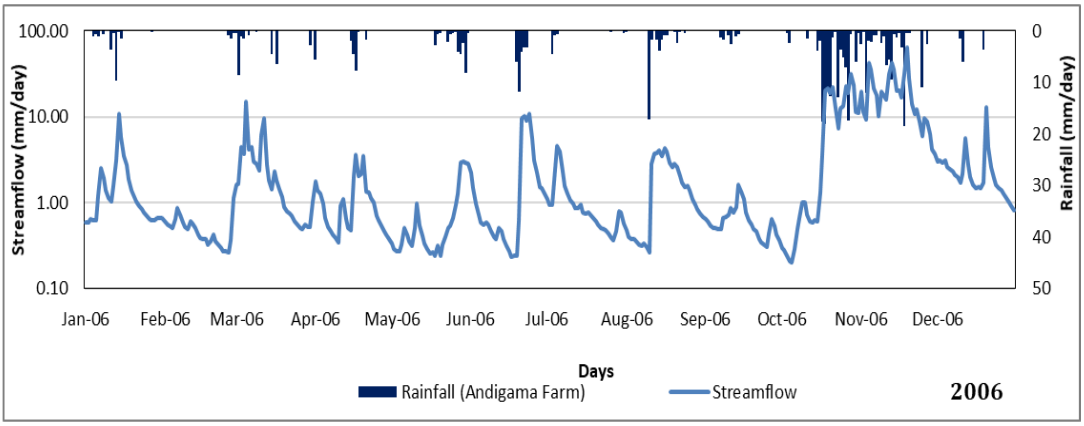

Stream flow (mm/day)
100.00
10.00
1.00
0.10
0.01
Rainfall (mm/day)
0
10
20
30
40
50
Missing
Jan-05
Feb-05
Mar-05
Apr-05
May-05
Jun-05
Jul-05
Aug-05
Sep-05
Oct-05
Nov-05
Dec-05
Days
Rainfall (Ambepussa Govt Farm)
Streamflow
2005

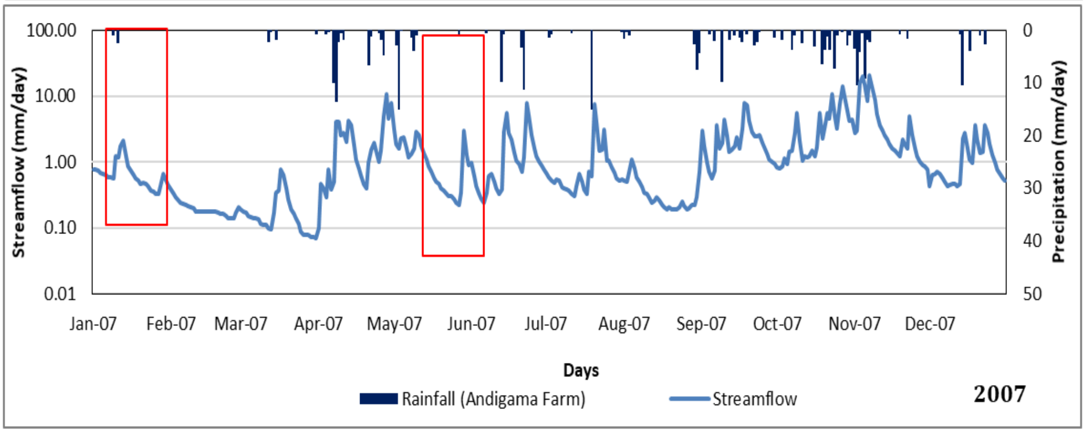

Stream flow (mm/day)
100.00
10.00
1.00
0.10
Rainfall (mm/day)
0
10
20
30
40
50
Jan-06
Feb-06
Mar-06
Apr-06
May-06
Jun-06
Jul-06
Aug-06
Sep-06
Oct-06
Nov-06
Dec-06
Days
Rainfall (Ambepussa Govt Farm)
Streamflow
2006

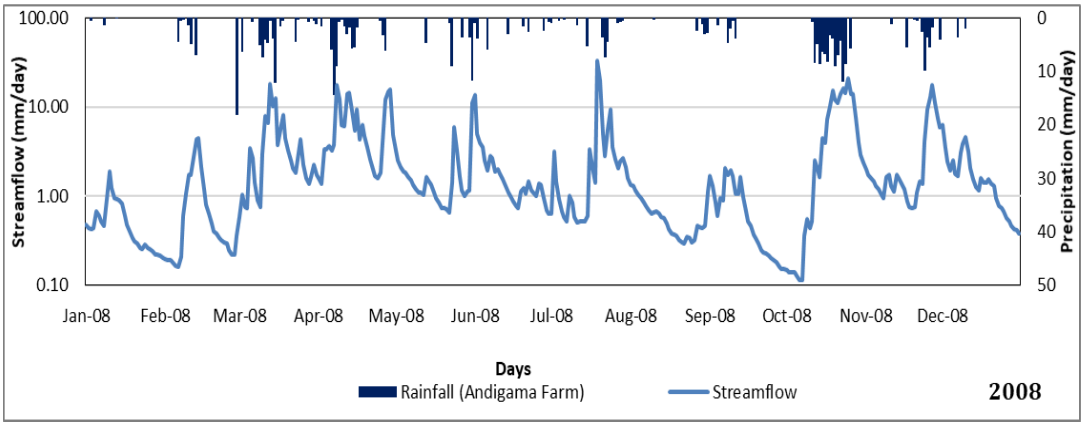

Streamflow (mm/day)
100.00
10.00
1.00
0.10
0.01
Rainfall (mm/day)
0
10
20
30
40
50
Jan-07
Feb-07
Mar-07
Apr-07
May-07
Jun-07
Jul-07
Aug-07
Sep-07
Oct-07
Nov-07
Dec-07
Days
Rainfall (Ambepussa Govt Farm)
Streamflow
2007

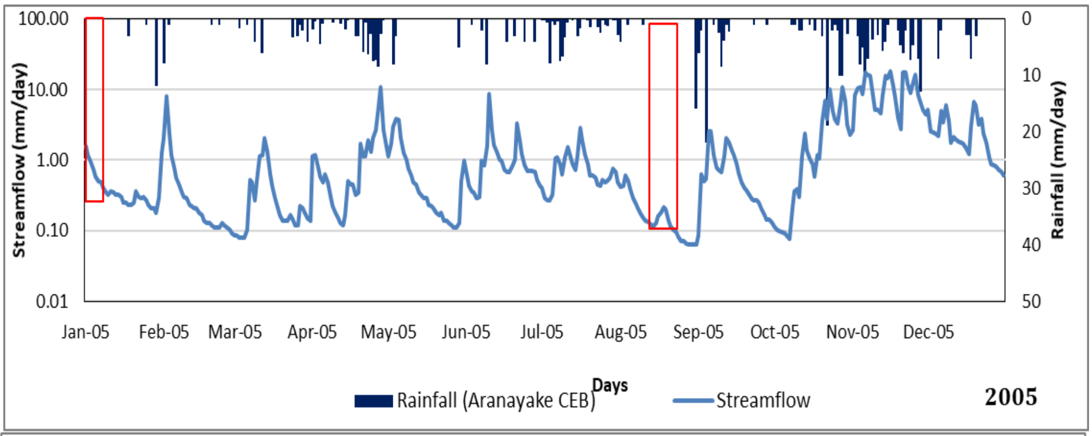

Streamflow (mm/day)
100.00
10.00
1.00
0.10
Rainfall (mm/day)
0
10
20
30
40
50
Jan-08
Feb-08
Mar-08
Apr-08
May-08
Jun-08
Jul-08
Aug-08
Sep-08
Oct-08
Nov-08
Dec-08
Days
Rainfall (Ambepussa Govt Farm)
Streamflow
2008

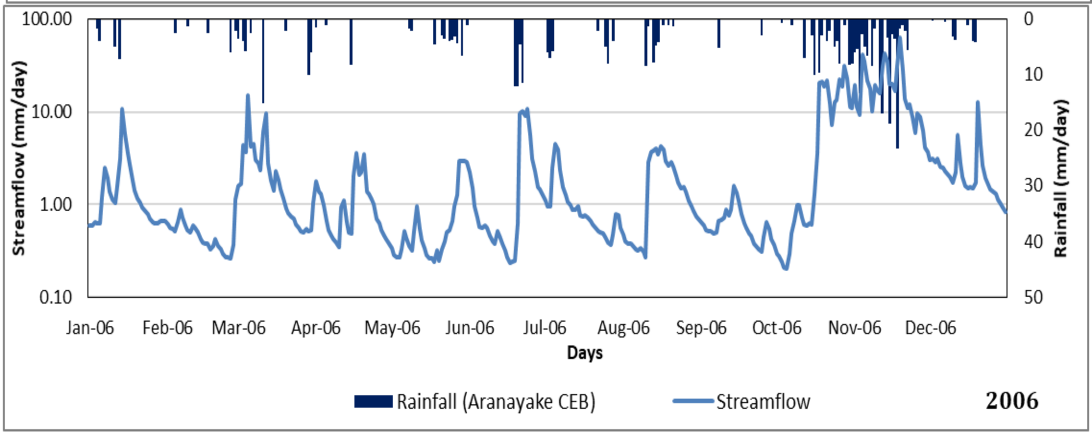

Stream flow (mm/day)
100.00
10.00
1.00
0.10
0.01
0
10
20
30
40
50
Rainfall (mm/day)
Jan-05
Feb-05
Mar-05
Apr-05
May-05
Jun-05
Jul-05
Aug-05
Sep-05
Oct-05
Nov-05
Dec-05
Days
Rainfall (Andigama Farm)
Streamflow
2005

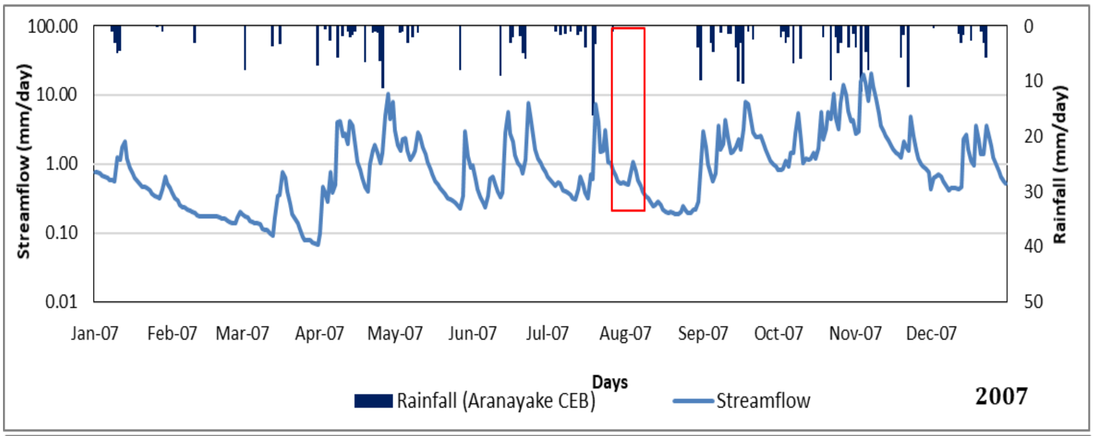

Streamflow (mm/day)
100.00
10.00
1.00
0.10
0
10
20
30
40
50
Rainfall (mm/day)
Jan-06
Feb-06
Mar-06
Apr-06
May-06
Jun-06
Jul-06
Aug-06
Sep-06
Oct-06
Nov-06
Dec-06
Days
Rainfall (Andigama Farm)
Streamflow
2006

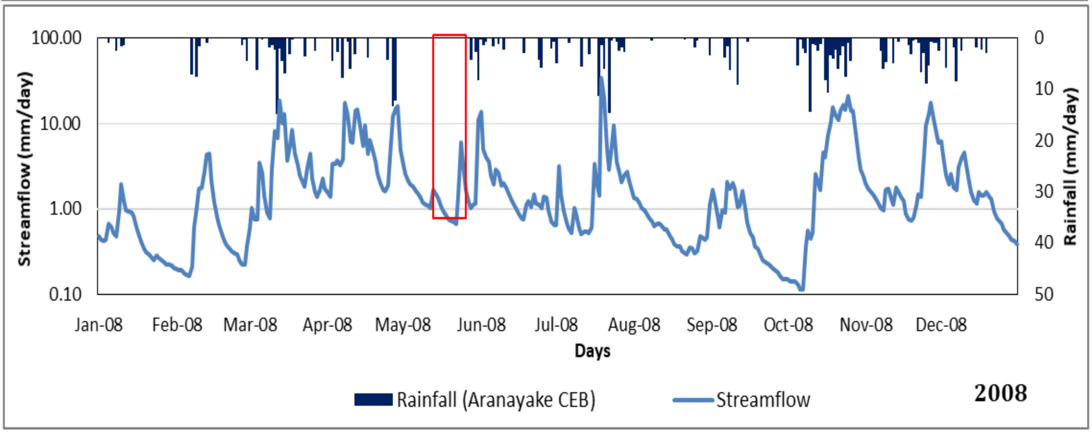

Streamflow (mm/day)
100.00
10.00
1.00
0.10
0.01
0
10
20
30
40
50
Precipitation (mm/day)
Jan-07
Feb-07
Mar-07
Apr-07
May-07
Jun-07
Jul-07
Aug-07
Sep-07
Oct-07
Nov-07
Dec-07
Days
Rainfall (Andigama Farm)
Streamflow
2007


Streamflow (mm/day)
100.00
10.00
1.00
0.10
0
10
20
30
40
50
Precipitation (mm/day)
Jan-08
Feb-08
Mar-08
Apr-08
May-08
Jun-08
Jul-08
Aug-08
Sep-08
Oct-08
Nov-08
Dec-08
Days
Rainfall (Andigama Farm)
Streamflow
2008

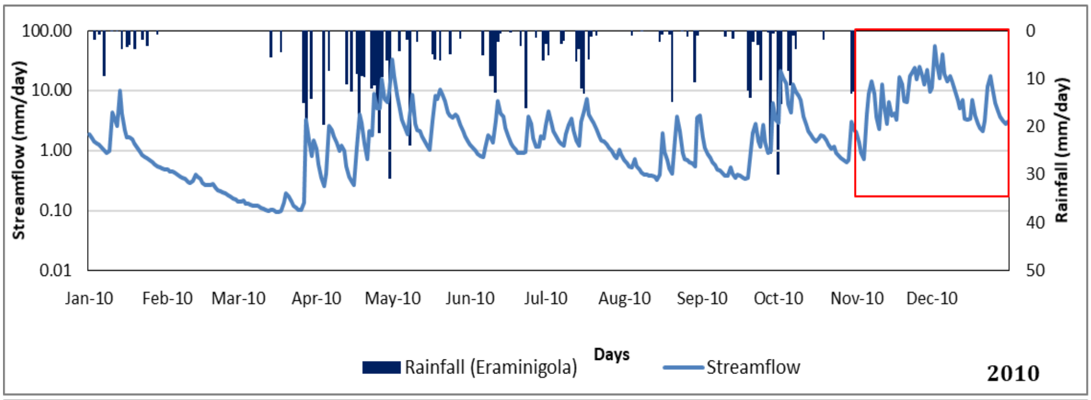

Streamflow (mm/day)
100.00
10.00
1.00
0.10
0.01
Rainfall (mm/day)
0
10
20
30
40
50
Jan-05
Feb-05
Mar-05
Apr-05
May-05
Jun-05
Jul-05
Aug-05
Sep-05
Oct-05
Nov-05
Dec-05
Days
Rainfall (Aranayake CEB)
Streamflow
2005

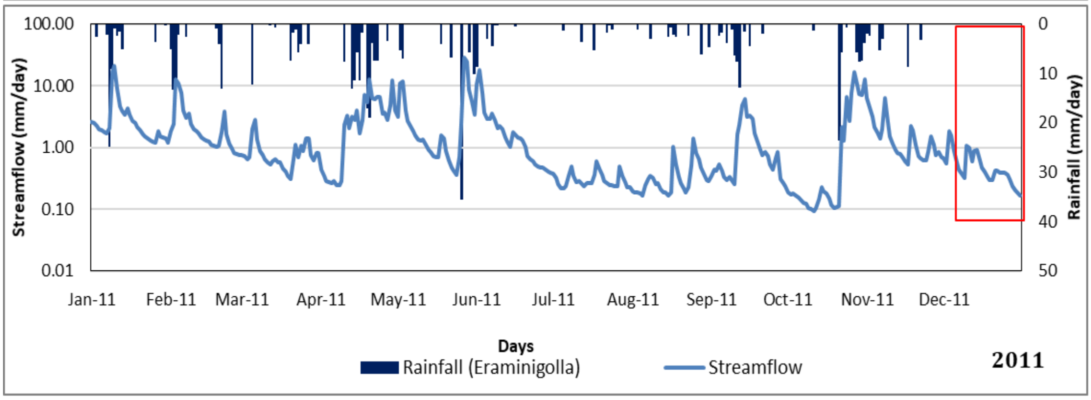

Streamflow (mm/day)
100.00
10.00
1.00
0.10
Rainfall (mm/day)
0
10
20
30
40
50
Jan-06
Feb-06
Mar-06
Apr-06
May-06
Jun-06
Jul-06
Aug-06
Sep-06
Oct-06
Nov-06
Dec-06
Days
Rainfall (Aranayake CEB)
Streamflow
2006

