HEC-HMS MODEL PARAMETER TRANSFERABILITY FOR DAILY STREAMFLOW ESTIMATION IN GIN GANGA BASIN

Jayaweera Muhandiramge Lalani Madhushankha

(189241J)

Degree of Master of Science

Department of Civil Engineering

University of Moratuwa
Sri Lanka

September 2019

HEC-HMS MODEL PARAMETER TRANSFERABILITY FOR DAILY STREAMFLOW ESTIMATION IN GIN GANGA BASIN

Jayaweera Muhandiramge Lalani Madhushankha

(189241J)

Supervised by
Professor N.T.S. Wijesekera

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

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

Department of Civil Engineering

University of Moratuwa
Sri Lanka

September 2019

DECLARATION

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

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

UOM Verified Signature

....19/09/2019.....

Jayaweera Muhandiramge Lalani Madhushankha Date

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

UOM Verified Signature

19.09.2019
....

Professor N.T.S.Wijesekera Date

ACKNOWLEDGMENT

I would like to express my sincere and heartfelt gratitude to my research supervisor, Professor N.T.S. Wijesekera for the unwavering support for my study with his patience, motivation and immense knowledge. Without his dedicated supervision and continued guidance, this thesis would not be completed within the time frame. During my period, he consistently allowed this research to be my work, but steered me in the right direction whenever he thought I needed it. He is a great teacher.

I have to extend my gratitude to the course coordinator Dr. R.L.H. Lalith Rajapakse for providing me all the necessary assistance and consistent encouragement while guidance when required even working under a busy schedule.

Further I would like to extend my gratitude to Mr. Wajira Kumarasinghe and staff of the University of Moratuwa for their support in different ways during this research period.

I would also like to thank Late. Shri Madanjeet Singh, Management of Fund and the University of Moratuwa for giving me this opportunity to study towards a Master Degree in Water Resource Engineering and Management, at UNESCO Madanjeet Singh Centre for South Asia Water Management, Department of Civil Engineering, University of Moratuwa, Sri Lanka.

Also, I must thank to Department of Irrigation for approvals to collect necessary data.

Specially I must express my very profound gratitude to my mother (R.A. Kamalawathi), my sisters and my best friends for encouragement and take care when I am having a hard time.

HEC-HMS Model Parameter Transferability for Daily Streamflow Estimation in Gin Ganga Basin

ABSTRACT

Rapid urbanization and population growth with economic advancement causes a conflict between limited freshwater supply and the demand. Accurate streamflow estimation in a watershed is a necessity for sustainable water resources management to overcome this conflict. Sustainable water management requires quantification of streamflow components for flood, drought and irrigation management. Hydrologic modeling is one of the most versatile options to estimate streamflow in watershed. Streamflow quantification by modeling had issues with ungauged watersheds due to lack of sufficient measured data to determine model parameters. The objective of this work is to apply HEC-HMS process-based model to simulate process-based river flow in an ungauged sub-watershed Thawalama at daily time scale, where the main watershed Baddegama is gauged, and check the possibility of parameter transferability from main to sub-watershed and vice versa. Here, spatiotemporal transferability approach was used to assess possibility of parameter transferability in order to estimate daily streamflow in an ungauged sub watershed. Temporal transferability approach also used to assess the comparison of selected transferability option for this work. Gin Ganga basin study area and HEC-HMS model were selected. Eight models developed for both Thawalama and Baddegama watersheds from 2007 to 2017 on a daily time scale. Calibration period was from 2007 to 2012 and validation period was from 2012 to 2017. Model efficiency was evaluated by the Root Mean Square Error (RMSE). Two models at Baddegama and Thawalama were calibrated and validated. For spatiotemporal approach, both model's calibrated parameters were transferred from Baddegama to Thawalama and vice versa for 10 years of period. For temporal approach calibrated parameters of both models were transferred to same watersheds for 10 years of period. Then the model performance evaluated with flow hydrograph, flow duration curve for low, high and intermediate flows to asses calibrated parameter transferability of HEC-HMS from Baddegama to Thawalama sub-watershed and vice versa. Thawalama and Baddegama models were calibrated with RMSE of 4.8 mm/day, 3.0 mm/day and validated with RMSE of 5.0 mm/day, 3.5 mm/day respectively. The spatiotemporal parameter transferability approach to Baddegama main watershed from Thawalama sub-watershed showed RMSE of 6.0 mm/day and vice versa showed RMSE of 5.8 mm/day. The temporal parameter transferability approach to Baddegama main watershed from Thawalama sub-watershed showed RMSE of 3.3 mm/day and vice versa showed RMSE of 4.9 mm/day. Results concluded that spatiotemporal transfer approach showed better achievement in model parameter transferability from main to sub-watershed. Temporal transfer approach showed better achievement in model transferability from sub to main watershed. Spatiotemporal transferability approach showed better model performance rating than temporal approach with RSR value of 0.5 for Thawalama sub-watershed to Baddegama main watershed and RSR value of 0.6 for vice versa. The HEC-HMS model can be successfully applied to assess the transferability approach within the Gin Ganga basin for sustainable water resource management. Furthermore, need to asses individual parameter influence on transferability approach with compared to watershed physical characteristics.

Key Words

Process-based hydrologic model, HEC-HMS, Sustainable Water Resources Management, Spatial Transferability

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF ABBREVIATION

Abbreviation	Description
FDC	Flow Duration Curve
MRAE	Mean Ratio of Absolute Error
MAR	Mean Annual Rainfall
NEM	North East Monsoon
NWSDB	National Water Supply and Drainage Board
RAEM	Ratio of Absolute Error to Mean Relative Error
RF	Rainfall
RMSE	Root Mean Square Error
SF	Streamflow
SMA	Soil Moisture Accounting
SWRM	Sustainable Water Resources Management

1 INTRODUCTION

1.1 Sustainable Water Resources Management

Satisfying the water requirement of the current generation without obstructing the capability of future generations to encounter their requirement, is expressed as sustainable water resource management (SWRM) (Mahmoud Abu-Zeid & I. A. Shiklomanov, 2003). The present-day world is more concerned about sustainable water resources management because they face the consequences of their previous mistakes.

Rapid urbanization and population growth have increased water demand because of limited water resources (Ojha, Surampalli, Bardossy, Zhang, & Kao, 2017). Water scarcity is a key problem in most parts of the world. Specially in developing countries with arid and semi-arid climate conditions (Feng, 2001). The main target of Integrated Water Resources Management is to reach a sustainable, efficient and equitable development to fulfill global management of limited water resources and resolve conflicts between supply and demand (Lopera, 2015). Loucks, (2000), mentioned that estimating the ways to sustainably manage and develop water and related environmental resources to face the future demand is a challenge. Existing water resources and future demands should be assessed in water planning. Possible development for water planning has to be assessed to evaluate the impact on society and the environment (Lopera, 2015). Therefore, sustainable water resources management has become very important.

1.2 Hydrologic Modeling in Streamflow Estimation

Environmental management, flood management and drought management are the main three distinct tasks in SWRM. A sufficient collection of continuous series of streamflow data is necessary to SWRM (Abimbola, Wenninger, Venneker, & Mittelstet, 2017).

The processes in the hydrologic cycle in a watershed are complex. Quantification of each hydrological process in a watershed is needed to manage flood, soil erosion, groundwater recharge, drought, etc. Advanced methods are required to simulate the hydrological processes appropriately. Lack of past observations and advances in technology have made hydrological models as a remarkable solution to quantify streamflow (Hunter, Bates, Horritt, & Wilson, 2007). Similary, Loucks, (2000) mentioned that hydrological models are versatile tools to manage watersheds to evaluate upcoming effects of the proposed water management plan. Therefore, a systematically developed continuous hydrologic model is an essential requirement for water managers to implement sustainable water resource management plans.

1.3 Spatial and Temporal Resolution in Streamflow Modeling

Water resources assessment requires the collection of hydrological data. Spatial and temporal changes in water balance components are required to assess water resources (Gumindoga, Rwasoka, Nhapi, & Dube, 2017). Wijesekera, (2001) mentioned that the use of monthly data in planning and managing reservoir water is very effective. To achieve high performance in hydrologic modeling requires the appropriate spatial and temporal resolution of data (Mohamoud & Prieto, 2012). Flood protection analysis requires daily results instead of monthly results. Although, irrigation and hydropower management are preferred to use monthly results (Tessema, 2011).

Regions with sparse data are the major concern when conducting hydrological studies. Therefore, predictions of poorly gauged or ungauged catchments become important but are highly uncertain (Abimbola et al., 2017). Comprehensive physically-based distributed models are more precise. It requires information such as land use data, meteorological data and properties of the watershed for their parameterization and adjustment, which are not readily existing (Ojha et al., 2017). Therefore, a daily lumped model option can be used for streamflow estimation in an ungauged watershed.

1.4 Process-Based Hydrologic Modeling

Appropriate model selection for a particular catchment is vital to guarantee optimum watershed management (Verma, Jha, & Mahana, 2010). The main problem is the lack of guidance to select a suitable rainfall-runoff model. A suitable hydrologic model can be selected by using several selection criteria. Criteria of selection mainly depend on the projects specification (J. M. Cunderlik, 2003).

Water managers need quantification of infiltration and evaporation for drought management, soil moisture for irrigation management and direct runoff for flood management. Physical processes in the watershed can be mimicked effectively by using a process-based model. It includes fundamental governing equations to represent different processes of hydrologic systems such as interception, infiltration, groundwater flow, lateral flow, etc. (Ojha et al., 2017). A process-based model can incorporate for hydrological processes with space-time variability (Fatichi et al., 2016). Therefore, this model is a useful tool in sustainable water management and planning.

1.5 Challenges in Watershed Modeling

Watersheds in the earth are mostly ungauged or poorly gauged, and in other cases existing hydrologic measuring networks are deteriorating. Therefore, estimating SF of ungauged or poorly gauged watersheds is highly unreliable under the above situations. (Abimbola et al., 2017; Sivapalan et al., 2005). At data scares or poorly gauged sites, data requirement is the challenge to flow estimation. Although, watershed managers face the problem of modeling of sub watershed when only the main watershed is gauged with constraints of watersheds and model characteristics.

In this kind of situation, modelers used neighboring watershed substitution or data transferring as the most reasonable method. Neighbor watersheds hydrologic data can contribute to offer a good quality streamflow estimation at poorly gauged catchment area, in case of the parameter set transferring for hydrologic model development and calibration (Randrianasolo, Ramos, & Andréassian, 2011). In some cases, to improve the simulation of subbasins hydrology, more attention should be given to the transferability of the parameter values when only the main watershed is gauged (Van Der Linde & Woo, 2003). The main problem faced by water managers is the parameter transferability for sub-watershed evaluations by process-based models. Distributed sub-watersheds require calibrated model parameters. Even if we have a calibrated parameter, we need to assure model parameter transferability from main to sub-watersheds and vice versa.

1.6 Problem Identification

After reviewing the literature on hydrological modeling in Sri Lanka, it can be identified that an appropriate process-based hydrologic model and parameters need to be identified, then assess the transferring approach of model parameters within the watershed for SWRM. Hereafter, this research demonstrates a methodology to develop a process-based model for a watershed for water resource management by a case study application for the Gin Ganga basin at Thawalama and Baddegama. The reasons for selecting the Gin Ganga basin is the availability of data at a finer resolution, the possibility of evaluating model parameter transferability from main gauged watershed to ungauged sub-watershed and vice versa. Among many options the HEC-HMS model is extensively operated for a vast range of studies and enable of parameter transferability will expand the previous studies applicability. Therefore, the above-mentioned model was chosen to evaluate potential model parameter transferability for daily streamflow estimation in the Gin Ganga basin.

1.7 Study Area

Gin Ganga basin is denoted as the fifth largest river in Sri Lanka. Gin Ganga basin is facing flooding frequently during the rainy seasons. Gin Ganga having a watershed area of about 932 km^2. Rainfall pattern in the watershed falls between May-September, and November-February. The remaining months are subjected to the inter-monsoon rains. Rainfall fluctuates with altitude wherein upper reaches mean yearly rainfall is above 3500mm and it is less than 2500mm for lower reaches of the watershed. Sandy clay loam is the main soil type in the watershed and temperature varies from 24° C to 32° C. The watershed has a considerable rainforest cover in its upper watershed (Wickramaarachchi, Ishidaira, & Wijayaratna, 2012). The watershed area of Baddegama and Thawalama (Figure1-1) is 749 km^2 and 377 km^2 respectively.

1.8 Overall Objective

To apply HEC-HMS to appraise of process-based SF in Thawalama ungauged sub-watershed at daily time scale, where the Baddegama main watershed is gauged, and check the possibility to use the same model and parameters of the main watershed to sub-watersheds and vice versa.

1.8.1 Specific objectives

1. To review the state-of-art on of process-based hydrologic model.
2. To gathering and checking data.
3. To develop, calibrate and validate the continuous HEC-HMS model for Baddegama and Thawalama watersheds.
4. To assess spatial transferability of HEC-HMS model parameters from Baddegama to Thawalama watershed and vice versa.
5. To make recommendations for sustainable water resources management.

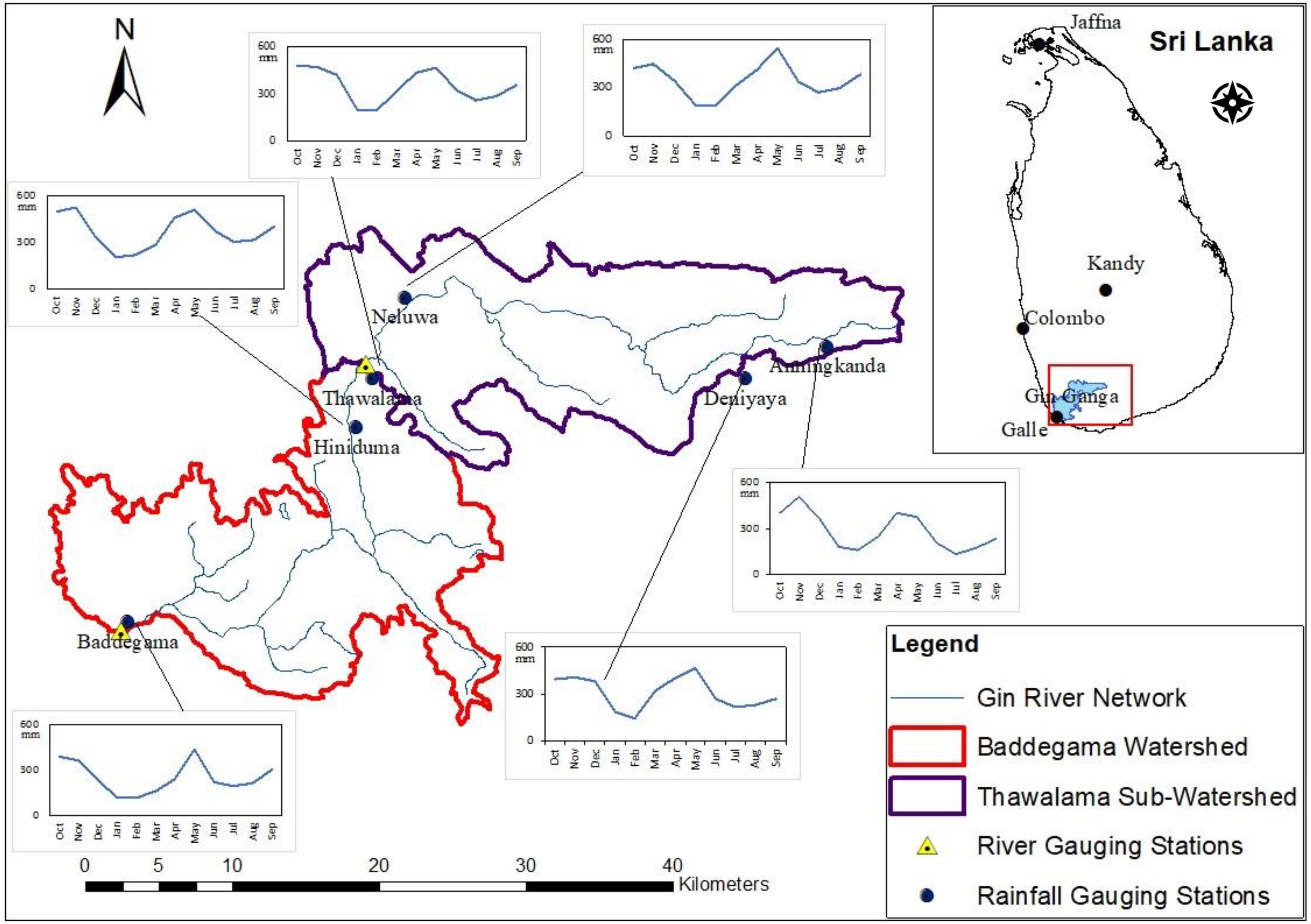


Figure 1-1:Study area

2 LITERATURE REVIEW

2.1 Hydrologic Models

The hydrologic model can be depicted as a rationalized picture of the existent world framework. It utilized for forecasting and understanding of hydrologic framework behavior with processes. Characteristics of the model defines by its different parameters. Further, a hydrologic model can be described as a collection of equations. These equations help in the assessment of runoff as a function of different parameters. Parameters of the models are used to describe the characteristics of watershed (Devia, Ganasri, & Dwarakish, 2015). Hydrological models are an essential tool in SWRM. To ensure efficient watershed management and planning, the selection of an appropriate model is a vital task (Verma et al., 2010). The main problem is the lack of guidance and existence guidance is not updated to select a suitable rainfall-runoff model for SWRM.

2.2 Types of Hydrologic Models

The models used to simulate hydrologic processes can be divided into different bunches depending on the diverse characteristics of the model. They can be grouped based upon the modeling approach, parameters of the model, the data that are used to the development of a model and the degree of physical theories applied in the model (Devia et al., 2015).

Various types of hydrologic-models can be classified primarily based on whether they are considered to be lumped or distributed in terms of their basic spatial structure. Besides, it is essential to identify whether the models are implemented based on continuous or event-based data. This classification should also be extended to the model calibration phase (World Meteorological Organization, 1992).

Lumped hydrologic model's parameters are spatially constant within a watershed. Therefore, a watershed response is estimated only at the outlet without considering the sub-watershed response. Lumped hydrologic models are not indicating better response for event scale hydrological processes. The lumped modeling approach is a good alternative to the complex physically-based models when the main focus is only streamflow prediction (Gebre, 2015).

2.3 Application of Types of Hydrologic Models

The HEC-HMS model is relevant to different kinds of geographic areas for solving watershed issues. Those issues consist of wide waterways, flood hydrology, and small natural or urban catchment streamflow (USACE, 2016). Gebre, (2015), had carried out a study of future impacts scenario prediction of climate changes on runoff by using the above-mentioned model. The continuous of this model can simulate in both wet and dry climatic behaviors (Mousavi, Abbaspour, Kamali, Amini, & Yang, 2012).

Lee, Yoon, Jung, & Hwang, (2010), have been assessed the applicability of hydrologic and water quality simulation by SWMM and HSPF models in Han River Basin. They recommended SWMM was sensibly indicated with observed data in a minor scale urban area. And for hourly observed data, the HSPF model was effective with some parameters which are related to streamflow and water quality.

SWAT application in intensive irrigation systems was carried by Dechmi, Burguete, & Skhiri, (2012). They said that the model can be used to evaluate the influences of different best management practices on nonpoint phosphorus losses in irrigated systems. Bouraoui, Benabdallah, Jrad, & Bidoglio, (2005), had developed the SWAT model in the Medjerda river basin (Northern Tunisia) to asses impact due to rapid increase of land in irrigation and agricultural activities. And also, the model could be reproduced streamflow very successfully.

In the case study of the WetSpa model, the application indicates the appearing impediment and needs of wetland catchment for precipitation runoff estimation (Jarosław & Batelaan, 2011).

In the Kelani river basin, HEC-HMS was used to model for both events and continuous. Research indicates several potential applications of the HEC-HMS model such as disaster mitigation, flood control, and water management. According to the obtained results, it has been concluded that the selected model can reproduce streamflows in the basin very accurately (Silva, Weerakoon, & Herath, 2014).

2.4 Continuous and Event Model

In contrast, continuous-process models take precise account of all runoff components, considering direct and indirect runoff also. It is considered that continuous abstractions from an aquifer or deep groundwater table account for regain of soil moisture level during no rainfall period. Continuous modeling is suited for forecasting SF on a daily time scale, monthly or seasonal time scale (J. M. Cunderlik, 2003). Single event methods can be seen frequently due to following reasons, (1) it is simpler to use,(2) computational accuracy and improvement does not greater in complex modeling; and (3) the complexity level in the continuous or long-term simulation models may not be suitable for the available streamflow data in a watershed (Hromadka, 1987). According to choose of the modeling approach, the event modeling is more preferable for flood-forecasting and drainage control structures studies (J. M. Cunderlik, 2003).

In this study of HEC-HMS parameter transferability long term objective for modeling is for water resource management. Therefore, continuous modeling can be preferable.

2.5 Lumped and Distributed Model

Model can be defined as "lumped" when the spatial derivatives are ignored, if not it can be defined as ''distributed'' and output can be expressed as a function of space and time. If all features of the model (parameters, initial and boundary conditions, sources and sinks) are distributed then only can say a model is truly distributed (V. P. Singh & Woolhiser, 2002). Lumped models aren't generally suitable for event-scale processes. But these models can provide better simulations for discharge prediction as complex physically-based models (J. M. Cunderlik, 2003). Therefore, the lumped model is much more preferable for this study because it is considering the continuous process for sustainable water resource management.

2.6 Temporal Resolution

For efficient planning and management of reservoirs, a monthly basis can be used (Wijesekera, 2001). Accordingly modeling with daily-time scale basis data and results accumulation into monthly can be more reliable for sustainable water management. Rational representation of the runoff process can be achieved by continuous modeling throughout a long period (Kaffas & Hrissanthou, 2014). If the analysis is for flood analyses, daily results will be more critical than the monthly results (Tessema, 2011).

2.7 Current Status of Process-Based Hydrologic Models

Process-based watershed models are extensively used because of its capability for evaluation of the effects of natural and human influences on water resources. It is capable of simulating each hydrological process like infiltration, evaporation, interception, etc. (Shen & Phanikumar, 2010). Although detailed physically-based distributed models need a lot of data and information (meteorological data, land use information, physical characteristics of the catchment for their parameterization and process of calibration) but it provides a more reliable output (Ojha et al., 2017).

Physically-based hydrological models are developed with the physical relationships connected with processes of the hydrologic cycle in a watershed and apply physic-related equations to explain the hydrologic cycle. The most widely accepted physically-based models in the market are, GSSHA, HSPF, KINEROS2, MIKE SHE, and SWAT (Daniel, Camp, Leboeuf, et al., 2011). Another study was directed to review lately developed or regularly updated models such as HEC-HMS, AnnAGNPS, SWAT, GSSHA, WinSRM, PRMS, HYPE, WetSpa, and MIKE-SHE. These models were compared according to evaluation criteria as follows:1. The processes of the hydrologic system that the model estimate, 2. Principal formulas that are used to determine and quantify the hydrologic processes, 3. Requirement of lesser input data to execute the model and 4. Resolution scale in spatially and temporally because these evaluation criteria are common, important points that are essential as always before selecting any hydrologic models (Dhami & Pandey, 2013). Therefore, a lumped continuous process-based model option can be considered for streamflow estimation in an ungauged watershed.

2.8 Model Comparison

After reviewing the studies of Daniel, Camp, LeBoeuf, et al., 2011; Dhami & Pandey, 2013; Fatichi et al., 2016; V. P. Singh & Woolhiser, 2002; World Meteorological Organization, 1992, the recently developed famous process-based models were selected and initially shortlisted according to some criteria. Criteria was selected according to the objective of this study such as parameter transferability options for process-based streamflow modeling of ungauged watersheds. After that each model was classified as high, medium and low according to judgment (Table 2-3) and assign weight as 5,3,1 for high, medium and low respectively to each criterion to find four models (Table 2-1). After that detailed comparison was done for shortlisted four models as similarly shortlisting procedure to select a model for parameter transferability option for process-based streamflow modeling in ungauged watersheds (Table 2-2).

With compared to recently developed and updated models, HEC-HMS is providing more options to simulate (Dhami & Pandey, 2013). According to evaluation criteria HEC-HMS can be recommended as one of the best options to simulated process-based streamflow of ungauged sub-watersheds.

Table 2-1:Model selection-initial shortlisting evaluation

Criteria	HEC-HMS	Wetspa	MIKE-SHE	SWAT	AnnAGNPS	GSSHA	HYPE	PRMS
Criteria1: Number of Model application	High (5)	Medium (3)	High (5)	Medium (3)	Medium (3)	Medium (3)	High (5)	High (5)
Criteria 2: Serve the purpose of water management	High (5)	Medium (3)	Low (1)	Low (1)	Low (1)	Medium (3)	Low (1)	High (5)
Criteria 3: Hydrological processes that the model can simulate	Medium (3)	Medium (3)	High (5)	High (5)	Medium (3)	High (5)	Medium (3)	Medium (3)
Criteria 4: Temporal resolution	High (5)	High (5)	High (5)	High (5)	Medium (3)	High (5)	Medium (3)	Medium (3)
Criteria 5: Capability of lumped modeling	High (5)	High (5)	High (5)	High (5)	Low (1)	Low (1)	Medium (3)	Low (1)
Criteria 6: Application in ungauged watersheds	High (5)	Medium (3)	High (5)	High (5)	Medium (3)	Low (1)	High (5)	Medium (3)
Criteria 7: Parameter transferability	Medium (3)	Medium (3)	Medium (3)	Medium (3)	Low (1)	Low (1)	Low (1)	Low (1)
Criteria 8: Technical support	High (5)	Medium (3)	High (5)	High (5)	Medium (3)	High (5)	Medium (3)	High (5)
Criteria 9: Availability of model	High (5)	High (5)	Low (1)	Medium (3)	High (5)	Low (1)	High (5)	High (5)
Criteria 10: Data Requirement	High (5)	High (5)	Low (1)	Low (1)	Medium (3)	Low (1)	High (5)	Low (1)
Average Weight	**5**	**4**	**4**	**4**	**3**	**3**	**3**	**3**
References	(J. M. Cunderlik, 2003; Daniel, Camp, LeBoeuf, et al., 2011; Devia et al., 2015; Dhami & Pandey, 2013; Dogan & Berktay, 2005; Fatichi et al., 2016; V. P. Singh & Woolhiser, 2002; World Meteorological Organization, 1992)							

Table 2-2:Model selection-detailed shortlisting evaluation

Criteria	HEC-HMS	Wetspa	MIKE-SHE	SWAT
Criteria 1: Number of hydrological processes that model can simulate	Medium (3)	High (5)	High (5)	High (5)
Criteria 2: Minimum input data requirement	High (5)	Medium (3)	Low (1)	Low (1)
Criteria 3: Number of parameters for default model configuration	High (5)	Low (1)	Low (1)	Medium (3)
Criteria 4: Spatial scale	High (5)	Low (1)	High (5)	High (5)
Criteria 5: Time scale	High (5)	High (5)	High (5)	High (5)
Criteria 6: Computational time step	Medium (3)	High (5)	High (5)	Low (1)
Criteria 7: Model processing time to run one model	High (5)	Medium (3)	Low (1)	Medium (3)
Criteria 8: Model application of parameter transferability	High (5)	Low (1)	Low (1)	High (5)
Criteria 9: Climate Region	High (5)	Medium (3)	Medium (3)	High (5)
Criteria 10: Number of applications in Sri Lanka	High (5)	Low (1)	Low (1)	Low (1)
Criteria 11: Easy of model development	High (5)	Medium (3)	Low (1)	Low (1)
Average	**5**	**3**	**3**	**3**
Reference	(Ali, Khan, Aslam, & Khan, 2011; Dhami & Pandey, 2013; Gebre, 2015; Gumindoga et al., 2017; Kaffas & Hrissanthou, 2014; Kalita, 2011; Mousavi et al., 2012; Razi, Ariffin, Tahir, & Arish, 2010; River & Lanka, 2010; Roy, Begam, Ghosh, & Jana, 2013; Sardoii, Rostami, Sigaroudi, & Taheri, 2012; USACE, 2016; Verma et al., 2010)	(Dhami & Pandey, 2013; Jarosław & Batelaan, 2011; Liu & Smedt, 2004; Safari, De Smedt, & Moreda, 2012)	(Christiaens & Feyen, 2002; Dhami & Pandey, 2013; DHI, 2017; McMichael, Hope, & Loaiciga, 2006; Zhang et al., 2008)	(Bouraoui et al., 2005; Dechmi et al., 2012; Dhami & Pandey, 2013; Jayakrishnan, Srinivasan, Santhi, & Arnold, 2005; Krysanova & Arnold, 2008)

Table 2-3:Judgments for model classification

Criteria		High	Medium	Low
Initial shortlisting	Criteria 1	all around the world	part of the world	only for major countries
	Criteria 2	capability in flood, drought and environmental management	capability in any of the two management tasks	capability in any one of the management tasks
	Criteria 3	most of the all hydrological processes	more than streamflow and evaporation but less than all the processes	only surface and evaporation
	Criteria 4	daily, hourly, minute	daily	monthly, yearly
	Criteria 5	option for lumped modeling	partially distributed modeling	only for distributed modeling
	Criteria 6	many applications in ungauged watershed	lesser application in ungauged watershed	no application in ungauged watershed
	Criteria 7	mention in parameter transferability	mention there may be possibility of parameter transferability	not mention in parameter transferability
	Criteria 8	technical published support with interactive web technical support	In between interactive web support and technical support and no interactive web-based technical support with only published technical support	no interactive web-based technical support-only published technical support
	Criteria 9	free available	partially free available	fully commercial model
	Criteria 10	if a model can do initial run with limited data requirements	In between limited and high data requirements	if model need all the data to do an initial run (90% of data requirements)
Detailed shortlisting	Criteria 11	higher number of processes: i.e. snow, groundwater	in between high and low; no snow and groundwater	less numbers-only streamflow
	Criteria 12	less number of data to the initial run of a model	in between high and low data requirement to model initial run	need a higher number of data to initial run
	Criteria 13	less number of parameters	In between higher and lesser	higher number of parameters

	Criteria 14	wide range of spatial extent/with no restriction	in between restricted and wide range of spatial extent	restricted spatial extent
	Criteria 15	daily with continuous process for all component	daily with continuous processes only for selected component	daily with event processes
	Criteria 16	can be changed according to a modeler	finer time steps are there but no selections	cannot change it according to a modeler
	Criteria 17	less total time to run model	moderate time allocation for model running	Higher number of parameters
	Criteria 18	many applications in parameter transferability	possibility of parameter transferability	Not mentioning parameter transferability
	Criteria 19	dry, wet and hilly	dry and wet	cannot model for whether it is too wet or dry, means moderate climate
	Criteria 20	a higher number of applications in Sri Lanka	in between higher and lesser	lesser number of applications Sri Lanka
	Criteria 21	less knowledge of the modeling, need of expertise, low intense of data	moderate knowledge is enough and no need high intense data	just a few pieces of knowledge are enough to run the model, high intensity of data

2.9 Parameter Transferability

The selection of the model with the simplest structure with compatible for the use of the model on the application is the basic rule (Diskin M.H & Simon E., 1977). To estimate the streamflow, rainfall-runoff models require real-time streamflow data and information for model setup, calibration, validation and updating of the initial conditions at the time of the predictions.

The catchment locations where poorly gauged or ungauged, need of data is the challenge to flow estimation. Estimation of the good quality streamflow at ungauged areas can be done by using data from nearby watersheds, specially with the case of parameter transferring to model development and simulation (Randrianasolo et al., 2011).

Information from gauged watersheds is usually transferred to the ungauged watersheds using regionalization processes. There are many methods used for parameter regionalization such as spatial proximity, model averaging and parameter regression etc. (Abimbola et al., 2017). As transferability depends on the considerations of climate, topography, land cover type and compatibility of scale, have to face several obstacles when applying or transferring data or parameter of a model from one basin to another for hydrologic modeling (Van Der Linde & Woo, 2003).

As a method of model parameter transferring, averaged calibrated model parameters can be applied to other data-limited basins to evaluate the spatial transferability of parameters for runoff prediction. There can be uncertainty in runoff simulation due to uncertainty in model parameters derived from regionalization schemes to judge it’s reliability for future use (Dulal et al., 2007). Though the model parameters can also vary in extraordinary basins because of differences in physical characteristics of basin and process in the hydrologic system, and the extent with the possibility of parameter transferability in extraordinary conditions needs to be investigated. The proxy-basin technique turned into well desirable as a means to test parameter transferability for the process-primarily based J2000 model (Nepal, Fischer, Flügel, Krause, & Fink, 2017).

Patil & Stieglitz, (2015) have been compared spatial, temporal and spatiotemporal schemes of parameter transferability of 294 catchments across the United States by using a lumped hydrological model called EXP-HYDRO. Results recommend that the spatiotemporal parameter transfer approach of the model has practicable to be an achievable option for climate alteration hydrological research.

It is difficult to select an appropriate model which is having a simple structure, lesser initial data needs and sensible reliability due to measurement of all parameters affect streamflow generated in watershed. HEC-HMS is one of the models that satisfying the above-mentioned criteria (Majidi & Shahedi, 2012). A lower number of parameters with assessing more hydrological processes in HEC-HMS tend to widely selected model (Bennett & Peters, 2000; Gumindoga, Rwasoka, Nhapi, & Dube, 2017; USACE, 2001). The Invariability of physical parameters in the lumped model is easy to transfer to other watersheds (J. M. Cunderlik, 2003). Therefore, the HEC-HMS model has been selected for this study by considering above mention criteria and the continuous modeling of the process to assess transferability by spatiotemporal transferability approach and temporal transferability approach for comparison purposes of transferability performance.

2.10 Filling Missing Data

To gain more realistic conclusions form hydrologic outputs needs identification of confidence level for used data by data checking (Wijesekera & Perera, 2016). Streamflow data at several sites are required for watershed management planning and designing when it is having complex water resource systems. Although a couple of series could also be sufficiently long, it's generally found that several are of inadequate. Also incomplete dataset make the model complex and unreliable (Jara Torres, Sánchez, Avilés, & Samaniego, 2016). Therefore, it is necessary to infill missing data before the practical application of the series (Gyau-Boakye & Schultz, 1994).

Spatial interpolation techniques are widely used methods for filling the gaps in daily rainfall series through estimating the unknown rainfall amount to some extent from the known data from adjacent stations (Hasan & Croke, 2013). Three main types of infill methods can be found in literature They are (i) the deterministic, (ii) stochastic and (iii) artificial intelligence methods (Jara Torres et al., 2016). The closet station method to fill daily is missing data shown very good performance (B. I. L. Garcia, Sentelhas, Tapia, & Sparovek, 2006). Spatial interpolation methods such as normal ratio, inverse distance, correlation coefficient, arithmetic average and etc. refer to the process of estimating the unknown data values for a point using the known data values from nearby stations (Ismail & Ibrahim, 2017). Another study compares four methods of data filling namely "simple substitution", "classical least squares univariate parametric regression", "ranked regression" and "Theil method". And also having 10 km as an average distance between meteorological stations are adequate to incorporate spatial variability of station. Thus, results show that, simple substitution shows acceptable reliability for filling missing data (Lo & Emanuele, 2010). Missing data can be estimated by using empirical methods, statistical methods and function fitting. Among the classical methods, multiple regression analysis method is the most appropriate method (Hasanpour Kashani & Dinpashoh, 2012). Therefore, Thiessen polygon spatial interpolation has been selected because station locations are fixed and not vary spatially.

2.11 Model Calibration and Validation

The process of model calibration is a methodical procedure of changing the value of model parameters until produced values are matched with the observed or base data within an acceptable level. The model should be calibrated for the recognized sensitive parameters to obtain a better agreement between the simulated and observed data (W. R. Singh & Jain, 2015). Objective function describes the quantitative measure of the matching between simulated and observed data. During the calibration process, the optimal parameter values to be found while minimizing the target function. Further, calibration estimates some model parameters which don't have any direct physical sound. Other hands these model parameters cannot estimate from observation or measurement. Calibration can either be manual or automated optimization. The manual calibration process depends on knowledge of the modeler about the physical properties of watershed and knowledge in hydrologic modeling. In the automated calibration model, parameters are iteratively adjusted until the value of the selected objective function is minimized (F. Garcia, Folton, & Oudin, 2017). The first step of the calibration of the continuous model consisted of a combination of both manual and automated calibrations (J. M. Cunderlik & Simonovic, 2004).

The verification or validation of the model can be defined as the method of checking the capability of the model to generate data closer to observed with acceptable accuracy while keeping freeze of parameters that were adjusted after the calibration process. Calibrated model parameters are kept constant during this process. By using sensitivity analysis, the number of parameters for the calibration can be reduced and most important and unreliable parameters can be identified (Salvadore, Bronders, & Batelaan, 2015).

2.12 Objective Function

The goal of continuous modeling is the water balance simulation at desired intervals throughout a long period, generally several months or years. Output is usually expressed as a monthly or annual flow volume. Under these situations, protracted low flow sequences are of importance and any goodness-of-fit criterion is chosen to evaluate the performance of such a model should be able to take this aspect of the hydrograph into account. Twenty-one objective functions were assessed in a previous study to compare hydrographs with different stormwater modeling applications to show the criteria highlight particular aspects (Diskin & Simon E., 1977). Another research group has studied about 21 number of criteria for hydrograph comparison in single event modeling and practically used for a particular stormwater modeling problem (Green & Stephenson, 1986). SSR, SAE (sum of absolute errors), model efficiency, RMSE, etc. are some of the objective functions. SAE, SSR, Percent error in peak, Peak-weighted RMSE, and graphical visualization are error indication that used in HEC-HMS model (USACE, 2000).

The study by Kamali, Mousavi, & Abbaspour, 2012 has been used four objective functions such as weighted root mean squared error (WRMSE), percent error in peak flow (F_{peak}), percent error in runoff volume (F_{vol}) and correlation coefficient (F_{time}). WRMSE has used in single-objective calibration and for multi-objective calibration different combinations of the functions have been investigated. In WRMSE function, give more priority to the higher flows by giving higher weights to them. However, this function thinks about all discharge points of a hydrograph. Peak flow criterion is the only factor taken in F_{peak} function while neglecting flood volume and time to peak criteria. F_{vol} emphasize on the flood volume. Finally, F_{time} is used to reduce the error in assessing the criterion of time to peak.

Least square errors generally favor the hydrograph matching for high flows (Garcia et al., 2017). Nash-Sutcliff (NSE), Mass Balance Error (MBE) and Coefficient of determination (R^2) have been used to assess the model performance (Gebre, 2015). Musiake & Wijesekera, (1990) expressed the difference between calculated and observed flow concerning that of the average mean of observation as the Ratio of Absolute Error to Mean (RAEM).

Coefficient of Determination (R^2) values in high flow vary by small vales, in medium flows it vary with slight high difference. In low flows R^2 values variation is small and it is the same as for high flows. For the whole data set, it's not showing any variation for overestimation and as well as less estimation of streamflow but showing better results as a prediction. Therefore, R^2 cannot take into account to asses all flow variation. R^2 values vary from 0 to 1 and 1 is showing the best match with observed and simulated values. RMSE varies from ∞ to 0 and 0 is reflecting best match with observed and predicted flow. Variation of RMSE values from observed flow for high, medium and low are reflecting with better deference with compared to observed when predicted flows are increasing. Coefficient of Efficiency (Nash-Sutcliff-NSE) range vary from $-\infty$ to 1 and 1 is reflecting best match with observed and predicted flow. When low streamflow increasing, the NSE value variation is slightly small compared to high and medium flow. The overall predicted flow variation is shown a little bit better with considerable variation. Mean Relative Absolute Error (MRAE) range varying from ∞ to 0 and 0 is reflecting best fit with observed and predicted flow. Variation change in low flow is not reflecting very well from MRAE. By the overall flow variation is reflecting better results. Percent Error in Peak Flow (PEP) is only showing results for High flow variation and the same for the overall flow variation and medium and low flow not giving sensible values. PBIAS is showing better variation between observed and predicted flow in high flow and medium flow variation. Low flow variation indicates by PBIAS is not considered representative. By the way, the overall variation is similar to RAEM and PEP values. Sum of Absolute Error and Sum of Squared Error ranges are varying from ∞ to 0 and 0 is indicating best match with observed and predicted streamflow. Both give high and low weights separately compared to the magnitude of the error. Mean Absolute Error values are better for low flows with less variations and values closer to zero when compared to high flow. High flow is better than intermediate and intermediate is better than overall. Logarithmic Root Squared Mean Error values are best for high flows and low flows with less variations. Intermediate flow and then overall flows show slight high variations but all values are near to zero. Standard x values are best for high flows and low flows with less variations. Intermediate flow and then overall flows show slight high variations but all values are near to zero. Peak-Weighted RMSE is showing similar behavior like RMSE. But the calculation is difficult compared to RMSE. Root Squared Relative Error has values near to zero for all flows. With closest to zero being low flows. With compared to above mentioned objective functions by considering overall, High, Medium and Low flows best match with predicted and observed is reflecting by RMSE. RMSE objective function is commonly used to establish quantitative statistics by the simulated values of less observed values (Hamedi & Fuentes, 2015; Verma et al., 2010). This objective function widely used in HEC-HMS for automatic calibration process too. Therefore, this RMSE indicator was selected in the HEC-HMS model as an objective function in the optimization process.

2.13 Model Warm-Up

The basics of all of the hydrologic model is the continuity equation and water balance relationship. So, the model needs to stabilize the soil moisture storage to success in a stabilized state called a warm-up process of the model. Typically periods for warming up the hydrological models vary from one to several years (Kim, Kwon, & Han, 2018). In a previous study, used a warm-up period to minimize model dependence on initial condition state variables which is one of assessing criteria in model parameterization (Amatya, Parajuli, Bonta, & Green, 2016). Furusho, Chancibault, & Andrieu, 2013, selected the first year for the model warm-up, because to simulate similar results from different initial soil water contents for ISBA-TOPMODEL application the model needed more than 6 months. The results of two case studies by Yang, Liu, Yang, & Chen, (2012), mentioned that a warm-up period is required for reducing the effect of the initial condition of variables to the stabilized model simulation. Furthermore, they found to remove the impact of initial status, a five-year warm-up period would be sufficient. Therefore, 5 years of data duration was considered for the model warmup period for this study compared to data duration and model parameters.

2.14 HEC-HMS Model Structure

This model can simulate continuous series and storm events. It is a promising model for providing multiple options to simulate hydrologic processes (Dhami & Pandey, 2013). The HEC-HMS model obtains the direct runoff volumes by calculating and subtracting from precipitation, the volume of water that is intercepted, infiltrated, stored, evaporated or transpired. The model has four major sections, such as precipitation, basin, control specification and input data manager. Basin model consisting; loss model, canopy storage, surface storage, transform model, baseflow model and routing model (USACE, 2016).

2.14.1 Precipitation model

Gauge weight with Thiessen polygon mean areal precipitation method is most widely used for continuous HEC-HMS modeling because stations are fixed and not vary with the time (Gumindoga et al., 2017; Roy et al., 2013).

2.14.2 Canopy model

HEC-HMS model user manuals clearly state that canopy interception should be incorporated with an initial deficit and constant method in continuous modeling (USACE, 2000, 2016). By choice, to denote interception and evapotranspiration, the user can select the canopy component. There are three methods available in a model such as dynamic, simple and gridded simple canopy (USACE, 2016). Simple canopy is preferable for this study considering the continuous process and compatibility with the loss method.

2.14.3 Loss model

A collection of various methods is out there to simulate losses by the infiltration process in this model. Event modeling consists of several options such as initial constant, SCS CN method, exponential, Green Ampt, and Smith Parlange. For primary continuous modeling, usually deficit and constant loss method is used. For complicated infiltration and evapotranspiration situations soil moisture accounting method can be applied. Gridded methods are available for the deficit constant, Green Ampt, SCS CN method and soil moisture accounting methods. To represent interception and capture processes, the canopy and surface components can be included (USACE, 2016). Deficit and constant loss method can be used for this study because it is considered initial loss can regain after a protracted duration of no rainfall. Also it is most suitable for continuous simulation and having a smaller number of parameters (Kalita, 2011).

2.14.4 Transform model

To convert excess rainfall into direct runoff, seven methods have been incorporated into this model. Unit hydrograph (UH) methods consist of several options like Clark, Snyder, and SCS techniques. User-specified UH or s-graph ordinates are another option to transform the model. The modified Clark method could also be a linear quasi-distributed UH method and have the ability to incorporate gridded rainfall and evaporation data. Also, the implementation of the kinematic wave method with multiple planes and channels is incorporated (USACE, 2016). SCS method is famous in several HEC-HMS applications due to several reasons. They are, SCS method adaptation in various environments and generate better results, Only two kinds of parameters are needed to estimate during the calculation which makes the calculation process easier, reliable and excellent results can be obtained as same as complex models (Salvadore et al., 2015).

2.14.5 Baseflow model

To represent the flow adding by baseflow to basin streamflow, five methods are included in this model. The recession method gives an exponential reduction of baseflow from an event or set of repeated events. The constant monthly method can apply efficiently for continuous simulation but need measured data of basin which may not available. The linear reservoir baseflow method can be incorporated mass conservation within a system by routing infiltrated rainfall to the channel. Same as the recession method, the nonlinear Boussinesq method also gives a similar answer. However, parameters have to be obtained from measured data of the catchment characteristics (USACE, 2016). Baseflow was calculated by the exponential recession method (Ali et al., 2011) due to applicability in a continuous process, less number of parameters and compatible with loss model. Recession baseflow model consists mainly of three parameters, such as Initial discharge, Recession constant and Ratio to peak.

2.14.6 Routing model

For imitating flow in open channels, six hydrologic routing methods are incorporated into this model. The lag method is often used to model routing with no attenuation. For easy estimates of attenuation, the conventional Muskingum method is included together with the straddle stagger method. When modeling required to incorporate the cascade series of channels, the modified Puls method can be used. Kinematic wave or Muskingum-Cunge methods are mostly used to model the channels with various cross-sections. Further, channel losses also can be incorporated within the routing. The constant loss method can be added to any routing method, in contrast the percolation method can be used only with the modified Puls or Muskingum-Cunge methods (USACE, 2016). A simple finite difference approximation of the continuity equation is used in the Muskingum routing method (Gumindoga et al., 2017). But in this study river routing was neglected due to the lumped modeling approach.

2.15 Data Requirement

Inputs and their categories describe under the input data component of the model in HEC-HMS user's guideline report. To define parameters and boundary conditions of the model, input data categories into three groups like paired, time-series and gridded type data. Input data include elevation, soil, area of catchment, evaporation, topography, land use, rainfall and observed streamflow data (Heimhuber, Hannemann, & Rieger, 2015; Mazzoli, 2002; Mousavi, Abbaspour, Kamali, Amini, & Yang, 2012; USACE, 2016; Verma, Jha, & Mahana, 2010).

2.16 Parameters

Before the model used for estimating the runoff, the value of each parameter must be quantified to fit the model to a specific catchment. By observing the physical characteristics of the catchment, some parameters can be obtained. However, other parameters should be obtained through the calibration process. After basin was established, area, slopes, river length and length to the watershed centroid must measure by using the topographic maps to get the most essential model parameters like lag time. These parameters are called watershed characteristics which are essential to determine the model parameters. The parameters such as loss rate and deficit values were directly related to impervious surface area and CN value of catchment to generate streamflow. Similarly, lag time and UH peak coefficient parameters for the runoff transform are required based upon the methods selected hydrological process to developed the model (USACE, 2001).

2.17 Parameter Optimization in HEC-HMS Model

HEC-HMS 4.2.1 version consists mainly of two automatic optimization search algorithms namely Univariate Gradient (UG) and Nelder and Mead (NM) methods (Mousavi, Abbaspour, Kamali, Amini, & Yang, 2012). The calibrated parameter value of the model depends on the selected objective function when the modeler selects fully automatic calibration as an optimization process (Mousavi et al., 2012). HEC-HMS model was calibrated with both manual and auto-calibration because the auto-calibration process in the model may not converge to preferred optimum results. Initially, auto-calibration methods available in the model can be used to calibrate the parameters. Then by using the manual calibration fine adjustment of parameters can be done (W. R. Singh & Jain, 2015). The NM method is used more frequently than the UG method. This is mainly due to the NM method uses downhill simplex to assess all parameters simultaneously (Gebre, 2015). Kamali et al., 2012, mentioned that, these two techniques do not apply to the problems with a huge number of parameters. Because they implement a local search procedure with a pre-defined and limited number of calibration parameters. The NM search algorithm is used response information as a guide to improve search direction (Duan, Sorooshian, & Gupta, 1994). Because of these NM can be used for this study to the optimization process.

3 METHODOLOGY

Figure 3-1 shows the general methodology used for the current study. After recognizing a problem, objective and specific objectives, a literature survey was conducted to identify the commonly used hydrological models and their applications and various objective functions. After reviewing the different types of hydrologic process-based models and their application in several basins in the world and Sri Lanka, the HEC HMS model was selected for the Gin Ganga basin as it is freely available and usage of more application. Two watersheds namely Thawalama and Baddegama were selected to compare the transferability of the parameters from main to sub-watershed and vice versa.

Duration of daily rainfall (2007-2017), streamflow and monthly evaporation data were collected at Thawalama, Baddegama, Hiniduma, Neluwa, Anningkanda, Deniyaya RF stations, Thawalama and Baddegama SF stations and Kottawa EVP station respectively. Visual checking and double mass curve for statistical data checking were done for all stations before developing the models to check data consistency.

Model was developed with mainly basin model, precipitation model, control specification and input data components. The canopy storage with simple canopy method, rainfall loss with the deficit and constant loss method, direct runoff with SCS UH method, baseflow with recession constant method, sub-models were chosen by considering several criteria. The monthly average method was selected to incorporate evaporation into the model and gage-weight method as areal precipitation distribution into the model. The weightage of each station was calculated from Theissen polygon method. Thawalama and Baddegama lumped models were developed for the 2007-2012 period for calibration, 2012-2017 period for validation and 2007-2012 period for transferability options separately. In chapter 5.3 describes the development process of models, selection and determination of initial parameters and objective function selection for calibration in detail. The first five-year period of 2007 to 2012 water years were taken as calibration duration and the next five-year period of 2012 to 2017 water years were taken as validation duration. To stabilize the moisture level, both models were warmed up by repeating 5 years data set five times and the last set of five years were taken as a warmed up model to the calibration process.

For the minimum value of RMSE objective function during several number of trials were taken to assess the model performance with evaluation criteria. Both models, Baddegama lumped and Thawalama lumped were calibrated and verified. Chapter 5.4 gives a detail description of the objective function values related to model calibration, verification and graphical presentations. Semi-automatic optimization was used with Nelder and Mead algorithm to calibrate both watersheds. Models were evaluated by using six criteria such as,

a) Annual water balance,

b) Hydrograph matching,

c) FDC matching,

d) FDC matching for high flows,

e) FDC matching for medium flows and

f) FDC for low flows matching.

Then to check parameter transferability from Baddegama to Thawalama and Thawalama to Baddegama, another two models were developed for Thawalama and Baddegama from 2007 to 2017 duration. Two options were assed for parameter transferability such as spatiotemporal (5 years calibrated model parameters directly apply to other watersheds for 10 years period) and temporal (5 years calibrated model parameters directly apply to the same watershed for 10 years period) transferability options to compare transferability ability for both watersheds. According to transferability approaches, Thawalama optimized the whole parameter set transferred to Baddegama watershed and Baddegama calibrated parameters set transferred to Baddegama 10 years duration of the period to compare parameter transferability according to Baddegama streamflow. Similarly, Baddegama optimized the whole parameter set spatially transferred to Thawalama watershed and Thawalama calibrated parameter set transferred to Thawalama 10 years duration of the period to compare parameter transferability according to Thawalama streamflow. Chapter 5.8 shows the parameter transferability results of Thawalama and Baddegama watersheds according to model evaluation criteria.

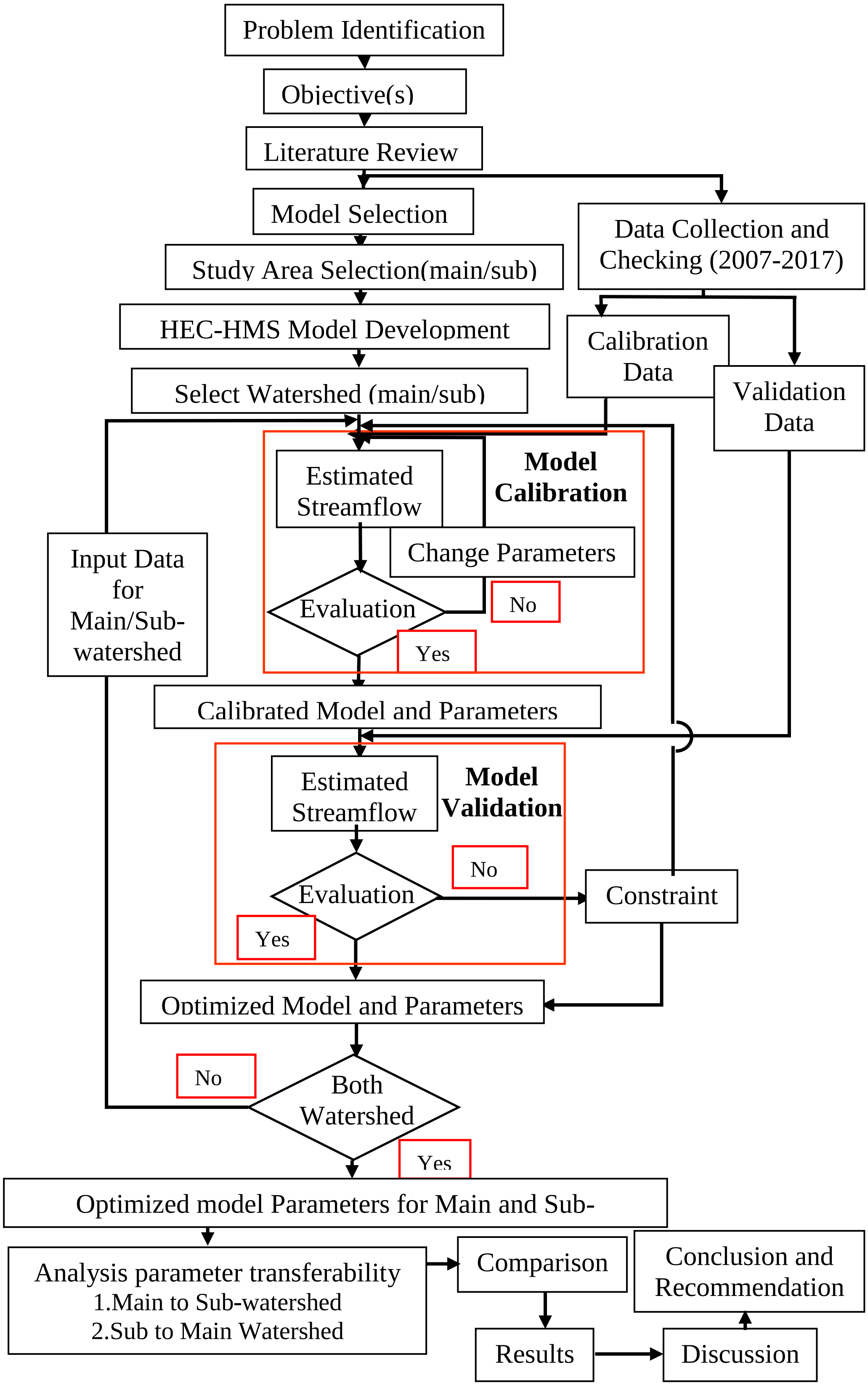


Figure 3-1:Methodology flowchart

4 DATA COLLECTION AND DATA CHECKING

4.1 Study Area

In the study area, there were two watersheds at gauging station Thawalama and Baddegama and the drainage area of these are 377 km^2 and 749 km^2 respectively. Thawalama, Anningkanda, Deniyaya, Neluwa rainfall stations were selected for Thawalama watershed. Neluwa and Baddegama with along above mentioned four rainfall stations were Baddegama watershed with Kottawa evaporation station. Locations of river gauging stations, rainfall and evaporation stations data source and resolutions are given in Table 4-1 and Table 4-2. Streamflow, rainfall and evaporation gauge station distribution along with WMO standards were shown in Table 4-3.

