INCORPORATION OF THE OPTIMUM RAINFALL SPATIAL VARIABILITY IN A MONTHLY RAINFALL RUNOFF MODEL

Ankit Bhatt

(179232A)

Degree of Master of Science

Department of Civil Engineering

University of Moratuwa
Sri Lanka

April 2020

INCORPORATION OF THE OPTIMUM RAINFALL SPATIAL VARIABILITY IN A MONTHLY RAINFALL RUNOFF MODEL

Ankit Bhatt

(179232A)

Supervised by
Professor N.T.S Wijesekera

Thesis submitted in partial fulfilment of the requirements for the degree of Master of Science in Water Resources Engineering and Management

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

Department of Civil Engineering

University of Moratuwa

Sri Lanka

April 2020

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, 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).

.... Date: 2020 . 04. 20

Ankit Bhatt

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

.... Date: 2020 . 04. 27

Professor N.T.S. Wijesekera

Incorporation of the Optimum Rainfall Spatial Variability in a Monthly Rainfall Runoff Model

ABSTRACT

Most common method of accounting spatial variability of rainfall in hydrologic modelling is with the use of Thiessen Weights whereas some authors consider it illogical as it can result in biased distribution of rainfall. Mathematical rainfall-runoff models need a representative rainfall input and adequacy of a geometric method of rainfall accounting requires an investigation. Lack of sufficient information about spatial distribution of rainfall had always been one of the most important sources of errors in runoff estimations. Water resources planning is mostly done at a monthly time scale and hence a simple watershed model with the capability of moisture accounting is a desirable tool for practicing engineers. In 1990, a study of Mahaweli and Kalu Ganga watersheds had demonstrated an application of optimising rainfall station weights. Present study focusing on optimizing rainfall gauging station weights using the two-parameter monthly water balance model Xiong & Guo (1999), used daily rainfall from 2006-2017 of five rainfall gauging stations, evaporation and streamflow of Attanagalu Oya Basin at Dunamale to evaluate the spatial variability to contribute towards efficient water resources applications. Accordingly, the objective of the present study is to estimate streamflow using the 2P monthly water balance model by incorporating optimised rainfall spatial variability for water management, planning and design. First the model was developed, and the two model parameters c and SC were optimized using Thiessen average rainfall. Then in a stepwise manner, the station weights, parameter c and Sc were treated as parameters for optimisation. MRAE was used as the objective function for evaluation while observing the High, Medium and Low flow behaviour during optimisation. Water balance, soil moisture level, evaporation and the NSE model efficiencies were observed for comparison. Initial soil water content was found to be 186.13mm using a warmup period of 5 repetitions. The optimum model parameter (SC and C) values and optimized rainfall weights achieved during first and second optimization stages are 782.47 mm, 1.87 and 0.387, 0.325, 0.145, 135, & 0.008 for Vincit, Pasyala, Nittambuwa, Karasnagala, & Chesterford respectively. The values achieved while simultaneously optimizing both rainfall & model parameters are 846.42 mm, 1.95, and 0.528, 0.199, 0.12, 0.144, 0.009. The mean MRAE value for calibration period is 0.43 and verification period 0.41. The 2P monthly water balance model with Thiessen rainfall station weights when compared with the optimised station weights indicated a difference of 8-9% in MRAE with an average MRAE value of 0.42 and a difference of 67 and 53 mm in average annual water balance error during calibration and verification respectively. On a monthly scale even a small change in rainfall station weight aggregates and gets reflected in the model estimates especially for stations receiving high intensity rainfall. Therefore, using a method of areal averaging that predetermines rainfall station weights and disregards the spatial mobility of a rainfall event will lead to erroneous results.

Keywords: two-parameter model; rainfall weight optimization; monthly water balance

ACKNOWLEDGEMENT

I would like to express my sincere gratitude to my research supervisor, Professor N.T.S Wijesekera for the continuous support of my study, for his patience, motivation and immense knowledge. Without his dedicated supervision and continued guidance, this thesis would not be in success. I am grateful to him for spending his valuable time with me in materializing this research work in time. He consistently allowed this research to be my own work but steered me in the right direction whenever he thought I needed it.

I will never hesitate to convey my thanks to the course coordinator Dr R.L.H Rajapakse by extending all necessary help. He was kind enough to provide help and support with his busy schedule. His sincere and consistent encouragement is greatly appreciated.

I am grateful to Mr. Wajira Kumarasinghe who looked after day to day needs during research period, would thank him for his help and support all the way during this research work.

My thanking list also includes the late Shri Madanjeet Singh and the University of Moratuwa for furnishing this outstanding opportunity to study towards a Master's Degree of Water Resource Engineering and Management, at UNESCO Madanjeet Singh Center for South Asia Water Management, Department of Civil Engineering, University of Moratuwa, Sri Lanka.

CONTENTS

LIST OF FIGURES

LIST OF TABLES

Incorporation of the Optimum Rainfall Spatial Variability in a Monthly Rainfall Runoff Model

1 INTRODUCTION

1.1 Overview

Water is a finite resource, increasing global population and demand has put pressure on water resource managers to sustainably manage water resources all over the world failing of which will adversely affect various sector subsequently affecting the whole society, economy of a country and the entire world. This research focuses on Water Resource Management Sector i.e. water availability and planning of water resources. Water resource management and strategic planning is carried out to fulfil the shortage between demand and supply (Xiong and Guo, 1999). As it is of utmost importance to maintain a constant supply of water for daily drinking and sanitation purposes in order to improve the quality of living of people and provides water for irrigation in both dry and wet seasons.

Water balance is based on the principle of conservation of mass and is a method of accounting the repetitive cycle of hydrology of an area with prominence on soil moisture and plants. Water balance models are tools which can help us understand the hydrology of a catchment, the relationship between rainfall and runoff and quantification of flow of water in and out of a system. Such models can be either very complex or relatively simple depending upon the assumptions of various hydrological domains present in the system.

Over the years water balance models have been developed to work for various time scales, among them are monthly water balance models (MWBM) which provides easy but refined ways of explaining hydrological processes and has low input requirements, well-performing conceptual framework with simple model calibration (Bai, Liu, Liang, & Liu, 2015). MWBMs have their own significance and are used for various purposes such as water resource management, long-range streamflow forecasting, drought assessment, reconstruction of hydrology of a catchment (Mouelhi et al.,2006;

Xu & Singh,1998), as well as planning, design and management of water resources because of their simplicity and efficiency. Water balance models that simulates streamflow hydrographs using available meteorological data can be a very helpful tool to practicing engineers for water resource planning (Jayatilaka, Sakthivadivel, Shinogi, Makin, & Witharana, 2003), design and construction of water infrastructure and policies. All over the world evaluation of the net available resources be it any natural resource has utmost importance, in this study, the net water resources available on both the surface and the subsurface are calculated for a monthly timescale using a water balance model having two model parameters.

A numerous amount of runoff models based on rainfall as a significant model input have been established in the past to estimate streamflow, but those models do not incorporate the spatial variability of rainfall which "plays a very important role in hydrological modelling, disaster prediction, and watershed management" and topographic factors have variable effects on the spread of precipitation spatially (Chen, et al., 2017). Rainfall runoff estimates, or forecasts can be more accurate if spatial variability of rainfall is also incorporated which has been demonstrated by Wijesekera & Musiake, (1990a, 1990b) and mentioned by Sugawara, (1992) and Cristiano et. al. (2017).

Patrick & Stephenson, (1990) in a study of spatial variability of rainfall mentions that traditional techniques of areal averaging can result in disproportionate amount of rainfall in a certain area of catchment entirely deu to the weight value. Since a rainfall occurrence over the catchment is mobile, ignoring this will certainly introduce an error while modelling a catchement.

Sugawara (1992) mentions that Thiessen polygon method as illogical, and states that in principle, the weights of rainfall stations should be determined by the meteorological conditions and not by their geometrical positions. According to Sugawara, weights should be determined considering the reliability of the observed data of gauging stations in order to obtain good results in discharge.

The problems related to spatial variability of rainfall are not new says Berndtsson & Niemczynowicz, (1988) and yet according to Cristiano et. al, (2017), the relationships between variability in rainfall and hydrological response are still poorly understood, even with developments in hydrological models over the years.

This research is carried out to fulfil the gap in accuracy of streamflow estimates from a monthly water balance model due to non-accountability of spatial variation for efficient water resource management. Present study focuses on improving the areal average rainfall input in rainfall runoff models by means of rainfall station weights optimization and based on matching of model simulated streamflow with observed streamflow.

The location of the catchment, rainfall station and streamflow gauging station are shown in Figure 1-1.

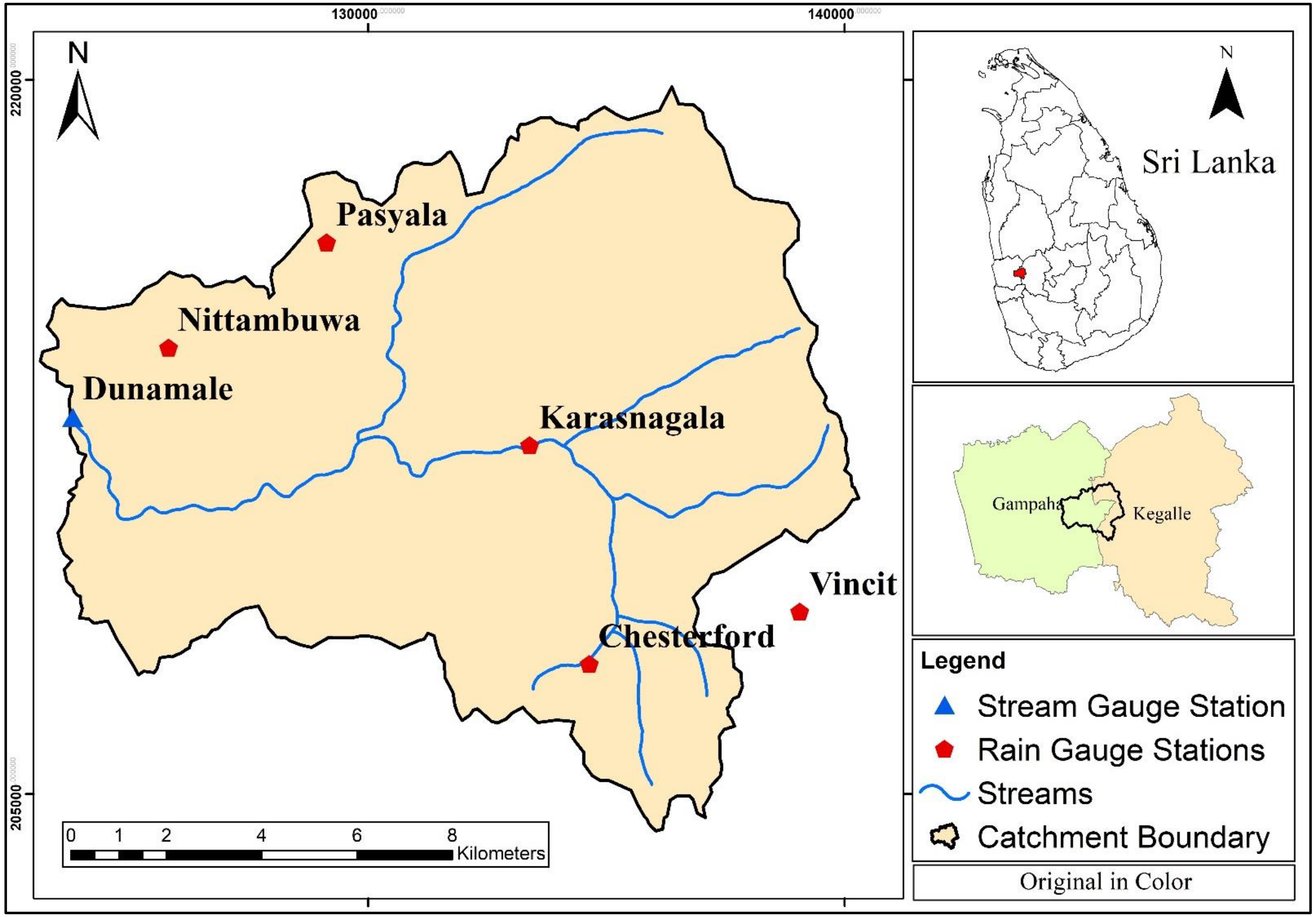


Figure 1-1 Catchment Area of Attanagalu Oya at Dunamale

1.2 Objective of the Study

1.2.1 Overall objective

The overall objective of the research is to study the effects of rainfall spatial variability on streamflow estimates using a two-parameter monthly water balance model by means of optimization of rainfall station weights for water management, planning and design.

1.2.2 Specific objective

1. Literature Review: To capture the state-of-the-art water balance models, catchment modelling, parameter optimization & spatial variability.

2. To collate and analyse data, do data checking and split it into calibration and verification data sets.

3. Develop the model to carry out various computations for optimizing model parameters and rainfall station weights.

4. Evaluation of results and comparison of optimized parameters with discussion.

5. Conclude results and give recommendations for the model's potential application in water resources assessment.

2 LITERATURE REVIEW

2.1 Types of Water Balance Models

2.1.1 General

Water balance models were developed to estimate the balance between inflow and outflow of water in a specific area or catchment. An inflow is the result of precipitation and snowmelt. Whereas, an outflow is the result of evapotranspiration, streamflow and groundwater recharge. Pioneered in 1940's by Thornthwaite (1948), water balance models were further modified by Thornthwaite and Mather in 1955.

Over the years, water balance models were developed based on temporal resolution such as annual, monthly, daily, hourly etc., intended use like water resource management or flood management, number of parameters, input data such as rainfall, evaporation, soil moisture etc., (Mouelhi et al., 2006; Xu & Singh, 1998; Zhang, Engel, Ahiablame, & Liu, 2015) and are acknowledged for their significance in modelling catchment hydrology (Jayatilaka, Sakthivadivel, Shinogi, Makin, & Witharana, 2003; Bai, Liu, Liang, & Liu., 2015; Chen, et al, 2017) due to their varied applications and accuracy with minimal data requirement. Models can be distinguished according to their ability to replicate the catchment's spatial variability into lumped, semi-distributed and fully distributed models (Cristiano et. al, 2017).

Al-Lafta, Al-Tawash, & Al-Baldawi (2013) refers to these models as tools for water resource management. These models also have the capability of evaluating theories and assumptions about the hydrological processes of a basin.

Xu & Singh, (1998) reviewed monthly water balance models and found out that in many countries rainfall data is available but streamflow data are either limited or rarely available so there's a need to develop models specially based on precipitation (rainfall) as input. In these model's evapotranspiration is calculated as a part of precipitation while remaining is calculated empirically as surface runoff or infiltration.

Water balance model need not be complex in order to get better estimates, simple models have performed comparable to complex models. Simple models with less input requirement serve better purpose as in most areas climatological data is not sufficiently available for modelling.

2.1.2 Monthly water balance models

Out of all the available hydrological models, simple monthly water balance models perform good in wet or humid catchments (Bai, Liu, Liang, & Liu, 2015; Xiong & Guo, 1999) with just 3-5 parameters being enough to produce majority of the hydrological information on a monthly time step (Xu & Singh, 1998).

These Models have various applications such as long-range streamflow forecasting, reconstruction of the hydrology of catchments, assessment of climate change, assessment of water supply, irrigation demand, seasonal and geographical patterns, design and operation of reservoirs etc (Kim, Hong, Kang, Noh, & Kim, 2015; Makhlouf & Michel, 1994; Xiong & Guo, 1999; Xu & Singh, 1998; Mouelhi, Michel, Perrin, & Andreassian, 2006).

Comparative study of 12 MWBMs in 153 different climatic catchments of China by Bai, Liu, Liang, & Liu, (2015), recommends working on the process of runoff generation rather than evapotranspiration (ET) for model improvements due to its limited influence on performance.

Xu & Singh (1998) found that models such as the Tennessee Valley Authority (TVA) developed by Snyder in 1963, the time variant of the single reservoir model developed by Gabos and Gasparri in 1983, and more were developed based on precipitation as the main input due to the limited availability of streamflow data in many countries.

Wang, et al., (2011) in a comparison study, Wapada model with daily & monthly WBMs in simulating monthly runoff using daily rainfall and monthly PET from 1960-2007 in 331 unimpaired catchments of Australia - Area varying from 51-1979 km^2. For Australian catchments Wapada model's aggregate skill was better than other WBMs (SimHyd, AWBM, ABCD & Budyko framework model) with NSE value greater than 0.8 for 40% catchments and 0.6 for 80% catchments during verification period.

The new GR2M model developed by Mouelhi, Michel, Perrin, & Andreassian, (2006) compared with other widely used MWBMs in which two out of the three two-parameter models performed good indicating that two-parameters can be sufficient on a monthly time step.

2.1.3 Two-parameter monthly water balance models

Water balance models have advanced over a long period of time based on various aspects such as data resolution, number of parameters, data type, etc.

Makhlouf & Michel, (1994) developed a two-parameter GR2M model for French watersheds and it was applied to 91 catchments with area varying from 315-5560 km^2 with a data duration of 27 years. Comparison with 4 widely used MWBMs showed that GR2M model was second to only ABCD model based on the NASH criteria. X1, a positive parameter realtive to the soil moisture reservoir's max capacity & X2 ranges between 0 to 1 is a factor in a linear reservoir which adds up to the total discharge from the model.

Xiong & Guo, (1999) developed a MWBM with two parameters and tested it in 70 sub catchments of China with catchment area varying from 230-5257 km^2 using yearly rainfall, pan evaporation and runoff data. Two-parameter model with R2 value mean as 85.66% and 84.78% proved highly efficient & comparison with a five-parameter MWBM in 8 sub-catchments showed mean R2 values as 88.60% & 89.55% during calibration and 90.98% & 88.59% during verification respectively. The two-parameters of their model are c which takes into account the time scale change and catchment field capacity is represented by SC.

Mouelhi, Michel, Perrin, & Andreassian, (2006) developed a two-parameter MWBM based on parameter reduction process using a parent model scheme (PMS) and used 410 basins located in Spain, France, Australia, United States and Ivory Coast with variety of climatic conditions to test and improve their new GR2M model. Their two-parameter model performed agreeably compared to two-parameter model by Guo et al. (2002), and some of the other widely used three and four parameter models.

Kim, Hong, Kang, Noh, & Kim, (2015) modified the two-parameter MWBM by Xiong & Guo, (1999) and introduced a method of parameter estimation using catchment characteristics, a reduction factor k which converts pan evaporation to actual evaporation and considered that field capacity SC is related to the curve number of Antecedent Moisture Condition II and can be determined with the land use and the type of soil. With the possibility to estimate the model parameters using geological and meteorological conditions of the watershed, their model can be applied in ungauged basins as well.

2.2 Rainfall Spatial Variability

The accumulated total volume for any duration of time counts as the amount of precipitation which is one of the main inputs for rainfall-runoff models. There are various methods to determine areal average rainfall which accounts for variability of rainfall on spatial context, out of which the most common methods are Thiessen polygon, isohyt, inverse distance weighted etc. The methods maybe different but for a longer duration of time most of these methods give comparable results as concluded by Singh and Chowdhury, (1986).

2.2.1 Methods of areal averaging rainfall

Bhavani (2013) in a study mentions the role of rainfall as a significant input for any hydrological model, making it a critical task with paramount importance to choose an effective average area-based approach for measuring representative catchment rainfall, taking account of each and every rainfall stations in the basin.

Some methods are more often used than others for their simplicity such as arithmetic mean, isohyetal, thiessen average etc. (Akin, 1971; Edwards, 1972; Shaw & Lynn, 1972; Bhavani, 2013; Barbalho forest, & Formiga, 2014)

Arithmetic Mean Method - It is one of the simplest ways of calculating the mean rainfall of a catchment or basin. The resulting rainfall is calculated by the available mean or average rain gage data and the average term refers to any of the central tendency measurements.

$$P_{av} = \frac{P_1+P_2+\cdots+P_n}{n} \qquad 1$$

Where P_{av} is mean or average rainfall, P_i is the representative rainfall recorded at a rainfall station and n denotes the total number of rainfall stations.

Thiessen Polygon Method – Thiessen Polygon method which is based on the station geometry was developed by (Thiessen & Alter, (1911) and is described by equation 2.

$$Q = \frac{A_aR_a+A_bR_b+\cdots+A_nR_n}{A_a+A_b+\cdots+A_n} \qquad 2$$

Where Q is the calculated thiessen rainfall, R_i is station rainfall and A_i is the spatial area of a particular rainfall station.

Isohyetal Method – Isohyetal method (VenteChow 1988) computes the average rainfall using equation 3.

$$P_{av} = \frac{A_1\frac{P_1+P_2}{2}+A_2\frac{P_2+P_3}{2}+\cdots+A_{n-1}\frac{P_{n-1}+P_n}{2}}{A_1+A_2+\cdots+A_n} \qquad 3$$

Where, P_{av} is the areal average rainfall, P_i is rainfall isohyet, A_i represents the area between isohyets.

2.2.2 Importance spatial variability of rainfall

Methods for areal estimation of rainfall have been developed over the years however their accuracy is not supported with streamflow observations. Wijesekera & Musiake, (1990a, 1990b), in their study demonstrates the incorporation of spatial variability of rainfall by means of optimizing rain gauging station weights and comparing model predictions with streamflow observations.

Apart from the geometric method of areal averaging accuracy of areal average rainfall also depends upon the distribution and desinty of rainfall gauging stations. Absolute error over the region varied drastically from 15% to 64% as the number of rain gauges representating the rainfall of the region decreased from 8 to 1 in a study carried out by Mishra, (2013).

2.3 Model Evaluation and Parameter Optimization

The process in which a model is tested and trained with a known dataset with assumptions to achieve a desired result is known as model evaluation. It aims to estimate the generalization accuracy of the model for an unknown dataset. Parameter optimization is the process of searching for optimum model parameters to achieve highest degree of matching of an objective function.

According to Moriasi, et al., (2007), calibration is a process of estimating model parameters for a given dataset with assumed conditions by comparing observed data with model generated results, whereas verification is the process of running a calibrated model with input parameters determined in calibration. Calibration dataset is used to determine the best model parameter values while the dataset is used to check the model suitability for the population by using the model parameters values obtained during calibration period is known as verification dataset.

Duan et. al., (1994) concludes their study on SCE-UA global optimization method by pointing out to the fact that incapability to search global optima for parameters by traditional optimization methods has limited the usefulness of conceptual models. Also, global optimization method can produce reliable global optimization estimates even for large and complex optimization problems. In another study of automatic calibration by Gan and Biftu (1996) where a comparison of automatic optimization technique was done using four different rainfall-runoff models and models calibrated using the shuffle complex evolution method (SCE-UA) which has high-parameter dimensionality and can complete parameter search of all the models tested during the study in one stage is comparable only to that of the local simplex and multiple start simplex (MSX). Xu and Singh (1998) mentioned that automatic optimization has been a commonly opted method for calibrating monthly water balance models.

Monthly water balance models in general have simple composition with limited parameters therefore are believed to yield a unique set of parameter values using automatic optimization techniques which can be reproduced. Xiong and Guo, (1999) used simplex method to search for the optimum values of model parameters which is robust enough for many applications but for it to be effective, it has to be applied in stages which requires the user to be knowledgeable with the model being used (Gan and Biftu, 1996). According to Perrin, (2001) global search techniques have marginal advantage which is only limited to the calibration period. In their study a simple local search method was used as it requires less computations and was considered sufficient for their study.

2.3.1 Calibration and Verification data requirement

Xiong and Guo, (1999) in their study has used a data duration varying from 6 – 27 years for calibration and 2 – 8 years for verification, whereas they did not specify or suggested a data duration period to be used for the study.

Boughton, (2006) studied the data length impacts on hydrological models for calibration data duration varying from 2 to 30 years found out that overestimations of long term streamflow were minimized while considering 10 or more years duration for calibration dataset; but, the possibilities of underestimating were marginally minimized by even considering a period of 30 years.

Liu and Han, (2010) carried out a study to identify the calibration data duration indices for mathematical models where authors have selected various calibration data duration with adequate lengths (6, 12 and 24 months) and suitable durations in which prior to calibration work, the spectral characteristics of data sequences are examined. The absence of a proper numerical guide that can assist hydrologic modellers in selection of data duration for calibration work has forced the hydrologic models to adopt rule of thumb in selection of a certain period for calibration dataset while modelling (normally 6 years of data). The study also indicates that the information inside the dataset is of a more importance than duration of the data, therefore, a short duration of data may be sufficient in some cases.

Performance of Artificial Neural Network based models improve when 9 year or more data years for calibration was used which is not true in case of conceptual models as stated by Anctil, Perrin and Andreassian (2004) in a study of influence of observed data length on the performance conceptual rainfall-runoff prediction models using ninety-two different scenarios varying from 1 – 15 year time. They also found out that models with 3 to 5 years of calibration dataset resulted in best performance. It has been concluded by many researchers that lengthy calibration dataset does not necessarily provide superior model results (Li et al., 2010) as the information inside of the dataset and efficiency within which the information is extracted is more important than the data series length (Sorooshian et al., 1983; Liu & Han., 2010). Data duration required for calibration can vary from model to model and study regions from three months to ten years such as catchments with humid climates will need less calibration data length to provide good results and parameters with stable values (Li et al., 2010) while in general arid catchments are comparatively difficult to model due to their noisy data, more complex and variable hydrological processes (Gan and Biftu, 1996).

2.3.2 High, Medium, and Low flows

It is of utmost importance to classify flows into various categories to evaluate the model performance specific to modelling targets such as management of water resource, flood forecasting and management, assessment for droughts etc. According to Wijesekera (2017) a clear differentiation in the characteristics of high, medium and low flows is missing.

Flows have been classified by EPA (2007) into five groups i.e. high, moist condition, mid-range, dry and low flows and the differentiation percentages are 10, 40, 60, and 90% where 0-10% is for high, 10-40% for moist condition and so on. Researchers (Khandu 2016, Sharifi, 2015, Dissanayaka, 2017) have identified various flows based on natural breaks determined by shape or slope of the flow curve.

Standardization is lacking in the determination of these flow regimes as there is a wide variety of opinions, methods and ways to separate flows into categories. The selection of method is subjective to the researcher.

2.3.3 Objective function

Mathematical indicators used to determine the best possible solution for a specific objective are known as objective functions. It then uses the correlation of variables to determine the value of the final outcome. According to Mata-Lima, (2011) objective functions are statistical indices of capability of any model.

There are many commonly used objective functions. Nash Sutcliff Efficiency (NSE) coefficient has been used by Xiong & Guo, (1999); Guo, (1995); Zhang, Engel, Ahiablame, & Liu,(2015), Mean Ratio of Absolute Error (MRAE) has been used by Wijesekera and Musiake (1990), Wijesekera & Ghanapala, (2003); Perera and Wijesekera 2011; Wijesekera 2000; Sharifi 2015; Khandu 2016; Thapa (2014).

Following is a brief description of objective functions.

Sum of squared deviations (R2) – R2 has been used as an evaluation tool for hydrological simulations by (Diskin. M.H. & Simon. E.,1977).

$$R2 = \Sigma(q_o - q_s)^2 \quad 4$$

Where q_o and q_s are the observed and simulated streamflow values.

Nash-Sutcliff Efficiency – NSE was first proposed by Nash & Sutcliff, (1970), which is a normalized statistic function. It is one the most commonly used objective functions in hydrology Buzacott et. al. (2019). According to Servat & Dezetter (1991) NSE and R^2 regression analysis offer a similar kind of efficiency in a model. The range for NSE varies from negative infinity to 1, results get better as the value of NSE inclines towards 1.

$$NSE = 1 - \frac{\Sigma(Y_{obs} - Y_{sim})^2}{\Sigma(Y_{obs} - Y_{mean})^2} \quad 5$$

Where $Y_{sim,}$ Y_{mean} and Y_{obs} is the simulated value, mean of observed data, and observed values respectively.

Mean Ratio of Absolute Error (MRAE) – It is among one of the proposed numerical criteria for verification of a model by World Meteorological Organization (WMO, 1982; WMO, 1975).

MRAE considers the magnitude of error at each and every point and provides a mean average indicator of the observed and simulated hydrograph at that point of observed value.

Wijesekera & Perera, (2010) and Wijesekera & Ghanapala, (2003) used MRAE to find out the degree of accuracy and for the optimization of model parameters. MRAE can be calculated by using equation 6.

$$MRAE = \frac{1}{n} \Sigma \frac{|Q_C - Q_o|}{Q_o} \qquad 6$$

Where Q_o, Q_c is the observed and calculated streamflow values respectively and the number of observations is denoted by n.

Wijesekera & Ghanapala, (2003) used MRAE to compare model generated streamflow with observed streamflow while studying low-lying watersheds for environment flows and drainage in greater Colombo.

Mean Absolute Percentage Error (MAPE) – MAPE is popularly used in budgeting as an objective function since it produces error percentages as a result which are suited for reporting accounting data Makridakis, (1993). MAPE has also been defined as a percentage of MRAE by authors like Makridakis, (1993), and Tofallis.C., (2014).

$$MAPE = \frac{100}{n} \Sigma \frac{|Q_C - Q_o|}{Q_o} \qquad 7$$

Where Q_o, Q_c is the observed and calculated streamflow respectively and the total number of observations is denoted by n.

Root Mean Square Error (RMSE) – According to Singh et al., (2004); Moriasi, Wilson, Douglas-Mankin, Arnold, & Gowda, (2012) RMSE is amongst popularly used error indices.

$$RMSE = \sqrt{\frac{\Sigma(Y_O - Y_S)^2}{n}} \quad 8$$

Where Y_o and Y_s denotes observed and simulated streamflow while n is the number of observations used for calculation.

RMSE was used as a criterion for comparing hydrographs in a study to evaluate the outputs of a runoff model by Patry & Marino (1983).

2.3.4 Evaluation criteria

Moriasi, et al., (2007) states that model evaluation techniques can be broadly classified into graphical and statistical techniques. Therefore, it is adviced to use graphical techniques, along with quantitative statistics such as, NSE, percent bias (PBIAS), etc. to be used for evaluation of the model.

Wijesekera & Musiake, (1990) simulated the flow of Mahaweli river using a basic tank model and evaluated the model parameters with justifiable results using Ratio of Absolute Error to Mean.

Wijesekera (2000) states using a number of indices such as visual or graphical comparisons, water balance calculation, flow duration curves, and numerical indicators along with an objective function for achieving optimum parameters with realistic values.

2.3.5 Initial parameter values

Xiong and Guo, (1999) have mentioned the importance of initial soil water content and its impact on the simulation results. It is assumed that the initial soil moisture content value must not vary much for a months with similar rank within a year. They suggest the range for S(o) value varying from 150-200 mm for the initial model run which are only tested for the basins situated in China.

$$S(o) = \frac{\Sigma S(J \times 12)}{m} \quad 9$$

Where, S(o) is the initial value of soil water content, number of years of calibration data is represented by m, Warm-up period can help determining soil moisture for the initiation stage which is more reliable as on an annual scale climatic and meteorological conditions do not vary much. Therefore, leading to a stable soil moisture value annually. Sharifi, (2015); Khandu, (2016) and Dissanayake, (2017) stabilized the initial soil water content for a two-parameter model simulation using 5 repetitions during the warm-up period.

2.3.6 Warm-up period

Warmup period is the period which is required by the model to come to a steady state. Model also requires soil moisture content for the day before the data period used for calibration. Literature suggests a warm-up period of 3-5 repetitions for wet/humid catchments to determine a stabilized value of initial soil water content which is a critical input in the model as it influences the model performance during calibration.

In order to calculate the model storages at the beginning of the simulation cycle, Perrin (2001) used a one-year warm-up duration, where the initial amount of the storage values were set to the average value of the season for that corresponding year which was overlooked in the measurement of goodness-of-fit.

Robinson, (2004) was of the opinion that models should be in warming up period before it hits a practical or stable state with non-terminating simulations. According to Hoad, Robinson and Davies, (2008) five replications of the data produced better results in removing the initialisation bias compared to the single run.

Daggupati, P., et al. (2015) describes the use of warm-up period as a means to allow the model to attain dynamic equilibrium by running the simulation for an adequate amount of time. Length of this period may vary depending upon the different scale of hydrological processes.

Sharifi, (2015) in a study used repetition of 5 cycles as warming up period to stabilize the initial soil water content of a water balance model having two parameters on a monthly time scale for water resource evaluation and application potential of the model.

Khandu, (2016) used a warm up period of 5 periodic cycles and found the initial soil water content values as 138 mm and 280 mm for Sri Lankan catchments namely: Kelani Ganga and Gin Ganga respectively.

Dissanayake, (2017) in a study of applicability of monthly water balance model with two parameters in forecasting daily streamflows used 5 repetitions of warming up period for the whole calibration and verification datasets.

Literature does not suggest an exact duration for warm-up period for a monthly hydrological model but it has been observed that the whole dataset (calibration and verification) is used with 3 – 5 repetitions for a model to obtain stable state.

2.3.7 Parameter threshold values

Model parameter ranges not being mentioned by Xiong & Guo (1999) makes it difficult for modellers modelling a catchment outside china to have a reference of the parameter values or to evaluate if the resultant values from the model can be accepted. For catchments under their study parameter c ranges from 0.28 - 1.23 and field capacity SC ranges from 300 - 2000 mm.

Khandu, (2016) used the parameter ranges from 0.10 to 1.00 for c and 200 to 3500 for SC for the minimum value of MRAE that was obtained as 0.143 for Kelani Ganga and 0.144 for Gin Ganga after calibrating the model.

2.4 Data Checking Methods

2.4.1 Graphical

These methods allows results of data checks to be displayed in pictoral form for visual checking to find inconsistencies and outliers in the dataset. These checks include various time series analysis such as rainfall to streamflow for catchment response, rainfall trend for yearly/seasonal/monthly series etc for a realistic course of events.

2.4.2 Statistical

Statistical data checking techniques are used to extract quantitative information from the data such as mean, median, mode, annual water balance computations, etc. These methods can be used to find structure of the data, assumptions in statistical models, and communicate the results of an analysis.

2.4.3 Filling of missing data

Paulhus & Kohler, (1952) investigated the use of normal ratio method and 3 station average method for interpolating missing precipitation records and found out that these methods can be used when the error in the estimated data and data of respective index station is 10% or less. Normal ratio method estimates were better and in 4 out of 5 data sets its average error of estimate was less than one-half to that of 3 station average method. Suhaila, Sayang, & Jemain, (2008) compared traditional methods such as inverse distance weighting (IDW), normal ratio (NR), coefficient of correlation weighting (CCW) and their own revised versions of the same for estimating missing rainfall data and their results shows that the modified methods performed better which were compared using mean absolute error (MAE), coefficient of correlation (R), and similarity index (S-index). Teegavarapu, Tufail, & Ormsbee, (2009) proposed a method that uses inherent algorithms and a nonlinear optimization to find ideal practical values and model coefficients, for estimating the missing data. Their studies demonstrate that improved precipitation figures can be achieved relative to those of the conventional inverse distance weighting methods.

Garcia, Sentelhas, Tapia, & Sparovek, (2006) proposed a method called closest station in which they found the two closest stations using cluster analysis and then after identification of closest station the data for a missing station was replaced by the data from the 1st closest station and if 1st station also had missing data then 2nd station was used to fill the data. The method showed a moderate performance for daily data while for 7, 15 and 30 days it showed a very good performance.

None of the literature strongly suggests using a particular method for estimating missing meteorological and climatological data. Therefore, data of missing station is replaced with the data from the nearest available station.

3 METHODOLOGY

The methodology applied in this analysis as seen in Figure 3-1 and a comprehensive approach has been shown in ANNEX C – Methodology. Optimization is one of the most important part of the study. It is carried out in 3 incremental stages where initially the model parameters are optimized keeping the rainfall station weights fixed (In this particular study thiessen weights were used as the initial rainfall station weights). The optimized parameters are then fixed and rainfall station weights are allowed to adjust freely. Lastly, both model parameters and rainfall station weights are optimized simultaneously. Further evaluation of these parameters and weights from the three stages is carried out based on various indices broadly classified into graphical and statistical indices such as annual water balance, box plots, duration curves along with a function that best serves the objective of the particular study, which in present study is Mean Ratio of Absolute Error (MRAE).

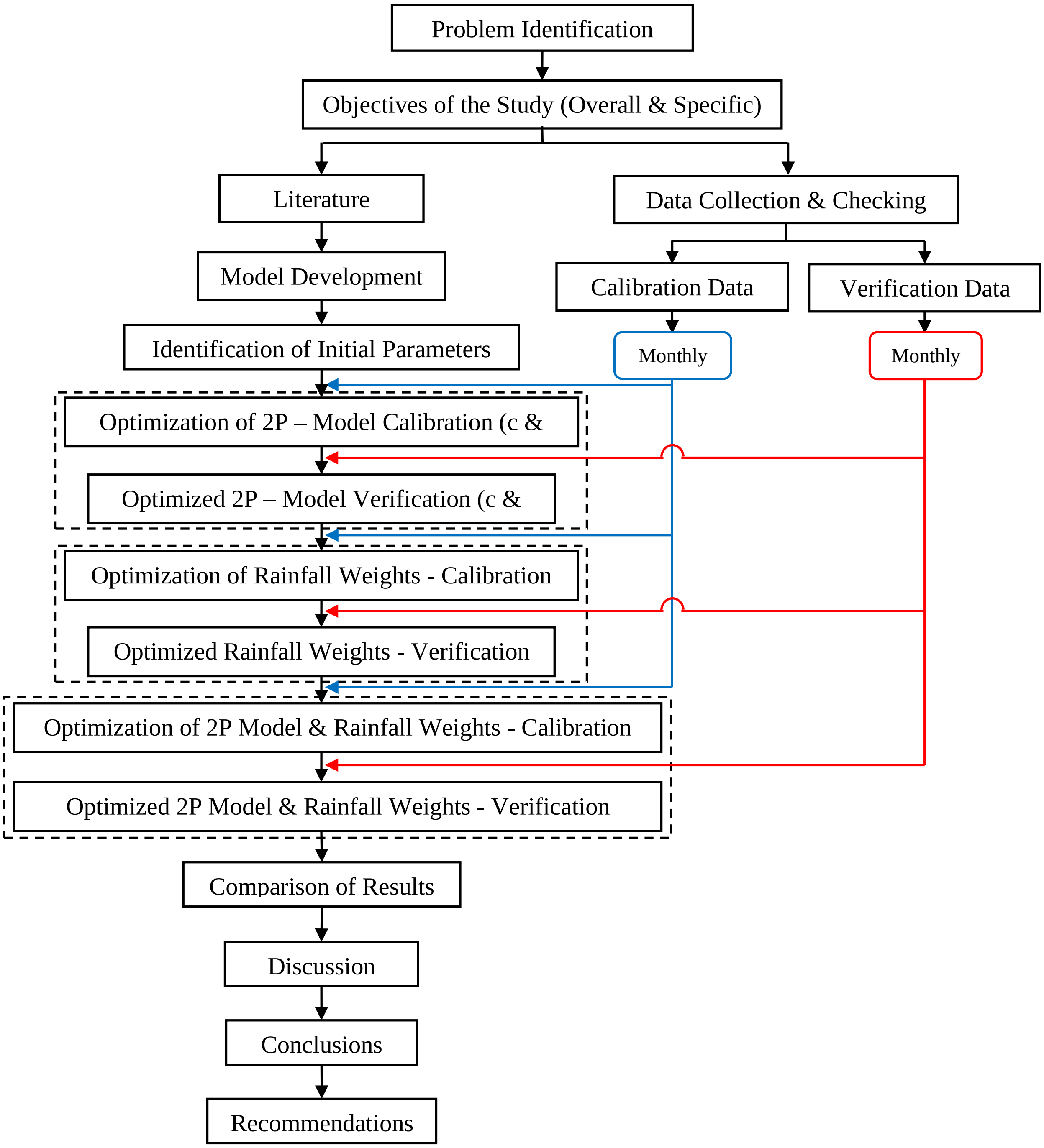


Figure 3-1 Methodology Flow Chart

4 DATA AND DATA CHECKING

Dunamale sub-basin which is a part of Attanagalu Oya basin of Sri Lanka was selected for the present study. Daily rainfall, evaporation and streamflow data from 2005-2017 for Attanagalu oya basin at Dunamale were collected. Various data checking methods were used in order to check for inconsistencies, outliers and filling of missing data such as visual and statistical methods. Distribution of gauging station were compared with the recommended station density of WMO (2008) and is shown in Table 4.1.

Table 4.1 Distribution of Gauging Stations of Dunamale Watershed

Gauging Station	Number of Stations	Station Density (km^2/station)	WMO Standards (km^2/station)
Rainfall	5	31.32	575
Streamflow	1	156.6	1875
Evaporation	1	156.6	5000

4.1 Attanagalu Oya Basin

Attanagalu Oya basin that drains over an area of 889 km^2 is located between the latitudes of 7° 00' and 7° 17' N, longitudes of 79° 50' and 80° 15' E. Its main tributaries are Diyella oya and Uruwal oya. It falls under four Agro ecological zones of Sri Lanka namely WL3, WL2a, WL1a and WL1b with an average rainfall ranging from 1200-2000 mm and the average annual runoff coefficient is 0.41.

Dunamale sub-basin of Attanagalu Oya basin, is considered for the research based on the availability of data. It has a catchment area of 153 km^2 and drains within two administrative district boundaries i.e. Gampaha and Kegalle. River gauging station of the watershed selected for the study is at Dunamale. There are five Rainfall gauging stations namely Vincit, Pasyala, Nittambuwa, Karasnagala and Chesterford. Figure 4-1 illustrates the locations and spatial distribution of monthly average rainfall of rain gauging station along with the river gauging station located at Dunamale.

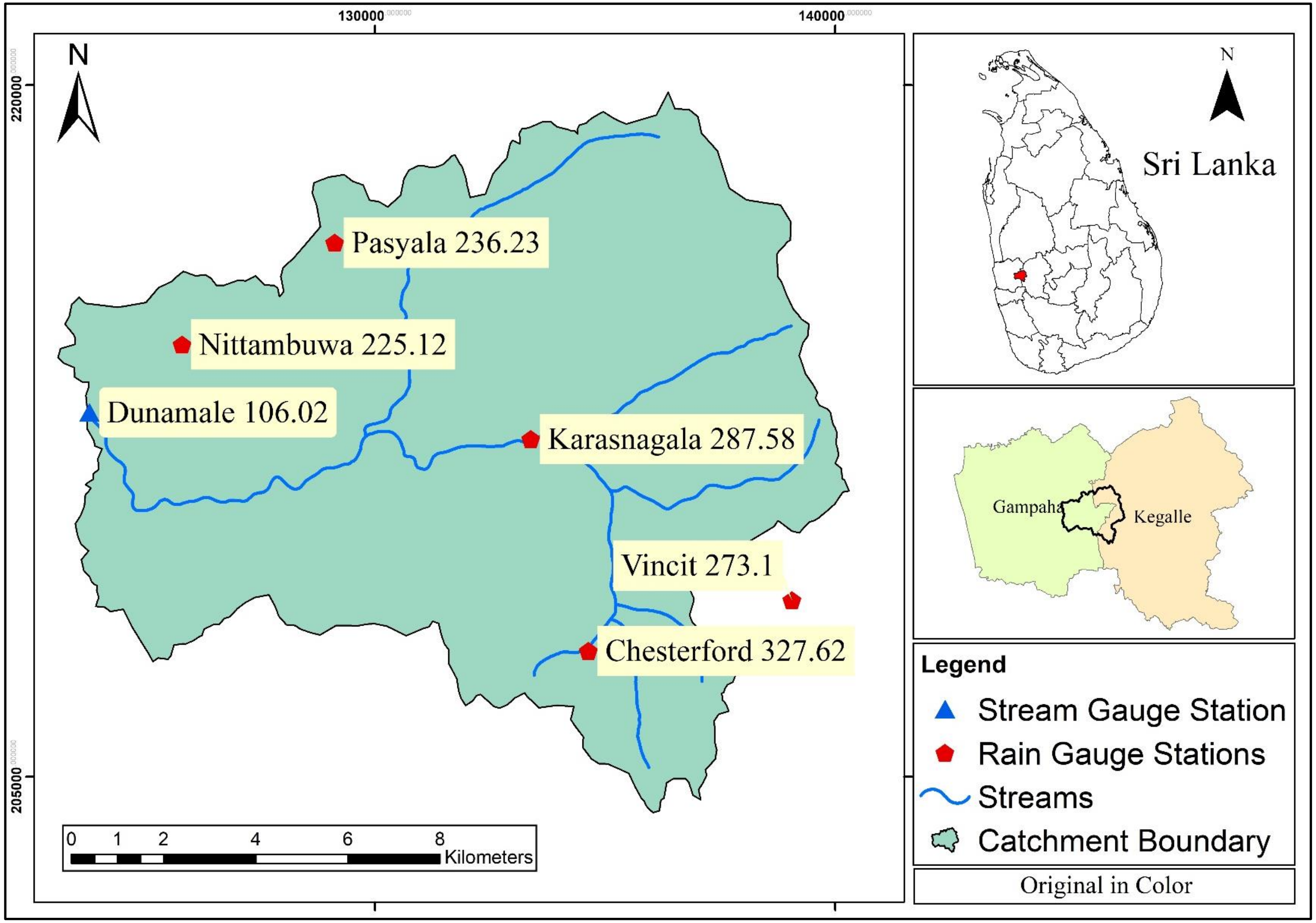


Figure 4- 1 Average monthly rainfall (mm) and Average monthly streamflow (mm/month) from the available observations

4.2 Data Summary

Summary of the data collected for the present study is mentioned in Table 4.2 with details of spatial resolution, data period, name of stations, type of data, and the source of data.

Table 4.2 Data Details of Attanagalu Oya at Dunamale

Data Type	Spatial Resolution	Station Name	Data Period	Source
Rainfall	Monthly	Karasnagala	2005-2017	Department of Meteorology & Irrigation Department
		Pasyala		
		Vincit		
		Chesterford		
		Nittambuwa		
Streamflow	Monthly	Dunamale	2005-2017	Department of Irrigation
Pan Evaporation	Monthly	Colombo	2005-2017	Department of Meteorology
Land Use Map	1: 50000		2015	Department of Survey
Topographic	1: 50000		2015	Department of Survey

4.2.1 Rainfall Stations and Missing Data

Locations of the stations are mentioned in Table 4.3 and missing data details are in Table 4.4.

Table 4.3 Rainfall Gauging Station Details of Attanagalu Oya at Dunamale

Rainfall Station	Coordinates	
	Longitude	Latitude
Karasnagala	80° 10' 15.6" E	7° 06' 43.2" N
Pasyala	80° 07' 48" E	7° 09' 00" N
Vincit	80° 11' 56" E	7° 05' 24" N
Chesterford	80° 11' 00" E	7° 04' 00" N
Nittambuwa	80° 06' 00" E	7° 07' 48" N

Table 4.4 Missing Rainfall Data of Attanagalu Oya at Dunamale

Year	Vincit	Pasyala	Nittambuwa	Karasnagala	Chesterford
2005					
2006	Sep			Feb, Mar, Apr, May, Jun, Jul, Aug, Sep	
2007		Sep		Oct, Nov	
2008	Feb			Mar	
2009					Jun, Dec
2010		Apr	Sep	Jul	Nov
2011	Jan, Jul, Oct, Nov		Nov		
2012	Jun, Jul, Sep, Nov, Dec				
2013	Dec	Oct, Nov, Dec		Jan, Aug, Nov	
2014	Jan		Sep		Apr
2015				May, Jun	
2016					
2017		Sep		Feb, Aug, Sep	

Karasnagala Station had 9 month of continuous missing rainfall data for the water year 2005-2006, filling of which using the closest station method would lead to similarity of rainfall and directly impact the model estimations. Therefore, the data for water year 2005-2006 was not used in the analysis.

4.2.2 Stream Gauging Station and Missing Data

Daily streamflow was aggregated to monthly and was used in the analysis of Attanagalu oya catchment. Latitude 7° 07' 00'' N and Longitude 80° 04' 54.5'' E are the coordinates of the river gauging station at Dunamale. There were some unrealistic values such as zero observed in the data which are unnatural for a catchment in wet and intermediate zone, these values been mentioned in Table 4.5.

Table 4.5 Missing Streamflow Data of Attanagalu Oya at Dunamale

Year	Dunamale Stream Gauging Station
2007	Feb (11 days), Mar
2008	Feb (3 days), Mar (2 days)
2009	Feb (12 days), Mar (9 days)
2010	Feb (8 days), Mar (7 days)
2012	Feb (6 days), Mar (3 days)
2014	Feb (23 days), Mar (7 days)
2016	Feb (7 days), Mar (3 days), Aug (9 days), Sep (14 days), Oct (18 days)
2017	Jan (15 days), Feb (22 days), Mar (3 days), Aug (4 days)

4.3 Annual Data Checking

4.3.1 Annual Data Statistics

Annual streamflow, evaporation and rainfall of each station and thiessen average rainfall is mentioned in Table 4.6 for Dunamale watershed corresponding to each water year. Mean, Maximum and Minimum data statistics are shown in graphical form in Figure B - 1.

Table 4.6 Annual Data Statistics for each Water Year - Dunamale Watershed

Water Year (Oct-Sep)	Rainfall (mm)						Streamflow (mm)	Evaporation (mm)
	Vincit	Pasyala	Nittambuwa	Karasnagala	Chesterford	Thiessen		
2006/07	3535	3742	3036	3612	3393	3457	1369	1369
2007/08	4029	3211	3076	3352	4530	3511	1552	1552
2008/09	3662	2790	2560	3238	3639	3116	1053	1053
2009/10	3250	2848	3201	3567	4252	3462	1307	1307
2010/11	3525	2984	2810	3948	5029	3685	1375	1375
2011/12	2844	2177	2145	2604	3257	2560	733	733
2012/13	2706	3198	3157	3801	4806	3637	1448	1448
2013/14	2675	2493	2371	3320	3088	2893	1129	1129
2014/15	2578	3190	2554	3768	4026	3350	1560	1560
2015/16	3478	3108	2612	3396	3868	3256	1546	1546
2016/17	3767	1443	2195	3356	3863	2926	923	923

Annual average rainfall in Dunamale watershed during the study period is 3259 mm, while annual average streamflow is 1272 mm. Therefore, the annual average runoff coefficient of the watershed during the study period is 0.39.

The annual variation in runoff coefficient during the study period corresponding to annual rainfall and observed streamflow is shown in Figure 4- 2.

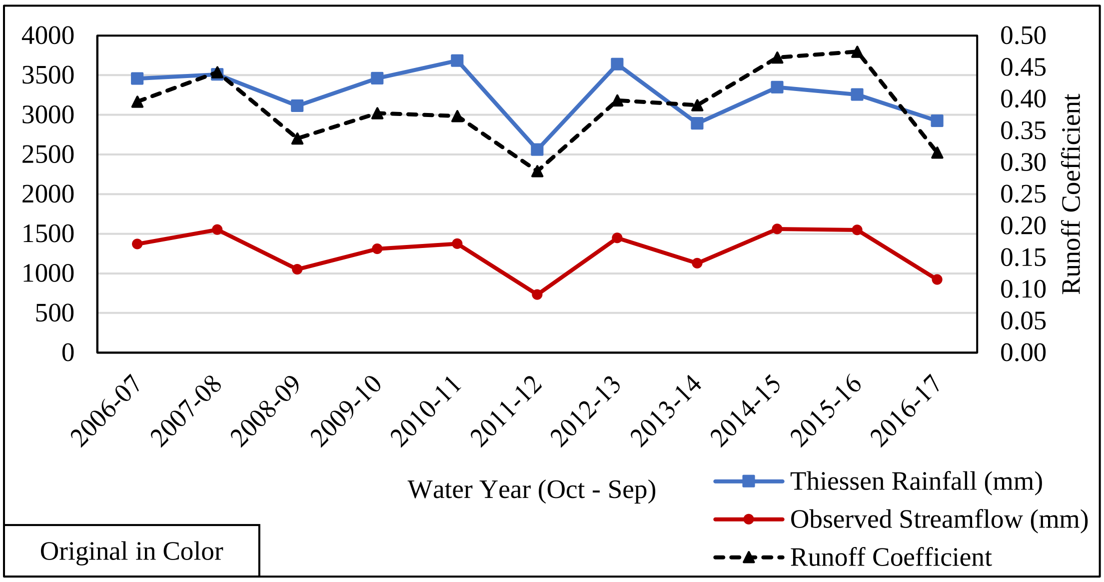


Figure 4- 2 Annual variation of runoff coefficient - Dunamale watershed

4.3.2 Annual Water Balance

Water Balance in simple terms means flow of water in and out of a system which is described using an equation which is based on the principle of conservation of mass. Annual Water Balance uses the water balance equation with an assumption that on an annual water cycle the change in storage will be negligible since the climatic conditions will be the same. This check is performed to check for the overall magnitude of error by comparing observed streamflow, measured rainfall and evaporation which is shown in Table 4.7 along with the runoff coefficient. It is also used as an indicator for catchment response.

It is clear from Figure 4- 3 that missing values of rainfall in water year 2005-2006 has led to a major shift from the annual water balance trend apart from which rest of the data has a similar movement.

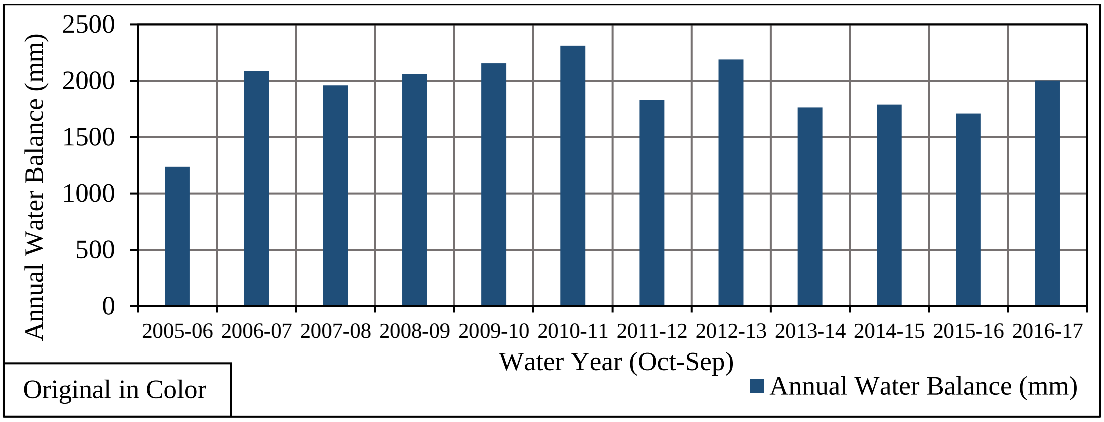


Figure 4- 3 Annual Water Balance - Dunamale Watershed

Table 4.7 Annual Water Balance - Dunamale Watershed

Water Year (Oct-Sep)	Thiessen Rainfall (mm/year)	Observed Streamflow (mm/year)	Pan Evaporation (mm/year)	Annual Water Balance (mm/year)	Runoff Coefficient
2005/06	2613.58	1375.82	1187.41	1237.76	0.53
2006/07	3457.07	1368.62	1241.01	2088.45	0.40
2007/08	3511.04	1552.28	1187.04	1958.75	0.44
2008/09	3115.69	1052.70	1267.52	2062.99	0.34
2009/10	3462.38	1307.48	1205.61	2154.90	0.38
2010/11	3685.05	1374.70	1171.05	2310.34	0.37
2011/12	2560.15	732.73	1269.82	1827.42	0.29
2012/13	3637.35	1447.55	1207.24	2189.81	0.40
2013/14	2892.58	1128.85	1317.94	1763.74	0.39
2014/15	3349.65	1560.00	1198.95	1789.65	0.47
2015/16	3255.93	1545.99	1393.59	1709.94	0.47
2016/17	2926.17	923.42	1217.23	2002.75	0.32

4.4 Monthly Data Checking

Thiessen rainfall variation for the catchment is presented in Figure 4- 4 on a monthly time scale for each water year. It is observed from the graphs that the overall rainfall pattern for all the stations show a two-peak pattern as Sri Lanka has two monsoons namely North East Monsoon and South West Monsoon, but some variations can also be observed for each individual station.