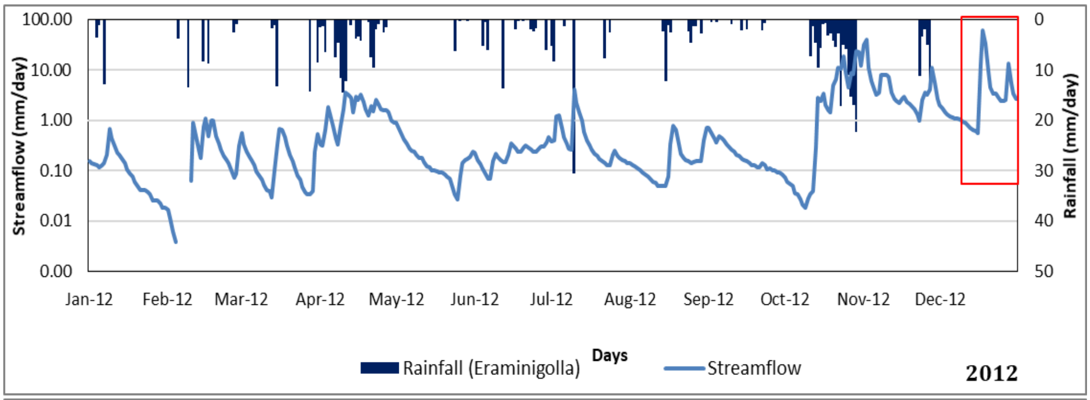

Streamflow (mm/day)
100.00
10.00
1.00
0.10
0.01
Rainfall (mm/day)
0
10
20
30
40
50
Jan-07
Feb-07
Mar-07
Apr-07
May-07
Jun-07
Jul-07
Aug-07
Sep-07
Oct-07
Nov-07
Dec-07
Days
Rainfall (Aranayake CEB)
Streamflow
2007

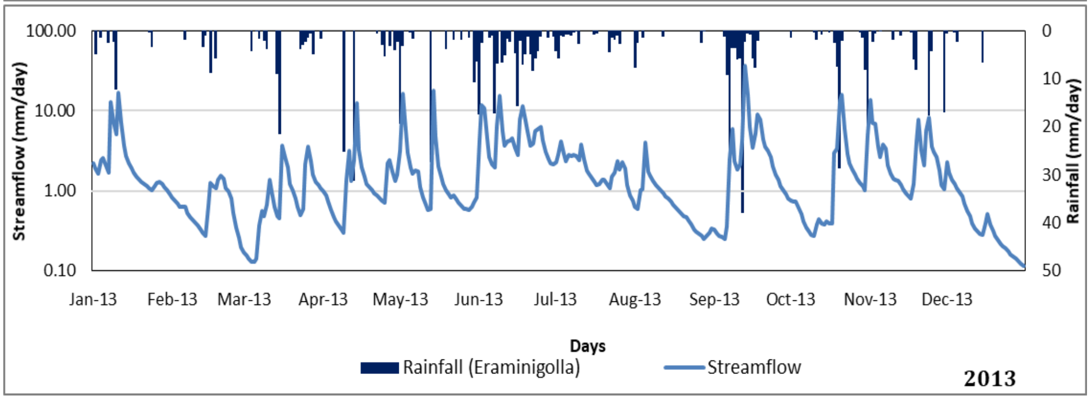

Streamflow (mm/day)
100.00
10.00
1.00
0.10
Rainfall (mm/day)
0
10
20
30
40
50
Jan-08
Feb-08
Mar-08
Apr-08
May-08
Jun-08
Jul-08
Aug-08
Sep-08
Oct-08
Nov-08
Dec-08
Days
Rainfall (Aranayake CEB)
Streamflow
2008

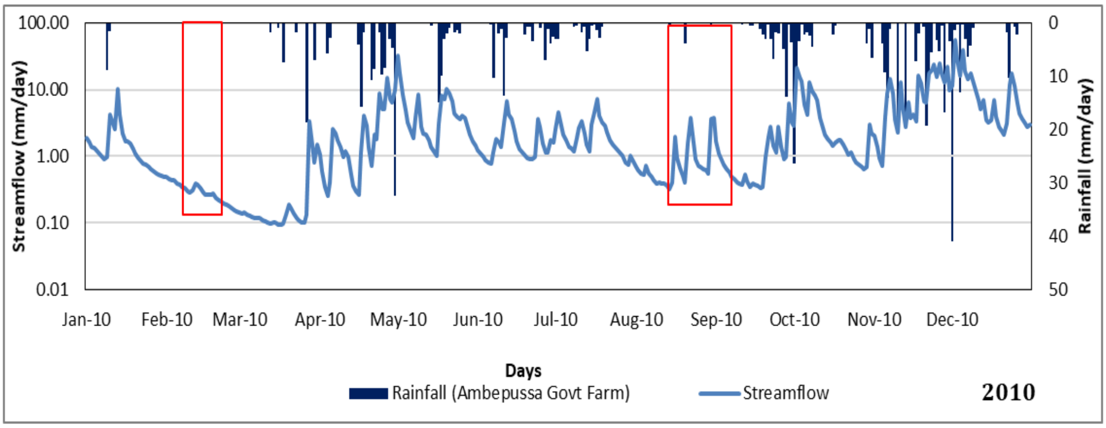
Visual checking without filling missing data in validation period

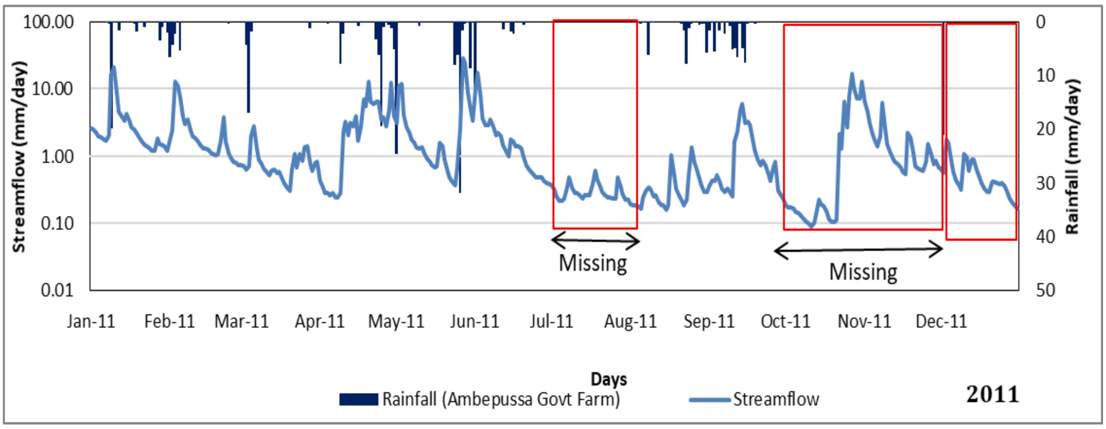


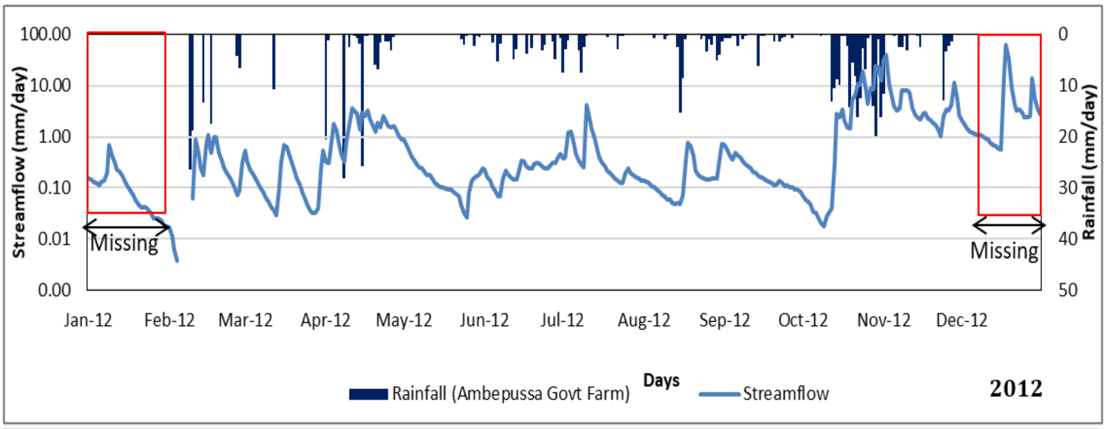


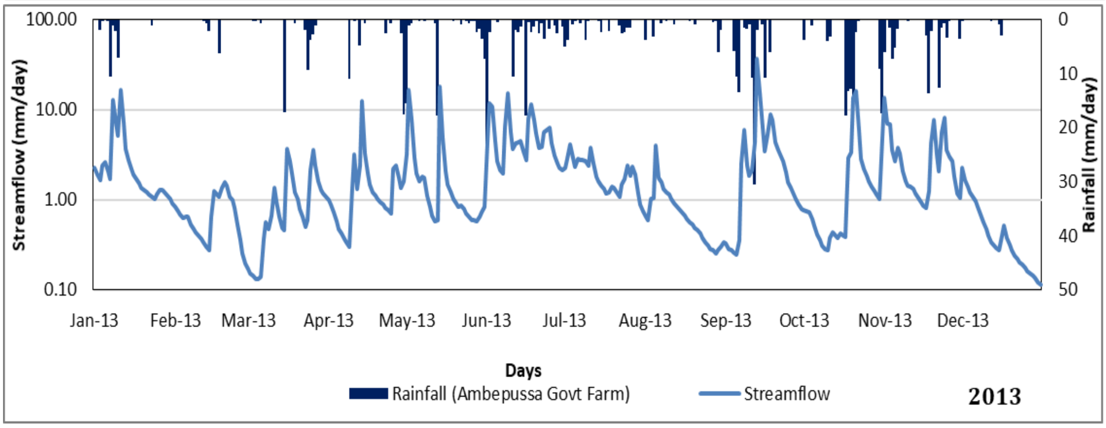


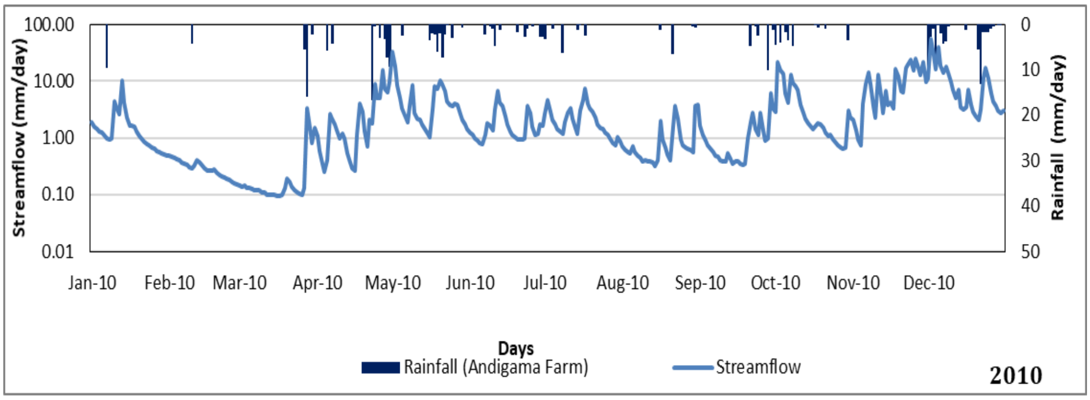


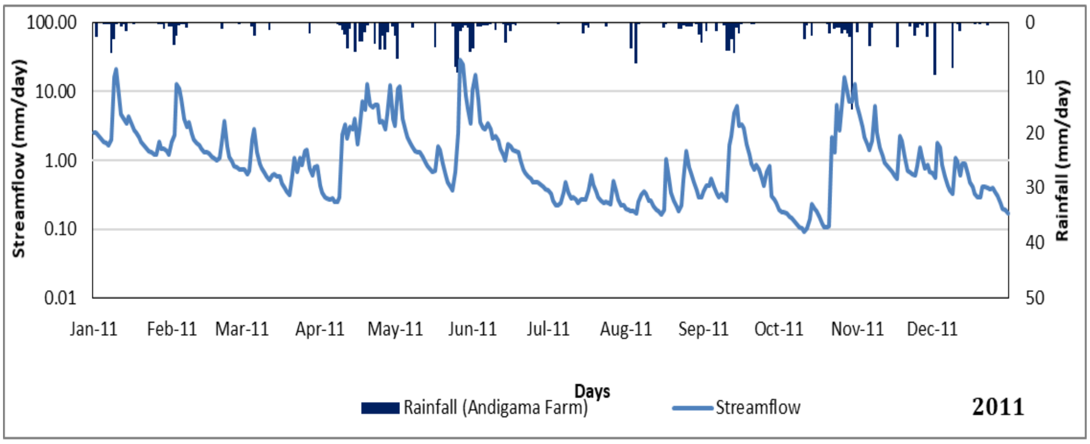

Streamflow (mm/day)
100.00
10.00
1.00
0.10
0.01
Rainfall (mm/day)
0
10
20
30
40
50
Jan-10 Feb-10 Mar-10 Apr-10 May-10 Jun-10 Jul-10 Aug-10 Sep-10 Oct-10 Nov-10 Dec-10
Days
Rainfall (Ambepussa Govt Farm)
Streamflow
2010

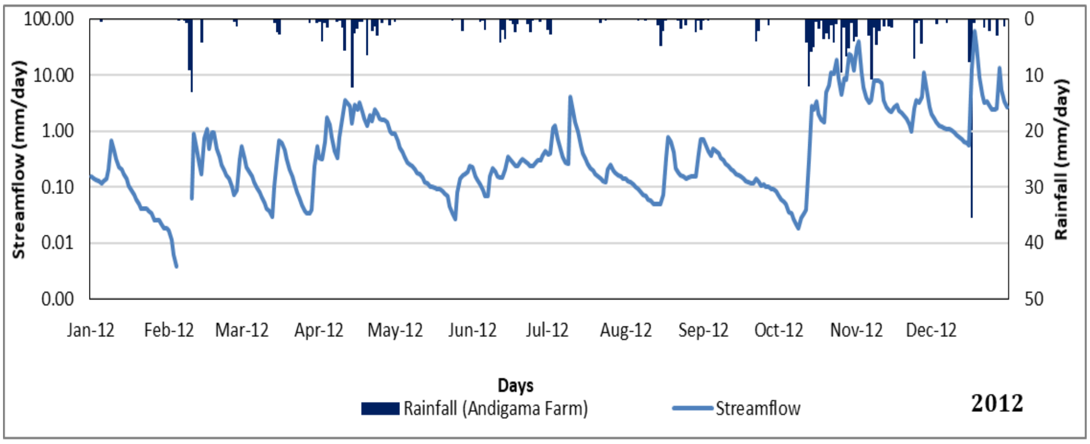

Streamflow (mm/day)
100.00
10.00
1.00
0.10
0.01
Rainfall (mm/day)
0
10
20
30
40
50
Missing
Missing
Jan-11 Feb-11 Mar-11 Apr-11 May-11 Jun-11 Jul-11 Aug-11 Sep-11 Oct-11 Nov-11 Dec-11
Days
Rainfall (Ambepussa Govt Farm)
Streamflow
2011

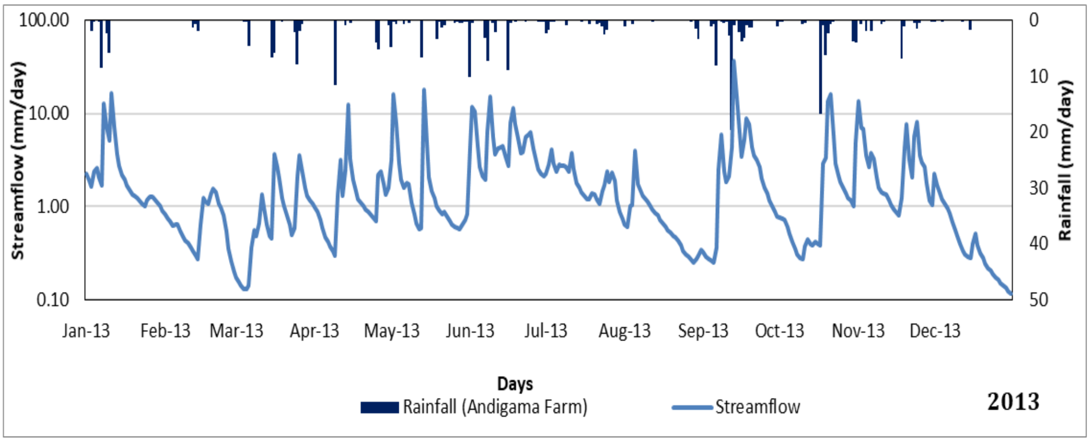

Streamflow (mm/day)
100.00
10.00
1.00
0.10
0.01
0.00
Rainfall (mm/day)
0
10
20
30
40
50
Missing
Missing
Jan-12 Feb-12 Mar-12 Apr-12 May-12 Jun-12 Jul-12 Aug-12 Sep-12 Oct-12 Nov-12 Dec-12
Days
Rainfall (Ambepussa Govt Farm)
Streamflow
2012