Table 4-1:Locations of gauging stations

Gauging Station	Station Coordinates	
Anningkanda	80.61^{o}E	6.35^{o}N
Thawalama	80.33^{o}E	6.33^{o}N
Deniyaya	80.56^{o}E	6.33^{o}N
Neluwa	80.35^{o}E	6.38^{o}N
Hiniduma	80.32^{o}E	6.30^{o}N
Baddegama	80.18^{o}E	6.18^{o}N
Thawalama River Gauging	80.33^{o}E	6.34^{o}N
Baddegama River Gauging	80.18^{o}E	6.17^{o}N
Kottawa Evaporation Gauging	80.31^{o}E	6.08^{o}N

Table 4-2:Data source and resolution

Data type	Temporal/spatial resolution	Data period	Data source
Rainfall	Daily	October 2007 to September 2017	Department of Irrigation and Department of Meteorology
Streamflow	Daily		Department of Irrigation
Evaporation	Monthly		Department of Meteorology
Topographic	1:50,000		Department of Survey
Contour	1:50,000		Department of Survey
Landuse	1:50,000		Department of Survey

Table 4-3:Distribution of gauging stations at Thawalama and Baddegama

Gauging Station	Number of Stations at each watershed		Station Density (km^2/station)		WMO Standards (km^2/station)
	Thawalama	Baddegama	Thawalama	Baddegama	
Rainfall	4	6	94.25	124.83	575
Streamflow	1	1	377	749	1875
Evaporation	1	1	377	749	

4.2 Thiessen Rainfall

Watershed's mean areal average rainfall was determined by the method of Theissen polygon (Chow, V.T., Maidment & Mays, 1988) because stations are fixed and not vary with the spatial and temporal changes.

4.2.1 Thawalama watershed

The developed Thiessen Polygons with weights at Thawalama watershed is illustrated in below Figure 4-1 and Theissen weights for Thawalama watershed is in Table 4-4.

Table 4-4:Thiessen weights for Thawalama watershed

Rainfall Station	Thiessen Weight
Thawalama	0.16
Neluwa	0.37
Anningkanda	0.12
Deniyaya	0.35

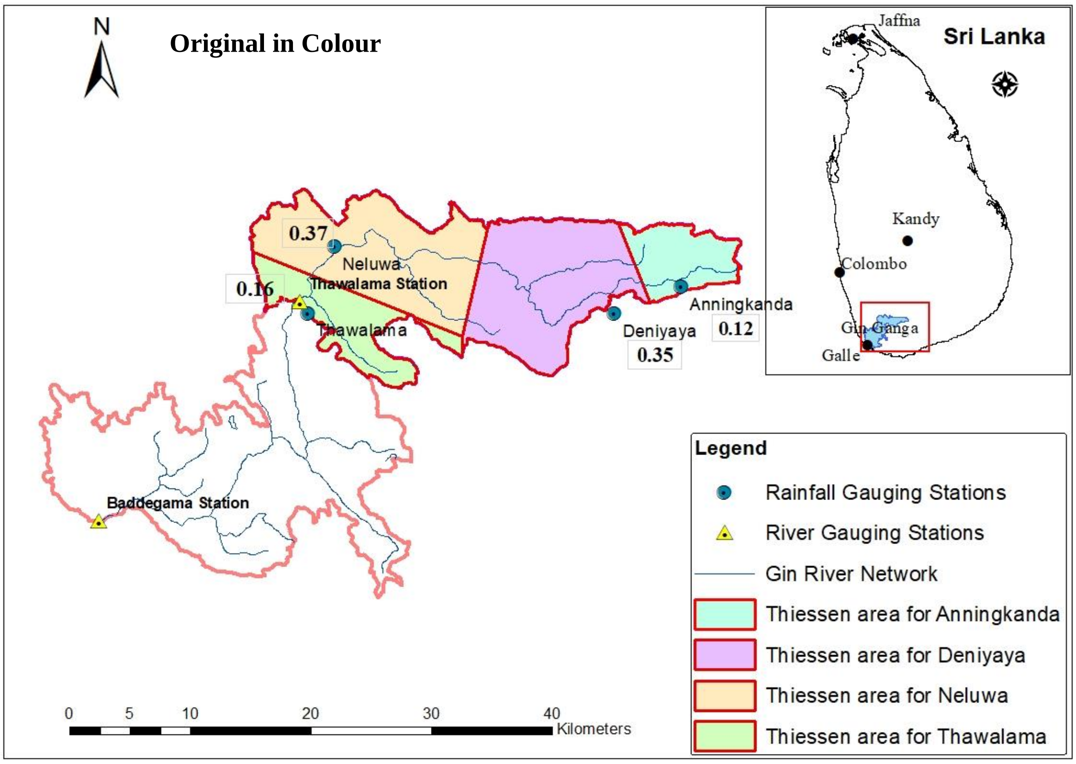


Figure 4-1:Thiessen polygon-Thawalama watershed

4.2.2 Baddegama watershed

The developed Thiessen Polygons with weights at Baddegama watershed is illustrated in below Figure 4-2 and Theissen weights for Baddegama watershed is in Table 4-5.

Table 4-5:Thiessen weights for Baddegama watershed

Rainfall Station	Thiessen Weight
Hiniduma	0.27
Deniyaya	0.18
Anningkanda	0.06
Baddegama	0.23
Neluwa	0.18
Thawalama	0.08

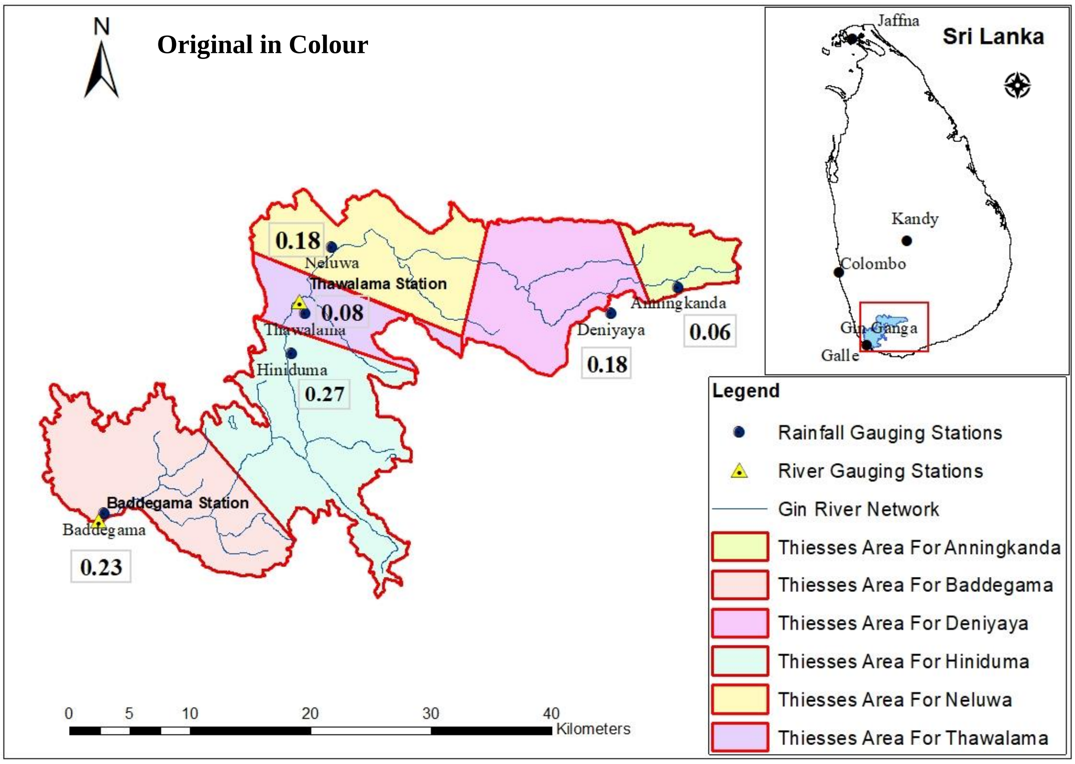


Figure 4-2:Thiessen polygon-Baddegama watershed

4.3 Data and Data Checking

The annual water balance, visual checking by plotting hydrographs and double mass curve plotting for all stations to check consistency of collected data. Missing data periods and inconsistencies identified by visual and statistical checking. The details of all checking steps were clearly illustrated and tabulated in the following sub-chapters till 4.6.2.

4.3.1 Annual water balance at Thawalama

To check the water budget at each water year, the annual water balance was calculated for both Thawalama and Baddegama watersheds. Table 4-6 tabulated annual water balance at Thawalama watershed concerning annual rainfall, annual evaporation and annual streamflow on each water year.

Table 4-6:Annual water walance of Thawalama watershed

Water year	Average Annual Rainfall (mm/year)	Annual Streamflow (mm/year)	Annual Pan Evaporation (mm/year)	Annual Water Balance (mm/year)
2007/08	4228	3377	826	851
2008/09	4083	2613	1031	1469

2009/10	3674	2650	951	1024
2010/11	4033	2931	977	1102
2011/12	3315	2290	978	1025
2012/13	4285	3395	951	890
2013/14	3661	2411	852	1250
2014/15	4673	3126	812	1548
2015/16	3583	2582	849	1002
2016/17	4148	2480	900	1667

4.3.2 Variation of annual runoff coefficients and evaporation of Thawalama

The runoff coefficient at Thawalama fluctuates from 0.6 to 0.8 from 2007 to 2017. In the water year 2007/2008, a very high runoff coefficient can be observed compared to other years. In the year 2016/2017, the lowest runoff coefficient can be observed as illustrated in Figure 4-3. The runoff coefficient value of the Gin Ganga basin was compared and verified with the values given in previous studies. Annual runoff coefficient values were again compared with those given in the Hydrological Annual report prepared by the Hydrology Division of Irrigation Department. In 2007/2008 and 2014/15, evaporation values were lowest throughout the selected period. In year 2008/2009 indicate the highest evaporation among other years.

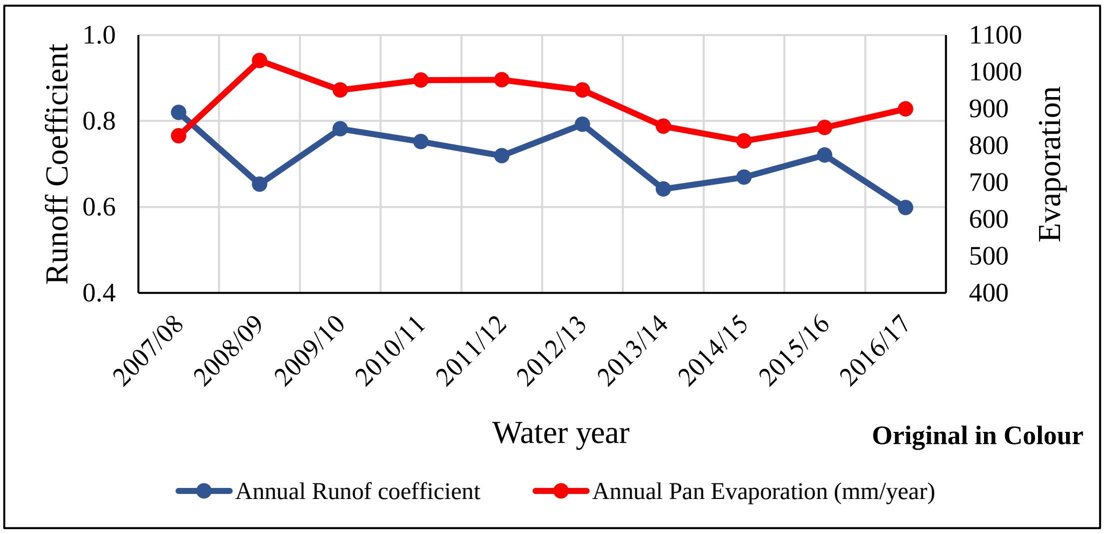


Figure 4-3:Variation of annual evaporation and runoff coefficient at Thawalama

4.3.3 Variation of annual rainfall and streamflow of Thawalama

Streamflow in year 2007/08 and 2012/13 is indicating relatively higher values as shown in Figure 4-4. Year 2013/14 and 2011/12 represent the driest years compared to other water years and the lowest streamflow is produced in 2011/12 with a high value of evaporation.

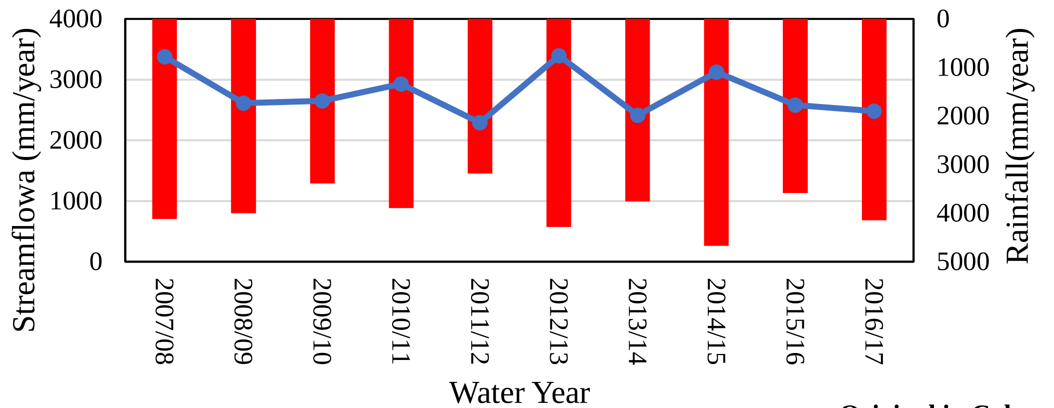


Figure 4-4:Variation of annual rainfall and streamflow at Thawalama

4.3.4 Annual water balance at Baddegama

The water budget at each water year at Baddegama watersheds were tabulated in Table 4-7. The lowest water balance as indicated in the 2015/2016 water year caused by lesser rainfall compared to streamflow.

Table 4-7:Annual water balance of Baddegama watershed

Water year	Average Annual Rainfall (mm/year)	Annual Streamflow (mm/year)	Annual Pan Evaporation (mm/year)	Annual Water Balance (mm/year)
2007/08	4245	3311	826	934
2008/09	3754	2681	1031	1073
2009/10	3795	2741	951	1053
2010/11	4004	2992	977	1012
2011/12	3313	2430	978	884
2012/13	4098	3080	951	1018
2013/14	3527	2371	852	1156
2014/15	4461	2995	812	1466
2015/16	3517	2851	849	666
2016/17	3853	2571	900	1281

4.3.5 Variation of annual runoff coefficients and evaporation of Baddegama

The value of 0.7 to 0.8 runoff coefficient variation can be noticed for the entire modeling period of 2007 to 2017. The highest runoff coefficient value was indicated in the 2015/2016 water years while the 2013/2014 water year indicating the lowest value for the runoff coefficient as illustrated in Figure 4-5. In contrast the lowest and highest evaporation values can be seen in 2014/2015 and 2008/2009 water years respectively.

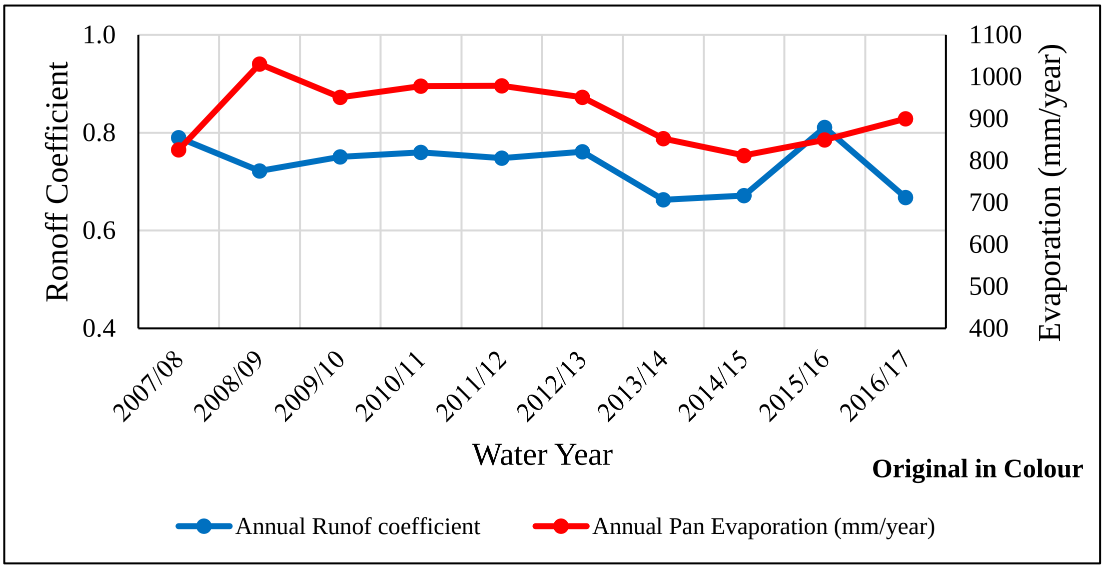


Figure 4-5:Variation of annual evaporation and runoff coefficient at Baddegama

4.3.6 Variation of annual rainfall and streamflow of Baddegama

The observed rainfall in 2007/08, 2012/13 and 2014/15 water years are almost the same as indicated in Figure 4-6. Streamflow in 2007/08 is very high and this is unexpected respect to other water years. In contrast, the streamflow in 2014/15 is the highest rainfall during this study period. Year 2013/14 indicating the driest year with the lowest streamflow and evaporation concerning other water years. This indication may cause due to discrepancies in streamflow or rainfall data.

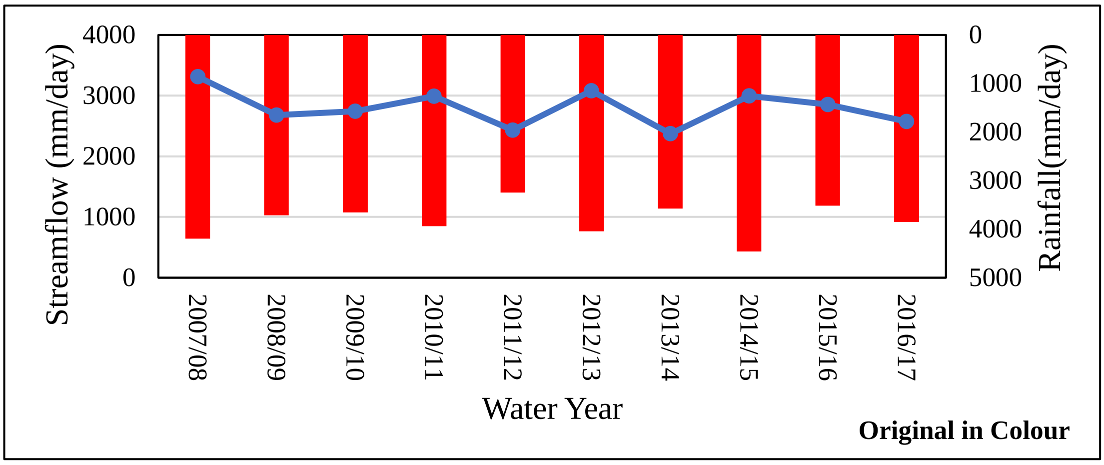


Figure 4-6:Variation of annual rainfall and streamflow at Baddegama

4.4 Double Mass Curve

To check the consistency of precipitation, streamflow and evaporation data for each watershed, a double mass curve was illustrated for each station in one graph as in Figure 4-7. Separate double mass curve plots were shown in Annex B for each meteorology stations at both watersheds. All plots show consistency with straight line to all rainfall, streamflow and evaporation stations. Therefore, it indicates that no inconsistency in data that will be used in this study.

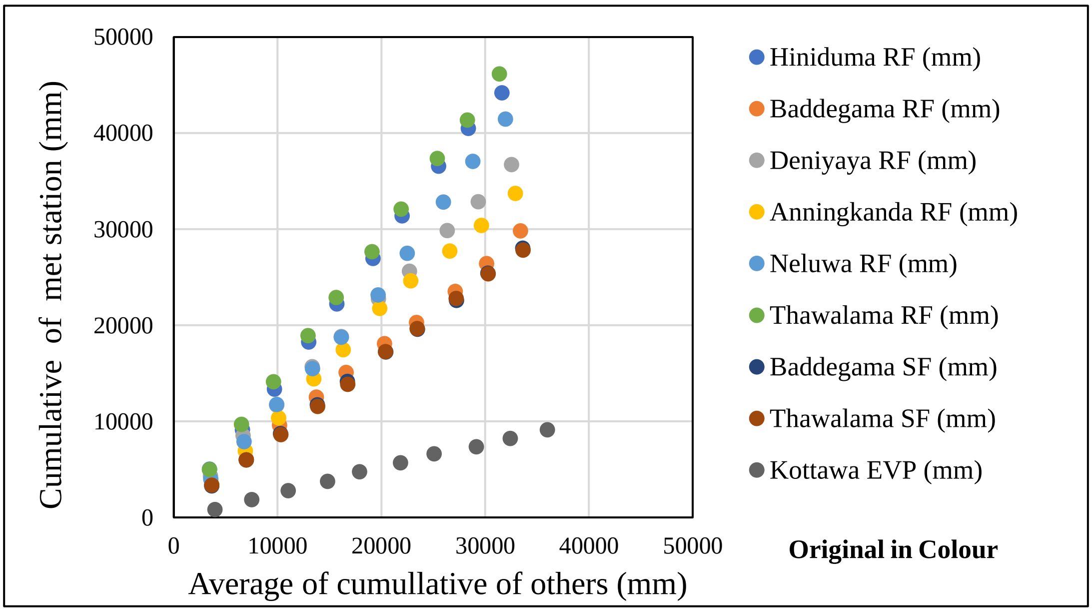


Figure 4-7:Double mass cures for each RF, SF and EVP stations

4.5 Visual Data Checking

To check inconsistencies with missing data was assessed by visual checking. SF vs RF for each rain gauging station and Streamflow vs Thiessen average rainfall for both watersheds were plotted to check consistency of rainfall and streamflow data. The places where shows abnormal or unexpected streamflow response to rainfall were identified.

4.5.1 Thawalama watershed

Daily streamflow responses to the rainfall were observed and for the year 2015/2016 is shown in Figure 4-8. According to Figure 4-8 only a few points were not good response with streamflow and these points are marked with red color circles. All four station’s rainfall data give a good response to the streamflow. But in August, Anningkanda and Deniyaya rainfall response is showing abnormal compared to rainfall at Thawalama and Deniyaya rainfall. The end of September showing low streamflow but rainfall at Neluwa is not compatible with streamflow response. Thawalama rainfall data in March gives abnormal response to streamflow. Mid of October and June showing high streamflow and rainfall response at all the locations are also compatible with streamflow data. The streamflow response with Thiessen average rainfall for years 2007/08, 2008/09, 2009/2010, 2010/11 and 2011/2012 are shown in Figure 4-9 for Thawalama watershed. Thiessen average rainfall data response to the streamflow a not indicate a good response in these years. In 2007/08 rainfall data in November and August showing abnormal response to streamflow. In 2008/09 and 2009/10 on mid of October and November, Thiessen average rainfall response to streamflow showing high abnormality. May and June in 2010/11 also showing a high abnormality rainfall response to streamflow. In Figure 4-10 shows the validation data period Thiessen rainfall vs streamflow. In 2012/13 August and September shows abnormal streamflow response to rainfall.

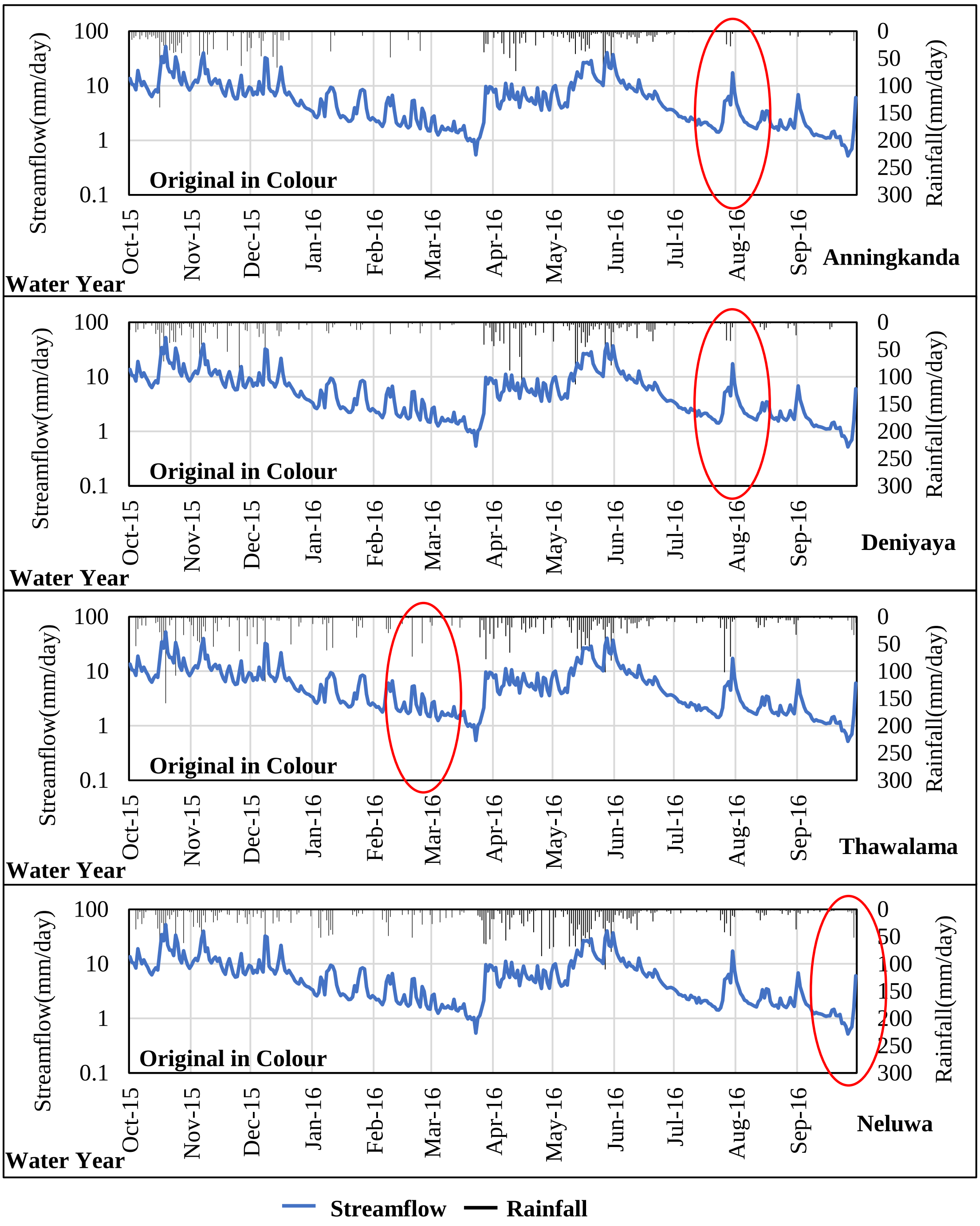


Figure 4-8:Thawalama SF vs RF at each Station 2015/16 – semi log plot

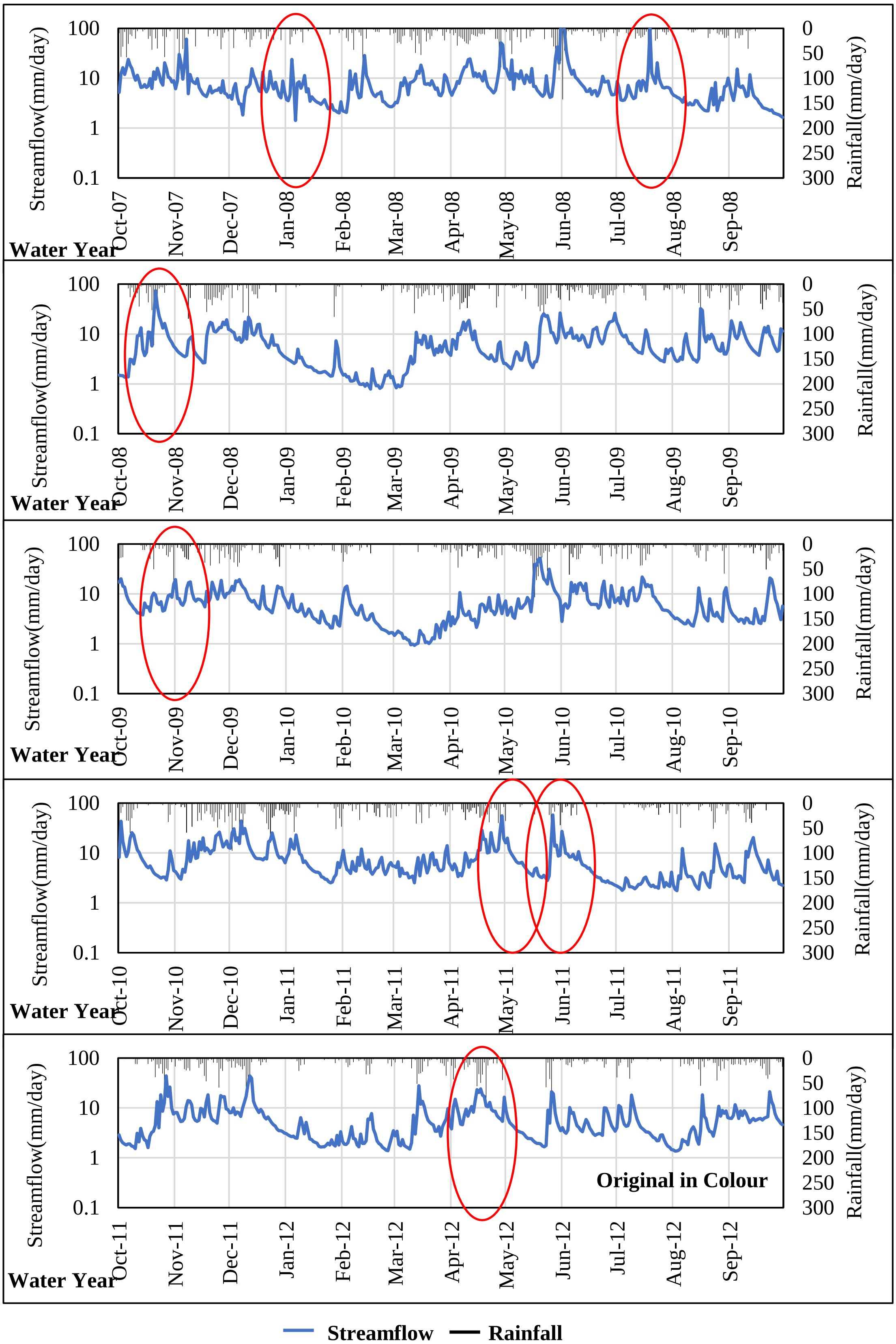


Figure 4-9:Thawalama SF vs Thiessen RF during calibration period

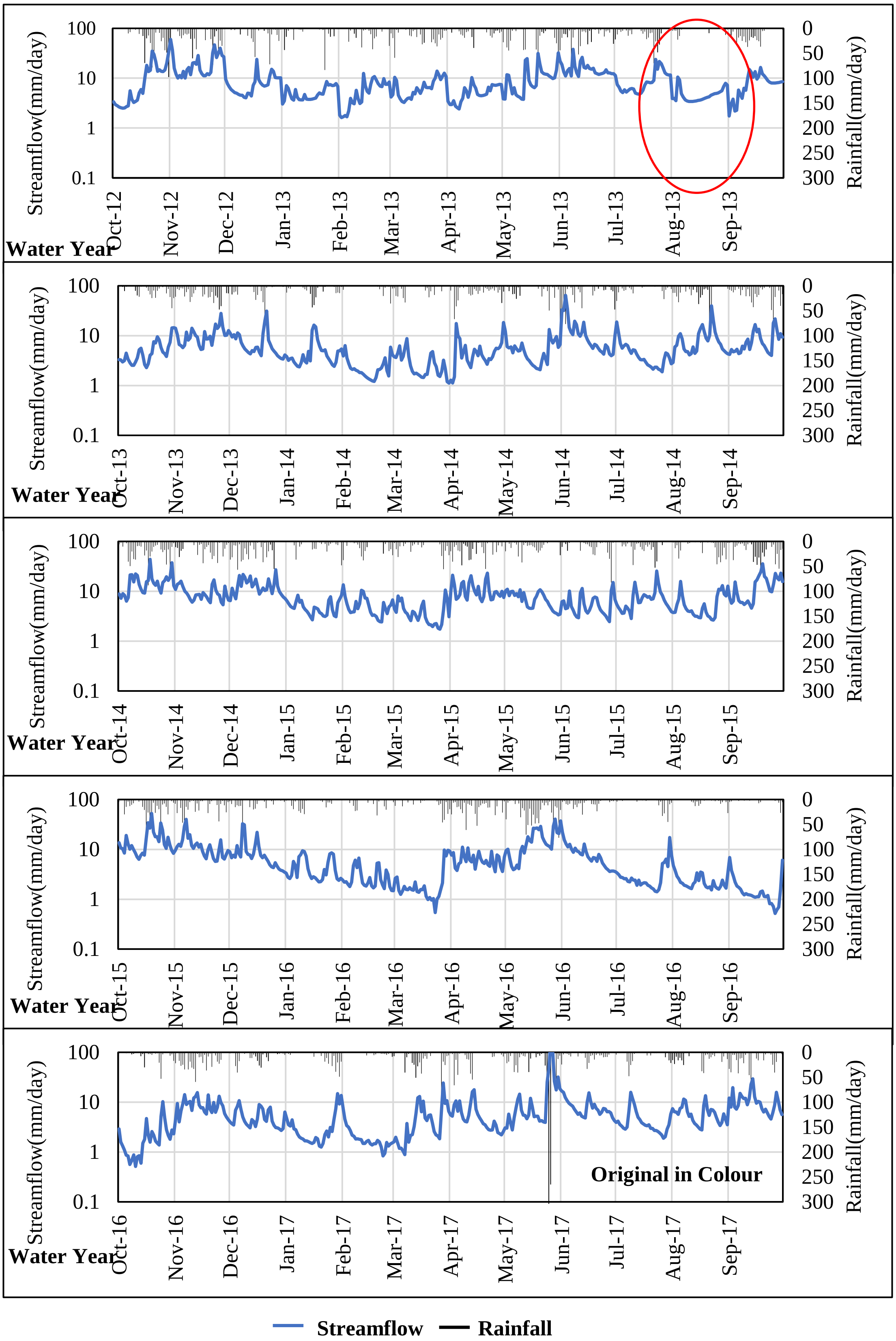
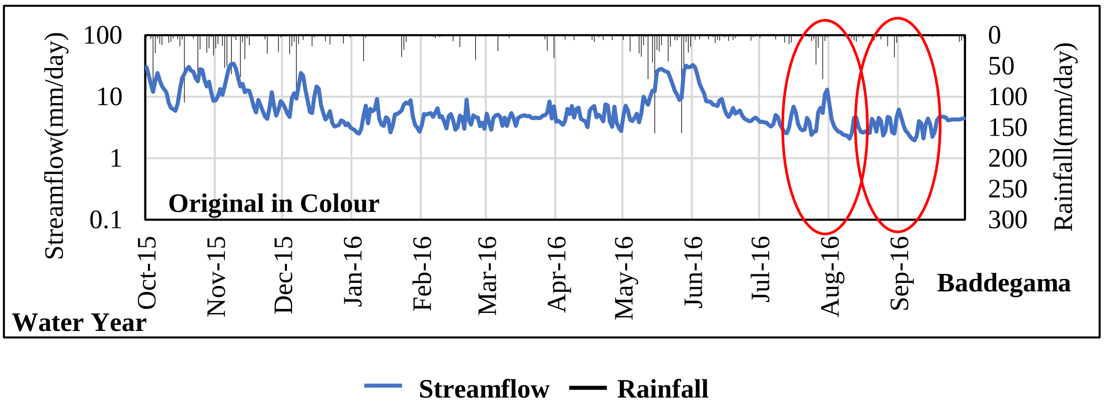


Figure 4-10:Thawalama SF vs Thiessen RF-during validation period

4.5.2 Baddegama watershed

Daily streamflow responses to the daily rainfall were observed and for the year 2015/2016 is shown in Figure 4-11. According to Figure 4-11 few locations were not good responses with streamflow and these points are marked with red color circles. Thawalama and Anningkanda rainfall data gives a good response to the streamflow. But in August, Anningkanda rainfall response is showing abnormal with compared to rainfall at Thawalama. Hiniduma and Neluwa rainfall in February and April were not responded to the streamflow. During the period from January to May indicate low streamflow but during this period rainfall at Hiniduma, Neluwa and Thawalama are higher compared to other stations. At Deniyaya rainfall data on April show abnormal high rainfall and streamflow response is abnormal. In February, at Baddegama showing no rainfall and streamflow is not responded by rainfall at this location.

The streamflow response with Thiessen average rainfall for years 2007/08, 2008/09, 2009/2010, 2010/11 and 2011/12 are shown in Figure 4-12 for Baddegama watershed. Thiessen average rainfall data responded to the streamflow at Baddegama very well in these years. Although in 2007/08 in August and 2008/09 in November rainfall response to streamflow showing abnormal behavior. Figure 4-13 shows Thiessen rainfall for the validation period concerning streamflow was shown.



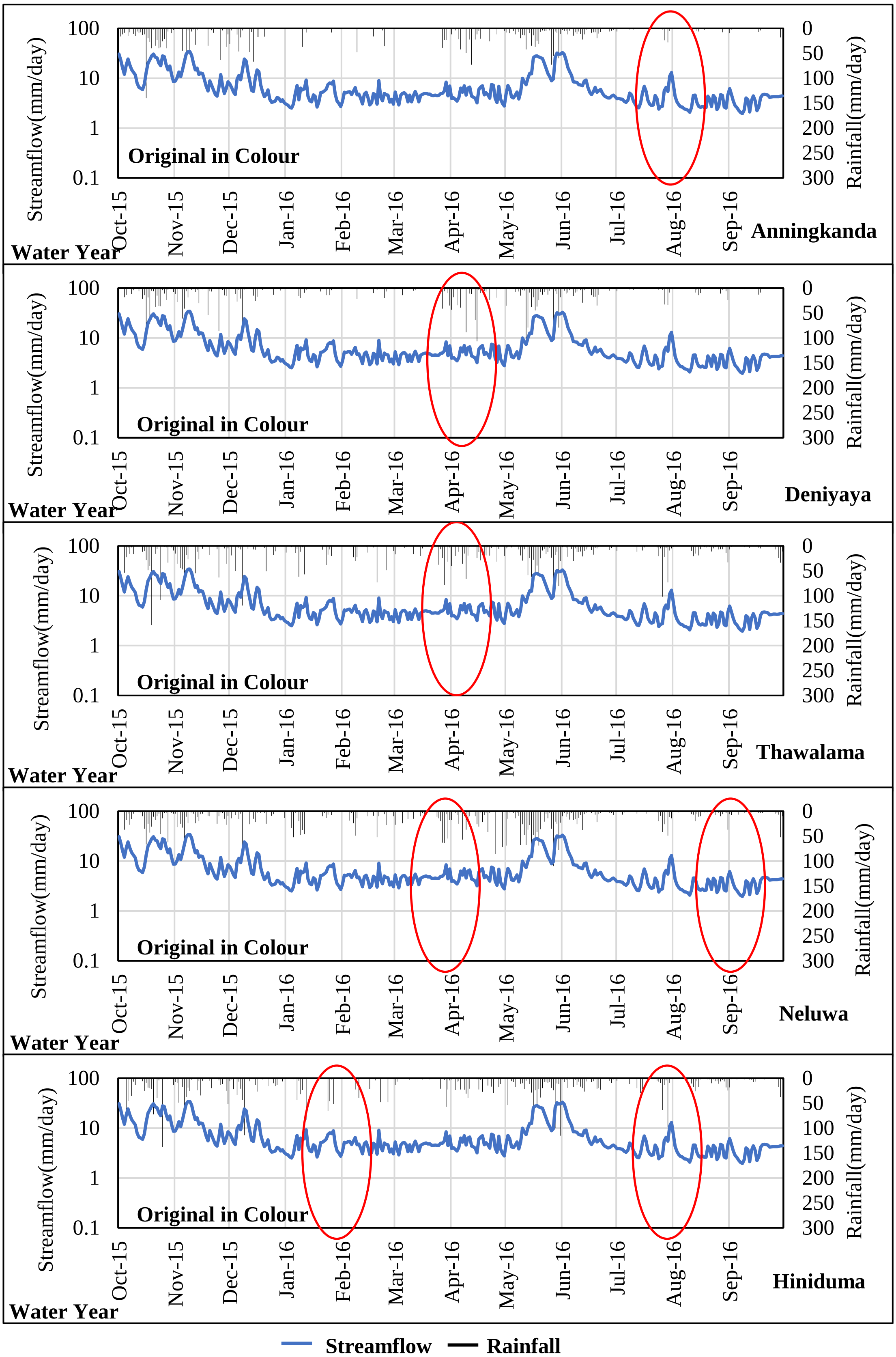


Figure 4-11:Baddegama SF vs RF at each station 2015/16 – semi log plot

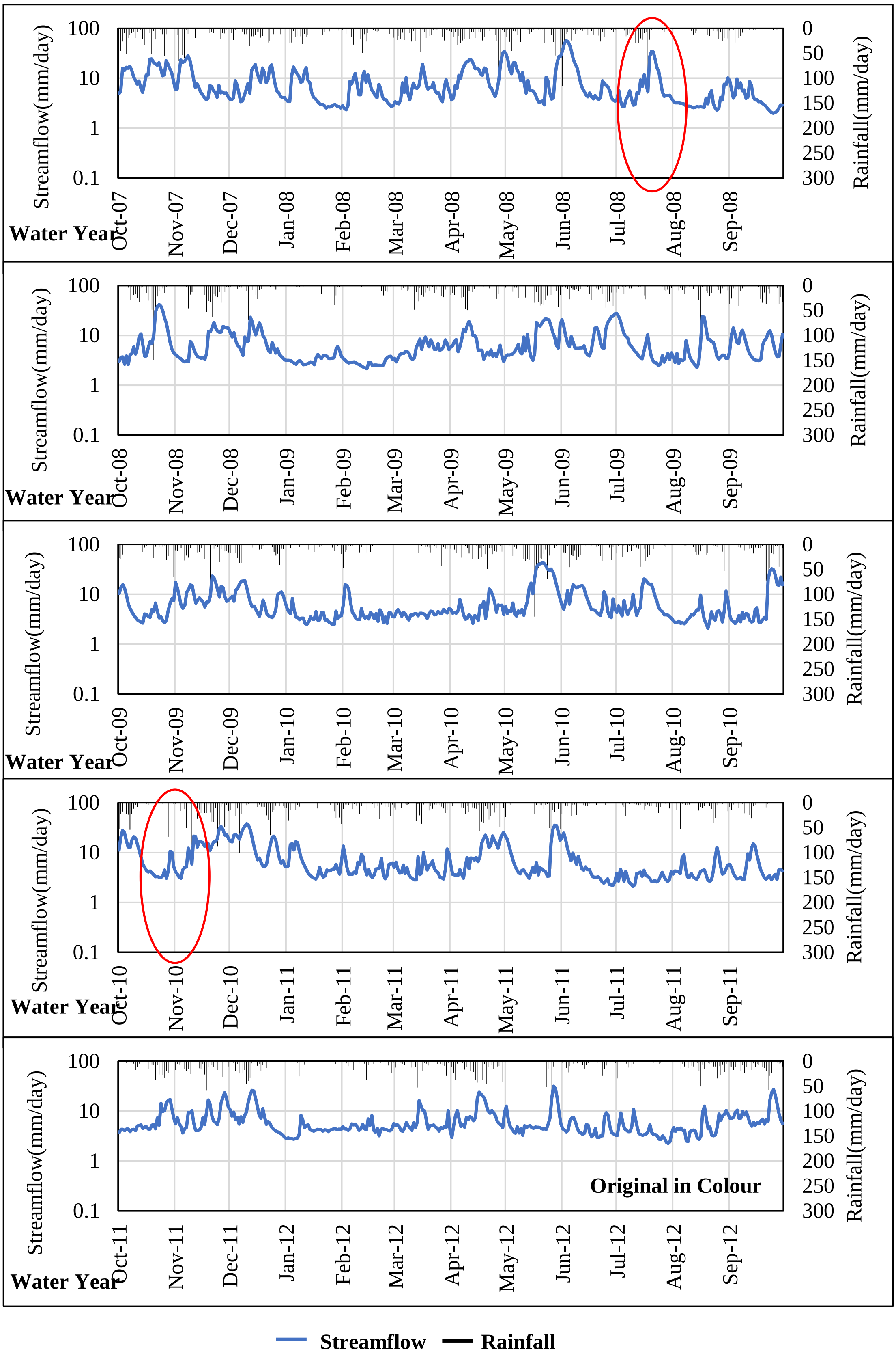


Figure 4-12:Baddegama SF vs Thiessen RF- during calibration period

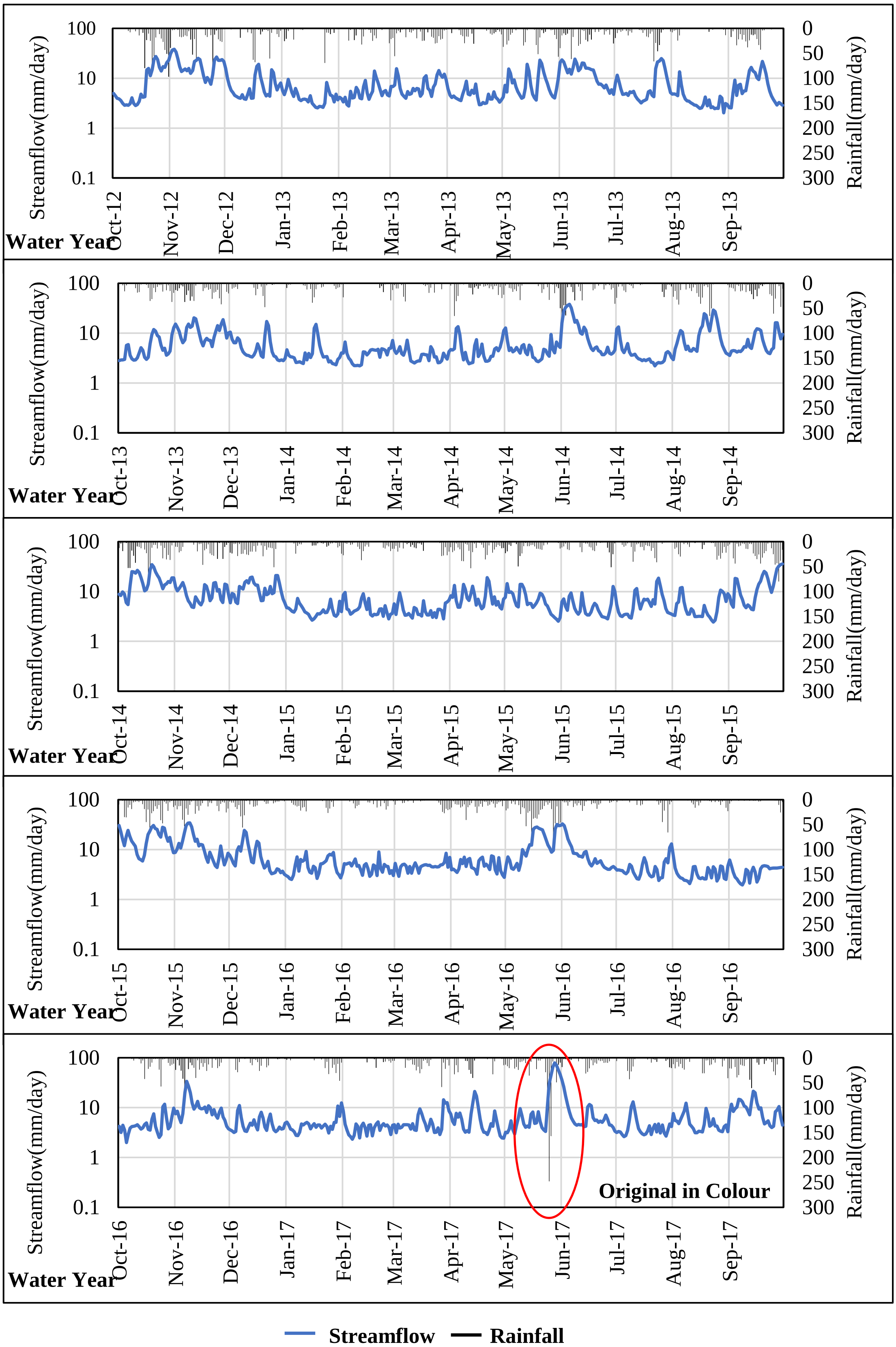


Figure 4-13:Baddegama SF vs Thiessen RF- during validation period

4.6 Monthly and Annual Rainfall

In Table 4-8, the rainfall on a monthly scale at Anningkanda, Deniyaya, Thawalama, Hiniduma and Baddegama rain gauging stations were tabulated. The graphical representation of monthly average rainfall variation at Thawalama and Baddegama presented in Figure 4-14. The seasonal pattern of rainfall for seasons such as North-East Monsoon (October-March) and South-West Monsoon (April-September) can be figured out in the graph. Monthly average rainfall of Baddegama indicate lowest compared to other station and Anningkanda station shows reduction of monthly rainfall during the south-west monsoon. This may lead to lesser Thiessen average rainfall for both watersheds.

Table 4-8:Comparison of monthly average rainfall

Month	Monthly Average Rainfall(mm)					
	Anningkanda	Deniyaya	Thawalama	Neluwa	Hiniduma	Baddegama
October	403	396	506	421	501	386
November	507	410	477	444	524	359
December	367	381	372	340	326	231
January	177	185	198	190	203	112
February	162	145	221	186	215	116
March	247	324	306	315	286	162
April	401	401	489	410	458	260
May	377	470	568	550	515	433
June	202	273	399	340	376	216
July	131	207	306	274	300	191
August	170	212	332	291	317	213
September	228	270	441	385	399	303

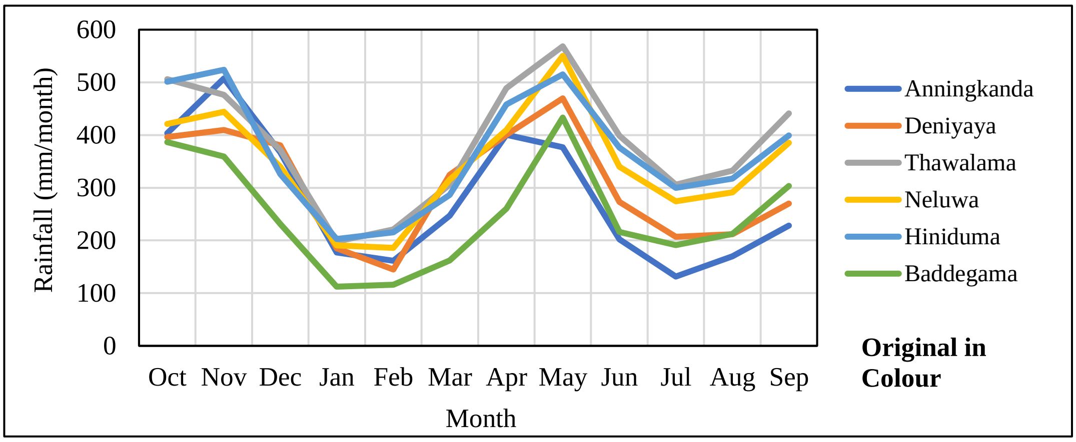


Figure 4-14:Variation of monthly average rainfall

4.6.1 Monthly comparison of streamflow and Thiessen rainfall

In figure 4-16 shows a monthly comparison of streamflow concerning the Thiessen average rainfall in Thawalama and Baddegama watersheds respectively. Graphically in both watershed monthly streamflow response to Thiessen average rainfall seem to be acceptable. But in Baddegama low flow seems to be high compared to Thawalama low flow values.

4.6.2 Monthly evaporation

Monthly evaporation was compared with monthly streamflow at each watershed respectively Thawalama and Baddegama (Figure 4-15). Evaporation is varying range from 20 mm/month to 130 mm/month during 10 years of period. Forgiven period, only April 2008 shown a sudden decrease of evaporation while other years showing similar evaporation value for April. Maximum evaporation is always recorded in February of each year.