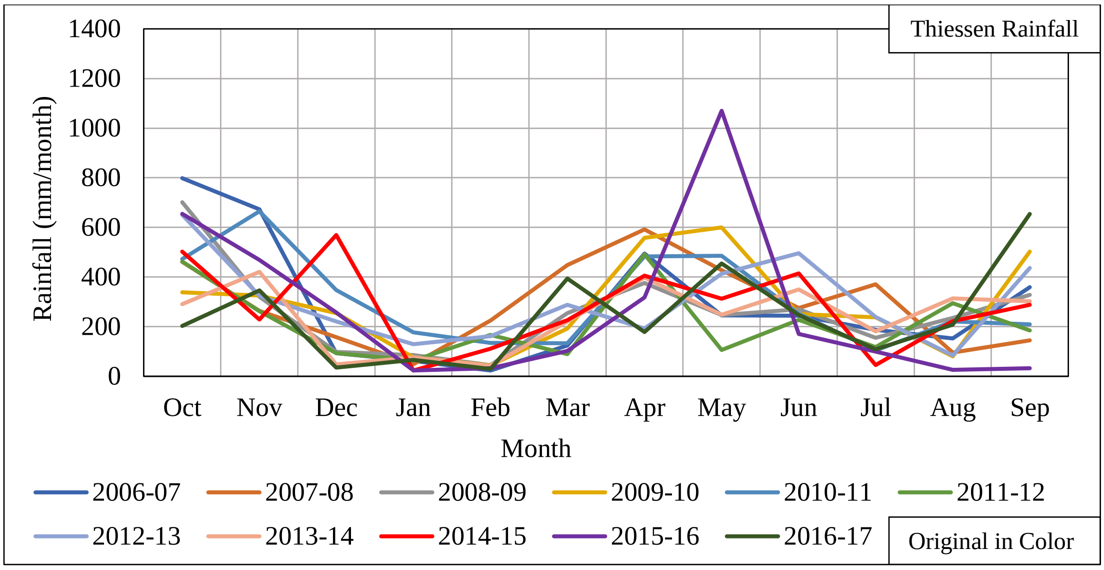


Figure 4- 4 Monthly Thiessen Rainfall Pattern - Dunamale Watershed

Monthly rainfall patterns show that most rainfall occurred during first and second inter-monsoon periods i.e. March to April and October to November respectively. However, high rainfall has also been experienced in September. After careful observations it is clear that rainfall in May 2015-16 is extremely high compared to other years and for Oct-Nov in year 2005-06 and 2006-07 show a variation in pattern. In the month of May 2010, Apr 2008, and Dec 2014 shows unusually high rainfall for that particular month for Nittambuwa Station. Jun 2013 and Mar 2013 has higher rainfall for Karasnagala Station. May-Jun 2013, Nov-Dec 2010, and Apr- Jul 2009 had either high or very low rainfall with respect to the monthly pattern for Chesterford Station. Nov 2006, Aug 2006, Jun-Jul 2012, Aug 2006, Apr 2006, and Apr 2013 shows either high or low rainfall compared with the regular pattern for Vincit Station. Mar 2012, May 2012, Dec 2014, Oct 2006, and Nov 2010 show a variation in the regular pattern for Pasyala Station.

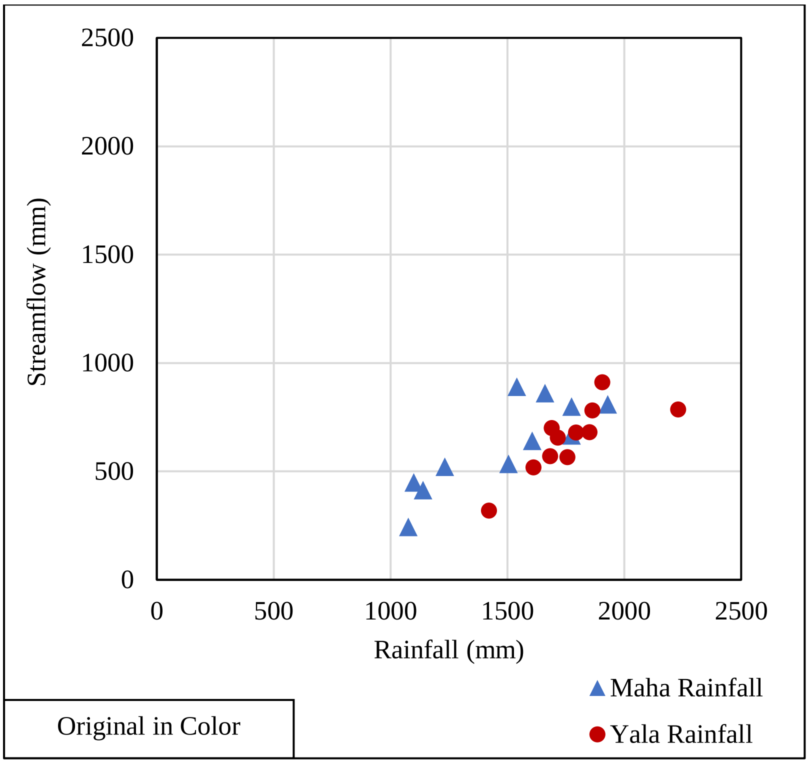


Figure 4- 5 Seasonal Comparison of Streamflow & Rainfall – Dunamale Watershed

The seasonal behaviour is shown in Figure 4- 5 which reflects that Yala season (April – September) receives higher rainfall with most values clustered near the leading side of the trendline and trailing with mostly Maha season (October – March) values which signifies high influence of Yala season rainfall on streamflow.

Seasonal data checks (Figure 4- 6 and Figure 4- 7) show that high rainfall for the first inter-monsoonal period as well as during the month of September makes Yala season experience equivalent or higher volume of rainfall than that of Maha season.

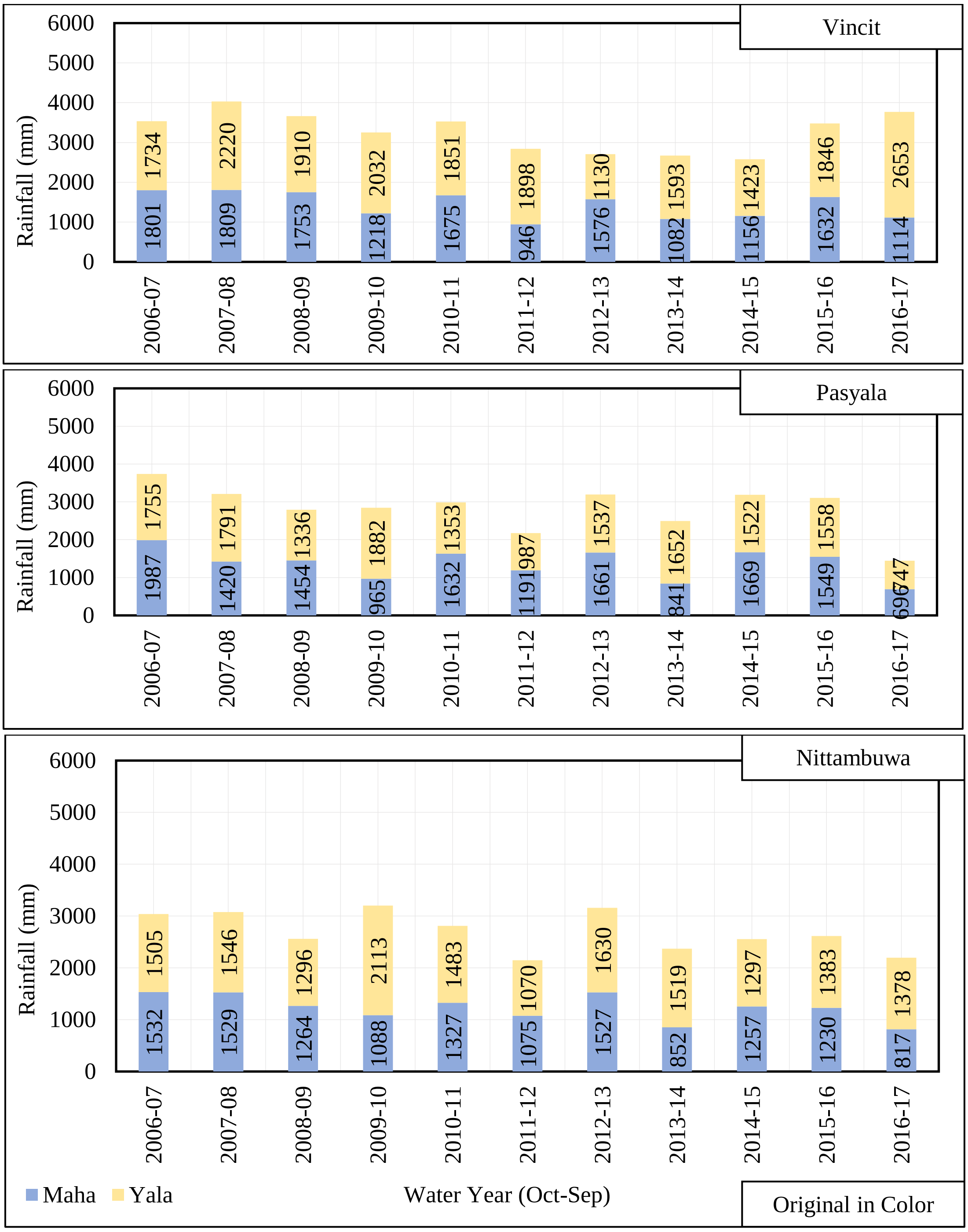


Figure 4- 6 Seasonal Rainfall of Vincit, Pasyala and Nittambuwa Stations

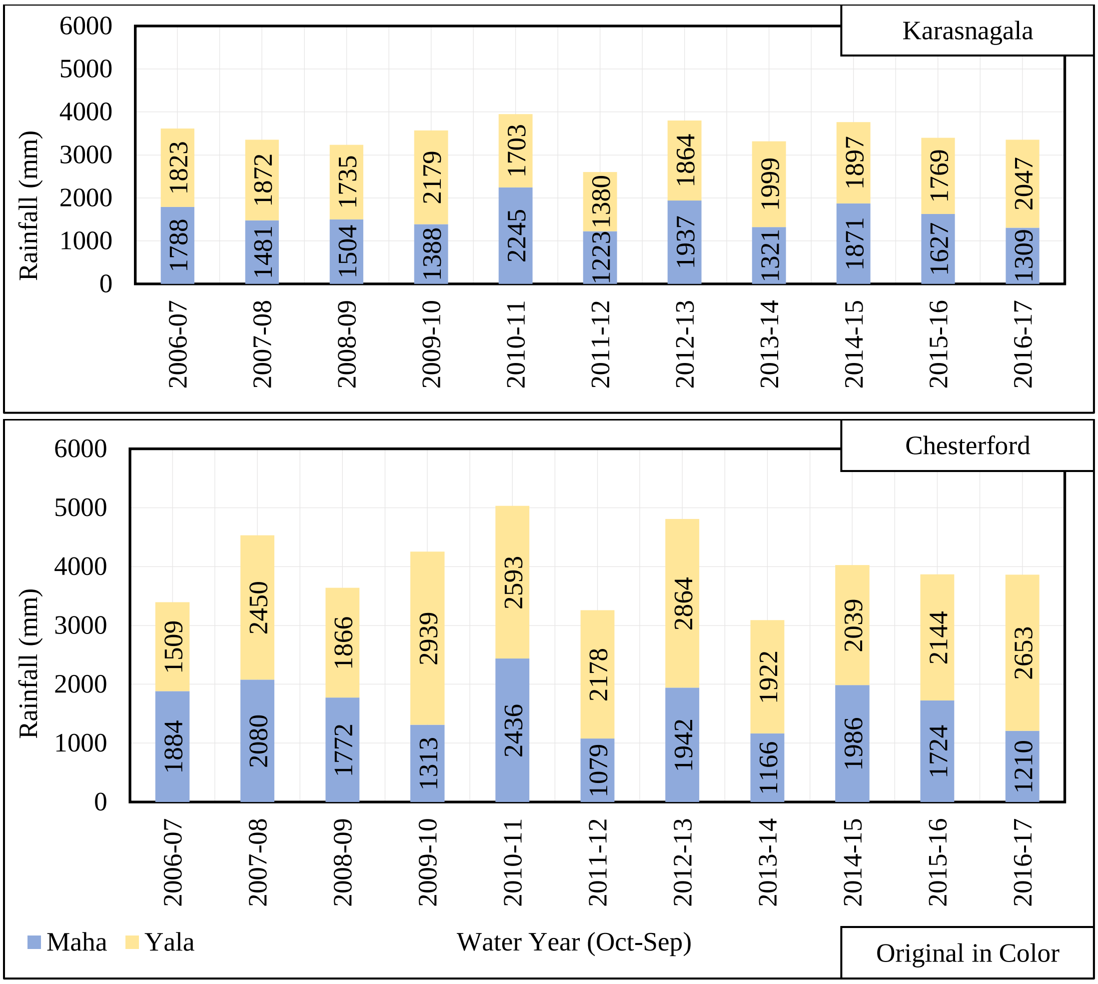


Figure 4- 7 Seasonal Rainfall of Karasnagala and Chesterford Stations

4.4.1 Rainfall Data Statistics

Statistics of Monthly thiessen rainfall is shown in Table 4.8 for each water year from 2006 to 2017. Median of the monthly data is mostly lower than the mean except for the month of August which means most of the water year received lower rainfall than average. Standard deviation shows that there is a high variation in the rainfall periods with highest in the month of May and lowest being in the month of Jan.

Table 4.8 Statistics of Monthly Thiessen Rainfall Data (mm) for each Water Year (2006 to 2017) – Dunamale Watershed

Statistics	Max	Mean	Min	Median	Std. Dev.
Oct	798.47	503.25	203.22	472.35	175.32
Nov	672.37	390.83	228.48	326.19	146.45
Dec	569.31	197.74	34.85	158.27	150.75
Jan	177.34	75.75	23.29	66.75	42.53
Feb	225.16	92.34	23.32	45.07	66.92
Mar	448.87	225.07	88.77	221.15	111.45
Apr	591.96	408.13	177.96	405.97	129.71
May	1070.02	419.06	106.19	413.06	245.12
Jun	496.49	290.86	170.58	251.64	89.16
Jul	370.88	167.94	45.04	155.43	86.23
Aug	314.26	175.75	25.55	207.98	89.92
Sep	654.14	312.68	32.51	301.96	166.46

4.4.2 Streamflow Data Statistics

Statistics of Monthly streamflow data is shown in Table 4.9 for each water year from 2006 to 2017. Median of the monthly data is mostly lower than the mean except for the month of October and April which means most of the water year received lower streamflow than average. Standard deviation shows highest variation in the month of May and lowest being in the month of February.

Table 4.9 Statistics of Monthly Streamflow Data for Water Year (2006 to 2017) – Dunamale Station

Statistics	Max	Mean	Min	Median	Std. Dev.
Oct	302.23	191.39	13.46	207.07	81.79
Nov	389.64	216.49	115.62	188.32	80.47
Dec	274.15	121.46	23.76	94.51	77.11
Jan	65.33	32.26	5.37	31.00	15.88
Feb	25.36	10.46	0.35	8.02	9.61
Mar	197.17	48.68	0.00	26.69	53.91
Apr	237.72	122.00	39.88	124.68	52.00
May	399.21	168.82	48.41	142.08	97.39
Jun	245.65	142.51	40.31	135.80	54.77
Jul	163.79	65.92	29.95	48.66	39.52
Aug	111.16	32.32	6.26	24.39	27.48
Sep	290.45	119.90	3.06	113.88	74.74

4.4.3 Evaporation Data Statistics

Statistics of Monthly evaporation data is shown in Table 4.10 for each water year from 2006 to 2017. There has been very subtle variation in the monthly evaporation over the years.

Table 4.10 Statistics of Monthly Evaporation Data for Water Year (2006 to 2017) – Colombo Station

Statistics	Max	Mean	Min	Median	Std. Dev.
Oct	125.42	99.73	81.58	100.51	12.02
Nov	102.10	81.98	57.93	85.84	13.51
Dec	105.36	87.47	65.75	88.88	12.44
Jan	131.61	113.49	93.10	115.65	9.80
Feb	125.83	108.49	83.59	109.67	13.14
Mar	153.88	121.44	93.33	120.60	15.73
Apr	137.38	111.52	93.01	108.69	14.84
May	122.19	104.66	78.62	107.52	12.42
Jun	105.66	98.02	84.01	99.39	5.85
Jul	120.83	107.14	89.00	109.43	10.17
Aug	163.10	114.44	100.19	109.29	16.58
Sep	130.11	103.33	88.42	99.83	10.59

4.5 Daily Data Checking

Daily plots of rainfall to streamflow response were plotted for each year to check for inconsistencies, missing values and outliers in the collected data. Data disparities were discovered from visual checks of rainfall vs streamflow plots on a daily temporal scale, primarily because of missing rainfall or streamflow values resulting in a mismatch in the catchment response for the representative rainfall.

Areal average rainfall calculated using thiessen method for the Dunamale catchment is shown in Figure 4- 8 alongside streamflow for the water year period 2006-2009 to verify the catchment response. Streamflow response for each individual rainfall station was also explored by plotting rainfall of each station corresponding to the streamflow of the catchment and are shown in ANNEX B – Data Checking. Some discrepancies were discovered in streamflow data from the comparison plots as some values were zero for many days hence, they were not plotted in the logarithmic graphs, while sometimes rainfall verses runoff did not match.

Daily data checking also shows the variation in rainfall intensity and rainy days for both Maha and Yala season. Maha season experiences more rainy days whereas Yala season experiences more dry days. However, rainy days during Yala season receive high intensity rainfall making it almost the same amount of rainfall as that of Maha season with some years experiencing even greater rainfall.

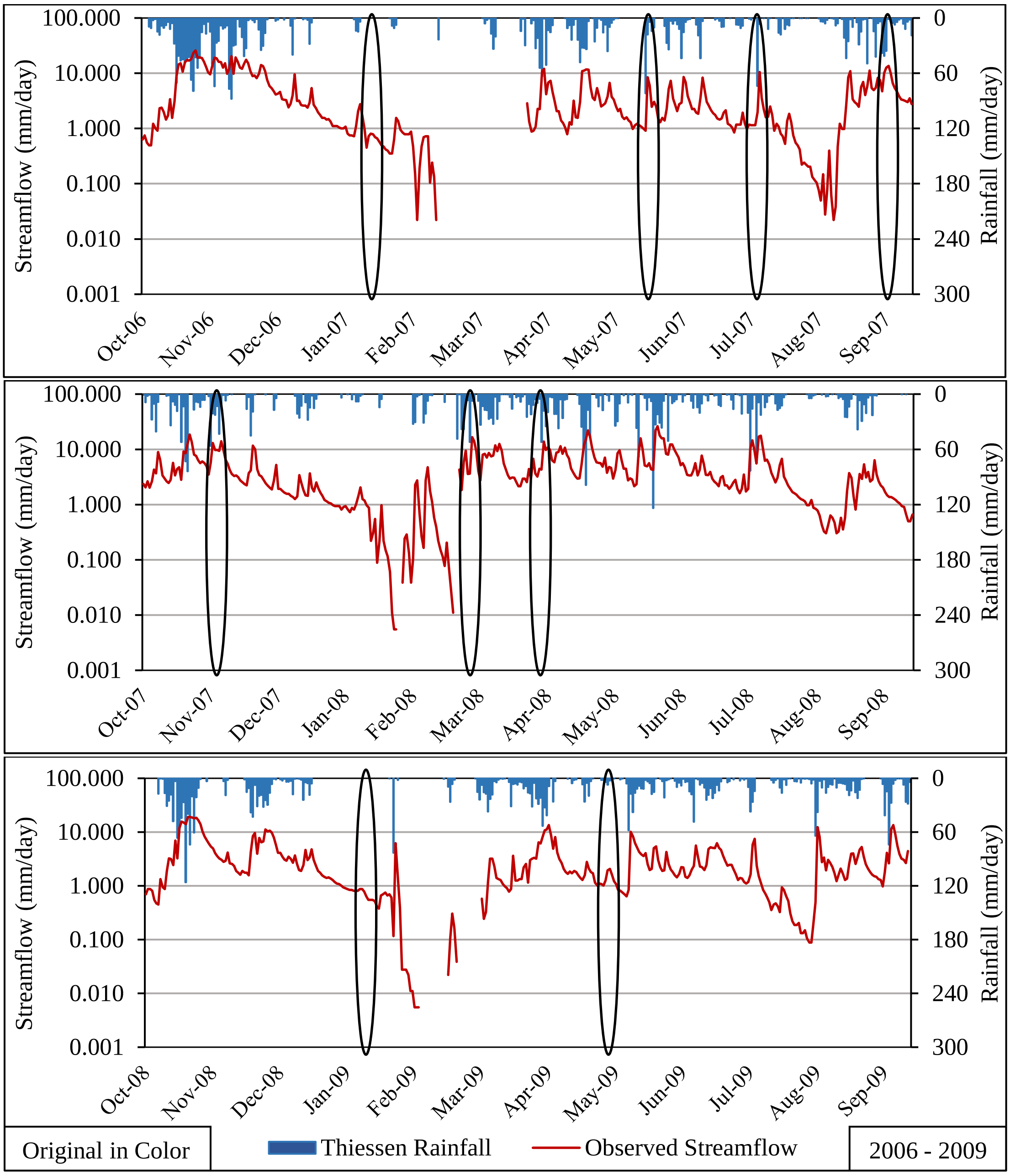


Figure 4- 8 Dunamale Streamflow response to Thiessen Rainfall in 2005-2009 - Semi-Log Plot

5 ANALYSIS

Model evaluation has two significant steps namely; calibration and verification. The dataset was split into two smaller datasets, one for calibration and another for verification. Calibration dataset is used to optimize the model parameters for a sample of data based on the objective function while Verification dataset is used to check if the optimized parameters are good for population. According to literature there is no method to quantitatively select data duration for calibration or verification dataset. Some researchers prefer dividing the dataset into two equal halves for calibration and verification respectively but since the dataset has odd number of water years calibration dataset is bigger than that of verification dataset by 1 year.

5.1 Thiessen Averaged Rainfall

ArcMap was used to create thiessen polygons using rainfall station locations, area of these polygons was used to determine thiessen weights for each rainfall gauging station. Thiessen weights and the area of each polygon are mentioned in Table 5.1. Thissen weight showed that Vincit station had the least influence because of its location being outside of the catchment area while Karasnagala Station had the highest influence with its weight being more than twice than that of the other stations. Thissen polygons are shown in Figure 5-1 along with the rainfall stations and thiessen weights.

Table 5.1 Thiessen Areas and Weights of Rainfall Stations in Attanagalu Oya at Dunamale

Rainfall Gauging Station	Thiessen Area (km^2)	Thiessen Weights (%)
Vincit	12.7	8.0
Pasyala	22.7	14.5
Nittambuwa	36.0	23.0
Karasnagala	60.2	38.5
Chesterford	25.0	16.0

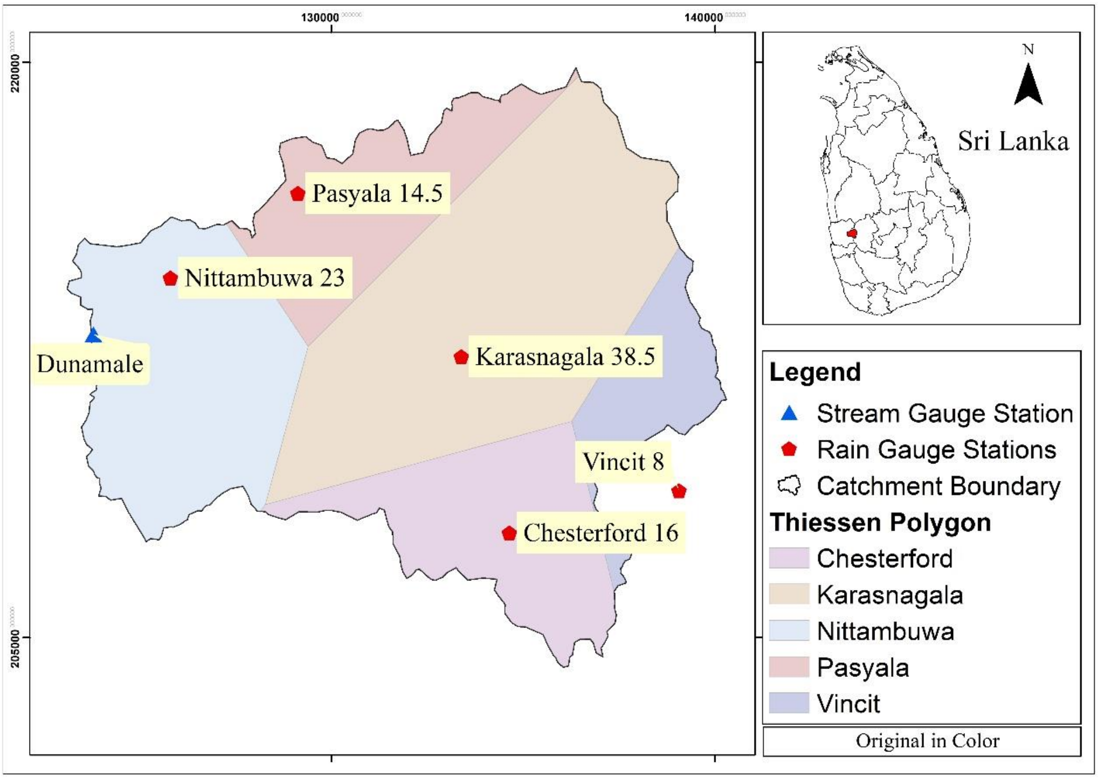


Figure 5-1 Thiessen polygon for Dunamale Watershed

5.2 Identification of High, Medium and Low Flows

To focus specifically on the objective i.e. water resource management it is important to identify the intermediate flows because they are more stable and easier to predict which is why they are taken into consideration for water resource planning and management whereas the high and low flows are very unpredictable and are used for extreme scenarios such as flood, droughts, environmental flows, disaster management etc.

Flow duration curves for monthly time scale were prepared to identify various flow regimes, and the demarcations in the data was made based on natural breaks. The threshold values used for distinguishing between different flow regimes for Attanagalu Oya watershed at Dunamale on monthly scale is shown in Table 5.2 and the flow duration curves for the two datasets are shown in Figure 5-2 and Figure 5-3 respectively.

Table 5.2 High, Medium & Low flow limits with Monthly Data for Calibration & Verification Datasets

Flow Type	Percentage Time Exceedance	
	Calibration Dataset	Verification Dataset
High	< 31	< 35
Medium	> 31 & < 69	> 35 & < 72
Low	> 69	> 72

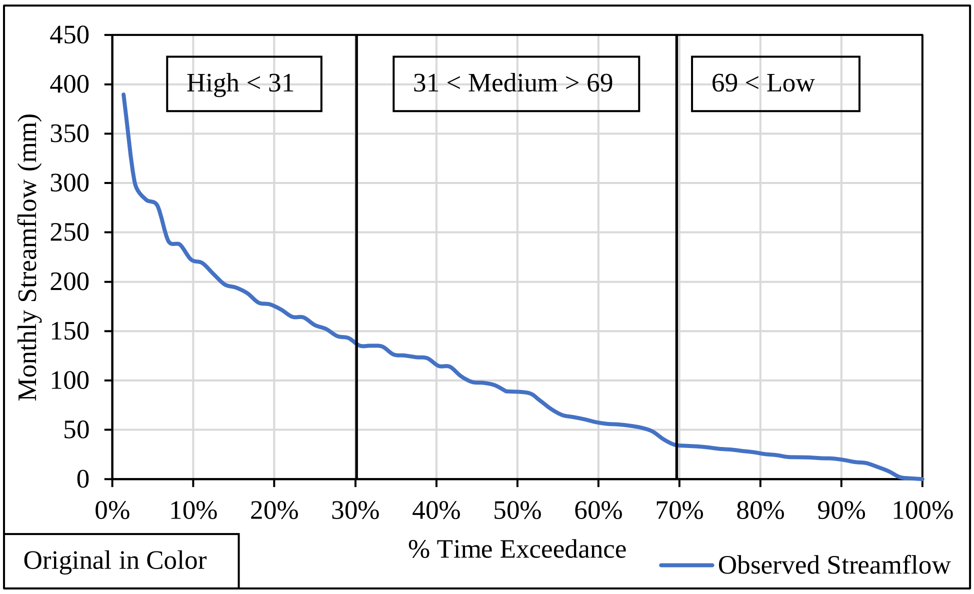


Figure 5-2 Flow Duration Curve for Calibration Dataset – 2006 to 2012

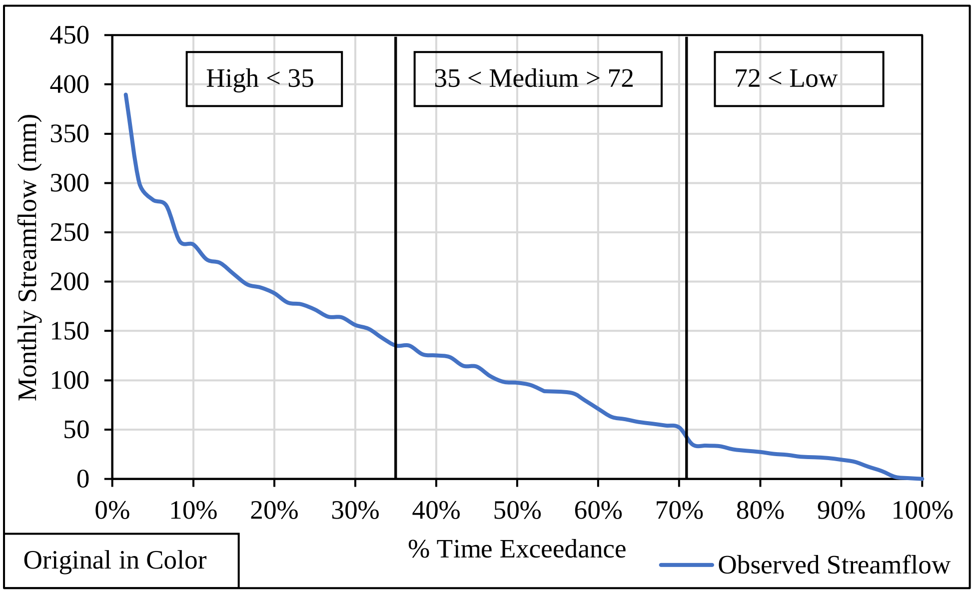


Figure 5-3 Flow Duration Curve for Verification Dataset – 2012 to 2017

5.3 Selected Model Structure and Parameters

The model selected for the present study was proposed by Xiong and Guo (1999) has only two parameters and is very efficient in estimating streamflow on monthly time scale. Selection of the model was based on the simplicity, availability of data and high efficiency of the model in Sri Lanka catchments. It has been previously used for various Sri Lankan watersheds and has yielded good results for Kalu Ganga, Gin Ganga, Kelani Ganga and Mahaweli Ganga by others (Sharifi, 2015; Khandu, 2016; Dissanayake, 2017). The current study uses this model to research and investigate the impacts of spatially varying rainfall on monthly water estimates for Dunamale watershed of Attanagalu Oya basin.

The model with two parameters was developed based on the following governing equations;

$$E(t) = c \times EP(t) \times tanh\left[\frac{P(t)}{EP(t)}\right] \qquad 10$$

$$Q(t) = [S(t-1) + P(t) - E(t)] \times tanh\left[\frac{S(t-1)+P(t)-E(t)}{SC}\right] \qquad 11$$

$$S(t) = S(t-1) + P(t) - E(t) - Q(t) \qquad 12$$

Where, E(t) represents actual monthly evapotranspiration,

Q(t) is the t^{th} runoff for the month,

EP(t) is pan evaporation on monthly timescale,

P(t) is rainfall on monthly timescale,

S(t-1) is the moisture content in the soil at the beginning of the t^{th} month,

S(t) is the moisture content in the soil at the end of t^{th} month,

Parameter C accounts for the effect of change of time scale,

Parameter SC represents the field capacity of catchments.

These equations are based on certain key assumptions and fundamentals of hydrology. It is assumed that the catchment behaves as a reservoir of linear or non-linear function, therefore Q is considered as a hyperbolic tangent function of soil moisture content (S) and is considered to be a realistic rotation of hydrological conditions and variables for determining a stable value of initial water content of soil which also affects the model forecasting accuracy per year. Finally, for developing the model to achieve realistic values or estimates fundamental conditions were applied. Actual evapotranspiration, streamflow and soil water content are non-negative and should not be less than zero at any given point in time. Therefore,

$$E(t) \geq 0 \qquad 13$$

$$Q(t) \geq 0 \qquad 14$$

$$S(t) \geq 0 \qquad 15$$

5.3.1 Model Development

A very important part of model development is to verify that the model results are accurate which was done using manual specimen calculations and compared with the results that model gave for the same. The specimen calculation is shown in ANNEX D – Model Development.

5.4 Objective Function and Parameter Optimization

5.4.1 Selected objective function

Out of all the objective functions studied under Literature Review section, Mean Ratio of Absolute Error (MRAE) is best suited for the study interest of water resource management and it would respond well compared to other popular objective functions such as NSE and RAEM as both of them show deviation from the mean of observed value which might be skewed in a dataset with non-uniform distribution while MRAE evaluates error at every point of observation and then the summation of error is distributed to the whole dataset.

Though multi-objective functions are contemporary but at the same time dealing with more than one objective function means broadening the purpose of the study as well as increasing difficulty in achieving relevant results during calibration. Therefore, a single objective function is used for calibrating the model while other indicators such as NSE and Annual water balance are used to monitor the performance of the model.

5.4.2 Initial soil moisture

Initial Soil Moisture content plays an important role on the accuracy of the model. In order to remove the initialization bias from model simulations, a repetition of 5 cyclic periods was used to determine stabilized soil moisture content value for the dataset used in analysis.

The initial soil moisture content for the dataset stabilized at 186.13mm and the soil moisture content at the beginning of each cycle is shown in Figure 5-4.

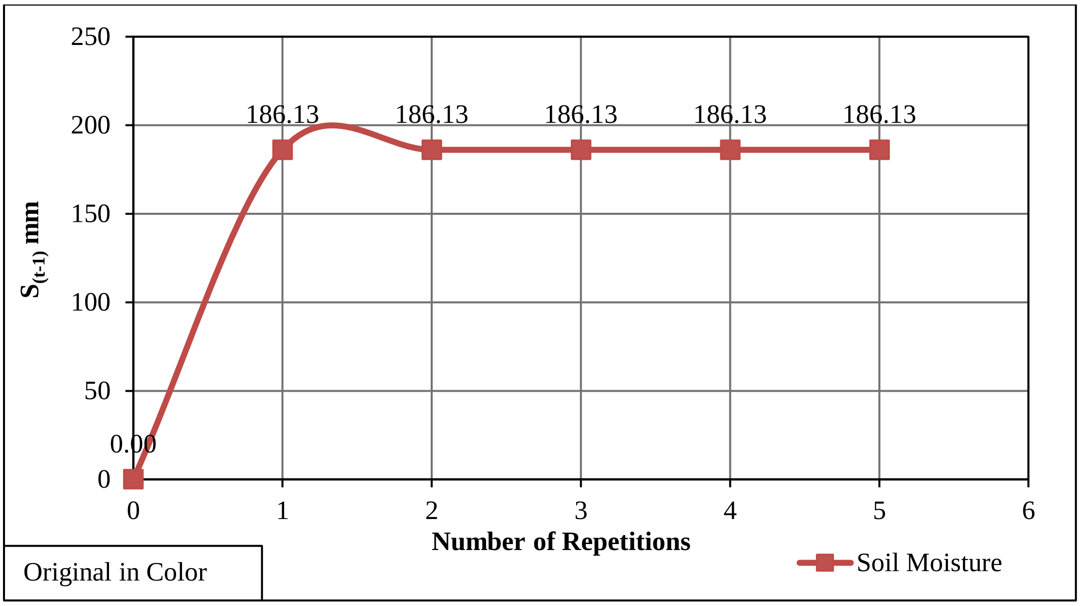


Figure 5-4 Determination of Initial Soil Moisture using Warmup Period

5.4.3 Search for Global minimum

The range of parameters mentioned by Xiong and Guo (1999) for catchments in China varies from 0.2 to 1.9 for parameter c and 300 to 2000 for parameter SC. Since, the parameter ranges were not stated as universal in literature and field capacity parameter SC which depends on factors that change from various climatic conditions, soil type, land use type etc. are subject to change for catchments outside of China especially for the present study area, as Sri Lanka has a tropical climate which is far from the climatic conditions in China. Therefore, the range for parameters SC and c may vary because of catchment characteristics.

The principle equations of the model determine that the minimum values of the parameters should be non-negative and non-zero while the maximum values of the parameters are not known. Therefore, many trials of various values of model parameters were made to capture the global minima on the objective function surface.

The trial and error manual computations revealed the range for global minimum identification using the objective function surface shown in Figure 5-5. The parameter search with coarser resolution of input parameters and using solver function an automatic calibration tool in MS Excel, identified the most likely minimum of MRAE for Dunamale watershed.

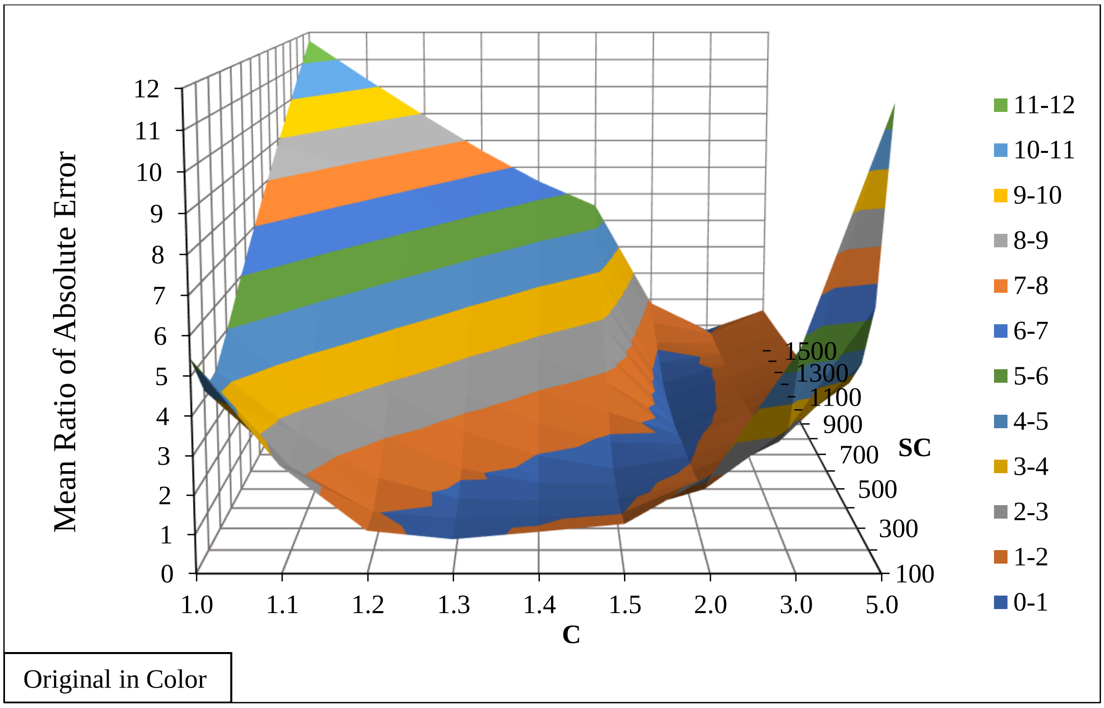


Figure 5-5 Variation of Objective function with Parameter Values - Dunamale Watershed

By means of Solver function, the objective function response corresponding to varying initial model parameter values as input is shown in Figure 5-6 along with the corresponding MRAE values achieved after optimization. Also, the movement of each observation from initial to optimized value for minimum MRAE is shown using arrows which shows a converging behaviour of all observations except for two.

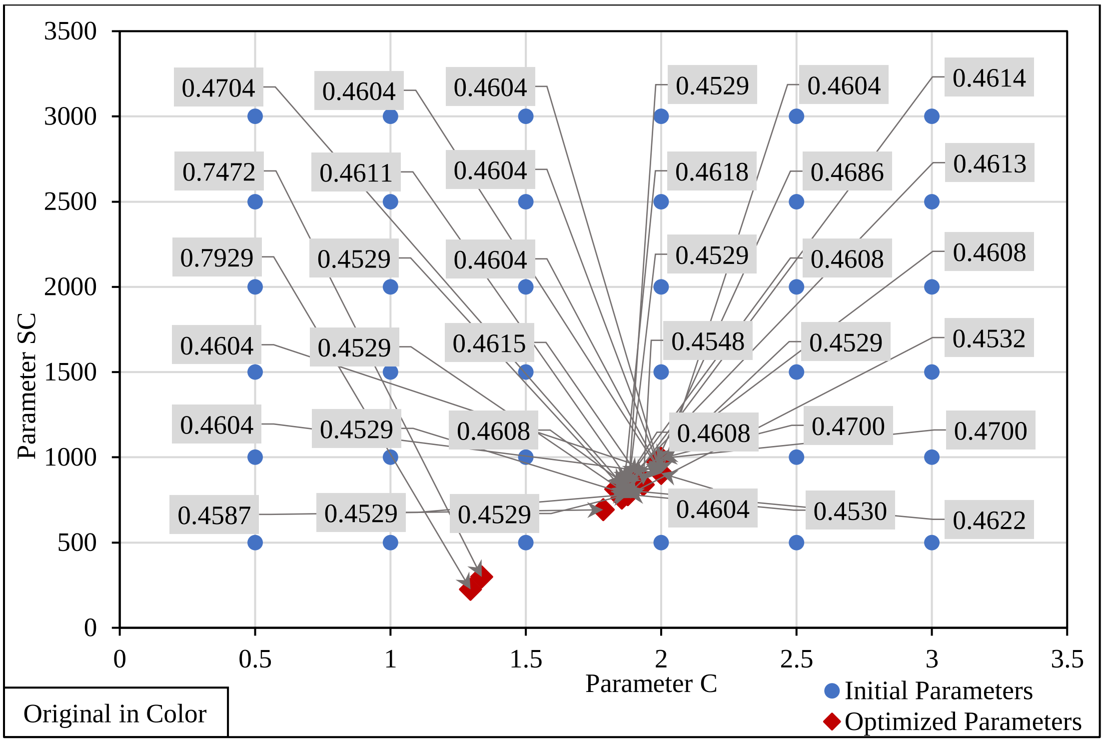


Figure 5-6 Search for Global Minimum of MRAE - Dunamale Watershed

5.5 Optimization of Model Parameters

The first step in optimization is to calibrate the model by optimizing the model parameters for global minimum MRAE using Thiessen rainfall as input.

5.5.1 Performance of model during Calibration period

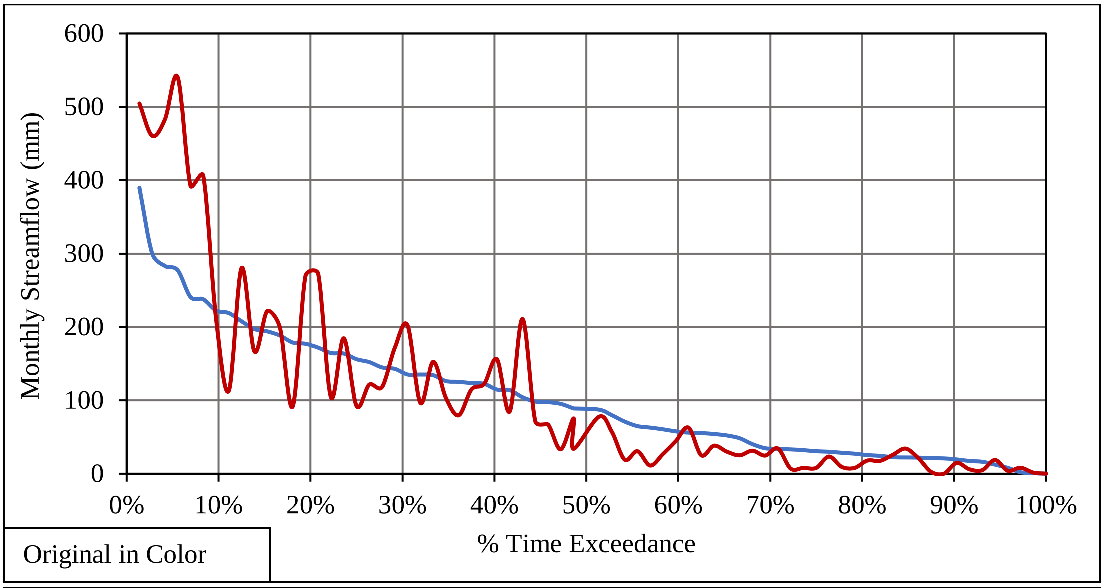
Input data on a monthly resolution were fed to the model for calibration and it was allowed to freely calibrate. Table 5.3 shows the performance of the model during calibration period using the data for water year 2006-2012.

Table 5.3 Model Performance during Optimization of Model Parameters for Calibration Period - Dunamale Watershed

Model Performance Indicators		Two Parameter Monthly Water Balance Model
SC		782.47
C		1.878
Pan Coefficient		0.973
Runoff Coefficient		0.395
Average Annual Water Balance Error		151.44
NASH Efficiency		0.700
MRAE	Overall	0.452
	High	0.387
	Medium	0.376
	Low	0.606

Table 5.4 Annual Water Balance for Optimization of Model Parameters - Calibration Period

Water Year	Thiessen Rainfall (mm)	Observed Streamflow (mm)	Observed Water Balance (mm)	Calculated Streamflow (mm)	Calculated Water Balance (mm)	Error (mm)
2006/07	3457	1369	2088	1485	1973	116
2007/08	3511	1552	1959	1588	1923	35
2008/09	3116	1053	2063	970	2145	-82
2009/10	3462	1308	2155	1531	1931	224
2010/11	3604	1375	2230	1654	1951	279
2011/12	2560	733	1827	560	2000	-172



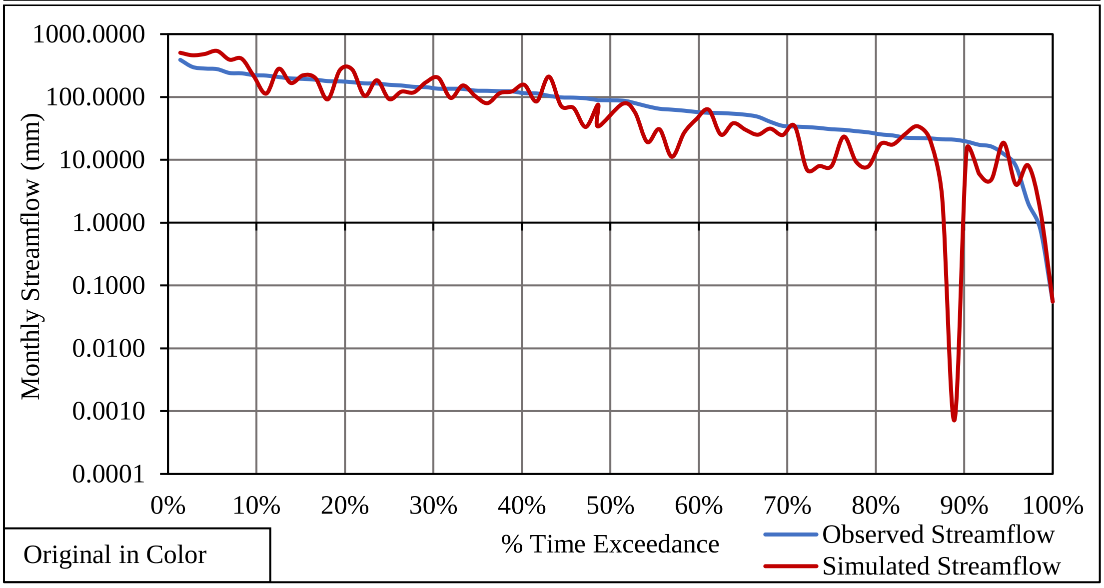


Figure 5-7 Flow Duration Curve of Two-parameter monthly water balance model for Dunamale Watershed of Calibration Period – Normal and Semi-Log Plot

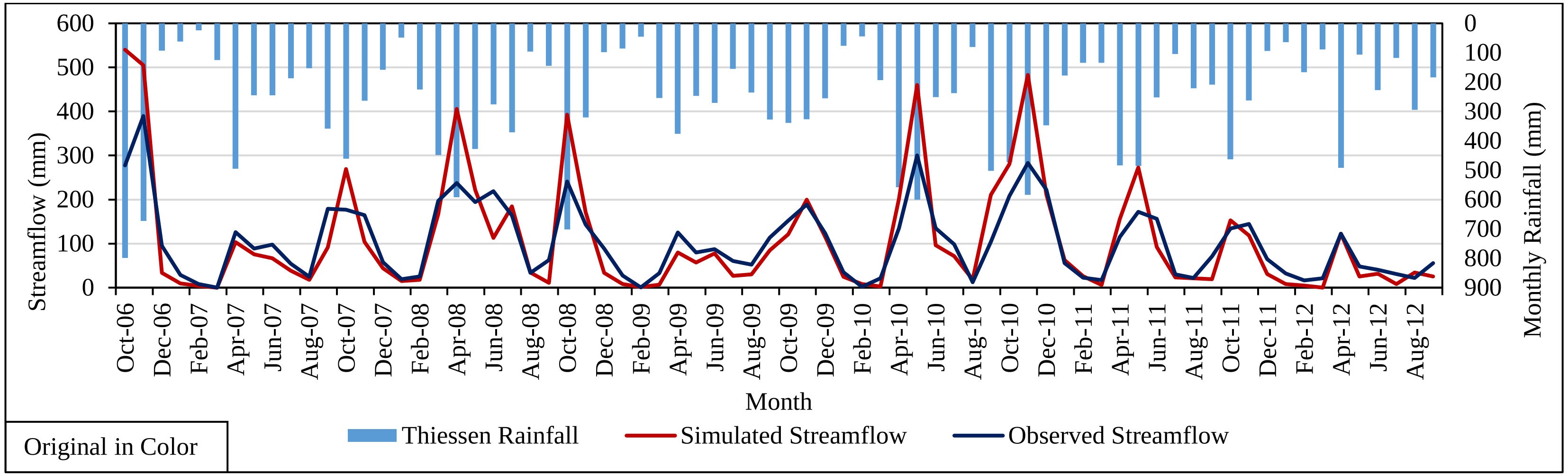


Figure 5-8 Hydrographs of Two-parameter monthly water balance model for Dunamale Watershed of Calibration Period (2006-2011) – Normal Plot

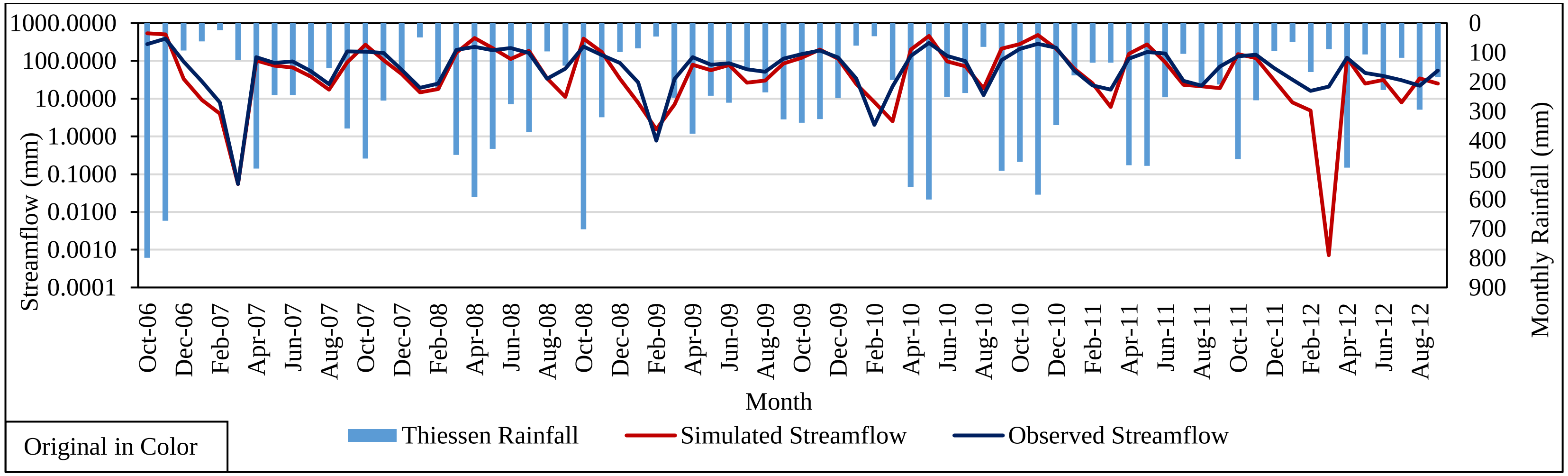


Figure 5-9 Hydrographs of Two-parameter monthly water balance model for Dunamale Watershed of Calibration Period (2006-2011) – Semi-log Plot

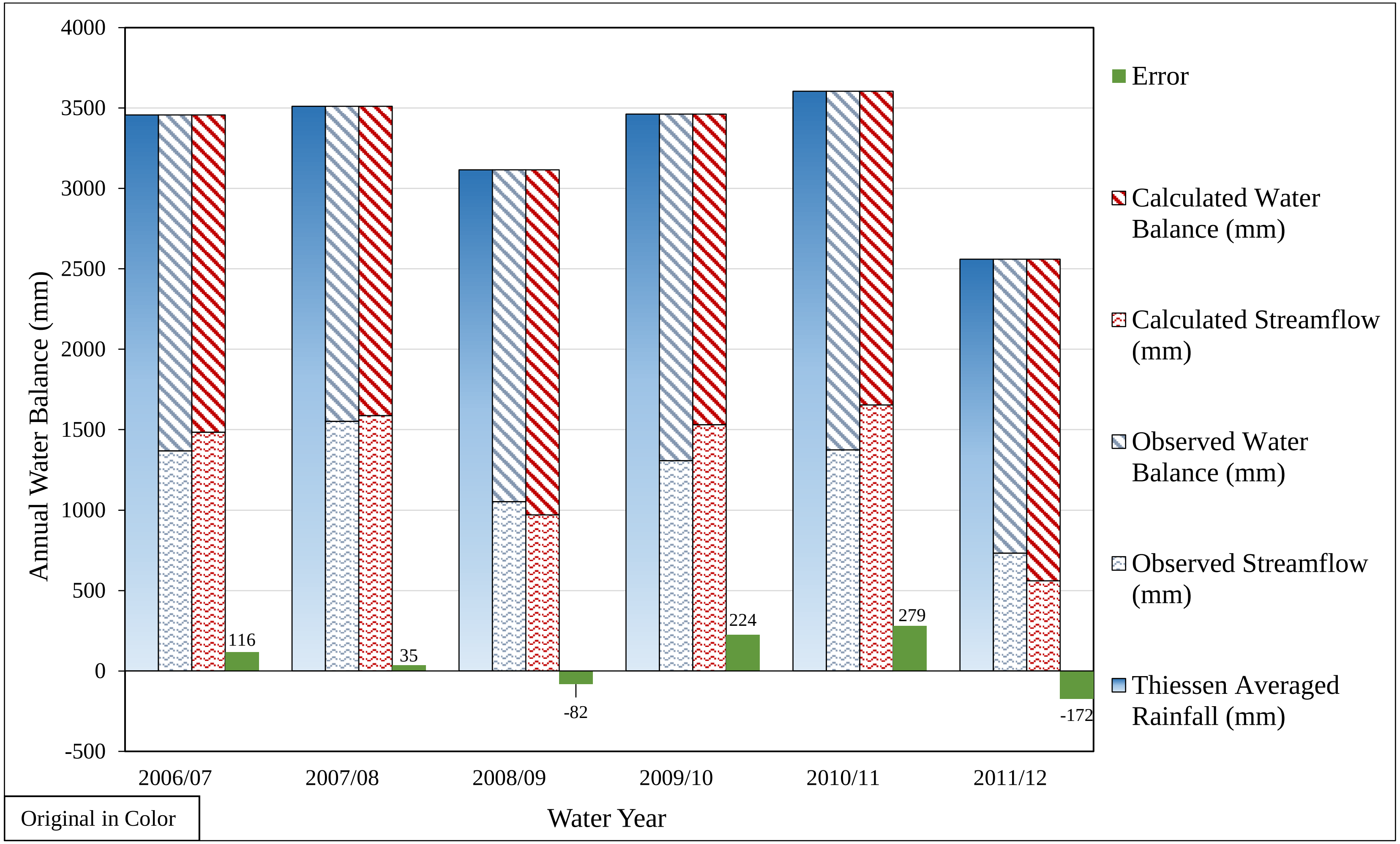


Figure 5-10 Annual Water Balance of Two-parameter model for Dunamale Watershed of Calibration Period (2006-2011)

5.5.2 Performance of model during Verification period

Optimized model parameters obtained during model calibration were used in the model with verification dataset of a data period of five years from 2012-2017 and indicators of model performance are shown in Table 5.5.