Streamflow (mm/day)
100.00
10.00
1.00
0.10
Rainfall (mm/day)
0
10
20
30
40
50
Jan-13 Feb-13 Mar-13 Apr-13 May-13 Jun-13 Jul-13 Aug-13 Sep-13 Oct-13 Nov-13 Dec-13
Days
Rainfall (Ambepussa Govt Farm)
Streamflow
2013

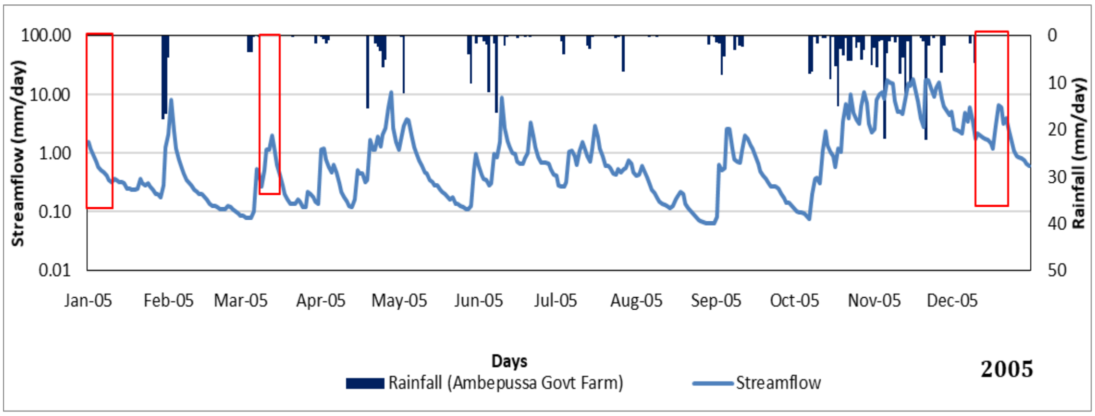

Streamflow (mm/day)
100.00
10.00
1.00
0.10
0.01
Rainfall (mm/day)
0
10
20
30
40
50
Jan-10
Feb-10
Mar-10
Apr-10
May-10
Jun-10
Jul-10
Aug-10
Sep-10
Oct-10
Nov-10
Dec-10
Days
Rainfall (Andigama Farm)
Streamflow
2010

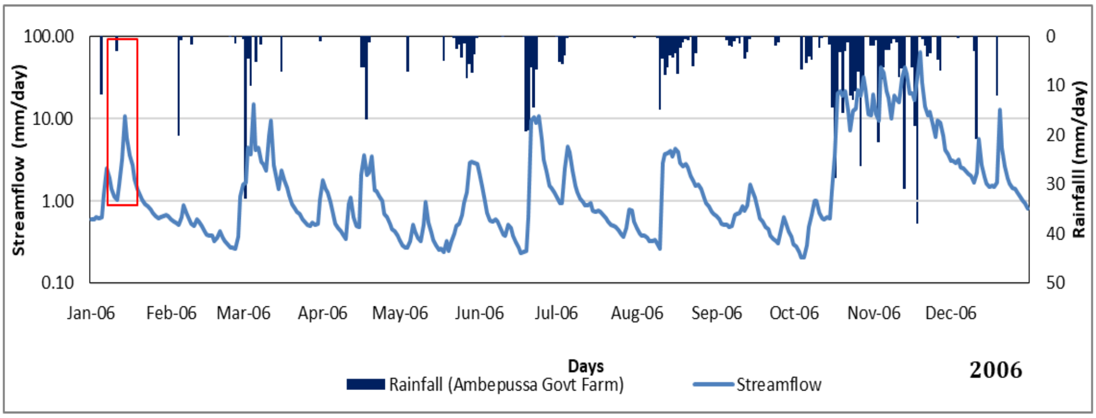

Streamflow (mm/day)
100.00
10.00
1.00
0.10
0.01
Rainfall (mm/day)
0
10
20
30
40
50
Jan-11
Feb-11
Mar-11
Apr-11
May-11
Jun-11
Jul-11
Aug-11
Sep-11
Oct-11
Nov-11
Dec-11
Days
Rainfall (Andigama Farm)
Streamflow
2011

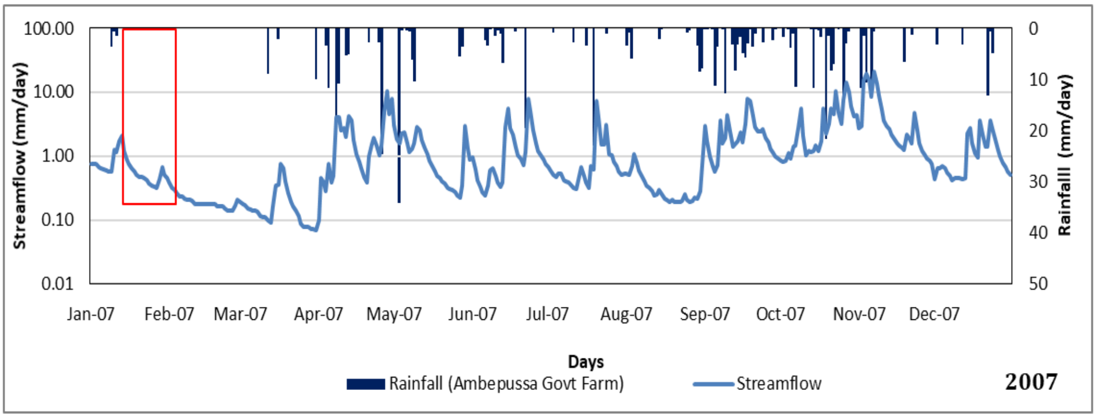

Streamflow (mm/day)
100.00
10.00
1.00
0.10
0.01
0.00
Rainfall (mm/day)
0
10
20
30
40
50
Jan-12
Feb-12
Mar-12
Apr-12
May-12
Jun-12
Jul-12
Aug-12
Sep-12
Oct-12
Nov-12
Dec-12
Days
Rainfall (Andigama Farm)
Streamflow
2012

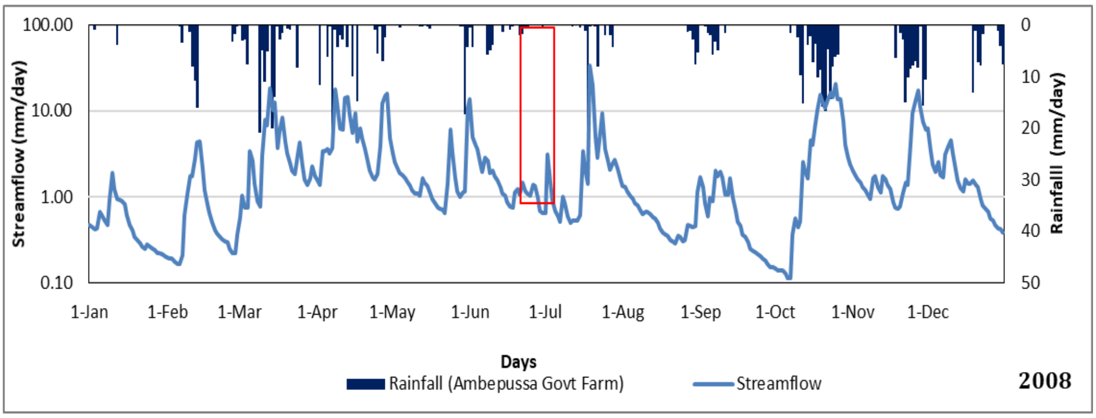

Streamflow (mm/day)
100.00
10.00
1.00
0.10
Rainfall (mm/day)
0
10
20
30
40
50
Jan-13
Feb-13
Mar-13
Apr-13
May-13
Jun-13
Jul-13
Aug-13
Sep-13
Oct-13
Nov-13
Dec-13
Days
Rainfall (Andigama Farm)
Streamflow
2013

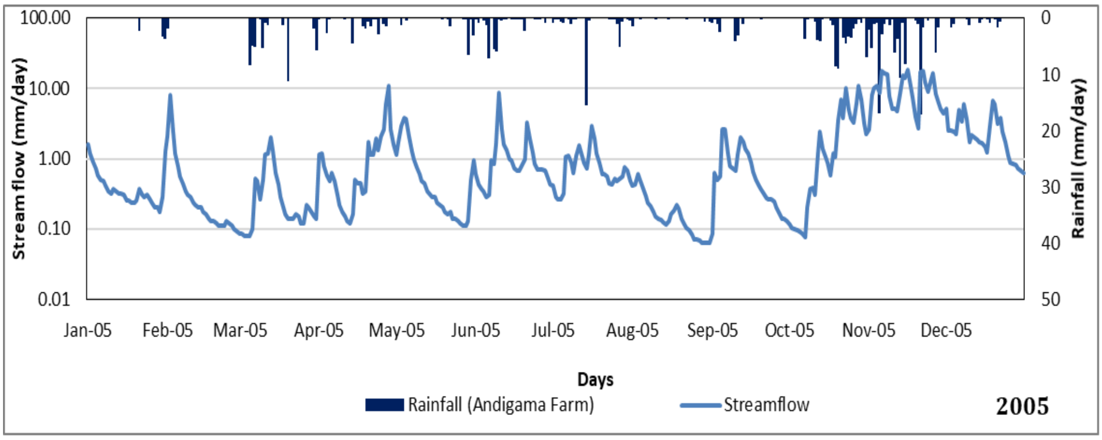
Visual checking with filling missing data for calibration period



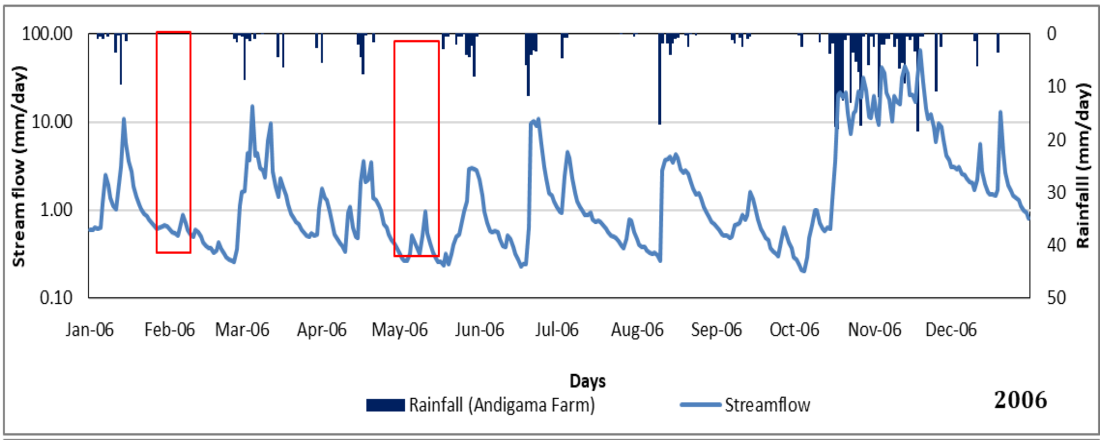




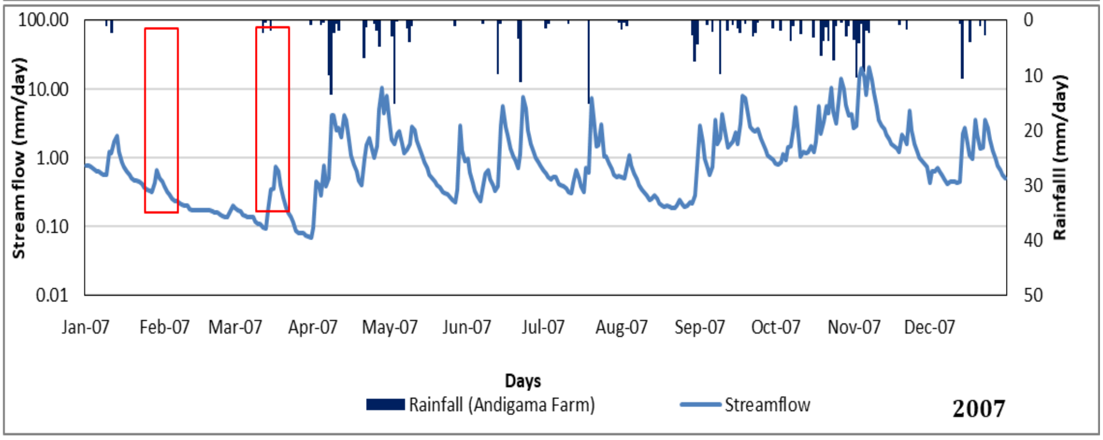




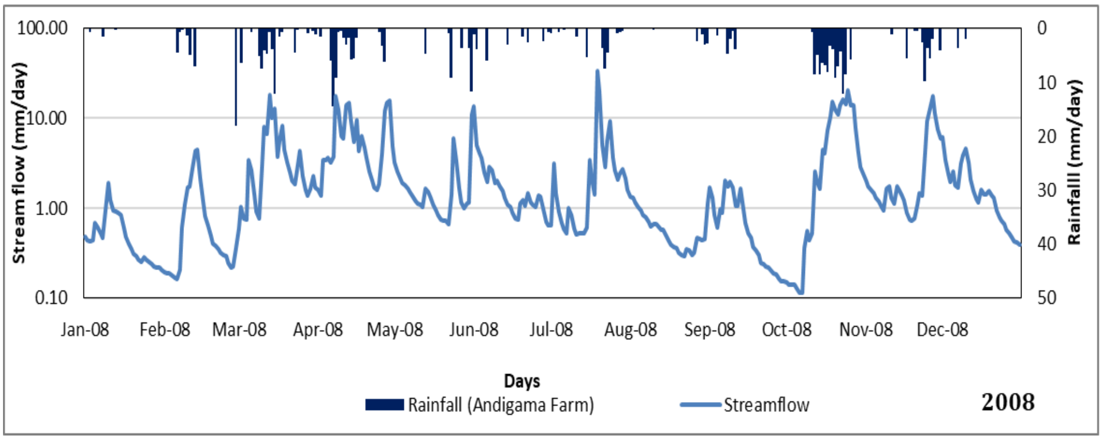
Stream flow (mm/day)
100.00
10.00
1.00
0.10
0.01
Rainfall (mm/day)
0
10
20
30
40
50
Jan-05
Feb-05
Mar-05
Apr-05
May-05
Jun-05
Jul-05
Aug-05
Sep-05
Oct-05
Nov-05
Dec-05
Days
Rainfall (Andigama Farm)
Streamflow
2005



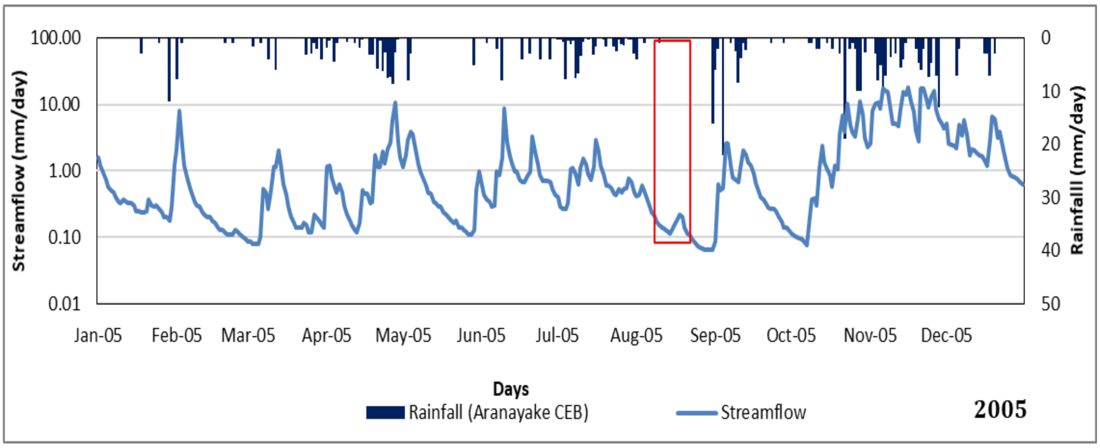
Stream flow (mm/day)
100.00
10.00
1.00
0.10
Rainfall (mm/day)
0
10
20
30
40
50
Jan-06
Feb-06
Mar-06
Apr-06
May-06
Jun-06
Jul-06
Aug-06
Sep-06
Oct-06
Nov-06
Dec-06
Days
Rainfall (Andigama Farm)
Streamflow
2006

