OPTIMIZATION OF RAINFALL SPATIAL VARIABILITY FOR DAILY STREAMFLOW ESTIMATION WITH A MONTHLY WATER BALANCE MODEL

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Thesis submitted in partial fulfillment of the requirements for the Degree of Master of Science in Water Resources Engineering and Management

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DECLARATION

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ABSTRACT

Precipitation varies significantly over space and time within a watershed. Precipitation has a vital role in determining surface hydrological processes because of its influence on streamflow estimations using mathematical models. Though monthly rainfall data provides ease of access due to availability and affordability, daily data is the preferred option of engineers, planners and water managers. This is because daily time resolution is considered as a unit which reasonably represent the catchment time lag. If a water model calibrated using monthly data could estimate daily streamflow from a watershed, then this would be of immense value for sustainable water resources management. The three-parameter monthly water balance model (3PMWBM) proposed by (Dissanayake, 2017) has demonstrated the capability with an application on 2 watersheds in Sri Lanka while using Thiessen averaging method for rainfall input. Wijesekera and Musiake (1990a, 1990b) had optimized both rainfall station weights and model parameters for improved streamflow estimations by enabling the calibration of point rainfall measurements to generate a spatially averaged rainfall to reflect the response of the corresponding watershed. The study objective is to estimate streamflow in daily timescale using a monthly water balance model while optimizing the spatial variability of rainfall leading to enhanced water security and sustainable water management. Daily data from 2005 to 2014 of 4 rainfall stations of Badalgama watershed (1360 km^2) in Ma Oya Basin, Sri Lanka are used to evaluate the streamflow predictions with the 3PMWBM when rainfall station weights are optimized. The 3PMWBM was developed, calibrated and verified with and without optimizing the rainfall gauging station weights. A spreadsheet tool and an object oriented modelling tool was used for the model development. Mean Ratio of Absolute Error (MRAE) was selected as the objective function during calibration and verification. The high, medium and low flow determined from observations and annual water balance were also were used during evaluation. The optimum value based on literature and analysis for Sc, C and k are 908, 2.5 and 0.69 respectively for monthly model. The MRAE calibration and verification results obtained at consecutive steps 0.41,0.409 and 0.36 and 0.60,0.62,0.50 i.e. optimizing model parameters, optimizing rainfall weights, optimizing model parameter and rainfall weights at the same time Thiessen weights are (0.26,0.19,0.20,0.35), (0.20,0.16,0.26,0.38) and (0.23,0.14,0.27,0.36) respectively for Ambepussa, Andigama, Aranayake and Eraminigolla stations. Daily streamflow estimations in Badalgama watershed using 3PMWBM with the optimization of rainfall station weights with optimum average MRAE 0.64. The study found that spatial variability of rainfall can significantly affect model results about 17% improvement in average MRAE at monthly scale when station weights and parameters are simultaneously optimized and under same case when the model is used for daily streamflow estimation, up to 8% improvements in average MRAE are noticed.

KEYWORDS: Daily streamflow estimation with monthly model, Station Weights, Rainfall spatial variability

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LIST OF ABBREVIATIONS

Abbreviation	Description
2PMWBM	Two Parameter Monthly Water Balance Model
3PMWBM	Three Parameter Monthly Water Balance Model
AWBM	Australian Water Balance Model
c	Parameter c
CRR	Conceptual Rainfall Runoff
E	Nash–Sutcliffe coefficient
Ef	Nash-Sutcliffe coefficient
ET	Evapotranspiration
FDC	Flow Duration Curve
GR2M	Global Reservoir 2 Parameter Model
GR5M	Global Reservoir 5 Parameter Model
K	Runoff Adjustment Factor
MRAE	Mean Ratio of Absolute Error
MRAE	Mean Ratio of Absolute Error
MSE	Mean Square Root
MWB	Monthly Water Balance
MWB-3	Monthly Water Balance Model with 3 Parameters
MWB-6	Monthly Water Balance Model with 6 Parameters
NAM	Nedbor-Afstromnings mode
NOPEX	A NOrthern hemisphere climate Processes landsurface EXperiment)
NSE	Nash Sutcliffe Efficiency
NSE	Nash-Sutcliffe Efficiency
P (t)	Rainfall
P Models	Precipitation Models
Par	Parameter
PE Models	Precipitation Evaporation Models
PTM	The Pitman model
Q (t)	Runoff
RAEM	Ratio of Absolute Error to Mean
RE	Relative Error
RE	Relative Error
RMSE	Mean Square Root Error
S (t)	Soil Moisture Content
SC	Field capacity of the catchment
SMA	The Sacramento model
TWS	Total Water Storage
USA	United States of America
WBM	Water Balance Model
XNJ	The Xinanjiang model

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1. INTRODUCTION

1.1. General

Growing global population is considered as a major factor behind today's water scarcity (SIWI, 2014) which results in an intense competition for scarce water resources in many places of the world (Molden, 2007). Correspondingly, changes to the water quantity with time is due to climate change leaving behind its adverse impacts on water resources (OECD, 2013). South Asian region which has its significant importance based on water resources (Jansen, 2009) has been experiencing long-term warming trends continuing into the future with anthropogenic climate change (Hijioka, et al., 2014). Warmer future climate increases evaporation and hence the demand for water rises with presence in projected changes in precipitation influencing and resulting in variations in the streamflow (Zheng, Chiew, & Charles, 2015).

In the context of Sri Lanka, from ancient times, water is considered as main natural resource for the economic development of the country due to which efforts made for the improvement of the social development indicator elevated the country ahead of other South Asian countries (NWSDB, 2002). Even though, the consumption of water in industry, in supply of services such as, drinking, recreation, tourism and hydro power generation has valued it as a prominent resource. However still new strategic approaches are proposed for water resources management in the national development program of Sri Lanka. The development in water resources will help in harnessing the optimum use of surface and groundwater resources for the augmentation of mega projects.

Since, water resources planners and managers play vital role in the proposal of mega projects with mathematical models for scientific studies and contribution to the society where data availability is deliberated as a key prerequisite for hydrological modelling studies. Data availability in terms of sufficient duration, resolution and access is a significant factor which planners find difficult but information demanding situation. Even the simplest mathematical models for hydrological studies requires at least eight years of daily data with sufficient rainfall, streamflow and evaporation stations (WMO, 2008). In view of a coarser resolution such as monthly will require about thirty years (Xiong & Guo, 1999) of data for the hydrological studies of water resources management.

Though monthly rainfall data provides ease of access due to availability and affordability (National Climatic Data Center [NCDC], 2019) & (Department of Meteorology [DoM], 2016), Since monthly data is affordable in cost than daily data a mathematical modelling exercise becomes more affordable if a monthly model is applied for water resources planning and management. In Sri Lanka monthly outputs are generated by Irrigation Department (Ponrajah, 1988).

Recently, with more competition for water there is a need for water resource planning at a finer data resolution. Daily models are being demanded by the industry as daily data is the preferred option of engineers, planners and water managers because daily time resolution is considered as a unit which reasonably represent the catchment time lag. To solve the need for the daily resolution "What if" a watershed model can be calibrated and verified with monthly data and put into use with the same parameters for a daily generated outputs? This will provide a solution for the affordability and availability associated with daily scale watershed models.

An attempt has been previously made by Dissanayake (2017) over two watersheds in Sri Lanka with satisfactory results but with concerns about making modifications with an additional parameter. This parameter may be due to a representation need in the soil mass modelling or a need to make modifications to the computation of areal average rainfall. In most of mathematical models the rainfall averaging is with the help of Thiessen method (Ball & Luk, 1998). However, since streamflow is a reflection of watershed response to rainfall, it is prudent to calibrate models providing the opportunity for the rain gauging station weights to be optimized by enabling the matching hydrographs.

The present research is an attempt to investigate the applicability of a monthly watershed model for daily predictions and to identify the effect on the results with the optimization of rainfall gauging station weights to better represent the rainfall station variability. Ma Oya basin at Badalgama watershed was selected to apply a Monthly Water Balance Model (MWBM) for daily streamflow estimation.

1.2. Study Objectives

1.2.1. Overall objective

The overall objective is to investigate the potential of a monthly water balance model with parameters calibrated using monthly data, in order to predict daily streamflow using daily inputs and then to identify the effect of optimizing rainfall station weights for effective and efficient water resources planning and management.

1.2.2. Specific objectives

1. To study current state of art for hydrologic modelling, develop simple water balance models, optimization of parameters and study behavior of spatial variability of rainfall.
2. Collection of Data, performing data checking and specifying the calibration and verification datasets for evaluation of model.
3. Developing, calibrating and verifying the three parameter monthly model to carry out computations for applicability of estimating daily streamflow.
4. Evaluating the results with discussions and making appropriate recommendations.

2. STUDY AREA

Badalgama is a sub-basin of the Ma Oya basin which basically hilly region locked by Aranyaka, Bible rock and Kadugnannwa with total catchment area of 1538 km^2 having river length of 130 km. In most of the parts of the catchment the average rainfall typically crosses 3800 mm per annum which results in the generation of 1485 million cubic meters of runoff. Ma Oya basin originates and flows through major four districts of the Sri Lanka which are Kegalle, Kurnegala, Gampha and a portion of Puttalum district covering Central, Sabaragamuwa and Western provinces. The extensive paddy, rubber, tea and coconut plantation characterizes the Ma Oya basin as a catchment with variety of land use. Ma Oya has very little hydro-power potential where the most important use of water is supplied for drinking purposes. The selected Badalgama watershed is a sub-watershed of Ma Oya Basin with a catchment area of 1324 km^2 (Figure 1.1).

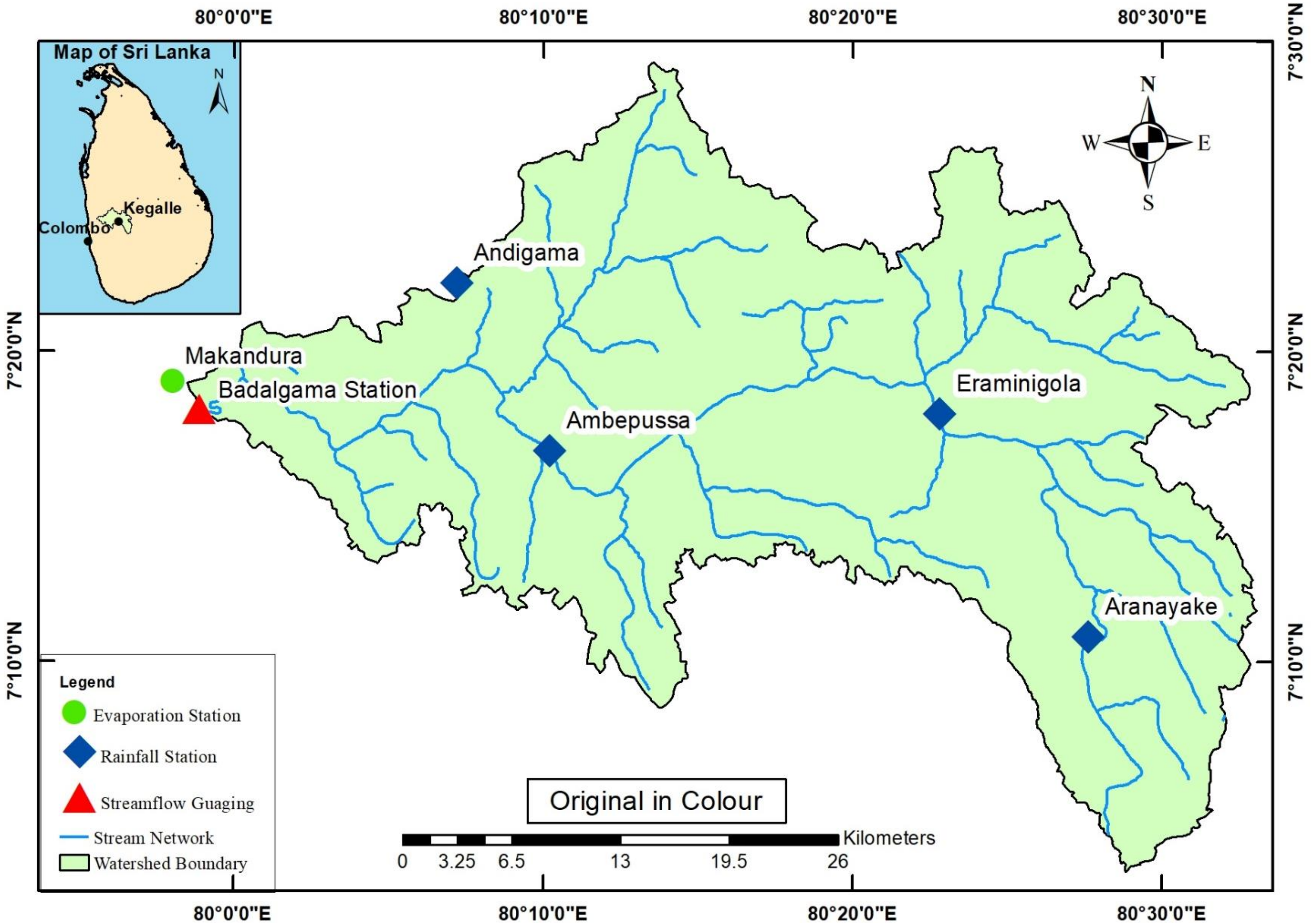


Figure 1.1: Project area – Badalgama watershed

3. LITERATURE REVIEW

3.1. Hydrological Models

As stated by Wheather, Sorooshian and Sharma (2008), a model is a simplified representation of a real world system and an ideal model is the one which provides outputs near to reality with use of least parameters (Bardossy & Singh, 2008) and lesser model complexity (Tegegne, Park, & Kim, 2017). Ekenberg (2016) describing a model as a system of inter-related components and relationships, a system analysis involves in breaking down the associated complexities into simple and manageable subsystems connected by flows of causality, matter, energy and information.

Therefore, this literature review focuses on streamflow estimation models which are simple for field applications in data scarce situations by optimizing the rainfall weights from gauged rainfall data so as to study the spatial variability of rainfall; in conjunction with an estimation of soil wetness for watershed management. Hence, the recent efforts on model evaluation, modelling, data access and evaluations, model calibration and model verification were studied and reviewed.

3.2. Types of Hydrological Models

Hydrological models are classified based on model input, parameters and the extent of physical principles applied in the model (Gayathri, Ganasri, & Dwarakish, 2015). There are various approaches to characterize and classify hydrological models. The most prominent distinction can be made based on the representation of spatial variability of the catchment. Models that do not take into account spatial variability of the input, and utilizes spatial averaging to deal with catchment behavior are known as Lumped Models. Contrariwise, models which describe spatial variability are called distributed models which usually has a node-link structure that present sub-catchment components (Fletcher et al., 2013).

3.3. Monthly Water Balance Models

Over the last century numerous models have been suggested for the estimation of streamflow from precipitation at the outlet of a basin. In which coarser time-steps have been called as water balance models, with assumptions that response time to be negligible compared to time step. Monthly water balance models are valuable tools for water resources management, reservoir simulation, drought assessment or long-term drought forecasting. There are a number of reasons that make monthly water balance models useful because of their inherent parsimony, lending to regionalization and their application over the ungauged basins. Since these models possess a very simple structure, monthly water balance models are easy to handle. Due to the low level of complexity, water balance models deal with most prominent features to transform rainfall transformation into streamflow (Muelhi, Michel, Perrin, & Andre´assian, 2006).

The growing inequality between supply and demand of water has grabbed the attention of the water resource planning programs. In this context the long-term forecasting of water cycle and its distribution has been one of the essential and popular topics. Monthly water balance models are used for long term forecasting of water resources distribution. These applications are mainly for assessment of climatic change impacts, reconstruction of the hydrology of catchments, and evaluation of the seasonal and geographical patterns of water supply and irrigation demand. Monthly Water balance models were initially introduced by Thornthwaite in 1940s which was well ahead reviewed by Thorthwaite and Mather(Singh & Xu, 1998).

Comparison of twelve monthly water balance models in different climate catchments of China has been carried out using daily precipitation data and monthly runoff data has been used between 1960 and 1989 for Yellow River Basin, and data between 1960 and 2000 for the Songhuajiang, the Pearl and Southeast River Basins which were respectively consist of 47, 45 and 61 catchments with the same order the catchments sizes varying from 385 to 65439 sq.km, 282 to 19019 sq.km and 102 to 128938 sq.km. Rainfall data has been collected from 256 stations for 153 catchments. After an analysis, authors stated that the median NSE values ranges between 0.30 and 0.50 for ten models, among which GR5M model with superior results, followed by the GR2M and WBM model. From results it was also mentioned that streamflow simulation in wet catchments is significantly better than that of dry catchments and reasons for poor performance in dry catchments are attributed to the high non-linearity and heterogeneity of rainfall-runoff process in these regions. The conclusions indicate that increasing the model complexity does not necessarily aid in better model performance. Complex models can achieve comparable or even worse performance than the simple models. While performing monthly simulations of hydrological processes, two parameter monthly model is sufficient to achieve a good result in simulation of monthly runoff (Bai, Liu, Liang, & Liu, 2015).

Trask, Fogg and Puente (2017) resolving hydrologic water balances through a novel error analysis approach with an application at Tahao basin of USA, introduced a new statistical method for refining estimates of water balance components which may be applicable to multi-period water balance series for a lake, watershed, or other areas of any size.

3.4. Two Parameter Water Balance Models

Xiong and Guo (1999) developed a two parameter monthly runoff model for seventy sub-catchments in the Dongjiang, Ganjiang and Hanjiang Basins in the south of China where the model results showed high efficiencies both in the calibration and validation datasets. Comparison of monthly water balance models shows that the two-parameter model results are as equal as a five parameter model performance (Xiong and Guo, 1999). This paper suggested that the two parameter monthly model can easily and efficiently be used for water resources planning and the climate impact studies for simulation of monthly streamflow for regions having humid and semi-humid climates.

Makhlouf & Michel (1994) carried out a two parameter monthly model study for 91 catchments of France, in which a conceptual lumped model was fed with monthly snow-free inputs. This study had indicated that monthly model operation cannot be applied on a daily basis for evaluating monthly outputs that makes the model without a physical basis. Hence with reasons that snow data cannot be applied to the model. Dissanayake (2017) identified that using the daily inputs for monthly model to compute daily outputs could estimate better streamflow for water resources management.

Muelhi, Michel, Perrin, & Andre´assian (2006) purposed a step wise development for monthly water balance models by studying 410 basins with a variety of climate conditions varying from semi-arid through temperate to tropical humid. The study had been performed to answer the relationship between parameters and catchment response. This step wise approach was adopted for the development of a pre-structured model which can encompass the components of existing model in a more efficient way and later the complexity is reduced systematically with final section to perform assessment with parent model scheme. Results revealed that rainfall-streamflow transformation at the basin scale is best answered at monthly time-step with successful application of GR2M.

3.5. Daily Water Balance Models

Singh and Xu (1998) performed a review of monthly water balance models where daily data was incorporated as input for monthly models. Daily time step was taken as input for the simulation of monthly streamflow in a model developed by Haan (1972). The inputs for the developed model were average potential evaporation and daily rainfall. Model was of two storages and four parameters applicable for small catchments without consideration of lag time. A water balance model was developed by Kuczera (1983a, 1983b) from previous efforts of Langford et al. (1978) for the Slip Creek catchment, which estimates monthly streamflow by incorporating daily time step and nine parameters. The water balance model having two storages where first storage behaving as quick response storage contributing to quick response flow and the later contributing to the base flow; additionally, the seepage loss function also remained as one of the components in the model for undertaking the behavior of annual water and stream chemistry recommended to strengthen the representation of streamflow (Singh & Xu, 1998).

McMahon and Mein adjusted the daily water balance model introduced by Boughton (1973) by introducing a baseflow routine with a double recession characteristics, and applied model to estimate monthly streamflow for Thomson River in Narrows. Authors came to a conclusion that daily precipitation as input can improve the estimation for such processes like infiltration, interception, depression storage and evapotranspiration. On the other hand, application of daily data may increase the amount of effort required for modelling and may limit research to fewer catchments instead of water balance calculations over large geographical units (Singh & Xu, 1998).

A conceptual daily model was developed by Bari and Smettem (2006) to illustrate changes in the runoff generation processes ensuing land use changes and successfully executed over two catchments in South West of Australia. By taking into account the most important parameters of the catchment such as average surface slope, porosity, hydraulic conductivity, soil depth and distribution. With the help of catchment characteristics most of the parameters were already estimated. Daily model performed very well for daily streamflow estimations and it was found that estimated groundwater level both beneath the native forest and cleared areas also estimated streamflow volume from daily to monthly and annual scale was closely matching with the observed data (Bari and Smettem, 2006).

Monthly versus daily water balance models in simulating monthly runoff by two daily water balance models used were AWBM (Boughton,2004) and SimHyd (Chiew et al. ,2002) each of the models consisting of seven parameters had been compared. The performance for simulating monthly runoff over 331 catchments in Australia area varying from 51 to 1979 sq.km having daily data resolution had been evaluated. Wapaba monthly model later was compared with a monthly water balance model, abcd model and monthly Budyko framework model. After analysis it was stated that Wapaba monthly model had the best results compared to AWBM and SimHyd. The authors concluded that monthly water balance models were found advantageous over daily models since they required less computations and low cost but are disadvantageous for reason that it cannot cover up finer resolution applications i.e. daily data (Wang, et al., 2011).

3.6. Three Parameter Water Balance Models

A study has been conducted on the estimation of parameters of a conceptual water balance model for ungauged catchments with application of three parameter monthly water balance model (MWB-3 Model) and six parameter monthly water balance model (MWB-6) where MWB-6 model was used over 26 seasonally snow-covered watersheds in central Sweden. MWB-3 model which exempted snow routine, was applied on 24 watersheds in Northern Belgium for an area varying from 6 to 1293 sq.km. Both scenarios showed that optimum parameters were reverted on a number of catchment characteristics. Equations required for prediction were derived and incorporated for the calculation of model parameters from the catchment properties for independents test catchments and using these estimated parameters, simulation of streamflow records were gained and matched with observed streamflow. Considerable matching between observed and estimated streamflow was reported for both long-term mean values and the monthly hydrograph. The parameters of NOPEX WBM are indeed physically such relevant for the reason that the optimum parameters were calculated from catchment characteristics (Xu, 1999).

Monthly Water Balance models for 55 basins in 10 countries (North/South Belgium, Bolivia, UK,North/South China, France, Myanmar, Senegal, Mali, Guinea, Ivory Coast) with catchment size varying from 19 Sq.km to 6230 sq.km applying P (6 & 5 Parameter) and PE (3 & 5 Parameter) water balance models, revealed there are no universal models which delivers satisfactory results for all basins. After using five model-basin combinations for 11 types of models, and 55 catchments showing the 3 parameter PE models performed very well since that three continuous parameters suffice in 34 basins (62%) and six continuous parameters were really necessary in two basins (Vandewiele & Ni-Lar-Win, 1998).

Studying the applicability of two parameter monthly watershed model to simulate daily rainfall runoff for evaluation of catchment yield on two watersheds in Sri Lanka, Dissanayake (2017) reported the calibrated values for c and Sc parameters from monthly model for Thawalama and Ellagawa to simulate the daily streamflow from daily rainfall for water resources planning and management of Kalu ganga and Gin ganga basins. Third parameter in three parameter monthly water balance model had increased the estimation accuracy of monthly model for both Thawalama and Ellagawa watersheds. The accuracy of the daily streamflow estimations using 3 parameter monthly water balance model resulted in MRAE value of 0.31 and 0.53 for Thawalama and Ellagawa watersheds respectively. The introduction of new parameter to the model aided in minimizing MRAE value for daily inputs and streamflow estimation for both basins (Dissanayake, 2017 unpubl).

3.7. Rainfall Spatial Variability

Precipitation plays a significant role in estimating surface hydrological process (Haddeland et al. 2002). Following Peleg et. al (2017) rainfall spatial variability has been defined as the variability derived from having multiple spatially distributed rainfall fields for a given point in time. Insufficient knowledge about the spatial distribution of rainfall always remained one of the key sources of errors in streamflow estimations (Niemczynowizs, 1988; Cristiano et. al, 2017). Many researchers by looking into observed rainfall (Obled et al., 1994; Lopes, 1996; Liang et al., 2004; Das, Bardossy, & Zehe, 2006) or stochastic precipitation models (Wilson et al., 1979; Krajewski et al., 1991; Das, Bardossy, & Zehe, 2006) have put efforts to examine the spatial variability of rainfall in response to basins.

The most common gauging stations that measures rainfall data series present point values, whilst the areal rainfall that produces streamflow remains unknown. Just because the actual rainfall takes place over an area which is an end stage of a number of various processes occurring on various scales, the derivation of areal estimation from point observation as well as the forecasting of rainfall, has been and probably will remain one of the problematic issues in hydrology (Berndtsson and Niemczynowicz, 1987).

Hydrological processes are considered at a wide range of scales in space, which generally differ from 1mm to ten thousands of kilometers in space. A scale should be defined to understand the regional characteristics in space at which processes are occurring or the spatial resolution at which processes can be measured at its best (Salvadore et al, 2015; Cristiano et. al, 2017). Data from rainfall gauges are the prime instruments utilized to record rainfall and widely used, due to its relatively low in cost and convenience in method of installation (WMO, 2008). The purpose for which observed data is to be used defines the optimum density of a precipitation network. For instance, accurate recording of precipitation for flood forecasting may require denser networks as compared to rainfall-runoff modelling. WMO (2008) suggested tables that can be referred for minimum densities of precipitation stations. An ideal network should assist determining a required characteristics with adequate accuracy by interpolating between values of dissimilar stations (Jain and Singh, 2003; WMO, 2008).

After performing a study on stochastic watershed modelling Chow (1978) concluded based on the result of its analysis that the precipitation record of only one station is sufficient for the description of precipitation influence on streamflow. To lighten up more on this, Berndtsson and Niemczynowicz (1987) mentions in their study conducted for spatial and temporal ranges of rainfall assessment that merely a single gauging station data can ordinarily be considered for streamflow estimations; thus, most of rainfall-runoff modelling are applicable for urban hydrology at which it does not consider neither spatial distribution nor dynamic properties of rainfall.

A very important questions that is raised with respect to rainfall-runoff modelling investigations is: “How important is the spatial nature of rainfall to runoff response?”

To respond to this, Singh (1997) mentioned that the specialty of spatial variability of rainfall may depend upon catchment antecedent condition, catchment rainfall properties, catchment type and scale. Addition work has been performed by (Bell and Moore, 2000, Smith et al., 2004, Segond et al., 2007; Pechlivanidis, McIntyre and Wheater, 2008) to better visualize the impacts of rainfall spatial variability on streamflow. Authors also concluded that the noticeable impacts spatial variability of rainfall may have on discharge characteristics will include peak discharge, volume of discharge and time to peak.

The optimal spatial resolution of recorded rainfall for the purpose of hydrological studies is dependent upon the size of catchment along with significance of spatial resolution of rainfall declining at larger catchment sizes (Woods and Sivapalan, 1999; Pechlivanidis, McIntyre and Wheater, 2008). A catchment with area of less than 100 km^2 may be defined as small, in range of 100-2000 km^2 as medium and greater than 2000km^2 as large catchment for which rainfall spatial resolution is needed and a more precise rainfall estimation are necessary (Arnaud et al., 2002; Pechlivanidis, McIntyre and Wheater, 2008). Investigations have revealed that with the increase in catchment scale, catchment response time distribution becomes the most important governing factor for discharge estimation (Bell and Moore, 2000). Antecedent catchment conditions may also be affected due to spatial average rainfall (Singh, 1997; Pechlivanidis, McIntyre and Wheater, 2008). Most prominently, under wet conditions a good matching of discharge can be achieved with spatially average rainfall inputs. However, for catchments having dry conditions, the discharge estimation errors are noted to be siginifcanltly higher than for catchments in wet conditions (Arnaud et al., 2002; Pechlivanidis, McIntyre and Wheater, 2008). These results prove the connection among the spatial distribution of rainfall and spatial distribution of soil moisture which basically controls the discharge estimations. The amount of rainfall converted into direct discharge may also be controlled by the permeability of the catchment, which can indicate the impact of spatial distribution of rainfall (Tetzlaff and Uhlenbrook, 2005; Pechlivanidis, McIntyre and Wheater, 2008). If a catchment is impervious it may fast respond and during runoff modelling research shows the requirement of a high density raingauge network (Berne et al., 2004; Pechlivanidis, McIntyre and Wheater, 2008). In addition, the discharge response is sensitive to rainfall type (Koren et al., 1999; Pechlivanidis, McIntyre and Wheater, 2008). Knowledge of spatial distribution of rainfall and variability is essential in hydrological modelling specifically when simulating extreme events in the summer (Bell and Moore, 2000).

In convective rainfall events the errors in discharge simulation drops down when spatially high resolution data are used. Though, longer duration of single frontal events, the spatial distribution of rainfall has less impact on average catchment rainfall due to the low variability of such type of events (Arnaud et al., 2002; Pechlivanidis, McIntyre and Wheater, 2008).

Pechlivanidis, McIntyre & Wheater (2008) assessed the impact of spatial variability of rainfall with the help of recorded data in the Thames region for UK in Upper Lee catchment with an area of 1040 km^2. The mean annual precipitation of 632mm over the catchment and characterized as humid temperate, with an elevation variation of between 20 to 250 meters above UK ordnance datum. The significance of spatial variability of rainfall on discharge with the consideration of catchment size and type rainfall characteristics was shown in the effort made by the authors using a semi distributed hydrological model. Three cases of rainfall were studied with various degrees of spatial distribution of rainfall aggregation for the catchment, whilst five rainfall events were statistically analyzed representing the significance and impact of spatial variability of rainfall on model performance criteria and hydrograph characteristics. The study exposes how the rainfall spatial distribution can impact the achieved model performance by elevating the NSE value up to 15% while investigating events with high spatial variability. Although from previous studies it was acknowledged, there was no clear evidence that the sensitivity of runoff generation to spatial distribution rainfall has a relation with catchment scale. sensitivity is noted in impermeable catchments than permeable catchments to spatial variability of rainfall, especially when spatially varied rainfall events take place. Results also show the sensitivity considerably declines under the circumstance of less spatially variable events.

Identification of spatial variability of runoff coefficients of three wet zone watersheds of Sri Lanka had studied three sub-basins of Kalu ganga basin , Kelani ganga basin and Attangalu oya basins having respective sizes of 539 sq.km, 1537 sq.km and 2627 sq.km (Wijesekera & Perera, 2011). A Geographic Information System (GIS) was applied for the assessment of spatial variability of runoff coefficients and development of simple conceptual model was done for the estimation of runoff from catchments characteristics and rainfall data. The model had predicted observed values quite well by providing MRAE of 0.90, 0.44, and 0.30 for Attanagalu Oya, Kelani Ganga and Kalu Ganga sub-basins respectively with R^2 overall value of 0.73 (Wijesekera & Perera, 2011).

Streamflow modelling of a Sri Lankan catchment considering spatial variation of rainfall using a tank model and considering four rainfall gauging stations within an area of 1167 and 2598 sq.km with daily data resolution from 1969 to 1980 has been done by Musiake & Wijesekera (1990). Rain gauge weights has been considered as parameters and optimized. Results showed the ratio of absolute error to mean in case of uniform and spatially varied rainfall were 0.273 to 0.239 showing an improvement while spatial variability. At the end authors concluded that the optimized parameters were acceptable with the rainfall distributions and the location of rainfall stations (Musiake & Wijesekera, 1990). Authors had concluded that optimization of rainfall weights can be a method which can be applied on rainfall gauging network to retrieve better streamflow estimates in rainfall-runoff modelling.

A study on spatial and temporal variation of precipitation in Haihe river basin had been conducted for a catchment area which had an estimated of 317,900 sq.km that includes Haihe River and Luan River systems. These were studied using daily precipitation data from 58 stations for more than 53 years data, precipitation spatial and temporal variations were assessed using M-K test method with help of ArcGIS application. The results achieved after the analysis show that precipitation of the whole basin had a declining trend and the spatial distribution of precipitation was not same in annual precipitation and after the mutations (Wang & Xu, 2015).

The techniques such as Krigging, Spline, Thiessen or IDW are available for areal average modelling spatial variability of rain based on rainfall station networks which are still common in use compared to low cost or introduction of weather radar to estimate spatial distribution. Also most recently, commercial microwave links are also utilized for prediction of rainfall spatial and temporal variability (Liejnse et al., 2007; Cristiano, Veldhuis, & Giesen, 2017). The new approach, microwave, can prove to be particularly beneficial in cities where rain gauges or radars are not available or inaccessible, but areas where the network of commercial cellular communication is normally dense (Liejnse et al., 2007). Rainfall data obtained from radar are used to study the hydrological response in natural watersheds (Cristiano, Veldhuis, & Giesen,

2017) may mostly be combined with rainfall recorded on rain gauges networks.

Georgakakos (1987) carried out a hydrological analysis, modelling and estimation of precipitation in which the author shed light on present characteristic research investigation that uses only rain gauge data, radar data and satellite data under classification of a) Rain gauge on-site sensors b) Radar remote sensor c) Satellite remote sensor d) Multiple sensors. The authors discussed the study performed by Cruetin and Obled (1982) for comparison of techniques available for precipitation spatial extrapolation such as kriging, Thiessen polygon, arithmetic mean techniques, spline fitting method, and a technique established on an expansion of the random rainfall filled to orthogonal functions. It was stated that not even one of the methods that were inspected had the capability to fully account for the statistical properties of the recorded rainfall fields.

3.8. Parameter Optimization

Three various methods can be adopted to evaluate the parameter significance and sensitivity; parameter values evaluation while optimizing, searching for the global minimum and detail analysis of the variance covariance matrix (Xu, 1997; Xu & Singh, 1998). Calibration of hydrological models with respect to the observed data is a computationally complex issue, for the reason that there may be a large number of parameters fixed within the model and these parameters in most cases are in real space. In common practice, to resolve the calibration problem it is suggested to use meta-heuristics, such as genetic algorithms (Cohen et. al, 2013). Such techniques were found very effective while calibrating models within a practical computational runtime. Another name for Meta-heuristics is global search algorithms due to their capability of locating the global minimum in the parameter search space.

These techniques are considered for searching the optimum of a given objective function in a comparatively short amount of time: in such a context, an objective can be either the calibration matric of a hydrological model (an applied problem), or a test function. Meta-hueristics is too different from the local search techniques (for instance hill climbing algorithm) which normally uses a “greedy” approach for searching the optimum solution. Even though local solutions can be fast but they are more likely to staty at a local optima without finding the best solution to the problem (Cohen et. al, 2013).

Wijesekera (2000) have adopted Mean Ratio of Absolute Error (MRAE) as objective function to indicate the degree of matching of calculated and observed streamflow hydrographs while performing an evaluation of optimized parameters, annual water balance and duration curves. Using a manual and a semi-automatic optimization and it had been found that the parameter optimization using a manual method was extremely difficult, time consuming and requiring experience to optimize a large number of parameters having probability of interdependence. This study had also used an automatic calibration method using a computer program written in FORTRAN77 to carry out parameter search proposed by Powell (1965).

Xu & Singh (1998) contend that search techniques with help of automatic optimization remained to be the most common when calibrating a monthly water balance model. Since most of the monthly water balance models possess a simpler structure with lesser number of parameters. Automatic optimization techniques are preferred because they are supposed to yield a reproducible and unique parameter set.

Xiong & Guo (1999) used automatic optimization to get the optimum parameter values. The two step optimization procedure first optimizes the parameters SC and c based on the criterion of Relative Error (RE) and secondly, optimizes the parameter SC for the second time using the other criterion which is R^2. This two-step optimization approach had aided in minimizing effects of the inter-relationship between the two parameters on model performance. The application of manual calibration procedures are more time taking than automatic search algorithms calibration procedures. However, the major disadvantage of the single-criterion algorithm is that their result is completely based on single objective function which may actually result in solutions matching to one aspect of the observed hydrograph at the expense of another criterion (Wagener et. al, 2001). To overcome this difficulty, a multi-criteria calibration procedures is suggested (Gupta et al., 1998a, 1998b). In such an approach, performing an automatic search of the feasible parameter in space is performed for searching the set of solutions which is called "Pareto optimal" region which at the same time optimizes more than one user identified criteria that measure various aspects of the closeness of the model calculated results and observed data. This produces results which reflect a range of different ways in which the hydrograph can be simulated with different kinds of "minimal" error (Wagener et. al, 2001).

The range of parameters cited for two parameter monthly water balance model differs within 0.2 and 1.9 for the value of parameter C. Parameter range Sc in literature varies between 300 - 2000. It is important to state here that the range of C and Sc are not specifically mentioned in the literature neither compared in particular; the C and Sc value mentioned are picked from literature based on the performance outputs of the study conducted among several number of catchments (Xiong & Guo, 1999). With this it can be concluded the range of Sc and C will slightly vary within the given range based on characteristics of watershed, data resolution and data duration. The governing equation determines the minimum level of C and Sc to be greater than zero criteria. Whilst the upper limits have not been specifically stated.

3.9. Initial Parameter Values

There can be uncertainties in the input of initial values for parameters of a model prior to optimization for instance Xiong and Guo (1999) indicated clearly that S(0) initial soil water content value range may vary between 150 to 200mm for all the catchments tested. Whilst the c and Sc calibrated value for seventy sub-catchments were within the range of 0.286 to 1.238 and 300 to 2000 respectively. Evaluation of a Two Parameter Monthly Water Balance Model in tropical watersheds had showed the values for the c ranging from 0.46 to 1.42, while for Sc values were in range of between 800 and 1322 for Gin Ganga , Kalu Ganga , Mahaweli and Kelani river basins which can be considered as initial parameter values (Wijesekera, 2017).

3.10. Warm up Period

A warm up period is to let a model to run for a ample period of time prior to a simulation in order to initialize important model variables or allow an important process to reach a dynamic equilibrium (Daggupati et al., 2015). To deal with initialization bias there are main five methods introduced by Robinson (2004). They are: 1. Running a model for warm-up periods until model reaches the desired realistic state also called as “a steady state for nonterminating simulations” and removing collected data from the warm-up period. 2. Setting up the initial conditions of the model until the simulation reaches a realistic condition. 3. Setting up partially initial conditions and later warming-up the model and removing the warm-up dataset. 4. Running the model for a lengthy period of time to bring the bias effect negligible. 5. Approximating the steady state of parameters by a short transient simulation run

(Hoad et.al 2008). The duration of warm-up period cannot be the same for various watershed scale procedure (Daggupati et al., 2015). However, for hydrological process model developers suggest to consider two to three years of warm-up periods and for sediment and nutrient related process five to ten years (Srinivasan et al., 2010). Similarly, Makhlouf and Michel (1994) had employed a warm-up duration of two years in their models and sub periods i.e. calibration and verification in order to overcome the problem with storage initialization in their study. In the event of conceptual models, the warm-up year has to be included at the beginning of the training and test sets which will avoids unknown initial conditions that may have an effect on model performance and allow the model internal state variables to adjust to appropriate values (Anctil, Perrin & Andreassian, 2004). Makhlouf and Michel (1994) suggested that two years for warm-up period is sufficient based on which authors used the same amount for the models in their investigation. Madsen (2003) applied 2-year warm-up period in the study on distrubtion hydrological catchment modelling for parameter estimation by employing automatic calibration while dealing with multiple objectives on daily scale data. In two parameter monthly water balance model (Xiong, 1999), calculation of warm up period was performed in order to find initial soil water content. It was calculated based on the warm up period and the value of S_0 was decided while assuming that one year is reasonable for a hydrologic cycle. At the start of every test period, the starting year of simulated runoff was excluded from the evaluation criteria (Mouelhi, Michel, Perrin & Andre´assian, 2006).

3.11. Flow Duration Curves and Classification

Searcy (1959) defines Flow Duration Curve as A cumulative frequency curve that represents the percent of time-dependent discharge that may have equaled or exceeded during a given period. Flow-duration curves have been in general use since about 1915; their theory has been discussed by many researchers (Searcy, 1959). There are two major approaches utilized to prepare flow-duration curves are (1) annual flow duration method (Barrows, 1943; Saville and Watson, 1933) and (2) total period flow duration method. Wijesekera (2017) performed a study for classification of streamflow observations for water management has discussed briefly about the threshold values for high, medium and low flows of a flow duration curve. It also states that there are many options for streamflow modelling, the lack of a clear demarcation of thresholds to recognize high, medium and low flow types creates an ambiguity when attempting to evaluate the model performance with respect to modelling objectives such as flood, water resources, drought and environmental flow management. With literature provided by the author the current state-of-art signifies there is no certain criteria to describe the qualitative threshold for flow classifications for instance EPA (2007) identifies 5% for high and 95% for low whilst Li et. al (2007) identifies value same as EPA(2007) for high flows, Smakhtin (2001) for lows flows between 70-90%, also USGS and Risley et al. (2008) report considers 5-10% as high flows range similarly Risley et al. (2008) considers 95% a threshold for low flows. U.S. Geological Survey adopted 50% for available flow (intermediate flow) and 90% to limit the low flows. Sugiyama et al. (2003) selected 97% for lows while Sung and Chung (2014) had mentioned 70% exceedance threshold for drought evaluation. Subjective identification of high, medium and low flow regions of the flow duration curves by observing the shape and slope of the curve has also been the case in Khandu(2015); Sharifi, (2015); Jayadeera (2016) & Dissanayake (2017).

3.12. Model Calibration and Verification Dataset

So as to completely develop a hydrological model, ample data of various watersheds are required to evaluate performance of the model. Evaluation of a model in general is executed in two stages, first calibration and second verification. In this, the complete dataset is split into these two parts. Calibration refers to the process of using the first part of dataset to search for the optimum values of the unknown model parameters by optimization. Whereas, Verification signifies the procedure of applying an independent dataset to defend the persistence of the model performance functioning with the parameter values attained during the calibration period. If the model performance was satisfactory in both calibration and verification stages, only then the model could be used with confidence in practice. The calibration periods for 70 catchments varies from 72 to 324 months while verification period differs from 24 to 72 months (Xiong and Guo, 1999).

Li et al. (2010), carrying out a research on the effect of calibration data series length on performance and optimal parameters of hydrological model, states that lengthy calibration data series do not necessarily result in better model performance. Sorooshian et al (1983) suggested that one full hydrological year for CRR model calibration as the minimum data requirement. Also, Li et al. (2010) states that Non-continuous years including different climatic conditions were sufficient to obtain robust estimates of model performance and parameters. In each case, the data from the first year were also used to warm up the model in order to minimize initialization errors. Authors concluded that all parameters get steadier with increase in the length of calibration data series, and most parameters vary little once the length of calibration data series reaches eight years. Three or five years as shorter period for calibration in humid catchments have obtained good performance and five, eight and ten years for verification period have also presented closer results.

Literature points to split sampling which uses of half from the entire dataset for calibration and the other half for verification of the accuracy of estimation. The split sampling method has little value when dealing with short periods of data in modelling (Boughton, 2007). The samples of two and five years of calibration data had resulted in a similar error range which is represented in tabular form by Boughton (2007). The overestimation of long term discharge ("+" error range) decreases significantly when 10 or more years of calibration data are available, but the underestimation ("–"error range) remains high even when 20 years of calibration data are available for AWBM. The conclusions made were in two significant points are a) Potential errors while using short periods of data, and are in order of 20-30% with 2 to 5 years of calibration data. b) Results depended mostly on the specific dataset but not a lot on the hydrological model adopted. The most significant output is that base flow parameters may be calibrated with short periods of data and with little error, while more focus can be given to the discharge produced parameters. Author also concludes that data properties may have a huge influence on the results, and undoubtedly a revised investigation with other datasets may be required with the same model (Boughton, 2007). For 3 years and 5 years training sets, performance were very satisfactory until the training is not on the grounds of succession of dry years (Anctil, Perrin & Andreassian, 2004). Mouelhi, Michel, Perrin & Andreassian (2006) divided the recorded data of every basin into two parts of almost same length. The split-sampling approach was implemented for the assessment of every model in simulation mode during each period the calibrated parameter values were for verification (Klemes, 1986).

3.13. Data Requirement

Gan et. al (1996) performed a study on effects of model complexity and structure, data quality and objective function on hydrologic modeling over 3 catchments from Africa and USA using four conceptual rainfall runoff models with varing complexities. The models in the study were namely Pitman model, Sacremento model, NAM model, Xinanjiang model and SMAR model. Authors describe about the effects of the data length that can have on the model calibration, which states that theoretically, a longer set of calibration data would achieve a better calibration because by going through a longer calibration experience resulting more accurately calibrated model parameters.

Sorooshian et al. (1983) found this viewpoint to be generally not right, from the results of Tests I, II, and IV, in which calibration data lengths of 2, 5, and 10 years were used respectively and all of them were evaluated with an eleven years verification period in common.To elaborate more as an example, For 2 and 5 wet years and 10-mixed-year calibration scenarios applied in the PTM model resulted in E values of 66.2%, 58.4%, and 70.8% respectively for the eleven years during verification. In a similar fashion, NAM model produced an E of 64.6%, 61%, and 62.5%, despite the fact that 65.6, 64.2, and 68.7% were achieved for E under XNJ's model. As a result authors concluded that there was no certain indication that model performance is dependent upon the calibration data period. In some instances, a model with two years of calibration data could produce better outputs compared to a model with 10 years of calibration data. This itself is an indication that data length is not that crucial, until it is not less than one hydrological year, and as long as the data utilized contains sufficient information for calibrating the parameters. Ideally, there should be 3 to 5 years data which must contain wet, average and dry years to facilitate the data formation with enough range of hydrologic events in order to activate all model parameters during calibrate stage (Gan et. al ,1996).

3.14. Methodology of Evaluation

Since early stages of hydrological modeling, there is a need to evaluate the results of models and to quantify their flow prediction efficiency. In their early proposals of conceptual models, Linsley and Crawford (1960) and Dawdy and O'Donnell (1965) already quantified the residuals of their models, simply by plotting observed and simulated hydrographs or by calculating the percent difference between observed and simulated flows. This is called the mathematical criteria which evaluates the difference between the measured and simulated flow values over a chosen time period to suit the objective and this has been described as quantitative (Genet & Crochemore, 2011).

At the early days, computation times were an actual constraint and hence limited the calculation of various evaluation criteria. However, the question of how to evaluate models was rapidly identified as a key issue and Nash and Sutcliffe (1970) were among the first to propose an efficiency index for evaluating hydrological simulations. Their aim was to provide an objective mean for giving a mark to a simulation. Retrospectively, this proved very good as their index remains as the most widely used in hydrological modelling despite its identified weaknesses (Gupta et al., 2009). Similarly, the other methods in evaluation criteria can be the most straightforward possibility by using graphical means and compare observed and simulated values (Genet & Crochemore, 2011). Moriasi et. al (2007) in the study of model evaluation guidelines for systematic quantification of accuracy in watershed simulations discusses the evaluation of models using the quantitative statistics which were separated into three main categories: standard regression, dimensionless, and error index and several graphical techniques. Discussing about evaluation of hydrological models by Genet & Crochemore (2011) the evaluation methods are classified as the mathematical criteria and graphical criteria. Cheng et. al (2017) in a study of model performance evaluation for real-time flood forecasting had evaluated models based on the flow duration curves with graphical and numerical indices for cumulative impulse response. Donigian and Imhoff (2009) discusses in evaluation and performance assessment of watershed models briefed about the graphical comparisons and statistical tests for watershed modelling. Moriasi et.al (2012) performed a study on hydrologic and water quality models discussing about statistical and graphical model evaluation criteria.

Since then, a large variety of evaluation criteria and tools have been used by many authors (Moriasi et. al, 2007; Genet & Crochemore, 2011; Cheng et. al, 2017; Hwang, Ham and Kim, 2012; Donigian and Imhoff, 2009 ; Moriasi et.al, 2012; Khandu, 2016 unpubl; Dissanayake, 2017 unpubl; Sharifi, 2015 unpubl; Kamran,2016) corresponding to various modelling objectives. As pointed out by above, model evaluation remains as an ad hoc process and is strongly related to the modelling objectives, authors (Perrin et al., 2006; Genet & Crochemore, 2011). This makes the results of various existing studies most often very difficult to compare, due to the large panel of existing criteria even when the modelling objectives are similar.

Water balance is predicted on the principles of conservation of mass and the annual separation of precipitation into ET and discharge, which is measured by the temporal distribution of precipitation (supply) and ET (demand) by balancing the water storage in the soil (Thapa et. al, 2017). To determine estimation accuracy of various elements in the hydrological cycle, model outputs of all elements should be evaluated. As a matter of fact, always there are inconsistencies between the observed values and model estimates because of the measurement errors, inadequate data capturing networks, and the difficulty of representing real-life complex spatial heterogeneity in the model (Thapa et. al, 2017). Typical graphical representations of results from hydrological models used for evaluations include: a) Observed and simulated flow hydrographs over time b) simulated flows against the observed flow c) the cumulative distribution function of observed and simulated flows also known as flow duration curves. d) Annual water balance and e) scatter plots.

3.15. Model Performance Criteria and Objective Function

3.15.1. Model Performance Criteria

For more than 30 years, the model performance criteria commonly known as, calibration or validation criteria has remained an argumentative topic (Duda, Hummel, Donigian, & Imhoff, 2012). Even though there is no certain agreement on model performance criteria which is apparent from past and recent literature, there are a number of fundamentals that are agreed by a majority of modelers when modeling natural systems they are: a) modelling is performed for approximation of reality; which cannot precisely reflect natural systems. b) Lack of single, accepted check that shows whether or not a model is validated. c) For model calibration and verification both statistical and graphical comparisons are needed. d) Models cannot be expected to be more accurate than the confidence intervals in the input and gauged data. While developing an appropriate approach for model performance and quality assurance of modeling efforts, all the above or a majority of basic fundamentals must be taken into account. A comparative study of different objective functions to improve the flood forecasting accuracy by Jie et. al (2016) using single and multiple objective functions.

Results showed that a very big threshold will add to worsen the performance of simulations when calibrating with a combination of two objective functions.

3.15.2. Objective Function

The function used to match the model results with reality is known as the objective function. The objective function is dependent upon the modeling aims such as flood control, environmental management, water resources planning and management. Selection of an objective function even for the same objective varies from researcher to researcher. The mathematical measures of how well a model simulation fits the available observation are defined as objective functions (Krause et al., 2005). A most commonly used objective function for hydrological model simulation is the sum of squared deviations (Diskin & Simin, 1977). Stephenson (1979) assumed the sum of absolute value of residual as a goodness of fit criterion in an optimization study. Since the purpose of monthly water balance models are for long term water resources management the objective function must be able to provide a higher weightage to water that can be harnessed from a stream and therefore this should be to realistically to match the intermediate flow.

3.15.2.1. Nash-sutcliffe efficiency (NSE):

The efficiency indicator (NSE) established by Nash (1969) and Nash and Sutcliffe (1970) is defined as one minus the sum of the absolute squared differences between the estimated and recorded values normalized by the variance of the recorded values during the period under investigation (Krause et. al, 2005; Gupta et al., 2009; Cheng, 2014).

$$NSE = 1 - \frac{\sum_{i=1}^{N} (M_i - O_i)^2}{\sum_{i=1}^{N} (O_i - \bar{O})^2} \quad \text{...Equation 3.1}$$

Where O_i is the i^{th} observed value, M_i is the i^{th} calculated value, out of which N is the total number of observations and $\bar{O}$ is mean of the calculated. This efficiency criterion has the normalized least square function. A perfect matching between the recorded and estimated value provides an efficiency value of one, perfect hydrological model. But, an NSE value less than zero will show that the mathematical model is not better estimator using the average of the observations which indicates lack of agreement or which indicates unacceptable performance (Gupta et. al., 2009; Cheng, 2014; Moraisi et.al, 2007). NSE values can be between 0.0 and 1.0 which are generally viewed as acceptable levels of performance (Moraisi et al., 2007). The biggest drawback of the NSE is the fact that the differences between the recorded and estimated values are considered as squared values. Thus larger values in the dataset are strongly overestimated whilst lower values are ignored (Legates and McCabe, 1999) which is a major reason during quantification of discharge calculation for overestimation of the model performance during peak flows and an underestimation during low flow conditions (Krause et. al, 2005). Use of NSE has been due to two key reasons, (1) NSE is suggested for use by Legates and McCabe (1999), and (2) its very common in use, provides extensive set of information. From all the objective functions, the Nash-Sutcliffe efficiency (NSE) is most widely used ((Servat and Dezetter, 1991; Legates and McCabe, 1999; Xiong & Guo, 1999; Chen et al., 2007; Cheng, 2014;Jie et al., 2016; Khandu, 2016 unpubl). It is generally accepted that if the NSE is larger than 0.65, the mathematical model could be considered as, and if Otherwise, then should be taken unsatisfactory (Moriasi et al., 2007; Cheng, 2014).

3.15.2.2. Relative Error (RE)

The relative error of the volumetric fit between the observed runoff series and the simulated series (Xiong & Guo, 1999; Khandu, 2016 unpubl) is represented by the Relative Error indicator.

$RE_t = \frac{|Q_t - \hat{Q}_t|}{Qt} \times 100$ ……………………………………….………..Equation 3.2

Qt for the recorded value (Q) at time t, $\hat{Q}_t$ for the predicted value at time t. RE is normally embraced for identification of percentage of samples classified in by Author (Cheng et. al, 2017) under three categories and they are: a) if RE>35% then High Error b) if 15%<RE≤35% then Medium Error c) if RE≤15% then Low Relative Error

In hydrological modeling, for a good simulation of the total volume of observed discharge series, the value of Relative Error (RE) needs to be close to zero (Khandu, 2016 unpubl). The advantage of RE is that the simulations show a good performance on the total volume (Jie et. al ,2016). The disadvantage is that it may have a negative influence on the shape of the hydrograph and peak discharge (Moussa & Chahinian, 2009).

3.15.2.3. Mean Ratio of Absolute Error (MRAE)

Mean Ratio of Absolute Error (MRAE) is defined as the difference between calculated and observed flow with respect to that particular observation (Wijesekera and Musaike, 1990). Chen et. al 2017 adds that the error range of the calculated values by reflecting the relative errors of different data sets, and the effect is intuitive. Wijesekera and Musaike (1990); Wijesekera & Abeynayake (2003); Dissanayake (2017 unpubl) also mentioned that MRAE is the difference between calculated and observed flow with respect to a particular observation that is subjected to estimation by the model. MRAE is as in equation below:

$$MRAE = \frac{1}{n}\sum\left[\frac{|y_{obs}-y_{cal}|}{y_{obs}}\right] \qquad \text{Equation 3.3}$$

Where, y_{obs} is observed streamflow value and y_{cal} is estimated streamflow value while n is the number of readings in the data series.

Wanniarachchi (2013) who performed a study of mathematical modelling of watershed runoff coefficient for reliable estimation to meet the future challenges for water resources development in Sri Lanka also developed and achieved decent model performance using MRAE that resulted in values 0.39 for calibration and 0.35 for verification period. Wijesekera & Rajapaske (2013) implemented a hydrological model for wetland crossings for groundwater improvement and flood mitigation by taking Attanagalu Oya river basin as the study area. The mathematical model was used for identification of the water retention capability, Model performance evaluations were done using NSE, MRAE and coefficient of correlation. The MRAE value for calibration period was 0.66 and verification period was 0.70. Dissanayake (2017 unpubl) in Applicability of a two parameter water balance model to simulate daily rainfall, achieved good results for Tawalama and Ellagawa watershed, and the average MRAE values were 0.16 and 0.31 for calibration and verification periods. Sharifi (2015 unpubl) in an assessment of calibration and verification for a two parameter monthly water balance model, used MRAE and found calibration of Mahaweli Ganga River Basin at Morape and Kalu Ganga River Basin at Ellagawa and found very good matching with values of 0.15 and 0.14 respectively. The same for verification period was also very good with value of 0.15 and 0.15 respectively. Khandu (2016 unpubl) conducted research on a monthly water balance model for evaluation of climate change impacts on the streamflow of Gin Ganga and Kelani Ganga in which the selected objective function was MRAE. Results portray that the achieved MRAE during calibration for Kelani Ganga basin is 0.097 and for Gin Ganga basin is 0.089; similarly, 0.117 and 0.116 for Gin Ganga and Kelani Ganga respectively. The study for daily streamflow modeling of Kalu river basin in Sri Lanka with the application of HEC-HMS (Mutumala, 2016 unpubl) examined the appropriateness of NSE, RAEM and MRAE. NSE indicates that it is a better option for high flows while the RAEM and MRAE show advantages over the NSE when low flows and intermediate flows are estimated. Mean Absolute Percentage Error (MAPE) indicated in Tofallis (2015); Hyndman & Koehler (2006); Makridakis (1993) also reflects similar characteristics as MRAE (Wijesekera, 2017).

3.15.2.4. Ratio of Absolute Error to Mean (RAEM)

World Meteorological Organization (1982; IAHS Publ. no. 138) in the publication titled intercomparison of conceptual models of snow melt runoff recommends several objectives functions RAEM described below is one of the methods:

$$RAEM = \frac{1}{n}\left[\frac{\sum|y_c - y_o|}{\bar{y}_o}\right] \qquad \text{Equation 3.4}$$

Where, y_o is the observed streamflow, y_c is the calculated streamflow, n is the number of observations incorporated for comparison and $\bar{y}_o$ is the mean of the observed discharge. This method indicates that ratio between observed and calculated discharge with respect to the mean of observed discharges. General concept is that the variations between the observed and simulated streamflow are normalized by the observed value and optimum parameters are achieved at the minimum mean value. Also, RAEM identifies the average at any point with respect to average of observed value (Khandu, 2016 unpubl).

3.15.2.5. Mean Squared Error (MSE)

Green and Stephenson, (1986) stated that mean squared error (MSE) is widely proposed for model calibration. Mean Squared Error (MSE) is a distance-based objective function which is defined as the distance (similar to the spatial distance) between model estimations and recorded data that is proposed for model calibration and to emphasize special runoff component specially (baseflow and flood) the difference between the model estimations and recorded data are often multiplied with a user defined weights in the distance-based objective function (Kamran, 2017 unpubl).

Mean Squared Error (MSE) objective function also implies statistical assumptions that a mathematical model residuals should be independent and identically distributed (I.I.D.) according to a Gaussian distribution with zero-mean and a constant variance (Cheng, 2014). Cheng (2014) pointed out the MSE is better than Mean Absolute Error (MAE), since MAE at zero value makes a kink (none smoothness), due to during optimization it fact produces a non-smooth operator, whilst the MSE shows a smooth function for the model residuals.

$$MSE = \frac{\sum_{i=1}^{N} ABS\,(M_i - O_i)^2}{N} \text{...Equation 3.5}$$

Where O_i is the i^{th} observed value, M_i is the i^{th} estimated value, and the total number of observations is denoted by N.

3.15.2.6. Mean Square Root Error (RMSE)

RMSE is also considered as one of widely used error index statistics (Moriasi et. al, 2007). Even though it is widely accepted that minimum RMSE provides a superior model performance, Singh et al. (2004) conducted investigations to show the range of a low RMSE based on the observations of standard deviation (Moriasi et. al, 2007). RMSE which basically reflects the interpolative sensitivity and extreme effects associated with the collected data; (Chen et. al., 2017) is as in the equation 3.6:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N} ABS\,(M_i - O_i)^2}{N}} \text{...Equation 3.6}$$

Where O_i is the i^{th} observed data, M_i is the i^{th} estimated data, and the total number of observations is denoted by N. Most often RMSE is preferred to MSE for the same range of the data. In past, RMSE and MSE were famous due to their theoretical relevance in statistical modelling, but both are not more sensitive to outliers than Mean Absolute Error (MAE), that is a reason for researchers (Hyndman & Koehler, 2006) recommending against their use in forecast accuracy evaluation.

3.15.2.7. Coefficient of Determination

The coefficient of determination is a weak form based objective function (Cheng, 2014), the coefficient of determination (R^2) is implemented to predict the statistical properties of model residuals or deviations between the model estimations and recorded data (Guinot et al., 2011) which may range between 0 to 1, with higher values indicating less error variance, and typically values greater than 0.5 are considered acceptable (Morasi et al., 2007). Coefficient of determination is very sensitive to peak flows, at the expense of better performance during low flow conditions. Krause, Boyle & Base (2005) do not suggest using coefficient of determination (R^2) alone for model quantification, because it can produce high values for very bad model results since it is correlation based. Legates and McCabe (1999) also points out the reason not to use coefficient of determination due to its oversensitivity to high discharge but it is because insensitive to additive and proportional differences between model estimations and observations.

$$R^2 = \frac{(\sum_1^n (obs_i - \overline{obs})(sim_i - \overline{sim}))^2}{\sum_1^n (obs_i - \overline{obs})^2 (sim_i - \overline{sim})^2} \quad \text{...Equation 3.7}$$

Where, obs_i and sim_i are the observed value and the simulated value for i^{th} time step, correspondingly, and $\overline{sim}$ are the average of observed and calculated data.

Even though R^2 is widely adopted for model evaluations, the statistics of which is oversensitive to high extreme values (outliers and insensitive to additive and proportional differences between model simulations output and observed data Legates and McCabe (1999).

3.16. Calibration with Single/Multi-Objective

The estimation of model parameters in order to achieve a system that nearly matches the real system in which the model represents is defined as Calibration (Sorooshian et al., 1998; Yu and Yang, 2007). In other words, the objective of model calibration is the selection of model parameters so that the model estimates the hydrological behavior of the catchment as closely as possible (Madsen, 2000). Calibration process of a model can be performed manually or with automatic approach. In manual calibrations a trial and error parameter adjustments are considered in which the goodness-of-fit of model is calibrated basically based on a visual judgment by comparing the estimated and observed hydrographs Though, due to lack of a generally unaccepted objective measure of comparison, and as a consequence of judgment involved, it is very difficult to predict accurate model simulations. Additionally, calibration performed manually take more time. In calibration performed by automatic approach, the parameter adjustments takes place automatically on the basis of a specified search and a numerical measures of the goodness-of-fit (Madsen, 2000).

It is an iterative process as long as a specified criterion is satisfied, and examples are maximum number of model evaluation, convergence of the parameter set or convergence of the objective function (Madsen, 2003).

The reason automatic calibration is embraced is because of speed, and because the confidence of the model simulations can be openly stated (Koutsoyiannis and Efstratiadis, 2010; Madsen, 2000).

Calibration on the basis of a single performance criteria is often insufficient to measure appropriately the simulation of all the important characteristics of the system that reflect the observations. This aspect is essentially what causes a definite skepticism in the hydrological profession while applying automatic calibration procedures (Madsen, 2000; Sorooshian et. al, 1988; Koutsoyiannis and Efstratiadis, 2010). Because It is essential to interpret the overall calibration objective into more operational terms while performing a proper evaluation for a calibrated model. Normally, the objectives stated below are taken into account: 1) A fine match between the averages calculated and gauged catchment discharge volume (acceptable water balance). 2) A satisfactory overall agreement for the shape of the discharge hydrograph. 3) An acceptable matching of the peak discharge with respect to timing, rate and volume. 4) A good match for high, medium and low flows (Madsen, 2000).

Fenicia et. al, (2007) also defines four similar steps in the SCA (stepped calibration approach) stated as Madsen (2000). Significant interchange among the various objectives are sought in case no unique set of parameter values is able to optimize all objectives at the same time (Madsen, 2000). Likewise, Sorooshian et. al, (1998) also points out that applied experience for model calibration recommends that no single objective function is adequate to calculate the ways in which the model fails to match the important properties of the gauged data. Madsen (2003) describes the structure of a correct framework for automatic calibration involves below major components: a) choice of calibration for parameters and model parameterization b) specifying the criteria for calibration, and c) optimization algorithm selection.

As a result it can be concluded that the traditional single objective optimization procedure functions under the fundamental assumption that a single objective function has the ability to properly extract all the contained information out of the observation time series. Though, applied experience while calibration mathematical models recommends that the scale of error in model structure for some parts of the model response may, in general, be equivalent to or even substantially bigger than the measurement error and these structural or model errors do not importantly have any inherent probabilistic property that be exploited in the construction of objective function (Gupta et al., 1998; Koutsoyiannis and Efstratiadis, 2010). Because of the presence of structural inadequacies in a mathematical model, any single (distance) objective function, no matter how meticulously selected, is insufficient to correctly measure all the properties of the observed data (Koutsoyiannis and Efstratiadis, 2010).

3.17. Data Filling Methods

Caldera, Piyathisse & Nandalal (2016) performed the comparison of methods (Arithmetic Method, Normal Ratio Method, Inverse Distance Weighting Method, Linear Regression Method, Weighted Linear Regression Method, Multiple Linear Probabilistic Method and Regression Method) to estimate daily rainfall data and found that Linear Regression method and Probabilistic method gives satisfactory estimates with one adjacent station having high correlation coefficient. Concluded Based on analysis the authors conclusions was that it is impossible to find a single method out of the seven methods considered in the study as the most appropriate one for all of missing data stations.

Hasan & Croke (2013) filled gaps of daily rainfall missing data with a statistical approach "Poisson Gamma Distribution Method" using 20 weather stations in Brahmani Basin, Rachi , India by means of putting daily data from 1969 to 2004 with half of the studied stations having less than 50% coverage due to gaps in the data.

De Silva, Dayawansa & Ratnasiri (2007) compared methods (Arithmetic Mean, Normal Ratio, Inverse Distance and Aerial Precipitation Ratio Method) which are applied for estimating rainfall missing data. 30 weather stations to represent the upcountry wet, upcountry intermediate, mid-country intermediate, low-country wet, low country intermediate and dry zone in Sri Lanka with the data duration from 1970 to 2000 were selected. Normal ratio method was found to be the most appropriate method in comparison to rest of the three methods. Inversed Distance Method considered to be most proper method for all three low-country zones (wet, intermediate, and dry) but for mid-country and up-country intermediate zones Normal Ratio Method is considered to be ideal. Furthermore, Arithmetic Mean Method is mentioned as more suitable if considered for mid-country wet zone.

Several Studies (Simolo, Bruneti, Maugeri and Nanni, 2013; Hasan & Croke, 2013; Sattari, Joudi & Kusaik, 2016;Garcia et. al,2006) and comparison of methods (Caldera, Piathisse & Nadalal,2016; De Silva, Dayawansa & Ratnasiri,2007) have been conducted in which the performance of methods such as Linear Regression, Probabilistic Method, Inverse Distance Method, Normal Ratio Method, Multiple Imputation Method, Novel Method, Closest Station Method, Simple Substitution Methods are discussed. Caldera, Piyathisse & Nadalal (2016) found that Probabilistic method and Linear Regression method gives good predictions with one neighboring station with high correlation coefficient whereas, Hasan & Croke (2013) acknowledged Poisson Gamma Distribution Method (Probabilistic Method) performs better than Inverse Distance Interpolation Method. Simolo, Bruneti, Maugeri and Nanni (2013) showed a novel method performed very well for estimation of missing values in daily precipitation series. Sattari, Joudi and Kusaik (2016) showed after assessment of different methods that multiple imputation method produced the most accurate results for precipitation data. Lo Presti, Barca & Passarella (2010) after carrying out comparison of four Linear Regression methods, determined the simplest method is Simple Substitution. Authors (Simolo, Bruneti, Maugeri & Nanni,2013; Hasan & Croke,2013; Sattari, Joudi & Kusaik,2016;Garcia et. al,2006; Caldera, Piyathisse & Nadalal, 2016; De Silva,Dayawansa & Ratnasiri,2007) have not clearly indicated any method which can be adopted for estimation of filling missing daily precipitation values as there are limitation and certain conditions which apply to each of these methods.

Garcia et. al (2006) studied cluster analysis approach for filling in missing rainfall data in the Andes region of Venezeuela, the study area with 106 weather stations with data duration of 31 years (1967-1997). A total of 1,199,390 days of missing data, about 17% of the total. Considering the closest station empirical method (Xia et al.m 1999) and the characteristics of cluster analysis (Unal et al.,2003), the hypothesis established that daily rainfall data from a weather station which can be used to fill missing data from another surrounding weather station. The following goals are set, using Ward’s method, with Euclidian distance a) determining the two closest stations for each one of 106 stations using in study considering cluster analysis; b) fill in missing rainfall data with those form closest stations; c) Evaluate the performance of proposed method considering 1,000 rainy periods for daily, weekly, bi-weekly, and monthly time scales.

Table 3.1 : Literature review for daily missing rainfall data filling techniques available

Author	**Data Resolution**	**Methods Compared**	**Results**
Caldera,Piathisse & Nadalal (2016)	Daily	Arithmetic Method, Normal Ratio Method, Inverse Distance Weighting Method, Linear Regression Method, Weighted Linear Regression Method, Multiple Linear Regression Method and Probabilistic Method	Probabilistic method & Linear Regression performed very well
Presti,Barca & Passarella (2010)	Daily	4 Linear Regression methods	Simple Substitution is the simplest method with acceptable results
Hasan & Croke (2013)	Daily	Poisson Gamma Distribution Method & Inverse Distance Interpolation	Poisson Gamma Distribution Method
De Silva,Dayawansa & Ratnasiri,2007	Daily-Monthly	Normal Ratio Method, Arithmetic Method, Inverse Distance Method, Aerial	Inverse Distance Method for low country and Normal Ratio Method for mid and up country is most suitable.
Simolo,Bruneti,Maugeri and Nanni (2013)	Daily	Assessment of Different Methods	novel method performed very well for estimation of missing values in daily precipitation series
Sattari,Joudi and Kusaik (2016)	Daily	Multiple Imputation Method , Inversed Distance Method	Multiple Imputation Method produced the most accurate results

Table 3.2 : Objective function performance matching evaluation

Objective Function	*Matching flow type			*Overall Matching	Reference Literature
	Peak flow	**Intermediate flow**	**Low flow**		
Nash	Very Good	Medium	Medium	Good	Xiong & Guo (1999), Guo et al. (2002), Krause et. al (2005), Chen et al.(2007) and Fish, Zhang & Savenije (2005);Beven and Binley, (2013); Cheng (2014); Szcześniak and Piniewski (2015); Jie et al (2016); Khandu (2016 unpubl)
REAM	Poor	Medium	Medium	Medium	Recommended by World Meteorological Organization (1974), not very common in use
MRAE	Medium	Very Good	Medium	Very Good	Wijesekera & Abeynayake (2003), Wijesekera (2000), Wanniarachchi (2013), Wijesekera & Rajapakse (2013), Khandu (2016 unpubl), unpubl) , Sharifi (2014 unpubl), Kamran (2015 unpubl) and Muthumala.P (2016), Dissanayake (2017)
RMSE	Medium	Medium	Poor	Medium	Oudin et al. (2006); Pushpalatha et al. (2012), Yu and Yang (2000) , Moreda (1999) in daily rainfall runoff comparisons, Szcześniak and Piniewski (2015)
RE	Poor	Medium	Medium	Medium	Xiong & Guo, (1999) and Guo et al., (2002), Jie et. al (2016), Szcześniak and Piniewski (2015)

**.The flow matching is evaluation is classified based on Very good, good, medium and poor*

Table 3.3 : Objective function summary list

Indicator	Objective Function	Characteristics for Selection	Purpose	References
Nash-Sutcliffe Coeff. (E)	$NSE = 1 - \frac{\sum_{i=1}^{N} (M_i - O_i)^2}{\sum_{i=1}^{N} (O_i - \bar{O})^2}$	Larger values overestimated and lower values neglected	Quantification of runoff predictions and model performance	Krause et. al ,2005, Beven and Binley, 2013; Cheng, 2014; Xiong & Guo, 1999; Guo et al., 2002; Zhang & Savenije, 2005; Chen et al., 2007 and Fish, 2011; Jie et al (2016)., 2016; Khandu,2016 unpubl, Vis et al. (2015)
RE	$RE_t = \frac{\lvert Q_t - \hat{Q}_t \rvert}{Qt} \times 100$	Total volume performance is preferred than hydrograph shape and peak flows	Volumetric fit between the observed runoff series and the simulated series	Xiong & Guo, (1999) and Guo et al., (2002)
MRAE	$MRAE = \frac{1}{n} \sum \left[\frac{\lvert y_{obs} - y_{cal} \rvert}{y_{obs}} \right]$	The objective function with more focus on intermediate flows as the error is distributed among observations	Indicates an average relative error of model output with reference to a given observed Streamflow at the point evaluated.	Wijesekera (2000), Wanniarachchi (2013),Wijesekera & Abeynayake (2003), Wijesekera & Rajapakse (2013), Khandu (2016 unpubl), Dissanayake (2017 unpubl) , Sharifi (2014 unpubl), Kamran (2015 unpubl) and Muthumala.P (2016), Vis et al. (2015)
RAEM	$RAEM = \frac{1}{n} \left[\frac{\sum \lvert y_c - y_o \rvert}{\bar{y}_o} \right]$	Balance consideration of the high flows and the low flows	Indicates the ratio between observed and calculated discharge at a given time point with respect to the mean of observed discharge	World Meteorological Organization (1974)
MSE	$MSE = \frac{\sum_{i=1}^{N} ABS\,(M_i - O_i)^2}{N}$	Most common; emphasize on high flows; neglect the low flows	Measures the fit of the modeled streamflow to the observed streamflow in order to evaluate the performance of the model.	McCuen et al. (2006); Krause et al. (2005)
RMSE	$RMSE = \sqrt{\frac{\sum_{i=1}^{N} ABS\,(M_i - O_i)^2}{N}}$	Put equal emphasis on high- and low- flows; focus on mean flow	RMSE serves to aggregate them into a single measure of predictive power.	Oudin et al. (2006); Pushpalatha et al. (2012), Yu and Yang (2000)
Coefficient of Determination	$R^2 = \frac{(\sum_1^n (obs_i - \overline{obs})(sim_i - \overline{sim}))^2}{\sum_1^n (obs_i - \overline{obs})^2 (sim_i - \overline{sim})^2}$	Inappropriate for model performance assessment; emphasize on high flows	Indicates the strength and direction of a linear relationship between two variable	Legates and McCabe (1999)

Table 3.4 : Summary list for model evaluation criteria

Author	Visual criteria	Mathematical criteria
Moriasi et. al (2007)	Hydrographs and percent exceedance probability curves, are especially valuable. Other graphical techniques, such as bar graphs and box plots, can also be used to examine Seasonal variations and data distributions.	Statistical: Standard Regression, Statistics (dimensionless) and error index
Perrin and Guerin (2011)	**Typical graphical representations:** observed and simulated flow hydrographs over time, simulated flows against the observed flow, and the cumulative distribution function of observed and simulated flows (known as flow duration curves.)	Absolute (non-relative): MAE Relative to a benchmark or dimensionless: RAE
Cheng et. al (2016)	The cumulative impulse response (CIR), graphically Compares time series plots of the predicted series and the observed series, whereas the latter uses numerical indices as evaluation criteria. Flow Duration Curves	Numerical Indices: RE , MAE, Correlation Coefficient (r) , RMSE, NRMSE, CE, CP, Error in Peak flow (Ep)
Hwang, Ham and Kim (2012)		The quantitative statistics were divided into three major categories: scale dependent error measures (SDM), which quantify the deviation in the units of the data; measures based on relative errors (MBR), which provide a relative model valuation assessment; and relative measures (RM), which determine the strength of the relationship between forecast and measured data.
Donigian and Imhoff (2010)	1. Time series plots of observed and simulated values for fluxes (e.g. flow) or state variables (e.g. stage, sediment concentration, biomass concentration) 2. Observed vs. simulated scatter plots, with a 45° linear regression line displayed, for fluxes or state variables 3. Cumulative frequency distributions of observed and simulated fluxes or state variable (e.g. flow duration curves)	1. Error statistics, e.g. mean error, absolute mean error, relative error, relative bias, standard error of estimate, etc. 2. Correlation tests, e.g. linear correlation coefficient, coefficient of model-fit efficiency, etc. 3. Cumulative distribution tests, e.g. Kolmogorov-Smirnov (KS) test

Table 3.4: Summary list for model evaluation criteria (Continued)

Author	Visual criteria	Mathematical criteria
Moriasi et.al (2012)	Graphical: 1:1, time series. Scatter, cumulative frequency distribution.	Statistical: Root mean square error, Nash-Sutcliffe efficiency, index of agreement, Percent error, mean absolute error, correlation coefficient.
Dorji Khandu (2016)	Hydrographs, Global Minimum, Flow Curves, Scatter Plots	For the Evaluation of Model Assessed : Nash , Relative Error, MRAE, RMSE, RMSE only Nash and MRAE selected
Pramila (2017)	Hydrographs , Global Minimum, Flow Curves, Scatter Plots	Nash and MRAE
Kamran (2016)	Hydrographs , Flow Curves, Scatter Plots	Nash and MRAE selected
Sharifi (2015)	Hydrographs , Global Minimum, Flow Curves, Scatter Plots	Nash and MRAE selected

4. METHODOLOGY

This methodology describes the steps followed for the application of three parameter model estimation for daily streamflow estimation with assumption that geometry of rainfall contributing area is spatially undefined illustrated in Figure 3.1. The detail methodology flow chart is attached under Annex B-1. After establishing the objective of the study, the literature survey was carried out to understand the state-of-art monthly water balance and daily water balance models including application, data requirement, data filling methods, techniques for the model evaluation, model optimization techniques, objective to describe the model efficiency and model warm-up period. In data collection and checking stage, Ma Oya basin was selected and required rainfall, streamflow and pan evaporation data was collected from the Meteorological and Irrigation Department of Sri Lanka. Data checking was performed based on the literature under various steps. The nearest station method was used for filling the missing data at daily scale before determining two datasets for calibration and validation. After which, the monthly water balance model was developed for the selected dataset. Afterward, few trials were carried for global minimum search with the help of optimum objective function for the evaluation and correspondence of high, medium and low flow conditions. Next, initial soil water content which is an important factor for performance of the model was calculated by running the model for a number of years until initial soil water content has been stabilized. Once the initial soil water content has been identified, objective function was designated for calibration. Six years of data from 2004 to 2010 was selected for calibration while 2010 to 2017 data were taken as verification period.

Since, few months of streamflow data was missing, the water year 2013-2014 was excluded from verification period of the model i.e. total six years of data is allocated for verification of the model.

Models was calibrated using monthly data under various cases which are (1) application of three parameter for daily streamflow estimation with parameters optimized only, application of three parameter model with rainfall station weights optimization only, application of three parameter model with optimization of rainfall stations weights and parameters simultaneously. (2) These monthly models were tested with daily inputs for daily streamflow estimation and rainfall station optimization after each of the scenarios daily streamflow estimation has taken place and best possible option is selected based on the model evaluation criteria, results were summarized and discussed. The conclusive findings and recommendations were then made for water resources management.

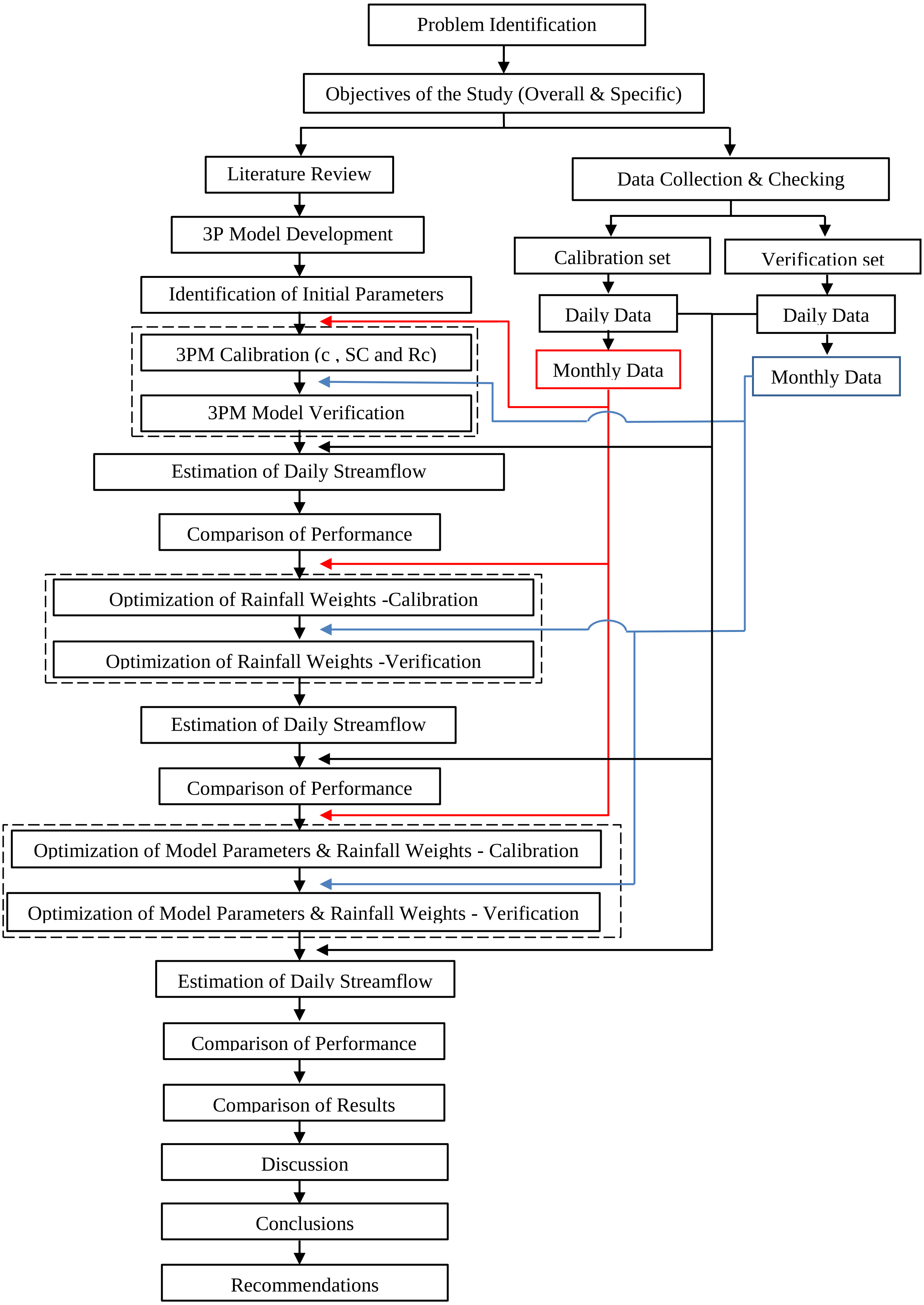


Figure 4.1: Flow Methodology Chart

5. DATA AND DATA CHECKING

Rainfall, pan evaporation and streamflow data at daily scale was collected from 2004 to 2017 for Badalgama watershed. Data use in the mathematical models is in water year format. Water year is also known as the hydrological year. In Sri Lanka the water year begins with start of October and ends with the completion of September while same time points are defined by United States Geological Survey Department. The data collected for the research study is in calendar year format and was reorganized to water year arrangement. Visual data checking was carried out for the collected data (streamflow, rainfall and pan evaporation) mentioned above to capture any inconsistencies and outliers. Hydrographs at daily scale were plotted for each rainfall station to compare with streamflow. Thiessen average rainfall also was incorporated (Figure 5.4). Annual water balance was checked for comparison with pan evaporation data. Double mass curves were used to check the consistency within the dataset. Distribution of gauging stations were compared with the WMO guidelines (1975) in (Table 5.9).

5.1. Ma Oya Basin at Badalgama Watershed

In the Badalgama watershed there are four rain gauging stations namely Ambepussa, Andigama, Aranayake and Eraminigolla which are all situated within the boundary of the Badalgama watershed (Figure 5.3). In the meantime, The River gauging station for the selected watershed is at Badalgama. There is only one evaporation station situated close to the downstream boundary. Location of streamflow gauging station and rain stations along with evaporation station are shown in Figure 1.1 and Coordinates are given in Table 5.5. Data sources and resolutions are in Table 5.6. Land-use details of the watershed area are in Table 5.7, reclassified in Table 5.8 and illustrated in Figure 5.3. Classification of landuse in the watershed were extracted from land use map of Sri Lanka (Table 5.7). Landuse was later reclassified (Table 5.8) into seven major classes to assess runoff coefficient.

The Reclassification of land use was performed based on the similarities between Landuse for instance coconut, tea, chena, paddy and other cultivations are classified under Agricultural Landuse.