Table 5.5 Model Performance during Optimization of Model Parameters for Verification Period - Dunamale Watershed

Model Performance Indicators		Two Parameter Monthly Water Balance Model
SC		782.47
C		1.878
Pan Coefficient		0.969
Runoff Coefficient		0.421
Average Annual Water Balance Error		144.874
NASH Efficiency		0.694
MRAE	Overall	0.446
	High	0.396
	Medium	0.391
	Low	0.569

Table 5.6 Annual Water Balance for Optimization of Model Parameters - Verification Period

Water Year	Thiessen Rainfall (mm)	Observed Streamflow (mm)	Observed Water Balance (mm)	Calculated Streamflow (mm)	Calculated Water Balance (mm)	Error (mm)
2012/13	3457	1369	2088	1473	1984	104
2013/14	3511	1552	1959	1588	1923	35
2014/15	3116	1053	2063	970	2145	-82
2015/16	3462	1308	2155	1531	1931	224
2016/17	3604	1375	2230	1654	1951	279

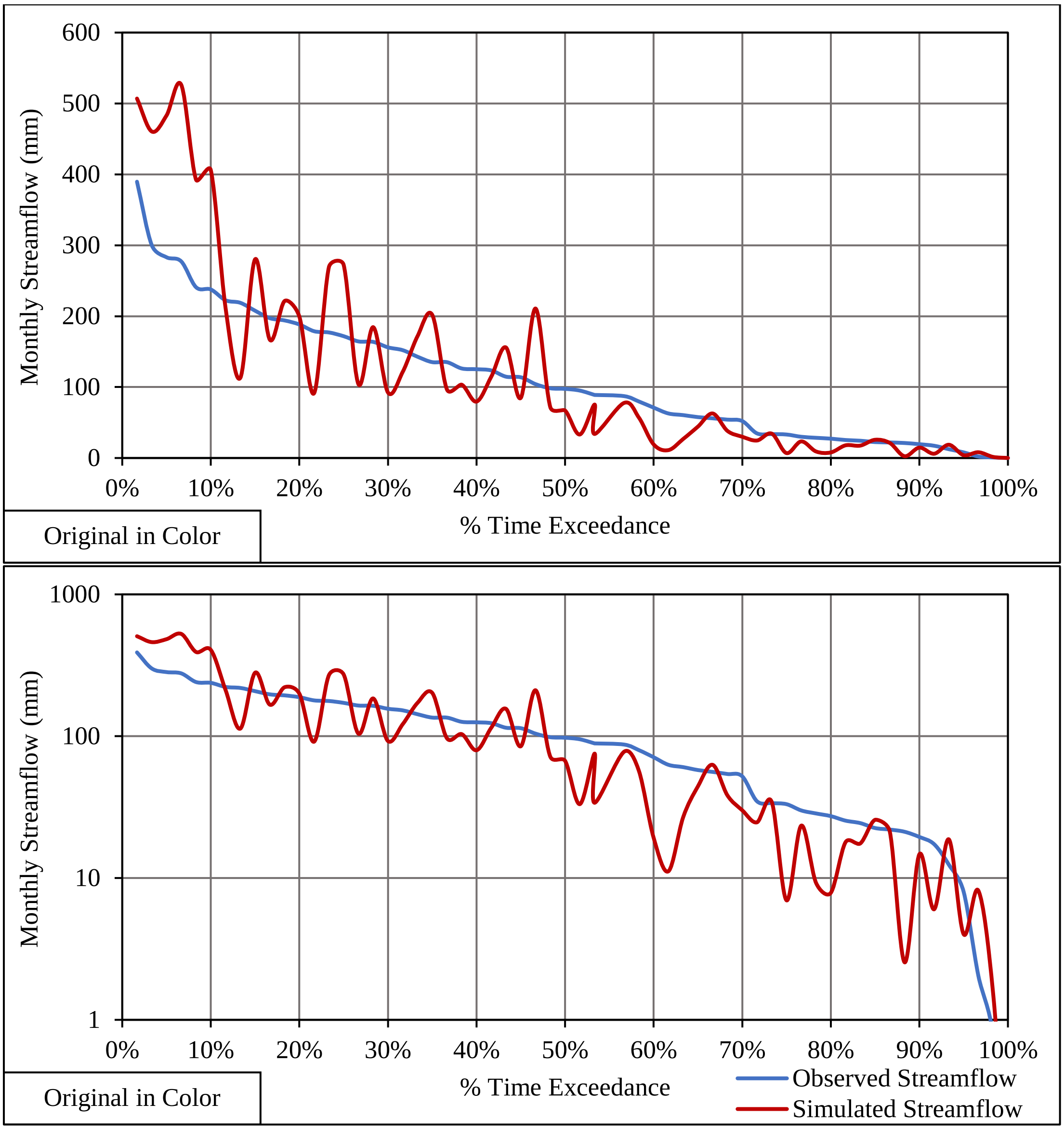


Figure 5-11 Flow Duration Curve of Two-parameter monthly water balance model for Dunamale Watershed of Verification Period – Normal and Semi-Log Plot

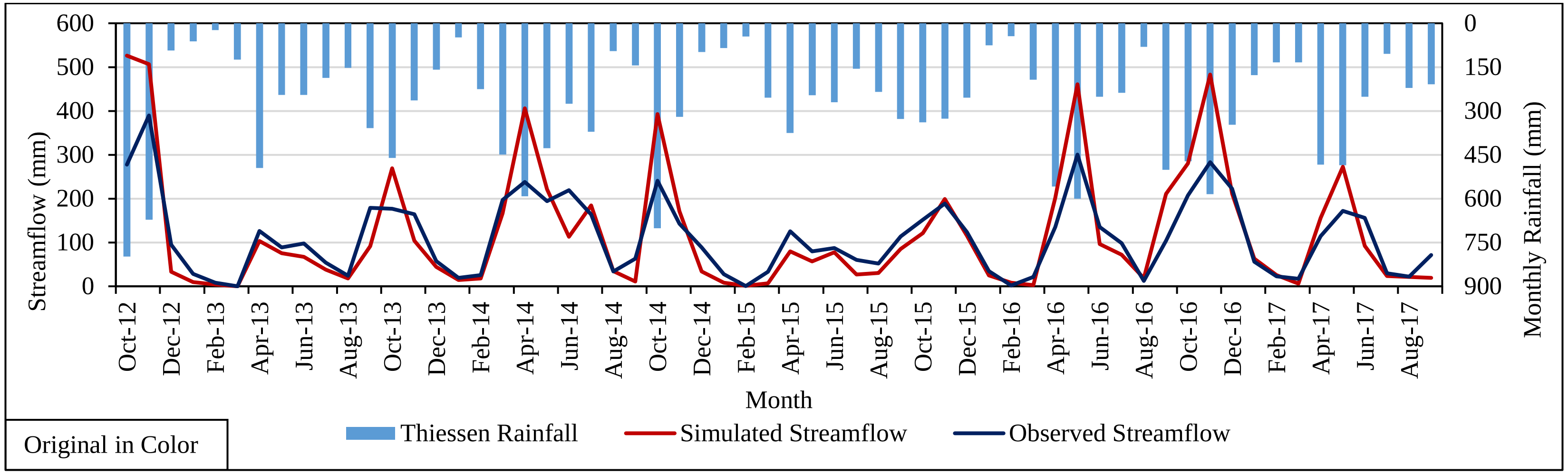


Figure 5-12 Hydrographs of Two-parameter monthly water balance model for Dunamale Watershed of Verification Period (2011-2017) – Normal Plot

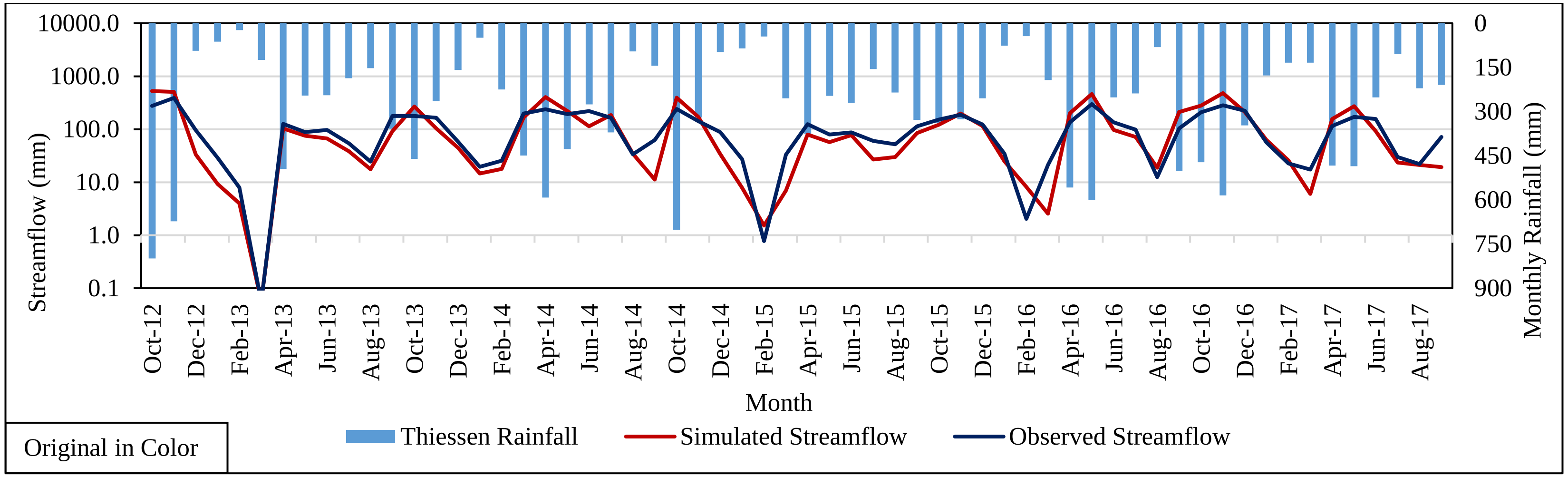


Figure 5-13 Hydrographs of Two-parameter monthly water balance model for Dunamale Watershed of Verification Period (2011-2017) – Semi-log Plot

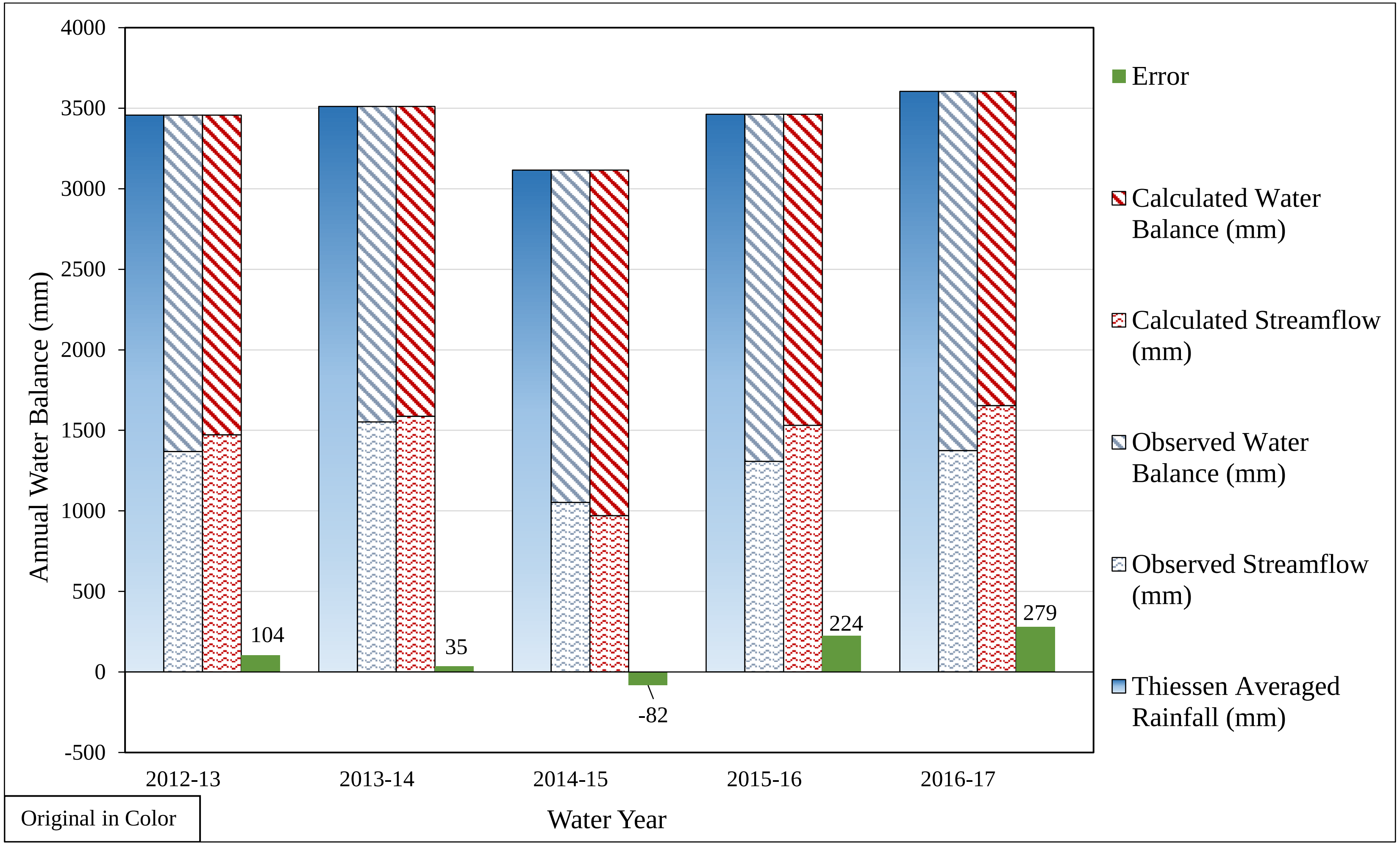


Figure 5-14 Annual Water Balance of Two-parameter model for Dunamale Watershed of Verification Period (2011-2017)

5.6 Optimization of Rainfall Station Weights

The second step in optimization is to calibrate the model by optimizing the rainfall station weights for global minimum MRAE by keeping the model parameters obtained in first step as constant.

5.6.1 Performance of model during Calibration period

Solver tool was used to optimize the rainfall station weights during calibration of the model and the performance indicators are shown in Table 5.7.

Table 5.7 Model Performance during Optimization of Rainfall Station Weights for Calibration Period - Dunamale Watershed

Model Performance Indicators		Two Parameter Monthly Water Balance Model
	SC	782.47
	C	1.878
	Pan Coefficient	0.964
	Runoff Coefficient	0.384
	Average Annual Water Balance Error	98.30
	NASH Efficiency	0.699
MRAE	Overall	0.433
	High	0.355
	Medium	0.388
	Low	0.557

Table 5.8 Annual Water Balance for Optimization of Rainfall Station Weights - Calibration Period

Water Year	Thiessen Rainfall (mm)	Observed Streamflow (mm)	Observed Water Balance (mm)	Calculated Streamflow (mm)	Calculated Water Balance (mm)	Error (mm)
2006/07	3539	1369	2170	1538	2001	169
2007/08	3538	1552	1986	1669	1869	117
2008/09	3161	1053	2109	974	2187	-78
2009/10	3163	1308	1856	1282	1881	-26
2010/11	3311	1375	1936	1382	1929	7
2011/12	2497	733	1764	540	1957	-192

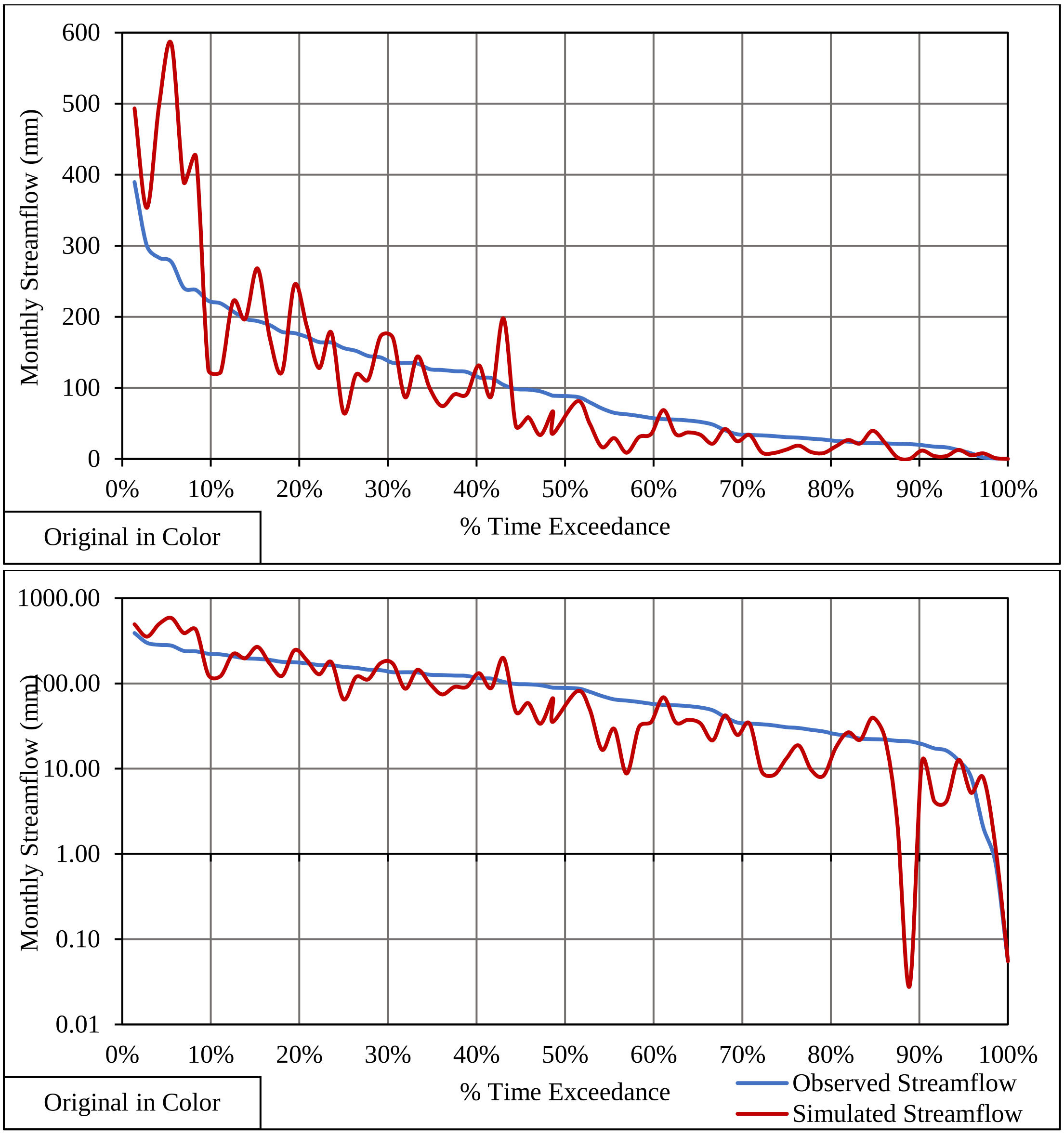


Figure 5-15 Flow Duration Curve of Two-parameter monthly water balance model for Dunamale Watershed of Calibration Period – Normal and Semi-Log Plot

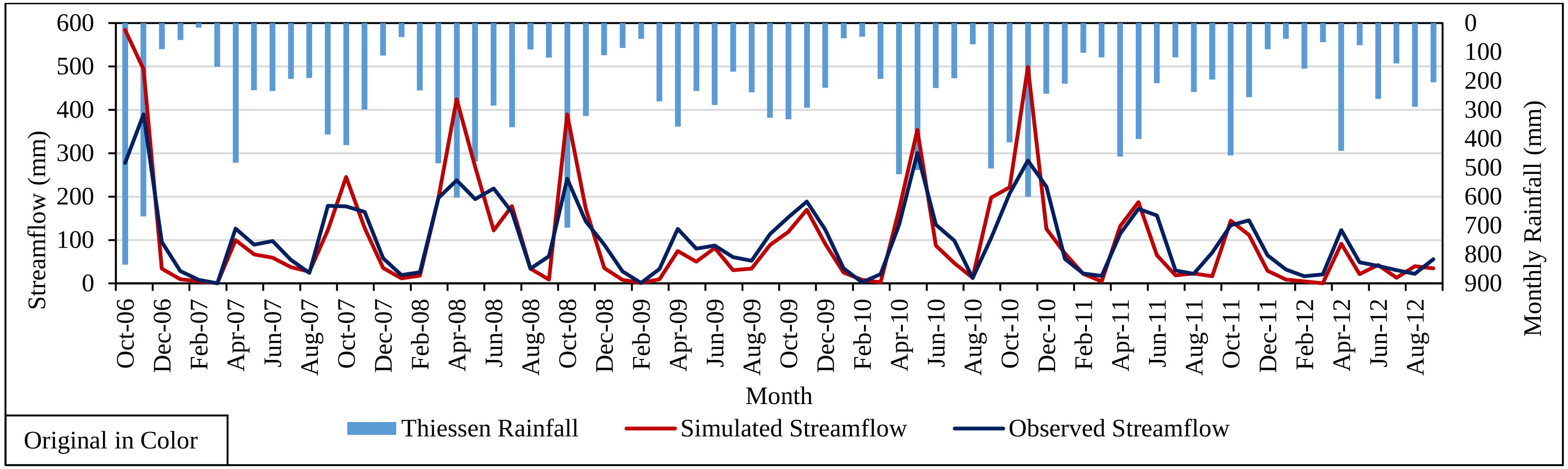


Figure 5-16 Hydrographs of Two-parameter monthly water balance model for Dunamale Watershed of Calibration Period (2006-2011) – Normal Plot

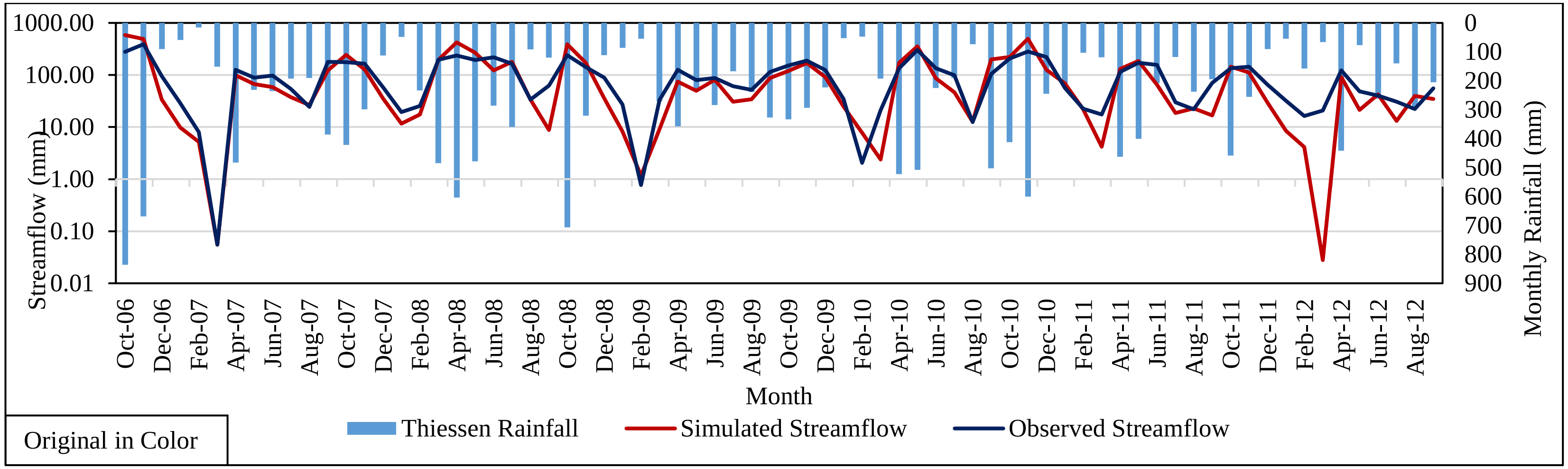


Figure 5-17 Hydrographs of Two-parameter monthly water balance model for Dunamale Watershed of Calibration Period (2006-2011) – Semi-Log Plot

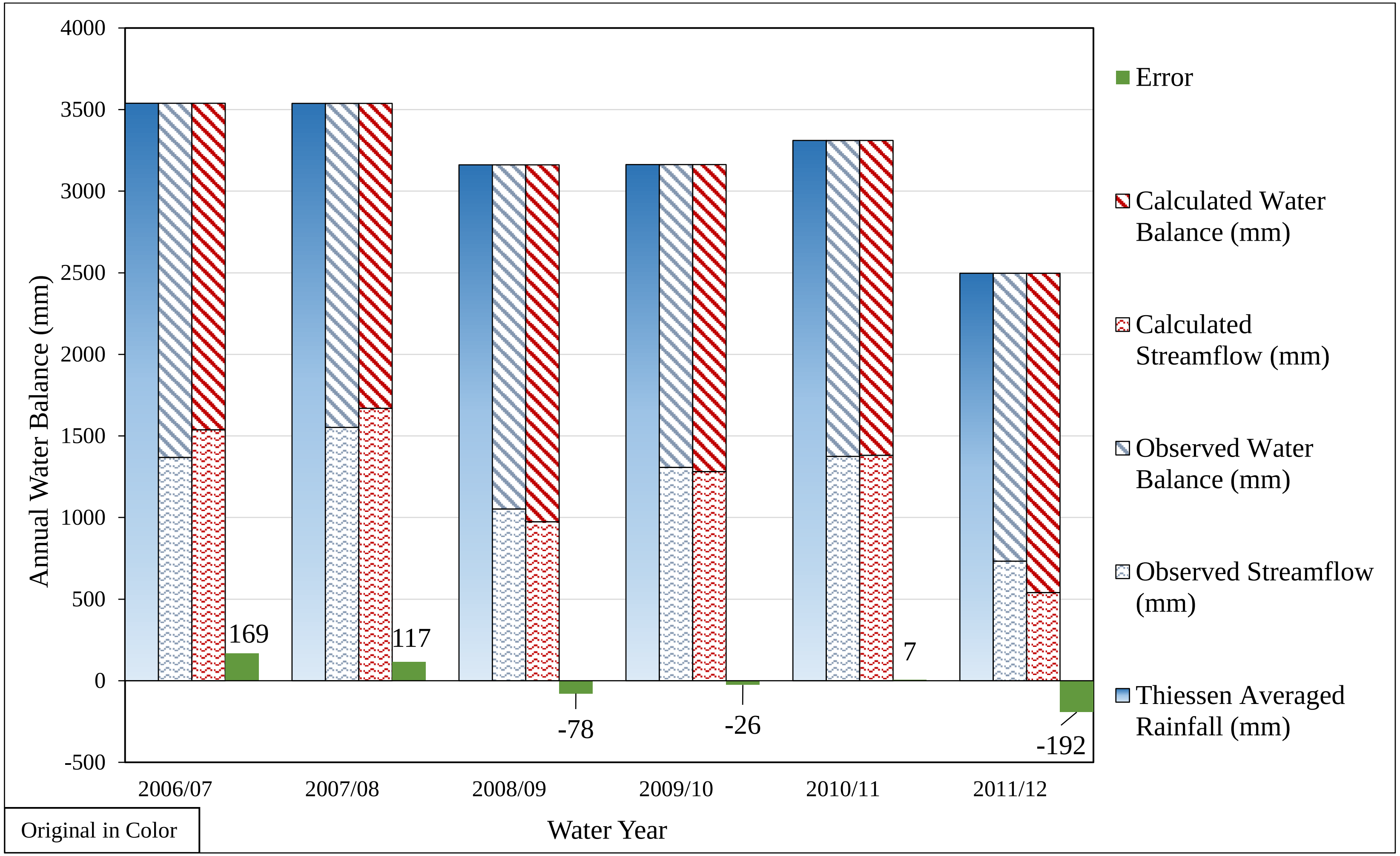


Figure 5-18 Annual Water Balance of Two-parameter model for Dunamale Watershed of Calibration Period (2006-2011)

5.6.2 Performance of model during Verification period

Model was allowed to run using optimized rainfall station weights with verification dataset and indicators of model performance are mentioned in Table 5.9.

Table 5.9 Model Performance during Optimization of Rainfall Station Weights for Verification Period - Dunamale Watershed

Model Performance Indicators		Two Parameter Monthly Water Balance Model
SC		782.47
C		1.878
Pan Coefficient		0.963
Runoff Coefficient		0.408
Average Annual Water Balance Error		77.07
NASH Efficiency		0.694
MRAE	Overall	0.420
	High	0.359
	Medium	0.410
	Low	0.500

Table 5.10 Annual Water Balance for Optimization of Rainfall Station Weights - Verification Period

Water Year	Thiessen Rainfall (mm)	Observed Streamflow (mm)	Observed Water Balance (mm)	Calculated Streamflow (mm)	Calculated Water Balance (mm)	Error (mm)
2012/13	3539	1369	2170	1526	2013	157
2013/14	3538	1552	1986	1669	1869	117
2014/15	3161	1053	2109	974	2187	-78
2015/16	3163	1308	1856	1282	1881	-26
2016/17	3311	1375	1936	1382	1929	7

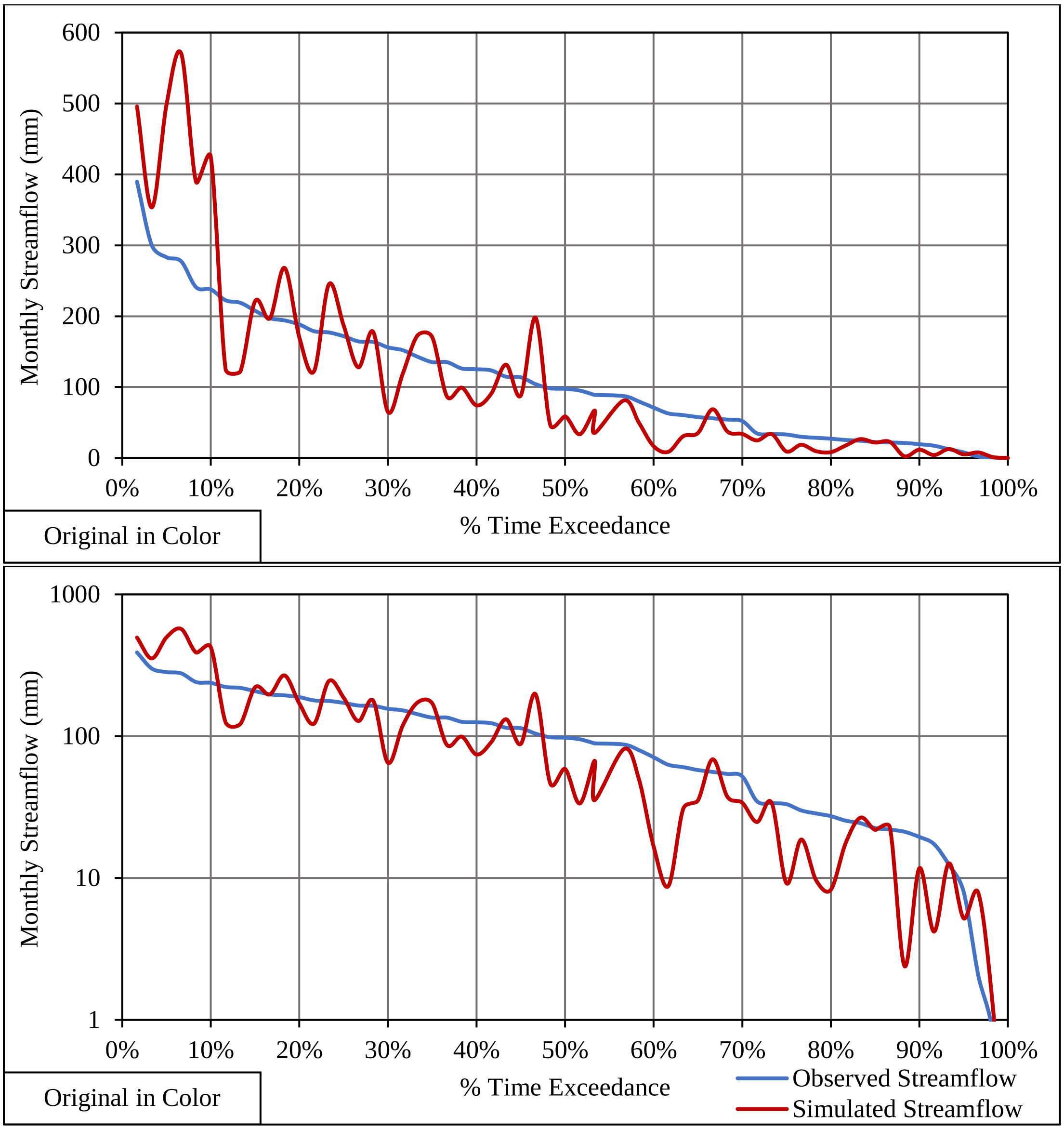


Figure 5-19 Flow Duration Curve of Two-parameter monthly water balance model for Dunamale Watershed of Verification Period – Normal and Semi-Log Plot

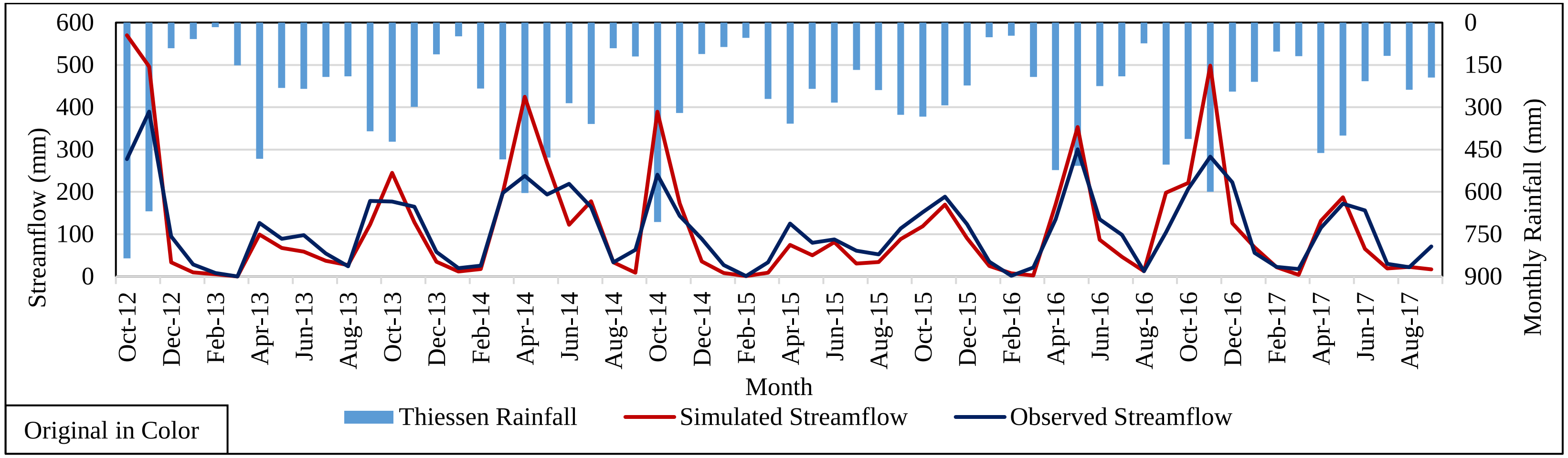


Figure 5-20 Hydrographs of Two-parameter monthly water balance model for Dunamale Watershed of Verification Period (2011-2017) – Normal Plot

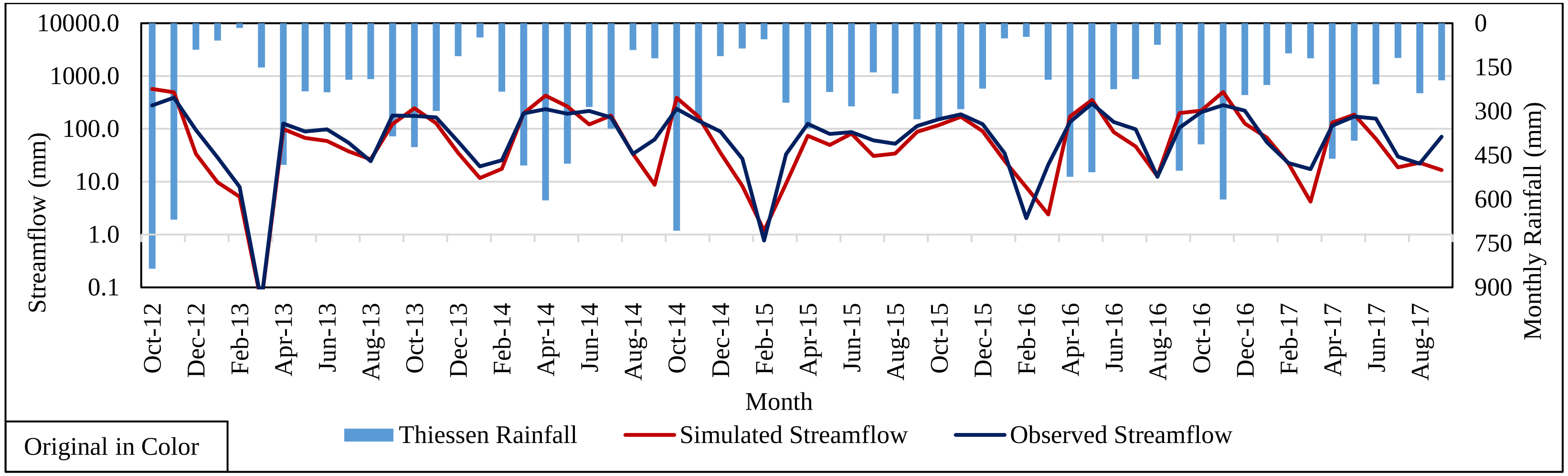


Figure 5-21 Hydrographs of Two-parameter monthly water balance model for Dunamale Watershed of Verification Period (2011-2017) – Semi-log Plot

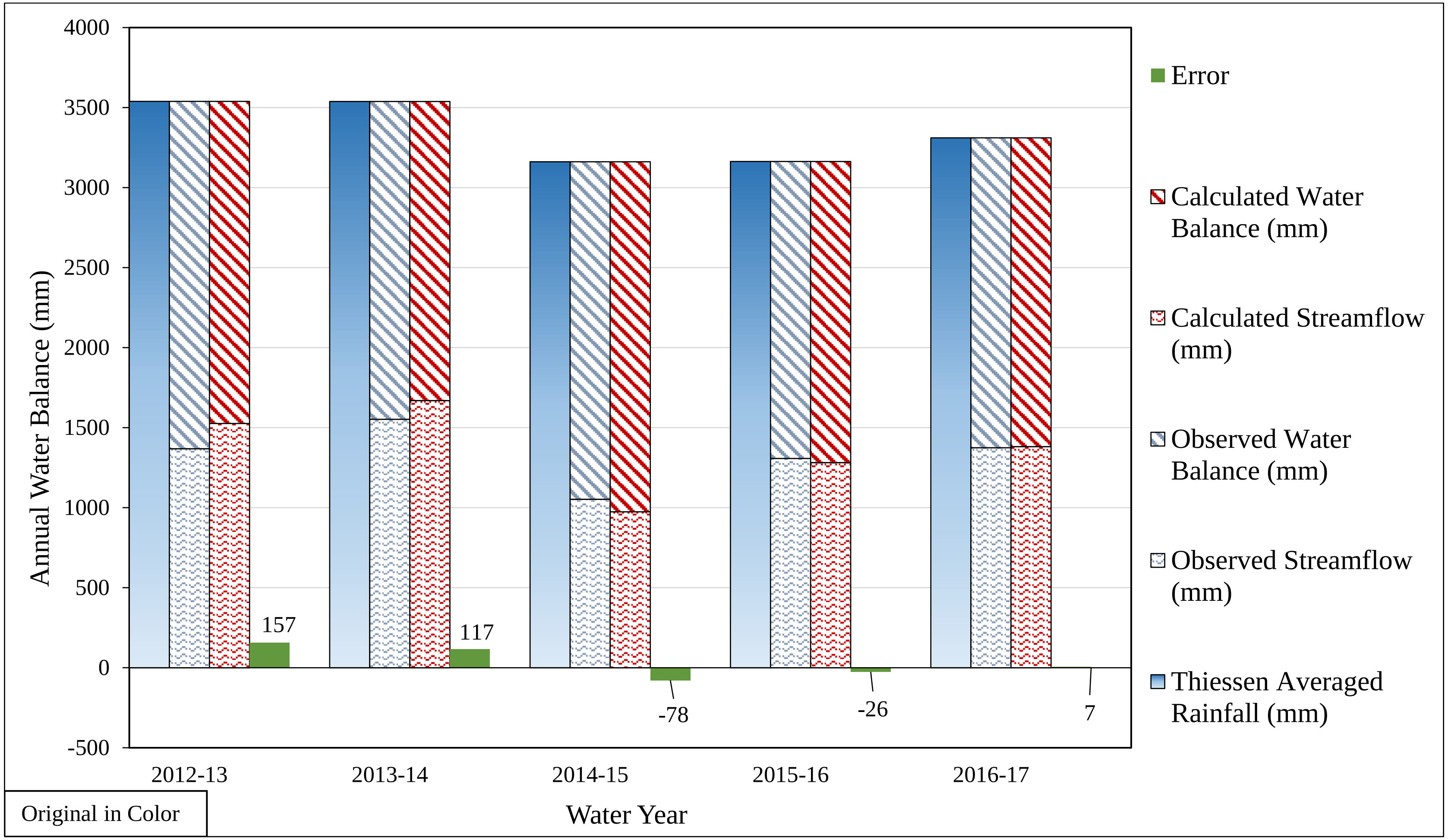


Figure 5-22 Annual Water Balance of Two-parameter model for Dunamale Watershed of Verification Period (2011-2017)

5.7 Optimization of Model Parameters and Rainfall Station Weights

Third and final step in optimization is to simultaneously optimize both model parameters and rainfall station weights for global minimum of MRAE.

5.7.1 Performance of model during Calibration period

Solver tool was used to search for optimum model parameters as well as the rainfall station weights simultaneously during calibration of the model and the performance indicators are mentioned in Table 5.11.

Table 5.11 Model Performance during Optimization of Model Parameters and Rainfall Station Weights for Calibration Period - Dunamale Watershed

Model Performance Indicators		Two Parameter Monthly Water Balance Model
SC		846.42
C		1.954
Pan Coefficient		0.970
Runoff Coefficient		0.372
Average Annual Water Balance Error		85.46
NASH Efficiency		0.740
MRAE	Overall	0.431
	High	0.350
	Medium	0.372
	Low	0.578

Table 5.12 Annual Water Balance for Optimization of Model Parameters and Rainfall Station Weights - Calibration Period

Water Year	Thiessen Rainfall (mm)	Observed Streamflow (mm)	Observed Water Balance (mm)	Calculated Streamflow (mm)	Calculated Water Balance (mm)	Error (mm)
2006/07	3526	1369	2157	1455	2071	87
2007/08	3658	1552	2106	1699	1959	147
2008/09	3295	1053	2242	1008	2287	-45
2009/10	3218	1308	1910	1257	1961	-51
2010/11	3401	1375	2026	1357	2044	-18
2011/12	2596	733	1863	566	2029	-166

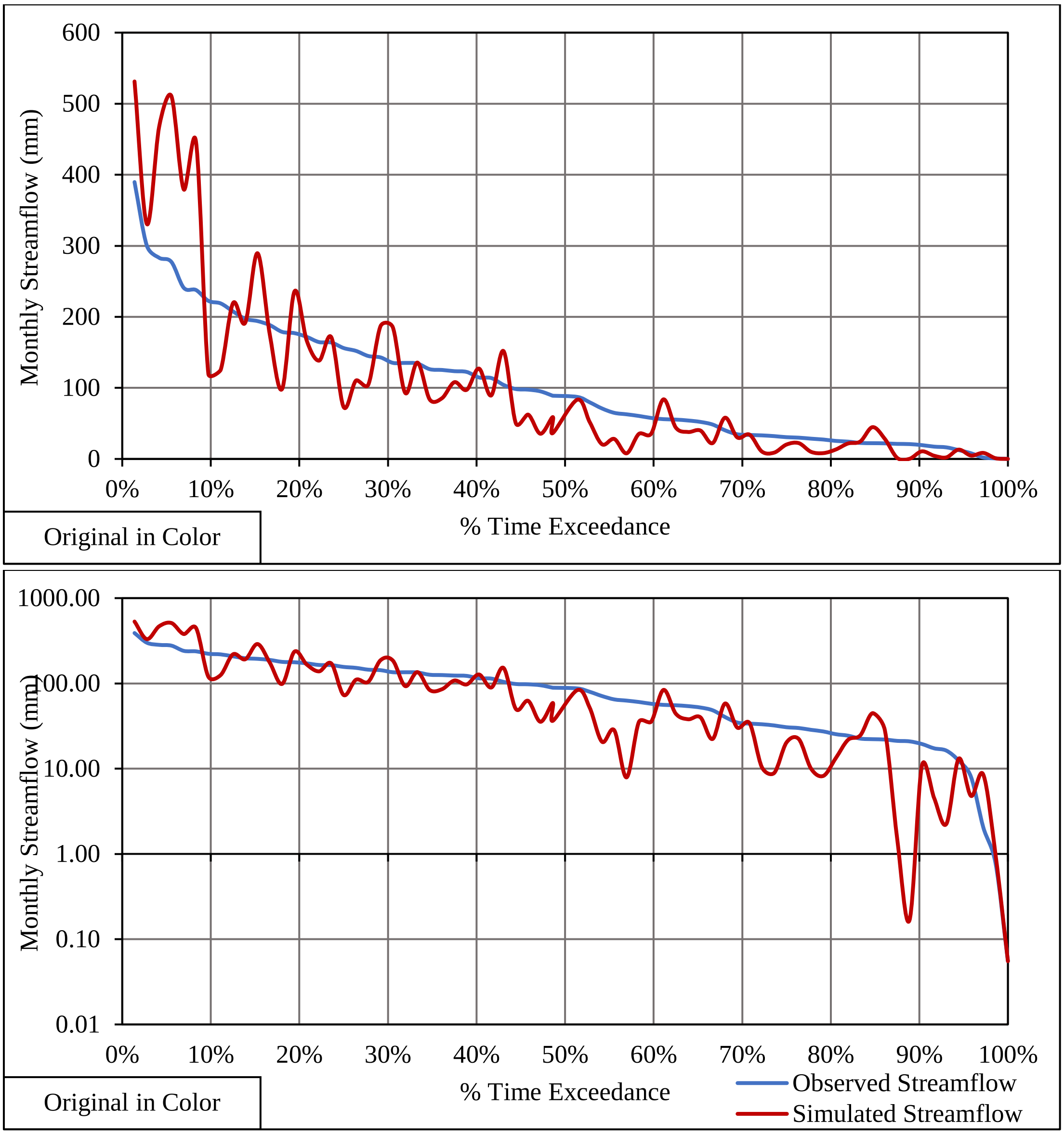


Figure 5-23 Flow Duration Curve of Two-parameter monthly water balance model for Dunamale Watershed of Calibration Period – Normal and Semi-Log Plot

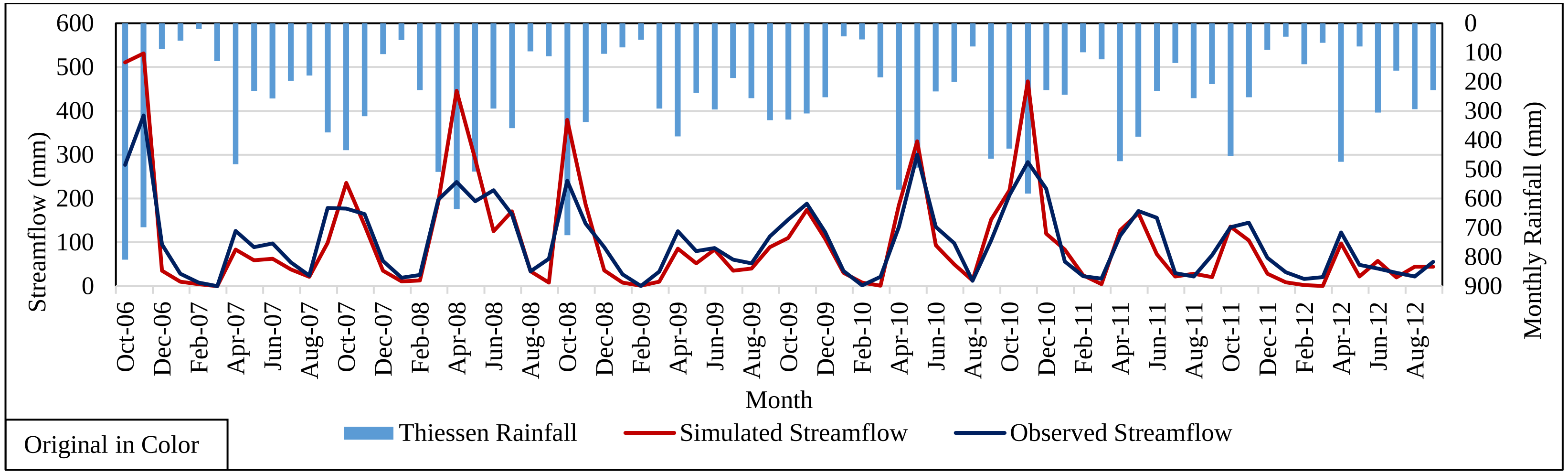


Figure 5-24 Hydrographs of Two-parameter monthly water balance model for Dunamale Watershed of Calibration Period (2006-2011) – Normal Plot

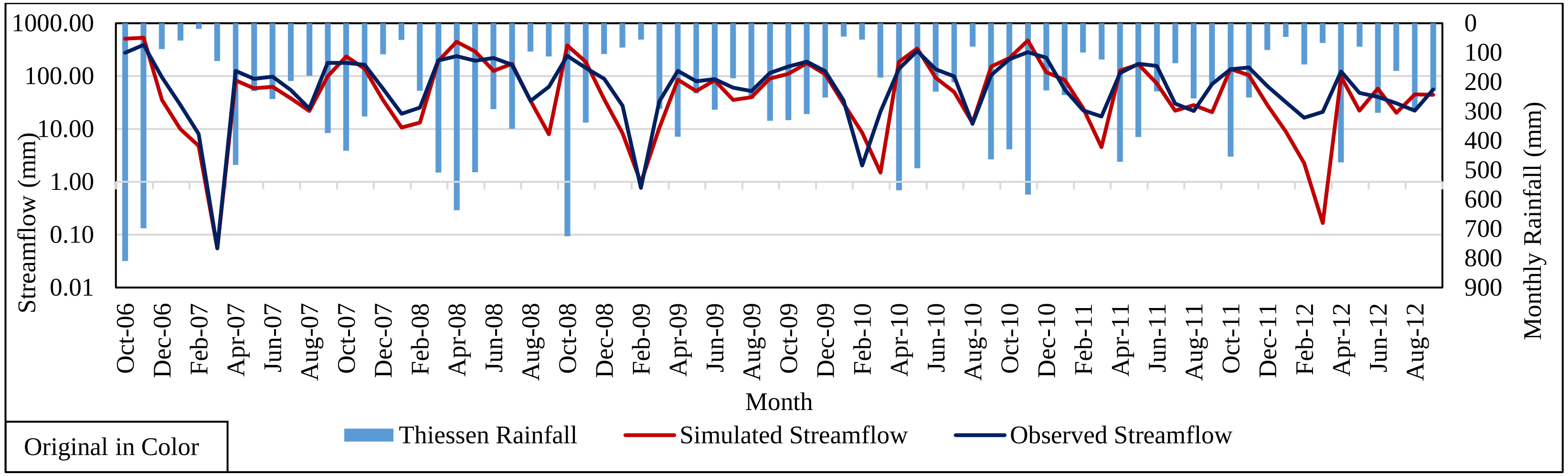


Figure 5-25 Hydrographs of Two-parameter monthly water balance model for Dunamale Watershed of Calibration Period (2006-2011) – Semi-Log Plot

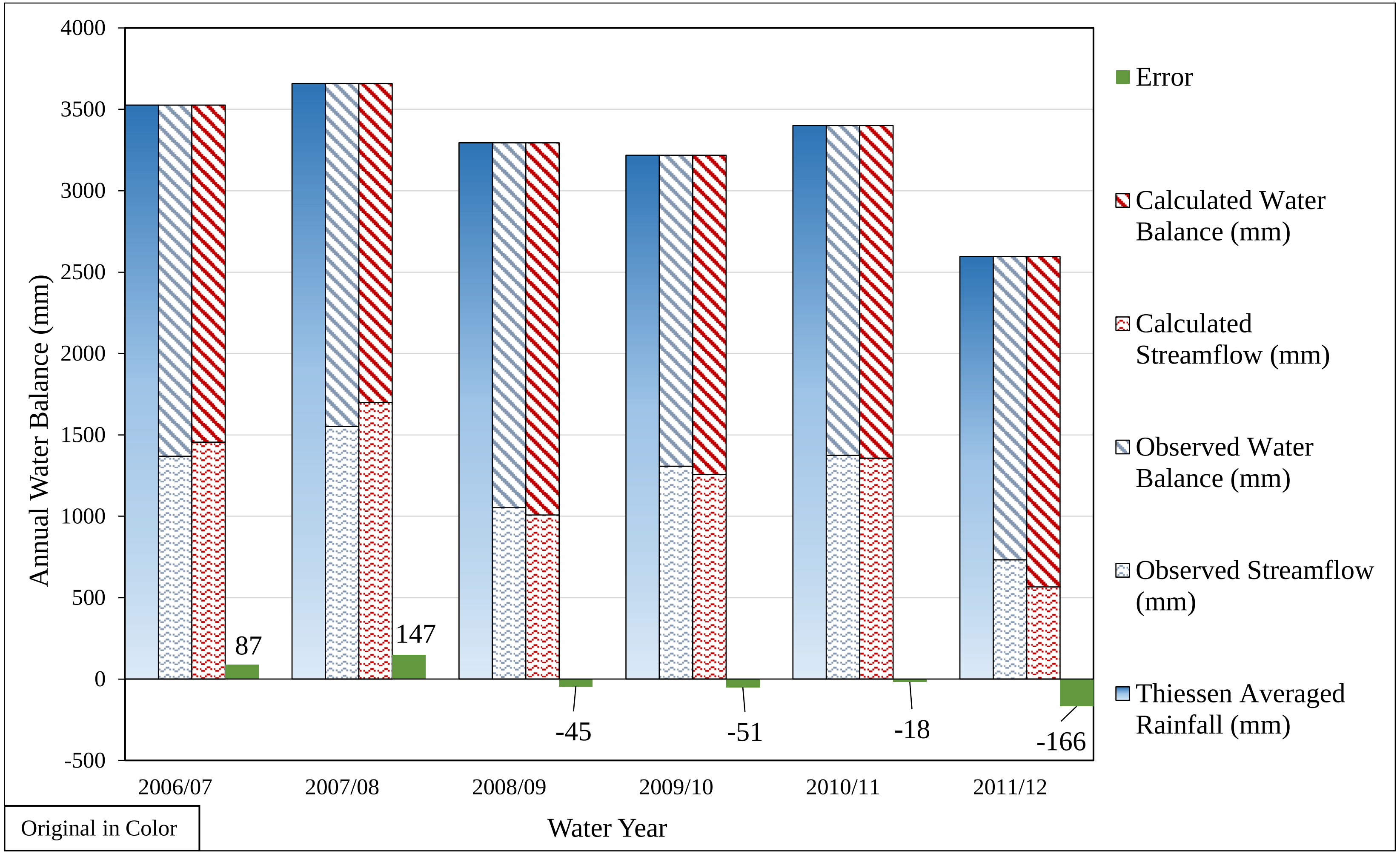


Figure 5-26 Annual Water Balance of Two-parameter model for Dunamale Watershed of Calibration Period (2006-2011)

5.7.2 Performance of model during Verification period

Model was allowed to run using optimized model parameters and rainfall station weights with verification dataset and indicators of model performance are mentioned in Table 5.13.

