# APPLICABILITY OF MODEL PARAMETER TRANSFERABILITY OF TANK MODEL IN STREAMFLOW SIMULATION IN GIN RIVER BASIN


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Degree of Master of Science in

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

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## DECLARATION

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

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

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Professor N.T.S. Wijesekera Date

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## ABSTRACT

Amidst of the population growth and increased demand due to rising level of living standard, stress on the water resources has been increased rapidly in recent years. Water practitioners, researchers have been stressing on the need of development of water resources in integrated and cohesive manner. Hydrological modelling has become the essential tool for planning and designing of water resources development as it gives the quantity of water available. Many modelers face the problem of developing solutions at ungauged basins. Typically, hydrological models are developed at gauged locations and whenever necessary, modelers tend to use the same model structure with verified parameters. This is a gray area in hydrological society as the model transferability is yet to be convinced. The need of more researches is essential in this regard for increase confidence of use of model parameter transferability.

This study developed a lumped conceptual tank model with four tanks for simulating streamflow in Gin Ganga basin at Tawalama and Baddegama and appraise the effectiveness of the model parameter transferability in ungauged basins of Gin basin. Model is developed in MS Excel and multi-start GRG-nonlinear search engine is used as parameter optimizing method while employing Mean Ratio of Absolute Error (MRAE) as the objective function to evaluate goodness of fit of the optimized parameters. Daily precipitation and evaporation data from water years 2008/09 to 2017/18 is used for the modeling. Model was warmed up using five water years to stabilize soil moisture in each calibration and validation. Calibration for each catchment was done using first five years of data and validation was done using remaining portion of data. Thereafter, optimized parameters were transferred under spatiotemporal, spatial and temporal approaches to simulate the flow of each catchment. Then model performance was evaluated in each scenario by comparing goodness of fit, annual water balances, flow hydrographs and flow duration curves for low, high, and medium.

The models were calibrated at Baddegama and Tawalama with MRAE value of 0.233 and 0.246 respectively for daily streamflow simulation. Then both models were validated for the two location with MRAE of 0.298 and 0.346 respectively. Better matching in high and medium flow is observed while average annual water balance error varying from 1.7% to 19% on average. All three transferability methods showed adequate results while maintaining accuracy ranges from 59% to 72% in daily streamflow simulation and model predicted average annual and average monthly flow estimations with an accuracy of 81% and 77% respectively under any transferability approach. Among the three approaches spatial transferability is selected as the best since it shows streamflow simulation accuracy over 66% and annual water balance errors varying with 1.7% to 3.4% on average. Further, spatiotemporal transfer method shows accuracy over 56% and temporal transfer has showed accuracy over 69% in daily streamflow simulation. In all modelling effort it was observed that accuracy of monthly flow estimations was over 77% and accuracy of annual water balance was over 81% on average.

Finally, the model could be used to predict daily streamflow with an accuracy of 68% and monthly scale flow estimations with an accuracy of 89% by applying either set of optimized parameters, indicating the model suitability for parameter transferability & water management in ungauged catchments in Gin Ganga basin.



**Key Words:** Conceptual Lumped Tank model, Parameter regionalization, Hydrological modelling, ungauged catchment, water resources management, Daily data

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| Abbreviation | Description |
|---|---|
| AWB | Annual Water Balance |
| FDC | Flow Duration Curve |
| MAR | Mean Annual Rainfall |
| MRAE | Mean Ratio of Absolute Error |
| RF | Rainfall |
| SF | Streamflow |
| WMO | World Meteorological Organization |

# 1 Introduction

## 1.1 Water Resources Planning and Management

Global population expansion and increased demand due to rising level of living standard amidst growing expectations, have developed primary concerns on the resources of air, water, and land resources. It is understood that demand on these resources should be developed and managed in an integrated and cohesive manner (Singh & Frevert, 2001). In recent years, water stress and water crisis have become commonly referred phrases whenever water resources around the globe are mentioned. WHO has mentioned that water scarcity is already affecting four out of ten people and 2.1 billion people lack access to safe drinking water while 4.5 billion People lack safely managed sanitation services. 90% of all natural disasters around the globe are water related; agriculture accounts for 70% of global water withdrawal; and around two-thirds of world's trans-boundary rivers do not have a cooperative management framework (Water, 2015). According to many this situation is to get worse in the coming future and in order to alleviate this with sustainable management methods, it is of utmost importance to find options for accurate streamflow predictions.

Application of integrated water resources managment principles for sustainable water development it is necessary to posses a better understanding of the enviornmental, socio-economic, and cultural, environments together with accurate water quantity and water quality data such as riverflows and abstraction (Mcdonnell, 2008). Furthermore, the mathematical models need to have to capability to accurately and reliably predict streamflows for the rational decision making on the manatement of water resources, natural disasters or the natural enviornment (Sivapalan et al., 2003). Such streamflow estimation capabilities are considered especially important for the design of hydraulic structures, flood protection engineering, reservoir operations, implementation of water resources development projects etc. (Cao Don et al., 2005).

Water managers often face the tedious and challenging task of water allocation and building of water related infrastructure for various purposes. Hence water resources planning has become a critical exercise. It is a complex process because water resources systems consist of many elements such as rivers, canals, pumping station and reservoirs which consist of many structures having many different objectives (Plate, 1993). Therefore, mathematical rainfall runoff modelling is fundamental for water resources planning, design and management (Singh & Frevert, 2001). Some mathematical models focus on the strengthening of knowledge on hydrological processes while there are models such as regression models which only targets an accurate prediction of watershed streamflow for improved decision making (K. Beven, 2012).