Table 5.5: Gauging stations location in Badalgama watershed

Gauging Station	Data Type	Location
Badalgama	Streamflow	7° 18' 54" N 80° 0' 16" E
Ambepussa	Rainfall	7° 16' 48" N 80° 10' 12" E
Andigama farm	Rainfall	7° 22' 12" N 80° 7' 12" E
Eraminigola	Rainfall	7° 17' 60" N 80° 22' 48" E
Arayanake	Rainfall	7° 10' 48"N 80°27' 36" E
Makandura	Evaporation	7° 19' 12"N 79° 58' 48" E

Table 5.6: Details of data for Ma Oya basin at Badalgama

Data Type	Spatial Reference	Temporal/Spatial Resolution	Data Period	Data Source
Rainfall	Ambepussa	Daily	2005-2017	Department of Meteorology
	Andigama			
	Eraminigola			
	Arayanake			
Streamflow	Badalgama	Daily	2005-2017	Department of Irrigation
Pan Evaporation	Makandura	Daily	2005-2017	Department of Meteorology
Land use	Kegalle Attangalla Kochchikade Kandy	1:50,000	Updated 2003	Department of Survey
Topographic Map	Kegalle Attangalla Kochchikade Kandy	1:50,000	Updated 2003	Department of Survey

Table 5.7: Landuse data – Ma Oya Basin at Badalgama

Land Use	Area (km^2)	Percentage (%)
Builtup Area	0.34	0.025
Coconut	493.85	36.84
Chena	0.73	0.054
Chena	0.02	0.002
Cemetry	0.04	0.003
Forest (Unclassified)	32.71	2.441
Grassland	0.03	0.002
Homesteads	269.76	20.126
Marsh	0.07	0.005
Other cultivation	17.78	1.327
Paddy	185.35	13.829
Rubber	203.83	15.207
Rock	17.29	1.290
Scrub land	50.78	3.789
Stream (LINE/AREA)	9.48	0.707
Tank boundaries	0.80	0.060
Tea	57.29	4.275
Water holes boundaries	0.19	0.014
Total	1340.34	100.0

Table 5.8: Landuse Data Reclassified – Ma Oya Basin at Badalgama

Land Use	Area (km^2)	Percentage
Builtup Area	17.66	1.32%
Agricultural	261.28	19.49%
Forest	32.71	2.44%
Scrub Area	50.78	3.79%
Water Bodies	10.47	0.78%
Plantation	697.68	52.05%
Homestead	269.76	20.13%
Total	1340.34	100%

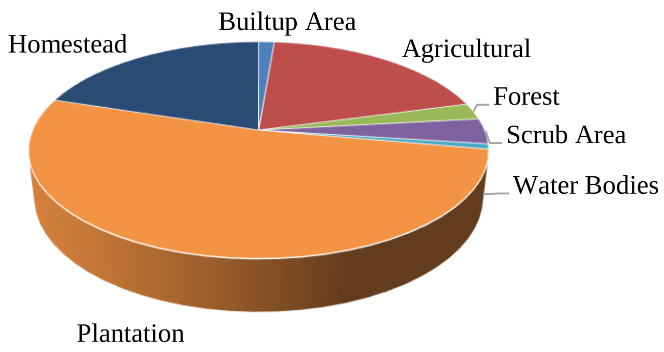


Figure 4.2: Landuse Data Reclassified – Ma Oya Basin at Badalgama

Table 5.9: Gauging Stations Densities of Ma Oya Basin at Badalgama Watershed

Gauging Station	Number of Stations	Station Density (km^2/station)	WMO Standards (km^2/station)
Rainfall	4	332	575
Streamflow	1	1325	1,875
Evaporation	1	1325	5,000

5.1.Thiessen Weights

Thiessen average method was used to compute the mean areal precipitation. Accordingly rainfall recorded at each station was given a weightage based on the geometry of stations. Thiessen weights for Badalgama sub-basin in Ma Oya are given in Table 5.10 and illustrated in Figure 5.4.

Table 5.10: Thiessen weights for rain gauging station of Badalgama watershed

Rainfall station	Thiessen Area (km^2)	Thiessen Weight
Ambepussa	345.64	0.26
Aranayake	259.75	0.20
Eraminigola	466.03	0.35
Andigama Farm	254.12	0.19

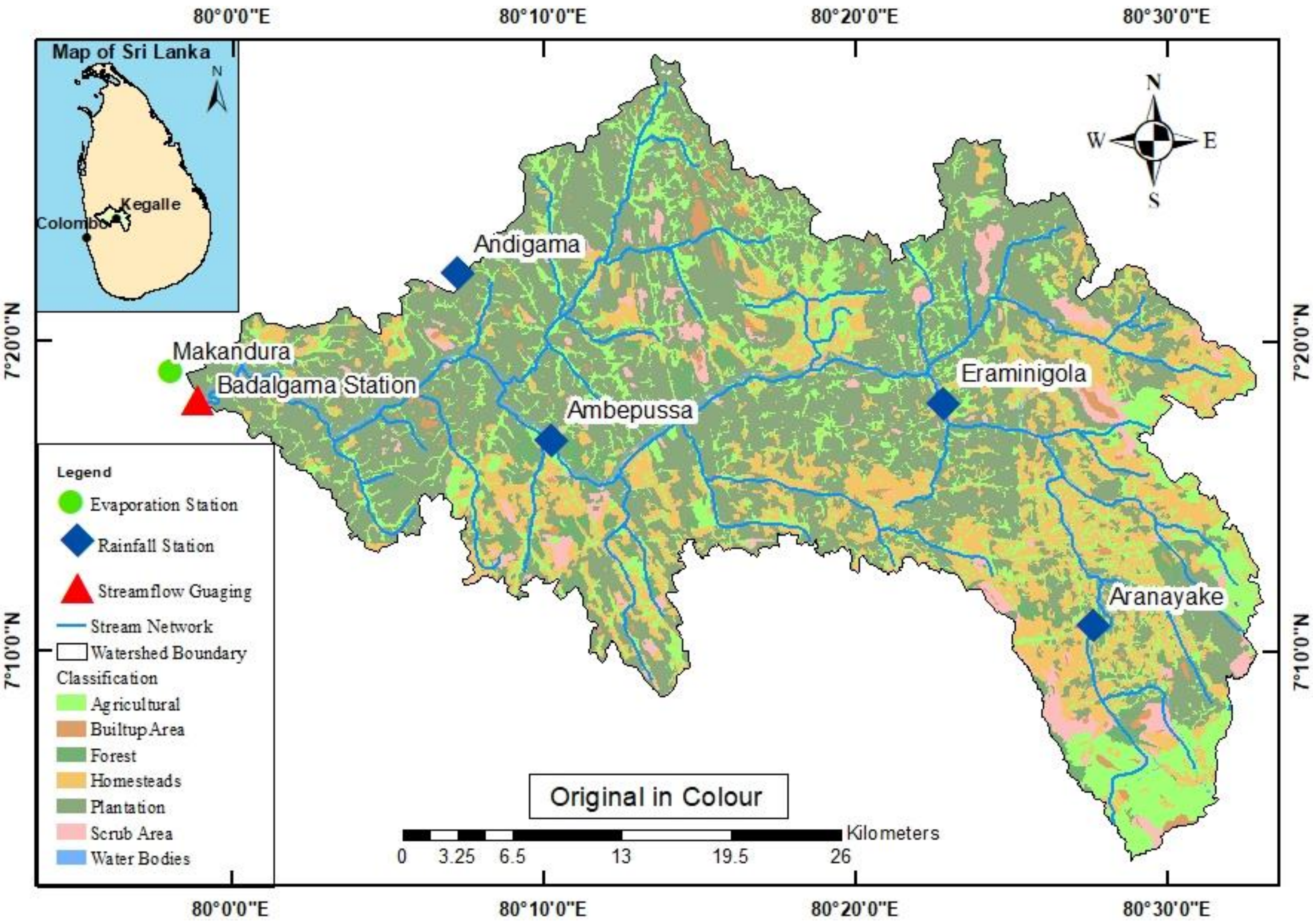


Figure 5.3: Landuse map Ma Oya Basin at Badalgama

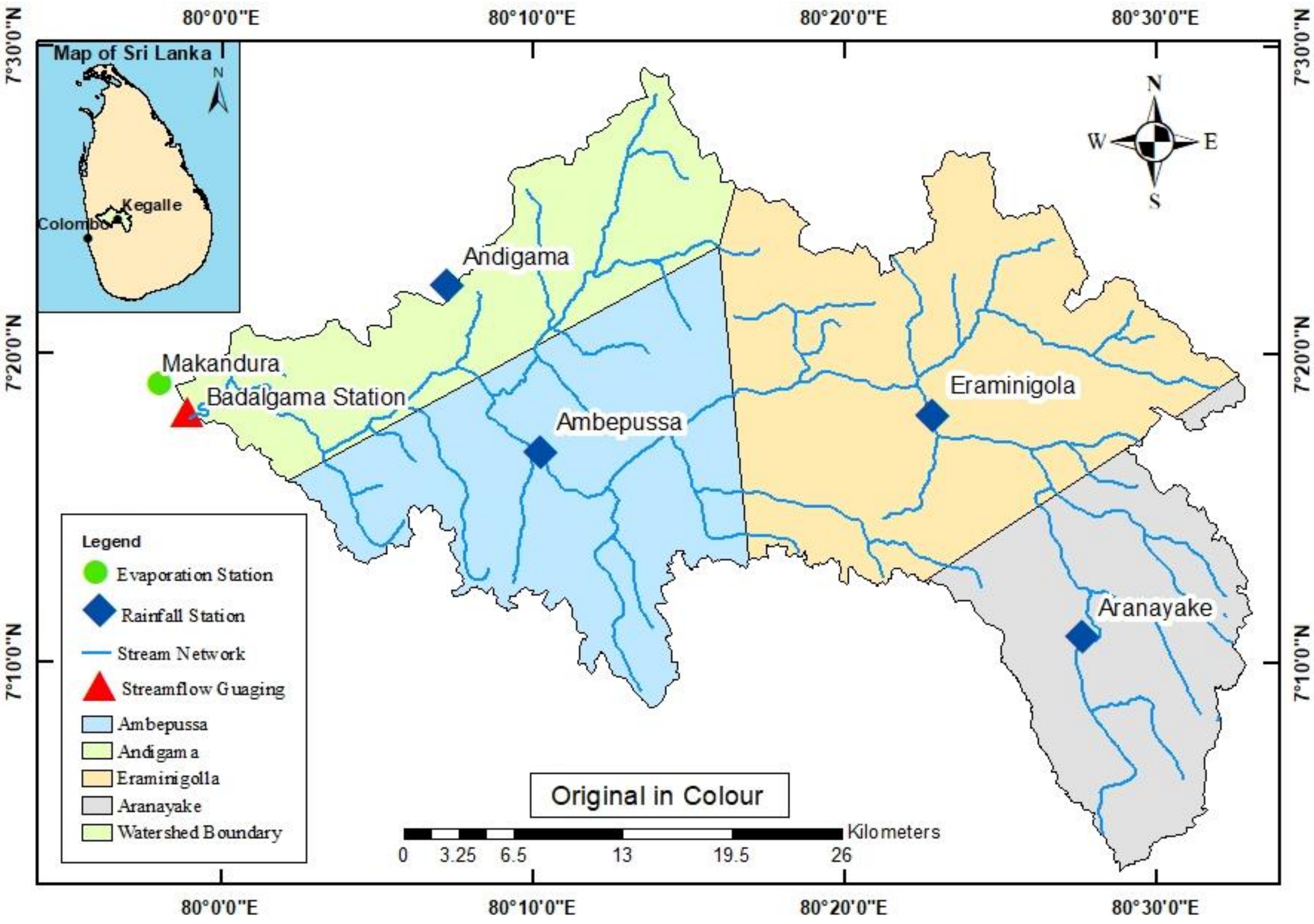


Figure 5.4: Thiessen polygons – Badalgama watershed

5.2. Missing Data

After the initial check, it was realized that data has been missing in the collected data for a few of the months. Missing data details are given in Table 5.11.

Table 5.11: Details of Missing data months (Rainfall)

Ambepussa Gov. Farm	Andigama Farm	Aranayake (CEB)	Eraminigolla
November 2005	March 2014	October 2011	November 2010
July 2011	August 2014		December 2010
October 2011			February 2011
November 2011	September 2014	December 2012	December 2011
Jan 2012			December 2012
Dec 2012			

Based on the literature review, the nearest station approach was adopted for filling the missing rainfall data. Table 5.12 shows the details of missing evaporation and streamflow data. More than 60 days of daily streamflow data are missing from, the water year 2013/2014, which was not considered in calculations. In case of the evaporation data of the nearest evaporation station Lunuvila was used to substitute data for May and June of 2013.

Table 5.12: Details of missing data (streamflow and evaporation)

Makandura Evaporation Station	Badalgama Streamflow Station
May 2013	February 2012 (5Days)
June 2013	February 2014 (5Days)
	March 2014 (8Days)
	April 2014 (5Days)

5.3. Annual Average Rainfall

Average monthly rainfall and average annual rainfall values for gauging stations of Badalgama watershed are shown in Table 5.13.

Table 5.13: Rainfall of Badalgama watershed

Rainfall Station	Avg. Monthly Rainfall (mm/Month)	Avg. Annual Rainfall (mm/year)
Ambepussa	180	2,163
Andigama	166	1,996
Aranayake	175	2,106
Eraminigolla	171	2,052
Thiessen Average	173	2,078

5.4. Streamflow

Average, minimum and maximum monthly streamflow and annual averages are in Table 5.14.

Table 5.14: Streamflow of Badalgama watershed

	Streamflow	
	Monthly Streamflow (mm/Month)	Annual Streamflow (mm/Year)
Max	562.8	1,271
Mean	110.0	809
Min	0.7	244

5.5. Pan Evaporation

Daily pan evaporation maximum, mean and minimum evaporation values are given in Table 5.15.

Table 5.15: Variation in evaporation data in Makandura station

	Pan Evaporation	
	Monthly (mm/Month)	Annual (mm/Year)
Max	148	1,404
Mean	108	1,303
Min	68	1,153

5.6. Visual Data Checking

Visual checks were carried out to identify inconsistences and outliers in the collected daily data. Daily streamflow responses against daily rainfall were plotted for each rain gauging station data and for each year. Similarly monthly, seasonal and annual comparison are also performed. The overall dataset max, min, and average for rainfall, streamflow and pan evaporation is plotted (Annex A-3). Observing at overall dataset maximum rainfall occurred during October, November, December and May. Minimum rainfall can be seen in months of January, February. Simultaneously, maximum streamflow is observed in months of October, November, December and May and minimum streamflow for months of January and February which indicates a wide-ranging relationship with rainfall. Concurrently, maximum pan evaporation is in the months of January, February, and March while minimum for the months of December, November and October.

5.7. Daily Data

Streamflow responses at Badalgama river gauging station for rainfall at each rain gauging station were visually checked. Variation for year of 2013/2014 is shown in Figure 5.5. Badalgama streamflow is missing for January, February and March of 2014. The streamflow response to rainfall data in February and March for the year of 2011/2012. The streamflow which does not very well respond to rainfall or vice-versa are marked in purple color in full version of daily data comparison under Annex A-1. September 2016 there is no rainfall in the specified month but there is streamflow response. However, while observing the entire data series, data does not indicate major issues other than missing values in streamflow. Daily Rainfall-Streamflow responses separately for all four stations of Badalgama watershed are shown under Annex A-1.

Thiessen average rainfall response with streamflow during year 2011 to 2014 is shown in Annex A-2. Non-responsive data are marked with purple color circles. Considering overall data checking for inconsistency and homogeneity it was assumed that after filling and using Thiessen averaged rainfall would be reasonable for the present study shown (Annex A-2).

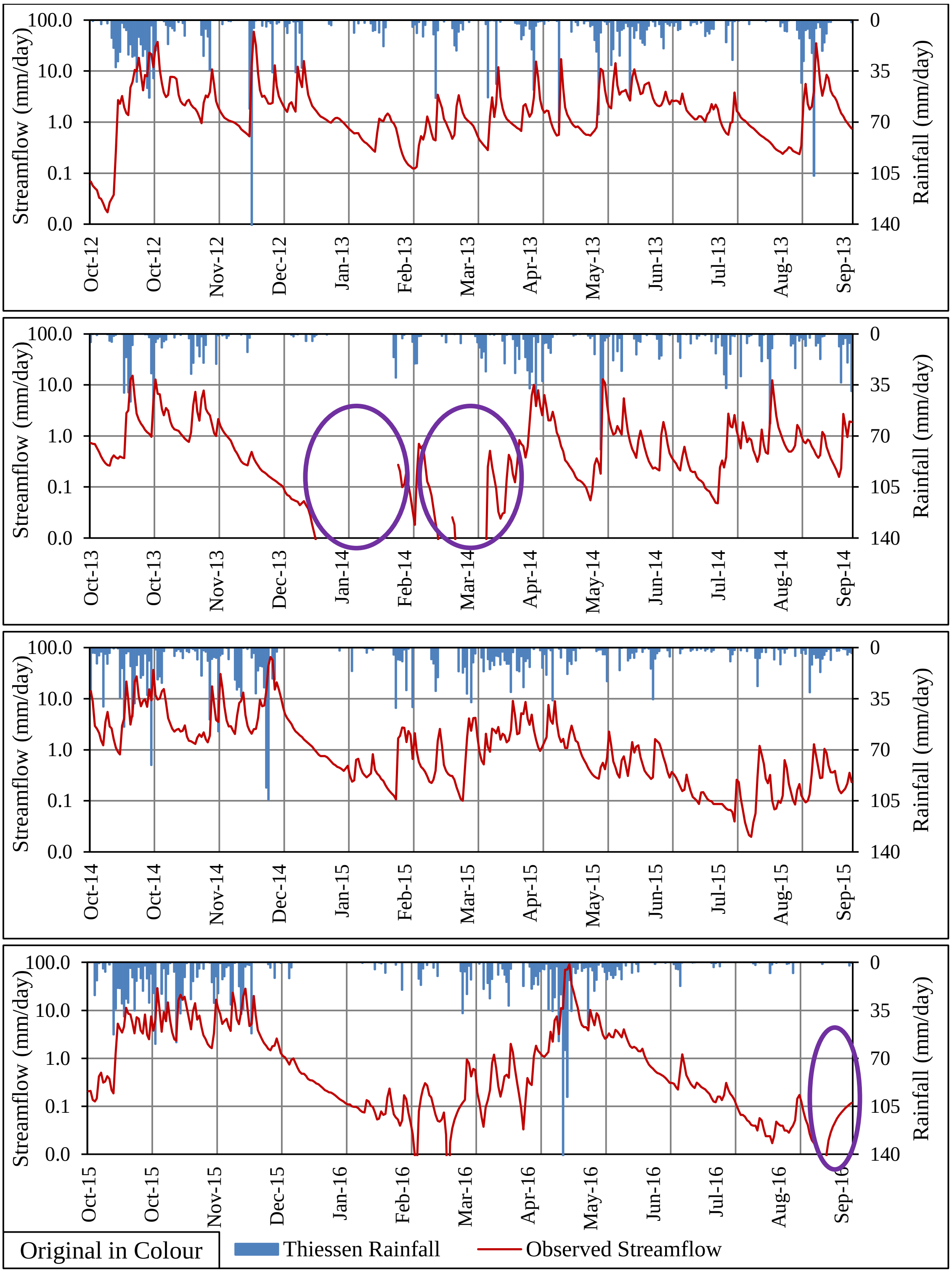


Figure 5.5: Thiessen average rainfall and observed streamflow of Badalgama (Oct 2012- Sep 2016)

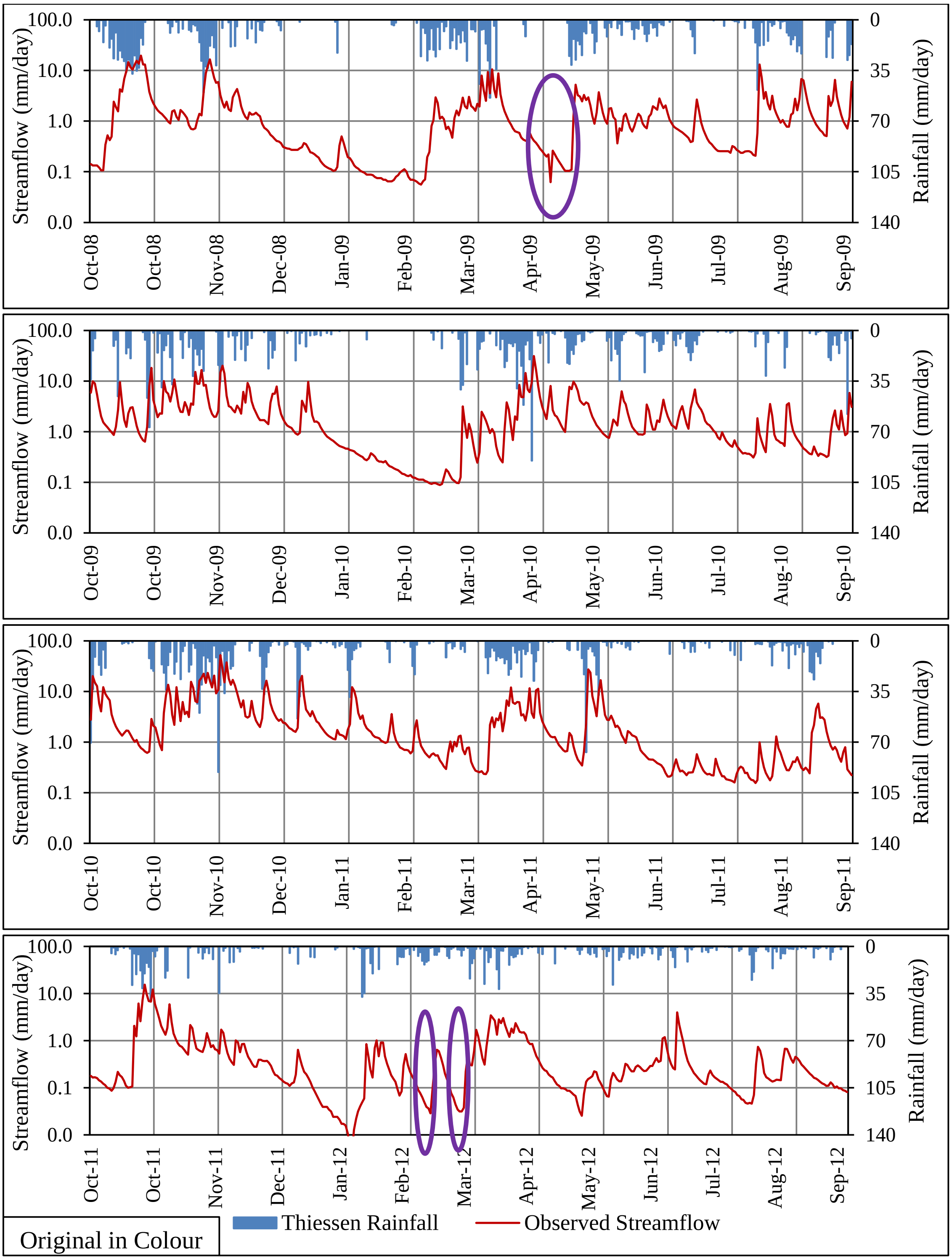


Figure 5.6: Thiessen average rainfall and observed streamflow of Badalgama (Oct 2008- Sep 2012)

5.8. Monthly Data

The monthly comparison has its importance, it is to identify the mismatches which cannot be spotted by the daily rainfall-runoff graphs. It also is helpful to investigate the affect and visibility of mismatches that occurred on the daily scale. Monthly variations for each year has been also plotted to check the behavior of rainfall for each individual station (Annex A-4). Year 2015/2016 shows higher rainfall in the month of May 2006/2007 shows higher rainfall in the month of October and November (Figure 5.7). Monthly comparison of streamflow, pan evaporation and rainfall for Badalgama watershed were plotted for visual checking (Figure 5.10 and Fig 5.11). Monthly comparison shows that October 2004, April 2006, October 2007, April 2009, June 2010 , December 2010, May 2011, October 2015, May 2016, June and April 2016 have inconsistent streamflow response to the Thiessen rainfall. The monthly average, maximum and minimum rainfall variations were checked and are shown in Figure 5.10 and Figure 5.11.

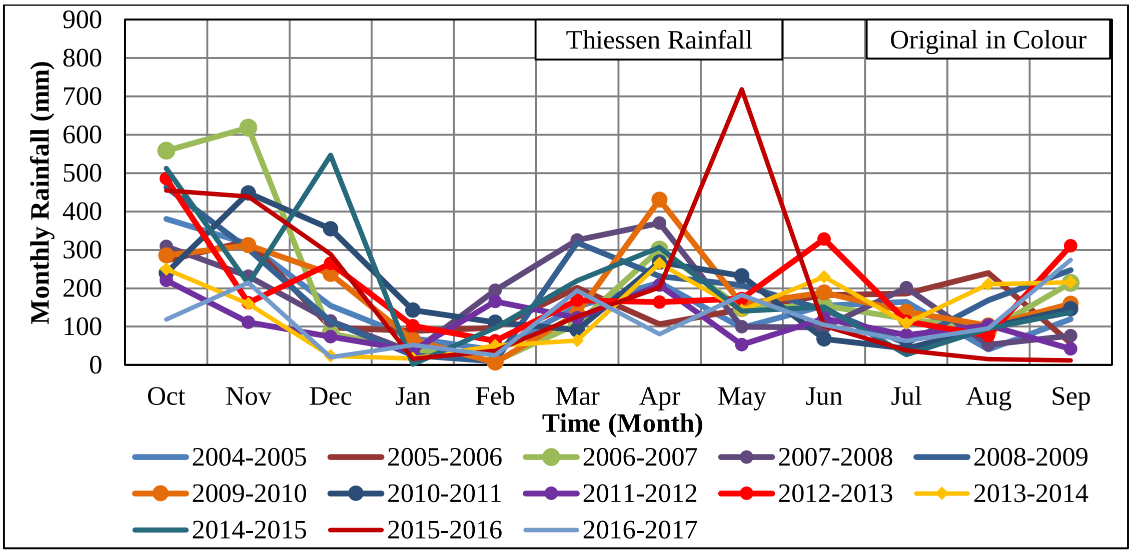


Figure 5.7: Annual seasonal Thiessen rainfall pattern – Badalgama watershed

5.9. Seasonal Data

The seasonal data summaries, reveal the similarity of seasonal rainfall pattern. The seasonal comparison is performed with bar chart between two major seasons of the water year which are Maha and Yala. Few years such as 2010/2011 all rainfall stations show less rainfall in Maha than Yala; 2013/2014 data is already missing, the figures are represented under Annex B-2 in which mismatches are shown with red circle and the seasonal summary is presented in tabular form in Annex B-2.

5.10. Annual Data

In order to check the dataset, annual Thiessen rainfall was plotted against annual streamflow (Figure 5.8 and Figure 5.9), there is a mismatch in year 2008/2009 where the streamflow shows a relatively low value compared to rainfall. The annual rainfall comparison for each respective station along with data is presented in Annex D-1.

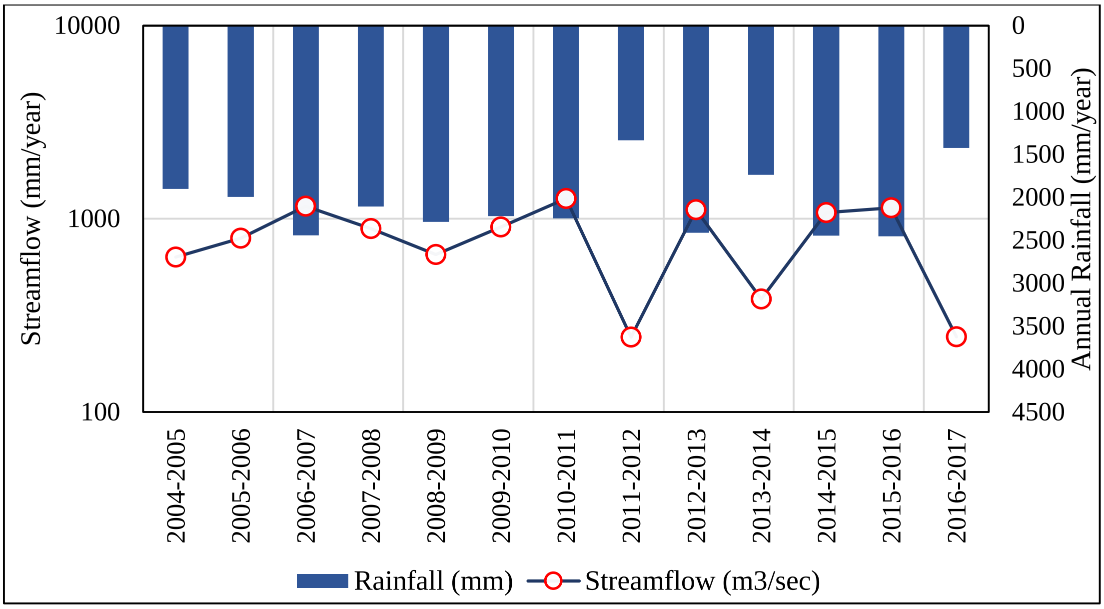


Figure 5.8: Annual variation of Thiessen rainfall and observed Streamflow: Semi –Log Scale

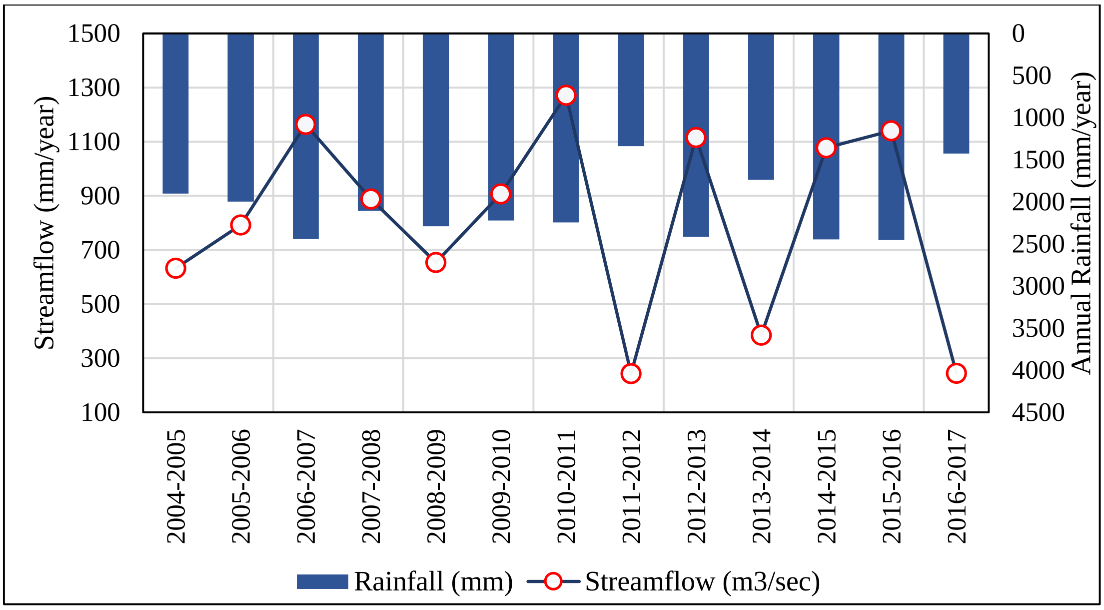


Figure 5.9: Annual variation of Thiessen Rainfall and observed streamflow: Normal Scale

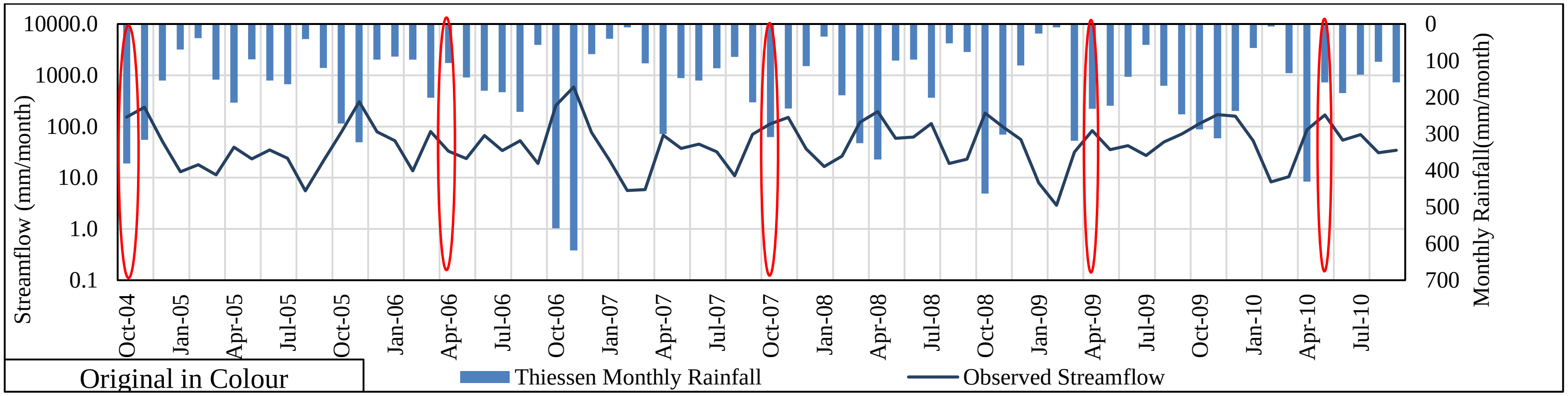


Figure 5.10: Variation of Monthly Thiessen rainfall with observed streamflow for Badalgama watershed 2004-2010

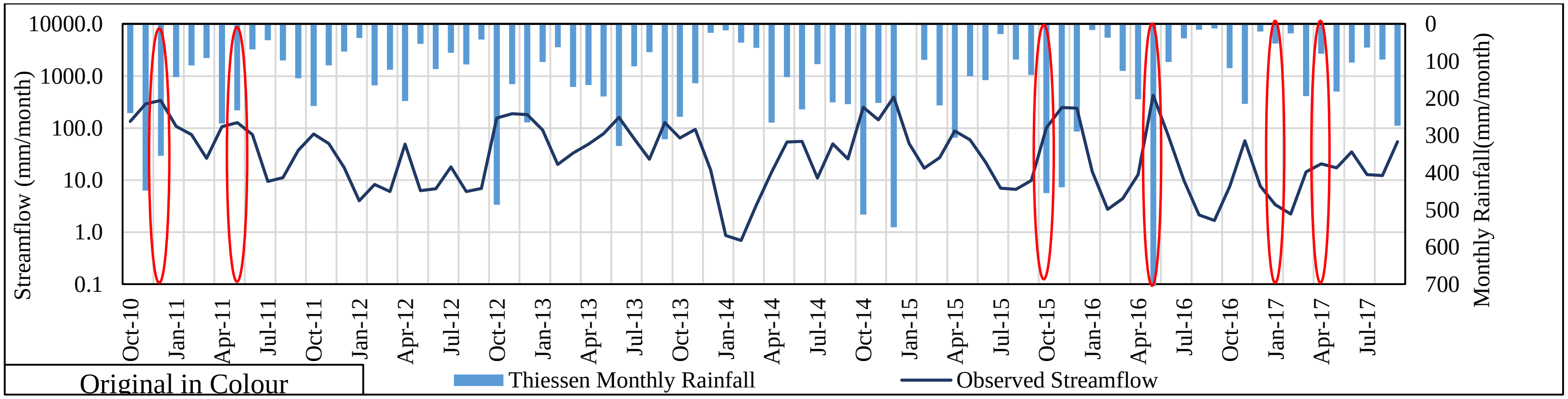


Figure 5.11: Variation of Monthly Thiessen rainfall with observed streamflow for Badalgama watershed 2010-2017

5.11. Annual Water Balance

As discussed in literature, water years are considered for the mathematical model. Sokolov and Chapman (1974) described continuity equation for any water balance as:

$(Precipitation\ +\ GW_{in}) - (ET + GW_{out} + SF) = \left(\frac{\Delta S}{\Delta t}\right)$ ….. Equation 5.8

Where, "Precipitation" can have any form such as snowfall, rainfall, sleet and drizzle. GW_{in} represents groundwater inflow to the catchment. GW_{out} represents groundwater outflow. ET is evapotranspiration. SF is streamflow.

The equation can further be simplified as:

$Inflow - Outflow\ = \left(\frac{\Delta S}{\Delta t}\right)$…………………………………….. Equation 5.9

The above equation can applied to any time step. At annual time step, which shows a cyclic weather characteristic it is assumed that soil moisture returns to the same point. In order to be more realistic the same point is taken as beginning of water year. If so, cyclic weather, considering beginning of the water year the continuity equation becomes the annual water balance which can be written as below:

$(Precipitation\ +\ GW_{in}) - (ET + GW_{out} + SF) = 0$ ……….. Equation 5.10

Since GW_{out} and GW_{in} are difficult to measure and compared to other components these quantities are very small and approximately zero therefore final equation of annual water balance becomes:

$(Precipitation\ ) - (SF) = ET$ …………………………..…….. Equation 5.11

Looking at the equation 5.10, it can be evidently supported that aim of annual water balance is to check the overall error with respect to the evaporation with the base data between rainfall and streamflow occurred i.e. to observe the watershed behavior over the study period, In order to do that annual water balance was calculated with the Thiessen rainfall and streamflow data at Badalgama gauging station. If pan evaporation is correlated to actual evaporation then the ratio between them must be within the range ratio of 0.6 to 0.8. By considering annual water balance there are three criteria which must qualify for the check which are 1) over the year if rainfall and sunshine remains similar then water balance of the same order of magnitude. 2) Ratio between actual evaporation and pan evaporation must be very similar. 3) Runoff co-efficient can be checked from water balance and land use. Annual water balance of Badalgama watershed data is shown in Table 5.16, Figure 5.12 and Figure 5.13.

Table 5.16: Annual water balance – Badalgama watershed

Water Year	Annual Rainfall (mm/year)	Annual Observed Streamflow (mm/year)	Annual Pan Evaporation (mm/year)	Annual Water Balance (mm/year)	Runoff Coefficient
2004/2005	1,901	633	1,200	1,268	0.3
2005/2006	1,997	792	1,243	1,205	0.4
2006/2007	2,442	1,164	1,292	1,278	0.5
2007/2008	2,106	889	1,129	1,217	0.4
2008/2009	2,322	654	1,326	1,668	0.3
2009/2010	2,219	907	1,356	1,312	0.4
2010/2011	2,244	1,272	1,281	973	0.6
2011/2012	1,338	244	1,402	1,093	0.2
2012/2013	2,413	1,115	1,305	1,298	0.5
2013/2014	1,737	385	1,400	1,352	0.2
2014 /2015	2,446	1,077	1,282	1,369	0.4
2015/2016	2,452	1,140	1,362	1,312	0.5
2016/2017	1,425	245	1,237	1,180	0.2

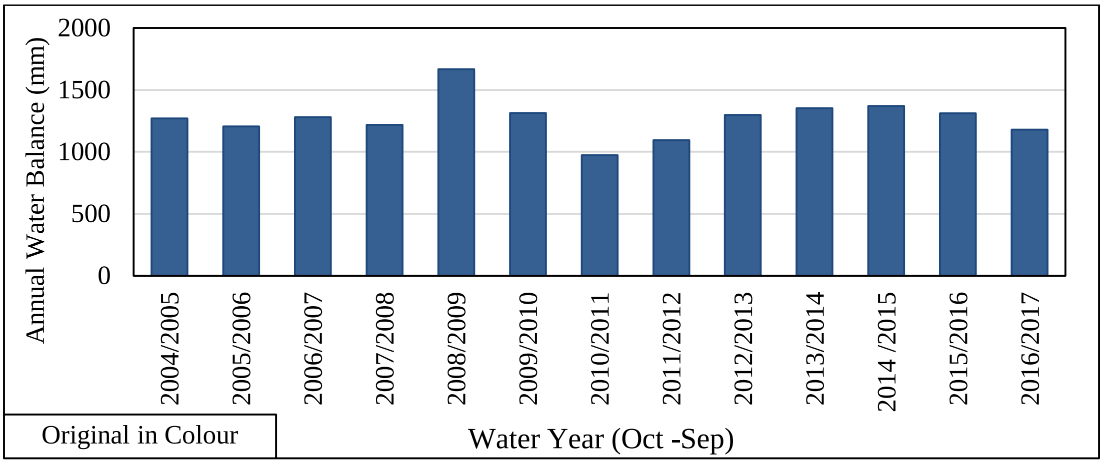


Figure 5.12: Annual water balance for Badalgama watershed

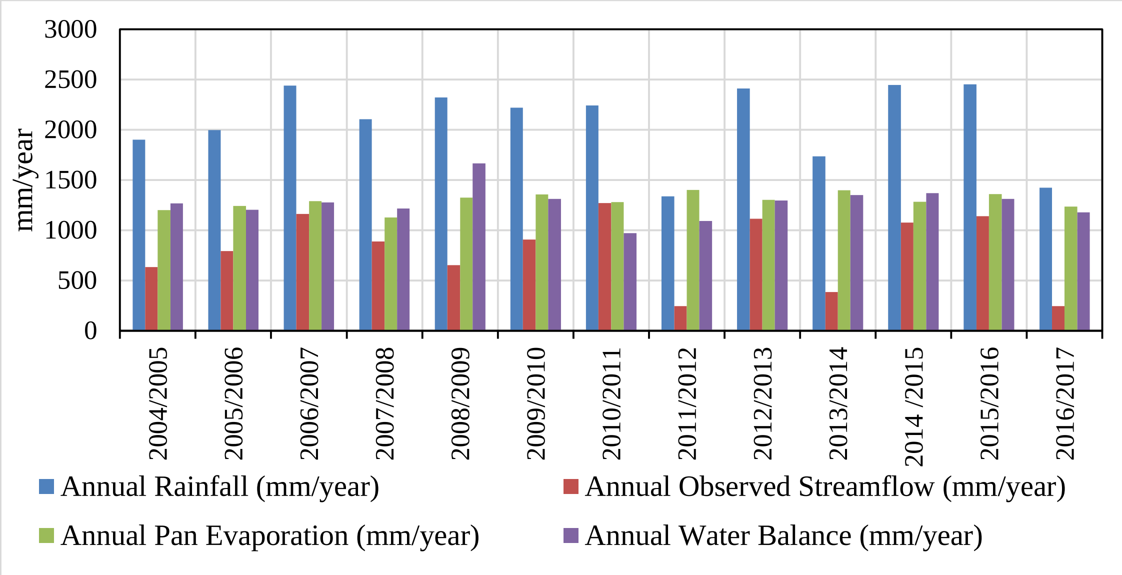


Figure 5.13: Annual Water Balance for Badalgama Watershed

The annual water balance revealed that observed streamflow for the year 2013/2014 has missing streamflow data as it is giving the maximum water balance value. Runoff coefficient of the year 2010/2011 is the highest. The lowest runoff coefficient was during 2016/2017 and 2011/2012. Both water years 2016/2017 and 2011/2012 are with almost equal rainfall and when compared with other years, also the lowest rainfall occurred during these water years. To justify the runoff coefficient, the runoff coefficient of all the years was averaged which was 0.4 for the Badalgama watershed and similarly the weighted runoff coefficient was calculated for the land use types available in the study area (Chow, Maidment, & Mays, 1988). It was found that the runoff coefficient value achieved from the data has close match with the study area. However, annual water balance does not show a systematic behavior. The annual water balance comparison with pan evaporation shows a better correlation.

5.12. Double Mass Curve

Double mass curve was applied for consistency check of the hydrologic data which must portray no slope breaks and kinks are there, if there are any, then it is an indication of data inconsistency. Double mass curves plotted respectively for Ambepussa, Andigama, Aranayake and Eraminigolla are in Figure 5.14. Double mass curve data are provided in Table 5.17, Table 5.18, Table 5.19 and Table 5.20. No significant inconsistency were observed in rainfall data for Badalgama watershed.

Table 5.17: Double Mass Curve Data for Ambepussa Station – Badalgama watershed

Water Year	Ambepussa (mm)	Ambepussa Cumulative (mm)	Avg. cumulative except Ambepussa (mm)
2004/2005	1,644.6	1,644.6	2,007.7
2005/2006	1,808.9	3,453.5	4,087.7
2006/2007	2,750.9	6,204.4	6,444.2
2007/2008	1,998.4	8,202.8	8,577.8
2008/2009	2,493.5	10,696.3	1,0840.2
2009/2010	1,749.2	12,445.5	1,3180.7
2010/2011	2,197.8	14,643.3	1,5466.5
2011/2012	1,822.6	16,465.9	1,6654.5
2012/2013	2,456.3	18,922.2	1,9146.2
2013/2014	2,179.5	21,101.7	2,0695.6
2014 /2015	2,942.8	24,044.5	2,2956.7
2015/2016	2,677.8	26,722.3	2,5152.7
2016/2017	1,400.9	28,123.2	2,6558.5

Table 5.18: Double Mass Curve Data for Andigama Station – Badalgama watershed

Water Year	Andigama (mm)	Andigama Cumulative (mm)	Avg. cumulative except Andigama (mm)
2004/2005	1,955.9	1,955.9	1,903.9
2005/2006	2,113.8	4,069.7	3,882.3
2006/2007	2,576.9	6,646.6	6,296.8
2007/2008	2,325.6	8,972.2	8,321.3
2008/2009	2,213.3	11,185.5	1,0677.1
2009/2010	1,898.7	13,084.2	1,2967.8
2010/2011	2,241.6	15,325.8	1,5239.0
2011/2012	1,371.3	16,697.1	1,6577.5
2012/2013	2,404.4	19,101.5	1,9086.4
2013/2014	1,398.0	20,499.5	2,0896.3
2014 /2015	2,169.9	22,669.4	2,3415.1
2015/2016	1,542.7	24,212.1	2,5989.5
2016/2017	1,416	25,628.1	2,7390.2

Table 5.19: Double Mass Curve Data for Aranayake Station – Badalgama watershed

Water Year	Aranayake (mm)	Aranayake Cumulative (mm)	Avg. cumulative except Aranayake (mm)
2004/2005	2,135.1	2,135.1	1,844.2
2005/2006	2,123.4	4,258.5	3,819.4
2006/2007	2,240.4	6,498.9	6,346.0
2007/2008	1,879.7	8,378.6	8,519.2
2008/2009	2,446.7	10,825.3	10,797.2
2009/2010	2,571.0	13,396.3	12,863.8
2010/2011	2,453.8	15,850.1	15,064.2
2011/2012	1,068.8	16,918.9	16,503.5
2012/2013	2,895.1	19,814.0	18,848.9
2013/2014	1,559.2	21,373.2	20,605.1
2014 /2015	2,312.2	23,685.4	23,076.4
2015/2016	2,426.2	26,111.6	25,356.3
2016/2017	1,262.6	27,374.2	26,808.2

Table 5.20: Double Mass Curve Data for Eraminigolla Station – Badalgama watershed

Water Year	Eraminigolla (mm)	Eraminigolla Cumulative (mm)	Avg. cumulative except Eraminigolla (mm)
2004/2005	1,932.0	1,932.0	1,911.9
2005/2006	2,002.9	3,934.9	3,927.2
2006/2007	2,252.2	6,187.1	6,450.0
2007/2008	2,195.5	8,382.6	8,517.9
2008/2009	2,127.2	10,509.8	10,902.4
2009/2010	2,551.8	13,061.6	12,975.3
2010/2011	2,161.9	15,223.5	15,273.1
2011/2012	1,124.1	16,347.6	16,694.0
2012/2013	2,175.5	18,523.1	19,279.2
2013/2014	1,691.0	20,214.1	20,991.5
2014 /2015	2,301.2	22,515.3	23,466.4
2015/2016	2,619.2	25,134.5	25,682.0
2016/2017	1,538.7	26,673.2	27,041.8

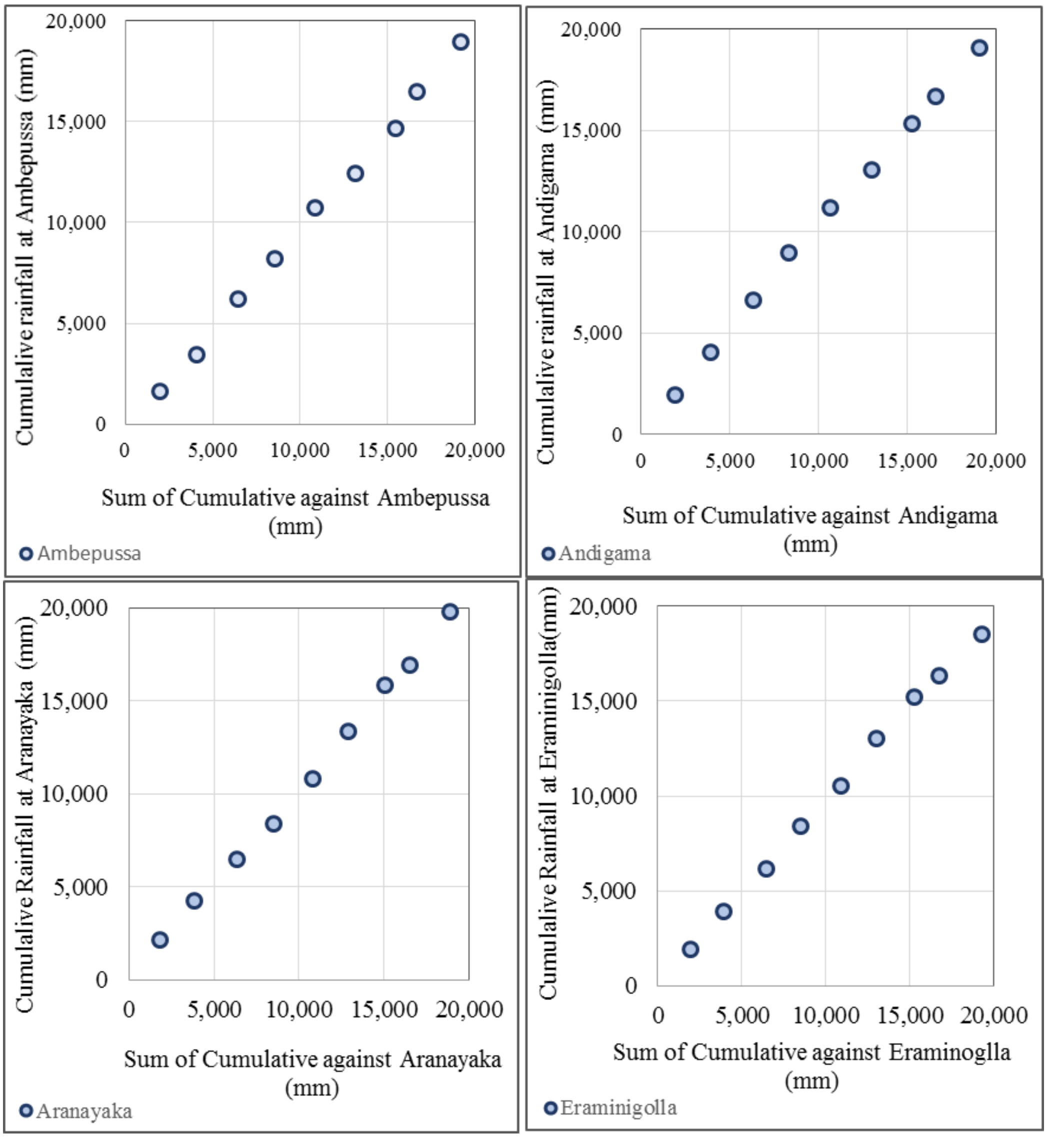


Figure 5.14: Double Mass Curve for Ambepussa, Andigama, Aranayke and Eraminigolla Stations – Badalgama watershed

6. ANALYSIS AND RESULTS

6.1. Introduction

The two parameter model proposed by Xiong and Guo (1999) is considered as simple rainfall runoff model and a model which has the capability of predicating streamflow and soil moisture. Two parameter model is for the estimation of monthly streamflow with the use of monthly data as input (Xiong & Guo ,1999).The fundamental model used for the analysis is the three parameter monthly water balance model (Dissanayake,2017 unpubl).

The main objective of this study is to evaluate the capability of the three parameter monthly model.

6.2. Model Development

Xiong & Guo, 1999 developed the two parameter model with a set of fundamental equations. There are three equations which were introduced by the authors (Xiong & Guo, 1999) and they are as follows:

$$\frac{E(t)}{EP(t)} = C \cdot Tanh\left[\frac{P(t)}{EP(t)}\right] \text{......Equation 6.12}$$

$$Q(t) = S_{(t-1)} + Tanh\left[\frac{S_{(t-1)}+P(t)-E(t)}{Sc}\right] \text{......Equation 6.13}$$

$$S(t) = S_{(t-1)} + P(t) - E(t) - Q(t) \text{......Equation 6.14}$$

Where, C – Monthly evaporation coefficient (This coefficient is introduced to change the model from annual resolution to monthly) , EP(t) – Pan evaporation , P(t) – Rainfall , E(t) – Evaporation Estimation of Model, S(t) - Soil water content at the end of (t) month , Q(t) – Runoff discharge , S(t-1) – Soil water content at the end of (t-1) month

Certain conditions have been applied during the calculations in model just to make sure the realistic values are achieved as output from the model; Dissanayake (2017 unpubl) has used the conditions. After the investigating the conditions it was noticed that the conditions are applied based on the basic engineering rules for instance the soil storage can never take a negative value or the actual evapotranspiration cannot be greater the pan evaporation. The following conditions were imposed on the computations:

Condition 1; E(t) at any given time must be greater than or equal to zero.

Hence, $E(t) \geq 0$……………………………………………………….Equation 6.15

Condition 2; Actual evapotranspiration at any time t is less than or equal to potential

Evaporation at that particular time.

Hence, $E(t) \leq EP(t)$ ………………………………………………… Equation 6.16

Condition 3; Daily or Monthly Streamflow estimation by the model at any time (t) is greater than and equal to zero.

Hence, $Q(t) \geq 0$ …………………………………..…………………Equation 6.17

Condition 4;

Watershed moisture storage at any given time (t) is non negative.

$St \geq 0$……………………………..………………………………… Equation 6.18

As excel spreadsheet was developed for the model functionality using above equations (6.12, 6.13 and 6.14) with a combination of (6.15, 6.16, 6.17 and 6.18). The model manual search method and Microsoft Excel 'solver' was used for the parameter optimization.

6.3. Model Checking

A step by step approach for checking of model was adopted to make sure whether the developed spread sheet model is accurate. The equations applied in spreadsheet were compared by hand calculation (Annex C-1).

6.4. Evaluation of Objective Function

MRAE (Mean Ratio of Absolute Errors) was selected as the objective function for the current study. Selection of objective function was based on the following; MRAE objective function gives the relative error and then averages the relative error on the entire dataset. MRAE is well suited for medium flow evaluation and it was been successfully applied for many suitable studies (Khandu, 2016; Sharifi, 2015; Jayadeera 2016 & Dissanayake, 2017).

6.5. Identification of High, Medium and Low Flows

In identification of high, medium and low flow was done by using monthly and daily flow duration curves for Badalgama watershed. Threshold for flow duration curves of daily and monthly scales for Badalgama watershed is based on the section 3.11 as it can be clearly seen in Table 6.21. The range for high, medium and low flows are clearly dependent based on a number of reasons including shape and slope of the flow duration curve. Most of authors (Khandu, 2016; Sharifi, 2015; Jayadeera 2016 & Dissanayake, 2017) for monthly studies focused on water resources management had considered the flows ≤ 25% of time as high flows. The medium flows were taken as between 75% and 25%. Low flows were taken as >75%. In a similar fashion, value for daily scale were computed (Table 6.21).

Table 6.21 : High, Medium and Low flow threshold for monthly and daily data

Percentage of Exceedance		
Flow Type	Badalgama Watershed	
	Monthly (%)	Daily (%)
High	≤25	≤15
Medium	>25 & ≤75	>15 & ≤75
Low	>75	>75

6.6. Calibration of Two Parameter Monthly Model

6.6.1. General

Xiong & Guo (1999) performed the parameter optimization in their study in two steps. The first is to optimize both (Sc, c) parameters at the same time using a single objective function. After that while keeping the parameter c constant, the parameter Sc is optimized with a secondary objective function. Xiong & Guo (1999) at initial stage optimized using Relative Error (RE) as objective function and later optimized Sc for Nash-Sutcliffe. In the present research, the initial optimization was carried out using MRAE as the objective function and later in the step 2 both parameters were optimized to match the intermediate flows with optimization of (Sc, c) parameters for MRAE intermediate flows with the help of flow duration curves (FDC). [NM1]

6.6.2. Determination of Global Minimum

The search for global minimum was conducted in two different stages, the coarser stage and the finer. In coarser search, the parameters were manually increased at a fixed interval rate using a spreadsheet and MRAE value was observed. Later, the finer search was performed by considering a closer boundary value to the best MRAE value. These search techniques were used to capture the global minimum of objective function surface by doing numerous trials with varying c and Sc. The input average rainfall used for the search of global minimum was calculated using station weights computed using the Thiessen polygon (Table 5.10). Pan evaporation data of Makandura pan evaporation station were used. Search for global minimum is illustrated in Figure 6.15.

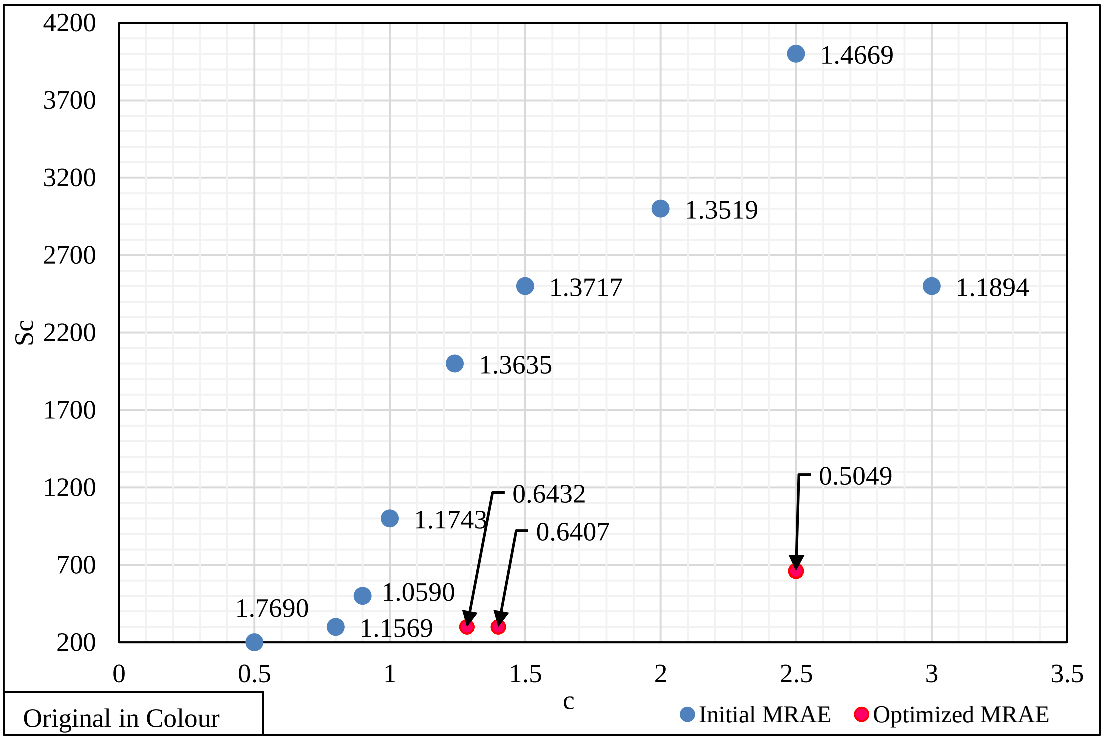


Figure 6.15: Search for global minimum of MRAE– Badalgama watershed

6.6.3. Comparison of 2PM (Monthly Input) Performance

Initially for monthly calibration and verification average rainfall input was calculated using Thiessen method. A number of trials performed for the search of global minimum results in calibration for c and Sc parameter values are 2.5 and 661 respectively with MRAE of 0.504. If the two step optimization is embraced and search of global minimum is continued for the second step by trying to achieve minimum value on MRAE in medium flows was 0.586 with the c and Sc values of 2.5 and 1061 respectively. The two stage optimization can have significant impact on the overall MRAE value which means two steps parameter optimization. The two-step optimization was initially considered for the study but looking rest of model evaluation criteria (Annual Water Balance, Comparison Hydrograph, and Flow Duration Curve), it was noted that it can have a negative impact over the results therefore, the two step optimization was neglected, because the in two step optimization the global minimum does not remain the same and it changes based on the model evaluation indicator optimization for instance if model is overall optimized for MRAE and then ideal hydrograph matching can be achieved but if the optimization at second stage occurs for water balance this may disrupt the results achieved for hydrograph and minimum MRAE.

6.6.4. Calibration period (2004 – 2010)

MRAE during calibration was 0.5865. This value appeared as a reasonable estimation. The scatter diagram in Figure 6.16 shows the behavior of simulated streamflow against observed streamflow. The duration curves clearly reflect an over estimation in the low and medium flow with an under estimation in high flows (Figure 6.17 and Figure 6.18). The water content in soil with response to rainfall is provided (Figure 6.19 and Figure 6.20). Hydrograph comparisons made using Figure 6.20 and Figure 6.21 for overall calibration period in normal and semi-log scale show that peaks match reasonably well. Considerable mismatching can be spotted between October 2008 and June 2009. Good matching was observed for intermediate flows. The summary of results is in Table 6.22. A near match between calculated and observed annual water balance is visible in Table 6.23 and graphically shown in Figure 6.22.

6.6.5. Results

6.6.5.1.Calibration Results of Two Parameter Monthly Water Balance Model:

Table 6.22: Summary Results of Calibration for Badalgama Watershed

Model Performance Indicators (Outputs & Parameters)	**2 Parameter Monthly Water Balance Model**
	Calibration (Monthly)
Sc	1,061
c	1.51
MRAE - Overall	0.5865
MRAE - High	0.32
MRAE - Medium	0.47
MRAE - Low	0.84
Average Water Balance Difference	117.95 mm
Maximum Soil Moisture	292.75 mm
Minimum Soil Moisture	61.94 mm
Starting Soil Moisture	271.90 mm
Ending Soil Moisture	96.52 mm
Data Period	October 2004 - September 2010

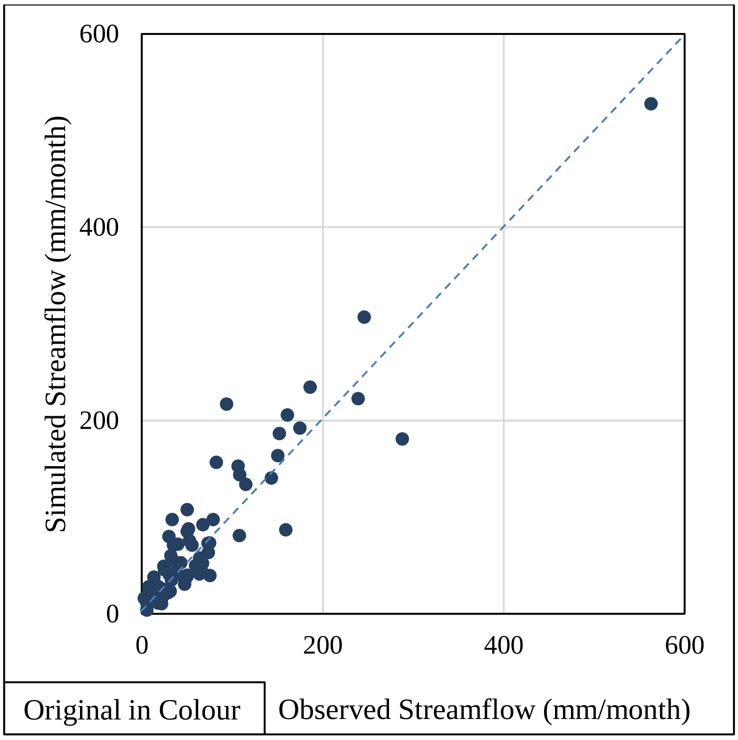


Figure 6.16: 2PM (Monthly Input) – Monthly Streamflow Estimation – Calibration Period – Badalgama Watershed

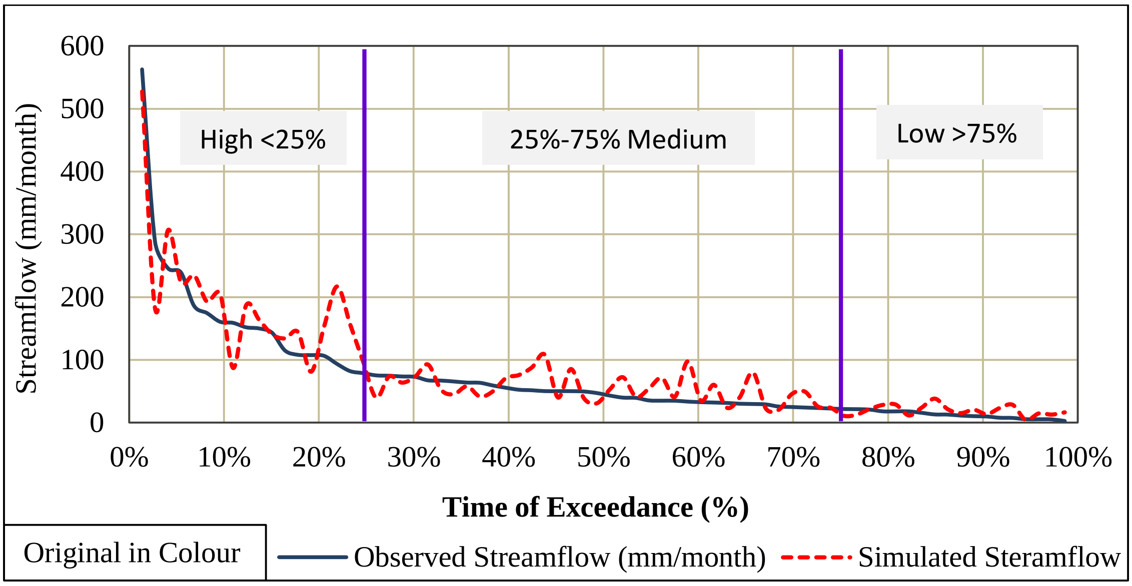


Figure 6.17: Flow Duration Curve [Normal] for 2PM Water Balance Model during calibration (October 2004 – September 2010)

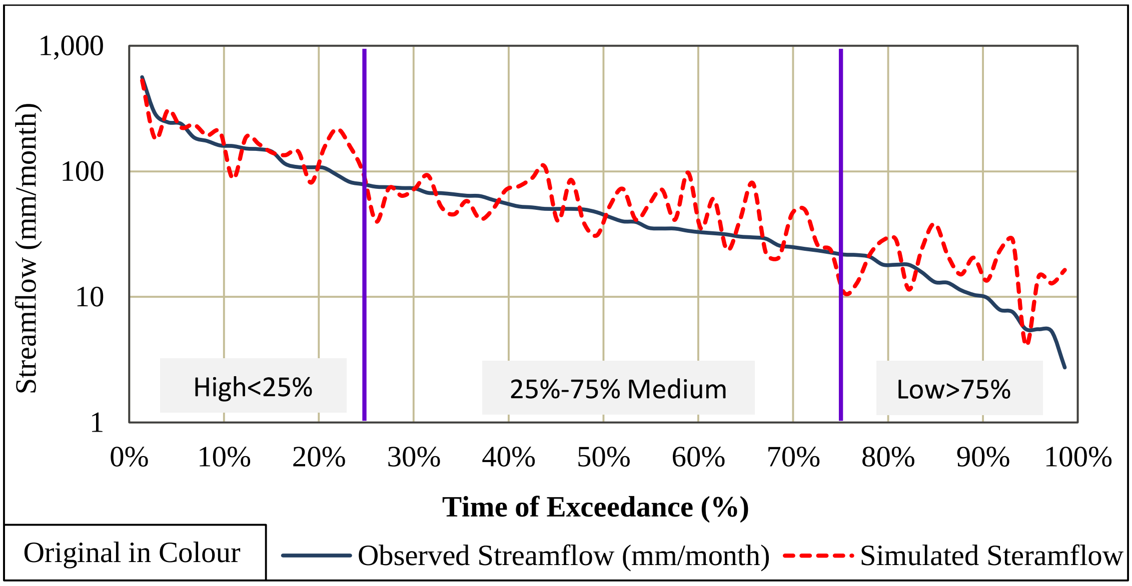


Figure 6.18: Flow Duration Curve [Log Scale] for 2PM Water Balance Model during calibration (October 2004 – September 2010)

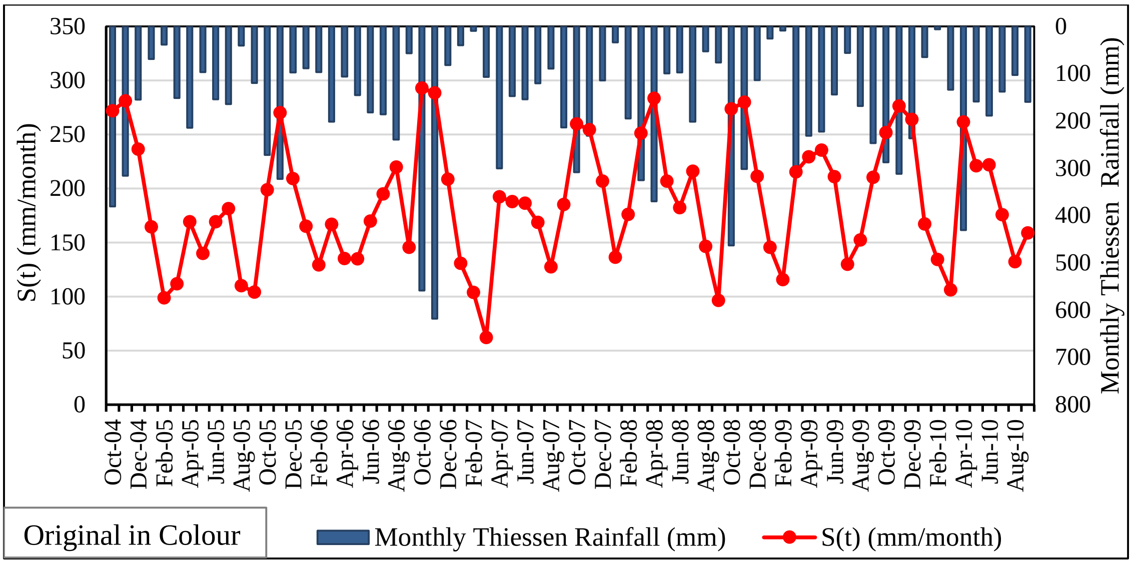


Figure 6.19: Water Content in Soil against rainfall [Normal] for 2PMWB Model during calibration (October 2004 – September 2010)

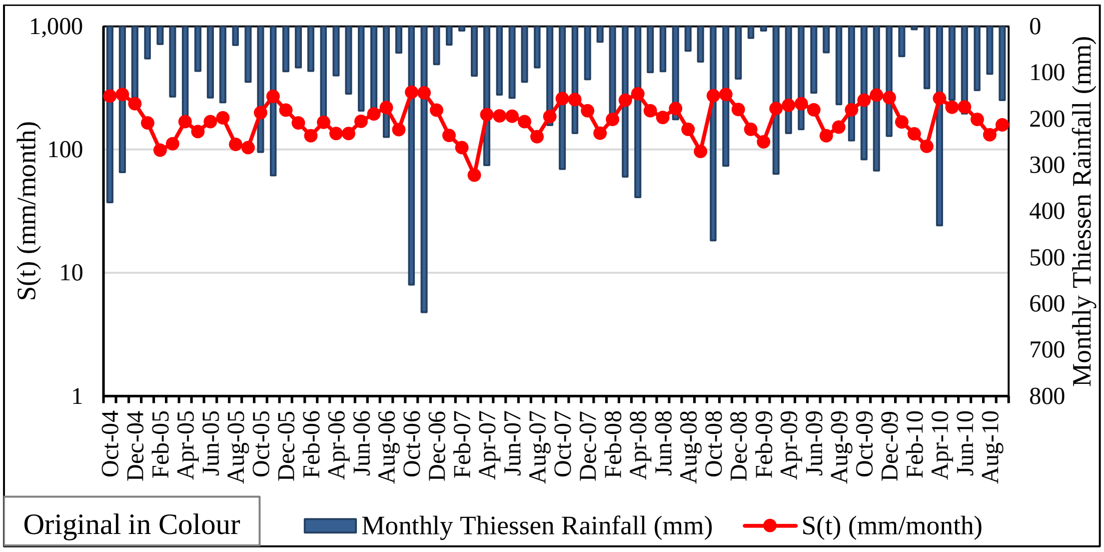


Figure 6.20: Water Content in Soil a rainfall [Semi-log] for 2PMWB Model during calibration (October 2004 – September 2010)

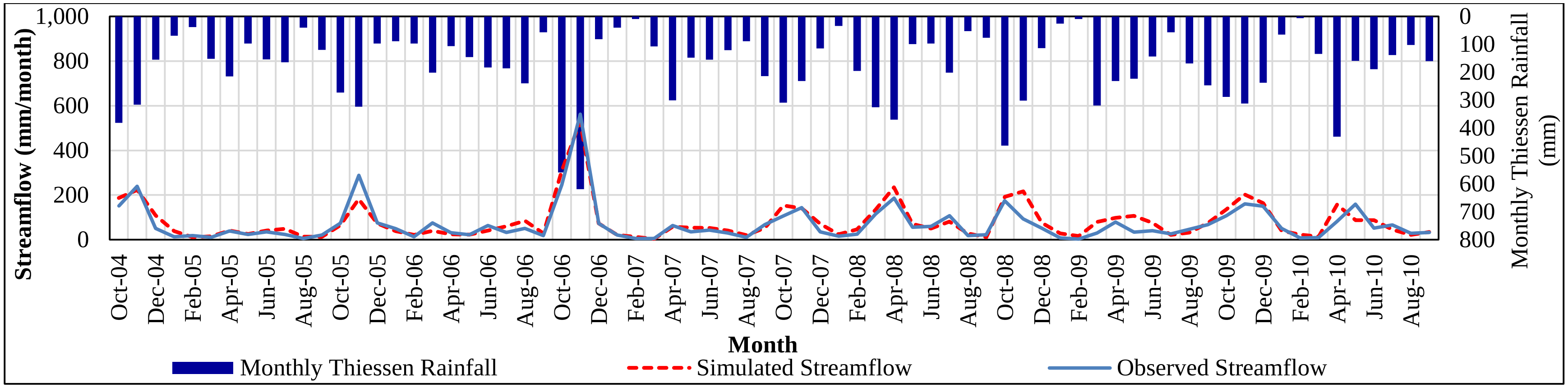


Figure 6.21: Comparison of Monthly Hydrograph [Normal] – Two Parameter Monthly Water Balance Model – Calibration (2004-2010)

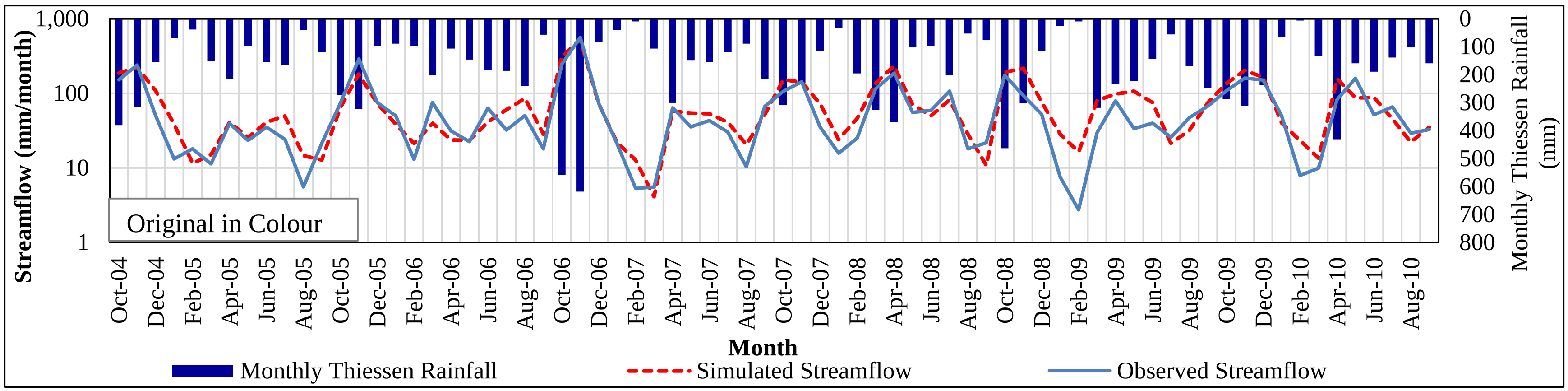


Figure 6.22: Comparison of Monthly Hydrograph [Semi-log] Two Parameter Monthly Water Balance Model – Calibration (2004-2010)

Table 6.23: Annual Water Balance - 2PM (Monthly Input) – Calibration Period – Badalgama

Water Year	Thiessen Averaged Rainfall (mm)	Simulated Streamflow (mm)	Observed Streamflow (mm)	Observed Water Balance (mm)	Simulated Water Balance (mm)	Annual Water Balance Difference (mm)
2004 / 2005	1901	767	633	1268	1135	134
2005 /2006	1997	680	792	1205	1317	-112
2006 / 2007	2442	1225	1164	1278	1217	62
2007 / 2008	2106	1045	889	1217	1061	156
2008 / 2009	2322	1021	654	1668	1300	368
2009 / 2010	2219	1025	907	1312	1194	118

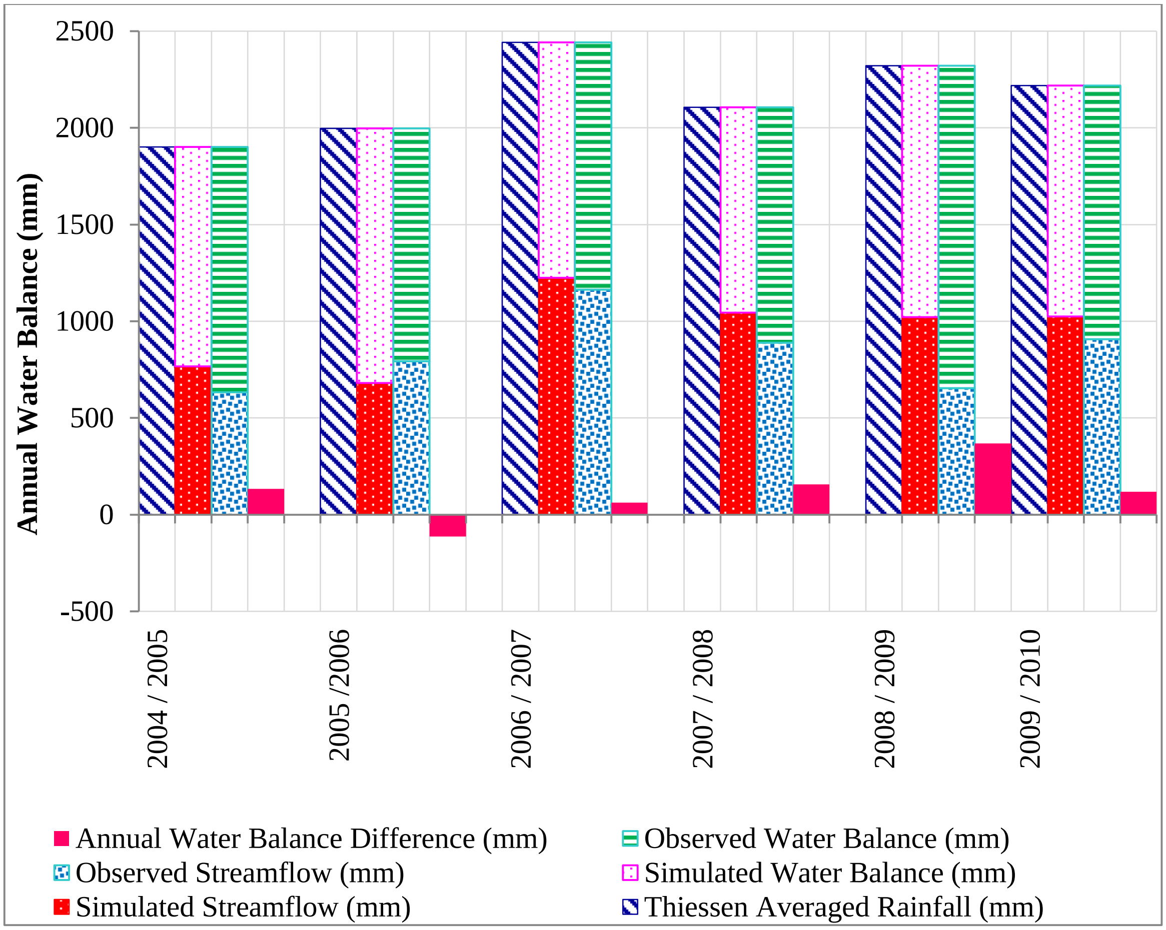


Figure 6.23: Annual Water Balance - 2PM (Monthly Input) – Calibration Period – Badalgama

6.6.5.2.Verification Period (2010 – 2017)

MRAE during verification was 0.7061. The scatter diagram in Figure 6.24 shows the behavior of simulated streamflow against observed streamflow. The duration curves clearly reflect an over estimation in the high flow with an under estimation in medium and low flows (Figure 6.25 and Figure 6.26). The water content in soil with response to rainfall is provided (Figure 6.27 and Figure 6.28). Hydrograph comparisons made using Figure 6.29 and Figure 6.30 for overall verification period in normal and semi-log scale show that peaks match reasonably well. Considerable underestimation can be spotted between October 2011 upto June 2013. Good matching was observed for high flows mostly. The summary of results is in Table 6.24. A near match between calculated and observed annual water balance is visible in Table 6.25 and graphically shown in Figure 6.31.