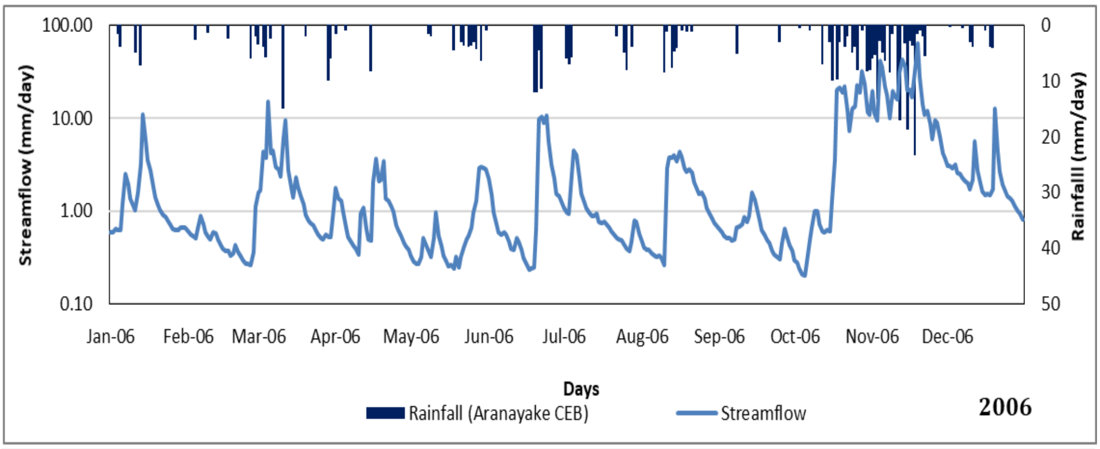


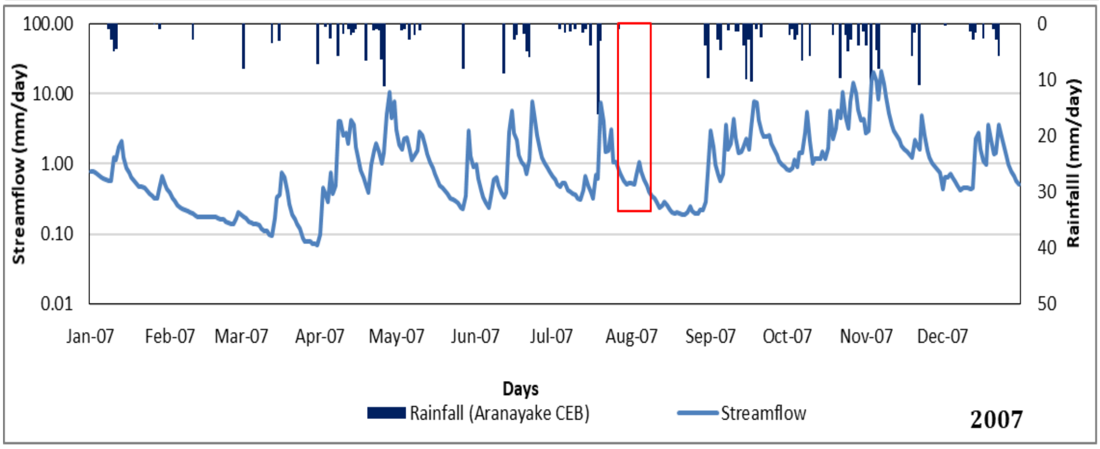
Stream flow (mm/day)
100.00
10.00
1.00
0.10
0.01
Rainfall (mm/day)
0
10
20
30
40
50
Jan-07
Feb-07
Mar-07
Apr-07
May-07
Jun-07
Jul-07
Aug-07
Sep-07
Oct-07
Nov-07
Dec-07
Days
Rainfall (Andigama Farm)
Streamflow
2007

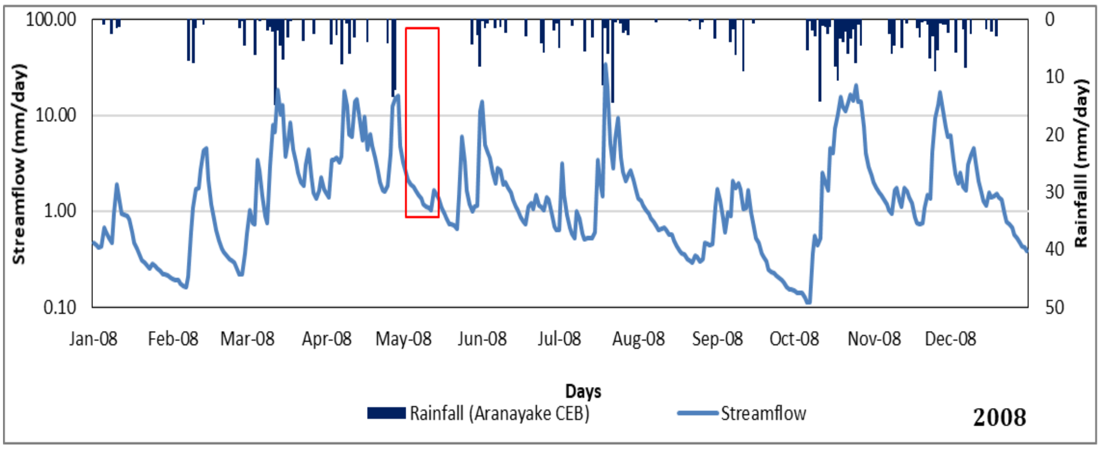


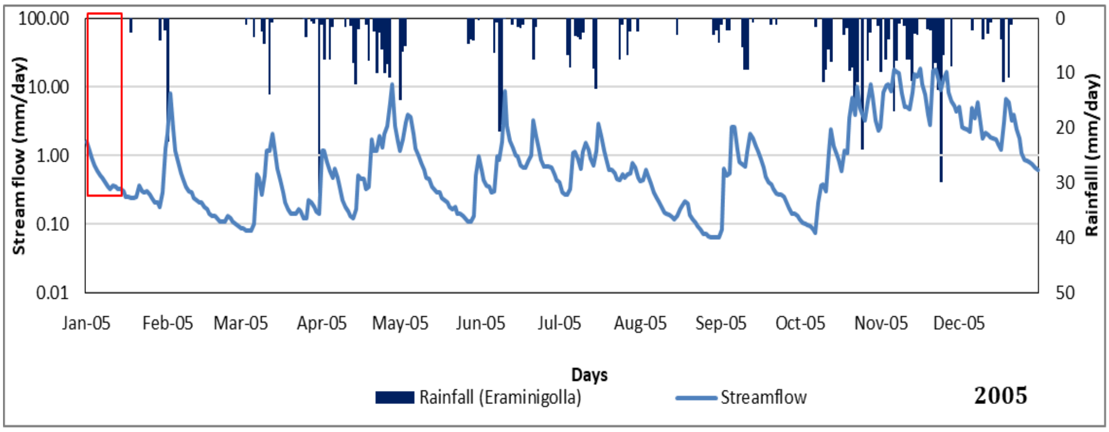
Stream flow (mm/day)
100.00
10.00
1.00
0.10
Rainfall (mm/day)
0
10
20
30
40
50
Jan-08
Feb-08
Mar-08
Apr-08
May-08
Jun-08
Jul-08
Aug-08
Sep-08
Oct-08
Nov-08
Dec-08
Days
Rainfall (Andigama Farm)
Streamflow
2008

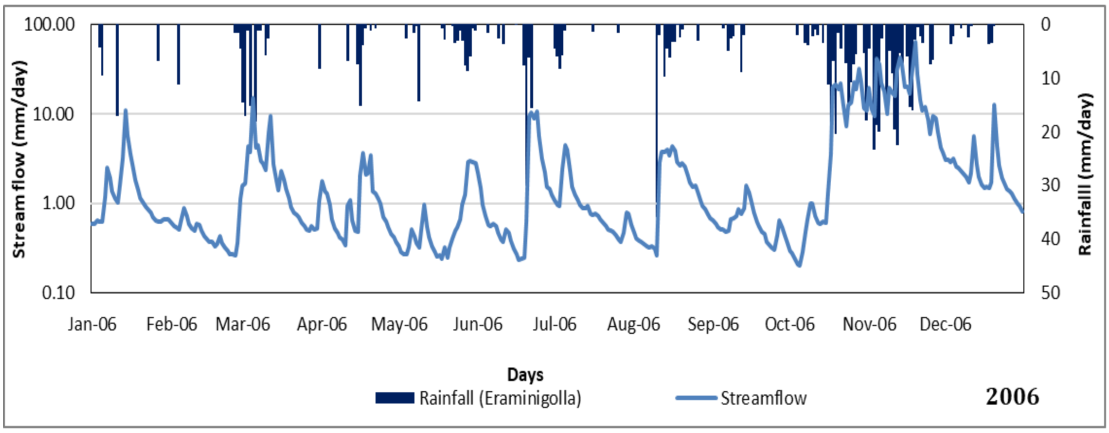

Streamflow (mm/day)
Rainfall (mm/day)
100.00
10.00
1.00
0.10
0.01
0
10
20
30
40
50
Jan-05
Feb-05
Mar-05
Apr-05
May-05
Jun-05
Jul-05
Aug-05
Sep-05
Oct-05
Nov-05
Dec-05
Days
Rainfall (Aranayake CEB)
Streamflow
2005

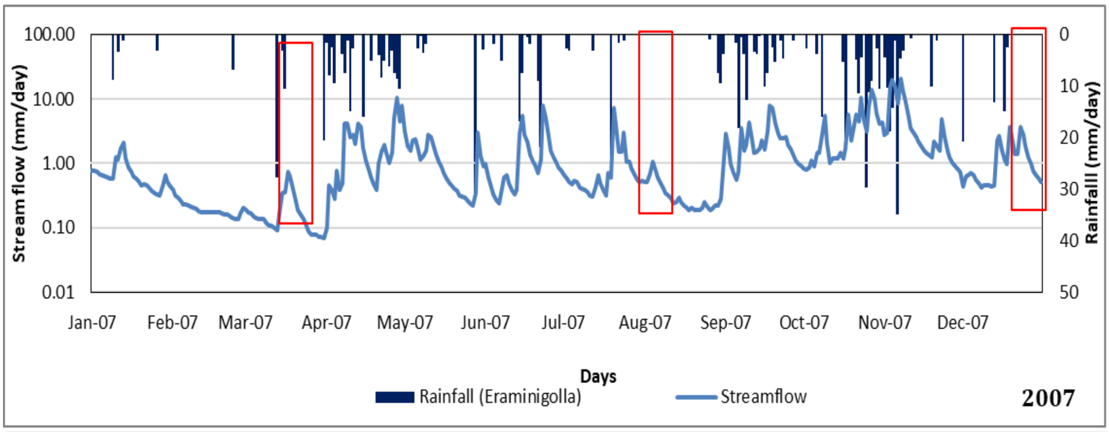

Streamflow (mm/day)
Rainfall (mm/day)
100.00
10.00
1.00
0.10
0
10
20
30
40
50
Jan-06
Feb-06
Mar-06
Apr-06
May-06
Jun-06
Jul-06
Aug-06
Sep-06
Oct-06
Nov-06
Dec-06
Days
Rainfall (Aranayake CEB)
Streamflow
2006

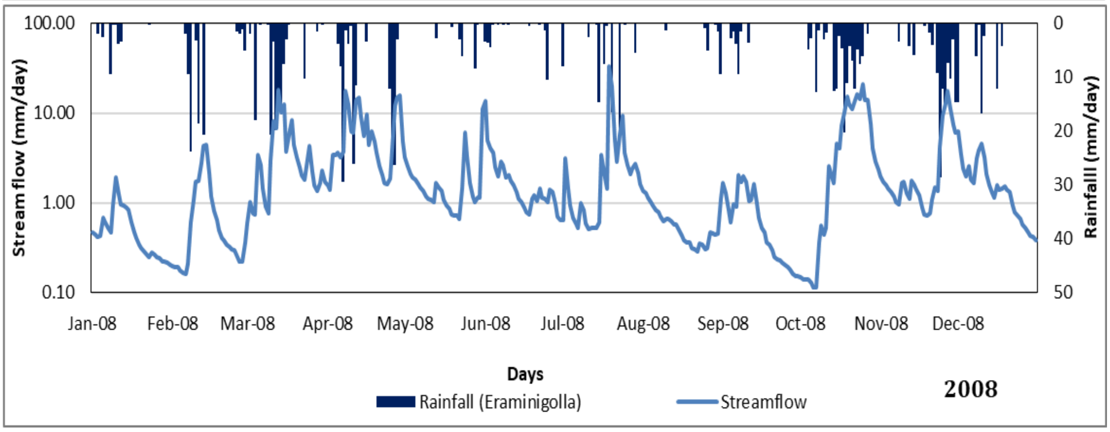

Streamflow (mm/day)
Rainfall (mm/day)
100.00
10.00
1.00
0.10
0.01
0
10
20
30
40
50
Jan-07
Feb-07
Mar-07
Apr-07
May-07
Jun-07
Jul-07
Aug-07
Sep-07
Oct-07
Nov-07
Dec-07
Days
Rainfall (Aranayake CEB)
Streamflow
2007


Streamflow (mm/day)
Rainfall (mm/day)
100.00
10.00
1.00
0.10
0
10
20
30
40
50
Jan-08
Feb-08
Mar-08
Apr-08
May-08
Jun-08
Jul-08
Aug-08
Sep-08
Oct-08
Nov-08
Dec-08
Days
Rainfall (Aranayake CEB)
Streamflow
2008

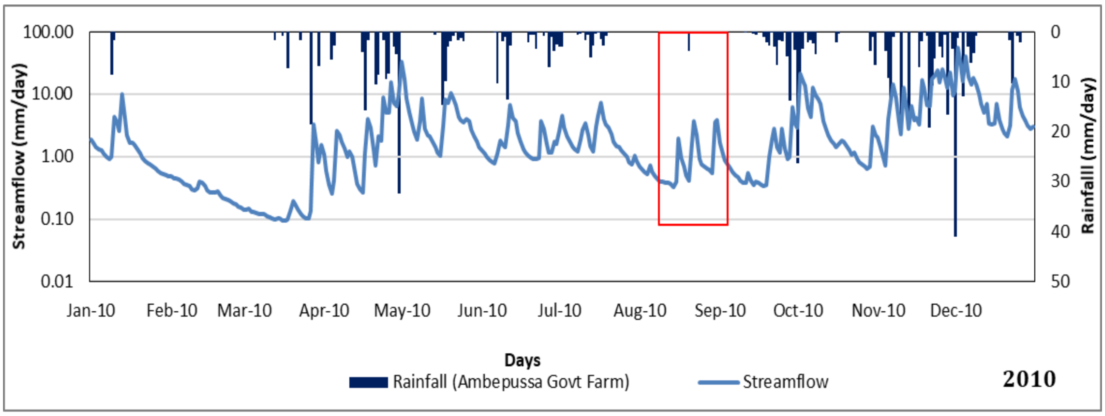

100.00
10.00
1.00
0.10
0.01
Stream flow (mm/day)
Rainfall (mm/day)
Jan-05
Feb-05
Mar-05
Apr-05
May-05
Jun-05
Jul-05
Aug-05
Sep-05
Oct-05
Nov-05
Dec-05
Days
Rainfall (Eraminigolla)
Streamflow
2005

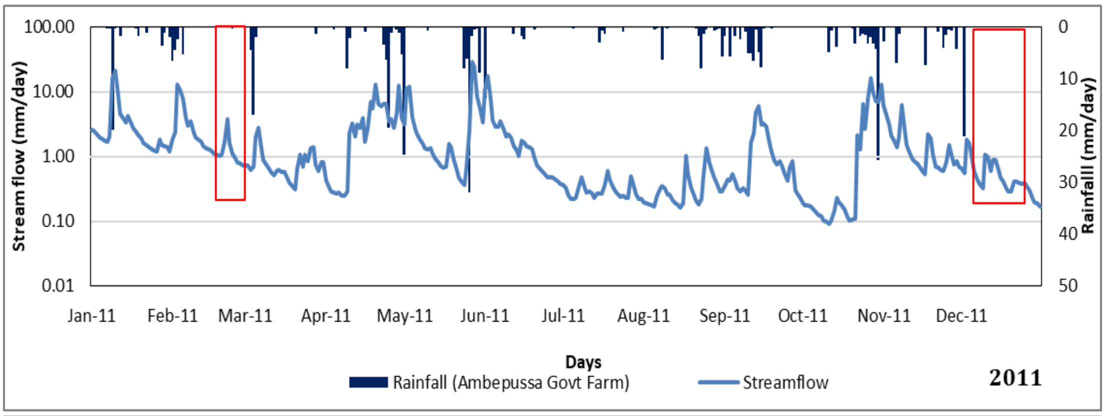

Stream flow (mm/day)
Rainfall (mm/day)
Jan-06
Feb-06
Mar-06
Apr-06
May-06
Jun-06
Jul-06
Aug-06
Sep-06
Oct-06
Nov-06
Dec-06
Days
Rainfall (Eraminigolla)
Streamflow
2006