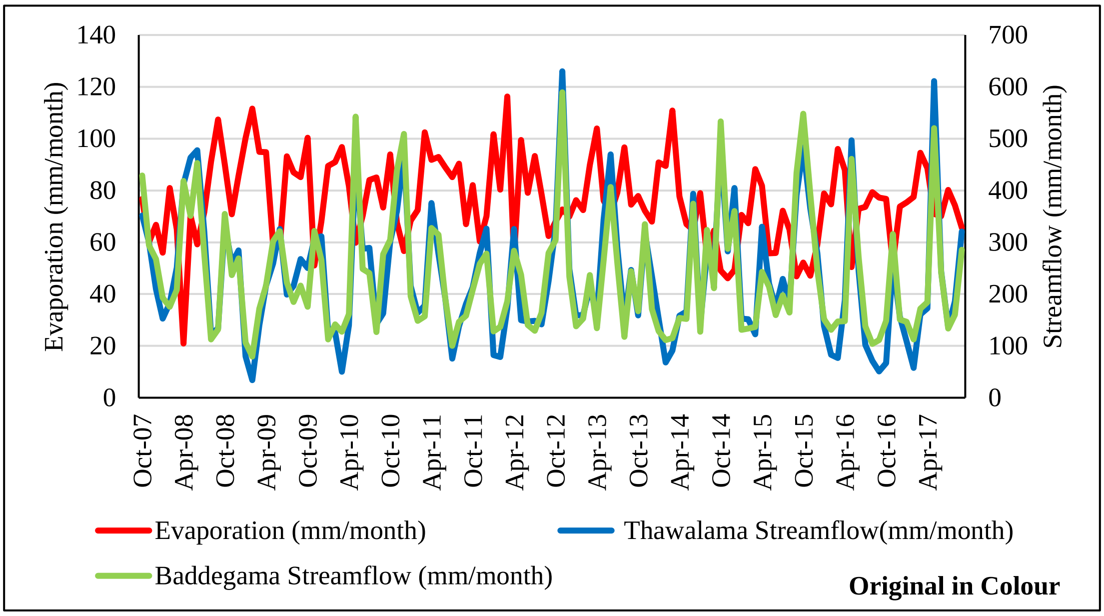


Figure 4-15:Comparison of monthly evaporation with streamflow

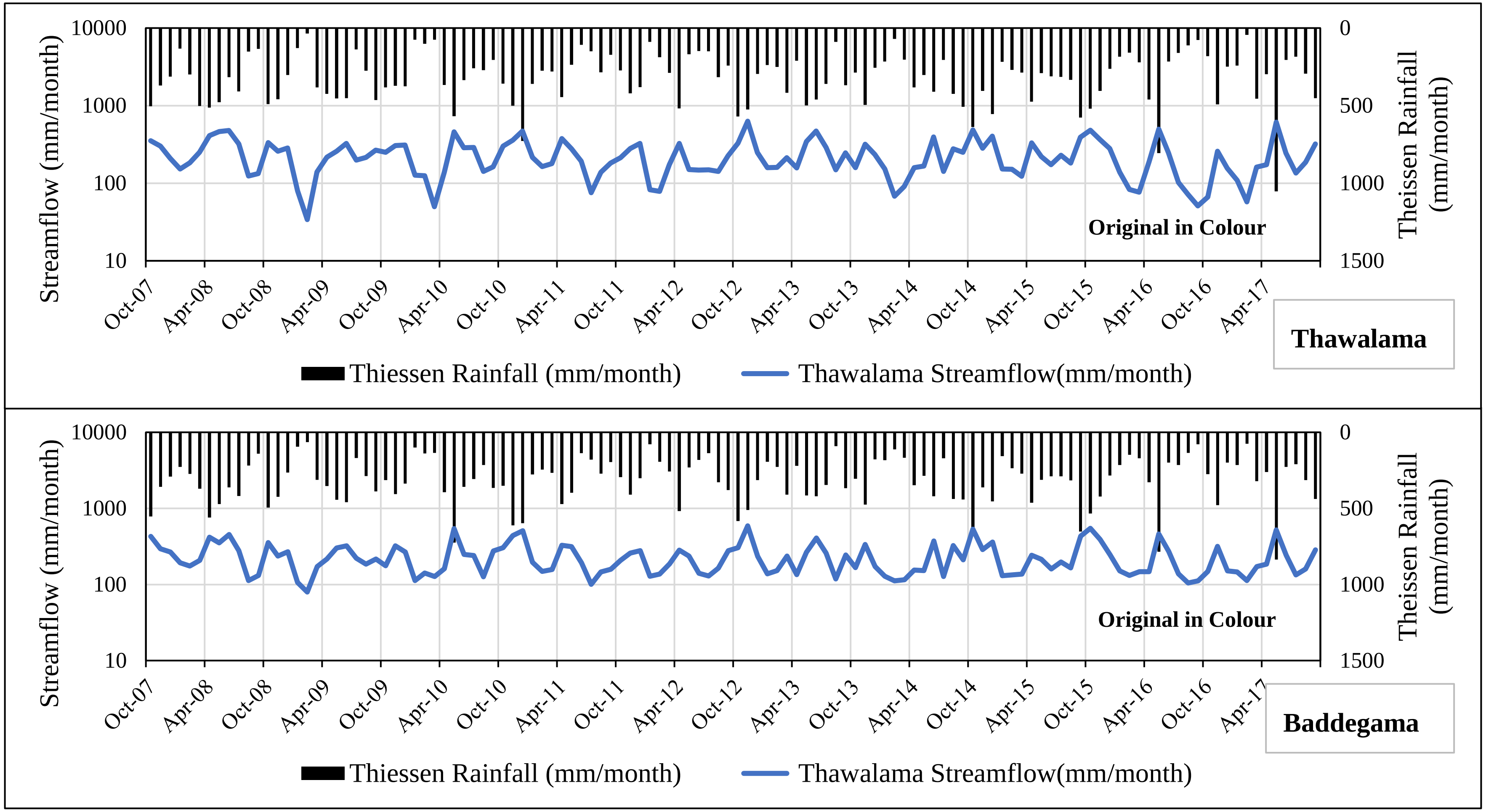


Figure 4-16:Comparison of monthly thiessen rainfall and streamflow in Thawalama and Baddegama watersheds

4.7 Filling Missing Data

To fill the missing data in rainfall the Theisen interpolation method was used to fill. Theisen weights for each scenario of missing data in each station was tabulated in Table 4-9. ND shows the rainfall station which data is missing.

Table 4-9:Thiessen weights for data filling scenarios

Anningkanda	Baddegama	Deniyaya	Hiniduma	Neluwa	Thawalama
0.1	0.23	0.19	0.27	ND	0.25
0.06	0.26	0.18	ND	0.18	0.32
0.2	0.2	ND	0.3	0.2	0.1
0.20	0.26	ND	ND	0.22	0.32
ND	0.23	0.24	0.27	0.18	0.08
0.06	ND	0.18	0.50	0.18	0.08

5 ANALYSIS AND RESULTS

5.1 Selection of Two Watersheds

Two numbers of watersheds were delineated in the Gin Ganga basin according to the availability of river gauging stations and to check the parameter transferability of selected hydrologic models. For both Thawalama and Baddegama watershed's daily time scale streamflow and sufficient rainfall data were available. Hence, Thawalama and Baddegama watersheds were selected for model development to assess the parameter transferability of the selected model.

5.2 Model Selection

After reviewing process-based models, model comparison and selection of a model for parameter transferability in literature (Chapter 2.7, 2.8 and 2.9), the HEC-HMS model was carefully chosen to continue this study at Thawalama and Baddegama watersheds. Because it is one of the freely available software and a vast range of model applications will be further continued after the applicability of model parameter transferability within the basin.

5.3 HEC-HMS Model Development

5.3.1 Review of modeling practices in HEC-HMS

5.3.1.1 Review of rainfall

A sample data set from 01st October 2007 to 06th November 2007 was selected and used with the selected model at Thawalama to compare the Theissen average rainfall output of the model with manual calculation. It was found that the same rainfall values were obtained from both methods. Comparison of Theissen average rainfall variation by the model and manual calculation is shown in Figure C-1 of Appendix C.

5.3.1.2 Review and selection of optimization criteria

In a review of automatic optimization there was a recommendation of Nelder and Mead method is better than Univariant Gradient. Therefore, NM automatic optimization method was selected.

5.3.1.3 Review and selection of objective function

In literature (Chapter 2.12) described several objective functions that are commonly used in hydrologic simulations applications. In this study objective function was select based simulated flow shows best results with all model evaluation criteria such as 1) hydrograph matching, 2) annual water balance, 3) FDC matching, 4) FDC matching for high flows, 5) FDC matching for medium flows, and 6) FDC matching for low flows. After reviewing the HEC-HMS application of each objective function and applicability in HEC-HMS automatic optimization, Root Mean Square (RMSE) objective function was selected to evaluate the model performance. Appendix D shown the selection of objection function for model automatic optimization.

5.3.1.4 Review of simulation time interval

When selecting the time interval for simulation in the HEC HMS model, USACE, 2000 states that the simulation time interval cannot exceed the lag time times 0.29 for a subbasin. As according to this maximum simulation time intervals are 8hrs and 15hrs for Thawalama and Baddegama watersheds respectively. Therefore, 6hrs simulation time interval selected for both watersheds. 01st October 2007 to 30th September 2012 was taken as the beginning and end time or control specification for calibration.

5.3.1.5 Review of model warm-up

Initial soil moisture storage was stabilized after running the model with 5 times duplication of 5years calibration period. After that soil moisture level at the beginning and end of each water years for each cycle was plotted for both watersheds. All figures in Appendix E showing soil moisture level and flow components at each cycle for both watersheds.

5.3.2 Development of the basin model

In this study, it was necessary to simulate streamflow at Thawalama and Baddegama streamflow gauge stations where daily time scale streamflow data are available. Thawalama lumped model and Baddegama lumped model were developed for evaluate model parameter transferability. Both watersheds delineated in ArcMap with using 1:50000 topographic map, stream network layers and river gauging locations. In addition to that 1:50000 contour data also used to cross-check with topographic map elevation.

5.3.2.1 Development of canopy model

The simple canopy method was chosen among three methods which are available in the selected model for canopy interception estimation. This method was selected according to (1) number of parameters, (2) applicability in continuous modeling and (3) compatibility with selected loss model. Max. Canopy of Thawalama 0.456 mm and Baddegama 0.421 mm were calculated according to a type of vegetation(Ahbari, Stour, Agoumi, & Serhir, 2018). Appendix E Table E-1 shows the estimations. Initial canopy storage was estimated by optimization. Both dry and wet season was selected to encounter the evapotranspiration.

5.3.2.2 Development of the precipitation loss model

HEC-HMS offers different five number of methods to determine loss due to infiltration. Based on the following criterion, an appropriate loss method was chosen for this study. They are (1) Number of parameters (2) applicability for event and continuous modeling. Based on the above criterion, the initial deficit and constant loss method had chosen for the study. Initial deficit (ID), maximum deficit (MD) and constant loss rate (CR) parameters were estimated by optimization. For the first simulation of the model required to determine initial values for the parameters. Maximum potential retention which is similar to maximum storage can be calculated by using the SCS equation. Weighted CN value for Thawalama and Baddegama watersheds were determined by incorporating AMC (antecedent moisture condition) with hydrological soil group, land-use coverage. Figure 5-1 shows land-use coverage at both watersheds. Constant loss rate (CR) initial value was estimated according to literature minimum given rate for hydrological soil type C is 1.27mm/hrs (USACE, 2000).

CN values for both watersheds were initially derived from the standard tables for AMC II and type C hydrological soil group. As per the computation in Table 5-1 and Table 5-2, the weighted CN value was 79.9. SCS abstraction method formula was used to determine maximum potential retention and it was taken as the value for the MD parameter. To derive the value for the ID parameter, the formula which related to maximum retention times 0.2 equals initial abstraction was considered. Table 5-3 shows these parameter values for both watersheds.

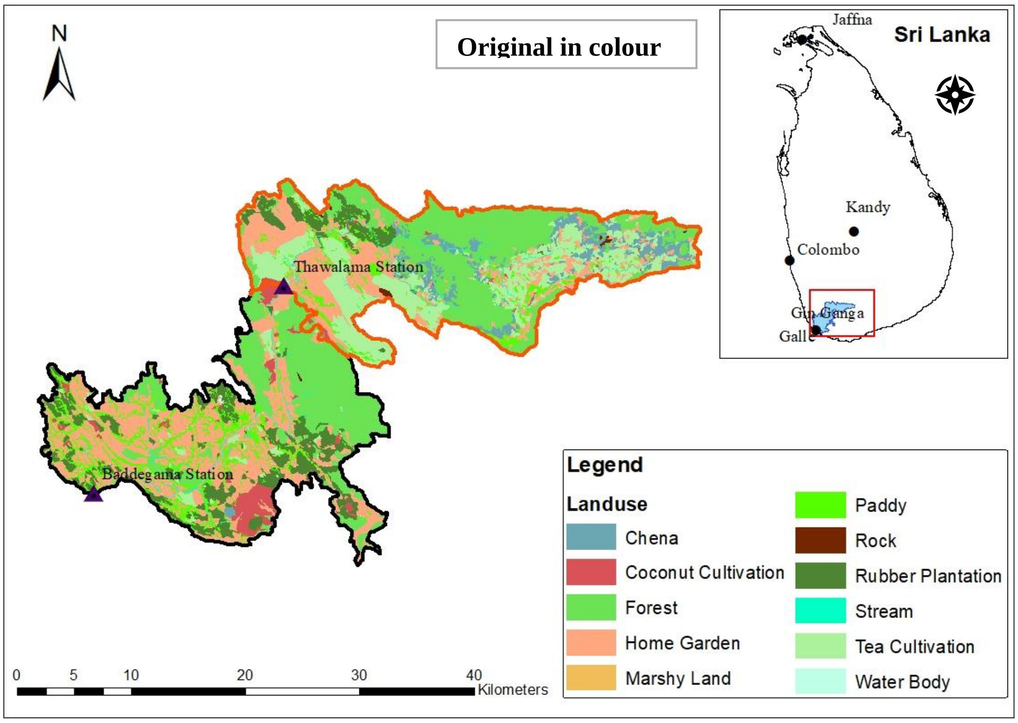


Figure 5-1:Landuse map for Baddegama and Thawalama watersheds

Table 5-1:Weighted CN calculation for Thawalama watershed

Landuse Type	Area %	CN	Weighted CN
Chena	6.18%	74	4.6
Coconut Cultivation	0.95%	88	0.8
Forest	47.71%	77	36.7
Home Garden	15.25%	74	11.3
Marshy Land	0.01%	88	0.0
Paddy	3.45%	88	3.0
Rock	0.39%	98	0.4
Rubber Cultivation	3.75%	88	3.3
Stream	0.82%	100	0.8
Tea Cultivation	21.49%	88	18.9
Total	100.00%		**79.9**

Table 5-2:Weighted CN calculation for Baddegama watershed

Landuse Type	Area %	CN	Weighted CN
Chena	3.47%	74	2.6
Coconut Cultivation	2.95%	88	2.6
Forest	39.19%	77	30.2
Home Garden	24.16%	74	17.9
Marshy Land	0.01%	88	0.0
Paddy	7.21%	88	6.3
Rock	0.25%	98	0.2
Rubber Plantation	8.77%	88	7.7
Stream	0.83%	100	0.8
Tea Cultivation	13.14%	88	11.6
Water Body	0.03%	100	0.0
Total	100.00%		**79.9**

5.3.2.3 Development of transform model

To convert excess rainfall into direct runoff, the transform method was chosen to implement this study according to modeling objective criteria. They are, modeling application parameters, appropriateness of assumptions and number of parameters. SCS UH method was chosen to develop the model because this method is widely used and a smaller number of parameters. The only parameter in SCS UH method is Lag time and calculated by considering the relationship of lag time with time of concentration (TC). TC was calculated using the Kirpich formula. Lag time for both watersheds were calculated and tabulated in Table 5-3 below.

5.3.2.4 Development of baseflow model

Among the four methods that are given in HEC HMS, the recession baseflow method was chosen to model baseflow contribution for streamflow. Less number of parameters and accounting the soil moisture contribution in the dry season were considered as selection criteria for baseflow method. Initial discharge (ID) is one of the parameters in recession constant baseflow method and it was taken as flow at the beginning from flow hydrographs of watersheds (Table 5-3). Other parameters for baseflow recession is recession constant (RC) and peak to ratio (PR) estimated by literature given for typical recession constant for groundwater(USACE, 2000) and according to average flow ratio to the peak in observed hydrograph.

5.3.2.5 Development of routing model

In this study, a case study is considered a lumped model. Therefore, river routing is not considered for this study.

5.3.2.6 Development of precipitation model

Gauge weight method to determine mean areal rainfall and monthly average method to incorporate evaporation contribution were selected as methods in the meteorological model. Theissen polygons to estimate weightage for Both Thawalama and Baddegama watersheds had delineated by using ArcGIS as shown in Figures 4-1 and 4-2. Theissen weights for subbasins were tabulated in Table 4-4 and 4-5. Daily and monthly time scale precipitation and evaporation data were feed into the model respectively.

Table 5-3:Selected initial parameters and values for watersheds

Parameter	Range	Unit	Baddegama	Thawalama
Initial Deficit	0.001-1000	mm	12.74	12.79
Maximum Storage	0.001-1000	mm	63.7	63.94
Constant Loss	0.001-300	mm/hrs	1.27	1.27
Lag Time	0-30000	min	3220	1660
Initial Baseflow	0-100000	m^3/s	42	22
Recession factor	0-1		0.95	0.95
Ratio	0-100		0.2	0.2
Initial Canopy	0.001-100	%	0.001	0.001
Maximum Canopy	0-1500		0.456	0.421

5.3.2.7 HEC-HMS model schematic

The schematic diagram of the HEC-HMS model was developed as shown in Figure 5-2 by considering the modeling objective of this study as water resource management and checking model parameter transferability.

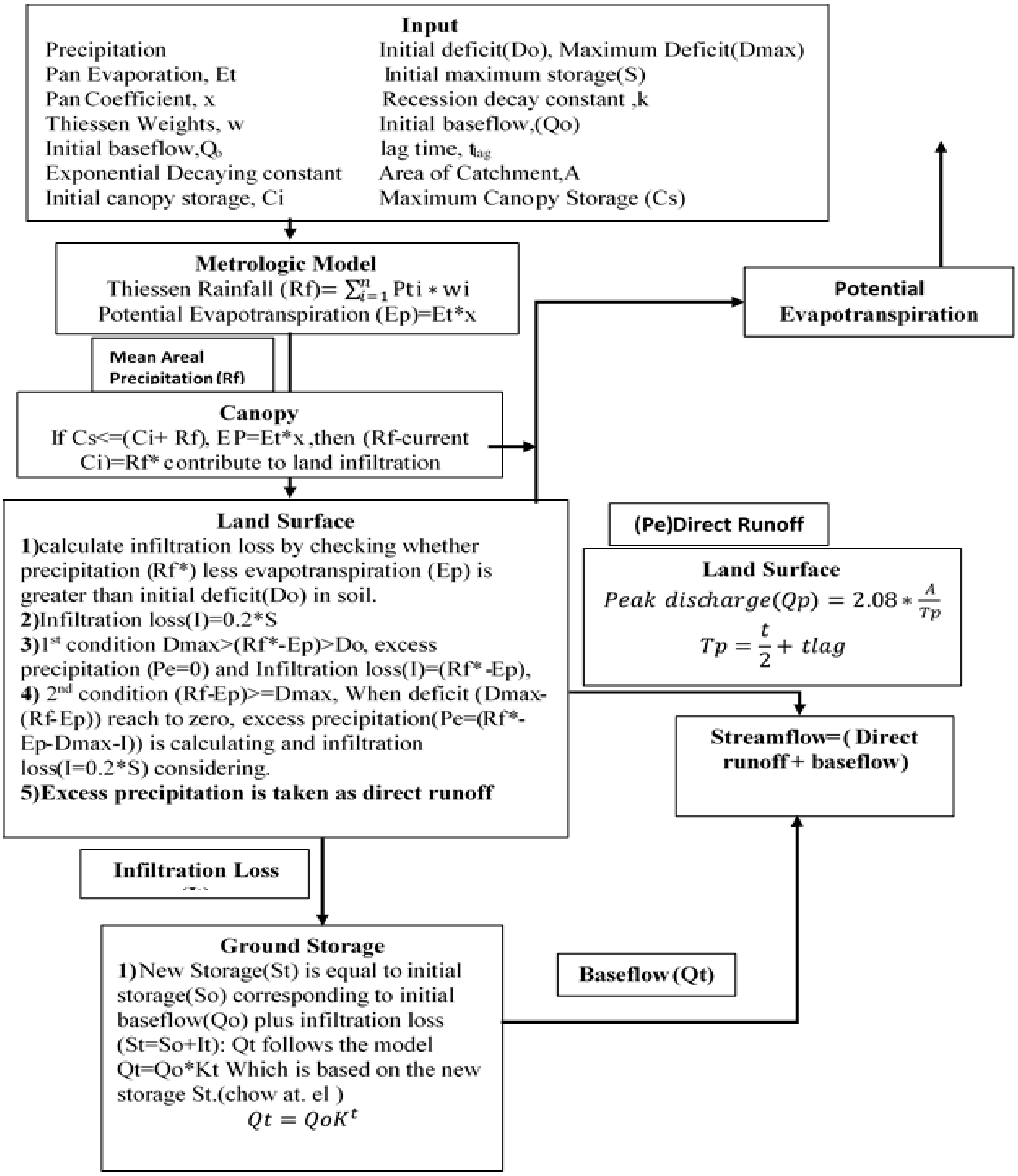


Figure 5-2:HEC-HMS model schematic diagram

5.3.3 Control specification

The beginning and termination date period for the calibration process was taken from 01st October 2007 to 30th September 2012 after the model warm-up. As determined previously in Chapter 5.3.2.1, the simulation time interval was set to 6 hours.

5.3.4 Model simulation

Simulation run was created by selecting the developed basin model, precipitation model and set model simulation period.

5.3.5 Model warmup

Calibration 5 years data set was duplicated five times to introduce five years cyclic warm-up period to stabilized soil moisture. Annex E, Figures E 1 and E 2 show soil moisture levels during the warm-up period at Thawalama and Baddegama watershed respectively. The modeled flow component at both watersheds for the calibration period is plotted in Figure E 3 and Figure E 4.

5.4 Model Calibration

Once the model is selected and developed, the efficiency of the model depends on its parameters. Matching was done by optimizing these parameters. For model calibration, five years of data from 2007/2008 to 2012/2013 was used. RMSE was used as statistical measures for model calibration. After each calibration trial, the model's generated streamflow was evaluated by model performance criteria which is given in Chapter 3. The optimum or best-calibrated parameter set was gained by varying the parameter' initial values until the model performance criteria shown considerable indication for each criterion. A semi-automatic calibration method was done. This calibration method was adopted for both the Thawalama and Baddegama lumped model and then the model parameters were found.

5.4.1 Automatic parameter optimization

In automatic parameter optimization, one search algorithm and one objective function were selected. Fully automatic calibration results were not good and a semi-automatic calibration approach was used to optimized the parameters.

5.4.1.1 Selection of a search algorithm

To select a search algorithm Nelder and Mead search method was selected. According to literature the Nelder and Mead method is better than the Univariant Gradient method.

5.4.1.2 Selection of objective function in HEC-HMS

To select an objective function for parameter optimization, the Thawalama lumped model was run for the entire calibration period from 2007/08 using seven most used objective functions given in the HEC HMS model. Peak Weighted-RMSE, RMSE, SSR, Percent Error in Peak, Percent Error in Volume, Nash Sutcliff Error (NSE) and Log-RMSE. The results generated from different objective functions were compared based on the model performance criteria described in Chapter 3. Mean Ration of Absolute Error indicator was taken to assess the evaluation criteria. A comparison of different objective functions is given in Table D-3 in Appendix D. The NM search method was applied and parameters corresponding to the warmed up model were input to the model. It was identified that there were no significant changes in the error values for RMSE, SSR and NSE objective functions (Table D-3). In Appendix D, Figure D-4 shows the variation of error values for each objective function.

It could be seen that there is no significant change in the calculated flow with the change of SSR, RMSE and NSE objective function. RMSE objective function which had widely used in HEC-HMS application was selected as the objective function in automatic parameter optimization.

5.5 Streamflow Separation

According to the order of magnitude of probability of exceedance and variation of FDC gradient, high flow and low flow threshold for each watershed were determined. As per Figure 5-3 and Figure 5-4, High flow thresholds are 18% and 15% and low flow thresholds are 79% and 70% for Thawalama and Baddegama watersheds respectively.

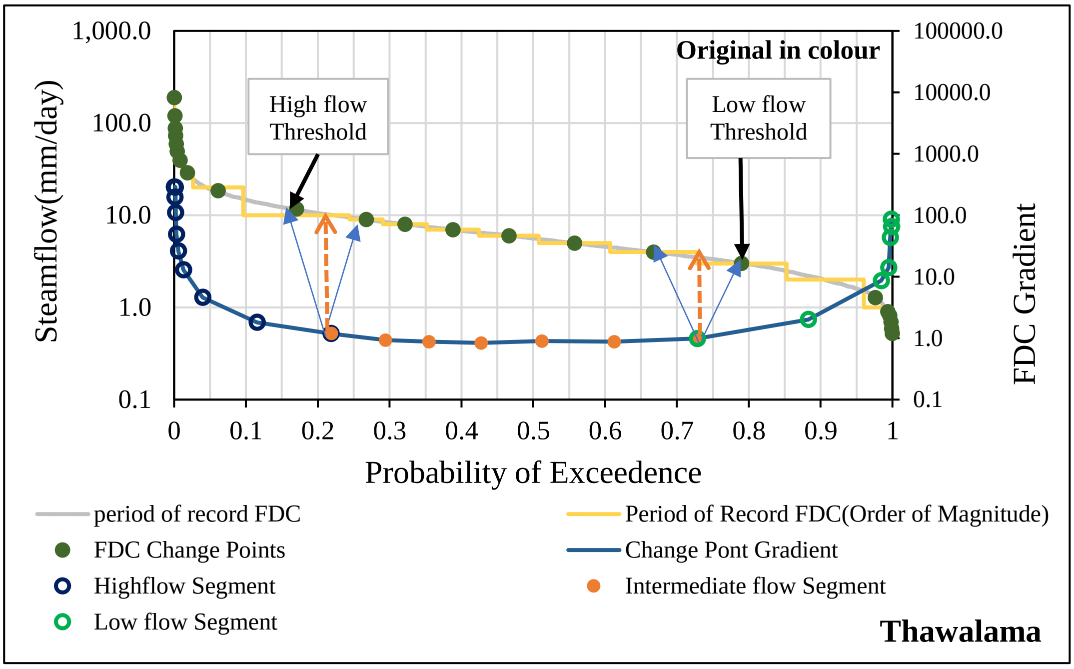


Figure 5-3:Streamflow separation in Thawalama watershed

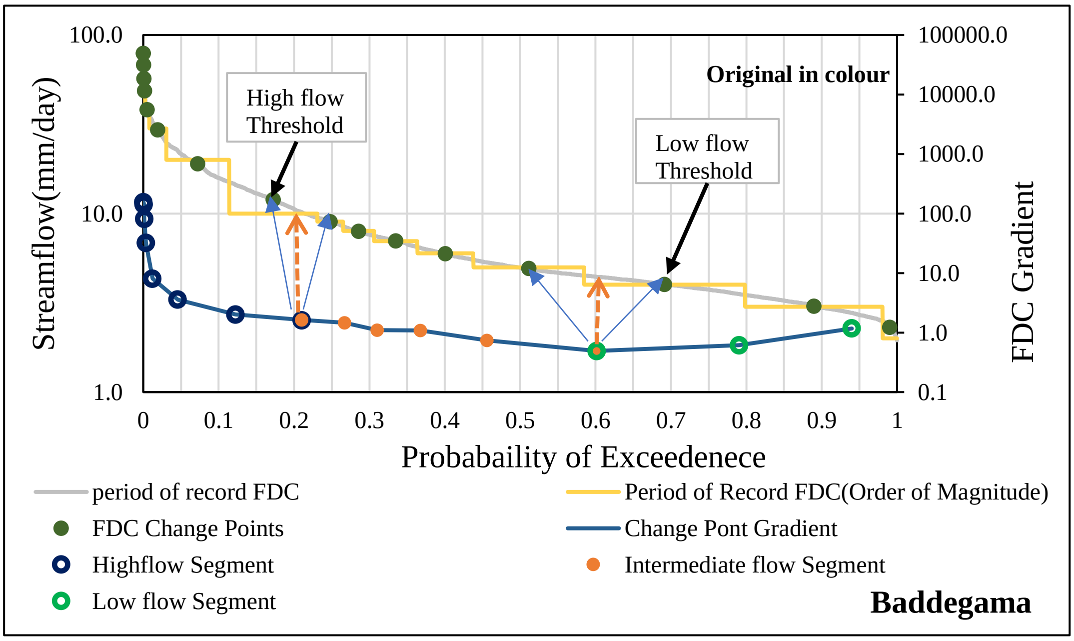


Figure 5-4:Streamflow separation in Baddegama watershed

5.6 Calibration Results

5.6.1 Statistical goodness of fit measures

RMSE statistical measures in mm/day for calibration results at Thawalama and Baddegama lumped models are tabulated in Table 5-4.

Table 5-4:Comparison of model calibration results

Gauging Station	RMSE (mm/day)	Annual Water Balance Error	FDC			
				High	Medium	Low
			RMSE	RMSE	RMSE	RMSE
Thawalama	4.8140	-3.29%	4.8140	9.6381	3.0295	1.4987
Baddegama	3.0813	-0.30%	3.0814	6.2848	2.3278	1.2136

5.6.2 Parameters of Thawalama and Baddegama Watersheds Parameters

The optimized set of parameters for both watersheds at Baddegama and Thawalama are listed in Table 5-5.

Table 5-5:Optimized parameters of Thawalama and Baddegama

Parameters	Units	Thawalama	Baddegama
Constant Rate	mm/hours	0.72151	1
Initial Deficit	mm	12.892	12.998
Maximum Deficit	mm	46.047	50.483
Initial Discharge	m^3/s	22.572	42.6
Ratio to Peak		0.196	0.0484378
Recession Constant		0.9	0.9985
Lag Time	minutes	1661.4	3268
Initial Canopy Storage	%	0.10349	0.0022648
Maximum canopy storage	mm	0.91205	0.42571

5.6.3 Matching observed and calculated hydrograph and FDC

Hydrographs comparison for both observed and simulated streamflow in normal and semi-log scales for Thawalama and Baddegama watersheds are illustrated in Figure 5-5 to 5-8 respectively. Flow duration curves for both sorted and sort only observed streamflow at both watersheds are illustrated in Figures 5-9 and 5-10 for Thawalama and Figure 5-11 and 5-12 for Baddegama.

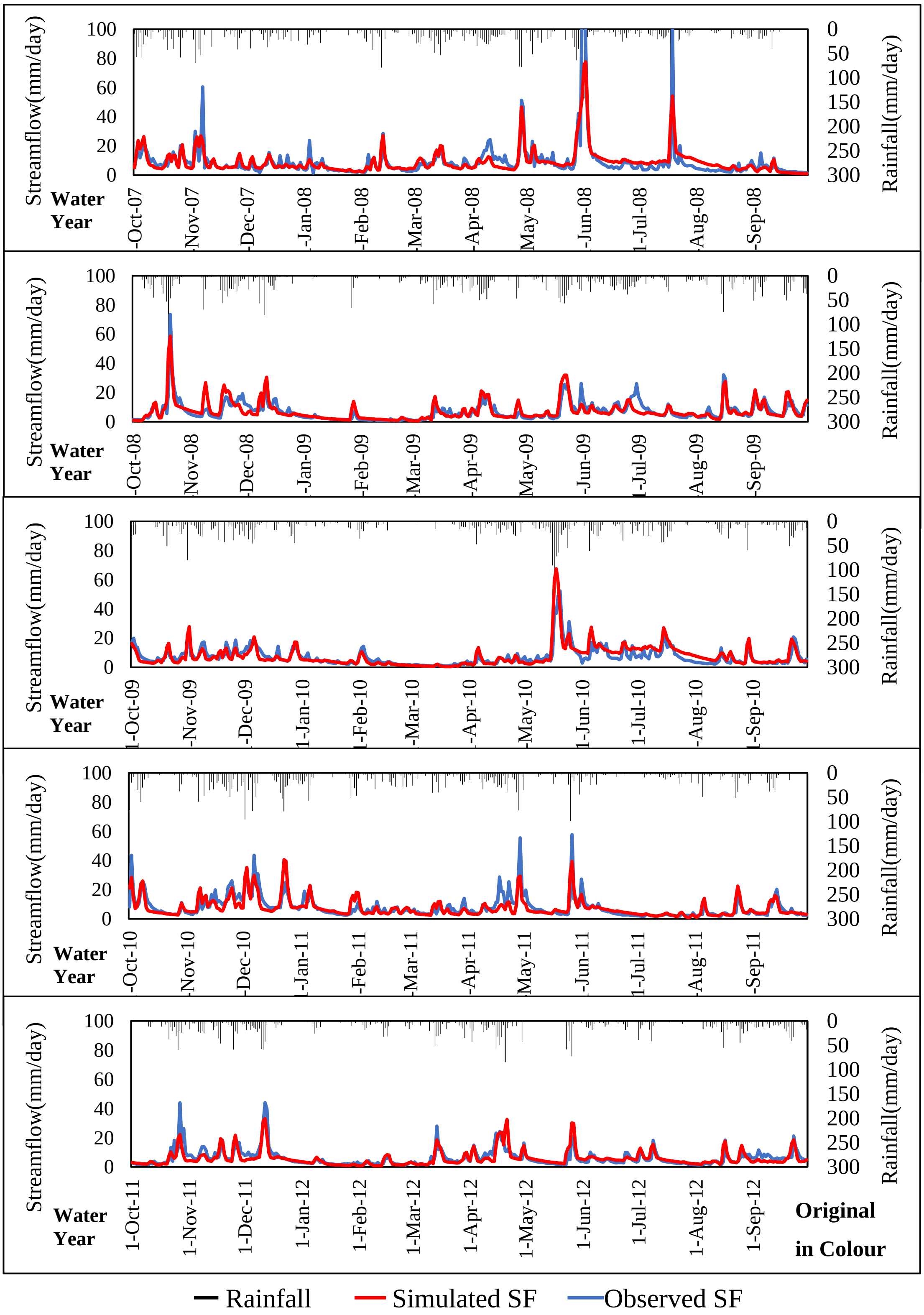


Figure 5-5:Performance of Thawalama model calibration-normal plot

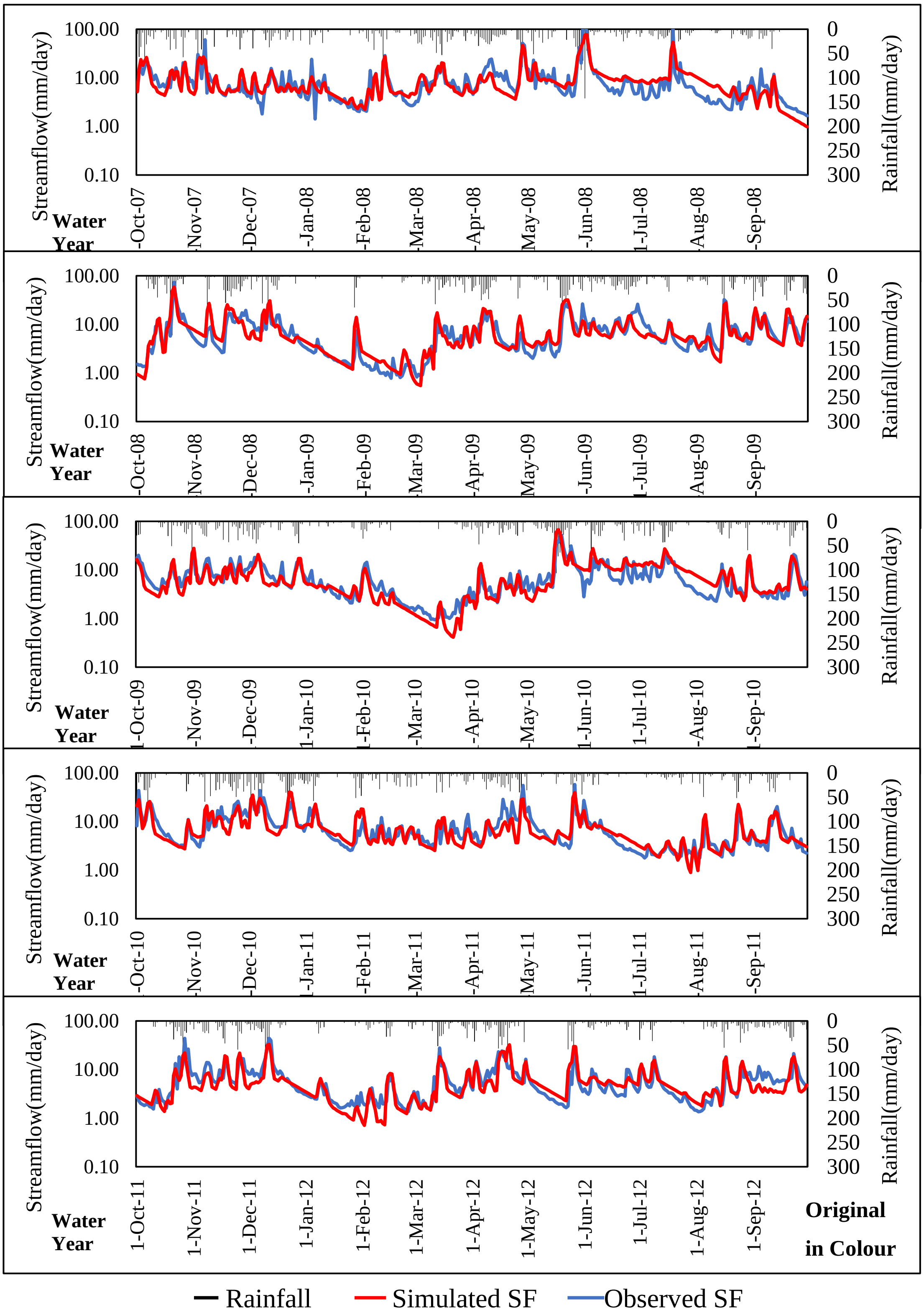


Figure 5-6:Performance of Thawalama model calibration-log plot

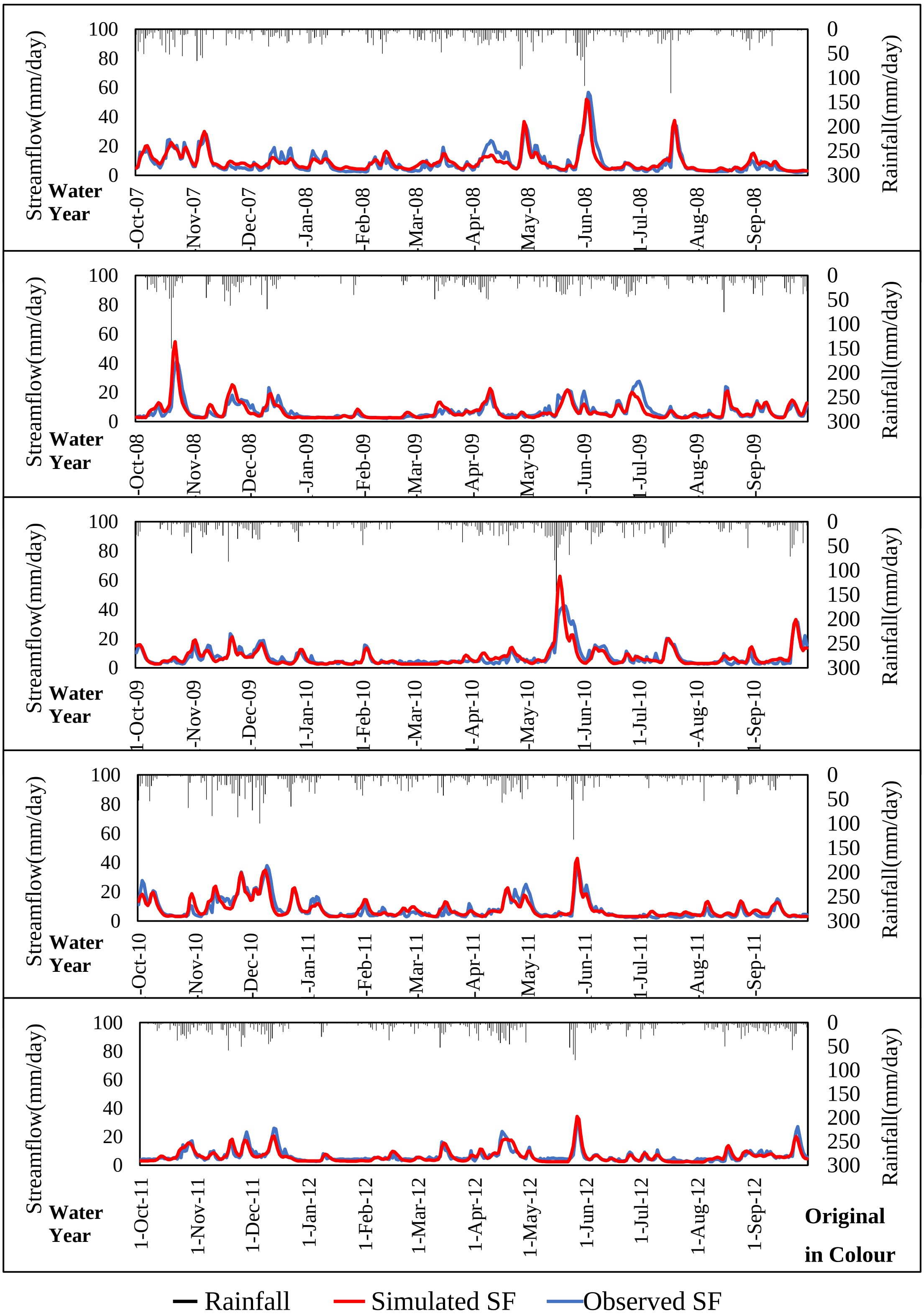


Figure 5-7:Performance of Baddegama model calibration-normal plot

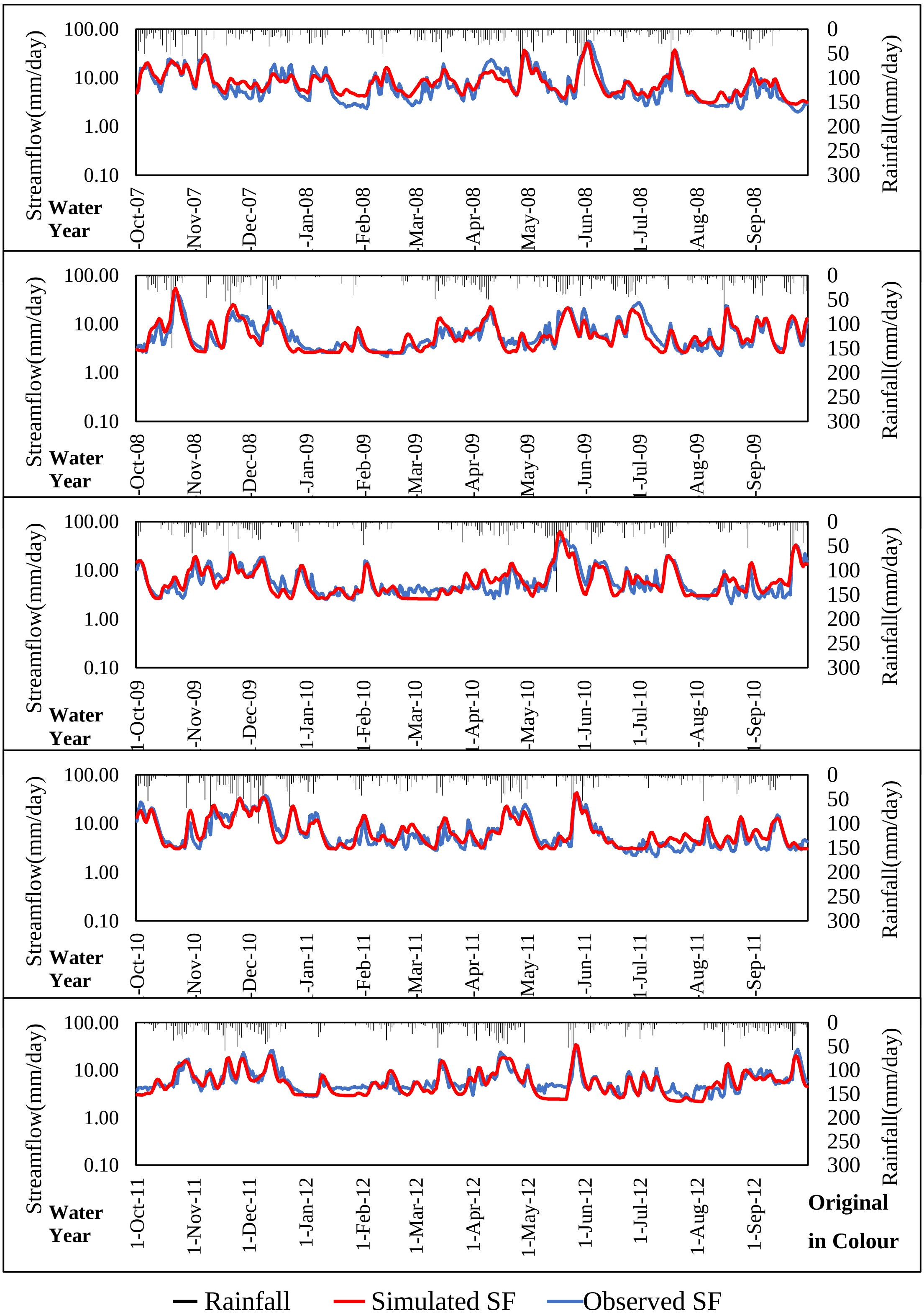


Figure 5-8:Performance of Baddegama model calibration-log plot

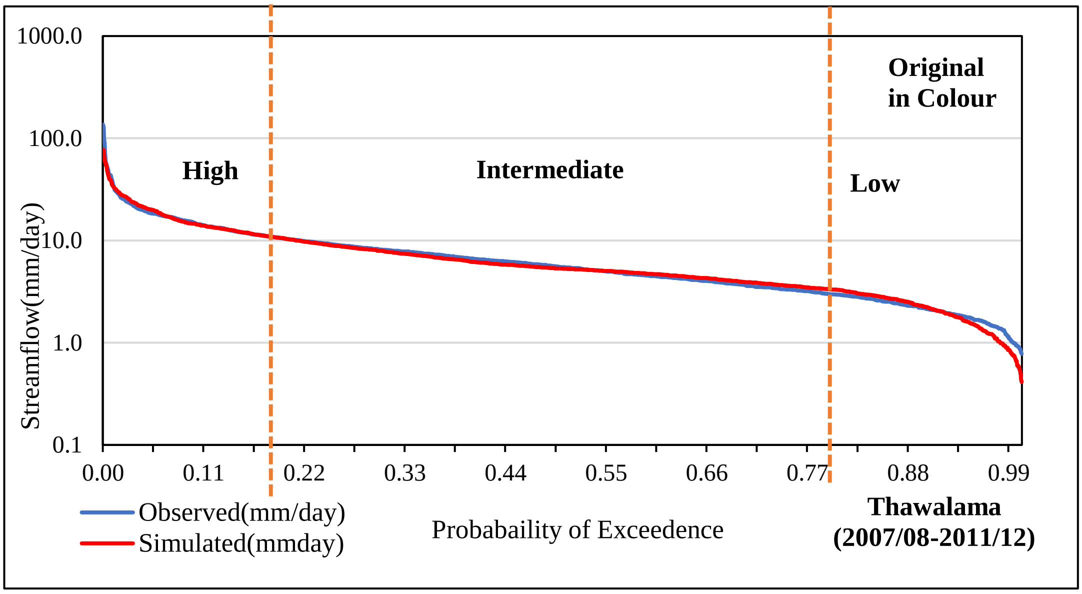


Figure 5-9:FDC of Thawalama model-both sorted

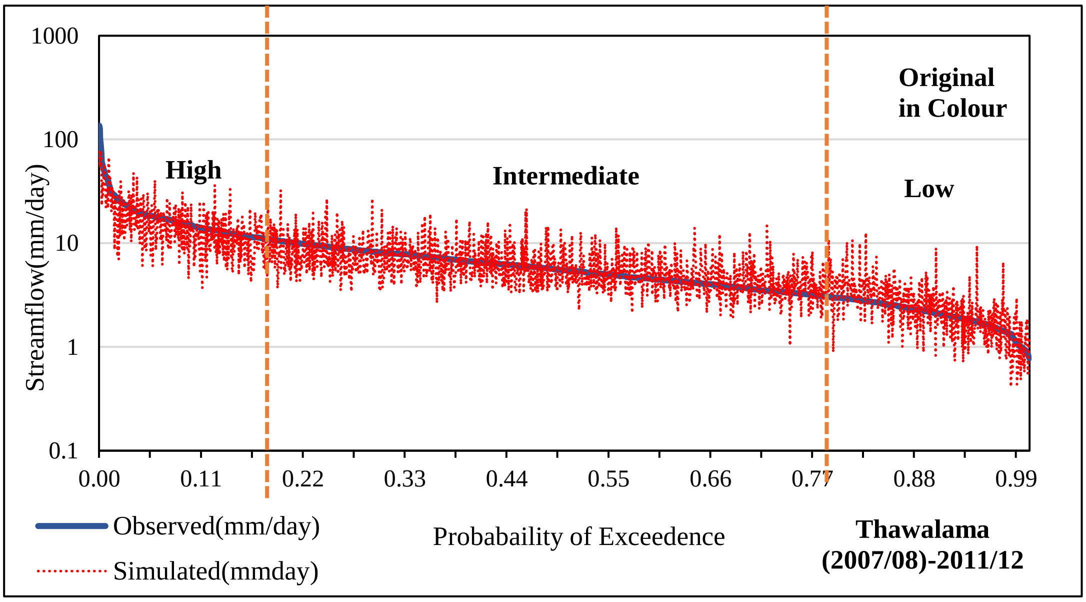


Figure 5-10:FDC of Thawalama model-sort only observed

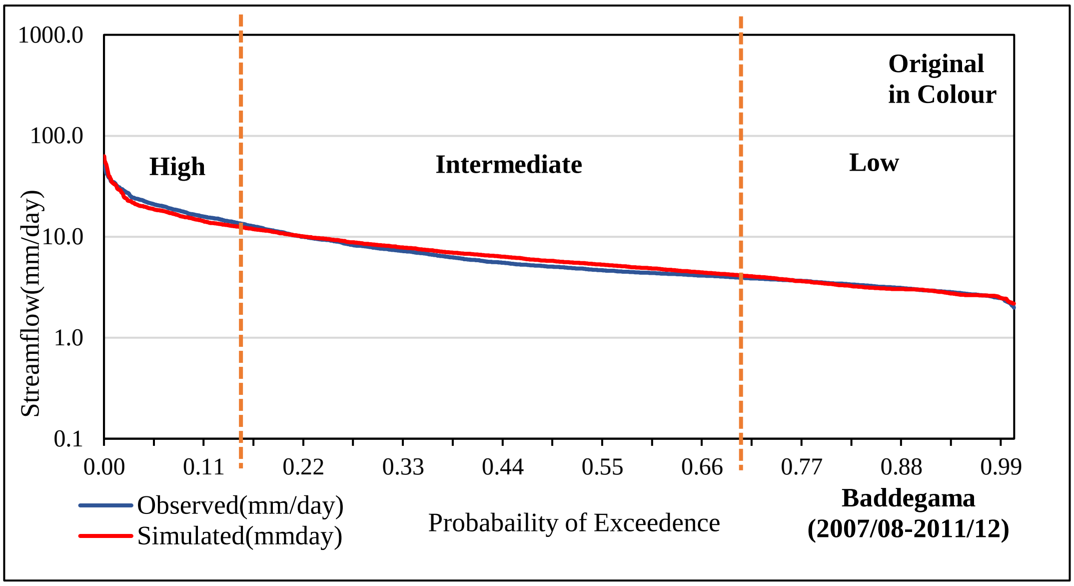


Figure 5-11:FDC at Baddegama model-both sorted

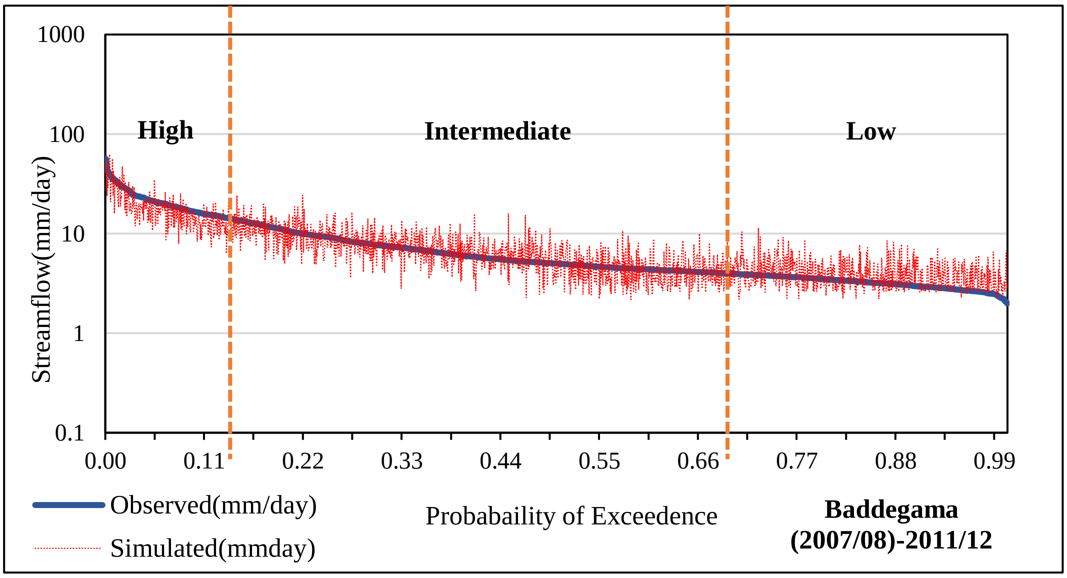


Figure 5-12:FDC at Baddegama model-sort only observed

5.6.4 Annual water balance

Hydrologic annual water budget for Thawalama and Baddegama models were illustrated in Figure 5-13 and 5-14 respectively. According to the values, Thawalama showing -3.3% and Baddegama showing -0.3% of error for average annual water balance for the period of calibration.