Table 6.24: Summary Results of Verification for Badalgama Watershed

Model Performance Indicators (Outputs & Parameters)	**2 Parameter Monthly Water Balance Model**
	Verification (Monthly)
Sc	1,061
c	1.51
MRAE - Overall	0.7061
MRAE - High	0.20
MRAE - Medium	0.61
MRAE - Low	1.34
Average Water Balance Difference	3.38 mm
Maximum Soil Moisture	294.96 mm
Minimum Soil Moisture	0.00 mm
Starting Soil Moisture	231.01 mm
Ending Soil Moisture	108.02 mm
Data Period	October 2010 - September 2017

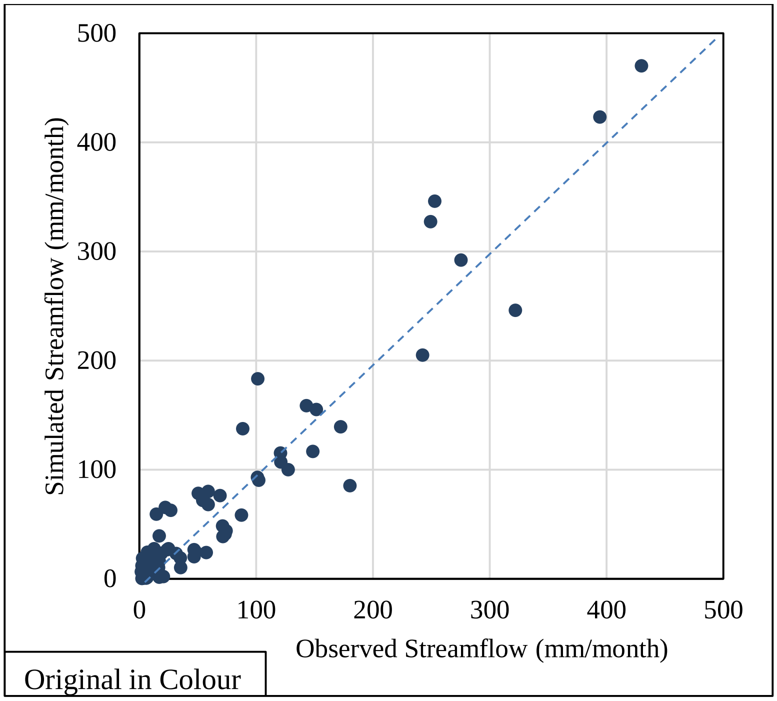


Figure 6.24: 2PM (Monthly Input) – Monthly Streamflow Estimation – Verification Period – Badalgama Watershed

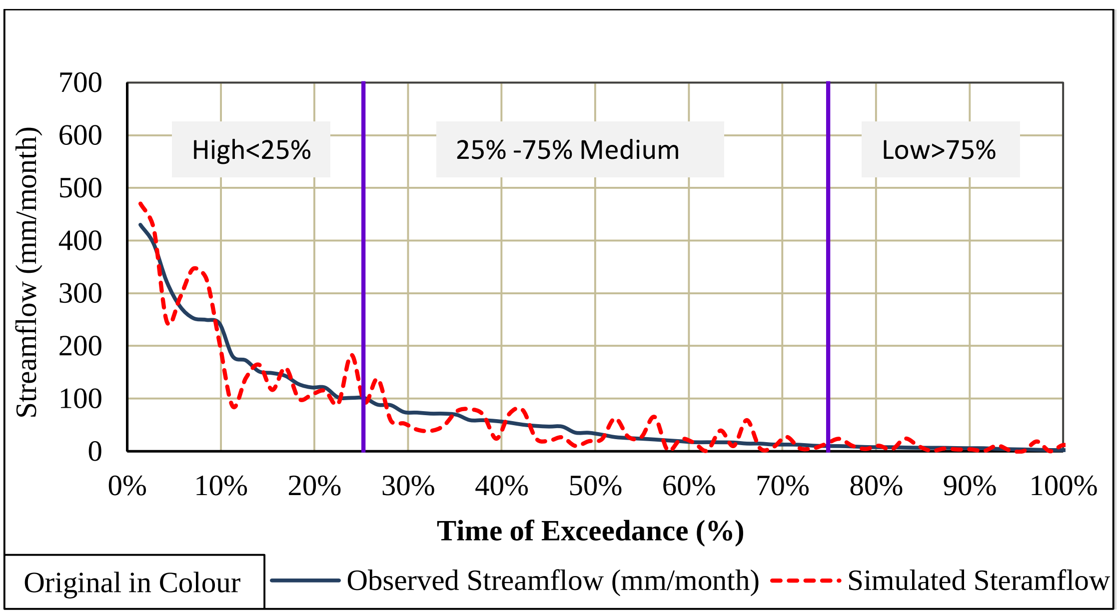


Figure 6.25: Flow Duration Curve [Normal] of 2PM Water Balance Model during verification (October 2010 – September 2017)

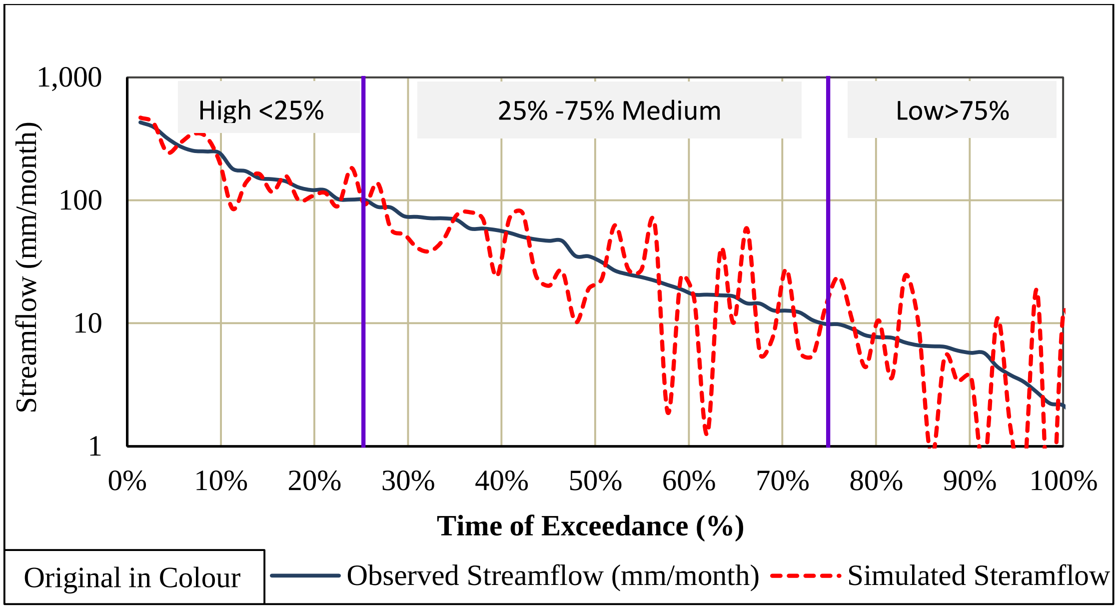


Figure 6.26: Flow Duration Curve [Log Scale] of 2PM Water Balance Model during verification (October 2010 – September 2017)

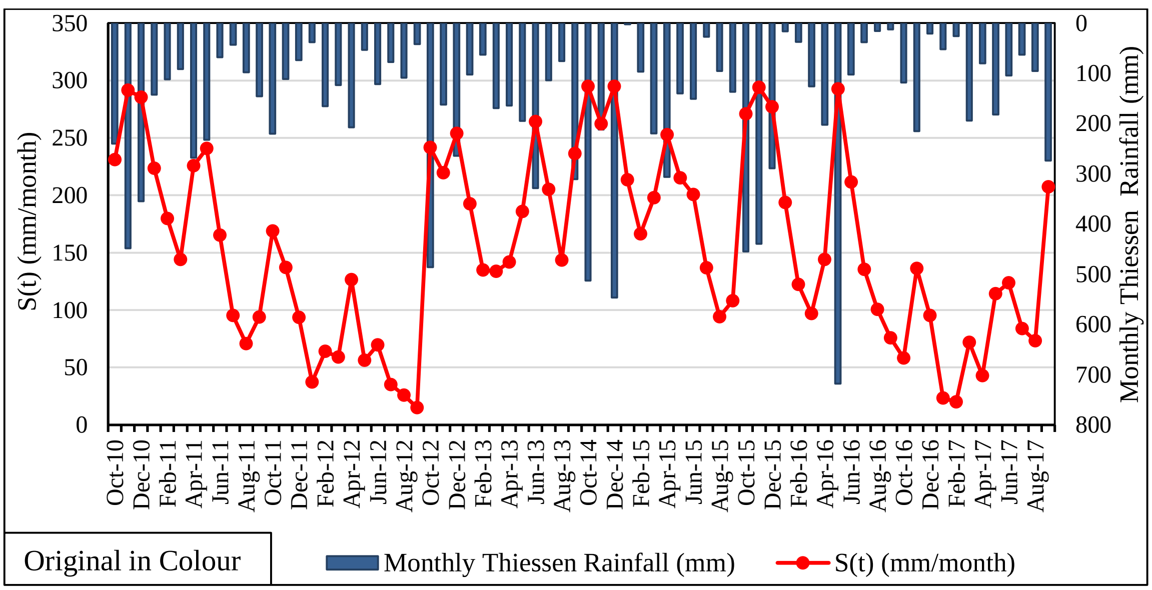


Figure 6.27: Water Content in Soil against rainfall [Normal] for 2PM Water Balance Model during verification (October 2010 – September 2017)

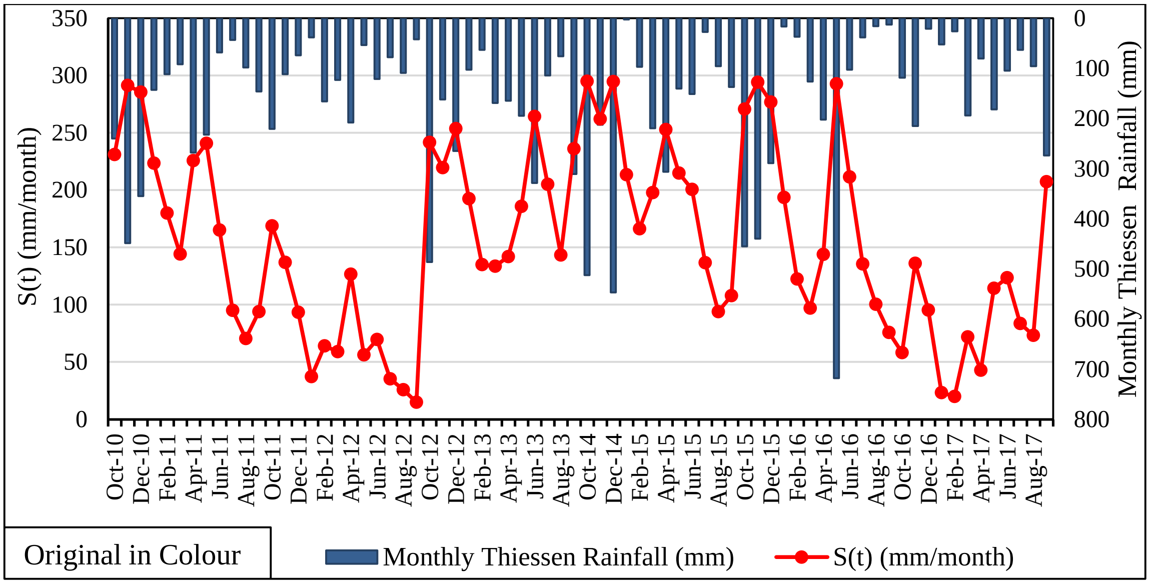


Figure 6.28: Water Content in Soil against rainfall [Semi-log] for 2PM Water Balance Model during verification (October 2010 – September 2017)

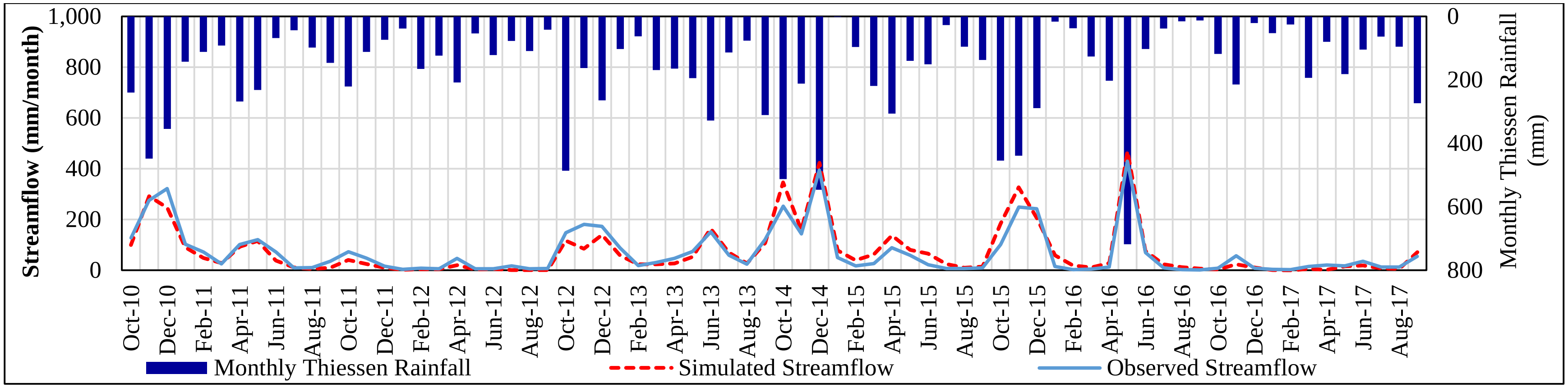


Figure 6.29: Comparison of Monthly Hydrograph [Normal] – Two Parameter Monthly Water Balance Model – Verification (2010-2017)

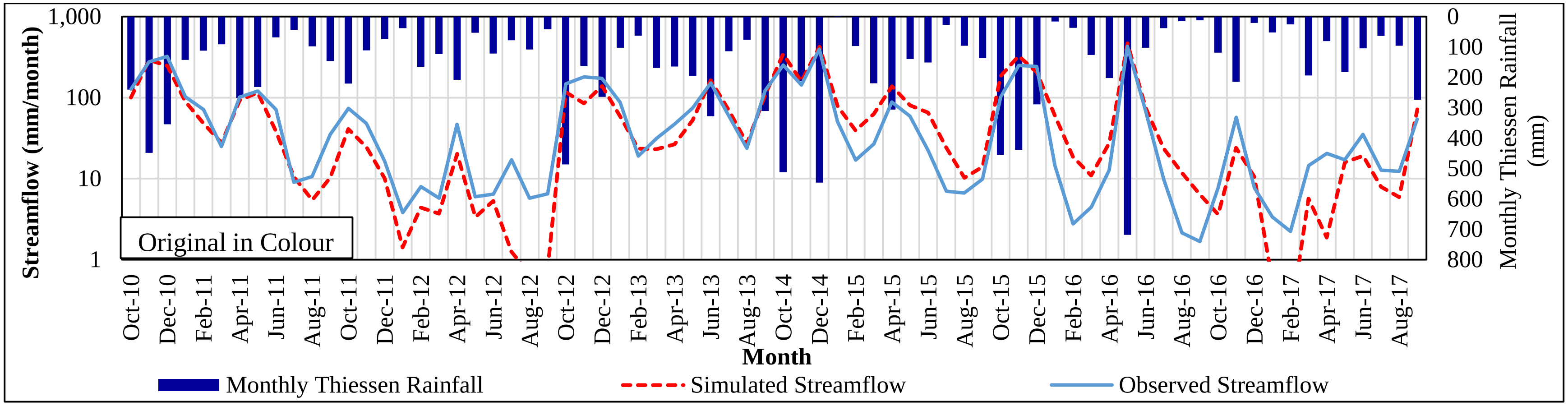


Figure 6.30: Comparison of Monthly Hydrograph [Semi-log]– Two Parameter Monthly Water Balance Model – Verification (2010-2017)

Table 6.25: Annual Water Balance - 2PM (Monthly Input) – Verification Period – Badalgama

Water Year	Thiessen Averaged Rainfall (mm)	Simulated Streamflow (mm)	Observed Streamflow (mm)	Observed Water Balance (mm)	Simulated Water Balance (mm)	Annual Water Balance Difference (mm)
2010 / 2011	2244	1077	1272	973	1167	-195
2011 / 2012	1338	117	244	1093	1221	-128
2012 / 2013	2413	873	1115	1298	1540	-243
2014 / 2015	2446	1439	1077	1369	1007	362
2015 / 2016	2452	1420	1140	1312	1032	279
2016 / 2017	1425	167	245	1180	1258	-78

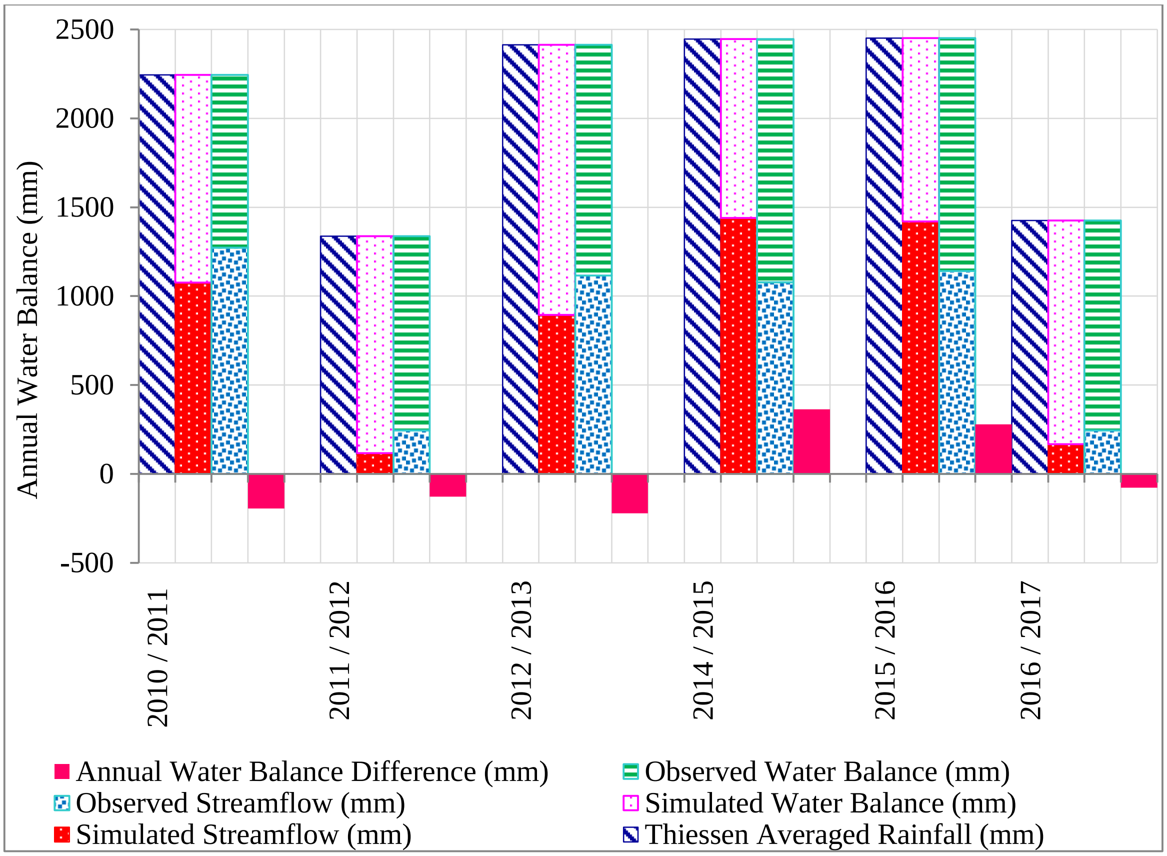


Figure 6.31: Annual Water Balance - 2PM (Monthly Input) – Verification Period – Badalgama

6.7. Three Parameter Monthly Model (K Optimized)

The third parameter is introduced to two parameter monthly water balance model, to control the final estimated discharge which may represent soil storage or rainfall spatial variability. During the calibration, value of two initial parameters Sc and c is kept unchanged and the third parameter (K) parameter is optimized to check the impacts on monthly water balance model results. The equations (5.19 and 5.20) would remain unchanged same as equation (6.12 and 6.13) , but in addition to that a new parameter (third parameter) can be added as an adjusting factor denoted by (K), which can basically control the overestimation in daily flows. Based on the justification provided by Dissanayke (2017 unpubl) this adjusting factor can be incorporated in the three parameter model, adding more as founding of this research parameter can be a representation of soil moisture level in the catchment.

$E(t)/ EP(t) = C\times \text{Tanh}\ [P(t)/ EP(t)$ ……………………………………………Equation 6.19

$Q(t) = S(t-1) + \text{Tanh}\{(S(t-1)+P(t)-E(t)/Sc)\}$ ………………………………..Equation 6.20

$(Q\ \text{calculated})\ t = K\times Q(t)$ ……………………………………………….Equation 6. 21

The observations in comparison of hydrograph, minimizing MRAE value, diminishing the difference of the annual water balance to a considerable has been noted by the incorporation of adjusting factor (k) to equation 5.21.

6.7.1. Results

6.7.1.1. Calibration Results of 3PM Water Balance Model (K optimized):

MRAE during calibration was 0.4115. This value appeared as a reasonable estimation. The duration curves clearly reflect an under estimation in the high flow with better estimation in intermediate and low flows (Figure 6.32 and Figure 6.33). The water content in soil with response to rainfall is provided (Figure 6.34 and Figure 6.35). Hydrograph comparisons made using Figure 6.36 and Figure 6.37 for overall calibration period in normal and semi-log scale show that peaks match reasonably well. Considerable mismatching can be spotted between October 2005 and June 2010. Underestimation in February 2009 was observed. The summary of results is in Table 6.26. A near match between calculated and observed annual water balance is presented in Table 6.27 and graphically shown in Figure 6.38.

Table 6.26: Summary Results of Calibration for Badalgama Watershed

Model Performance Indicators (Outputs & Parameters)	**3 Parameter Monthly Water Balance Model**
	Calibration (Monthly)
Sc	1063
c	1.51
K	0.69
MRAE - Overall	0.4115
MRAE - High	0.32
MRAE - Medium	0.47
MRAE - Low	0.84
Average Water Balance Difference	(176.07) mm
Maximum Soil Moisture	293.24 mm
Minimum Soil Moisture	62.22 mm
Starting Soil Moisture	272.26 mm
Ending Soil Moisture	96.73 mm
Data Period	October 2004 – September 2010

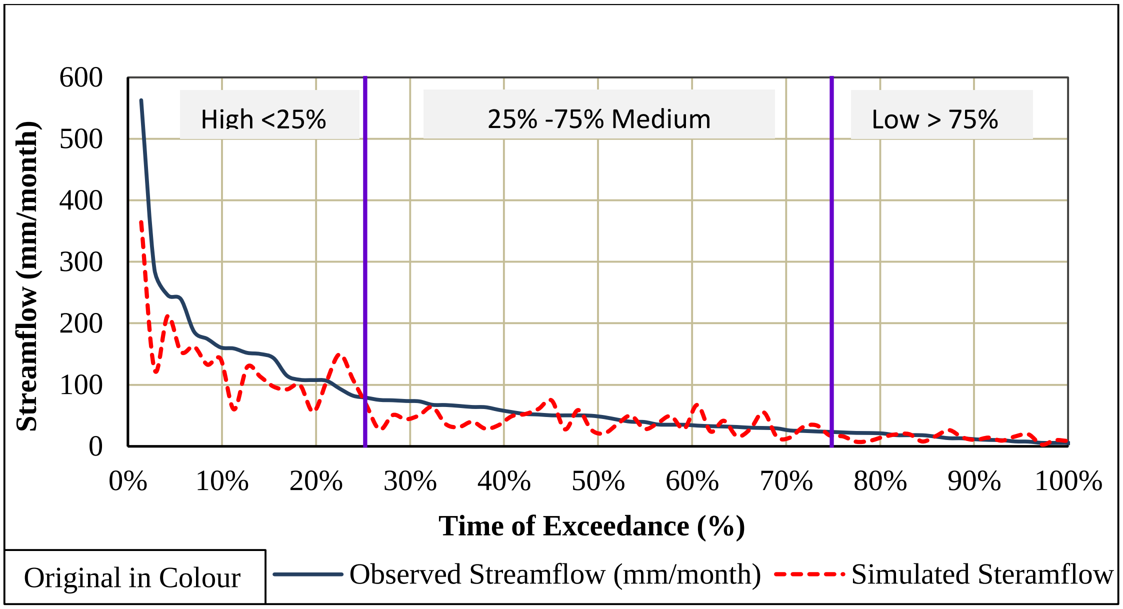


Figure 6.32: Flow Duration Curve [Normal] of 3PM Water Balance Model during calibration (October 2004 – September 2010)

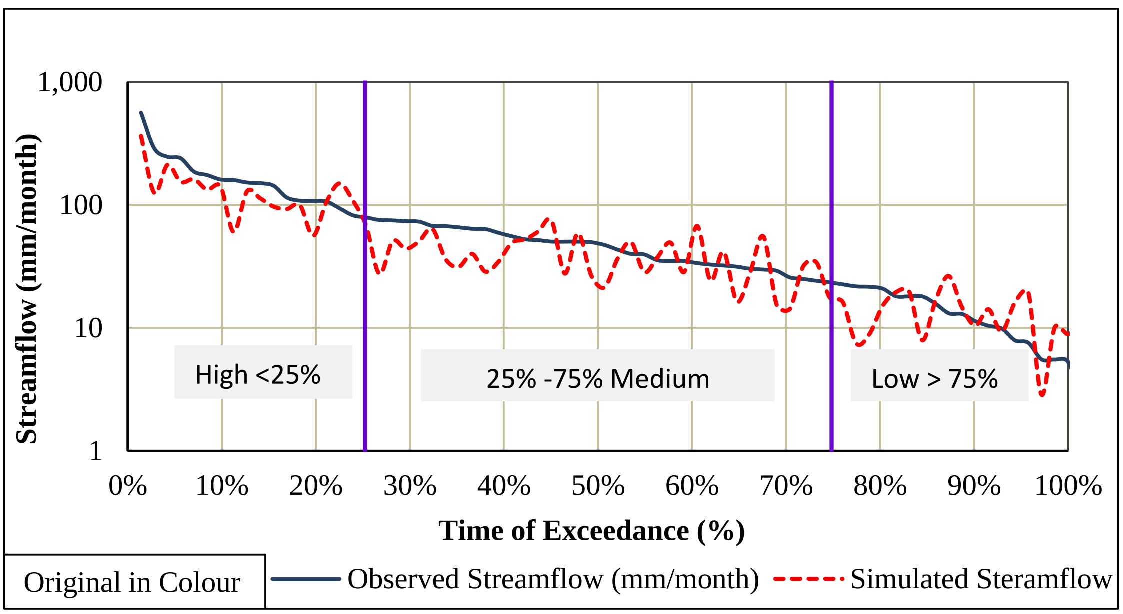


Figure 6.33: Flow Duration Curve [Log Scale] for 3PM Water Balance Model during calibration (October 2004 – September 2010)

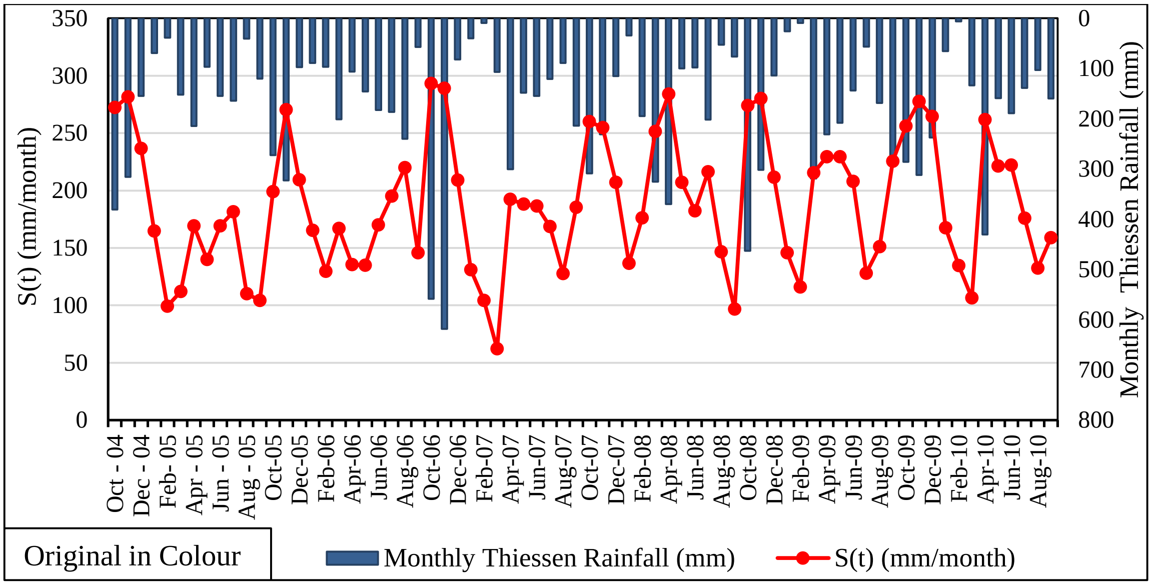


Figure 6.34: Water Content in Soil against rainfall [Normal] for 3PM Water Balance Model (K optimized only) during Calibration

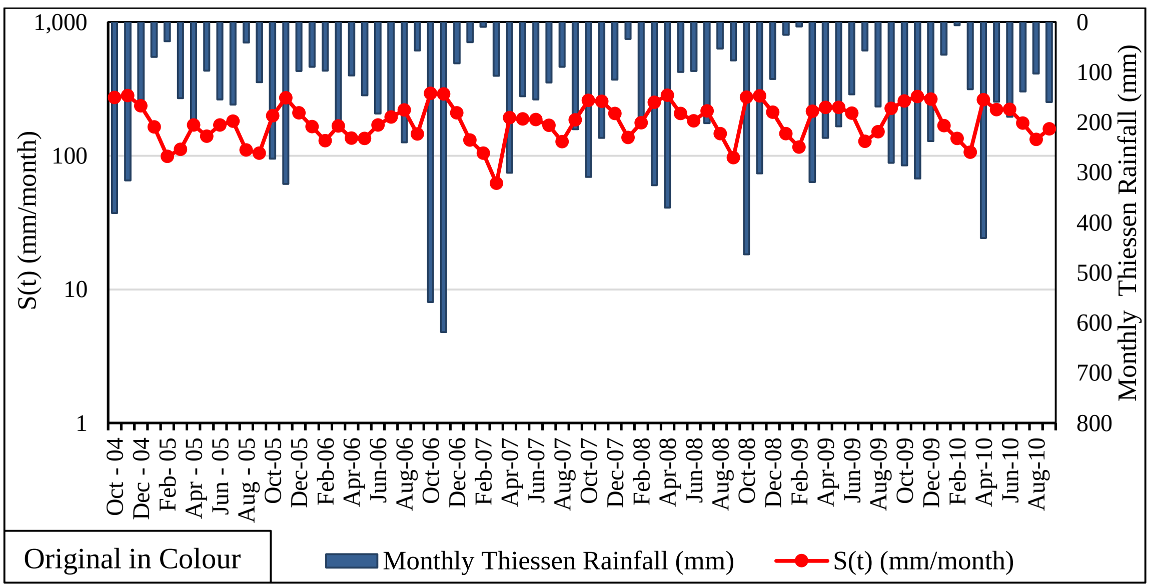


Figure 6.35: Water Content in Soil against rainfall [Log Scale] of 3PM Monthly Water Balance Model (K optimized only) during Calibration

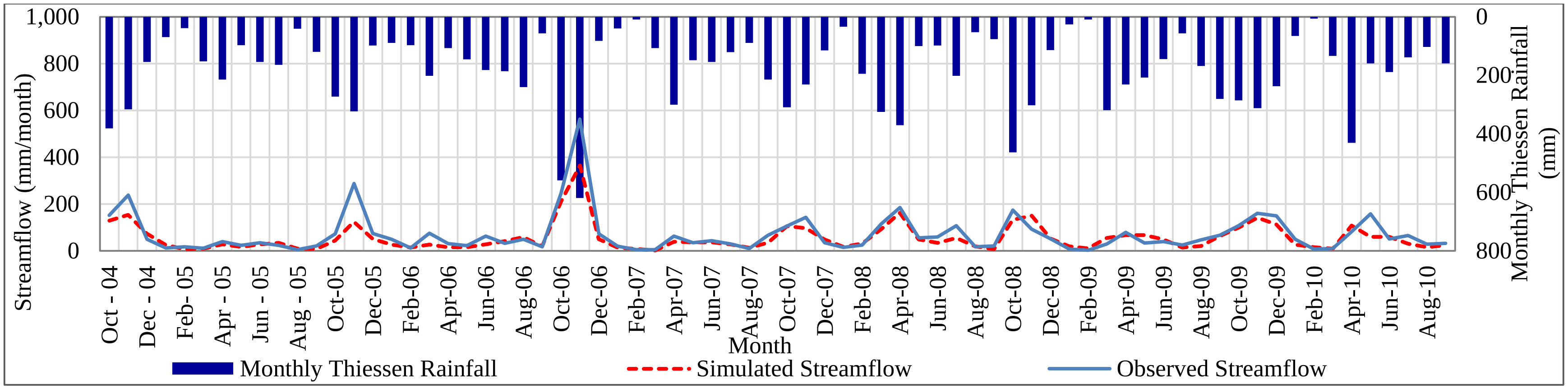


Figure 6.36 : Comparison of Monthly Hydrograph [Normal] – 3 Parameter Monthly Water Balance Model – Calibration (2004-2010)

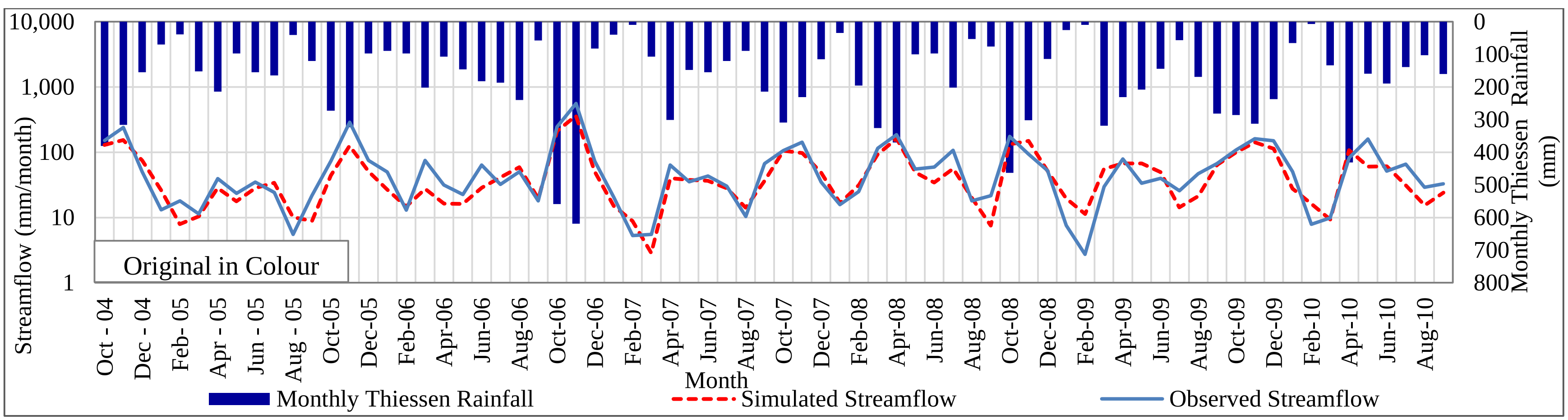


Figure 6.37: Comparison of Monthly Hydrograph [Semi-log] – 3 Parameter Monthly Water Balance Model – Calibration (2004-2007)

Table 6.27: Annual Water Balance - 3PM (Monthly Input) K optimized – Calibration Period – Badalgama

Water Year	Thiessen Averaged Rainfall (mm)	Simulated Streamflow (mm)	Observed Streamflow (mm)	Observed Water Balance (mm)	Simulated Water Balance (mm)	Annual Water Balance Difference (mm)
2004 / 2005	1901	530	633	1268	1371	-103
2005 /2006	1997	471	792	1205	1527	-322
2006 / 2007	2442	848	1164	1278	1595	-316
2007 / 2008	2106	723	889	1217	1383	-166
2008 / 2009	2322	707	654	1668	1615	53
2009 / 2010	2219	709	907	1312	1510	-198

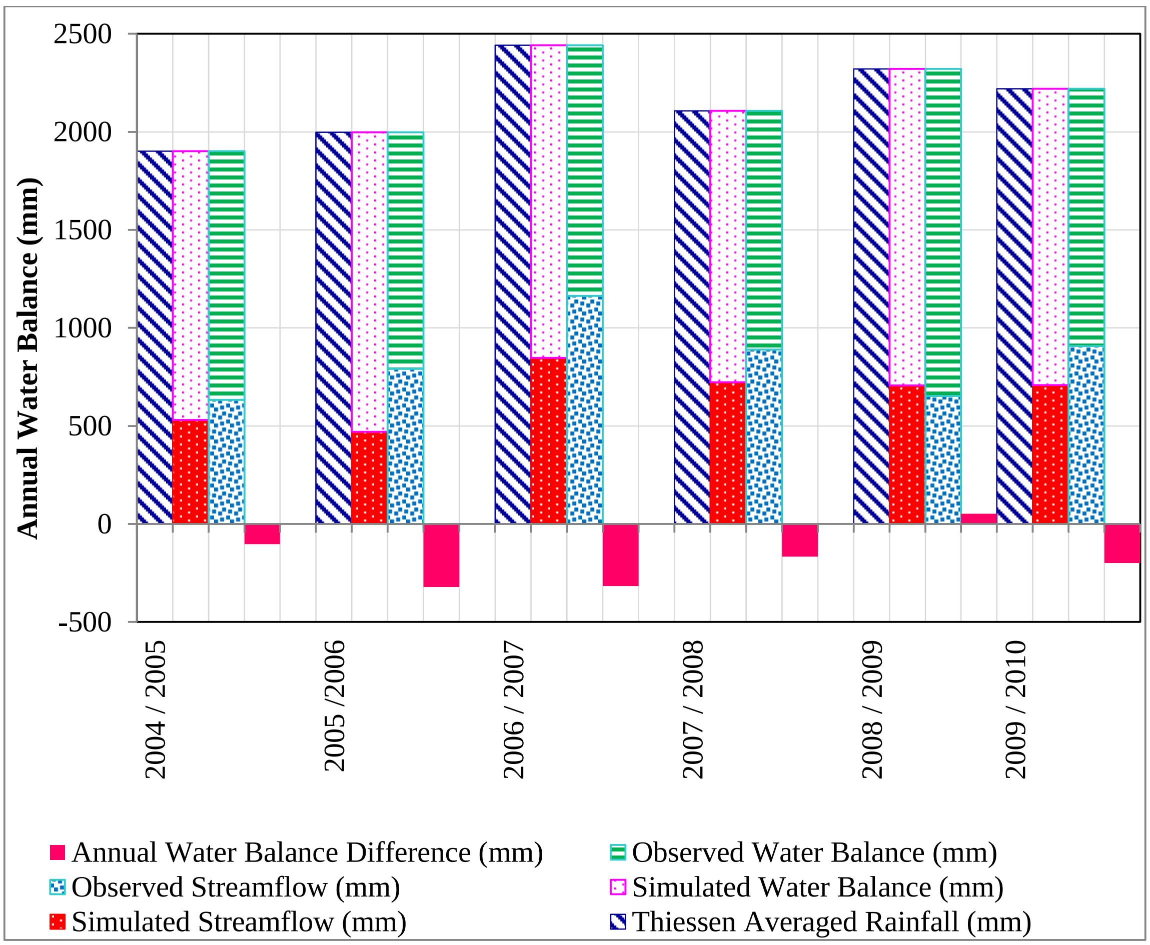


Figure 6.38: Annual Water Balance - 3PM (Monthly Input) K optimized – Calibration Period – Badalgama

6.7.1.2. Verification Results of 3PM Water Balance Model (K optimized)

MRAE during verification was 0.6042 which is has improved compared to 2PM water balance model. The duration curves clearly reflect an underestimation in the high, medium and low flows (Figure 6.39 and Figure 6.40). The water content in soil with response to rainfall is provided (Figure 6.41 and Figure 6.42). Hydrograph comparisons are made (Figure 6.43 and Figure 6.44) for overall verification period in normal and semi-log scale show from October 2010 to August 2012 observed underestimations while later that peaks match reasonably well. Considerable mismatching can be spotted between October 2005 and June 2010. Underestimation in February 2009 was observed. The summary of results is in Table 6.28. A near match between calculated and observed annual water balance is presented in Table 6.29 and graphically shown in Figure 6.45.

Table 6.28: Summary Results of Verification Period for Badalgama Watershed

Model Performance Indicators (Outputs & Parameters)	**3 Parameter Monthly Water Balance Model**
	Verification (Monthly)
Sc	1,063
c	1.51
K	0.691
MRAE - Overall	0.6042
MRAE - High	0.20
MRAE - Medium	0.61
MRAE - Low	1.34
Average Water Balance Difference	(262.54) mm
Maximum Soil Moisture	295.40 mm
Minimum Soil Moisture	0.00 mm
Starting Soil Moisture	231.22 mm
Ending Soil Moisture	108.19 mm
Data Period	October 2010 – September 2017

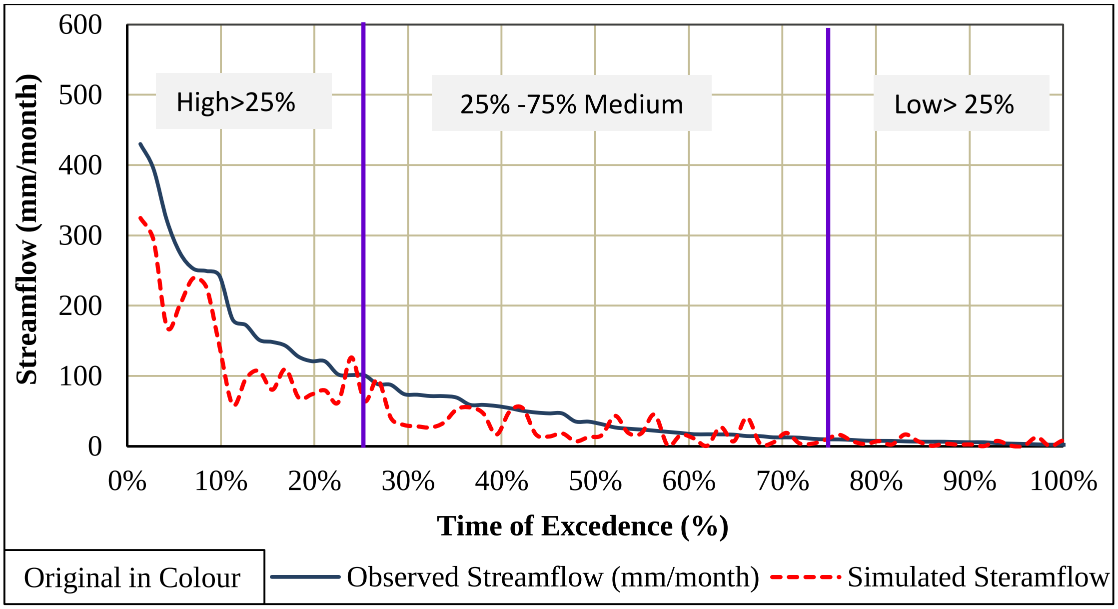


Figure 6.39: Flow Duration Curve [Normal] of Three Parameter Monthly Water Balance Model during Verification (October 2010 – September 2017)

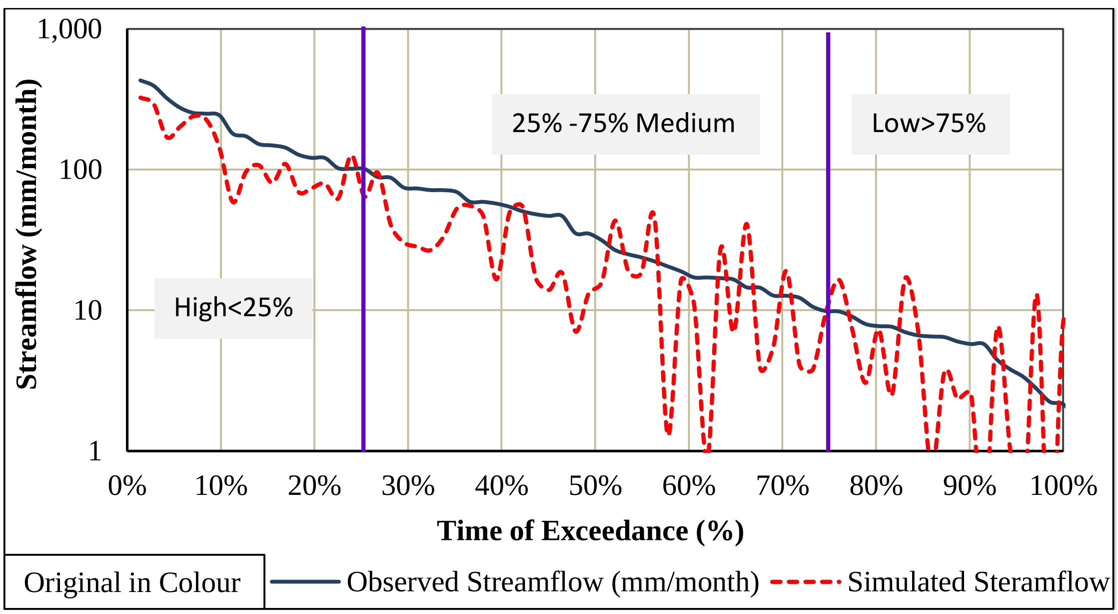


Figure 6.40: Flow Duration Curve [Log] of Three Parameter Monthly Water Balance Model during Verification (October 2010 – September 2017)

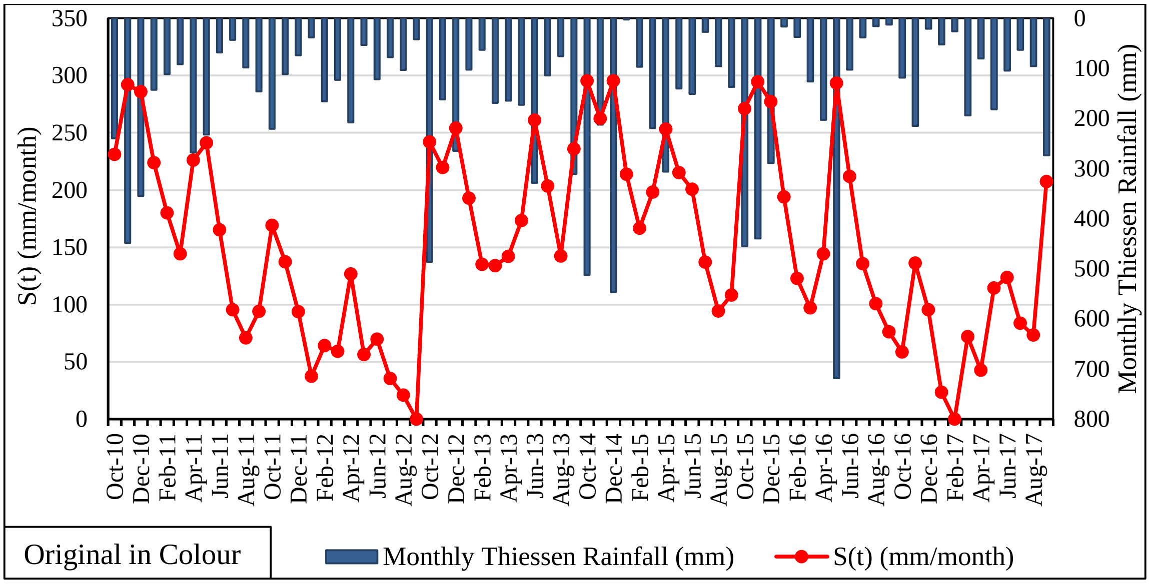


Figure 6.41: Water Content in Soil against rainfall [Normal] for 3PM Water Balance Model (K optimized) during Verification (October 2010 – September 2017)

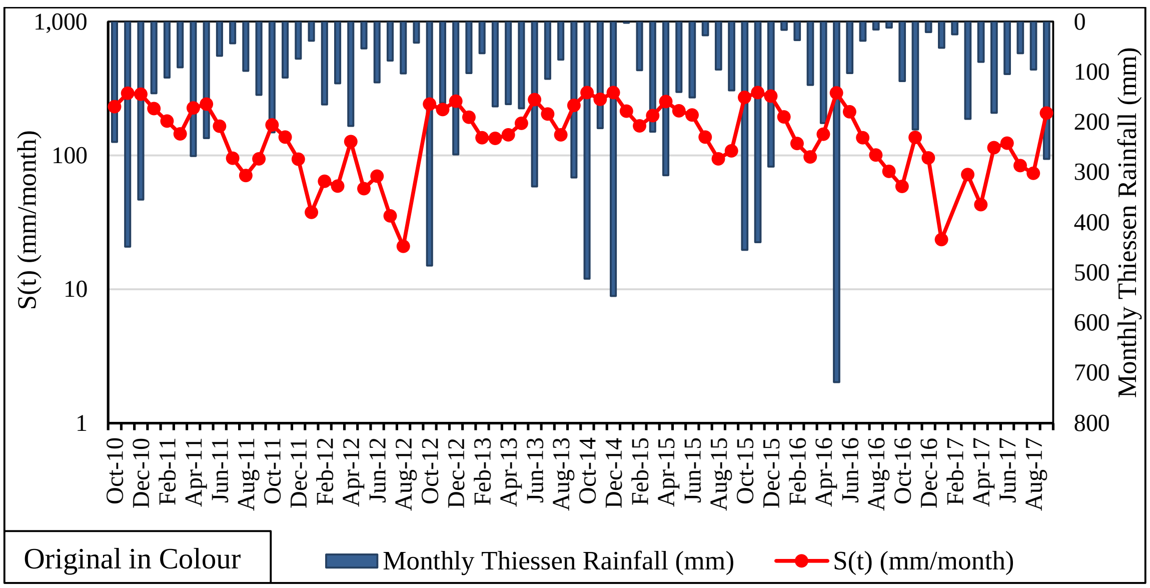


Figure 6.42: Water Content in Soil against rainfall [Semi-log] for 3PM Water Balance Model (K optimized) during Verification (October 2010 – September 2017)

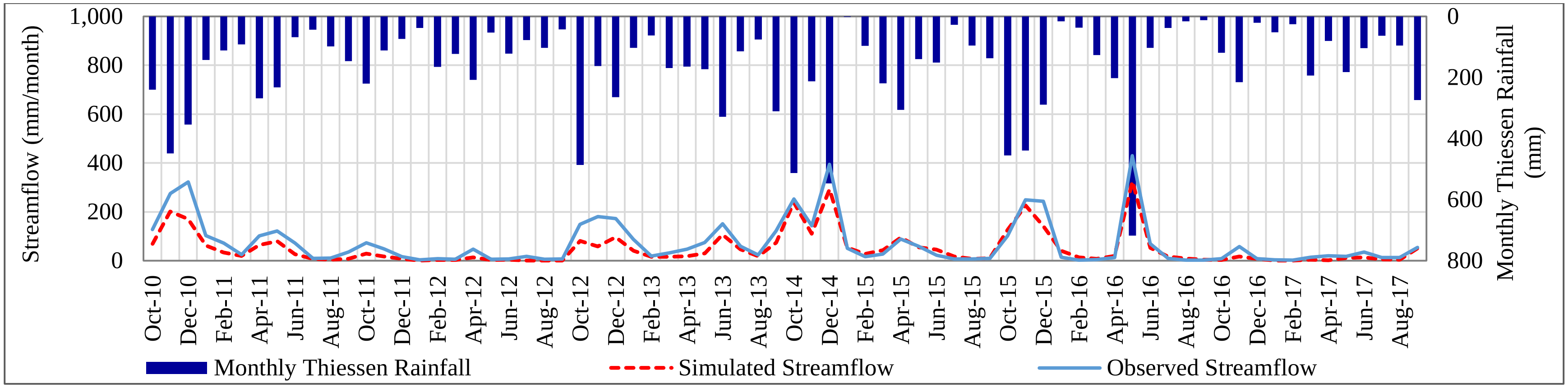


Figure 6.43: Comparison of Monthly Hydrograph [Normal] – 3 Parameter Monthly Water Balance Model – Verification (2010-2017)

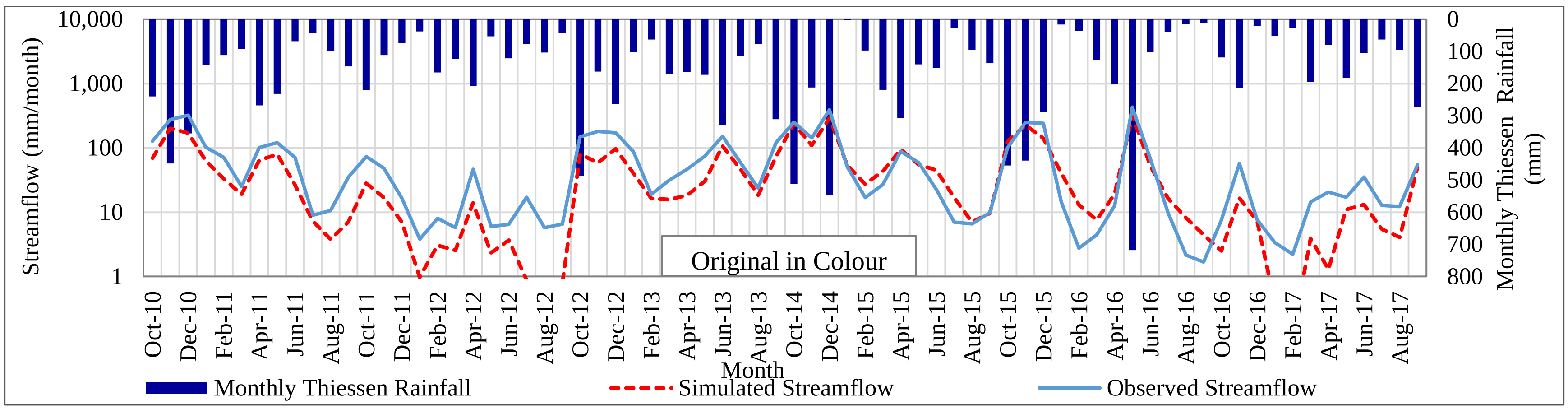


Figure 6.44: Comparison of Monthly Hydrograph [Semi-log] – 3 Parameter Monthly Water Balance Model – Verification (2010-2017)

Table 6.29: Annual Water Balance - 3PM (Monthly Input) K optimized – Verification Period – Badalgama

Water Year	Thiessen Averaged Rainfall (mm)	Simulated Streamflow (mm)	Observed Streamflow (mm)	Observed Water Balance (mm)	Simulated Water Balance (mm)	Annual Water Balance Difference (mm)
2010 / 2011	2244	744	1272	973	1500	-527
2011 / 2012	1338	81	244	1093	1257	-164
2012 / 2013	2413	603	1115	1298	1810	-513
2014 / 2015	2446	995	1077	1369	1452	-83
2015 / 2016	2452	981	1140	1312	1471	-159
2016 / 2017	1425	115	245	1180	1310	-130

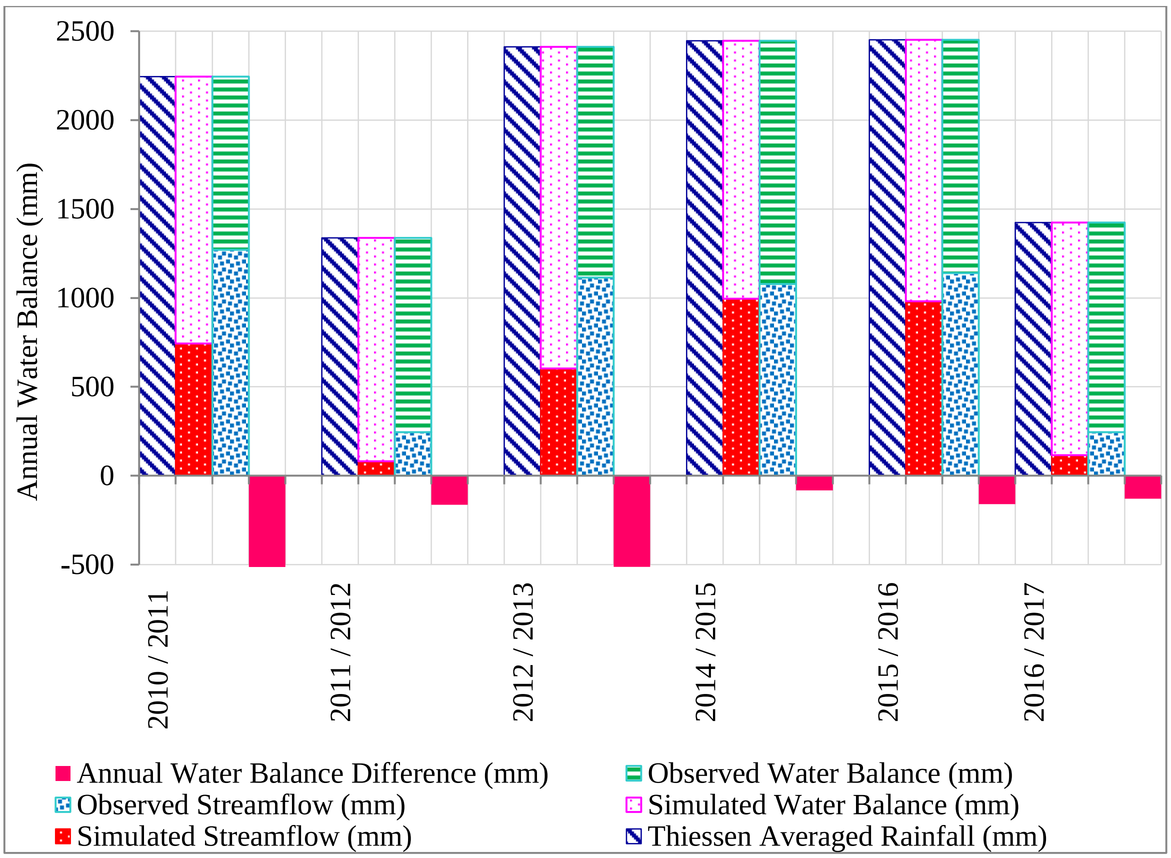


Figure 6.45: Annual Water Balance - 3PM (Monthly Input) K optimized – Verification Period – Badalgama

6.8. Three Parameter Monthly Model (All Parameters Calibrated Sc ,C & K)

All three parameters (Sc, c & k) were calibrated at monthly scale simultaneously using the input average rainfall generated from Theissen Rainfall. The optimization has been performed using Excel solver in the excel spreadsheet. Later, keeping all the three parameters unchanged the verification is performed.

6.8.1. Results:

6.8.1.1.Three parameter calibration results (All Parameters Calibrated Sc ,c & K)

MRAE during calibration was 0.4117 which is has improved compared to 2PM water balance model. The duration curves clearly reflect an underestimation in the high but improved medium and low flows (Figure 6.46 and Figure 6.47). The water content in soil with response to rainfall is provided (Figure 6.48 and Figure 6.49). Hydrograph comparisons are made (Figure 6.50 and Figure 6.51) for overall calibration period in normal and semi-log. The summary of results is in Table 6.28. Comparison between calculated and observed annual water balance is presented in Table 6.31 and graphically shown in Figure 6.52.

Table 6.30: Summary Results of Calibration Period for Badalgama Watershed

Model Performance Indicators (Outputs & Parameters)	3 Parameter Monthly Water Balance Model
	Calibration (Monthly)
Sc	1,051
c	2.5
K	0.645
MRAE - Overall	0.4117
MRAE - High	0.635
MRAE - Medium	0.483
MRAE - Low	0.368
Average Water Balance Difference	(221.86) mm
Maximum Soil Moisture	290.51 mm
Minimum Soil Moisture	60.68 mm
Starting Soil Moisture	270.24 mm
Ending Soil Moisture	95.54 mm
Data Period	October 2004 – September 2010

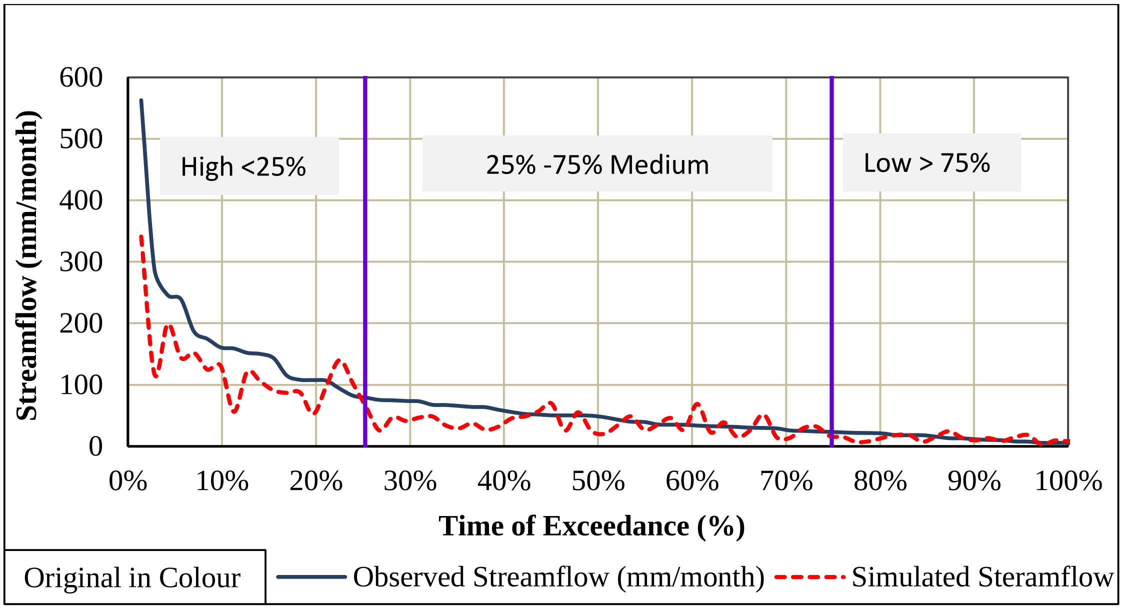


Figure 6.46: Flow Duration Curve [Normal] of 3PM Water Balance Model Calibration (October 2004 – September 2010)

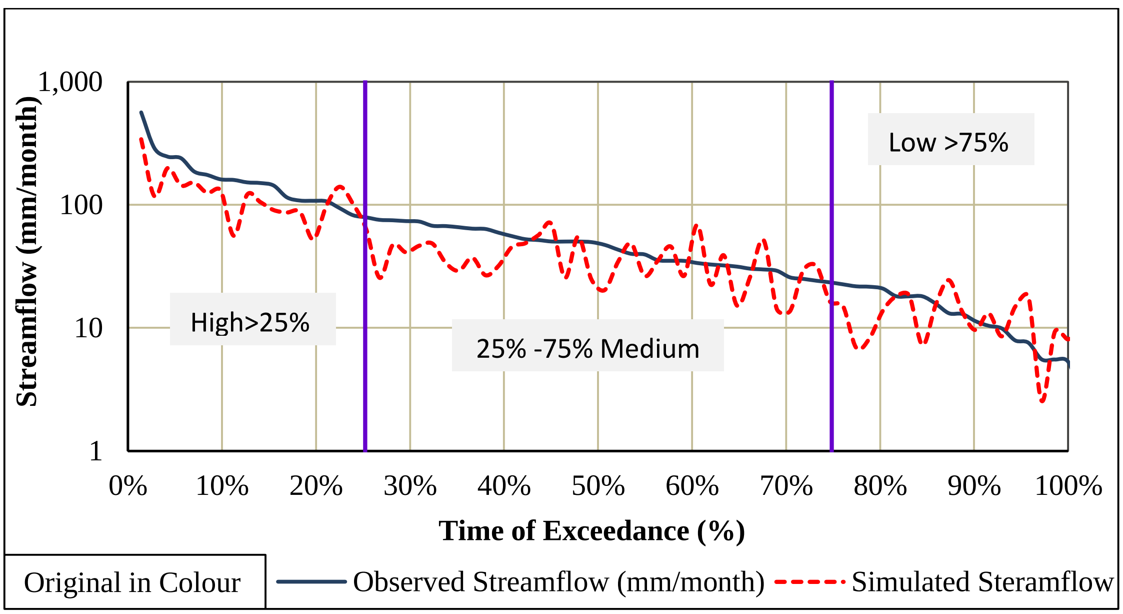


Figure 6.47: Flow Duration Curve [Log] of 3PM Water Balance Model Calibration (October 2004 – September 2010)

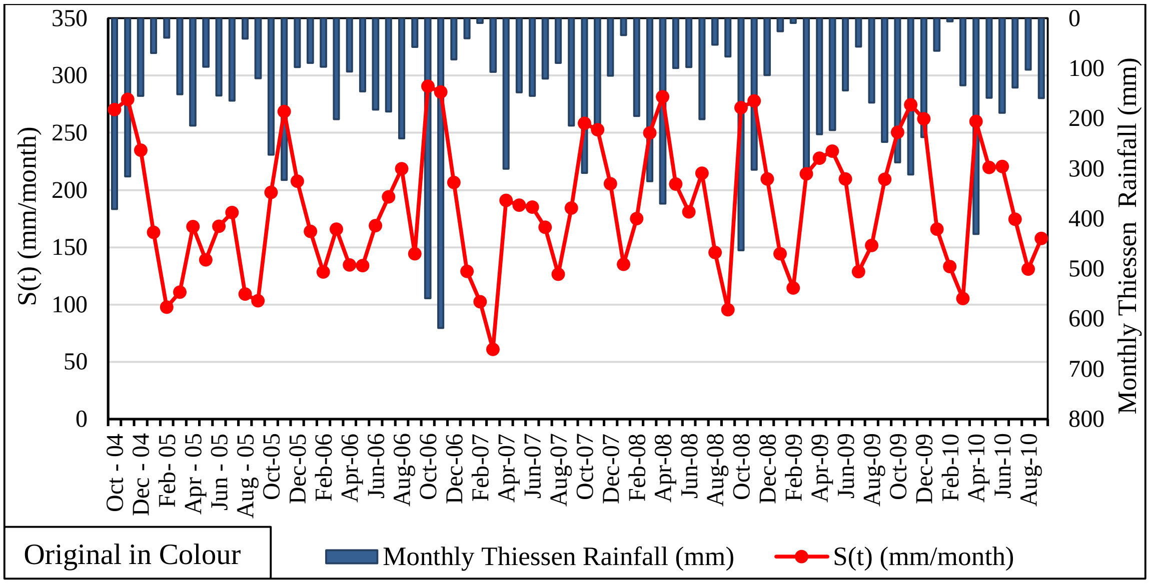


Figure 6.48: Water Content in Soil against rainfall [Normal] for 3PM Water Balance Model during Calibration (October 2004 – September 2007)

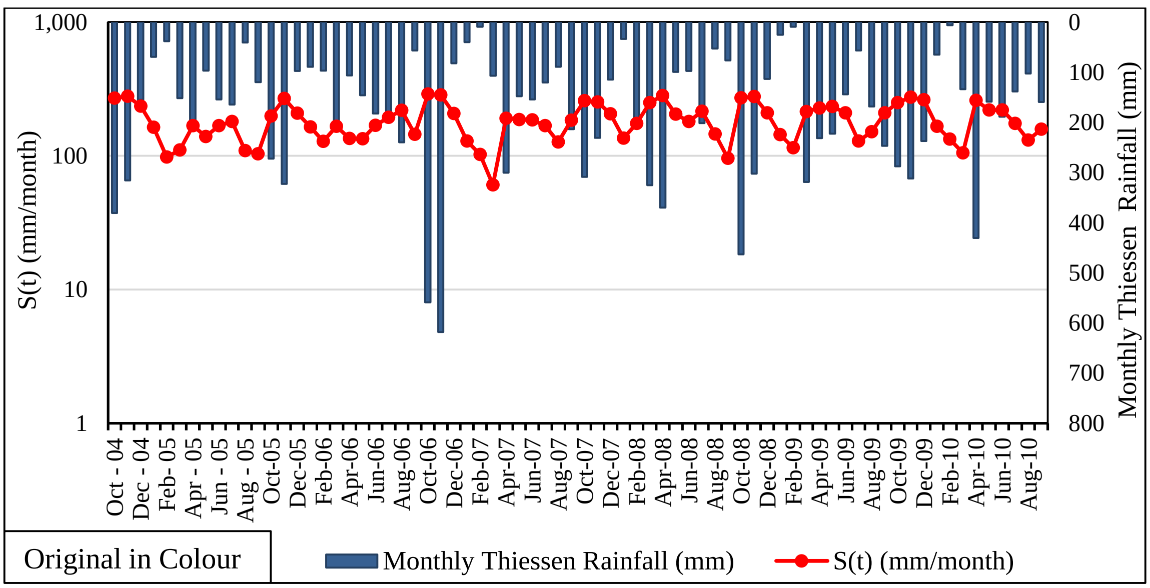


Figure 6.49: Water Content in Soil against rainfall [Semi-log] for 3PM Water Balance Model during Calibration (October 2004 – September 2007)

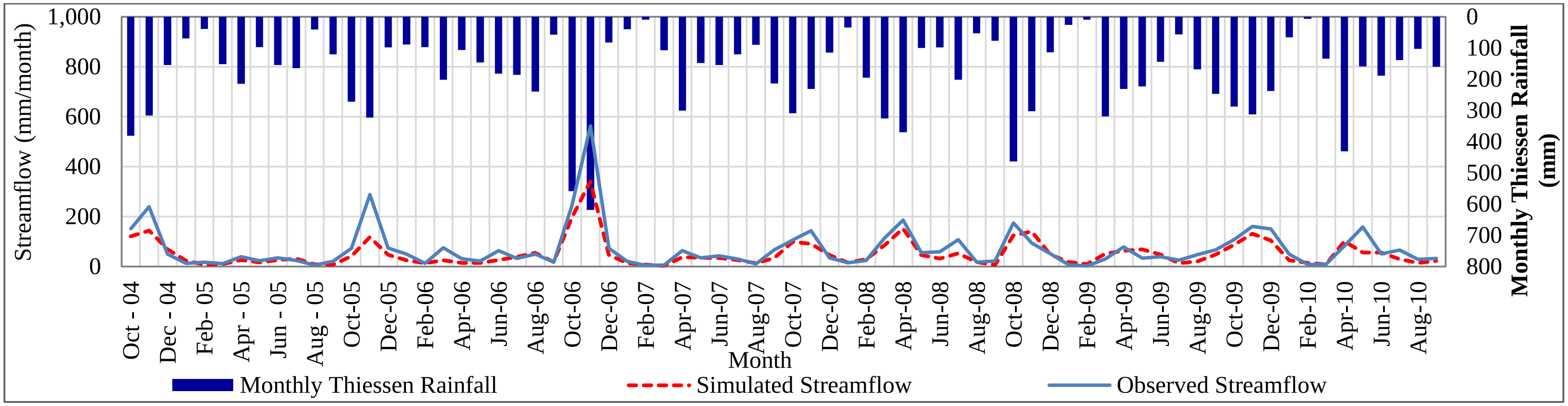


Figure 6.50: Comparison of Monthly Hydrograph [Normal] – 3 Parameter Monthly Water Balance Model – Calibration (2004-2010)

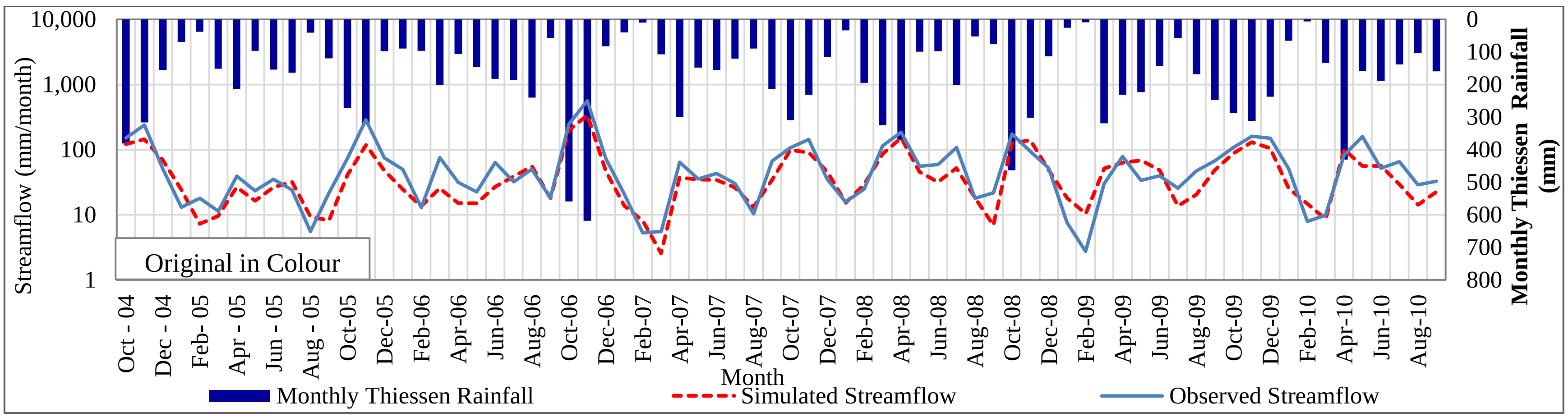


Figure 6.51: Comparison of Monthly Hydrograph [Semi-log] – 3 Parameter Monthly Water Balance Model – Calibration (2004-2010)

Table 6.31: Annual Water Balance - 3PM (Monthly Input)– Calibration Period – Badalgama

Water Year	Thiessen Averaged Rainfall (mm)	Simulated Streamflow (mm)	Observed Streamflow (mm)	Observed Water Balance (mm)	Simulated Water Balance (mm)	Annual Water Balance Difference (mm)
2004 / 2005	1901	542	633	1268	1360	-91
2005 /2006	1997	487	792	1205	1510	-306
2006 / 2007	2442	869	1164	1278	1573	-295
2007 / 2008	2106	742	889	1217	1364	-147
2008 / 2009	2322	729	654	1668	1593	75
2009 / 2010	2219	724	907	1312	1495	-183

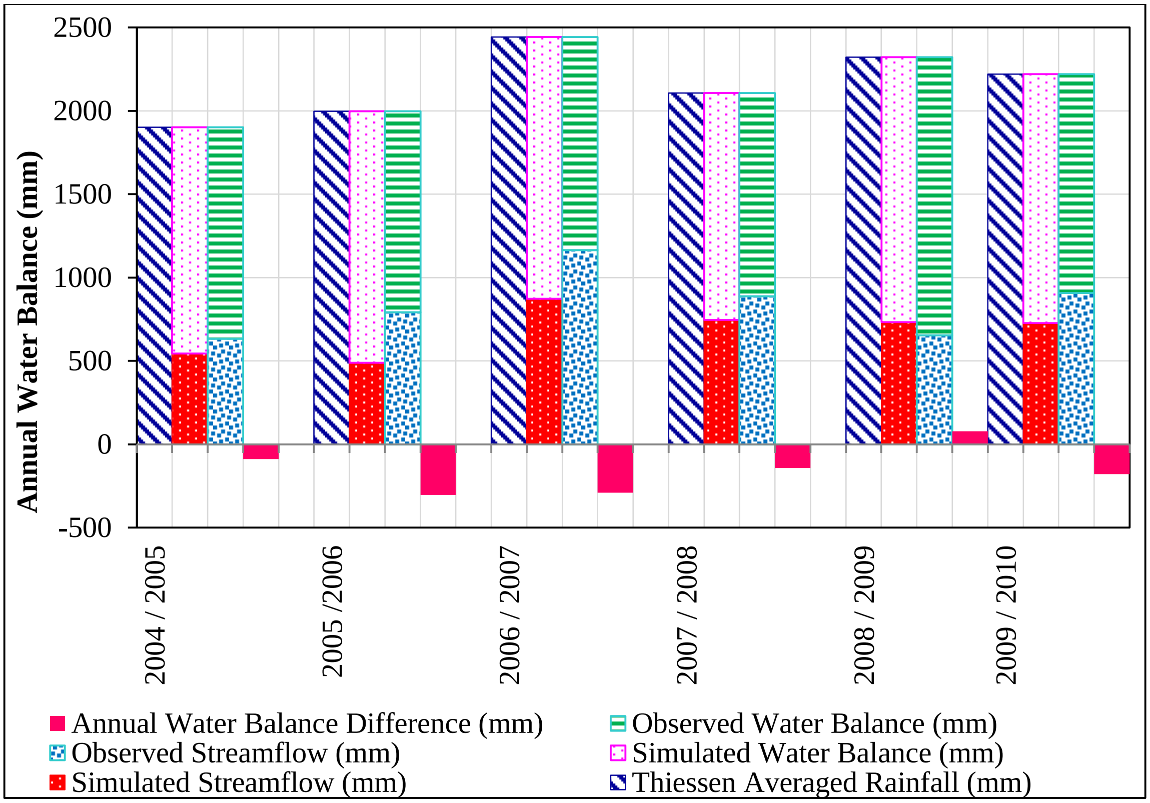


Figure 6.52: Annual Water Balance - 3PM (Monthly Input) – Calibration Period – Badalgama

6.8.1.2.Three parameter verification results (All Parameters Calibrated Sc ,c & K)

MRAE during verification was 0.5972 which is has improved compared to 2PM water balance model and 3PM (k parameter optimized only). The duration curves clearly reflect an underestimation in the high but improved medium and low flows during verification period as well (Figure 6.53 and Figure 6.54). The water content in soil with response to rainfall is provided (Figure 6.55 and Figure 6.56). Hydrograph comparisons are made (Figure 6.57 and Figure 6.58) for overall calibration period in normal and semi-log. The summary of results is in Table 6.32. Comparison between calculated and observed annual water balance is presented in Table 6.33 and graphically shown in Figure 6.59.

Table 6.32: Summary Results of Verification Period for Badalgama Watershed

Model Performance Indicators (Outputs & Parameters)	**3 Parameter Monthly Water Balance Model**
	Verification (Monthly)
Sc	1,051
c	2.5
K	0.65
MRAE - Overall	0.5972
MRAE - High	0.37
MRAE - Medium	0.54
MRAE - Low	0.91
Average Water Balance Difference	(298.84) mm
Maximum Soil Moisture	292.46 mm
Minimum Soil Moisture	0.00 mm
Starting Soil Moisture	229.85 mm
Ending Soil Moisture	107.14 mm
Data Period	October 2010 – September 2017

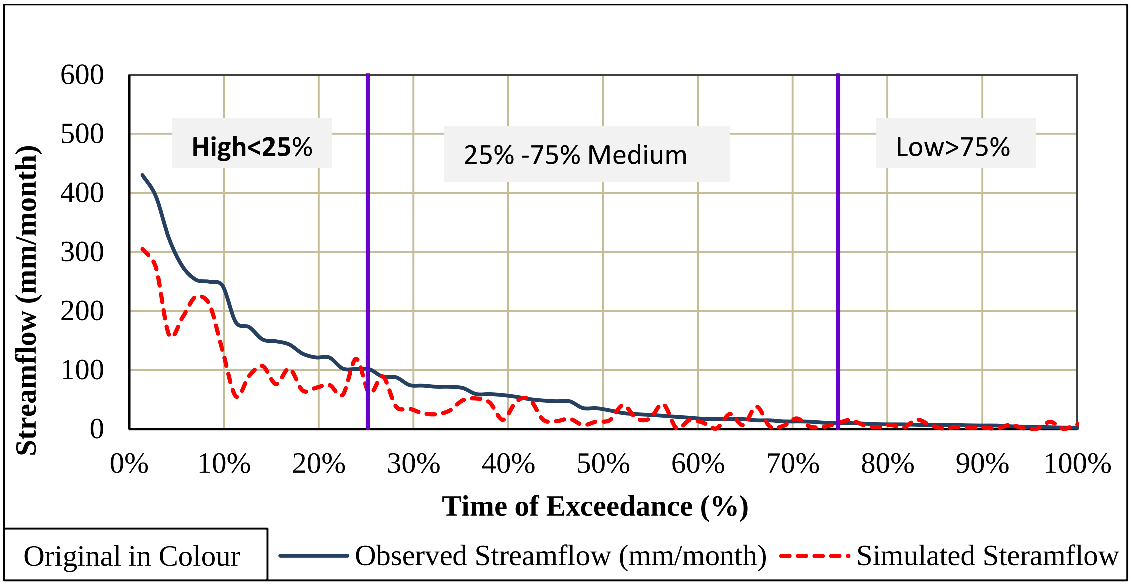


Figure 6.53: Flow Duration Curve [Normal] of 3PM Water Balance Model during Verification (October 2010 – September 2017)

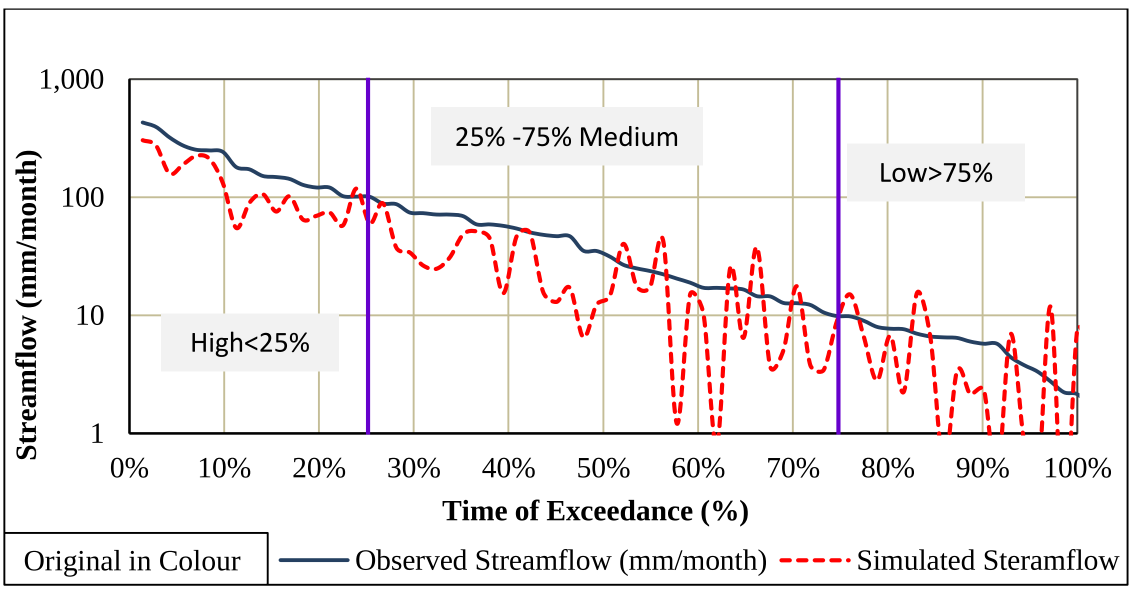


Figure 6.54: Duration Curve [Log] of 3PM Water Balance Model during Verification (October 2010 – September 2017)

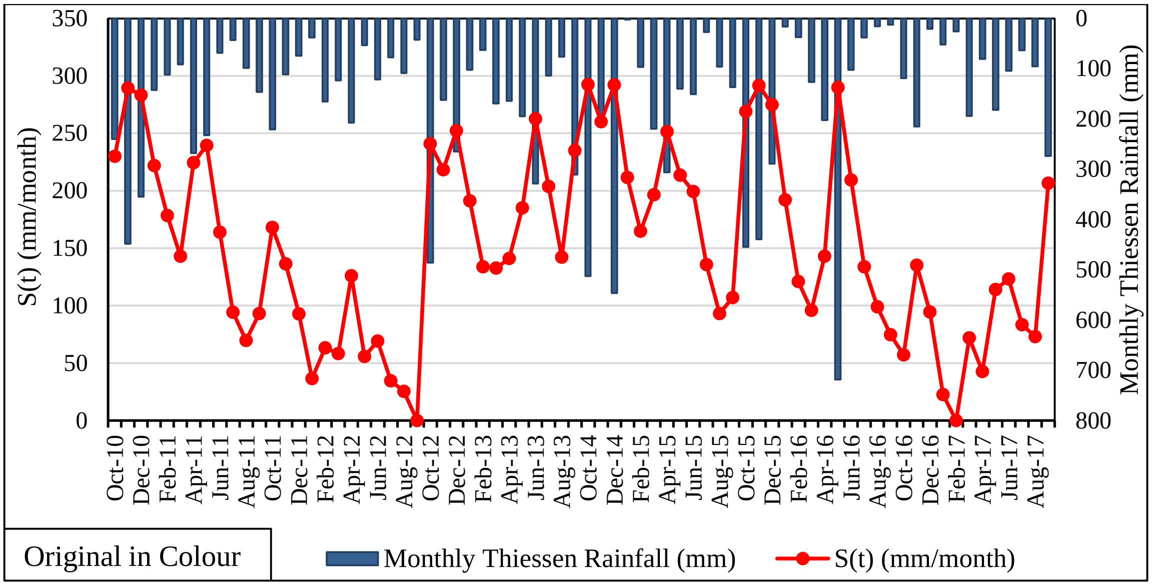


Figure 6.55: Water Content in Soil against rainfall [Normal] for 3PM Water Balance Model during Verification (October 2010 – September 2017)

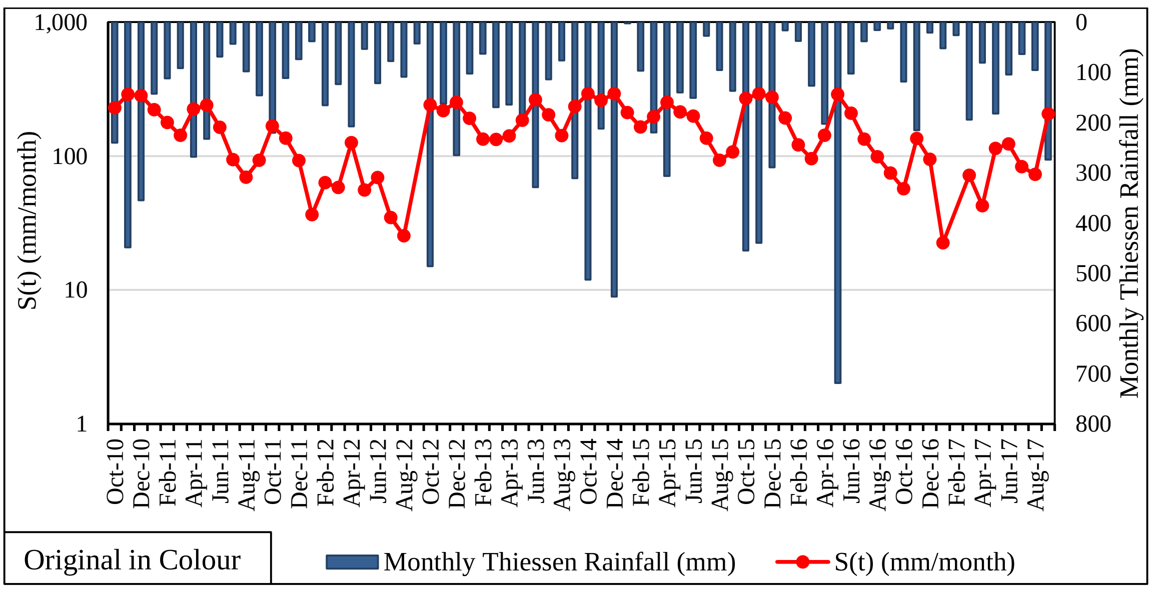


Figure 6.56: Water Content in Soil against rainfall [Semi Log] for 3PM Water Balance Model during Verification (October 2010 – September 2017)

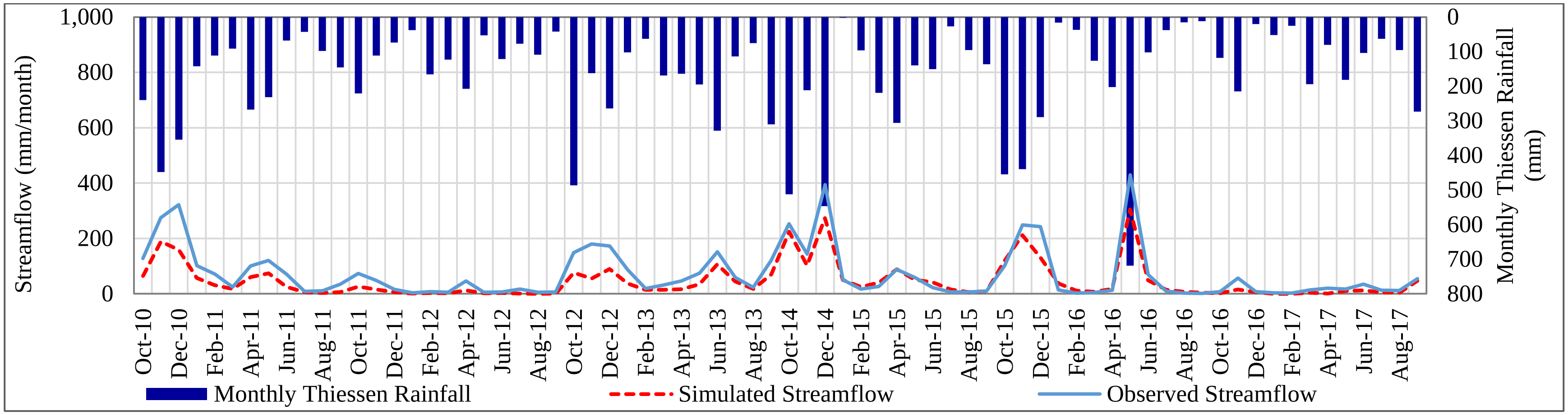


Figure 6.57: Comparison of Monthly Hydrograph [Normal] – 3 Parameter Monthly Water Balance Model – Verification (2010-2017)

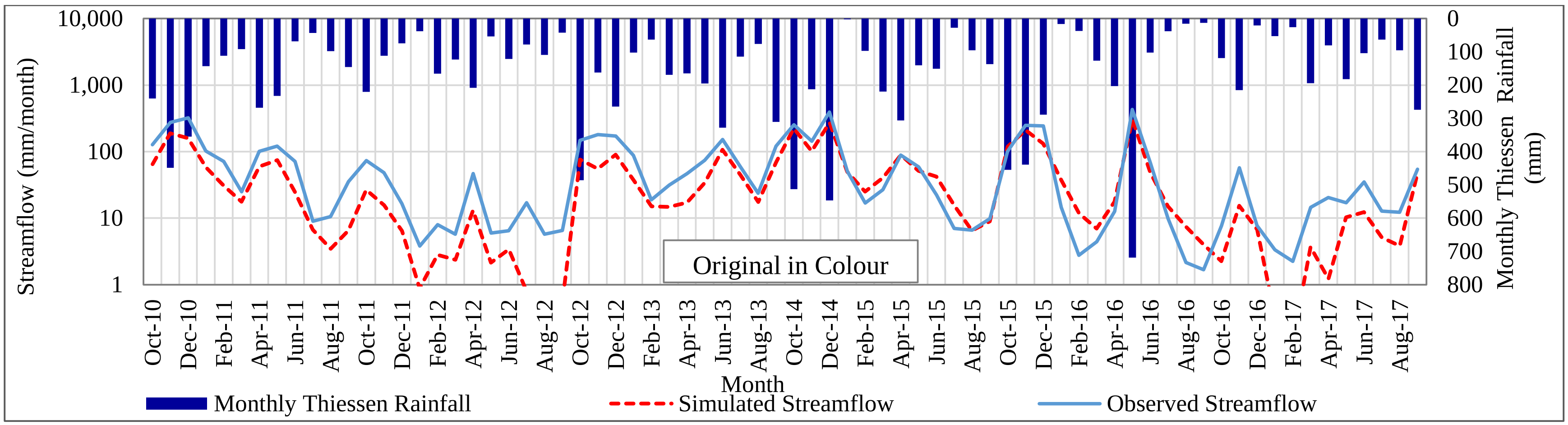


Figure 6.58: Comparison of Monthly Hydrograph [Semi-log] – 3 Parameter Monthly Water Balance Model – Verification (2010-2017)

Table 6.33:Annual Water Balance - 3PM (Monthly Input) – Verification Period – Badalgama Watershed

Water Year	Thiessen Averaged Rainfall (mm)	Simulated Streamflow (mm)	Observed Streamflow (mm)	Observed Water Balance (mm)	Simulated Water Balance (mm)	Annual Water Balance Difference (mm)
2010 / 2011	2244	765	1272	973	1479	-506
2011 / 2012	1338	78	244	1093	1259	-166
2012 / 2013	2413	640	1115	1298	1773	-476
2014 / 2015	2446	1015	1077	1369	1432	-63
2015 / 2016	2452	1014	1140	1312	1438	-126
2009 / 2010	1425	126	245	1180	1299	-119

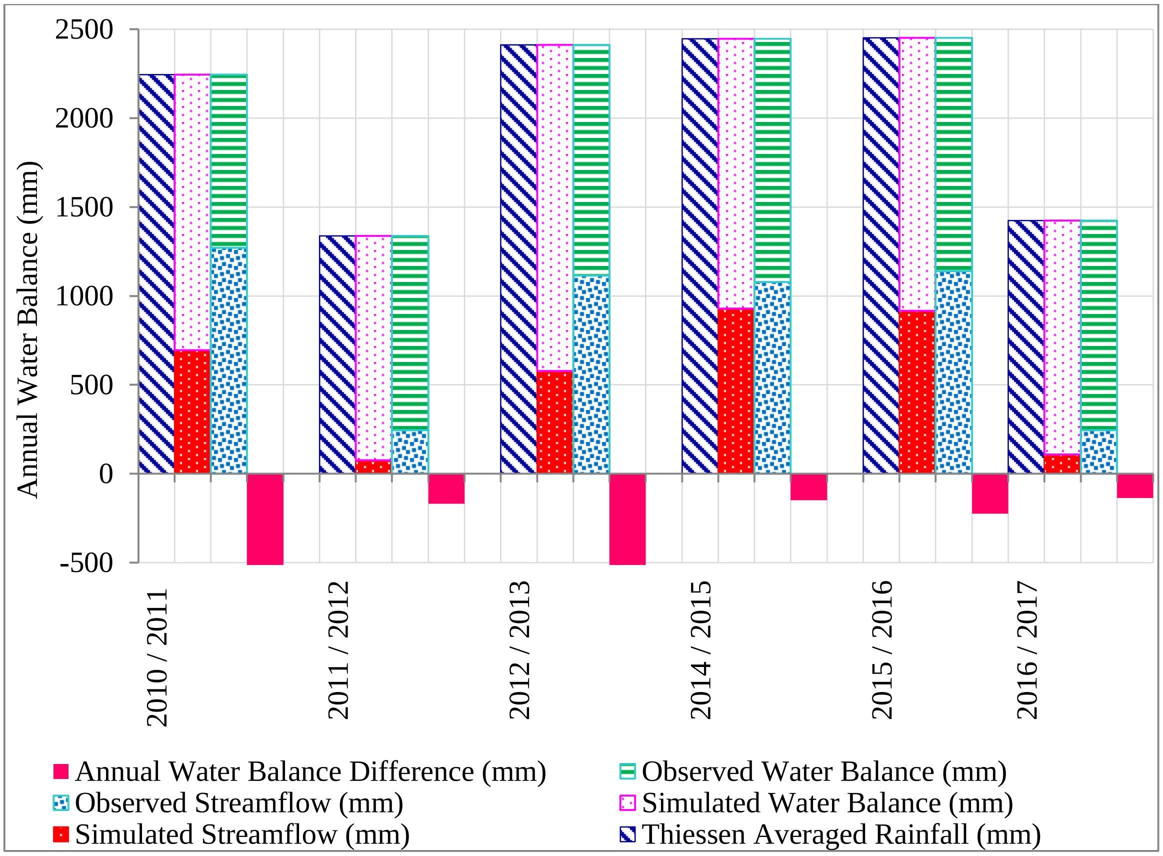


Figure 6.59: Annual Water Balance - 3PM (Monthly Input) – Verification Period – Badalgama Watershed

6.9. Results Summary

A comparison of the calibrated model of the two parameter water balance monthly model, three parameter monthly water balance model (if 3rd parameter is optimized) and three parameter monthly water balance model (all three parameters optimized at once) was carried out (Table 6.34). The objective of the comparison was to identify the model performance with least error and best response on the monthly scale. Considering the performance indicators it is clear that 3 Parameter monthly water balance model (all 3 optimized parameters) resulted in best MRAE value for overall hydrograph. 3 parameter monthly water balance model when all parameters were together optimized showed an underestimation of the annual water balance comparison while two parameter monthly water balance shows an overestimation of the annual water balance comparison. However, if the average water balance is evaluated then two parameter monthly water balance output is showing good results. Looking at the flow duration curves, two parameter monthly water balance and 3 parameter monthly water balance model seem similar with minor variations. Thus, for daily estimations two parameter monthly water balance model and three parameter monthly water balance models will be further studied and checked which of them is best for daily streamflow estimations. The water content in soil tables are provided (Annex E-1). The optimization case amongst both monthly water balance models which can estimate daily runoff accurately will be further studied for station weight optimization and station weight optimization and parameters simultaneously. Two parameter monthly model resulted in average MRAE of 0.646 while Three parameter monthly model if only K is optimized resulted in 0.508 average MRAE; similarly, Three parameter monthly model with all three parameters optimized provide an average MRAE of 0.504 output (Table 6.34). Keeping average MRAE as the criteria for evaluation, the best average MRAE during both calibration and verification has been achieved when all the three parameter of three parameter monthly water balance model are optimized simultaneously.