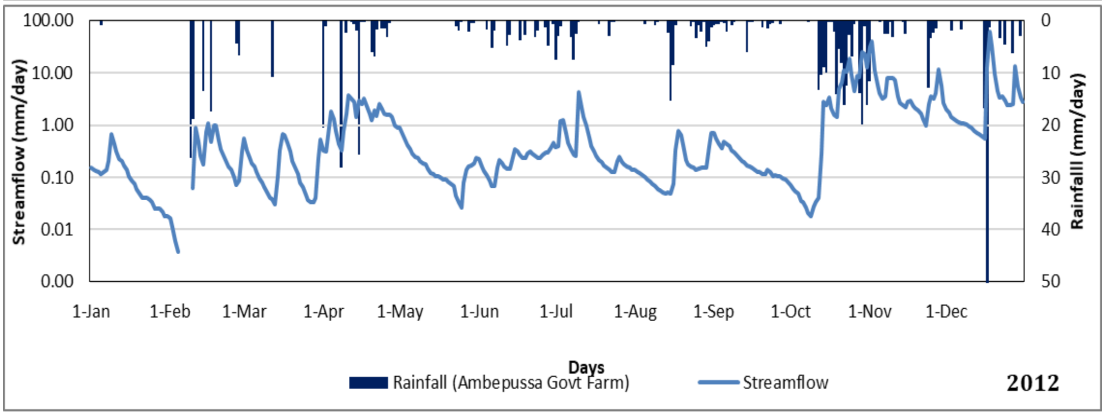

Stream flow (mm/day)
Rainfall (mm/day)
Jan-07
Feb-07
Mar-07
Apr-07
May-07
Jun-07
Jul-07
Aug-07
Sep-07
Oct-07
Nov-07
Dec-07
Days
Rainfall (Eraminigolla)
Streamflow
2007

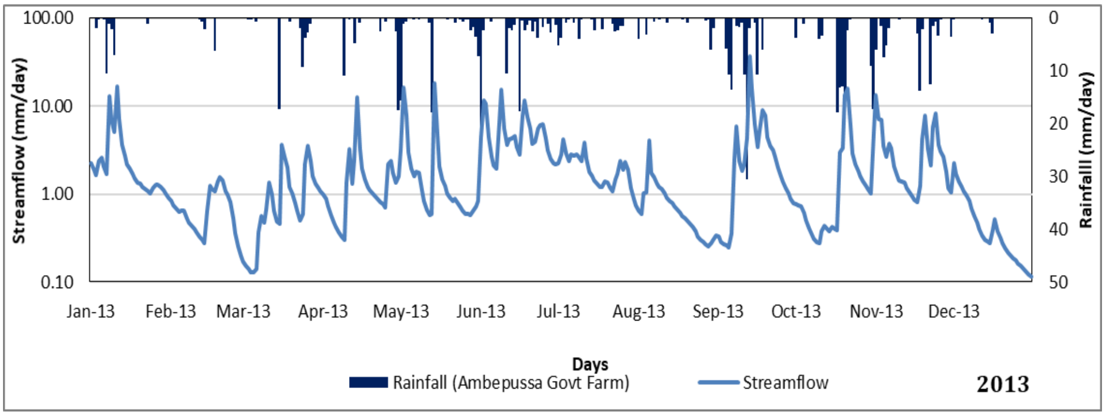

Stream flow (mm/day)
Rainfall (mm/day)
Jan-08
Feb-08
Mar-08
Apr-08
May-08
Jun-08
Jul-08
Aug-08
Sep-08
Oct-08
Nov-08
Dec-08
Days
Rainfall (Eraminigolla)
Streamflow
2008

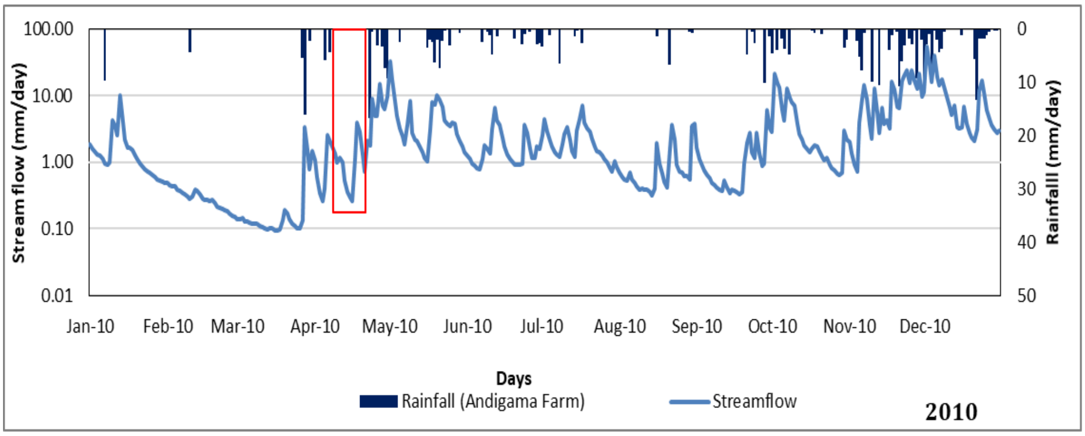
Visual checking with filling missing data in validation period

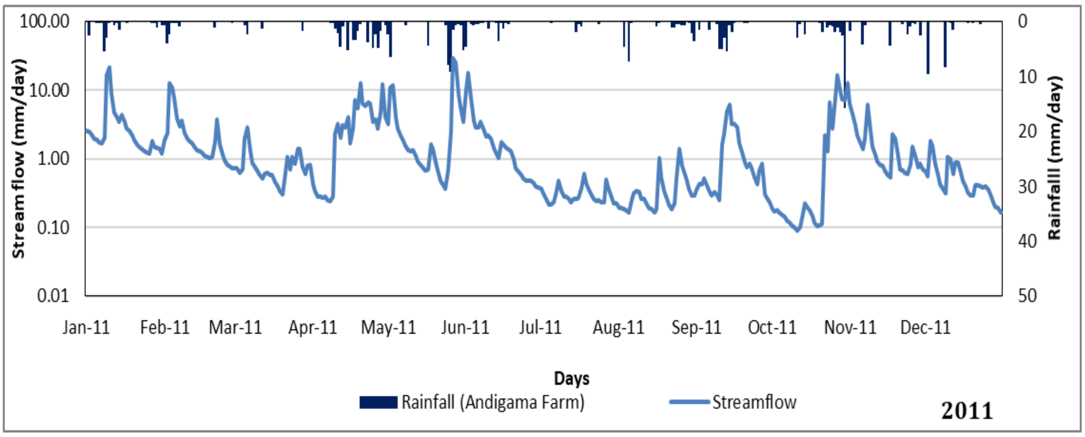


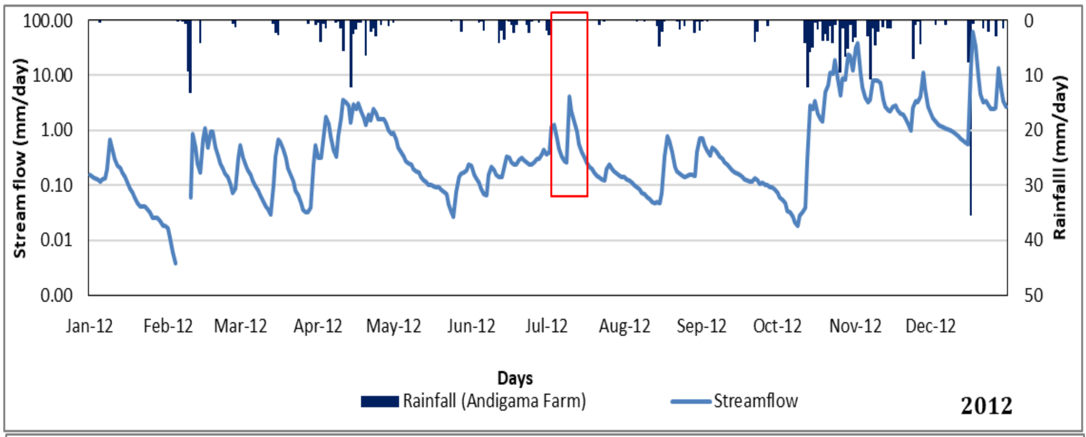


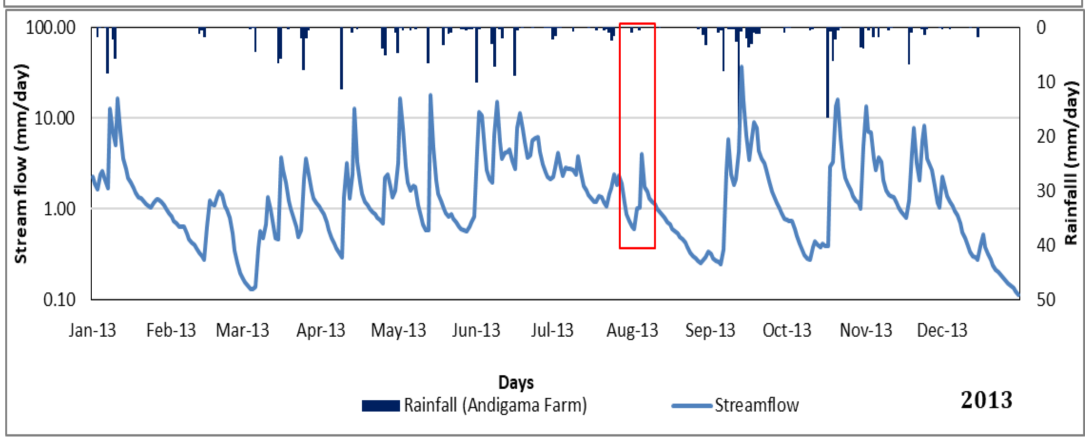


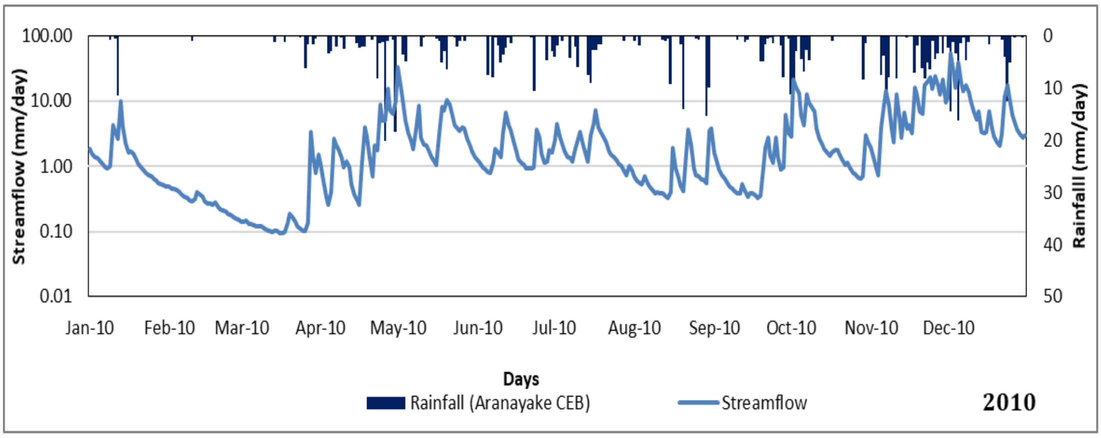


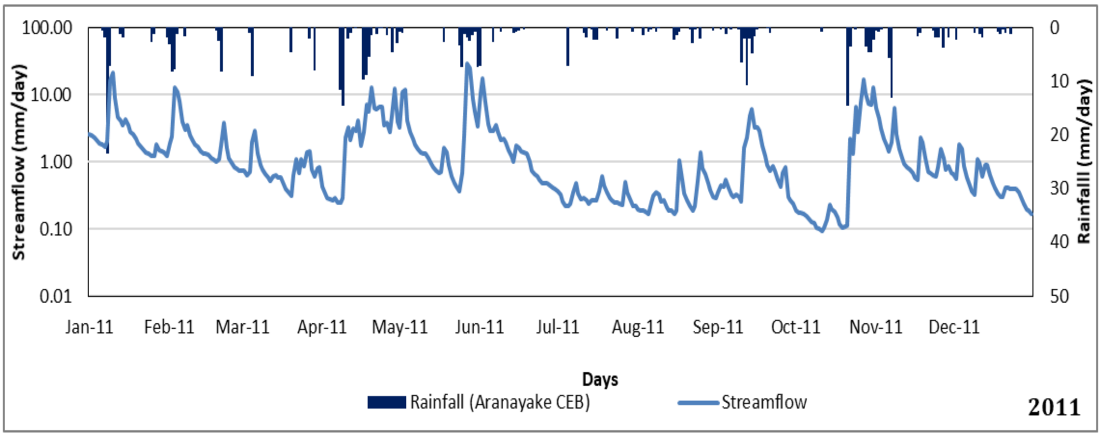

Stream flow (mm/day)
100.00
10.00
1.00
0.10
0.01
Rainfall (mm/day)
0
10
20
30
40
50
Jan-10
Feb-10
Mar-10
Apr-10
May-10
Jun-10
Jul-10
Aug-10
Sep-10
Oct-10
Nov-10
Dec-10
Days
Rainfall (Andigama Farm)
Streamflow
2010

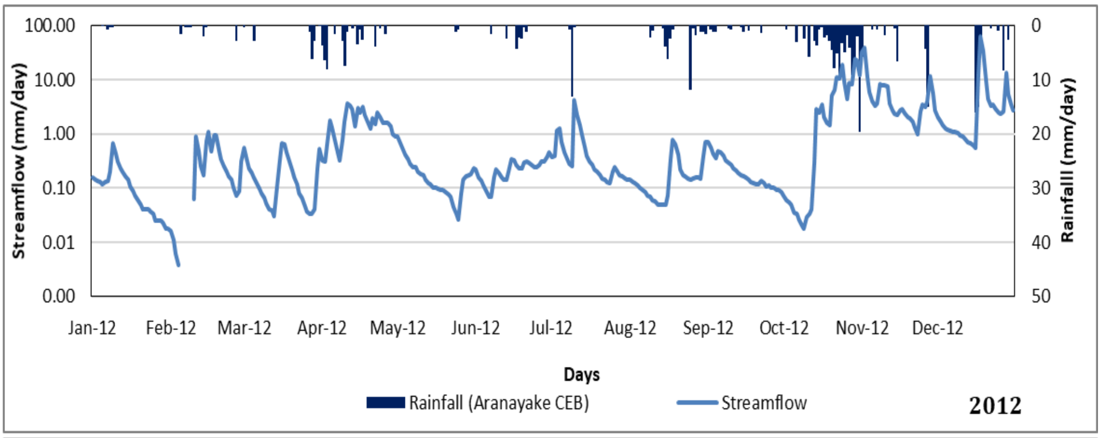

Stream flow (mm/day)
100.00
10.00
1.00
0.10
0.01
Rainfall (mm/day)
0
10
20
30
40
50
Jan-11
Feb-11
Mar-11
Apr-11
May-11
Jun-11
Jul-11
Aug-11
Sep-11
Oct-11
Nov-11
Dec-11
Days
Rainfall (Andigama Farm)
Streamflow
2011

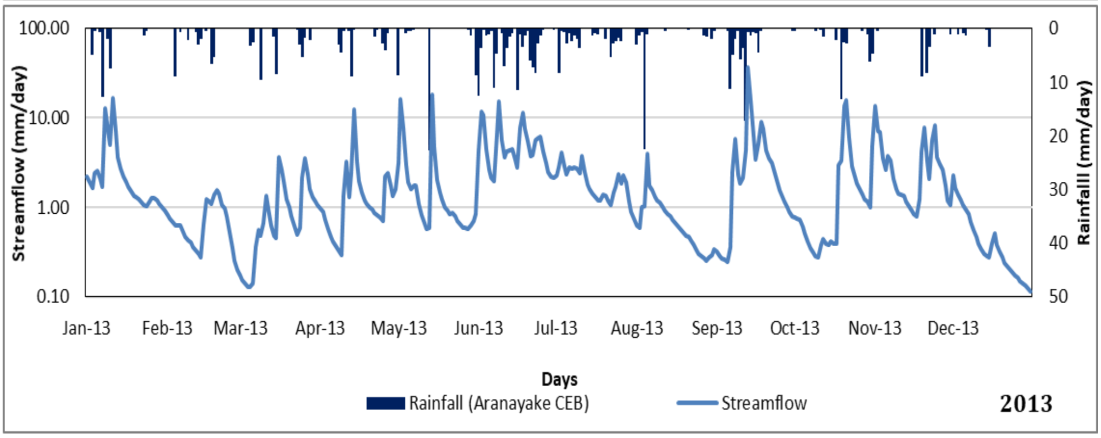

Stream flow (mm/day)
100.00
10.00
1.00
0.10
0.01
0.00
Rainfall (mm/day)
0
10
20
30
40
50
Jan-12
Feb-12
Mar-12
Apr-12
May-12
Jun-12
Jul-12
Aug-12
Sep-12
Oct-12
Nov-12
Dec-12
Days
Rainfall (Andigama Farm)
Streamflow
2012