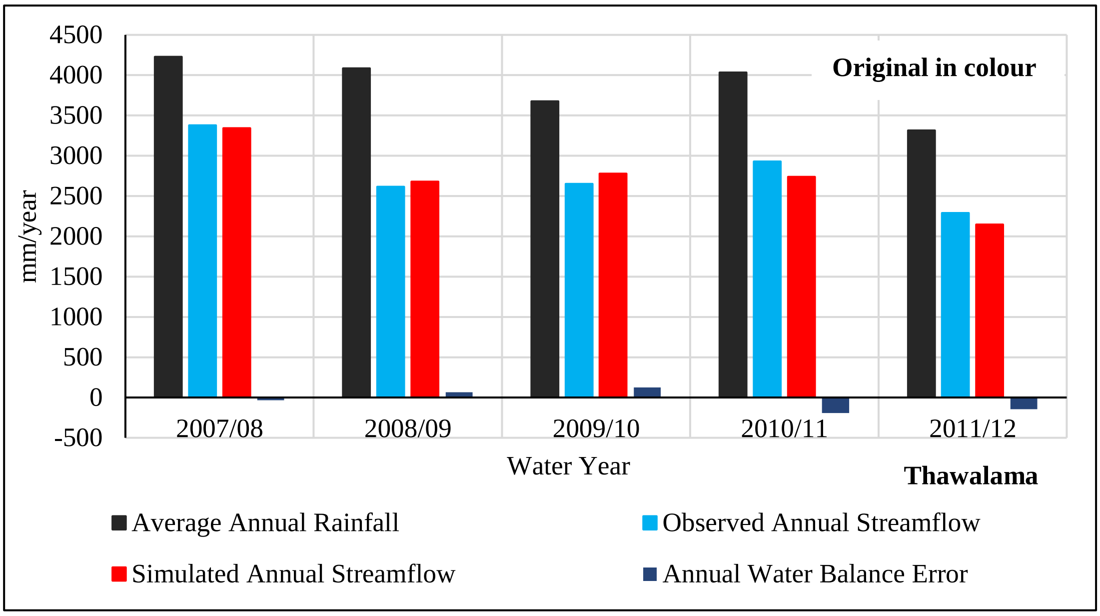


Figure 5-13:Annual water balance error at Thawalama

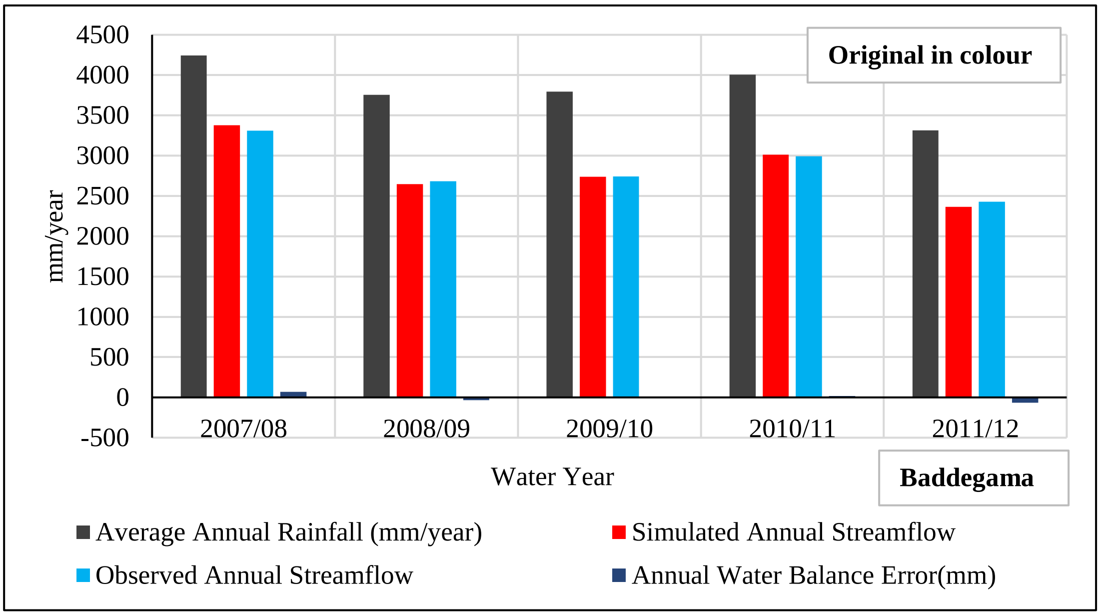


Figure 5-14:Annual water balance error at Baddegama

5.6.5 Monthly and seasonal performance

Monthly mass balance error and seasonal mass balance error at Thawalama and Baddegama show in Figure 5-15 to Figure 5-18 with detail of tables in Table 5-6 to Table 5-9 respectively.

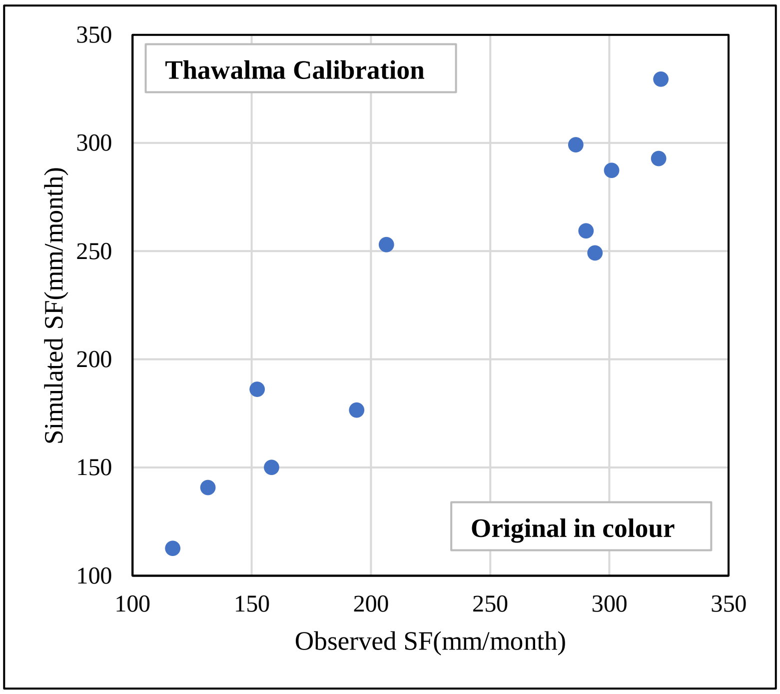


Figure 5-15:Thawalama monthly average simulated and observed SF

Table 5-6:Thawalama monthly average mass balance error

Month	Monthly Average Observed Flow(mm)	Monthly Average Simulated Flow(mm)	Mass Balance Error
January	131.6	140.7	6.9%
February	116.8	112.6	-3.6%
March	158.3	150.0	-5.3%
April	293.9	249.1	-15.2%
May	321.6	329.4	2.4%
June	285.9	299.1	4.6%
July	206.5	252.9	22.5%
August	152.3	186.2	22.3%
September	194.0	176.6	-9.0%
October	290.2	259.4	-10.6%
November	300.9	287.3	-4.5%
December	320.6	292.9	-8.7%

Table 5-7:Thawalama seasonal error at each water year

Year	Season	Seasonal Average Observed Flow(mm)	Seasonal Averaged Simulated Flow(mm)	Error
2007/08	Yala	1930	1901	1%
	Maha	1448	1441	0%
2008/09	Yala	1483	1452	2%
	Maha	1131	1229	-9%
2009/10	Yala	1480	1795	-21%
	Maha	1171	982	16%
2010/11	Yala	1241	1113	10%
	Maha	1690	1624	4%
2011/12	Yala	1138	1207	-6%
	Maha	1152	939	19%

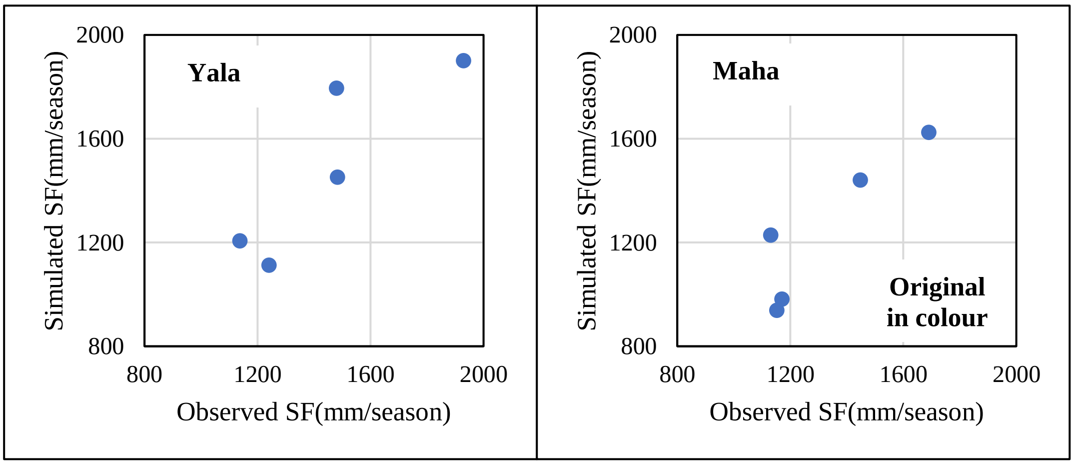


Figure 5-16:Thawalama seasonal behavior of observed and simulated SF

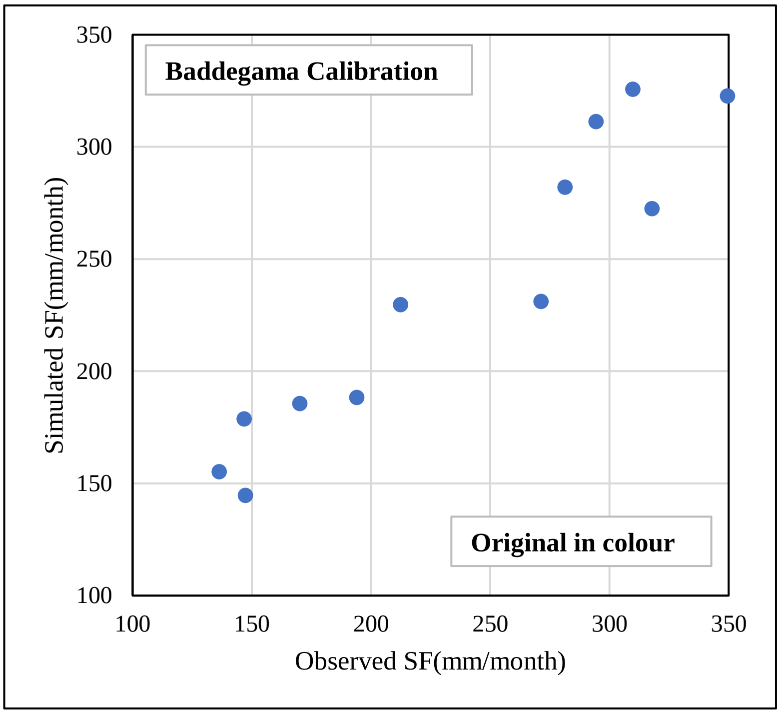


Figure 5-17:Baddegama monthly average simulated and observed SF

Table 5-8:Baddegama monthly average mass balance error

Month	Monthly Average Observed Flow(mm)	Monthly Average Simulated Flow(mm)	Mass Balance Error
January	147.3	144.6	-2%
February	136.3	155.2	14%
March	170.1	185.7	9%
April	281.4	282.1	0%
May	349.5	322.8	-8%
June	271.2	231.2	-15%
July	194.0	188.3	-3%
August	146.8	178.8	22%
September	212.4	229.7	8%
October	294.4	311.4	6%
November	309.8	325.8	5%
December	317.9	272.5	-14%

Table 5-9:Baddegama seasonal error at each water year

Year	Season	Seasonal Average Observed Flow(mm)	Seasonal Average Simulated Flow(mm)	Error
2007/08	Yala	1744	1664	5%
	Maha	1567	1715	-9%
2008/09	Yala	1464	1360	7%
	Maha	1218	1286	-6%
2009/10	Yala	1596	1641	-3%
	Maha	1145	1098	4%
2010/11	Yala	1239	1282	-3%
	Maha	1753	1729	1%
2011/12	Yala	1234	1217	1%
	Maha	1196	1148	4%

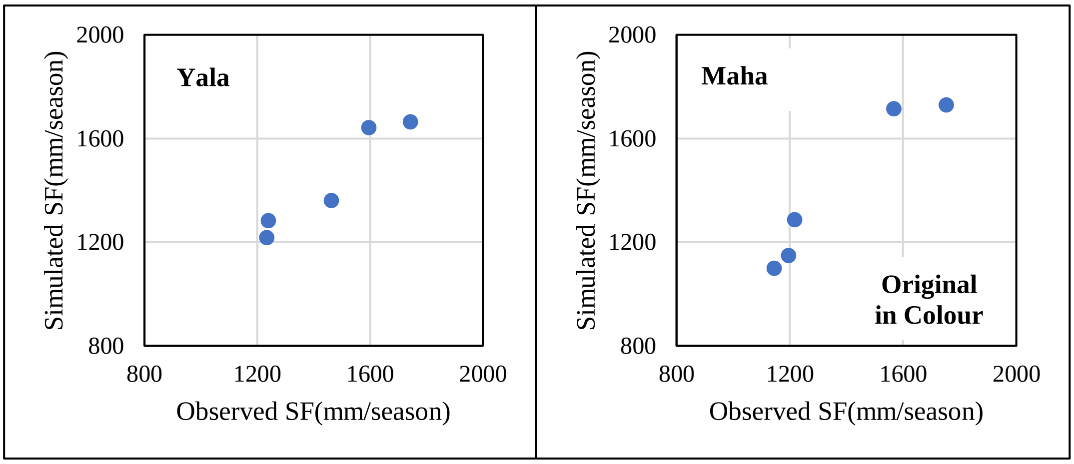


Figure 5-18:Baddegama seasonal behavior of observed and simulated SF

5.7 Model Verification

The water year starts from 2012/2013 to 2016/2017 water year's daily time scale precipitation and observed river flow data were taken to verify the calibrated model. During this validity process, the model parameters which are determined from the calibration process were kept freeze. As military the calibrated model evaluation, the model performance was assessed with the RMSE (mm/day) indicator for model performance criteria.

5.7.1 Statistical goodness of fit measures

RMSE statistical measures in mm/day for validation results at Thawalama and Baddegama lumped models are tabulated in Table 5-10.

Table 5-10:Comparison of model validation results

Gauging Station	RMSE (mm/day)	Annual Water Balance Error	FDC			
				High	Medium	Low
			RMSE	RMSE	RMSE	RMSE
Thawalama	5.0048	6.06%	5.0048	8.9796	4.0073	1.5132
Baddegama	3.5597	-16.69%	3.5597	7.4550	2.5851	1.2138

5.7.2 Matching observed and calculated hydrograph and FDC

Hydrographs comparison for both observed and simulated streamflow in normal and semi-log scales for Thawalama and Baddegama watersheds are illustrated in Figure 5-19 to 5-22 respectively. Flow duration curves for both sorted and sort only observed streamflow at both watersheds are illustrated in Figure 5-23 and 5-24 for Thawalama and Figure 5-25 and 5-26 for Baddegama.

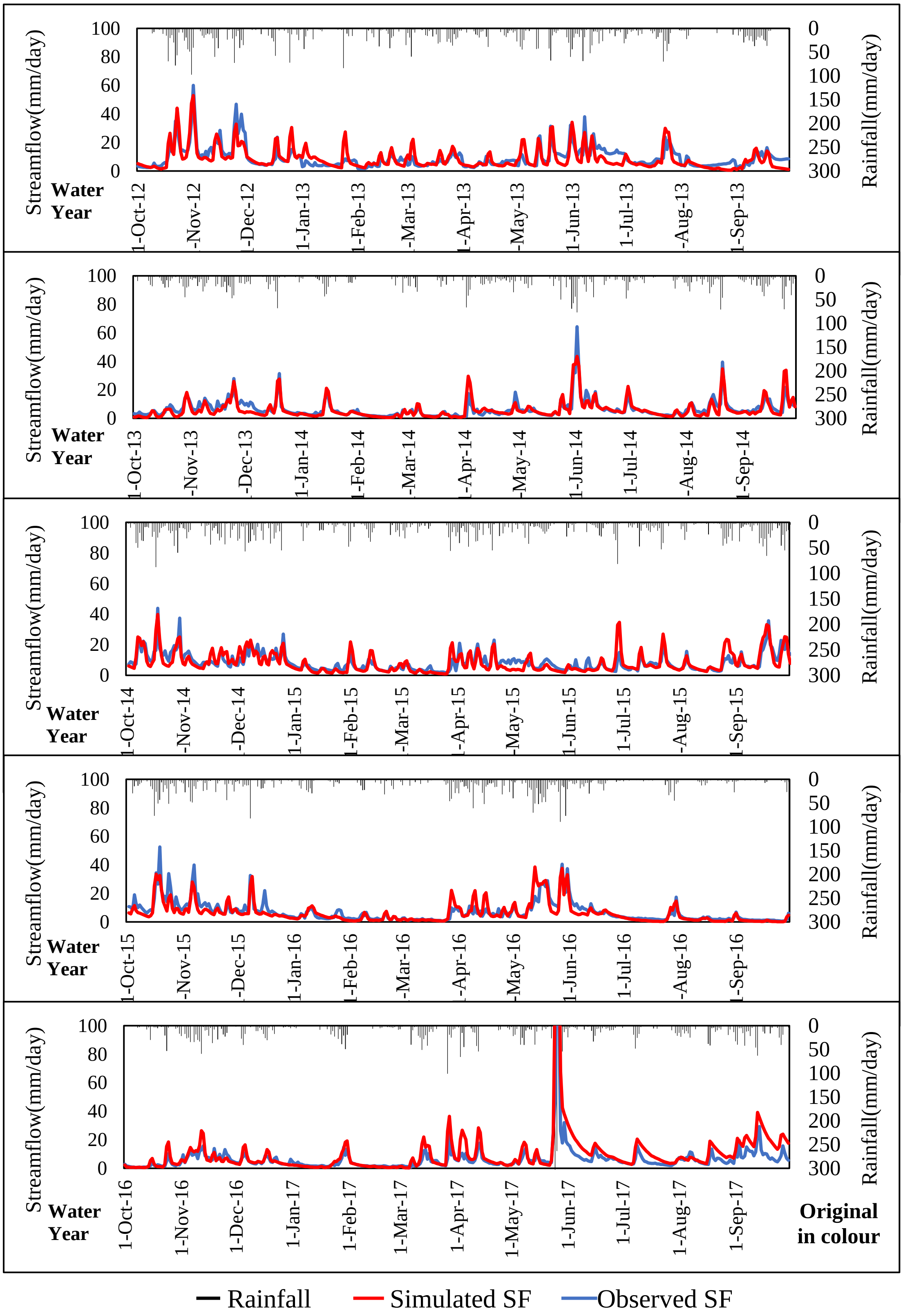


Figure 5-19:Performance of Thawalama model validation-normal plot

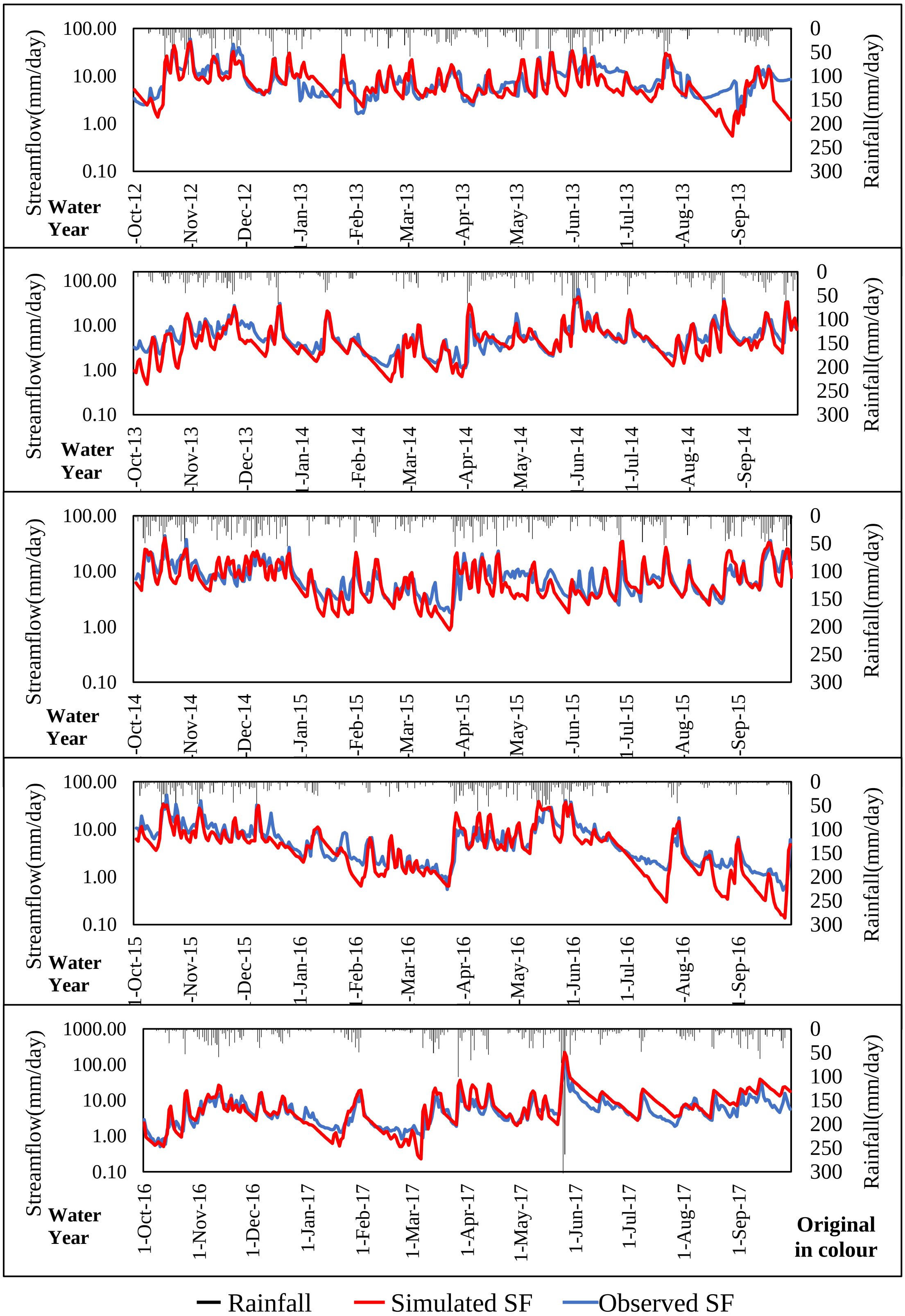


Figure 5-20:Performance of Thawalama model validation-log plot

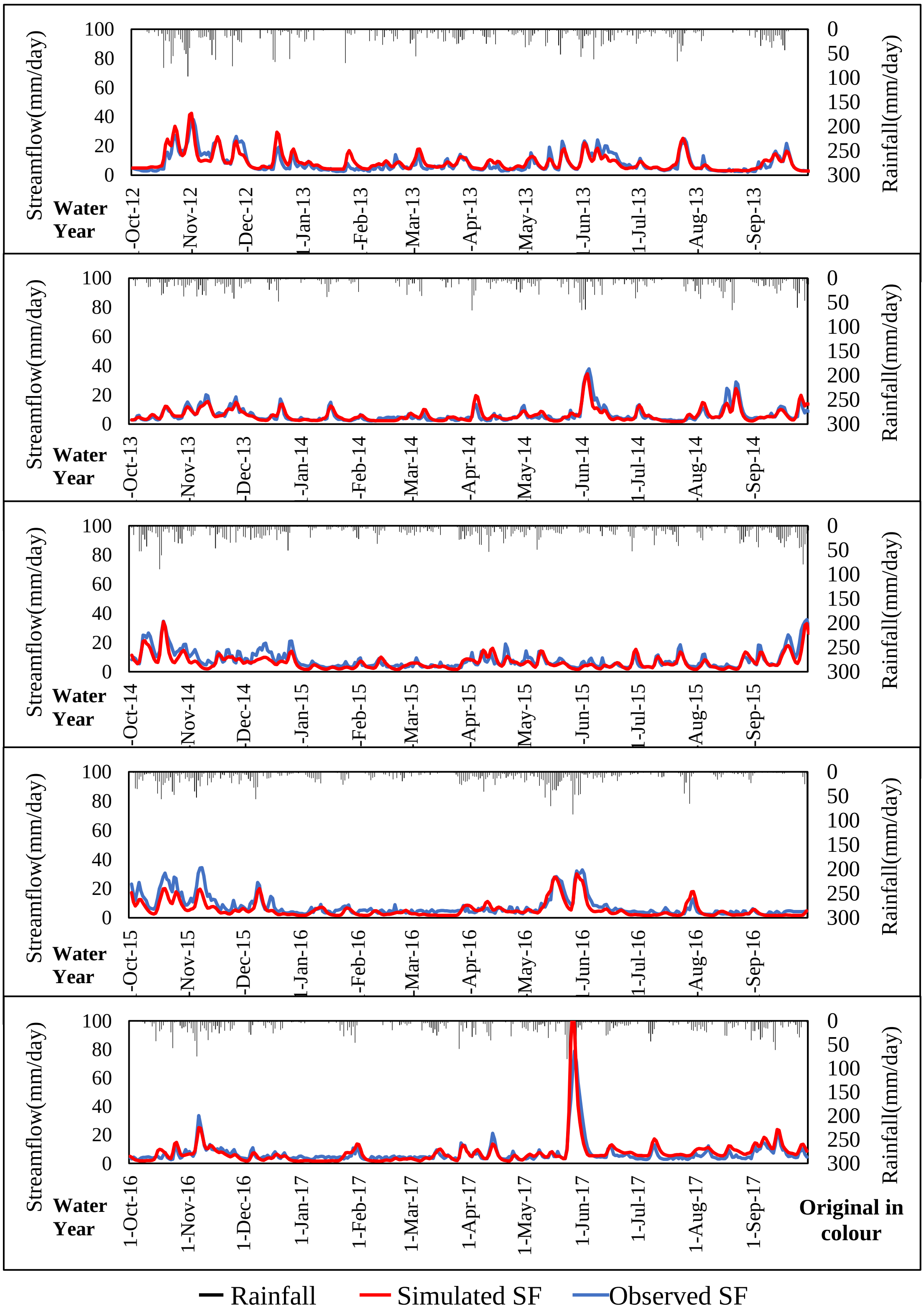


Figure 5-21:Performance of Baddegama model validation-normal plot

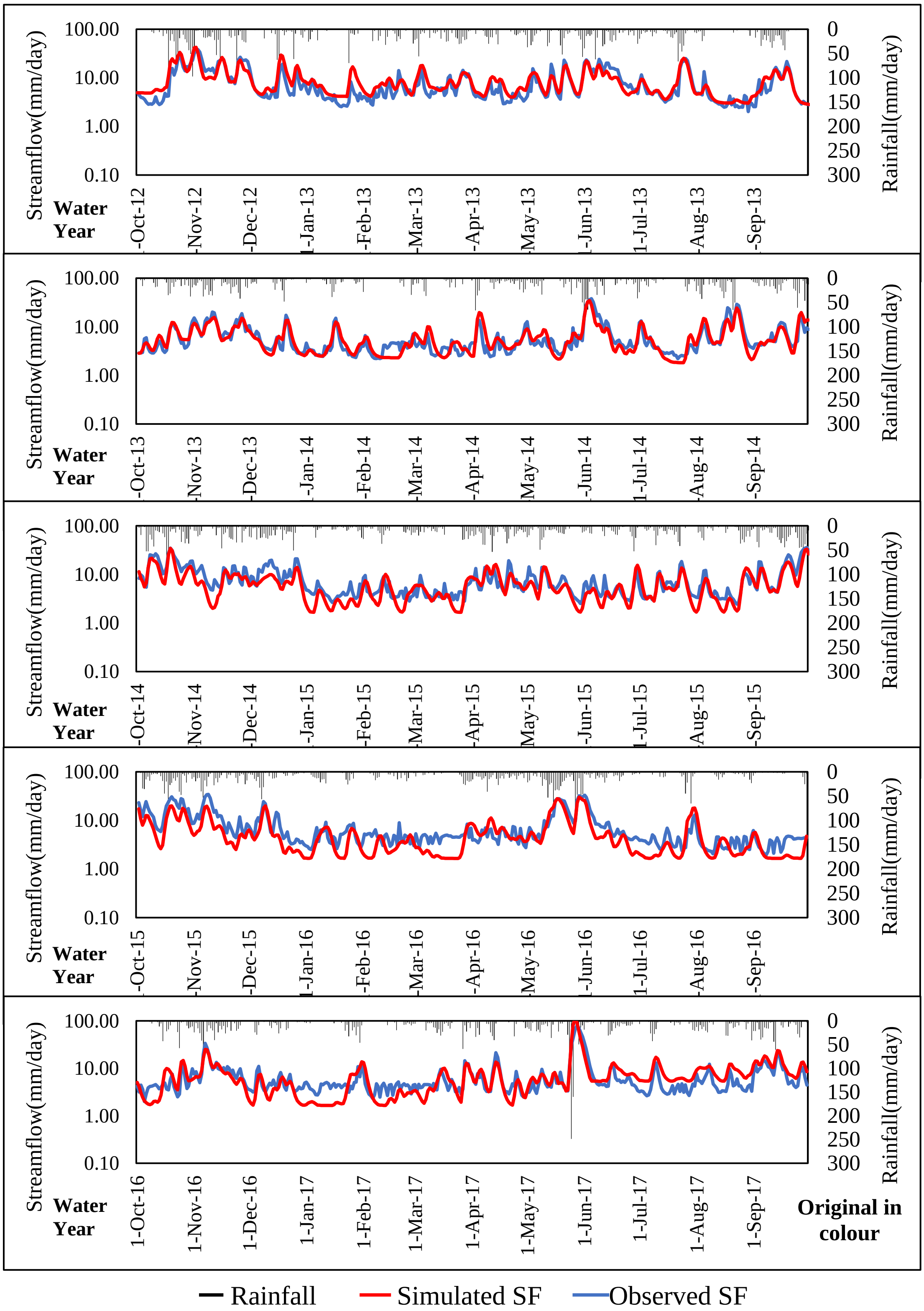


Figure 5-22:Performance of Baddegama model validation-log plot

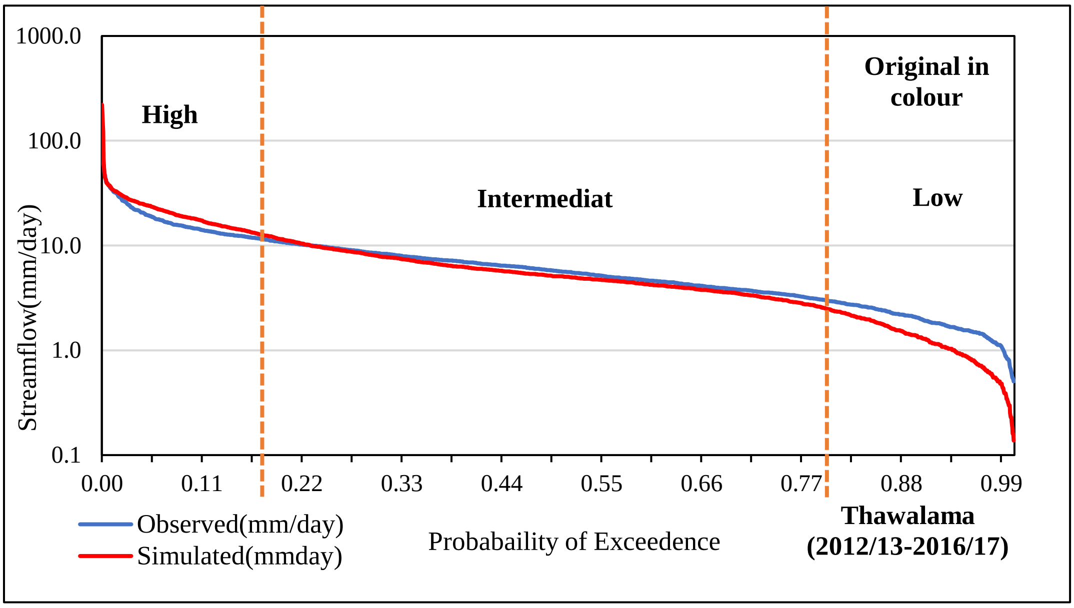


Figure 5-23:FDC of Thawalama model-validation-both sorted

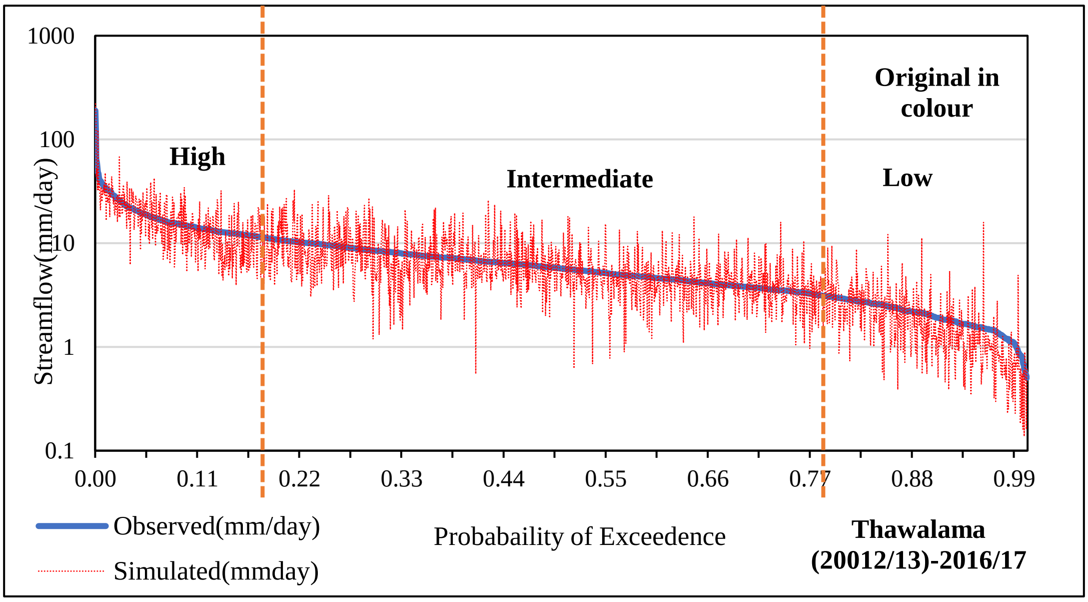


Figure 5-24:FDC of Thawalama model-validation-sort only observed

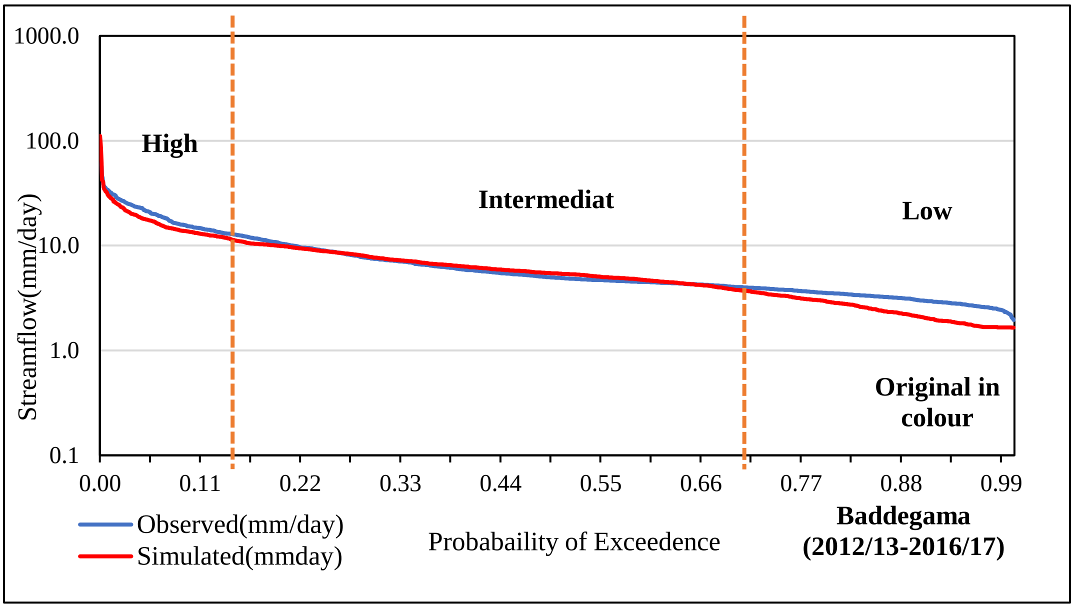


Figure 5-25:FDC of Baddegama model-validation-both sorted

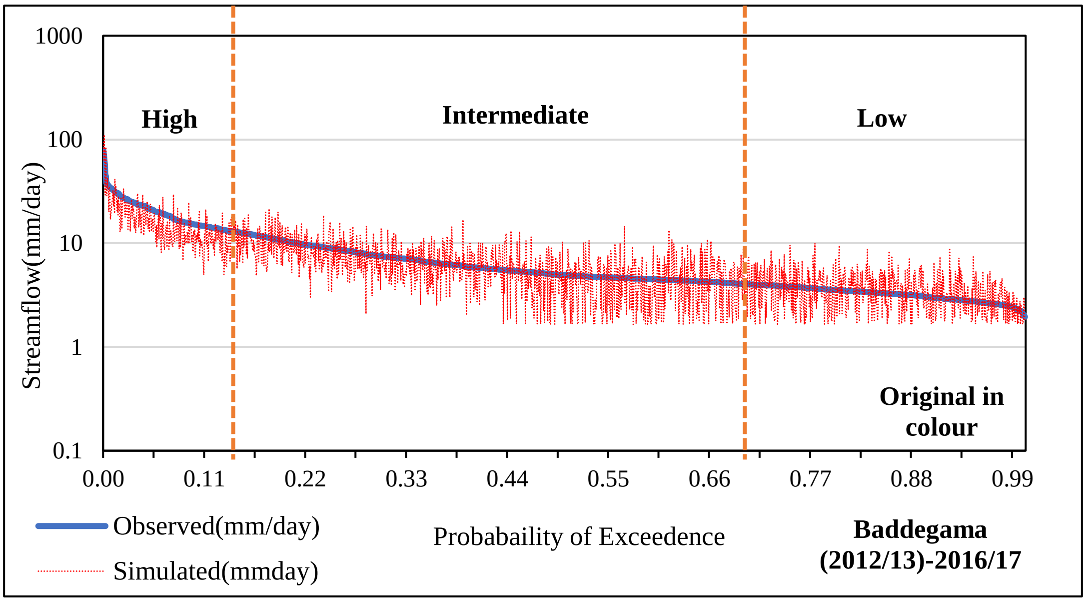


Figure 5-26:FDC of Baddegama model-validation-sort only observed

5.7.3 Annual water balance

Hydrologic annual water budget for Thawalama and Baddegama models were illustrated in Figure 5-27 and 5-28 respectively. According to the values, Thawalama showing 6.1% and Baddegama showing -16.7% of error for average annual water balance for the period of validation.

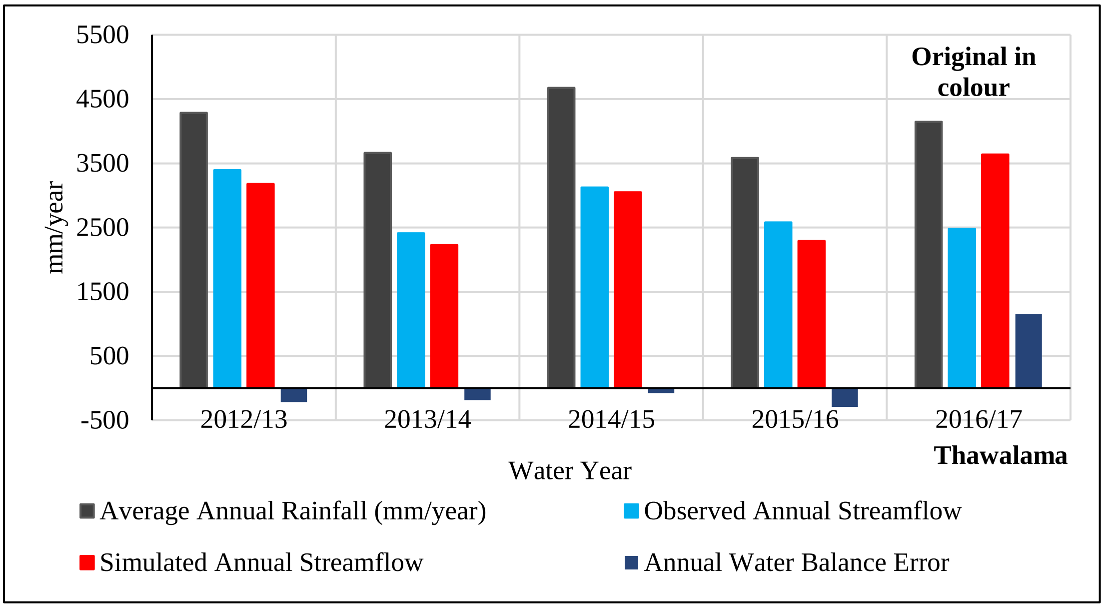


Figure 5-27:Thawalama annual water balance error

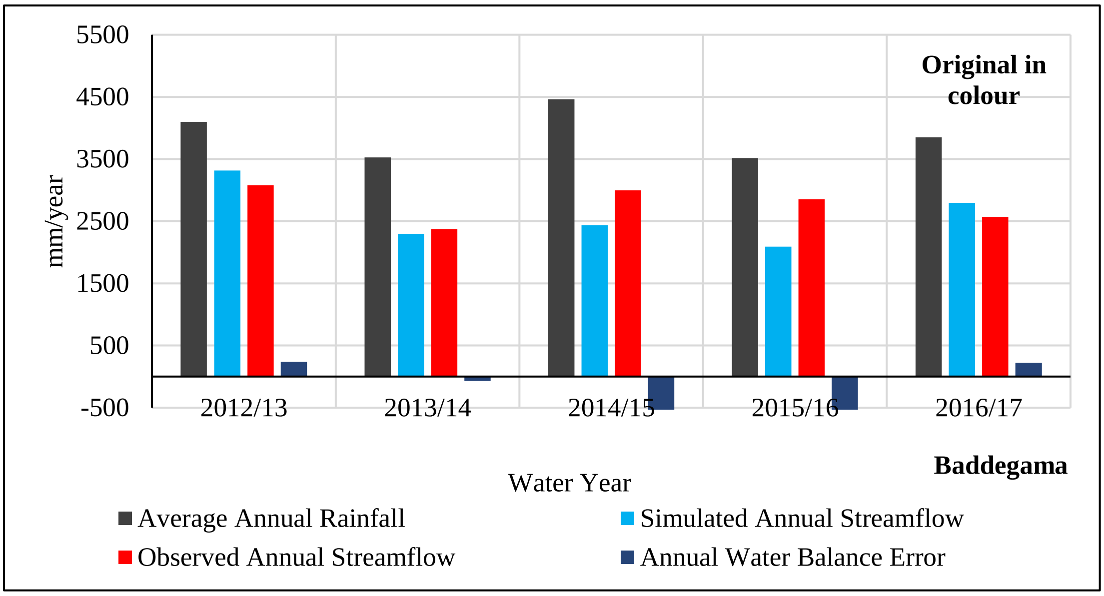


Figure 5-28:Baddegama annual water balance error

5.7.4 Monthly and seasonal performance

Monthly mass balance error and seasonal mass balance error at Thawalama and Baddegama show in Figure 5-29 to Figure 5-32 with detail of tables in Table 5-11 to Table 5-13 respectively.

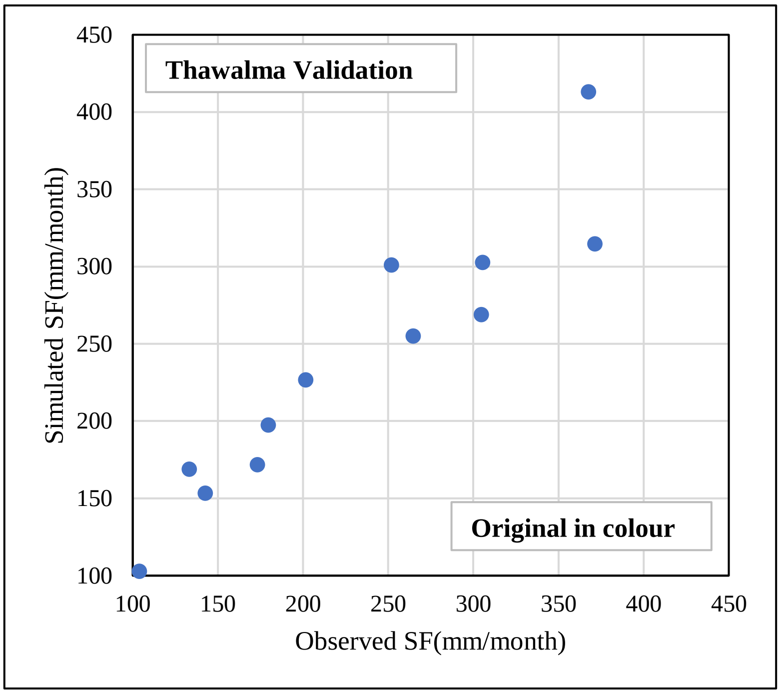


Figure 5-29:Thawalama monthly average observed vs simulated SF

Table 5-11:Thawalama monthly mass balance error

Month	Monthly Average Observed Flow(mm)	Monthly Average Simulated Flow(mm)	Mass Balance Error
January	142.4	153.2	7.6%
February	103.9	102.7	-1.2%
March	133.0	168.9	26.9%
April	201.5	226.6	12.4%
May	367.6	412.9	12.3%
June	305.3	302.6	-0.9%
July	179.6	197.5	10.0%
August	173.2	171.8	-0.8%
September	251.8	301.0	19.5%
October	304.6	268.9	-11.7%
November	371.2	314.7	-15.2%
December	264.7	255.0	-3.7%

Table 5-12:Thawalama seasonal error at each water year

Year	Season	Seasonal Average Observed Flow(mm)	Seasonal Averaged Simulated Flow(mm)	Error
2012/13	Yala	1656	1347	19%
	Maha	1739	1833	-5%
2013/14	Yala	1387	1403	-1%
	Maha	1025	821	20%
2014/15	Yala	1526	1501	2%
	Maha	1600	1548	3%
2015/16	Yala	1155	1131	2%
	Maha	1426	1161	19%
2016/17	Yala	1671	2681	-60%
	Maha	810	954	-18%

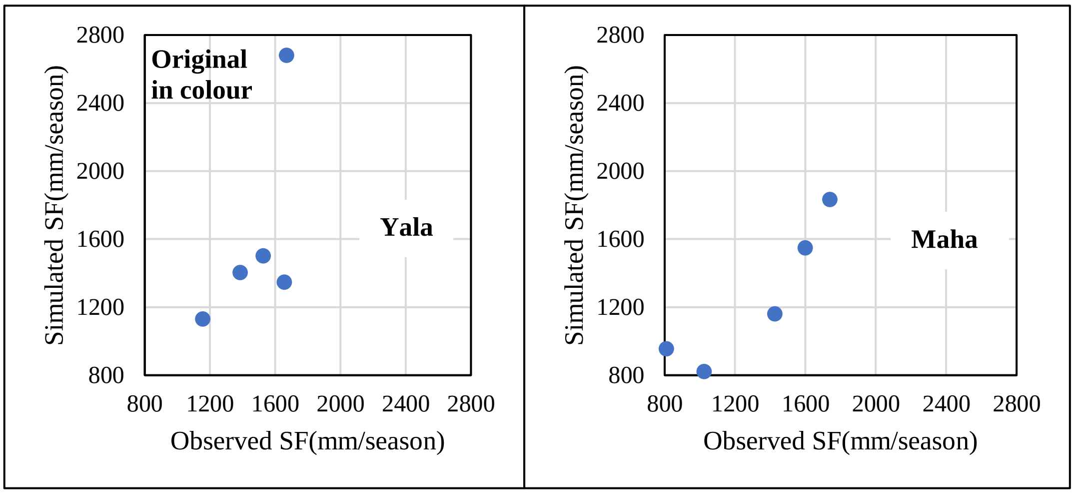


Figure 5-30:Thawalama seasonal behavior of observed and simulated SF

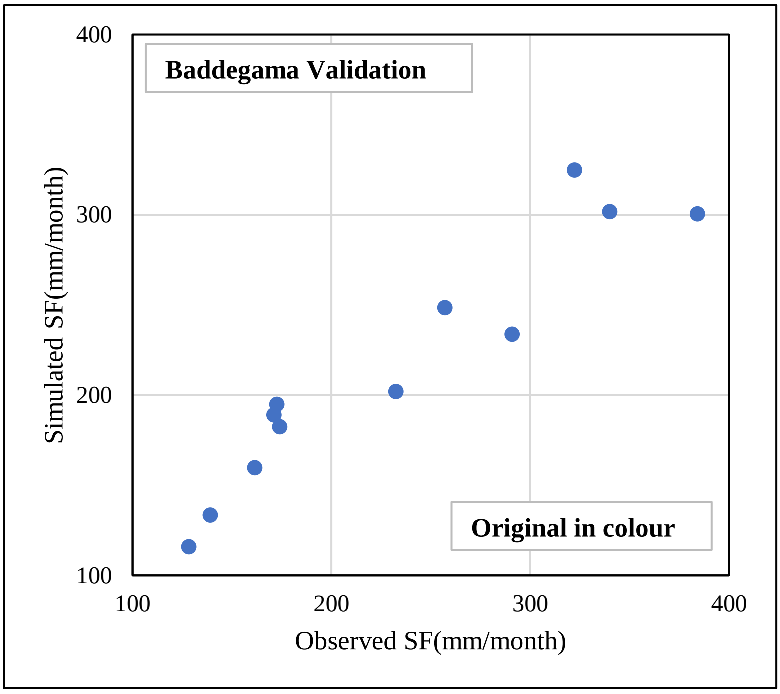


Figure 5-31:Baddegama monthly average observed vs simulated SF

Table 5-13:Baddegama monthly mass balance error

Month	Monthly Average Observed Flow(mm)	Monthly Average Simulated Flow(mm)	Mass Balance Error
January	139.1	133.5	-4.0%
February	128.3	116.0	-9.6%
March	161.4	159.8	-1.0%
April	172.6	194.9	12.9%
May	322.3	324.9	0.8%
June	290.9	233.8	-19.6%
July	171.2	189.1	10.5%
August	174.1	182.4	4.8%
September	257.1	248.4	-3.4%
October	340.0	301.7	-11.3%
November	384.2	300.6	-21.8%
December	232.5	202.1	-13.1%

Table 5-14:Baddegama seasonal error at each water year

Year	Season	Seasonal Average Observed Flow(mm)	Seasonal Averaged Simulated Flow(mm)	Error
2012/13	Yala	1426	1416	1%
	Maha	1654	1902	-15%
2013/14	Yala	1343	1281	5%
	Maha	1028	1018	1%
2014/15	Yala	1413	1237	12%
	Maha	1582	1200	24%
2015/16	Yala	1234	1069	13%
	Maha	1617	1020	37%
2016/17	Yala	1525	1866	-22%
	Maha	1046	929	11%

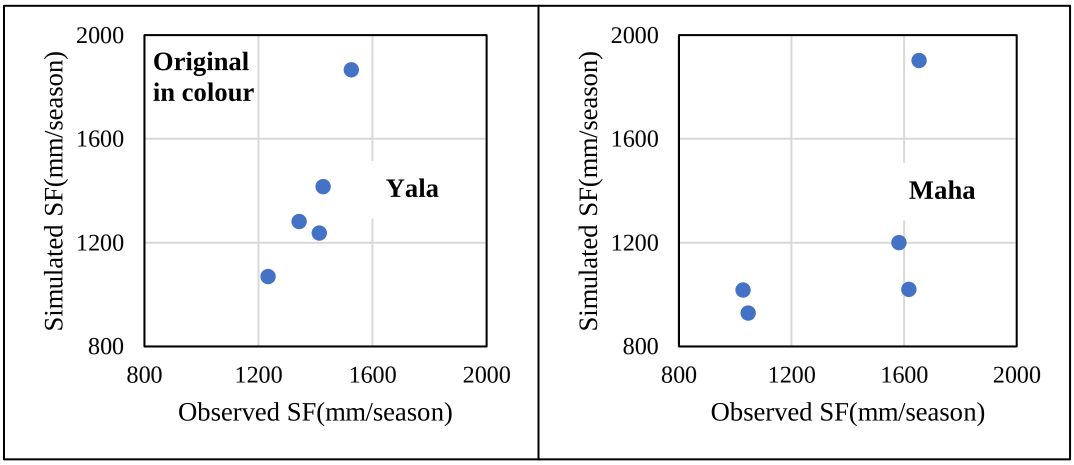


Figure 5-32:Thawalama seasonal behavior of observed and simulated SF

5.8 Parameter Transferability

5.8.1 Parameter transferability from Baddegama to Thawalama watershed

Calibrated parameter for Baddegama watershed transferred to Thawalama for 2007 to 2017 period and Thawalama calibrated parameters transferred to Thawalama 2007 to 2017 period to assess the transferability. Both model results were shown in Table 5-15.

Table 5-15:Model performance after calibrated parameter transferring from Baddegama to Thawalama watershed

Thawalama	RMSE (mm/day)	Annual Water Balance Error	FDC			
				High	Medium	Low
			RMSE	RMSE	RMSE	RMSE
With Transfer	5.8448	-11.66%	5.8448	11.8470	3.4717	2.1105
With Actual	4.9103	-2.27%	4.9103	9.2970	3.5640	1.5167

5.8.1.1 Statistical goodness of fit measures on parameter transferability

To assess parameter transferability in HEC-HMS lumped model, developed Baddegama calibrated data whole parameter set were transferred to the Thawalama for 10 years period and Thawalama calibrated parameters to Thawalama 10 years period were transferred. Model performance criteria given in Chapter 3 was evaluated by RMSE objective function. The graphs for hydrograph and FDC matching were illustrated in below Figure 5-33 to 5-38.