Table 6.34: Comparison of Summary Results for Badalgama watershed (monthly input)

Model Performance Indicators	2PMWBM		3PMWBM with k optimized		3PMWBM with all 3 optimized	
Outputs & Parameters	Calibration	Verification	Calibration	Verification	Calibration	Verification
Sc	1,061	1,061	1063	1,063	1,051	1,051
c	1.51	1.51	1.51	1.51	2.5	2.5
K	-	-	0.691	0.691	0.645	0.645
MRAE - Overall	0.586	0.706	0.412	0.604	0.412	0.597
MRAE - High	0.324	0.208	0.324	0.208	0.368	0.228
MRAE - Medium	0.472	0.615	0.472	0.615	0.483	0.566
MRAE - Low	0.846	1.346	0.846	1.346	0.635	0.901
Average Water Balance Difference	117.952 mm	3.389 mm	-176.074 mm	-262.548 mm	-221.861 mm	- 298.843mm
Maximum Soil Moisture	292.754 mm	294.961 mm	293.241 mm	295.402 mm	290.517 mm	292.466 mm
Minimum Soil Moisture	61.949 mm	0.000	62.225 mm	0.000 mm	60.682 mm	0.000 mm
Starting Soil Moisture	271.902 mm	231.016 mm	272.262 mm	231.225 mm	270.248 mm	229.856 mm
Ending Soil Moisture	96.521 mm	108.025 mm	96.735 mm	108.19 mm	95.542 mm	107.137 mm
Data Period	2004 - 2010	2010 - 2017	2004 -2010	2010 - 2017	2004 -2010	2010 - 2017

6.10. Daily Outflow Estimation with 2PM (Daily Input)

6.10.1. General

The result of comparison in Table 6.34 shows that two parameter monthly water balance model and three parameter monthly balance model is essential to understand which of the models is better for the estimation of daily runoff. Two parameter monthly water balance model which is already calibrated and verified will be used at this stage for daily streamflow estimations. Xiong & Guo (1999) in their study have not indicated any changes required to estimate from monthly resolution to daily except the assumption that the equations represent and assuming no change in conceptualization of model for any given time step. Two parameter monthly water balance model is tested in this study for the daily time resolution and it is the two parameter monthly model with daily inputs.

No further calibration was performed for daily streamflow estimations, to observe the model estimation of the daily streamflow.

6.10.2. Calibration Period (2004/2005 – 2009/2010)

The model estimated streamflow hydrographs for calibration period are in Figure 6.64 and Figure 6.65 where there are sudden drops while estimating daily streamflow which may be due to consecutive dry period, where evaporation occurs and no contribution from rainfall is there which eventually affects the water content in soil.. The flow duration curves (Figure 6.63), Annual water balance data (Table 6.35) and comparison (Figure 6.57) and objective function values (Table 6.37) indicate the corresponding MRAE value. The value of MRAE (Table 6.37) is out of acceptable range (greater than one) and the overestimation in high flows and underestimation causes sudden value drops in hydrographs. On the other hand the duration curves reflect an over estimation in the low and medium flows. The scatter diagram in Figure 6.60 shows the behavior of observed streamflow and simulated streamflow. Daily streamflow estimates were aggregated to monthly value to compare with the monthly estimations with observed monthly streamflow (Figure 6.61).

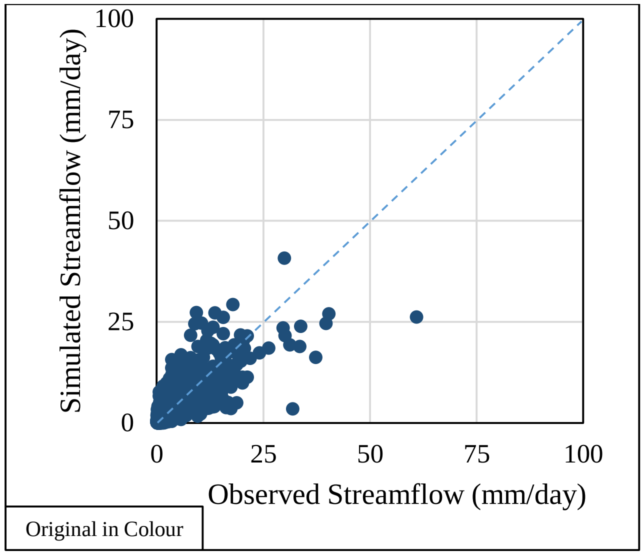


Figure 6.60: 2PM (Daily Input) – Daily Streamflow Estimation – Calibration Period – Badalgama Watershed

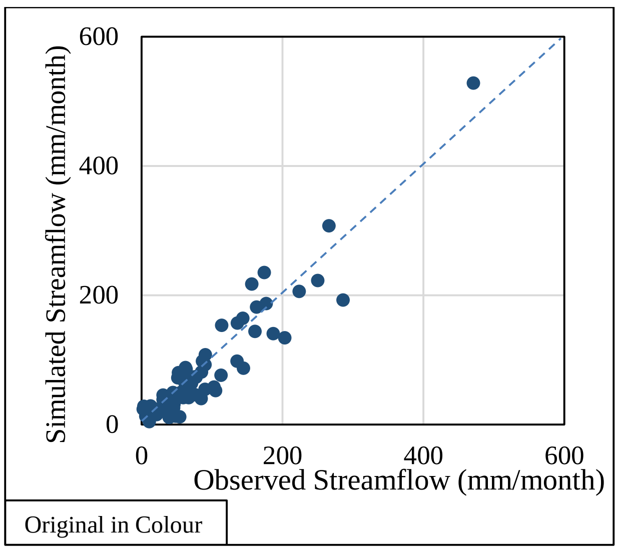


Figure 6.61: 2PM (Daily Input) – Monthly Streamflow Estimation – Calibration Period – Badalgama Watershed

Table 6.35: Annual Water Balance Data - 2PM (Daily Input) – Calibration Period – Badalgama Watershed

Water Year	Thiessen Averaged Rainfall (mm)	Simulated Streamflow (mm)	Observed Streamflow (mm)	Observed Water Balance (mm)	Simulated Water Balance (mm)	Annual Water Balance Difference (mm)
2004 / 2005	1901	896	633	1268	1006	263
2005 /2006	1997	708	792	1205	1290	-85
2006 / 2007	2442	1294	1164	1278	1148	131
2007 / 2008	2106	1108	889	1217	998	219
2008 / 2009	2322	1065	654	1668	1256	411
2009 / 2010	2219	984	907	1312	1236	77

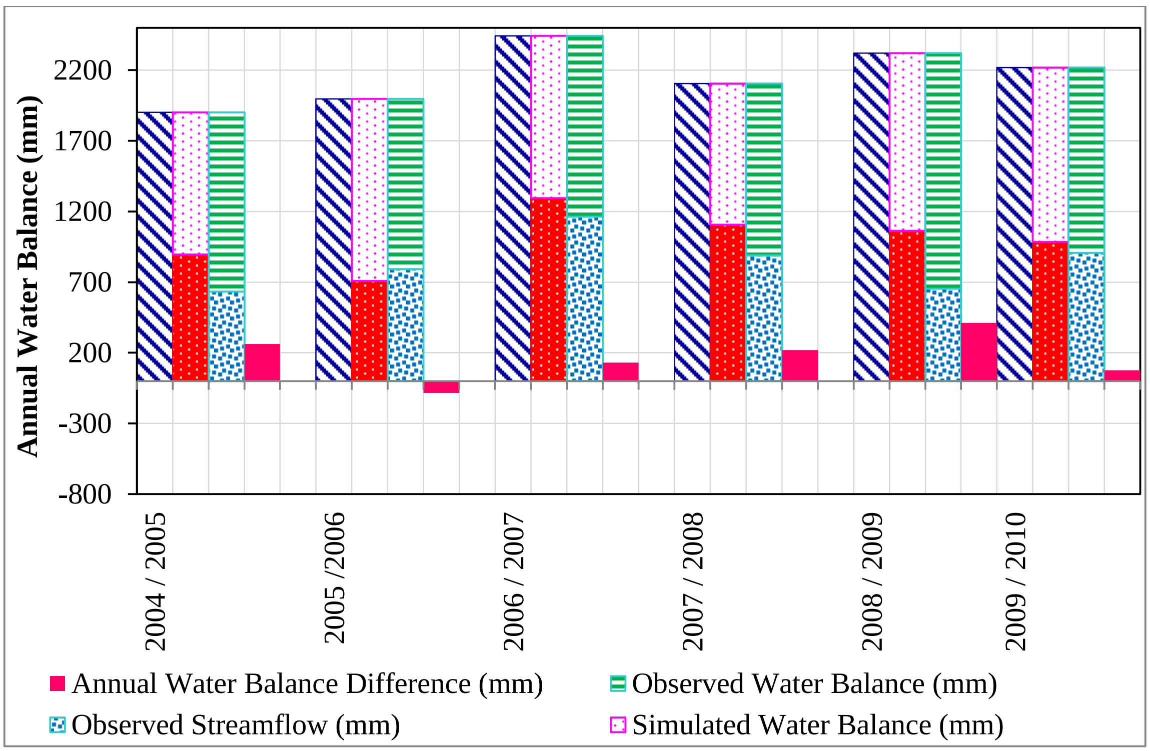


Figure 6.62: Annual Water Balance - 2PM (Daily Input) – Calibration Period – Badalgama Watershed

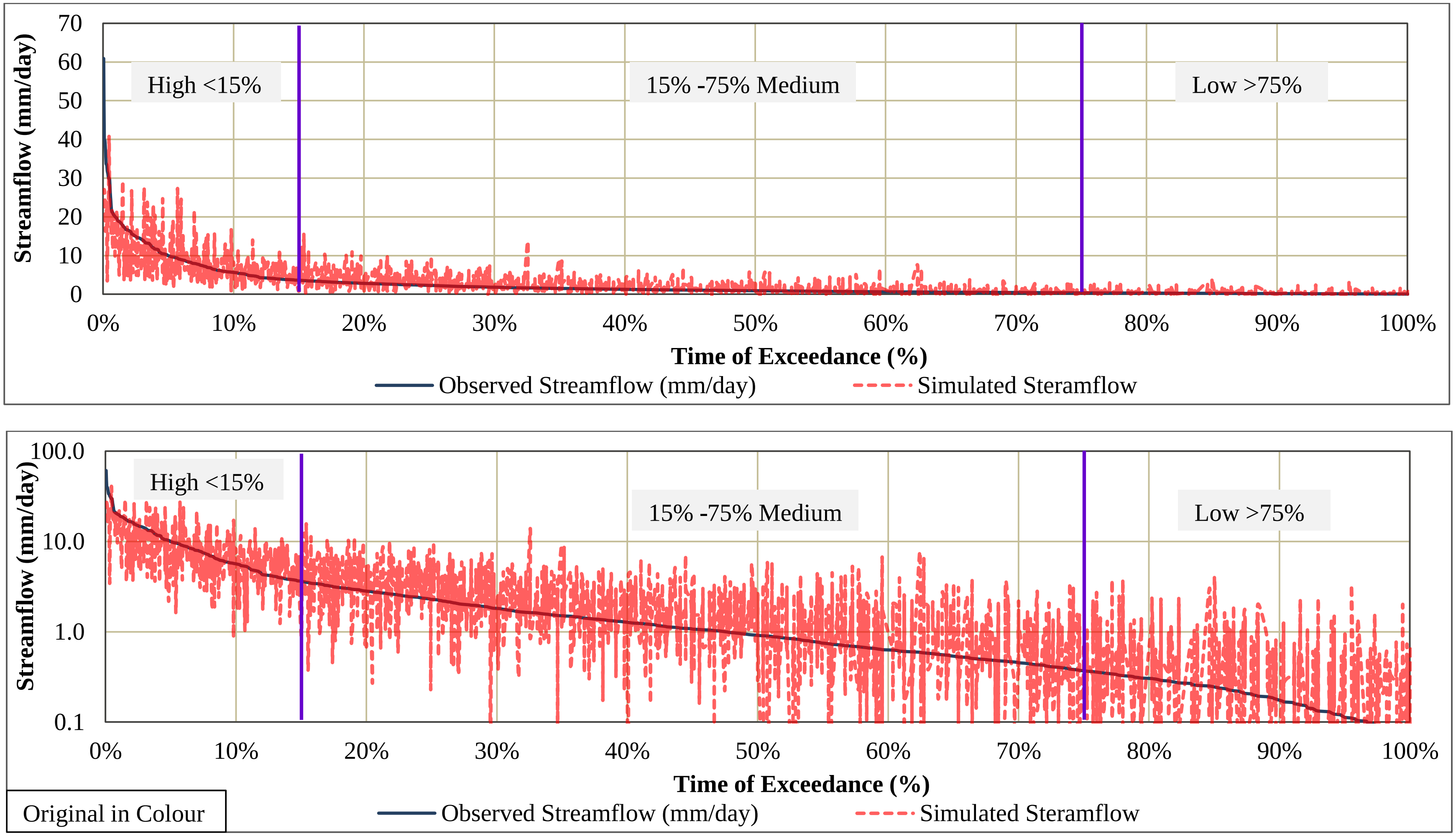


Figure 6.63: Flow Duration curve – 2PM (Daily Input - Calibration Period) for Badalgama Watershed

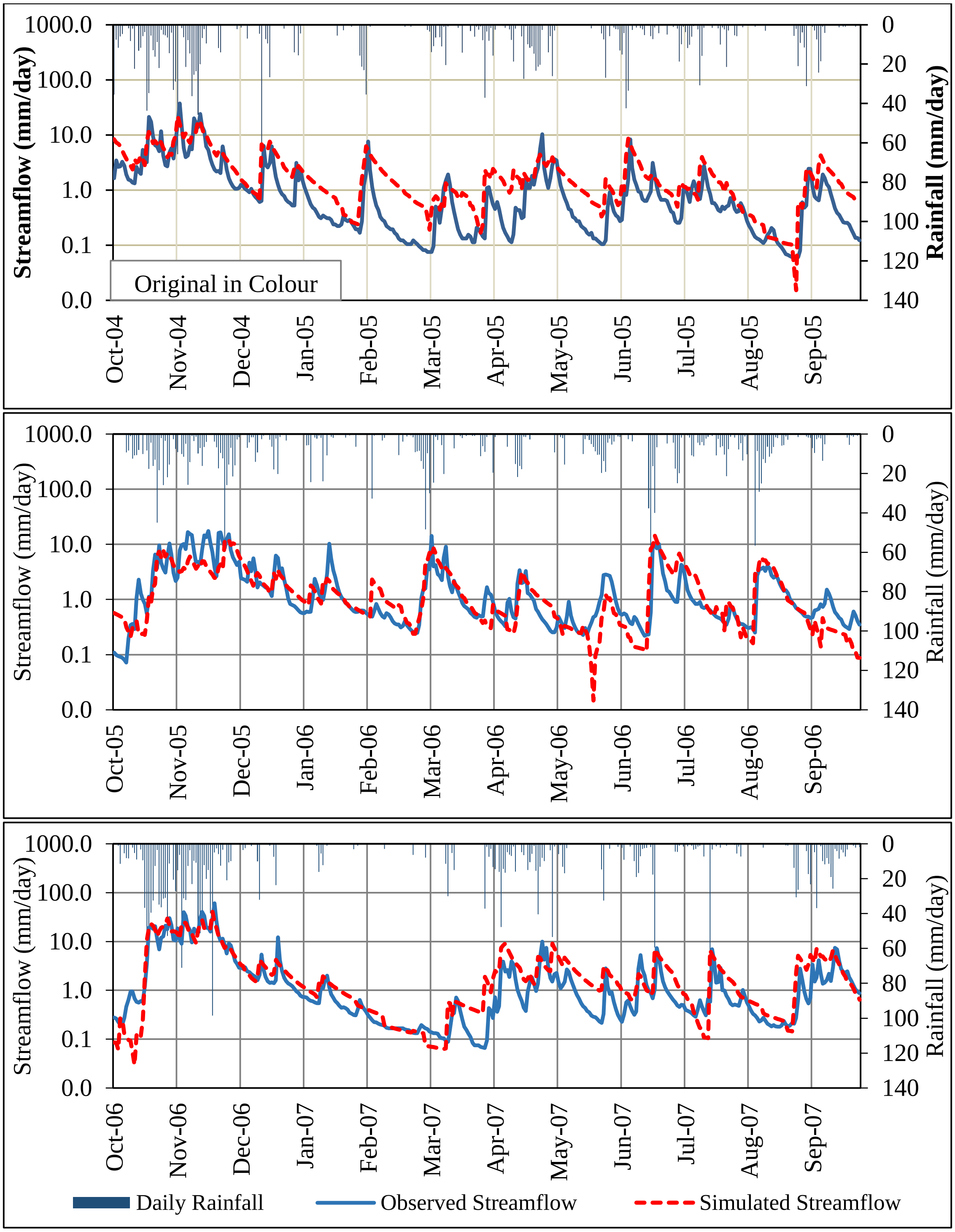


Figure 6.64: Output hydrographs – 2PM (Daily Input) – Calibration Period – Badalgama Watershed (Semi Logarithmic Plot)

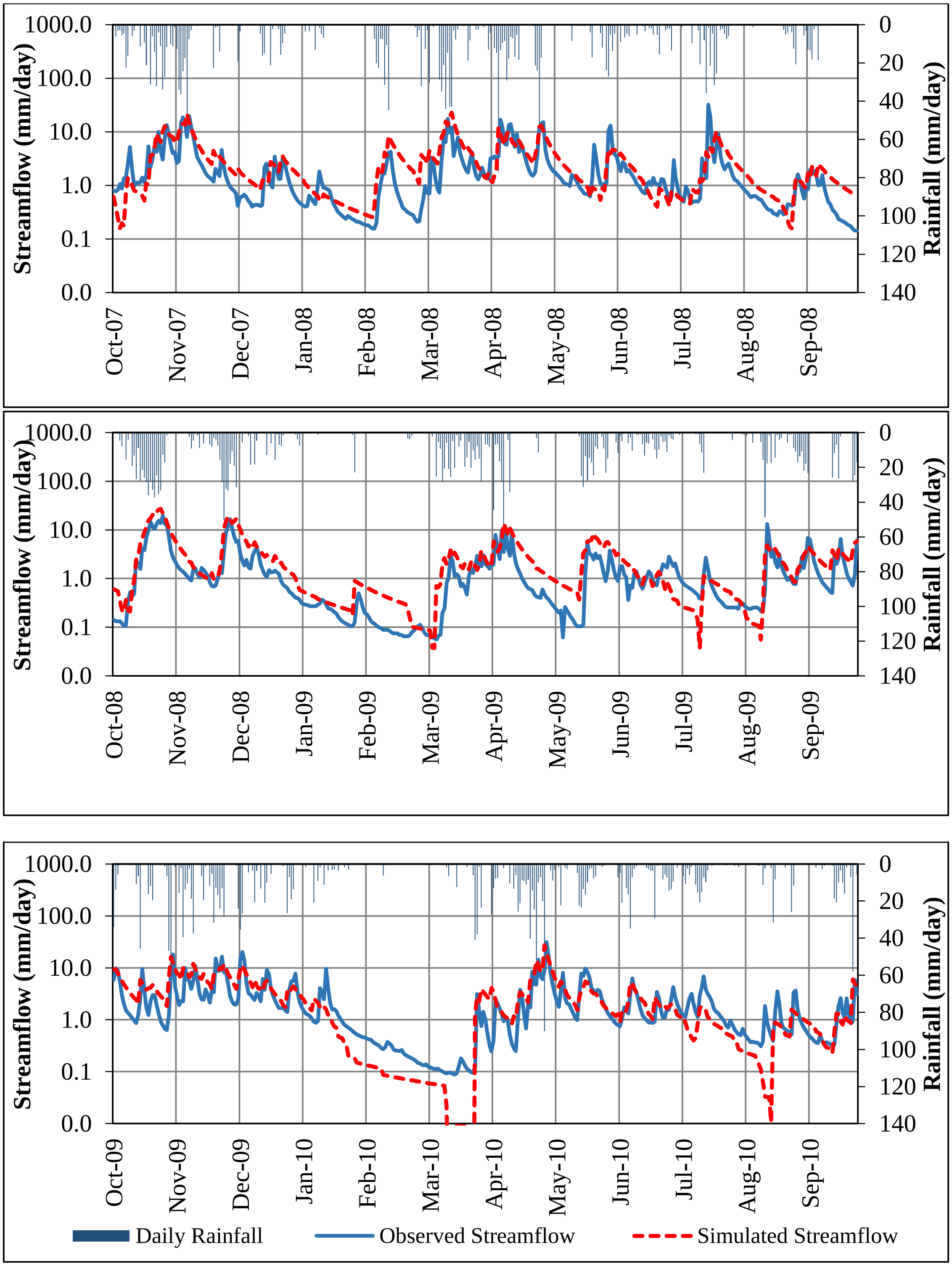


Figure 6.65: Output hydrographs – 2PM (Daily Input) – Calibration Period – Badalgama Watershed (Semi Logarithmic Plot)

6.10.3. Verification Period (2010/2011 – 2016/2017)

Model outflow hydrographs (Figure 6.68, Figure 6.69), Annual water balance (Figure 6.70) And objective function values (Table 6.37) indicate a MRAE. Duration curves show an underestimation for medium flows (Figure 6.67). A few places in the hydrograph the estimated runoff has dropped which is due to evaporation happening on daily basis eventually affecting soil moisture and dry period (no rainfall) in the model. Scatter plots show close match (Figure 6.66 and Figure 6.67).

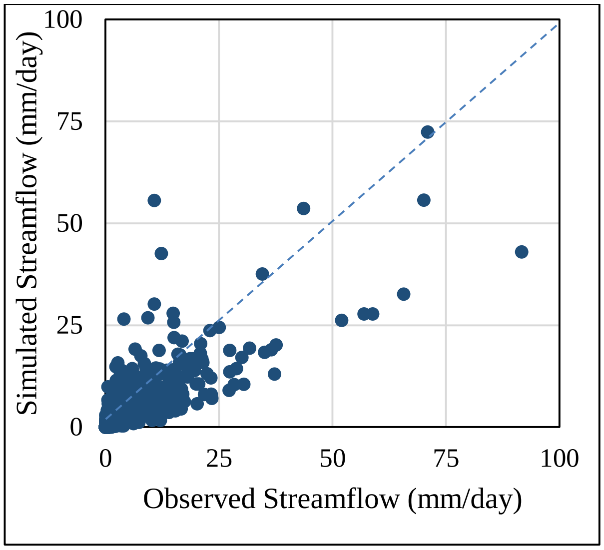


Figure 6.66: 2PM (Daily Input) – Daily Streamflow Estimation – Verification Period – Badalgama Watershed

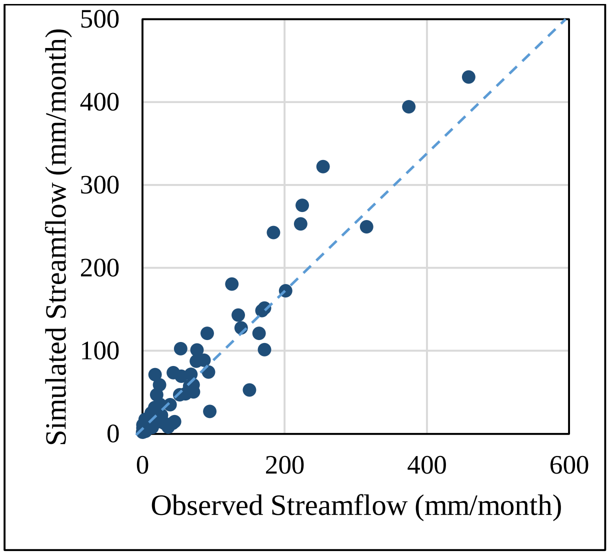


Figure 6.67: 2PM (Daily Input) – Monthly Streamflow Estimation – Verification Period – Badalgama Watershed

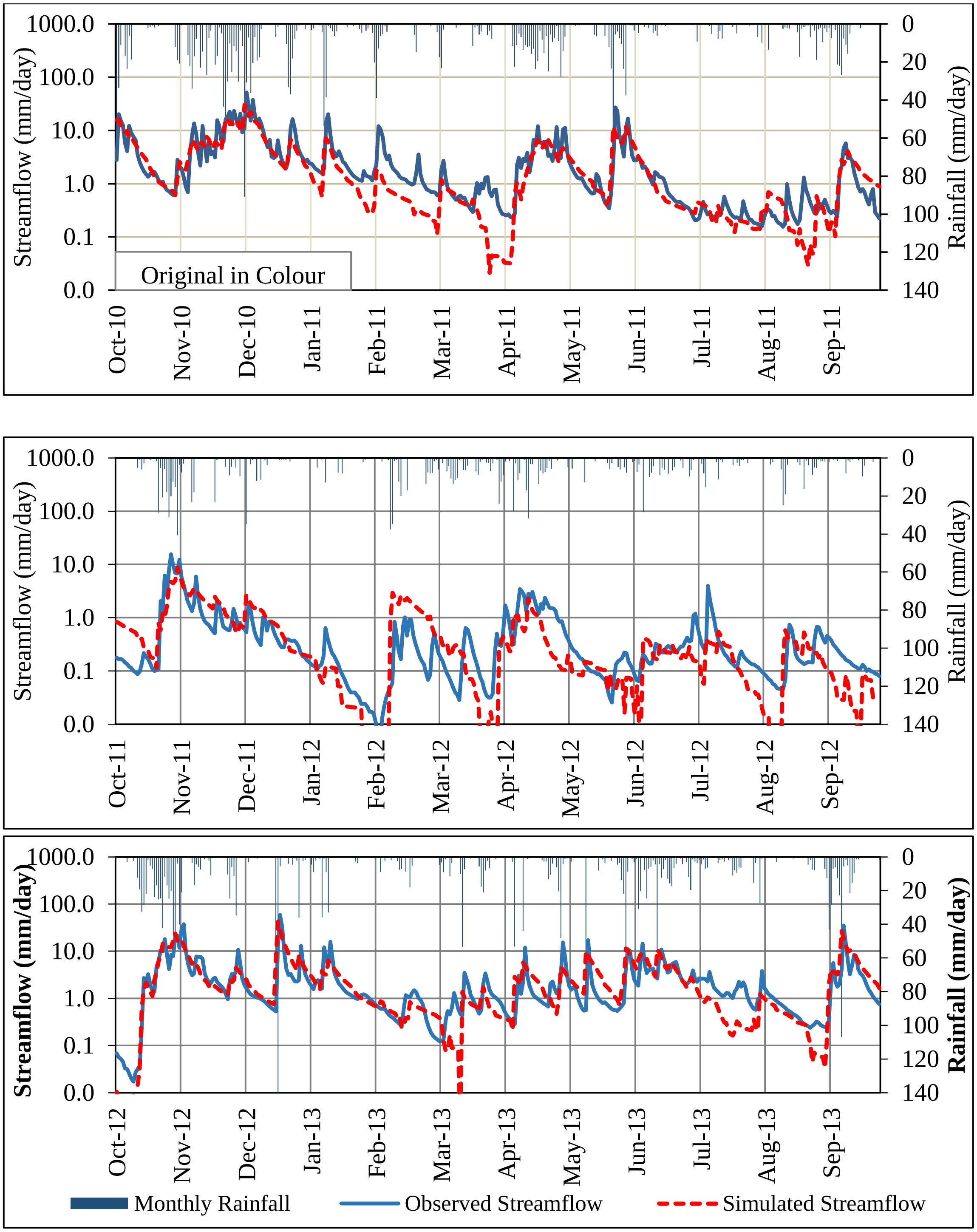


Figure 6.68: Output hydrographs – 2PM (Daily Input) – Verification Period – Badalgama Watershed (Semi Logarithmic Plot)

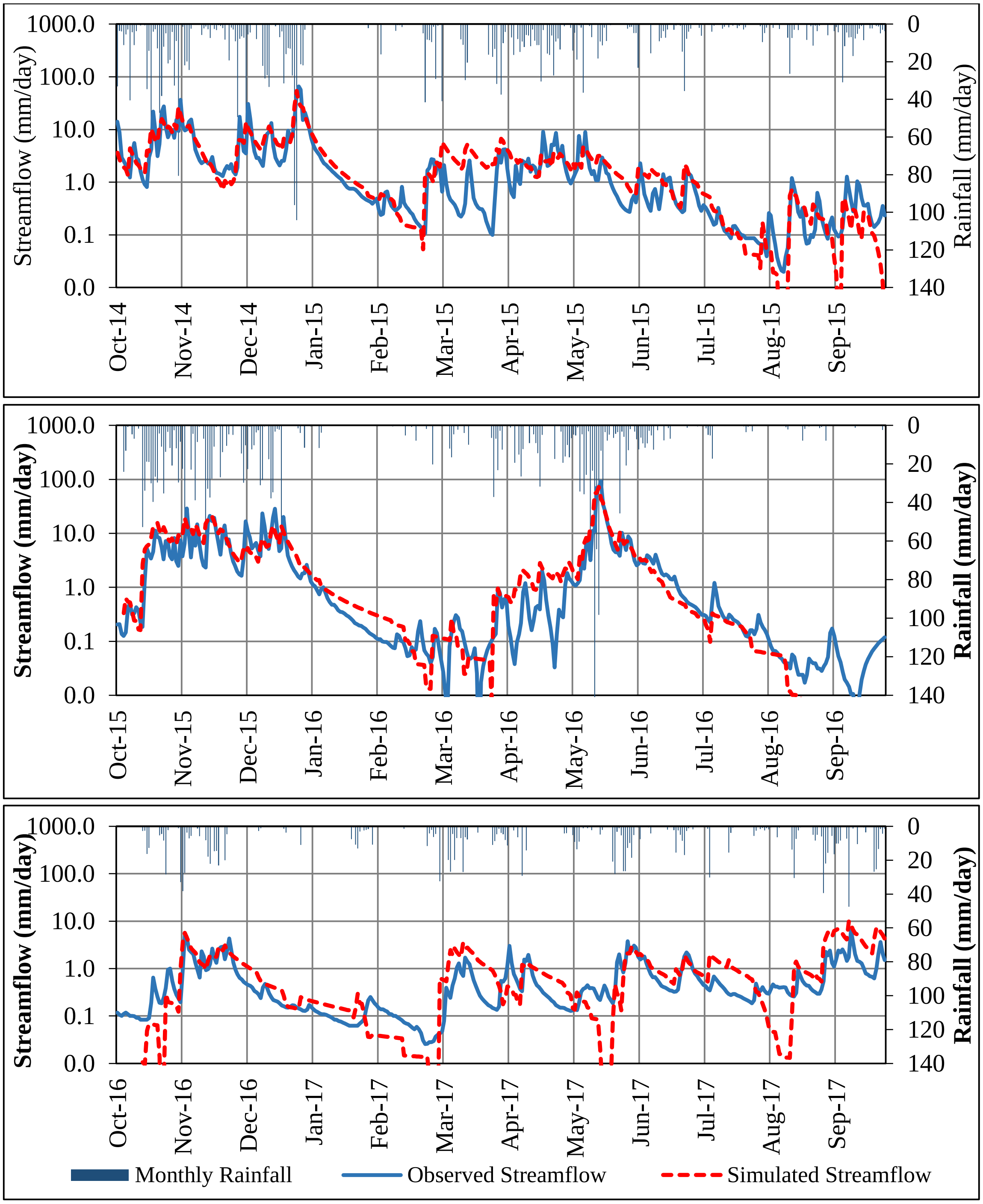


Figure 6.69: Output hydrographs – 2PM (Daily Input) – Verification Period – Badalgama Watershed (Semi Logarithmic Plot)

Table 6.36: Annual Water Balance Data - 2PM (Daily Input) – Verification Period – Badalgama Watershed

Water Year	Thiessen Averaged Rainfall (mm)	Simulated Streamflow (mm)	Observed Streamflow (mm)	Observed Water Balance (mm)	Simulated Water Balance (mm)	Annual Water Balance Difference (mm)
2010 / 2011	2244	966	1272	973	1278	-305
2011 / 2012	1338	207	244	1093	1130	-37
2012 / 2013	2413	1123	1115	1298	1290	8
2014 / 2015	2446	1108	1077	1369	1338	31
2015 / 2016	2452	1265	1140	1312	1187	125
2016 / 2017	1425	400	245	1180	1025	155

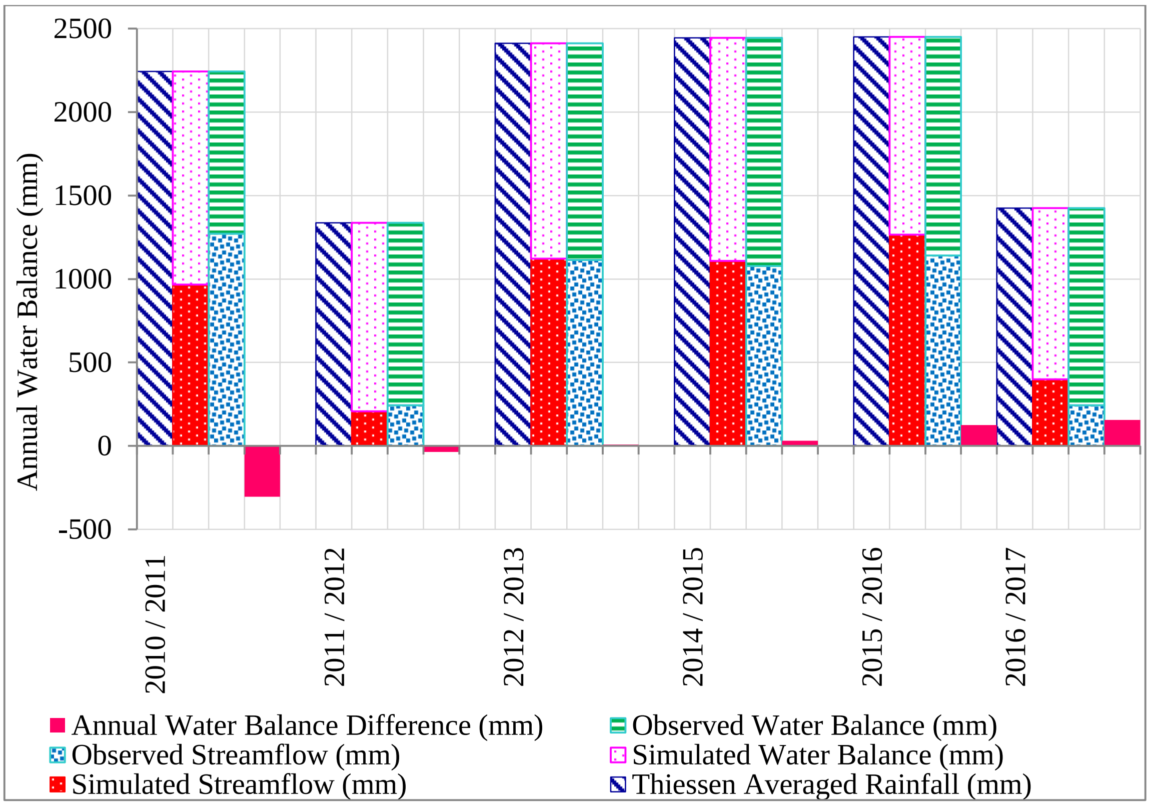


Figure 6.70: Annual Water Balance - 2PM (Daily Input) – Verification Period – Badalgama Watershed

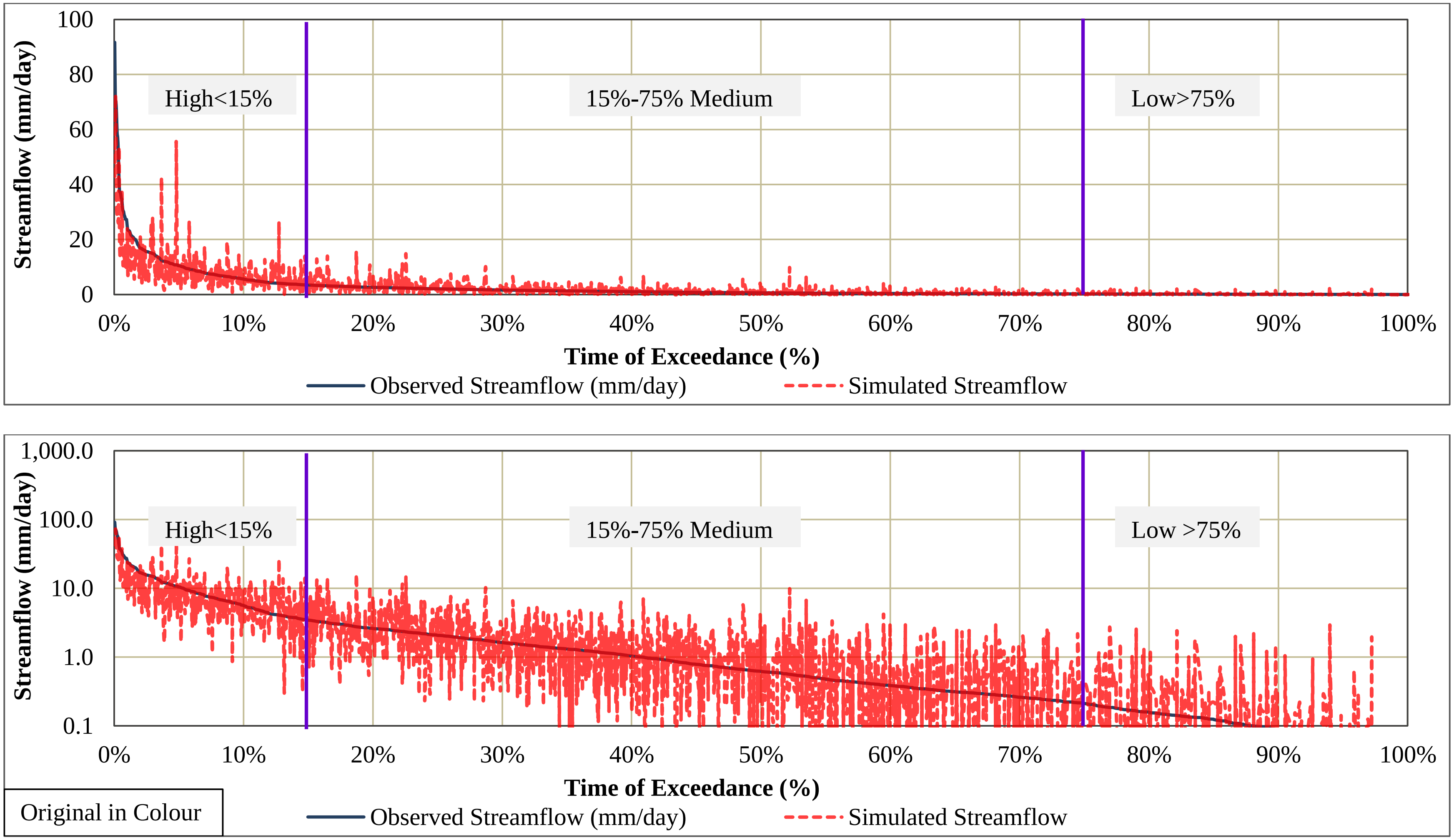


Figure 6.71: Flow Duration curve – 2PM (Daily Input - Verification Period) for Badalgama Watershed

6.10.4. Summary of 2PM (Daily Input) Model Performance

In the watershed the performance of the two parameter model with daily data revealed an over estimation of streamflow (Figure 6.63). The annual water balance difference is not very high but MRAE value is greater than one which is not in range (Table 6.37). The two parameter monthly water balance model was very sensitive in the estimation of low flows due to insufficient soil storage i.e. water content in soil, daily streamflow very soon drops out of the order of providing closer match with observed streamflow because of sudden drops which affected the module results in providing closer estimate to the observed value. Based on the literature (Xiong and Guo, 1999), two parameter monthly water balance models performs well in wet catchments which means a sequential dry period can results in such drops which can be added to major findings of this research.

Monthly flow estimations with daily inputs were also resulted in a scattered behavior (Figure 6.61 and Figure 6.67). Evaluation of both monthly and daily estimations reflects a similar, near uniform underestimation of streamflow when compared with observed data for high and low flows (Figure 6.71 and Figure 6.63); while hydrographs reveal even overestimations for high flows in years such as 2016/2017 and 2011/202; however, the annual water balance difference is very close.

Table 6.37: Summary Table of 2PMWBM (Daily Input)

Model Performance Indicators (Outputs & Parameters)	**2PMWBM**	
	Calibration Dataset	**Verification Dataset**
Sc	1061	1061
c	2.5	2.5
K	-	-
MRAE - Overall	1.199	1.122
MRAE - High	0.46	0.49
MRAE - Medium	0.98	0.92
MRAE - Low	2.20	1.78
Average Water Balance Difference	169.28 mm	(4.00) mm
Data Period	Oct 2004 –Sept 2010	Oct 2010 – Sept 2017

6.11. Three Parameter Model (Daily Input)

6.11.1. General

The evaluation results of two parameter model (Xiong, 1999) show that the monthly model overestimates at the daily resolution. From the model it can been seen the events with smaller rainfall values show lesser over estimations than the periods subjected to higher rainfall in it. Therefore, it is felt to adjust this overestimation, the model has been conceptualized based on proposed factor for adjusting the overestimation by incorporating the adjustment factor (K), and all three parameters were optimized on with monthly data.

6.11.2. Calibration period (Daily Input) 2004/2005-2009/2010

Performance corresponding to daily flow estimation showed an improvement in estimations which can be clearly seen in the hydrographs (Figure 6. 72 and Figure 6.73), flow duration curves (Figure 6.74) , annual water balance (Figure 6.75), and scatter plot (Figure 6.76 and Figure 6.76) the value of MRAE has been reduced which can be noticed in the summary Table 6.40.

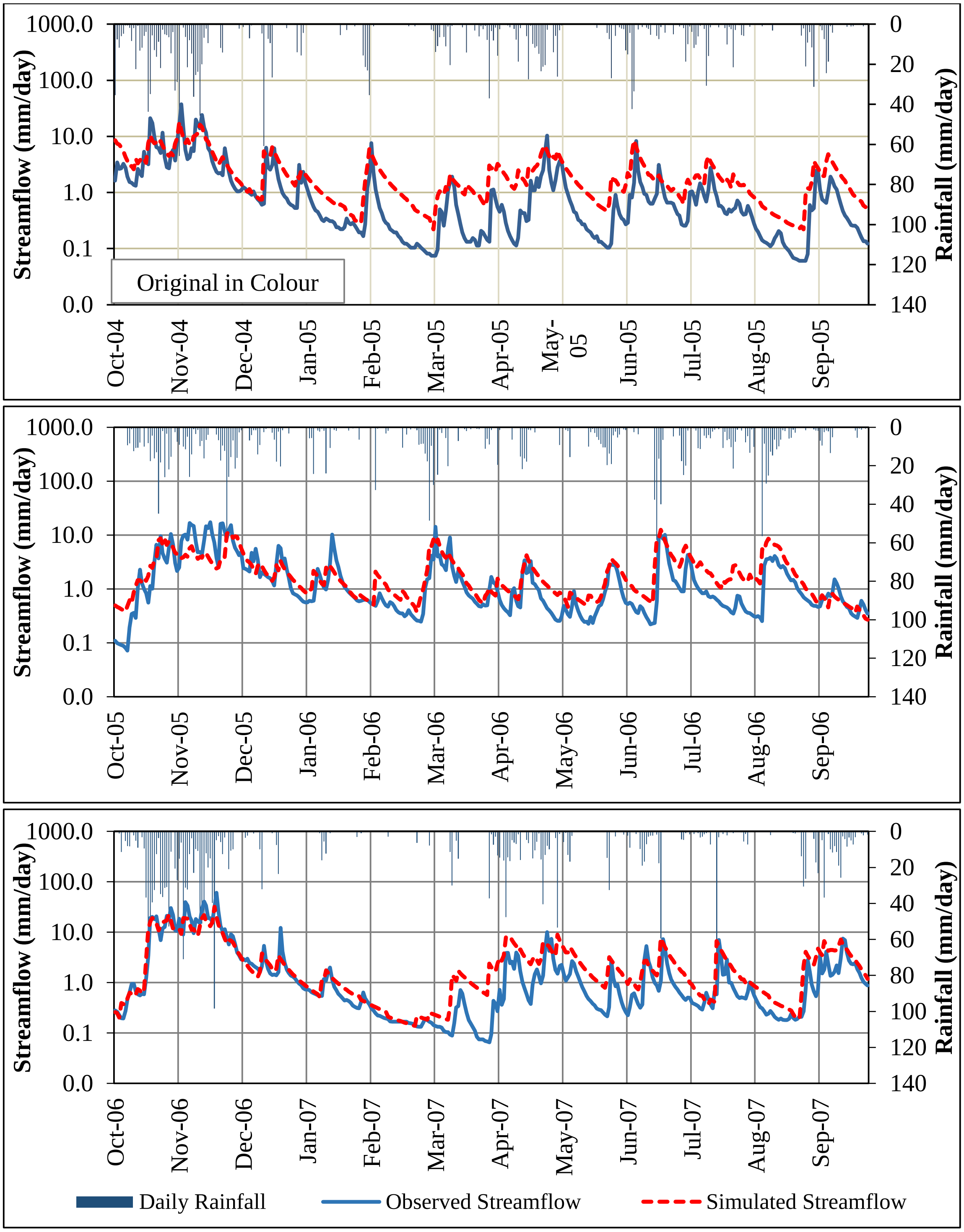


Figure 6.72: Output hydrographs – 3PM (Daily Input) – Calibration Period – Badalgama Watershed (Semi Logarithmic Plot)

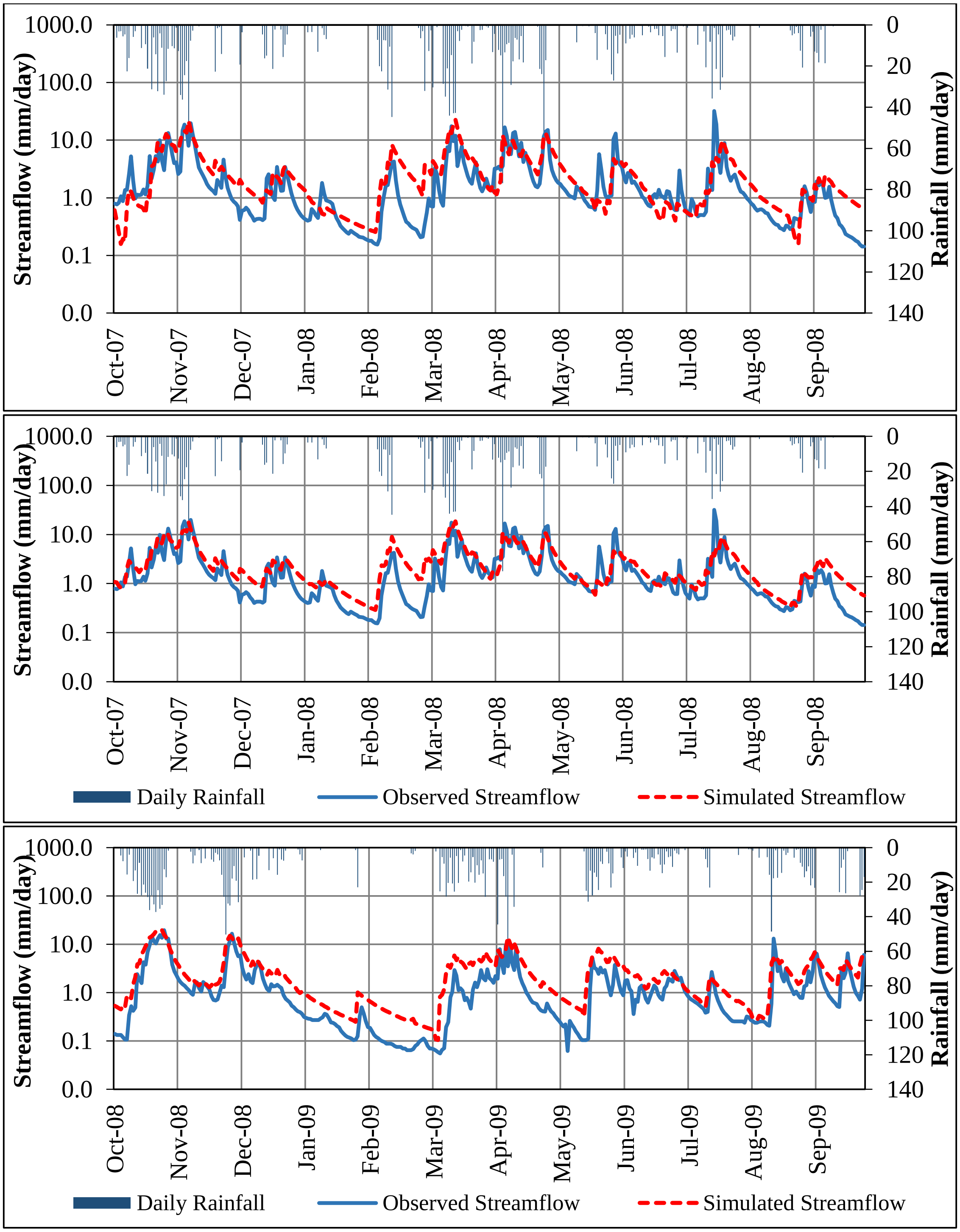


Figure 6.73: Output hydrographs – 3PM (Daily Input) – Calibration Period – Badalgama Watershed (Semi Logarithmic Plot)

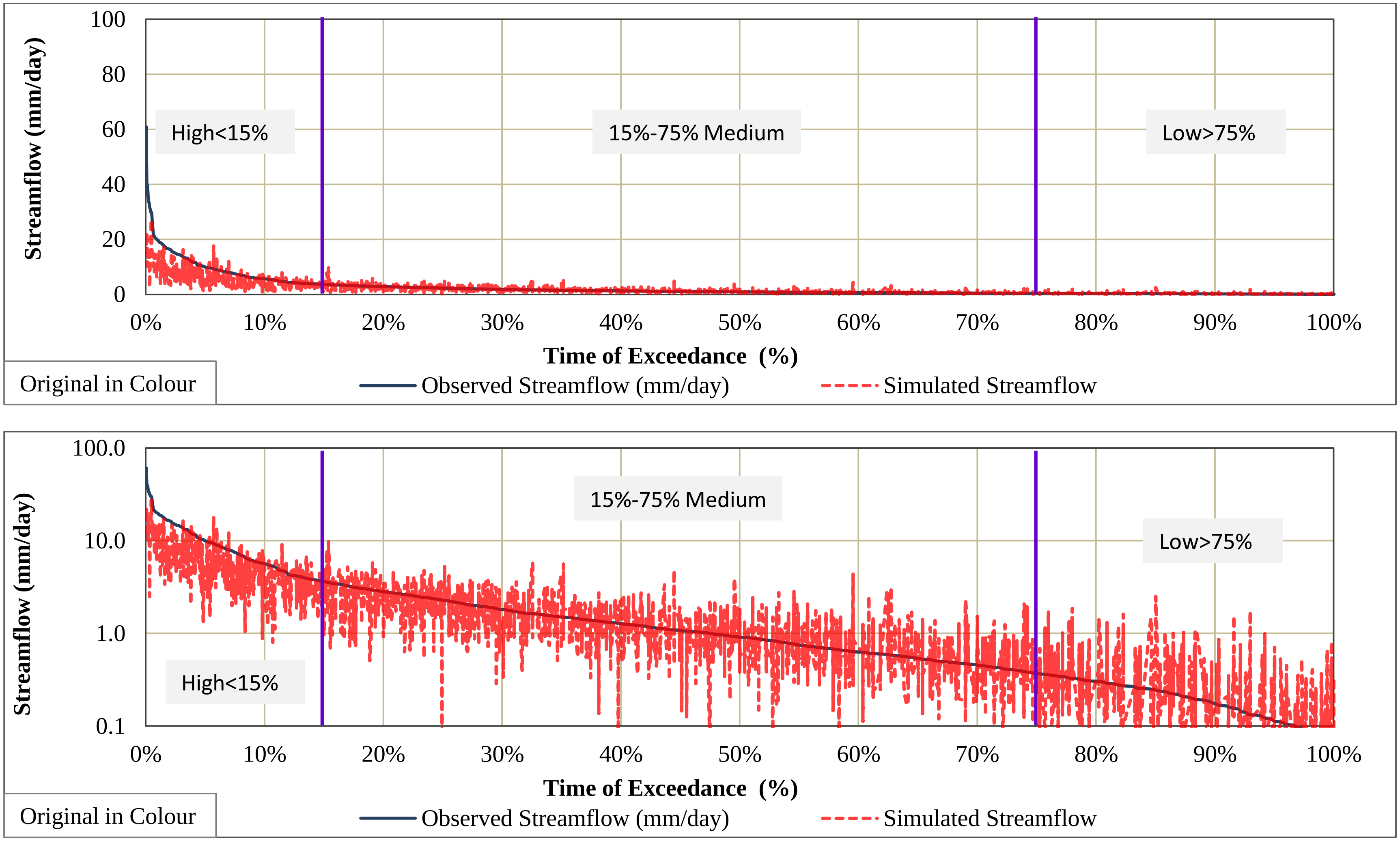


Figure 6.74: Flow Duration curve – 3PM (Daily Input - Calibration Period) for Badalgama Watershed

Table 6.38: Annual Water Balance - 3PM (Daily Input) – Calibration Period – Badalgama

Water Year	**Thiessen Averaged Rainfall (mm)**	**Simulated Streamflow (mm)**	**Observed Streamflow (mm)**	**Observed Water Balance (mm)**	**Simulated Water Balance (mm)**	**Annual Water Balance Difference (mm)**
2004 / 2005	1901	917	633	1268	984	284
2005 /2006	1997	863	792	1205	1134	70
2006 / 2007	2442	1211	1164	1278	1231	48
2007 / 2008	2106	1068	889	1217	1038	179
2008 / 2009	2322	1135	654	1668	1186	481
2009 / 2010	2219	1049	907	1312	1171	141

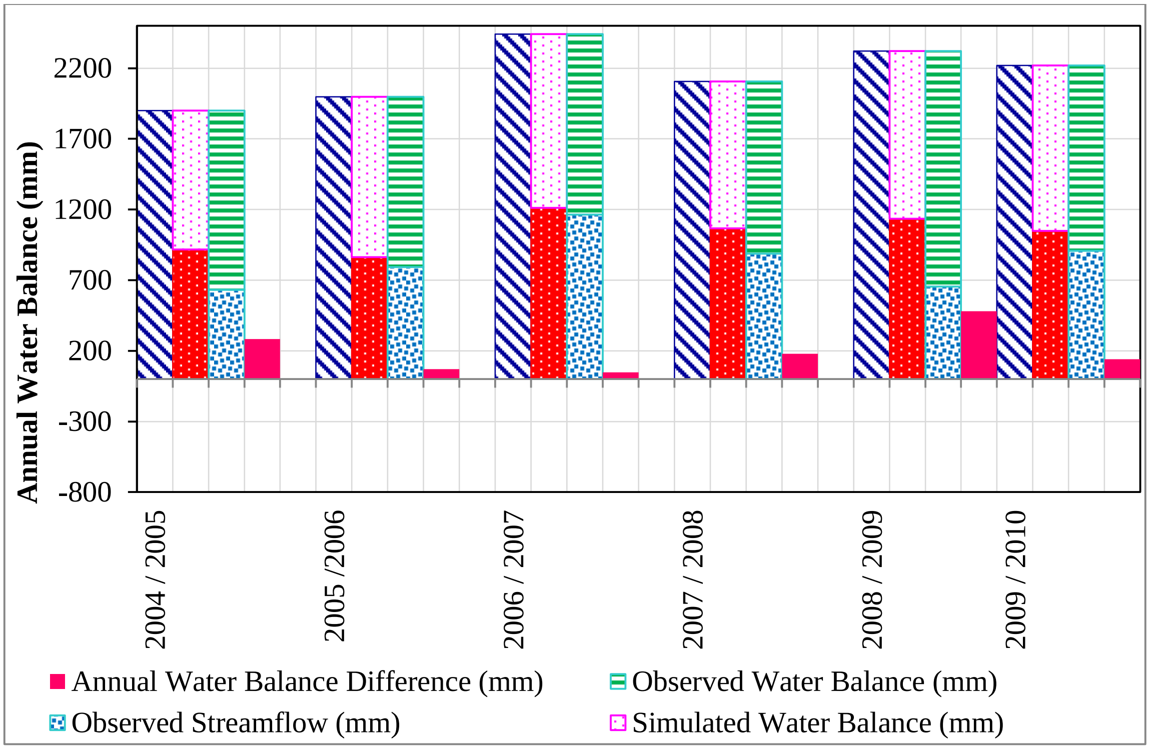


Figure 6.75: Annual Water Balance - 3PM (Daily Input) – Calibration Period – Badalgama

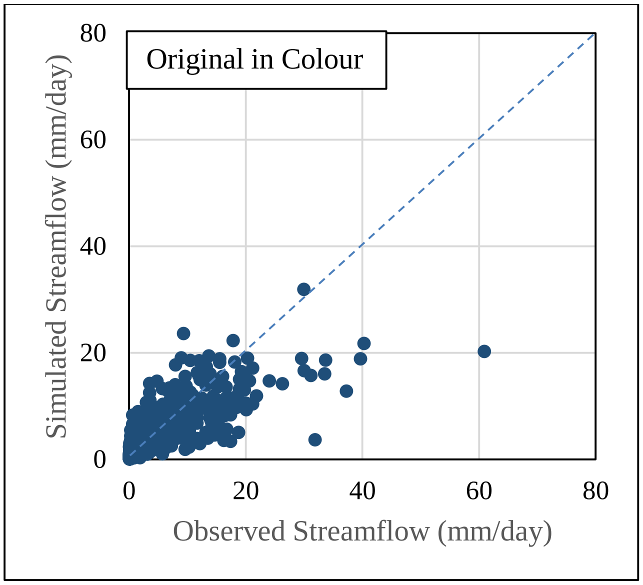


Figure 6.76: 3PM (Daily Input) – Daily Streamflow Estimation – Calibration Period – Badalgama Watershed

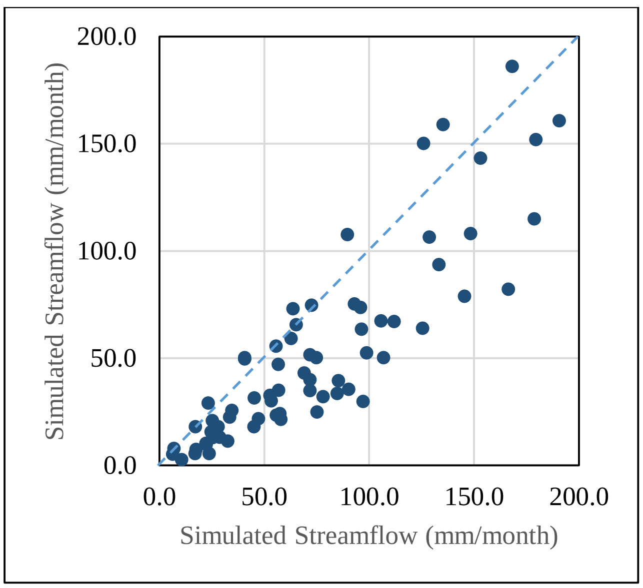


Figure 6.77: 3PM (Daily Input) – Monthly Streamflow Estimation – Calibration Period – Badalgama Watershed

6.11.3. Verification Period (Daily Input) 2010/2011-2016/2017

Performance corresponding to daily flow estimation showed an improvement in estimations which can be clearly seen in the hydrographs (Figure 6.78 , 6.79), flow duration curves (Figure 6.80) , annual water balance (Figure 6.81), and scatter plot (Figure 6.82 and Figure 6.83) the value of MRAE has been improved which can be noticed in the summary Table 6.40.

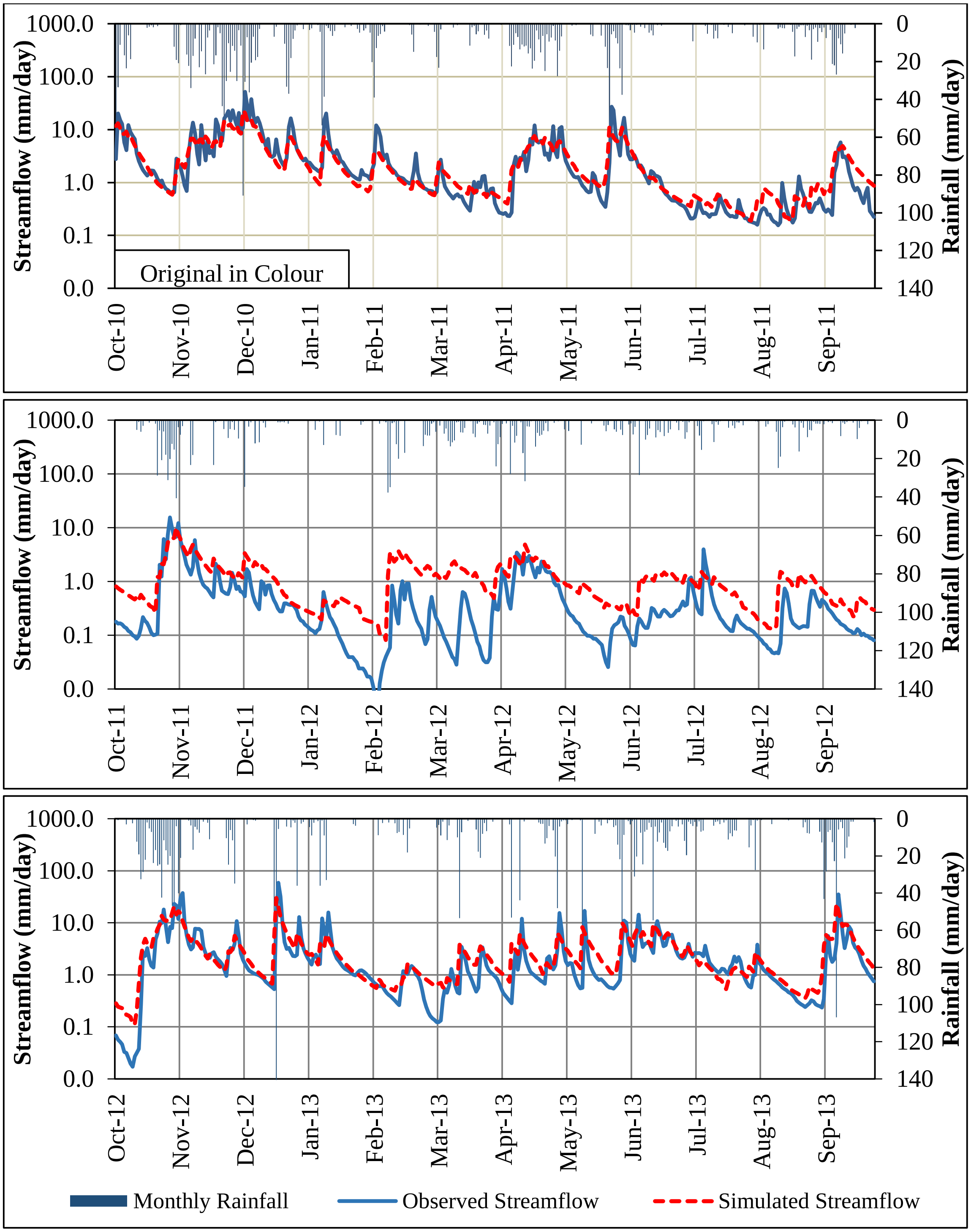


Figure 6.78: Output hydrographs – 3PM (Daily Input) – Verification Period – Badalgama Watershed (Semi Logarithmic Plot)

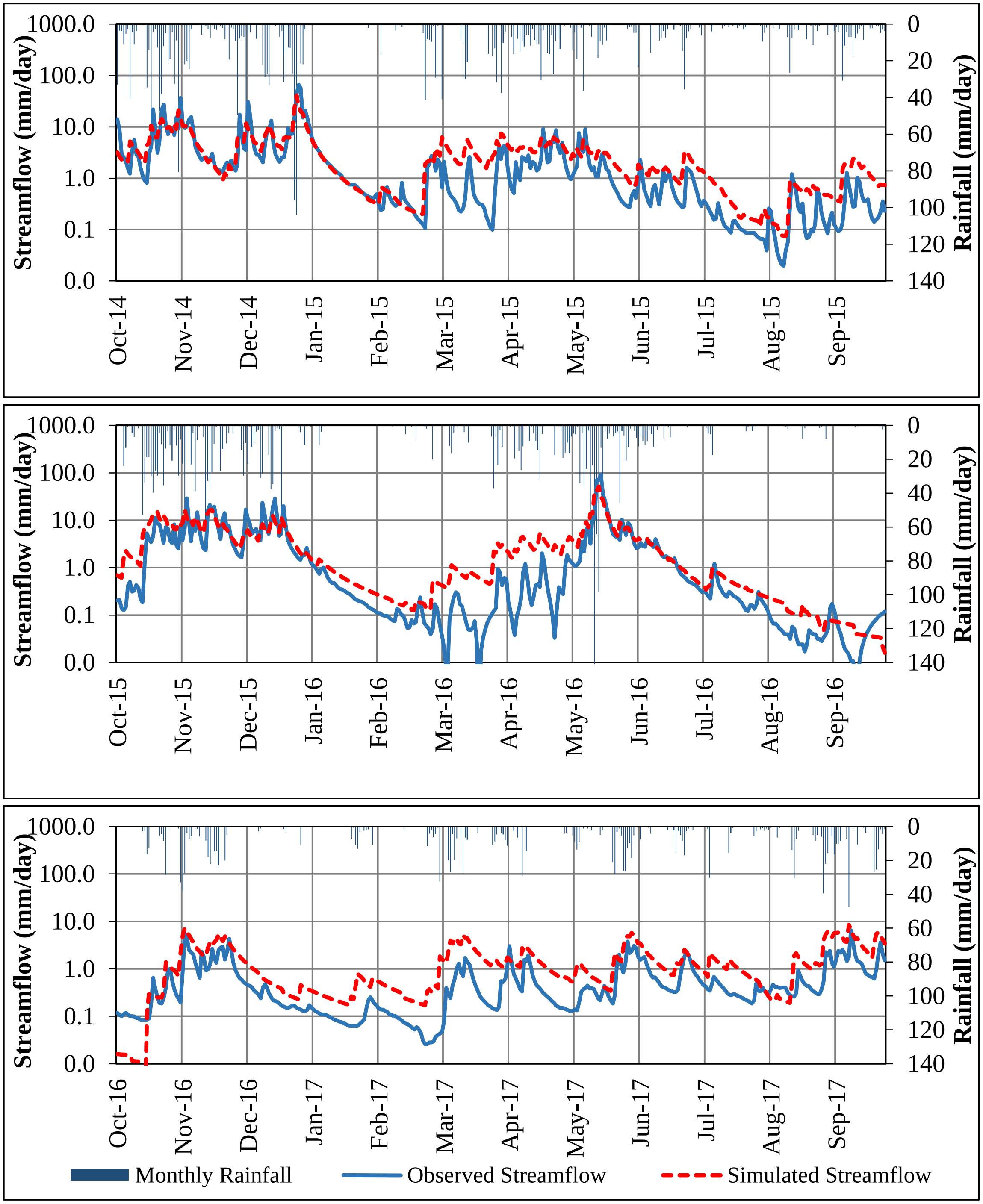
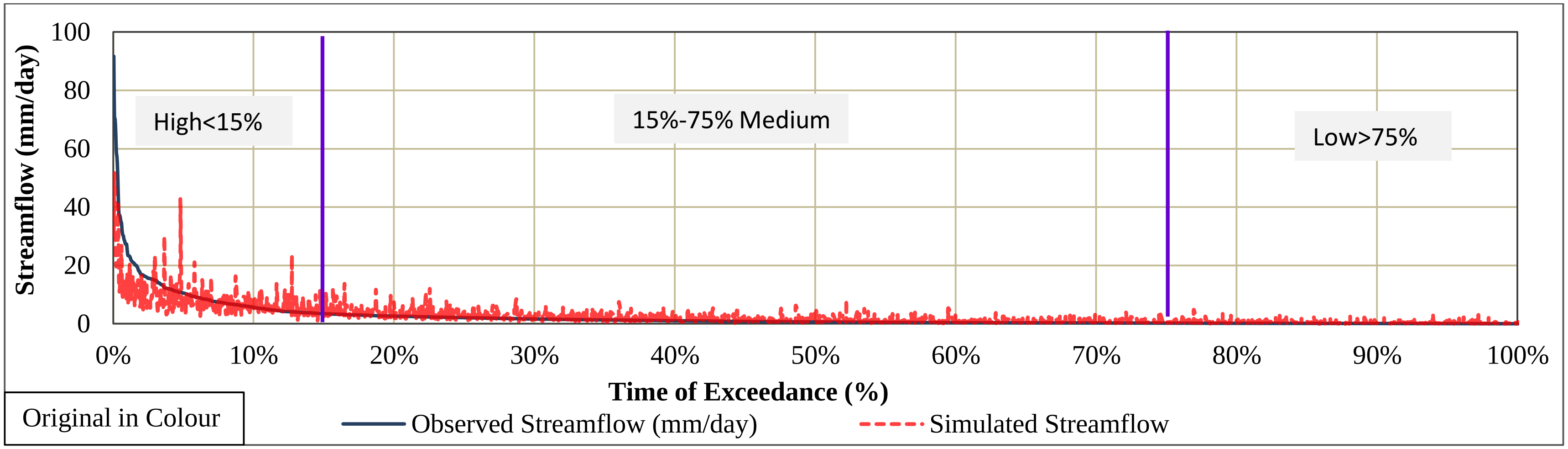


Figure 6.79: Output hydrographs – 3PM (Daily Input) – Verification Period – Badalgama Watershed (Semi Logarithmic Plot)



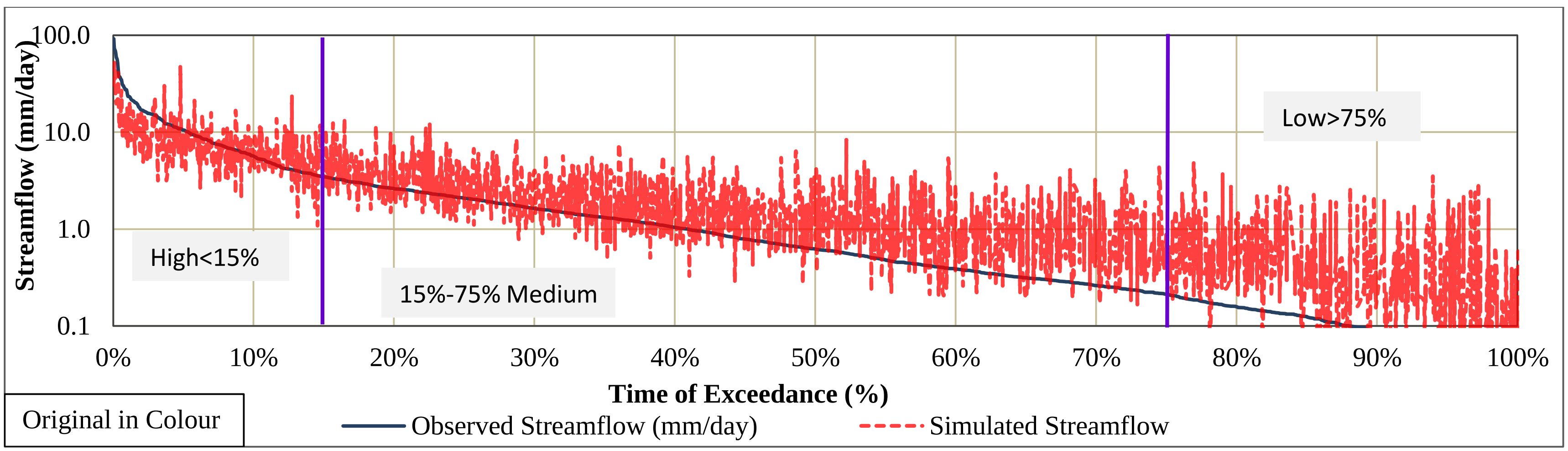


Figure 6.80: Flow Duration curve – 3PM (Daily Input – Verification Period) for Badalgama Watershed

Table 6.39: Annual Water Balance - 3PM (Daily Input) – Verification Period – Badalgama

Water Year	Thiessen Averaged Rainfall (mm)	Simulated Streamflow (mm)	Observed Streamflow (mm)	Observed Water Balance (mm)	Simulated Water Balance (mm)	Annual Water Balance Difference (mm)
2010 / 2011	2244	628	1272	973	1616	-644
2011 / 2012	1338	134	244	1093	1204	-110
2012 / 2013	2413	725	1115	1298	1688	-390
2014 / 2015	2446	715	1077	1369	1731	-362
2015 / 2016	2452	816	1140	1312	1636	-324
2016/ 2017	1425	258	245	1180	1166	14

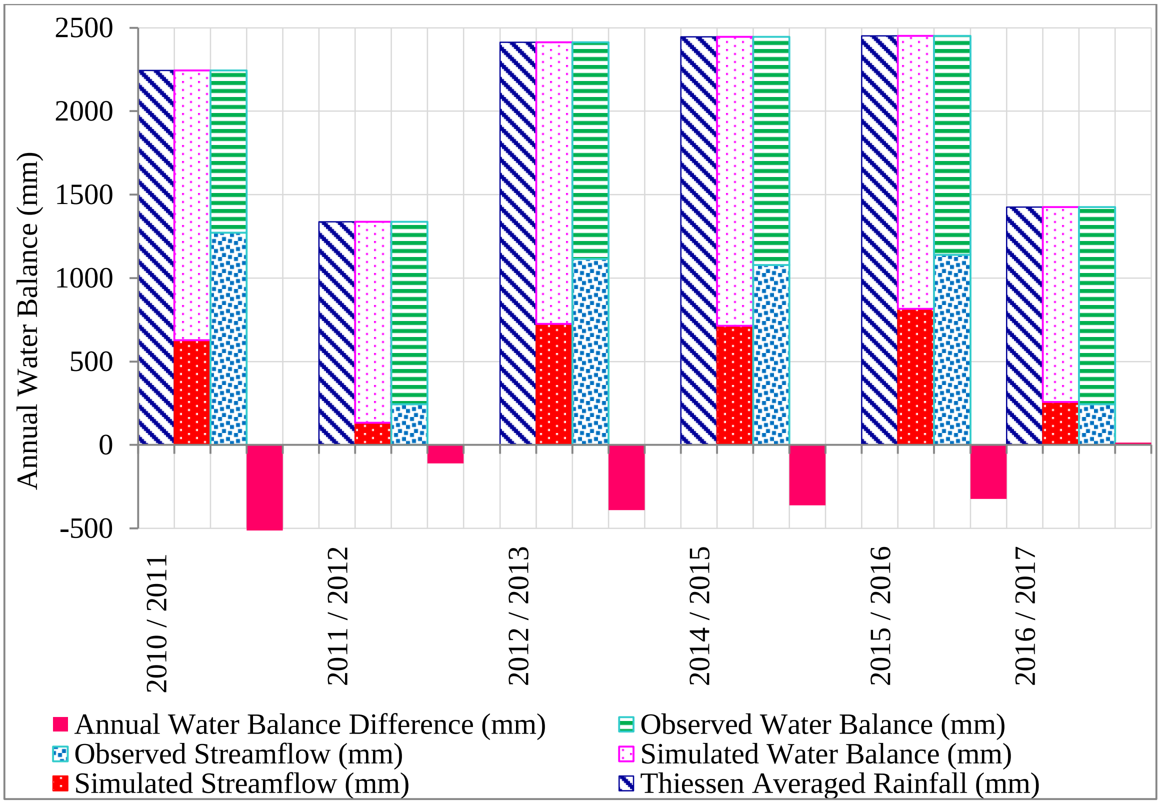


Figure 6.81: Annual Water Balance - 3PM (Daily Input) – Verification Period – Badalgama

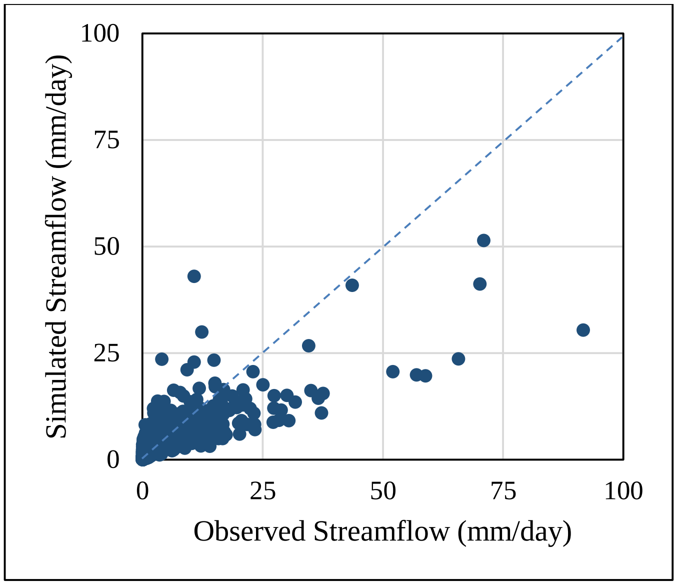


Figure 6.82: 3PM (Daily Input) – Daily Streamflow Estimation – Calibration Period – Badalgama Watershed

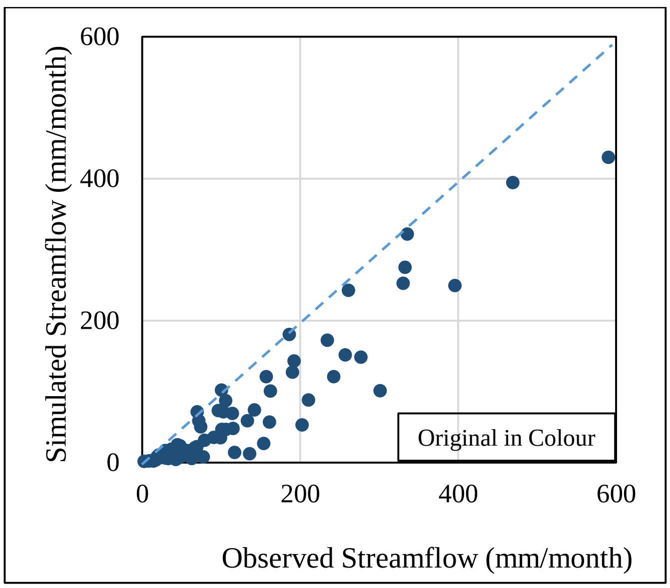


Figure 6.83: 3PM (Daily Input) – Monthly Streamflow Estimation – Verification Period – Badalgama Watershed

6.11.4. Result Summary

Both datasets calibration and verification has been added to the model in daily form for the estimation of daily runoff. It is noticed that overall MRAE value has resulted in much improved results compared to two parameter monthly water balance model, summary of results is shown (Table 6.40).

Table 6.40: Summary Table of 3PMWBM (Daily Input)

Model Performance Indicators (Outputs & Parameters)	3PMWBM	
	Calibration	Verification
Sc	1051	1,051
c	2.5	2.5
K	0.64	0.64
MRAE - Overall	0.577	0.822
MRAE - High	0.49	1.32
MRAE - Medium	0.47	0.525
MRAE - Low	0.98	0.73
Average Water Balance Difference	(186.00) mm	(769.00) mm
Data Period	Oct 2004 – Sept 2010	Oct 2010 – Sept 2017

6.12. Three Parameter with Optimizing Station Weights

6.12.1. General

The 3 Parameter Monthly model has been utilized using monthly input for optimizing station weights where the Parameters Sc, c and K are already optimized before. Thiessen rainfall station weights were allowed for the optimization and using Microsoft Excel Solver is applied. Since all the three parameters (Sc, c and K were calibrated earlier in the analysis part) now it is time to allow the aerial geometry of rainfall contributing to rainfall input into model. Weight of each rainfall stations must be within the range of 1 to 0 which means maximum contribution from one of the following stations can be either whole area if weight is one or no contribution if the weight is zero. Thiessen polygon limits the geometry of rainfall contributing for average rainfall which is not the actual case, optimization is necessary in rainfall-runoff modelling since it makes the model calibration to better respond to observed streamflow. The stations weights for

Ambepussa, Andigama, Aranayake and Eraminigolla were 0.26, 0.19, 0.20 and 0.35 respectively. After the optimization the station weights did not remain the same but changed to 0.20, 0.16, 0.26 and 0.38 for Ambpussa, Andigama, Aranayake and Eraminigolla correspondingly. For the verification dataset the optimized station weights were used.