Table 5.13 Model Performance during Optimization of Model Parameters and Rainfall Station Weights for Verification Period - Dunamale Watershed

Model Performance Indicators		Two Parameter Monthly Water Balance Model
SC		846.42
C		1.954
Pan Coefficient		0.971
Runoff Coefficient		0.395
Average Annual Water Balance Error		67.37
NASH Efficiency		0.734
MRAE	Overall	0.415
	High	0.351
	Medium	0.384
	Low	0.522

Table 5.14 Annual Water Balance for Optimization of Model Parameters and Rainfall Station Weights - Verification Period

Water Year	Thiessen Rainfall (mm)	Observed Streamflow (mm)	Observed Water Balance (mm)	Calculated Streamflow (mm)	Calculated Water Balance (mm)	Error (mm)
2012/13	3526	1369	2157	1446	2080	77
2013/14	3658	1552	2106	1699	1959	147
2014/15	3295	1053	2242	1008	2287	-45
2015/16	3218	1308	1910	1257	1961	-51
2016/17	3401	1375	2026	1357	2044	-18

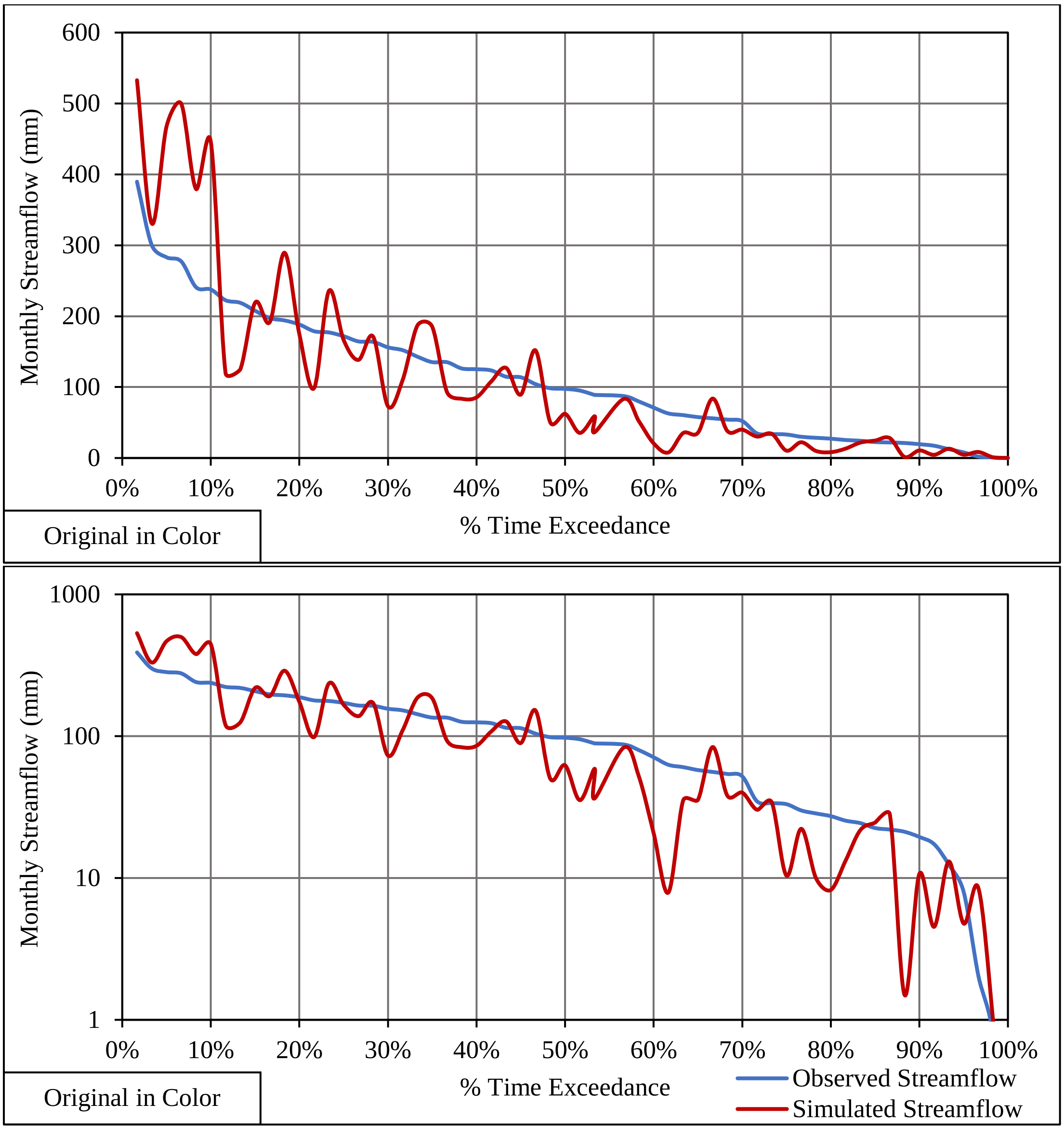


Figure 5-27 Flow Duration Curve of Two-parameter monthly water balance model for Dunamale Watershed of Verification Period – Normal and Semi-Log Plot

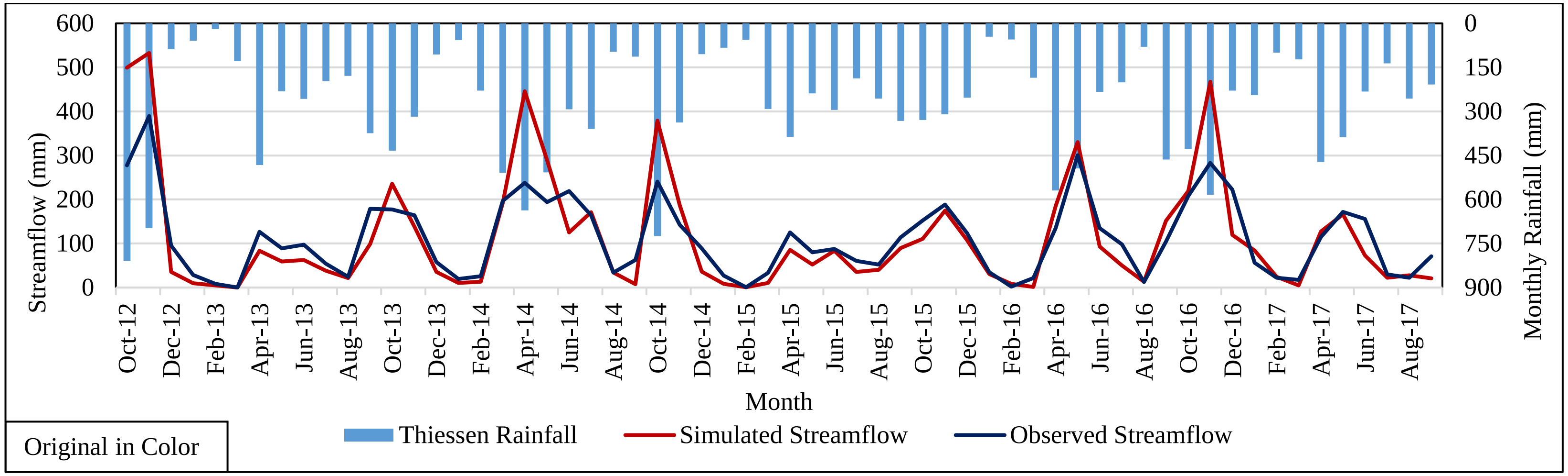


Figure 5-28 Hydrographs of Two-parameter monthly water balance model for Dunamale Watershed of Verification Period (2011-2017) – Normal Plot

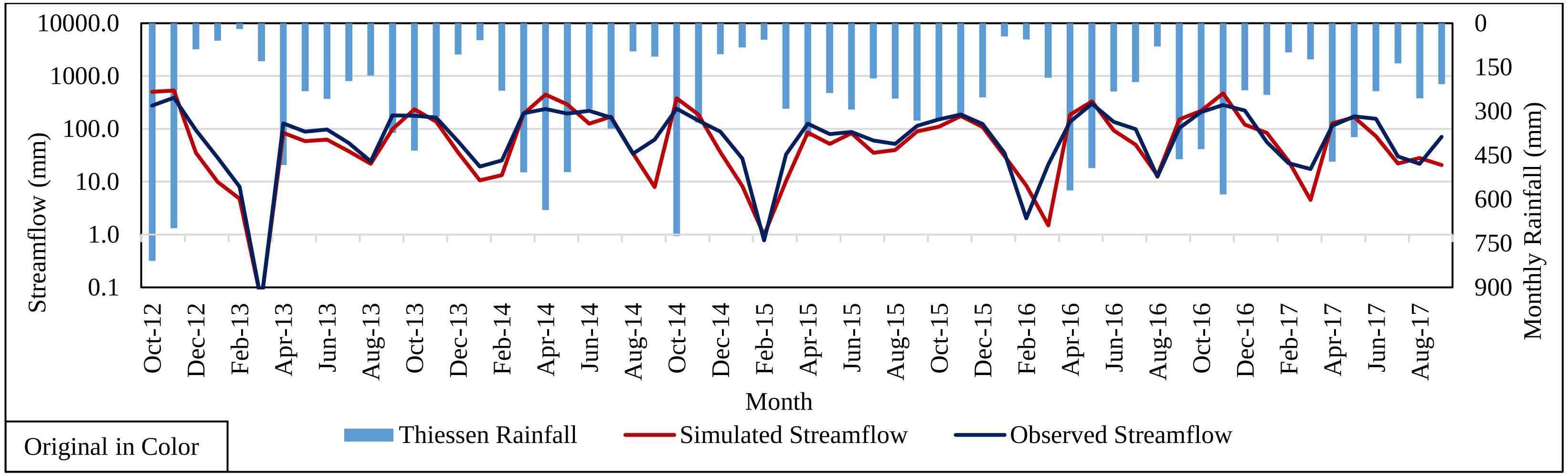


Figure 5-29 Hydrographs of Two-parameter monthly water balance model for Dunamale Watershed of Verification Period (2011-2017) – Semi-Log Plot

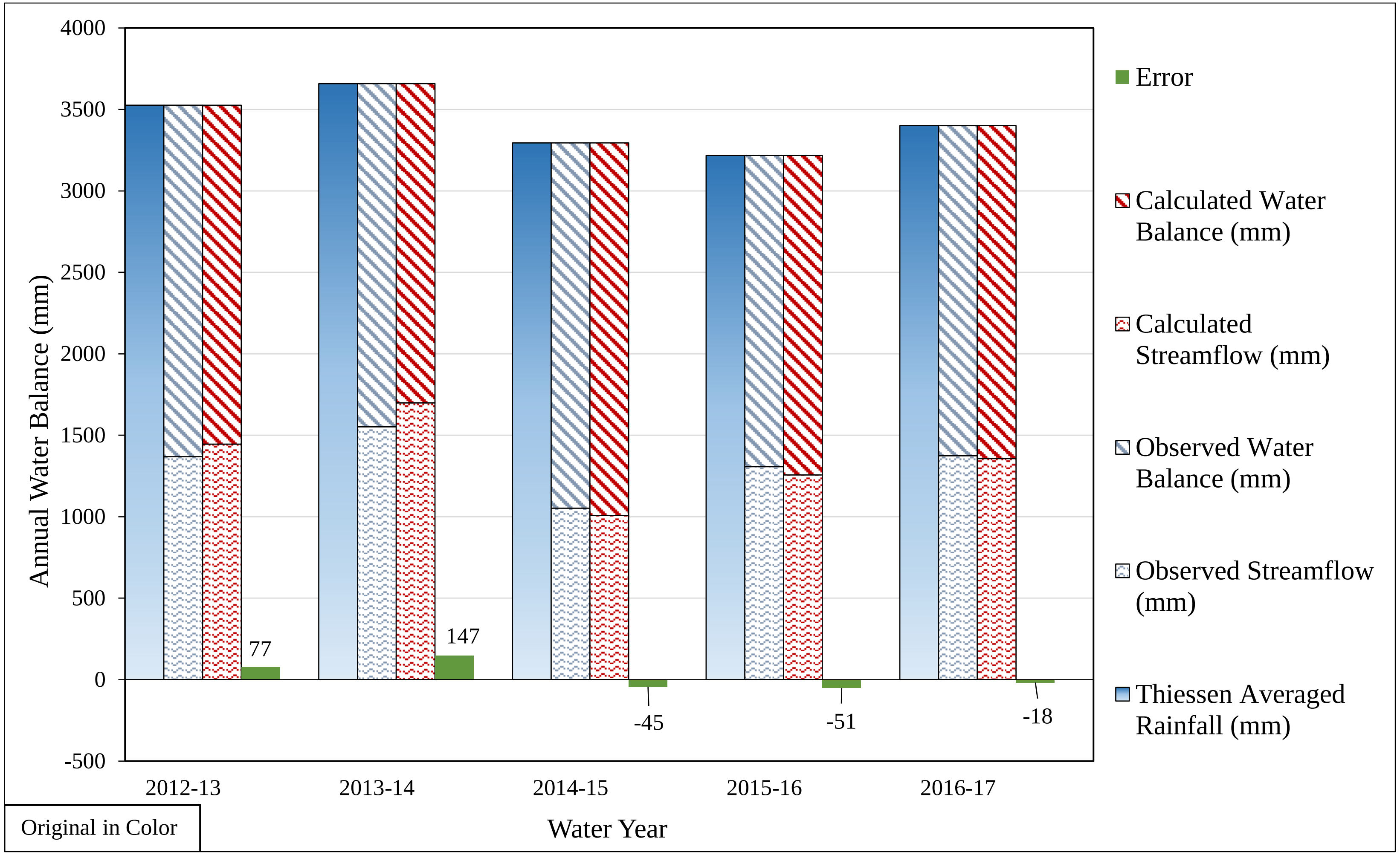


Figure 5-30 Annual Water Balance of Two-parameter model for Dunamale Watershed of Verification Period (2011-2017)

6 RESULTS

6.1 Optimization of Model Parameters

Thiessen Weights were used for calculating areal average rainfall while optimizing the model parameters. The station weights for each station are mentioned in Table 6.1 and the performance results of the model during calibration and verification is shown in Table 6.3 and the optimized model parameters are shown in Table 6.2. Scattered plots show that simulated streamflow had significant positive relationship.

Table 6.1 Rainfall Station Weights used for calculating Areal Average Rainfall

Rainfall Gauging Station	Rainfall Station Weights (%)
Vincit	8.0
Pasyala	14.5
Nittambuwa	23.0
Karasnagala	38.5
Chesterford	16.0

Table 6.2 Optimized Model Parameters

Model Parameters	Optimized Values
Parameter – C	1.878
Parameter – Sc	782.47 mm

Table 6.3 Comparison of results during calibration and verification of optimized model parameters

Optimization I	Calibration	Verification
Average Water Balance Error	151.44 mm	144.87 mm
NASH Efficiency	0.700	0.694
MRAE – Overall	0.452	0.446
MRAE – High	0.387	0.396
MRAE – Medium	0.376	0.391
MRAE – Low	0.606	0.569
Data Period	2006-2012	2012-2017

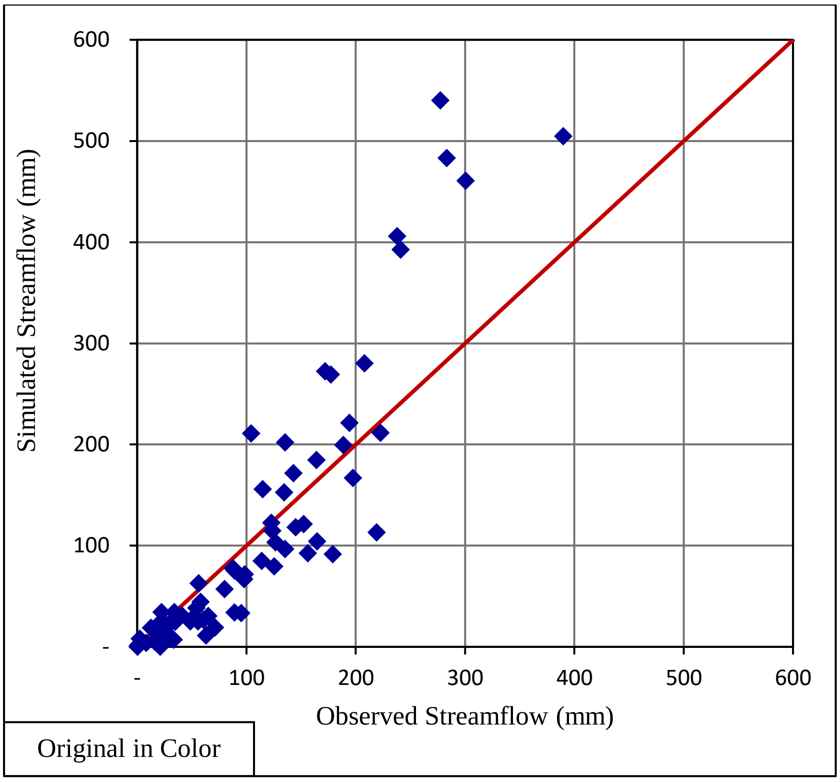


Figure 6-1 Observed and Simulated Streamflow Comparison of Dunamale Watershed for Model Parameter Optimization - Calibration Period

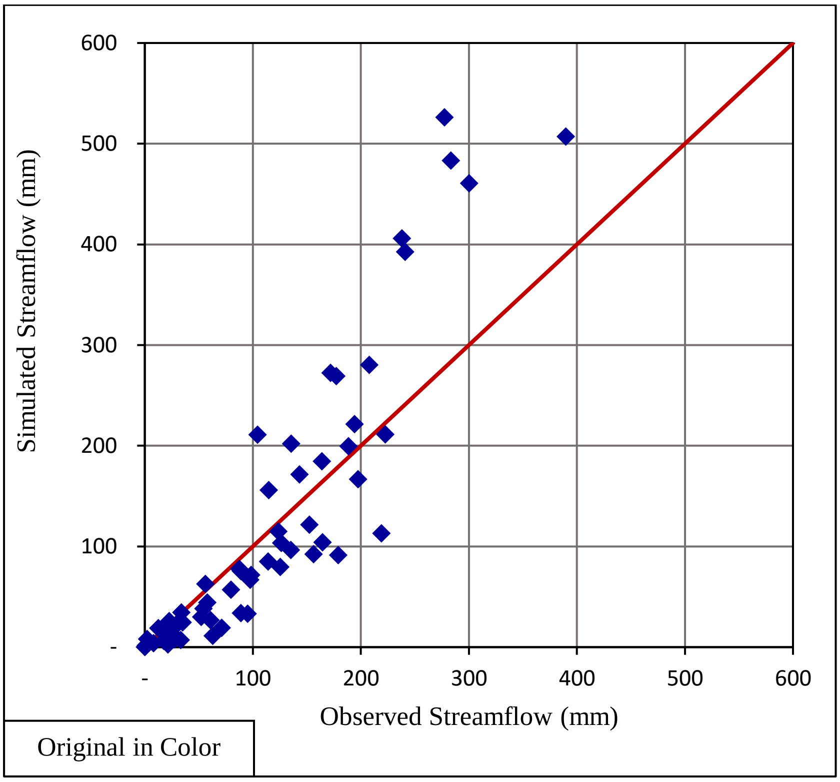


Figure 6-2 Observed and Simulated Streamflow Comparison of Dunamale Watershed for Model Parameter Optimization - Verification Period

6.2 Optimization of Rainfall Station Weights

Thiessen Weights were used for calculating areal average rainfall while optimizing the model parameters. The optimum station weights for each station are mentioned in Table 6.5 and the performance results of the model during calibration and verification is shown in Table 6.6 and the optimized model parameters are shown in Table 6.4.

Table 6.4 Selected Model Parameters

Model Parameters	**Optimized Values**
Parameter – C	1.878
Parameter – Sc	782.47 mm

Table 6.5 Optimized Rainfall Station Weights used for calculating Areal Average Rainfall

Rainfall Gauging Station	**Rainfall Station Weights (%)**
Vincit	38.7
Pasyala	32.5
Nittambuwa	14.5
Karasnagala	13.5
Chesterford	0.8

Table 6.6 Comparison of results during calibration and verification of optimized rainfall station weights

Optimization II	**Calibration**	**Verification**
Average Water Balance Error	98.30 mm	77.07 mm
NASH Efficiency	0.699	0.694
MRAE – Overall	0.433	0.420
MRAE – High	0.355	0.359
MRAE – Medium	0.388	0.410
MRAE – Low	0.557	0.500
Data Period	2006-2012	2012-2017

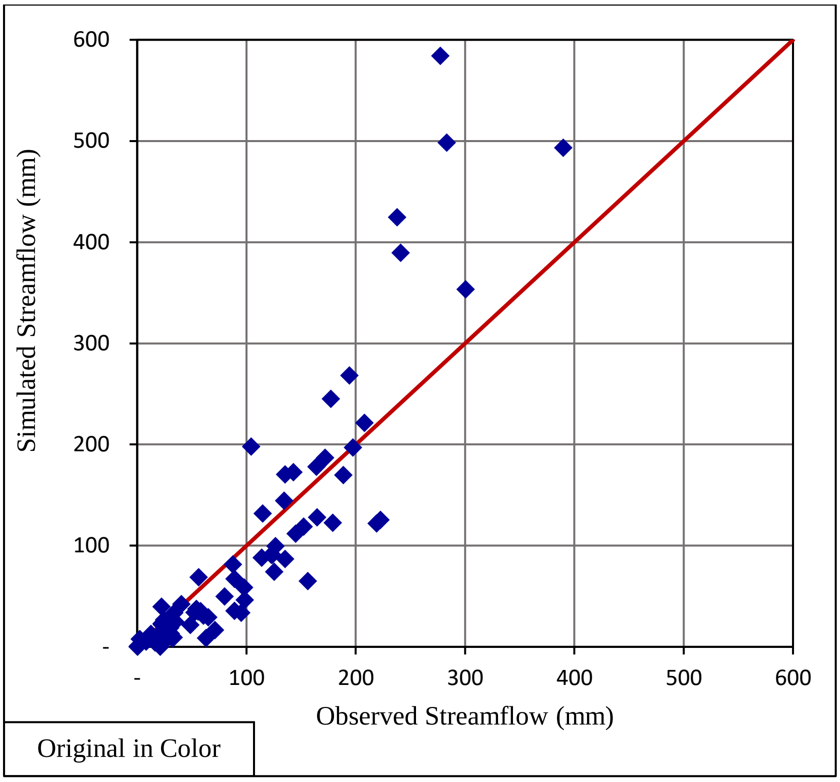


Figure 6-3 Observed and Simulated Streamflow Comparison of Dunamale Watershed for Rainfall Station Weights Optimization - Calibration Period

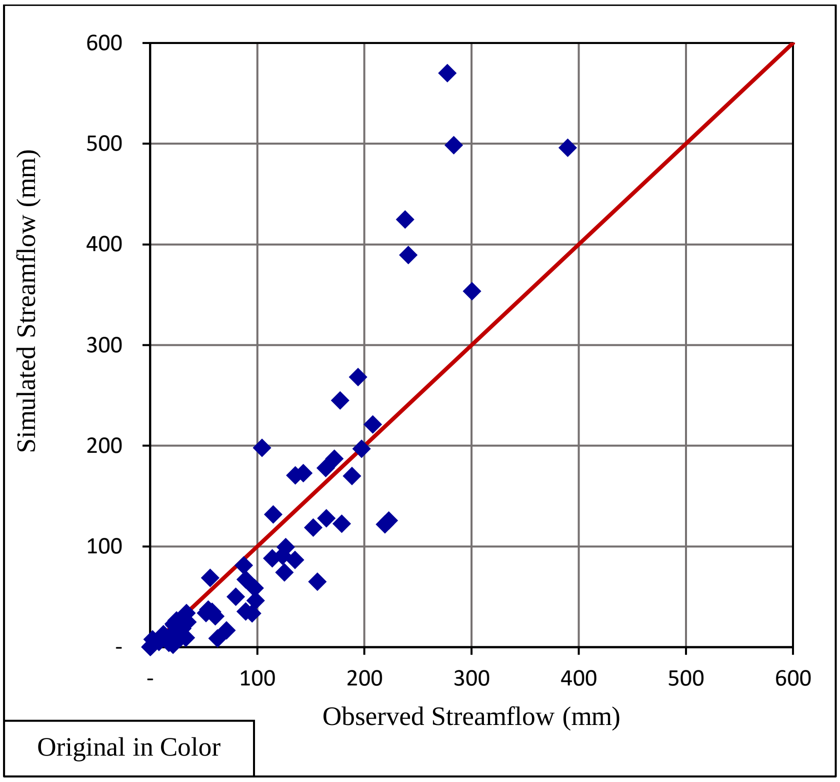


Figure 6-4 Observed and Simulated Streamflow Comparison of Dunamale Watershed for Rainfall Station Weights Optimization - Verification Period

6.3 Optimization of Model Parameters and Rainfall Station Weights

Model parameters and rainfall station weights were allowed to freely optimize simultaneously. The optimized model parameters, rainfall station weights and performance indicators are shown in Table 6.7, Table 6.8, Table 6.9 respectively.

Table 6.7 Optimized Model Parameters

Model Parameters	**Optimized Values**
Parameter – C	1.955
Parameter – Sc	846.42 mm

Table 6.8 Optimized Rainfall Station Weights used for calculating Areal Average Rainfall

Rainfall Gauging Station	**Rainfall Station Weights (%)**
Vincit	52.8
Pasyala	19.9
Nittambuwa	12.0
Karasnagala	14.4
Chesterford	0.9

Table 6.9 Comparison of results during calibration and verification of optimized model parameters and rainfall station weights

Optimization III	**Calibration**	**Verification**
Average Water Balance Error	85.46 mm	67.37 mm
NASH Efficiency	0.740	0.734
MRAE – Overall	0.431	0.415
MRAE – High	0.350	0.351
MRAE – Medium	0.372	0.384
MRAE – Low	0.578	0.522
Data Period	2006-2012	2012-2017

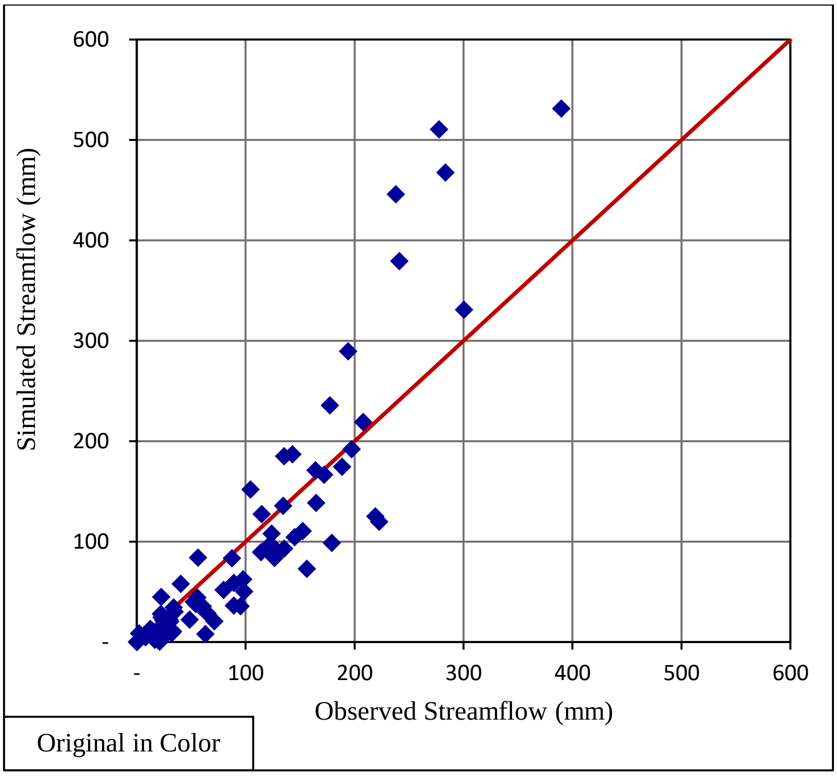


Figure 6-5 Observed and Simulated Streamflow Comparison of Dunamale Watershed for Rainfall Station Weights and Model Parameter Optimization - Calibration Period

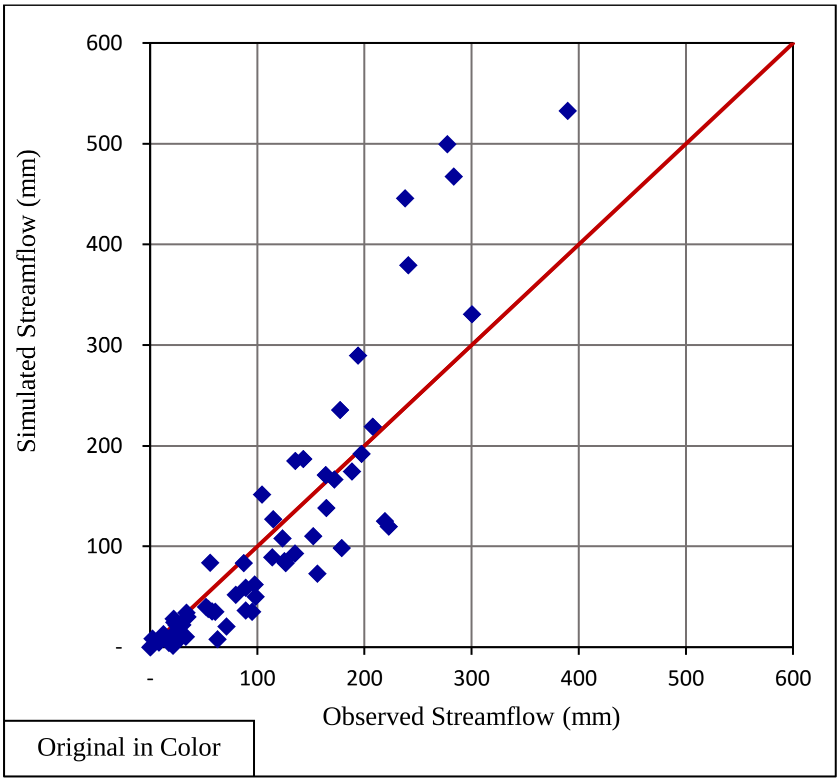


Figure 6-6 Observed and Simulated Streamflow Comparison of Dunamale Watershed for Rainfall Station Weights and Model Parameter Optimization - Verification Period

6.4 Comparison of various cases of Optimization

After the calibration and verification of all the optimization cases is complete, a comparison of results from each was performed to check if there has been any improvement or not.

6.4.1 Comparison of Rainfall station weights

Areal average rainfall comparison based on the rainfall station weights for each optimization stage which is mentioned in Table 6.10.

Table 6.10 Comparison of Rainfall Station Weights for each Optimization case

Rainfall Gauging Station	Rainfall Station Weights (%)		
	Optimization I	Optimization II	Optimization III
Vincit	8.0	38.7	52.8
Pasyala	14.5	32.5	19.9
Nittambuwa	23.0	14.5	12.0
Karasnagala	38.5	13.5	14.4
Chesterford	16.0	0.8	0.9

Vincit station has the highest influence after optimizing the rainfall station weights while initially when using the thiessen weights it had least influence on areal average rainfall.

6.4.2 Comparison of model performance during Calibration period

Comparison of model performance of two stages at once based on various indicators during calibration period has been shown in Table 6.11, Table 6.12 & Table 6.13.

Table 6.11 Comparison of model performance for Optimization stage I and II during Calibration (2006-2012)

Model Performance Indicators	Optimization I	Optimization II	% Improvement
Average Water Balance Error	151.44 mm	98.30 mm	35.1
NASH Efficiency	0.700	0.699	- 0.1
MRAE – Overall	0.452	0.433	4.2
MRAE – High	0.387	0.355	8.3
MRAE – Medium	0.376	0.388	- 3.2
MRAE – Low	0.606	0.557	8.1

Table 6.12 Comparison of model performance for Optimization stage I and III during Calibration (2006-2012)

Model Performance Indicators	Optimization I	Optimization III	% Improvement
Average Water Balance Error	151.44 mm	85.46 mm	43.6
NASH Efficiency	0.700	0.740	5.7
MRAE – Overall	0.452	0.431	4.6
MRAE – High	0.387	0.350	9.6
MRAE – Medium	0.376	0.372	1.1
MRAE – Low	0.606	0.578	4.6

Table 6.13 Comparison of model performance for Optimization stage II and III during Calibration (2006-2012)

Model Performance Indicators	Optimization II	Optimization III	% Improvement
Average Water Balance Error	98.30 mm	85.46 mm	13.1
NASH Efficiency	0.699	0.740	5.9
MRAE – Overall	0.433	0.431	0.5
MRAE – High	0.355	0.350	1.4
MRAE – Medium	0.388	0.372	4.1
MRAE – Low	0.557	0.578	-3.8

6.4.3 Comparison of model performance during Verification period

Comparison of model performance of two stages at once based on various indicators during calibration period has been shown in Table 6.14, Table 6.15 & Table 6.16.

Table 6.14 Comparison of model performance for Optimization stage I and II during Verification (2012-2017)

Model Performance Indicators	Optimization I	Optimization II	% Improvement
Average Water Balance Error	144.87 mm	77.07 mm	46.8
NASH Efficiency	0.694	0.694	0.0
MRAE – Overall	0.446	0.420	5.8
MRAE – High	0.396	0.359	9.3
MRAE – Medium	0.391	0.410	- 4.9
MRAE – Low	0.569	0.500	12.1

Table 6.15 Comparison of model performance for Optimization stage I and III during Verification (2012-2017)

Model Performance Indicators	Optimization I	Optimization III	% Improvement
Average Water Balance Error	144.87 mm	67.37 mm	53.5
NASH Efficiency	0.694	0.734	5.8
MRAE – Overall	0.446	0.415	7.0
MRAE – High	0.396	0.351	11.4
MRAE – Medium	0.391	0.384	1.8
MRAE – Low	0.569	0.522	8.3

Table 6.16 Comparison of model performance for Optimization stage II and III during Verification (2012-2017)

Model Performance Indicators	Optimization II	Optimization III	% Improvement
Average Water Balance Error	77.07 mm	67.37 mm	12.6
NASH Efficiency	0.694	0.734	5.8
MRAE – Overall	0.420	0.415	1.2
MRAE – High	0.359	0.351	2.2
MRAE – Medium	0.410	0.384	6.3
MRAE – Low	0.500	0.522	-4.4

7 DISCUSSION

7.1 Data Disparities

After through data checking in the present study and for all the observed data it was identified that because of more than 8 months of missing data in a Karasnagala rain gauging station data for water year 2005-2006 could not be used for the study. Data checking was performed on various scale such as daily, monthly and annual. The missing data on daily scale cannot be easily captured during model calculations as the data was aggregated to monthly, hence decreasing the sum of total rainfall in a month. Streamflow data values of zero were a major concern in the study as these points would be difficult to capture by the model.

7.2 Data Filling Importance and Drawbacks

In order to optimize the rainfall station weights, it was important to fill missing data to learning about the influence of changing station weights on streamflow forecasts from the model. After a through literature review, selecting a data filling method was difficult as each and every method has its drawbacks and their accuracy depends on various conditions that they are fit to be applied or on the distribution/density of rainfall gauging stations. Therefore, the data filling method used for the present study is replacement method or otherwise known as closest station method based on the simplicity of the method. The major drawback of this method is that if the closest station is principle rainfall gauging station being used in the study then the spatial variation between the two-rainfall station has no significance at all. Unfortunately, in the present study the closest station used for replacing the missing data are the principle stations of the study itself and hence it will have an impact on the improvement in streamflow estimates due to spatial variation of rainfall if any.

7.3 Areal Average Rainfall

Thiessen Polygon method being one of the most common method among hydrological modellers for computing areal average rainfall has been used in the present study as none of the literature suggests using a method with confidence. Thiessen average rainfall was only used during the optimization of model parameters in optimization stage I in other two optimization stages rainfall station weights were optimized for calculating areal average rainfall.

7.4 Model Identification

Model identification required a well suited and realistic value of initial soil water content. A cyclic period of 5 repetitions of the dataset was used as warmup period to make sure that the soil water content value is steady as suggested in literature. This work recognized that a warm period of 2-3 years would be sufficient to stabilize soil moisture value for non-erratic data.

7.5 Search for Global Minimum

During the calibration it was observed that the initial parameter values have its effect on the results generated by solver function tool after optimization. Therefore, there was need to search for the global minimum to make sure that the results generated from the model are optimum values corresponding to minimum MRAE.

7.6 Model Parameter Ranges

Model parameter ranges not being mentioned in the original work by Xiong and Guo (1999) makes it difficult for modellers modelling a catchment outside China to have a reference of the parameter values or to evaluate if the resultant values from the model can be accepted. Therefore, search for global minimum was required to obtain best set of model parameters with respect to minimum objective function surface.

7.7 Model Conceptualization

Results of the present study indicate that the two-parameter model conceptualization is sufficient to represent majority of the flows in a catchment while it is not adequate in representing the catchment response or delay to either high rainfall period or a prolonged dry period as from the model results for such periods are very instantaneous.

7.8 Two-parameter Model Performance

Main objective of the research is to study the influence of spatial unpredictability of rainfall on streamflow estimates using a monthly water balance model. The selected two-parameter monthly water balance model was calibrated for Dunamale watershed to obtain a benchmark value of minimum objective function and comparing the influence of optimizing rainfall station weights. The two-parameter model was successfully calibrated for Dunamale watershed and performance was satisfactory with an average MRAE of 0.44 for optimized parameter value of c as 1.87 and SC as 782.47 mm.

7.9 Influence of Model Parameters

While searching for global minimum, various manual trial and error computations with parameter c and SC were carried out in order to study the influence of individual parameter on the water estimates. It was observed that while increasing value of parameter SC, the recession periods became more regular than peaks while with increasing value of parameter c decreased the magnitude of streamflow estimates to some extent after which further increase leads to more frequent peaks and irregularity in the magnitude.

7.10 Influence of Rainfall Spatial Variability

Incorporation of rainfall spatial variability by optimizing rainfall station weights improved the water estimates by 8-9% of MRAE, while simultaneous optimization of model parameters and rainfall station weights further improved the estimates by 0-1%. This improvement solely depends upon the spatial variation with the catchment and among the rainfall gauging stations. Factors affecting spatial variation of rainfall captured by a point station are distance between the two stations, and micro-climatic conditions within the catchment. Since the catchment has less spatial variation between rainfall captured at each rainfall station there was not a major improvement in the results after optimizing rainfall station weights which was further affected due to filling of rainfall data using replacement method.

7.11 Model Development and Modelling Difficulties

A model is a simple depiction of complex reality. There are various difficulties faced during the development of the model based on the conceptualization by Xiong and Guo (1999) such as search for global minimum, model identification, and calibration of the model. Data collation and checking is a demanding task which needs a crucial amount of time and work to make certain that the information, resolution, and other modelling related data parameters are adequate to be used for model simulations.

Parameter optimization has its own difficulties such as when there are more than 2 parameters to be optimized a visual check for the objective function surface cannot be performed such as in the case of rainfall station weight optimization where there were five rainfall station to be optimized.

7.12 Improvements on Streamflow Estimates

A small change in rainfall station weight aggregates to a noticeable change in the monthly rainfall input to the model. A rainfall station receiving high intensity rainfall will have more impact on the rainfall due to the magnitude. Optimization of rainfall station weights and model parameters led to marginal improvement in MRAE values whereas there were improvements in flow duration curves and hydrographs which were very critical. There were zero values in observed streamflow which were misgiving considering that Attanagalu Oya basin received on an average 1200-2000mm rainfall annually. Model predicted much better theoretical estimations with improved hydrograph matching using rainfall station weight optimization for such instances proving that an areal averaging method that predetermines rainfall station weights and disregards the mobile nature of any rainfall event will lead to erroneous results.

8 CONCLUSIONS

1. Comparative evaluation of the model with and without rainfall optimisation revealed that the incorporation of the former would result in 4-6% increase in the overall hydrograph matching, 8-9%, 3-4% and 8-12% respective improvements in high, medium and low flow duration curves along with a 46-53% improvement in the water balance estimations
2. The spatial variability of rainfall used for the modelling indicated a variation 5-10 % thereby reflecting the similarity of rainfall in the region. This can be considered as the cause for limited improvement when gauging station weights are optimised.
3. The Two-parameter model with Thiessen Rainfall input resulted C and Sc values of 1.878 and 782.47 mm respectively with a MRAE value of 0.44 in the overall hydrograph matching, 0.396, 0.391, and 0.569 MRAE values for high, medium and low flow duration curves and an average water balance error of 144.87 mm.
4. The Two-parameter model with Optimised Rainfall input resulted C and Sc values of 1.955 and 846.42 mm respectively with a MRAE value of 0.41 in the overall hydrograph matching, 0.351, 0.384, and 0.522 MRAE values for high, medium and low flow duration curves and an average water balance error of 67.37 mm.
5. As observed from the results of the present study model parameter SC governs the smoothness of the peak, mainly affecting the recession and ascend of the peaks while parameter c governs the magnitude as well as the frequency of peaks.

9 RECOMMENDATIONS

1. It is recommended to incorporate optimization of rainfall station weight along with model parameters to improve the accuracy of water estimates.
2. It is recommended to carry out a similar research in a different basin which has high spatial variability of rainfall.
3. It is also recommended to change the monthly water balance model to a model which incorporates the catchment characteristics responsible for spatial variability of rainfall.

REFERENCES

Akin, J. E. (1971). Calculation of Mean Areal Depth of Precipitation. *Journal of Hydrology Vol. 12*, 363-376.

Al-Lafta, H. S., Al-Tawash, B. S., & Al-Baldawi, B. A. (2013). Applyng tthe "abcd" Monthly Water Balance Model for some regions in the United States. *Advances in Physics Theories and Applications*, 36-47.

Anctil, F., Perrin, C., & Andreassian, V. (2004). Impact of the length of observed records on the performance of ANN and of conceptual parsimonious rainfall-runoff forecasting models. *Environmental Modelling & Software Vol, 19,* 357-368.

Bai, P., Liu, X., Liang, K., & Liu, C. (2015). Comparison of performance of twelve monthly water balance models in different climatic catchments of China. *Journal of Hydrology*, 1030-1040.

Barbalho, F. D., Silva, G. F., & Formiga, K. T. (2014). Average Rainfall Estimation : Methods Performance Comparison in the Brazilian Semi-Arid. *Journal of Water Resource and Protection*, 97-103.

Berndtsson, R., & Niemczynowicz, J. (1988). Spatial and Temporal Scales in Rainfall Analysis - Some Aspects and Future Perspectives. *Journal of Hydrology*, 293-313.

Berne, A., Delrieu, G., Creutin, J.-D., & Obled, C. (2004). Temporal and Spatial resolution of rianfall measurements required for urban hydrology. *Journal of Hydrology*, 166-179.

Bhavani, R. (2013). Comparison of Mean and Weighted Annual Rainfall in Anantapuram District. *International Journal of Innovative Research in Science, Engineering and Technology*, 2794-2800.

Boughton, W. (2006). *A review of Australian model parameterization studies using large basin samples.* IAHS-AISH Publication.

Buzacott, Alexander & Tran, Bruce & Van Ogtrop, Floris & Vervoort, Rutger Willem. (2019). *Conceptual Models and Calibration Performance—Investigating Catchment Bias*. Water. 11. 2424. 10.3390/w11112424.

Chen, T., Ren, L., Yuan, F., Yang, X., Jiang, S., Tang, T., . . . Zhang, L. (2017). Comparison of Spatial Interpolation Schemes for Rainfall Data and Application in Hydrological Modeling. *Water*.

Cristiano, E., Veldhuis, M.-c., & Giesen, N. (2017). Spatial and temporal variability of rainfall and their effects on hydrological response in urban areas – a review. *Hydrology and Earth System Sciences*, 3859-3878.

Cunderlik, J. M., & Simonovic, S. P. (2004). *Selection of calibration and verification data for the HEC-HMS hydrologic model.* London, Ontario: The University of Western Ontario.

Diskin, M. H., & Simon, E. (1977). A Procedure for the Selection of Objective Functions for Hydrologic Simulation Models. *Journal of Hydrology, 34*, 129-149.

Dissanayake, P. K. (2017). *Applicability of a Two Parameter Water Balance Model to Simulate Daily Rainfall Runoff - Case Study of Kalu and Gin River Basins in Sri Lanka (Unpublished Master's Thesis).* Colombo, Sri Lanka: University of Moratuwa.

Dzubakova, K. (2010). Rainfall-Runoff Modelling: Its development, Classification and Possible Applications. *ACTA, Geographica Universitat Comenianae, Vol. 54*, pp. 173-181.

Edwards, K. A. (1972). A Note on the "Calculation of Mean Areal Depth of Precipitation" by J. A. Akin. *Journal of Hydrology*, 171-173.

EPA. (2007). *An Approach for Using Load Duration Curves in the Development of TMDLs.* Pennsylvania Ave. NW, Washington: U.S. Environmental Protection Agency.

Gan, T. Y., & Biftu, G. F. (1996). Automatic Calibration of Conceptual rainfall-runoff models: Optimization algorithms, catchment conditions, and model structure. *Water Resources Research Vol 32, No. 12*, 3513-3524.

Hoad, K., Robinson, S., & Davies, R. (2008). Automating Warm-Up Length Estimation. *Winter Simulation Conference* (pp. 532-540). Coventry, UK: IEEE.

Jayatilaka, C. J., Sakthivadivel, R., Shinogi, Y., Makin, I. W., & Witharana, P. (2003). A simple water balance modelling approach for determining water availability in an irrigation tank cascade system. *Journal of Hydrology*, 81-102.

Khandu, D. (2016). *A Monthly Water Balance Model for Evaluation of Climate Change Impacts on the Streamflow of Gin Ganga and Kelani Ganga Basins, Sri Lanka (Unpublished Master's Thesis).* Colombo, Sri Lanka: University of Moratuwa.

Kim, S., Hong, S., Kang, N., Noh, H., & Kim, H. (2015). A comparative study on the simple two-parameter monthly water balance model and Kajiyama formula for monthly runoff estimation. *International Conference Water Resources Assessment and Seasonal Prediction.* Koblenz, Germany: Taylor & Francis & IAHS.

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

Lebel, T., Bastin, G., Obled, C., & Creutin, J. D. (1987). On the accuracy of areal rainfall estimation: A case study. *Water Resources Research Vol 23, No. 11*, 2123-2134.

Li, C.-z., Wang, H., Liu, J., Yan, D.-h., Yu, F.-l., & Zhang, L. (2010). Effect of calibration data series length on performance and optimal parameters of hydrological model. *Water Science and Engineering*, 378-393.

Liu, J., & Han, D. (2010). Indices for calibration data selection of the rainfall-runoff model. *Water Resource Research, Vol. 46*, 1-17.

Mahinda, R. (2006). *Mahinda Chintana.* Panaluwa, Padukka: Department of National Planning Ministry of Finance and Planning.

Makhlouf, Z., & Michel, C. (1994). A two-parameter monthly water balance model for French watersheds. *Journal of Hydrology*, 299-318.

Makridakis, S. (1993). Accuracy measures: theoretical and practical concerns. *Internation Journal of Forecasting 9*, 527-529.

Mata-Lima, H. (2011). Evaluation of the objective functions to improve production history matching performance based on fluid flow behaviour in reservoirs. *Journal of Petroleum Science and Engineering*, 42-53.

Mishra, A. K. (2013). Effect of rain guage density over the accuracy of rainfall: a case study over Bangalore, India. *Springer Plus*.

Moriasi, D. N., Gitau, M. W., Pai, N., & Daggupati, P. (2015). Hydrologic and Water Quality Models: Performance measures and evaluation criteria. *Vol 58*, 1763-1785.

Moriasi, D. N., Wilson, B. N., Douglas-Mankin, K. R., Arnold, J. G., & Gowda, P. H. (2012). Hydrologic and Water Quality Models: Use, Calibration, and Verification. *Vol 55(4)*, 1241-1247. American Society of Agricultural and Biological Engineers. doi:http://dx.doi.org/10.13031/2013.42265.

Moriasi, D., Arnold, J., Van Liew, M., Bingner, R., Harmel, R., & Veith, T. (2007). Model Evaluation Guidelines for Systematic Quantification of Accuracy in Watershed Simulations. *American Society of Agricultural and Biological Engineers, Vol 50(3),* 885-900.

Mouelhi, S., Michel, C., Perrin, C., & Andreassian, V. (2006). Stepwise development of a two-parameter monthly water balance model. *Journal of Hydrology*, 200-214.

Nash, J. E., & Sutcliffe, J. V. (1970). River Flow Forecasting through Conceptual Models: Part I - A Discussion of Principles. *Journal of Hydrology, 10*, 282-290.

Patrick, N., & Stephenson, D. (1990). Spatial variation of rainfall intensities for short duration storms. *Hydrological Sciences Journal*, 667-680.

Patry, G. G., & Marino, M. A. (1983). Nonlinear Runoff Modelling: Parameter Identification. *Journal of Hydraulic Engineering*, 865-880.

Paulhus, J. L., & Kohler, M. A. (1952). Interpolation of Missing Precipitation Records. *Monthly Weather Review, 80*, 129-133.

Perera, K. R., & Wijesekera, N. T. (2011). Identification of the Spatial Variability of Runoff Coefficients of Three Wet Zone Watersheds of Sri Lanka. *Engineer - Vol XXXXIV*, 1-10.