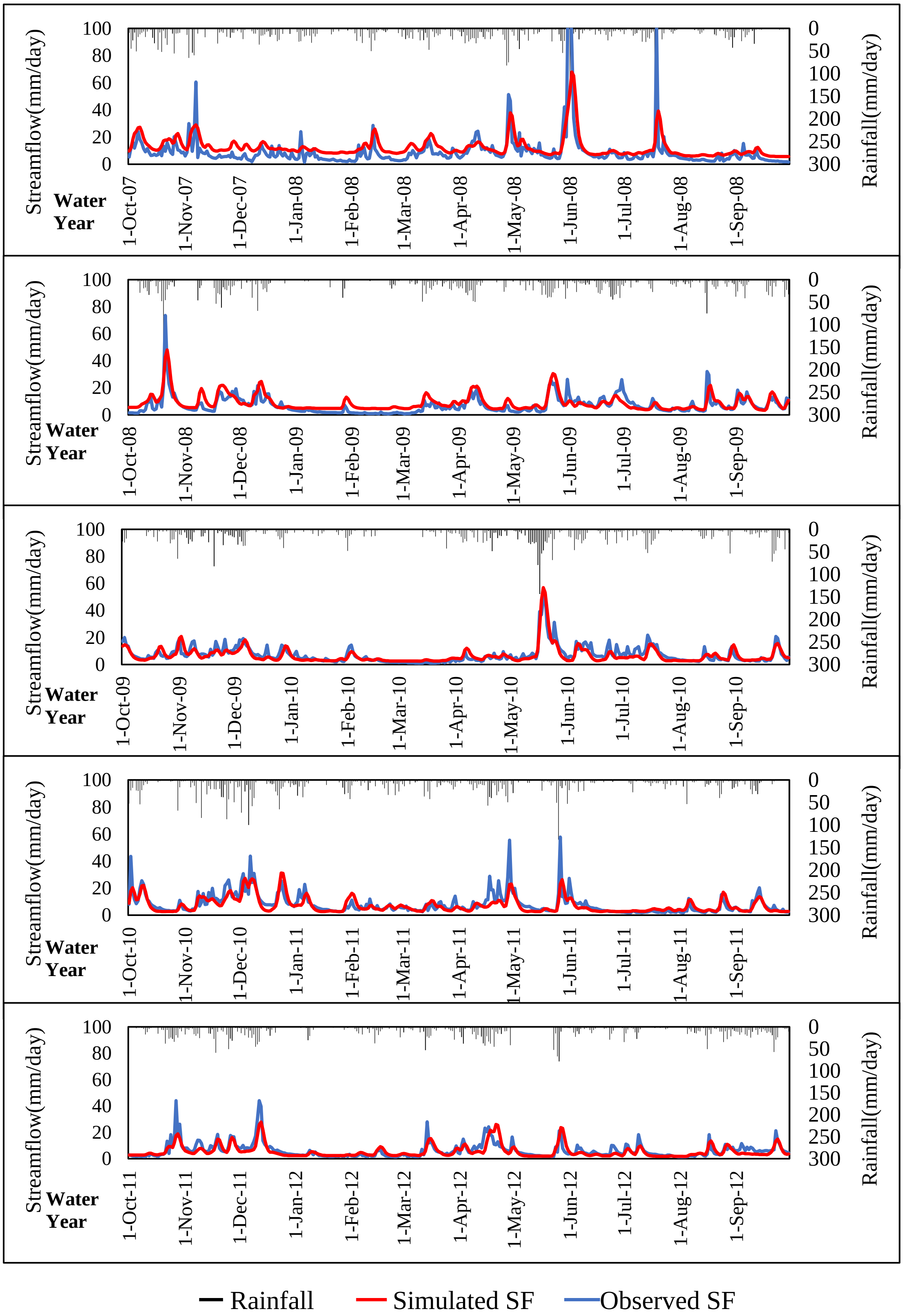


Figure 5-33:SF vs RF at Thawalama from Baddegama transferred parameter [normal plot]-I

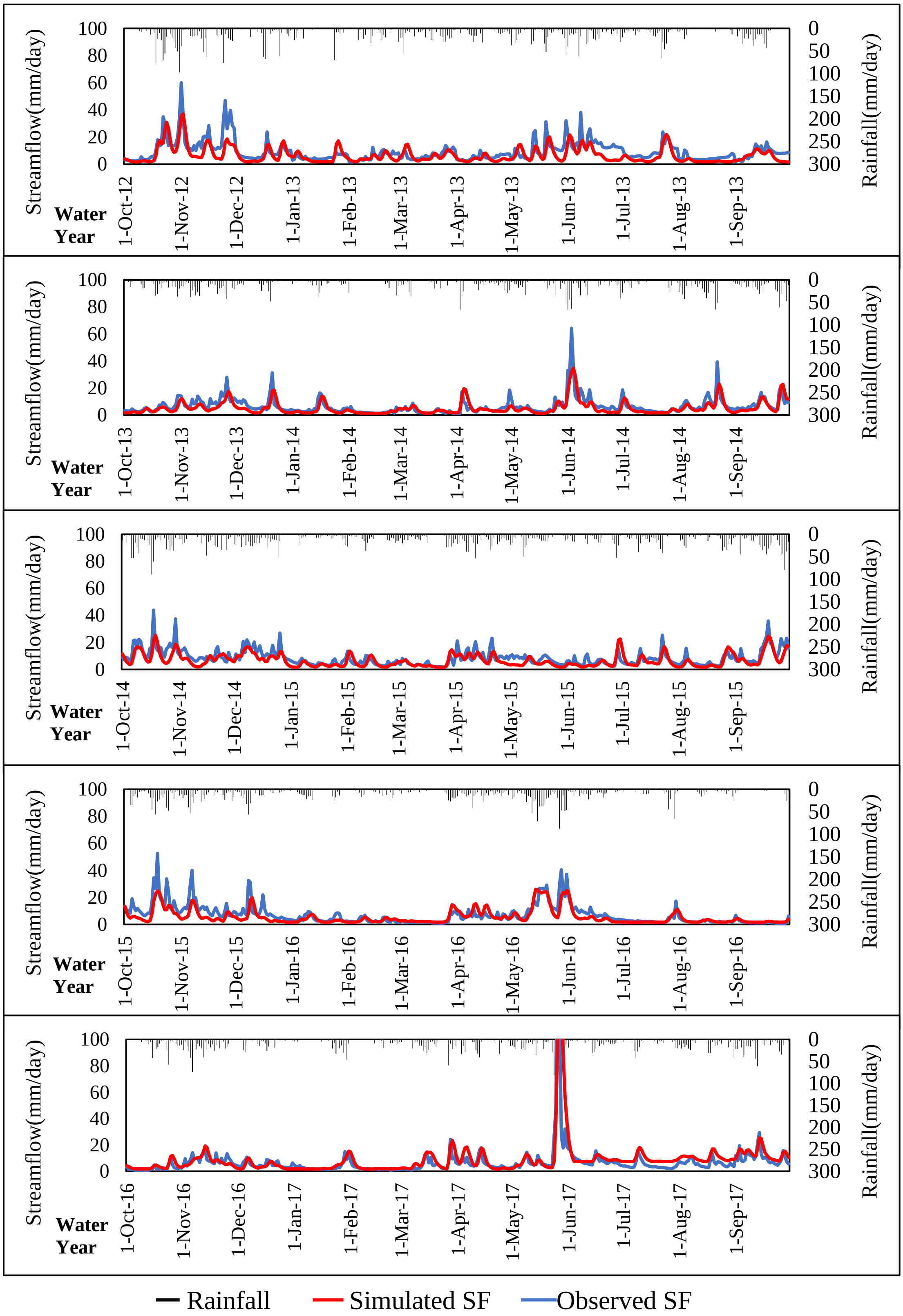


Figure 5-34:SF vs RF at Thawalama from Baddegama transferred parameter [normal plot]-II

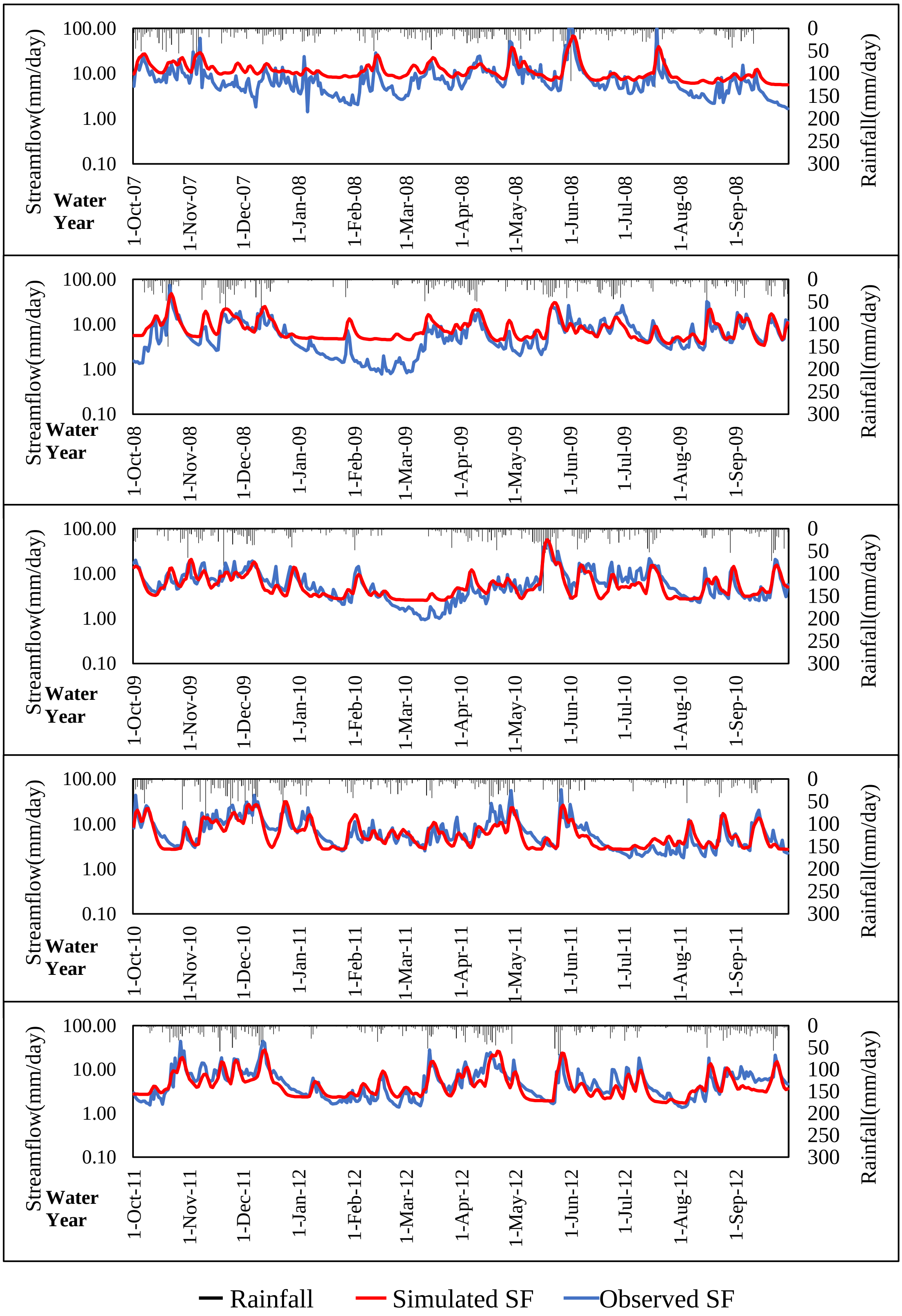


Figure 5-35:SF vs RF at Thawalama from Baddegama transferred parameter [log plot]-I

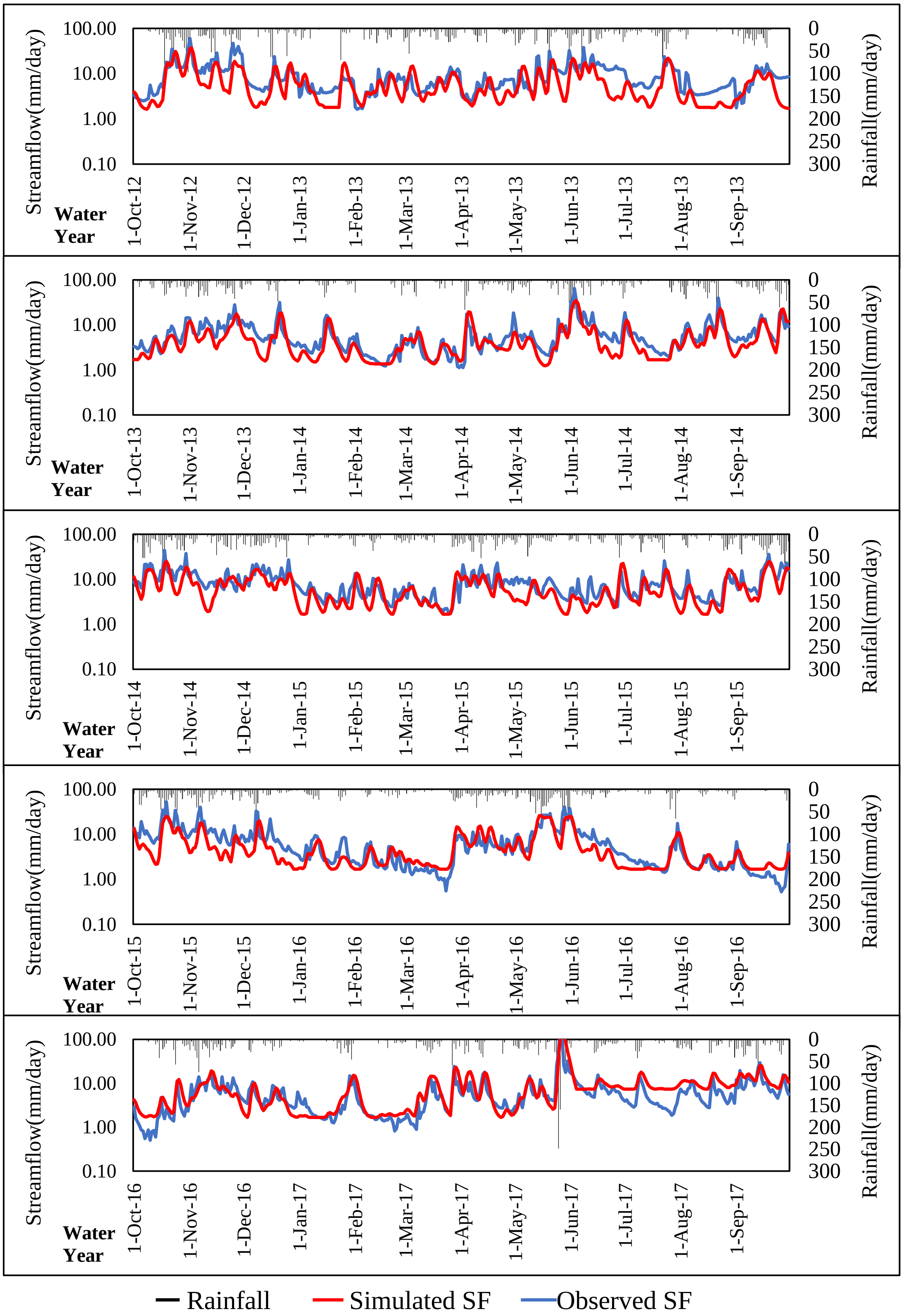


Figure 5-36:SF vs RF at Thawalama from Baddegama transferred parameter [log plot]-II

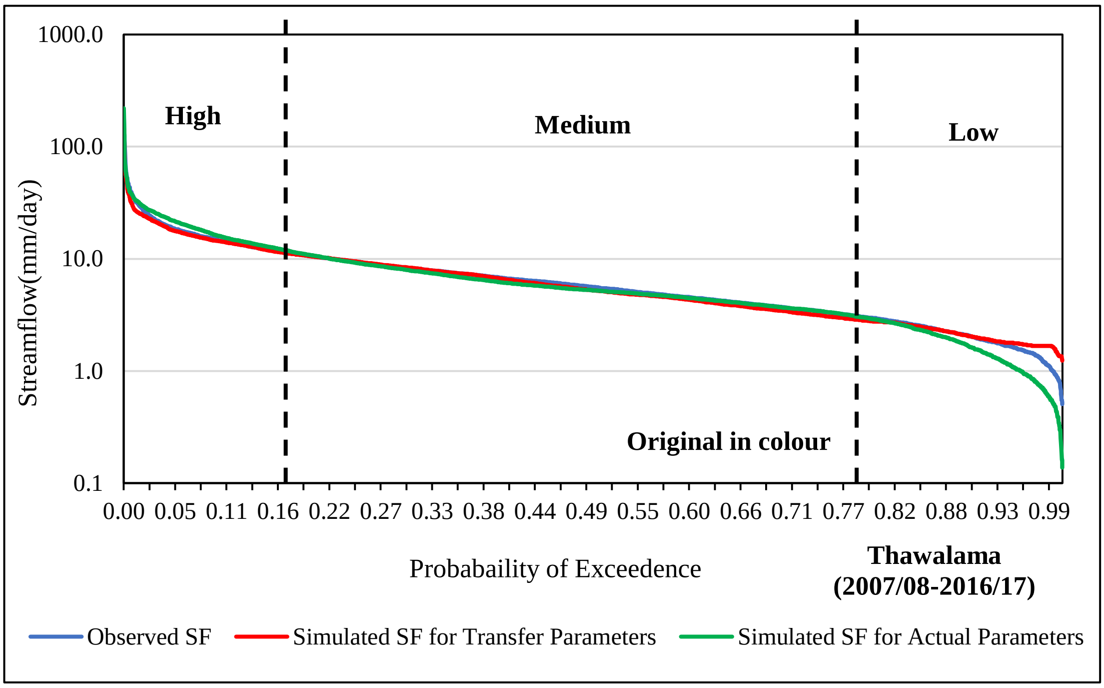


Figure 5-37:FDC at Thawalama after parameter transferability-both sorted

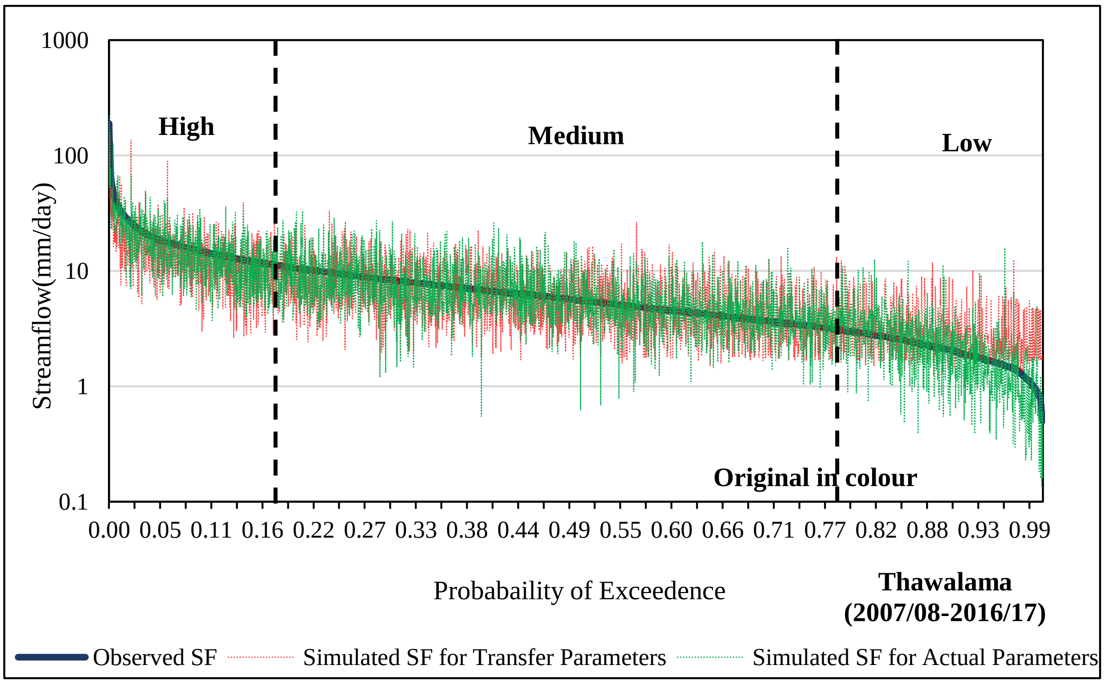


Figure 5-38:Thawalama after parameter transferability-sort only observed SF

5.8.1.2 Annual water balance on parameter transferability

The annual water balance at the Thawalama model with the transferred parameter for Baddegama and with the actual parameter of Thawalama models from 2007 to 2017 period were shown in Figure 5-39. The average annual water balance errors for this period are -11.66% and -2.27% respectively.

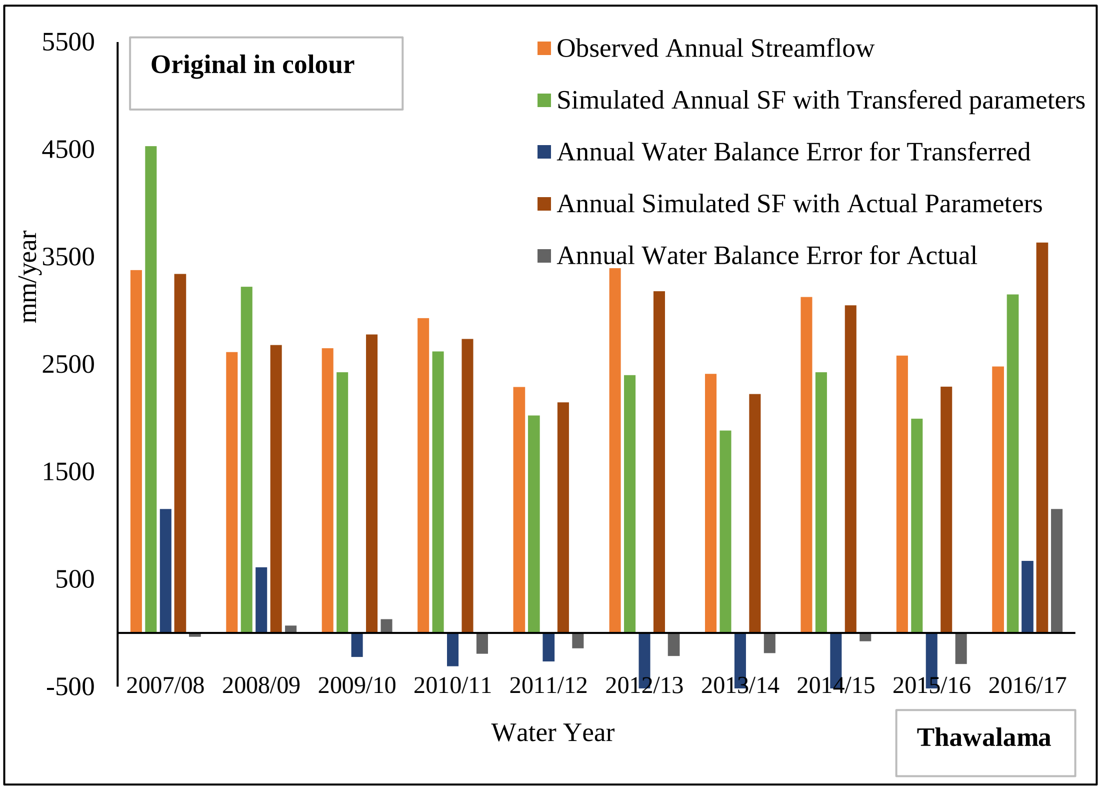


Figure 5-39:Annual water balance at Thawalama after transferability

5.8.2 Parameter transferability from Thawalama to Baddegama watershed

Calibrated parameter for Thawalama watershed transferred to Baddegama for 2007 to 2017 period and Baddegama calibrated parameters transferred to Baddegama 2007 to 2017 period to assess the transferability. Both models' results were shown in Table 5-16.

Table 5-16:Model performance after calibrated parameter transferring from Thawalama to Baddegama watershed

Baddegama	RMSE (mm/day)	Annual Water Balance Error	FDC			
				High	Medium	Low
			RMSE	RMSE	RMSE	RMSE
With Transfer	6.0365	0.73%	6.0365	12.4134	4.4453	2.4905
With Actual	3.3663	-2.08%	3.3663	6.4377	2.7464	1.6569

5.8.2.1 Statistical goodness of fit measures on parameter transferability

To assess the parameter transferability in HEC-HMS lumped model, developed Thawalama calibrated whole parameter set were transferred to the Baddegama for 10 years period and Baddegama calibrated parameters to Baddegama 10 years period were transferred. Model performance criteria given in Chapter 3 was evaluated by RMSE objective function. The graphs for hydrograph and FDC matching were illustrated in below Figure 5-40 to 5-45.

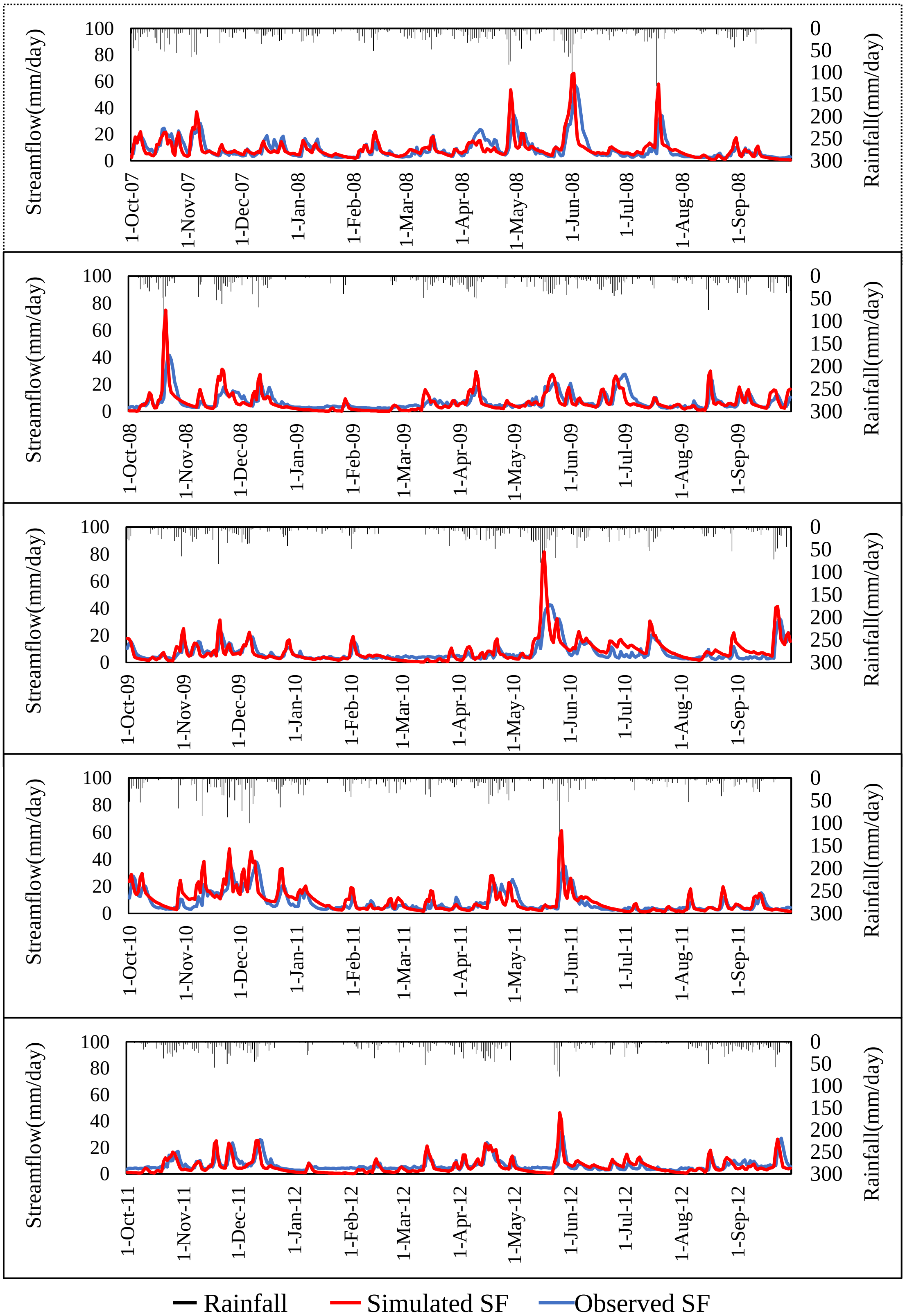


Figure 5-40:SF vs RF at Baddegama from Thawalama transferred parameters [normal plot]-I

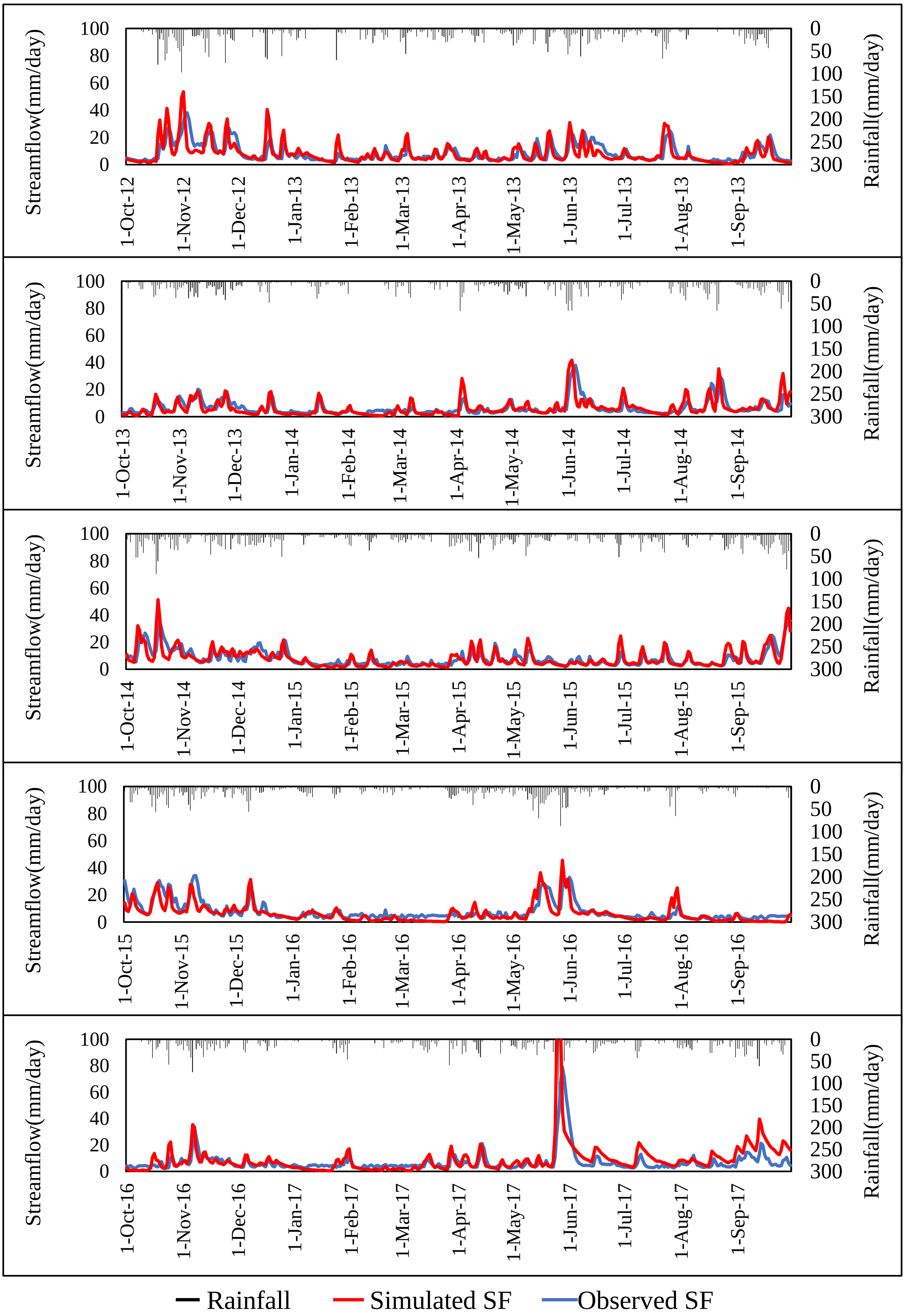


Figure 5-41:SF vs RF at Baddegama from Thawalama transferred parameters [normal plot]-II

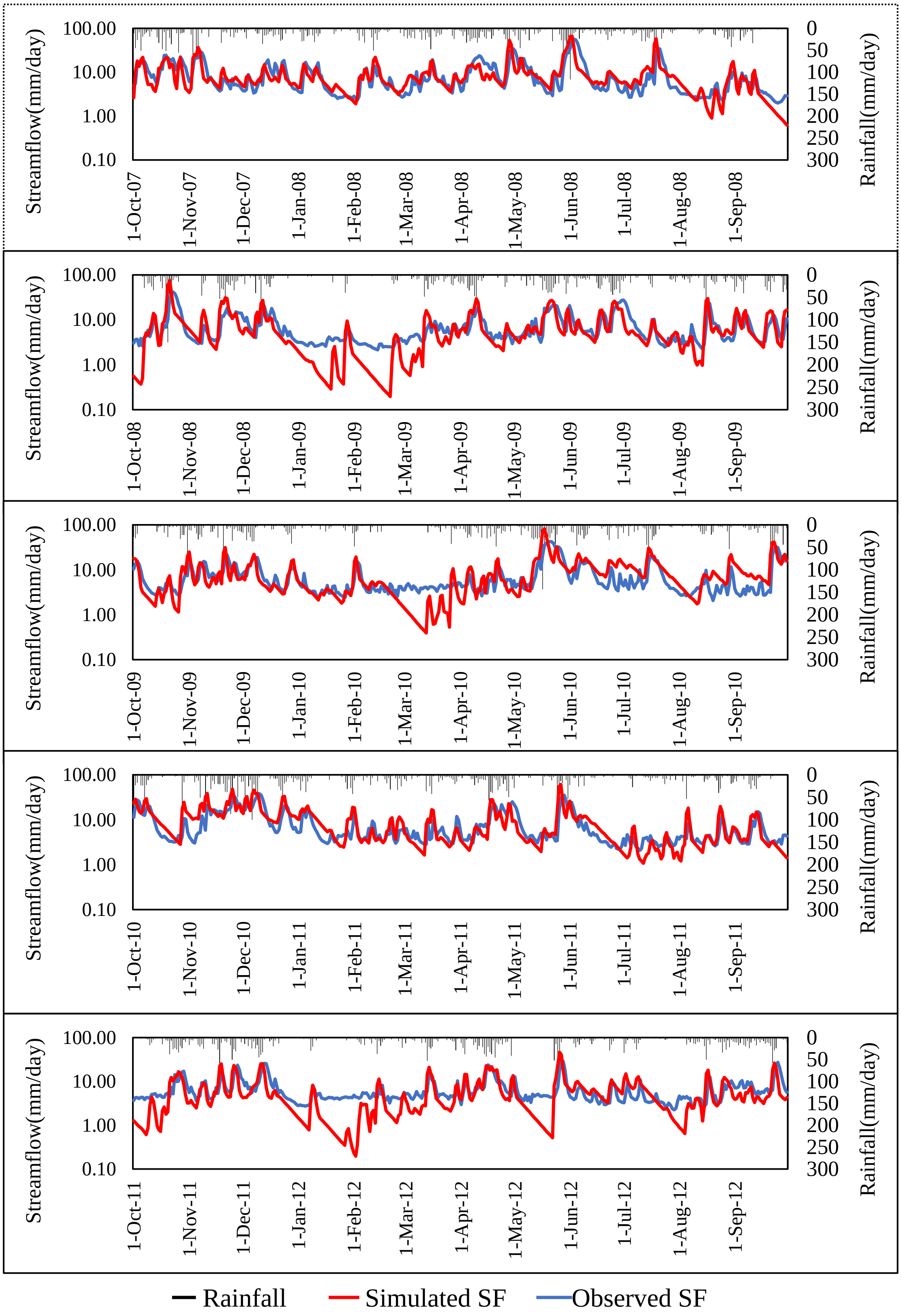


Figure 5-42:SF vs RF at Baddegama from Thawalama transferred parameters [log plot]-I

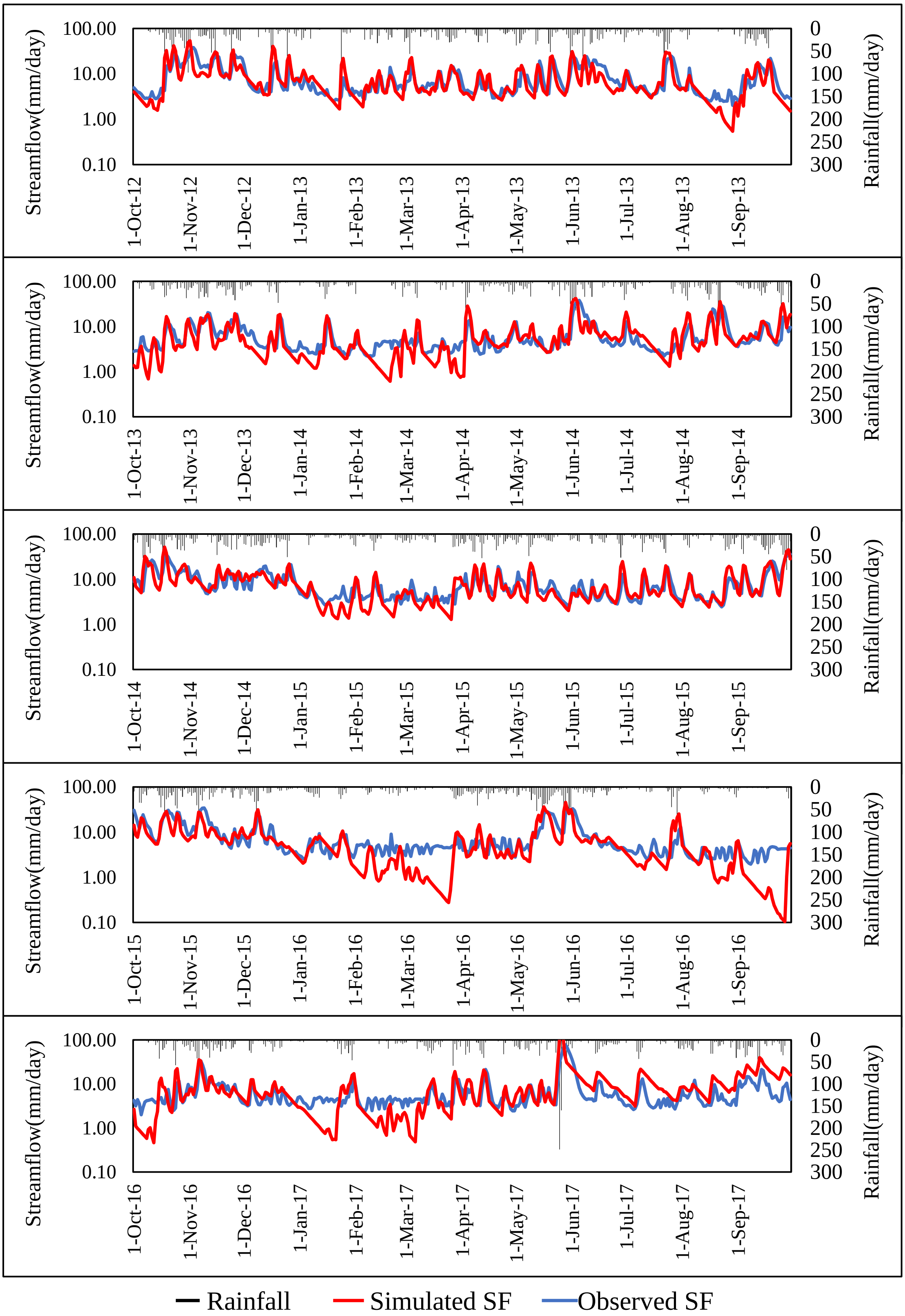


Figure 5-43:SF vs RF at Baddegama from Thawalama transferred parameters [log plot]-II

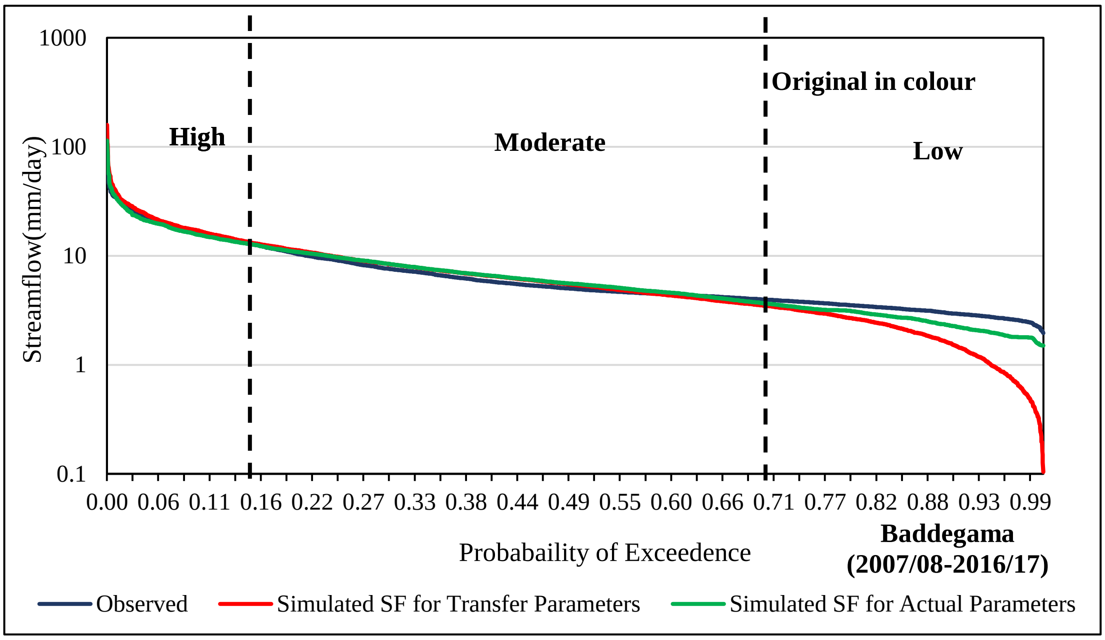


Figure 5-44:FDC at Baddegama after parameter transferability-both sorted

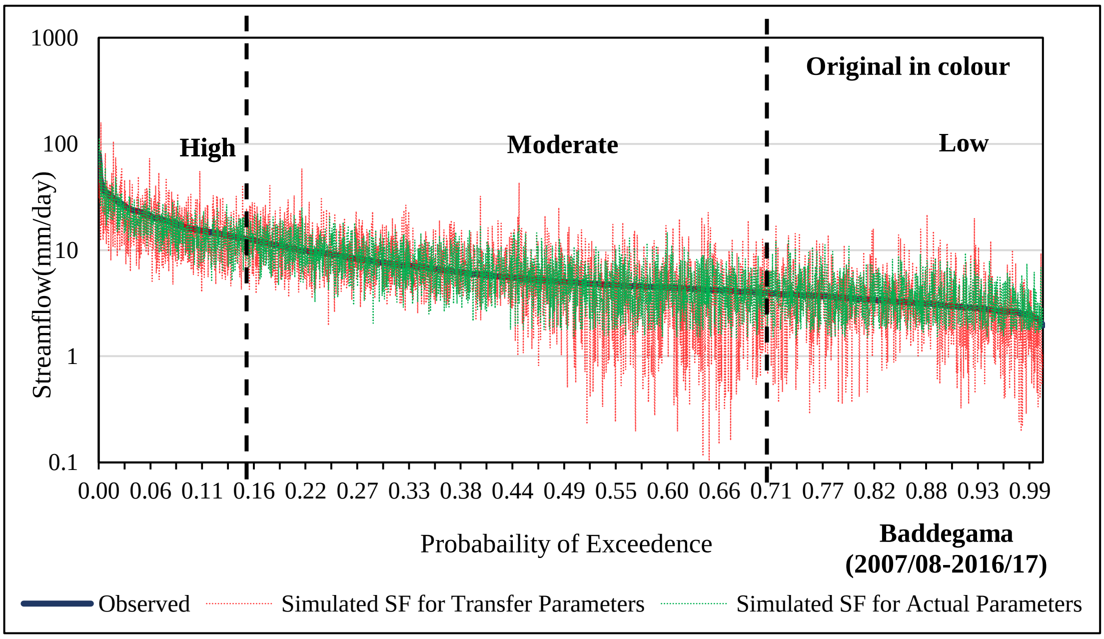


Figure 5-45:FDC at Baddegama after parameter transferability-Sort only observed

5.8.2.2 Annual water balance on parameter transferability

Annual water balance at the Baddegama model with the transferred parameter for Thawalama and with the actual parameter of Baddegama models from 2007 to 2017 period were shown in Figure 5-46. The average annual water balance errors for this period are 0.73% and -2.08% respectively.

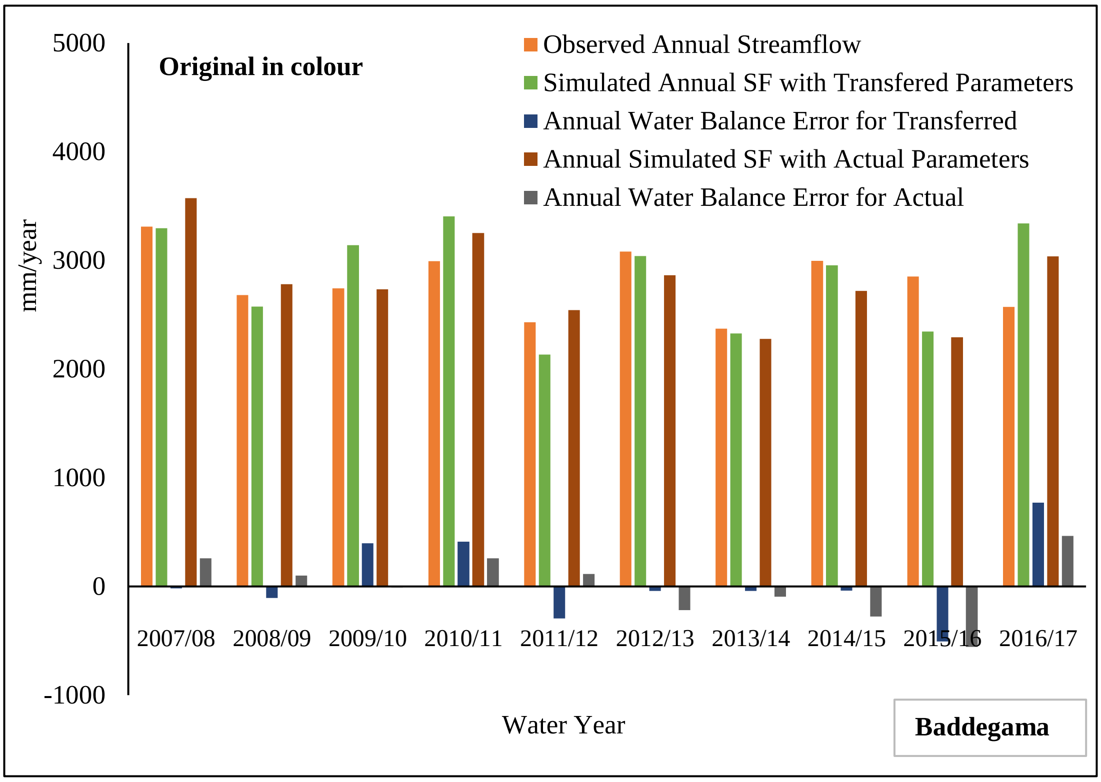


Figure 5-46:Annual water balance at Baddegama after parameter transferability

6 DISCUSSION

6.1 Model Component Selection

Transform, loss, canopy, and baseflow basin components were selected because it’s necessary for a continuous lumped model. Chapter 2.14 reviewed the selection of simulation methods for each model component concerning the modeling objective.

6.1.1 Loss model

Chapter 5.3.2.2 clearly states that development of the loss model with ‘initial deficit and constant loss’ method. Here, this method had chosen for simple continuous modeling and its ability to regain loss after a protracted period of zero rainfall. If the three-layer soil moisture accounting method chosen it needs more measured parameters to estimate loss and those measurements are not available for selected watershed. The objective of this study needs a less complex model with a smaller number of parameters to avoid model consistency. Therefore, the selection of initial deficit and constant loss method for loss model component is relatively preferable for this study.

6.1.2 Baseflow model

Development of the baseflow model described in Chapter 5.3.2.4 after considering literature review statements and study objectives. The most important component in the basin is baseflow when no rainfall period baseflow is the only contribution to the streamflow generation. For continuous modeling there are four alternatives which namely ‘recession constant’, ‘nonlinear Boussinesq’, ‘constant monthly’ and ‘linear reservoir’. Linear reservoir method may best selection but a linear reservoir cannot be used with deficit and also constant loss method (USACE, 2001) and the rest of two methods except recession constant need watershed measurable data which are not available. Because of these reasons, selected recession constant method as baseflow is the best selection with compared to selected other models such as loss model.

6.1.3 Transform model

According to literature most of the HEC-HMS applications used SCS UH transform and development of this model state in Chapter 5.3.2.3. The land-use variability and imperviousness of the watershed can be incorporated in the model by using the SCS UH transform model. Even the lag time parameter in the SCS method is calculated by using Kirpich formula which is considering most of the watershed physical characteristics such as water path length, slope of the watershed. Therefore, this empirical formula is to model direct runoff in transform model can be considered as a preferable selection.

6.1.4 Canopy model

Even though surface storage is not a must in continuous modeling the canopy storage should be modeled in continuous modeling with initial deficit and constant loss method to incorporate the evapotranspiration process. Chapter 5.3.2.1 describes the development of the canopy model. Selected simple canopy methods are incorporate with canopy storage according to plant types coverage in a watershed. The evaporation effect on streamflow response is very less compared to the rainfall effect. And the results of this model are a lesser effect on streamflow generation. Therefore, the selection as a simple method is more preferable to this study.

Therefore, the HEC-HMS model with selected loss method as described in Chapter 6.1.1, SCS UH direct runoff method to transform model and baseflow recession model with simple canopy storage model is more suitable to model continuous, lumped model to assess model parameter transferability.

6.2 Data and Data Period

6.2.1 Selection of data period.

To select the data period for both watersheds, 10years availability of data for continuous simulation and transferability period were considered. Baddegama river gauging station establish since 2000 and recent years of data is more reliable than old data with updates. Therefore, the common data period 2007 to 2017 was considered for Thawalama and Baddegama and the existence of extreme events was checked. In Figure 4-4 and 4-6 indicate 2011/12 and 2013/14 are driest years and 2007/08 and 2012/13 are wettest years for both watersheds. Calibration and validation period of both watersheds consist of dry and wet extreme events to assumed that the models were excited and results are independent of the data period.

Therefore, the selected data period for both watersheds can be considered as considerably identical to model development to assess parameter transferability.

6.2.2 Existence of Data Error

Thiessen average rainfall at both watersheds show comparatively high rainfall to less streamflow generation and excepted streamflow dropped after the storm event as an example in Figure 4.9, Thawalama 2007/08 water year beginning month of January showing high streamflow response to rainfall but in individual rainfall influence to Thawalama watershed in Figure A1, Neluwa and Thawalama rainfall station shows lesser rainfall event compared to Anningkanda and Deniyaya rainfall station.

In Figure 4-11 at Baddegama streamflow indicate high low flows during less rainfall period throughout the calibration and validation period. This may due to the closeness of river gauge to the sea and terrain is flat. But no influence of backwater effect to Baddegama gauge was confirmed by the authorized party by constructed a saltwater barrier to released river flow data. These factors reveal the inconsistencies of streamflows at watersheds.

By considering the data period and less existence of erroneous data were assessed in Chapter 4.3 to indicate consistent data were used in this study.

6.3 The Selection and Determination of Initial Parameter Values

Parameter initial values can be estimated using literature values and empirical formulas(Ahbari et al., 2018; USACE, 1994, 2016). According to literature, initially estimated parameters are considered fit for both watersheds initial run without errors and warnings. Table 5-3 indicate that selected initial model parameters.

6.3.1 Canopy model

Canopy storage for both Thawalama and Baddegama was derived as 0.465 mm and 0.421 mm (Table E1 and Table E2) by area average of maximum canopy storage for given vegetation types. This may very less due to the high impervious percentage of both watersheds as 20% at Thawalama and 40% at Baddegama watersheds. Silva et al., 2014 indicated maximum canopy storage for the Kelani river basin is 10 mm.

Therefore, estimated values can be considered as within a range of 0 mm-10 mm for optimization.

6.3.2 Loss model

MD, ID and CR are the three parameters of the selected loss method as described in Chapter 5.3.2.2. Deficit values calculated using SCS abstraction formula and the constant rate are taken from literature according to hydrological soil type C, it varies from 1.27 mm/hr-3.81 mm/hr (USACE, 2000). Figure 5-1 and Figure 5-2 for Thawalama and Baddegama shows similar land-use coverage for both but the impervious percentage is differing from 20% to 40% from Thawalama to Baddegama watershed concerning homestead area percentage. The minimum value of the infiltration rate of 1.27 mm/hr was selected for both and it's relatively better liked with the rest of the parameter values.

6.3.3 Transform model

Lag time parameter for the transform model estimated using an empirical formula and was justified by visualizing observed hydrograph. With compared to Thawalama, Baddegama shows a 1560min increment of lag time may be due to flatter slope in most downstream of Baddegama with lengthier stream channel.

6.3.4 Baseflow model

Baseflow ID, CR and RP are the parameters of the recession baseflow method as described in Chapter 5.3.2.4. Here ratio to peak was taken as 0.2 and it was justified with observed hydrograph of both watersheds. Recession constant was estimated from typical values proposed in (USACE, 2000) for watershed area range 300Km^2-1600 Km^2 for daily groundwater flow component as 0.95.

All the facts reveal that estimated initial parameters and ranges for both watersheds were considerable.

6.4 Objective Function Selection

Appendix D consists of the results of the objective function selection criteria. Among RMSE, PWRMSE, SSR, Log-RMSE, NSE, PEP and PEV the best hydrograph matching in Figure D1 show by RMSE, NSE and SSR as 0.49 MRAE for selected water year. -6% of annual water balance error and 0.64,0.48 and 0.36 MRAE indicator values respectively for flow regions such as high, medium and low in FDC graphs were shown in all RMSE, SSR, and NSE objective functions in Table D 1. In literature says that the least square error function is more goodness of fit or high flows but when semi-automatic calibration RMSE objective function was used to indicate the error between observed and simulation (J. Cunderlik & Simonovic, 2004; Halwatura & Najim, 2013; Hrissanthou & Kaffas, 2014).