6.12.2. Calibration Period (Monthly): 2004/2005-2009/2010

MRAE during calibration was 0.4090 which has improved compared to 3PM water balance model. Scatter plot shows underestimation of high monthly flows (Figure 6.84). The summary of results is in Table 6.41. Hydrograph comparisons are made (Figure 6.87 and Figure 6.88) for overall calibration period in normal and semi-log. The duration curves clearly reflect an underestimation in the high but comparatively good match in medium and low flows (Figure 6.85 and Figure 6.86) than 3PM. The water content in soil with response to rainfall is provided (Figure 6.90 and Figure 6.91). Comparison between calculated and observed annual water balance is presented in Table 6.42 and graphically shown in Figure 6.89.

Table 6.41: Summary of Results for Calibration Period for Badalgama Watershed

Model Performance Indicators (Outputs & Parameters)	**3 Parameter Monthly Water Balance Model**
	Calibration (Monthly) – Station Weight Optimized
Sc	1,051
c	2.5
K	0.65
MRAE - Overall	0.4090
MRAE - High	0.30
MRAE - Medium	0.48
MRAE - Low	0.81
Average Water Balance Difference	(219.00) mm
Maximum Soil Moisture	287.35 mm
Minimum Soil Moisture	60.61 mm
Starting Soil Moisture	269.25 mm
Ending Soil Moisture	97.27 mm
Data Period	October 2004 – September 2010

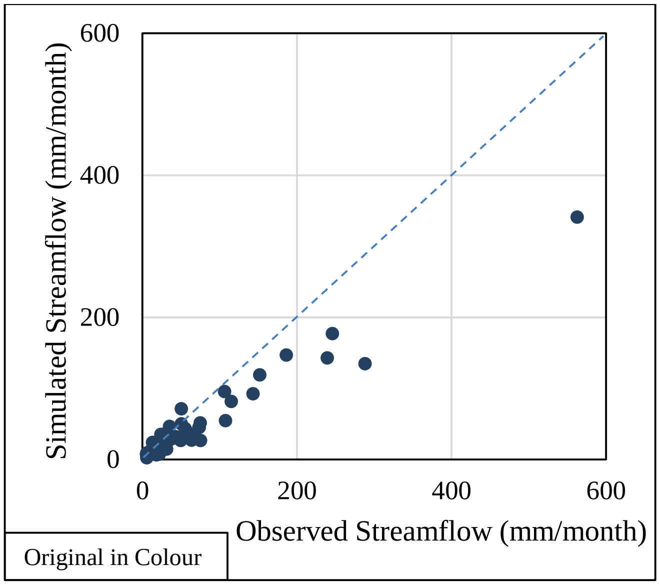


Figure 6.84: 3PM (Monthly Input) – Monthly Streamflow Estimation – Calibration Period – Badalgama Watershed

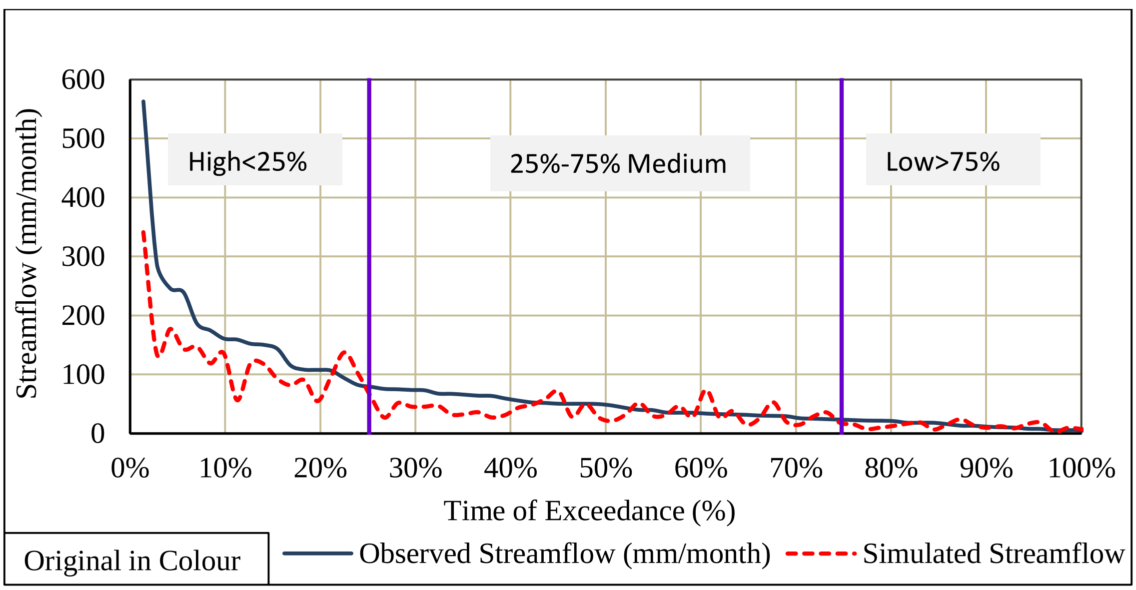
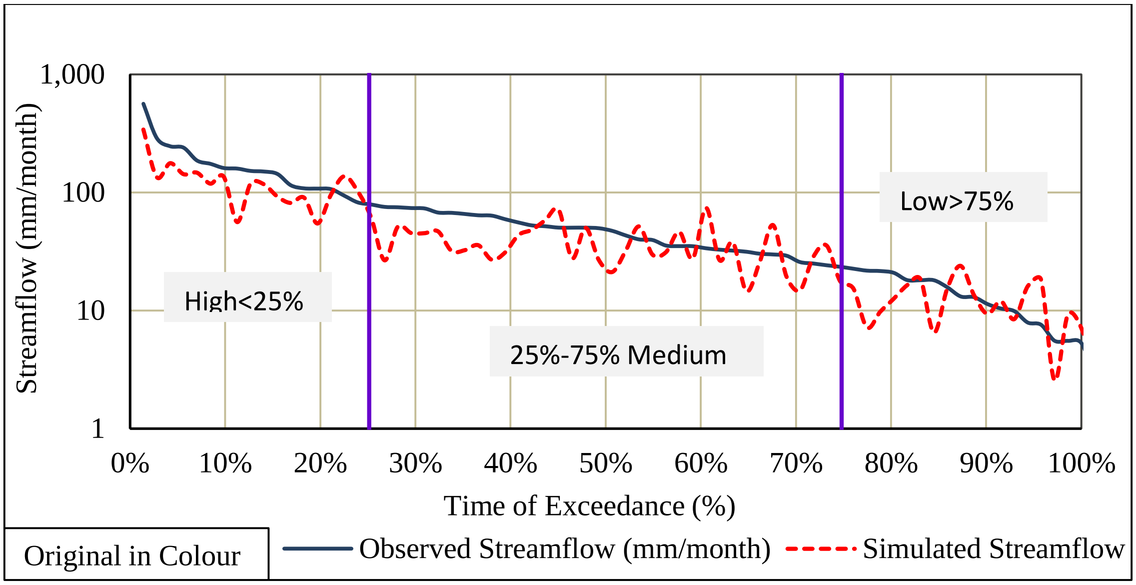


Figure 6.85: Flow Duration Curve [Normal] for 3PM Water Balance Model Rainfall Stations Optimized during Calibration



Original in Colour

Figure 6.86: Flow Duration Curve [Log Scale] for 3PM Water Balance Model Rainfall Stations Optimized during Calibration

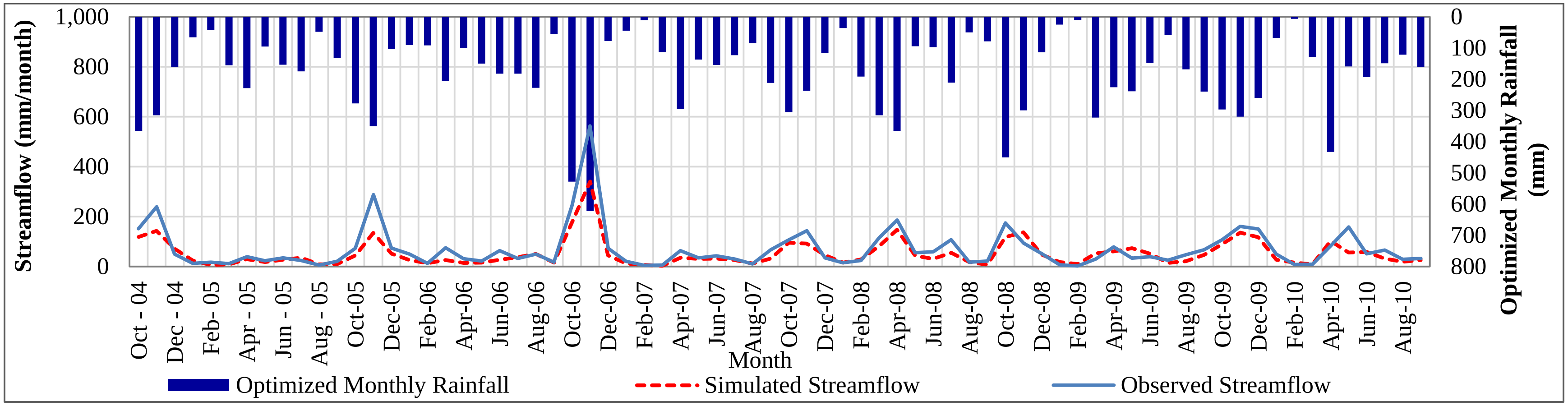


Figure 6.87 : Comparison of Monthly Hydrograph [Normal] – 3PM Station Weights Optimized: Calibration Period (2004-2010)

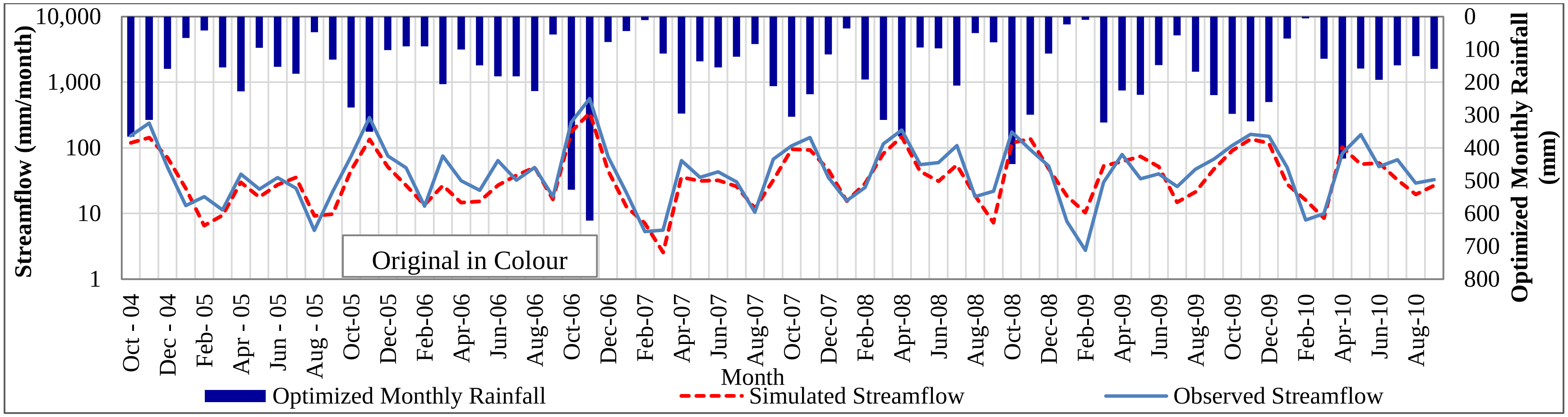


Figure 6.88 : Comparison of Monthly Hydrograph [Semi-log] – 3PM Station Weights Optimized: Calibration Period (2004-2010)

Table 6.42 : Annual Water Balance - 3PM Stations Weights Optimized (Monthly Input) – Calibration Period – Badalgama

Water Year	Thiessen Averaged Rainfall (mm)	Simulated Streamflow (mm)	Observed Streamflow (mm)	Observed Water Balance (mm)	Simulated Water Balance (mm)	Annual Water Balance Difference (mm)
2004 / 2005	1901	502	633	1268	1400	-131
2005 /2006	1997	460	792	1205	1538	-333
2006 / 2007	2442	754	1164	1278	1688	-409
2007 / 2008	2106	662	889	1217	1445	-227
2008 / 2009	2322	656	654	1668	1666	2
2009 / 2010	2219	691	907	1312	1529	-217

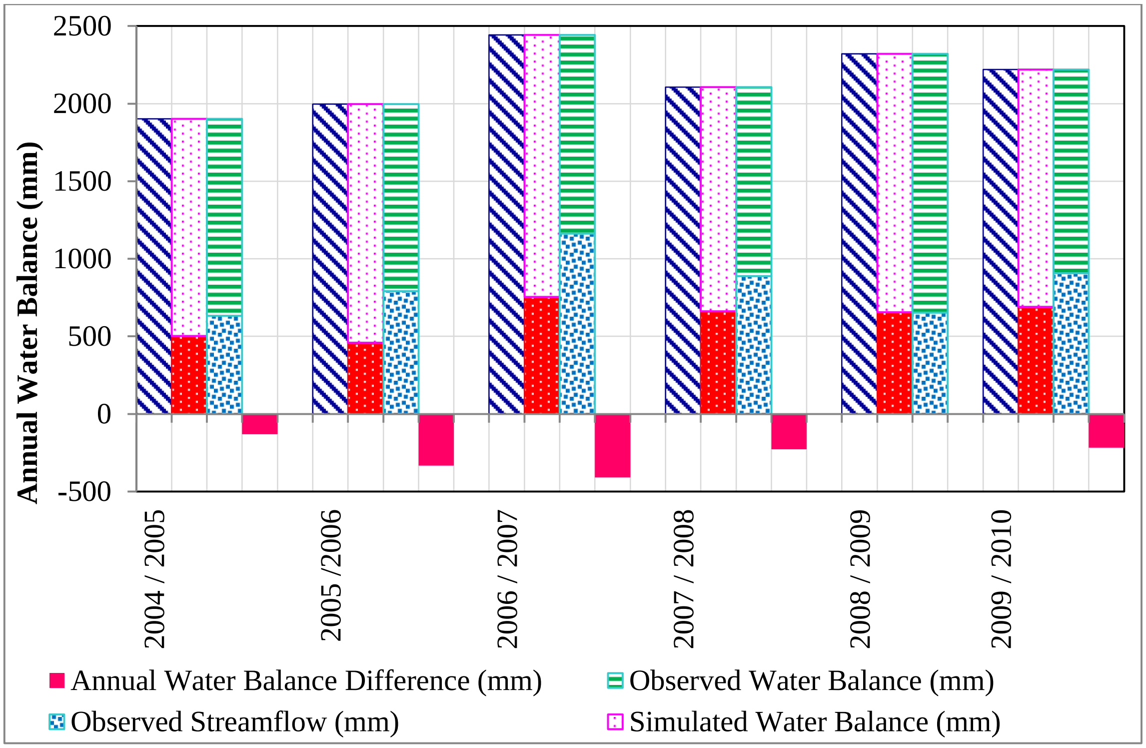


Figure 6.89: Annual Water Balance - 3PM Station Weights Optimized (Monthly Input) – Calibration Period – Badalgama

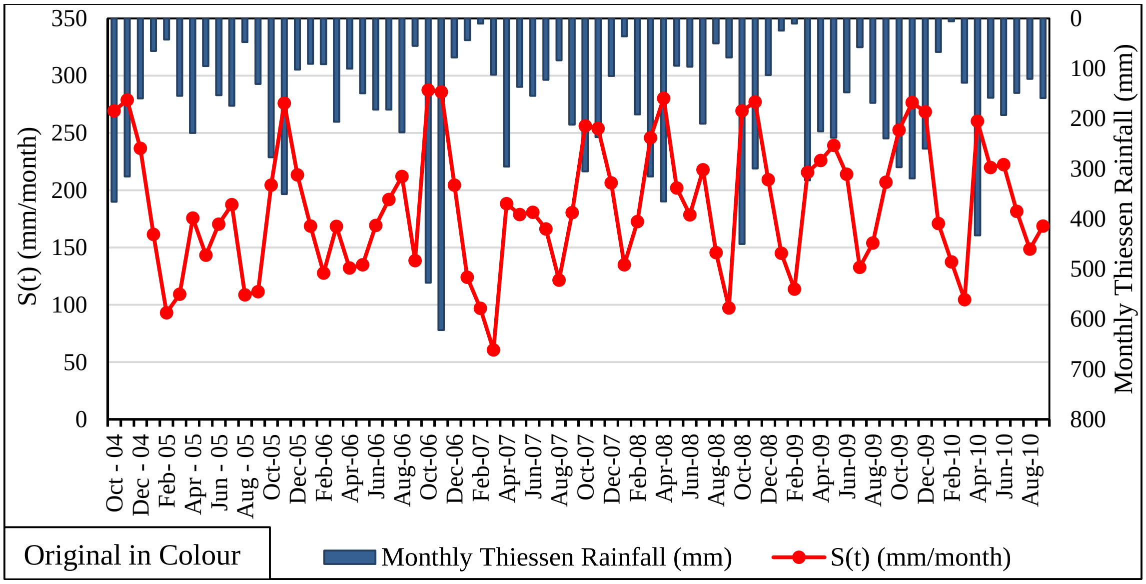


Figure 6.90: Water Content in Soil against rainfall [Normal] for 3PM Water Balance Model (rainfall stations optimized) during Calibration (October 2004 – September 2010)

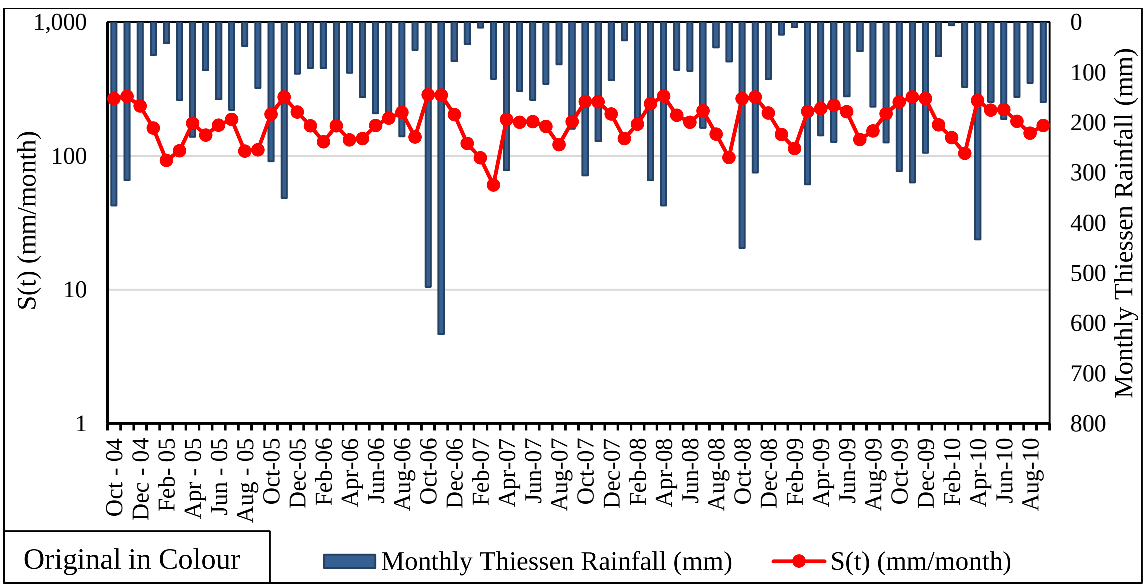


Figure 6.91: Water Content in Soil against rainfall [Log Scale] for 3PM Water Balance Model (rainfall stations optimized) during Calibration (October 2004 – September 2010)

6.12.3. Verification Period (Monthly) 2010/2011-2016/2017

After the stations weights were optimized, optimized Thiessen weights achieved during calibration are kept unchanged and are applied for the rainfall input over the verification dataset.

MRAE during verification was 0.6175 which has deteriorated in comparison to 3PM water balance model. Scatter plot shows underestimation of high monthly flows (Figure 6.94). The summary of results is in Table 6.43. Hydrograph comparisons are made (Figure 6.95 and Figure 6.96) for overall calibration period in normal and semi-log in which December 2011 to August 2012 the estimated flow reveals a sudden drop. In general, the duration curves clearly reflect an underestimation in the high, medium and low flows (Figure 6.92 and Figure 6.93). The water content in soil with response to rainfall is provided (Figure 6.97 and Figure 6.98) Shows sudden drop in August 2012 supporting with hydrographs. Comparison between calculated and observed annual water balance is presented in Table 6.44 and graphically shown in Figure 6.99.

Table 6.43: Summary of Results for Verification Period for Badalgama Watershed

Model Performance Indicators (Outputs & Parameters)	**3 Parameter Monthly Water Balance Model**
	Verification with Rainfall Station Optimized
Sc	1,051
c	2.5
K	0.65
MRAE - Overall	0.6175
MRAE - High	0.20
MRAE - Medium	0.62
MRAE - Low	1.40
Average Water Balance Difference	(305.00) mm
Maximum Soil Moisture	292.04 mm
Minimum Soil Moisture	0.00 mm
Starting Soil Moisture	229.87 mm
Ending Soil Moisture	93.77 mm
Data Period	October 2010 – September 2017

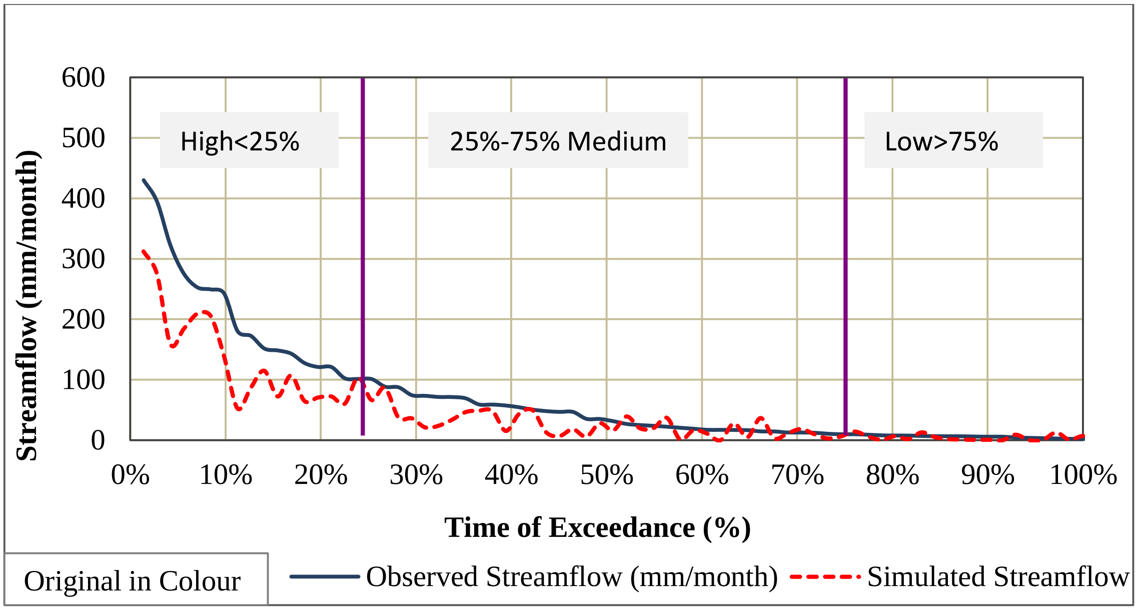


Figure 6.92: Flow Duration Curve [Normal] for 3PM Water Balance Model Rainfall Stations Optimized during Verification

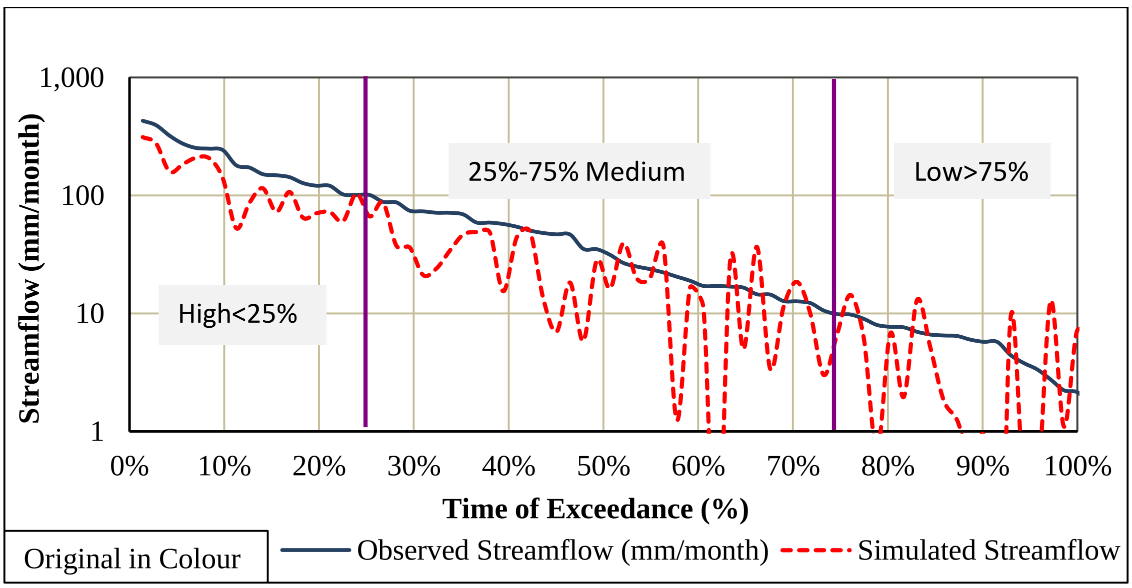


Figure 6.93: Flow Duration Curve [Log] for 3PM Water Balance Model Rainfall Stations Optimized during Verification

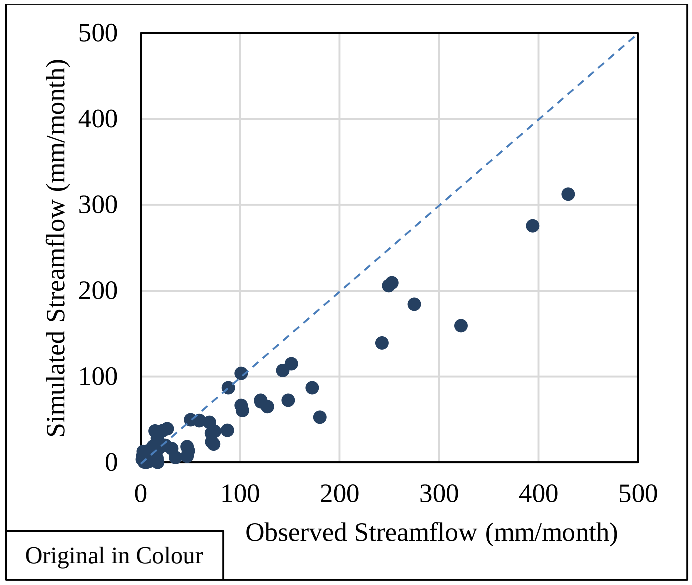


Figure 6.94: 3PM (Monthly Input) – Monthly Streamflow Estimation – Verification Period – Badalgama Watershed

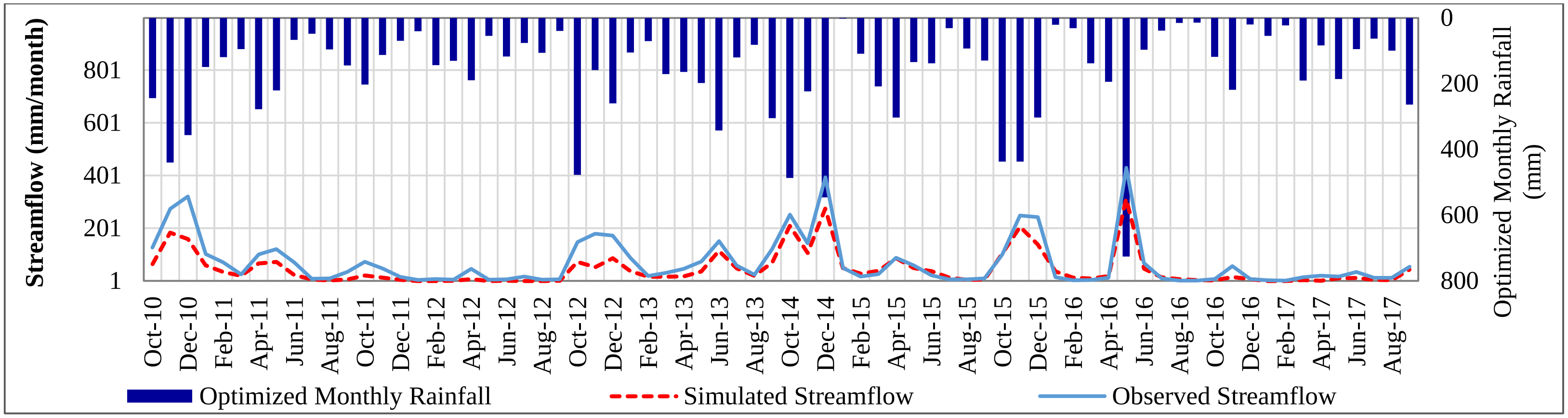


Figure 6.95 : Comparison of Monthly Hydrograph [Normal] – 3PM Station Weights Optimized: Verification Period (2010-2017)

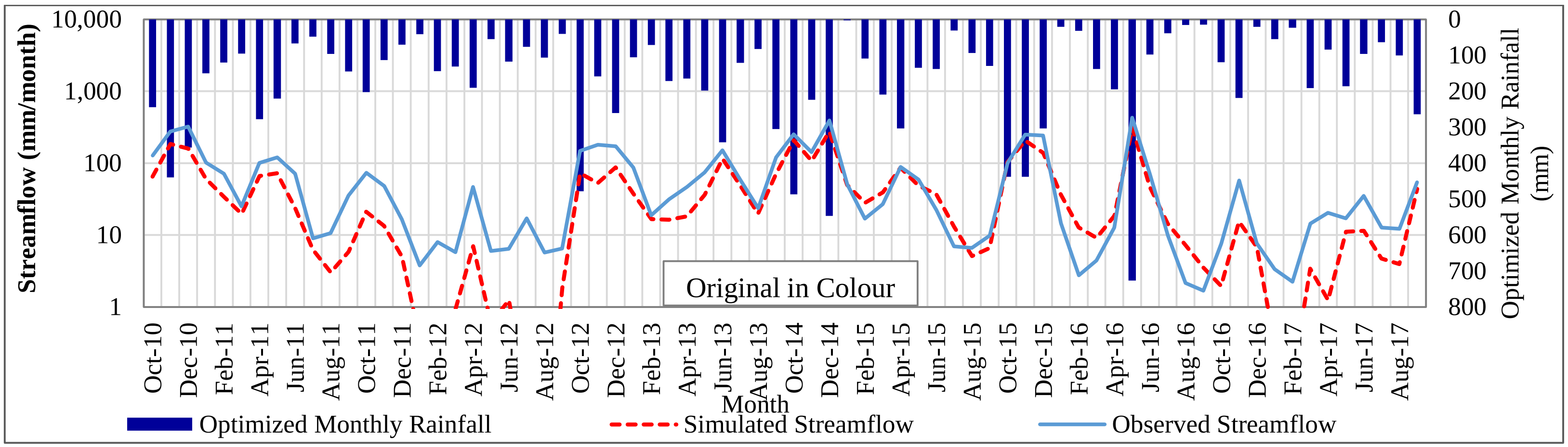


Figure 6.96 : Comparison of Monthly Hydrograph [Semi-log] – 3PM Station Weights Optimized: Verification Period (2010-2017)

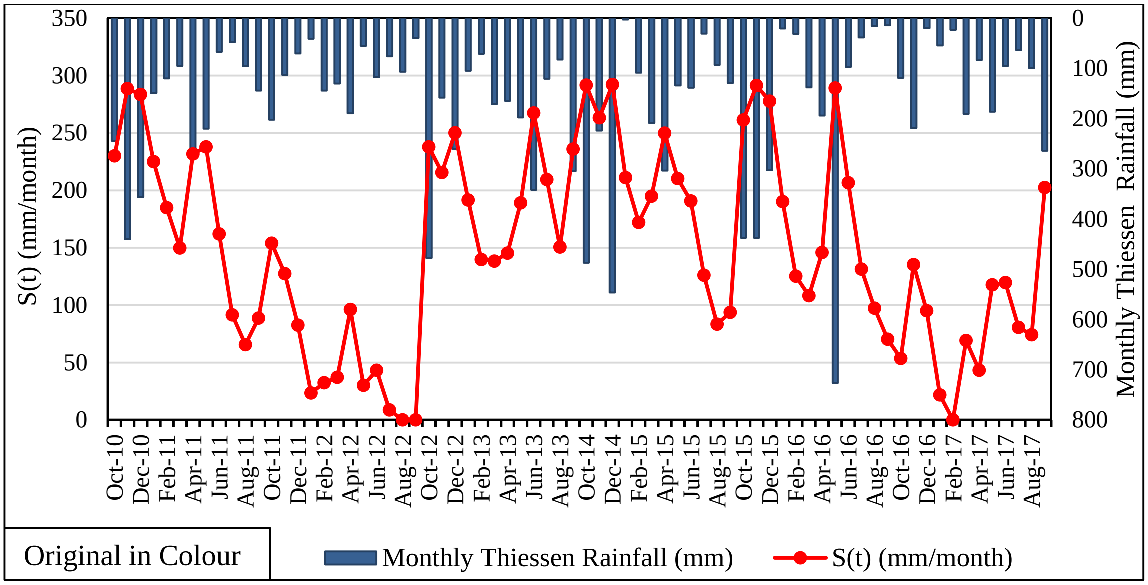


Figure 6.97: Water Content in Soil against rainfall [Normal] for 3PM Water Balance Model (rainfall stations optimized) during Verification (October 2010 – September 2017)

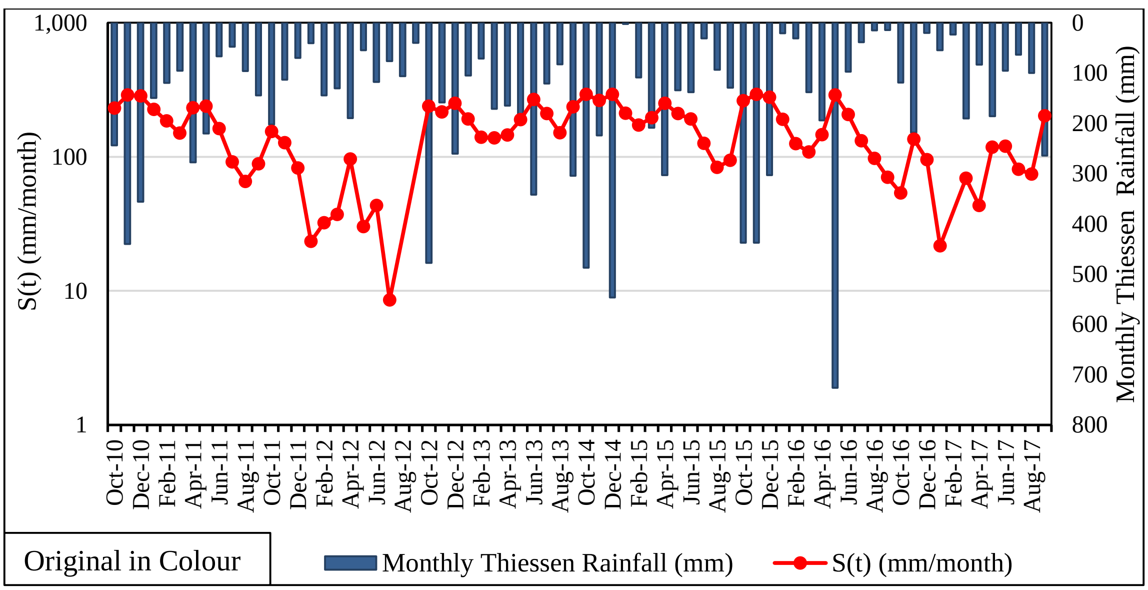


Figure 6.98: Water Content in Soil against rainfall [Log Scale] for 3PM Water Balance Model (rainfall stations optimized) during Verification (October 2010 – September 2017)

Table 6.44 : Annual Water Balance - 3PM Station Weights Optimized (Monthly Input) – Verification Period – Badalgama

Water Year	Thiessen Averaged Rainfall (mm)	Simulated Streamflow (mm)	Observed Streamflow (mm)	Observed Water Balance (mm)	Simulated Water Balance (mm)	Annual Water Balance Difference (mm)
2010 / 2011	2259	701	1272	987	1558	-571
2011 / 2012	1287	52	244	1043	1235	-192
2012 / 2013	2457	591	1115	1342	1866	-524
2014 / 2015	2408	907	1077	1330	1501	-171
2015 / 2016	2455	910	1140	1315	1545	-231
2016/ 2017	1419	104	245	1174	1315	-140

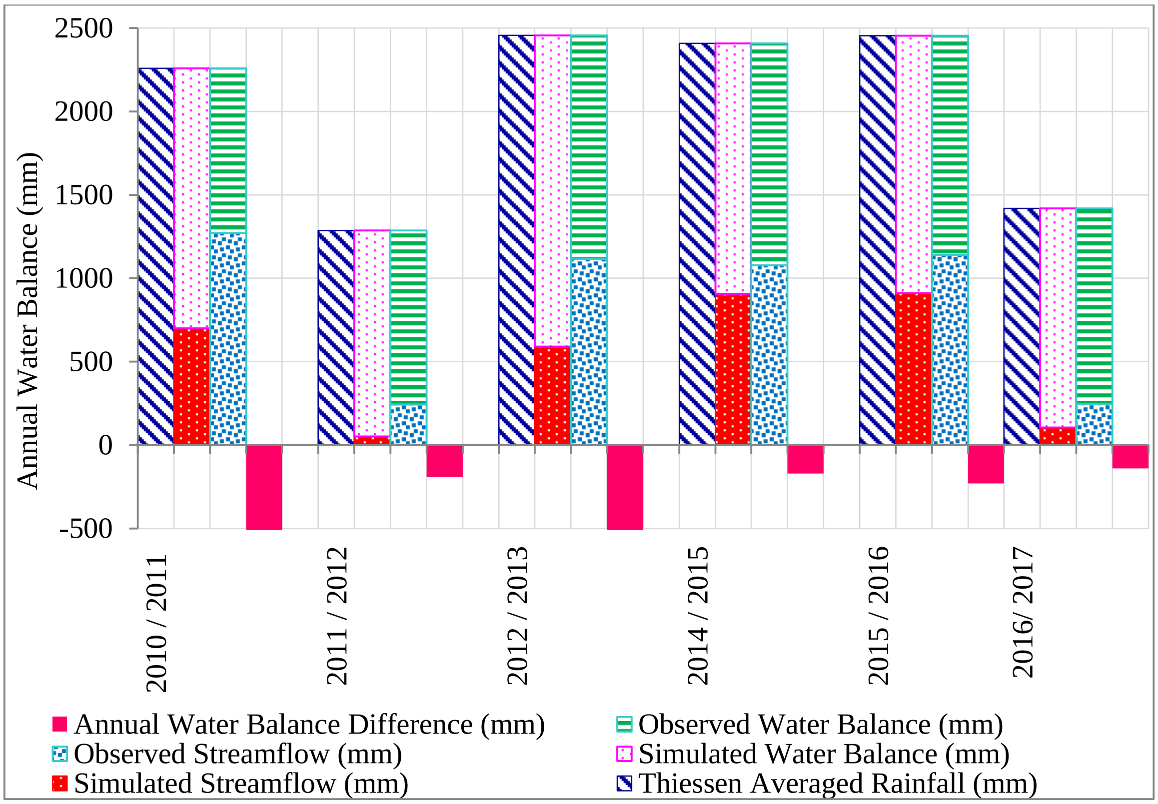


Figure 6.99: Annual Water Balance - 3PM Station Weights Optimized (Monthly Input) – Verification Period – Badalgama

6.13. Three Parameter Monthly Model Optimizing Station Weights along with Parameters

6.13.1. General

Three Parameter Monthly model has been utilized using monthly input for optimizing station weights with Parameters Sc, c and k are already optimized before. Thiessen rainfall station weights are used for the optimization and using Microsoft Excel Solver was applied for automatic optimization.

6.13.2. Calibration Period (Monthly) 2004/2005-2009/2010

MRAE during calibration period was 0.3992. Scatter plot shows underestimation for most of the high monthly flows (Figure 6.100). The summary of results is in Table 6.45. Hydrograph comparisons are made (Figure 6.101 and Figure 6.102) for overall calibration period in normal and semi-log in which February 2005, April 2007, September 2008 shows low flows are underestimated while from February 2006 to April 2006 all flows underestimated but overall medium flows are fairly estimated. The duration curves clearly reflect close match in the high, medium and low flows (Figure 6.103 and Figure 6.104). The water content in soil with response to rainfall is provided (Figure 6.106 and Figure 6.107) fine correspondence. Comparison between calculated and observed annual water balance is presented in Table 6.46 and graphically shown in Figure 6.105.

Table 6.45: Summary Results of Calibration for Badalgama Watershed

Model Performance Indicators (Outputs & Parameters)	**3 Parameter Monthly Water Balance Model Calibration (Monthly) – Parameters and Station Weights Optimized**
Sc	908
c	2.5
K	0.69
MRAE - Overall	0.3992
MRAE - High	0.30
MRAE - Medium	0.46
MRAE - Low	0.77
Average Water Balance Difference	(177.95) mm
Maximum Soil Moisture	252.03 mm
Minimum Soil Moisture	40.36 mm
Starting Soil Moisture	242.75 mm
Ending Soil Moisture	81.22 mm
Data Period	October 2004 – September 2010

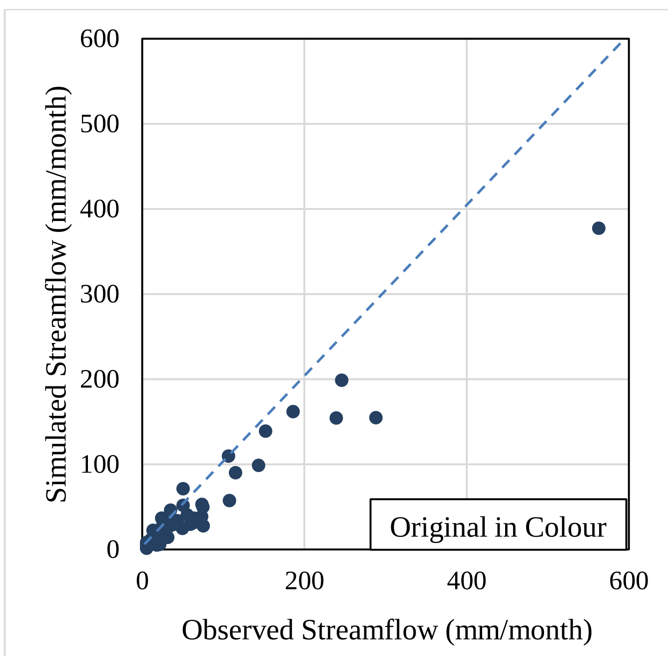


Figure 6.100: 3PM Station Weights Optimized (Monthly Input) – Monthly Streamflow Estimation – Calibration Period – Badalgama Watershed

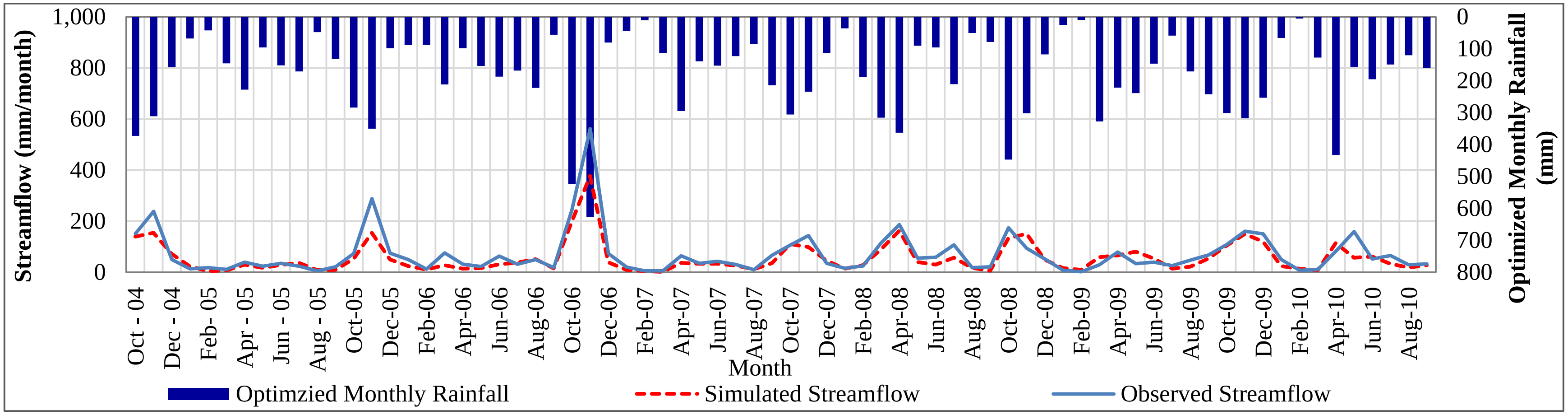


Figure 6.101: Comparison of Monthly Hydrograph [Normal] 3PM Parameters and Station Weights Optimized: Calibration (2004-2010)

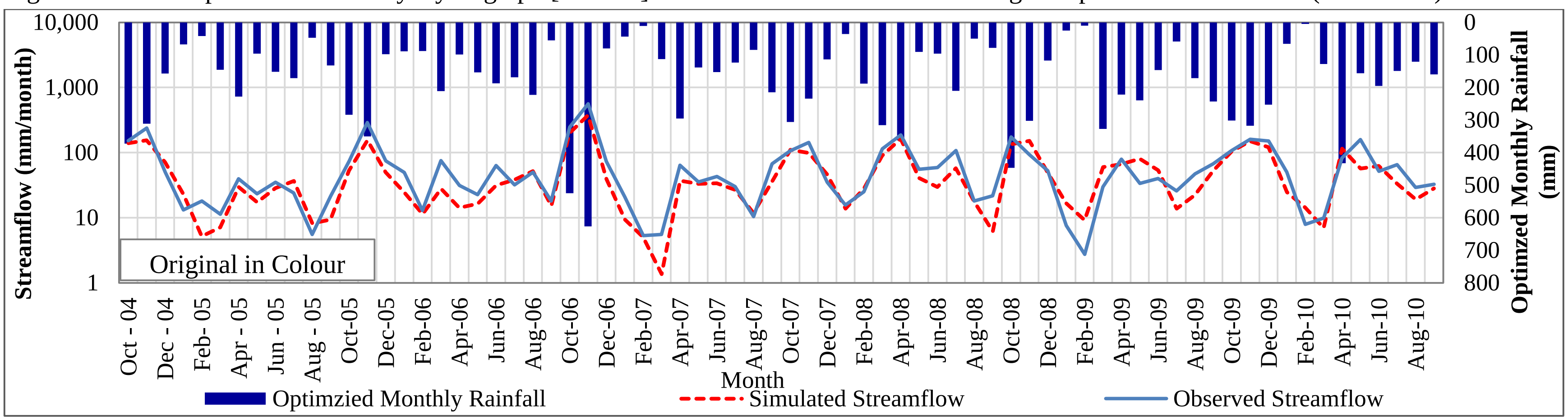


Figure 6.102: Comparison of Monthly Hydrograph [Semi-log] 3PM Parameters and Station Weights Optimized: Calibration (2004-2010)

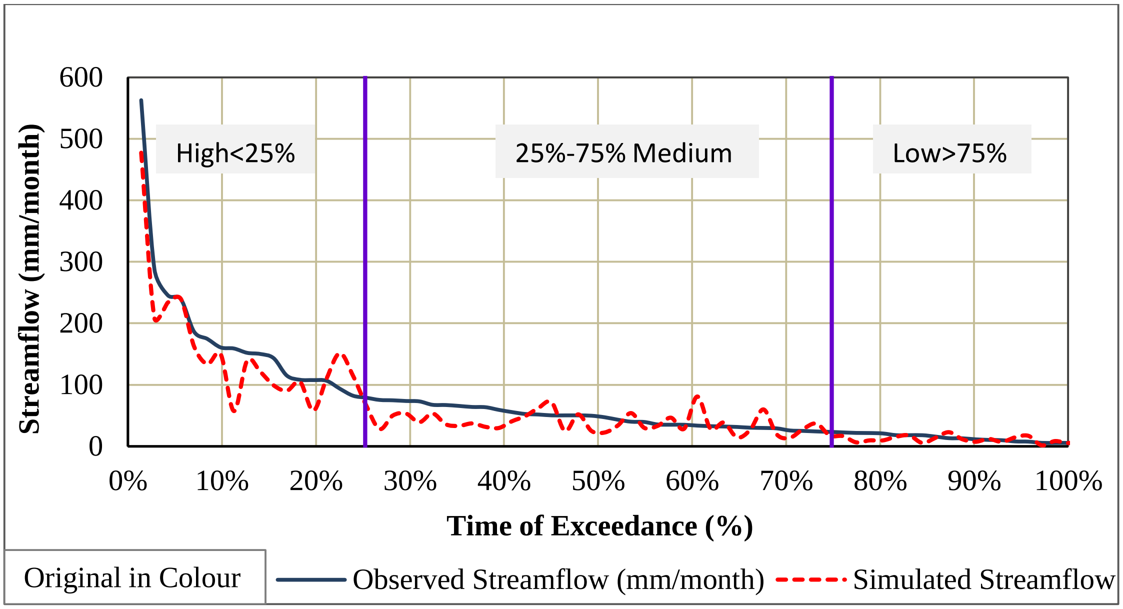


Figure 6.103: Flow Duration Curve [Normal] for 3PM Water Balance Model Rainfall Stations & Parameters Optimized during Calibration

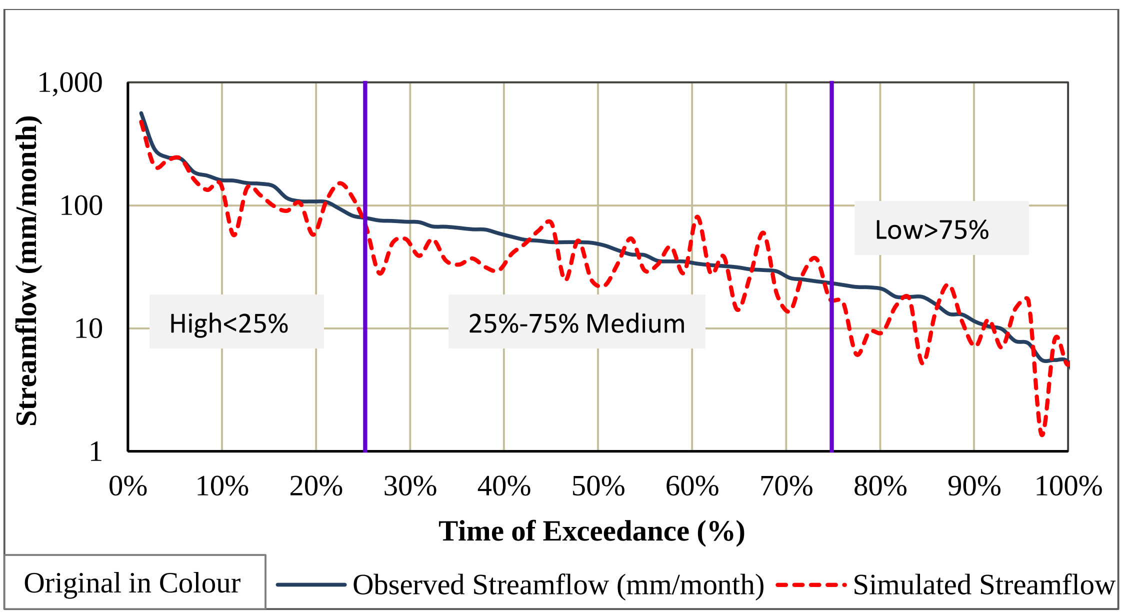


Figure 6.104: Flow Duration Curve [Log Scale] for 3PM Water Balance Model Rainfall Stations & Parameters Optimized during Calibration

Table 6.46 : Annual Water Balance - 3PM Station Weights & Parameters Optimized (Monthly Input) – Calibration Period – Badalgama

Water Year	Thiessen Averaged Rainfall (mm)	Simulated Streamflow (mm)	Observed Streamflow (mm)	Observed Water Balance (mm)	Simulate d Water Balance (mm)	Annual Water Balance Difference (mm)
2004 / 2005	1901	529	633	1268	1372	-104
2005 /2006	1997	480	792	1205	1517	-313
2006 / 2007	2442	848	1164	1278	1595	-316
2007 / 2008	2106	699	889	1217	1407	-189
2008 / 2009	2322	728	654	1668	1593	75
2009 / 2010	2219	687	907	1312	1532	-220

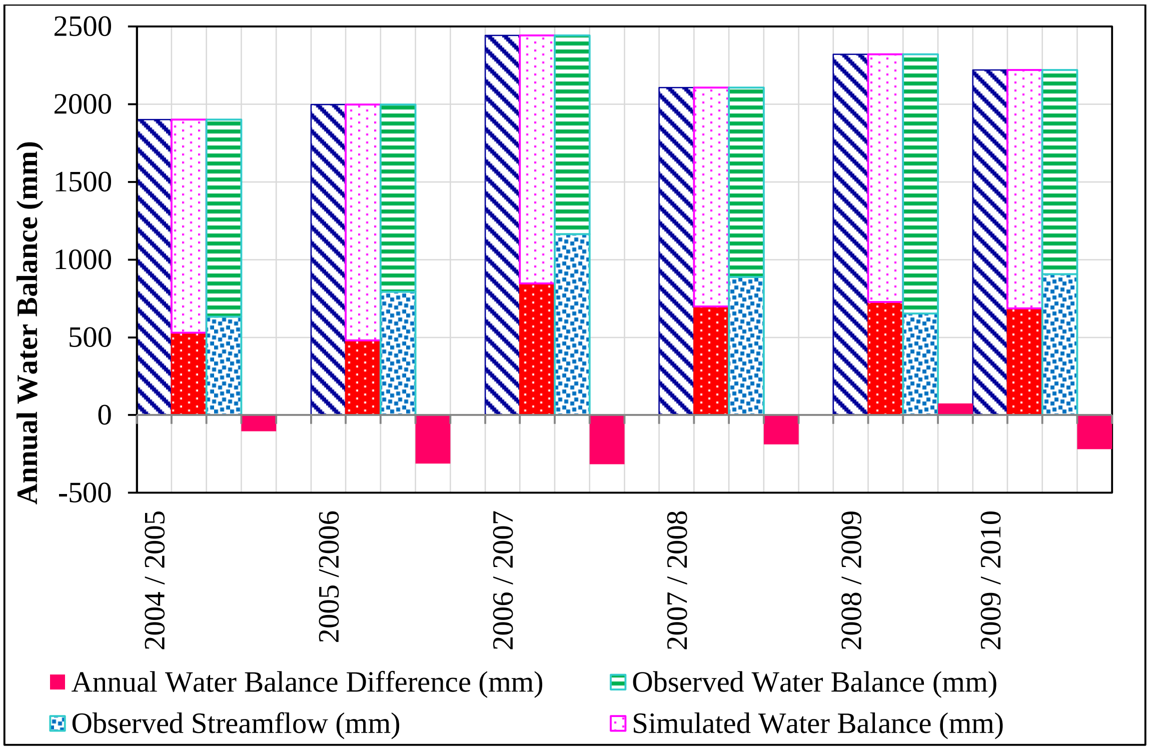


Figure 6.105: Annual Water Balance - 3PM Station Weights & Parameters Optimized (Monthly Input) – Calibration Period – Badalgama

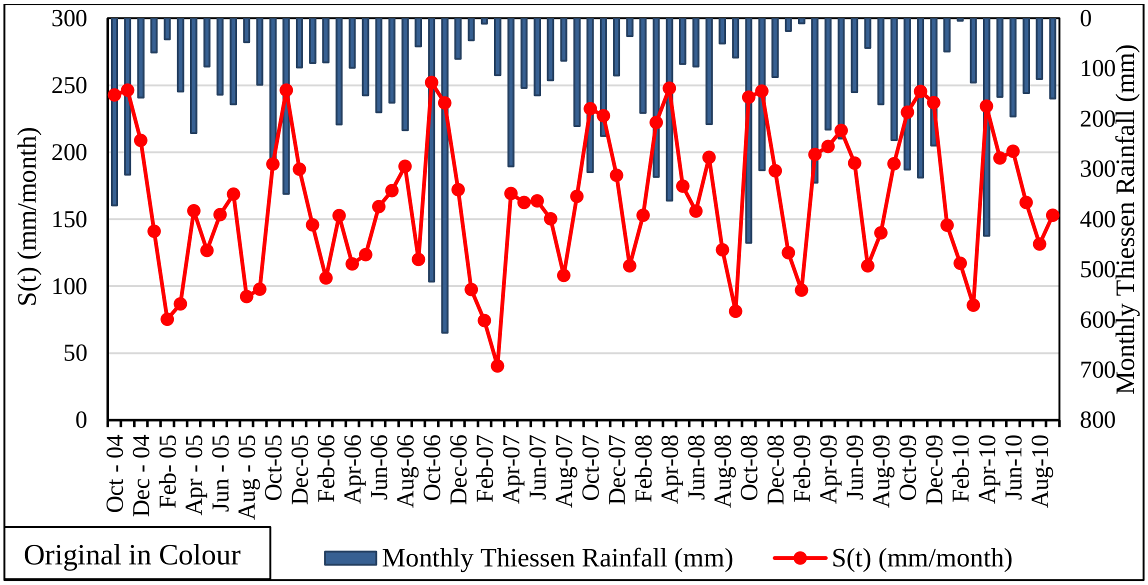


Figure 6.106: Water Content in Soil against rainfall [Normal] for 3PM Water Balance Model (rainfall stations and parameters optimized) during Calibration (October 2004 – September 2010)

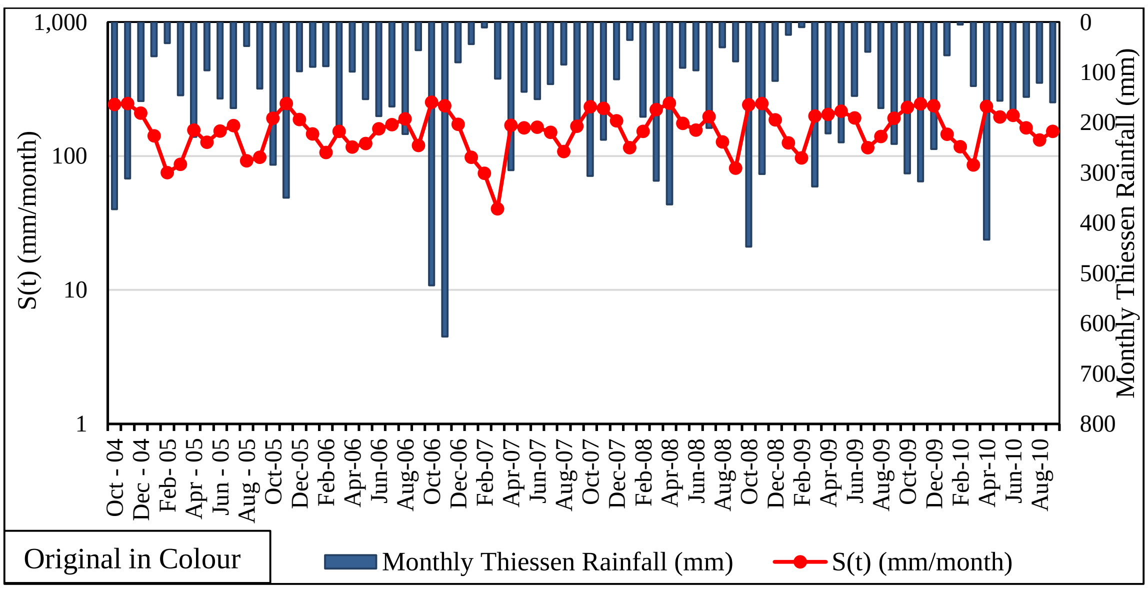


Figure 6.107: Water Content in Soil against rainfall [Normal] for 3PM Water Balance Model (rainfall stations and parameters optimized) during Calibration (October 2004 – September 2010)

6.13.3. Verification Period (Monthly) 2010/2011-2016/2017

MRAE during verification period was 0.4983. Scatter plot shows underestimation for most of the high monthly flows (Figure 6.110). The summary of results is in Table 6.47. Hydrograph comparisons are made (Figure 6.114 and Figure 6.115) for overall calibration period in normal and semi-log in which from October 2010 to June 2013 all flows underestimated also October 2016 to October 2017; however, good matching is observed between periods of June 2013 to October 2016. The duration curves clearly reflect close match in the high, medium and low flows (Figure 6.108 and Figure 6.109). The water content in soil with response to rainfall is provided (Figure 6.112 and Figure 6.113) sudden drop in September 2012. Comparison between calculated and observed annual water balance is presented in Table 6.48 and graphically shown in Figure 6.111.

Table 6.47: Summary Results of Verification for Badalgama Watershed

Model Performance Indicators (Outputs & Parameters)	**3 Parameter Monthly Water Balance Model**
	Verification (Monthly) Parameter and Stations Optimized
Sc	908
c	2.5
K	0.686
MRAE - Overall	0.4983
MRAE - High	0.22
MRAE - Medium	0.56
MRAE - Low	0.90
Average Water Balance Difference	(252.24) mm
Maximum Soil Moisture	252.82 mm
Minimum Soil Moisture	0.00 mm
Starting Soil Moisture	211.07 mm
Ending Soil Moisture	91.67 mm
Data Period	October 2010 – September 2017

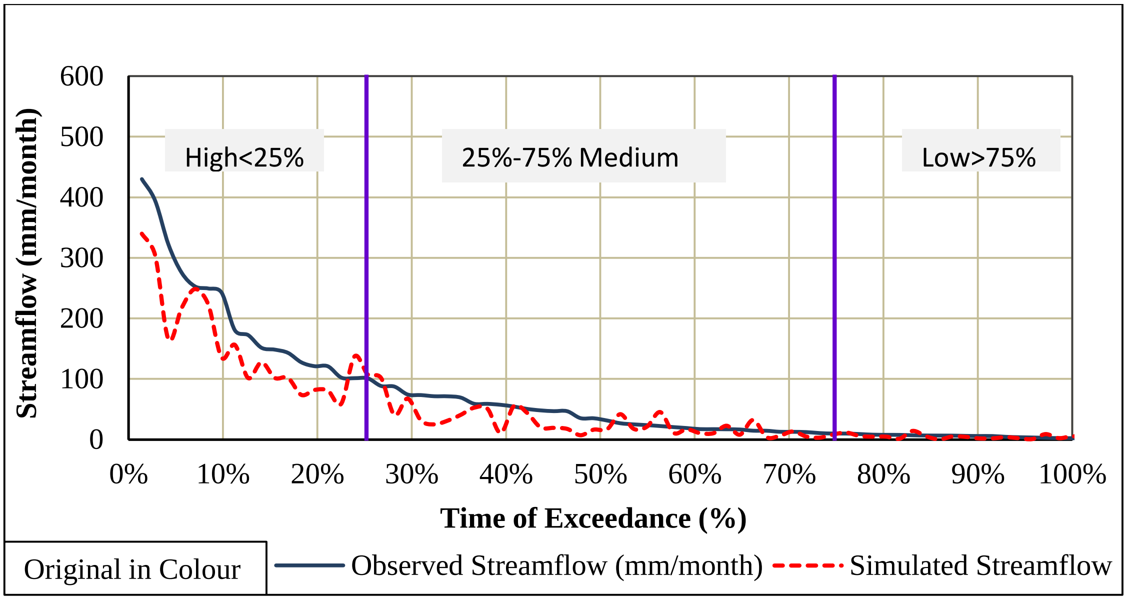


Figure 6.108: Flow Duration Curve [Normal] for 3PM Water Balance Model Rainfall Stations & Parameters Optimized during Verification

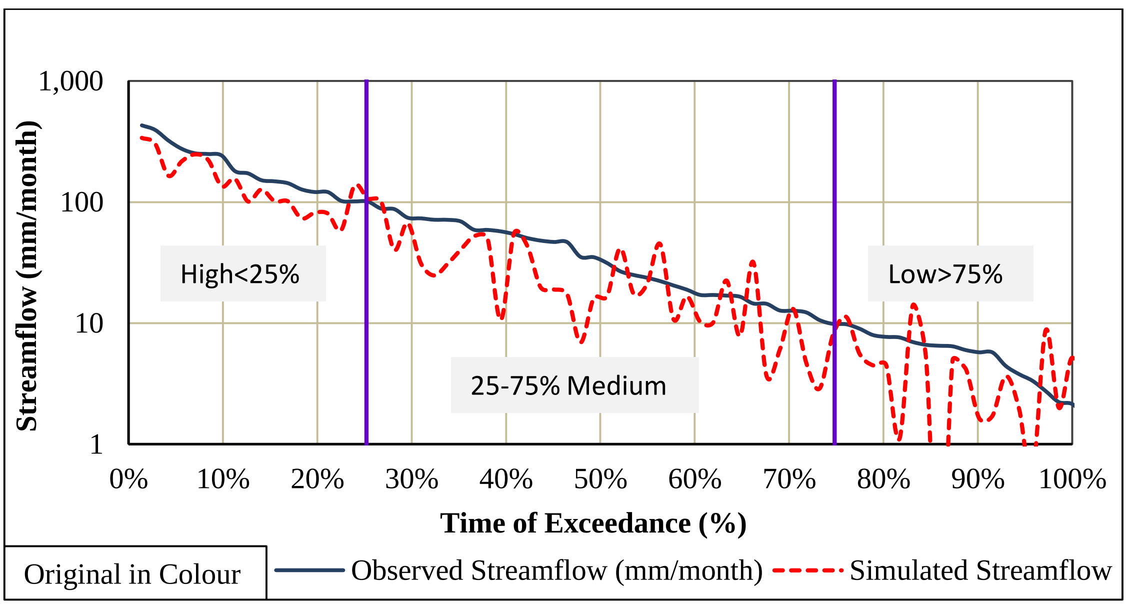


Figure 6.109: Flow Duration Curve [Log Scale] for 3PM Water Balance Model Rainfall Stations & Parameters Optimized during Verification

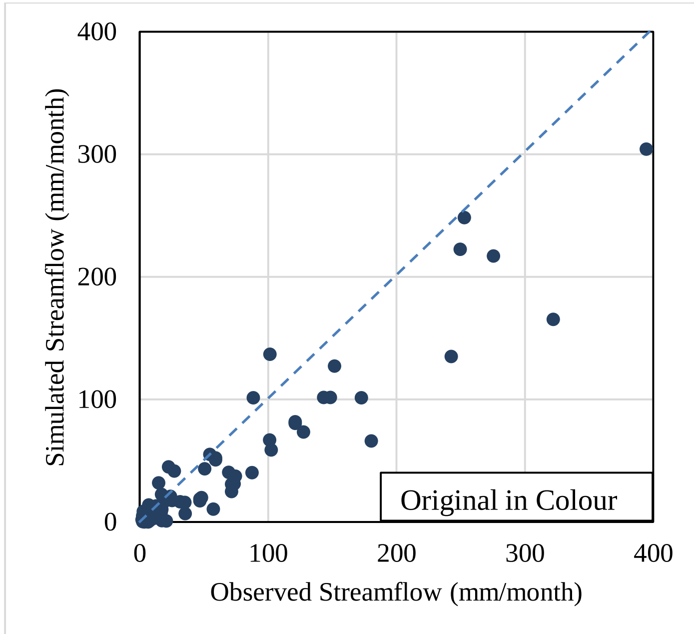


Figure 6.110: 3PM Station Weights Optimized (Monthly Input) – Monthly Streamflow Estimation – Calibration Period – Badalgama Watershed

Table 6.48 : Annual Water Balance - 3PM Station Weights & Parameters Optimized (Monthly Input) – Verification Period – Badalgama

Water Year	Thiessen Averaged Rainfall (mm)	Simulated Streamflow (mm)	Observed Streamflow (mm)	Observed Water Balance (mm)	Simulated Water Balance (mm)	Annual Water Balance Difference (mm)
2010 / 2011	2244	751	1272	973	1493	-521
2011 / 2012	1338	98	244	1093	1239	-146
2012 / 2013	2413	678	1115	1298	1735	-437
2014 / 2015	2446	988	1077	1369	1458	-90
2015 / 2016	2452	951	1140	1312	1501	-189
2016 / 2017	1425	114	245	1180	1311	-131

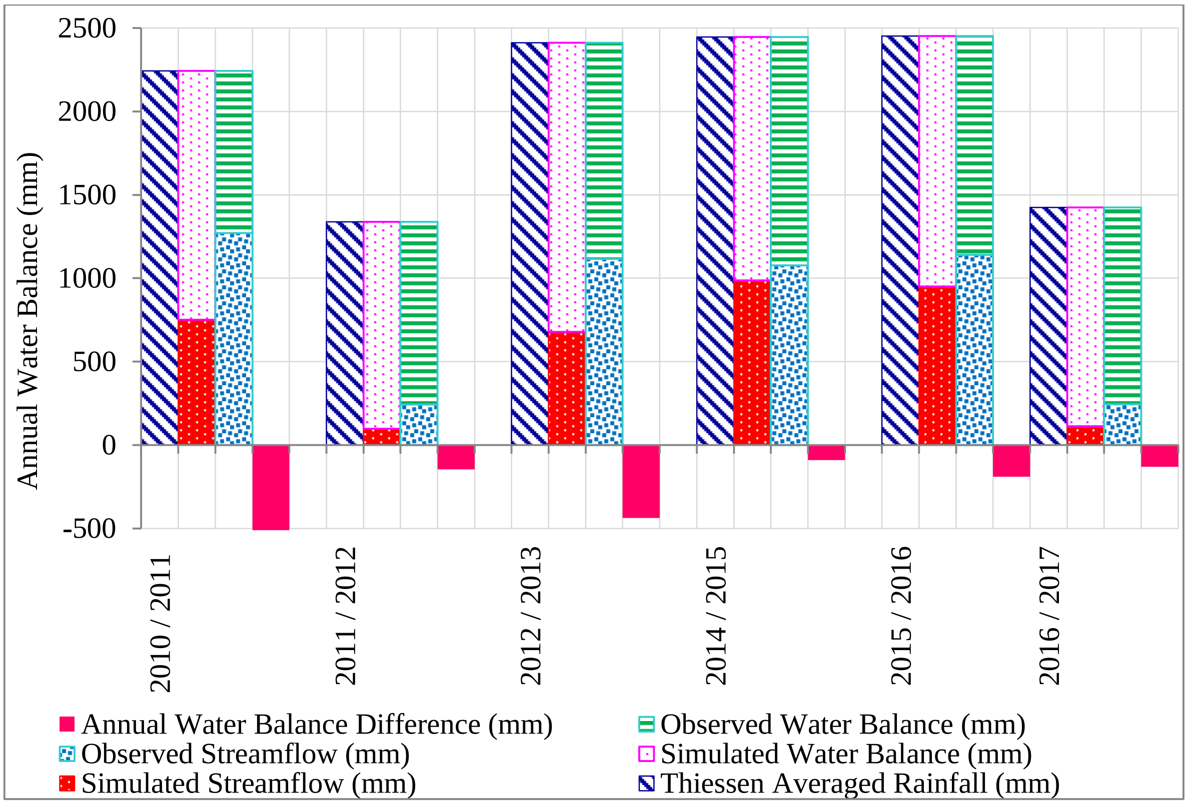


Figure 6.111: Annual Water Balance - 3PM Station Weights & Parameters Optimized (Monthly Input) – Verification Period – Badalgama

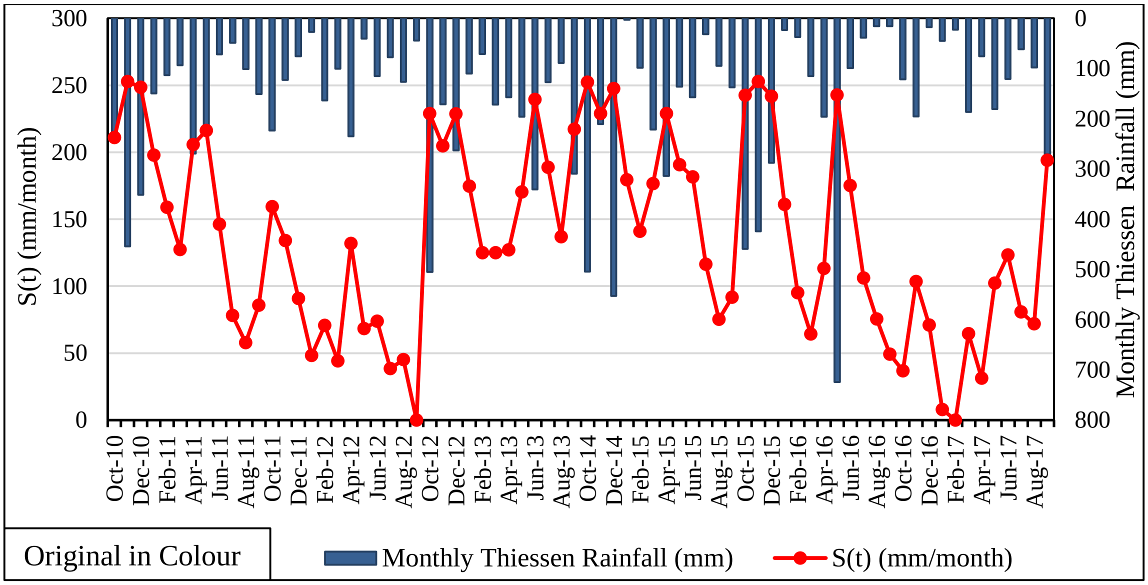


Figure 6.112: Water Content in Soil against rainfall [Normal] for 3PM Water Balance Model (rainfall stations & parameters optimized) during Verification (October 2010 – September 2017)

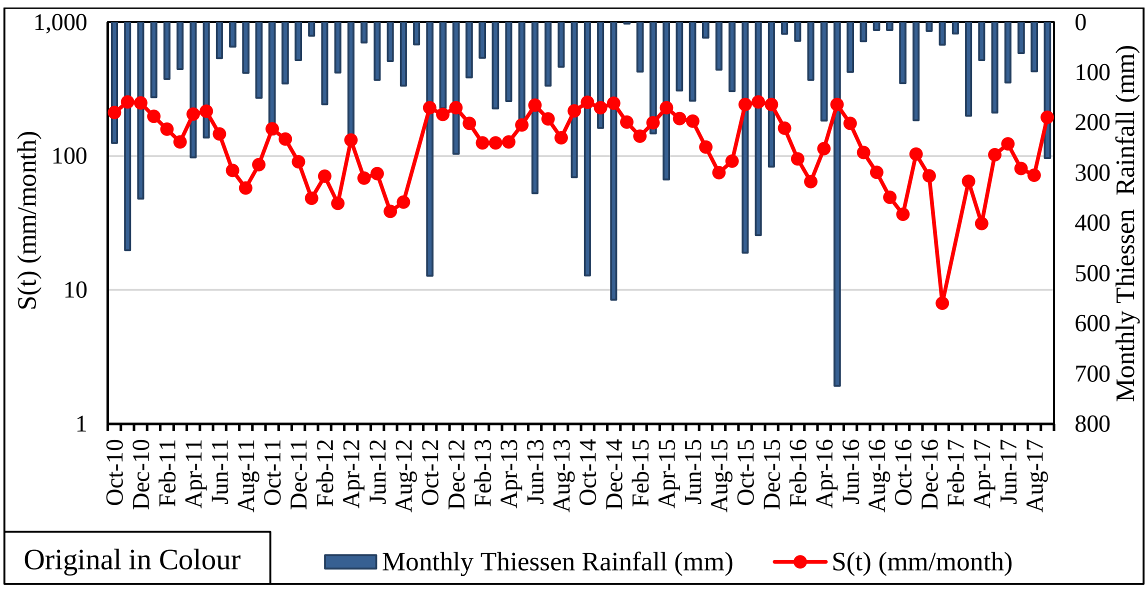


Figure 6.113: Water Content in Soil against rainfall [Log Scale] for 3PM Water Balance Model (rainfall stations & parameters optimized) during Verification (October 2010 – September 2017)

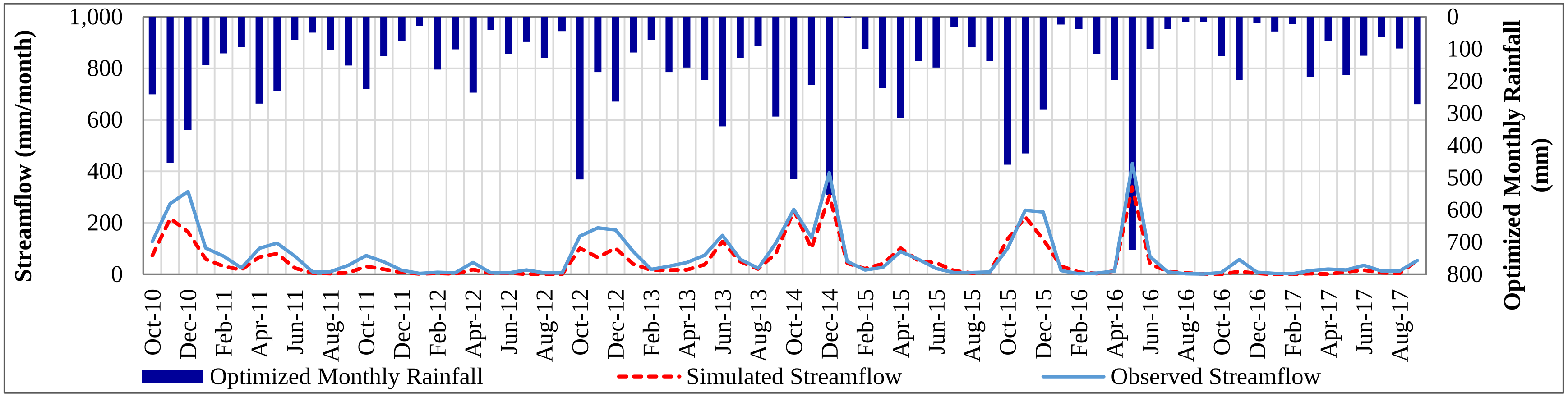


Figure 6.114 : Comparison of Monthly Hydrograph [Semi-log] - 3PM Parameters and Station Weights Optimized: Verification Period

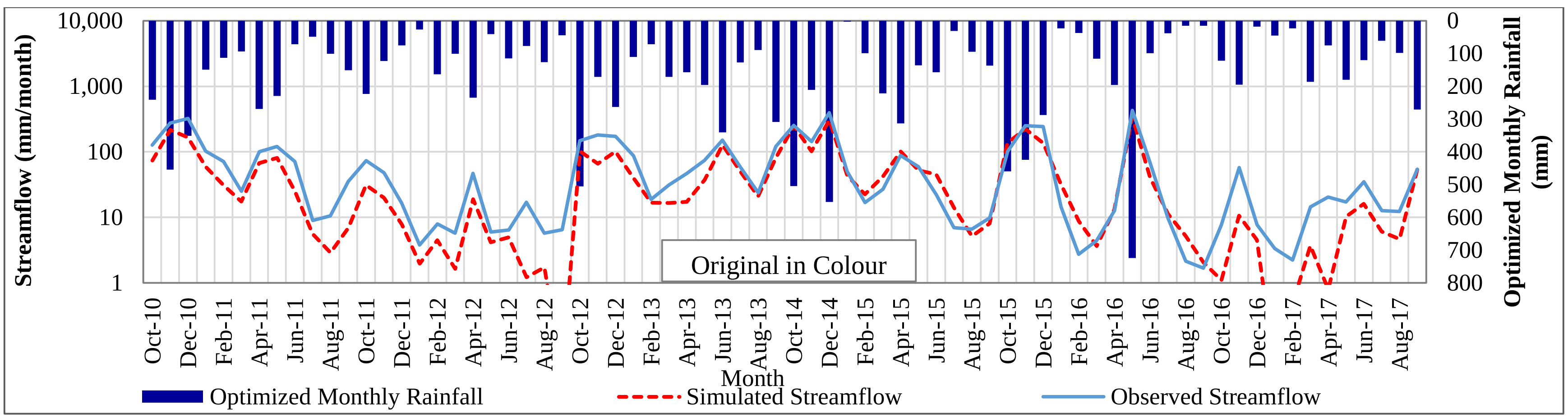


Figure 6.115 : Comparison of Monthly Hydrograph [Semi-log] - 3PM Parameters and Station Weights Optimized: Verification Period

6.14. Three Parameter Daily Model with Optimized Station Weights

6.14.1. General

Three Parameter Monthly model has been utilized using monthly input for optimizing station weights the Parameters Sc, c and k are already optimized before. Thiessen rainfall station weights are used for the optimization and using Microsoft Excel Solver is applied now the same monthly calibrated model values are applied on the daily scale for daily streamflow estimation.

6.14.2. Calibration Period (Daily) 2004/2005-2009/2010

For the calibration period the model outflow hydrographs are plotted in Model outflow hydrographs (Figure 6.117, Figure 6.118) also the flow duration curves (Figure 6.120 and Figure 6.121), Annual water balance (Figure 6.119) and the MRAE value in Table 6.49. The value of MRAE is within acceptable range and the overestimation in high flows and underestimation causes sudden drops in hydrographs. On the over hand the duration curves reflect an over estimation in the low and medium flows. The scatter diagram in Figure 6.116 shows the behavior of observed stream and simulated streamflow.