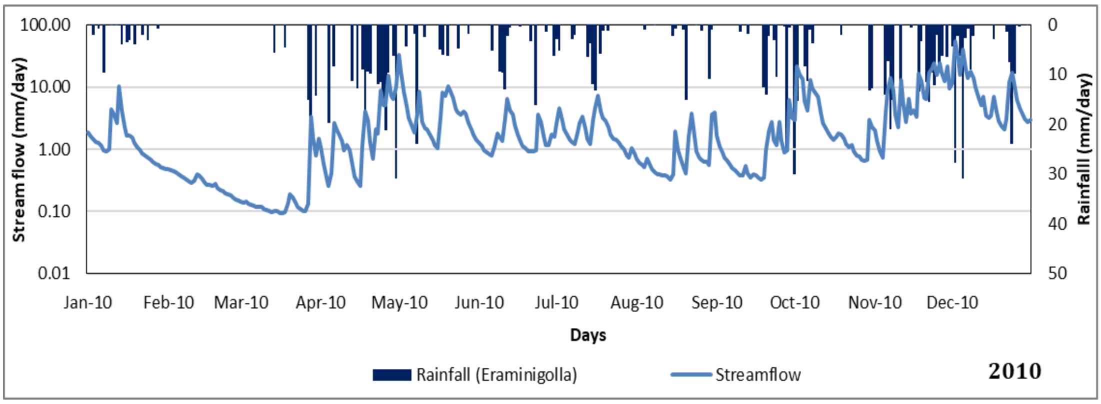

Stream flow (mm/day)
100.00
10.00
1.00
0.10
Rainfall (mm/day)
0
10
20
30
40
50
Jan-13
Feb-13
Mar-13
Apr-13
May-13
Jun-13
Jul-13
Aug-13
Sep-13
Oct-13
Nov-13
Dec-13
Days
Rainfall (Andigama Farm)
Streamflow
2013


Streamflow (mm/day)
Rainfalll (mm/day)
100.00
10.00
1.00
0.10
0.01
0
10
20
30
40
50
Jan-10 Feb-10 Mar-10 Apr-10 May-10 Jun-10 Jul-10 Aug-10 Sep-10 Oct-10 Nov-10 Dec-10
Days
Rainfall (Aranayake CEB)
Streamflow
2010

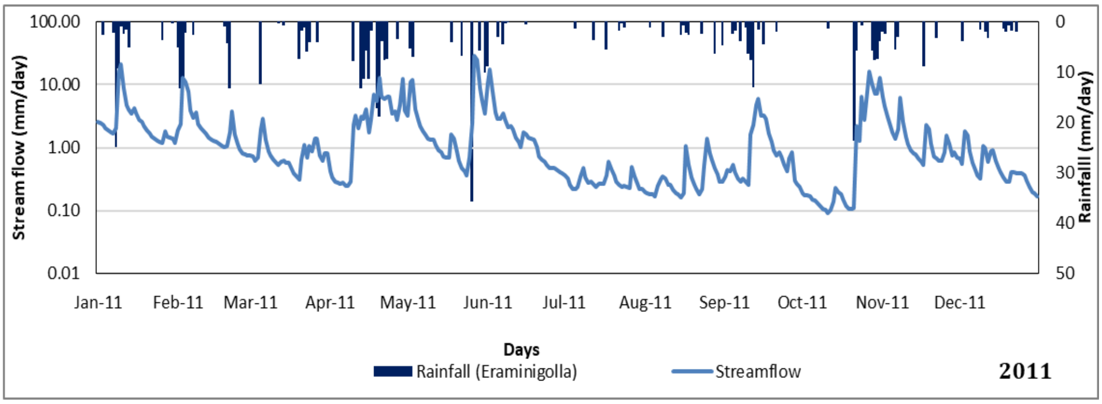

Streamflow (mm/day)
Rainfalll (mm/day)
100.00
10.00
1.00
0.10
0.01
0
10
20
30
40
50
Jan-11 Feb-11 Mar-11 Apr-11 May-11 Jun-11 Jul-11 Aug-11 Sep-11 Oct-11 Nov-11 Dec-11
Days
Rainfall (Aranayake CEB)
Streamflow
2011


Streamflow (mm/day)
Rainfalll (mm/day)
100.00
10.00
1.00
0.10
0.01
0.00
0
10
20
30
40
50
Jan-12 Feb-12 Mar-12 Apr-12 May-12 Jun-12 Jul-12 Aug-12 Sep-12 Oct-12 Nov-12 Dec-12
Days
Rainfall (Aranayake CEB)
Streamflow
2012

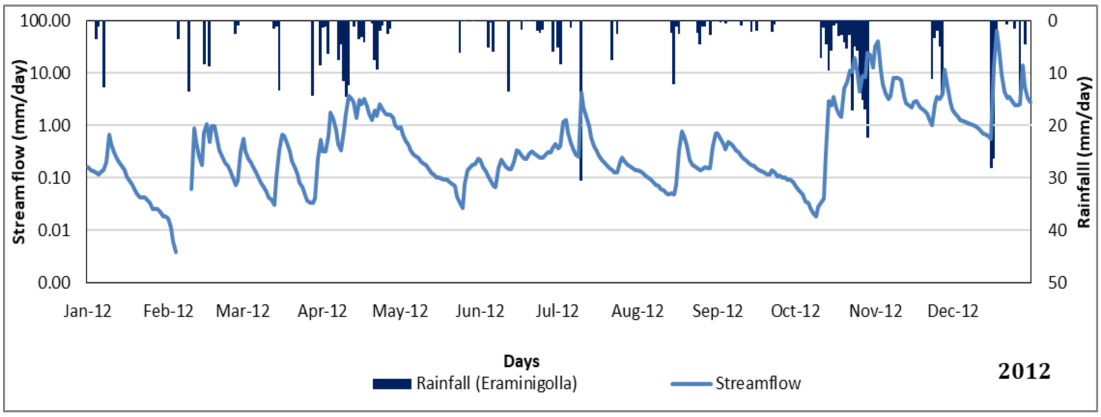

Streamflow (mm/day)
Rainfalll (mm/day)
100.00
10.00
1.00
0.10
0
10
20
30
40
50
Jan-13 Feb-13 Mar-13 Apr-13 May-13 Jun-13 Jul-13 Aug-13 Sep-13 Oct-13 Nov-13 Dec-13
Days
Rainfall (Aranayake CEB)
Streamflow
2013



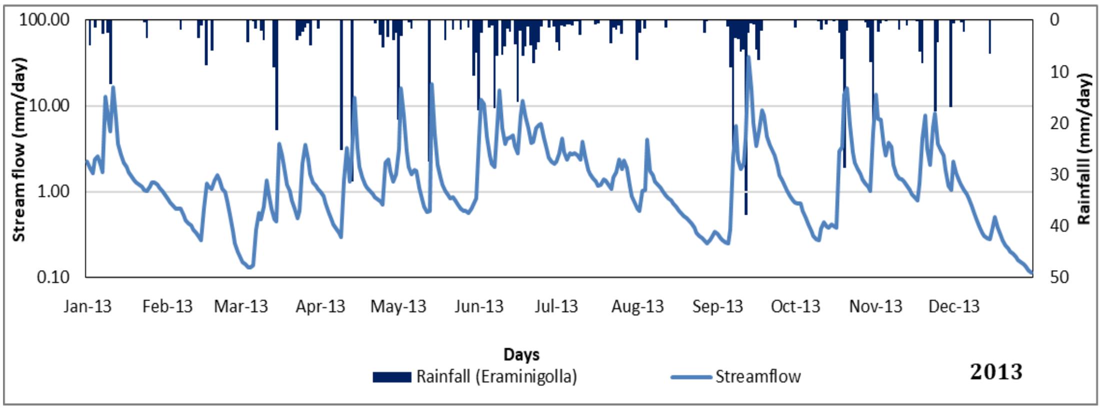
Stream flow (mm/day)
100.00
10.00
1.00
0.10
0.01
Rainfall (mm/day)
0
10
20
30
40
50
Jan-10 Feb-10 Mar-10 Apr-10 May-10 Jun-10 Jul-10 Aug-10 Sep-10 Oct-10 Nov-10 Dec-10
Days
Rainfall (Eraminigolla)
Streamflow
2010



Stream flow (mm/day)
100.00
10.00
1.00
0.10
0.01
Rainfall (mm/day)
0
10
20
30
40
50
Jan-11 Feb-11 Mar-11 Apr-11 May-11 Jun-11 Jul-11 Aug-11 Sep-11 Oct-11 Nov-11 Dec-11
Days
Rainfall (Eraminigolla)
Streamflow
2011



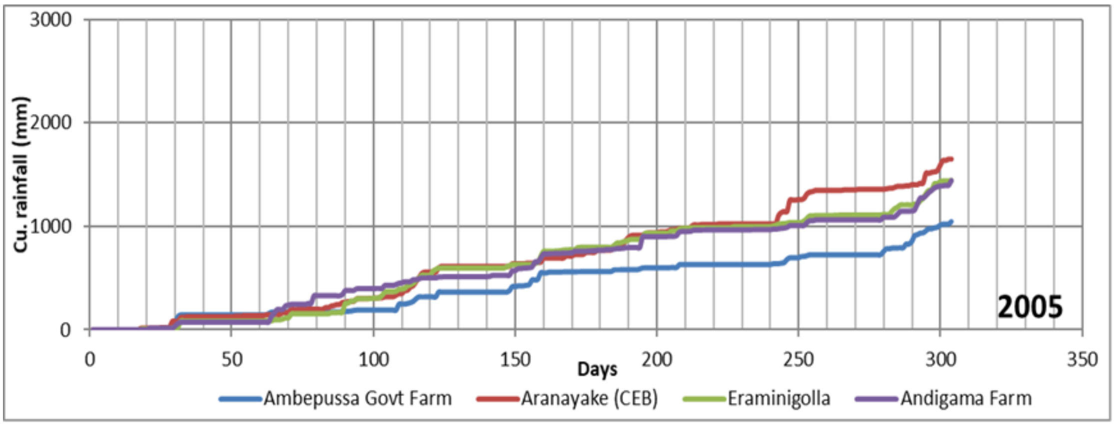
Stream flow (mm/day)
100.00
10.00
1.00
0.10
0.01
0.00
Rainfall (mm/day)
0
10
20
30
40
50
Jan-12 Feb-12 Mar-12 Apr-12 May-12 Jun-12 Jul-12 Aug-12 Sep-12 Oct-12 Nov-12 Dec-12
Days
Rainfall (Eraminigolla)
Streamflow
2012

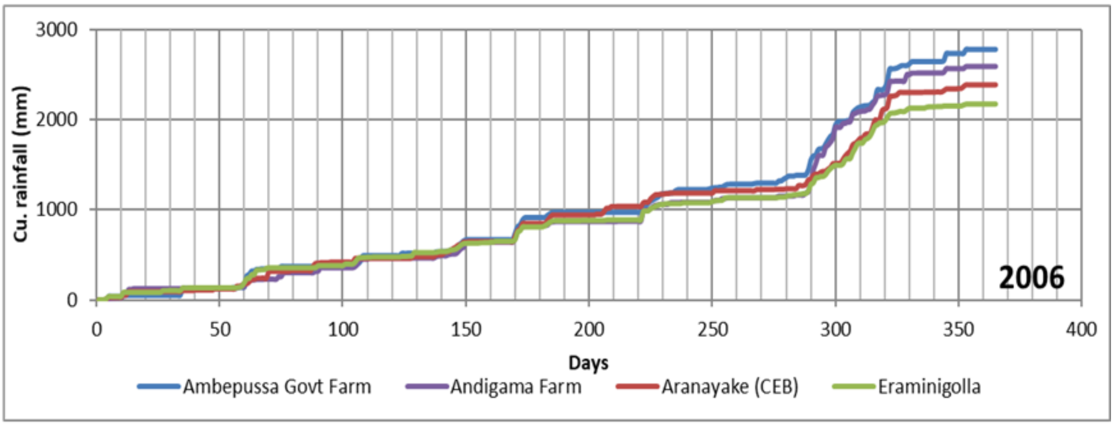


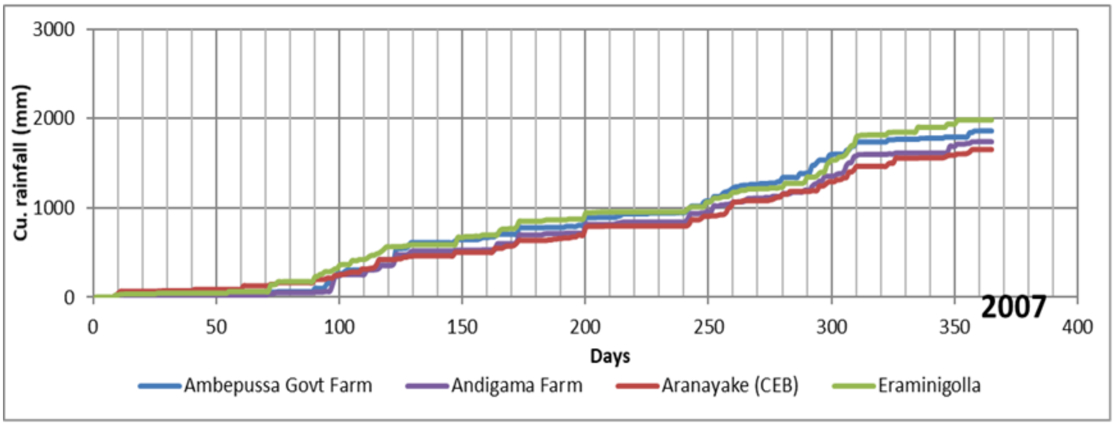
Stream flow (mm/day)
100.00
10.00
1.00
0.10
Rainfall (mm/day)
0
10
20
30
40
50
Jan-13 Feb-13 Mar-13 Apr-13 May-13 Jun-13 Jul-13 Aug-13 Sep-13 Oct-13 Nov-13 Dec-13
Days
Rainfall (Eraminigolla)
Streamflow
2013

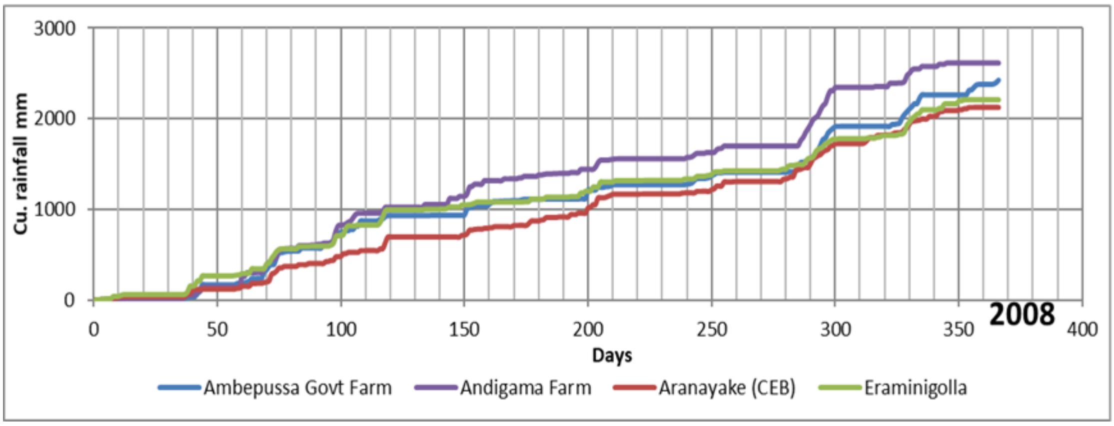
Appendix B: Single mass curve without filling missing data in calibration and validation period