To assess the best objective function for automatic optimization, model performance evaluation criteria were used. RMSE is a having unit which relates to streamflow. Therefore RMSE/Standard Deviation of Observation indicator was used to indicate model performance rating to neglect units in RMSE in some literature (Legates & McCabe, 1999; Moriasi et al., 2007).

Therefore, RMSE objective function selection for automatic optimization in HEC-HMS is considerable because of its widely used statistic to indicate model error between observed and simulated values.

6.5 Flow Threshold Selection

According to the literature, the flow thresholds values for both watersheds were determined by the order of magnitude flow duration curves and the corresponding slopes (Wijesekera, 2018). High and low flow thresholds of Thawalama are 18% and 79% as showing in Figure 5-3. Figure 5-4 shows that high flow threshold is 15% and low flow threshold is 70% for Baddegama watershed.

However, Wijesekera, (2018), concluded that the flow threshold for Gin Ganga is 20% and 80% for low flows and high flows respectively. These difference with previous studies may due to change of data set duration which was considered in both studies. However, the estimated values are approximately similar to literature values.

Therefore, estimated flow thresholds values for Thawalama and Baddegama can be considered as 18% and 15% for low flow threshold and 79% and 70% for high flow thresholds of Thawalama and Baddegama watersheds respectively.

6.6 Evaluation Criteria of Model Performance

6.6.1 Model performance in calibration of Thawalama and Baddegama

6.6.1.1 Validity of calibration results

Table 5-4 gives satisfactory objective function values for RMSE Thawalama and Baddegama lumped model in hydrograph matching after twelve number of trials. The ratio of the root mean square error to the standard deviation of measured data, RSR (RMSE/ $STDV_{observed}$) values of 0.58, 0.46 for respective Thawalama and Baddegama lumped models show good and very good model performance rating according to model performance classification given in model evaluation guideline in watershed simulation (Legates & McCabe, 1999; Moriasi et al., 2007). Table 5-6 and Table 5-7 shows relatively less mass balance error in monthly scale and seasonal scat than daily time step in both watersheds.

Therefore, the calibrated daily time-step model accumulated into monthly and seasonal for water resource management planning is more preferable in both watersheds specially with irrigation and reservoir projects.

6.6.1.2 Behavior of hydrographs

There is no significant difference in the behavior of simulated hydrographs in Thawalama and Baddegama lumped models. Figure 5-5 to Figure 5-8 show normal and semi-log plot respectively for Thawalama and Baddegama. Most of the high peaks were captured by the model but there are shifts in the magnitude of peak flow occurrence in small peaks due to Theissen rainfall spatial variation in both models. Peak after no rainfall period is not captured in both models (mid of January 2008/09 water year in Figure 5-6 and Figure 5-8) due to the model's difficulty in capturing baseflow contribution variation during a dry period. So low flow matching at both models were not shown perfect capturing when looking at semi-log Figure 5-6 and Figure 5-8. In this study main objective is to manage water resources and more concern is for medium flow. Therefore, low flow lesser matching during dry periods can be neglected. During wet season both models show good matching of all flow components in both catchments. But only at Baddegama model shows high and less varied low flow compared to Thawalama due to closeness to the sea and flat terrain of the slope of Baddegama watershed.

Therefore, Thawalama and Baddegama model can be used to water resource managing projects and flood management plans with 4.8140 mm and 3.0813 mm error of simulated streamflow per day.

6.6.1.3 Matching flow duration curve

FDC plots are illustrated in Figure 5-9 to 5-12. It is observed that the model doesn't respond well during low flow periods in both Thawalama (Figure 5-9) and Baddegama (Figure 5-11) watershed. In Thawalama 18% is a high flow margin and 79% is a low flow margin. It can be observed that 9.6381 mm/day RMSE value for Thawalama high flow matching and it unable to capture the highest peak and lead to high RMSE value. The medium flow at Thawalama is matching perfectly with the 3.0295 mm/day value of RMSE. But low flow matching at Thawalama shows underestimation with acceptable matching 1.4978 mm/day value of RMSE.

In Baddegama 15% is a high flow margin and 70% is a low flow margin. FDC at Baddegama shows a 6.2848 mm/day value of RMSE for high flow matching and it is slightly underestimated with better matching. Medium flow at Baddegama is showing good matching and slightly overestimation with 2.3278 mm/day value of RMSE. Low flow matching at Baddegama shows perfect matching with 1.2136 mm/day value of RMSE.

As this study objective focus on medium flow to water resource management both watersheds flow duration curve fitting for medium flow is considerable level.

6.6.1.4 Annual Water Balance

The average annual water balance at Thawalama is -3.3% for -36 mm of water balance error. According to Figure 5-13, the water years of 2007/08, 2010/11 and 2011/12 show underestimation of water balances with -4.2%, -17.6% and -14.1% of mass balance errors respectively at Thawalama. 2008/09 and 2009/10 years show overestimation of water balance with 4.6% and 12.4% respectively at Thawalama. Overall Thawalama model shows -3.3% of fit in annual water balance during calibration.

Also, at Baddegama average annual water balance is -0.3% for -3 mm of water balance error. As per the Figure of 5-14, 2008/09, 2009/10 and 2011/12 water years show an underestimation of water balances with -3.2%, -0.2% and -7.3% respectively at Baddegama. 2007/08 and 2010/11 years show overestimation of water balance with 7.2 % and 1.9% respectively at Baddegama. Overall Baddegama model shows -0.3% of fit in annual water balance during calibration.

Therefore, during the calibration period both watersheds show a satisfactory level of annual water balance with 36 mm and 3 mm amount per annum respectively Thawalama and Baddegama.

6.6.2 Model performance in verification of Thawalama and Baddegama

6.6.2.1 Validity of verification results

As given in Table 5-6, the objective function values of RMSE considerably increases as 5.0048 mm/day at Thawalama and 3.5597mm/day at Baddegama during model verification. The value of RSR indicates a good performance rating as 0.61 and 0.53 respectively for Thawalama and Baddegama. By visually and RMSE indicator, high flows and medium flows show good fitting in both watersheds Figure 5-19 to Figure 5-22. Streamflow vs rainfall graphs reveals that matching of hydrograph shapes is not satisfactory specially in low flows while RMSE reflects acceptable values (Figure 5-20 and figure 2-22). Hence, hydrograph matching in low flows needs more improvement. In Figure 2-29 and Figure 5-31 shows monthly data matching of observed vs simulated were laid in a linear relationship with less bias from best matching in both watersheds. Table 5-14 indicate seasonal mass balance error at Thawalama seems acceptable except in 2016/17 may be due to flood event occur during this period. But in Baddegama seasonal mass balance error in Table 5-15 indicate higher values comparatively except in 2012/13 and Yala season in 2011/12.

Thus, overall the daily data accumulated in to monthly and seasonal is more preferable for water resource management and planning projects in both watersheds specially with irrigation and reservoir projects.

6.6.2.2 Behavior of hydrographs

There is no significant difference in the behavior of simulated hydrographs except the low flow region in Thawalama and Baddegama lumped models (Figure 5-19 to Figure 5-22). During the wet season all flow shows a considerable level of matching at both watersheds but in dry season models were not capable to respond to lesser rainfall and high rainfall after dry or no rainfall period similar to the calibration process. This may cause due to spatial variabilities of rainfall over the watersheds and maybe some observe data errors in some years. These reasons may lead to a high objective function value during verification.

Although, during the verification period both Thawalama and Baddegama watershed shows a relatively considerable level of high flow matching can be used for flood management with 5.0 mm and 3.5 mm error of streamflow depth per day respectively.

6.6.2.3 Matching flow duration curve

FDC graph plots were illustrated in Figure 5-23 to 5-26. It is observed that the model doesn't respond well during low flow periods in both watersheds. It can be observed that 8.9796 mm/day RMSE value for Thawalama high flow matching and it's overestimated. Medium flow at Thawalama is matching perfectly with 4.0073 mm/day value of RMSE. Low flow matching at Thawalama shows underestimation with lesser matching 1.5132 mm/day value of RMSE.

FDC at Baddegama shows 7.4550 mm/day value of RMSE for high flow matching and its underestimated with better matching. The medium flow at Baddegama is matching perfectly with 2.5851 mm/day value of RMSE. Low flow matching at Baddegama shows underestimation with moderate matching 1.2138 mm/day value of RMSE.

As this study objective focuses on medium flow to water resource management both watersheds flow duration curve fitting for medium flow is very good and this may lead to a model capable of using in water resource management better than in drought management.

6.6.2.4 Annual Water Balance

During the validation period, at Thawalama average water balance is 6.1% for 77 mm of water balance error. 2012/13, 2013/14, 2014/15 and 2015/16 water years shows in Figure 5-27 indicate an underestimation of water balances with -24.2%, -14.9%, -5.0% and -29.0% respectively at Thawalama. 2016/17 years show the highest overestimation of water balance with 69.3% at Thawalama may due to high flood occurred during 2017. Overall Thawalama model shows a good fit in annual water balance during validation.

Also, at Baddegama average water balance is -16.7% for -187 mm of water balance error. 2013/14, 2014/15 and 2015/16 water years shown in Figure 5-28 indicate an underestimation of water balances with -6.3%, -38.1% and -114.5% respectively at Baddegama. This may cause due to very little rainfall in Baddegama station compared to other stations in 2015/16 year as shown in Figure 4-14. These reasons could have been led to a high-water balance error value during 2015/16. 2007/08 and 2016/17 years show overestimation of water balance with 23.3 % and 17.4% respectively at Baddegama. Overall Baddegama model shows a considerably good fit in annual water balance during calibration.

Therefore, during the validation period both watersheds show a comparatively satisfactory level of annual water balance with 77 mm and 187 mm amount per annum respectively at Thawalama and Baddegama.

6.7 Reliability of Model Results

6.7.1 Uncertainty in meteorological data

The reliability of model results depends on the uncertainty of feed data to the model. The uncertainty of precipitation data in the meteorological model has been arisen due to spatiotemporal variation in precipitation over the watershed. In addition to that evapotranspiration and catchment morphology data also affect uncertainty in model results. This is a common difficulty faced during model development which could not be avoided.

6.7.2 Uncertainty in catchment parameters

Uncertainty in parameter estimation was occurred due to limited and uncertain data that feed in to model. In the estimation of maximum canopy storage and CN value, there were many assumptions made for the catchment. Because of the assumption that made during initial parameter value estimation many difficulties were obtaining realistic parameter values by model calibration. The optimized maximum deficit value varies from 63.94 mm to 46.047 mm at Thawalama watershed and from 63.70 mm to 50.483 mm at Baddegama watershed. It was very difficult to optimize the recession constant because by looking at the overall period of hydrograph shows differentiate in baseflow recession limb in both watersheds in Figure 4-9 to Figure 4-13 in normal and log plots.

6.8 Comparison of Parameter Transferability

6.8.1 Thawalama to Baddegama

Baddegama lumped model shows a 6.0365 mm/day value of RMSE hydrograph matching for the transferred optimized parameter set from the Thawalama calibrated model. With compared to Baddegama optimized parameter sets, hydrograph matching varies from 3.3663 mm/day value of RMSE for 2007 to 2017 years of period. period (Table 5-16). The indicator value of the hydrograph error indicator shows unsatisfactory and very good performance rating values with RSR value of 0.89 and 0.50 for the Baddegama model for actual parameter set and transferred parameters set respectively. But visually in the flow hydrographs in Figure 5-40 to Figure 5-43 show the majority of estimated low flow region is not fitting perfectly due to major variation of baseflow recession ratio to peak from 0.0484378 at Baddegama to 0.196 at Thawalama when Baddegama model with a transferred parameter set of Thawalama model. Lag time variation from Baddegama to Thawalama indicated a shift on peak flows in Figure 5-40 and Figure 5-41.

Therefore, hydrograph matching for high flow and medium flow is moderately in a considerable level of fit in transferred duration for the Baddegama model with the transferred parameter of Thawalama compared to the actual parameter of Baddegama.

In FDC matching as shown in Figure 5-44 and Figure 5-45, high flows at Baddegama model shows an increment of error indicator values from 6.4377 mm/day to 12.4134 mm/day of RMSE, the medium flows show increment of error indicator values from 2.6474 mm/day to 4.4453 mm/day of RMSE and low flows show an increment of error indicator values from 1.6569 mm/day to 2.4905 mm/day of RMSE for spatiotemporal transferring approach with compared to temporal approach.

Overall, high flow and medium flow matching at the Baddegama model from the transferred parameter from Thawalama shows considerable matching compared to the actual parameter set of the Baddegama model with a 6.0365 mm per day error in simulated streamflow.

The average annual water balance is showing in Figure 5-46 as a decrease of water balance error from -2.08% for 5 mm to 0.73% for 53.46 mm after parameter transfer from Thawalama to Baddegama with compared to the actual parameter set of Baddegama to Baddegama model from 2007 to 2017 period. 2015/16 and 2016/17 water years shows considerable high-water balance error due to high rainfall event occurred during these water years.

Overall annual water balance of the Baddegama model with the transferred parameter of Thawalama is indicating better matching compared to a model with the actual parameter set of Baddegama.

Therefore, the spatiotemporal parameter transferability approach to Baddegama main watershed from Thawalama sub-watershed is not comparatively considerable achievement for water resource management and planning.

6.8.2 Baddegama to Thawalama

Thawalama lumped model shows a 5.8448 mm/day value of RMSE hydrograph matching for the transferred optimized parameter set from the Baddegama calibrated model. With compared to Thawalama optimized parameter sets, hydrograph matching varies from 4.9103 mm/day value of RMSE for 2007 to 2017 years of period (Table 5-15). The indicator value of the hydrograph error indicator shows satisfactory performance rating values with RSR value of 0.60 and 0.71 for the Thawalama model for actual parameter set and transferred parameter sets respectively. But visually majority of estimated low flow region is not good fitting (Figure 5-33 to Figure 5-38) due to major variation of baseflow recession ratio to peak from 0.196 at Thawalama to 0.0484378 at Baddegama. Lag time variation from Baddegama to Thawalama indicated a shift in peak flows shown in Figure 5-33 and Figure 5-34.

Therefore, hydrograph matching for medium flow is moderate fit in transferred duration for the Thawalama model with the transferred parameter of Baddegama compared to the actual parameter of Thawalama.

In the flow duration curve matching (Figure 3-37 and Figure 5-38), high flows at Thawalama model shows an increment of error indicator values from 9.2970 mm/day to 11.8470 mm/day of RMSE, the medium flows show variation of error indicator values from 3.5640 mm/day to 3.4717 mm/day of RMSE and low flows show an increment of error indicator values from 1.5167 mm/day to 2.1105 mm/day of RMSE for spatiotemporal transfer approach compared to temporal approach. In medium flow, it shows a decrease of RMSE for the Thawalama model with transferred parameters of the Baddegama model compared to the actual parameter of the Thawalama model, because of error difference in medium flow is high.

Overall, medium flow matching at Thawalama from transferred parameter from Baddegama shows considerable matching which indicating a model preferable in water resource management with spatiotemporal transferable of model parameter from Baddegama with 5.8448mm error per day.

The average annual water balance is showing in Figure 5-39 as an increment of underestimated water balance error from -2.27% for 20.54 mm to -11.66% for -117.65mm after parameter transfer from Baddegama to Thawalama with compared to Thawalama model with an actual parameter set of Thawalama during 2007 to 2017 period. 2007/08 shows high water balance error resulting in high error for the entire period in spatiotemporal approach. This may cause due to high initial baseflow discharge increased from 22.527 m^3/s to 42.6 m^3/s and decrease of baseflow recession peak to ratio when parameter transferring in spatiotemporal approach, cause to generate high direct runoff contribution to the streamflow.

Overall annual water balance of the Thawalama model with the transferred parameter not indicating better matching with compared to a model with the actual parameter set of Thawalama.

Therefore, the spatiotemporal parameter transferability approach to Thawalama sub-watershed from Baddegama main watershed is comparatively considerable achievement for water resource management and planning.

7 CONCLUSIONS

1. The spatiotemporal parameter transferability approach shows better performance when it transfers from Baddegama main watershed to Thawalama sub-watershed with RMSE values of 5.8 mm/day, 11.8 mm/day, 3.4 mm/day, 2.1 mm/day for hydrograph matching, high flows, medium flows and low flows respectively and annual water balance of -2.27% for 2007-2017 with compared to sub to main watershed.

2. The temporal parameter transferability approach shows better performance when it transfers from Thawalama sub-watershed to Baddegama main watershed with RMSE value of 6.0 mm/day, 12.4 mm/day, 4.4 mm/day, 2.4 mm/day for hydrograph matching, high flows, medium flows, low flows respectively and annual water balance of -0.73% for 2007-2017 with compared to main to sub-watershed.

3. Spatiotemporal transferability approach is shows better model performance rating than temporal approach with RSR value of 0.5 and 0.6 for sub to main and vice versa respectively.

4. The HEC-HMS models were systematically developed for Gin Ganga at Thawalama and Baddegama with 4.8 mm/day, 3.0 mm/day of RMSE in calibration and 5.0 mm/day, 3.5 mm/day in validation.

5. Thawalama and Baddegama models with RMSE value of 9.6 mm/day, 6.2 mm/day for high flows and 3.0 mm/day, 2.3 mm/day for medium flows indicate better capability of models on water resource and flooding management.

6. Thawalama and Baddegama daily models can be accumulated into monthly and seasonal scales to use in irrigation and reservoir project water resources and management planning in relatively high accuracy with compared to daily models.

7. Management and planning of water resources projects can be taken at Thawalama and Baddegama models with transferred parameters in a monthly scale with a considerable level of accuracy.

8 RECOMMENDATION

Further need to analyze the influence of each parameter separately special in case of parameters that are associated with watersheds unique physical characteristics when transferring parameters with from main to sub-watershed and vice versa.

REFERENCES

Abimbola, O. P., Wenninger, J., Venneker, R., & Mittelstet, A. R. (2017). The assessment of water resources in ungauged catchments in Rwanda. *Journal of Hydrology: Regional Studies*, *13*, 274–289. https://doi.org/10.1016/j.ejrh.2017.09.001

Ahbari, A., Stour, L., Agoumi, A., & Serhir, N. (2018). Estimation of initial values of the HMS model parameters: application to the basin of Bin El Ouidane (Azilal, Morocco). *Journal of Materials and Environmental Sciences*, *9*(1), 305–317. https://doi.org/10.26872/jmes.2018.9.1.34

Ali, M., Khan, S. J., Aslam, I., & Khan, Z. (2011). Simulation of the impacts of land-use change on surface runoff of Lai Nullah Basin in Islamabad, Pakistan. *Landscape and Urban Planning*, *102*(4), 271–279. https://doi.org/10.1016/j.landurbplan.2011.05.006

Amatya, D. M., Parajuli, P. B., Bonta, J. V, & Green, T. R. (2016). Parameterization Guidelines and Considerations for Hydrologic Models. *Transactions of the ASABE*, *58*(6), 1681–1703. https://doi.org/10.13031/trans.58.10709

Bennett, T. H., & Peters, J. C. (2000). Continuous Soil Moisture Accounting in the Hydrologic Engineering Center Hydrologic Modeling System (HEC-HMS). *ASCE Technical Publication*, *8806*(1), 1–10. https://doi.org/10.1061/40517(2000)149

Bouraoui, F., Benabdallah, S., Jrad, A., & Bidoglio, G. (2005). Application of the SWAT model on the Medjerda river basin (Tunisia). *Physics and Chemistry of the Earth*, *30*, 497–507. https://doi.org/10.1016/j.pce.2005.07.004

Chow, V.T., Maidment, D. R., & Mays, L. W. (1988). *Applied Hydrology*.

Christiaens, K., & Feyen, J. (2002). Use of sensitivity and uncertainty measures in distributed hydrological modeling with an application to the MIKE SHE model. *Water Resources Research*, *38*(9), 8-1-8–15. https://doi.org/10.1029/2001wr000478

Cunderlik, J. M. (2003). *Hydrologic Model Selection for the CFCAS Project:*

Assessment of Water Resources Risk and Vulnerability to Changing Climatic Conditions.

Cunderlik, J. M., & Simonovic, S. P. (2004). *Calibration, Verification and Sensitivity Analysis of the HEC-HMS Hydrologic Model CFCAS Project: Assessment of Water Resources Risk and Vulnerability to Changing Climatic Condition*. https://doi.org/10.1017/CBO9781107415324.004

Cunderlik, J., & Simonovic, S. P. (2004). *Selection of Calibration and Verification Data for the HEC-HMS Hydrologic Model CFCAS Project: Assessment of Water REsources Risk and Vulnerability to Changing Clmatic Conditions*.

Daniel, E. B., Camp, J., LeBoeuf, E., Penrod, J., Dobbins, J., & Abkowitz, M. (2011). Watershed Modeling and its Applications: A State-of-the-Art Review. *The Open Hydrology Journal*, *5*(1), 26–50. https://doi.org/10.2174/1874378101105010026

Daniel, E. B., Camp, J. V, Leboeuf, E. J., Penrod, J. R., Dobbins, J. P., & Abkowitz, M. D. (2011). Watershed Modeling and its Applications : A State-of-the-Art Review. *The Open Hydrology Journal*, *5*, 26–50.

Dechmi, F., Burguete, J., & Skhiri, A. (2012). SWAT application in intensive irrigation systems: Model modification, calibration and validation. *Journal of Hydrology*, *470–471*, 227–238. https://doi.org/10.1016/j.jhydrol.2012.08.055

Devia, G. K., Ganasri, B. P., & Dwarakish, G. S. (2015). A Review on Hydrological Models. In *International Conference on Water Resources, Coastal and Ocean Engineering (ICWRCOE 2015)* (Vol. 4, pp. 1001–1007). https://doi.org/10.1016/j.aqpro.2015.02.126

Dhami, B. S., & Pandey, A. (2013). Comparative Review of Recently Developed Hydrologic Models. *Journal of Indian Water Resources Society*, *33*(3), 34–42. Retrieved from http://www.iwrs.org.in/journal/jul2013/6jul.pdf

DHI. (2017). MIKE SHE User Manual, Volume 1: User Guide.

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

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

Dogan, S., & Berktay, A. (2005). Comparative Study Between Various Hydrological Models for Watershed Management: Robustnecc and Sustainability. *Ecology and Environmental Protection COMPARATIVE*, 629.

Duan, Q., Sorooshian, S., & Gupta, V. K. (1994). Optimal use of the SCE-UA global optimization method for calibrating watershed models. *Journal of Hydrology*, *158*, 265–284.

Dulal, K. N., Shrestha, S., Bastola, S., Kazama, F., Ishidaira, H., & Takeuchi, K. (2007). the Assessment of Spatial Transferability of a Distributed Hydrological Model Parameters in Different Physiographic Regions of Nepal. *Annual Journal of Hydraulic Engineering*, *51*, 37–42. https://doi.org/10.2208/prohe.51.37

Fatichi, S., Niswonger, R., Mascaro, G., Shen, C., Mirus, B., Kim, J., … Rigon, R. (2016). An overview of current applications, challenges, and future trends in distributed process-based models in hydrology. *Journal of Hydrology*, *537*, 45–60. https://doi.org/10.1016/j.jhydrol.2016.03.026

Feng, G. (2001). Strategies for sustainable water resources management in water scarce regions in developing countries. In *Integrated Water Resources Management* (pp. 107–112).

Furusho, C., Chancibault, K., & Andrieu, H. (2013). Adapting the coupled hydrological model ISBA-TOPMODEL to the long-term hydrological cycles of suburban rivers: Evaluation and sensitivity analysis. *Journal of Hydrology*, *485*, 139–147. https://doi.org/10.1016/j.jhydrol.2012.06.059

Garcia, B. I. L., Sentelhas, P. C., Tapia, L. &, & Sparovek, G. (2006). Filling in missing rainfall data in the Andes region of Venezulea, based on a cluster analysis apporach. *Revista Brasileira de Agrometeorologia*, *14*(2), 225–233.

Garcia, F., Folton, N., & Oudin, L. (2017). Which objective function to calibrate rainfall–runoff models for low-flow index simulations? *Hydrological Sciences Journal*, *62*(7), 1149–1166. https://doi.org/10.1080/02626667.2017.1308511

Gebre, S. L. (2015). Application of the HEC-HMS Model for Runoff Simulation of Upper Blue Nile River Basin. *Hydrology: Current Research*, *06*(02). https://doi.org/10.4172/2157-7587.1000199

Green, I. R. A., & Stephenson, D. (1986). Criteria for comparison of single event models. *Hydrological Sciences Journal*, *31*(3), 395–411. https://doi.org/10.1080/02626668609491056

Gumindoga, W., Rwasoka, D. T., Nhapi, I., & Dube, T. (2017). Ungauged runoff simulation in Upper Manyame Catchment, Zimbabwe: Application of the HEC-HMS model. *Physics and Chemistry of the Earth*, *100,* 371–382. https://doi.org/10.1016/j.pce.2016.05.002

Gyau-Boakye, P., & Schultz, G. A. (1994). Filling gaps in runoff time series in west africa. *Hydrological Sciences Journal*, *39*(6), 621–636. https://doi.org/10.1080/02626669409492784

Halwatura, D., & Najim, M. M. M. (2013). Application of the HEC-HMS model for runoff simulation in a tropical catchment. *Environmental Modelling and Software*, *46*, 155–162. https://doi.org/10.1016/j.envsoft.2013.03.006

Hamedi, A., & Fuentes, H. R. (2015). Comparative effectiveness and reliability of NEXRAD data to predict outlet hydrographs using the GSSHA and HEC-HMS hydrologic models. In *World Environmental and Water Resources Congress 2015: Floods, Droughts, and Ecosystems - Proceedings of the 2015 World Environmental and Water Resources Congress* (pp. 1444–1453). https://doi.org/10.1061/9780784479162.142

Hasan, M. M., & Croke, B. F. W. (2013). Filling gaps in daily rainfall data: a statistical approach. In *20th International Congress on Modelling and Simulation, Adelaide, Australia* (pp. 1–6). Retrieved from http://www.mssanz.org.au/modsim2013/A9/hasan.pdf

Hasanpour Kashani, M., & Dinpashoh, Y. (2012). Evaluation of efficiency of different estimation methods for missing climatological data. *Stochastic Environmental Research and Risk Assessment*, *26*(1), 59–71. https://doi.org/10.1007/s00477-011-0536-y

Hrissanthou, V., & Kaffas, K. (2014). Application of a continuous rainfall-runoff model to the basin of Kosynthos river using the hydrologic software HEC-HMS. *Global NEST Journal*, *16*(1), 188–203.

Hromadka, T. V. (1987). The state-of-the-art in hydrologic models. *Environmental Software*, *2*(1), 29–36. https://doi.org/10.1016/0266-9838(87)90026-8

Hunter, N. M., Bates, P. D., Horritt, M. S., & Wilson, M. D. (2007). Simple spatially-distributed models for predicting flood inundation: A review. *Geomorphology*, *90*(3–4), 208–225. https://doi.org/10.1016/j.geomorph.2006.10.021

Ismail, W. &, & Ibrahim, Z. (2017). Estimation of rainfall and stream flow missing data for Terengganu, Malaysia by using interpolation technique methods. *Malaysian Journal of Fundamental and Applied Sciences*, *13*(3), 213–217. https://doi.org/10.11113/mjfas.v13n3.578

Jara Torres, P., Sánchez, E., Avilés, Á., & Samaniego, E. (2016). Evaluation of Infilling Methods for Time Series of Daily Precipitation and Temperature: The Case of the Ecuadorian Andes. *Maskana*, *5*(1), 99–115. Retrieved from https://publicaciones.ucuenca.edu.ec/ojs/index.php/maskana/article/view/431

Jarosław, C., & Batelaan, O. (2011). Application of the WetSpa distributed hydrological model for catchment with significant contribution of organic soil. Upper Biebrza case study. *Annals of Warsaw University of Life Sciences - SGGW. Land Reclamation*, *43*(1), 25–35. https://doi.org/10.2478/v10060-008-0090-6

Jayakrishnan, R., Srinivasan, R., Santhi, C., & Arnold, J. G. (2005). Advances in the application of the SWAT model for water resources management. *Hydrological Processes*, *19*, 749–762. https://doi.org/10.1002/hyp.5624

Kaffas, K., & Hrissanthou, V. (2014). Application of a Continuous Rainfall-Runoff Model To the Basin of Kosynthos River Using the Hydrologic Software Hec-Hms. *Global NEST Journal*, *xx*(x).

Kalita, D. N. (2011). A Study of Basin Response using HEC-HMS and Subzone Reports Of CWC. In *13th National Symposium on Hydrology with focal theme on "Inflow Forecasting during Extremes."*

https://doi.org/10.1007/SpringerReference_28205

Kamali, B., Mousavi, S. M., & Abbaspour, K. C. (2012). Automatic calibration of HEC-HMS using single-objective and multi-objective PSO algorithms. *Hydrological Processes*. https://doi.org/10.1002/hyp

Kim, K. B., Kwon, H. H., & Han, D. (2018). Exploration of warm-up period in conceptual hydrological modelling. *Journal of Hydrology*, *556*(November), 194–210. https://doi.org/10.1016/j.jhydrol.2017.11.015

Krysanova, V., & Arnold, J. G. (2008). Advances in ecohydrological modelling with SWAT—a review. *Hydrological Sciences Journal*, *53*(5), 939–947. https://doi.org/10.1623/hysj.53.5.939

Lee, S. B., Yoon, C. G., Jung, K. W., & Hwang, H. S. (2010). Comparative evaluation of runoff and water quality using HSPF and SWMM. *Water Science and Technology*, *62*(6), 1401–1409. https://doi.org/10.2166/wst.2010.302

Legates, D. R., & McCabe, G. J. (1999). Evaluating the use of “goodness-of-fit” measures in hydrologic and hydroclimatic model validation. *Water Resources Research*, *35*(1), 233–241. https://doi.org/10.1029/1998WR900018

Liu, Y. B., & Smedt, F. De. (2004). *WetSpa Extension , A GIS-based Hydrologic Model for Flood Prediction and Watershed Management*.

Lo, R., & Emanuele, P. (2010). A methodology for treating missing data applied to daily rainfall data in the Candelaro River Basin (Italy), 1–22. https://doi.org/10.1007/s10661-008-0653-3

Lopera, R. A. (2015). *Water and Sustainable Development*. *“Water and Sustainable Development”, Water Monographies: Water for Life 2005-2015* (Vol. 3).

Loucks, D. P. (2000). Sustainable water resources management. *Water International*, *25*(1), 3–10. https://doi.org/10.1080/02508060008686793

Mahmoud Abu-Zeid, & I. A. Shiklomanov. (2003). *Water Resources as a Challenge of the Twenty-First Century*. *World Meteorological Organization*.

Majidi, A., & Shahedi, K. (2012). Simulation of rainfall-runoff process using Green-

Ampt method and HEC-HMS model (Case study: Abnama Watershed, Iran). *International Journal of Hydraulic Engineering*, *1*(1), 5–9. https://doi.org/10.5923/j.ijhe.20120101.02

McMichael, C. E., Hope, A. S., & Loaiciga, H. A. (2006). Distributed hydrological modelling in California semi-arid shrublands: MIKE SHE model calibration and uncertainty estimation. *Journal of Hydrology*, *317*(3–4), 307–324. https://doi.org/10.1016/j.jhydrol.2005.05.023

Mohamoud, Y. M., & Prieto, L. M. (2012). Effect of temporal and spatial rainfall resolution on hspf predictive performance and parameter estimation. *Journal of Hydrologic Engineering*, *17*(3), 377–388. https://doi.org/10.1061/(ASCE)HE.1943-5584.0000457

Moriasi, D. N., Arnold, J. G., Liew, M. W. Van, Bingner, R. L., Harmel, R. D., & Veith, T. L. (2007). Model Evaluation Guideline for Systematic Quantification of Accuracy in Watershed Simulation. *American Society of Agricultural and Biological Engineers*, *50*(3), 885–900.

Mousavi, S. J., Abbaspour, K. C., Kamali, B., Amini, M., & Yang, H. (2012). Uncertainty-based automatic calibration of HEC-HMS model using sequential uncertainty fitting approach. *Journal of Hydroinformatics*, *14*(2), 286. https://doi.org/10.2166/hydro.2011.071

Musiake, K., & Wijesekera, S. (1990). Stream Flow Modelling of Sri Lankan Catchments (2) : Kalu River Catchment at Putupaula. *Seisan Kenkyu*, *42*(11), 645–648.

Nepal, S., Fischer, C., Flügel, W. A., Krause, P., & Fink, M. (2017). Assessment of spatial transferability of process - based hydrological model parameters in two neighbouring catchments in the Himalayan Region. *Hydrological Processes*, (April), 2812–2826. https://doi.org/10.1002/hyp.11199

Ojha, C. S. P., Surampalli, R. Y., Bardossy, A., Zhang, T. C., & Kao, C.-M. (2017). *Sustainable Water Resources Management*. *American Society of Civil Engineers*. https://doi.org/10.1061/9780784414767

Patil, S. D., & Stieglitz, M. (2015). Comparing spatial and temporal transferability of hydrological model parameters. *Journal of Hydrology*, *525*, 409–417. https://doi.org/10.1016/j.jhydrol.2015.04.003

Randrianasolo, A., Ramos, M. H., & Andréassian, V. (2011). Hydrological ensemble forecasting at ungauged basins: Using neighbour catchments for model setup and updating. *Advances in Geosciences*, *29*, 1–11. https://doi.org/10.5194/adgeo-29-1-2011

Razi, M. A. M., Ariffin, J., Tahir, W., & Arish, N. A. . (2010). Flood Estimation Studies using Hydrologic Modeling System(HEC-HMS) for Johor River, Malaysia. *Journal of Applied Sciences*, *10*(11), 930–939.

River, K., & Lanka, S. (2010). Application of remote sensing and gis for flood risk analysis : A case study at APPLICATION OF REMOTE SENSING AND GIS FOR FLOOD RISK ANALYSIS :, (August 2017).

Roy, D., Begam, S., Ghosh, S., & Jana, S. (2013). Calibration and Validation of Hec-Hms Model for a River Basin in Eastern India. *Journal of Engineering and Applied Sciences*, *8*(1), 40–56.

Safari, A., De Smedt, F., & Moreda, F. (2012). WetSpa model application in the Distributed Model Intercomparison Project (DMIP2). *Journal of Hydrology*, *418–419*, 78–89. https://doi.org/10.1016/j.jhydrol.2009.04.001

Salvadore, E., Bronders, J., & Batelaan, O. (2015). Hydrological modelling of urbanized catchments: A review and future directions. *Journal of Hydrology*, *529*, 62–81. https://doi.org/10.1016/j.jhydrol.2015.06.028

Sardoii, E. R., Rostami, N., Sigaroudi, S. K., & Taheri, S. (2012). Calibration of loss estimation methods in HEC-HMS for simulation of surface runoff (case study: Amirkabir dam watershed, Iran). *Advances in Environmental Biology*, *6*(1), 343–348.

Shen, C., & Phanikumar, M. S. (2010). A process-based, distributed hydrologic model based on a large-scale method for surface-subsurface coupling. *Advances in Water Resources*, *33*(12), 1524–1541.

https://doi.org/10.1016/j.advwatres.2010.09.002

Silva, M. M. G. T. De, Weerakoon, S. B., & Herath, S. (2014). Modeling of Event and Continuous Flow Hydrographs with HEC – HMS : Case Study in the Kelani River Basin , Sri Lanka. *Journal of Hydrologic Engineering*, *19*(4), 800–806. https://doi.org/10.1061/(ASCE)HE.1943-5584.0000846.

Singh, V. P., & Woolhiser, D. A. (2002). Mathematical Modeling of Watershed Hydrology. *Journal of Hydrologic Engineering*, *7*(4), 270–292. https://doi.org/10.1061/(asce)1084-0699(2002)7:4(270)

Singh, W. R., & Jain, M. K. (2015). Continuous Hydrological Modeling using Soil Moisture Accounting Algorithm in Vamsadhara River Basin, India. *Journal of Water Resource and Hydraulic Engineering*, *4*(4), 398–408. https://doi.org/10.5963/jwrhe0404011

Sivapalan, M., Takeuchi, K., Schertzer, D., O'Connell, P. E., Liang, X., Karambiri, H., … Oki, T. (2005). IAHS Decade on Predictions in Ungauged Basins (PUB), 2003–2012: Shaping an exciting future for the hydrological sciences. *Hydrological Sciences Journal*, *48*(6), 857–880. https://doi.org/10.1623/hysj.48.6.857.51421

Tessema, S. M. (2011). *Hydrological Modeling as a Tool for Sustainable Water Resources Management: A Case Study of the Awash River Basin*.

USACE. (1994). *Flood-Runoff Analysis Engineer Manual*. Retrieved from http://140.194.76.129/publications/eng-manuals/EM_1110-2-1417_sec/Sections/c-9.pdf

USACE. (2000). *Hydrologic Modeling System Technical Reference Manual*.

USACE. (2001). *Hydrologic Modeling System HEC-HMS User ' s Manual*.

USACE. (2016). *Hydrologic Modelling System HEC-HMS User's Manual*.

Van Der Linde, S., & Woo, M. K. (2003). Transferability of hydrological model parameters between basins in data-sparse areas, subarctic Canada. *Journal of Hydrology*, *270*(3–4), 182–194. https://doi.org/10.1016/S0022-1694(02)00295-0

Verma, A. K., Jha, M. K., & Mahana, R. K. (2010). Evaluation of HEC-HMS and WEPP for simulating watershed runoff using remote sensing and geographical information system. *Paddy and Water Environment*, *8*(2), 131–144. https://doi.org/10.1007/s10333-009-0192-8

Wickramaarachchi, T. N., Ishidaira, H., & Wijayaratna, T. M. N. (2012). An Application of Distributed Hydrological Model , YHyM / BTOPMC to Gin Ganga Watershed , Sri Lanka. *The Institution of Enginerrs, Sri Lanka*, *V*(02), pp.(31-40).

Wijesekera, N. T. S. (2001). Water Balance to Identify Lunugamwehera Reservoir Management Requirements. *Journal of IESL*, *XXXIV*(02), 53–60.

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

Wijesekera, N. T. S., & Musiake, K. (1990). Streamflow Modelling of Sri Lankan Catchments (1) - Mahaweli River Catchment at Peradeniya. *Seisan Kenkyu*, *42*(11), 645–648.

Wijesekera, N. T. S., & Perera, L. R. H. (2016). Key Issues of Data and Data Checking for Hydrological Analyses - Case Study of Rainfall Data in the Attanagalu Oya Basin of Sri Lanka. *Journal of the Institution of Engineers, Sri Lanka*, *45*(2), 1. https://doi.org/10.4038/engineer.v45i2.6936

World Meteorological Organization. (1992). *Simulated Real-Time Intercomparison of Hydrological Models*.

Yang, J., Liu, Y., Yang, W., & Chen, Y. (2012). Multi-Objective Sensitivity Analysis of a Fully Distributed Hydrologic Model WetSpa. *Water Resources Management*, *26*(1), 109–128. https://doi.org/10.1007/s11269-011-9908-9

Zhang, Z., Wang, S., Sun, G., McNulty, S. G., Zhang, H., Li, J., … Strauss, P. (2008). Evaluation of the MIKE SHE model for application in the Loess Plateau, China. *Journal of the American Water Resources Association*, *44*(5), 1108–1120. https://doi.org/10.1111/j.1752-1688.2008.00244.x

APPENDIX A: STREAMFLOW RESPONSE WITH RAINFALL

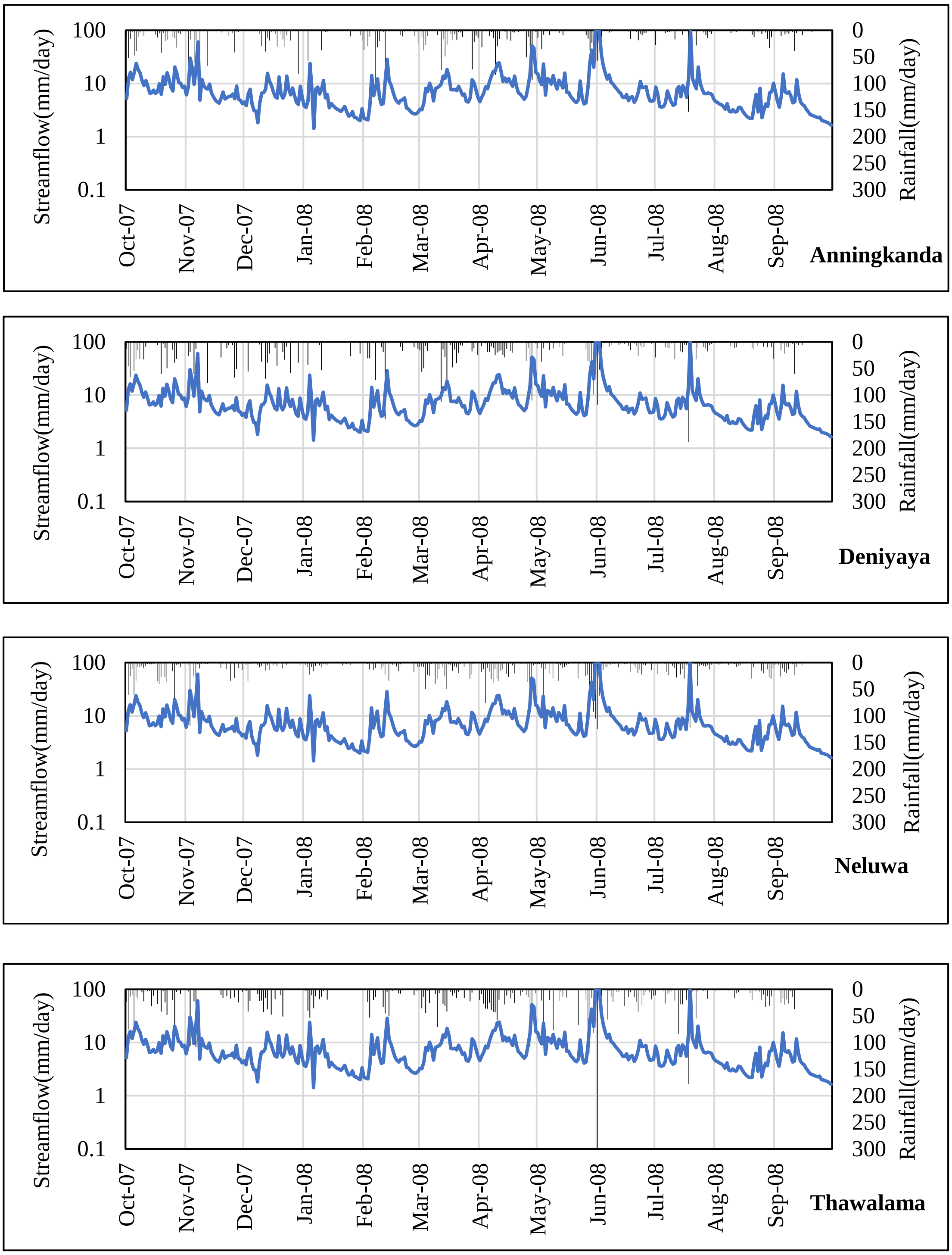
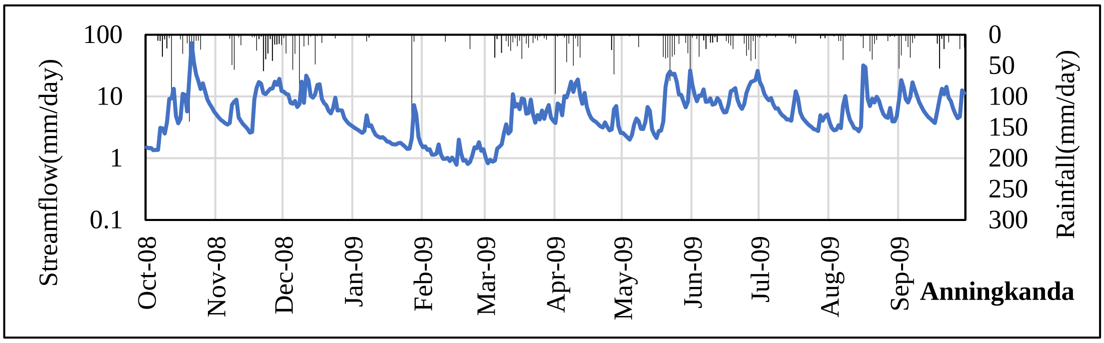
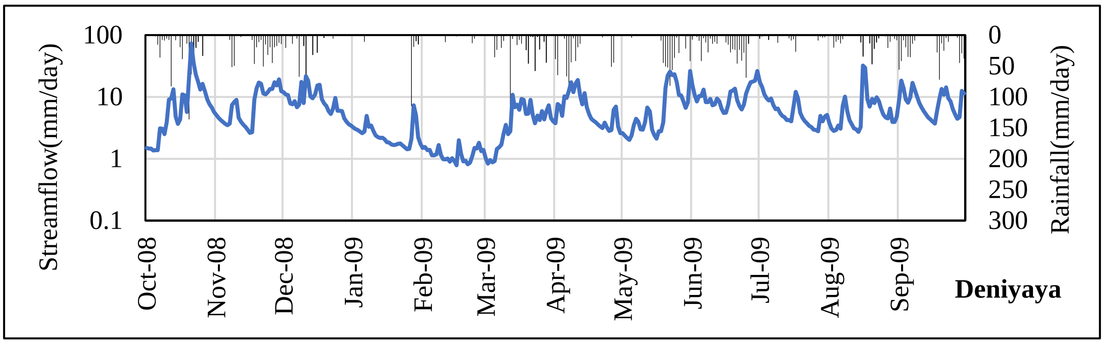
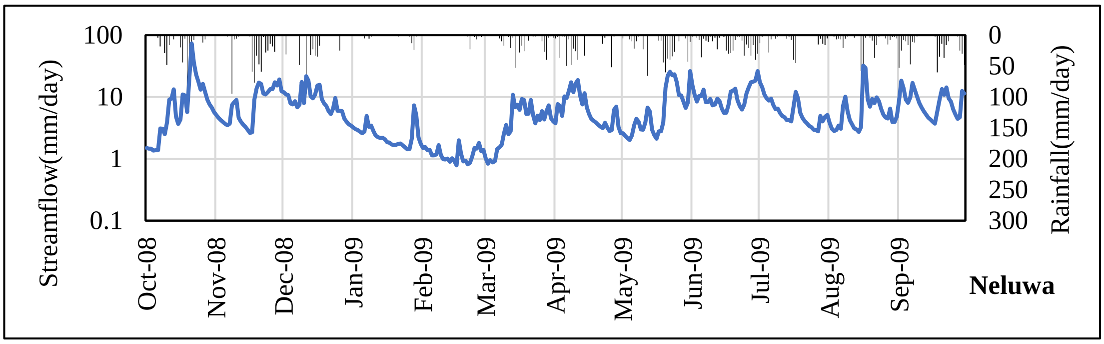


Figure A 1:SF vs RF at each station at Thawalama watershed-(2007/08)







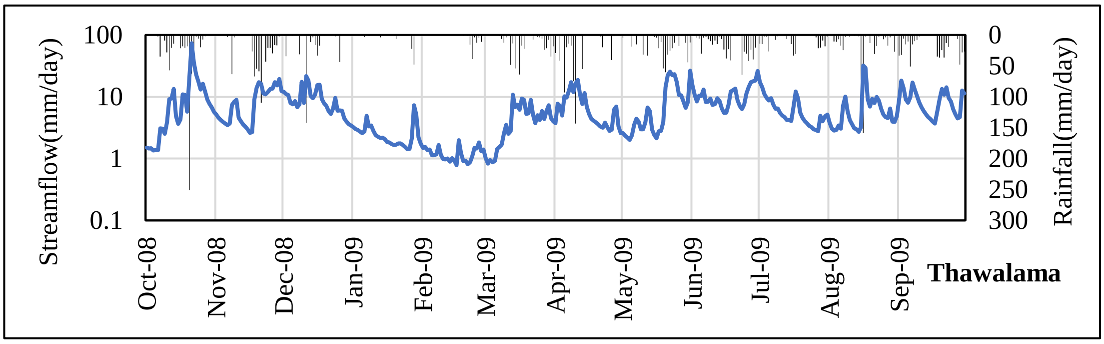
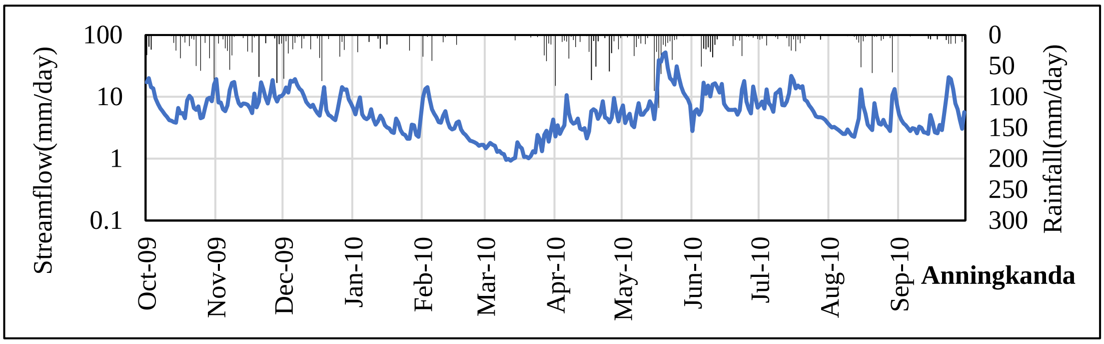
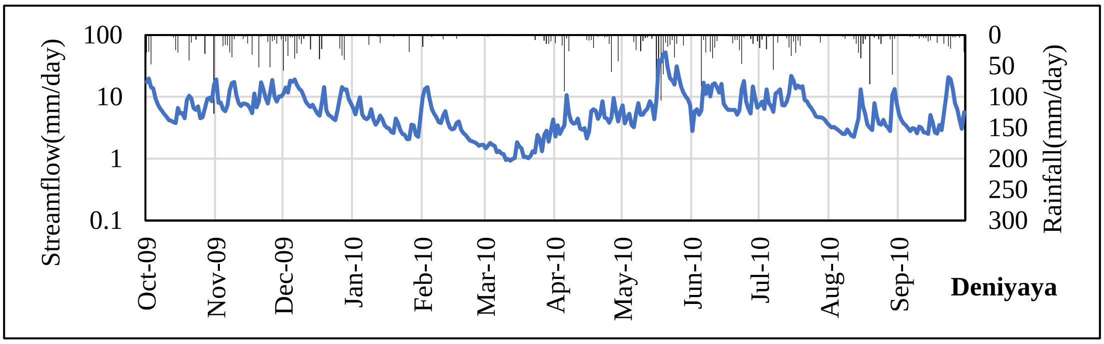
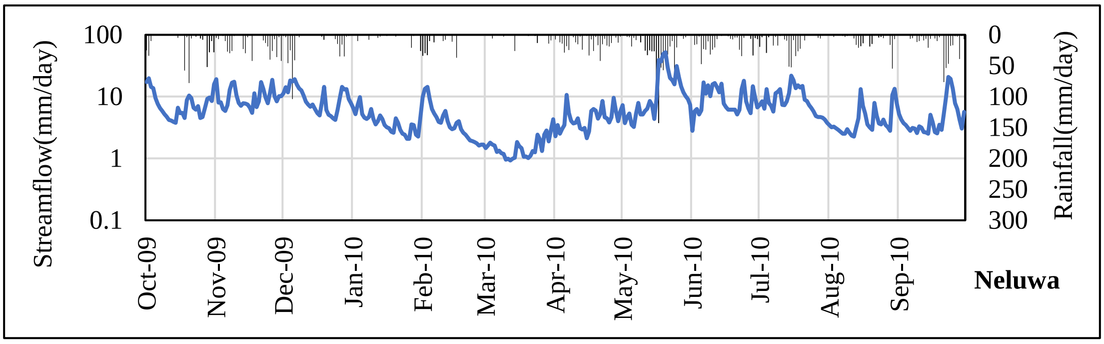


Figure A 2:SF vs RF at each station at Thawalama watershed-(2008/09)







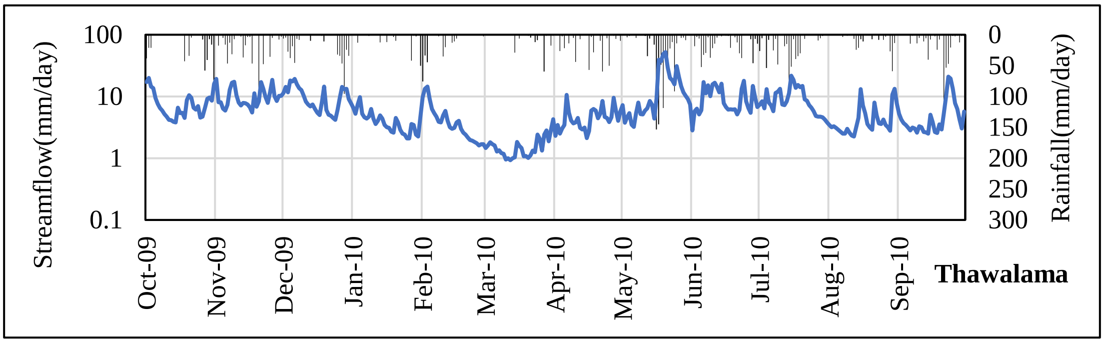


Figure A 3:SF vs RF at each station at Thawalama watershed-(2009/10)