Robinson, S. (2004). *Simulation. The practice of model development and use.* England: John Wiley & Sons Ltd.

Servat, E., & Dezetter, A. (1991). Selection of Calibration Objective Functions in the context of Rainfall-Runoff Modelling in a Sudanese Savannah Area. *Hydrological Sciences Journal, 36*, 307-330.

Sharifi, M. B. (2015). *Calibration and Verification of a two parameter monthly water balance model and its application potential for evaluation of water resources - A case study of Kalu ganga and Mahaweli rivers of Sri Lanka (Unpublished Master's Thesis).* Colombo, Sri Lanka: University of Moratuwa.

Shaw, E. M., & Lynn, P. P. (1972). Areal Rainfall Evaluation using Two Surface Fitting Techniques. *Bulletin of the International Association of Hydrological Sciences XVII*, 419-433.

Singh, V. P., & Chowdhury, P. K. (1986). Comparing some methods of estimating mean areal rainfall. *Americam Water Resource Association, Vol 22 (2)*, 275-282.

Sorooshian, S., & Gupta, V. K. (1983). Automatic Calibration of Conceptual Rainfall-Runoff Models: The Question of Parameter Observability and Uniqueness. *Water Resource Research Vol 19*, 260-268.

Sugawara, M. (1992). Chapter 5 – On the weights of precipitation stations. In J. O'Kane (Ed.), *Advances in Theoritical Hydrology: A tribute to James Dooge Volume 1 of European Geophysical Society: European Geophysical Society series on hydrological sciences* (pp. 59-74). Amsterdam: Elsevier Science Publishers B.V.

Suhaila, J., Sayang, M. D., & Jemain, A. A. (2008). Revised Spatial Weighting Methods for Estimation of Missing Rainfall Data. *Asia-Pacific Journal of Atmospheric Sciences, 44*, 93-104.

Teegavarapu, R. S., Tufail, M., & Ormsbee, L. (2009). Optimal functional forms for estimation of missing precipitation data. *Journal of Hydrology 374,* 106-115.

Thapa, G. (2014). *Event based modelling of streamflow for reliable flood mitigation and drainage infrastructure designs using Snyder's Synthetic Unit Hydrograph Method - A case study of Karasnagala Watershed in the Attanagalu Oya of Sri Lanka (Unpublished Master's Thesis).* Colombo, Sri Lanka: University of Moratuwa.

Thiessen, A. H., & Alter, J. C. (1911). Climatological Data for July, 1911 : District No. 10, Great Basin. *Monthly Weather Review*, 1082-1083.

Thornthwaite, C. W., & Mather, J. R. (1955). The Water Balance. In *Laboratory of Climatology*. Centerton, USA.

Thorthwaite, C. W. (1948). An approach toward a rational classification of climate. *Geogr. Rev. 38(1)*, 55-94.

Tofallis, C. (2014). A better measure of relative prediction accuracy for model selection and model estimation. *Journal of the Operational Research Society*, 1-11.

Wang, Q. J., Pagano, T. C., Zhou, S. L., Hapuarachchi, H. A., Zhang, L., & Robertson, D. E. (2011). Monthly versus daily water balance models in simulating monthly runoff. *Journal of Hydrology*, 166-175.

Wijesekera, N.T.S, & Ghanapala, P. (2003). Modeling of Two Low Lying Urban Watersheds in the Greater Colombo Area for Drainage and Environment Improvement. *Journal of the Institution of Engineers, Sri Lanka Vol.XXXVI*, 39-45.

Wijesekera, N.T.S, & Musiake, K. (1990). Streamflow Modelling of a Sri Lankan Catchment Considering Spatial Variation of Rainfall. *Japan Society of Hydrology and Water Resources* (pp. 127-129). Tokya: Institute of Industrial Science, University of Tokya.

Wijesekera, N.T.S., (2018). *Classification of Streamflow Observations for Water Management.* doi:10.13140/RG.2.2.23605.58089.

Wijesekera, N.T.S, & Perera, K. R. (2010). Identification of the spatial variability of runoff coefficient of three wet zone watershed of Sri Lanka for efficient River Basin Planning. *3rd International Perpective on Current & Future State of Water Resources & The Environment.* Chennai: American Society of Civil Engineers.

Xiong, L., & Guo, S. (1999). A two-parameter monthly water balance model and its application. *Journal of Hydrology*, 111-123.

Xu, C. Y., & Singh, V. P. (1998). A Review of Monthly Water Balance Models for Water Resources Investigations. *Water Resources Management*, 31-50.

Zhang, Y., Engel, B., Ahiablame, L., & Liu, J. (2015). Impacts of Climate Chnage on Mean Annual Water Balance for Watersheds in Michighan, USA. *Water*, 3564-3578.

ANNEX A – DATA

Table A - 1 Thiessen Average Rainfall Data - Dunamale Watershed

Month	2006-07	2007-08	2008-09	2009-10	2010-11	2011-12	2012-13	2013-14	2014-15	2015-16	2016-17
Oct	798.47	460.82	701.56	338.73	472.35	462.51	650.77	290.27	502.18	654.91	203.22
Nov	672.37	263.70	319.86	326.19	665.00	262.91	324.24	421.00	228.48	468.83	346.59
Dec	93.17	158.27	98.07	254.80	346.95	93.84	220.79	47.59	569.31	257.53	34.85
Jan	62.14	48.66	85.24	75.93	177.34	64.01	129.38	76.92	23.29	23.61	66.75
Feb	23.32	225.16	45.07	43.95	133.95	166.69	161.09	42.54	111.33	32.93	29.70
Mar	124.81	448.87	254.64	192.79	133.79	88.77	288.08	221.15	226.15	102.42	394.28
Apr	494.84	591.96	375.75	558.26	483.65	491.74	193.08	398.35	405.97	317.83	177.96
May	245.12	427.43	246.46	599.96	485.91	106.19	413.06	247.89	312.56	1070.02	455.07
Jun	244.79	275.40	270.63	251.34	251.64	227.59	496.49	349.61	414.94	170.58	246.44
Jul	186.96	370.88	155.43	237.94	104.37	117.42	239.69	181.05	45.04	99.26	109.26
Aug	152.38	95.58	235.18	80.73	221.12	294.13	84.14	314.26	222.18	25.55	207.98
Sep	358.69	144.36	327.83	501.80	209.03	184.36	436.57	301.96	288.23	32.51	654.14

Table A - 2 Thiessen Average Rainfall Data Summary - Dunamale Watershed

Water Year (Oct-Sep)	Monthly Rainfall (mm)			Annual Rainfall (mm)
	Maximum	Mean	Minimum	
2006-07	798.47	288.09	23.32	3457.07
2007-08	591.96	292.59	48.66	3511.08
2008-09	701.56	259.64	45.07	3115.72
2009-10	599.96	288.53	43.95	3462.42
2010-11	665.00	307.09	104.37	3685.10
2011-12	491.74	213.35	64.01	2560.18
2012-13	650.77	303.12	84.14	3637.39
2013-14	421.00	241.05	42.54	2892.60
2014-15	569.31	279.14	23.29	3349.66
2015-16	1070.02	271.33	23.61	3255.96
2016-17	654.14	243.85	29.70	2926.24

Table A - 3 Streamflow Data - Dunamale Watershed

Month	2006-07	2007-08	2008-09	2009-10	2010-11	2011-12	2012-13	2013-14	2014-15	2015-16	2016-17
Oct	277.23	177.07	240.87	152.10	207.71	134.28	207.07	112.24	281.02	302.23	13.46
Nov	389.64	164.45	142.89	188.32	283.11	144.88	220.06	220.80	186.98	324.60	115.62
Dec	95.11	57.68	88.95	123.51	222.48	64.87	94.51	69.93	274.15	221.11	23.76
Jan	28.52	19.50	27.28	34.74	56.01	32.12	35.82	19.21	65.33	31.00	5.37
Feb	8.02	25.36	0.77	2.05	22.51	16.27	23.63	0.35	13.10	2.40	0.58
Mar	0.00	197.17	33.15	21.19	17.30	20.92	85.54	26.69	40.20	8.74	84.53
Apr	126.27	237.72	125.21	135.22	114.72	122.49	63.67	124.68	180.44	39.88	71.65
May	88.96	194.05	79.74	300.20	171.79	48.41	142.08	133.49	179.80	399.21	119.35
Jun	97.56	218.91	87.26	135.18	156.09	40.31	245.65	147.65	135.80	167.92	135.31
Jul	54.13	163.79	60.54	98.38	29.95	30.61	109.97	47.25	42.21	39.57	48.66
Aug	24.39	33.75	52.16	12.40	21.96	22.19	29.32	111.16	27.32	6.26	14.68
Sep	178.79	62.84	113.88	104.19	71.07	55.38	190.22	115.39	133.67	3.06	290.45

Table A - 4 Streamflow Data Summary - Dunamale Watershed

Water Year (Oct-Sep)	Monthly Streamflow (mm)			Annual Streamflow (mm)
	Maximum	**Mean**	**Minimum**	
2006-07	389.64	114.05	0.00	1368.62
2007-08	237.72	129.36	19.50	1552.28
2008-09	240.87	87.72	0.77	1052.70
2009-10	300.20	108.96	2.05	1307.48
2010-11	283.11	114.56	17.30	1374.70
2011-12	144.88	61.06	16.27	732.73
2012-13	245.65	120.63	23.63	1447.55
2013-14	220.80	94.07	0.35	1128.85
2014-15	281.02	130.00	13.10	1560.00
2015-16	399.21	128.83	2.40	1545.99
2016-17	290.45	76.95	0.58	923.42

Table A - 5 Evaporation Data - Dunamale Watershed

Month	2006-07	2007-08	2008-09	2009-10	2010-11	2011-12	2012-13	2013-14	2014-15	2015-16	2016-17
Oct	277.23	177.07	240.87	152.10	207.71	134.28	207.07	112.24	281.02	302.23	13.46
Nov	389.64	164.45	142.89	188.32	283.11	144.88	220.06	220.80	186.98	324.60	115.62
Dec	95.11	57.68	88.95	123.51	222.48	64.87	94.51	69.93	274.15	221.11	23.76
Jan	28.52	19.50	27.28	34.74	56.01	32.12	35.82	19.21	65.33	31.00	5.37
Feb	8.02	25.36	0.77	2.05	22.51	16.27	23.63	0.35	13.10	2.40	0.58
Mar	0.00	197.17	33.15	21.19	17.30	20.92	85.54	26.69	40.20	8.74	84.53
Apr	126.27	237.72	125.21	135.22	114.72	122.49	63.67	124.68	180.44	39.88	71.65
May	88.96	194.05	79.74	300.20	171.79	48.41	142.08	133.49	179.80	399.21	119.35
Jun	97.56	218.91	87.26	135.18	156.09	40.31	245.65	147.65	135.80	167.92	135.31
Jul	54.13	163.79	60.54	98.38	29.95	30.61	109.97	47.25	42.21	39.57	48.66
Aug	24.39	33.75	52.16	12.40	21.96	22.19	29.32	111.16	27.32	6.26	14.68
Sep	178.79	62.84	113.88	104.19	71.07	55.38	190.22	115.39	133.67	3.06	290.45

Table A - 6 Evaporation Data Summary - Dunamale Watershed

Water Year (Oct-Sep)	Monthly Evaporation (mm)			Annual Evaporation (mm)
	Maximum	Mean	Minimum	
2006-07	133	103	87	1241.01
2007-08	113	99	83	1187.04
2008-09	126	106	81	1267.52
2009-10	132	100	58	1205.61
2010-11	121	98	62	1171.05
2011-12	129	106	83	1269.82
2012-13	128	101	83	1207.24
2013-14	129	110	89	1317.93
2014-15	121	100	67	1198.95
2015-16	163	116	81	1393.58
2016-17	132	110	84	1207.02

ANNEX B – DATA CHECKING

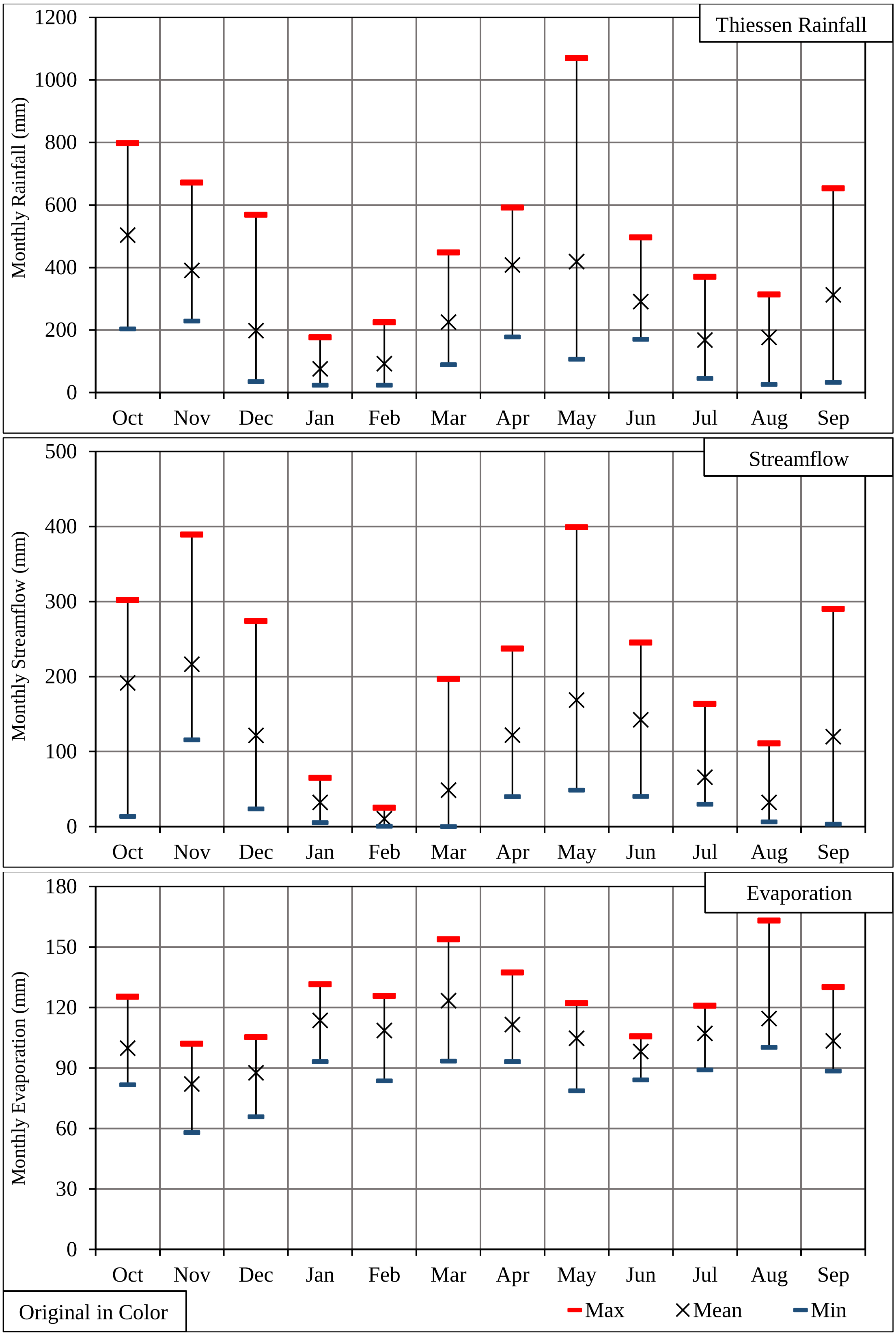


Figure B - 1 Variation of Maximum, Minimum and Average Monthly Rainfall, Streamflow & Evaporation

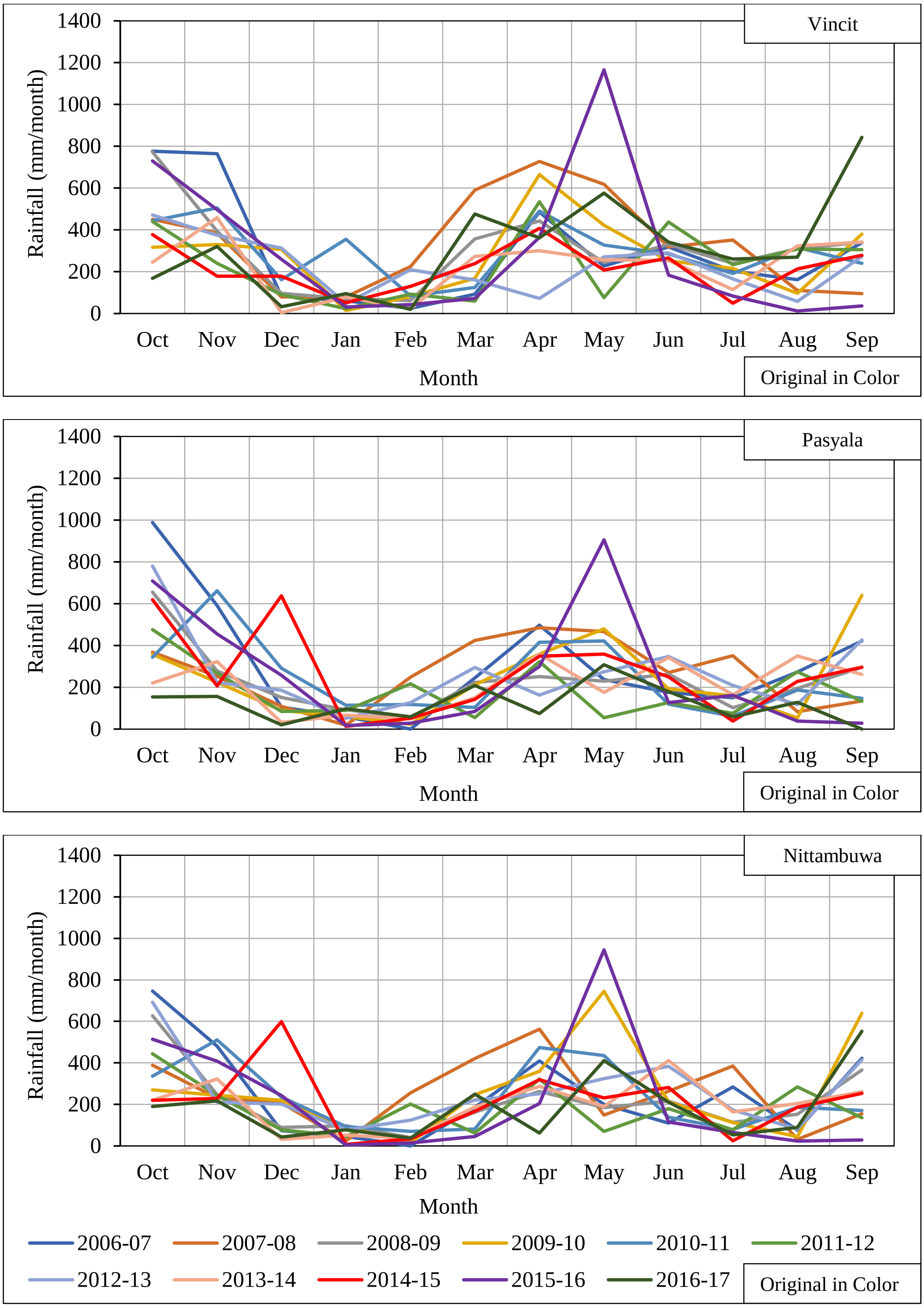


Figure B - 2 Monthly Rainfall Comparison - Dunamale Watershed (Vincit, Pasyala & Nittambuwa)

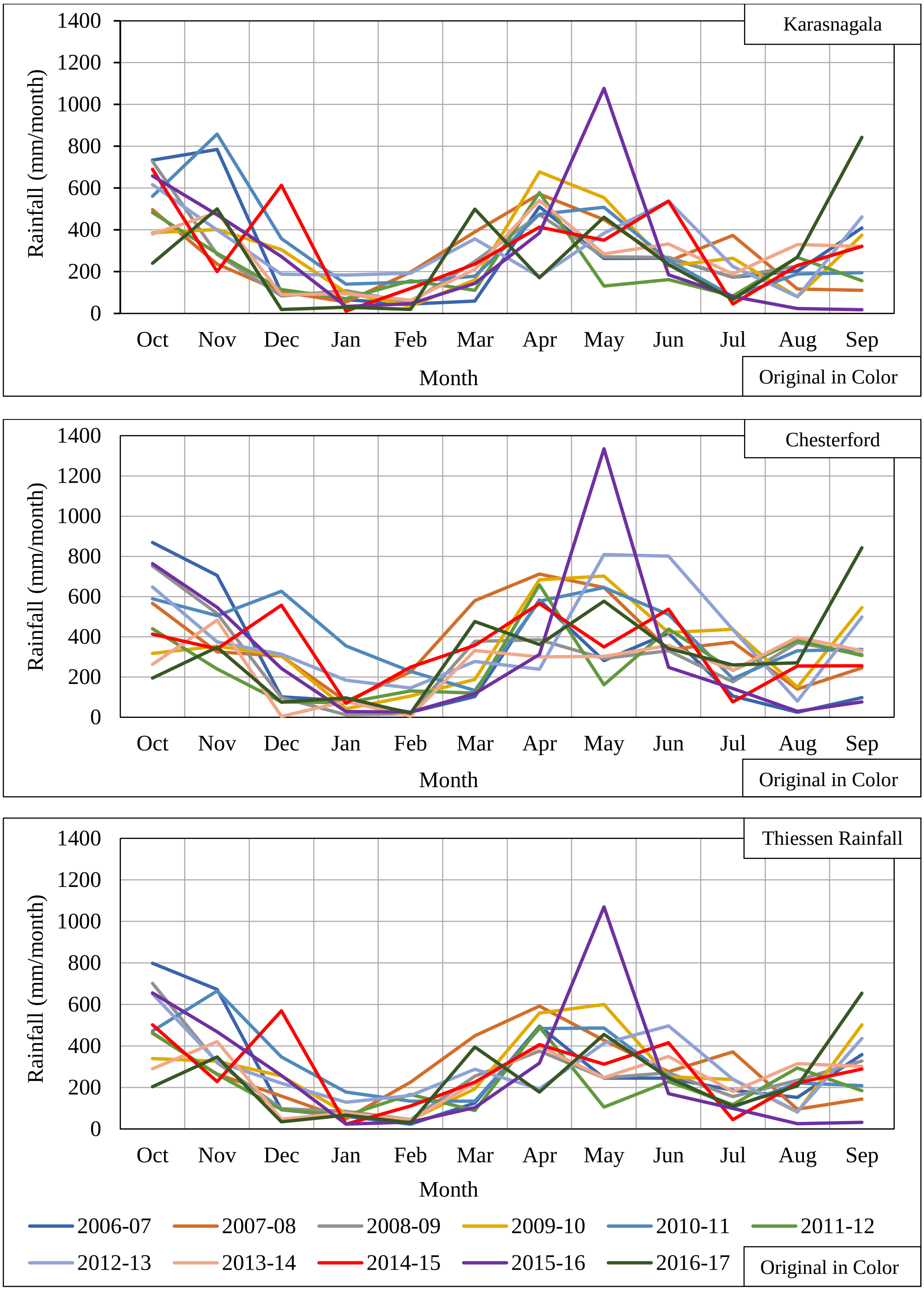


Figure B - 3 Monthly Rainfall Comparison - Dunamale Watershed (Karasnagala, Chesterford & Thiessen Rainfall)

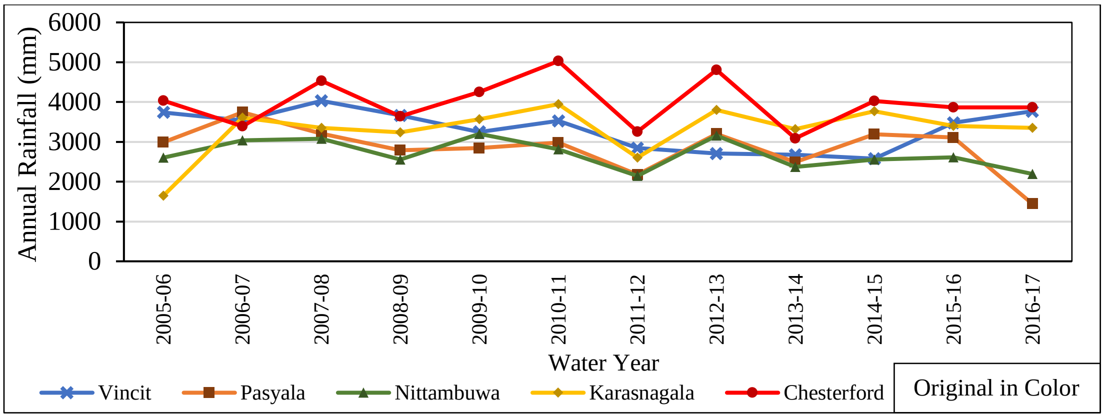


Figure B - 4 Comparison of Annual Rainfall - Dunamale Watershed

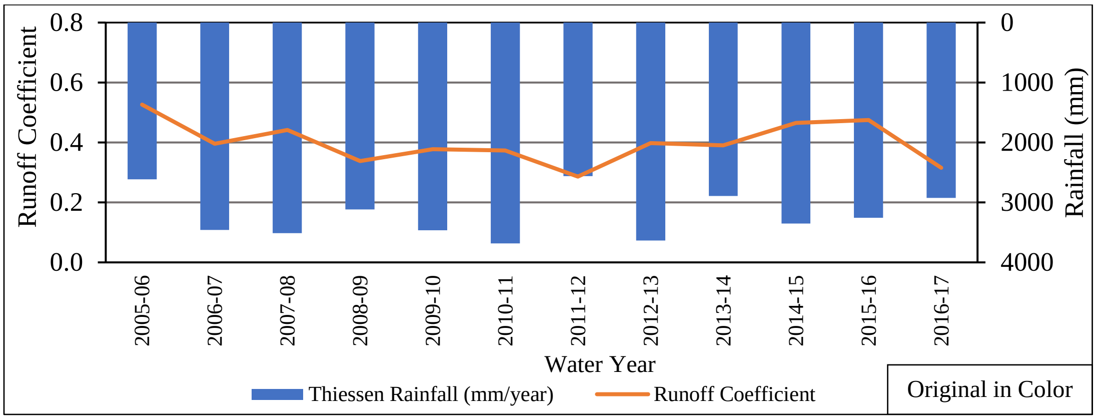


Figure B - 5 Thiessen Annual Rainfall and corresponding Runoff Coefficient - Dunamale Watershed

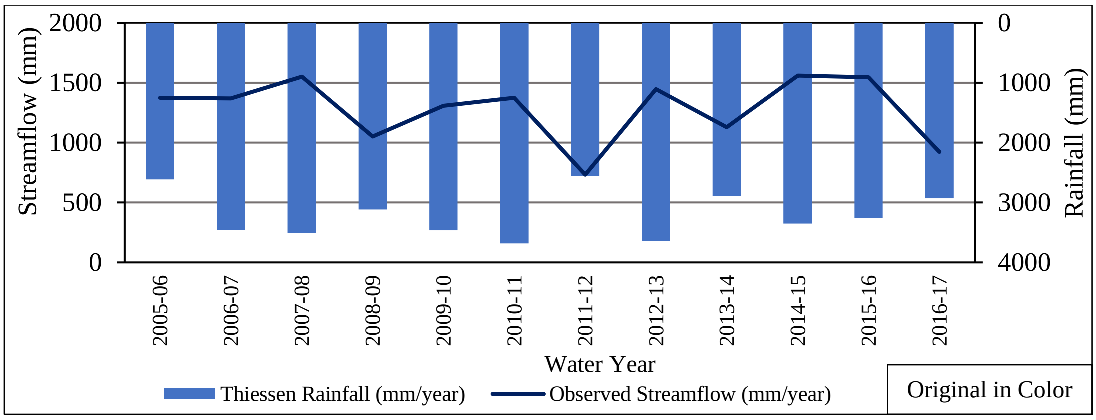


Figure B - 6 Thiessen Annual Rainfall and corresponding Observed Streamflow - Dunamale Watershed

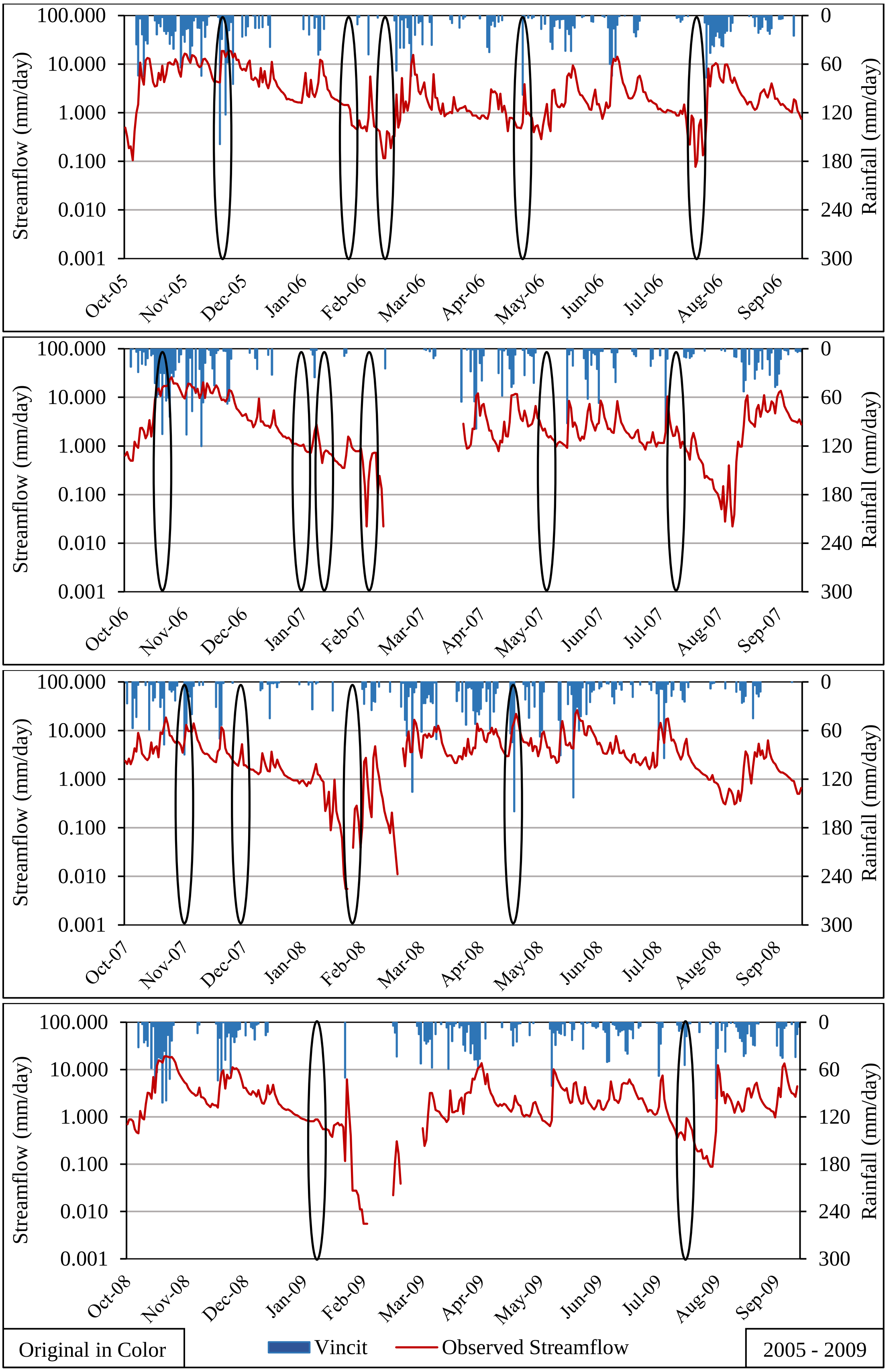


Figure B - 7 Dunamale Streamflow response to Vincit Rainfall (2005 - 2009) - Semi-Log Plot

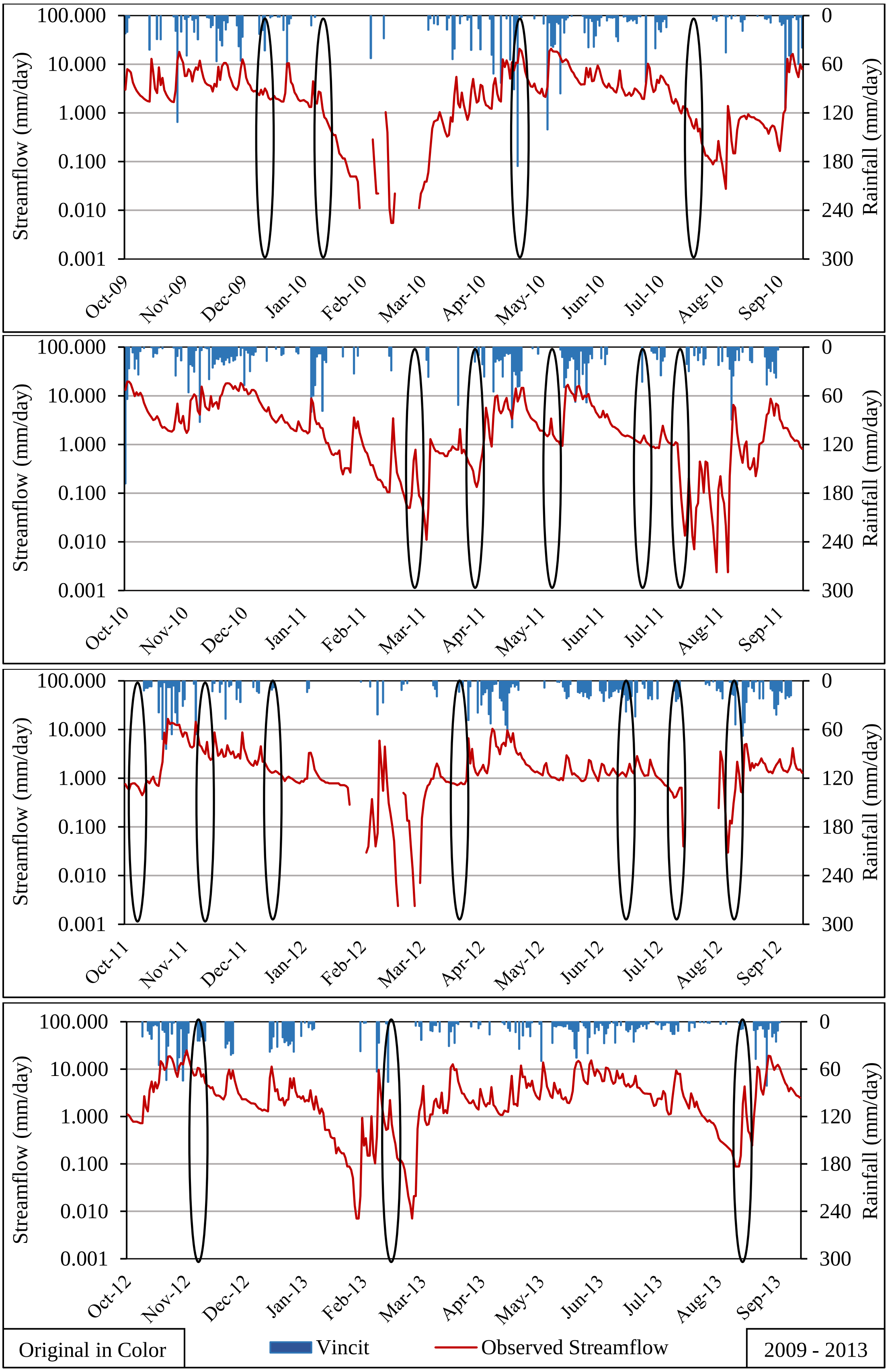


Figure B - 8 Dunamale Streamflow response to Vincit Rainfall (2009 - 2013) - Semi-Log Plot

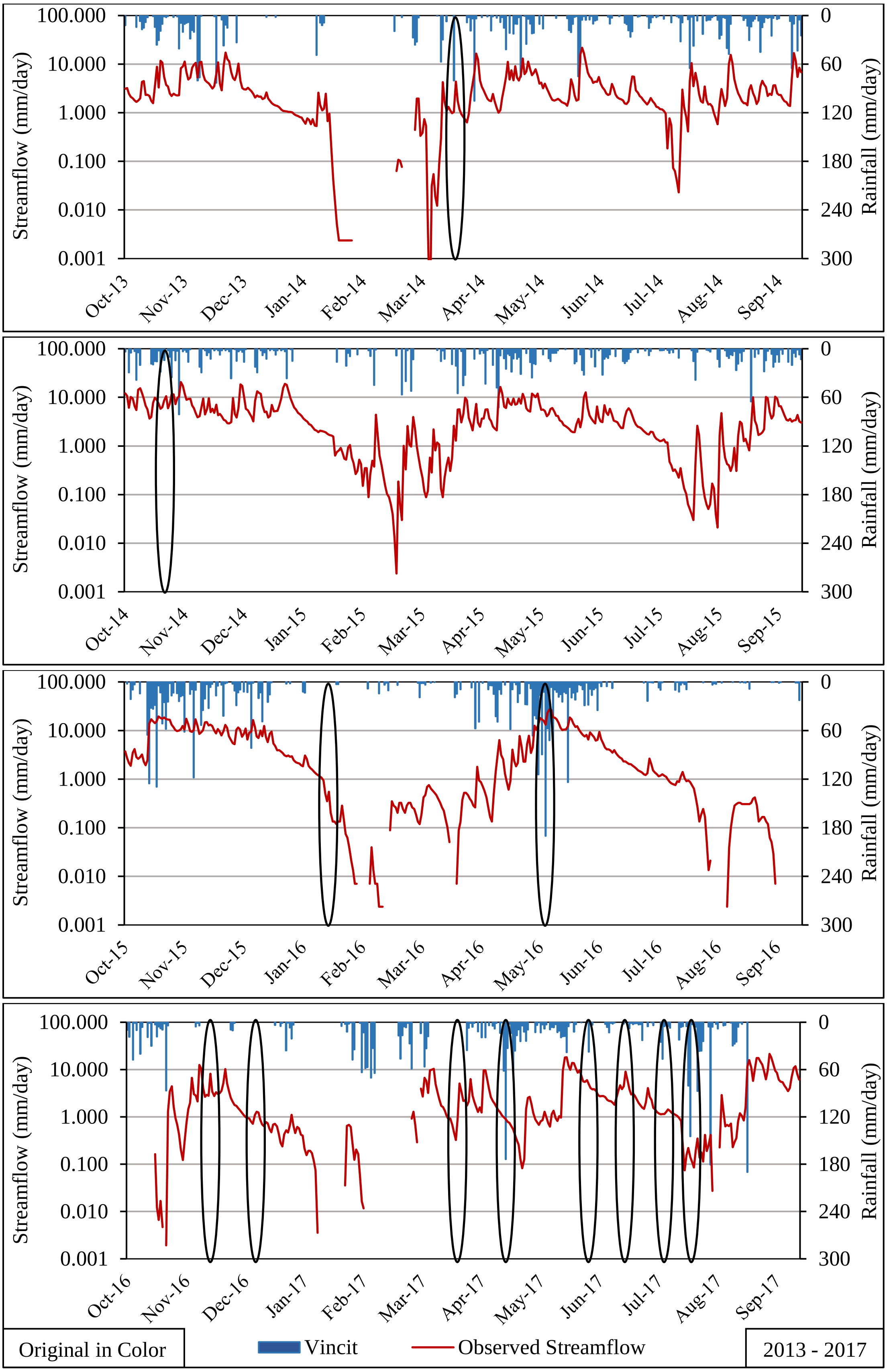


Figure B - 9 Dunamale Streamflow response to Vincit Rainfall (2013 - 2017) - Semi-Log Plot

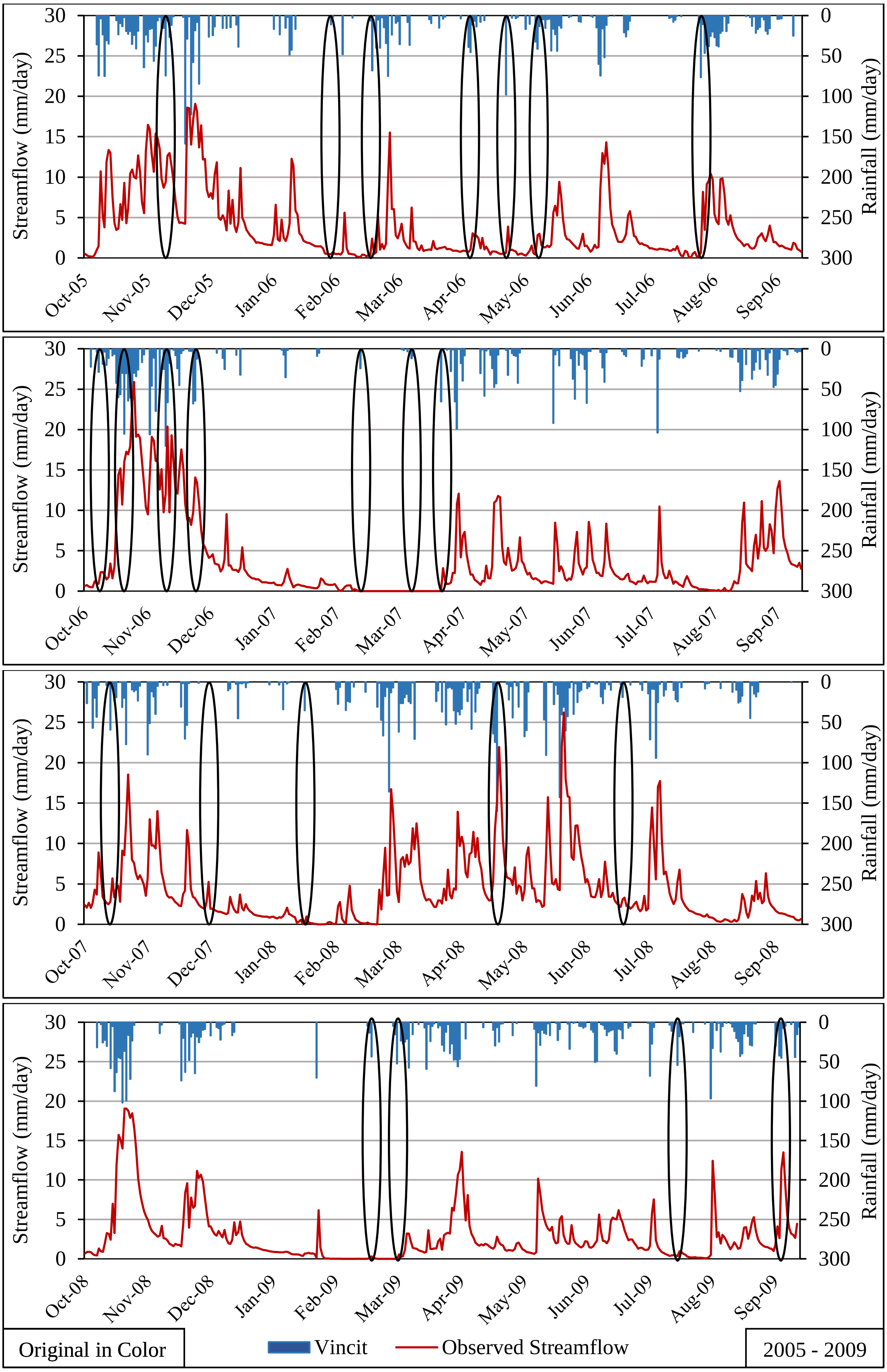


Figure B - 10 Dunamale Streamflow response to Vincit Rainfall (2005 - 2009) - Normal Plot

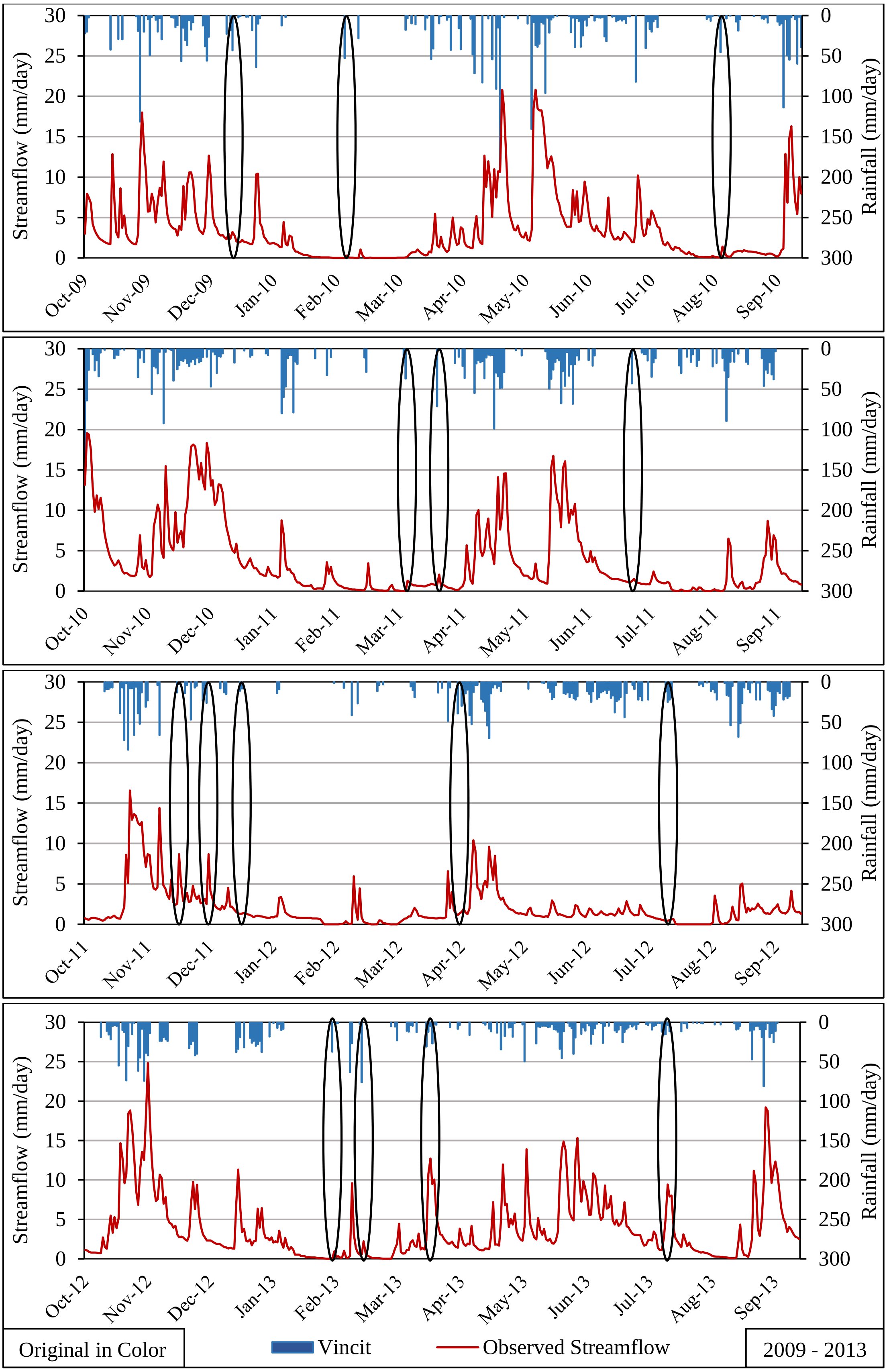


Figure B - 11 Dunamale Streamflow response to Vincit Rainfall (2009 - 2013) - Normal Plot

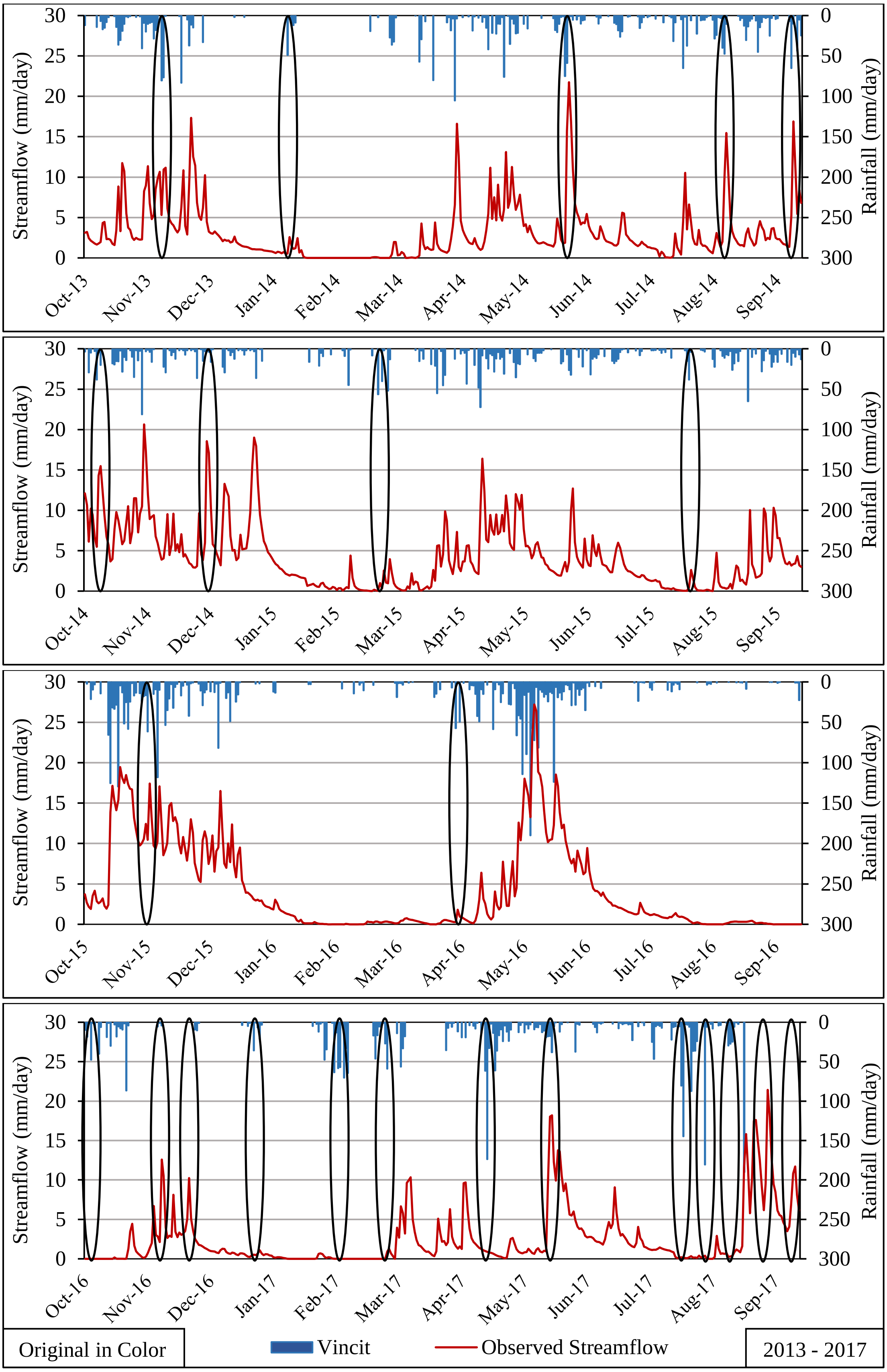


Figure B - 12 Dunamale Streamflow response to Vincit Rainfall (2013 - 2017) - Normal Plot

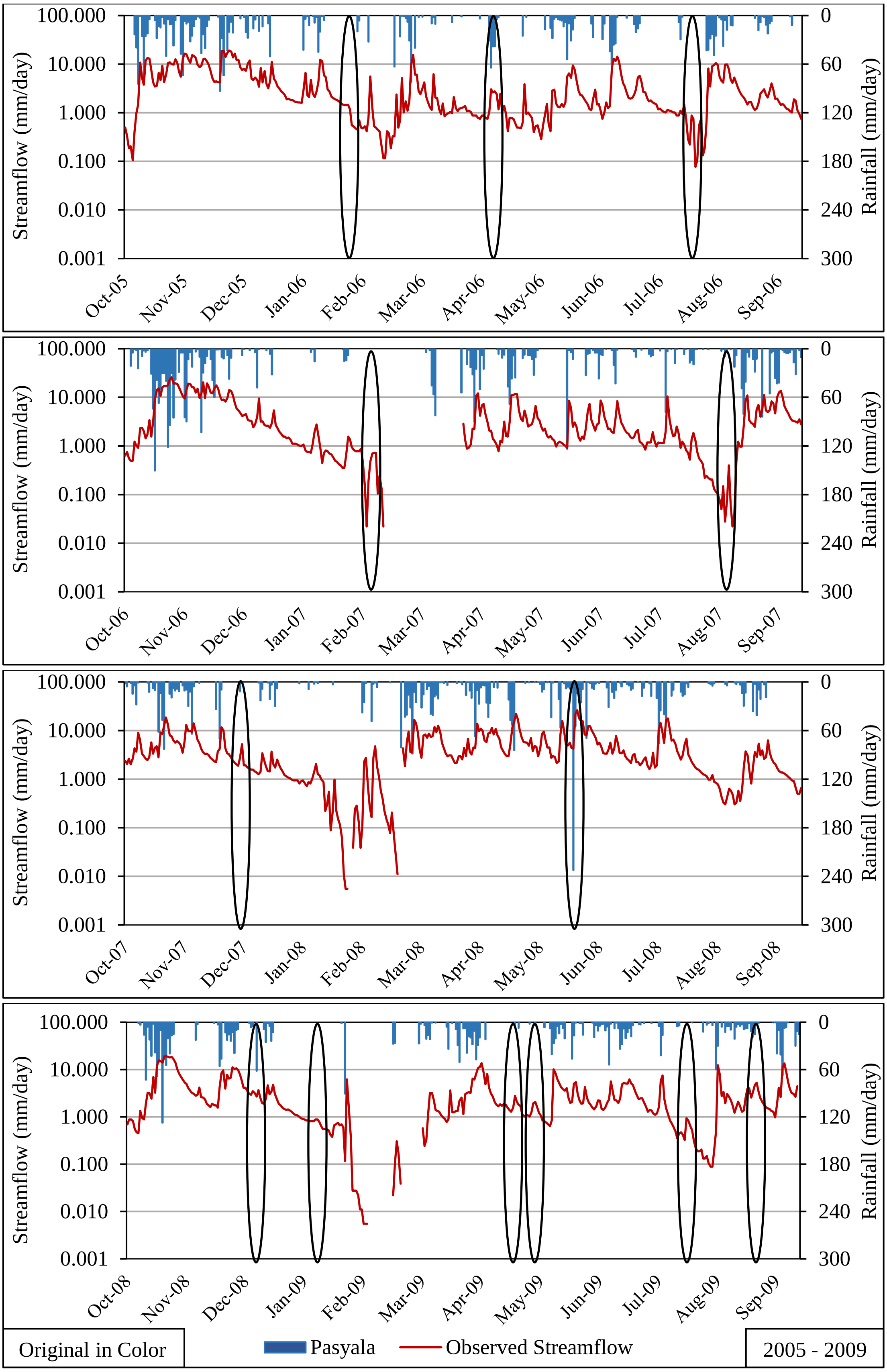


Figure B - 13 Dunamale Streamflow response to Pasyala Rainfall (2005 - 2009) - Semi-Log Plot