Single mass curve without filling missing data in calibration period

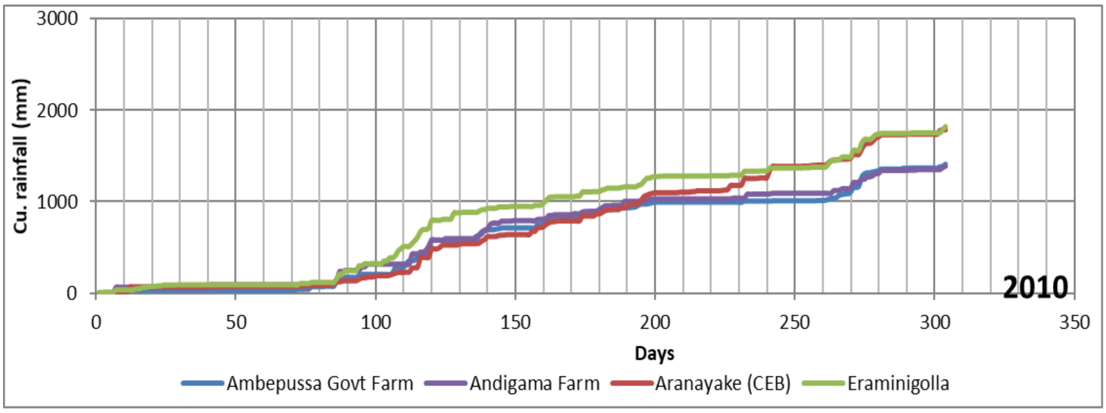


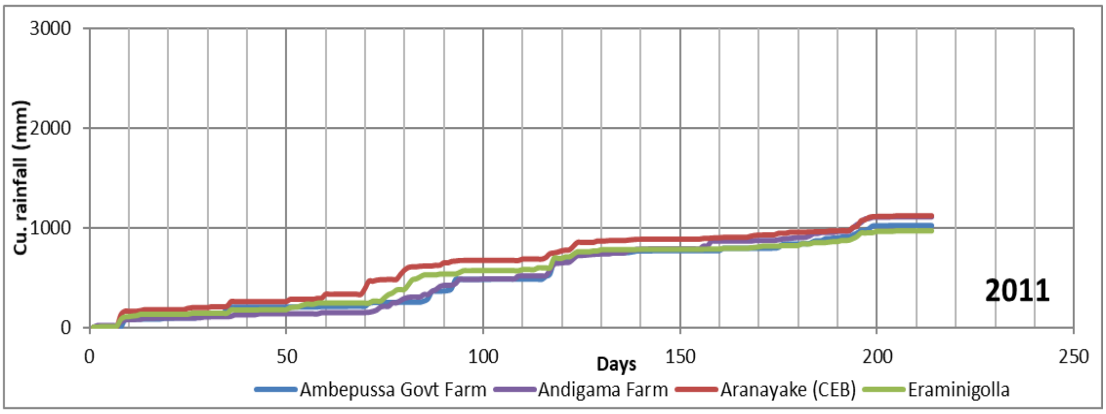


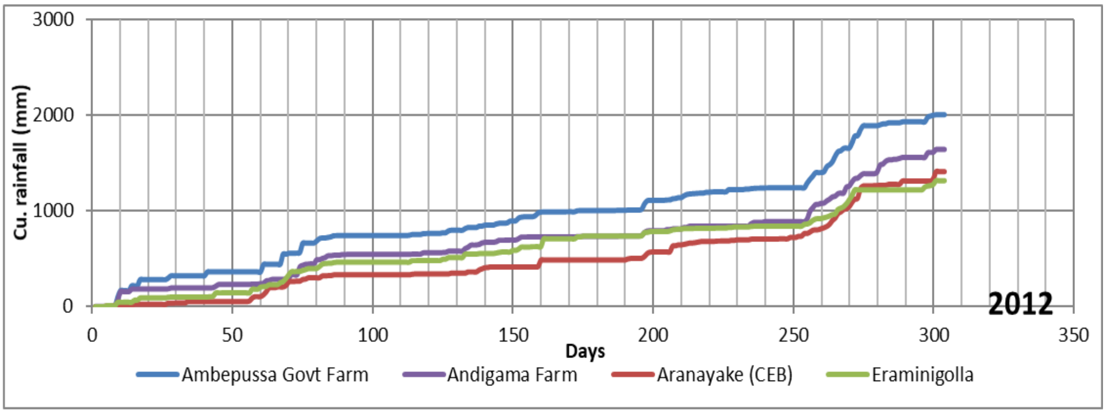


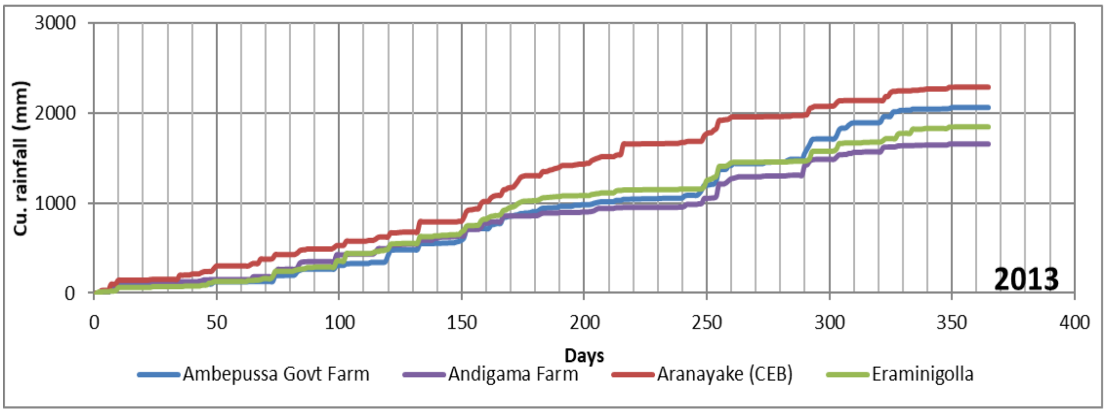


Single mass curve without filling missing data in validation period

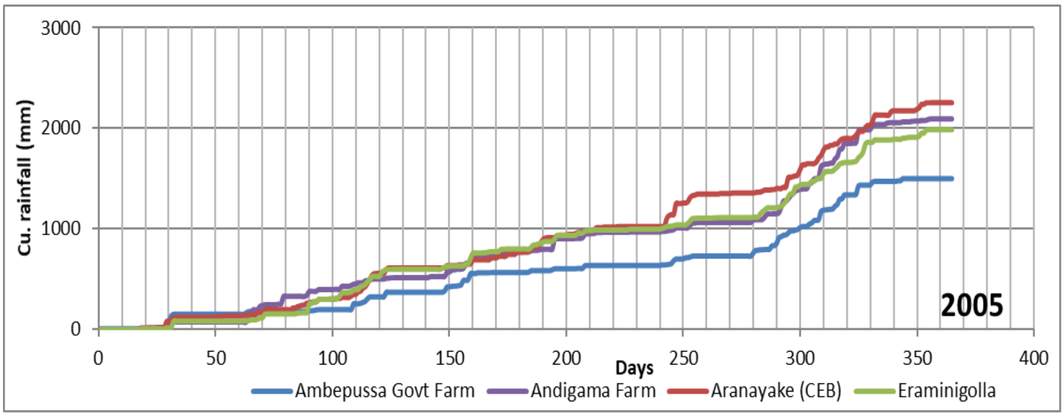


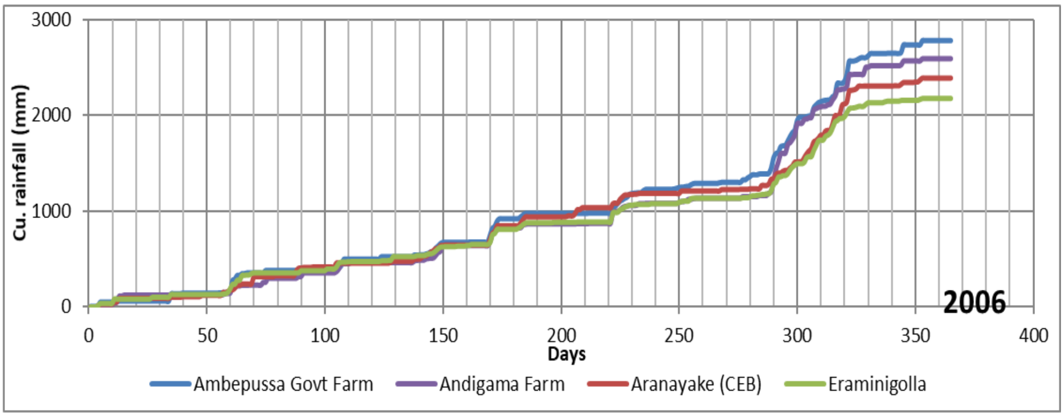


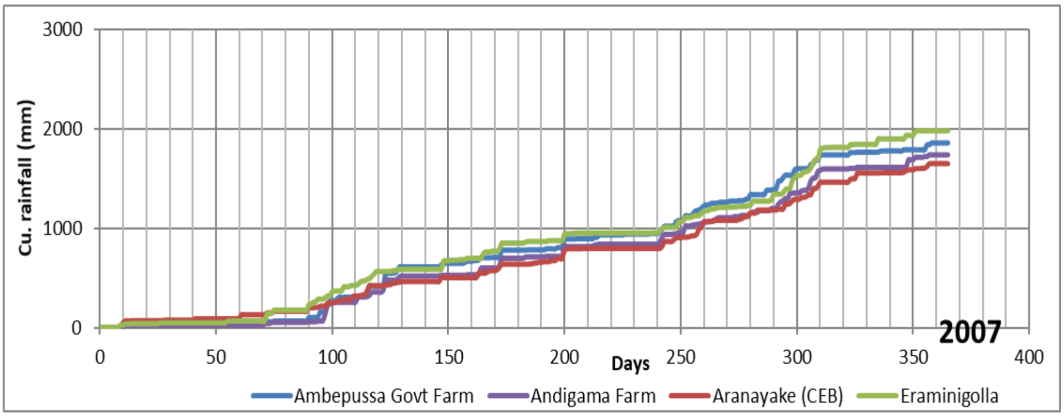


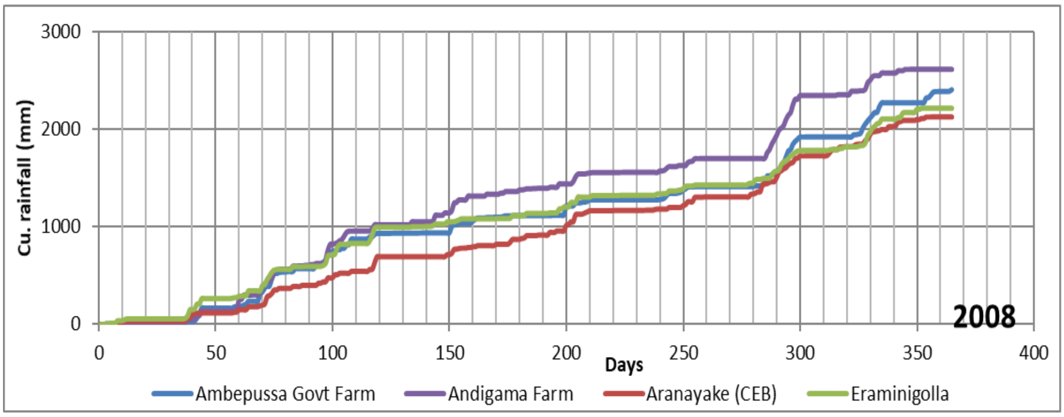


Single mass curve with filling missing data in calibration period

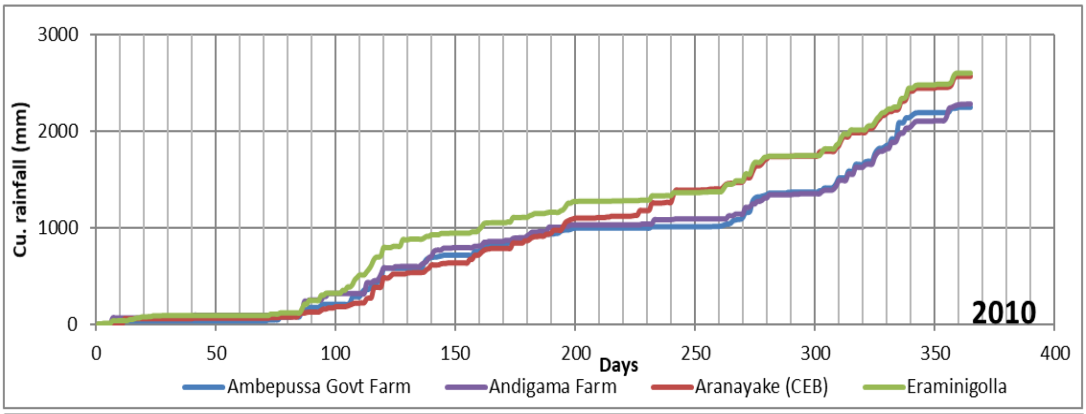


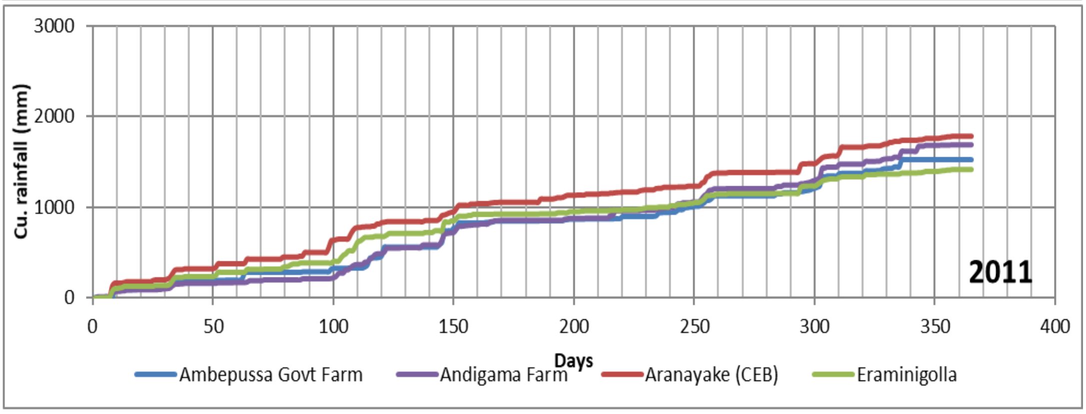


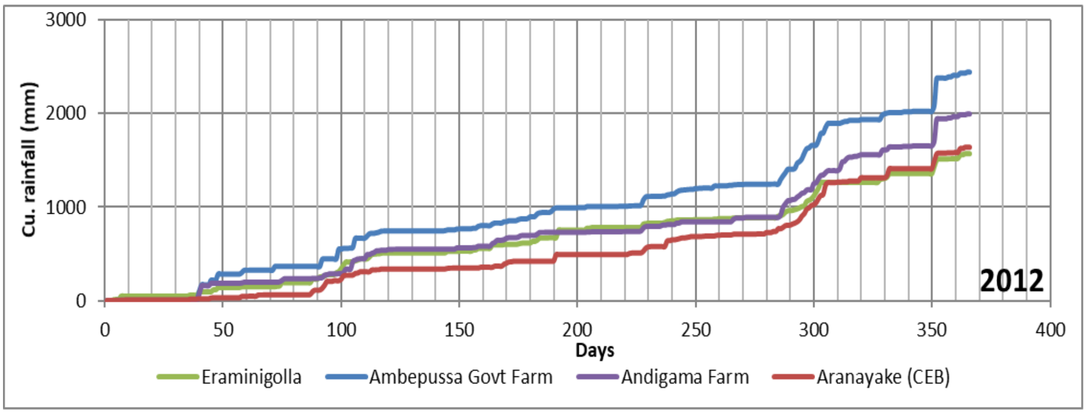


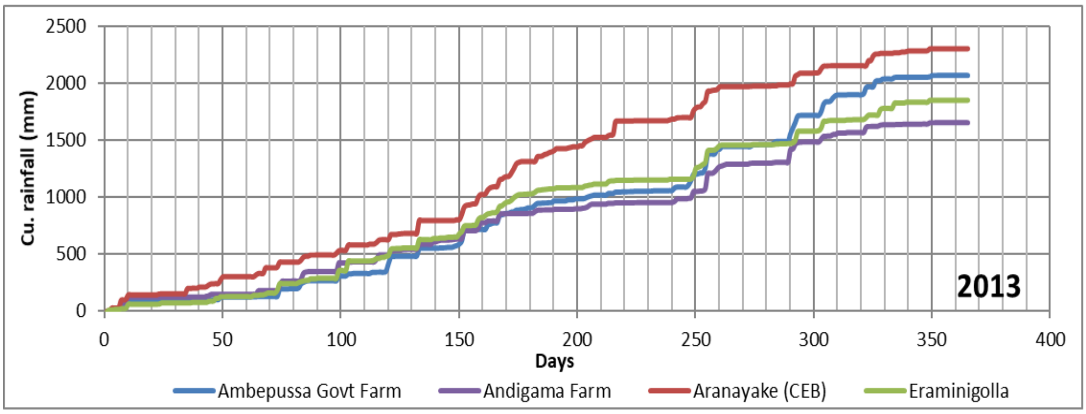


Single mass curve with filling missing data in validation period









Appendix C: Parameters of lumped and subdivision model and Thiessen weights

Thiessen weights for Nine Sub division Model

Subdivision	Area of sub division	Shape Area	Thiessen Area (km^2)	Rainfall station	Weight
Subdivision 1	104.05	68.45	342.0	Ambepussa Govt. Farm	0.658
Subdivision 1	104.05	35.56	192.0	Andigama Farm	0.342
Subdivision 2	97.85	32.51	342.0	Ambepussa Govt. Farm	0.332
Subdivision 2	97.85	65.31	192.0	Andigama	0.667
Subdivision 3	142.55	142.55	342.0	Ambepussa Govt. Farm	1.000
Subdivision 4	153.93	40.78	342.0	Ambepussa Govt. Farm	0.265
Subdivision 4	153.93	24.22	474.0	Eraminigolla	0.157
Subdivision 4	153.93	91.12	192.0	Andigama	0.592
Subdivision 5	167.16	56.74	342.0	Ambepussa Govt. Farm	0.339
Subdivision 5	167.16	7.13	264.0	Aranayake (CEB)	0.043
Subdivision 5	167.16	103.29	474.0	Eraminigolla	0.618
Subdivision 6	149.97	0.53	342.0	Ambepussa Govt. Farm	0.004