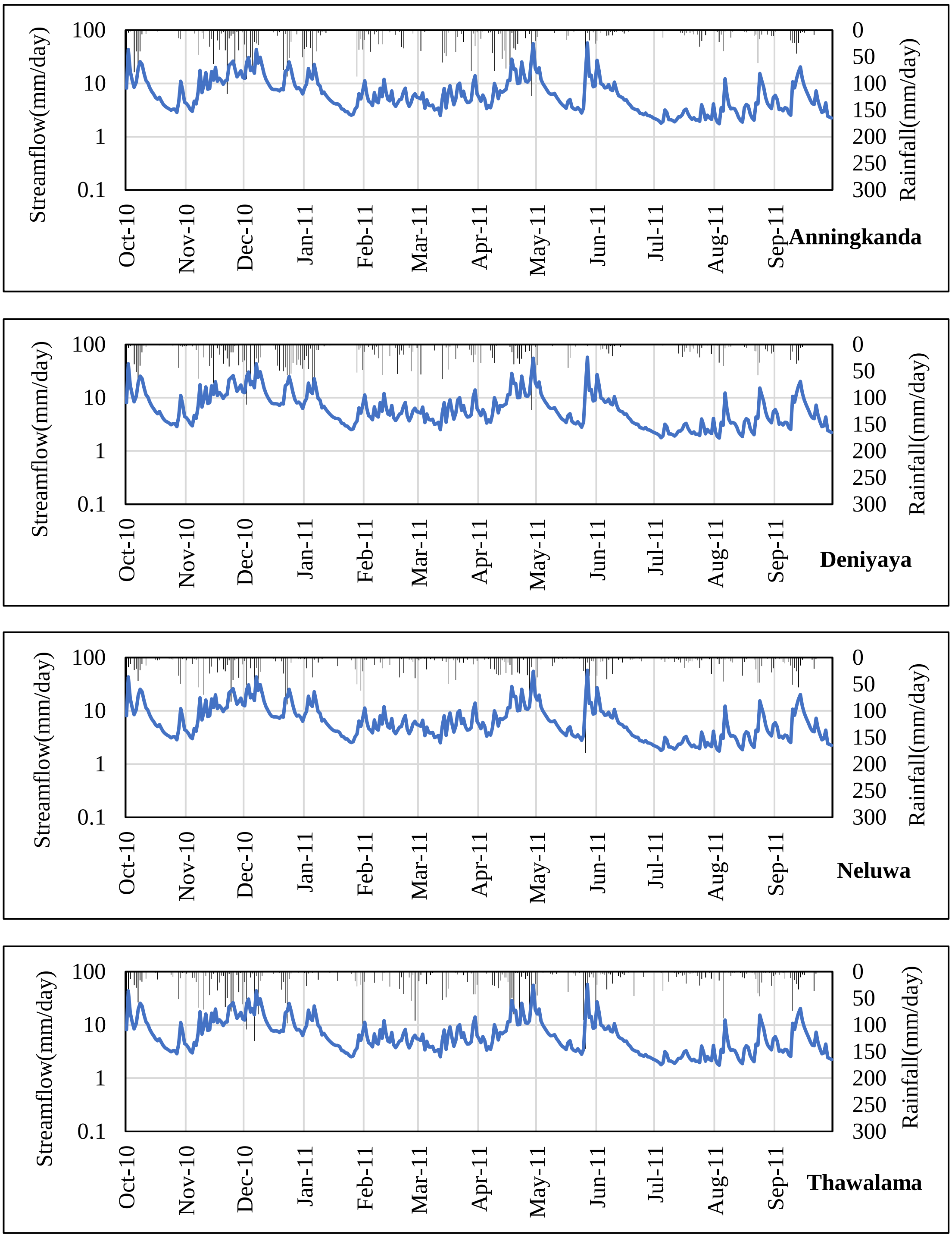


Figure A 4:SF vs RF at each station at Thawalama watershed-(2010/11)

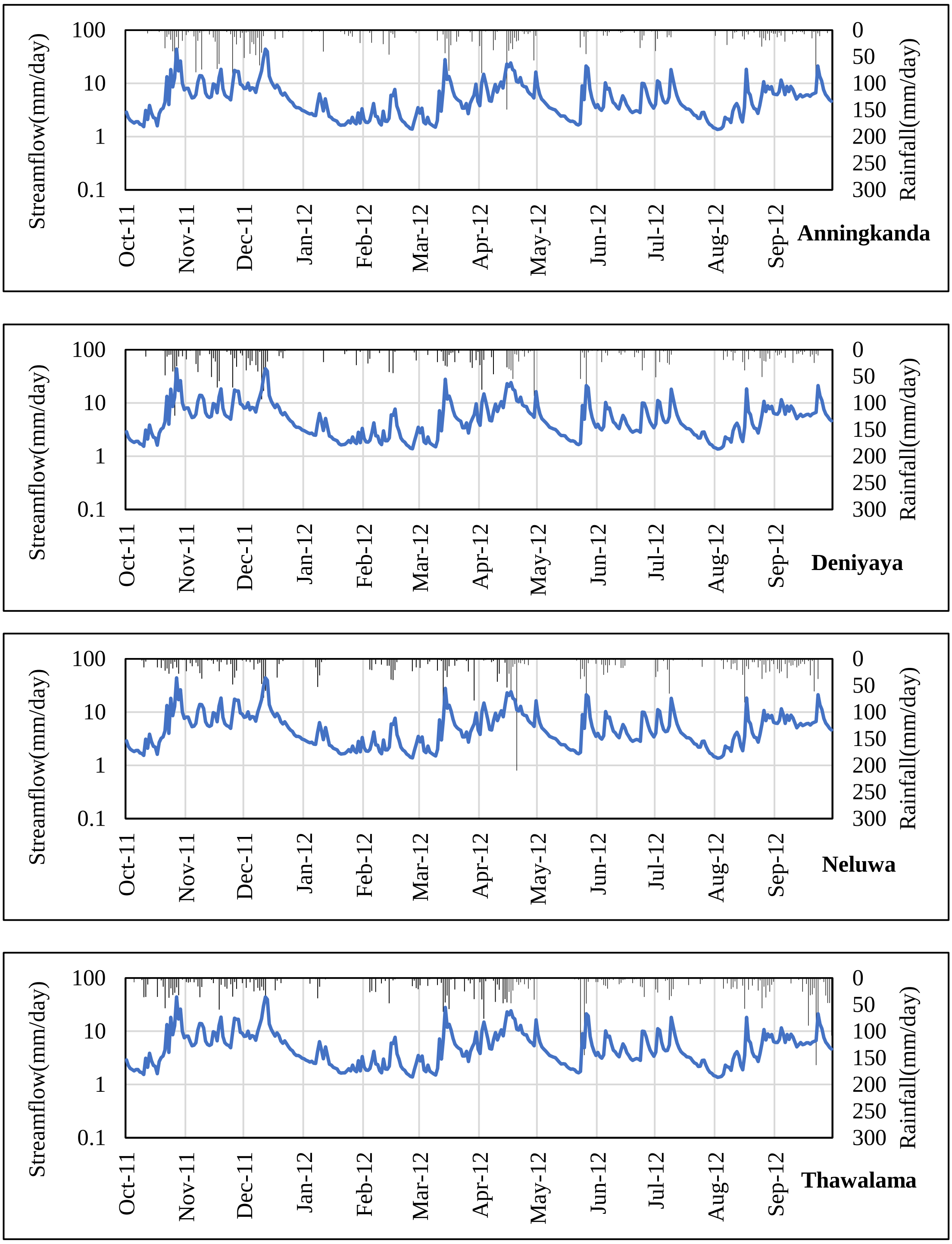


Figure A 5:SF vs RF at each station at Thawalama watershed-(2011/12)

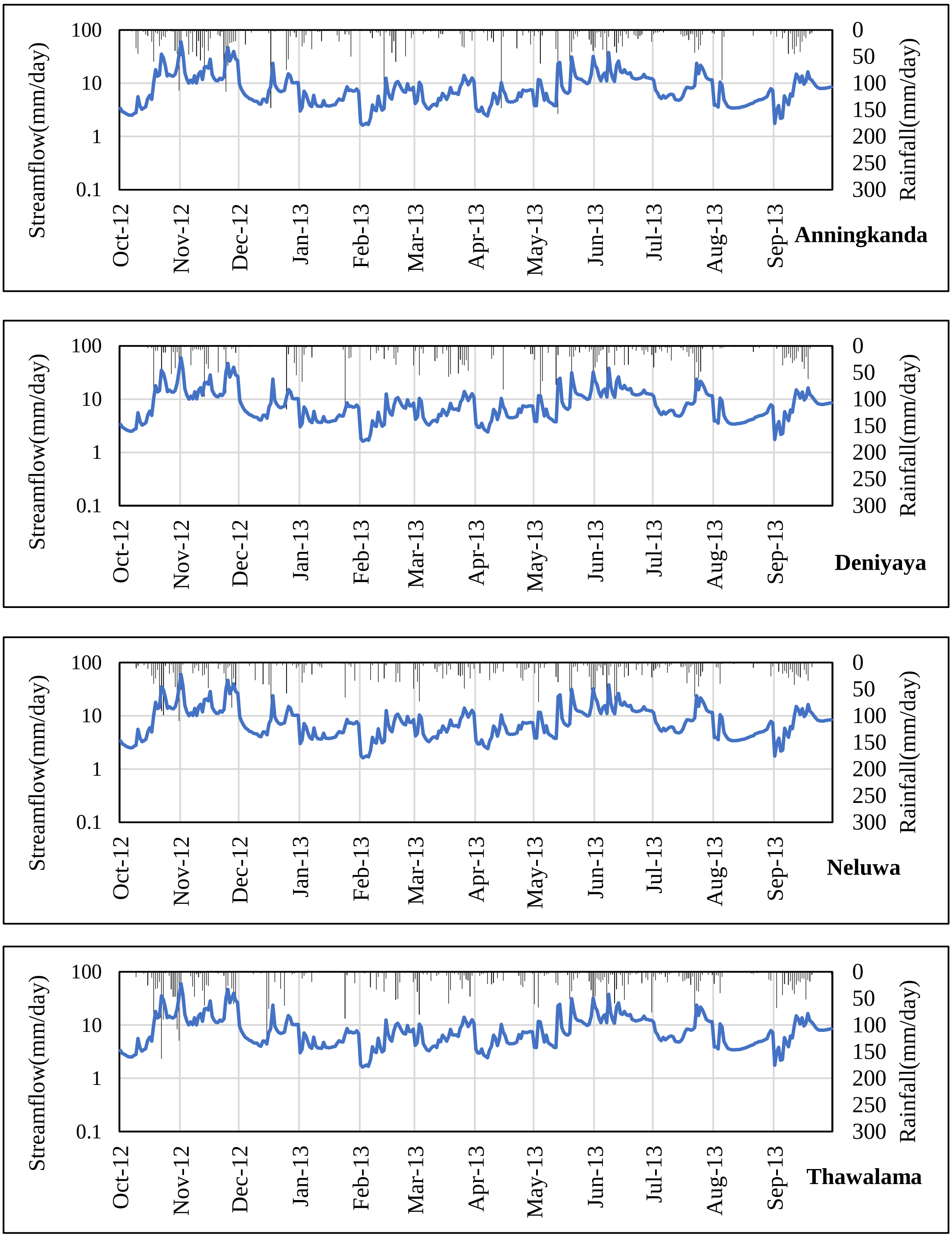
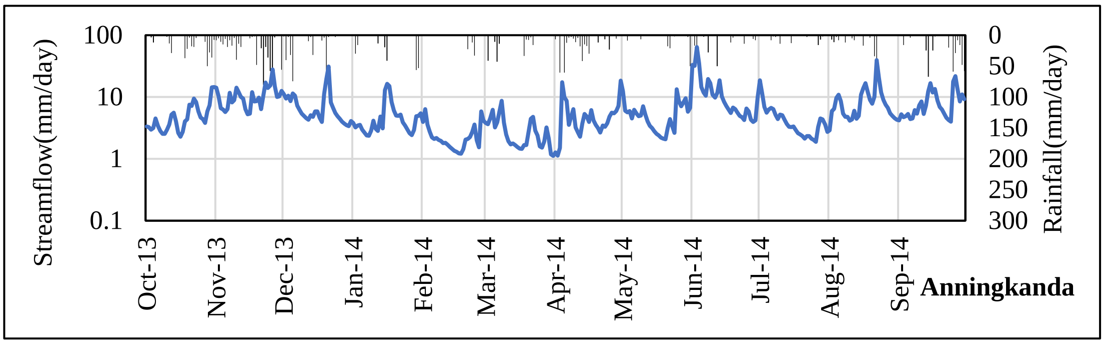
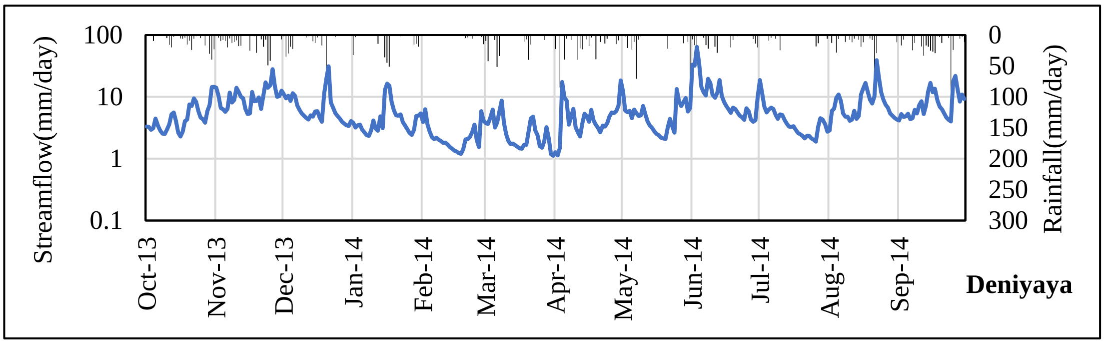
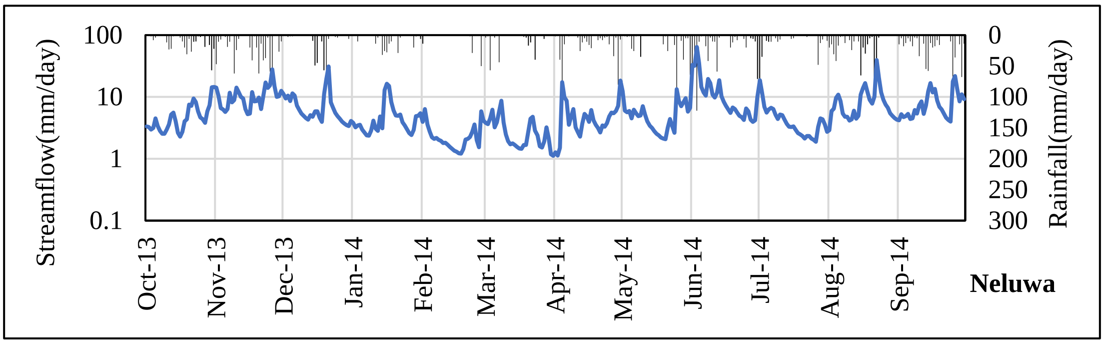


Figure A 6:SF vs RF at each station at Thawalama watershed-(2012/13)







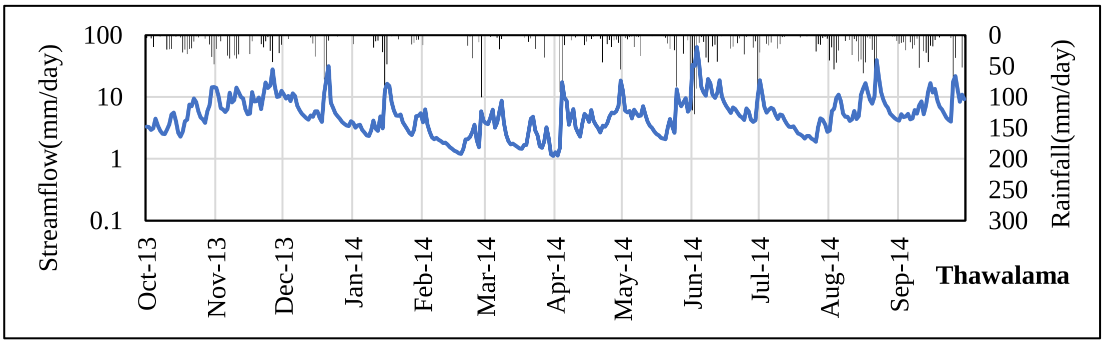


Figure A 7:SF vs Rf at each station at Thawalama watershed-(2013/14)

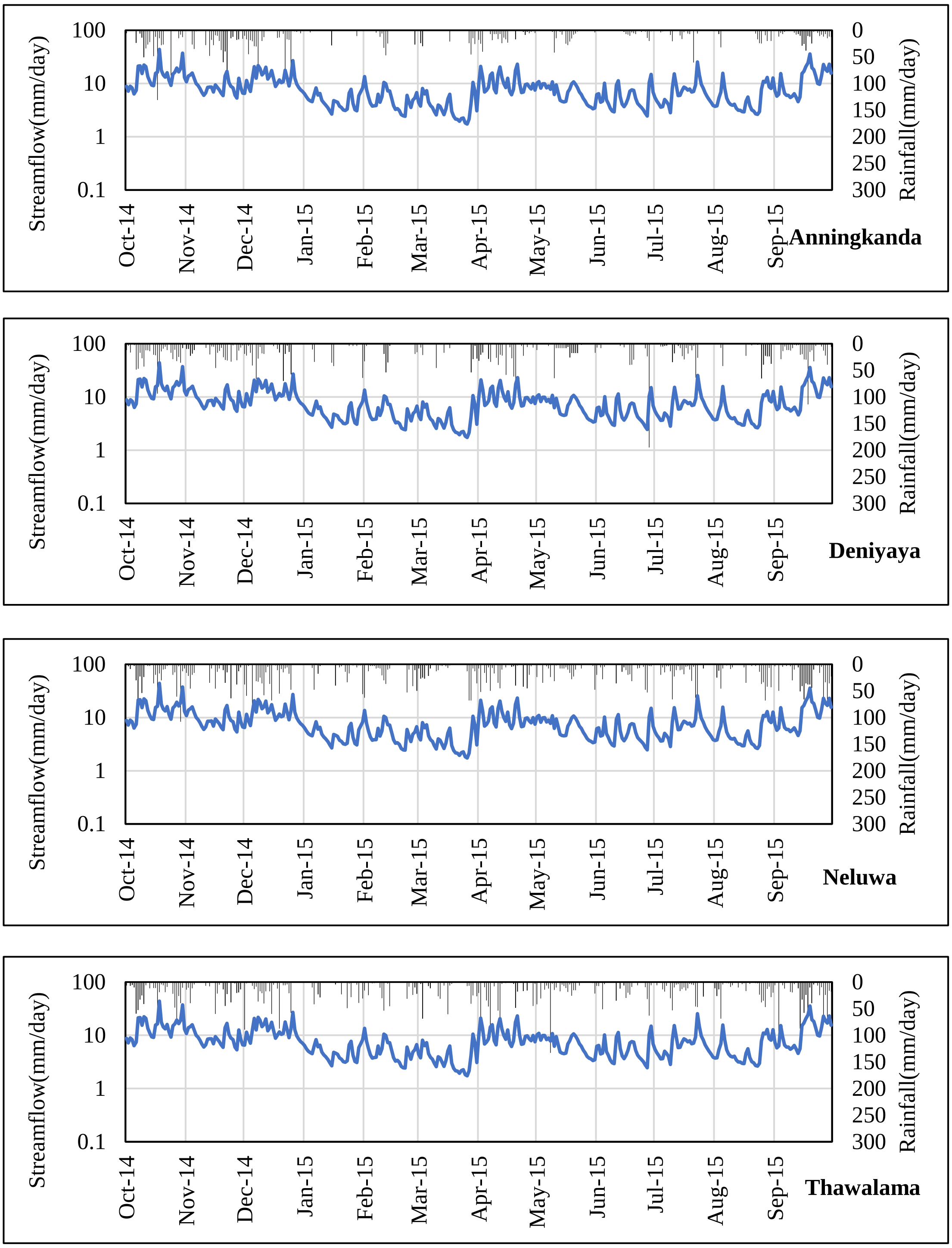


Figure A 8:SF vs RF at each station at Thawalama watershed-(2014/15)

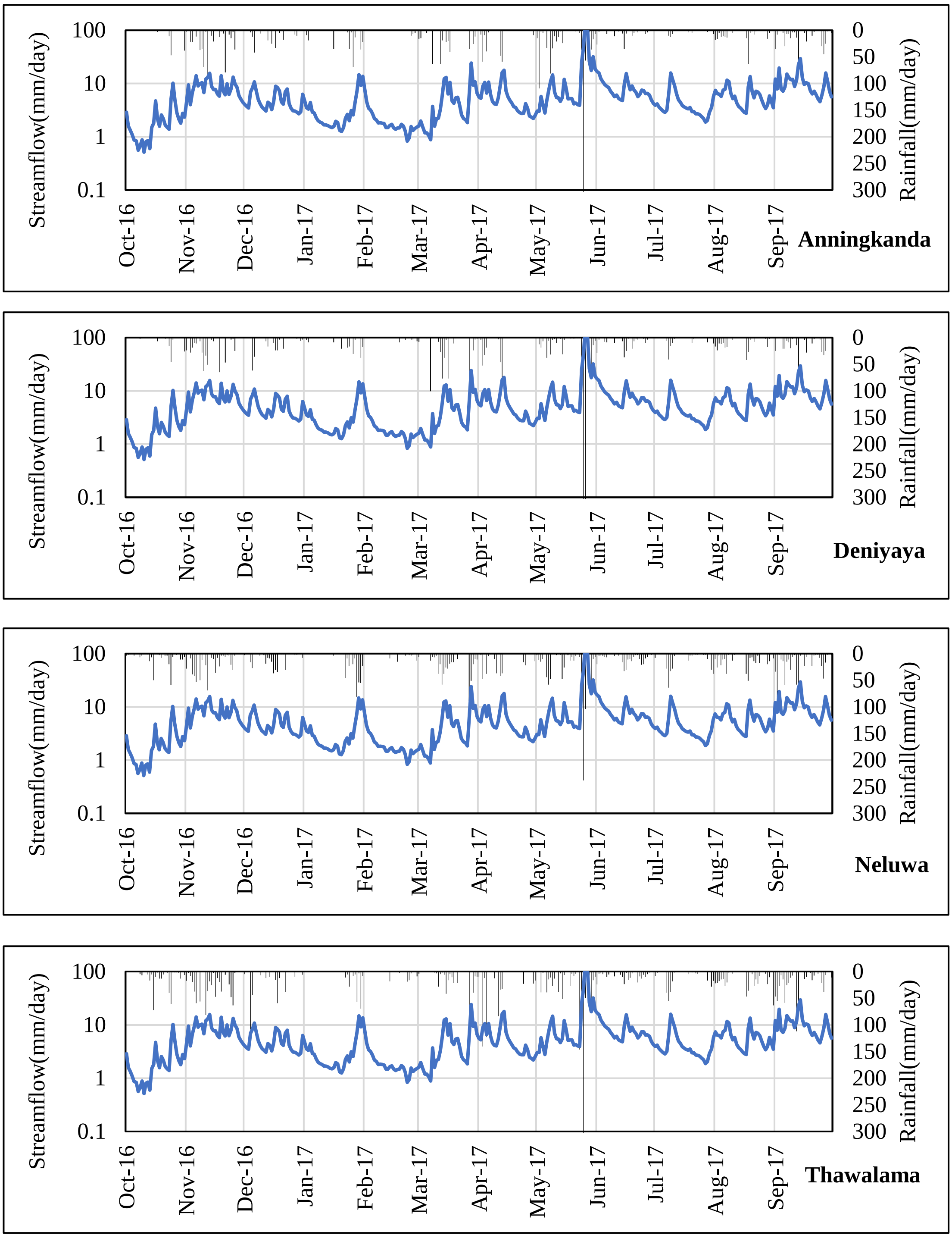


Figure A 9:SF vs RF at each station at Thawalama watershed-(2016/17)

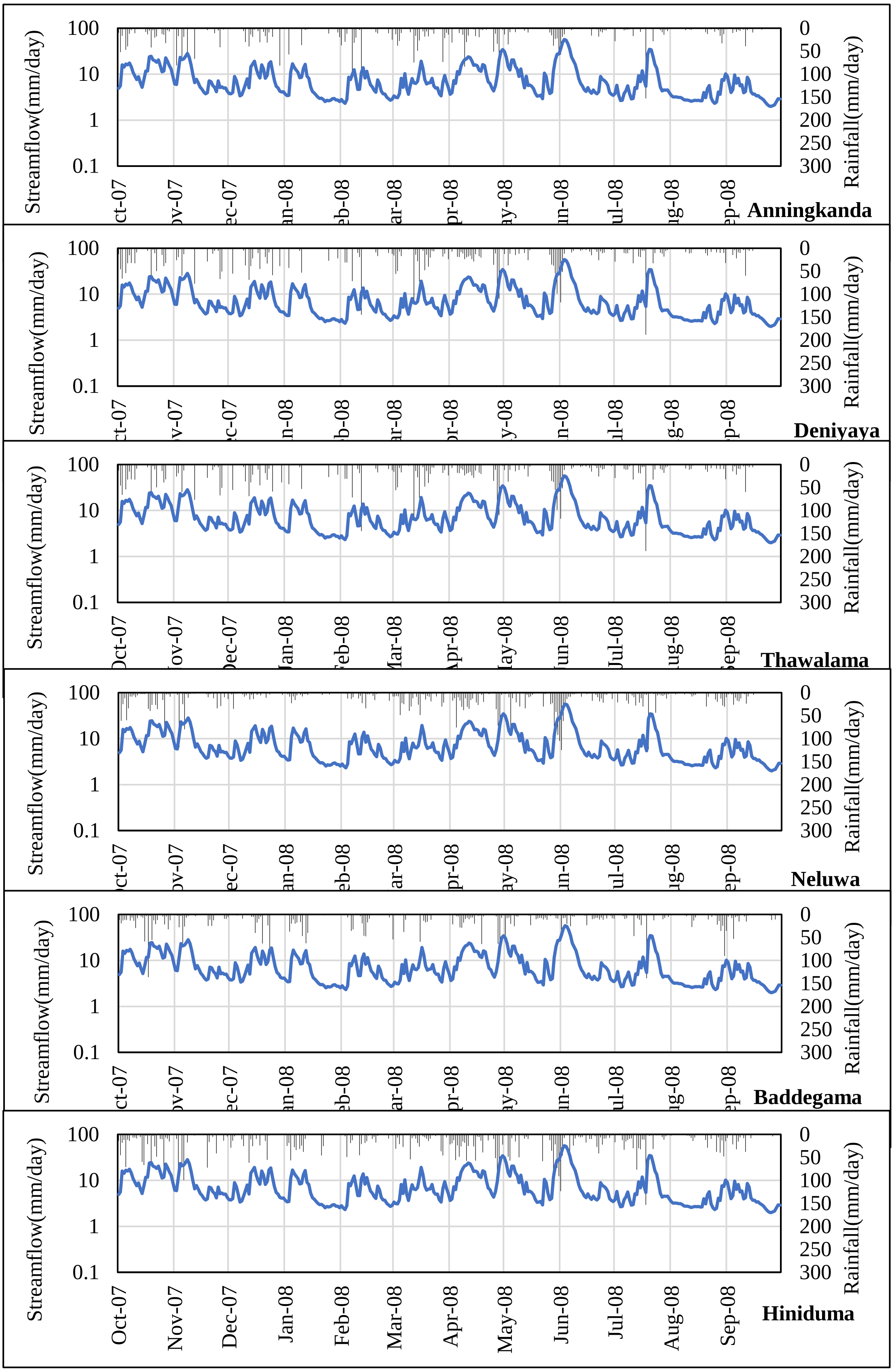


Figure A 10:SF vs RF at each station at Baddegama watershed-(2007/08)

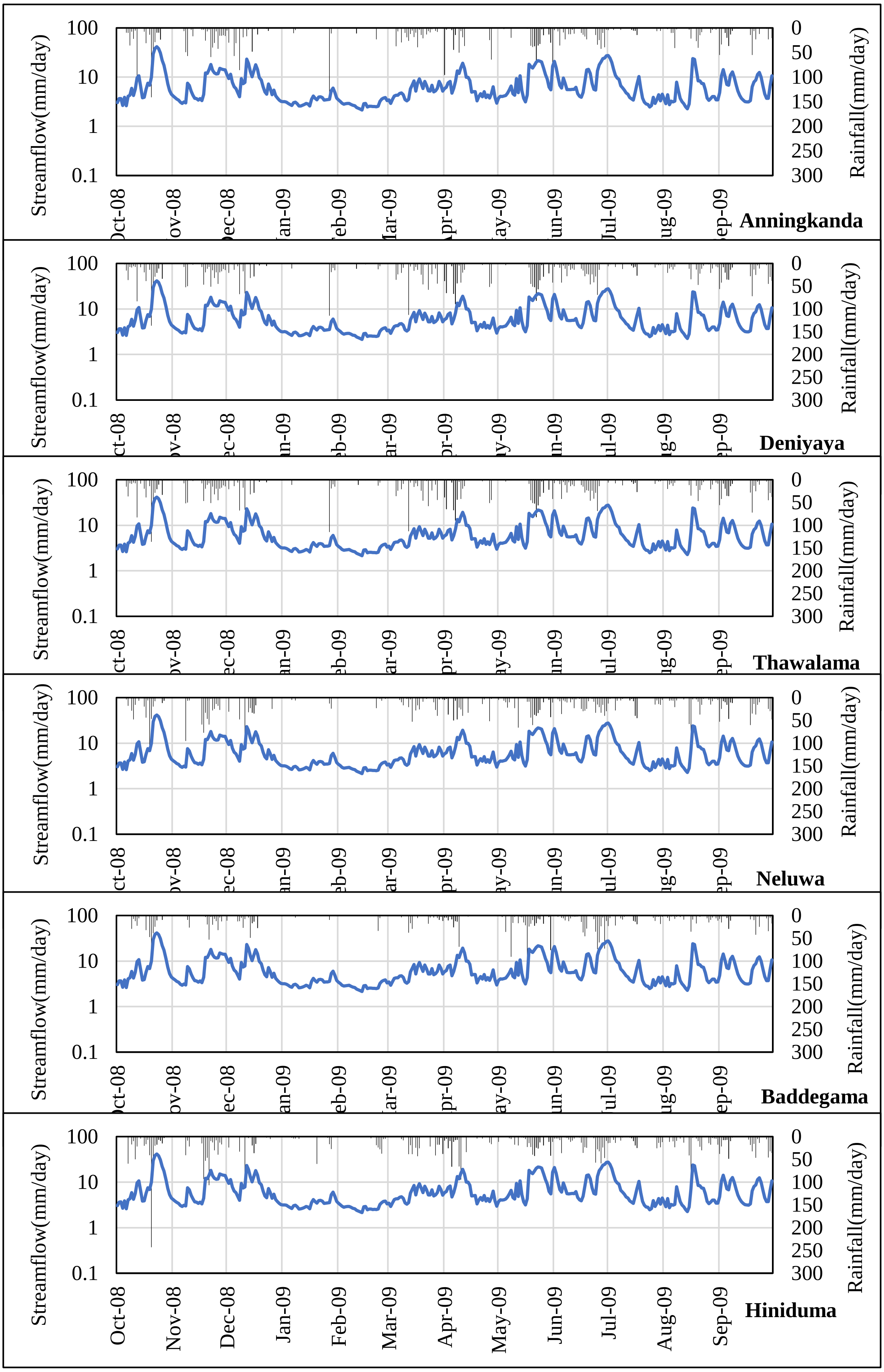


Figure A 11:SF vs RF at each station at Baddegama watershed-(2008/09)

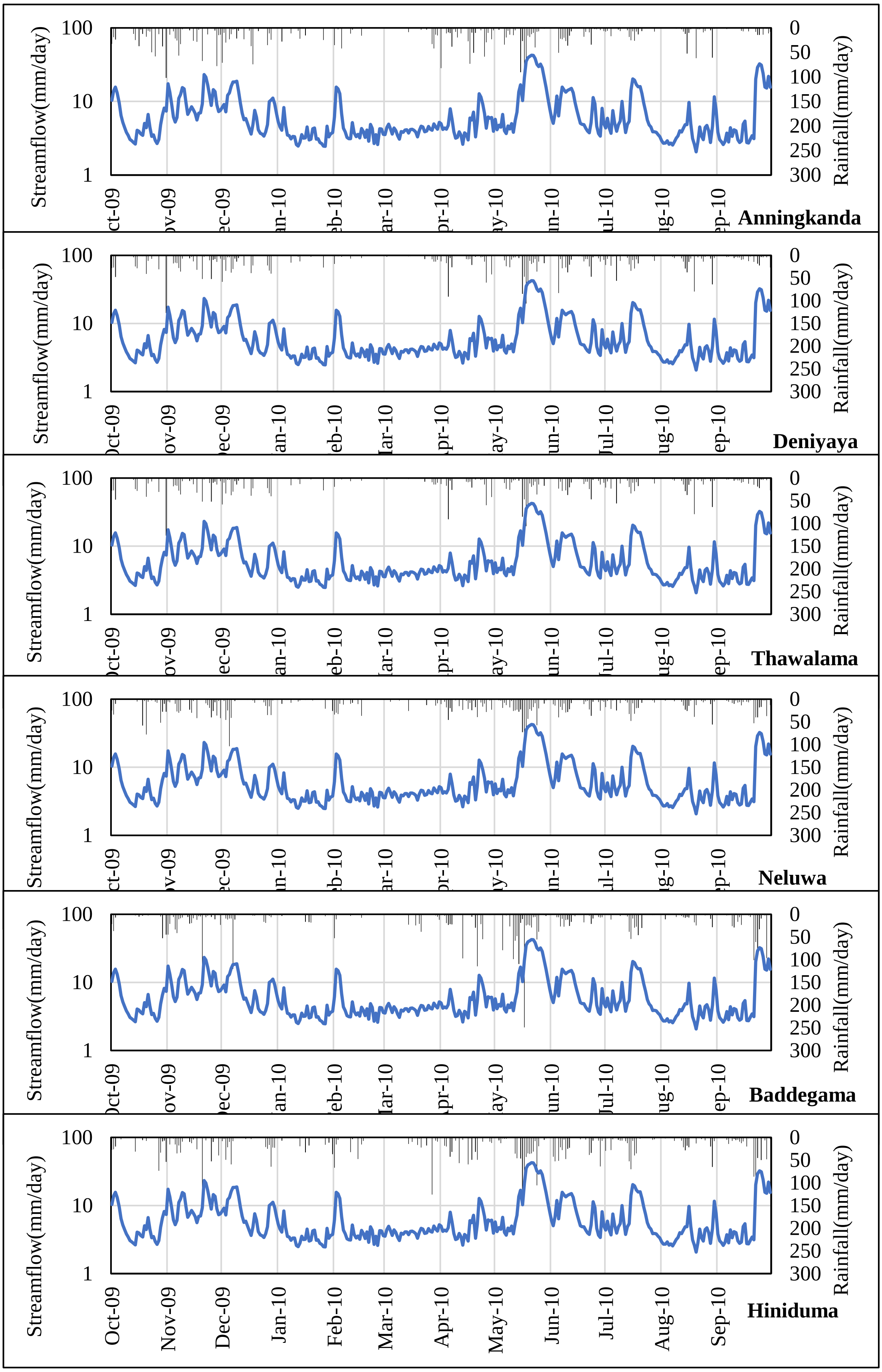


Figure A 12:SF vs RF at each station at Baddegama watershed-(2009/10)

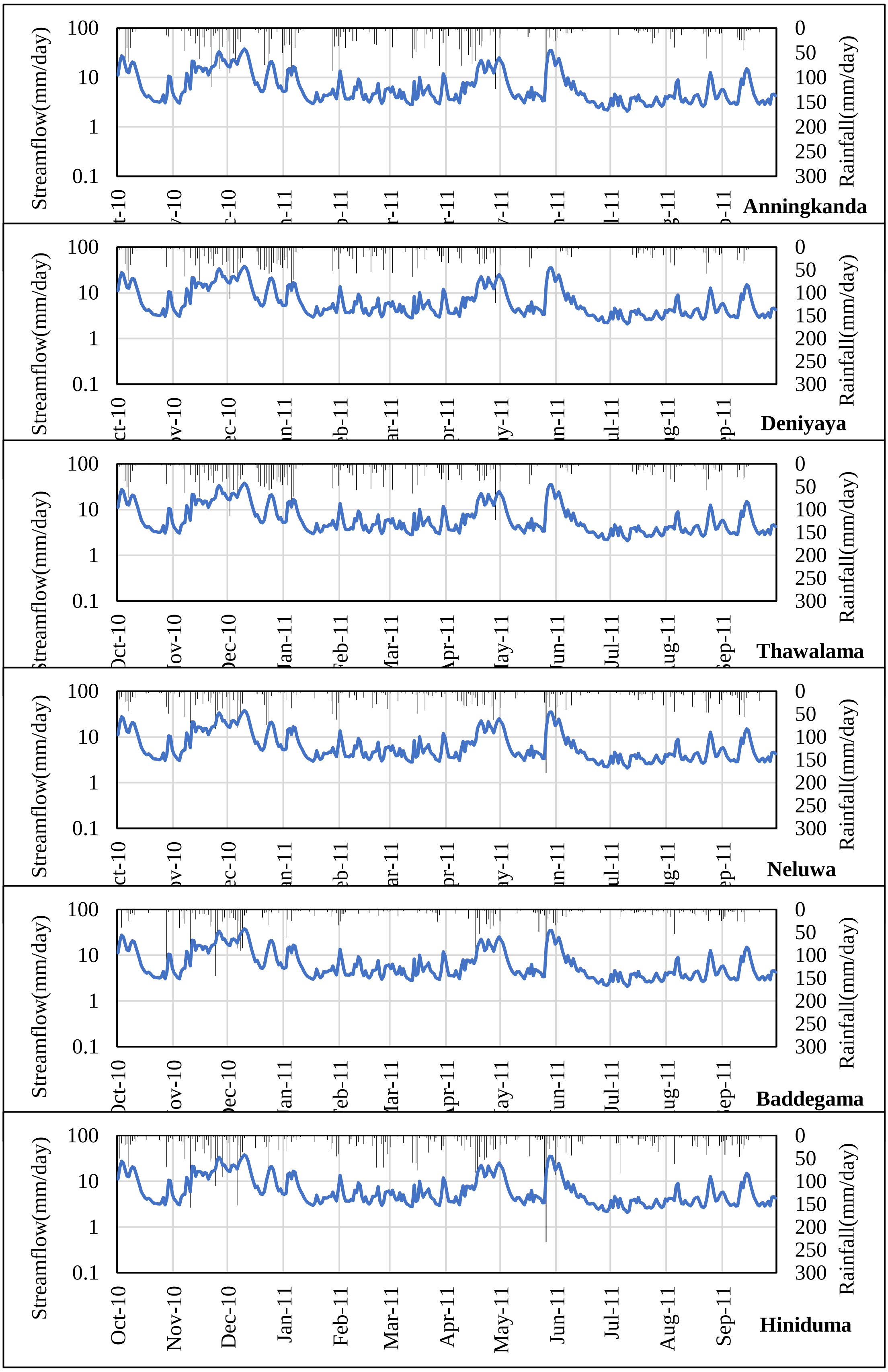


Figure A 13:SF vs RF at each station at Baddegama watershed-(2010/11)

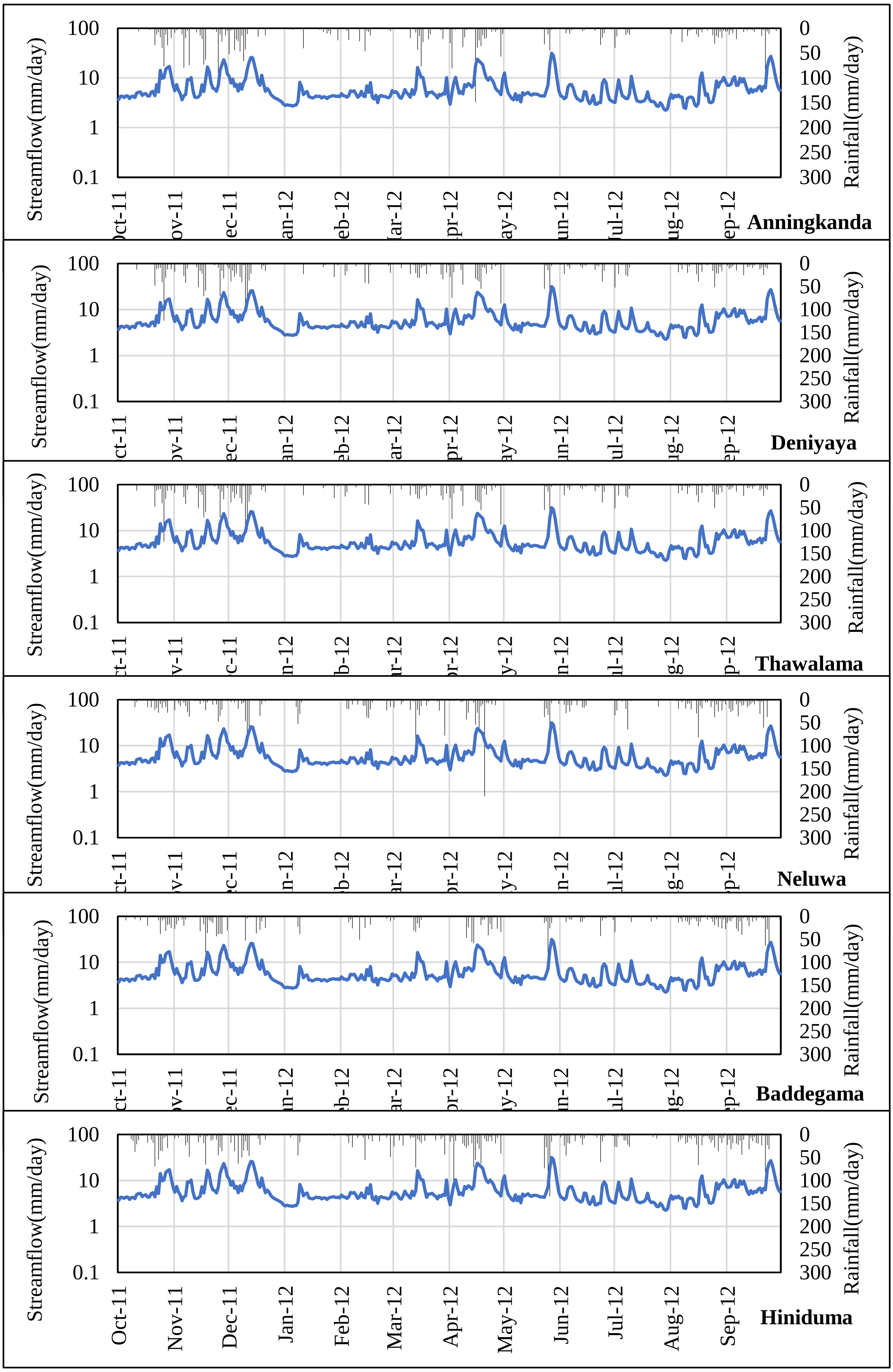


Figure A 14:SF vs RF at each station at Baddegama watershed-(2011/12)

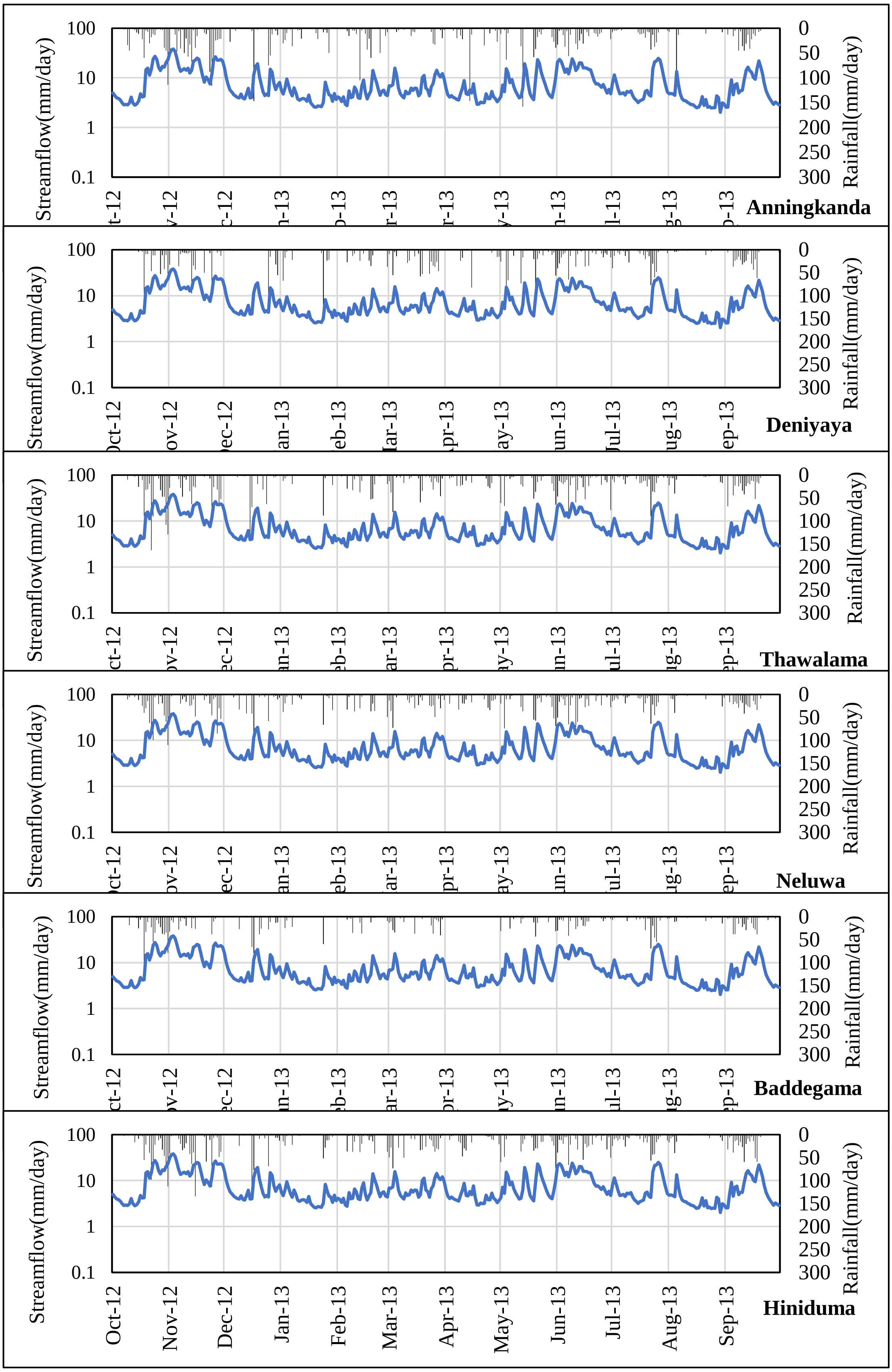


Figure A 15:SF vs RF at each station at Baddegama watershed-(2012/13)

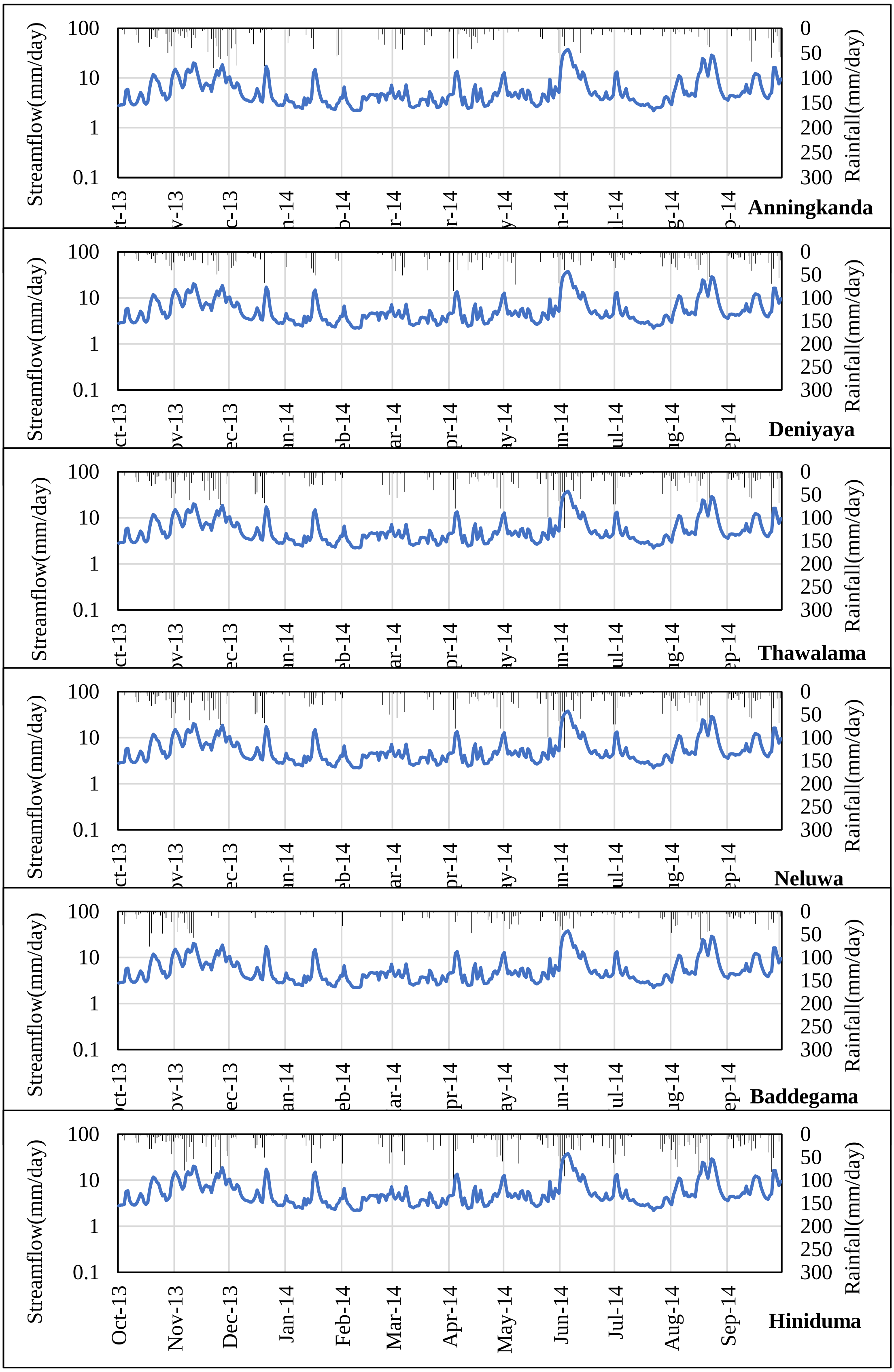


Figure A 16:SF vs RF at each station at Baddegama watershed-(2013/14)

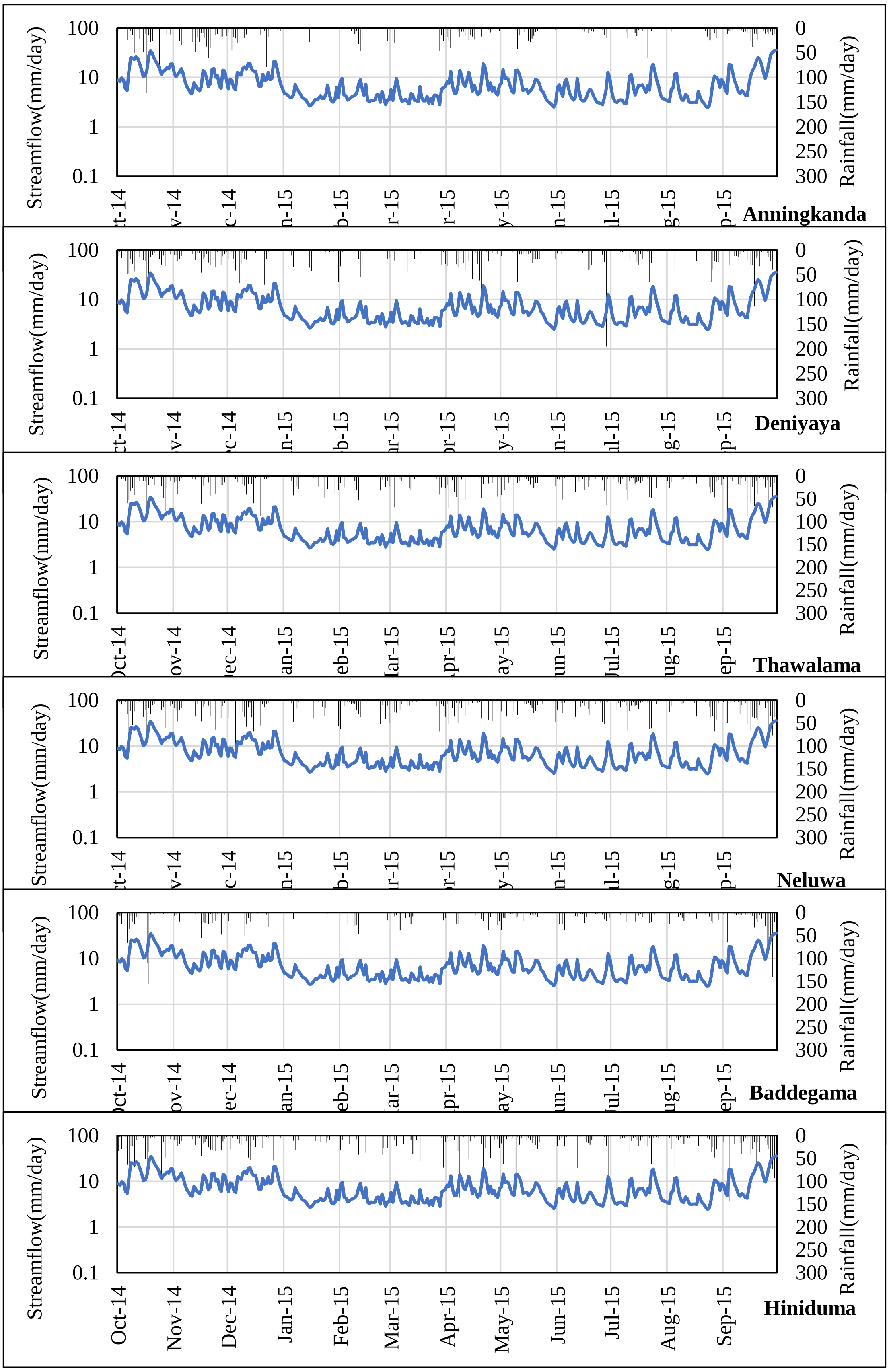


Figure A 17:SF vs RF at each station at Baddegama watershed-(2014/15)