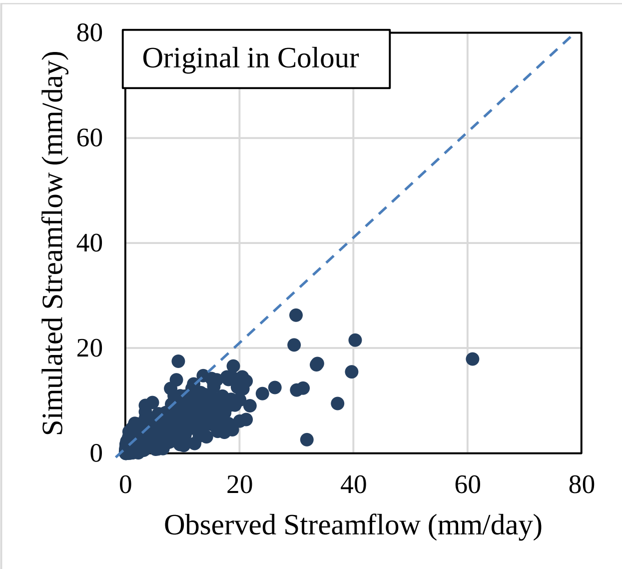


Figure 6.116: 3PM Station Weights Optimized (Daily Input) – Daily Streamflow Estimation – Calibration Period – Badalgama Watershed

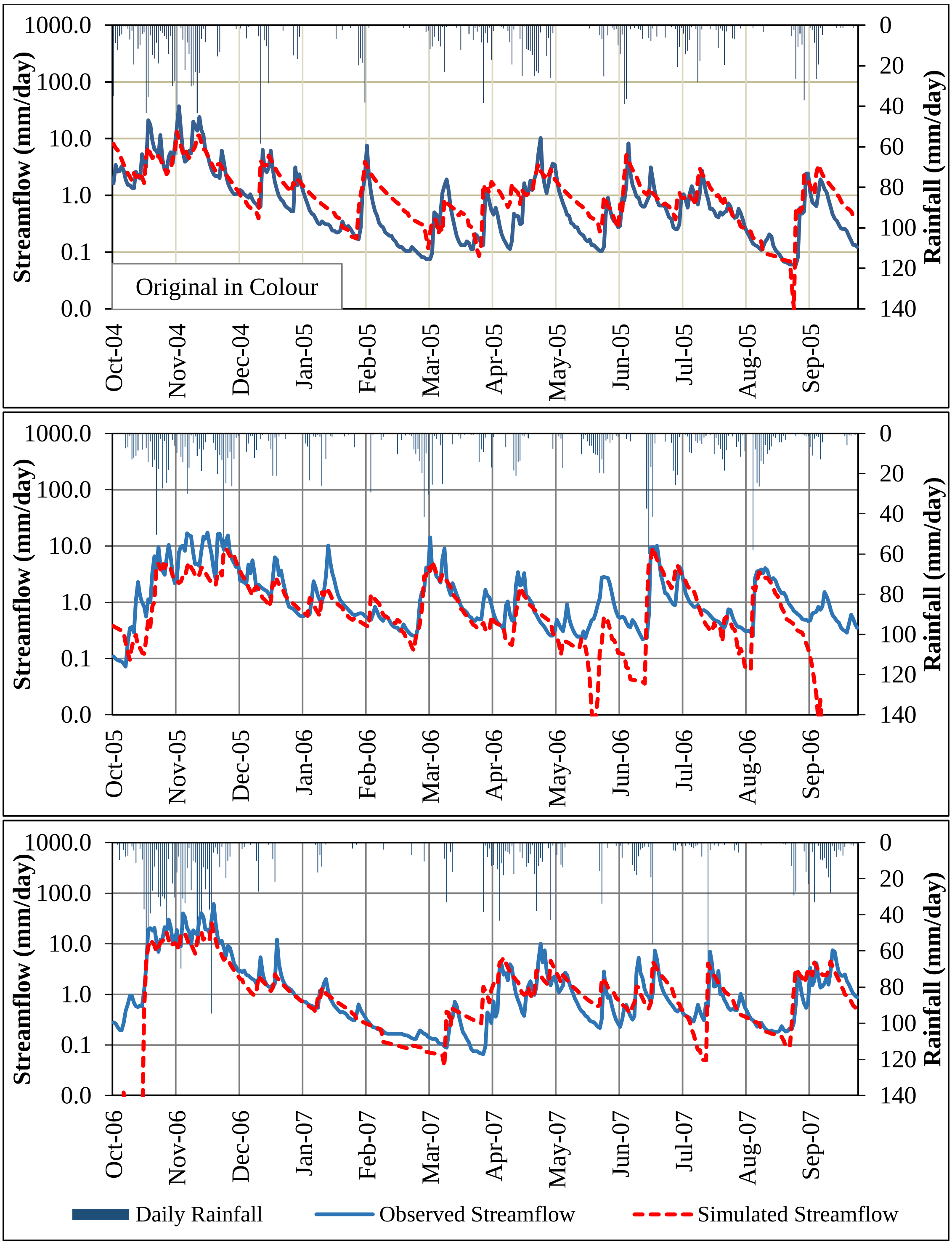


Figure 6.117: Output hydrographs – 3PM with Stations Weights Optimized (Daily Input) – Calibration Period – Badalgama Watershed (Semi Logarithmic Plot)

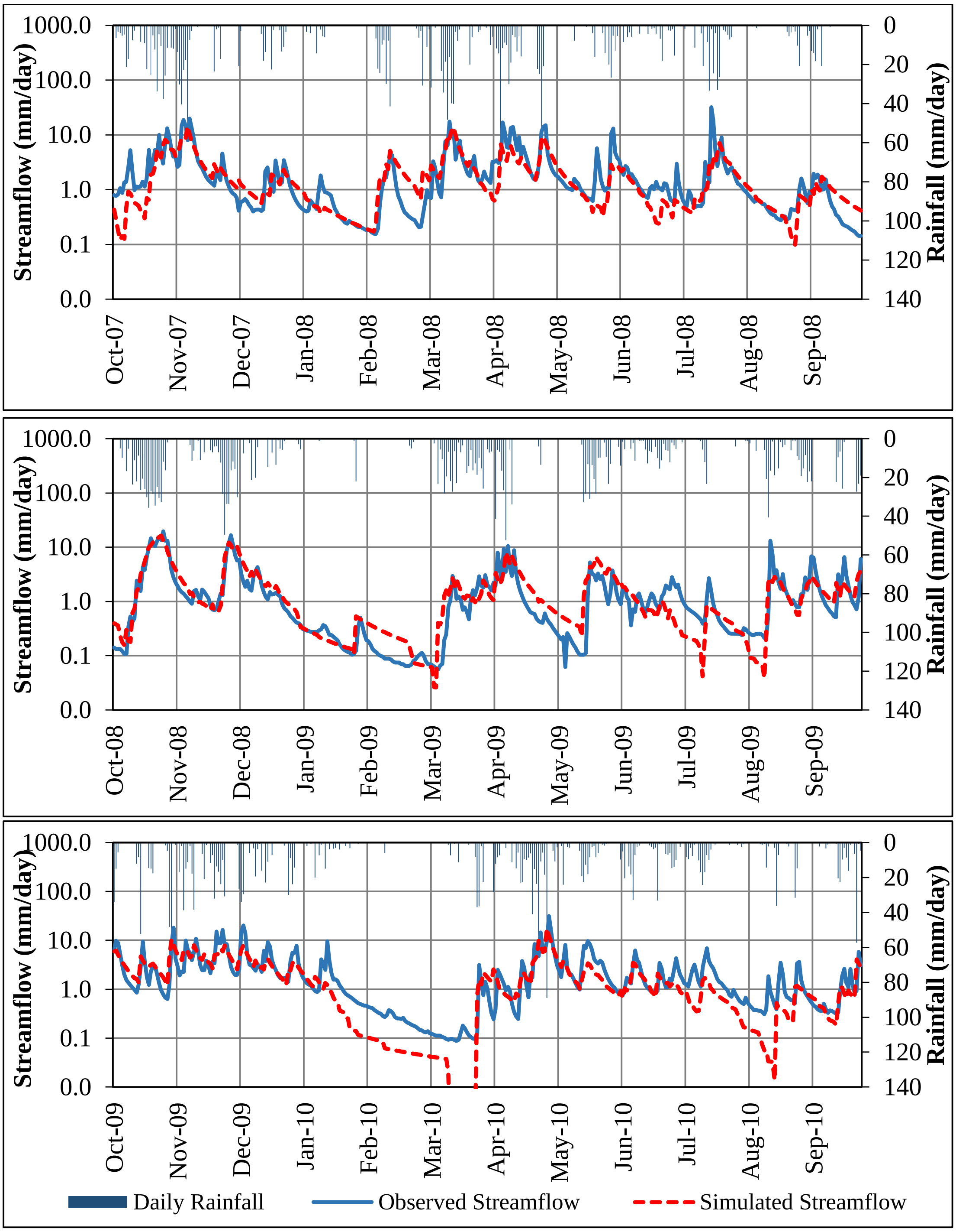


Figure 6.118: Output hydrographs – 3PM with Station Weights Optimized (Daily Input) – Calibration Period – Badalgama Watershed (Semi Logarithmic Plot)

Table 6.49 : Annual Water Balance - 3PM Station Weights Optimized (Daily Input) – Calibration Period – Badalgama

Water Year	Thiessen Averaged Rainfall (mm)	Simulated Streamflow (mm)	Observed Streamflow (mm)	Observed Water Balance (mm)	Simulated Water Balance (mm)	Annual Water Balance Difference (mm)
2004 / 2005	1933	565	633	1300	1369	-68
2005 /2006	2015	545	792	1222	1470	-247
2006 / 2007	2400	808	1164	1236	1592	-355
2007 / 2008	2096	709	889	1207	1386	-179
2008 / 2009	2375	647	654	1721	1728	-6
2009 / 2010	2292	743	907	1385	1550	-165

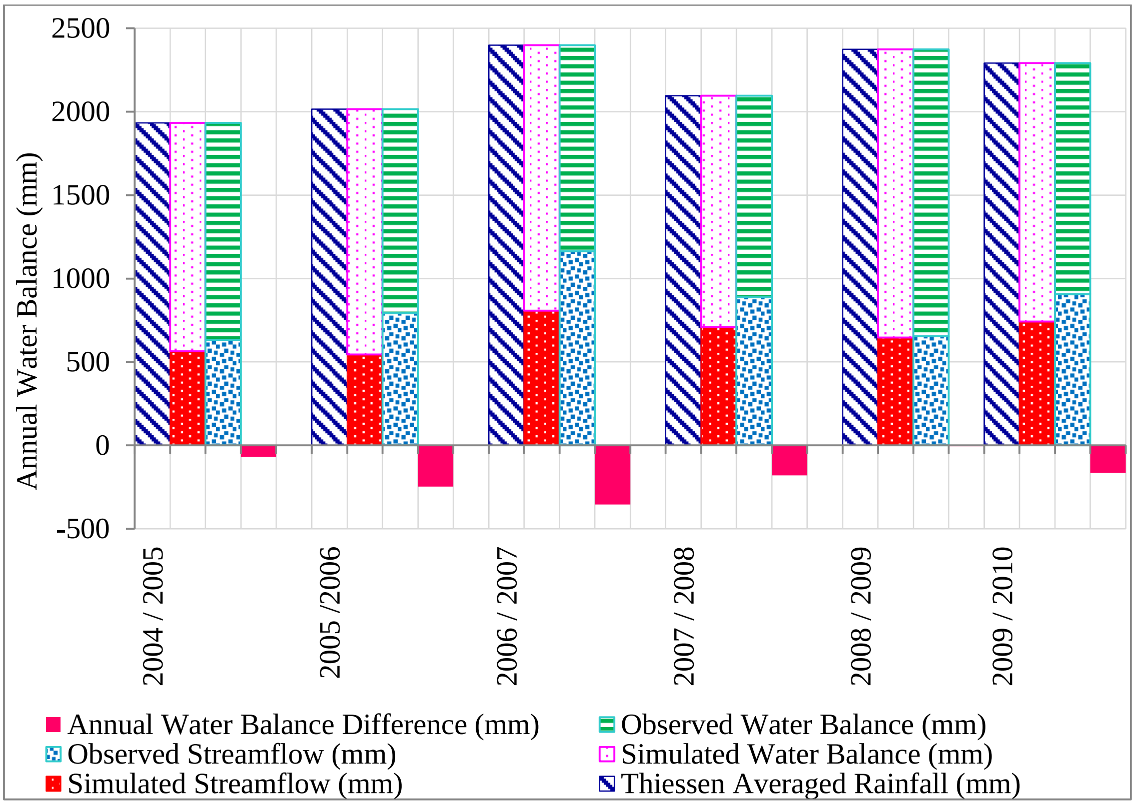


Figure 6.119: Annual Water Balance - 3PM Station Weights Optimized (Daily Input) – Calibration Period – Badalgama

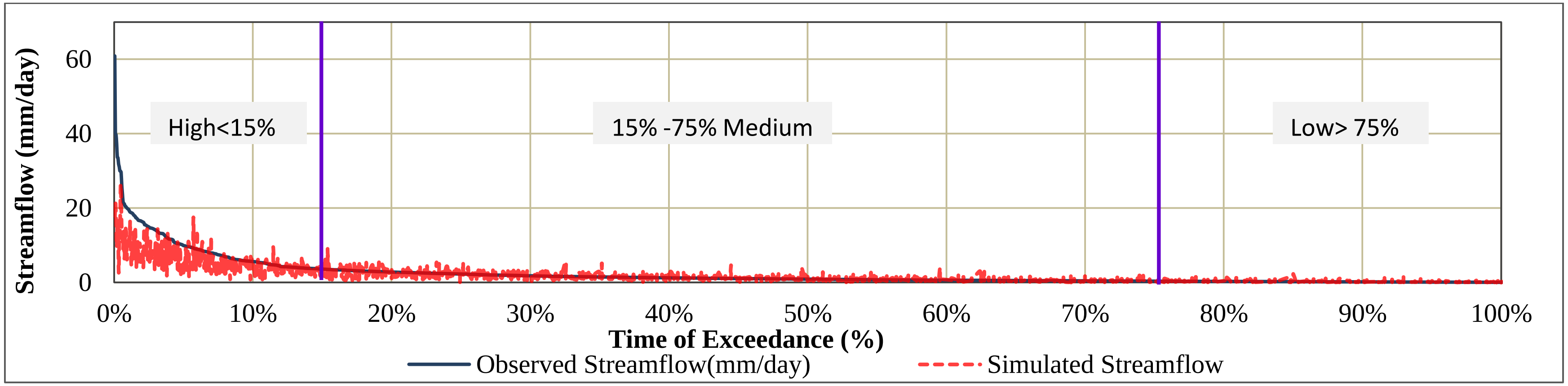


Figure 6.120: Flow Duration Curve – 3PM Station Weights Optimized Normal Scale (Daily Input - Calibration Period) for Badalgama

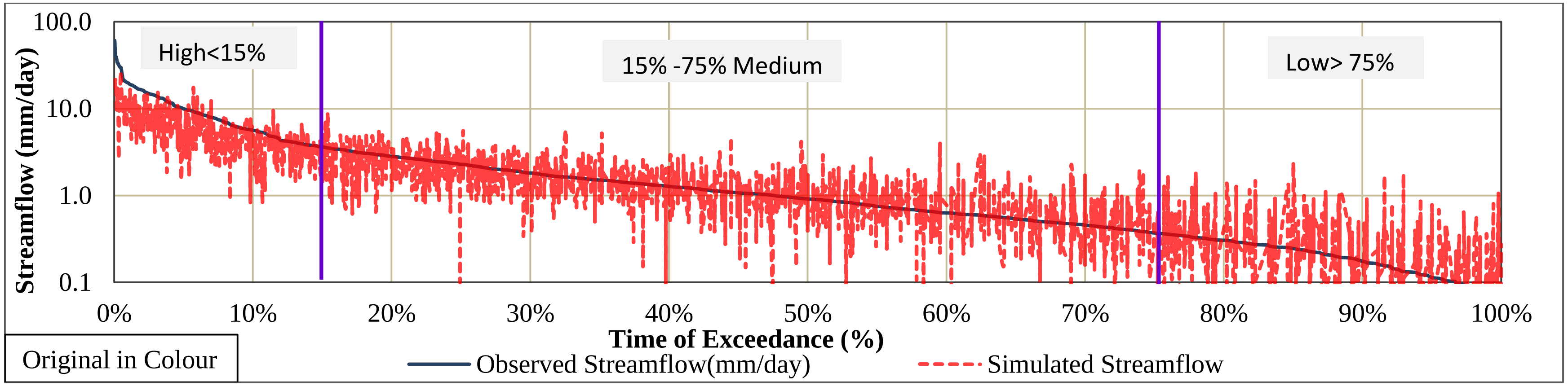


Figure 6.121: Flow Duration Curve – 3PM Station Weights Optimized Semi-Log Scale (Daily Input - Calibration Period) for Badalgama

6.14.3. Verification Period (Daily) 2010/2011-2016/2017

For the calibration period the model outflow hydrographs are plotted in Model outflow hydrographs (Figure 6.123 Figure 6.124) also the flow duration curves (Figure 6.125 and Figure 6.126), Annual water balance (Figure 6.127) and objective function values (Table 6.53) indicate a MRAE. The value of MRAE is within acceptable range and the overestimation in high flows and underestimation causes sudden drops in hydrographs. On the over hand the duration curves reflect an over estimation in the low and medium flows. The scatter diagram in Figure 6.122 shows the behavior of observed stream and simulated streamflow.

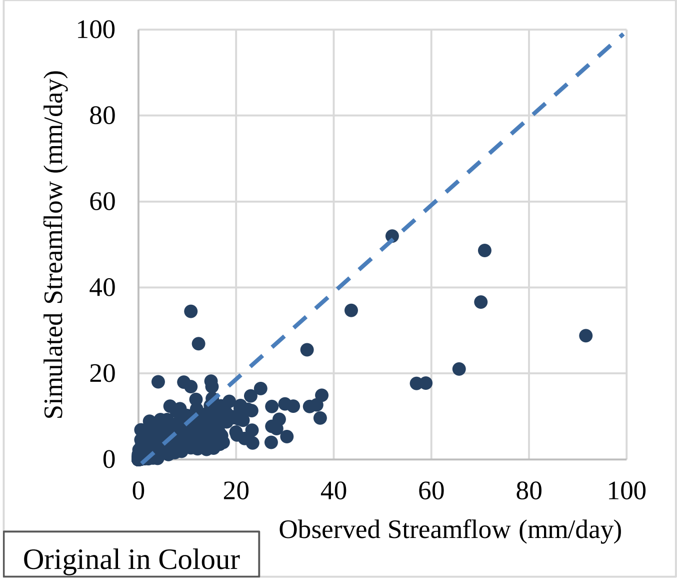


Figure 6.122: 3PM Station Weights Optimized (Daily Input) – Daily Streamflow Estimation – Verification Period – Badalgama Watershed

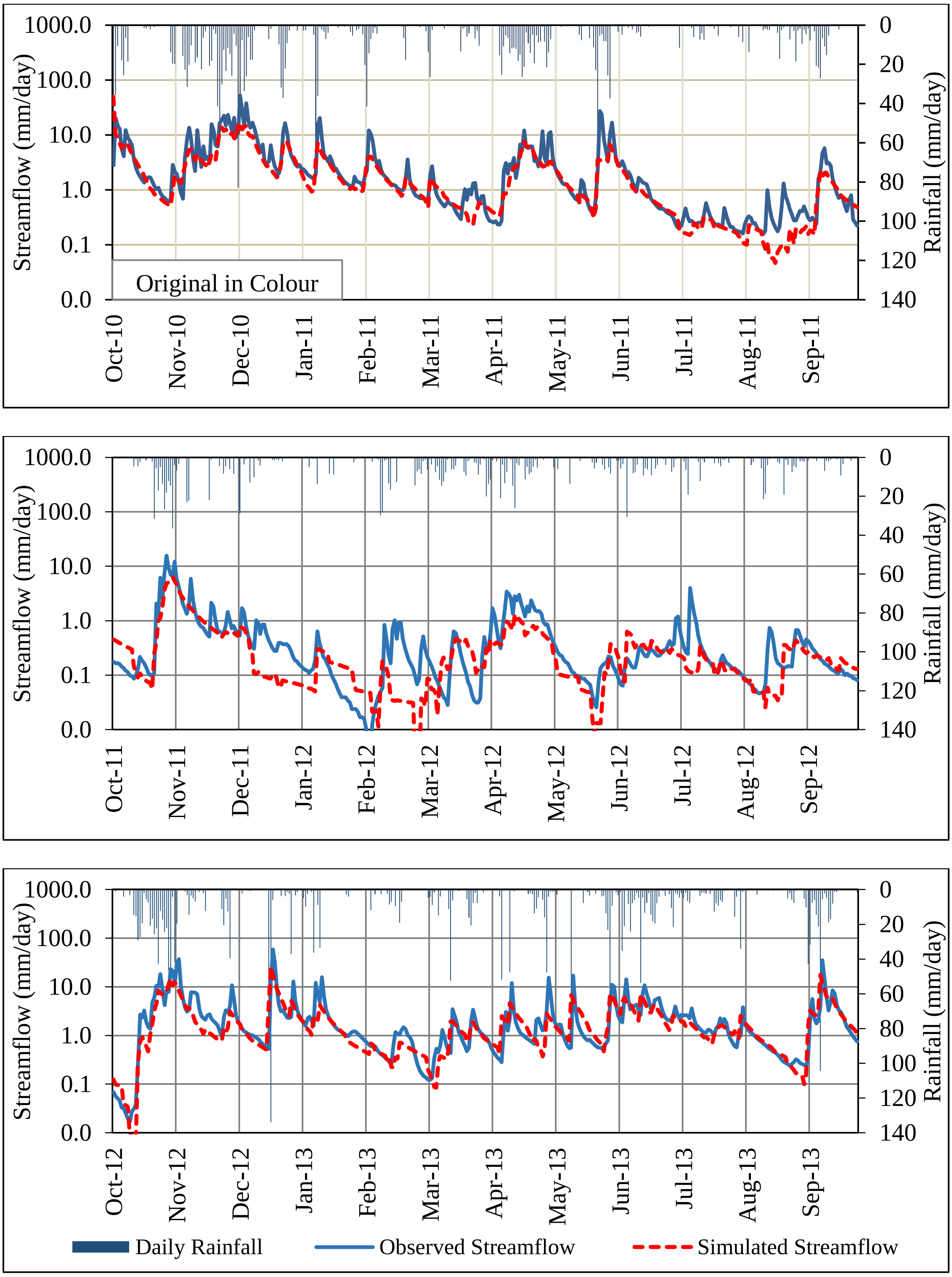


Figure 6.123: Output hydrographs – 3PM with Station Weights Optimized (Daily Input) – Verification Period – Badalgama Watershed (Semi Logarithmic Plot)

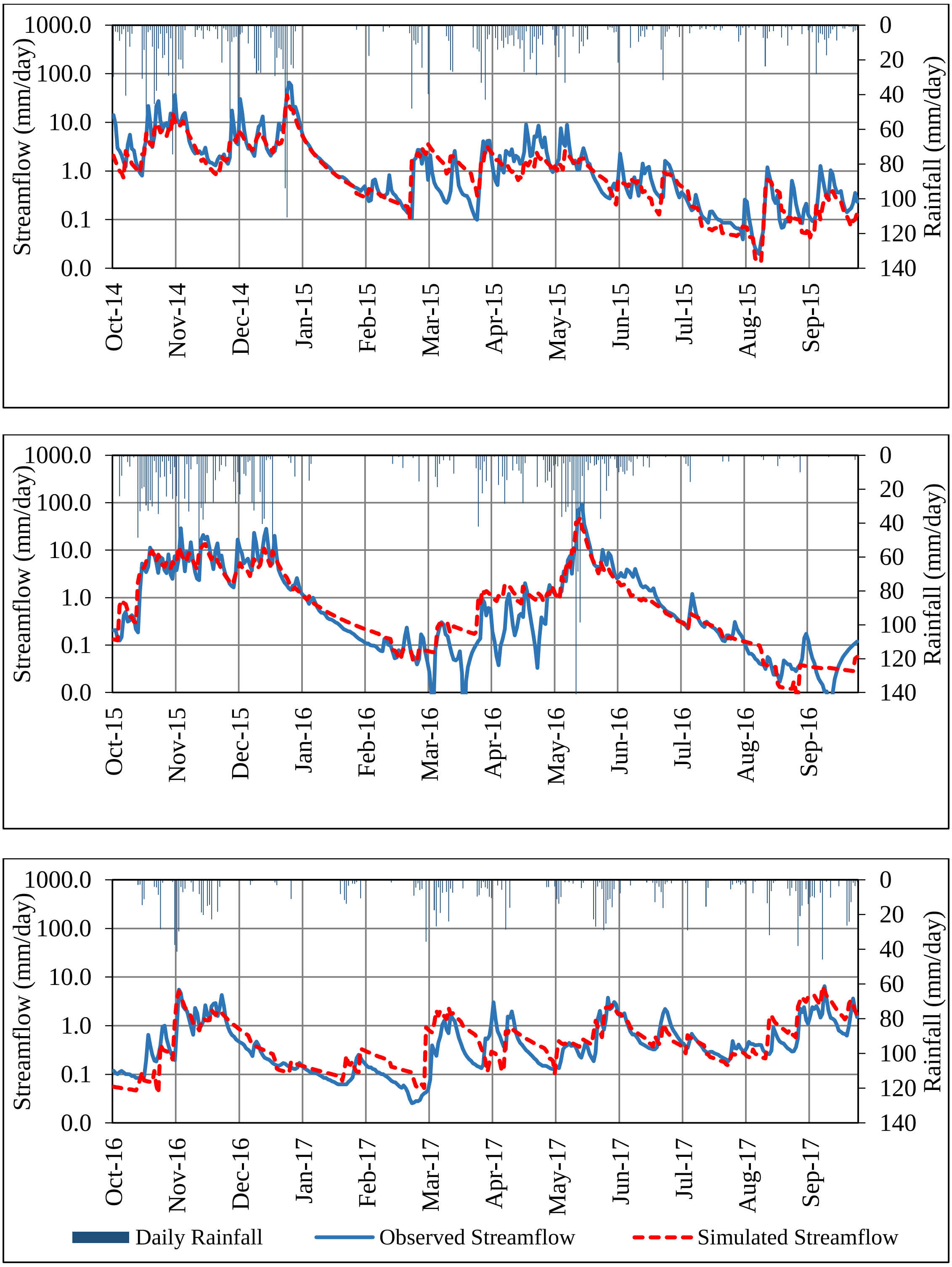


Figure 6.124: Output hydrographs – 3PM with Station Weights Optimized (Daily Input) – Verification Period – Badalgama Watershed (Semi Logarithmic Plot)

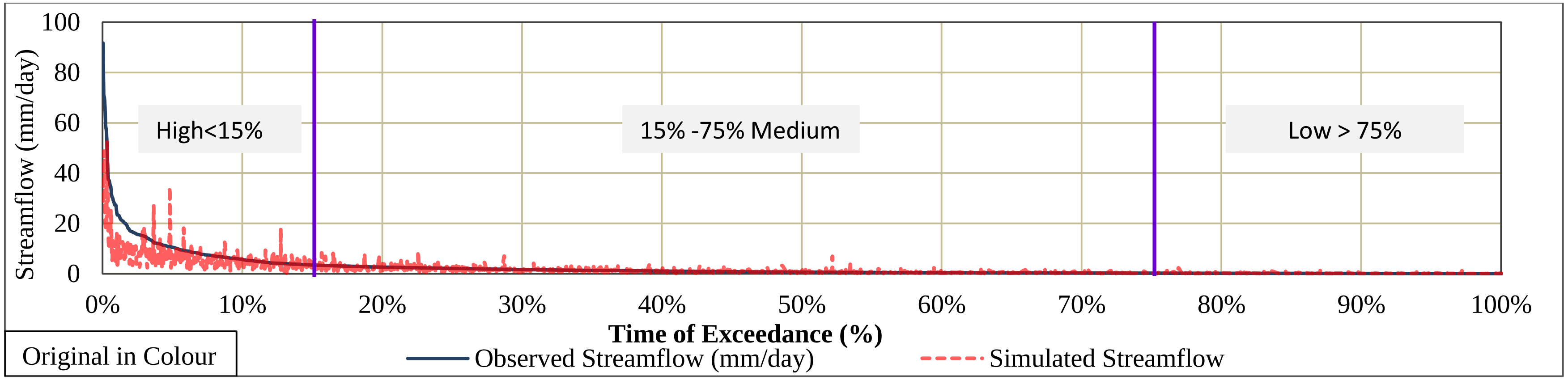


Figure 6.125: Flow Duration Curve – 3PM Station Weights Optimized Normal Scale (Daily Input - Verification Period) for Badalgama

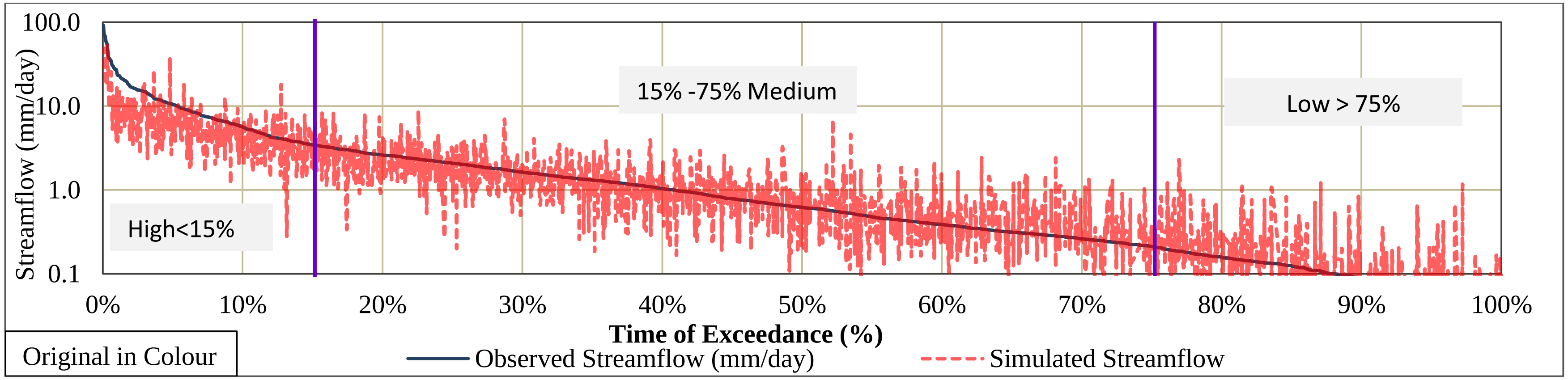


Figure 6.126: Flow Duration Curve – 3PM Station Weights Optimized Semi-Log Scale (Daily Input - Calibration Period) for Badalgama

Table 6.50 : Annual Water Balance - 3PM Station Weights Optimized (Daily Input) – Verification Period – Badalgama

Water Year	Thiessen Averaged Rainfall (mm)	Simulated Streamflow (mm)	Observed Streamflow (mm)	Observed Water Balance (mm)	Simulated Water Balance (mm)	Annual Water Balance Difference (mm)
2010 / 2011	2244	640	1272	973	1605	-632
2011 / 2012	1338	99	244	1093	1239	-145
2012 / 2013	2413	732	1115	1298	1680	-383
2014 / 2015	2446	691	1077	1369	1755	-386
2015 / 2016	2452	817	1140	1312	1635	-324
2016 / 2017	1425	256	245	1180	1169	11

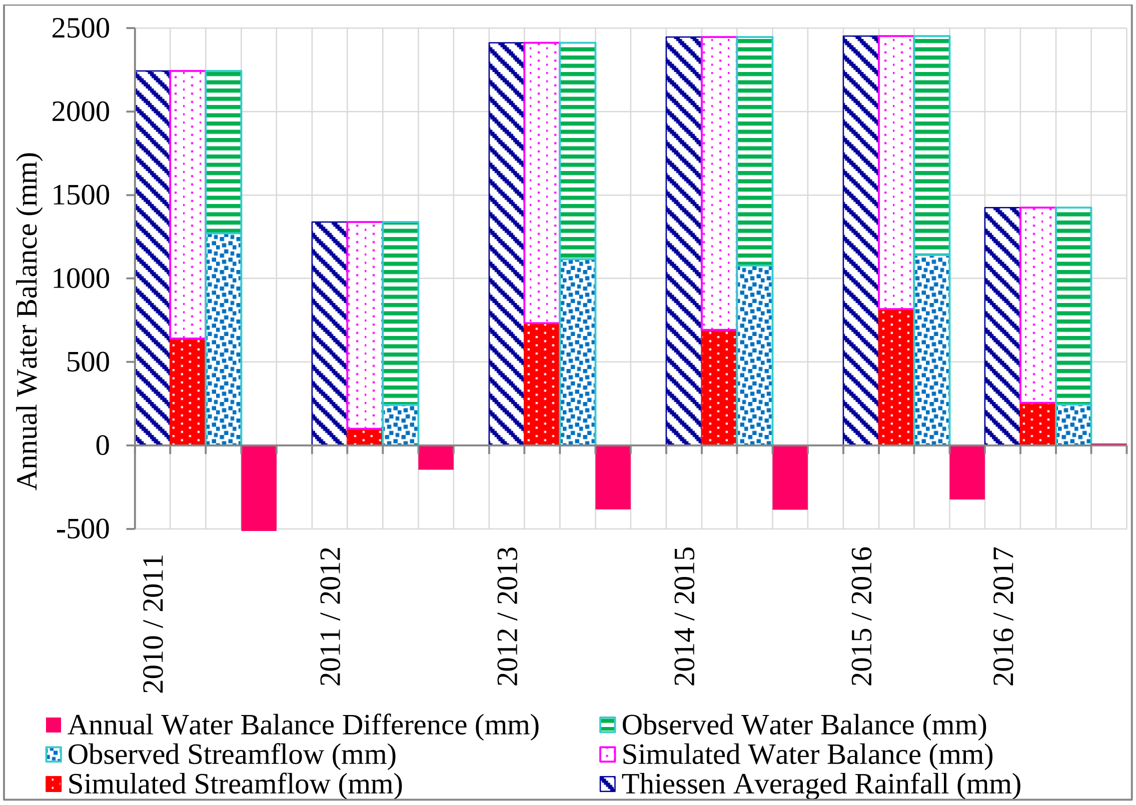


Figure 6.127: Annual Water Balance - 3PM Station Weights Optimized (Daily Input) – Verification Period – Badalgama

6.15. Three Parameter Daily Model with Parameters and Station Weights Optimized Simultaneously

6.15.1. General

The 3Paramter Monthly model has been utilized using monthly input for optimizing station weights along with the Parameters Sc, c and k simultaneously. Thiessen rainfall station weights are used as initial values for the optimization, Microsoft Excel Solver was used as tool. The monthly calibrated model values and station weights were applied with daily inputs for daily streamflow estimation.

6.15.2. Calibration Period (Daily) 2004/2005-2009/2010

Model outflow hydrographs for calibration were plotted (Figure 6.129, Figure 6.130). The flow duration curves (Figure 6.132 and Figure 6.133), Annual water balance (Figure 6.131) and the objective function values are in Table 6.53. The value of MRAE is within acceptable range. On the other hand the duration curves reflect an over estimation in the low and medium flows. The scatter diagram in Figure 6.128 shows the behavior of observed stream and simulated streamflow.

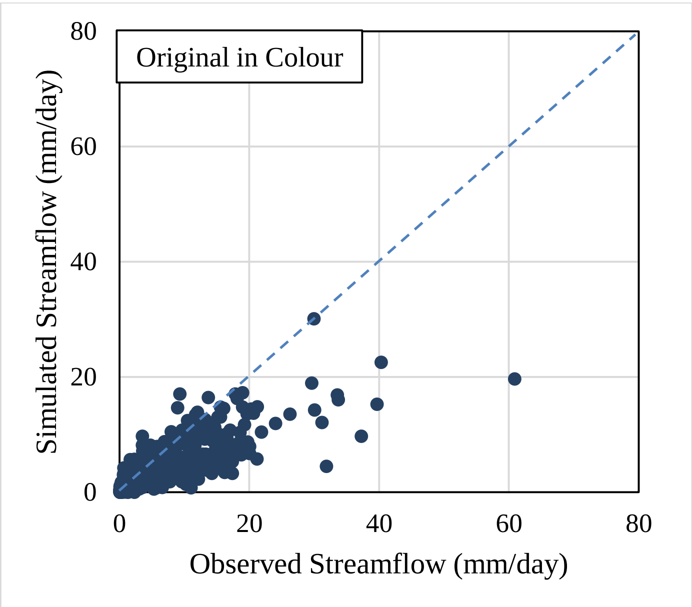


Figure 6.128: 3PM Station Weights & Parameters Optimized (Daily Input) – Daily Streamflow Estimation – Calibration Period – Badalgama Watershed

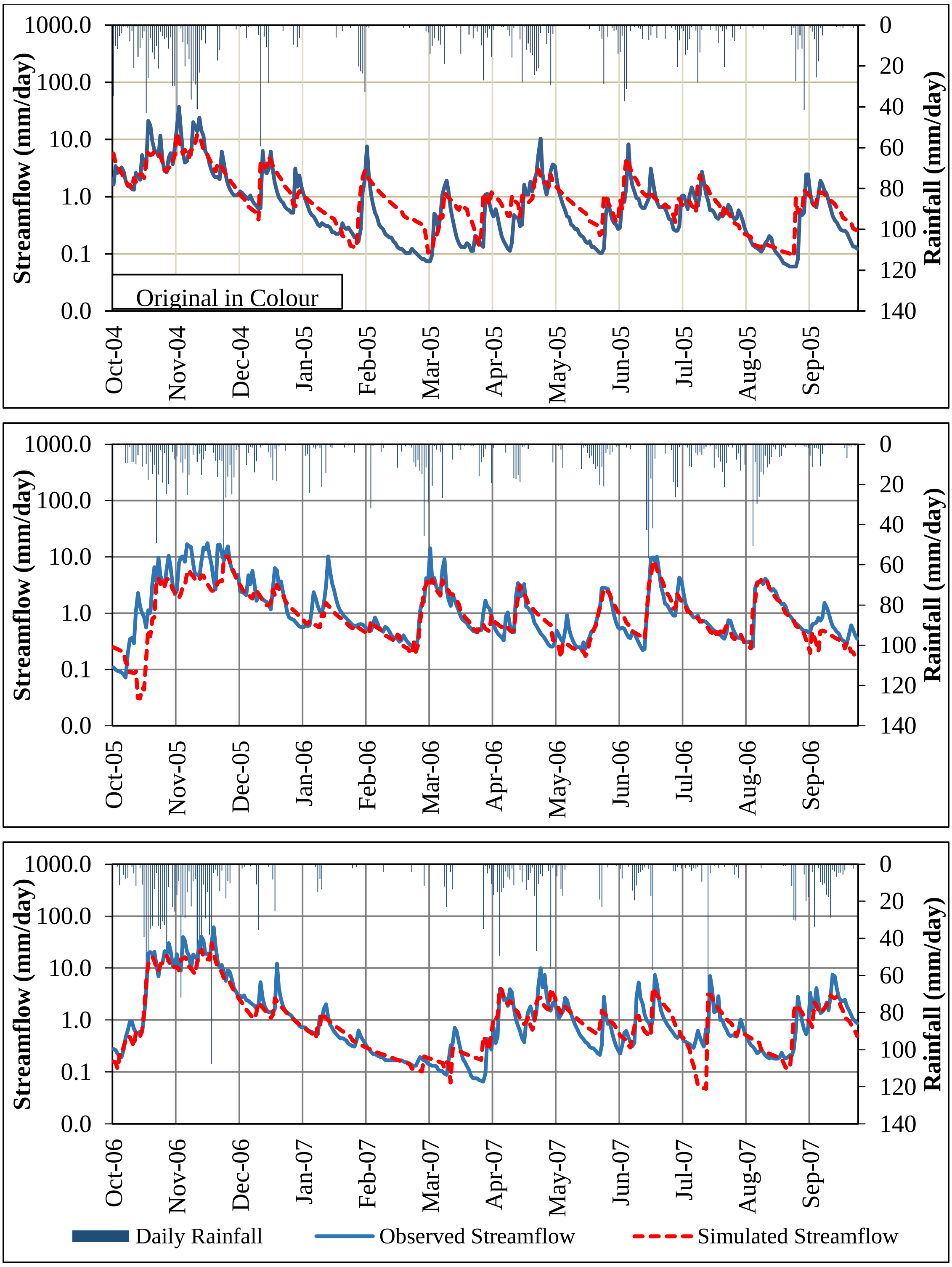


Figure 6.129: Output hydrographs – 3PM Station Weights & Parameters Optimized (Daily Input) – Calibration Period – Badalgama Watershed (Semi Logarithmic Plot)

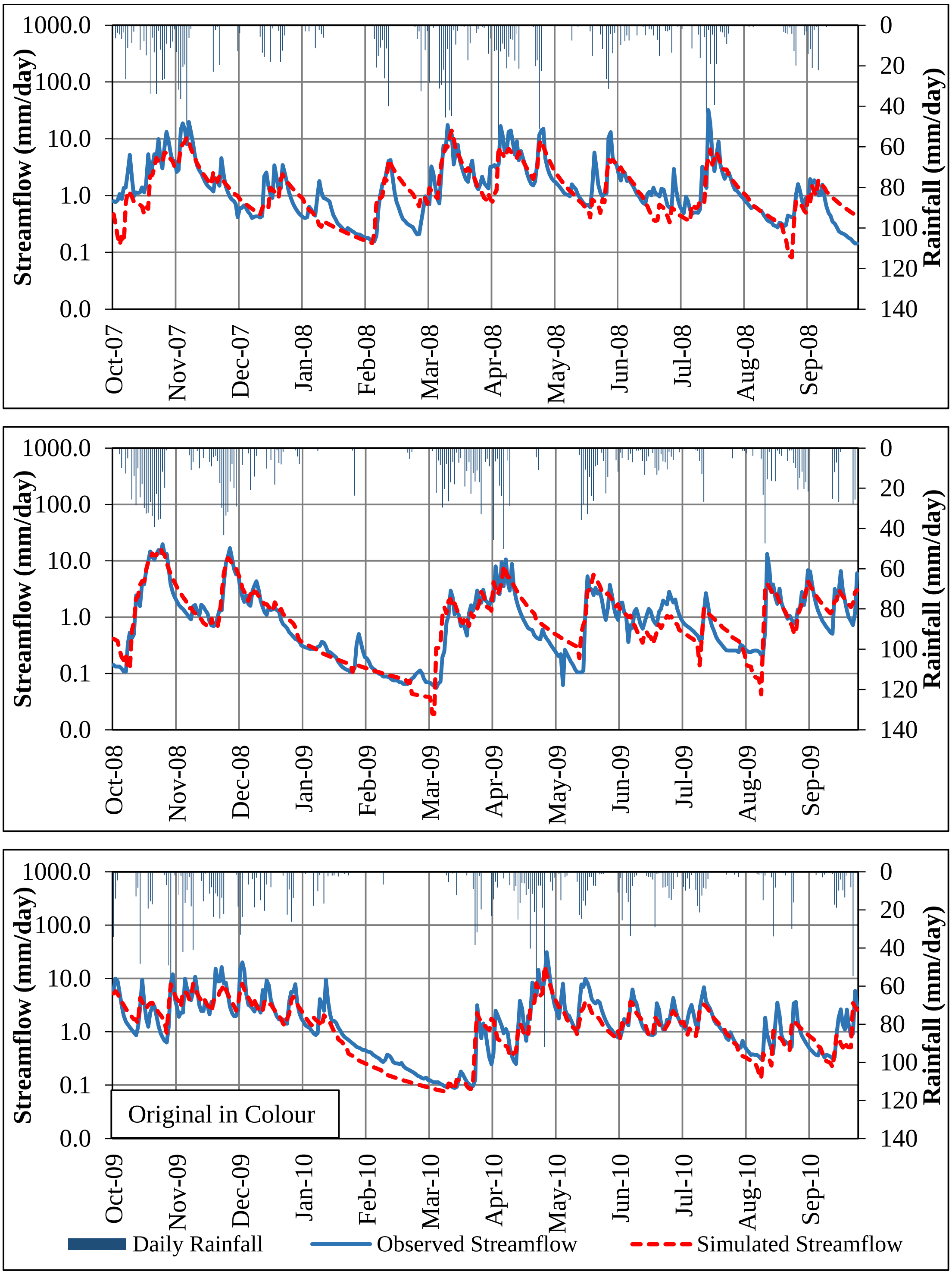


Figure 6.130: Output hydrographs – 3PM Station Weights & Parameters Optimized (Daily Input) – Calibration Period – Badalgama Watershed (Semi Logarithmic Plot)

Table 6.51 : Annual Water Balance - 3PM Station Weights & Parameters Optimized (Daily Input) – Calibration Period – Badalgama

Water Year	Thiessen Averaged Rainfall (mm)	Simulated Streamflow (mm)	Observed Streamflow (mm)	Observed Water Balance (mm)	Simulated Water Balance (mm)	Annual Water Balance Difference (mm)
2004 / 2005	1916	547	633	1283	1369	-86
2005 /2006	2005	529	792	1212	1476	-264
2006 / 2007	2451	849	1164	1287	1602	-315
2007 / 2008	2071	691	889	1182	1380	-198
2008 / 2009	2422	666	654	1769	1756	13
2009 / 2010	2207	692	907	1300	1515	-215

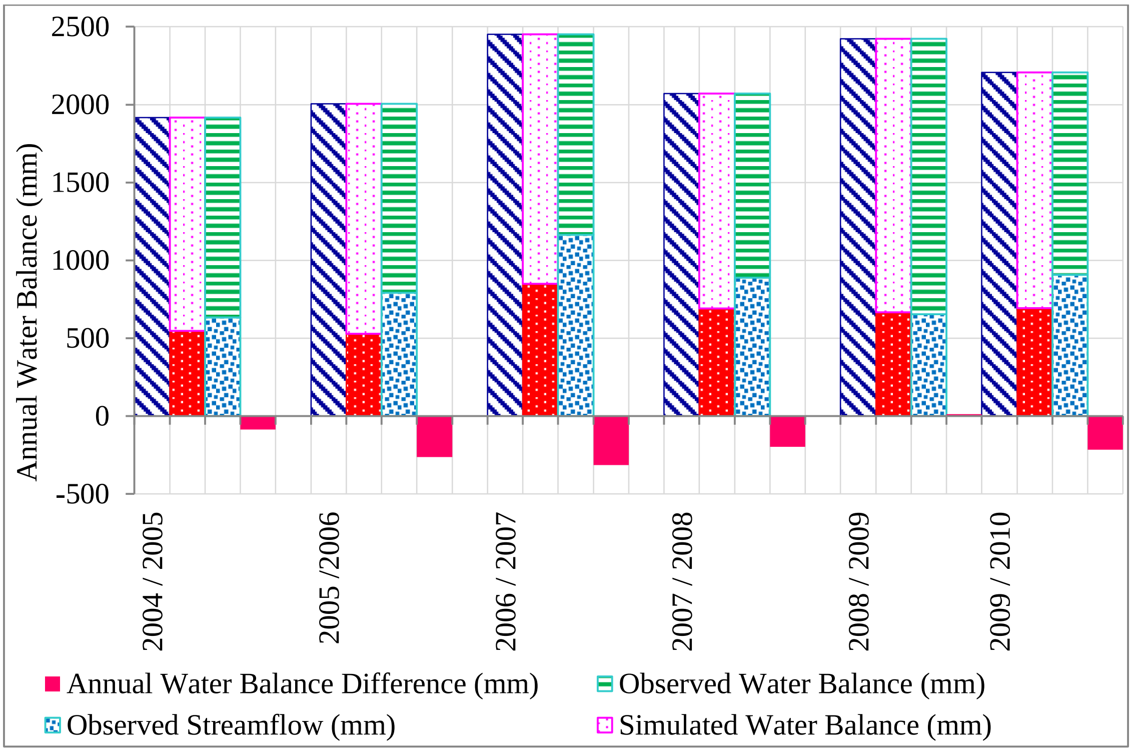


Figure 6.131: Annual Water Balance - 3PM Station Weights & Parameters Optimized (Daily Input) – Calibration Period – Badalgama

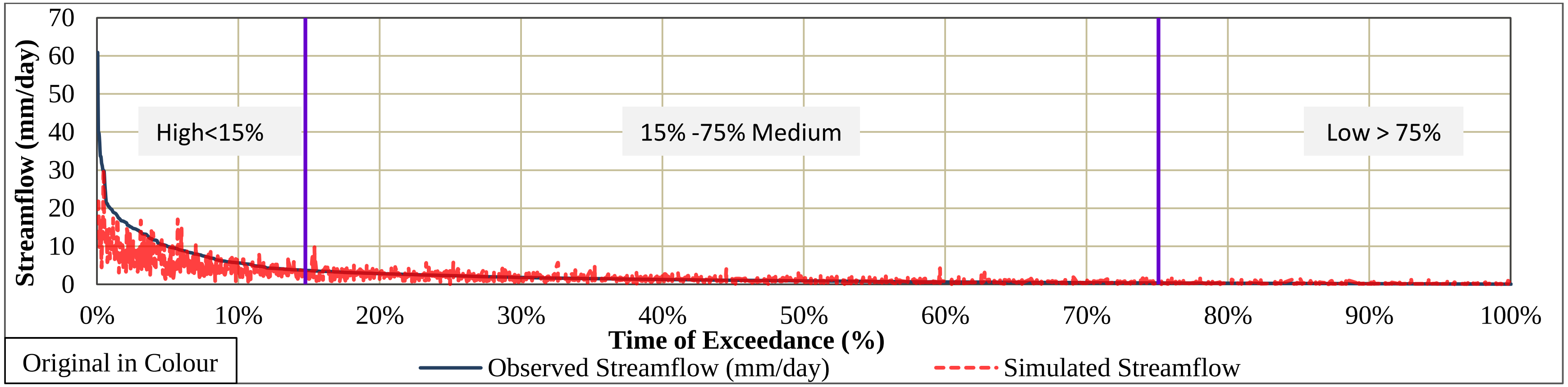


Figure 6.132: Flow Duration Curve – 3PM Parameters and Station Weights Optimized Normal Scale (Daily Input - Calibration Period) for Badalgama Watershed

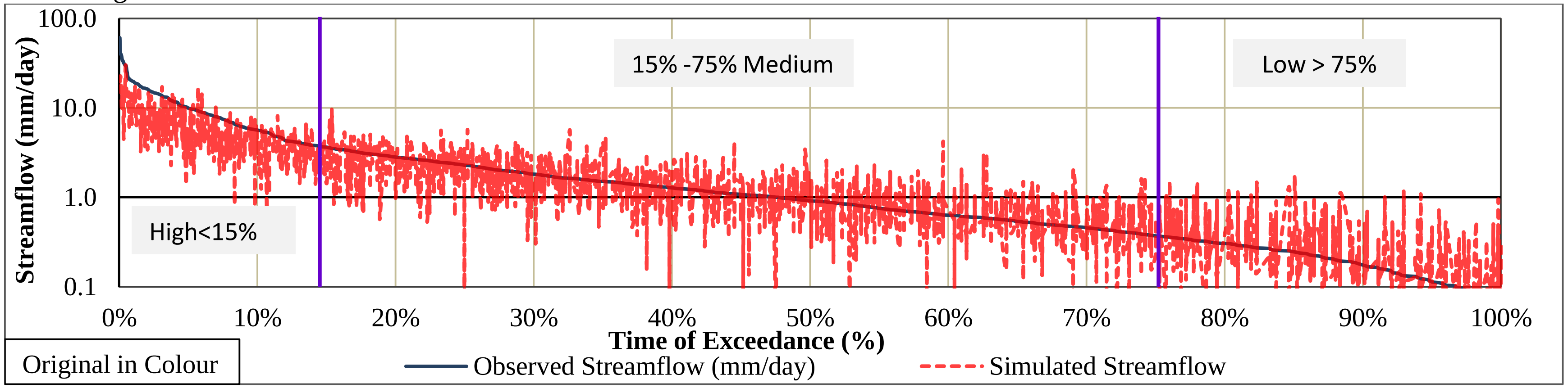


Figure 6.133: Flow Duration Curve – 3PM Parameters and Station Weights Optimized Semi-log Scale (Daily Input - Calibration Period) for Badalgama Watershed

6.15.3. Verification Period (Daily) 2010/2011-2016/2017

For the calibration period the model outflow hydrographs are plotted in Model outflow hydrographs (Figure 6.135 Figure 6.136) also the flow duration curves (Figure 6.138 and Figure 6.139), Annual water balance (Figure 5.137) and objective function values (Table 6.53) indicate a MRAE where the value of MRAE is within acceptable range. The scatter diagram in Figure 5.134 shows the behavior of observed stream and simulated streamflow with underestimations in high flows.

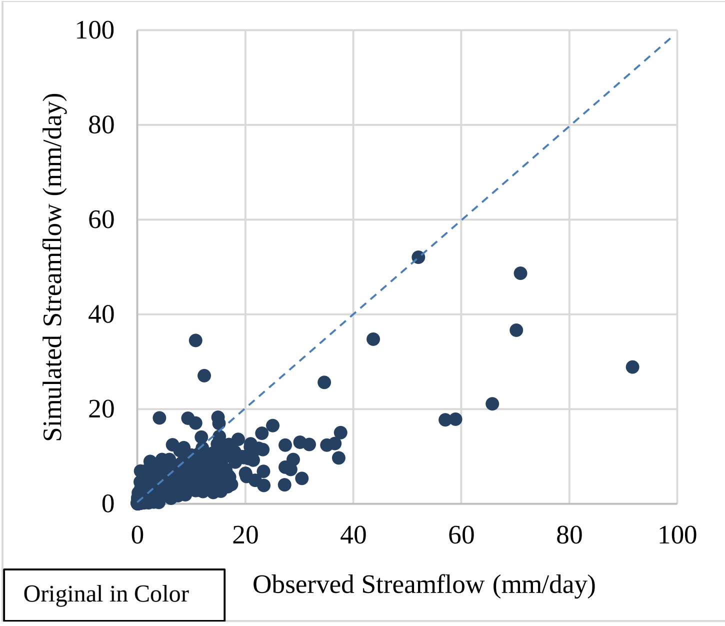


Figure 6.134: 3PM Station Weights & Parameters Optimized (Daily Input) – Daily Streamflow Estimation – Verification Period – Badalgama Watershed

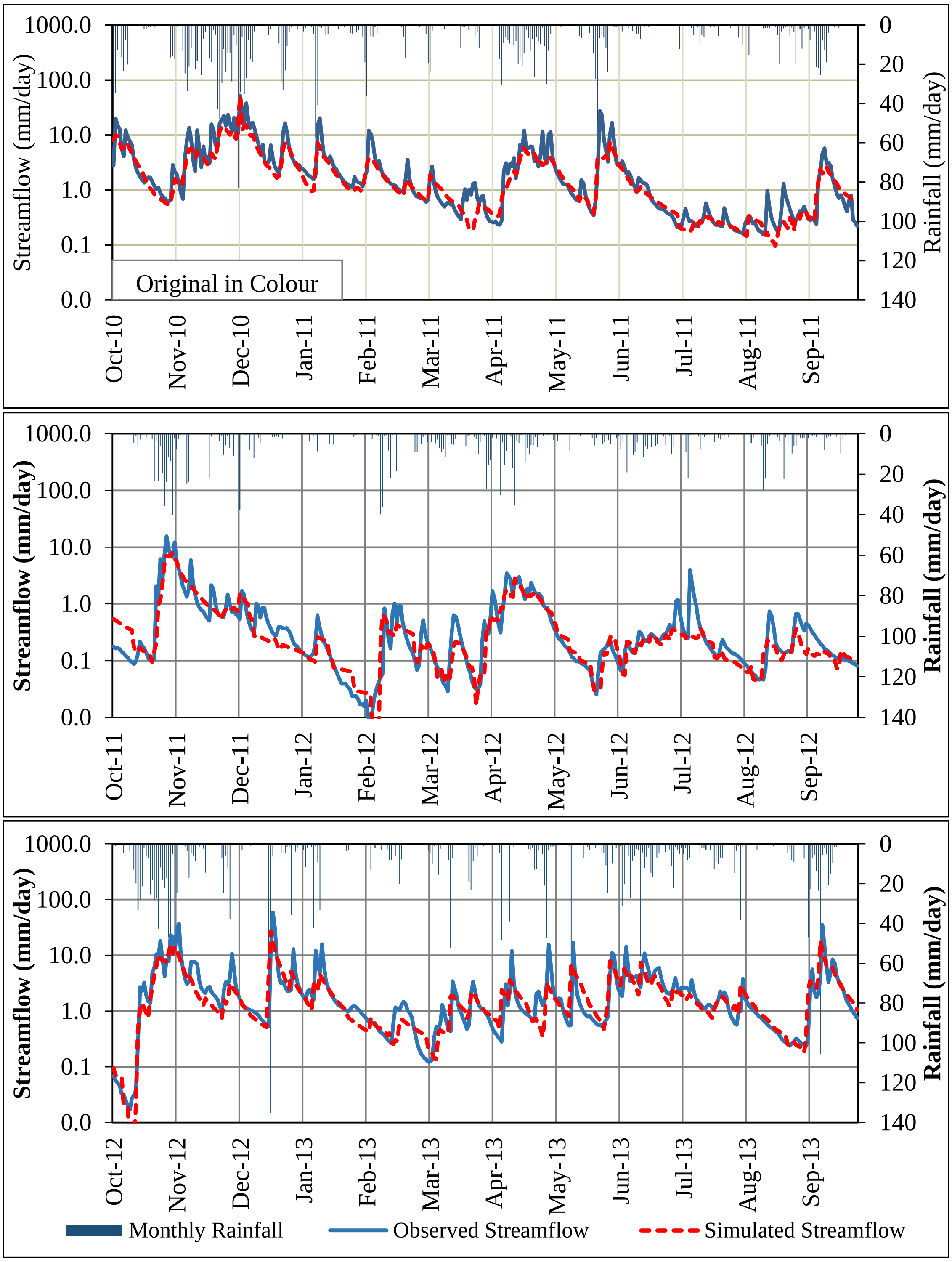


Figure 6.135: Output hydrographs – 3PM Station Weights & Parameters Optimized (Daily Input) – Verification Period – Badalgama Watershed (Semi Logarithmic Plot)

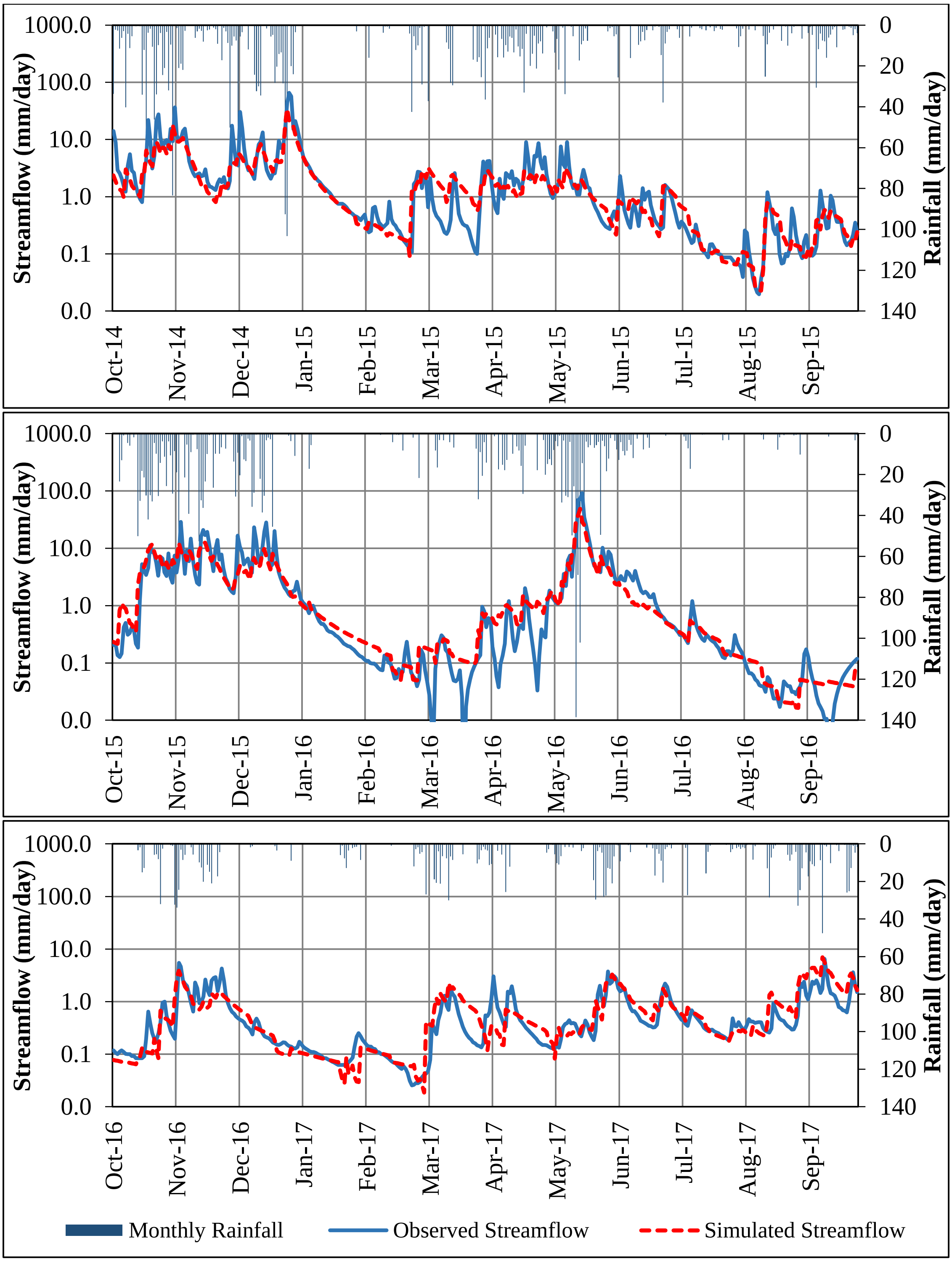


Figure 6.136: Output hydrographs – 3PM Station Weights & Parameters Optimized (Daily Input) – Verificiation Period – Badalgama Watershed (Semi Logarithmic Plot)

Table 6.52 : Annual Water Balance - 3PM Station Weights & Parameters Optimized (Daily Input) – Verification Period – Badalgama

Water Year	Thiessen Averaged Rainfall (mm)	Simulated Streamflow (mm)	Observed Streamflow (mm)	Observed Water Balance (mm)	Simulated Water Balance (mm)	Annual Water Balance Difference (mm)
2010 / 2011	2273	876	1272	1002	1397	-395
2011 / 2012	1352	190	244	1108	1162	-54
2012 / 2013	2510	839	1115	1395	1671	-276
2014 / 2015	2459	747	1077	1381	1711	-330
2015 / 2016	2436	861	1140	1295	1575	-280
2016 / 2017	1395	280	245	1150	1115	36

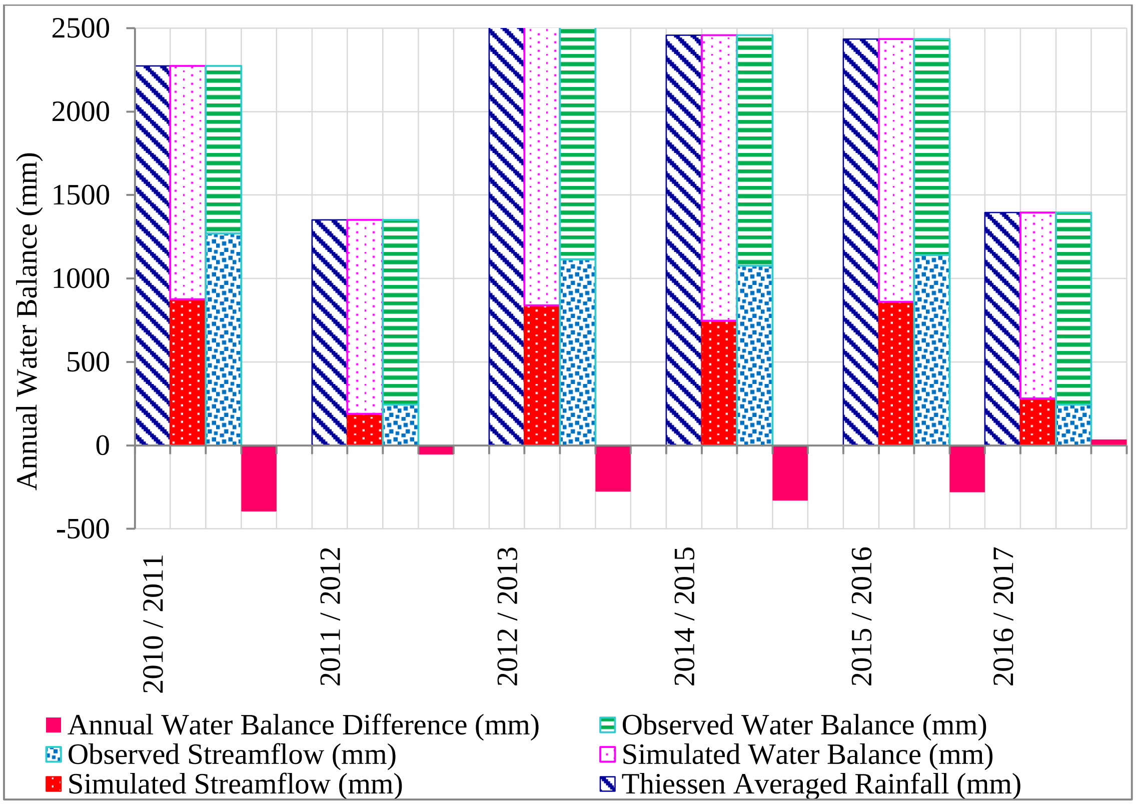


Figure 6.137: Annual Water Balance - 3PM Station Weights & Parameters Optimized (Daily Input) – Verification Period – Badalgama

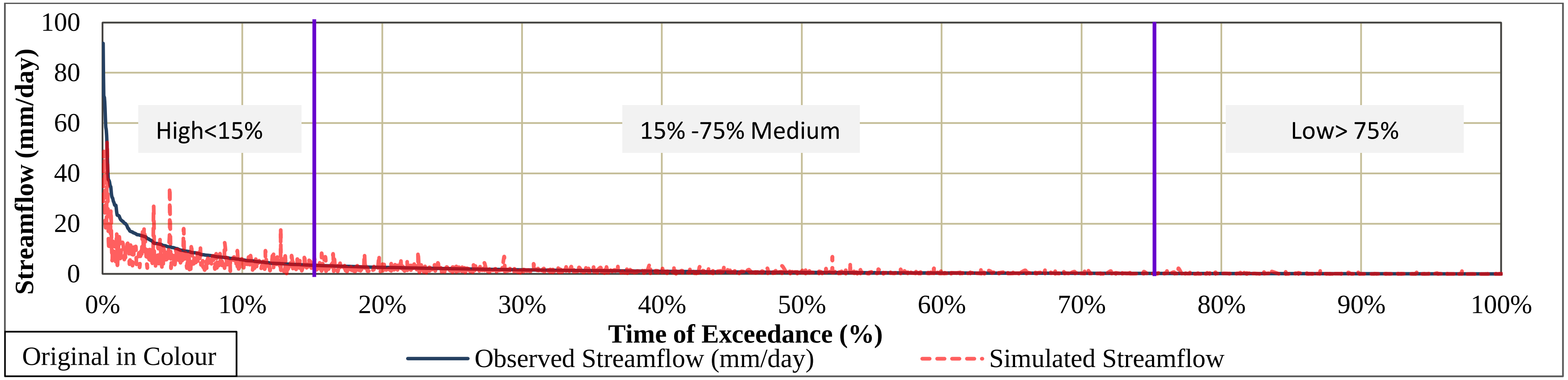


Figure 6.138: Flow Duration Curve – 3PM Parameters and Station Weights Optimized Normal Scale (Daily Input - Verification Period) for Badalgama Watershed

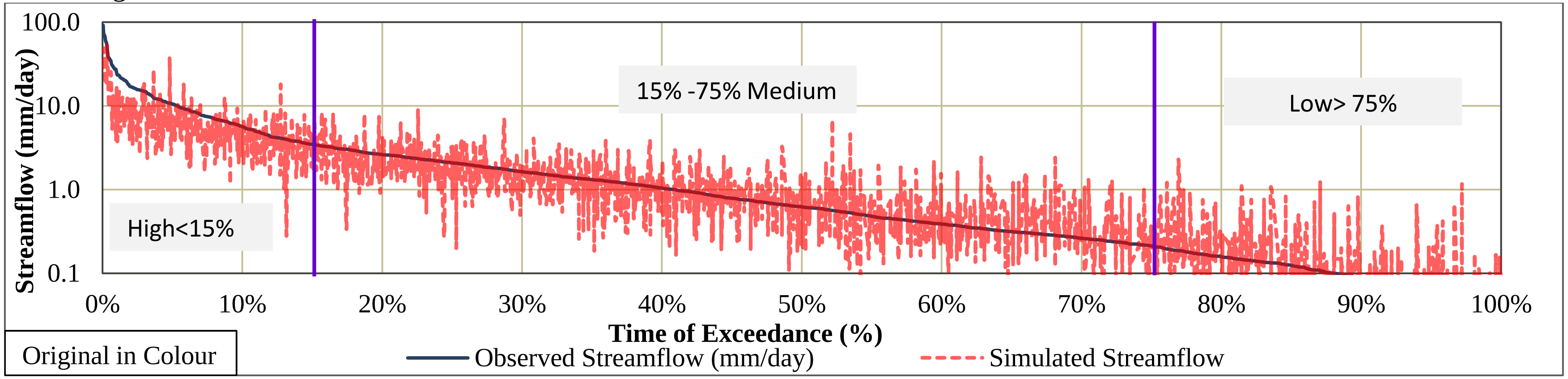


Figure 6.139: Flow Duration Curve – 3PM Parameters and Station Weights Optimized Semi-log Scale (Daily Input - Verification Period) for Badalgama Watershed

Table 6.53: Overall summary sheet of results

Comparison of Model Performance Parameter & Outputs	2PM (Monthly)		2PM (Daily)		3P (Monthly)		3P (Daily)		3P (Monthly) Station Weights Optimized		3P (Daily) Station Weights Optimized		3P (Monthly) Weights & Parameters Optimized Simultaneously		3P (Daily) Weights & Parameters Optimized Simultaneously	
	Calib	Verif	Calib	Verif	Calib	Verif	Calib	Verif	Calib	Verif	Calib	Verif	Calib	Verif	Calib	Verif
Sc	1063	1063	1063	1063	1051	1051	1051	1051	1051	1051	1051	1051	908	908	908	908
C	1.51	1.51	1.51	1.51	2.51	2.51	2.51	2.51	2.5	2.5	2.5	2.5	2.5	2.5	2.5	2.5
K	-	-	-	-	0.65	0.65	0.65	0.65	0.65	0.65	0.65	0.65	0.69	0.69	0.69	0.69
Stn Wt 1(Ambepussa)	0.26	0.26	0.26	0.26	0.26	0.26	0.26	0.26	0.20	0.20	0.20	0.20	0.23	0.23	0.23	0.23
Stn Wt 2 (Andigama)	0.19	0.19	0.19	0.19	0.19	0.19	0.19	0.19	0.16	0.16	0.16	0.16	0.14	0.14	0.14	0.14
Stn Wt 3 (Aranayake)	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.26	0.26	0.26	0.26	0.27	0.27	0.27	0.27
Stn Wt 4 (Eraminogolla)	0.35	0.35	0.35	0.35	0.35	0.35	0.35	0.35	0.38	0.38	0.38	0.38	0.36	0.36	0.36	0.36
MRAE – Overall	0.59	0.71	1.20	1.12	0.41	0.60	0.58	0.82	0.41	0.62	0.60	0.74	0.40	0.50	0.55	0.74
MRAE – High	0.32	0.21	0.47	0.49	0.37	0.23	0.38	0.41	0.3	0.20	0.37	0.49	0.30	0.23	0.47	0.29
MRAE – Med	0.47	0.61	0.99	0.92	0.48	0.57	0.45	1.32	0.48	0.62	0.46	0.92	0.47	0.57	0.46	0.56
MRAE – Low	0.85	1.34	2.21	1.78	0.63	0.9	1.01	0.88	0.81	1.4	1.09	1.76	0.77	0.90	2.0	0.73
Avg. WB Difference	118	-0.2	169	-4	-222	-299	-175	-303	-219	-305	-170	-217	-178	-252	-178	0.76
Max Soil Moisture	292.8	294..8	131.5	114.9	290.5	292.4	128.8	118	287.3	292.0	124.8	112	252	252	126	-217
Min Soil Moisture	61.9	0	47.7	24.8	60.6	0	46.0	24.74	60.6	0	45.1	28.5	40.3	0	45	112
Starting Soil Moisture	271.9	230.9	85.8	113.9	270.2	229.6	88.0	118.6	269.2	229.8	87.7	101.9	242	211	87	28
Ending Soil Moisture	96.5	107.9	77.8	74.28	95.5	107.1	77.2	73.9	97.2	93.7	76.8	68.81	81.2	91.7	78.5	101
Data Period	2004 2010	2010 2017	2004 2010	2010 2017	2004 2010	2010 2017	2004 2010	2010 2017	2004 2010	2010 2017	2004 2010	2010 2017	2004 2010	2010 2017	2004 2010	2010 2017

7. DISCUSSION

7.1. Rainfall

In the present study, total duration of data used for analysis include the period from 2004 to 2017 (Table 5.6). The data is organized in water year format i.e. the calibration dataset included October 2004 to September 2010 while the verification period was from October 2011 to September 2017 dropping out the water year 2013/2014 because of the sixty days streamflow daily data missing (Table 5.12). The fewer rainfall missing were filled with nearest station method and no major interference in data were performed.

At monthly resolution modelling two parameter model annual water balance and comparison hydrographs exhibited satisfactory matching but better results in terms of MRAE was achieved when three parameter monthly water balance model was applied.

The two parameter monthly water balance model when applied for daily estimations revealed poor results in terms of MRAE and in comparison hydrograph whilst three parameter monthly water balance model at the daily scale performed much better after its application on daily data.

The estimations with Three Parameter Monthly Water Balance Model was even improved when stations weights were optimized but not very significantly.

The rainfall station optimization improved the results, since the improvement was not significant it can be mentioned here that the overall spatial variability of rainfall is not much among the stations and spatial variably of rainfall cannot be the only factor to bring necessary adjustment of rainfall runoff response.

7.2. Soil Moisture in Model Identification

The model identification need an appropriate initial soil moisture value to start with therefore, with respect to literature reviewed, a cyclic warm up period of 6 years has been performed to make sure an accurate representative value. In the current study, it was found out that 6 years is sufficient for determination of initial soil moisture level which was verified based on the stabilization of soil moisture.

7.3. Two Parameter Monthly Model (Monthly Input)

The present research is to capture the capability of the three parameter model which is calibrated on monthly input basis. For this two parameter model based on monthly input is necessary so to develop a three parameter model. For that reason, two parameter model was developed and applied on the Badalgama watershed. Two parameter monthly model output MRAE overall results were 0.586 and 0.706 (Table 6.34), Scatter diagram showed reasonable results (Figure 6.16 and Figure 6.24). The c and Sc parameters and initial soil moisture values for Badalgama watershed are in Table 7.51.

Table 7.54: Model parameters and initial soil moisture values for two parameter monthly model

Watershed	c	Sc	Initial Soil Moisture Content	Avg. MRAE
Badalgama	1.51	1063	158.8 mm	0.65

7.4. Two Parameter Model (Daily Input)

The reason why the two parameter model with daily inputs was applied to the watershed, is because of the good matching that was observed in Monthly scale. Hence, it was necessary to find out if there is reasonably good matching using Two Parameter with daily data. MRAE values of 1.19 and 1.12 for calibration and validation periods respectively (Table 6.37) in Badalgama watershed for daily inputs showed poor model outputs. A reasonable match in intermediate flows and an over estimations in higher flows could be observed in hydrograph comparison (Figure 6.63 and Figure 6.71). There are sudden drops in the model estimates in the consecutive dry flow period i.e. absence of rainfall and presence of pan evaporation results in bring the soil moisture to the zero level which further can lead to inaccurate flow estimations in daily scales (Figure 6.64, Figure 6.65, Figure 6.68 and Figure 6. 69). This variation can be spotted in the low flows only. However, detailed investigations with duration curves, scatter diagrams and daily rainfall-streamflow graphs represented clear over estimations in watershed.

7.5. Three Parameter Model (Monthly Input)

The three parameter model with monthly inputs showed a significant improvement in the model estimations of monthly flow for the watershed. MRAE value (Table 6.24 and 6.30) during calibration was reduced with the incorporation of third parameter as (K). Hydrographs showed a significant improvement (Fgiure 6. 22 and Figure 6.30) when compared with two parameter model (Fgiure 6.50 and Figure 6.57), the first three peaks are not close but the rest matched very well, whereas this is not the case with two parameter model.

Table 7.55: Model parameters and initial soil moisture values for three parameter monthly model

Watershed	c	Sc	K	Initial Soil Moisture Content	Avg. MRAE
Badalgama	2.5	1051	0.65	158.8 mm	0.65

The two parameter model only peaks seem to match well but medium and low flows not very well (Figure 6.17 and Figure 6.25). The significant over estimations were very well handled by the third parameter (K) with an optimized parameter value of 0.65. Other indicators namely flow duration (Figure 6.46 and Figure 6.53), log and normal plots also showed significantly improved matching. 3PM with monthly inputs without stations optimization resulted better than 2PM with monthly outputs, 3PM output MRAE overall value during calibration and verification were 0.41 and 0.61 respectively (Table 6.34).

7.6. Three Parameter Model (Daily Input)

The three parameter model calibration for monthly data produced better representative streamflow estimation in the daily scale (Figure 6.72, Figure 6.73, Figure 6.78 and Figure 6.79). The three parameter model daily outputs reflected a reasonable estimated of the flow duration curve (Figure 6.74 and Figure 6.80) and fairly compatible streamflow hydrographs for the watershed. Monthly scatter plots (Figure 6.76, Figure 6.77, Figure 6.82 and Figure 6.83) indicated a highly well-suited estimate. The high flow and low flow estimates on extreme situations did not perform well but in general the medium flows (Figure 6.74 and Figure 6.80) which are the key to water resources management were well estimated. Three parameter model with daily inputs provided improved results than two parameter monthly model with daily inputs (Table 6.40), Three Parameter Monthly Model output for MRAE overall value during calibration and verification were 0.577 and 0.822 where the average MRAE values which were 0.6995 for Badalgama watershed..

7.7. Three Parameter Monthly Model (Monthly Input) with Station Weights Optimized

Since, the Two Parameter Monthly model results were not in the acceptable range therefore Three Parameter monthly model was selected under two cases i) rainfall station weights optimized ii) rainfall stations weights and model parameters optimized simultaneously. Three Parameter model station weights optimized for monthly outputs the MRAE overall value improved during calibration from 0.4117 to 0.4090 (0.69%) and during verification declined from 0.5972 to 0.6175 (3.4%). Average MRAE value 0.513 (Table 6.41 and Table 6.43) which did not improve as such which cannot show significant perfections in other indicators as well such as monthly hydrographs (Figure 6.87, Figure 6.88, Figure 6.95 and Figure 6.96) and Annual Water Balance (Figure 6.99 and 6.89). The optimized Thiessen station weights for Ambepussa, Andigama, Aranayake and Eraminigolla stations were 0.26,0.16,0.20 and 0.35 which were correspondingly optimized to 0.20, 0.16, 0.26 and 0.38 (Table 6.53). .

7.8. Three Parameter Monthly Model (Daily Input) with Station Weights Optimized

After station weights optimization, three parameter model for monthly data produced improved results in daily scale streamflow estimation. The daily overall MRAE average results improved from 0.743 to 0.771 (3.63%) which is insignificant. Slight improvement in flow duration curves (Figure 6.121 and Figure 6.126) and annual water balance (Figure 6.119 and 6.127) can be noticed. The performance of 3PM model after the station weights were optimized at monthly scale for daily streamflow estimation (Table 6.53), which deteriorated (3.4%) MRAE value from 0.58 to 0.6 (calibration) while an improvement of (10.8%) in MRAE of 0.822 to 0.74 can be noticed (verification). The three parameter model daily outputs reflected fairly compatible streamflow hydrographs for the watershed (Figure 6.117, Figure 6.118,

Figure 6.123 and Figure 6.124). The average MRAE value was 0.669 for Badalgama watershed, monthly scatter plot of three parameter model indicated a highly well-suited estimate with fewer overestimations (Figure 6.116 and 6.112)..

7.9. Three Parameter Monthly Model (Monthly Input) with Station Weights and Parameter optimization

The three parameter model calibration for monthly data produced with optimization of parameters (Sc, C and K) and station weights performed at the same time. Both station weight optimization and model parameters optimized resulted in reflection of optimum MRAE value during verification and calibration periods which were 0.3992 and 0.4983 correspondingly with Sc, C and K values of 0.69, 2.5 and 908 respectively (Table 6.47 and Table 6.45). Optimizing the stations and parameters at the same time Sc changed from 1051.8 to 908 where c remained same 2.5 and the adjusting factor changed to increase from 0.65 to 0.69 (Table 6.53). Three Parameter Monthly model stations and parameters are optimized simultaneously the station weights were 0.23, 0.014, 0.26 and 0.36. Reasonably matching for high and low flows, well match for intermediate flows from hydrographs (Figure 6.101, Figure 6.102, Figure 6.114 and Figure 6.115) and flow duration curves (Figure 6.104 and Figure 6.109). Avg. AWB Error of 178mm in calibration and 252mm in verification (Figure 6.105 and Figure 6.111). The station weights are optimized and changed to a considerable amount but yet not a huge difference in performance i.e. the behavior of stations relatively close to each or in other is less spatial variability in rainfall among the stations. In total results show that overall MRAE value improved by (17.6%) from 0.4117 to 0.3992 during calibration and (16.6%) from 0.5972 to 0.4983 in verification period. Scatter plot shows underestimations for high flows (Figure 6.100 and Figure 6.110).

7.10. Three Parameter Monthly Model (Daily Input) with Station Weights and Parameter optimization

The three parameter model calibration for monthly data produced with optimization of parameters (Sc, C, K) and station weights simultaneously done was used for the estimation of daily streamflow estimations with daily time scale. Whilst both station weight optimization and model parameters were optimized resulted to reflect a reasonable MRAE of 0.5478 (calibration) and 0.7395 (verification) for Badalgama watershed (Table 6.53) with average MRAE of 0.6436. Three Parameter Monthly model was used for daily streamflow estimation, which exhibited an improvement of (5.6%) in overall MRAE from 0.5770 to 0.5478 during calibration while for verification period an improvement (10.0%) in overall MRAE from 0.8215 to 0.7395. The flow duration curve looks reasonably well matching with several overestimations in low flows and high flows (Figure 6.133 and Figure 6.139) while the hydrograph matching is also unbiased (Figure 6.129, Figure 6.130, Figure 6.135 and Figure 6.136). With this it can be concluded that the high flow and low flow estimation on extreme situations did not perform well whereas in general the intermediate flows are the key for water resources management were reasonably estimated. The daily scatter plot delivered well result achieved (Figure 6.128 and Figure 6.134). The optimized Thiessen station weights results were 0.28, 0.19, 0.29, and 0.23 which corresponds for Ambepussa, Andigama, Aranayake and Eraminigolla stations in Badalgama watershed.

Amongst all the cases the lowest overall MRAE values is achieved while optimizing rainfall station weights and parameters at monthly output the same time which is 0.3992 during calibration and 0.5478 during verification. .

7.11. Importance of Three Parameter Model and Station Weights Optimization

The present study is a demonstrates of an immense value while performing the current research if the three parameter model developed along with station weights optimized. In Sri Lanka, the data with monthly resolution are easy to access with affordable prices which can be retrieved both state and government bodies for rainfall, pan evaporation and streamflow.

Therefore, three parameter model has the capability to be calibrated and verified effortlessly on monthly scale data available by water resource professionals and managers. Once the model is developed and optimized for station weights and parameters the final step was its application on finer resolution i.e. daily scale data which can be applied on watershed for daily applications in water resource.

7.12. Model Conceptualization

The purpose of current research study outcome can be summarized in terms of conceptualization that two parameter model was inadequate to conceptualize the catchment process at monthly and daily resolution with equations that had been proposed by the Xiong and Guo (1999).

With the introduction of the third parameter as adjusting factor 'K' was to further reflect the watershed runoff transfer characters which clearly indicated that three parameter model can be treated as a model which had captured the governing watershed response at both monthly and daily temporal scale. In addition to that under three different scenarios three parameter monthly water balance model was investigated a) model calibrated and verified with only model parameters optimization b) model stations weights optimized c) model station weights and parameters optimized simultaneously. After the application of each scenario the daily streamflow estimations were performed and it evidently revealed more accurate estimations.

This study is of a great advantage when it comes to the real application world by the water resources managers therefore it can be stated here that the study encourages the watershed modelers to investigated the possibilities for understanding catchment behavior with simpler governing equation and considering the spatial variability of rainfall for better knowledge of the natural systems in watersheds.

Whilst, this research can be an opening door for researchers and shows the ability in the hydrologic modelling across two temporal resolutions with the strength moving from coarser data to finer estimations. The coarser resolution can be helpful for the calibration of the model with verification and same model can be of great use for daily estimations.

8. CONCLUSIONS

1. The study found that spatial variability of rainfall can significantly affect the results of monthly water balance model, about 17% improvement in average MRAE at monthly scale when station weights and parameters are simultaneously optimized was observed.

2. Considering the spatial variability of rainfall when station weights were only optimized for monthly water balance model using monthly inputs is negligible since only optimization of stations weights improved the average overall MRAE by (1.5%).

3. Monthly water balance models can be applied for daily streamflow estimation with incorporation of spatial variability of rainfall when station weights and parameters were simultaneously optimized improved MRAE results by 7.8% which is not significant.

4. Three parameter monthly model when station weights and parameters optimized simultaneously can provide acceptable results for daily streamflow estimations with overall average MRAE value of 0.64.

5. Three parameter monthly water balance model suggested by Dissnayake (2017 upubl) for Ellagawa and Tawalama watersheds showed superior results than Two parameter monthly model of Xiong & Guo, (1999) for both daily and monthly streamflow estimations.

6. Three Parameter monthly model for daily streamflow estimations provided superior results when rainfall station weights and all parameters are optimized simultaneously with ideal results, which exhibited an improvement of (5.6%) in overall MRAE from 0.5770 to 0.5478 during calibration while for verification period an improvement (10.0%) in overall MRAE from 0.8215 to 0.7395.

7. Two parameter monthly water balance model showed high level of error for daily streamflow estimations for dry catchments due to observation of consecutive dry

periods which results in sudden drops affecting water content in soil of water balance model structure.

8. Hydrologic modelers need to account spatial variability of rainfall since the accurate input can lead in better estimations of streamflow in both monthly and daily resolutions in order to gain more accurate results in the modelling effort.

9. The three parameter monthly water balance model results revealed less error of MRAE in monthly than daily scale due to higher variance in occurrence of rainfall at daily temporal resolution.

9. RECOMMENDATIONS

1. The three parameter model should be applied on the dry watersheds to investigate the improvement and possibility of recognizing the modeling concept and the spatial variability of rainfall.
2. Further research should investigate not only on the conceptualization of watershed heterogeneity but also the identification of optimum rainfall averaging methods which could minimize the effects of the spatial variability of rainfall in a catchment.

9. REFERENCES

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*, 357–368.

Arnaud, P., Bouvier, C., Cisneros, L., & Dominguez, R. (2002). Influence of rainfall spatial variability on flood prediction. *Journal of Hydrology*, 216-230.

Bari, M., & Smettem, K. (2006). A conceptual model of daily water balance following partial clearing from forest to pasture. *Hydrology Earth System Sciences*, 321–337.

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.

Ball, J. E., & Luk, K. C. (1998). Modelling spatial variability of rainfall over a catchment. *Journal of Hydrologic Engineering* , 122-130.

Bardossy, A., & Singh, S. (2008). Robust estimation of hydrological model parameters. *Hydrology and Earth System Sciences* , 1273-1283.

Berndtsson, R., & Niemczynowicz, J. (1988). Spatial and temporal scales in rainfall analysis - some aspects and future perspectives. *Jounral of Hydrology*, 293-313.

Berne, A., G. Delrieu, J.D. Creutin, and C. Obled, (2004) Temporal and spatial resolution of rainfall measurements required for urban hydrology, *Journal of Hydrology*, vol. 299, no. 3-4, pp. 166-179,.

Bari, M., & Smettem, K. (2006). A conceptual model of daily water balance following partial clearing from forest to pasture. *Hydrology Earth System Sciences*, 321–337.

Barrows, H. (1943). *Water power engineering.* New York: McGraw-Hill Book Co.

Bell, V., & Moore, R. (2000). The sensitivity of catchment runoff models to rainfall data at different spatial scales. *Hydrology and Earth System Sciences*, 653-667.

Boughton, W.C. (2007). Effect of data length on rainfallerunoff modelling. *Environmental Modelling & Software*, 406e413.

Boughton, W.C., 2004. The Australian water balance model. *Environ. Modell. Softw.* 19 (10), 943–956.

Boyle, D. P., Gupta, H. V., Sorooshian, S., Koren, V., Zhang, Z., and Smith, M.: Towards improved streamflow forecasts: The value of semi-distributed modeling, Water Resour. Res., AGU, 37(11)

Caldera, H., Piyathisse, V., & Nandalal, K. (2016). A Comparison of Methods of Estimating Missing Daily Rainfall Data. *ENGINEER, Vol. XLIX*, 1-8.