Subdivision	**Area of sub division**	**Shape Area**	**Thiessen Area (km^2)**	**Rainfall station**	**Weight**
Subdivision 6	149.97	1.48	264.0	Aranayake (CEB)	0.010
Subdivision 6	149.97	147.95	474.0	Eraminigolla	0.987
Subdivision 7	174.13	5.08	264.0	Aranayake (CEB)	0.029
Subdivision 7	174.13	168.98	474.0	Eraminigolla	0.970
Subdivision 8	127.98	98.59	264.0	Aranayake (CEB)	0.770
Subdivision 8	127.98	29.35	474.0	Eraminigolla	0.229
Subdivision 9	151.67	152.09	264.0	Aranayake (CEB)	1.003

Optimum Parameters of subdivisions:

Sub division 3				
Parameters	**Initial Lumped Value**	**Optimized Parameter Value for sub division 1**	**Optimized Parameter Value for sub division 2**	**Optimized Parameter Value for sub division 3**
Initial Discharge	10	5	5	5
Ratio to peak	0.164	0.164	0.164	0.164
Recession-constant	0.923	0.923	0.923	0.923
Time of concentration	79	61	67	77
soil storage	445	310	310	310
Max infiltration	4.5	4.51	4.51	4.51
Storage Coefficient	59	49	50	58
Soil Percolation (mm/Hr)	0.32	0.45	0.45	0.45
Impervious	9.55	8	11	5
Soil %	90	90	90	90
Groundwater 1(%)	80	80	80	80
Groundwater 2(%)	90	90	90	90
Tension Storage (mm)	21	21	21	21
Groundwater 1 storage	70	120	120	120
GW1 Percolation (mm/HR)	0.3	0.3	0.3	0.3
GW1 Coefficient (HR)	10	10	10	10
GW2 Storage (mm)	10	10	10	10
GW2 Percolation (mm/hr)	0.3	0.3	0.3	0.3
GW2 Coefficient (Hr)	30	30	30	30

Sub division 6							
Parameters	**Initial Lumped Value**	**Optimized Parameter Value for sub division 1**	**Optimized Parameter Value for sub division 2**	**Optimized Parameter Value for sub division 3**	**Optimized Parameter Value for sub division 4**	**Optimized Parameter Value for sub division 5**	**Optimized Parameter Value for sub division 6**
Initial Discharge	10	2	2	2	2	2	2
Ratio to peak	0.164	0.164	0.164	0.164	0.164	0.164	0.164
Recession-constant	0.923	0.923	0.923	0.923	0.923	0.923	0.923
Time of concentration	79	61	61	61	61	61	61
soil storage	445	250	250	320	300	150	300
Max infiltration	4.5	4.54	4.54	4.54	4.54	4.5	4.5
Storage Coefficient	59	49	49	49	49	49	49
Soil Percolation (mm/Hr)	0.32	0.56	0.56	0.56	0.56	0.56	0.56
Impervious	9.55	8	8	10	10	114	13
Soil %	90	90	90	90	90	90	90
Groundwater 1(%)	80	80	80	80	80	80	80
Groundwater 2(%)	90	90	90	90	90	90	90
Tension Storage (mm)	21	21	21	21	21	21	21
Groundwater 1 storage	70	70	70	70	70	70	70

Parameters	**Initial Lumped Value**	**Optimized Parameter Value for sub division 1**	**Optimized Parameter Value for sub division 2**	**Optimized Parameter Value for sub division 3**	**Optimized Parameter Value for sub division 4**	**Optimized Parameter Value for sub division 5**	**Optimized Parameter Value for sub division 6**
GW1 Percolation (mm/HR)	0.3	0.35	0.35	0.35	0.35	0.35	0.35
GW1 Coefficient (HR)	10	10	10	10	10	10	10
GW2 Storage (mm)	10	10	10	10	10	10	10
GW2 Percolation (mm/hr)	0.3	0.3	0.3	0.3	0.3	0.3	0.3
GW2 Coefficient (Hr)	30	30	30	30	30	30	30

Sub division 9										
Parameters	**Initial Lumped Value**	**Optimized Parameter Value for sub division 1**	**Optimized Parameter Value for sub division 2**	**Optimized Parameter Value for sub division 3**	**Optimized Parameter Value for sub division 4**	**Optimized Parameter Value for sub division 5**	**Optimized Parameter Value for sub division 6**	**Optimized Parameter Value for sub division 7**	**Optimized Parameter Value for sub division 8**	**Optimized Parameter Value for sub division 9**
Initial Discharge	10	2	2	2	2	2	2	2	2	2
Ratio to peak	0.164	0.164	0.164	0.164	0.164	0.164	0.164	0.164	0.164	0.164
Recession-constant	0.923	0.923	0.923	0.923	0.923	0.923	0.923	0.923	0.923	0.923
Time of concentration	79	65	68	70	69	72	68	68	70	66
soil storage	445	250	195	250	190	300	350	400	250	380
Max infiltration	4.5	4.54	4.54	4.54	4.54	4.54	4.54	5.1	4.54	4.54
Storage Coefficient	59	54	54	55	50	50	52	55	57	50
Soil Percolation (mm/Hr)	0.32	0.45	0.45	0.45	0.45	0.56	0.56	0.56	0.45	0.45
Impervious	9.55	9.5	6	10	10	5	9	8	13	11
Soil %	90	90	90	90	90	90	90	90	90	90

Sub division 9										
Parameters	**Initial Lumped Value**	**Optimized Parameter Value for sub division 1**	**Optimized Parameter Value for sub division 2**	**Optimized Parameter Value for sub division 3**	**Optimized Parameter Value for sub division 4**	**Optimized Parameter Value for sub division 5**	**Optimized Parameter Value for sub division 6**	**Optimized Parameter Value for sub division 7**	**Optimized Parameter Value for sub division 8**	**Optimized Parameter Value for sub division 9**
Groundwater 1(%)	80	80	80	80	80	80	80	80	80	80
Groundwater 2(%)	90	90	90	90	90	90	90	90	90	90
Tension Storage (mm)	21	21	21	21	21	21	21	21	21	21
Groundwater 1 storage	70	70	70	70	70	70	70	70	70	70
GW1 Percolation (mm/HR)	0.3	0.35	0.35	0.35	0.35	0.35	0.35	0.35	0.35	0.35
GW1 Coefficient (HR)	10	10	10	10	10	10	10	10	10	10
GW2 Storage (mm)	10	10	10	10	10	10	10	10	10	10
GW2 Percolation (mm/hr)	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3
GW2 Coefficient (Hr)	30	30	30	30	30	30	30	30	30	30

Sub division 16																	
Parameters	**Lumped model**	**sub division 1**	**sub division 2**	**sub divis ion 3**	**sub divis ion 4**	**sub divis ion 5**	**sub divis ion 6**	**sub divis ion 7**	**sub divis ion 8**	**sub divis ion 9**	**sub divis ion 10**	**sub divis ion 11**	**sub divisio n12**	**sub division 113**	**sub divisio n14**	**subdivisi on15**	**sub divis ion 16**
Initial Discharge	10	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
Ratio to peak	0.164	0.164	0.164	0.164	0.164	0.164	0.164	0.164	0.164	0.164	0.164	0.164	0.164	0.164	0.164	0.164	0.164
Recession-constant	0.923	0.923	0.923	0.923	0.923	0.923	0.923	0.923	0.923	0.923	0.923	0.923	0.923	0.923	0.923	0.923	0.923
Time of concentration	79	67	68	68	71	71	70	72	69	70	70	70	62	65	69	65	60
soil storage	445	300	300	300	300	300	300	300	300	300	300	300	300	300	300	300	300
Max infiltration	4.5	4.54	4.54	4.54	4.54	4.54	4.54	4.54	4.54	4.54	4.54	4.54	4.54	4.54	4.54	4.54	4.54
Storage Coefficient	59	50	51	50	51	51	51	55	50	51	52	52	55	55	49	52	51
Soil Percolation (mm/Hr)	0.32	0.5	0.5	0.5	0.45	0.5	0.5	0.5	0.5	0.5	0.5	0.45	0.5	0.5	0.5	0.5	0.5
Impervious	9.55	10	5	8	9	6	7	8	5	9	6	10	8	10	10	8	10
Soil %	90	90	90	90	90	90	90	90	90	90	90	90	90	90	90	90	90

Sub division 16																	
Parameters	**Lumped model**	**sub division 1**	**sub division 2**	**sub division 3**	**sub division 4**	**sub division 5**	**sub division 6**	**sub division 7**	**sub division 8**	**sub division 9**	**sub division 10**	**sub division 11**	**sub division12**	**sub division 113**	**sub division14**	**subdivision15**	**sub division 16**
Groundwater 1(%)	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80	80
Groundwater 2(%)	90	90	90	90	90	90	90	90	90	90	90	90	90	90	90	90	90
Tension Storage (mm)	21	21	21	21	21	21	21	21	21	21	21	21	21	21	21	21	21
Groundwater 1 storage	70	70	70	70	70	70	70	70	70	70	70	70	70	70	70	70	70
GW1 Percolation (mm/HR)	0.3	0.35	0.35	0.35	0.35	0.35	0.35	0.35	0.35	0.35	0.35	0.35	0.35	0.35	0.35	0.35	0.35
GW1 Coefficient (HR)	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10
GW2 Storage (mm)	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10
GW2 Percolation (mm/hr)	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3
GW2 Coefficient (Hr)	30	30	30	30	30	30	30	30	30	30	30	30	30	30	30	30	30

Appendix D: Statically T-test for lumped and six subdivisions

Lumped model with Sub division 1 model		
t-Test: Two-Sample Assuming Unequal Variances		
	366	376
Mean	105	100
Variance	3200	4418
Observations	2	2
Hypothesized Mean Difference	0	
df	2	
t Stat	0.081	
P(T<=t) one-tail	0.471	
t Critical one-tail	2.920	
P(T<=t) two-tail	0.943	
t Critical two-tail	4.303	

Lumped model with Sub division 2 model		
t-Test: Two-Sample Assuming Unequal Variances		
	366	376
Mean	105	100
Variance	3200	4418
Observations	2	2
Hypothesized Mean Difference	0	
df	2	
t Stat	0.081	
P(T<=t) one-tail	0.471	
t Critical one-tail	2.920	
P(T<=t) two-tail	0.943	
t Critical two-tail	4.303	

Lumped model with Sub division 3 model		
t-Test: Two-Sample Assuming Unequal		
	366	373
Mean	105	101.5
Variance	3200	2964.5
Observations	2	2
Hypothesized Mean Difference	0	
df	2	
t Stat	0.063	
P(T<=t) one-tail	0.477	
t Critical one-tail	2.920	
P(T<=t) two-tail	0.955	
t Critical two-tail	4.303	

Lumped model with Sub division 4 model		
t-Test: Two-Sample Assuming Unequal Variances		
	366	382
Mean	105	97
Variance	3200	1568
Observations	2	2
Hypothesized Mean Difference	0	
df	2	
t Stat	0.164	
P(T<=t) one-tail	0.442	
t Critical one-tail	2.920	
P(T<=t) two-tail	0.885	
t Critical two-tail	4.303	

Lumped model with Sub division 5 model		
t-Test: Two-Sample Assuming Unequal Variances		
	366	367
Mean	105	104.5
Variance	3200	1404.5
Observations	2	2
Hypothesized Mean Difference	0	
df	2	
t Stat	0.01	
P(T<=t) one-tail	0.496	
t Critical one-tail	2.91998558	
P(T<=t) two-tail	0.992631705	
t Critical two-tail	4.30265273	

Lumped model with Sub division 6 model		
t-Test: Two-Sample Assuming Unequal Variances		
	366	361
Mean	105	107.5
Variance	3200	1624.5
Observations	2	2
Hypothesized Mean Difference	0	
df	2	
t Stat	-0.051	
P(T<=t) one-tail	0.482	
t Critical one-tail	2.920	
P(T<=t) two-tail	0.964	
t Critical two-tail	4.302	

Appendix E: Watershed subdivisions approach

Authors	Literature support	Methods
Kanchanamala, D. P. H. M., Herath, H. M. H. K., & Nandalal, K. D. W	Kanchanamala, D. P. H. M., Herath, H. M. H. K., & Nandalal, K. D. W. (2016). Impact of Catchment Scale on Rainfall Runoff Modeling: Kalu Ganga River Catchment upto Ratnapura. *Engineer: Journal of the Institution of Engineers, Sri Lanka*, *49*(2),	River network ,Landuse and Landuse
Kim, J.-G., Park, Y., Yoo, D., Kim, N.-W., Engel, B. A., Kim, S., Lim, K. J	Kim, J.-G., Park, Y., Yoo, D., Kim, N.-W., Engel, B. A., Kim, S., … Lim, K. J. (2009). Development of a SWAT Patch for Better Estimation of Sediment Yield in Steep Sloping Watersheds1. *JAWRA Journal of the American Water Resources Association*, *45*(4), 963–9	Threshold Area Using Stream Network
Zhang, H. L., Wang, Y. J., Wang, Y. Q., Li, D. X., & Wang, X. K.	Zhang, H. L., Wang, Y. J., Wang, Y. Q., Li, D. X., & Wang, X. K. (2013). The effect of watershed scale on HEC-HMS calibrated parameters: a case study in the Clear Creek watershed in Iowa, US. *Hydrol. Earth Syst. Sci.*, *17*(7), 2735–2745	Threshold Area Using Stream Network
Narayan Prasad Gautam	Narayan Prasad Gautam. (2015).Hydrological Modeling with HEC-HMS in Different Channel Sections in Case of Gandaki River ,Basin Global Journals Inc.,(USA) 2249-4596	Stream Network
Manoj Jha, Philip W. Gassman, Silvia Secchi, Roy Gu, and Jeff Arnold	Manoj Jha, Philip W. Gassman, Silvia Secchi, Roy Gu, and Jeff Arnold,(2004).EFFECT OF WATERSHED SUBDIVISION ON SWAT FLOW,SEDIMENT, AND NUTRIENT PREDICTIONS	Randomly using stream network
Tripathi, M. P., Raghuwanshi, N. S., & Rao, G. P	Tripathi, M. P., Raghuwanshi, N. S., & Rao, G. P. (2006). Effect of watershed subdivision on simulation of water balance components. *Hydrological Processes*, *20*, 1137–1156.	Automatic Delineation

Authors	Literature support	Methods
(Luong, 2008)	(Luong, 2008).Cleveland Subdivision of Texas Watersheds for Hydrologic Modeling, Texas Tech University College of Engineering	Equal Area Method
Wingeld (2008)	David B. Thompson, Theodore G. (2009).Cleveland Subdivision of Texas Watersheds for Hydrologic Modeling, Texas Tech University College of Engineering	Heuristic Approach

Appendix F:Evaluation criteria for AMC calculations

Authors	Literature Supports	Verify in Literature	RMSE (mm)	Rank
Sobhani	Sobhani G (1975) A review of selected small watershed design methods for possible adoption to Iranian conditions. M.S. Thesis, Utah State University, Logan, UT	S. K. Mishra & M. K. Jain & P. Suresh Babu &K. Venugopal & S. Kaliappan(200).Comparison of AMC-dependent CN-conversion Formulae,Water Resour Manage (2008) 22:1409–1420	13.683	2
Hawkins et al.	Hawkins RH, Hjelmfelt AT Jr, Zevenbergen AW (1985) Runoff probability, storm depth and curve numbers.J Irrig Drain Eng ASCE 111(4):330–340	S. K. Mishra & M. K. Jain & P. Suresh Babu &K. Venugopal & S. Kaliappan(200).Comparison of AMC-dependent CN-conversion Formulae,Water Resour Manage (2008) 22:1409–1420	13.509	1
Chow et al.	Chow VT, Maidment DR, Mays LW (1988) Applied hydrology. McGraw-Hill, New York	S. K. Mishra & M. K. Jain & P. Suresh Babu &K. Venugopal & S. Kaliappan(200).Comparison of AMC-dependent CN-conversion Formulae,Water Resour Manage (2008) 22:1409–1420	13.776	3

Authors	**Literature Supports**	**Verify in Literature**	**RMSE (mm)**	**Rank**
Neitsch et al.	Neitsch SL, Arnold JG, Kiniry JR, Williams JR, King KW (2002) Soil and water assessment tool (SWAT):theoretical documentation, version 2000. Texas Water Resources Institute, College Station, TX, TWRI Report TR-191	S. K. Mishra & M. K. Jain & P. Suresh Babu &K. Venugopal & S. Kaliappan(200).Comparison of AMC-dependent CN-conversion Formulae,Water Resour Manage (2008) 22:1409–1420	13.865	4