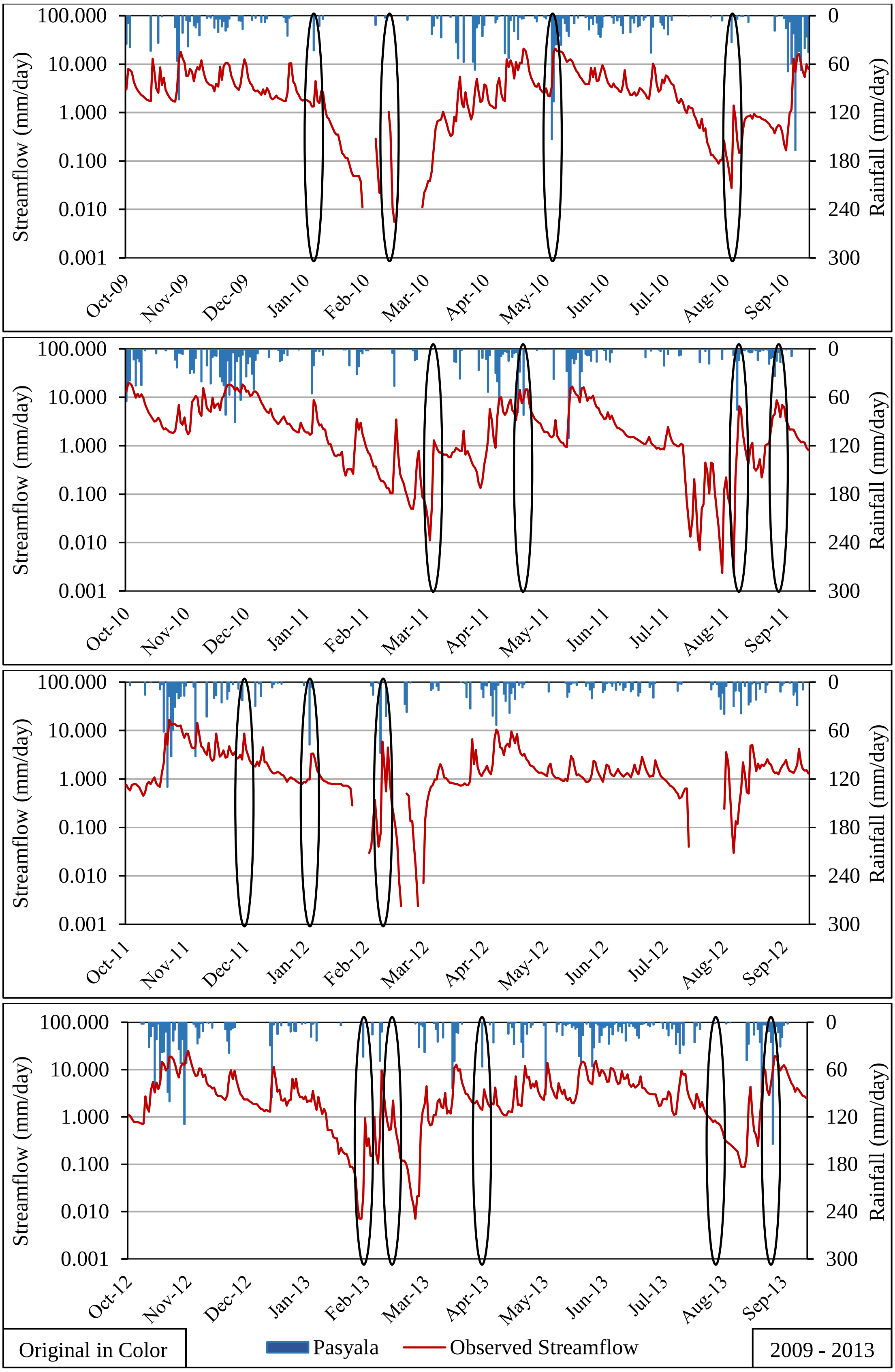


Figure B - 14 Dunamale Streamflow response to Pasyala Rainfall (2009 - 2013) - Semi-Log Plot

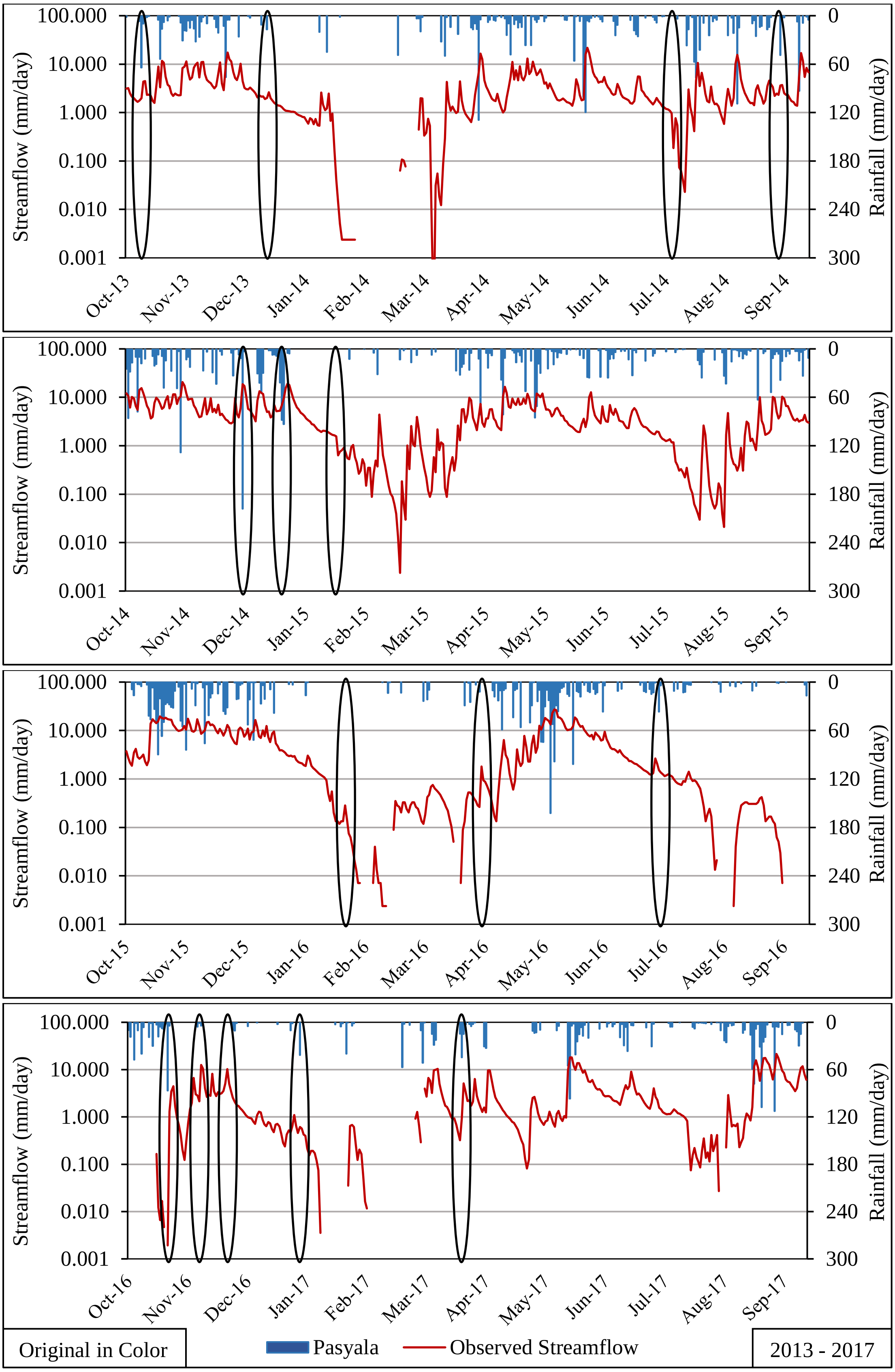


Figure B - 15 Dunamale Streamflow response to Pasyala Rainfall (2013 - 2017) - Semi-Log Plot

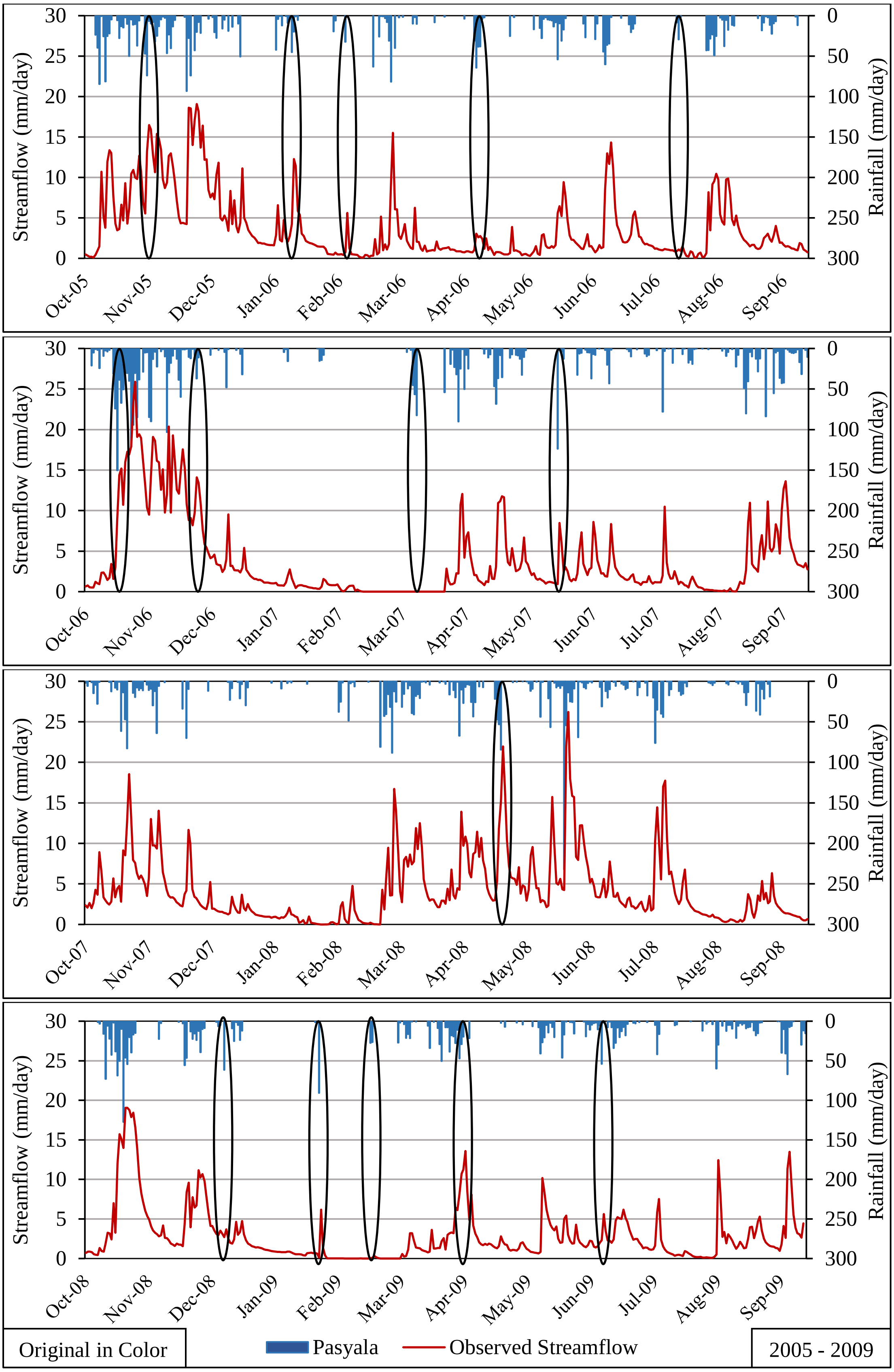


Figure B - 16 Dunamale Streamflow response to Pasyala Rainfall (2005 - 2009) - Normal Plot

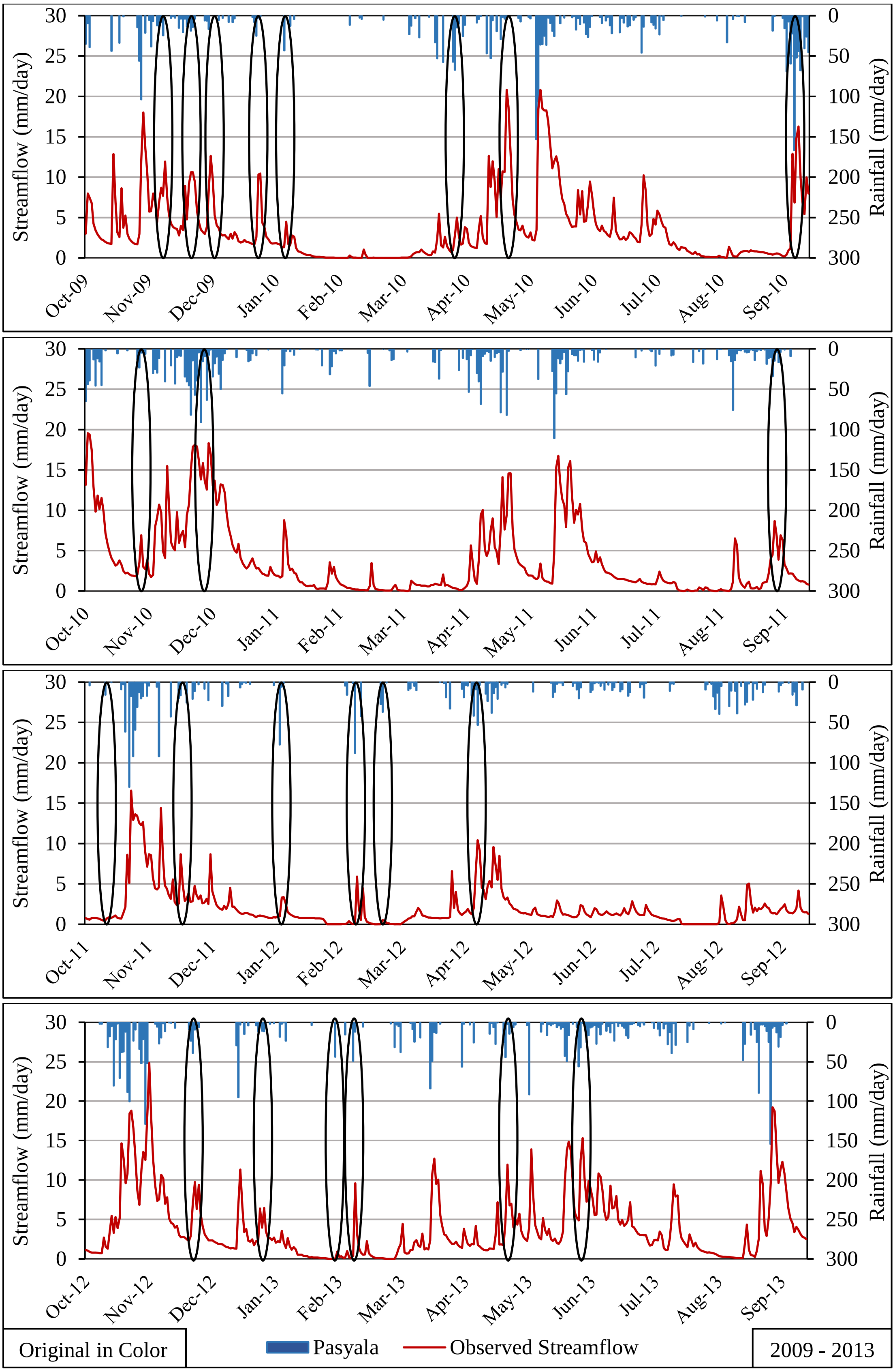


Figure B - 17 Dunamale Streamflow response to Pasyala Rainfall (2009 - 2013) - Normal Plot

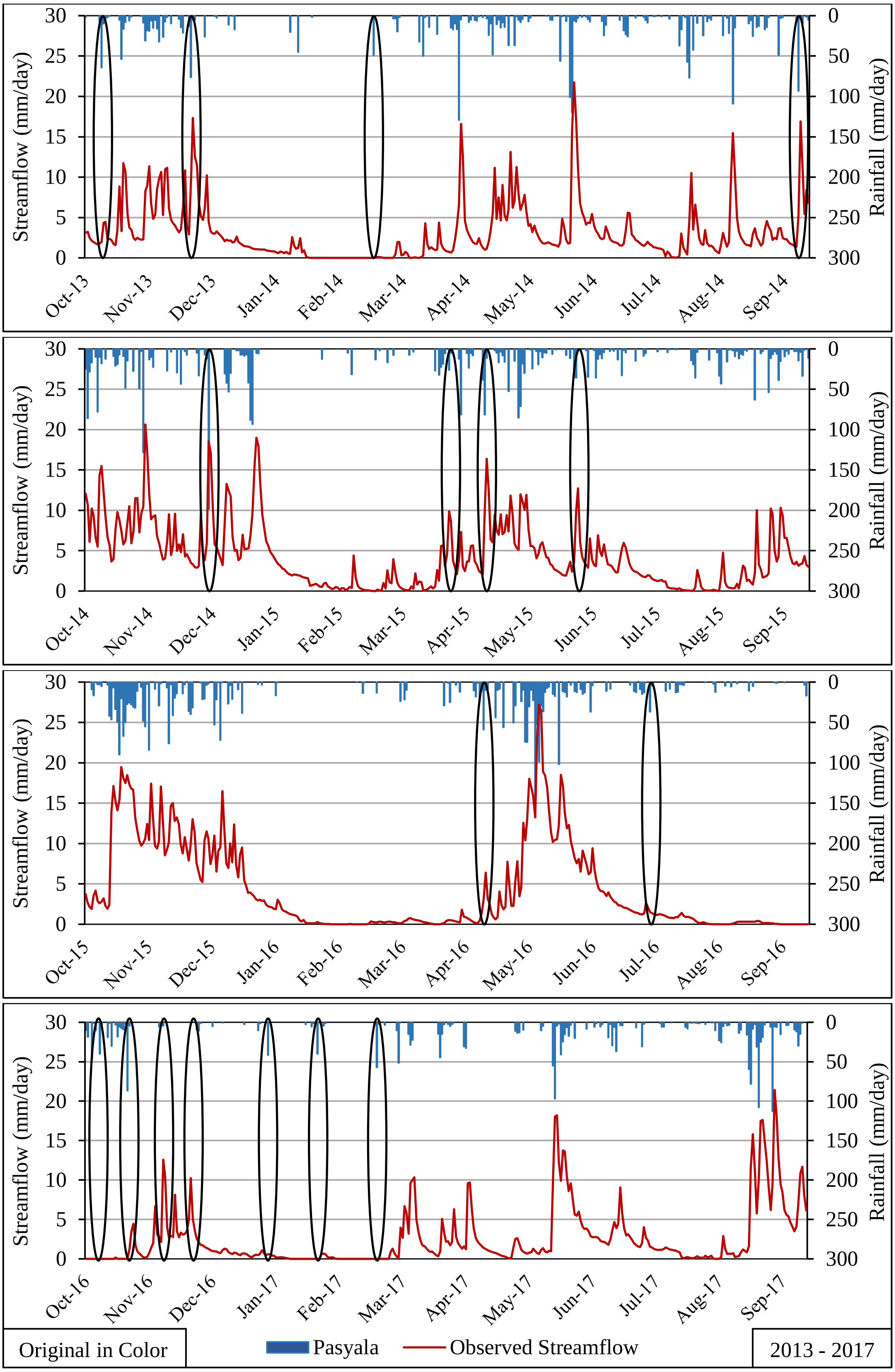


Figure B - 18 Dunamale Streamflow response to Pasyala Rainfall (2013 - 2017) - Normal Plot

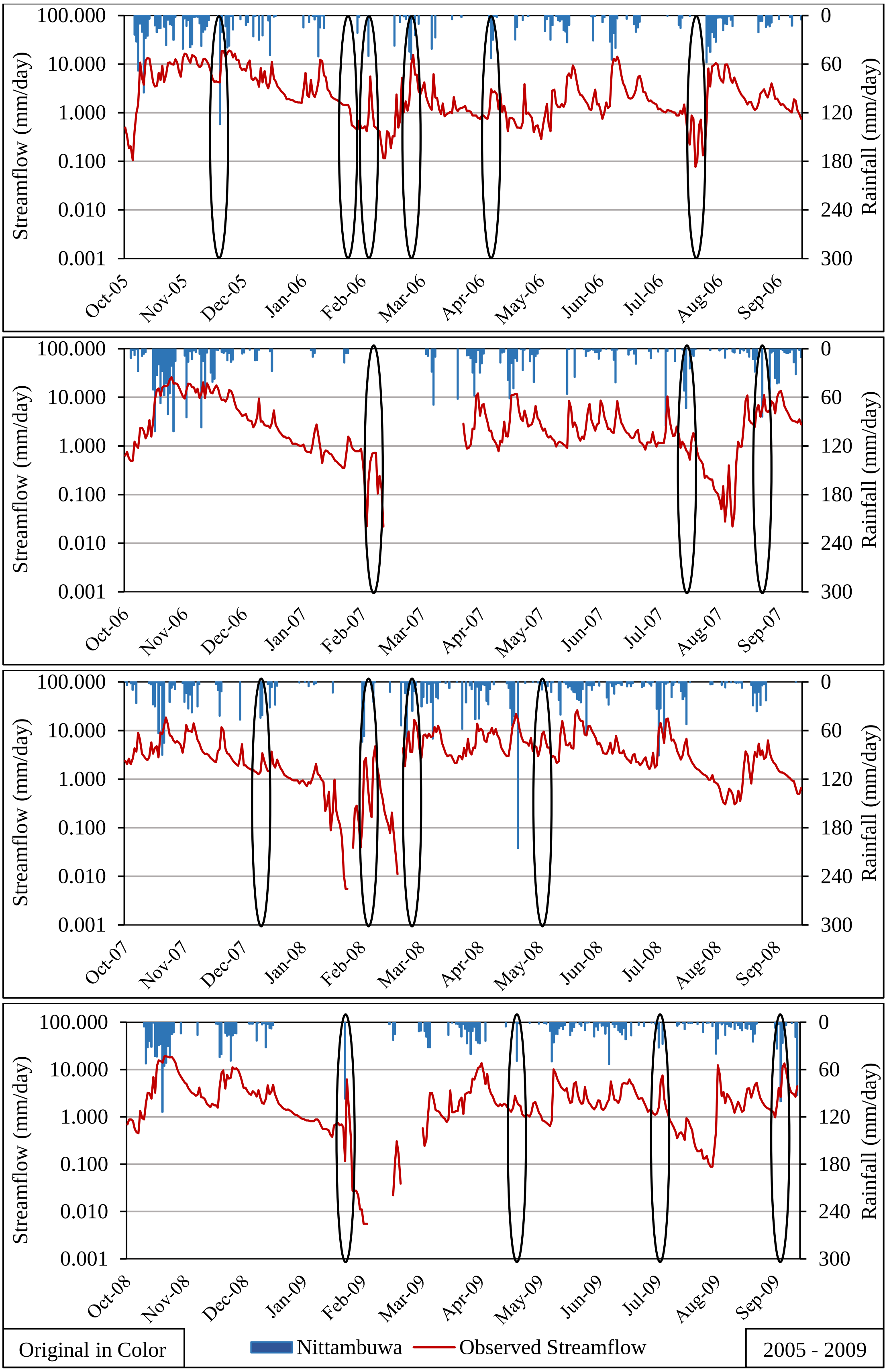


Figure B - 19 Dunamale Streamflow response to Nittambuwa Rainfall (2005 - 2009) – Semi-Log Plot

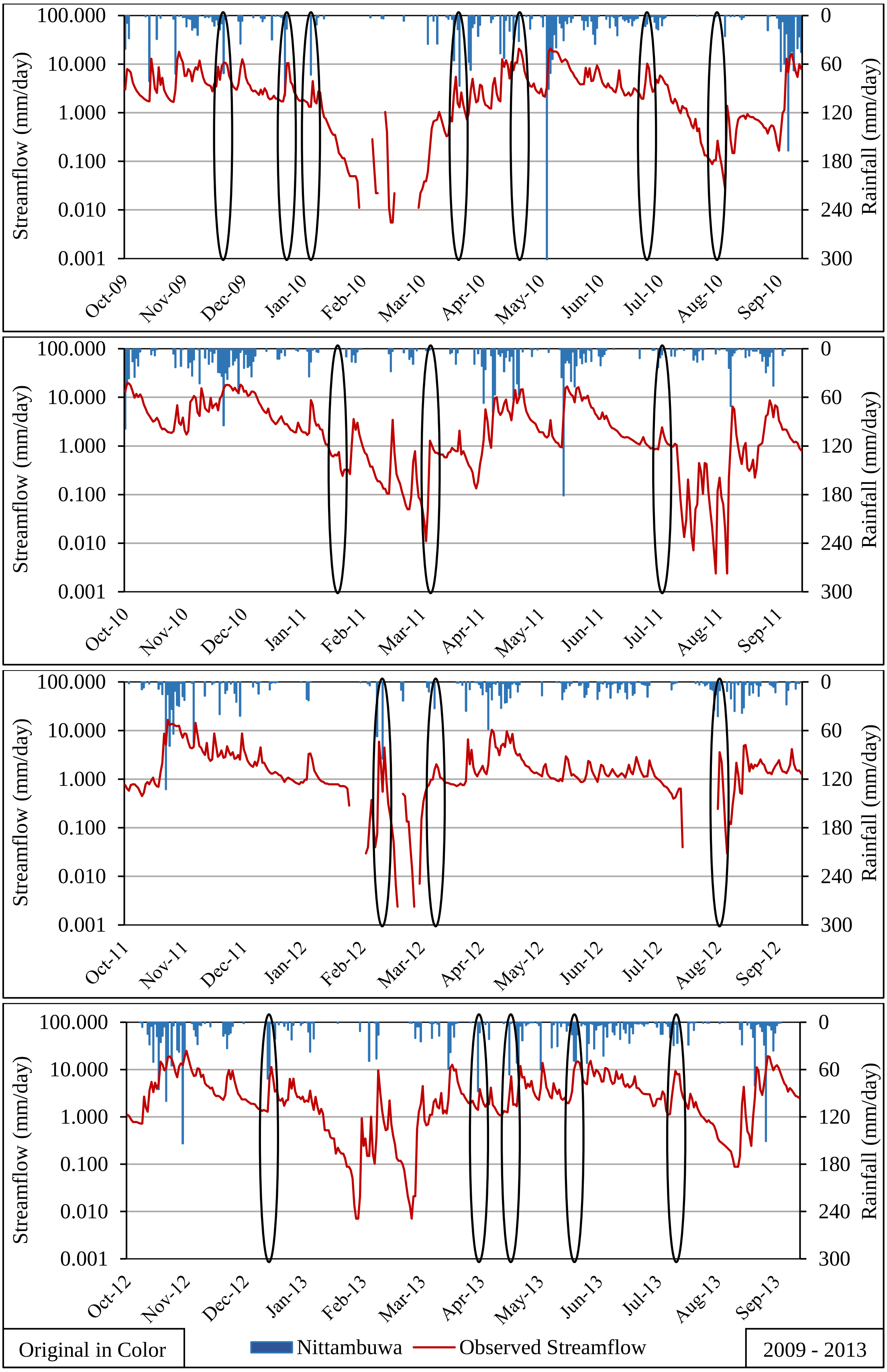


Figure B - 20 Dunamale Streamflow response to Nittambuwa Rainfall (2009 - 2013) – Semi-Log Plot

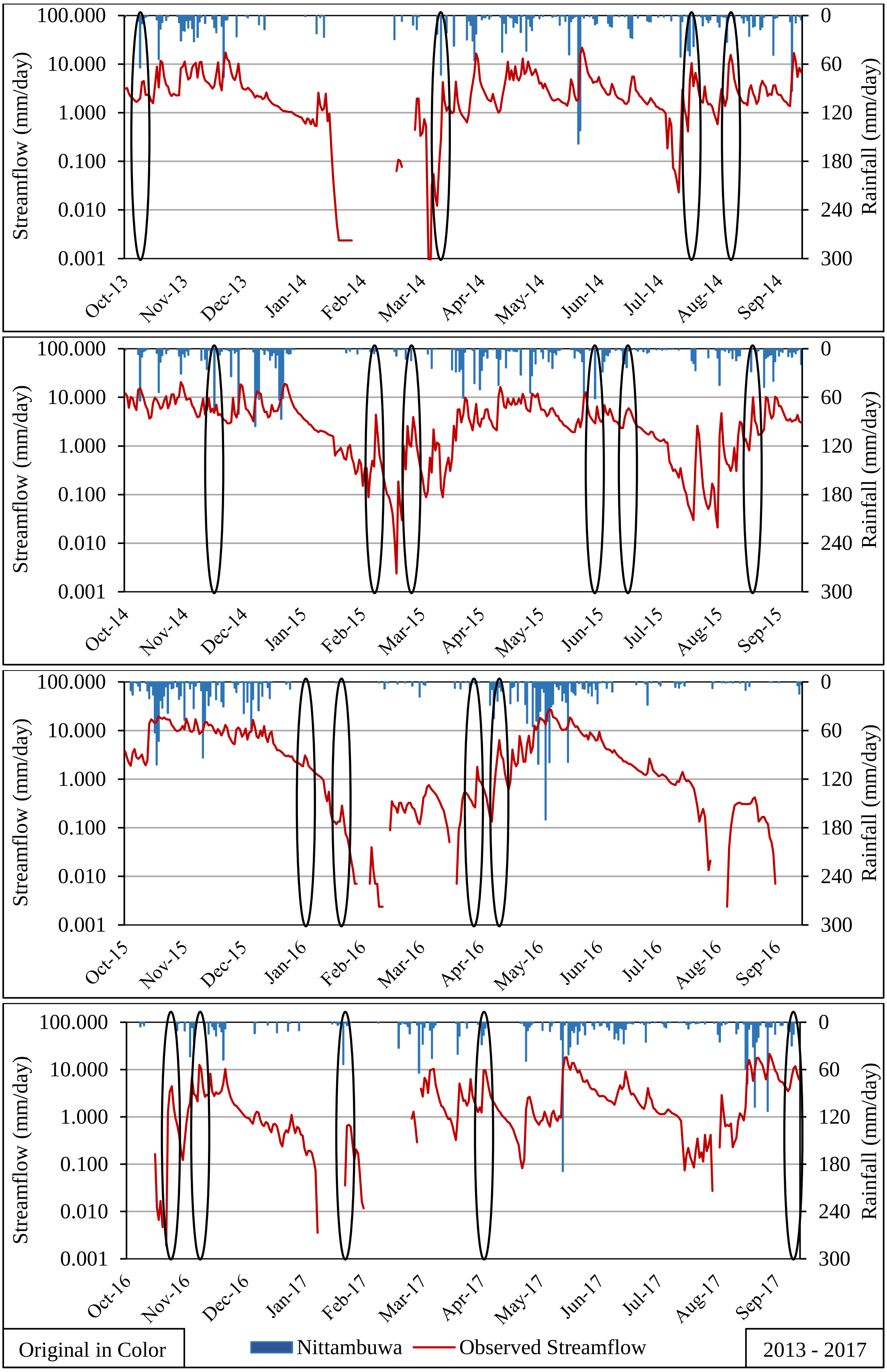


Figure B - 21 Dunamale Streamflow response to Nittambuwa Rainfall (2013 - 2017) – Semi-Log Plot

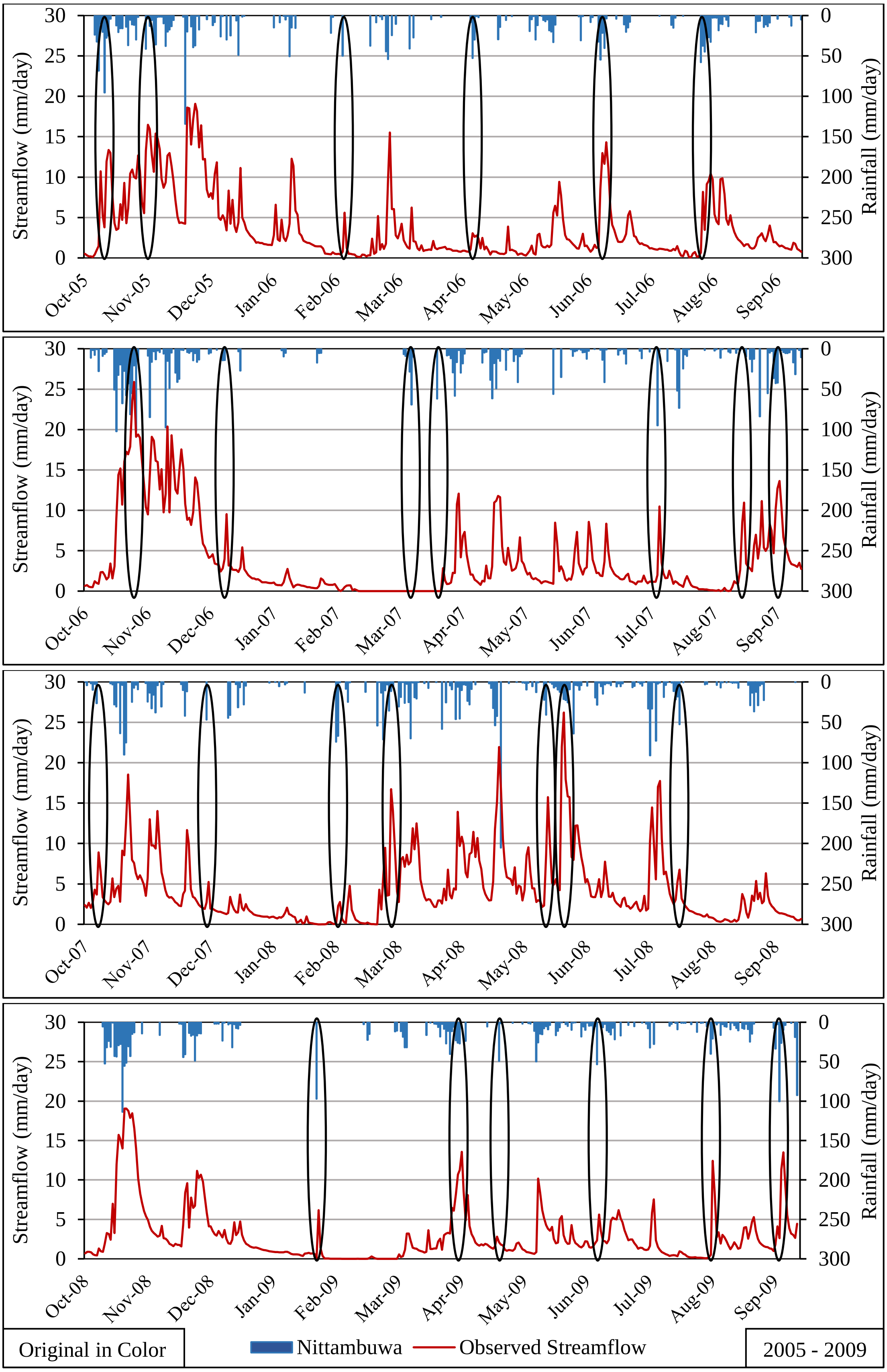


Figure B - 22 Dunamale Streamflow response to Nittambuwa Rainfall (2005 - 2009) – Normal Plot

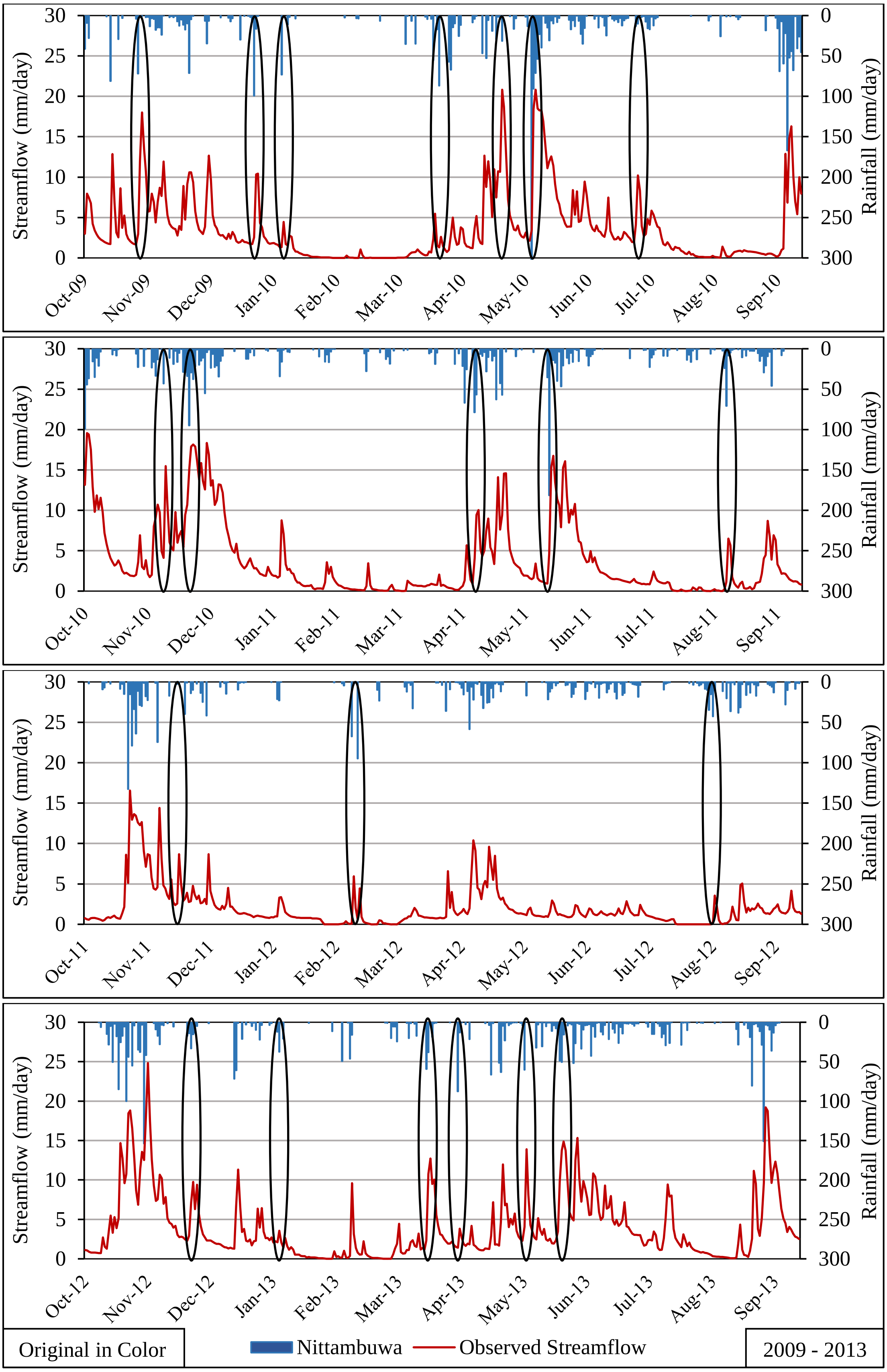


Figure B - 23 Dunamale Streamflow response to Nittambuwa Rainfall (2009 - 2013) – Normal Plot

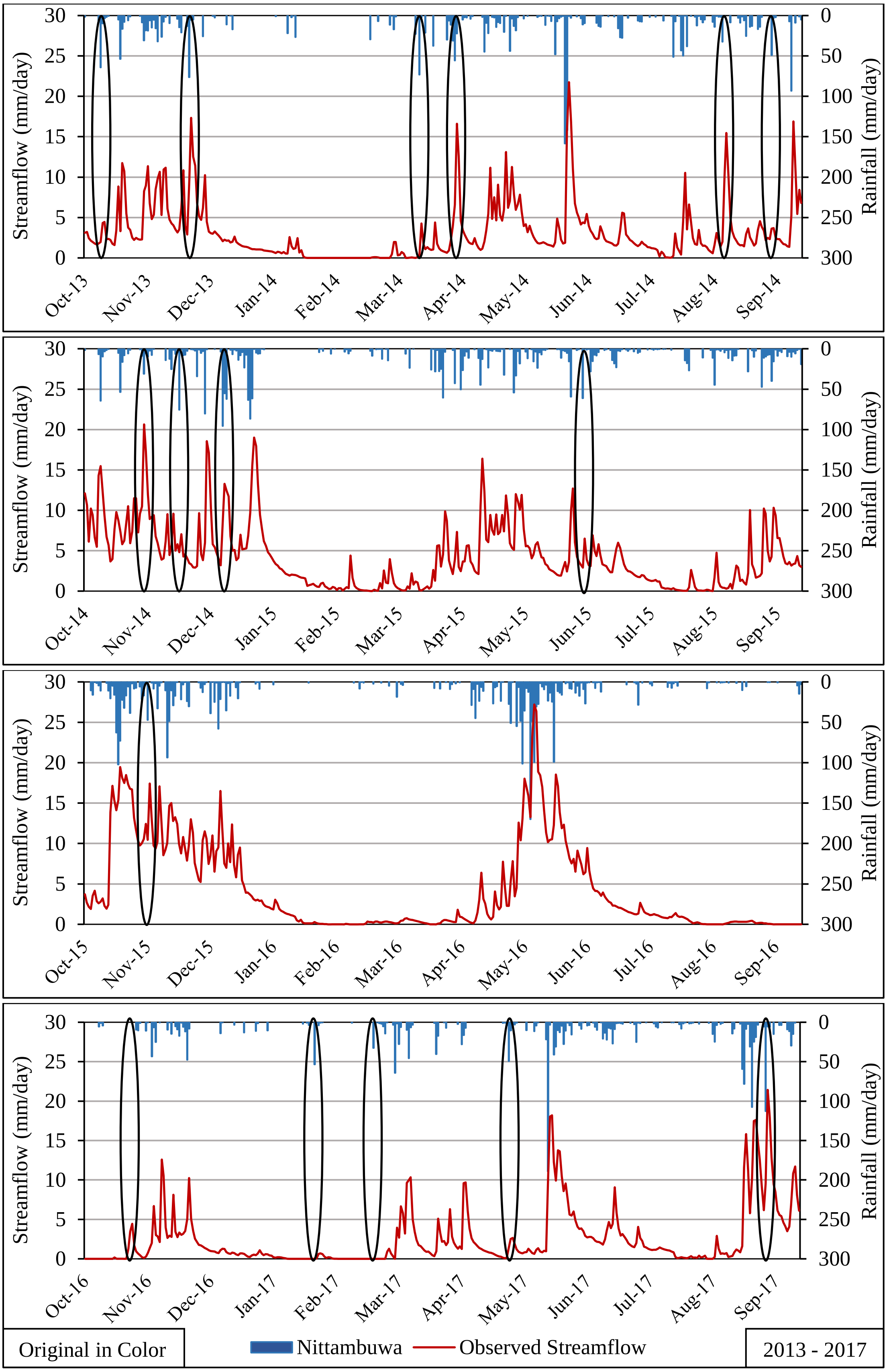


Figure B - 24 Dunamale Streamflow response to Nittambuwa Rainfall (2013 - 2017) – Normal Plot

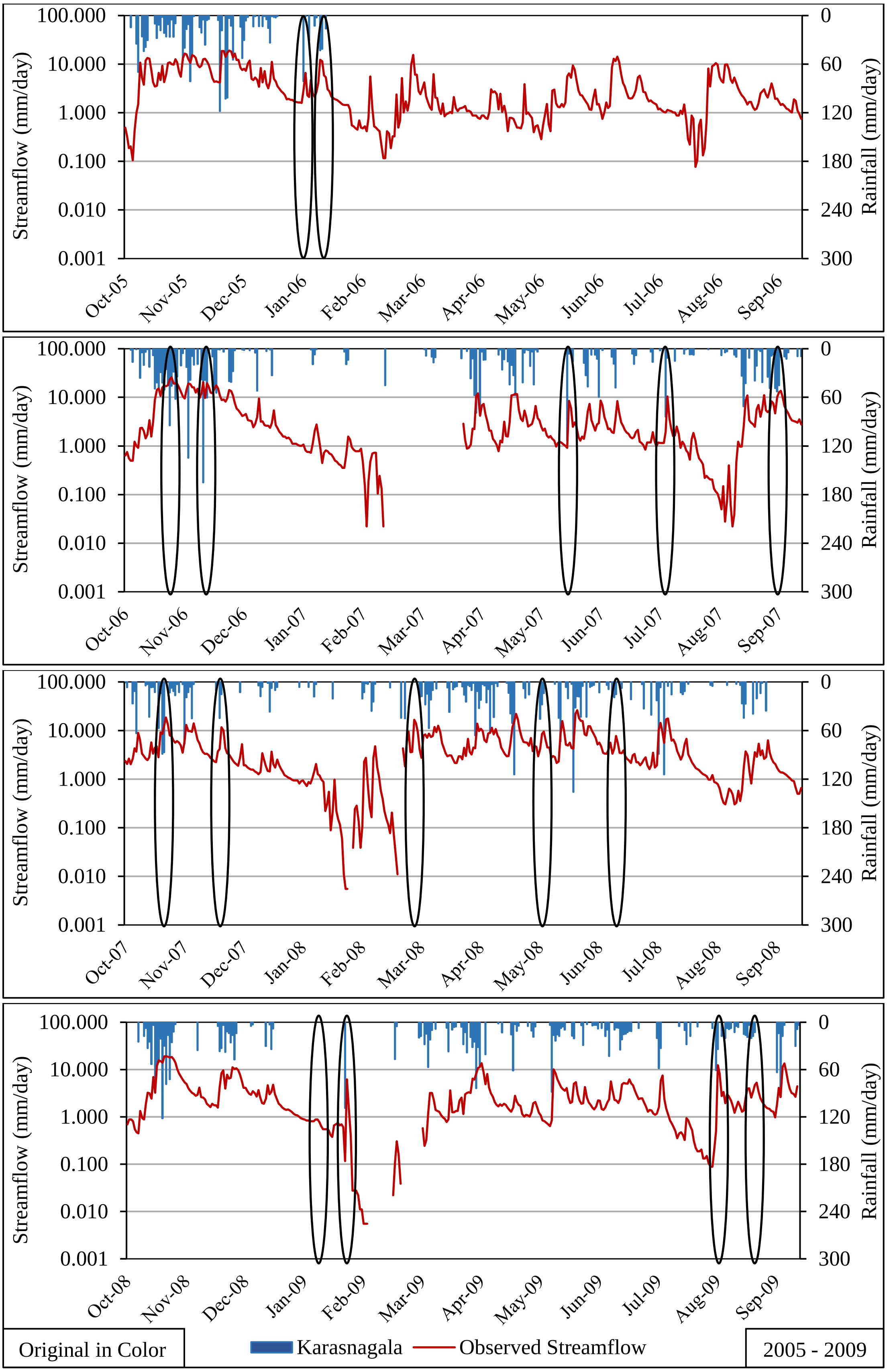


Figure B - 25 Dunamale Streamflow response to Karasnagala Rainfall (2005 - 2009) – Semi-Log Plot

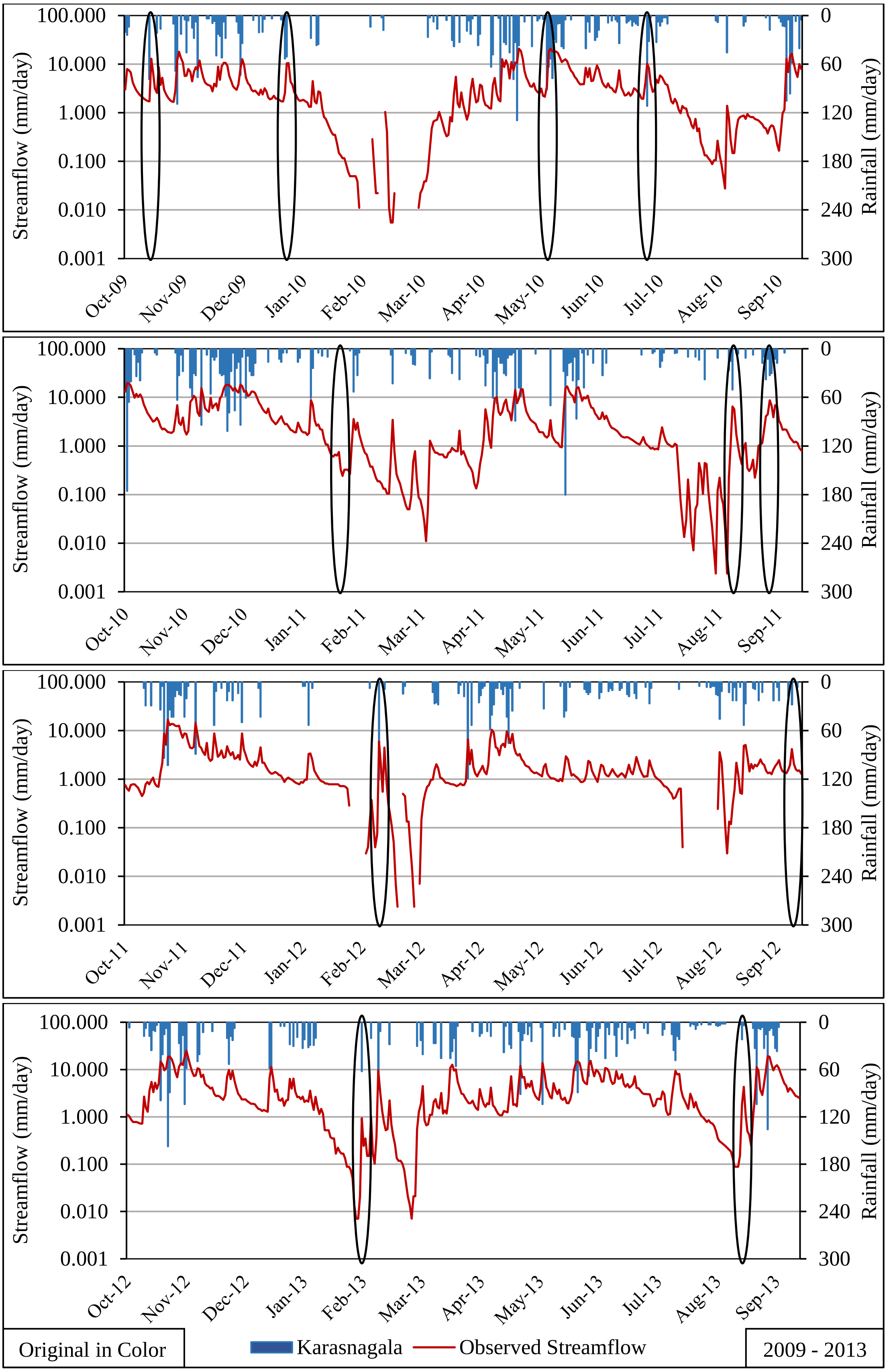


Figure B - 26 Dunamale Streamflow response to Karasnagala Rainfall (2009 - 2013) – Semi-Log Plot

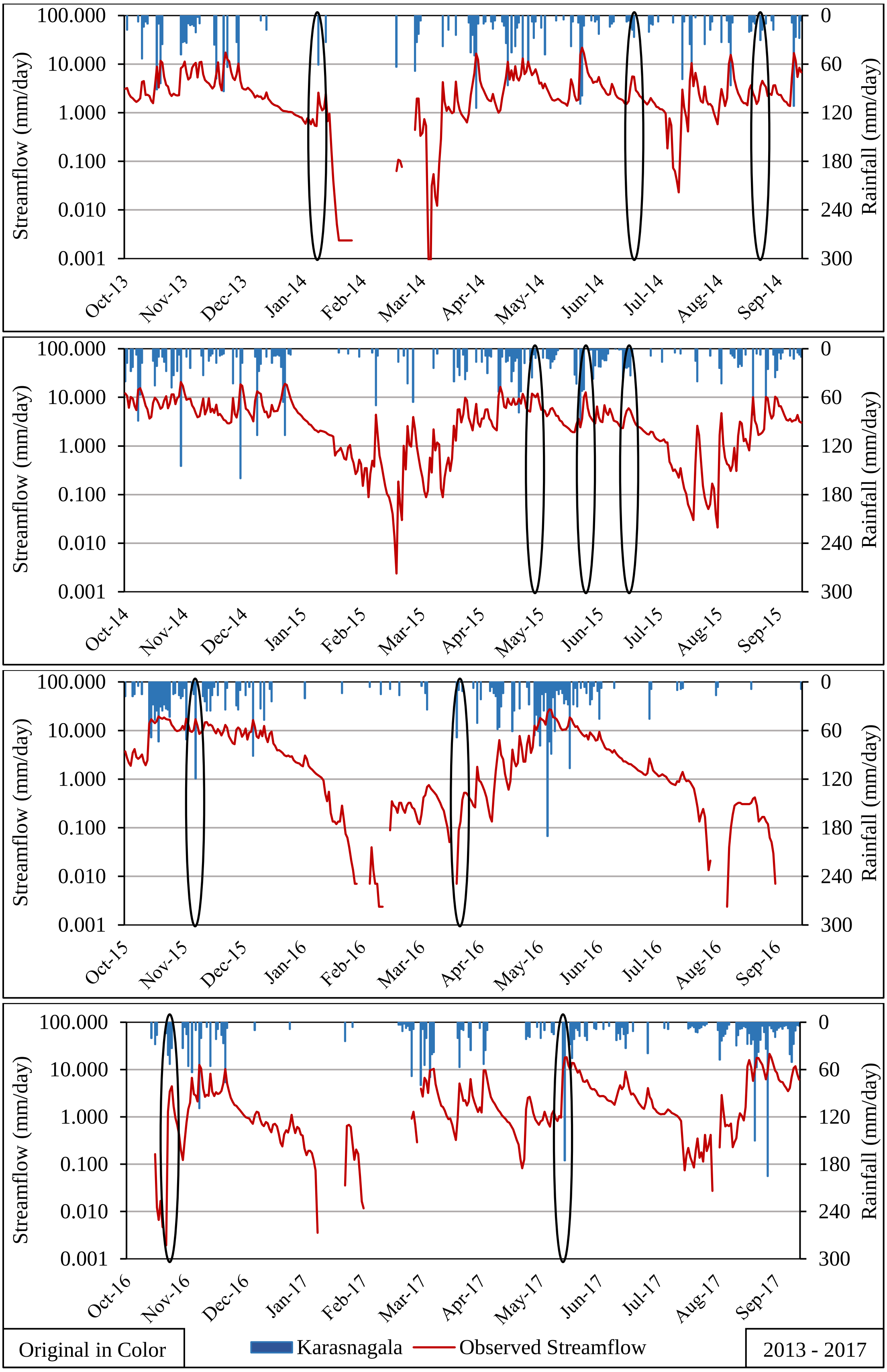


Figure B - 27 Dunamale Streamflow response to Karasnagala Rainfall (2013 - 2017) – Semi-Log Plot