Chang, T., Talei, A., Alaghmand, S., & Ooi, M. P.-L. (2017). Choice of Rainfall inputs for event-based rainfall-runoff modeling in a catchment with multiple rainfall stations using data-driven techniques. *Journal of Hydrology*, 100-108.

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*, 1-18.

Cheng, Q. (2014). *Evaluating the Effect of Objective Functions on Model Calibration.* Berlin: Institut Für Geographische Wissenschaften.

Cheng, K.-S., Lien, Y.-T., Wu, Y.-C., & Su, Y.-F. (2017). On the criteria of model performance evaluation for real-time flood forecasting. *Stoch Environment Research Risk Assess, 31*, 123–1146.

Chiew, F.H., Peel, M.C., Western, A.W., 2002a. Application and testing of the simple rainfall-runoff model SIMHYD. In: Singh, V.P., Frevert, S.K. (Eds.), *Mathematical Models of Small Watershed Hydrology and Applications.* Water Resources Publications, Littleton, Colo, pp. 335–367

Chow, V. (1978). *Advances in Hydroscience.* London: Academic Press Inc.

Chow, V. T., Maidment, D. R., & Mays, L. W. (1988). *Applied Hydrology.* Singapore: McGraw Hill series in water resources and environmental engineering .

Cohen, W., Ollington, R., & Ling, F. (2013, December 1-6). Hydrologic Model Parameter Optimisation. *20th International Congress on Modelling and Simulation*, pp. 677-683.

Confesor, J., Remegio, B., & Whittaker, G. W. (2007). Automatic Calibration of Hydrologic Models With Multi-Objective Evolutionary Algorithm and Pareto Optimization. *Journal Of The American Water Resources Association, 43*(4), 981-989.

Cristiano, E., Veldhuis, M.-c. t., & Giesen, N. v. (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.

Das, T., Bardossy, A., & Zehe, E. (2006). Influence of spatial variability of precipitation in a distributed rainfall–runoff model. *Predictions in Ungauged Basins: Promise and Progress Proceedings of symposium S7 IAHS Assembly* (pp. 195-203). Foz do Iguaçu: International Association of Hydrological Sciences.

Dataset Pricing at National Center for Environmental Information US. (2006, 06 20). Retrieved from National Climate Data Center: https://www.ncdc.noaa.gov/cdohtml/cdoprice.html

De Silva, R., Dayawansa, N., & Ratnasiri, M. (2007). A Comparison of Methods used in Estimating Missing Rainfall Data. *The Journal of Agricultural Sciences, III*, 101-108.

Department of Meteorology [DoM]. (2016). Weather and Climate Data. *Retrieved from Department of Meteorology Sri Lanka: http://www.meteo.gov.lk*

Diouf, R., Sambou, H., Traore, V., Ndiaye, M., Chaibo, A., Sambou, B., & Diaw, A. (2016). Frequency Analysis and Exploratory of Rainfall Variability in Bounkiling River Basin in a Context of Climate Change. *American Journal of Engineering Research*, 82-93.

Daggupati, P., Yen, H., Michael , W. J., Srinivasan, R., Jeffrey , A. G., Conor , K. S., & Scott , S. P. (2015). Impact of model development, calibration and validation decisions on hydrological simulations in West Lake Erie Basin. *Hydrological Processes*, 5307–5320.

Dawdy , D., & O'Donnell, T. (1965). Mathematical models of catchment behavior. *American Society of Civil Engineers Proceedings*, 123-137.

De Silva, R., Dayawansa, N., & Ratnasiri, M. (2007). A Comparison of Methods Used in Estimating Missing Rainfall Data. *The Journal of Agricultural Sciences, III*, 101-108.

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

Donigian, A., & Imhoff, J. (2009). Evaluation and Performance Assessment of Watershed Models. *Proceedings of Water Envrionment*, 11-27.

Dissanayake, P.K.M (2017). *Applicability of a two parameter water balance model to simulate daily rainfall runoff.* Moratuwa: University of Moratuwa Unpubl.

Duda, P., Hummel, P., Donigian, A., & Imhoff, J. (2012). BASINS/HSPF: MODEL USE, CALIBRATION AND VALIDATION. 1523-1547.

Efstratiadis , A., & Koutsoyiannis, D. (2010). One decade of multi-objective calibration approaches in hydrological modelling: a review. *Hydrological Sciences Journal*, *55*(1), 58-78.

Ekenberg, M. (2016). Using a lumped conceptual hydrological model for five different catchments in Sweden. Master's Thesis, Department of Physical Geography. Stockholm: Stockholm University.

EPA. (2007). *U.S. Environmental Protection Agency, An Approach for Using Load Duration Curves in the Development of TMDLs.* Washington: Watershed Branch (4503T), Office of Wetlands, Oceans and Watersheds.

Fencl, M., Rieckermann, J., Sýkora, P., Stránský, D., & Bareš, V. (2015). Commercial microwave links instead of rain gauges: fiction or reality? *Water Science & Technology* , 31–37.

Fenicia, F., Savenije, H. H., Matgen, P., & Pfister, L. (2007). A comparison of alternative multiobjective calibration strategies for hydrological modeling. *WATER RESOURCES RESEARCH*, 1-16.

Fletcher, T., Andrieu, H., & Hamel, P. (2013). Understanding, management and modelling of urban hydrology and its consequences for receiving waters: A state of the art. *Advances in Water Resources*, 261-279.

Gan, T. Y., Dlamini, E. M., and Biftu, G. F. 1997. Effects of model complexity and structure, data quality, and objective functions on hydrologic modelling. *Journal of Hydrology*, 192(1-4), 81-103. [doi:10.1016/S0022-1694(96)03114-9]

Garcia, B., Sentelhas, P. C., Tapia, L., & Sparovek, G. (2006). Filling in missing rainfall data in Andes region of Venezuela, based on a cluster analysis approach. *Rev. Bras Agrometeorologia*, 225-233.

Genet, R., & Crochemore, L. (2011). *Evaluation of Hydrologic Models: Experts judgement vs Numerical Criteria* . Paris: Polytechnic Paris-UPMC Sciences De La Terre.

Georgakakos, K. P., & Kavvas, M. L. (1987). PRECIPITATION ANALYSIS, MODELING, AND PREDICTION IN HYDROLOGY. *REVIEWS OF GEOPHYSICS*, 163-178.

Gayathri, K. D., Ganasri, B. P., & Dwarakish, G. S. (2015). A Review on Hydrological Models. *Science Direct*, 1001 – 1007.

Ghandhari, A., & Alavi Moghaddam, S. (2011). Water Balance Principles: A review of studies on five watersheds in Iran. *Journal of Environment Science and Technology*, 465-479.

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

Gupta, H., Bastidas, L., Sorooshian, S., Shuttleworth, W., & Yang , Z. (1998a). Parameter estimation of a land surface scheme. *Journal of Geophysics*, 19491-19503.

Gupta, H., Sorooshian, S., & Yapo, P. (1998b). Towards improved calibration of hydrologic models: Multiple and noncommensurable measures of information. *Water Resources*, 751-763.

Green, I., & Stephenson, D. (1986). Criteria for comparison of single event models. *Hydrological Sciences Journal*, 395-411.

Haan, C. (1972). A water yield model for small catchments. *Water Resources Research, 8*, 58-69.

Hwang, S. H., Ham, D. H., & Kim, J. H. (2012). A new measure for assessing the efficiency of hydrological data-driven forecasting models. *Hydrological Sciences Journal, 57*(7), 1257-1274.

Hyndman , R. J., & Koehler, A. B. (2006). Another look at measures of forecast accuracy. *International Journal of Forecasting, 22*, 679– 688.

Hijioka, Y., Lin , E., Pereira, J., Corlett, R., Cui, X., Insarov, G., Surjan, A. (2014).

Climate Change 2014*: Impacts, Adaptation, and Vulnerability. Part B: Regional Asp ects. Contribution of Working Group II* .Cambridge, United Kingdom and New York, NY, USA. :Cambridge University Press.

Hasan, M., & Croke, B. (2013). Filling gaps in daily rainfall data: a statistical approach. *20th International Congress on Modelling and Simulation*, (pp. 1-6). Adelaide.

Hoad, K., Robinson, S., & Davies, R. (2008). Automating Warm-up Length Estimation. *Proceedings of the 2008 Winter Simulation Conference*, (pp. 532-540). Coventry.

Hukmans, R., Meol, H. d., Aerts, J., & Troch, P. (2008). Water balance versus land surface model in the simulation of Rhine river discharges. *Water Resource Research, 44*, 1-14.

Jayadeera, P. (2016). Development of a rainfall runoff model for Kalu ganga basin of Sri Lanka using HEC-HMS model. *A thesis in Water Resources Engineering and Management (Master's Thesis), University of Moratuwa, Sri Lanka*. Retrieved from http://dl.lib.mrt.ac.lk/handle/123/1/browse?value=Jayadeera%2C+PM&type=author

Jain, S., & Singh, V. (2003). *Water Resources Systems Planning and Management.* Amsterdam: Elsevier.

Jie, M.-X., Chen, H., Xu, C.-Y., Zeng, Q., & Tao, X.-e. (2016). A comparative study of different objective functions to improve the flood forecasting accuracy. *Hydrology Research*, 718-735.

Jansen, M. (2009). *Environment matters.* Washington DC: World Bank.

Kamran, M. (2017). The Effect of Watershed Subdivisions and Antecedent Moisture Condition on HEC-HMS Model Performance In The Ma Oya Basin In Sri Lanka. *University of Moratuwa, Sri Lanka (Master Thesis).*

Khandu, D. (2015). Monthly Water Balance Model for Evaluation of Climate Change Impacts on the Streamflow of Ginganga and Kelani Ganga Basins, Sri Lanka. *A thesis in Water Resources Engineering and Management (Master's Thesis)*. Retrieved from http://dl.lib.mrt.ac.lk/handle/123/1/browse?value=Khandu%2C+D&type=author

Klemes, V. (1986). Operational testing of hydrological simulation models. *Hydrological Sciences*, 13-24.

Koren, V., Finnerty, B., Schaake, J., Smith, M., Seo, D., & Duan, Q. (1999). Scale dependencies of hydrologic models to spatial variability of precipitation. *Journal of Hydrology*, 285-302.

Krajewski, W. F., Lakshmi, V., Georgakakos, K. P. & Jain, S. C. (1991) A Monte Carlo study of rainfall sampling effect on a distributed catchment model. *Water Resour. Res.* **27**(1), 119–128.

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

Kuczera, G. (1983a). Improved parameter inference in catchment models. *Water Resources*, 1151–1162.

Kuczera, G. (1983b). Improved parameter inference in catchment models. *Water Resources*, 1163–1172.

Langford, K., Duncan, H., & Heeps, D. (1978). Forecasting streamflow and storage using a soil dryness index model. *Rep. MMBWW0031*.

Legates, D., & McCabe, G. (1999). Evaluating the use of "goodness-of-fit" measures in hydrologic and hydroclimatic model validation. *WATER RESOURCES RESEARCH*, 233-241.

Leijnse, H., Uijlenhoet, R., & Stricker, J. (2007). Rainfall measurement using radio links from cellular communication networks. *Water Resources*.

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, 3*(4), 378-393.

Li, L., Zhang, L., Wang, H., Wang, J., Yang, J., Jiang, D., . . . Qin, D. (2007). Assessing the impact of climate variability and human activities on streamflow from the Wuding River basin in China. *Hydrological processes*, 3485-3491.

Linsley, K. R., & Crawford, N. (1960). Computation of a synthetic streamflow record on a digital computer. *IAHS Publ.*, 526-538.

Leijnse, H., Uijlenhoet, R., and Stricker, J.: Rainfall measurement using radio links from cellular communication networks, Water Resour. Res., 43, 2007.

Liang, X., Guo, J. & Leung L.R. (2004) Assessment of the effects of spatial resolutions on daily water flux simulations. *J. Hydrol*. **298**, 287–310.

Li, H., & Zhang, Y. (2017). Regionalising rainfall-runoff modelling for predicting daily runoff:Comparing gridded spatial proximity and gridded integrated similarity appraoches against their lumped counterparts. *Journal of Hydrology*, 279-293.

Lopes, V. L. (1996) On the effect of uncertainty in spatial distribution of rainfall on catchment modelling. *Catena* **28**,107–119.

Madsen, H. (2000). Automatic calibration of a conceptual rainfall–runoff model using multiple objectives. *Journal of Hydrology*, 276–288.

Madsen, H. (2003). Parameter estimation in distjributed hydrological catchment modelling using automatic calibration with multiple objectives. *Advances in Water Resources*, 205–216.

Makridakis, S. (1993). Accuracy measures: theoretical and practical concerns. *International Journal of Forecasting, 2*, 527-529.

Mathevet, T., Michel, C., Andréassian, V., & Perrin, C. (2006). A bounded version of the Nash-Sutcliffe criterion for better model assessment on large sets of basins. *Large Sample Basin Experiments for Hydrological Model Parameterization: Results of the Model Parameter*, 211-219.

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

Mayer, D. G. and D. G. Butler (1993), Statistical validation, Ecological Modelling, 68, 21-32.

Molden, D. (2007). *A Comprehensive Assessment of Water Management in Agriculture.* London: International Water Management Institute.

Moussa, R., & Chahinian, N. (2009). Comparison of different multi-objective calibration criteria using a conceptual rainfall-runoff model of flood events. *Hydrology and Earth System Science*, 2009.

Muelhi, S., Michel, C., Perrin, C., & Adreassian, V. (2006). Stepwise Development of a two-parameter monthly water balance model. *Science Direct*, 200-214.

Mutumala, S. (2016). The study for daily streamflow modeling of Kalu river basin in Sri Lanka using HEC-HMS. *University of Moratuwa (Unpublished Master's Thesis).*

Moriasi, D., Arnold, J., Liew, M. V., 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, 50*(3), 885−900.

Moriasi, D., Wilson, B., Douglas-Mankin, K., Arnold, J., & Gowda, P. (2012). Hydrologic and Water Quality Models: Use, Calibration, and Validation. *American Society of Agricultural and Biological Engineers, 55*(4), 1241-1247.

Musiake, K., & Wijesekera, N.T.S. (1990). Streamflow modelling of a Sri Lankan catchment considering spatial variation of rainfall. *Association of Civil Engineers.* Tokyo: Japan Society of Hydrology and Water Resources.

Nash, J. E. and J. V. Sutcliffe (1970), River flow forecasting through conceptual models part I -- A discussion of principles, Journal of Hydrology, 10, 282-290.

National Water Supply and Drainage Board. (2002). *National Drinking Water Policy*. Colombo: Ministry of Water Supply & Drainage.

National Climatic Data Center [NCDC]. (2019). P*ricing and Other Information for Climatic Data Online*. *Retrieved from National Centers for Environmental Information*: https://www.ncdc.noaa.gov/

Niemczynowicz, J. (1988). The rainfall movement - A valuable complement to short-term rainfall data. *Journaly of Hydrology* , 311-326.

OECD. (2013). *Water and Climate Change Adaptation: Climate change impacts on water systems.* Sweden: OECD Secretariat.

Obled, C. H., Wendling, J. & Beven, K. (1994) The sensitivity of hydrological models to spatial rainfall patterns: anevaluation using observed data. *J. Hydrol*. **159**, 305–333.

Organization World Meteorological. (1982). WMO project for the intercomparison of conceputal models for snowmelt runoff. *Hydrological Aspects of Alpine and High Mountain Area*, 193-202.

Pechlivanidis, I., McIntyre, N., & Wheater, H. (2008). The Significance of Spatial Variability of Rainfall on Runoff. *International Congress on Environmental Modelling and Software*, 478-485.

Peleg, N., Blumensaat, F., Molnar, P., Fatichi, S., and Burlando,P.: Partitioning the impacts of spatial and climatological rainfall variability in urban drainage modeling, Hydrol. Earth Syst.Sci., 21, 1559–1572, ,2017.

Ponrajah, A. (1988). *Technical Guidelines for Irrigation Works.* Colombo: Irrigation Department of Sri Lanka.

Presti, R. L., Barca, E., & Passarella, G. (2009). A methodology for treating missing data applied to daily rainfall data in the Candelaro River Basin (Italy). *Environmental Monitoring and Assessment*, 1–22.

Risley, John, Stonewall, Adam, & Tana, H. (2008). *Estimating flow-duration and low-flow frequency statistics for unregulated streams in Oregon.* U.S. Geological Survey Scientific Investigations.

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

Salvadore, E., Bronders, J., & Batelaan, O. (2015). Hydrological modelling of urbanized catchments: A review and future directions. *Journal of Hydrology*, 61–81.

Saville, T., & Watson, J. (1933). An investigation of flow-drtition characteristics of North Carolina streams. *American Geophysics Union Trans*, 406-425.

Searcy , J. (1959). Manual of Hydrology: Part2. Low-Flow Techniques Flow-Duration Curves. *USGS WSP 1542-A.*, 542-A.

Segond, M.-L., Wheater, H., & Onof, C. (2007). The significance of spatial rainfall representation for flood runoff estimation: A numerical evaluation based on the Lee catchment. *Journal of Hydrology*, 116-131.

SERVAT, E., & DEZETTER, A. (1991). Selection of calibration objective fonctions in the context of rainfall-ronoff modelling in a Sudanese savannah area. *Hydrological Sciences Journal*, 307-330.

Sattari, M.-T., Joudi, A. R., & Kusiak, A. (2016). Assessment of different methods for estimation of missing data in precipitation studies. *Hydrology Research*, 1-13.

Sharifi, M. (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 and Mahaweli Rivers of Sri Lanka. *A thesis in Water Resources Engineering and Management (Master's Thesis), University of Moratuwa, Sri Lanka*.

Singh, V. (1997). Effect of spatial and temporal variability in rainfall and watershed characteristics on stream flow hydrograph. *Hydrological Processes,* 1649-1669.

Singh, J., H. V. Knapp, J. G. Arnold, and M. Demissie. 2005. Hydrologic modeling of the Iroquois River watershed using HSPF and SWAT. J. American Water Resources Assoc. 41(2): 361-375.

Sierra, K., Evans, J. W., MacKinnon, K., Cantrell, J., Livernash, R. T., Cantrell, J., & Sunderland, J. (2009). *Enivronment Matters at the World Bank.* Washington: World Bank Publications.

Simolo, C., Brunetti, M., Maugeri, M., & Nanni, T. (2010). Improving estimation of missing values in daily precipitation series by a probability density function-preserving approach. *INTERNATIONAL JOURNAL OF CLIMATOLOGY,* 1564–1576.

Singh, V., & Xu, C.-Y. (1988). A review on monthly water balance models for water resources investigations. *Water Resources Management*, 31-50.

SIWI. (2014). *World Water Week in Stockholm Engergy and Water.* Stockholm: Stockholm International Water Institute.

Sharma, K. D., Sorooshian, S. and Wheater, H., 2008. Hydrological Modelling in Arid and Semi-Arid Areas. New York : *Cambridge University Press*. 223 p. ISBN-13 978-0-511-37710-5.

Smakhtin, V. (2001). Low flow hydrology: a review. *Journal of hydrology*, 147-186.

Smith, M., Koren, V., Zhang, Z., Reed, S., Pan, J., & Moreda, F. (2004). Runoff response to spatial variability in precipitation: an analysis of observed data. *Journal of Hydrology*, 267-286.

Sokolov, A., & Chapman, T. (1974). Methods for water balance computation (An international guide for research and practice). *Paris: UNESCO Press.*

Sorooshian, S., Gupta, V., & Fulton, J. (1983). Evaluation of maximum likelihood parameter estimation techniques for conceptual rainfall-runoff models: Influence of calibration data variability and length on model credibility. *Water Resources Research*, 251-259.

Srinivasan, R., Jaehak , J., Narayanan , K., Jeff , A., Roger , G., & Leila, G. (2010). Development and Integration of Sub-hourly Rainfall–Runoff Modeling Capability Within a Watershed Model. *Water Resource Management*.

Stephenson, D. (1979) Direct optimization of Muskingum routing coefficients. *Journal of Hydrology*. 41, 161-165.

Sugiyama, H., Vudhivanich, V., Whitaker, A., & Lorsirirat, K. (2003). Stochastic flow duration curves for evaluation of flow regimes in rivers. *AWRA Journal of the American Water Resources Association*, 47-58.

Sung, J., & Chung, E. (2014). Development of streamflow drought severity–duration–frequency curves using the threshold level method. *Hydrological Earth Science*, 3341-3351.

Thapa, B. R., Ishidaira, H., & Pandey, V. P. (2017). A multi-model approach for analyzing water balance balancedynamics in Kathmandu Valley, Nepal. *Journal of Hydrology*, 149-162.

Tegegne, G., Park, D. K., & Kim, Y.-O. (2017). Comparison of hydrological models for assessment of water resources in a data-scarce region, the upper blue Nile river basin. *Journal of Hydrology : Regional Studies*, 49-66.

Tetzlaff, D. and S. Uhlenbrook, Significance of spatial variability in precipitation for process-oriented modelling: results from two nested catchments using radar and ground station data, *Hydrology and Earth System Sciences*, vol. 9, no. 1-2, pp. 29-41, 2005.

Tofallis, C. (2015). A better measure of relative prediction accuracy for model selection and model estimation. *Journal of the Operational Research Society, 66*, 1352–1362.

Trask, J., Fogg, G., & Puente, C. (2017). Resolving hydrologic water balances through a novel error analysis approach, with application to the Tahao basin. *Journal of Hydrology*, 326-340.

Vandewiele, G., & Ni-Lar-Win. (1998). Monthly water balance models for 55 basins in 10 countries. *Hydrological Sciences*, 667-699.

Wagener, T., Boyle, D. P., Lees, M. J., Wheater, H. S., Gupta, H. V., & Sorooshian, S. (2001). A framework for development and application of hydrological models. *Hydrology and Earth System Sciences, 5*, 13–26.

Wang, B., & Xu, Z. (2015). Spatial and Temporal variation of precipitation in Haihe River basin in the recent 53 years. (IAHS, Ed.) *Remote Sensing and GIS for Hydrology and Water Resources*, 138-143.

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

Wanniarchchi, S. (2013). Mathematical modelling of watershed runoff coefficient for reliable estimations to meet the future challenges of development in Sri Lanka. *ENGINEER, 2*, 59-68.

Wijesekera, N.T.S. (2000). Parameter estimation in watershed models a case study of Gin Ganga watershed. *The Institution of Engineer*.

Wijesekera, N. (2017). Classification of Streamflow Observations for Water Management. *Department of Civil Engineering, University of Moratuwa*.

Wijesekera, N.T.S, & Abeynayake, J. (2003). Watershed Similarity Conditions for Peakflow Transposition - A Study of River Basins in the Wet Zone of Sri Lanka. *Journal of the Institution of Engineers, Sri Lanka*, 26-31.

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

Wijesekera, N.T.S, & Rajapakse, R. (2013). Mathematical Modelling of Watershed Wetland Crossings for Flood Mitigation and Groundwater Enhancement - Case of the Attanagalu Oya River Basin. *Engineers*, 55-67.

Wijesekera, N.T.S, & Perera, L. (2012). Key issues of data and data checking for hydrological analyses - Case study of Rainfall data in the Attanagalu Oya basin of Sri Lanka. *Engineer*, 1-12.

Wilson, C. B., Valdes, J. B. & Rodriguez-Iturbe, I. (1979) On the influence of the spatial distribution of rainfall on storm runoff. *Water Resour. Res.* **15**(2), 321–328.

WMO. (2008). *Guide to Hydrological Practices.* Geneva: World Meteorological Organization (WMO).

WMO. (2008). *Guide to hydrological practices.* Geneva: Publications Board of World Meteorological Organization.

Woods , R., & Sivapalan, M. (1999). A synthesis of space-time variability in storm response rainfall, runoff generation and routing. *Water Resources Research*, 2469-2489.

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

Xu, C.-Y. (1999). Estimation of parameter of a conceptual water balance model for unguaged catchments. *Water Resources Management*, 353-368.

Yapo, P. O., Gupta, H. V., & Sorooshian, S. (1998). Multi-objective global optimization for hydrologic models. *Journal of Hydrology*, 83-97.

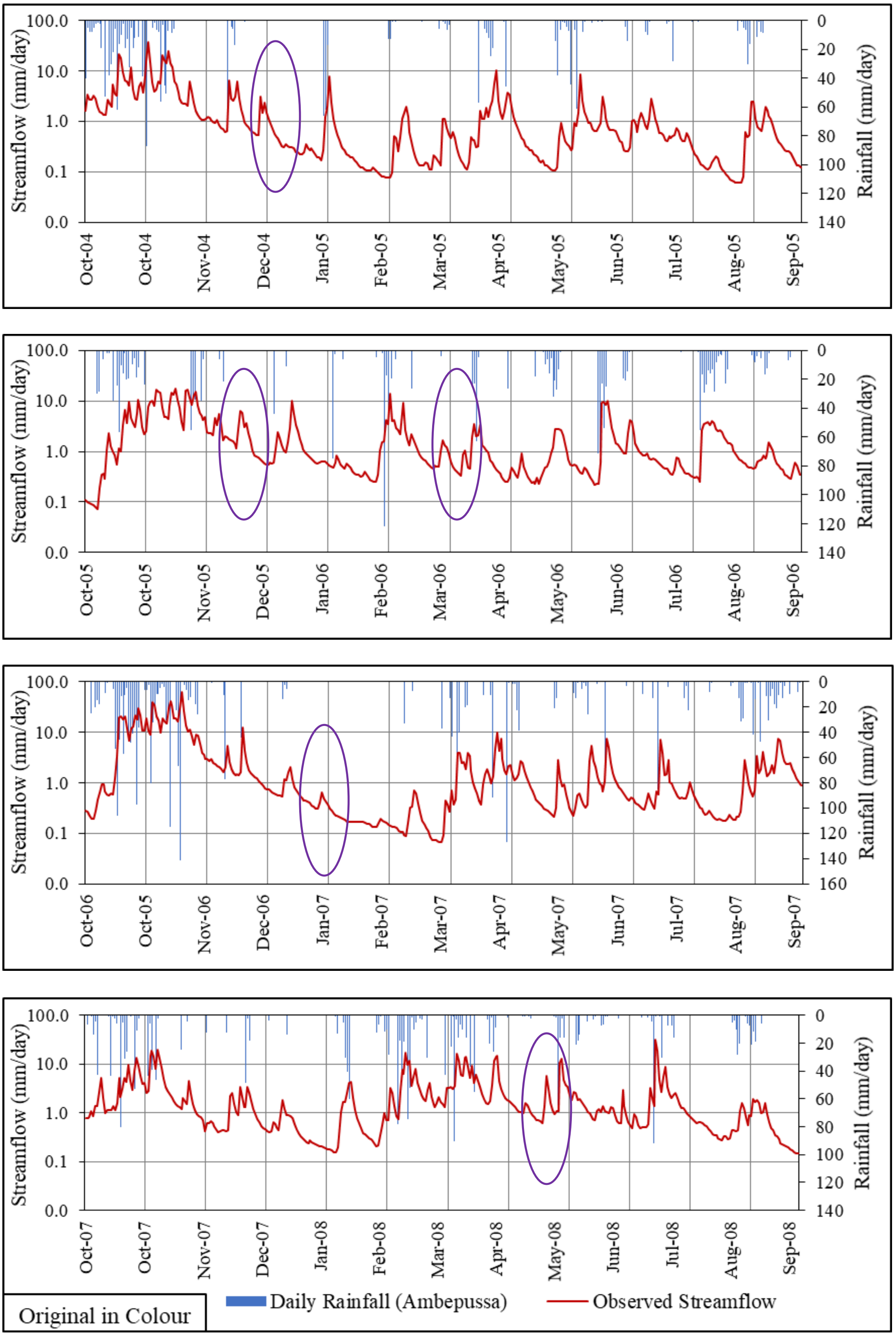
Yapo, O. P., Gupta, H. V., & Sorooshian, S. (1983). Automatic calibration of conceptual rainfall-runoff models:sensitivity to calibration data. *Journal of Hydrology*, 23-48.

Yu, P.-S., & Yang, T.-C. (2000). Fuzzy multi-objective function for rainfall-runoff model calibration. *Journal of Hydrology*, 1–14.

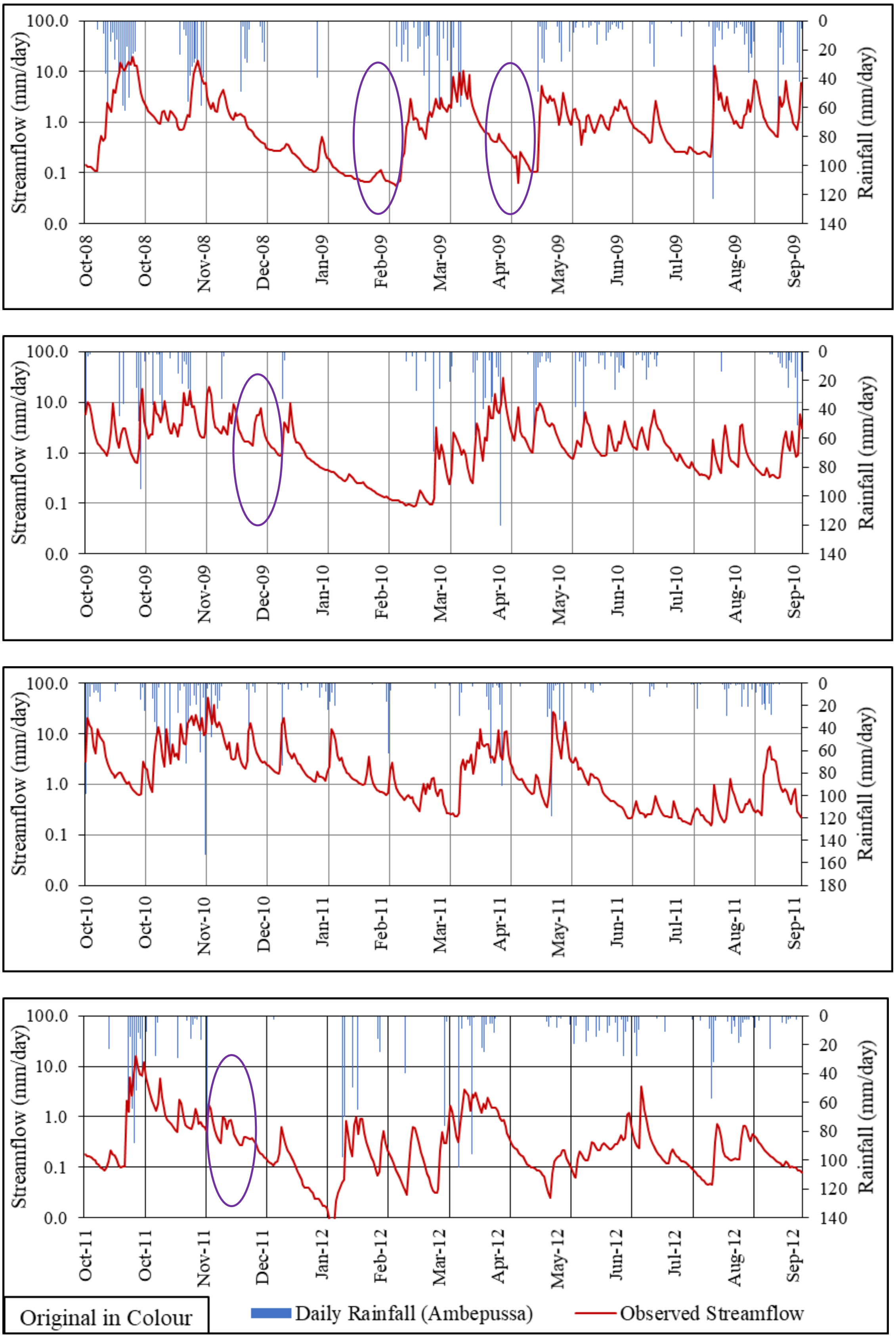
Zheng, H., Chiew, F. H., & Charles, S. (2015). CMIP5 climate change projections for hydrological. *21st International Congress on Modelling and Simulation*, (pp. 2409-2415). Gold Coast.

ANNEX A - 1

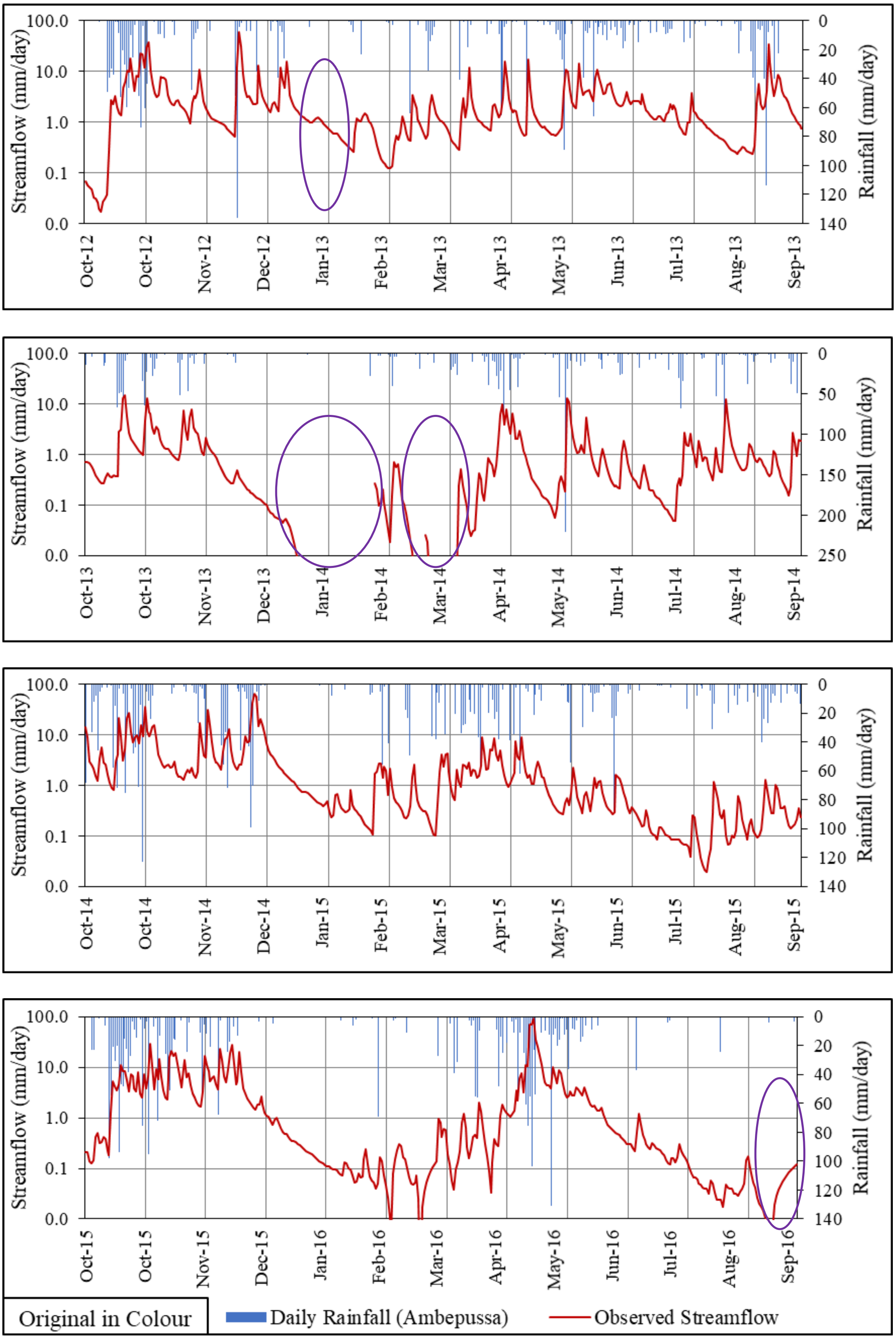
(Ambepussa, Andigama, Aranayaka & Eraminigolla Daily Rainfall – Runoff Graphs)



Figures (A.1) Daily rainfall and observed streamflow of Ambepussa (Oct 2004 – Sep 2008)



Figures (A.2) Daily rainfall and observed streamflow of Ambepussa (Oct 2008 – Sep 2012)



Figures (A.3) Daily rainfall and observed streamflow of Ambepussa (Oct 2012 – Sep 2016)

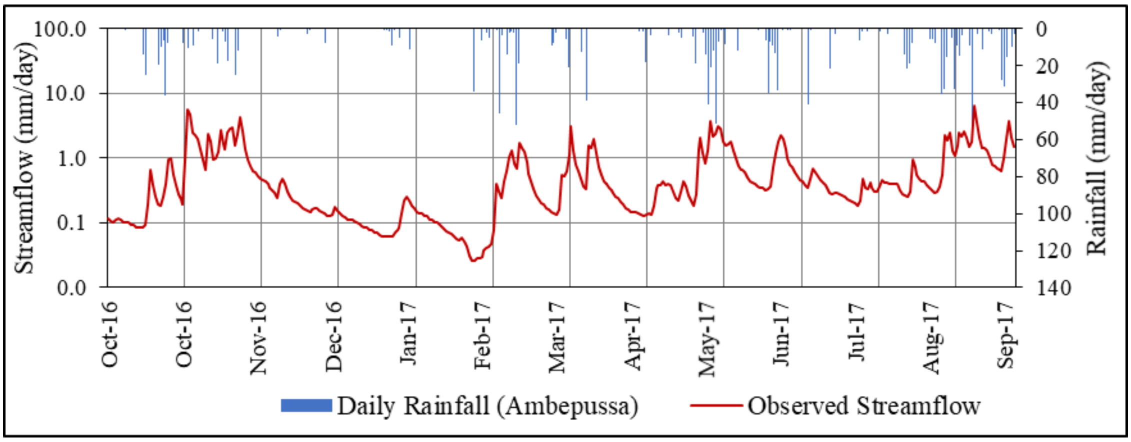
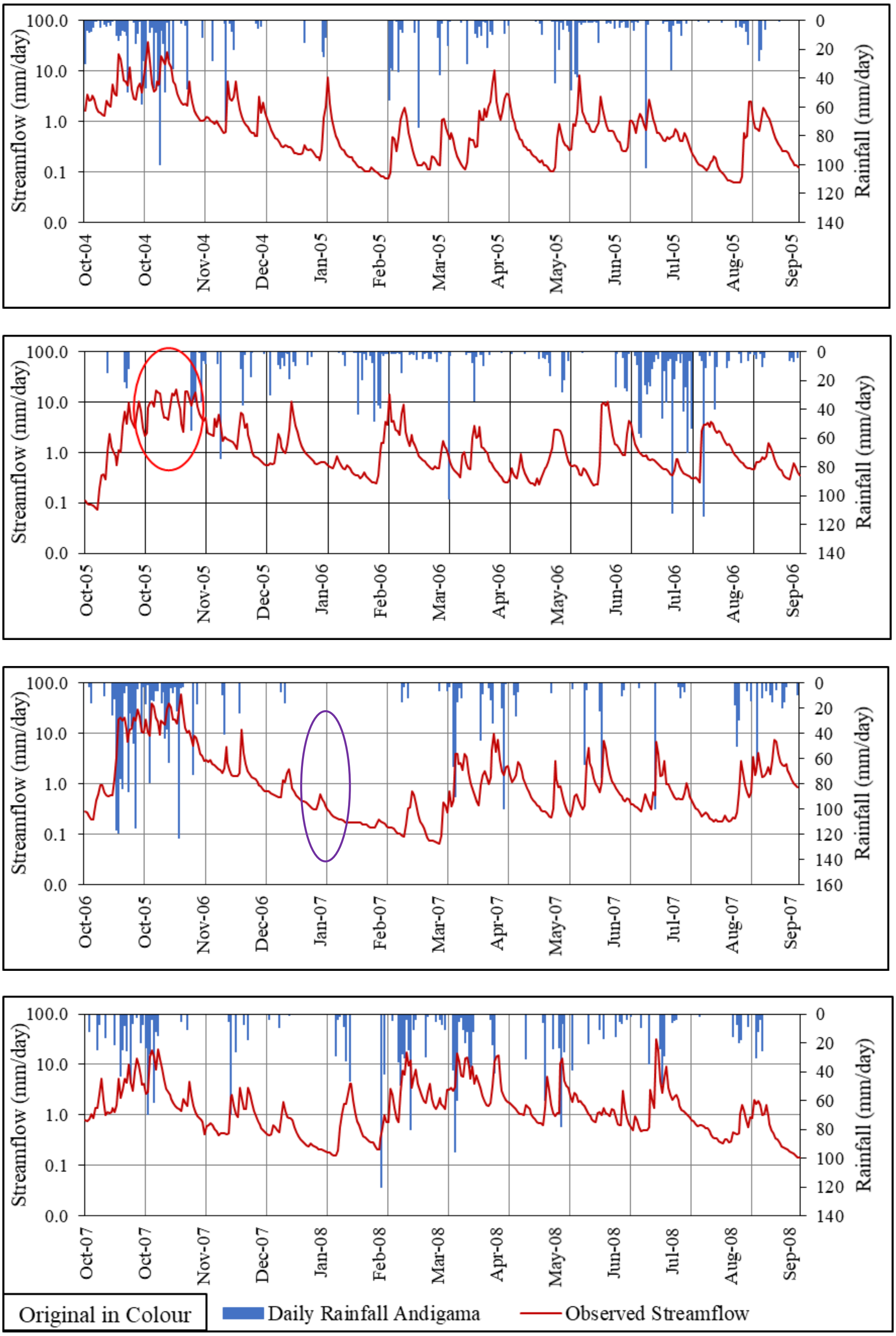
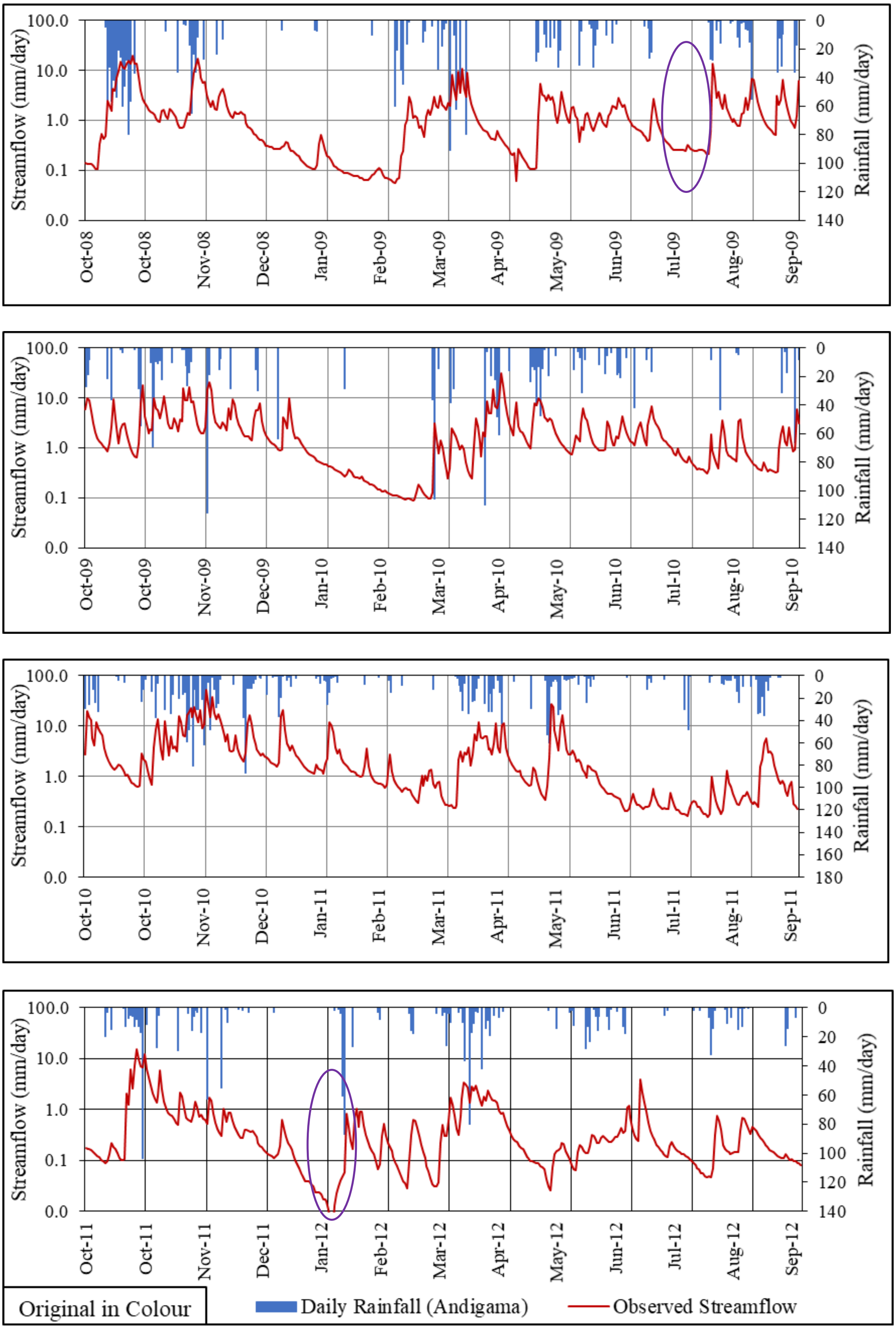


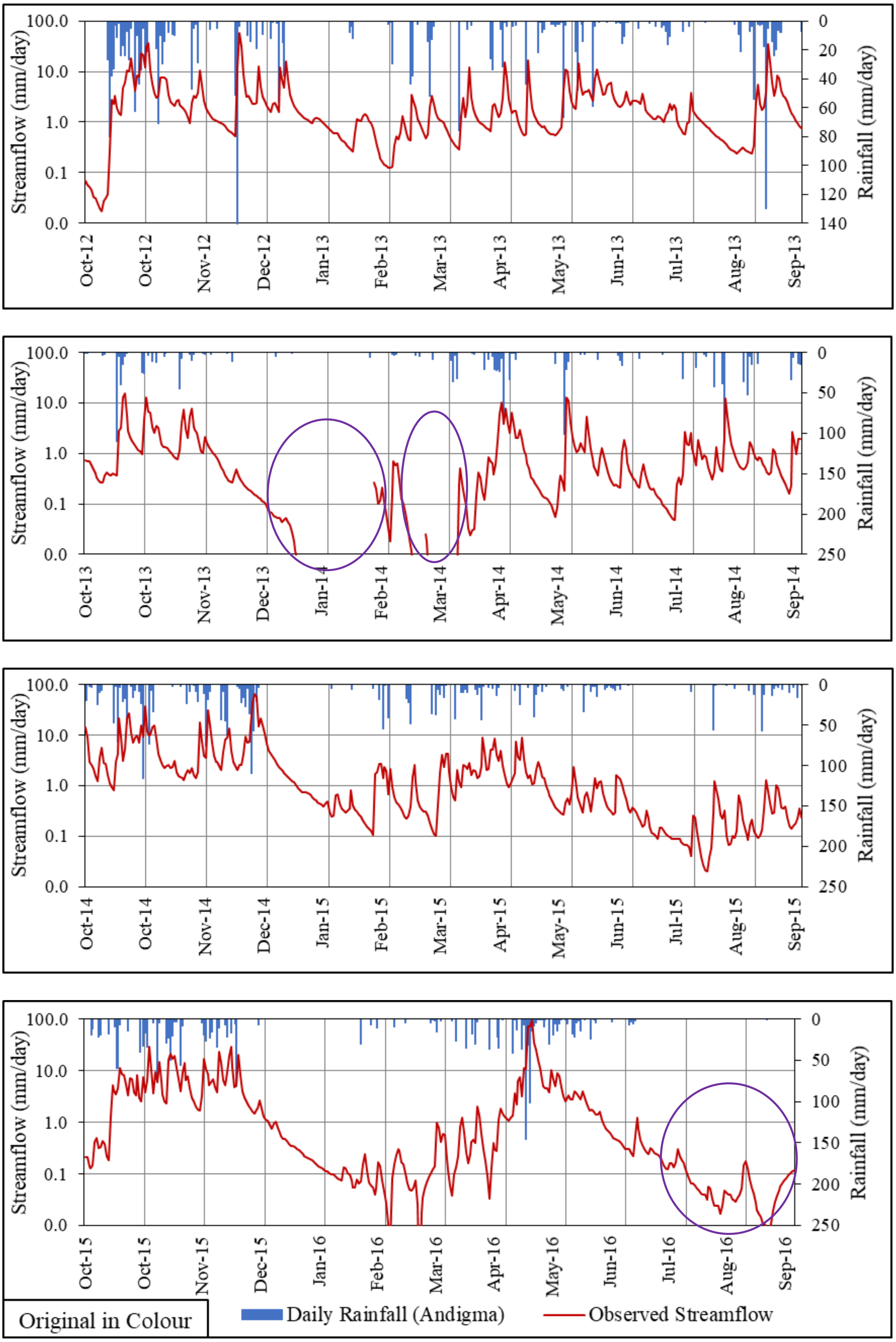
Figure (A.4) Daily rainfall and observed streamflow of Ambepussa (Oct 2016 – Sep 2017)



Figures (A.5) Daily rainfall and observed streamflow of Andigama (Oct 2004 – Sep 2008)



Figures (A.6) Daily rainfall and observed streamflow of Andigama (Oct 2008 – Sep 2012)



Figures (A.7) Daily rainfall and observed streamflow of Andigama (Oct 2012 – Sep 2016)

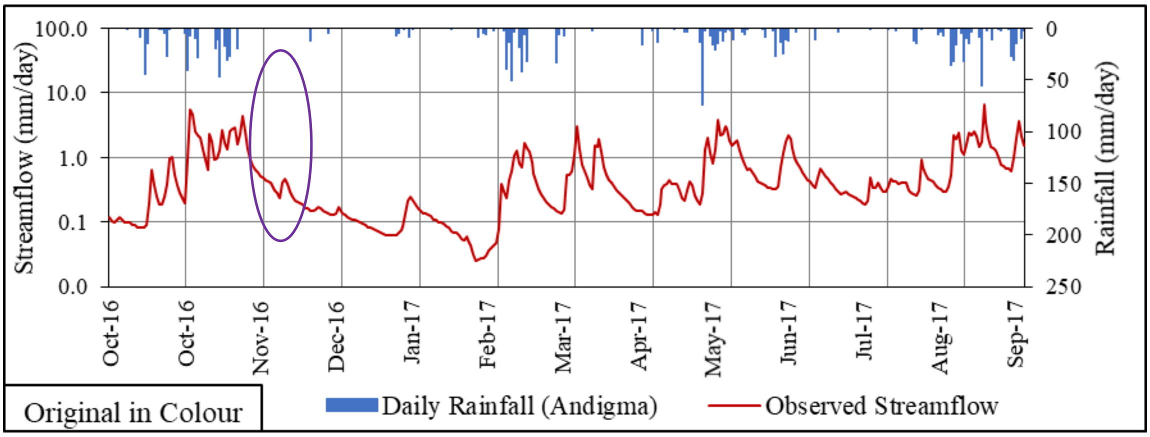
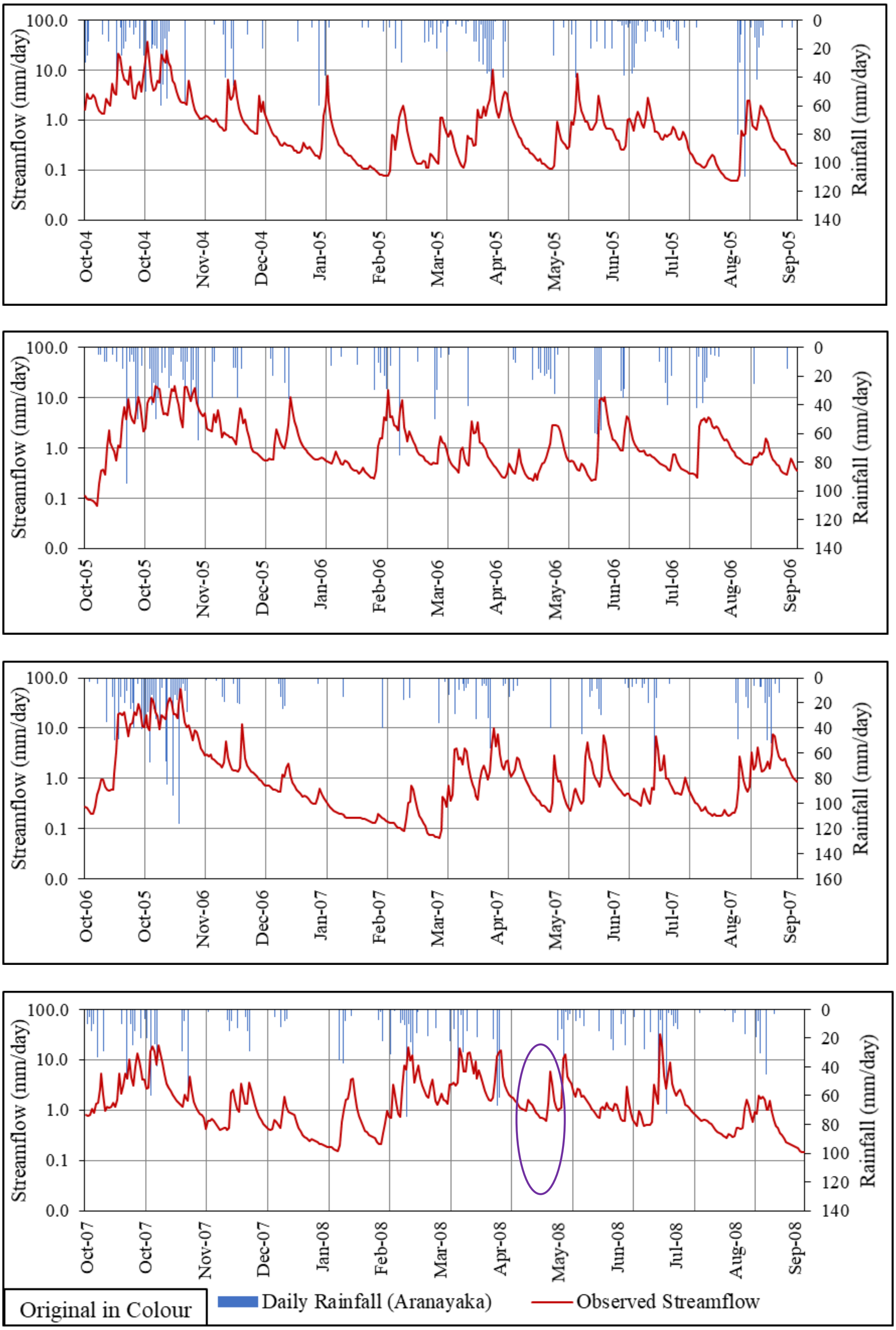
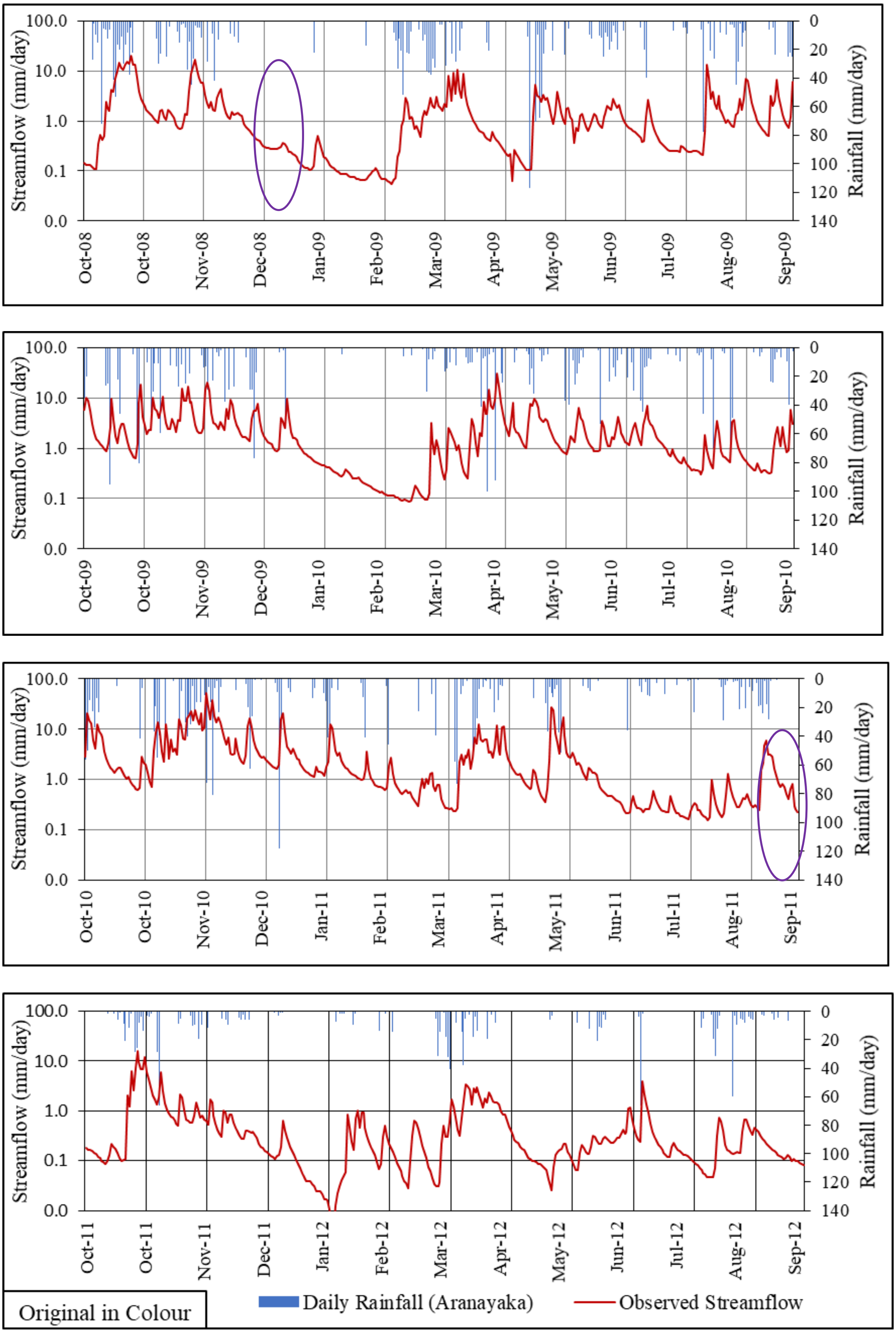


Figure (A.8) Daily rainfall and observed streamflow of Andigama (Oct 2017 – Sep 2016)



Figures (A.9) Daily rainfall and observed streamflow of Aranayaka (Oct 2004 -Sep 2008)



Figures (A.10) Daily rainfall and observed streamflow of Aranayaka (Oct 2008 - Sep 2012)

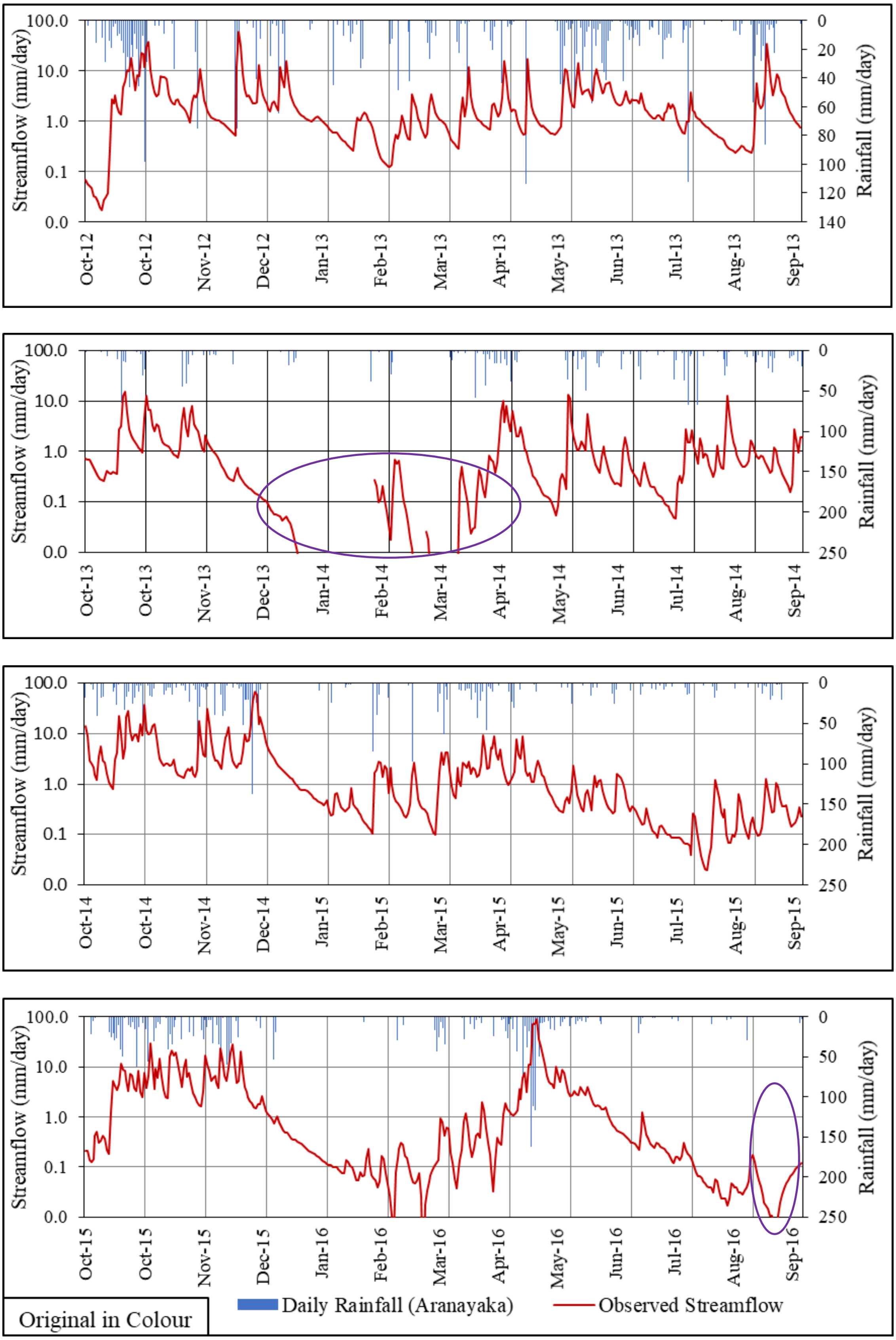
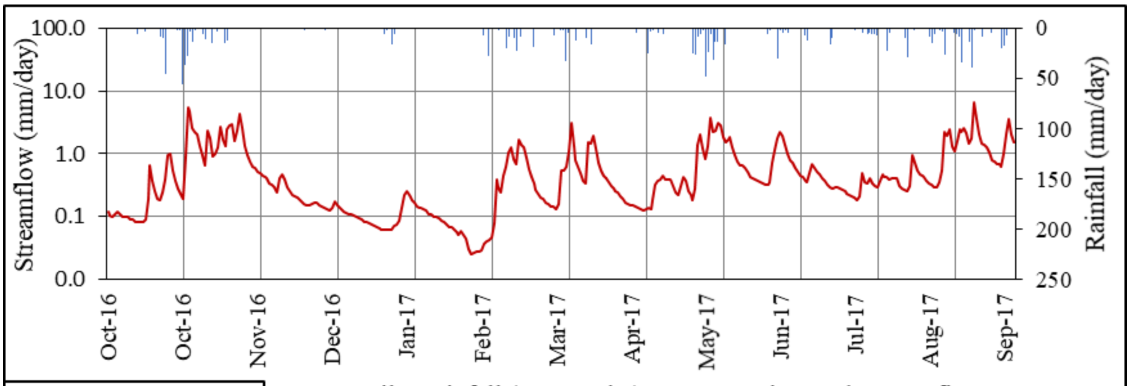
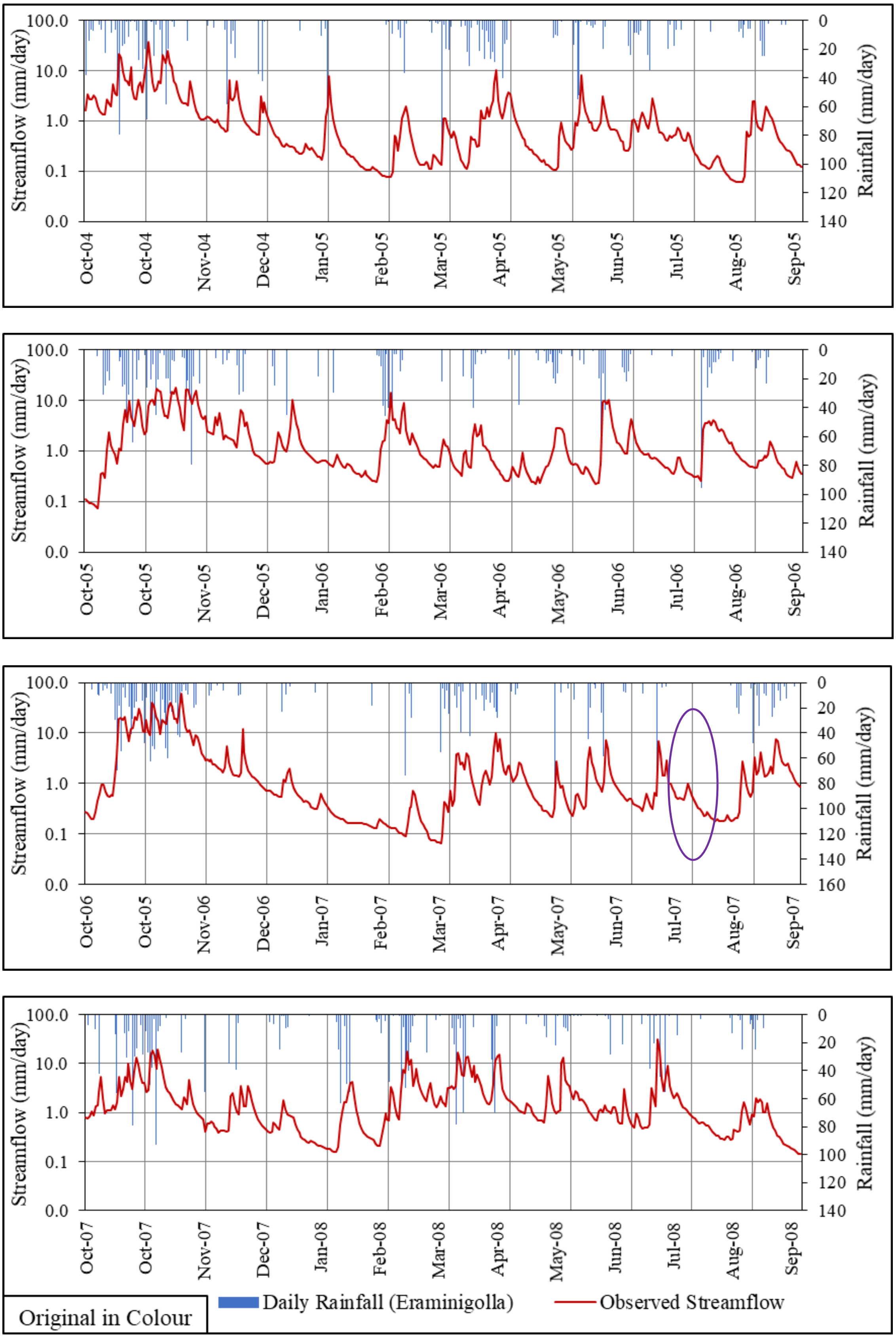


Figure (A.11) Daily rainfall and observed streamflow of Aranayaka (Oct 2012 - Sep 2016)

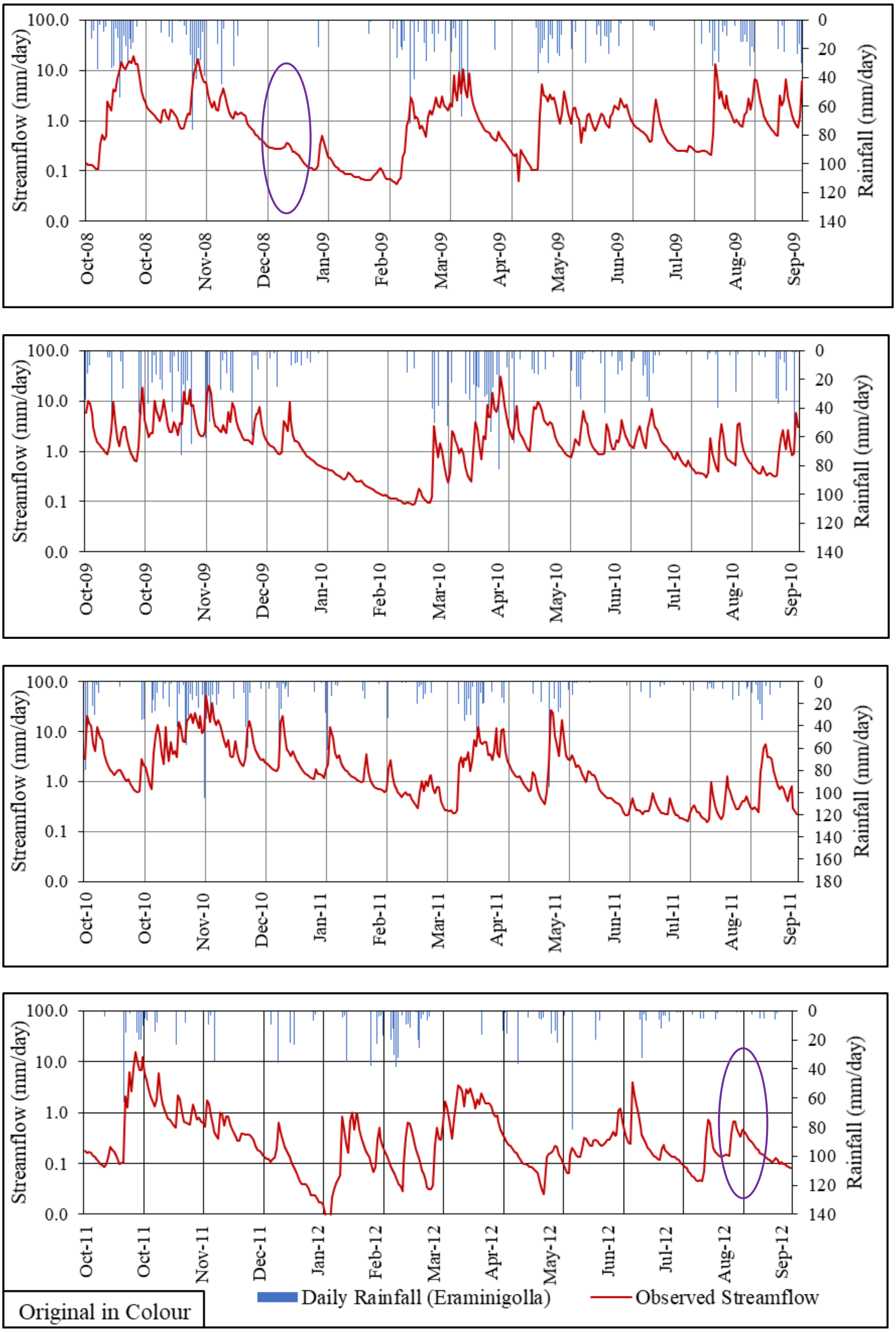


Original in Colour

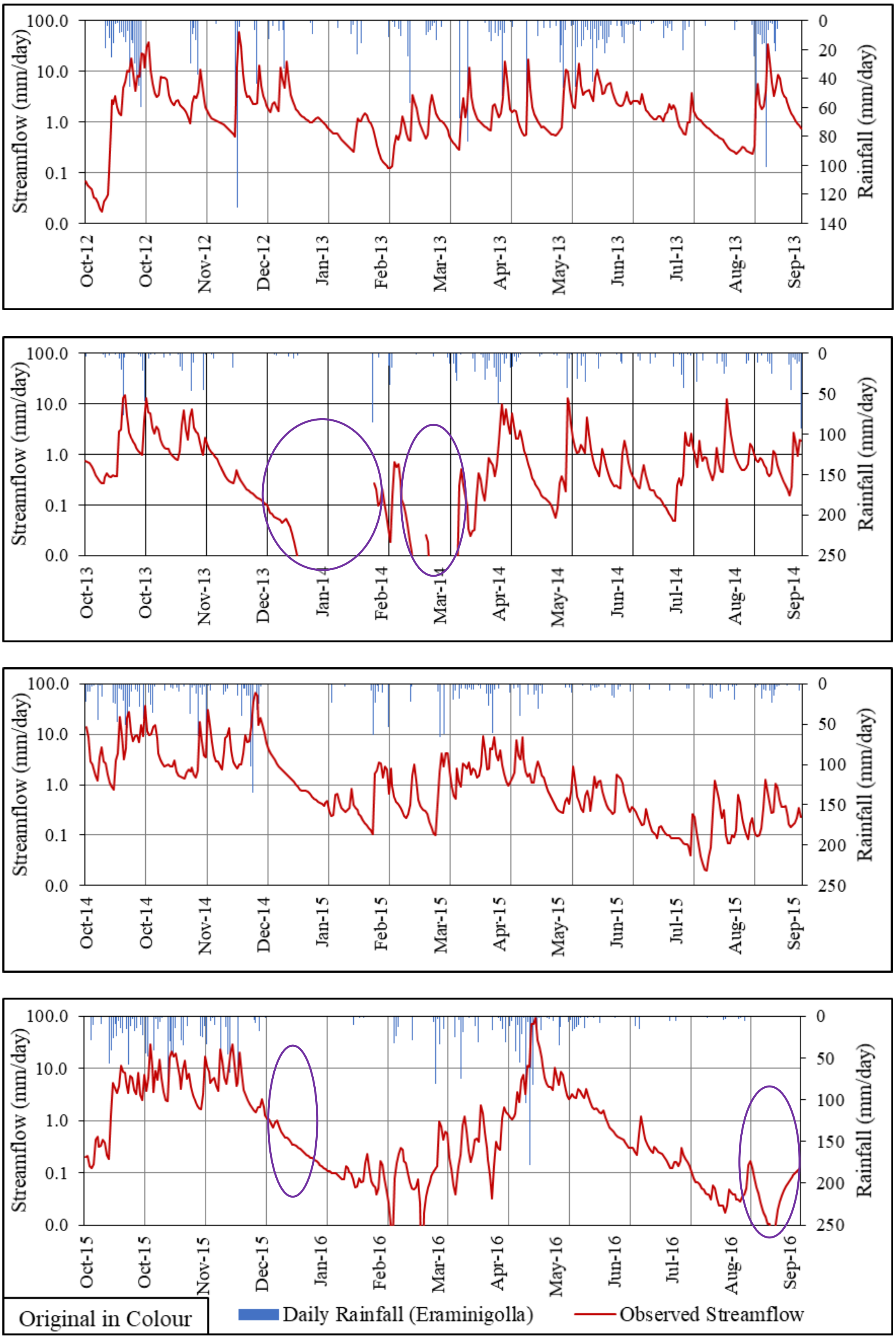
Figure (A.12) Daily rainfall and observed streamflow of Aranayaka (Oct 2016 – Sep 2017)



Figures(A.13) Daily rainfall and observed streamflow of Eraminigolla(Oct 2004-Sep 2008)



Figures(A.14) Daily rainfall and observed streamflow of Eraminigolla(Oct 2008-Sep 2012)



Figures(A.15) Daily rainfall and observed streamflow of Eraminigolla (Oct 2012-Sep 2016)

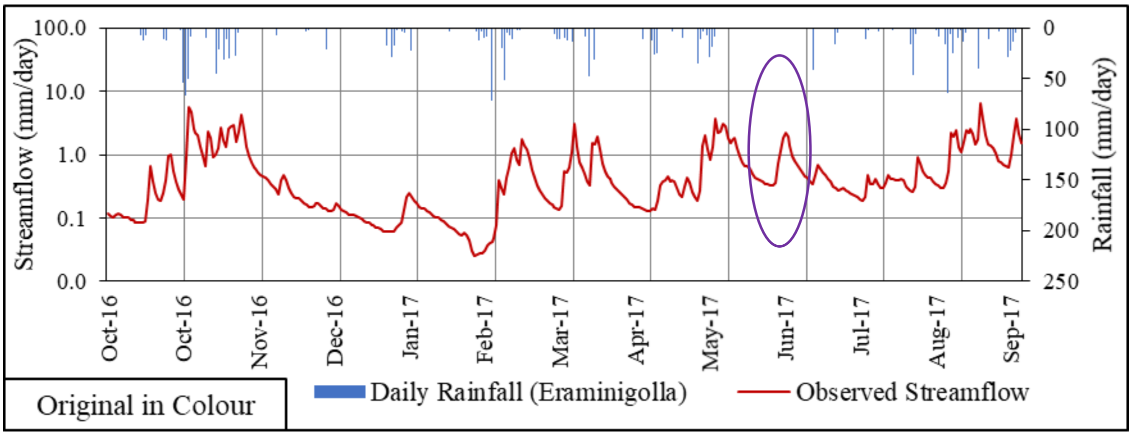
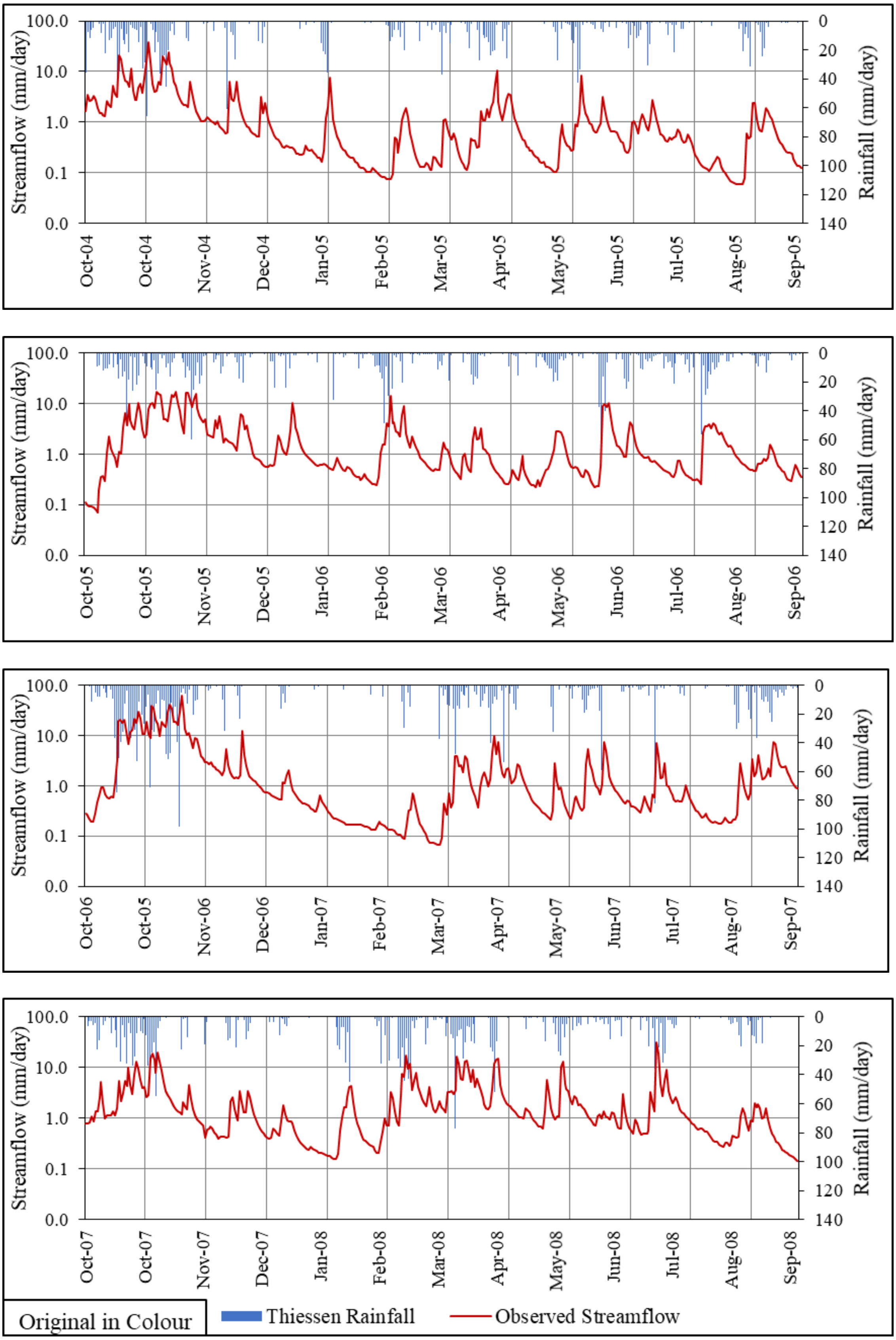


Figure (A.16) Daily rainfall and observed streamflow of Eraminigolla (Oct 2016-Sep 2017)

ANNEX A - 2

(Thiessen Daily Rainfall – Runoff Graphs)



Figures (A 2.1) Thiessen rainfall and observed streamflow of Badalgama (Oct 2004-Sep 2008)

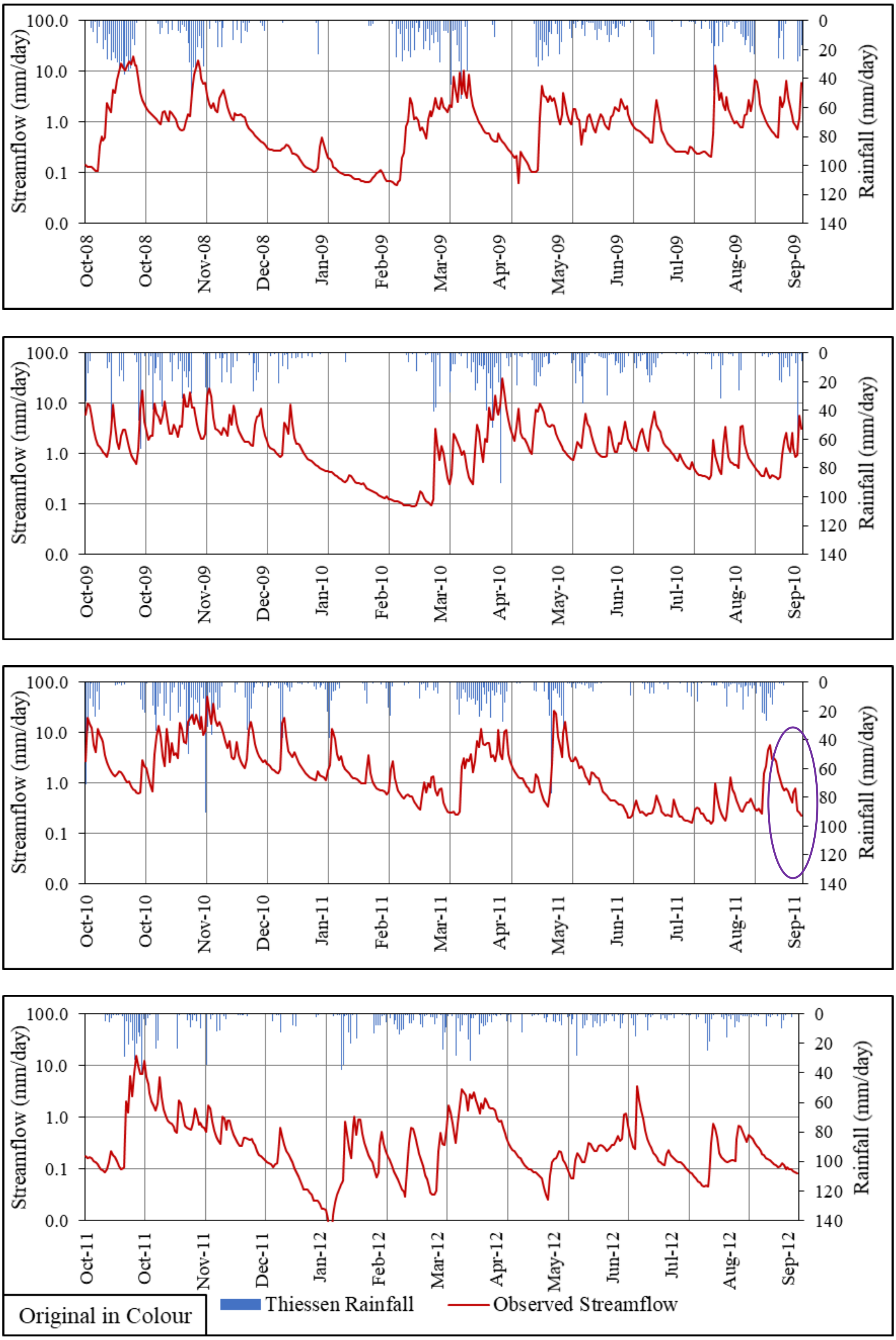


Figure (A 2.2) Thiessen rainfall and observed streamflow of Badalgama (Oct 2008- Sep 2012)