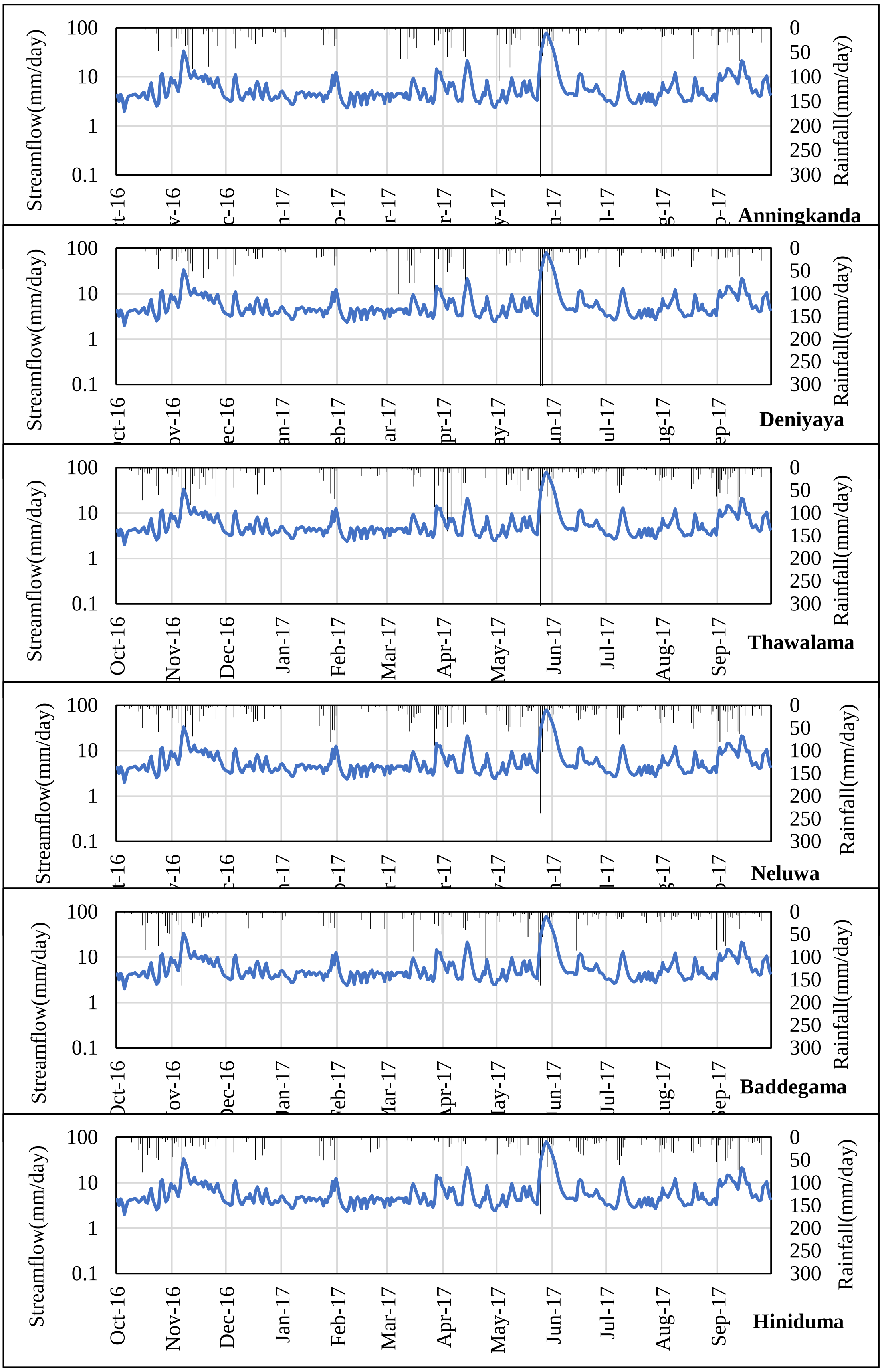


Figure A 18:SF vs RF at each station at Baddegama watershed-(2016/17)

APPENDIX B: DOUBLE MASS CURVES AFTER DATA FILLING

Table B 1:Variation of cumulative values

Water year	Cumulative Values								
	Anningkanda	Baddegama	Deniyaya	Hiniduma	Neluwa	Thawalama	Baddegama SF	Thawalama SF	Kottawa EVP
2007/08	3431	3401	4352	5022	4010	5016	3311	3377	826
2008/09	6943	6053	8531	9139	7912	9694	5993	5991	1856
2009/10	10373	9617	11721	13367	11775	14150	8734	8641	2807
2010/11	14433	12530	15688	18280	15510	18953	11726	11572	3785
2011/12	17471	15121	18842	22229	18776	22913	14156	13861	4763
2012/13	21784	18106	22770	26962	23166	27684	17236	17256	5714
2013/14	24629	20314	25640	31401	27511	32100	19607	19667	6631
2014/15	27735	23536	29869	36562	32845	37373	22602	22793	7379
2015/16	30419	26425	32867	40512	37087	41381	25453	25374	8228
2016/17	33729	29839	36740	44212	41470	46186	28024	27855	9127

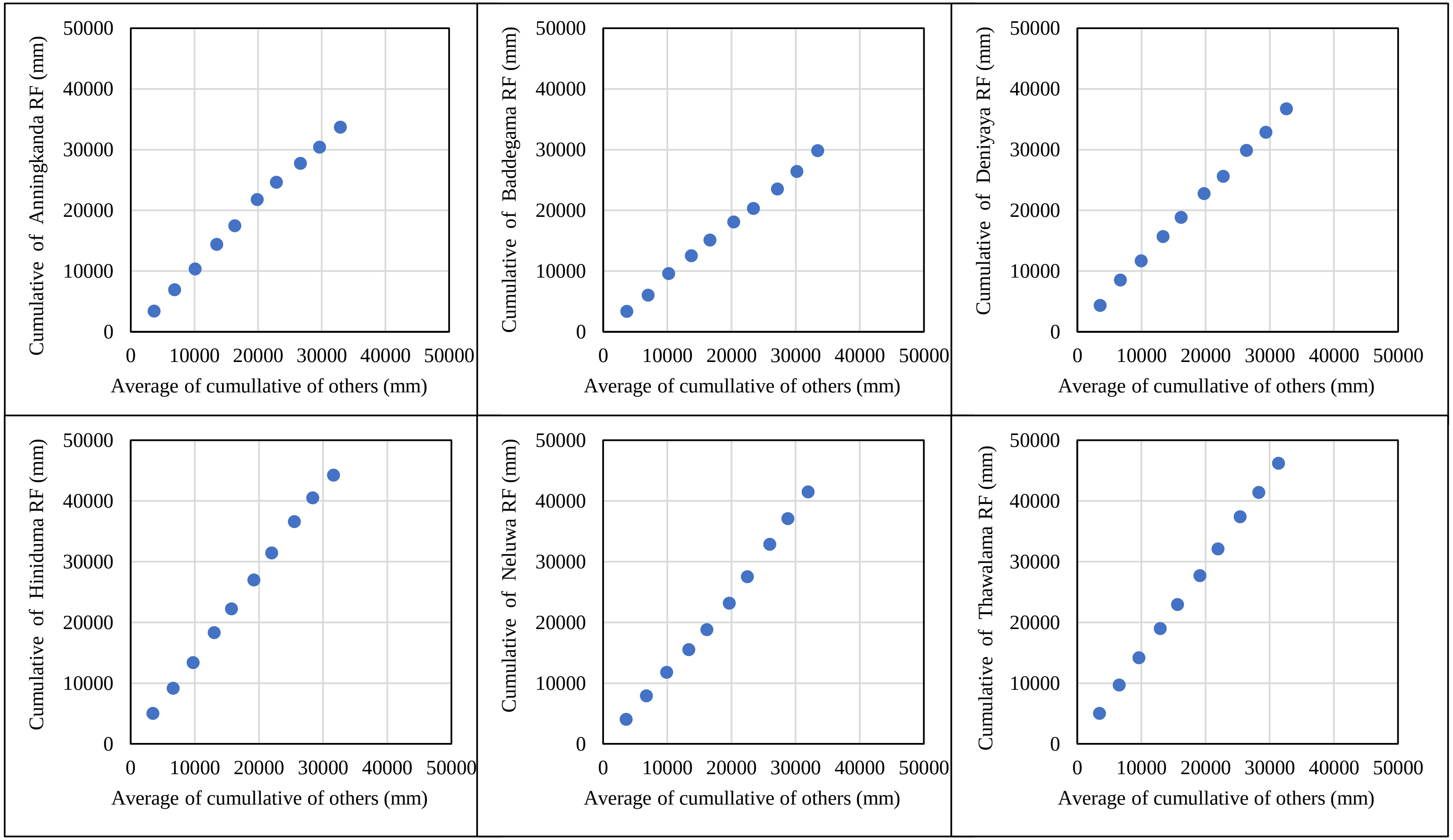


Figure B 1:Double mass curves for rainfall stations

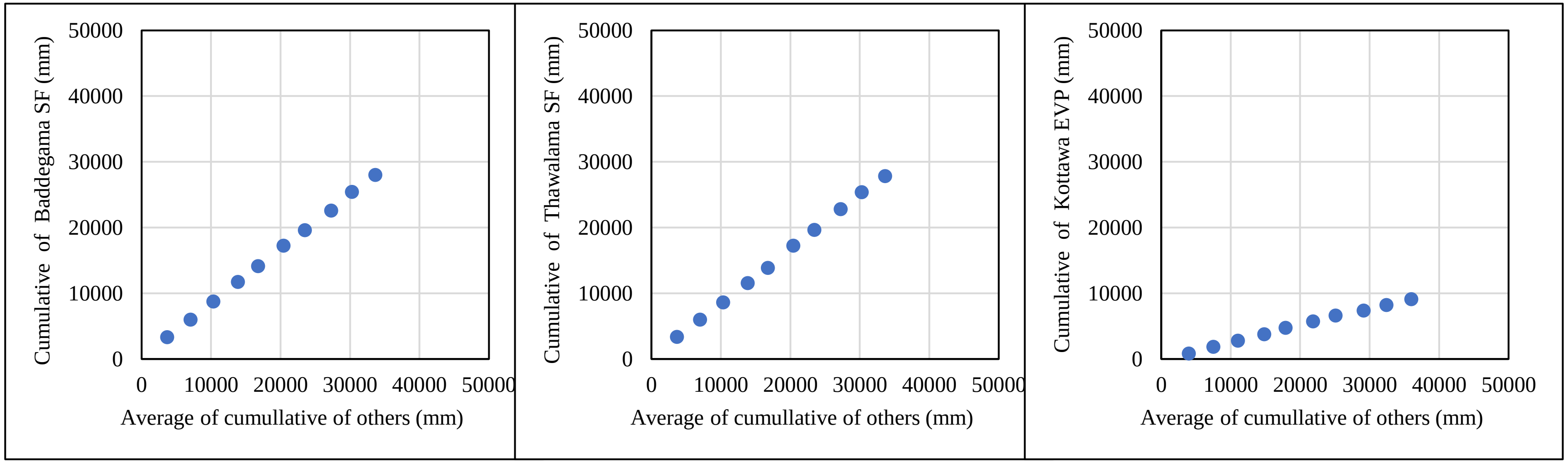


Figure B 2:Double mass curves for streamflow and evaporation stations

Table B 2:Variation of cumulative average values

Water year	Cumulative Average Values								
	Anningkanda	Baddegama	Deniyaya	Hiniduma	Neluwa	Thawalama	Baddegama SF	Thawalama SF	Kottawa EVP
2007/08	3664	3668	3549	3466	3592	3466	3679	3671	3990
2008/09	6896	7007	6698	6622	6775	6552	7015	7015	7532
2009/10	10101	10196	9933	9727	9926	9629	10306	10318	11047
2010/11	13505	13743	13349	13025	13371	12940	13844	13863	14837
2011/12	16332	16626	16161	15738	16169	15652	16747	16784	17921
2012/13	19862	20321	19738	19215	19689	19124	20430	20428	21871
2013/14	22859	23398	22732	22012	22499	21925	23487	23479	25109
2014/15	26620	27145	26353	25517	25981	25415	27261	27238	29164
2015/16	29666	30165	29360	28404	28832	28296	30287	30296	32440
2016/17	32932	33418	32555	31621	31964	31375	33645	33666	36007

APPENDIX C: COMPARISON OF RAINFALL CALCULATIONS

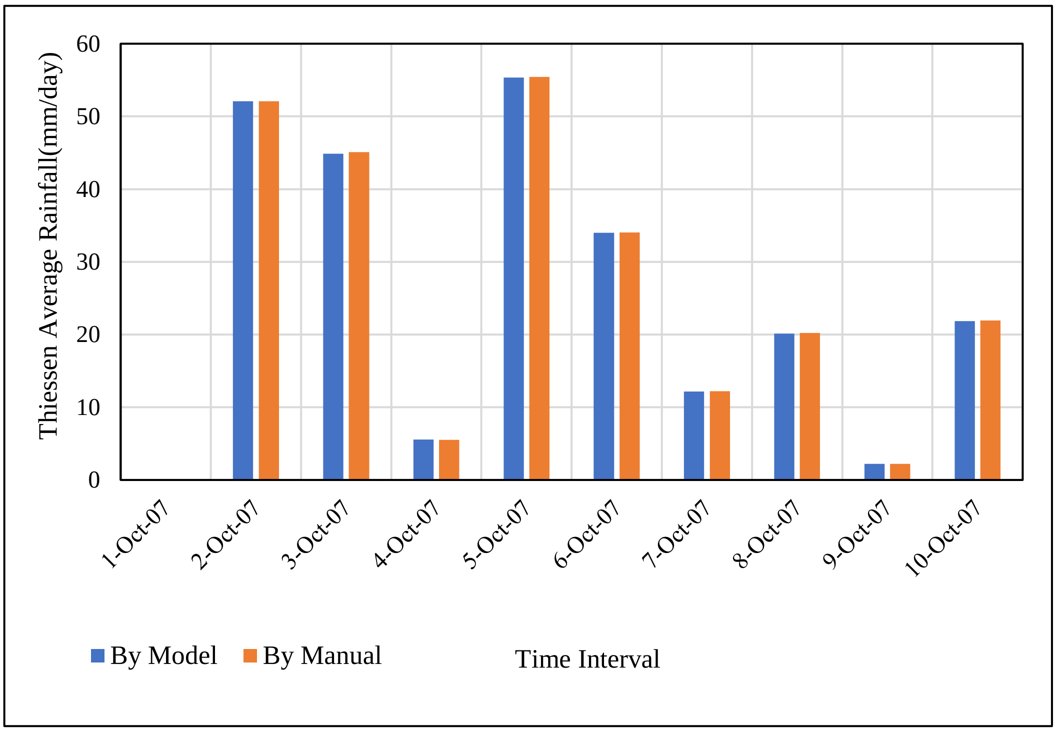


Figure C 1:Comparison of model and manual calculation of rainfall

APPENDIX D: REVIEW OF OPTIMIZATION CRITERIA

Table D 1:Variation of error values corresponding to different minimum objective function values

Criteria	RMSE	PWRMSE	Log-RMSE	PEP	PEV	SSR	NSE
Flow Hydrograph	30.1	61.72	0.19	0.01	0	330887.6	0.72
Hydroraph-MRAE	0.49	0.96	0.45	13.80	0.95	0.49	0.49
FDC-MRAE	0.49	0.96	0.45	13.80	0.95	0.49	0.49
High-MRAE	0.64	0.70	0.59	2.46	0.53	0.64	0.64
Medium-MRAE	0.48	0.84	0.32	9.91	0.52	0.48	0.48
Low-MRAE	0.36	1.51	0.67	34.35	2.50	0.36	0.36
Monthly Qsim/Qobs							
Oct	1.08	1.50	0.96	1.20	0.65	1.08	1.08
Nov	1.04	1.36	0.98	2.65	0.69	1.04	1.04
Dec	1.16	1.53	1.00	5.14	0.95	1.16	1.16
Jan	0.95	1.20	1.11	8.30	1.17	0.95	0.95
Feb	1.00	1.47	1.22	7.45	1.05	1.00	1.00
Mar	1.15	1.67	0.97	6.77	0.87	1.15	1.15
Apr	0.78	1.14	0.68	4.31	0.56	0.78	0.78
May	0.62	0.70	0.45	3.32	0.34	0.62	0.62
Jun	1.86	2.31	1.39	13.87	1.88	1.86	1.86
Jul	1.17	1.71	0.85	11.94	1.47	1.17	1.17
Aug	0.86	2.48	1.06	32.79	3.08	0.86	0.86
Sep	0.66	2.57	1.15	32.89	3.09	0.66	0.66
AWB Error%	-6.0	169.4	-48.2	2645.3	0.9	-6.0	-6.0

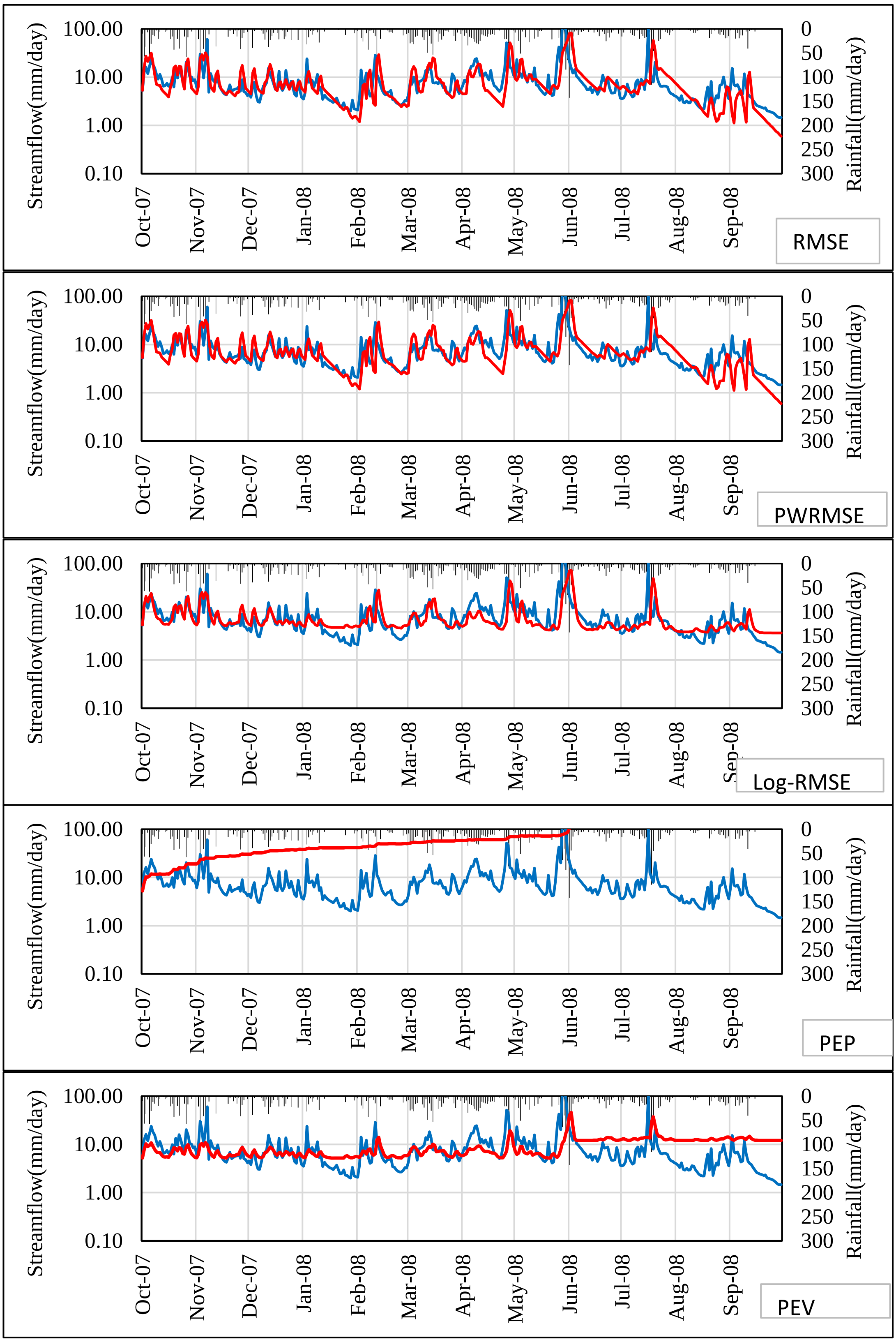


Figure D 1:Flow hydrograph matching for each objective function-I

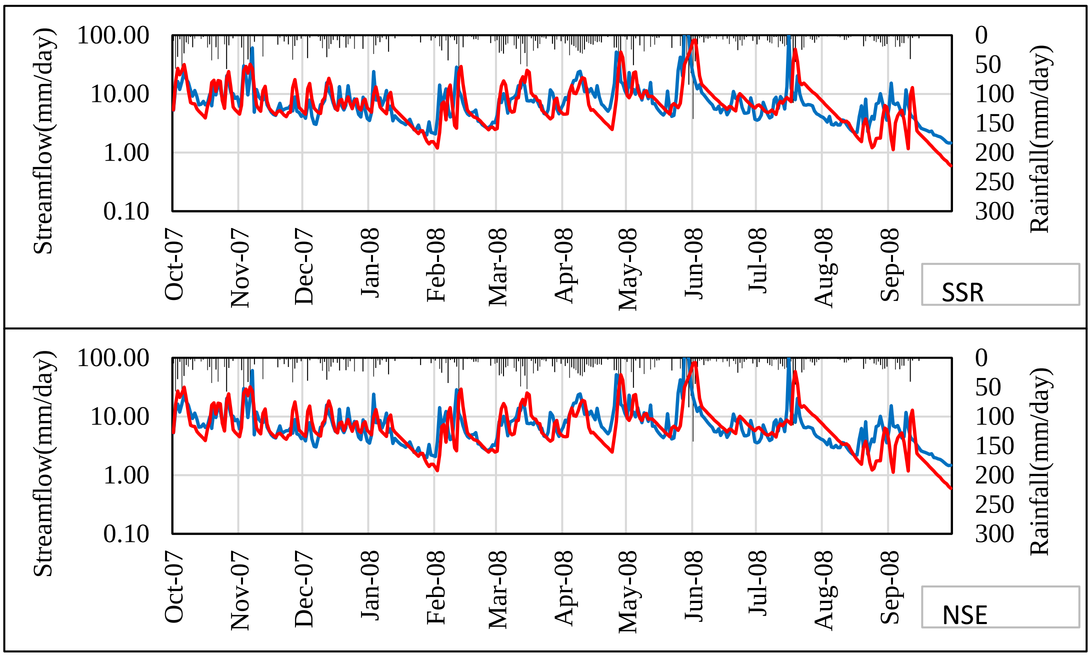


Figure D 2:Flow hydrograph matching for each objective function-II

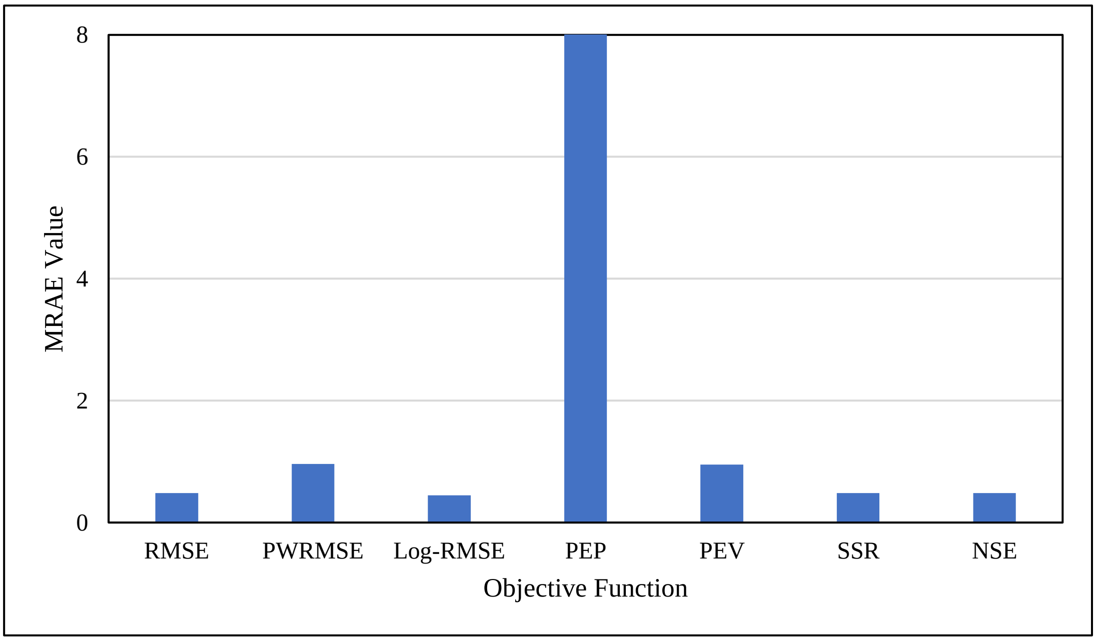


Figure D 3:Flow hydrograph matching indicator for each objective function

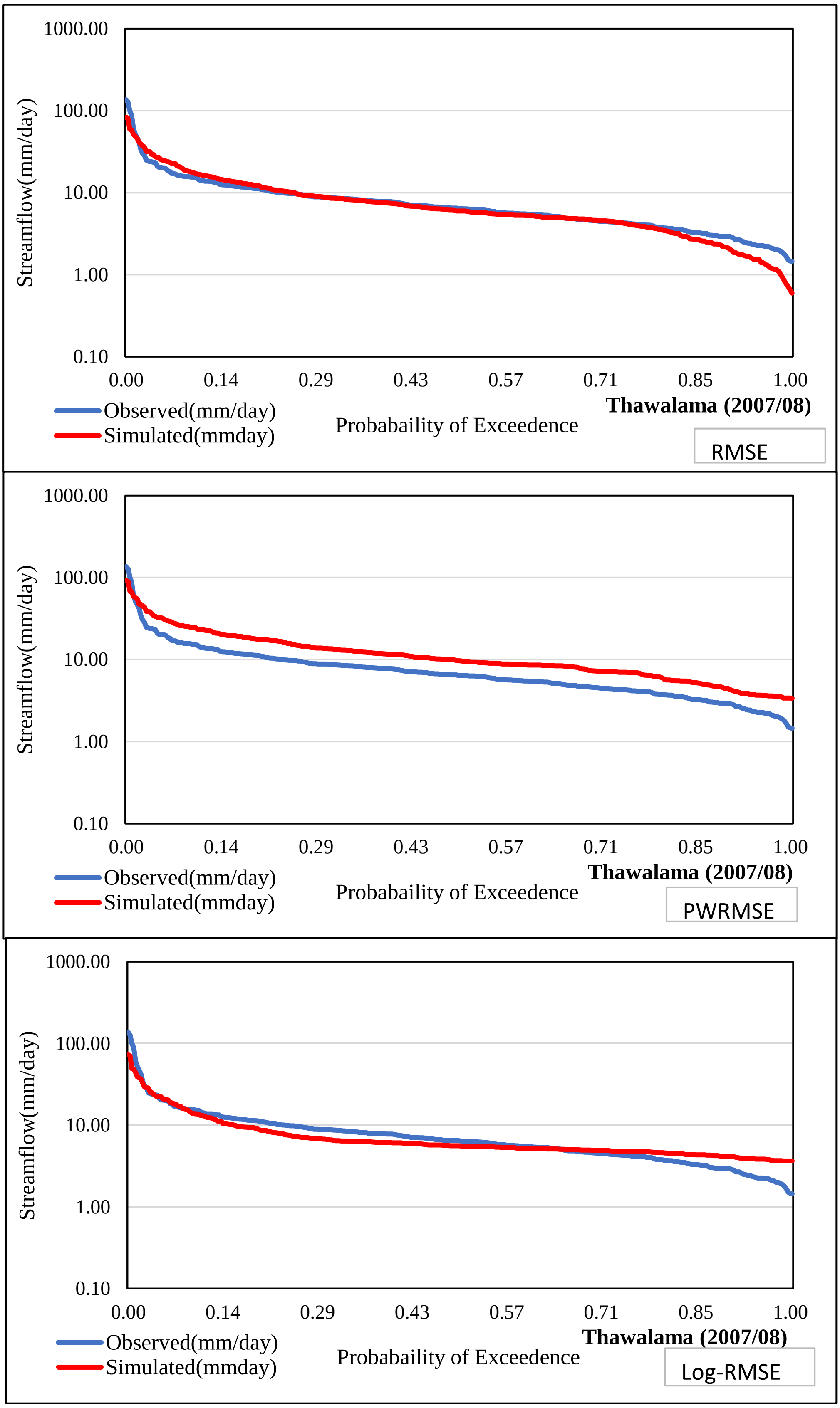


Figure D 4:FDC matching for each objective function-I

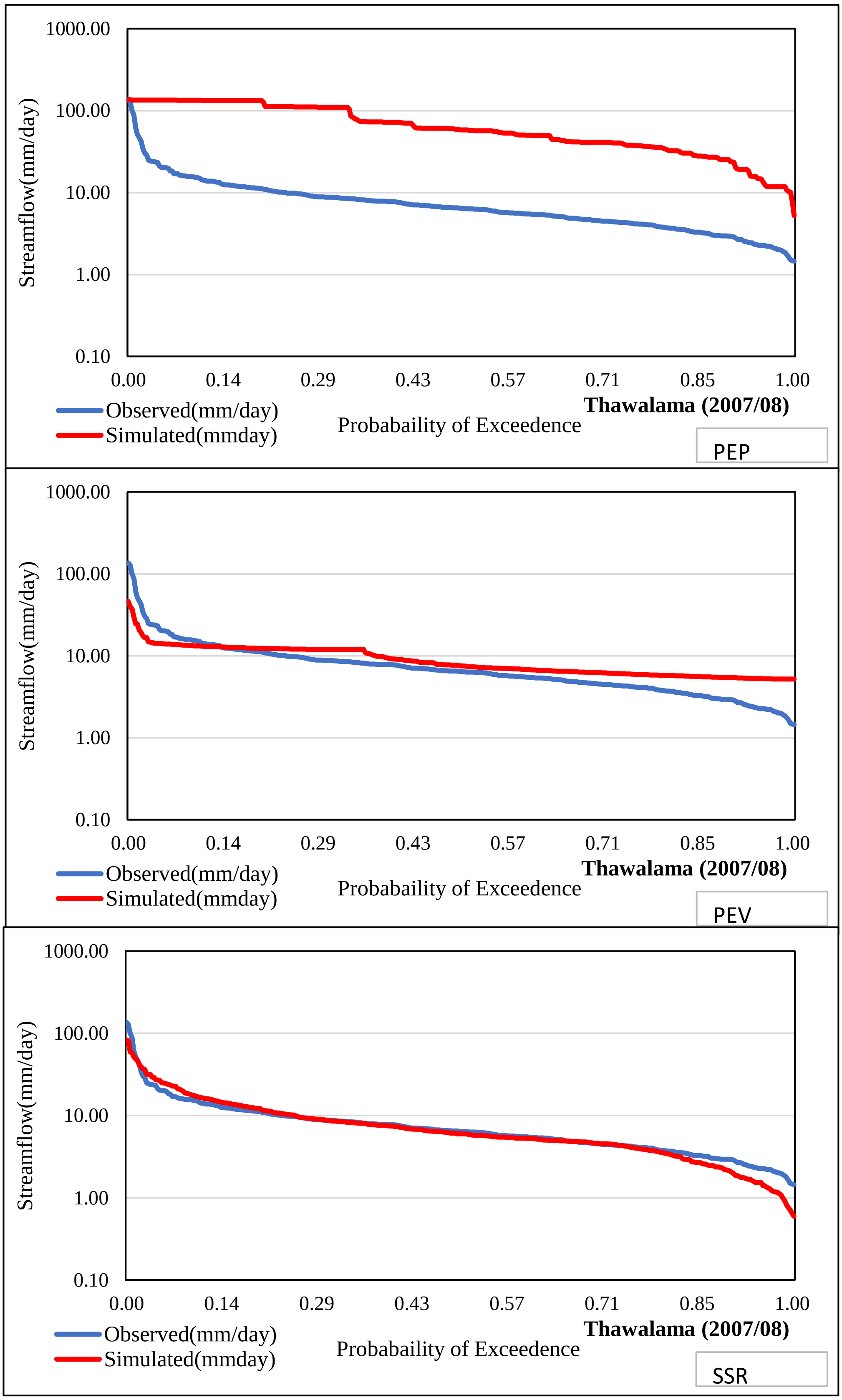


Figure D 5:FDC matching for each objective function-II

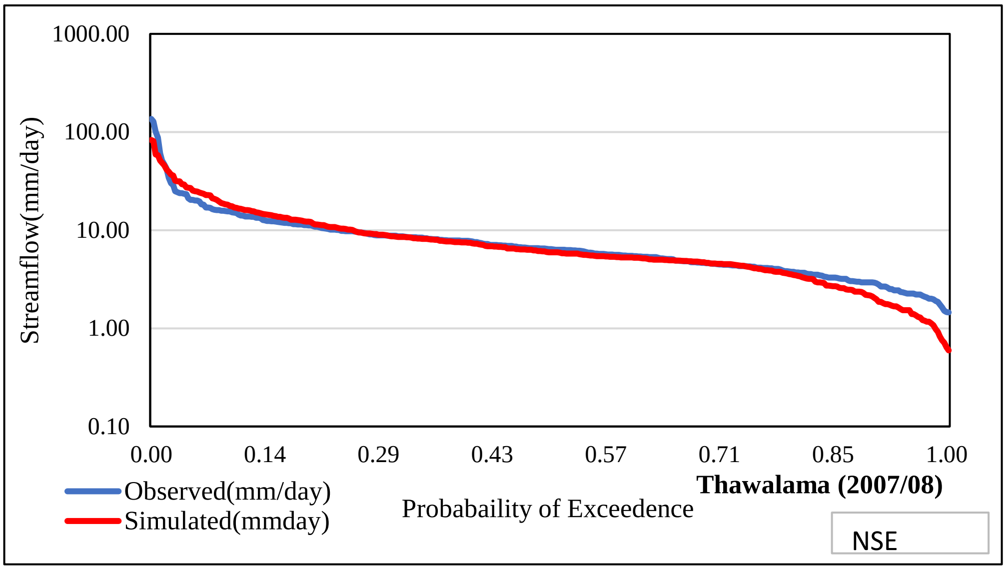


Figure D 6:FDC matching for each objective function-III

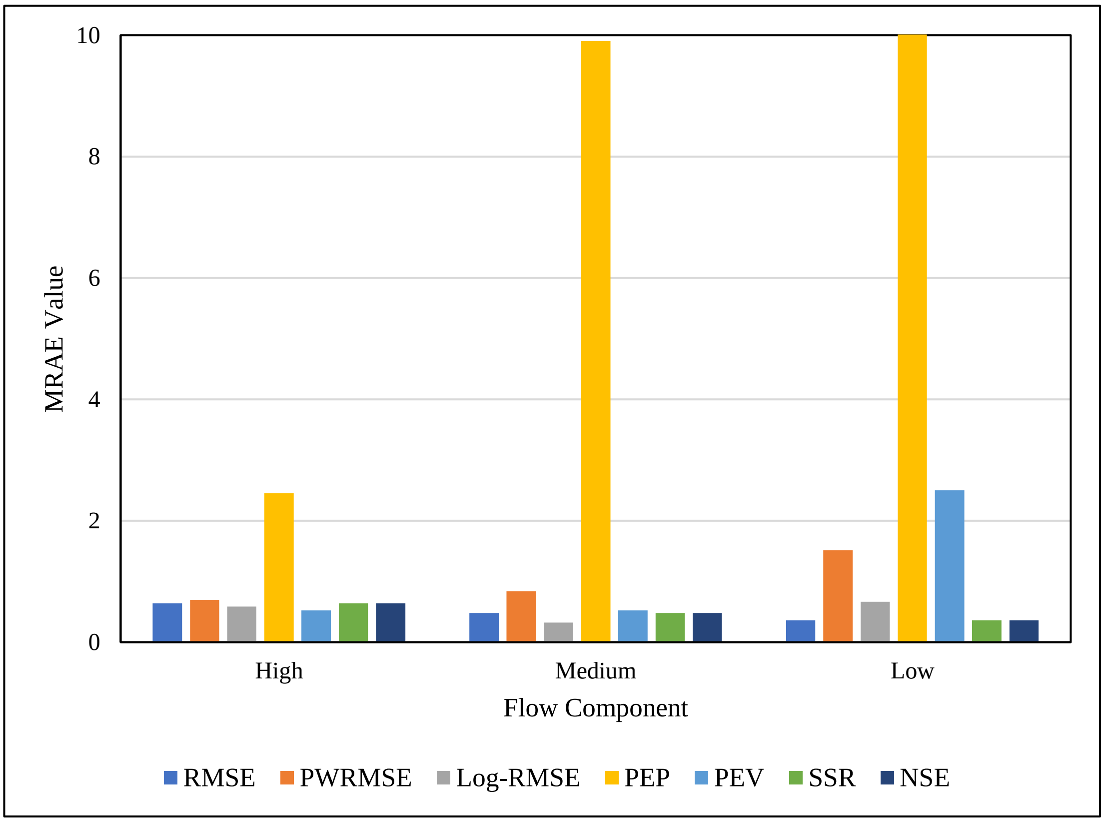


Figure D 7:FDC matching for high, medium and low flows for each objective function

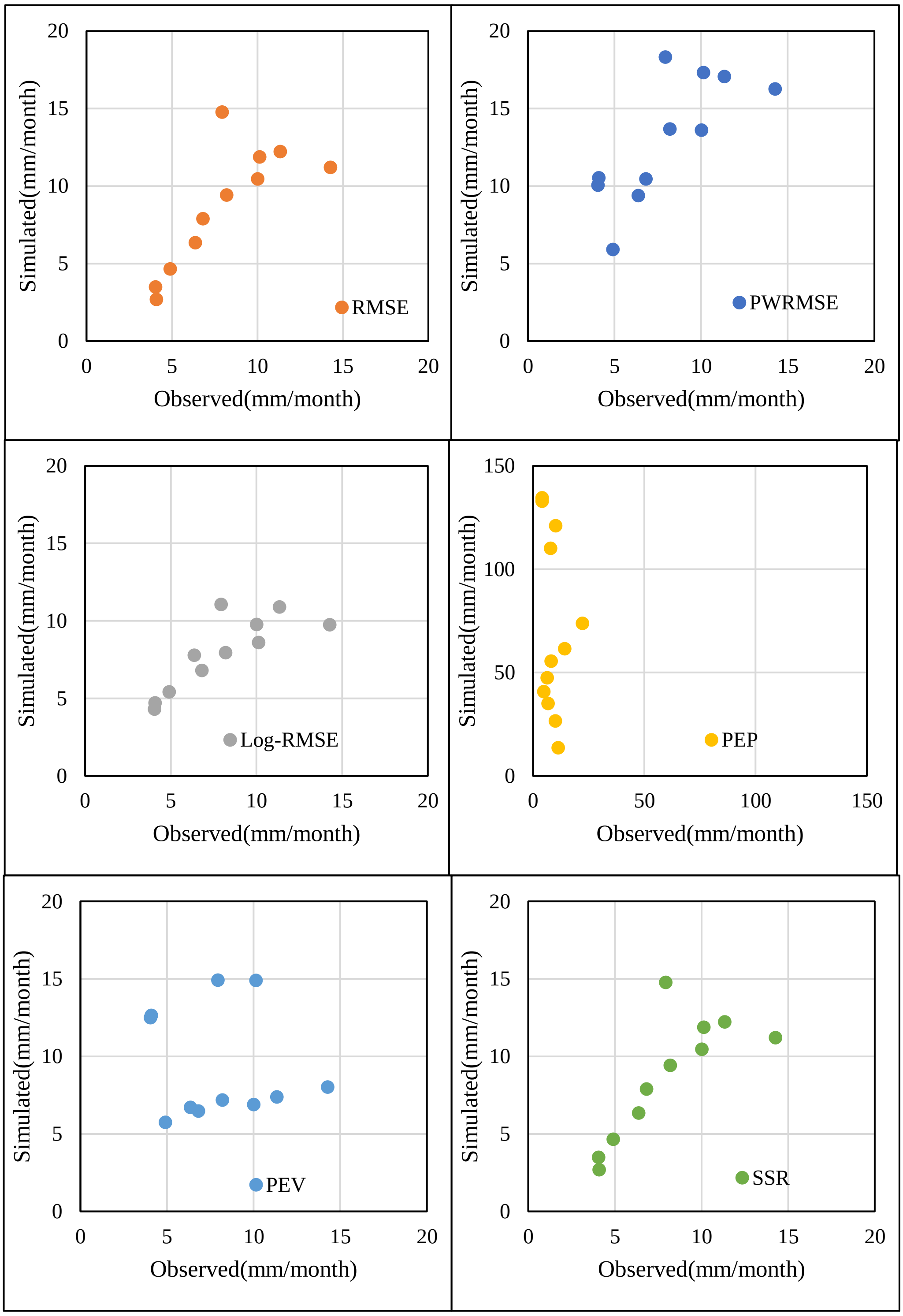


Figure D 8:Monthly simulated vs observed SF for each objective function-I

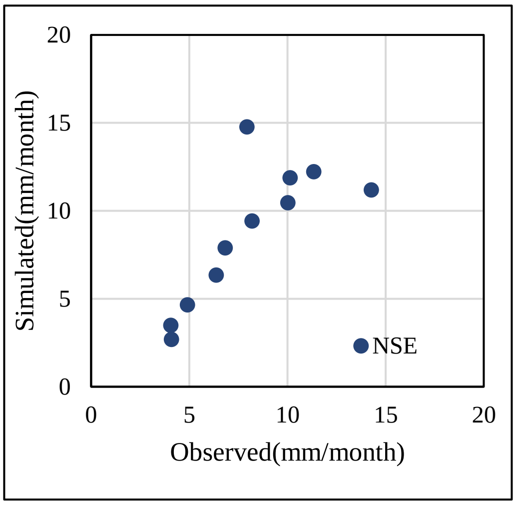


Figure D 9:Monthly simulated vs observed SF for each objective function-II

APPENDIX E: CANOPY STORAGE, WARM UP AND FLOW COMPONENT

Table E 1:Maximum canopy level at Thawalama according to vegetation cover

Type of vegetation	max canopy(mm)	Area%	weighted storage
species of vegetation is not directly known	1.27	6.18%	0.07854
grasses and deciduous trees	2.302	77.34%	1.78043
coniferous trees	2.54	0.01%	0.00032
other	0	16.46%	0
Overall Maximum Canopy(mm)		100.00%	**0.465**

Table E 2:Maximum canopy level at Baddegama according to vegetation cover

Type of vegetation	max canopy(mm)	Area%	weighted storage
species of vegetation is not directly known	1.27	3.47%	0.04408
grasses and deciduous trees	2.302	71.25%	1.64029
coniferous trees	2.54	0.01%	0.00018
other	0	25.27%	0
Overall Maximum Canopy(mm)		100.00%	**0.421**

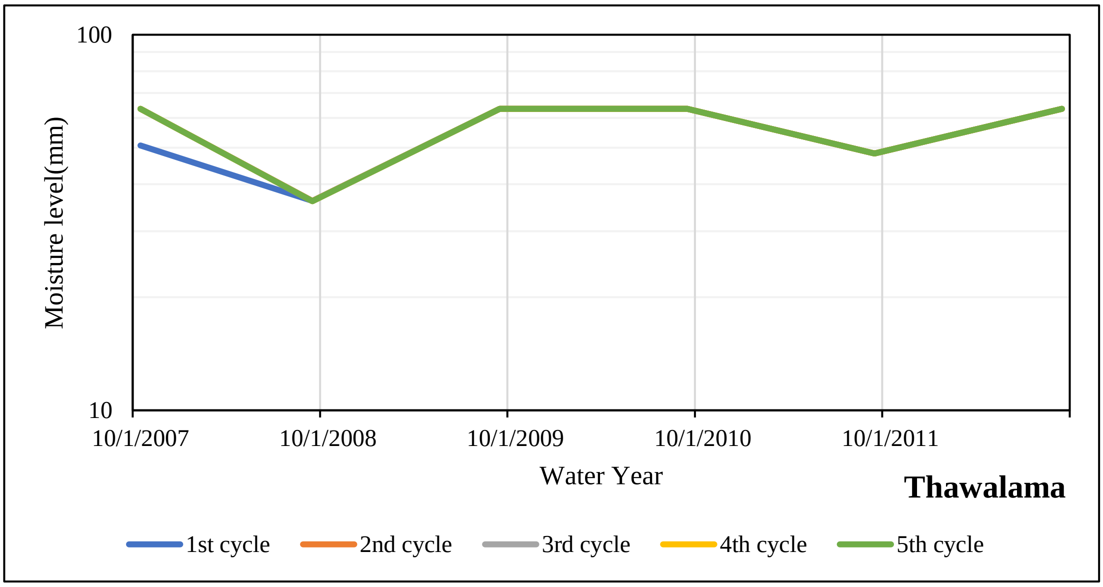


Figure E 1:Soil moisture level during warm-up period at Thawalama

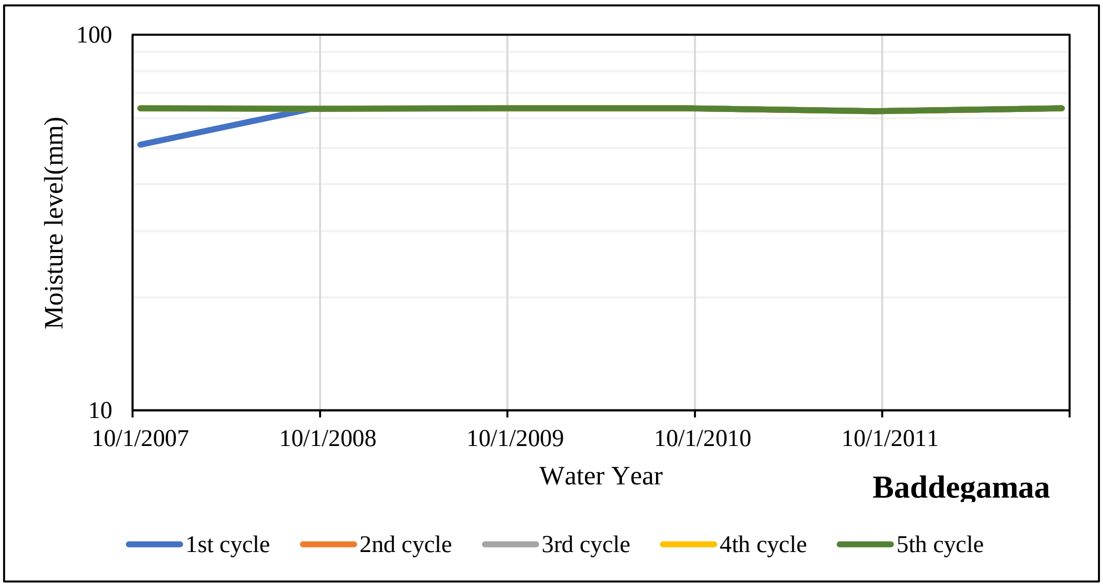


Figure E 2:Soil moisture level during warm-up period at Baddegama

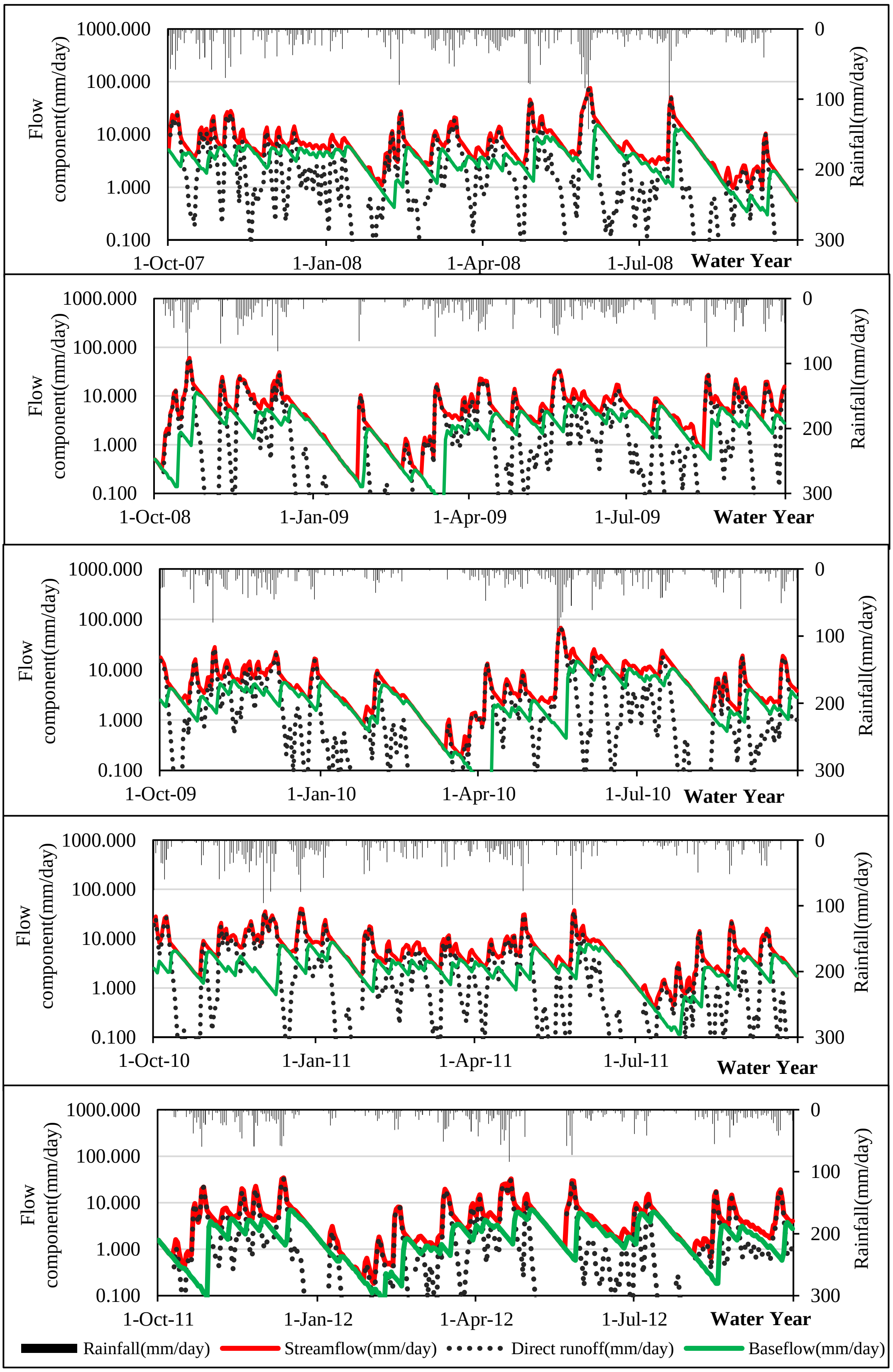


Figure E 3:Flow component during warm-up at Thawalama

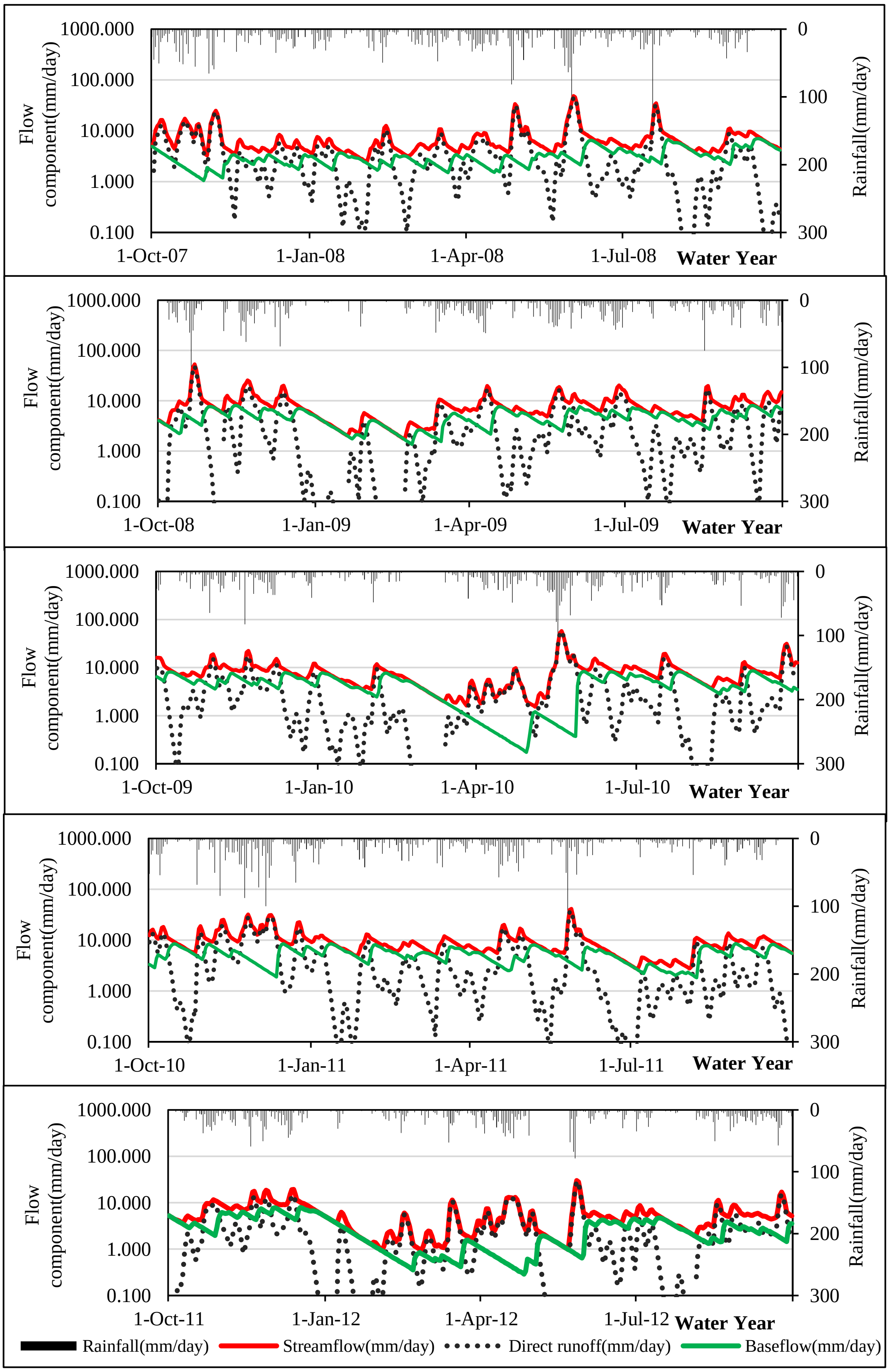


Figure E 4:Flow component during warm-up at Baddegama