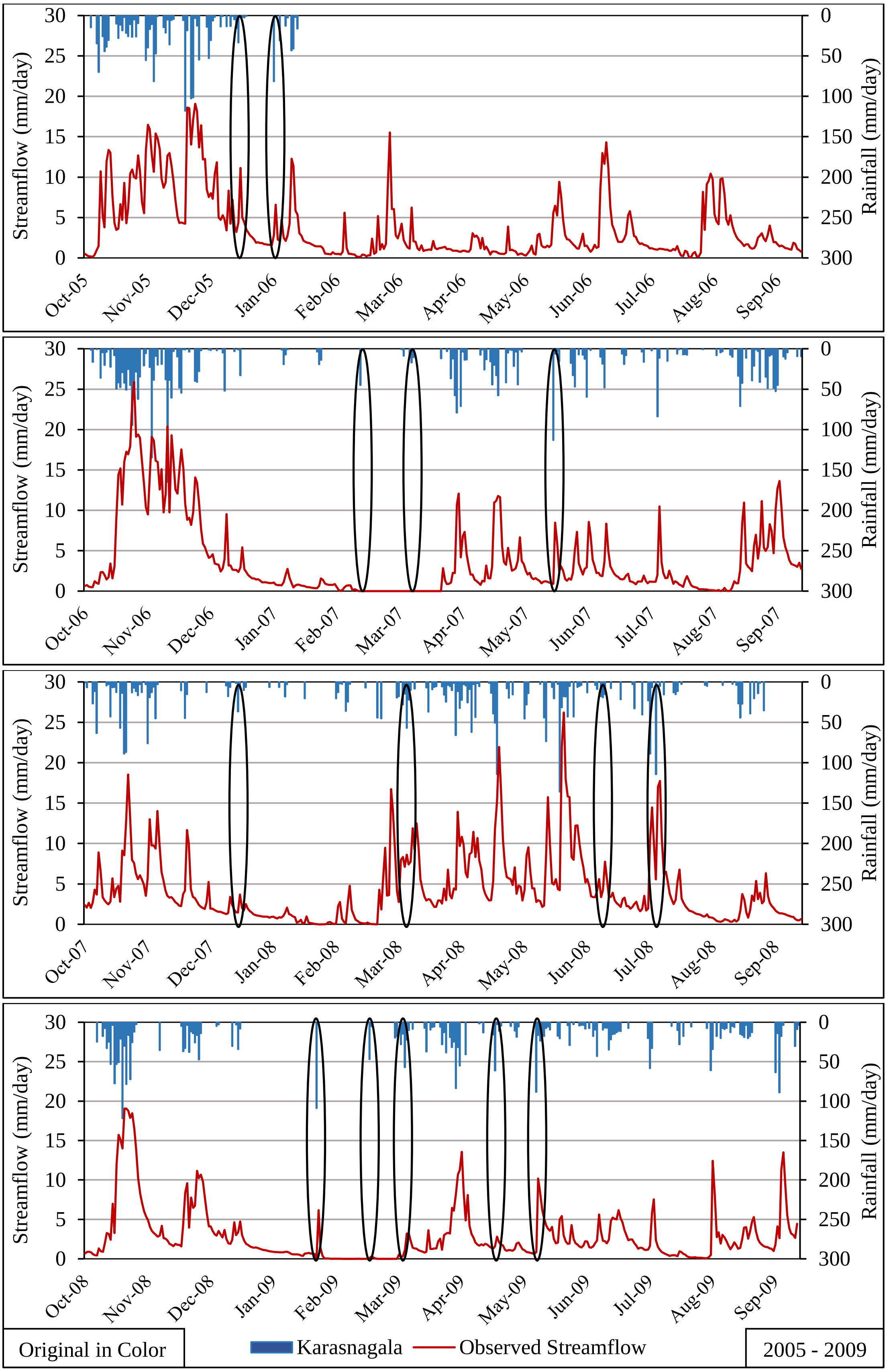


Figure B - 28 Dunamale Streamflow response to Karasnagala Rainfall (2005 - 2009) – Normal Plot

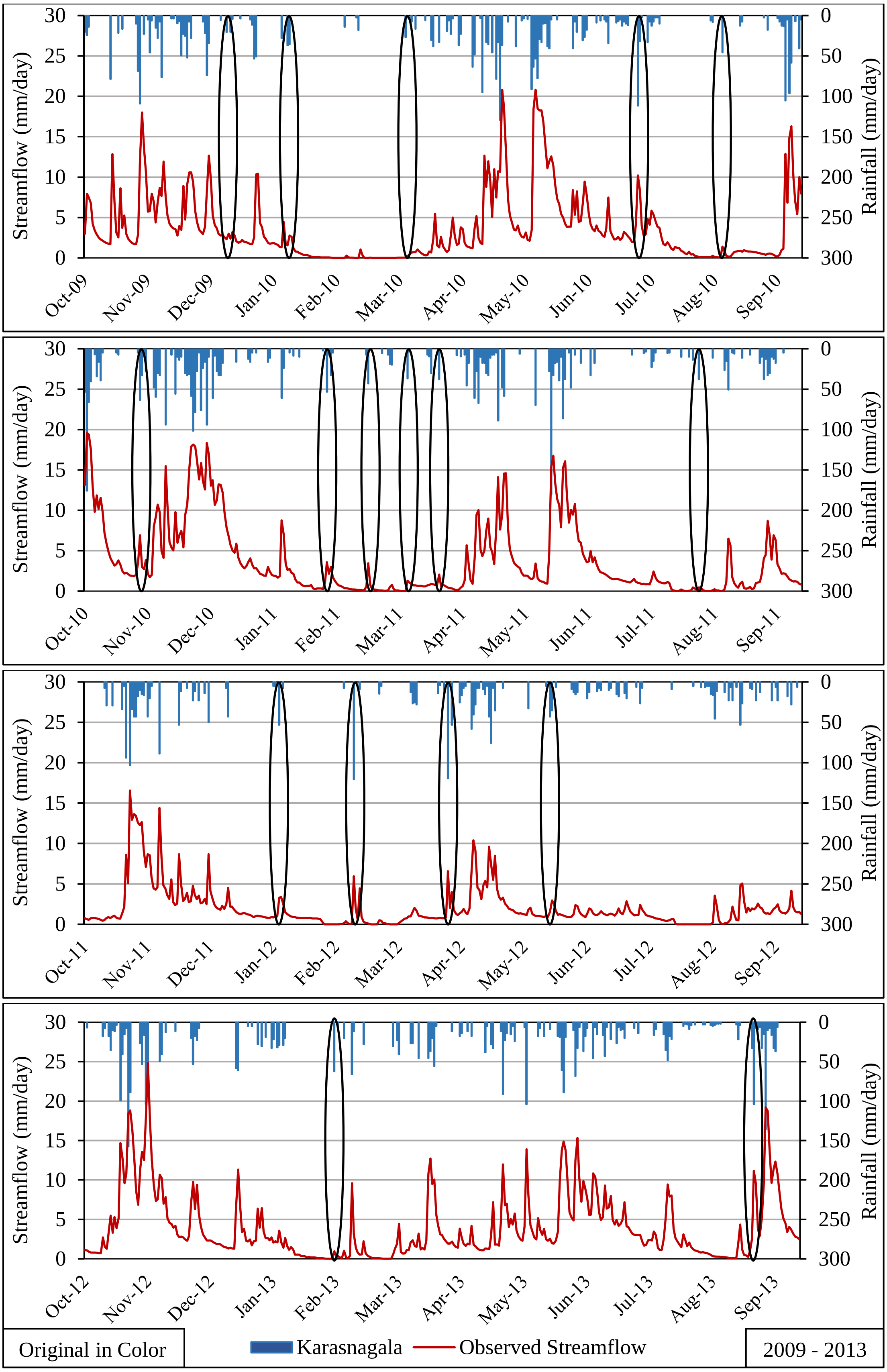


Figure B - 29 Dunamale Streamflow response to Karasnagala Rainfall (2009 - 2013) – Normal Plot

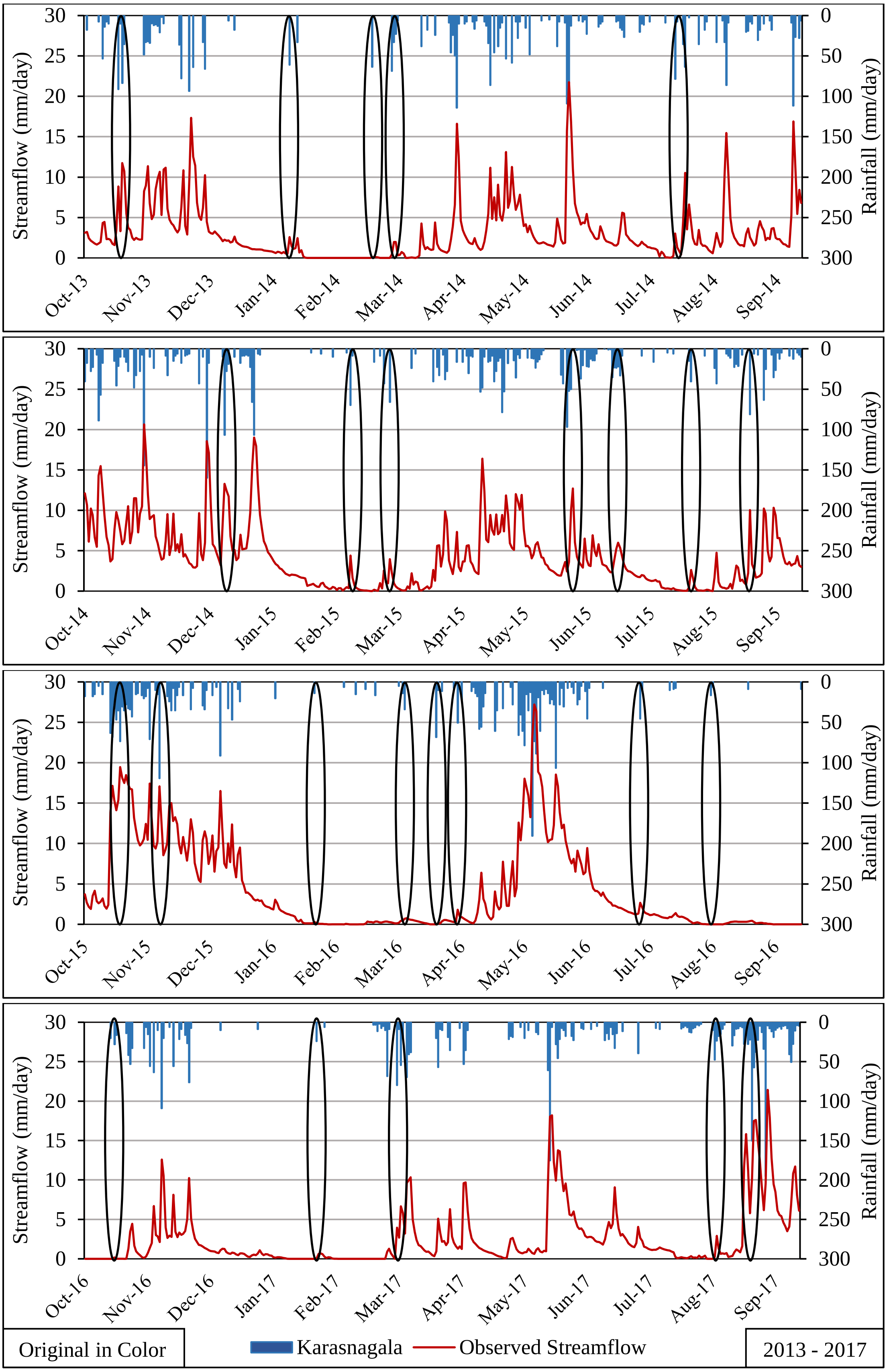


Figure B - 30 Dunamale Streamflow response to Karasnagala Rainfall (2013 - 2017) – Normal Plot

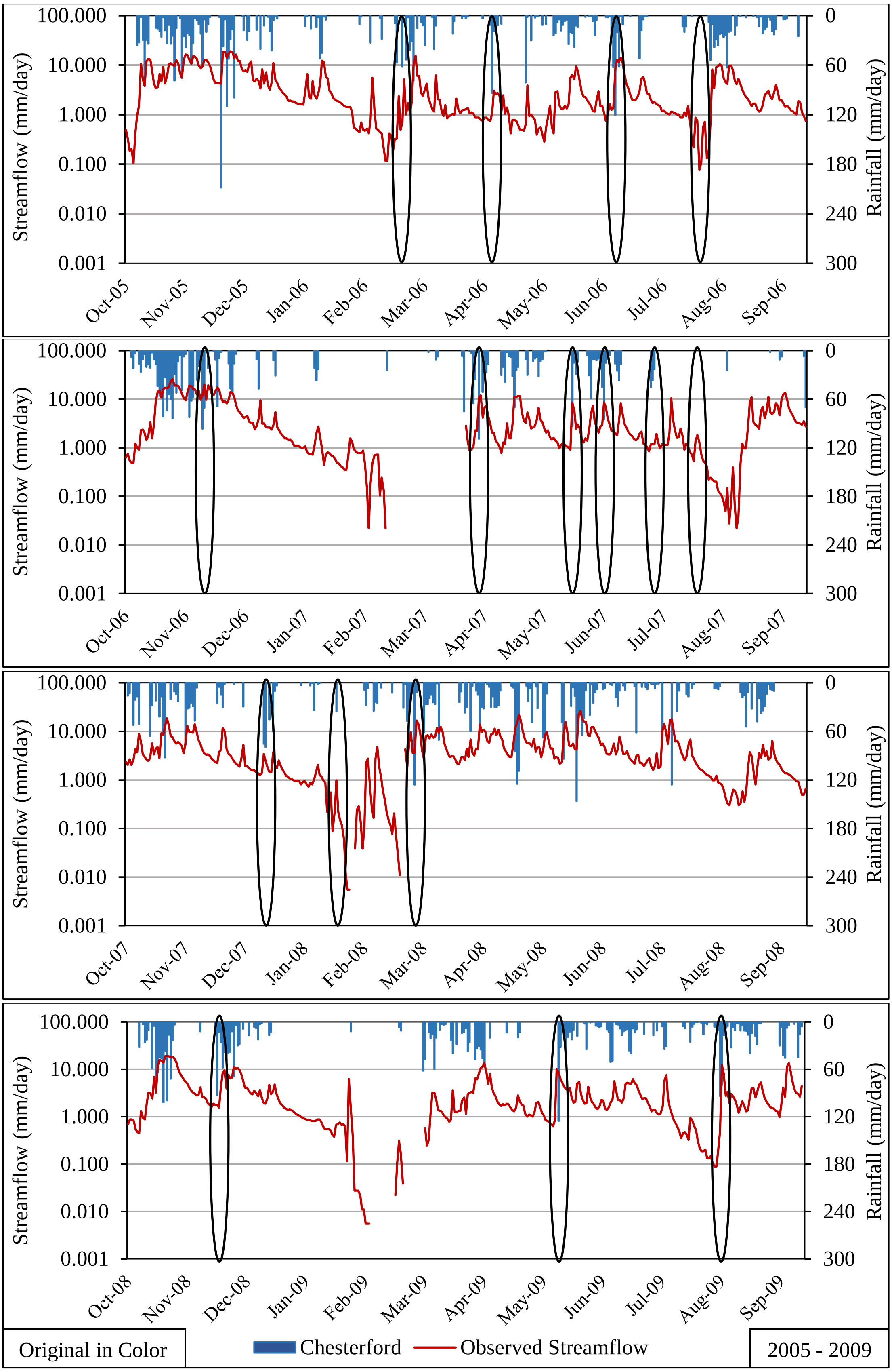


Figure B - 31 Dunamale Streamflow response to Chesterford Rainfall (2005 - 2009) – Semi-Log Plot

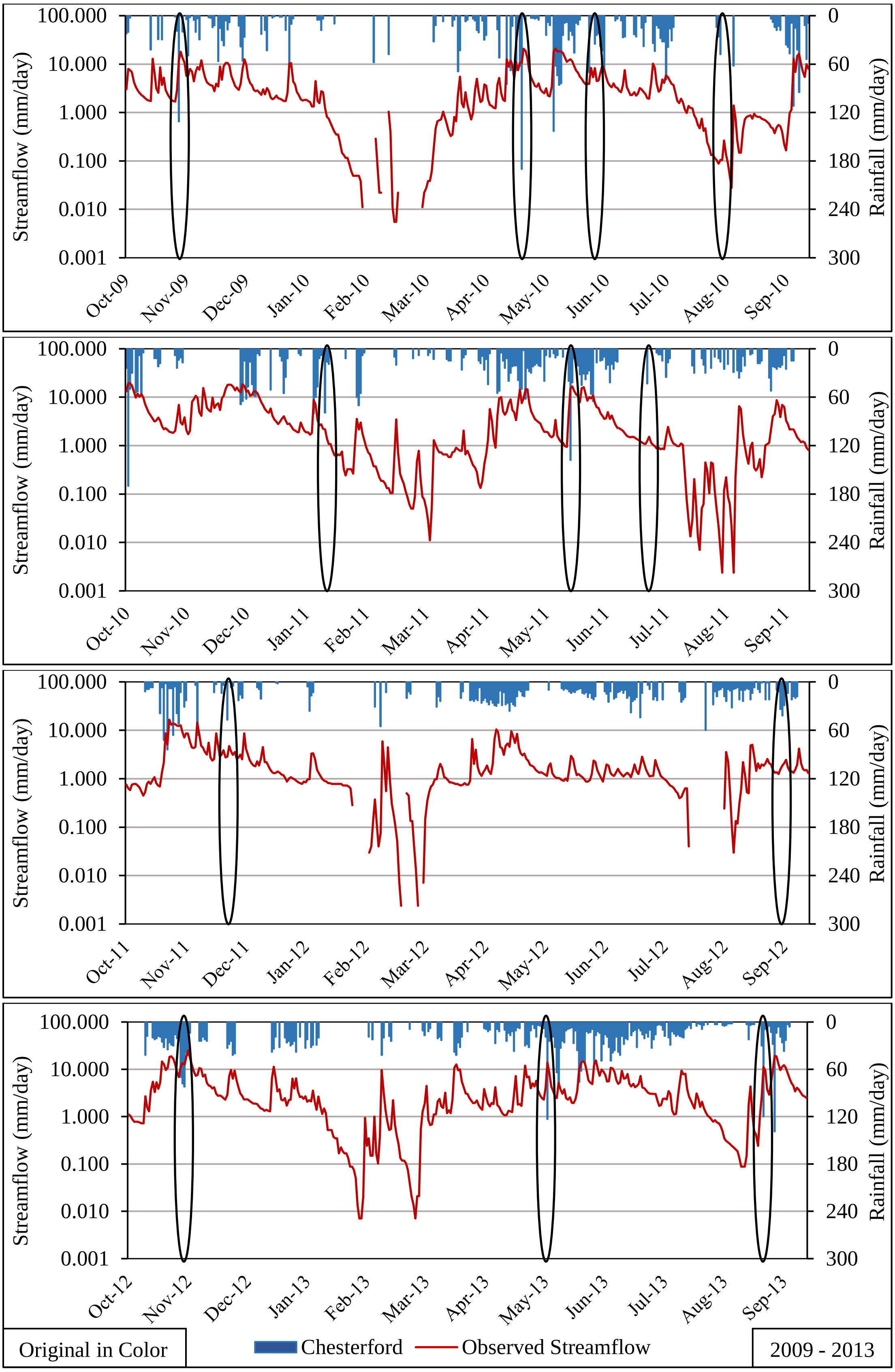


Figure B - 32 Dunamale Streamflow response to Chesterford Rainfall (2009 - 2013) – Semi-Log Plot

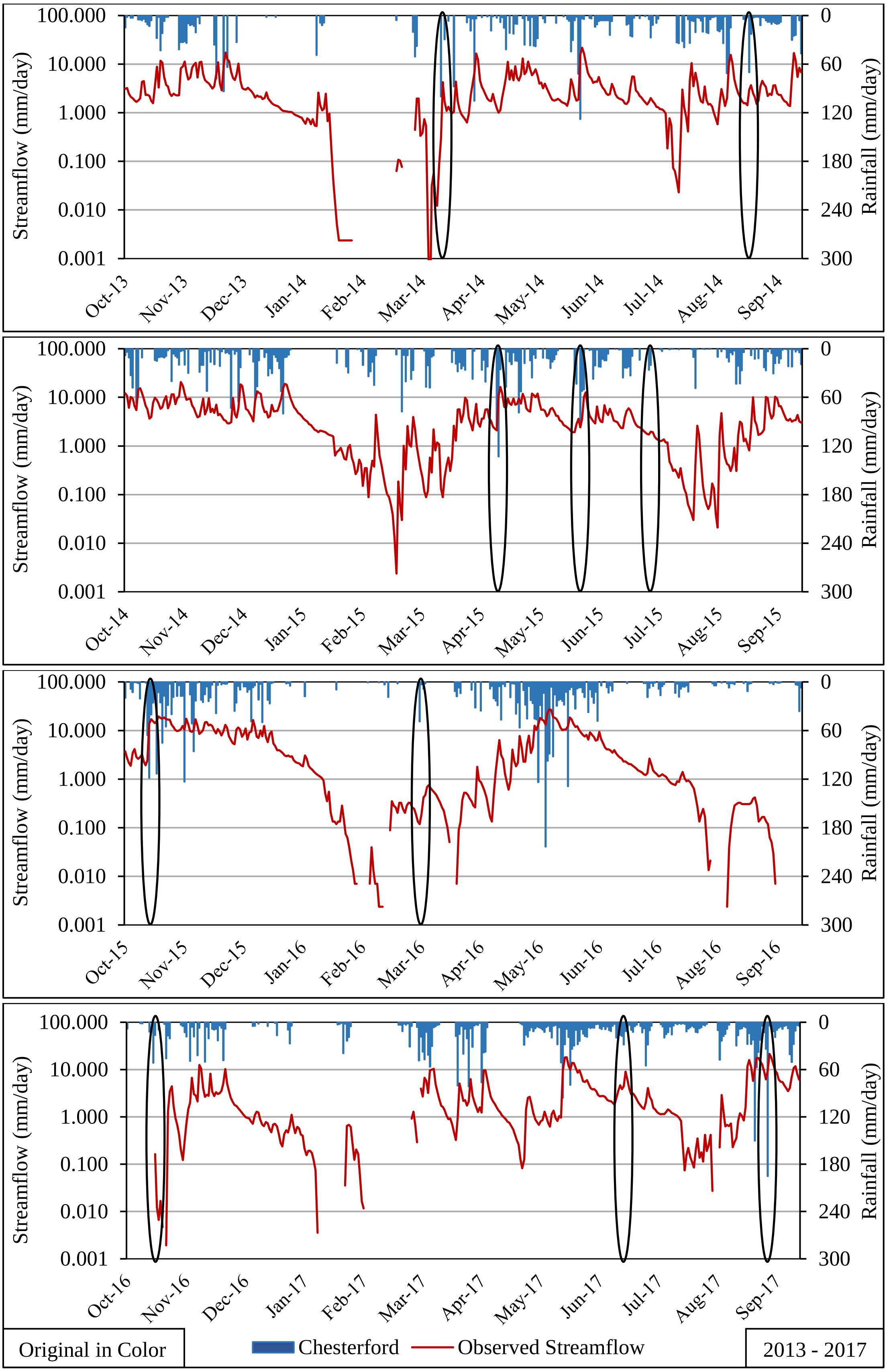


Figure B - 33 Dunamale Streamflow response to Chesterford Rainfall (2013 - 2017) – Semi-Log Plot

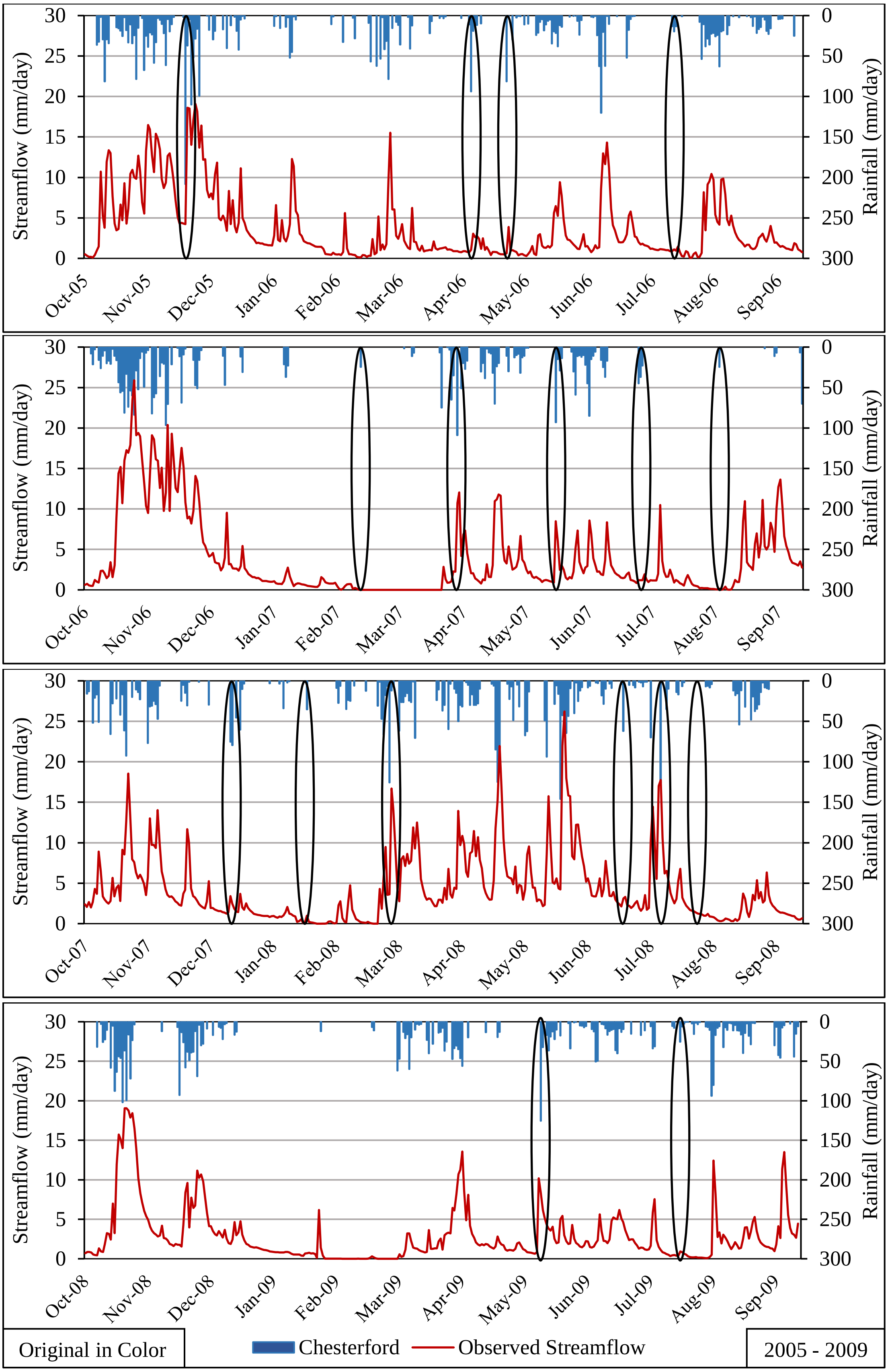


Figure B - 34 Dunamale Streamflow response to Chesterford Rainfall (2005 - 2009) – Normal Plot

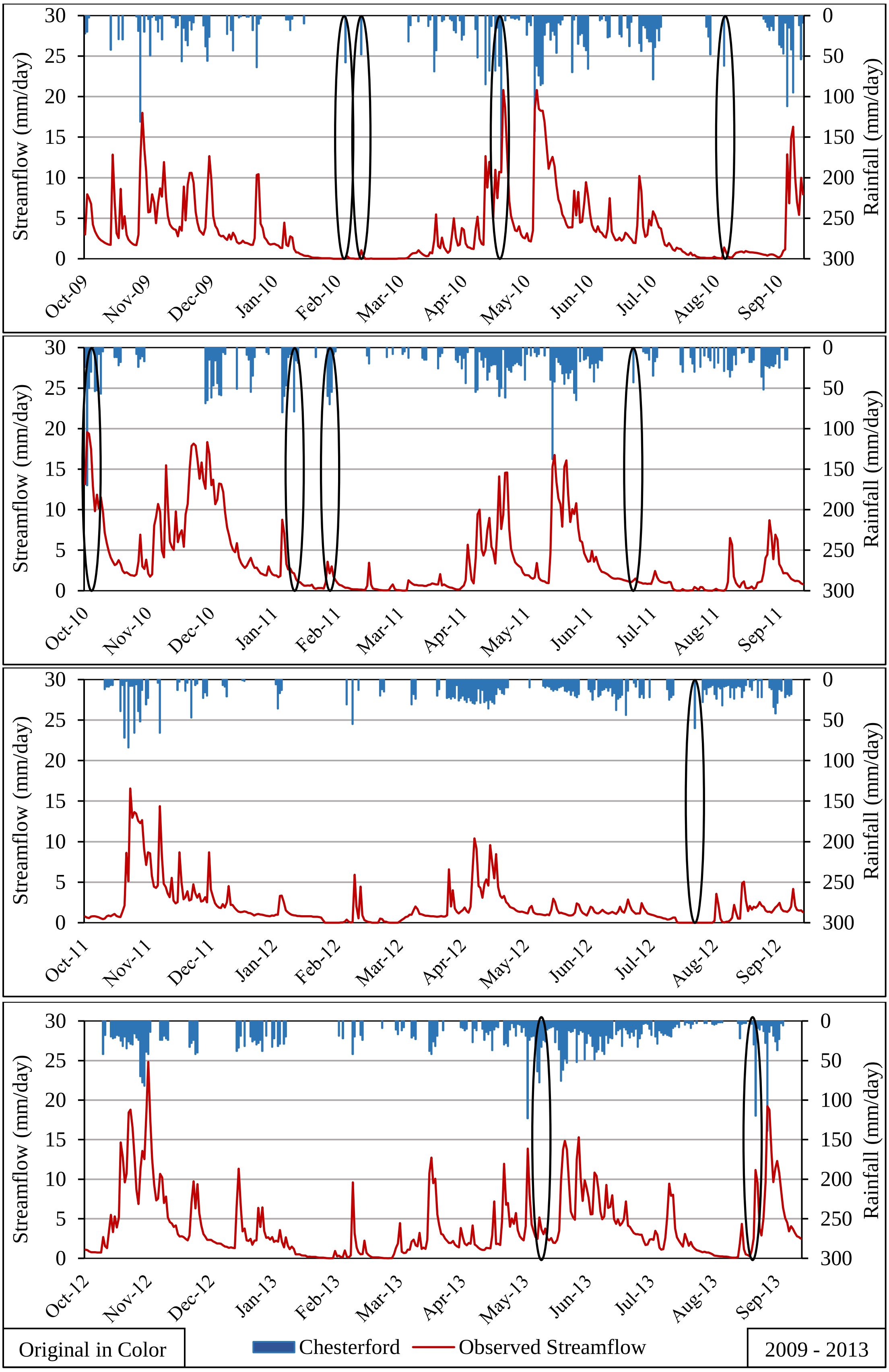


Figure B - 35 Dunamale Streamflow response to Chesterford Rainfall (2009 - 2013) – Normal Plot

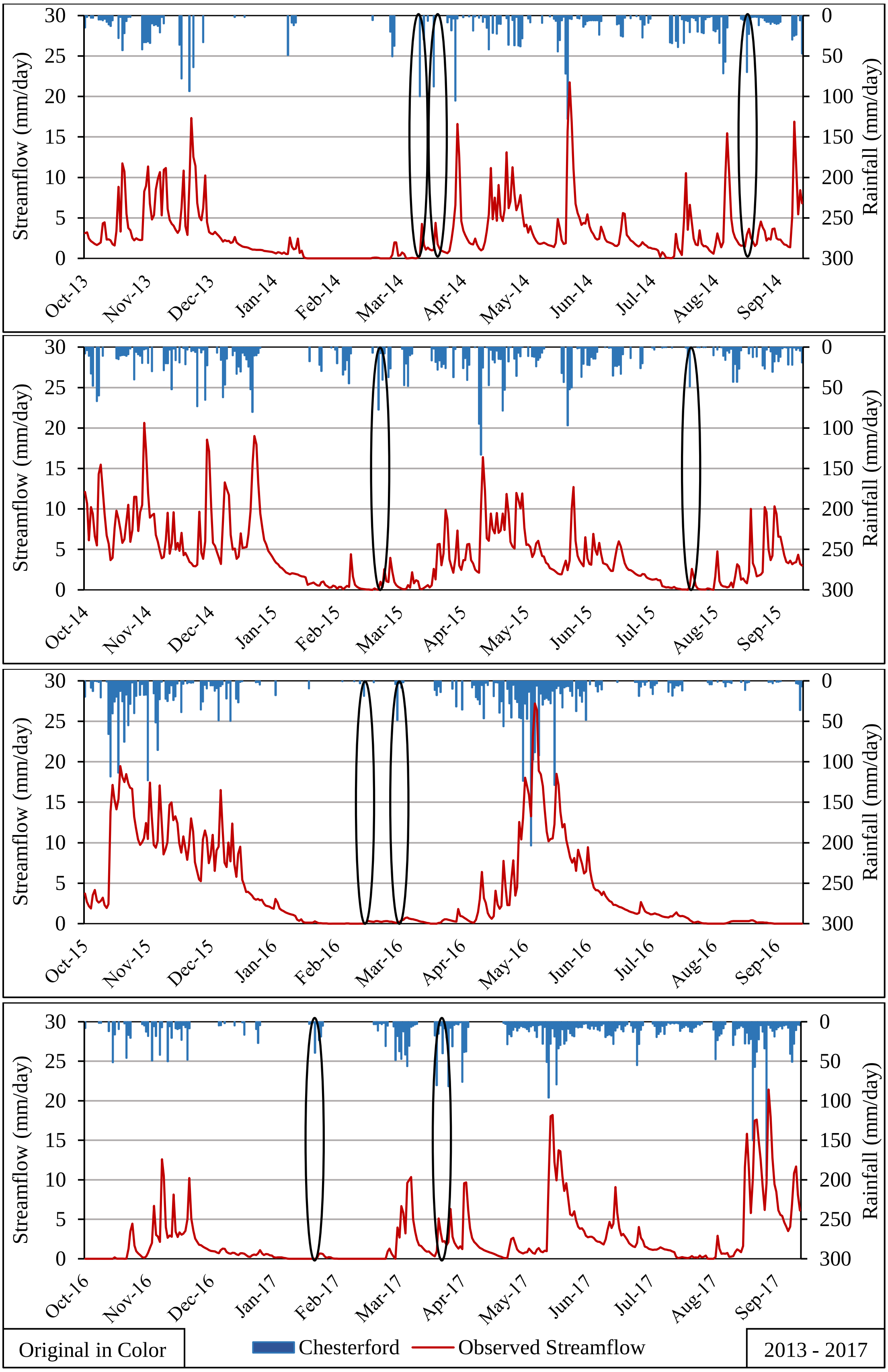


Figure B - 36 Dunamale Streamflow response to Chesterford Rainfall (2013 - 2017) – Normal Plot

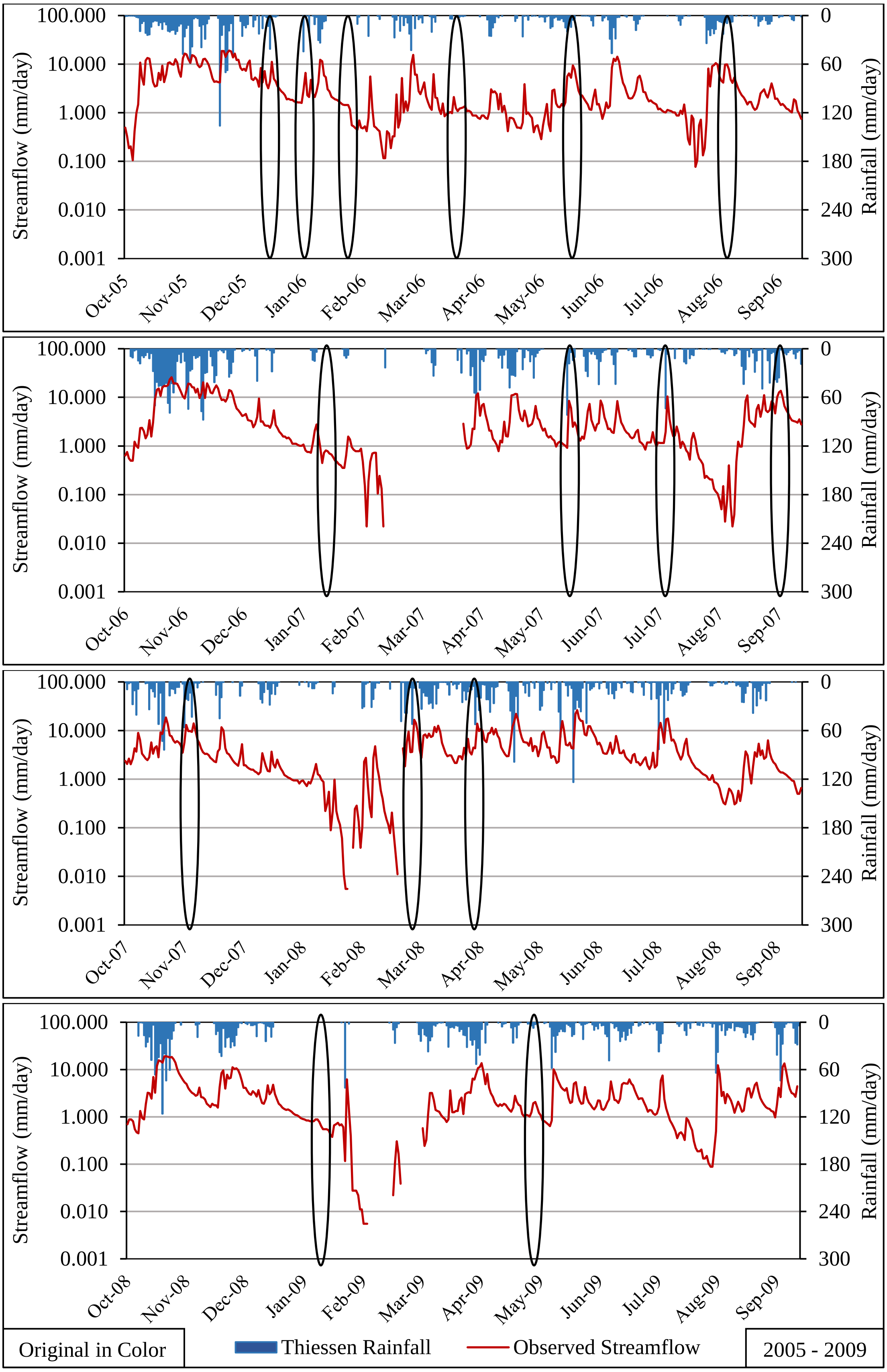


Figure B - 37 Dunamale Streamflow response to Thiessen Rainfall (2005 - 2009) – Semi-Log Plot

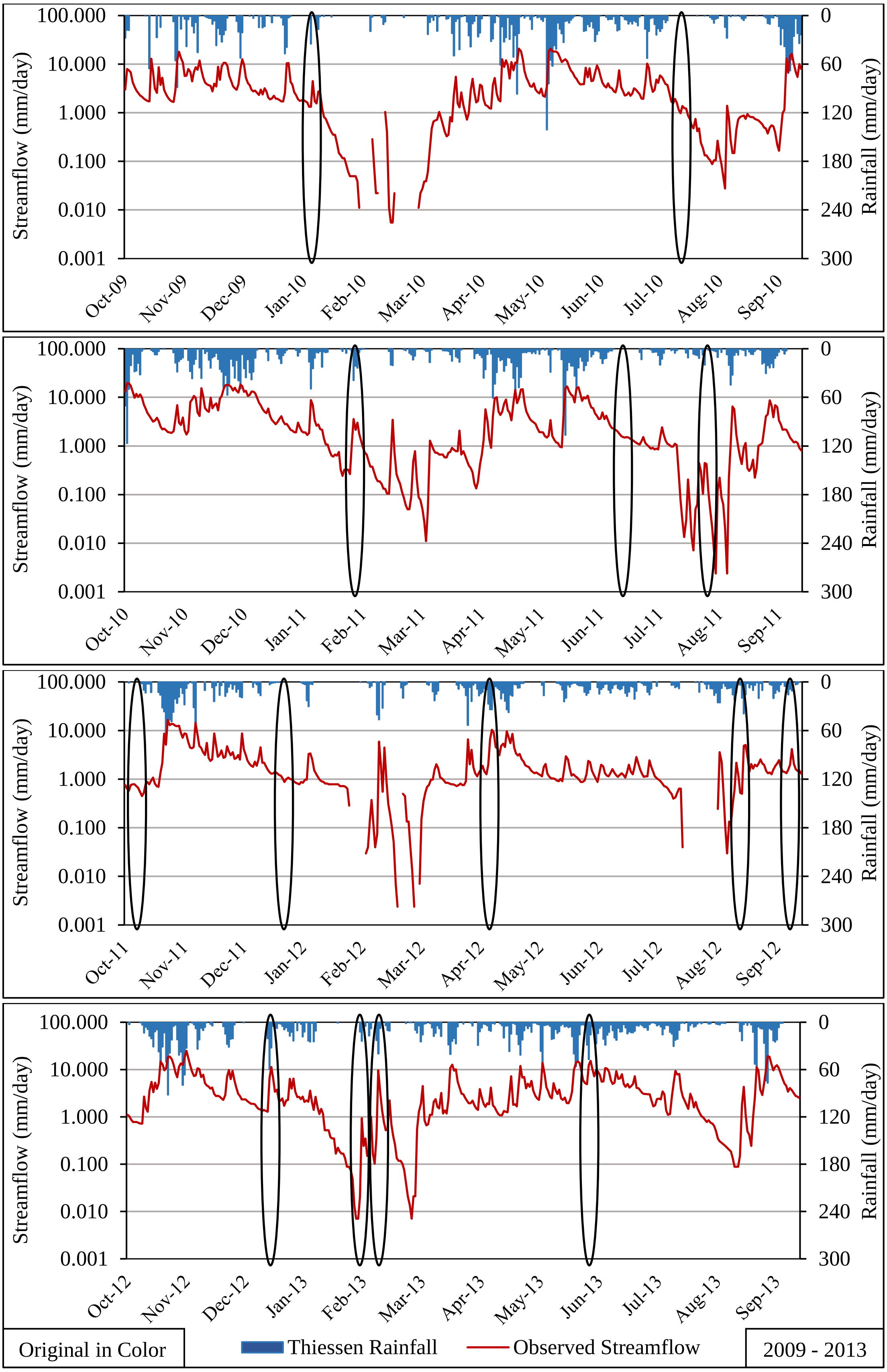


Figure B - 38 Dunamale Streamflow response to Thiessen Rainfall (2009 - 2013) – Semi-Log Plot

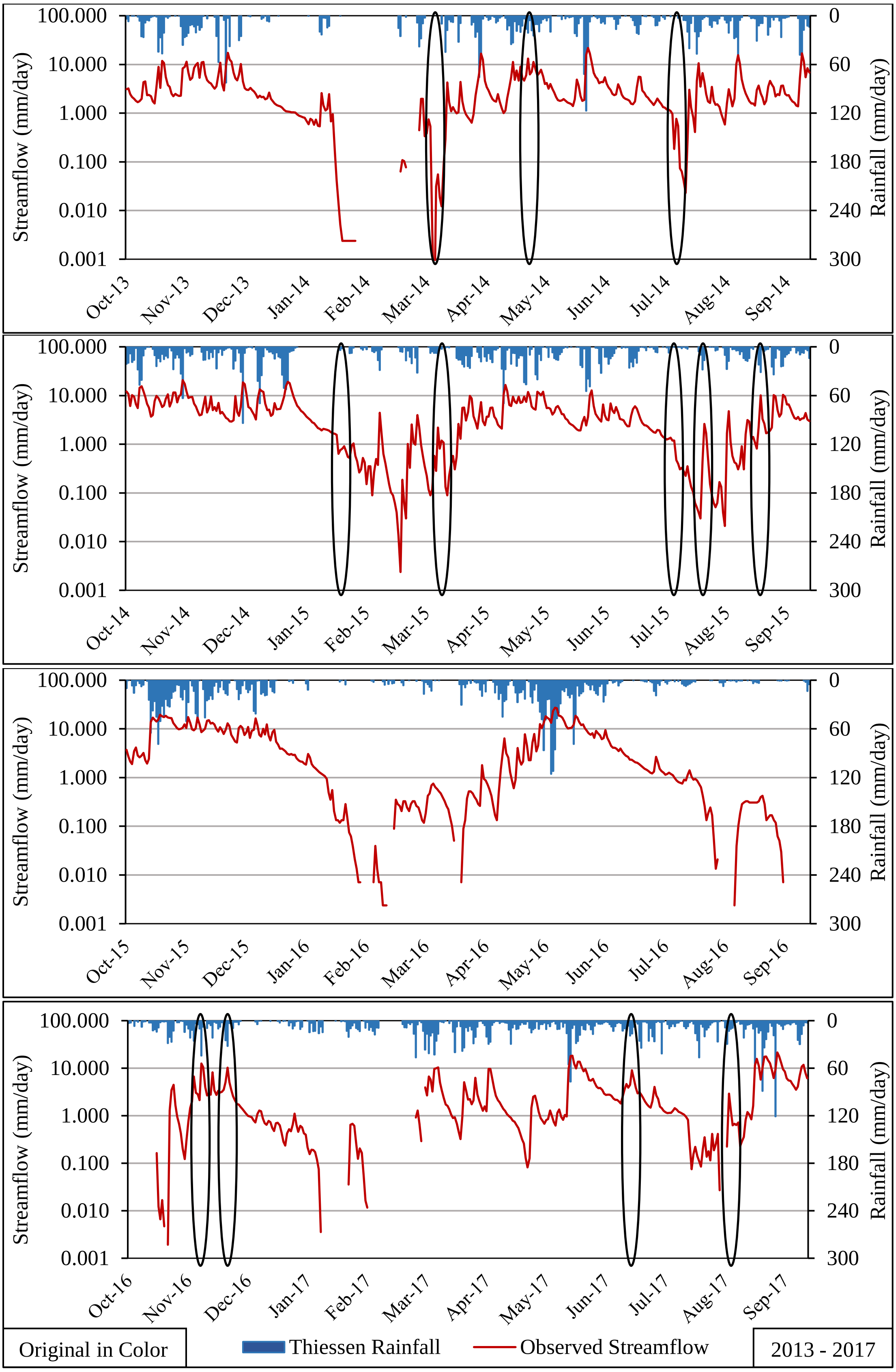


Figure B - 39 Dunamale Streamflow response to Thiessen Rainfall (2013 - 2017) – Semi-Log Plot

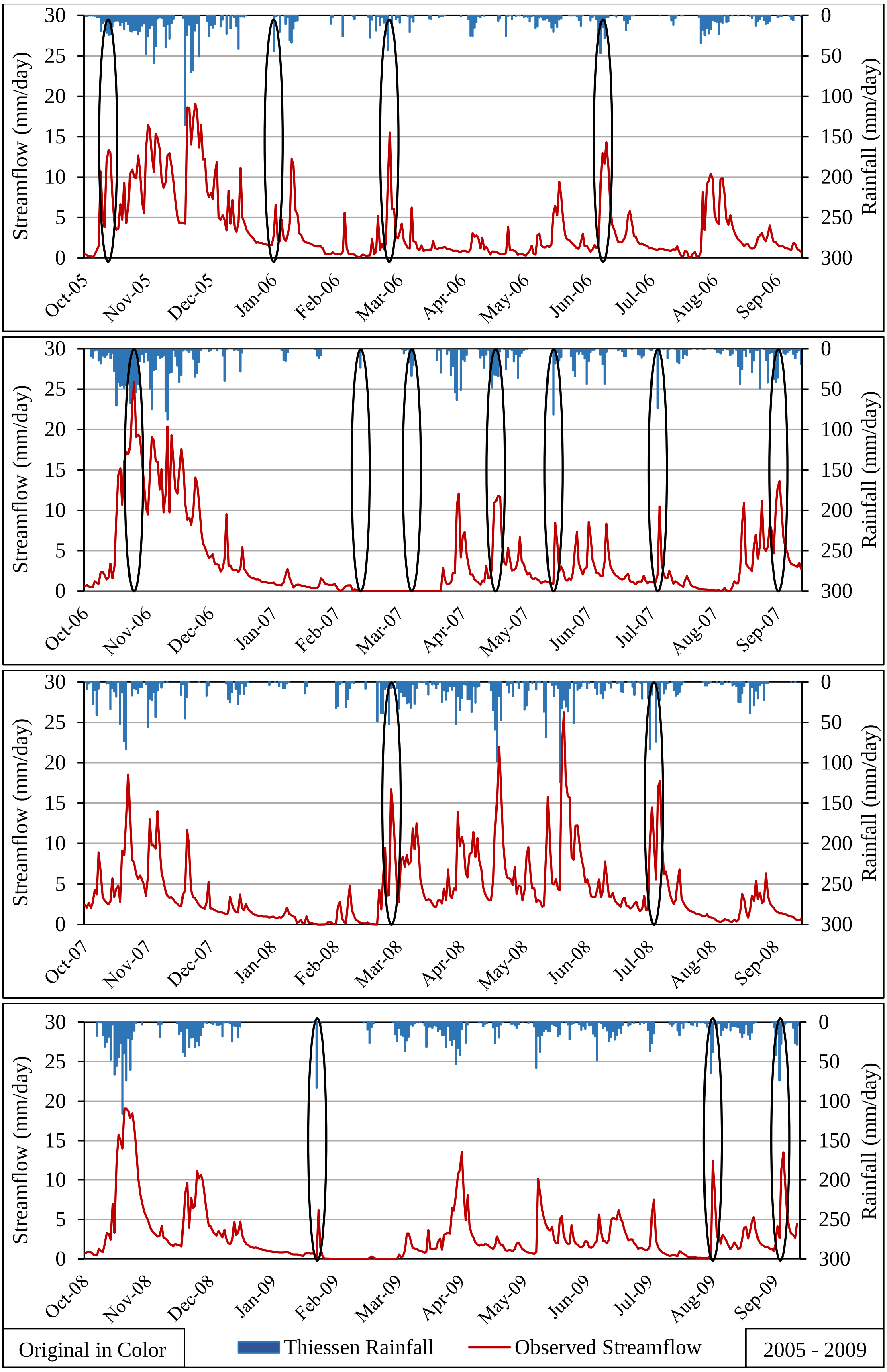


Figure B - 40 Dunamale Streamflow response to Thiessen Rainfall (2005 - 2009) – Normal Plot

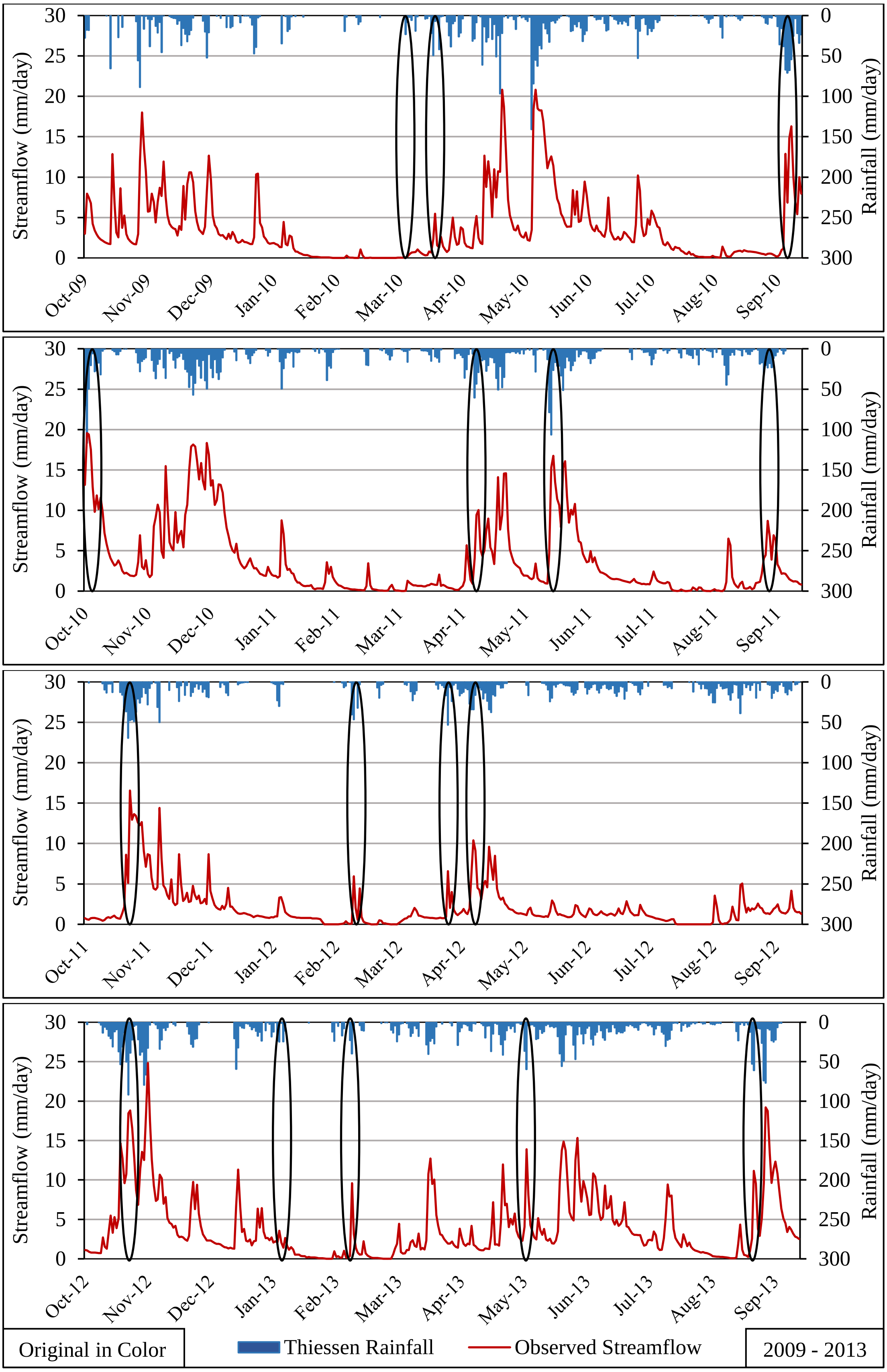


Figure B - 41 Dunamale Streamflow response to Thiessen Rainfall (2009 - 2013) – Normal Plot