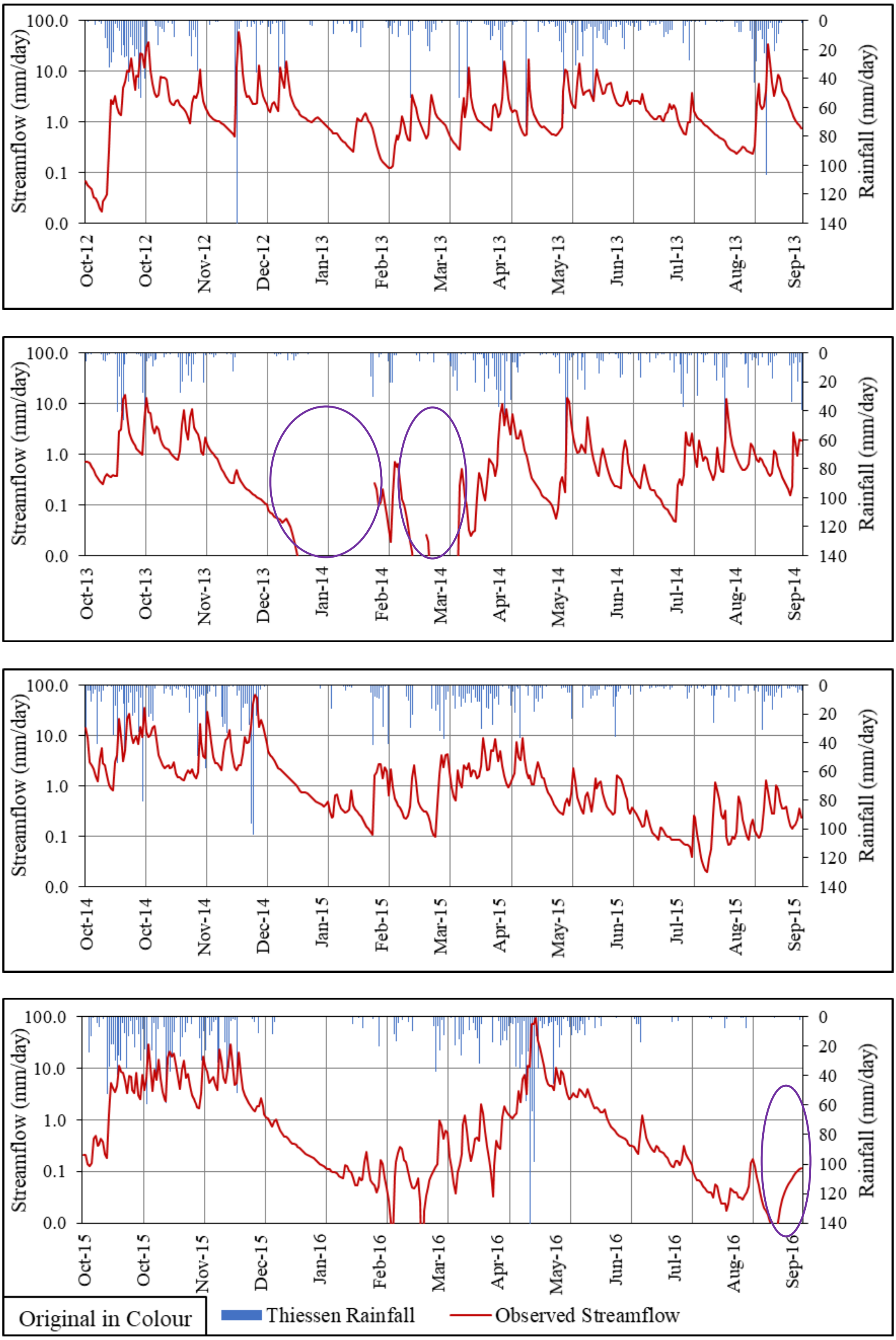


Figure (A 2.3) Thiessen rainfall and observed streamflow of Badalgama (Oct 2012- Sep 2016)

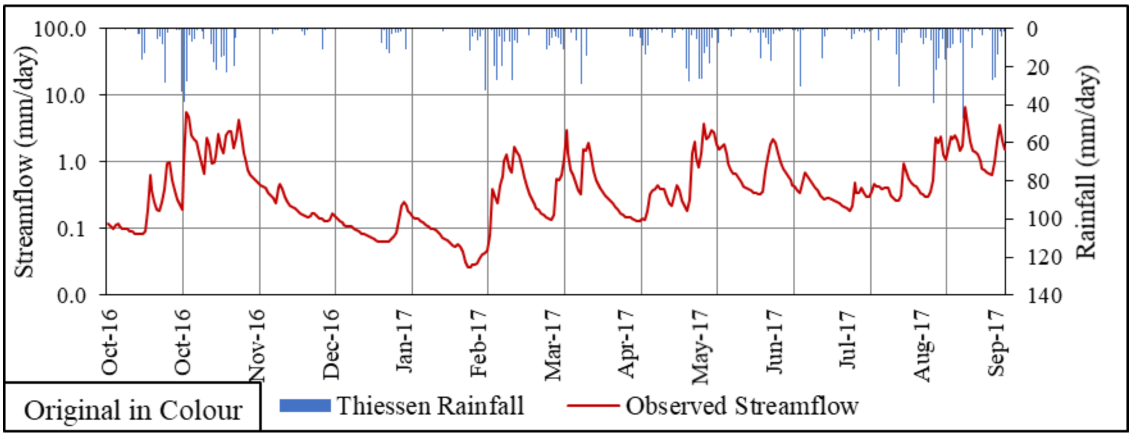


Figure (A 2.4) Thiessen rainfall and observed streamflow of Badalgama (Oct 2016- Sep 2017)

ANNEX A - 3

(Monthly Rainfall, Evaporation and Streamflow variation)

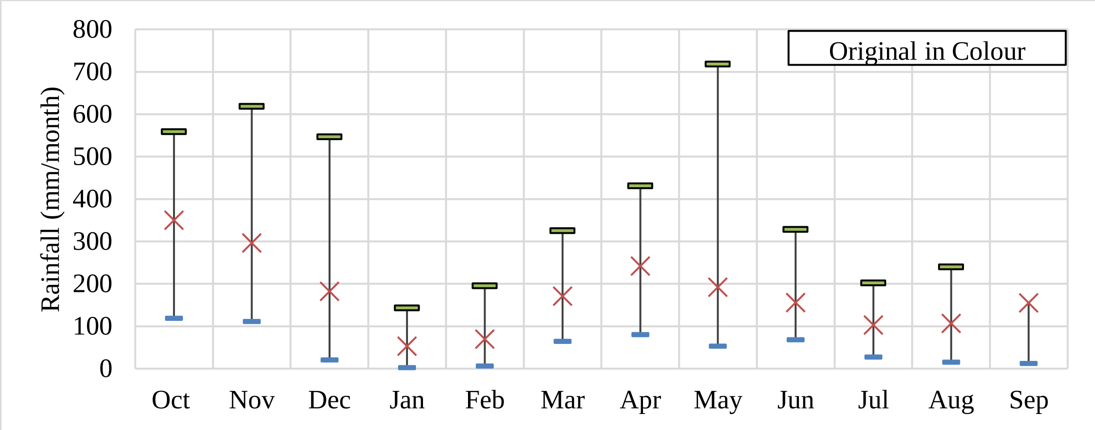


Figure (A-3.1): Thiessen Rainfall monthly data variation for Badalgama watershed

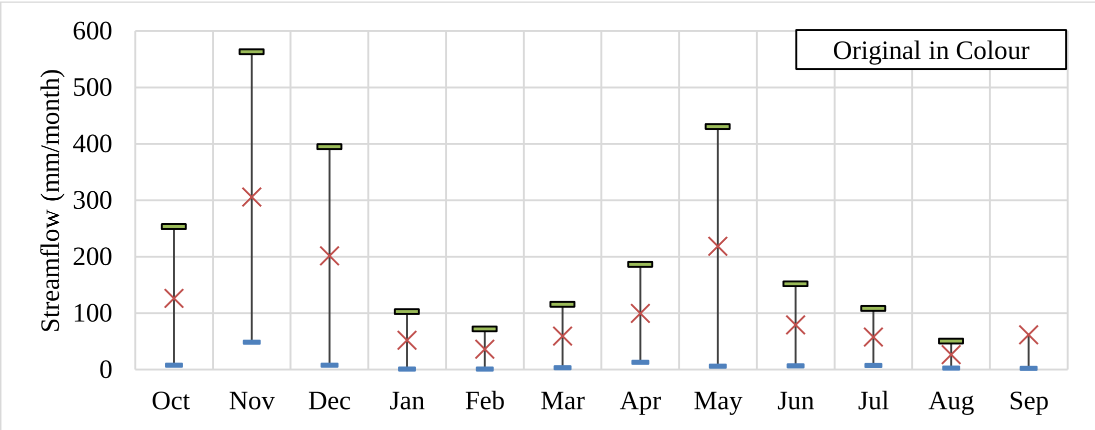


Figure (A-3.2): Streamflow monthly data variation for Badalgama watershed

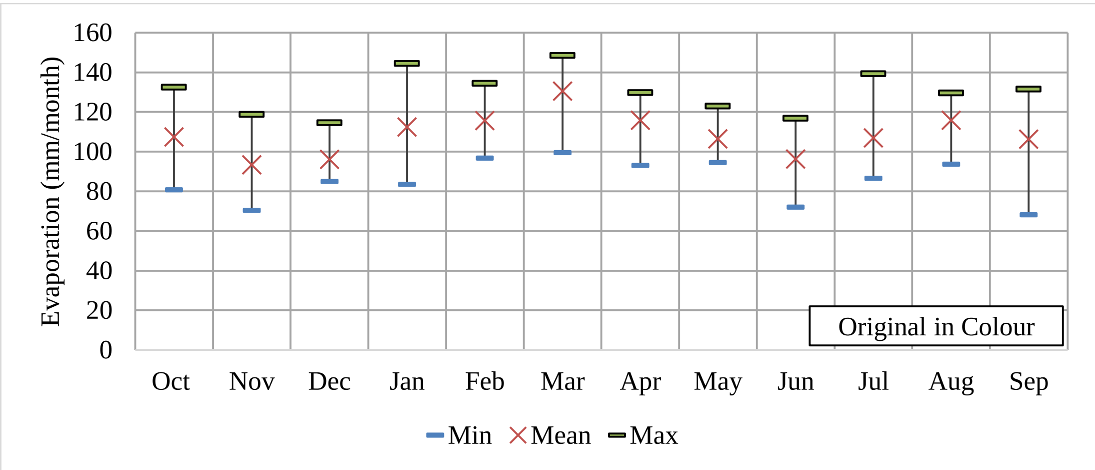


Figure (A-3.3): Evaporation monthly data variation for Badalgama watershed

ANNEX A - 4

(Monthly Variation for Year Wise Check of Rainfall Stations)

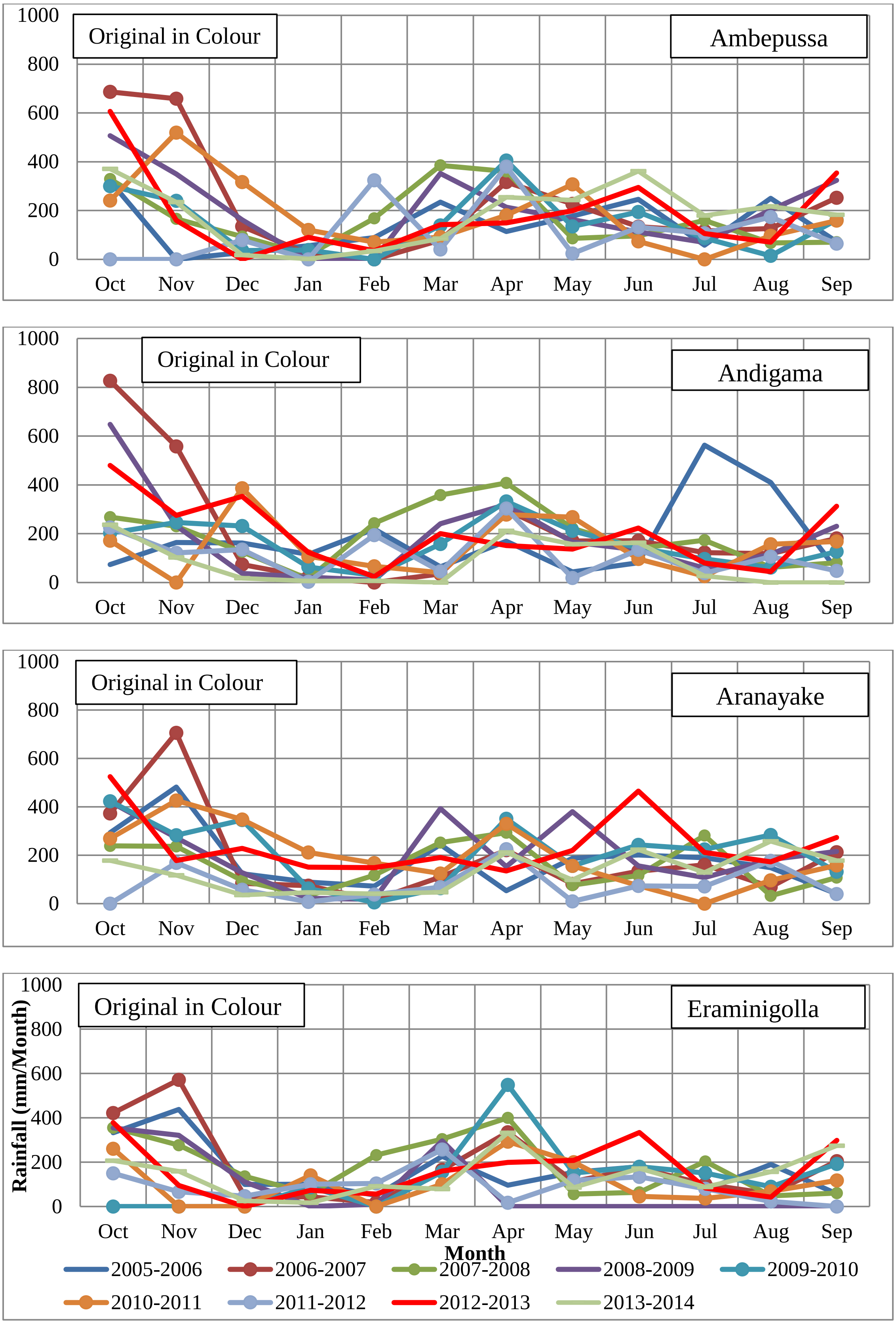


Figure (A-4.1) Year by year comparison for rainfall stations of Badalgama watershed

ANNEX A - 5

(Monthly Variation for year wise check of Streamflow and Pan Evaporation Stations)

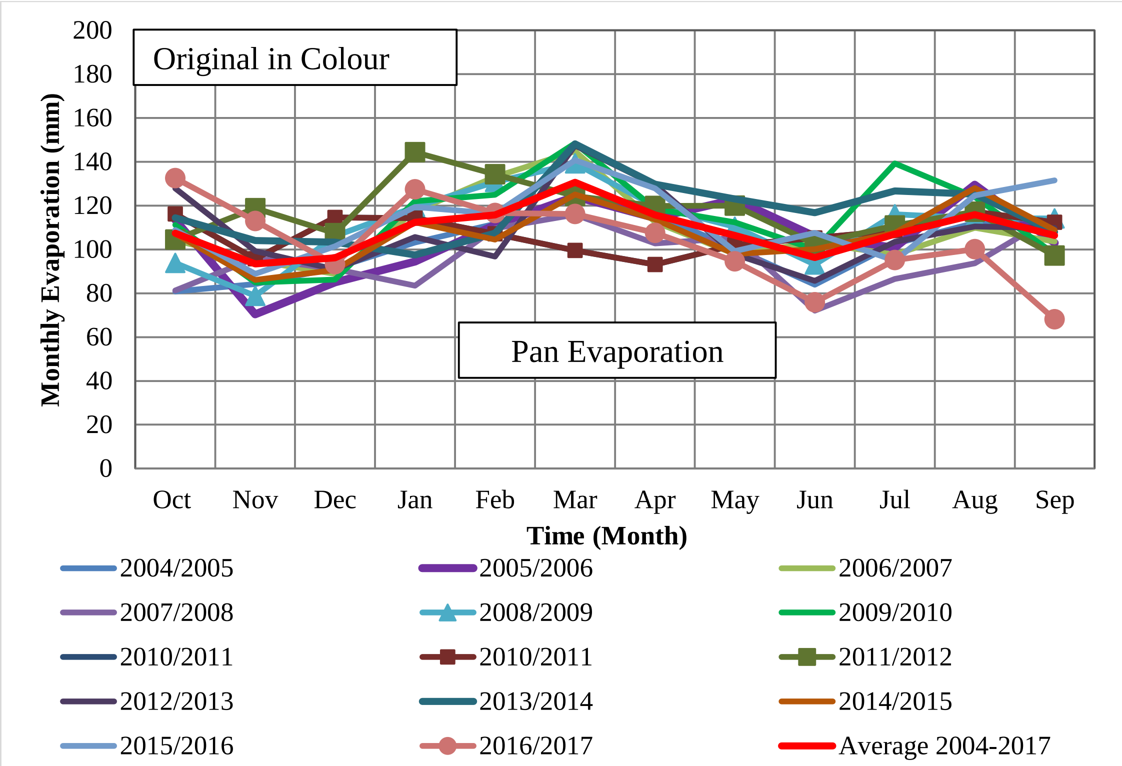


Figure (A-5.1) Year by year comparison for evaporation of Badalgama watershed

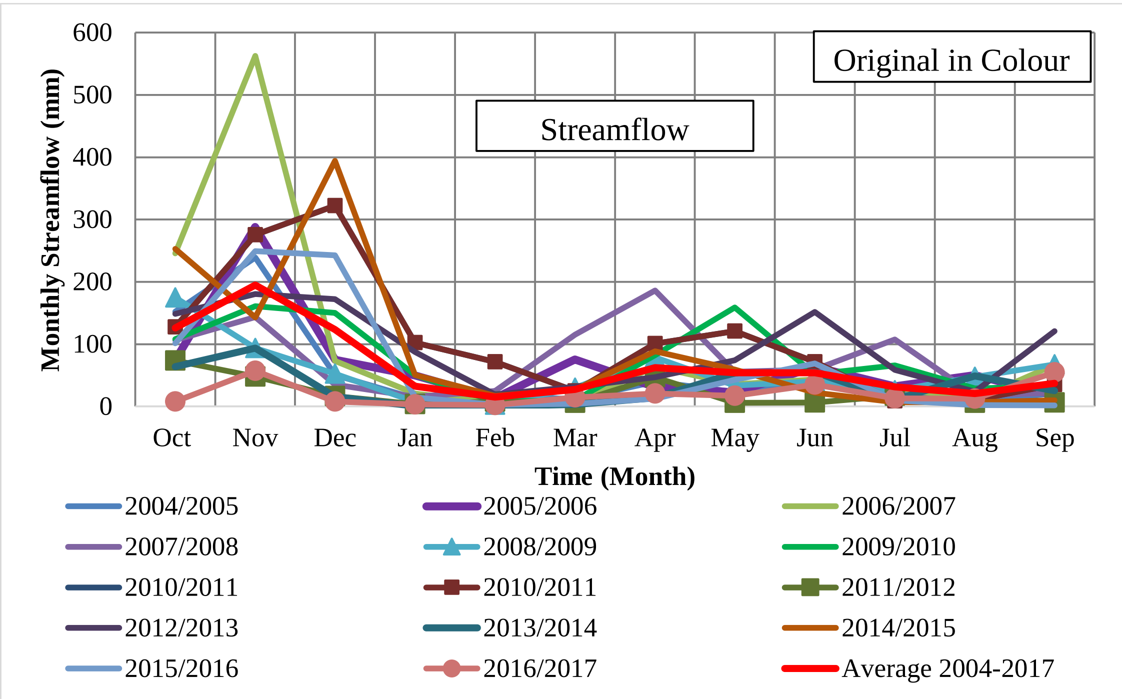


Figure (A-5.2) Year by year comparison for streamflow stations of Badalgama watershed

ANNEX B - 1

(Methodology Flow Chart)

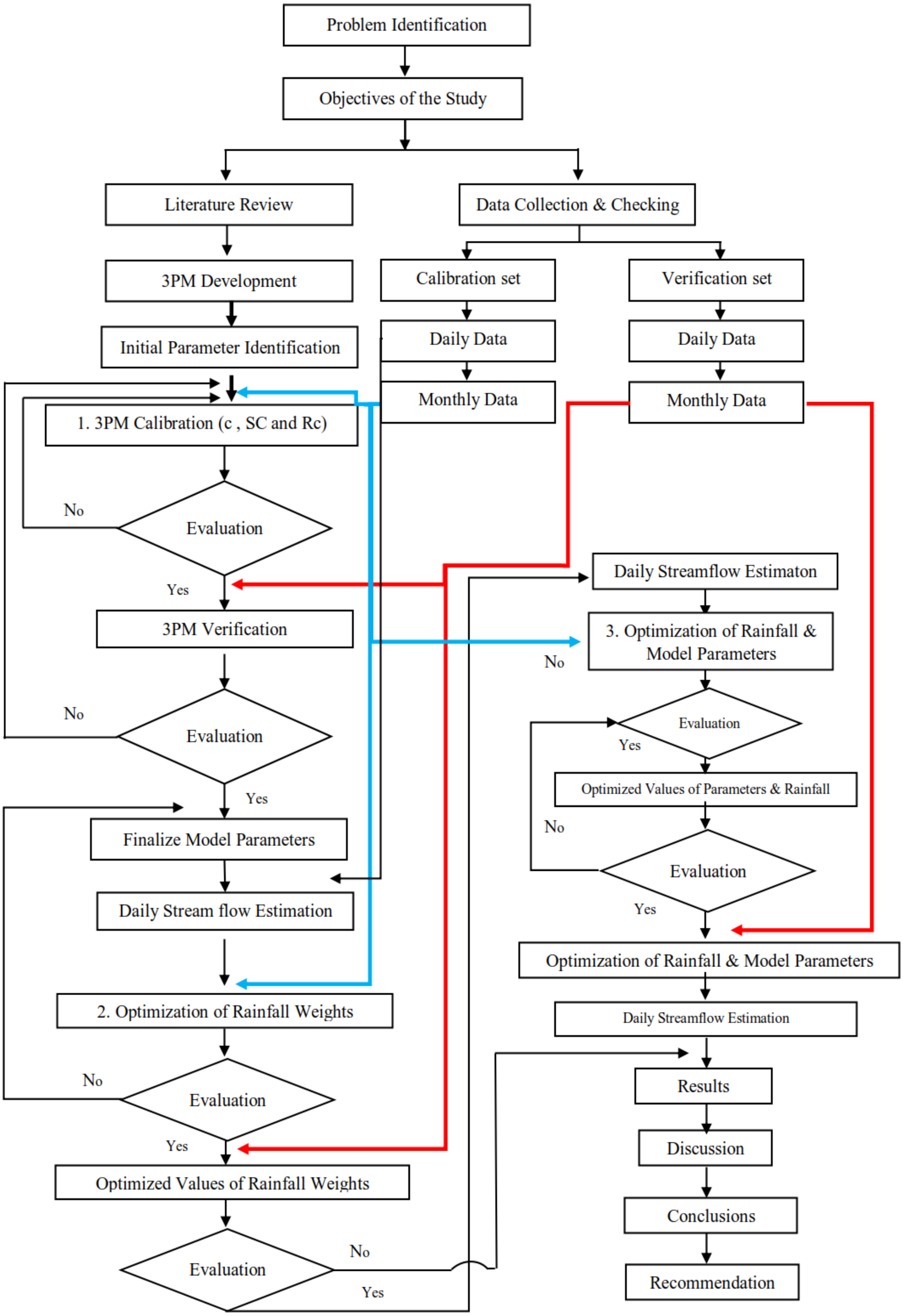


Figure (B-1): Methodology Flow Chart

ANNEX B - 2

(Seasonal Comparison of Rainfall)

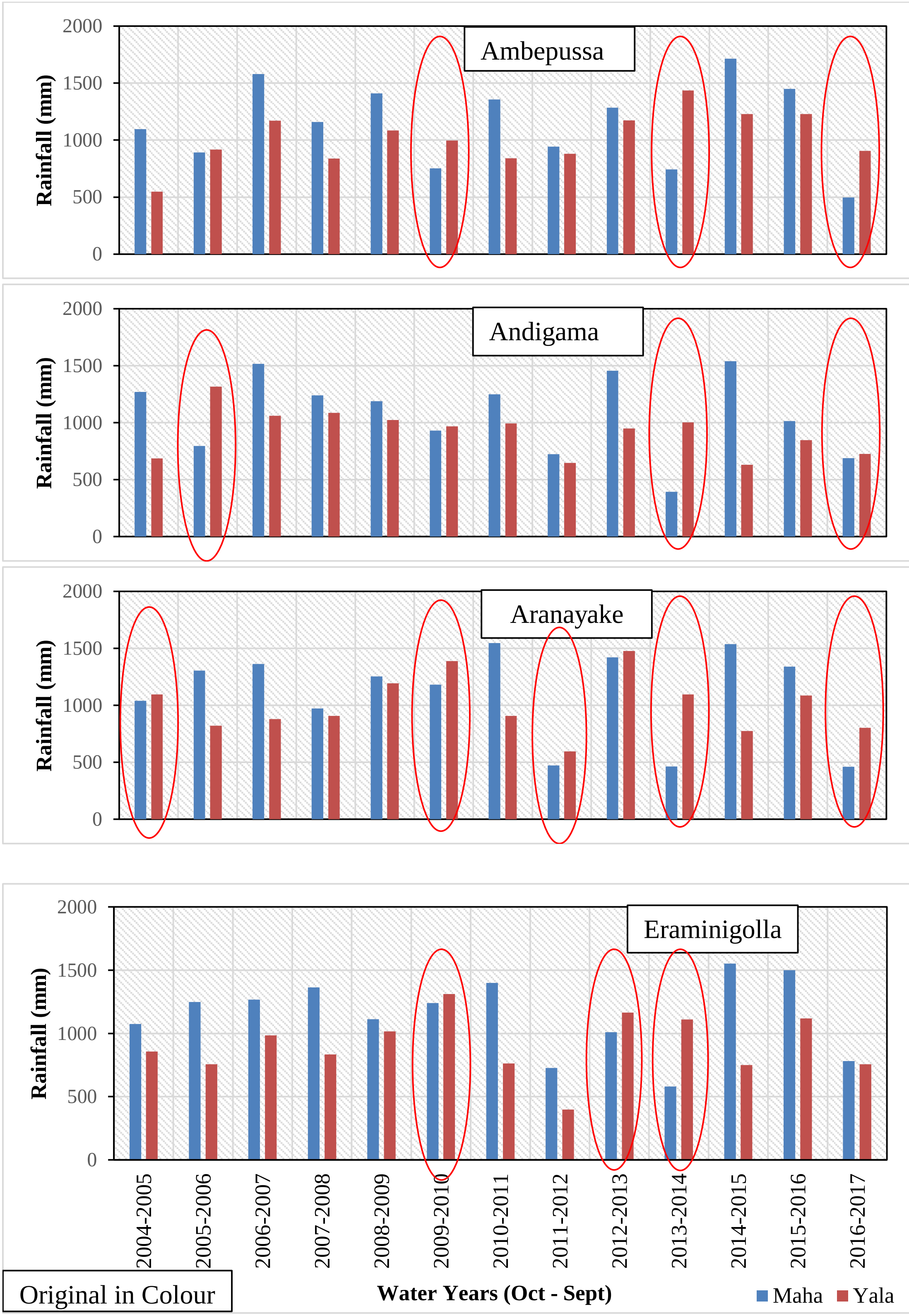

Ambepussa
Andigama
Aranayake
Eraminigolla
Rainfall (mm)
2000
1500
1000
500
0
2004-2005
2005-2006
2006-2007
2007-2008
2008-2009
2009-2010
2010-2011
2011-2012
2012-2013
2013-2014
2014-2015
2015-2016
2016-2017
Water Years (Oct - Sept)
Maha
Yala
Original in Colour

Figure (B-2.1): Seasonal comparison of rainfall station (Ambepussa, Andigama, Aranayake and Eraminigolla)

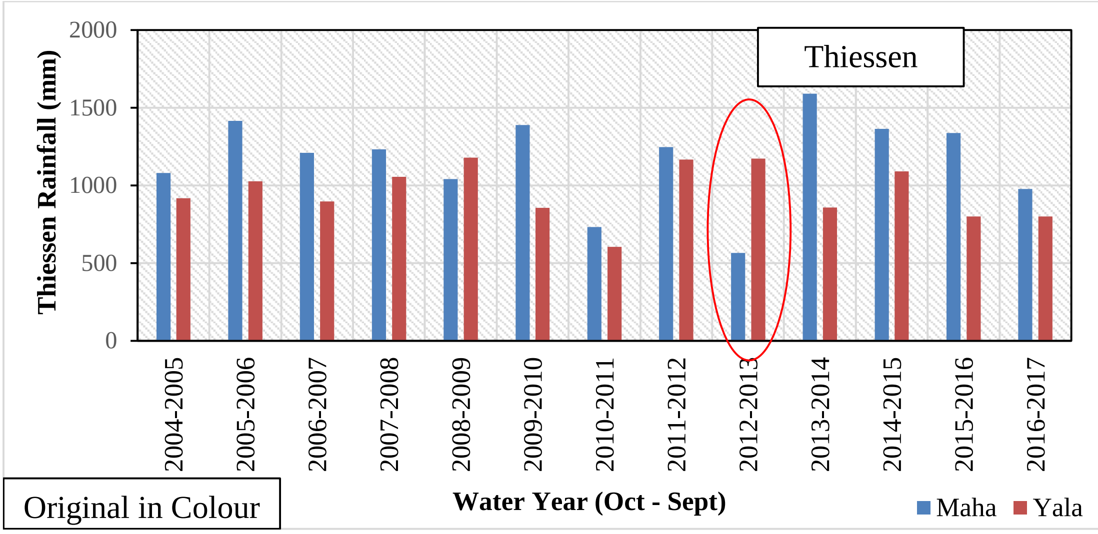


Figure (B-2.2): Seasonal comparison of Thiessen average rainfall

Table (B-2.1): Seasonal Summary of Rainfall for Ambepussa, Andigama, Aranayake and Eraminigolla Stations

Season	Maha	Yala	Maha	Yala	Maha	Yala	Maha	Yala
Water Year (Oct-Sept)	Ambepussa		Andigama		Aranayake		Eraminigolla	
2004-2005	1096.9	547.7	1270.2	685.7	1040	1095.1	1075.4	856.6
2005-2006	891.9	917	796.5	1317.3	1303.5	819.9	1247.7	755.2
2006-2007	1580	1170.9	1516.8	1060.1	1361.6	878.8	1267.4	984.8
2007-2008	1159.3	839.1	1238.9	1086.7	972.3	907.4	1362.9	832.6
2008-2009	1410	1083.5	1189.4	1023.9	1253	1193.7	1111.9	1015.3
2009-2010	752.9	996.3	929.9	968.8	1182.1	1388.9	1240	1311.8
2010-2011	1356.4	841.4	1249.1	992.5	1546.3	907.5	1399.8	762.1
2011-2012	943	879.6	723.8	647.5	472.8	596	726	398.1
2012-2013	1283.5	1172.8	1455	949.4	1419.6	1475.5	1010	1165.5
2013-2014	742.9	1436.6	394.5	1003.5	463.5	1095.7	580.4	1110.6
2014-2015	1715.1	1227.7	1538.6	631.3	1537.6	774.6	1552	749.2
2015-2016	1449.5	1228.3	1013.9	846.6	1340.4	1085.8	1500.6	1118.6
2016-2017	495.6	905.3	689.1	726.9	460.2	802.4	781.9	756.8

ANNEX C - 1

(Model Verification Checks)

Rainfall and Stream Flow Check					
Total RF	*Total E*	*Total SF*	*Co-efficient*	*Total EP*	*E/EP Ratio*
1901.5	2349.1	766.67	0.4	1189.538	0.5

Figure (C-1.1): Rainfall and streamflow check for model verification

Ratio of E/EP	Run Off Co-Efficient
0.4	0.4
0.4	0.8
0.4	0.3
0.7	0.2
1.2	0.5
0.5	0.1
0.4	0.2
0.5	0.2
0.4	0.2
0.4	0.1
1.2	0.1
0.5	0.2
0.4	**0.3**

Figure (C-1.2): Check for ratio of evaporation and pan evaporation and runoff coefficent check

	Annual Water Balance	$P = Qs + ET + \Delta S$
WB Eq.	Ea(t) =	1189.54
3P Model	Em(t) =	1189.54
Difference	Em(t) - Ea(t) =	0

Figure (C-1.3): Annual water balance check

Random Check			
c	1.02	Sc	1292.00
P(t)	310.0	S(t-1)	332.67
EP (t)	59.7		

$$E(t) = c \times \mathrm{EP}(t) \times \tanh[P(t)/\mathrm{EP}(t)],$$

E(t)	60.9

$$Q(t) = [S(t-1) + P(t) - E(t)] \times \tanh\{[S(t-1) + P(t) - E(t)]/\mathrm{SC}\}.$$

Q(t)	246.1
S(t)	336.9

Figure (C-1.3): Random check for model results generated

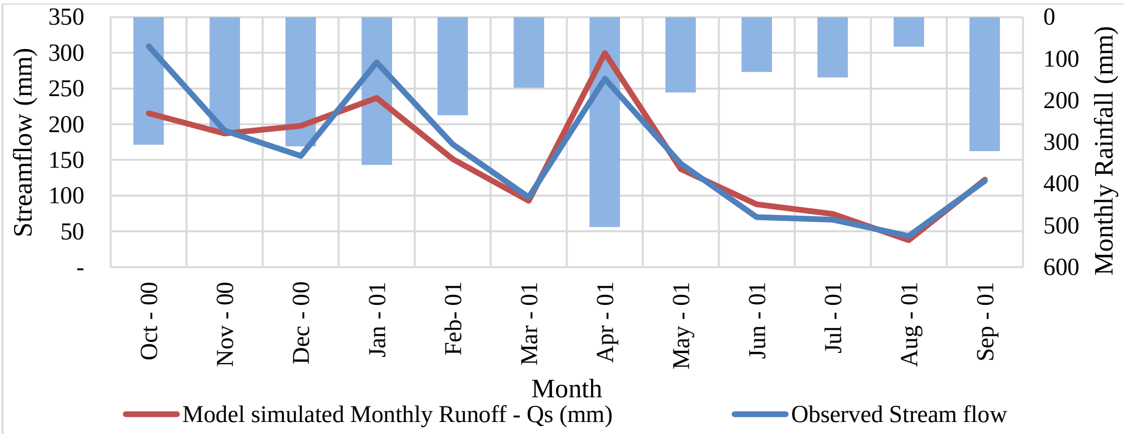


Figure (C-1.4): Specimen calculation for verification purpose

ANNEX D - 1

(Annual Rainfall with Tables)

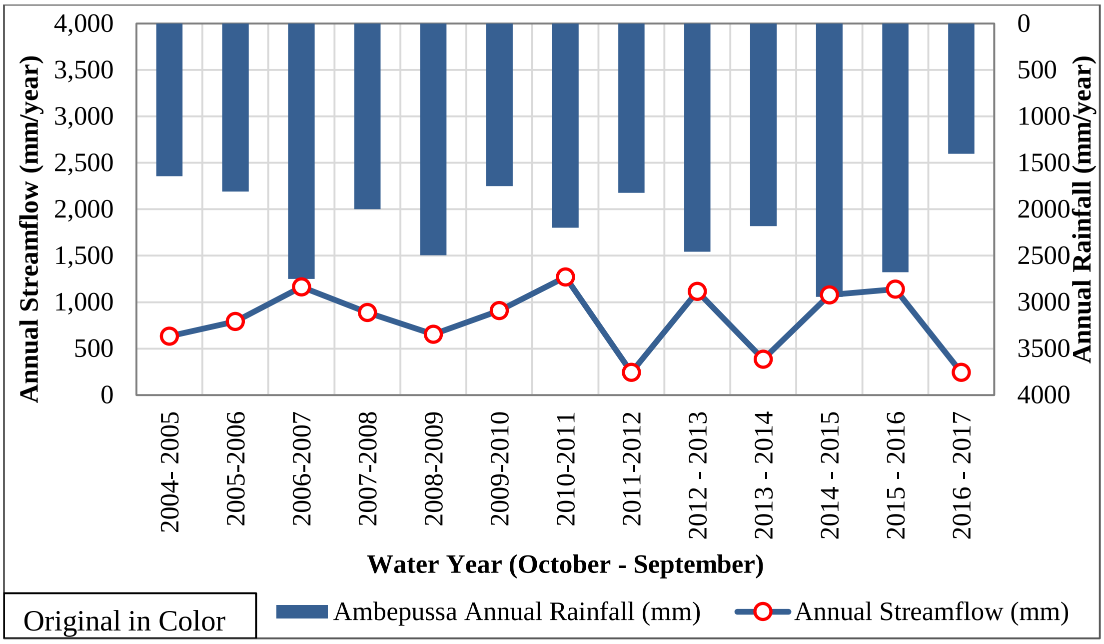


Figure D-1.1: Annual variation of Ambepussa rainfall and observed Streamflow: Normal Scale

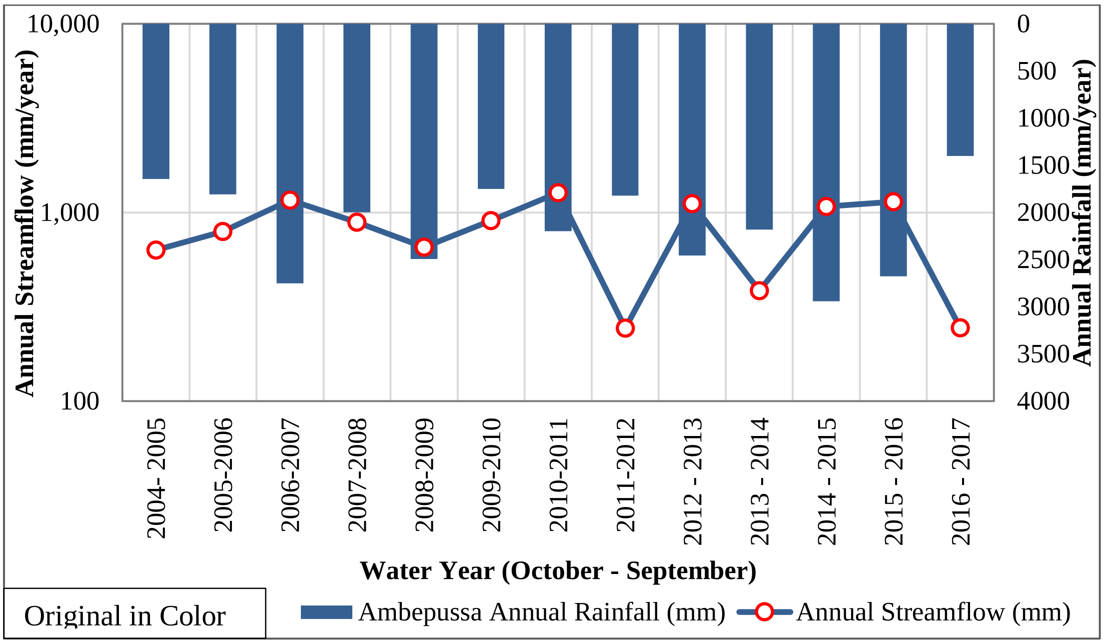


Figure D-1.2: Annual variation of Ambepussa rainfall and observed Streamflow: Semi – Log Scale

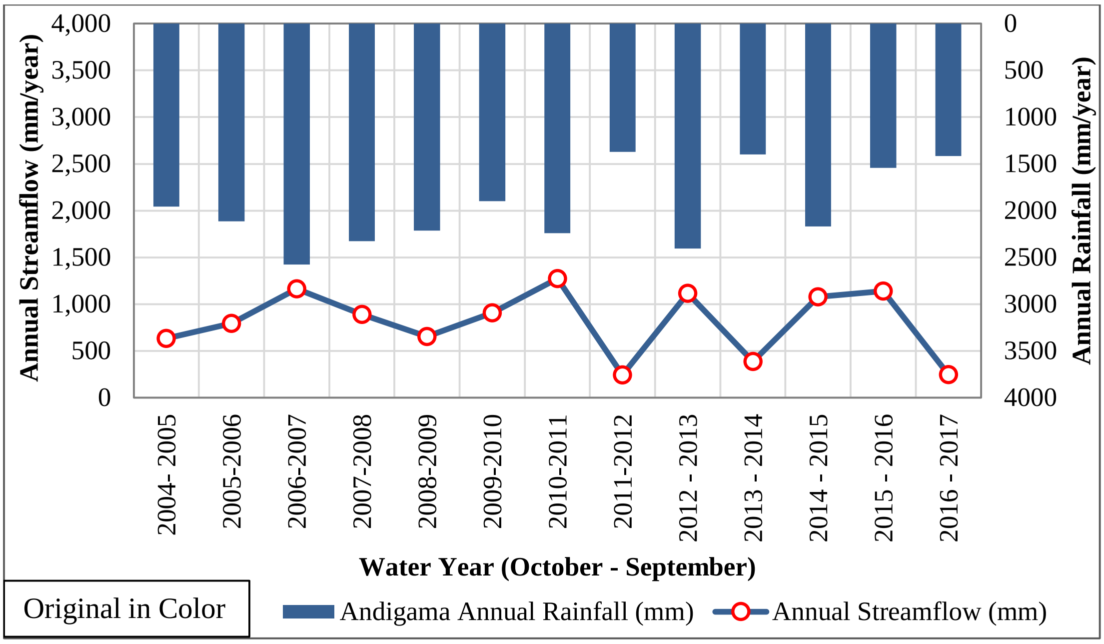


Figure D-1.3: Annual variation of Andigama rainfall and observed Streamflow: Normal Scale

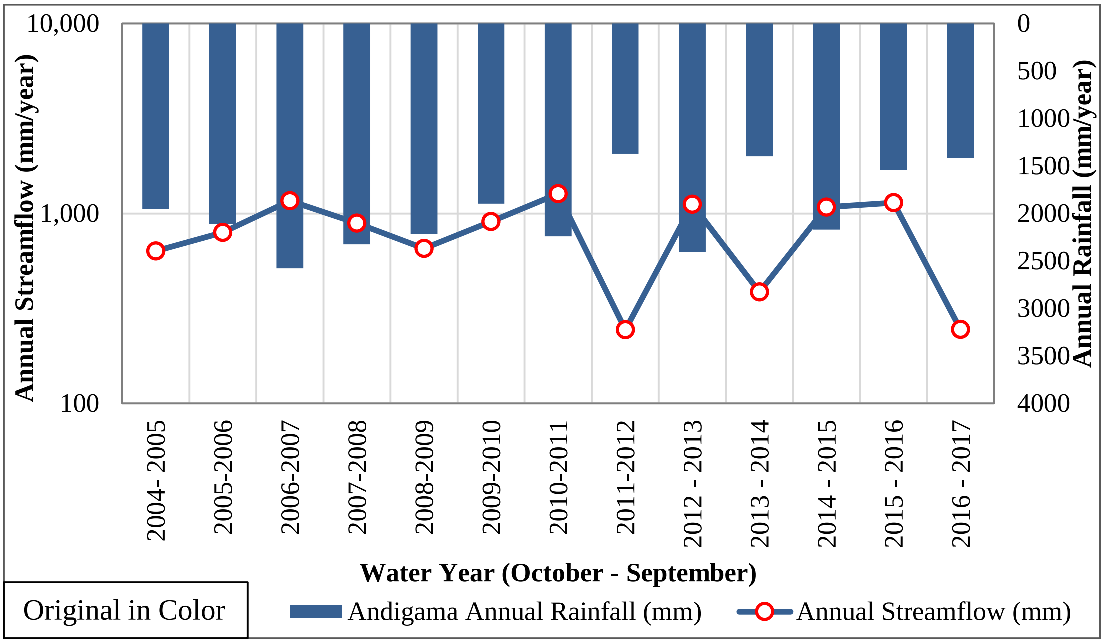


Figure D-1.4: Annual variation of Andigama rainfall and observed Streamflow: Semi –Log Scale

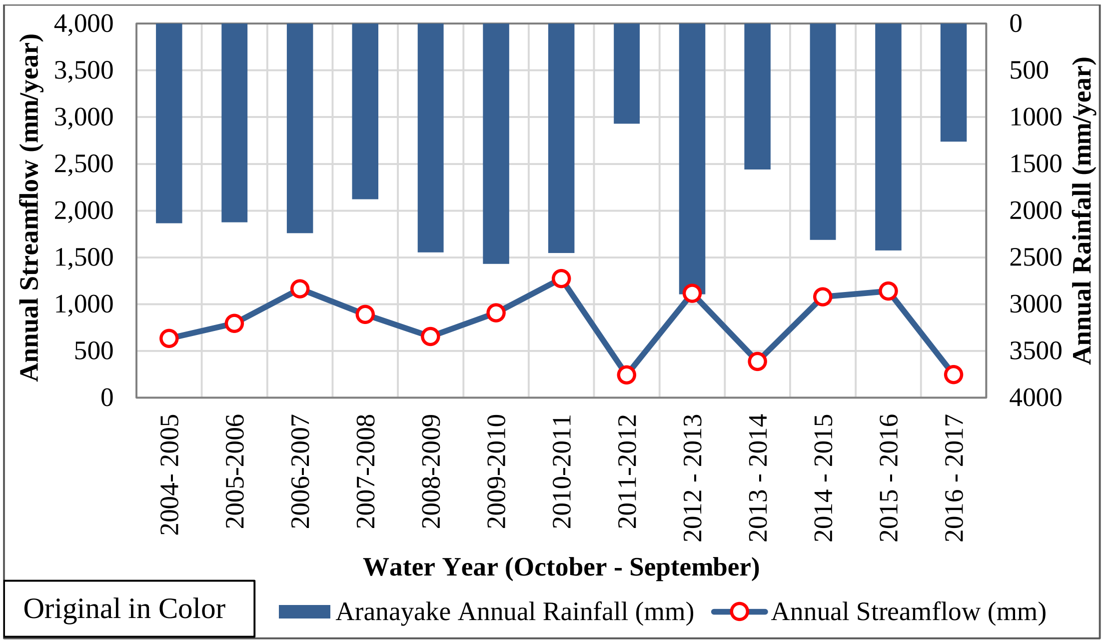


Figure D-1.5: Annual variation of Aranayake rainfall and observed Streamflow: Normal Scale

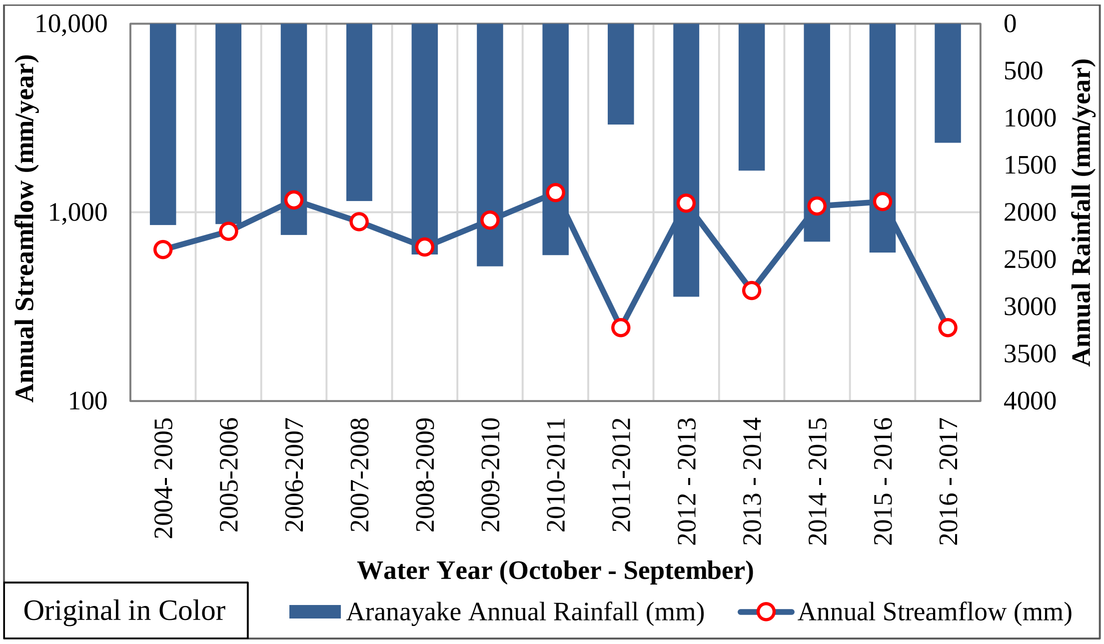


Figure D-1.6: Annual variation of Aranayake rainfall and observed Streamflow: Semi – Log Scale

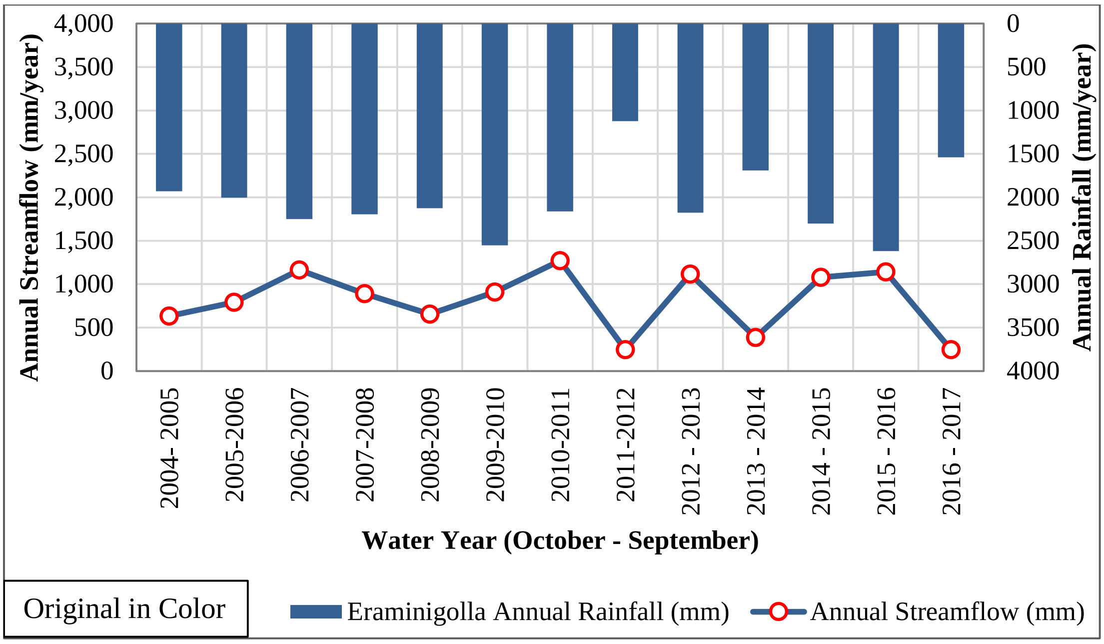


Figure D-1.7: Annual variation of Aranayake rainfall and observed Streamflow: Normal Scale

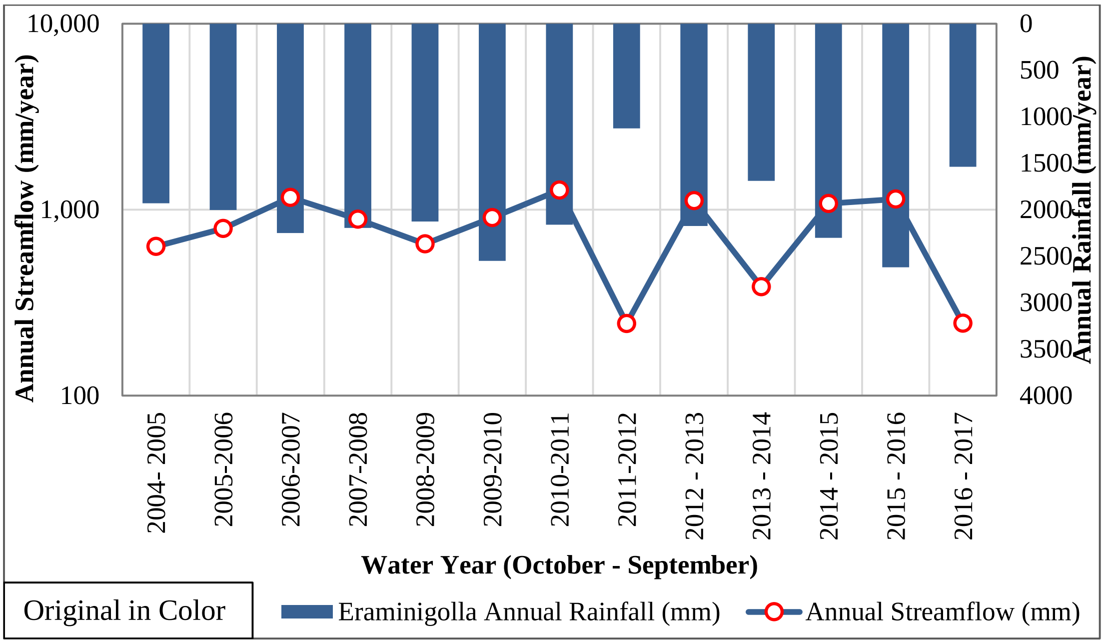


Figure D-1.8: Annual variation of Aranayake rainfall and observed Streamflow: Semi-log Scale

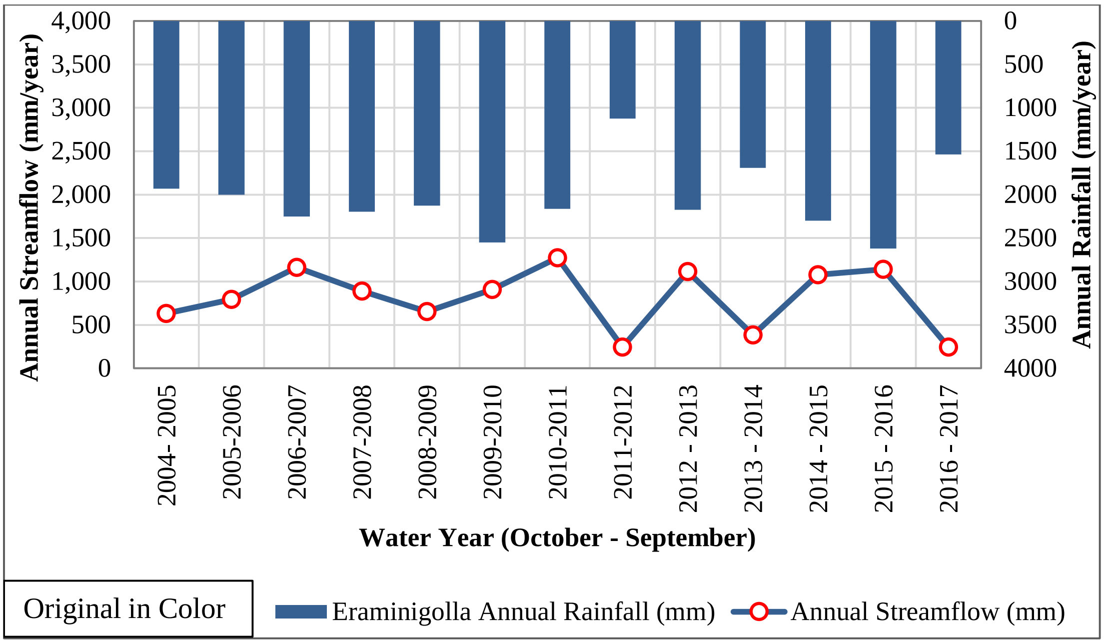


Figure D-1.9: Annual variation of Eraminigolla rainfall and observed Streamflow: Normal Scale

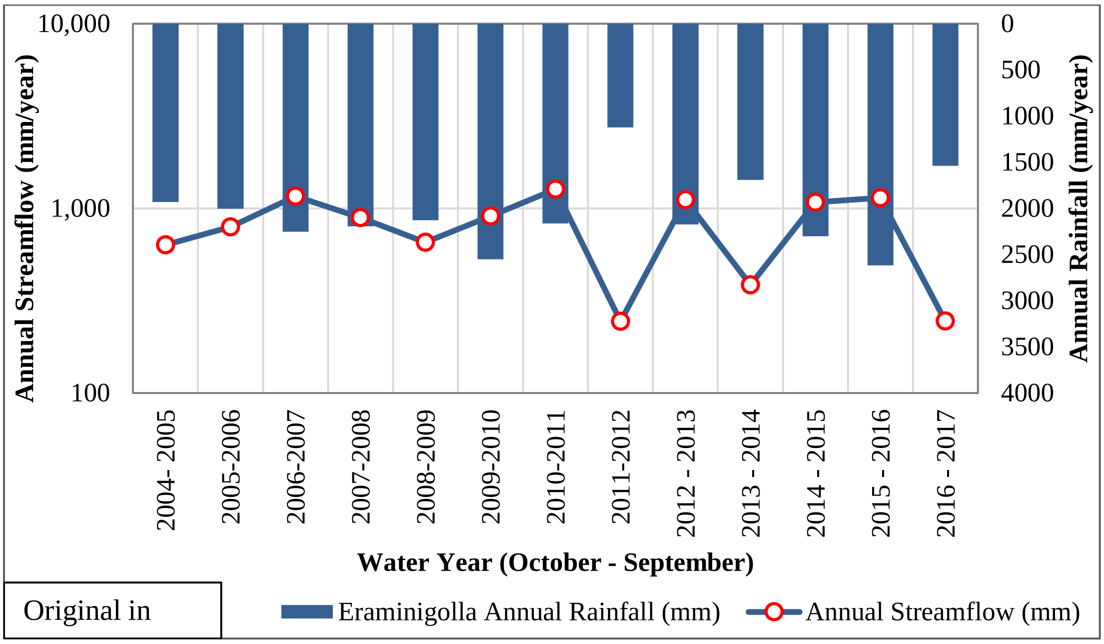


Figure D-1.10: Annual variation of Eraminigolla rainfall and observed Streamflow: Semi-log Scale

Table D-1.1: Summary of Annual rainfall of Ambepussa, Andigama, Aranayake and Eraminigolla and observed streamflow

Water Year (October to September)	Ambepussa Annual Rainfall (mm)	Andigama Annual Rainfall (mm)	Aranayake Annual Rainfall (mm)	Eraminigolla Annual Rainfall (mm)	Annual Observed Streamflow (mm)
2004- 2005	1,645	1,956	2,135	1,932	633
2005-2006	1,809	2,114	2,123	2,003	792
2006-2007	2,751	2,577	2,240	2,252	1164
2007-2008	1,998	2,326	1,880	2,196	889
2008-2009	2,494	2,213	2,447	2,127	654
2009-2010	1,749	1,899	2,571	2,552	907
2010-2011	2,198	2,242	2,454	2,162	1272
2011-2012	1,823	1,371	1,069	1,124	244
2012 - 2013	2,456	2,404	2,895	2,176	1115
2013 - 2014	2,180	1,398	1,559	1,691	385
2014 - 2015	2,943	2,170	2,312	2,301	1077
2015 - 2016	2,678	1,543	2,426	2,619	1140
2016 - 2017	1,401	1,416	1,263	1,539	245

ANNEX E - 1

(In Soil Water Content Tables)

Table E-1.1: Monthly Thiessen Rainfall and Soil Storage Results for Calibration and Verification of 2PM (Monthly)

Calibration (Oct 2004 – Sep 2010)			Verification (Oct 2010 – Sep 2017)		
Month	**Monthly Thiessen Rainfall (mm)**	**S(t) (mm/month)**	**Month**	**Monthly Thiessen Rainfall (mm)**	**S(t) (mm/month)**
Oct-04	380.79	271.90	Oct-10	240.02	231.02
Nov-04	316.00	281.06	Nov-10	448.28	291.53
Dec-04	154.68	236.28	Dec-10	354.63	285.56
Jan-05	69.35	164.31	Jan-11	142.68	223.66
Feb-05	38.43	98.87	Feb-11	111.66	179.88
Mar-05	151.88	111.69	Mar-11	91.42	144.16
Apr-05	214.41	169.10	Apr-11	267.80	225.84
May-05	96.76	139.86	May-11	232.07	240.83
Jun-05	154.30	169.09	Jun-11	68.28	165.16
Jul-05	164.26	181.30	Jul-11	43.19	95.23
Aug-05	40.64	110.02	Aug-11	98.14	70.65
Sep-05	119.99	104.06	Sep-11	145.95	94.01
Oct-05	272.21	198.90	Oct-11	220.50	168.97
Nov-05	322.84	270.15	Nov-11	111.38	137.14
Dec-05	97.49	209.05	Dec-11	73.91	93.56
Jan-06	89.08	165.06	Jan-12	37.96	37.32
Feb-06	96.78	129.36	Feb-12	165.46	63.99
Mar-06	201.35	166.81	Mar-12	123.14	58.99
Apr-06	106.44	135.30	Apr-12	207.69	126.63
May-06	145.75	134.77	May-12	53.13	56.39
Jun-06	182.33	169.74	Jun-12	121.36	69.76
Jul-06	186.21	194.91	Jul-12	77.60	35.21
Aug-06	239.68	219.69	Aug-12	108.70	25.95
Sep-06	56.93	145.44	Sep-12	42.14	15.00
Oct-06	558.61	292.75	Oct-12	486.13	241.73
Nov-06	618.47	288.51	Nov-12	162.19	219.55
Dec-06	81.98	208.60	Dec-12	264.52	253.84
Jan-07	39.96	130.62	Jan-13	102.47	192.53
Feb-07	9.31	103.91	Feb-13	62.70	134.98
Mar-07	106.93	61.95	Mar-13	169.15	133.73
Apr-07	300.67	192.18	Apr-13	164.22	141.98
May-07	147.91	187.82	May-13	194.69	185.98
Jun-07	154.58	186.28	Jun-13	328.29	264.33
Jul-07	120.55	168.50	Jul-13	113.93	205.15
Aug-07	89.24	127.38	Aug-13	75.90	143.41
Sep-07	213.94	185.30	Sep-13	310.46	236.26
Oct-07	308.78	259.84	Oct-14	512.50	294.96
Nov-07	231.10	254.36	Nov-14	212.05	262.21
Dec-07	114.76	206.82	Dec-14	546.63	294.90
Jan-08	33.89	136.30	Jan-15	2.11	213.51
Feb-08	195.01	175.99	Feb-15	96.66	166.26
Mar-08	325.37	251.27	Mar-15	219.32	197.83
Apr-08	369.84	283.50	Apr-15	306.21	252.92
May-08	99.48	206.64	May-15	140.04	215.03
Jun-08	97.55	182.12	Jun-15	150.94	200.60
Jul-08	201.64	216.06	Jul-15	27.32	136.80

Calibration (Oct 2004 – Sep 2010)			Verification (Oct 2010 – Sep 2017)		
Month	**Monthly Thiessen Rainfall (mm)**	**S(t) (mm/month)**	**Month**	**Monthly Thiessen Rainfall (mm)**	**S(t) (mm/month)**
Aug-08	52.69	146.40	Aug-15	95.58	94.06
Sep-08	76.25	96.52	Sep-15	136.84	108.03
Oct-08	463.20	273.53	Oct-15	454.86	270.81
Nov-08	302.07	279.81	Nov-15	439.38	294.13
Dec-08	113.53	211.32	Dec-15	289.15	276.97
Jan-09	25.62	145.62	Jan-16	16.20	193.76
Feb-09	9.09	115.68	Feb-16	37.11	122.46
Mar-09	318.98	215.23	Mar-16	126.23	97.02
Apr-09	231.25	229.18	Apr-16	202.42	144.08
May-09	222.88	235.32	May-16	718.21	292.80
Jun-09	143.91	210.80	Jun-16	102.45	211.56
Jul-09	56.53	129.89	Jul-16	38.14	135.48
Aug-09	168.52	152.44	Aug-16	15.54	100.51
Sep-09	246.93	210.36	Sep-16	12.27	75.84
Oct-09	287.77	251.73	Oct-16	118.52	58.26
Nov-09	312.01	276.30	Nov-16	214.86	136.16
Dec-09	237.11	263.92	Dec-16	20.69	95.41
Jan-10	65.12	167.16	Jan-17	52.22	23.39
Feb-10	6.35	134.39	Feb-17	25.67	20.00
Mar-10	133.74	106.17	Mar-17	193.86	71.92
Apr-10	430.69	261.43	Apr-17	80.34	42.76
May-10	158.99	221.02	May-17	181.96	114.31
Jun-10	188.82	221.88	Jun-17	104.25	123.61
Jul-10	138.44	175.61	Jul-17	63.17	83.78
Aug-10	102.64	132.07	Aug-17	95.49	73.27
Sep-10	159.62	158.77	Sep-17	273.74	207.24

Table E-1.2: Monthly Thiessen Rainfall and Soil Storage Results for Calibration and Verification of 3PM (Monthly) – K Optimized only

Calibration (Oct 2004 – Sep 2010)			Verification (Oct 2010 – Sep 2017)		
Month	**Monthly Thiessen Rainfall (mm)**	**S(t) (mm/month)**	**Month**	**Monthly Thiessen Rainfall (mm)**	**S(t) (mm/month)**
Oct-04	380.79	272.26	Oct-10	240.02	231.22
Nov-04	316.00	281.48	Nov-10	448.28	291.94
Dec-04	154.68	236.64	Dec-10	354.63	285.95
Jan-05	69.35	164.61	Jan-11	142.68	223.97
Feb-05	38.43	99.12	Feb-11	111.66	180.14
Mar-05	151.88	111.91	Mar-11	91.42	144.38
Apr-05	214.41	169.32	Apr-11	267.80	226.07
May-05	96.76	140.05	May-11	232.07	241.09
Jun-05	154.30	169.29	Jun-11	68.28	165.39
Jul-05	164.26	181.51	Jul-11	43.19	95.43
Aug-05	40.64	110.20	Aug-11	98.14	70.83
Sep-05	119.99	104.23	Sep-11	145.95	94.17
Oct-05	272.21	199.10	Oct-11	220.50	169.13
Nov-05	322.84	270.50	Nov-11	111.38	137.29
Dec-05	97.49	209.35	Dec-11	73.91	93.69
Jan-06	89.08	165.32	Jan-12	37.96	37.45
Feb-06	96.78	129.59	Feb-12	165.46	64.11
Mar-06	201.35	167.03	Mar-12	123.14	59.10
Apr-06	106.44	135.49	Apr-12	207.69	126.75
May-06	145.75	134.95	May-12	53.13	56.49
Jun-06	182.33	169.93	Jun-12	121.36	69.86
Jul-06	186.21	195.12	Jul-12	77.60	35.31
Aug-06	239.68	219.94	Aug-12	103.34	20.92
Sep-06	56.93	145.67	Sep-12	42.14	-
Oct-06	558.61	293.24	Oct-12	486.13	241.90
Nov-06	618.47	289.15	Nov-12	162.19	219.76
Dec-06	81.98	209.05	Dec-12	264.52	254.11
Jan-07	39.96	130.98	Jan-13	102.47	192.77
Feb-07	9.31	104.22	Feb-13	62.70	135.18
Mar-07	106.93	62.23	Mar-13	169.15	133.91
Apr-07	300.67	192.44	Apr-13	164.22	142.14
May-07	147.91	188.06	May-13	172.89	173.44
Jun-07	154.58	186.52	Jun-13	328.29	261.03
Jul-07	120.55	168.72	Jul-13	113.93	203.58
Aug-07	89.24	127.57	Aug-13	75.90	142.38
Sep-07	213.94	185.50	Sep-13	310.46	236.01
Oct-07	308.78	260.16	Oct-14	512.50	295.39
Nov-07	231.10	254.70	Nov-14	212.05	262.56
Dec-07	114.76	207.12	Dec-14	546.63	295.40
Jan-08	33.89	136.56	Jan-15	2.11	213.86
Feb-08	195.01	176.22	Feb-15	96.66	166.55
Mar-08	325.37	251.58	Mar-15	219.32	198.07
Apr-08	369.84	283.93	Apr-15	306.21	253.20
May-08	99.48	206.98	May-15	140.04	215.28
Jun-08	97.55	182.41	Jun-15	150.94	200.84
Jul-08	201.64	216.34	Jul-15	27.32	137.00

Calibration (Oct 2004 – Sep 2010)			Verification (Oct 2010 – Sep 2017)		
Month	**Monthly Thiessen Rainfall (mm)**	**S(t) (mm/month)**	**Month**	**Monthly Thiessen Rainfall (mm)**	**S(t) (mm/month)**
Aug-08	52.69	146.64	Aug-15	95.58	94.24
Sep-08	76.25	96.74	Sep-15	136.84	108.19
Oct-08	463.20	273.90	Oct-15	454.86	271.11
Nov-08	302.07	280.24	Nov-15	439.38	294.57
Dec-08	113.53	211.67	Dec-15	289.15	277.35
Jan-09	25.62	145.91	Jan-16	16.20	194.06
Feb-09	9.09	115.93	Feb-16	37.11	122.71
Mar-09	318.98	215.49	Mar-16	126.23	97.24
Apr-09	231.25	229.47	Apr-16	202.42	144.27
May-09	207.88	229.48	May-16	718.21	293.33
Jun-09	143.91	208.06	Jun-16	102.45	211.94
Jul-09	56.53	127.95	Jul-16	38.14	135.78
Aug-09	168.52	151.21	Aug-16	15.54	100.76
Sep-09	280.94	225.63	Sep-16	12.27	76.07
Oct-09	285.94	256.29	Oct-16	118.52	58.47
Nov-09	312.01	277.57	Nov-16	214.86	136.34
Dec-09	237.11	264.54	Dec-16	20.69	95.57
Jan-10	65.12	167.62	Jan-17	52.22	23.54
Feb-10	6.35	134.76	Feb-17	25.67	-
Mar-10	133.74	106.48	Mar-17	193.86	71.92
Apr-10	430.69	261.78	Apr-17	80.34	42.78
May-10	158.99	221.33	May-17	181.96	114.34
Jun-10	188.82	222.18	Jun-17	104.25	123.66
Jul-10	138.44	175.87	Jul-17	63.17	83.84
Aug-10	102.64	132.30	Aug-17	95.49	73.33
Sep-10	159.62	158.98	Sep-17	273.74	207.38

Table E-1.3: Monthly Thiessen Rainfall and Soil Storage Results for Calibration and Verification of 3PM (Monthly) – All parameters optimized

Calibration (Oct 2004 – Sep 2010)			Verification (Oct 2010 – Sep 2017)		
Month	**Monthly Thiessen Rainfall (mm)**	**S(t) (mm/month)**	**Month**	**Monthly Thiessen Rainfall (mm)**	**S(t) (mm/month)**
Oct-04	380.79	270.25	Oct-10	240.02	229.86
Nov-04	316.00	279.10	Nov-10	448.28	289.28
Dec-04	154.68	234.64	Dec-10	354.63	283.37
Jan-05	69.35	162.96	Jan-11	142.68	221.93
Feb-05	38.43	97.70	Feb-11	111.66	178.46
Mar-05	151.88	110.67	Mar-11	91.42	142.95
Apr-05	214.41	168.13	Apr-11	267.80	224.53
May-05	96.76	138.97	May-11	232.07	239.39
Jun-05	154.30	168.20	Jun-11	68.28	163.93
Jul-05	164.26	180.37	Jul-11	43.19	94.15
Aug-05	40.64	109.18	Aug-11	98.14	69.67
Sep-05	119.99	103.29	Sep-11	145.95	93.13
Oct-05	272.21	197.97	Oct-11	220.50	168.08
Nov-05	322.84	268.53	Nov-11	111.38	136.29
Dec-05	97.49	207.65	Dec-11	73.91	92.79
Jan-06	89.08	163.85	Jan-12	37.96	36.60
Feb-06	96.78	128.32	Feb-12	165.46	63.32
Mar-06	201.35	165.83	Mar-12	123.14	58.36
Apr-06	106.44	134.41	Apr-12	207.69	126.00
May-06	145.75	133.94	May-12	53.13	55.80
Jun-06	182.33	168.89	Jun-12	121.36	69.21
Jul-06	186.21	193.95	Jul-12	77.60	34.69
Aug-06	239.68	218.56	Aug-12	108.70	25.44
Sep-06	56.93	144.44	Sep-12	42.14	-
Oct-06	558.61	290.52	Oct-12	486.13	240.76
Nov-06	618.47	285.56	Nov-12	162.19	218.39
Dec-06	81.98	206.55	Dec-12	264.52	252.33
Jan-07	39.96	128.96	Jan-13	102.47	191.21
Feb-07	9.31	102.51	Feb-13	62.70	133.84
Mar-07	106.93	60.68	Mar-13	169.15	132.72
Apr-07	300.67	191.01	Apr-13	164.22	141.05
May-07	147.91	186.71	May-13	194.69	185.00
Jun-07	154.58	185.22	Jun-13	328.29	262.75
Jul-07	120.55	167.50	Jul-13	113.93	203.75
Aug-07	89.24	126.48	Aug-13	75.90	142.22
Sep-07	213.94	184.35	Sep-13	310.46	234.89
Oct-07	308.78	258.36	Oct-14	512.50	292.47
Nov-07	231.10	252.78	Nov-14	212.05	260.23
Dec-07	114.76	205.45	Dec-14	546.63	292.14
Jan-08	33.89	135.13	Jan-15	2.11	211.53
Feb-08	195.01	174.91	Feb-15	96.66	164.69
Mar-08	325.37	249.84	Mar-15	219.32	196.46
Apr-08	369.84	281.53	Apr-15	306.21	251.35
May-08	99.48	205.07	May-15	140.04	213.61
Jun-08	97.55	180.80	Jun-15	150.94	199.31
Jul-08	201.64	214.78	Jul-15	27.32	135.68

Calibration (Oct 2004 – Sep 2010)			Verification (Oct 2010 – Sep 2017)		
Month	**Monthly Thiessen Rainfall (mm)**	**S(t) (mm/month)**	**Month**	**Monthly Thiessen Rainfall (mm)**	**S(t) (mm/month)**
Aug-08	52.69	145.29	Aug-15	95.58	93.07
Sep-08	76.25	95.54	Sep-15	136.84	107.14
Oct-08	463.20	271.84	Oct-15	454.86	269.14
Nov-08	302.07	277.88	Nov-15	439.38	291.70
Dec-08	113.53	209.76	Dec-15	289.15	274.89
Jan-09	25.62	144.33	Jan-16	16.20	192.12
Feb-09	9.09	114.56	Feb-16	37.11	121.09
Mar-09	318.98	214.05	Mar-16	126.23	95.83
Apr-09	231.25	227.89	Apr-16	202.42	143.03
May-09	222.88	233.95	May-16	718.21	289.83
Jun-09	143.91	209.51	Jun-16	102.45	209.48
Jul-09	56.53	128.78	Jul-16	38.14	133.80
Aug-09	168.52	151.44	Aug-16	15.54	99.08
Sep-09	246.93	209.26	Sep-16	12.27	74.58
Oct-09	287.77	250.29	Oct-16	118.52	57.11
Nov-09	312.01	274.47	Nov-16	214.86	135.14
Dec-09	237.11	262.15	Dec-16	20.69	94.50
Jan-10	65.12	165.72	Jan-17	52.22	22.51
Feb-10	6.35	133.18	Feb-17	25.67	-
Mar-10	133.74	105.12	Mar-17	193.86	71.87
Apr-10	430.69	259.90	Apr-17	80.34	42.70
May-10	158.99	219.62	May-17	181.96	114.12
Jun-10	188.82	220.54	Jun-17	104.25	123.30
Jul-10	138.44	174.43	Jul-17	63.17	83.45
Aug-10	102.64	131.04	Aug-17	95.49	72.95
Sep-10	159.62	157.81	Sep-17	273.74	206.47

Table E-1.4: Monthly Thiessen Rainfall and Soil Storage Results during Calibration and Verification of 3PM (Monthly) – Station Weights Optimized

Calibration (Oct 2004 – Sep 2010)			Verification (Oct 2010 – Sep 2017)		
Month	**Optimized Monthly Thiessen Rainfall (mm)**	**S(t) (mm/month)**	**Month**	**Optimized Monthly Thiessen Rainfall (mm)**	**S(t) (mm/month)**
Oct-04	365.61	269.25	Oct-10	244.20	229.87
Nov-04	315.24	278.80	Nov-10	439.87	288.55
Dec-04	159.50	236.40	Dec-10	356.33	283.50
Jan-05	65.17	161.43	Jan-11	149.54	224.97
Feb-05	42.11	92.94	Feb-11	119.85	184.89
Mar-05	154.77	109.24	Mar-11	95.14	149.78
Apr-05	228.41	175.70	Apr-11	277.99	231.64
May-05	95.53	143.31	May-11	220.33	237.64
Jun-05	153.47	170.34	Jun-11	66.95	162.00
Jul-05	174.78	187.53	Jul-11	47.94	91.56
Aug-05	47.50	108.61	Aug-11	95.87	65.47
Sep-05	130.97	111.33	Sep-11	144.63	88.66
Oct-05	277.07	204.56	Oct-11	202.55	153.90
Nov-05	350.81	275.98	Nov-11	112.98	127.35
Dec-05	102.23	213.50	Dec-11	70.27	82.50
Jan-06	90.95	168.63	Jan-12	40.83	23.35
Feb-06	91.27	127.79	Feb-12	144.32	32.22
Mar-06	206.14	168.45	Mar-12	130.66	37.04
Apr-06	100.60	132.13	Apr-12	189.90	96.21
May-06	149.29	134.83	May-12	54.89	30.17
Jun-06	181.88	169.15	Jun-12	117.61	43.17
Jul-06	182.28	191.98	Jul-12	76.35	8.54
Aug-06	227.33	211.91	Aug-12	106.57	-
Sep-06	55.03	138.58	Sep-12	39.89	-
Oct-06	527.51	287.35	Oct-12	477.91	237.69
Nov-06	621.83	285.54	Nov-12	158.66	215.36
Dec-06	77.88	204.49	Dec-12	260.35	250.00
Jan-07	43.87	124.05	Jan-13	105.12	191.38
Feb-07	10.77	96.92	Feb-13	70.94	139.71
Mar-07	112.44	60.61	Mar-13	171.27	138.32
Apr-07	295.47	188.12	Apr-13	164.58	145.11
May-07	136.85	178.78	May-13	197.86	189.03
Jun-07	154.67	180.75	Jun-13	342.20	267.34
Jul-07	122.89	166.19	Jul-13	120.82	209.43
Aug-07	83.91	121.63	Aug-13	82.44	150.44
Sep-07	211.97	180.46	Sep-13	304.76	235.87
Oct-07	305.23	256.17	Oct-14	487.00	291.51
Nov-07	237.02	253.94	Nov-14	223.88	263.20
Dec-07	115.20	206.24	Dec-14	546.31	292.04
Jan-08	35.98	134.95	Jan-15	2.72	211.04
Feb-08	191.54	172.73	Feb-15	108.96	171.92
Mar-08	315.22	245.67	Mar-15	209.01	194.83
Apr-08	365.35	280.15	Apr-15	303.38	249.90
May-08	94.51	201.86	May-15	134.27	210.17
Jun-08	96.88	178.55	Jun-15	138.32	190.78

Calibration (Oct 2004 – Sep 2010)			Verification (Oct 2010 – Sep 2017)		
Month	**Optimized Monthly Thiessen Rainfall (mm)**	**S(t) (mm/month)**	**Month**	**Optimized Monthly Thiessen Rainfall (mm)**	**S(t) (mm/month)**
Jul-08	210.40	217.78	Jul-15	31.07	126.05
Aug-08	50.05	145.53	Aug-15	93.44	83.47
Sep-08	78.18	97.27	Sep-15	129.48	93.77
Oct-08	449.92	269.22	Oct-15	437.42	261.29
Nov-08	299.31	276.88	Nov-15	437.63	291.21
Dec-08	113.15	209.10	Dec-15	303.31	277.51
Jan-09	24.39	145.03	Jan-16	20.71	190.02
Feb-09	10.23	113.82	Feb-16	31.32	125.05
Mar-09	322.95	215.55	Mar-16	138.00	108.16
Apr-09	225.31	226.02	Apr-16	194.29	145.87
May-09	238.19	239.12	May-16	726.54	289.05
Jun-09	147.69	213.78	Jun-16	97.26	206.56
Jul-09	57.82	132.75	Jul-16	38.63	131.34
Aug-09	168.47	154.01	Aug-16	15.35	97.36
Sep-09	239.37	206.82	Sep-16	14.56	70.23
Oct-09	296.89	252.44	Oct-16	118.81	53.51
Nov-09	319.44	276.36	Nov-16	218.66	135.28
Dec-09	260.12	268.49	Dec-16	20.34	95.00
Jan-10	67.34	170.96	Jan-17	54.48	21.61
Feb-10	5.93	137.30	Feb-17	23.28	-
Mar-10	128.81	104.49	Mar-17	190.68	69.14
Apr-10	432.94	260.35	Apr-17	83.58	43.17
May-10	158.80	219.74	May-17	186.10	117.58
Jun-10	192.94	222.41	Jun-17	95.55	119.44
Jul-10	148.84	181.59	Jul-17	63.61	80.61
Aug-10	120.90	148.57	Aug-17	99.85	74.24
Sep-10	159.45	168.68	Sep-17	264.17	202.31

Table E-1.5: Monthly Thiessen Rainfall and Soil Storage Results during Calibration and Verification of 3PM (Monthly) – Station Weights Optimized

Calibration (Oct 2004 – Sep 2010)			Verification (Oct 2010 – Sep 2017)		
Month	**Optimized Monthly Thiessen Rainfall and Parameters Simultaneously**	**S(t) (mm/month)**	**Month**	**Optimized Monthly Thiessen Rainfall and Parameters Simultaneously (mm)**	**S(t) (mm/month)**
Oct-04	372.38	242.75	Oct-10	240.52	211.08
Nov-04	311.38	246.34	Nov-10	454.18	252.83
Dec-04	157.48	208.91	Dec-10	351.34	248.55
Jan-05	68.07	140.96	Jan-11	149.23	197.73
Feb-05	42.00	75.14	Feb-11	113.41	158.95
Mar-05	145.84	86.68	Mar-11	93.62	127.45
Apr-05	228.40	156.19	Apr-11	269.11	205.66
May-05	95.82	126.52	May-11	229.88	216.27
Jun-05	151.85	153.41	Jun-11	71.49	146.30
Jul-05	171.06	168.67	Jul-11	48.61	78.09
Aug-05	47.50	92.18	Aug-11	101.18	57.76
Sep-05	132.25	97.73	Sep-11	150.62	85.88
Oct-05	283.97	191.13	Oct-11	223.55	159.44
Nov-05	349.78	246.41	Nov-11	122.43	134.09
Dec-05	98.12	187.28	Dec-11	75.45	90.69
Jan-06	88.90	145.84	Jan-12	26.93	48.20
Feb-06	87.83	106.02	Feb-12	163.44	70.70
Mar-06	211.31	152.66	Mar-12	100.40	44.26
Apr-06	98.75	116.55	Apr-12	235.11	131.78
May-06	153.59	123.59	May-12	40.68	68.39
Jun-06	187.21	159.46	Jun-12	115.32	73.82
Jul-06	168.22	171.31	Jul-12	77.33	38.47
Aug-06	222.62	189.52	Aug-12	126.60	45.25
Sep-06	55.57	120.02	Sep-12	44.56	-
Oct-06	524.35	252.03	Oct-12	504.98	228.94
Nov-06	626.26	236.84	Nov-12	171.33	204.76
Dec-06	80.39	172.13	Dec-12	262.57	228.76
Jan-07	43.97	97.52	Jan-13	110.27	174.69
Feb-07	10.65	74.28	Feb-13	71.38	124.97
Mar-07	112.83	40.36	Mar-13	171.59	124.86
Apr-07	295.03	169.21	Apr-13	156.90	127.01
May-07	138.87	162.36	May-13	195.67	170.29
Jun-07	153.08	163.62	Jun-13	340.39	239.45
Jul-07	123.22	150.36	Jul-13	126.91	188.80
Aug-07	84.57	107.93	Aug-13	89.20	136.99
Sep-07	214.37	166.99	Sep-13	309.14	217.15
Oct-07	306.01	232.49	Oct-14	504.31	252.35
Nov-07	234.25	227.25	Nov-14	210.71	228.89
Dec-07	113.72	182.83	Dec-14	552.88	247.64
Jan-08	35.70	115.08	Jan-15	3.09	179.49
Feb-08	188.15	152.90	Feb-15	98.80	140.89
Mar-08	316.02	222.28	Mar-15	221.50	176.69
Apr-08	362.91	247.78	Apr-15	313.61	228.81

Calibration (Oct 2004 – Sep 2010)			Verification (Oct 2010 – Sep 2017)		
Month	**Optimized Monthly Thiessen Rainfall and Parameters Simultaneously**	**S(t) (mm/month)**	**Month**	**Optimized Monthly Thiessen Rainfall and Parameters Simultaneously (mm)**	**S(t) (mm/month)**
May-08	90.81	174.65	May-15	136.22	190.69
Jun-08	96.15	155.91	Jun-15	156.85	181.62
Jul-08	210.40	196.19	Jul-15	31.33	116.33
Aug-08	50.16	127.20	Aug-15	94.49	75.21
Sep-08	78.26	81.23	Sep-15	137.11	91.68
Oct-08	447.06	241.12	Oct-15	459.41	242.41
Nov-08	302.53	245.69	Nov-15	423.93	252.88
Dec-08	117.21	186.05	Dec-15	287.49	241.90
Jan-09	25.03	125.04	Jan-16	23.23	161.05
Feb-09	9.93	96.89	Feb-16	37.61	95.04
Mar-09	327.23	198.33	Mar-16	115.34	64.32
Apr-09	221.36	204.32	Apr-16	195.86	113.18
May-09	239.14	216.12	May-16	723.97	242.78
Jun-09	146.74	191.91	Jun-16	99.19	175.21
Jul-09	59.08	115.06	Jul-16	38.30	106.18
Aug-09	171.32	139.82	Aug-16	15.54	75.50
Sep-09	242.66	191.28	Sep-16	15.69	49.15
Oct-09	301.33	229.97	Oct-16	121.69	36.73
Nov-09	317.33	245.37	Nov-16	195.30	103.53
Dec-09	253.02	236.94	Dec-16	17.68	70.93
Jan-10	66.16	145.47	Jan-17	44.87	7.96
Feb-10	5.13	117.03	Feb-17	22.82	-
Mar-10	127.48	85.87	Mar-17	186.23	64.57
Apr-10	432.86	234.40	Apr-17	75.52	31.31
May-10	156.50	195.65	May-17	180.43	102.17
Jun-10	195.05	200.72	Jun-17	120.48	123.25
Jul-10	148.77	162.36	Jul-17	61.48	80.81
Aug-10	120.63	131.51	Aug-17	98.10	71.99
Sep-10	159.86	152.85	Sep-17	270.55	193.93