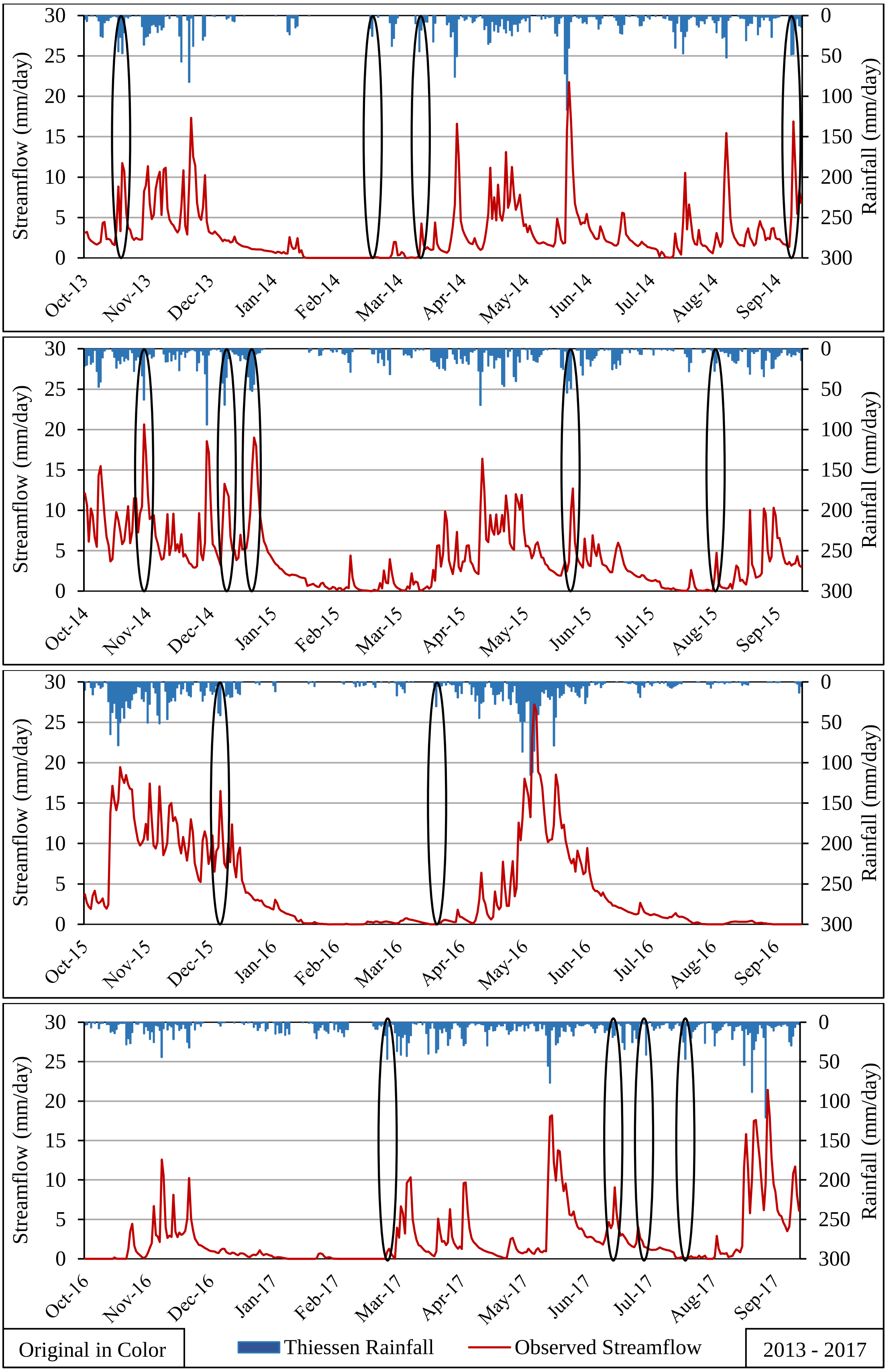


Figure B - 42 Dunamale Streamflow response to Thiessen Rainfall (2013 - 2017) – Normal Plot

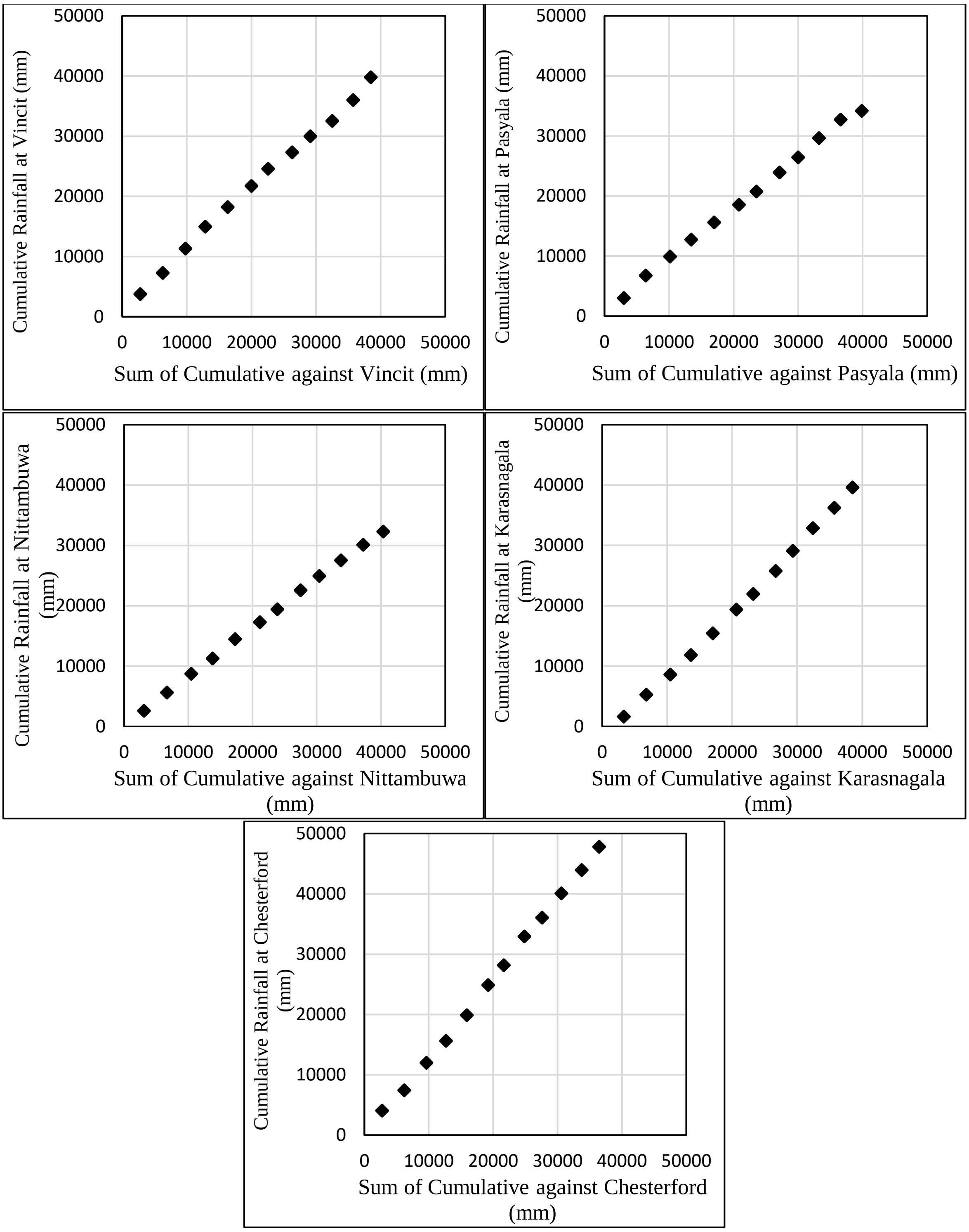


Figure B - 43 Double Mass Curve for Rainfall Data - Dunamale Watershed

ANNEX C – METHODOLOGY

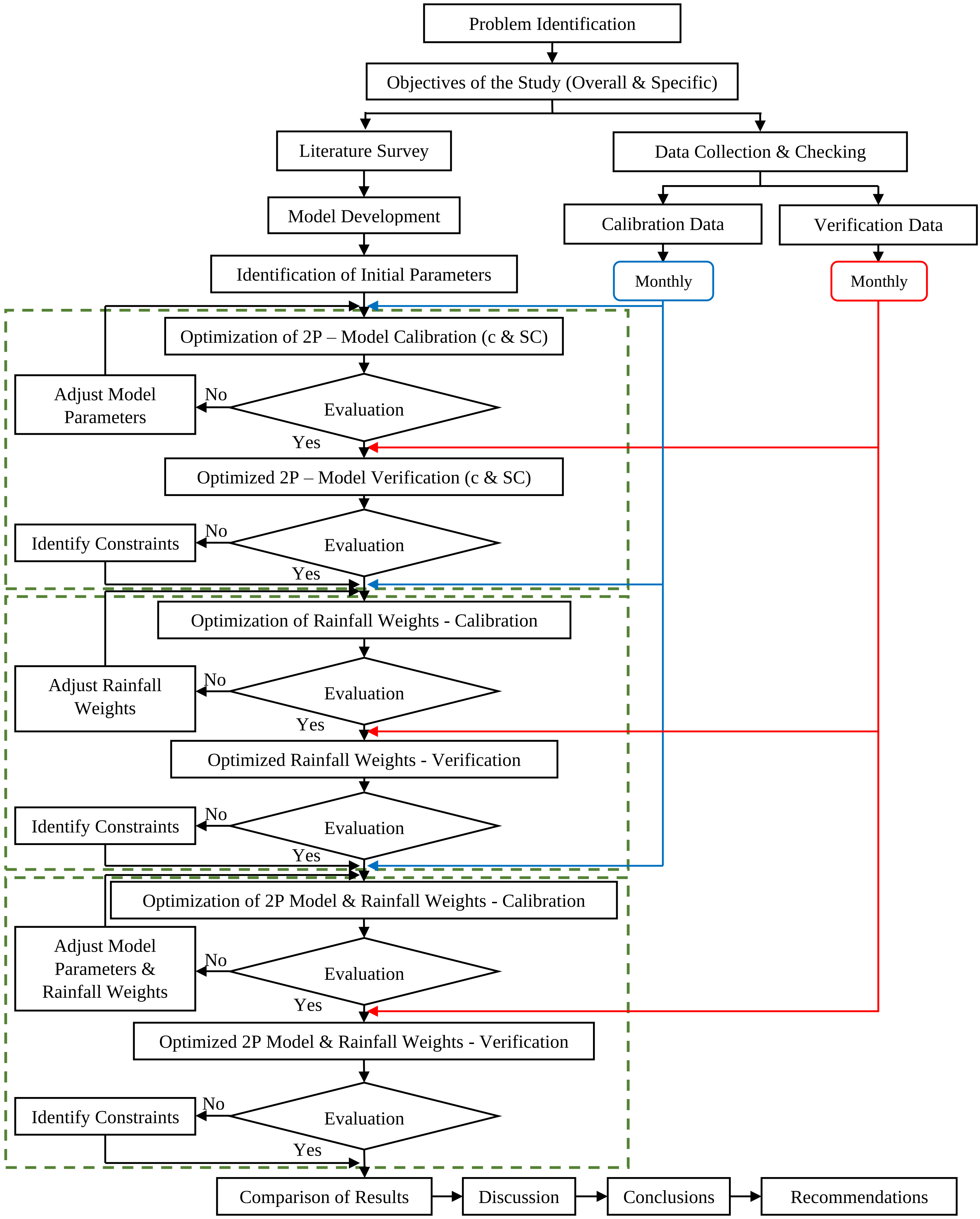


Figure C - 1 Detailed Methodology Flowchart

ANNEX D – MODEL DEVELOPMENT

Manual Specimen Calculation

Assuming C = 1, SC = 500

Initial storage = 0 MM

P = 100 MM

EP = 90 MM

$$\boldsymbol{E(t) = c * EP(t) * tanh\left[\frac{P(t)}{EP(t)}\right]}$$

E(T) = 1*90* TANH (100/90)

= 90 * TANH (1.1112)

= 90 * 0.80445

= 72.4005 MM

$$\boldsymbol{Q(t) = [S\,(t-1) + P(t) - E(t)] * tanh\left[\frac{S(t-1) + P - E(t)}{SC}\right]}$$

Q(T) = (0+100-72.40) * TANH (0+100-72.40/500)

= 27.6* TANH (27.6/500)

= 27.6 * TANH (0.0552)

= 27.6*0.05514

= 1.5218

$$\boldsymbol{S(t) = S\,(t-1) + P(t) - E(t) - Q(t)}$$

S(T) = 0 + 100 – 72.4005 – 1.5218

= 26.077 MM

Model Specimen Calculation

	Rainfall	Pan Evaporation		Reduction Factor	Actual Evapotranspiration			Initial Soil Water Content	Simulated Flow (mm)		Final Soil Water Content
Date	P(t) mm	EP(t) mm	P(t)/EP(t)	tanh[P(t)/EP(t)]	E(t) (mm)			S(t-1)	Qs(t) (mm)		S(t)
Oct-05	100.00	90.00	1.11	0.80	72.40	72.40	72.40	0.00	1.52	1.52	26.08

Figure D - 1 Model result for Specimen Calculation

ANNEX E – ANALYSIS

Table E - 1 Behaviour of MRAE with c & SC - Dunamale Watershed

Initial Parameters		Optimized Parameters		Optimized MRAE
C	SC	C	SC	
0.5	500	1.786	692.255	0.4587350
0.5	1000	2.000	906.403	0.4604155
0.5	1500	2.000	906.403	0.4604155
0.5	2000	1.296	225.043	0.7928854
0.5	2500	1.337	297.992	0.7472320
0.5	3000	1.870	816.318	0.4704305
1	500	1.878	782.498	0.4529028
1	1000	1.878	782.472	0.4528833
1	1500	1.878	782.482	0.4528825
1	2000	1.877	781.657	0.4528941
1	2500	1.881	864.150	0.4610947
1	3000	2.000	906.403	0.4604156
1.5	500	1.878	782.471	0.4528816
1.5	1000	1.864	845.632	0.4607643
1.5	1500	1.913	898.629	0.4614994
1.5	2000	2.000	906.403	0.4604158
1.5	2500	2.000	906.402	0.4604164
1.5	3000	2.000	906.403	0.4604156
2	500	1.876	780.919	0.4529031
2	1000	1.864	844.113	0.4617633
2	1500	1.878	782.441	0.4529100
2	2000	1.934	838.799	0.4548013
2	2500	1.864	845.632	0.4607647
2	3000	2.000	906.403	0.4604156
2.5	500	1.878	782.321	0.4529831
2.5	1000	2.000	993.750	0.4699631
2.5	1500	1.877	782.017	0.4528879
2.5	2000	1.864	845.618	0.4607653
2.5	2500	1.985	977.163	0.4686041
2.5	3000	2.000	906.403	0.4604156
3	500	1.833	812.985	0.4621626
3	1000	2.000	993.750	0.4699632
3	1500	1.855	760.315	0.4531872
3	2000	1.864	845.652	0.4607644
3	2500	1.864	845.006	0.4612605
3	3000	1.903	888.026	0.4613847

Table E - 2 Areal average rainfall comparison of various Optimization stages - Calibration Period (2006-2009)

Month-Year	Areal Average Rainfall (mm)		
	Optimization I	Optimization II	Optimization III
Oct-06	798.46	835.97	809.71
Nov-06	672.36	669.02	698.11
Dec-06	93.19	90.72	88.32
Jan-07	62.13	58.76	59.36
Feb-07	23.31	15.77	19.65
Mar-07	124.82	151.06	129.26
Apr-07	494.84	482.38	482.84
May-07	245.10	231.76	231.50
Jun-07	244.80	235.17	257.75
Jul-07	186.95	192.69	197.07
Aug-07	152.40	190.02	178.72
Sep-07	358.70	385.55	373.67
Oct-07	460.82	421.78	434.02
Nov-07	263.69	298.76	317.86
Dec-07	158.26	112.56	105.98
Jan-08	48.66	48.50	57.30
Feb-08	225.17	233.48	229.47
Mar-08	448.87	485.12	508.36
Apr-08	591.95	603.55	636.71
May-08	427.43	478.23	507.30
Jun-08	275.39	285.79	292.42
Jul-08	370.87	359.56	359.12
Aug-08	95.58	91.09	96.52
Sep-08	144.36	119.63	113.35
Oct-08	701.58	707.10	725.06
Nov-08	319.87	320.89	338.08
Dec-08	98.07	111.71	104.99
Jan-09	85.24	86.02	82.96
Feb-09	45.07	54.55	55.98
Mar-09	254.64	270.91	291.55
Apr-09	375.76	357.96	386.80
May-09	246.48	234.78	238.35
Jun-09	270.64	283.75	294.65
Jul-09	155.44	167.67	187.51
Aug-09	235.17	239.04	256.61
Sep-09	327.82	327.04	332.02

Table E - 3 Areal average rainfall comparison of various Optimization stages - Calibration Period (2009-2012)

Month-Year	Areal Average Rainfall (mm)		
	Optimization I	Optimization II	Optimization III
Oct-09	338.73	332.88	329.61
Nov-09	326.20	293.06	309.19
Dec-09	254.80	223.28	252.74
Jan-10	75.92	52.10	45.24
Feb-10	43.93	46.83	55.29
Mar-10	192.78	192.66	185.27
Apr-10	558.25	523.10	569.26
May-10	599.95	507.89	494.00
Jun-10	251.33	224.67	232.87
Jul-10	237.93	190.58	200.85
Aug-10	80.72	73.20	79.73
Sep-10	501.81	502.85	463.69
Oct-10	472.37	412.32	428.76
Nov-10	584.37	600.11	583.52
Dec-10	346.93	244.92	228.84
Jan-11	177.34	209.92	244.67
Feb-11	133.96	102.83	99.51
Mar-11	133.81	119.00	123.15
Apr-11	483.66	462.26	471.85
May-11	485.90	400.64	387.82
Jun-11	251.64	207.91	232.15
Jul-11	104.36	118.13	136.36
Aug-11	221.11	238.08	256.20
Sep-11	209.04	194.86	207.89
Oct-11	462.51	458.01	453.78
Nov-11	262.91	255.98	252.78
Dec-11	93.84	90.03	91.26
Jan-12	64.01	54.71	46.37
Feb-12	166.70	157.86	140.07
Mar-12	88.78	65.96	66.93
Apr-12	491.74	442.02	474.28
May-12	106.19	76.38	79.83
Jun-12	227.60	262.15	305.20
Jul-12	117.42	139.68	162.07
Aug-12	294.14	289.17	293.73
Sep-12	184.35	204.96	229.55

Table E - 4 Areal average rainfall comparison of various Optimization stages - Verification Period (2012-2015)

Month-Year	Areal Average Rainfall (mm)		
	Optimization I	Optimization II	Optimization III
Oct-12	650.79	624.63	581.73
Nov-12	324.25	304.73	328.22
Dec-12	220.80	238.52	256.17
Jan-13	129.38	72.86	72.87
Feb-13	161.08	167.11	179.51
Mar-13	288.09	240.36	223.69
Apr-13	193.07	142.91	128.15
May-13	413.05	299.55	298.79
Jun-13	496.49	360.03	352.95
Jul-13	239.69	191.10	185.96
Aug-13	84.14	83.92	75.92
Sep-13	436.58	370.76	349.75
Oct-13	290.26	251.76	256.79
Nov-13	421.00	398.43	419.11
Dec-13	47.60	28.71	25.31
Jan-14	76.93	73.29	75.58
Feb-14	42.54	38.15	34.73
Mar-14	221.14	212.65	229.71
Apr-14	398.35	349.95	345.16
May-14	247.90	225.15	237.26
Jun-14	349.59	317.14	303.07
Jul-14	181.04	148.91	142.12
Aug-14	314.26	316.51	316.30
Sep-14	301.96	301.09	313.05
Oct-14	502.18	475.74	452.16
Nov-14	228.49	199.18	194.76
Dec-14	569.31	450.51	386.46
Jan-15	23.28	27.50	33.21
Feb-15	111.34	90.06	102.14
Mar-15	226.15	197.38	211.31
Apr-15	405.99	377.65	387.26
May-15	312.56	281.12	262.91
Jun-15	414.94	301.92	306.10
Jul-15	45.03	42.06	44.01
Aug-15	222.19	216.64	215.50
Sep-15	288.23	286.15	284.88

Table E - 5 Areal average rainfall comparison of various Optimization stages - Verification Period (2015-2017)

Month-Year	Areal Average Rainfall (mm)		
	Optimization I	Optimization II	Optimization III
Oct-15	654.93	682.37	689.84
Nov-15	468.81	467.14	474.41
Dec-15	257.53	258.23	259.05
Jan-16	23.61	23.20	25.72
Feb-16	32.93	33.88	36.45
Mar-16	102.41	82.08	81.80
Apr-16	317.83	322.53	334.80
May-16	1070.03	1038.39	1075.74
Jun-16	170.57	155.94	164.91
Jul-16	99.27	106.30	96.98
Aug-16	25.57	23.78	20.36
Sep-16	32.52	30.29	31.38
Oct-16	203.20	176.96	178.93
Nov-16	346.60	276.72	301.76
Dec-16	34.87	28.43	29.53
Jan-17	66.75	84.83	84.43
Feb-17	29.70	35.27	29.89
Mar-17	394.28	359.55	398.93
Apr-17	177.98	199.12	240.96
May-17	455.07	449.60	486.46
Jun-17	246.45	255.10	277.77
Jul-17	109.26	138.70	167.42
Aug-17	207.98	197.72	220.08
Sep-17	654.15	526.83	639.96

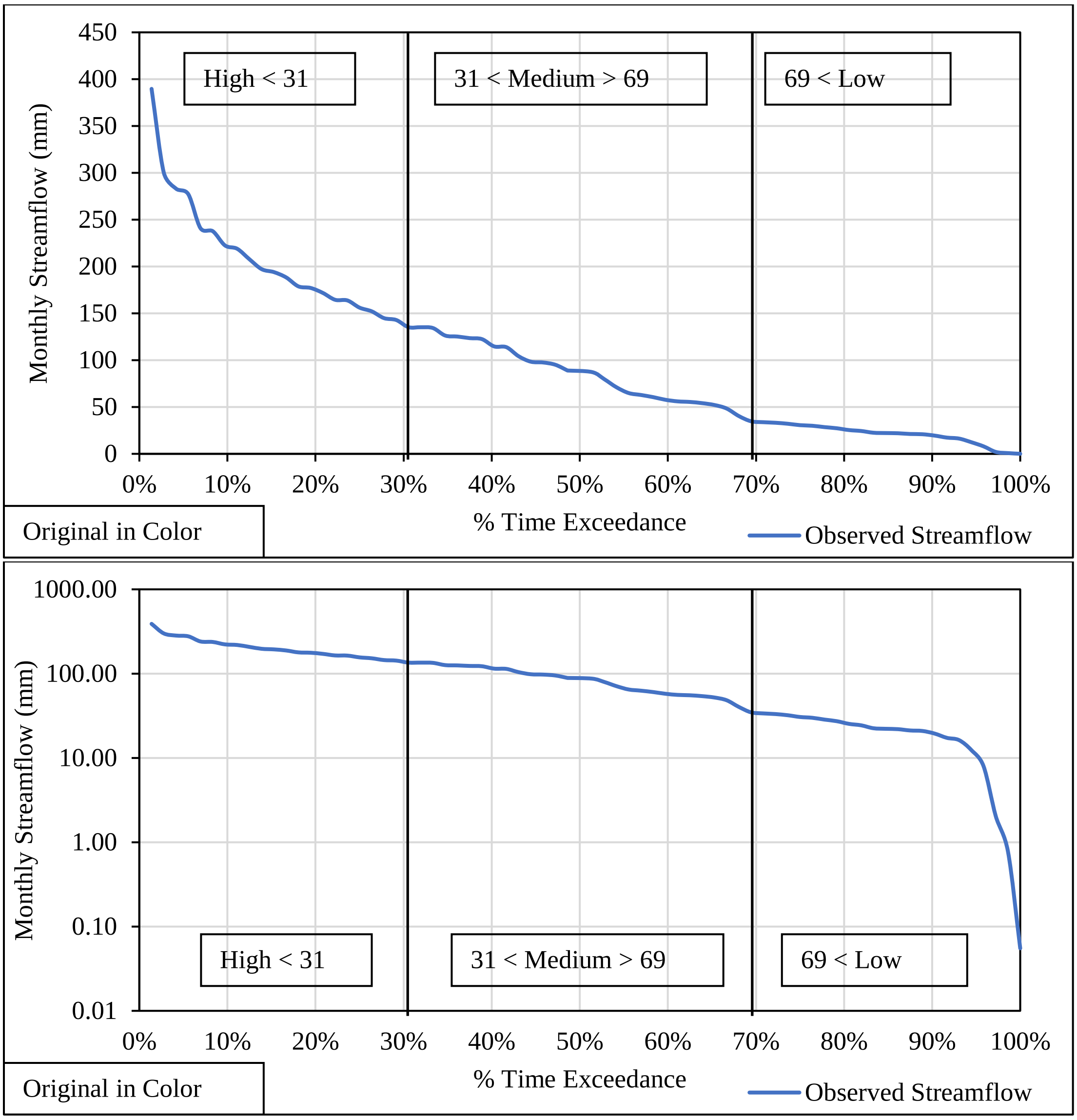


Figure E - 1 Flow duration curve for Calibration period - Dunamale Watershed

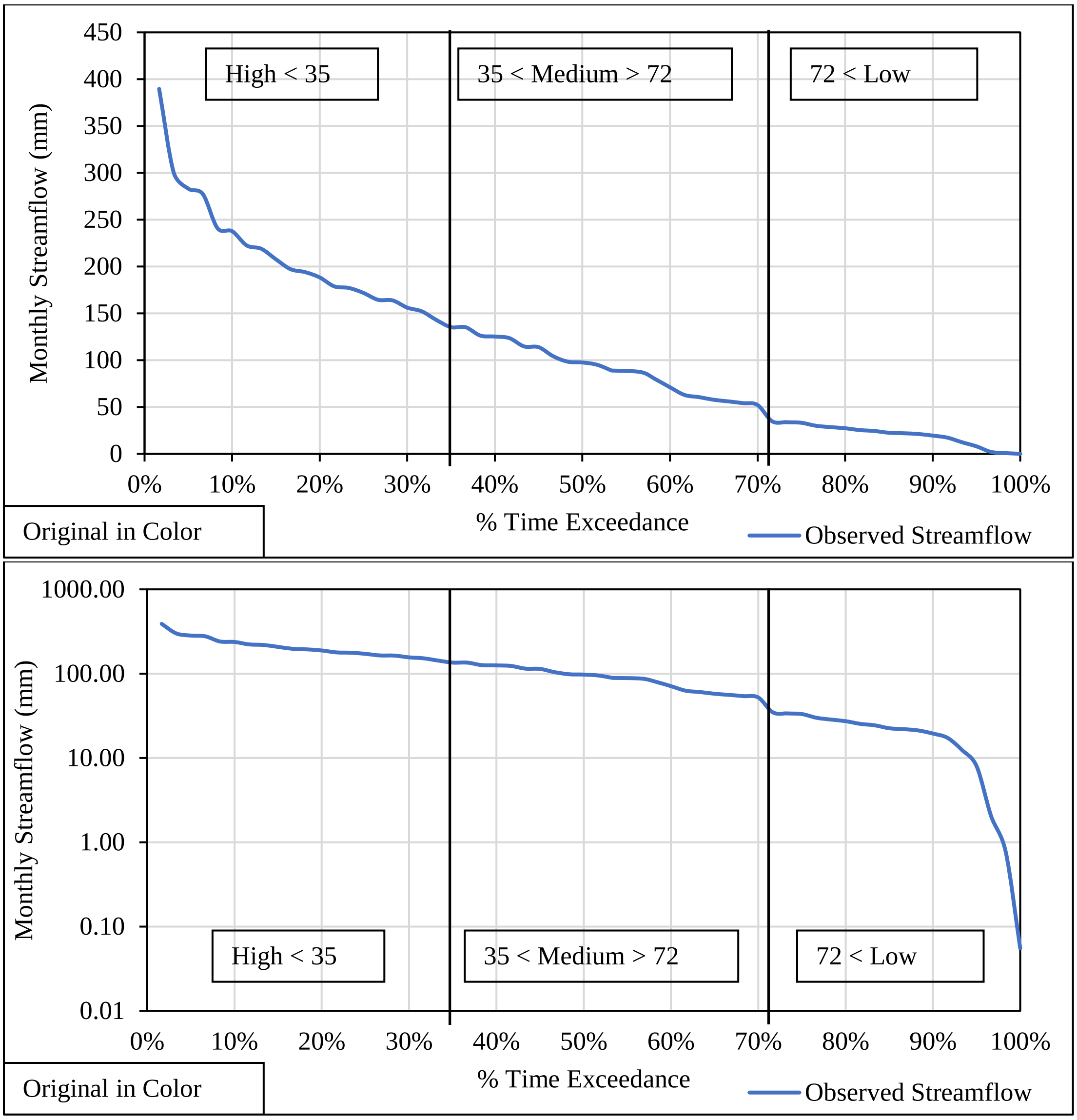


Figure E - 2 Flow duration curve for Verification period - Dunamale Watershed

Table E - 6 Two-Parameter Model Calibration for year 2006-2009 (Model Parameter Optimization) – Dunamale Watershed

Month-Year	Rainfall, P (mm)	Pan Evaporation, EP (mm)	Observed Streamflow, Qo (mm)	Simulated Streamflow, Qs (mm)
Oct-06	798.46	95.50	277.22	540.17
Nov-06	672.36	86.70	389.66	504.65
Dec-06	93.19	88.90	95.11	33.30
Jan-07	62.13	111.80	28.52	9.29
Feb-07	23.31	118.00	8.00	4.04
Mar-07	124.82	133.30	0.06	0.06
Apr-07	494.84	108.70	126.28	103.36
May-07	245.10	100.40	88.93	75.40
Jun-07	244.80	99.40	97.54	67.02
Jul-07	186.95	99.20	54.12	38.24
Aug-07	152.40	100.20	24.38	17.53
Sep-07	358.70	99.10	178.80	91.52
Oct-07	460.82	82.70	177.09	269.17
Nov-07	263.69	102.10	164.46	104.15
Dec-07	158.26	89.20	57.71	44.30
Jan-08	48.66	100.00	19.47	14.69
Feb-08	225.17	109.70	25.38	17.88
Mar-08	448.87	93.30	197.17	166.75
Apr-08	591.95	97.20	237.72	406.01
May-08	427.43	107.50	194.03	221.47
Jun-08	275.39	99.90	218.91	113.09
Jul-08	370.87	89.00	163.80	184.53
Aug-08	95.58	103.50	33.76	34.39
Sep-08	144.36	113.00	62.84	11.15
Oct-08	701.58	95.40	240.87	392.45
Nov-08	319.87	81.00	142.89	171.61
Dec-08	98.07	102.10	88.93	33.93
Jan-09	85.24	117.70	27.31	7.85
Feb-09	45.07	125.80	0.77	1.53
Mar-09	254.64	116.80	33.16	6.96
Apr-09	375.76	100.70	125.23	79.58
May-09	246.48	113.10	79.72	56.98
Jun-09	270.64	94.70	87.28	77.73
Jul-09	155.44	109.40	60.52	26.83
Aug-09	235.17	109.30	52.13	30.04
Sep-09	327.82	101.30	113.87	84.89

Table E - 7 Two-Parameter Model Calibration for year 2009-2012 (Model Parameter Optimization) – Dunamale Watershed

Month-Year	Rainfall, P (mm)	Pan Evaporation, EP (mm)	Observed Streamflow, Qo (mm)	Simulated Streamflow, Qs (mm)
Oct-09	338.73	106.80	152.10	121.46
Nov-09	326.20	57.90	188.35	199.35
Dec-09	254.80	86.10	123.52	114.76
Jan-10	75.92	131.60	34.76	24.70
Feb-10	43.93	121.20	2.04	8.14
Mar-10	192.78	129.80	21.18	2.54
Apr-10	558.25	98.50	135.22	201.92
May-10	599.95	78.60	300.17	460.50
Jun-10	251.33	94.70	135.16	96.55
Jul-10	237.93	98.20	98.37	71.69
Aug-10	80.72	106.70	12.41	18.73
Sep-10	501.81	95.50	104.21	210.82
Oct-10	472.37	100.50	207.71	280.31
Nov-10	584.37	62.10	283.13	483.08
Dec-10	346.93	65.80	222.50	211.41
Jan-11	177.34	93.10	56.00	62.79
Feb-11	133.96	90.50	22.51	25.72
Mar-11	133.81	120.60	17.32	6.02
Apr-11	483.66	98.60	114.70	155.85
May-11	485.90	107.10	171.80	272.40
Jun-11	251.64	105.70	156.07	92.46
Jul-11	104.36	106.00	29.96	23.41
Aug-11	221.11	113.30	21.96	21.21
Sep-11	209.04	107.80	71.06	19.19
Oct-11	462.51	111.50	134.28	152.53
Nov-11	262.91	83.10	144.87	118.21
Dec-11	93.84	90.30	64.88	30.62
Jan-12	64.01	121.10	32.11	7.96
Feb-12	166.70	101.20	16.27	4.81
Mar-12	88.78	129.20	20.91	0.00
Apr-12	491.74	93.00	122.47	122.48
May-12	106.19	122.20	48.38	25.06
Jun-12	227.60	101.10	40.33	31.35
Jul-12	117.42	112.70	30.62	7.94
Aug-12	294.14	107.60	22.18	34.22
Sep-12	184.35	96.90	55.39	25.12

Table E - 8 Two-Parameter Model Verification for year 2012-2015 (Model Parameter Optimization) – Dunamale Watershed

Month-Year	Rainfall, P (mm)	Pan Evaporation, EP (mm)	Observed Streamflow, Qo (mm)	Simulated Streamflow, Qs (mm)
Oct-12	650.79	91.90	375.30	526.18
Nov-12	324.25	87.50	398.90	406.93
Dec-12	220.80	82.80	171.30	133.17
Jan-13	129.38	112.40	64.90	89.25
Feb-13	161.08	103.80	42.80	104.02
Mar-13	288.09	117.90	155.00	230.06
Apr-13	193.07	127.70	115.40	103.36
May-13	413.05	95.60	257.50	375.40
Jun-13	496.49	84.00	445.30	367.02
Jul-13	239.69	93.90	199.30	138.24
Aug-13	84.14	109.80	53.10	17.53
Sep-13	436.58	99.80	344.80	391.52
Oct-13	290.26	104.20	203.50	269.17
Nov-13	421.00	88.80	400.20	304.15
Dec-13	47.60	105.40	126.70	44.30
Jan-14	76.93	116.70	34.80	14.69
Feb-14	42.54	118.20	0.60	17.88
Mar-14	221.14	129.20	48.40	166.75
Apr-14	398.35	118.40	226.00	406.01
May-14	247.90	108.20	242.00	221.47
Jun-14	349.59	102.80	267.60	113.09
Jul-14	181.04	115.00	85.70	184.53
Aug-14	314.26	104.30	201.50	334.39
Sep-14	301.96	106.80	209.20	211.15
Oct-14	502.18	81.60	509.40	392.45
Nov-14	228.49	67.30	338.90	171.61
Dec-14	569.31	67.80	496.90	533.93
Jan-15	23.28	118.30	118.40	7.85
Feb-15	111.34	100.20	23.70	91.53
Mar-15	226.15	109.70	72.90	206.96
Apr-15	405.99	114.40	327.10	379.58
May-15	312.56	115.70	325.90	256.98
Jun-15	414.94	95.20	246.10	477.73
Jul-15	45.03	120.80	76.50	26.83
Aug-15	222.19	119.50	49.50	230.04
Sep-15	288.23	88.40	242.30	184.89

Table E - 9 Two-Parameter Model Verification for year 2015-2017 (Model Parameter Optimization) – Dunamale Watershed

Month-Year	Rainfall, P (mm)	Pan Evaporation, EP (mm)	Observed Streamflow, Qo (mm)	Simulated Streamflow, Qs (mm)
Oct-15	654.93	101.70	547.80	521.46
Nov-15	468.81	85.80	588.40	499.35
Dec-15	257.53	81.30	400.80	114.76
Jan-16	23.61	110.10	56.20	24.70
Feb-16	32.93	121.20	4.40	8.14
Mar-16	102.41	153.90	15.80	62.54
Apr-16	317.83	137.40	72.30	201.92
May-16	1070.03	87.80	723.60	860.50
Jun-16	170.57	105.00	304.40	96.55
Jul-16	99.27	116.20	71.70	71.69
Aug-16	25.57	163.10	11.30	18.73
Sep-16	32.52	130.10	5.60	10.82
Oct-16	203.20	125.40	24.40	280.31
Nov-16	346.60	99.30	209.60	383.08
Dec-16	34.87	102.80	43.10	11.41
Jan-17	66.75	115.70	9.70	62.79
Feb-17	29.70	83.60	1.00	25.72
Mar-17	394.28	10.20	153.20	326.02
Apr-17	177.98	132.10	129.90	155.85
May-17	455.07	115.00	216.30	372.40
Jun-17	246.45	95.80	245.30	192.46
Jul-17	109.26	118.10	88.20	123.41
Aug-17	207.98	121.40	26.60	121.21
Sep-17	654.15	97.80	526.50	519.19

Table E - 10 Two-Parameter Model Calibration for year 2006-2009 (Rainfall Station Weight Optimization) – Dunamale Watershed

Month-Year	Rainfall, P (mm)	Pan Evaporation, EP (mm)	Observed Streamflow, Qo (mm)	Simulated Streamflow, Qs (mm)
Oct-06	835.97	95.50	277.22	584.17
Nov-06	669.02	86.70	389.66	493.32
Dec-06	90.72	88.90	95.11	33.65
Jan-07	58.76	111.80	28.52	9.72
Feb-07	15.77	118.00	8.00	5.22
Mar-07	151.06	133.30	0.06	0.06
Apr-07	482.38	108.70	126.28	99.35
May-07	231.76	100.40	88.93	67.09
Jun-07	235.17	99.40	97.54	58.76
Jul-07	192.69	99.20	54.12	37.35
Aug-07	190.02	100.20	24.38	26.62
Sep-07	385.55	99.10	178.80	122.69
Oct-07	421.78	82.70	177.09	244.95
Nov-07	298.76	102.10	164.46	127.87
Dec-07	112.56	89.20	57.71	35.22
Jan-08	48.50	100.00	19.47	11.72
Feb-08	233.48	109.70	25.38	17.53
Mar-08	485.12	93.30	197.17	197.09
Apr-08	603.55	97.20	237.72	424.53
May-08	478.23	107.50	194.03	268.07
Jun-08	285.79	99.90	218.91	121.99
Jul-08	359.56	89.00	163.80	177.86
Aug-08	91.09	103.50	33.76	33.77
Sep-08	119.63	113.00	62.84	8.77
Oct-08	707.10	95.40	240.87	389.46
Nov-08	320.89	81.00	142.89	172.69
Dec-08	111.71	102.10	88.93	35.38
Jan-09	86.02	117.70	27.31	8.25
Feb-09	54.55	125.80	0.77	1.17
Mar-09	270.91	116.80	33.16	9.19
Apr-09	357.96	100.70	125.23	74.28
May-09	234.78	113.10	79.72	49.88
Jun-09	283.75	94.70	87.28	81.28
Jul-09	167.67	109.40	60.52	30.67
Aug-09	239.04	109.30	52.13	33.95
Sep-09	327.04	101.30	113.87	88.15

Table E - 11 Two-Parameter Model Calibration for year 2009-2012 (Rainfall Station Weight Optimization) – Dunamale Watershed

Month-Year	Rainfall, P (mm)	Pan Evaporation, EP (mm)	Observed Streamflow, Qo (mm)	Simulated Streamflow, Qs (mm)
Oct-09	332.88	106.80	152.10	118.68
Nov-09	293.06	57.90	188.35	169.89
Dec-09	223.28	86.10	123.52	90.83
Jan-10	52.10	131.60	34.76	24.83
Feb-10	46.83	121.20	2.04	7.81
Mar-10	192.66	129.80	21.18	2.39
Apr-10	523.10	98.50	135.22	170.49
May-10	507.89	78.60	300.17	353.41
Jun-10	224.67	94.70	135.16	86.72
Jul-10	190.58	98.20	98.37	46.34
Aug-10	73.20	106.70	12.41	12.68
Sep-10	502.85	95.50	104.21	197.79
Oct-10	412.32	100.50	207.71	221.22
Nov-10	600.11	62.10	283.13	498.41
Dec-10	244.92	65.80	222.50	125.58
Jan-11	209.92	93.10	56.00	68.78
Feb-11	102.83	90.50	22.51	21.83
Mar-11	119.00	120.60	17.32	4.19
Apr-11	462.26	98.60	114.70	131.68
May-11	400.64	107.10	171.80	186.94
Jun-11	207.91	105.70	156.07	64.89
Jul-11	118.13	106.00	29.96	18.68
Aug-11	238.08	113.30	21.96	22.84
Sep-11	194.86	107.80	71.06	16.65
Oct-11	458.01	111.50	134.28	144.28
Nov-11	255.98	83.10	144.87	111.81
Dec-11	90.03	90.30	64.88	29.28
Jan-12	54.71	121.10	32.11	8.46
Feb-12	157.86	101.20	16.27	4.14
Mar-12	65.96	129.20	20.91	0.03
Apr-12	442.02	93.00	122.47	90.97
May-12	76.38	122.20	48.38	21.48
Jun-12	262.15	101.10	40.33	42.12
Jul-12	139.68	112.70	30.62	13.19
Aug-12	289.17	107.60	22.18	39.67
Sep-12	204.96	96.90	55.39	34.80

Table E - 12 Two-Parameter Model Verification for year 2012-2015 (Rainfall Station Weight Optimization) – Dunamale Watershed

Month-Year	Rainfall, P (mm)	Pan Evaporation, EP (mm)	Observed Streamflow, Qo (mm)	Simulated Streamflow, Qs (mm)
Oct-12	624.63	91.90	375.3	570.04
Nov-12	304.73	87.50	398.9	395.77
Dec-12	238.52	82.80	171.3	233.52
Jan-13	72.86	112.40	64.9	39.67
Feb-13	167.11	103.80	42.8	115.20
Mar-13	240.36	117.90	155	260.05
Apr-13	142.91	127.70	115.4	99.27
May-13	299.55	95.60	257.5	267.07
Jun-13	360.03	84.00	445.3	358.75
Jul-13	191.10	93.90	199.3	137.35
Aug-13	83.92	109.80	53.1	26.62
Sep-13	370.76	99.80	344.8	222.68
Oct-13	251.76	104.20	203.5	244.95
Nov-13	398.43	88.80	400.2	327.87
Dec-13	28.71	105.40	126.7	35.22
Jan-14	73.29	116.70	34.8	11.72
Feb-14	38.15	118.20	0.6	17.53
Mar-14	212.65	129.20	48.4	197.09
Apr-14	349.95	118.40	226	324.53
May-14	225.15	108.20	242	268.07
Jun-14	317.14	102.80	267.6	321.99
Jul-14	148.91	115.00	85.7	177.86
Aug-14	316.51	104.30	201.5	333.77
Sep-14	301.09	106.80	209.2	368.77
Oct-14	475.74	81.60	509.4	489.46
Nov-14	199.18	67.30	338.9	172.69
Dec-14	450.51	67.80	496.9	435.38
Jan-15	27.50	118.30	118.4	8.25
Feb-15	90.06	100.20	23.7	91.17
Mar-15	197.38	109.70	72.9	169.19
Apr-15	377.65	114.40	327.1	374.28
May-15	281.12	115.70	325.9	249.88
Jun-15	301.92	95.20	246.1	381.28
Jul-15	42.06	120.80	76.5	30.67
Aug-15	216.64	119.50	49.5	233.95
Sep-15	286.15	88.40	242.3	288.15

Table E - 13 Two-Parameter Model Verification for year 2015-2017 (Rainfall Station Weight Optimization) – Dunamale Watershed

Month-Year	Rainfall, P (mm)	Pan Evaporation, EP (mm)	Observed Streamflow, Qo (mm)	Simulated Streamflow, Qs (mm)
Oct-15	682.37	101.70	547.8	118.68
Nov-15	467.14	85.80	588.4	69.89
Dec-15	258.23	81.30	400.8	90.83
Jan-16	23.20	110.10	56.2	124.83
Feb-16	33.88	121.20	4.4	97.81
Mar-16	82.08	153.90	15.8	132.39
Apr-16	322.53	137.40	72.3	170.49
May-16	1038.39	87.80	723.6	53.41
Jun-16	155.94	105.00	304.4	186.72
Jul-16	106.30	116.20	71.7	146.34
Aug-16	23.78	163.10	11.3	112.68
Sep-16	30.29	130.10	5.6	197.79
Oct-16	176.96	125.40	24.4	121.22
Nov-16	276.72	99.30	209.6	98.41
Dec-16	28.43	102.80	43.1	125.58
Jan-17	84.83	115.70	9.7	168.78
Feb-17	35.27	83.60	1	21.83
Mar-17	359.55	10.20	153.2	4.19
Apr-17	199.12	132.10	129.9	131.68
May-17	449.60	115.00	216.3	186.94
Jun-17	255.10	95.80	245.3	64.89
Jul-17	138.70	118.10	88.2	118.68
Aug-17	197.72	121.40	26.6	82.84
Sep-17	526.83	97.80	526.5	516.65

Table E - 14 Two-Parameter Model Calibration for year 2006-2009 (Model Parameter & Rainfall Station Weight Optimization) – Dunamale Watershed

Month-Year	Rainfall, P (mm)	Pan Evaporation, EP (mm)	Observed Streamflow, Qo (mm)	Simulated Streamflow, Qs (mm)
Oct-06	809.71	95.50	277.22	510.53
Nov-06	698.11	86.70	389.66	531.27
Dec-06	88.32	88.90	95.11	35.46
Jan-07	59.36	111.80	28.52	9.99
Feb-07	19.65	118.00	8.00	4.79
Mar-07	129.26	133.30	0.06	0.06
Apr-07	482.84	108.70	126.28	83.57
May-07	231.50	100.40	88.93	58.93
Jun-07	257.75	99.40	97.54	62.38
Jul-07	197.07	99.20	54.12	37.96
Aug-07	178.72	100.20	24.38	21.75
Sep-07	373.67	99.10	178.80	98.64
Oct-07	434.02	82.70	177.09	235.64
Nov-07	317.86	102.10	164.46	138.38
Dec-07	105.98	89.20	57.71	35.57
Jan-08	57.30	100.00	19.47	10.69
Feb-08	229.47	109.70	25.38	13.23
Mar-08	508.36	93.30	197.17	191.87
Apr-08	636.71	97.20	237.72	445.84
May-08	507.30	107.50	194.03	289.51
Jun-08	292.42	99.90	218.91	125.23
Jul-08	359.12	89.00	163.80	171.09
Aug-08	96.52	103.50	33.76	34.18
Sep-08	113.35	113.00	62.84	7.90
Oct-08	725.06	95.40	240.87	379.32
Nov-08	338.08	81.00	142.89	186.99
Dec-08	104.99	102.10	88.93	36.39
Jan-09	82.96	117.70	27.31	8.23
Feb-09	55.98	125.80	0.77	0.97
Mar-09	291.55	116.80	33.16	10.39
Apr-09	386.80	100.70	125.23	85.56
May-09	238.35	113.10	79.72	51.96
Jun-09	294.65	94.70	87.28	83.44
Jul-09	187.51	109.40	60.52	35.22
Aug-09	256.61	109.30	52.13	40.01
Sep-09	332.02	101.30	113.87	89.42

Table E - 15 Two-Parameter Model Calibration for year 2009-2012 (Model Parameter & Rainfall Station Weight Optimization) – Dunamale Watershed

Month-Year	Rainfall, P (mm)	Pan Evaporation, EP (mm)	Observed Streamflow, Qo (mm)	Simulated Streamflow, Qs (mm)
Oct-09	329.61	106.80	152.10	310.31
Nov-09	309.19	57.90	188.35	374.53
Dec-09	252.74	86.10	123.52	208.00
Jan-10	45.24	131.60	34.76	30.29
Feb-10	55.29	121.20	2.04	98.49
Mar-10	185.27	129.80	21.18	101.50
Apr-10	569.26	98.50	135.22	585.10
May-10	494.00	78.60	300.17	430.72
Jun-10	232.87	94.70	135.16	293.02
Jul-10	200.85	98.20	98.37	250.13
Aug-10	79.73	106.70	12.41	13.09
Sep-10	463.69	95.50	104.21	451.76
Oct-10	428.76	100.50	207.71	419.09
Nov-10	583.52	62.10	283.13	467.53
Dec-10	228.84	65.80	222.50	219.77
Jan-11	244.67	93.10	56.00	183.86
Feb-11	99.51	90.50	22.51	24.59
Mar-11	123.15	120.60	17.32	104.53
Apr-11	471.85	98.60	114.70	427.19
May-11	387.82	107.10	171.80	366.49
Jun-11	232.15	105.70	156.07	173.03
Jul-11	136.36	106.00	29.96	122.23
Aug-11	256.20	113.30	21.96	228.09
Sep-11	207.89	107.80	71.06	220.68
Oct-11	453.78	111.50	134.28	435.62
Nov-11	252.78	83.10	144.87	204.45
Dec-11	91.26	90.30	64.88	78.14
Jan-12	46.37	121.10	32.11	48.91
Feb-12	140.07	101.20	16.27	132.25
Mar-12	66.93	129.20	20.91	60.17
Apr-12	474.28	93.00	122.47	497.24
May-12	79.83	122.20	48.38	22.31
Jun-12	305.20	101.10	40.33	358.05
Jul-12	162.07	112.70	30.62	120.26
Aug-12	293.73	107.60	22.18	244.77
Sep-12	229.55	96.90	55.39	244.17

Table E - 16 Two-Parameter Model Verification for year 2012-2015 (Model Parameter & Rainfall Station Weight Optimization) – Dunamale Watershed

Month-Year	Rainfall, P (mm)	Pan Evaporation, EP (mm)	Observed Streamflow, Qo (mm)	Simulated Streamflow, Qs (mm)
Oct-12	581.73	91.90	375.3	499.56
Nov-12	328.22	87.50	398.9	432.80
Dec-12	256.17	82.80	171.3	235.38
Jan-13	72.87	112.40	64.9	79.96
Feb-13	179.51	103.80	42.8	164.78
Mar-13	223.69	117.90	155	210.06
Apr-13	128.15	127.70	115.4	183.57
May-13	298.79	95.60	257.5	258.93
Jun-13	352.95	84.00	445.3	362.38
Jul-13	185.96	93.90	199.3	137.96
Aug-13	75.92	109.80	53.1	51.75
Sep-13	349.75	99.80	344.8	398.64
Oct-13	256.79	104.20	203.5	235.64
Nov-13	419.11	88.80	400.2	438.38
Dec-13	25.31	105.40	126.7	35.57
Jan-14	75.58	116.70	34.8	50.69
Feb-14	34.73	118.20	0.6	13.23
Mar-14	229.71	129.20	48.4	271.87
Apr-14	345.16	118.40	226	345.84
May-14	237.26	108.20	242	289.51
Jun-14	303.07	102.80	267.6	325.23
Jul-14	142.12	115.00	85.7	171.09
Aug-14	316.30	104.30	201.5	334.18
Sep-14	313.05	106.80	209.2	307.90
Oct-14	452.16	81.60	509.4	479.32
Nov-14	194.76	67.30	338.9	186.99
Dec-14	386.46	67.80	496.9	36.39
Jan-15	33.21	118.30	118.4	8.23
Feb-15	102.14	100.20	23.7	0.97
Mar-15	211.31	109.70	72.9	10.39
Apr-15	387.26	114.40	327.1	85.56
May-15	262.91	115.70	325.9	51.96
Jun-15	306.10	95.20	246.1	83.44
Jul-15	44.01	120.80	76.5	35.22
Aug-15	215.50	119.50	49.5	40.01
Sep-15	284.88	88.40	242.3	89.42

Table E - 17 Two-Parameter Model Verification for year 2015-2017 (Model Parameter & Rainfall Station Weight Optimization) – Dunamale Watershed

Month-Year	Rainfall, P (mm)	Pan Evaporation, EP (mm)	Observed Streamflow, Qo (mm)	Simulated Streamflow, Qs (mm)
Oct-15	689.84	101.70	547.8	670.31
Nov-15	474.41	85.80	588.4	464.53
Dec-15	259.05	81.30	400.8	248.00
Jan-16	25.72	110.10	56.2	30.29
Feb-16	36.45	121.20	4.4	38.49
Mar-16	81.80	153.90	15.8	71.50
Apr-16	334.80	137.40	72.3	285.10
May-16	1075.74	87.80	723.6	1030.72
Jun-16	164.91	105.00	304.4	193.02
Jul-16	96.98	116.20	71.7	50.13
Aug-16	20.36	163.10	11.3	13.09
Sep-16	31.38	130.10	5.6	51.76
Oct-16	178.93	125.40	24.4	219.09
Nov-16	301.76	99.30	209.6	367.53
Dec-16	29.53	102.80	43.1	119.77
Jan-17	84.43	115.70	9.7	83.86
Feb-17	29.89	83.60	1	24.59
Mar-17	398.93	10.20	153.2	374.53
Apr-17	240.96	132.10	129.9	127.19
May-17	486.46	115.00	216.3	166.49
Jun-17	277.77	95.80	245.3	273.03
Jul-17	167.42	118.10	88.2	122.23
Aug-17	220.08	121.40	26.6	128.09
Sep-17	639.96	97.80	526.5	520.68

The findings, interpretations and conclusions expressed in this thesis/dissertation are entirely based on the results of the individual research study and should not be attributed in any manner to or do neither necessarily reflect the views of UNESCO Madanjeet Singh Centre for South Asia Water Management (UMCSAWM), nor of the individual members of the MSc panel, nor of their respective organizations.