## 1.2 Ungauged Catchment Modelling

An ungauged basin is essentially a basin with inadequate records of hydrological observation both in terms of quality and quantity. Predication in ungauged basin means that hydrological response being predicted with no possibility or allowance for direct calibration (Sivapalan et al., 2003).

Drainage basins of many parts of the world are either ungauged or poorly gauged and even at some locations existing measurement infrastructures are deteriorating. Lack of gauged data does not enable calibration and verification of models and the determination of model parameters. Hence, there is a huge challenge to accurately predict streamflow of these basins to prevent further deterioration of ecosystems while underpinning sustainable management and this is often carried out by assuming that past data can be used to predict future and data or parameters derive for another can be safely used for predictions of hydrological response of other basins (Sivapalan et al., 2003). However, these options that include assuming data from gauged catchment can be used elsewhere will cause great deal of uncertainty in model outputs and this could be improved with better understanding of hydrological progresses and reduced uncertainties associated with the models (Bourdin et al., 2012).

Transferring streamflow measurements, models and or model parameters from gauged watersheds are the commonly used options for streamflow estimation in ungauged watersheds. The mostly used options are arithmetic mean method, spatial- proximity method, physical similarity method, scaling relationships, and regression based methods (Razavi et al., 2012).

Even though there are many references on streamflow transferability, specific recommendations for in basin transfer of parameters for many models remain an area of research. In case of such situations at least the accuracies that could be expected is a valuable information for a practicing watershed manager or a water engineer.

There are different opinions on model parameter transferability. As examples, Van der Linden & Woo (2003), while reporting that parameters can be transferable between sub basins of similar size and characteristics, have indicated that parameters of larger basin calibrated at outlet are less suitable for predictions of sub-basins. Broderick, Matthews, Wilby, Bastola, & Murphy (2016), had identified that transferability with respect to different climate periods produce results dependent on the testing scenario. The detail discussion on regionalization can be found on Section 2.3.

Hence it is of high importance to carry out a focused research to identify the accuracy that could be expected when transferring model parameters within the same river basin. Such research would especially help reliable water resources management and water infrastructure planning when there is only handful of stream gauges in a particular river basin.

## 1.3 Model Selection Options

Hydrological modelling has evolved to present many mathematical modelling options for the mathematical representation of a watershed heterogeneity. There are three main categories with respect to model representation of the spatial domain. They are lumped, semi distributed, and distributed models. The model structures also vary between empirical, conceptual and physics based (K. Beven, 2012; Chow et al., 1988; Sitterson et al., 2017)

Lumped conceptual models are considered as more hydrologically sound than empirical, with simple and easily understandable structures. Lumped models treat the watershed as a single unit. However, there are semi-lumped modelling approaches where several lumped models are combined to represent sub basins (Bourdin et al., 2012; Singh & Frevert, 2001). Tank model, XINANJIANG model, HBV model, TOP model, IHACRES, and SACRAMENTO model are some examples of conceptual models (Cao Don et al., 2005).

Most preferred model option is the simplest one that leads to reliable streamflow predictions and it has been demonstrated that very simple models can achieve the model performances similar to models with more parameters while avoiding the threat of over-parametrization (Perrin et al., 2001). Simple models are also preferred because they reduce the effects due to parameter uncertainty. However, if the model fails to adequately explain the matching with observed data, then model simplicity does not hold anymore. Similar findings have been cited by Sitterson et al., 2017 on their overview of rainfall runoff modelling. Further, it is noted AI based (Neural networks) modelling, general use of increase number parameters gives the model more freedom in calibration but certainly increase the chance of overparameterization while increasing uncertainty in predictions or extrapolation. And this will results model to not make accurate predictions when predicting outside the range of data which model has been calibrated (K. J. Beven, 2012).

The Tank Model is one of the famous lumped conceptual models used in Japan and Asian countries for streamflow predictions. There have been many applications of Tank models world over (Section 2.2.2). Also there are tank model applications in the "Kalu" River and "Mahaweli" River of Sri Lanka by Wijesekera and Musiake (Musiake & Wijesekera, 1990). Through the applicability of Tank Model for tropic has been documented, there is no systematic study pointing to the possibility of sharing or transferring model parameters for either nearby watersheds or in-basin estimations.

## 1.4 Temporal Resolution

Data resolution is an important consideration when mathematically modelling watershed. Daily data are considered more important for flood simulation and flood protection works while monthly data are recommended for water allocation and planning works such as irrigation, hydropower (Tessema, 2011). Kavetski, Fenicia, & Clark (2011) compared sub-daily and daily data impact on modelling and found out that mostly slow dynamics are invariant for data scale while fast dynamics are predicted with increase precision as data resolution is increased. Moreover, daily variations of the streamflow of a watershed can be easily comprehend when attempting to verify the modelling accuracies. However, monthly data are easily accessible, and less costly when compared with daily data of same data duration (Meterological Department, n.d.). Monthly data are the most commonly used temporal resolution for water resources planning in Sri Lanka (Ponrajah, 1984). Even though for water resources applications daily data would be preferred if available.

## 1.5 Research Gap

There is a lack of information for the transfer of parameters when using a simple lumped model for a daily time scale application. There is also lack of guidance to transfer of parameters of the tank model which has a very simple model structure and many successful applications. Two catchments gauged at Baddegama and Tawalama of Gin Ganga basin in the wet zone of Sri Lanka were selected to investigate the applicability of Tank model and study the accuracy of direct parameter transferability.

## 1.6 Overall Objective

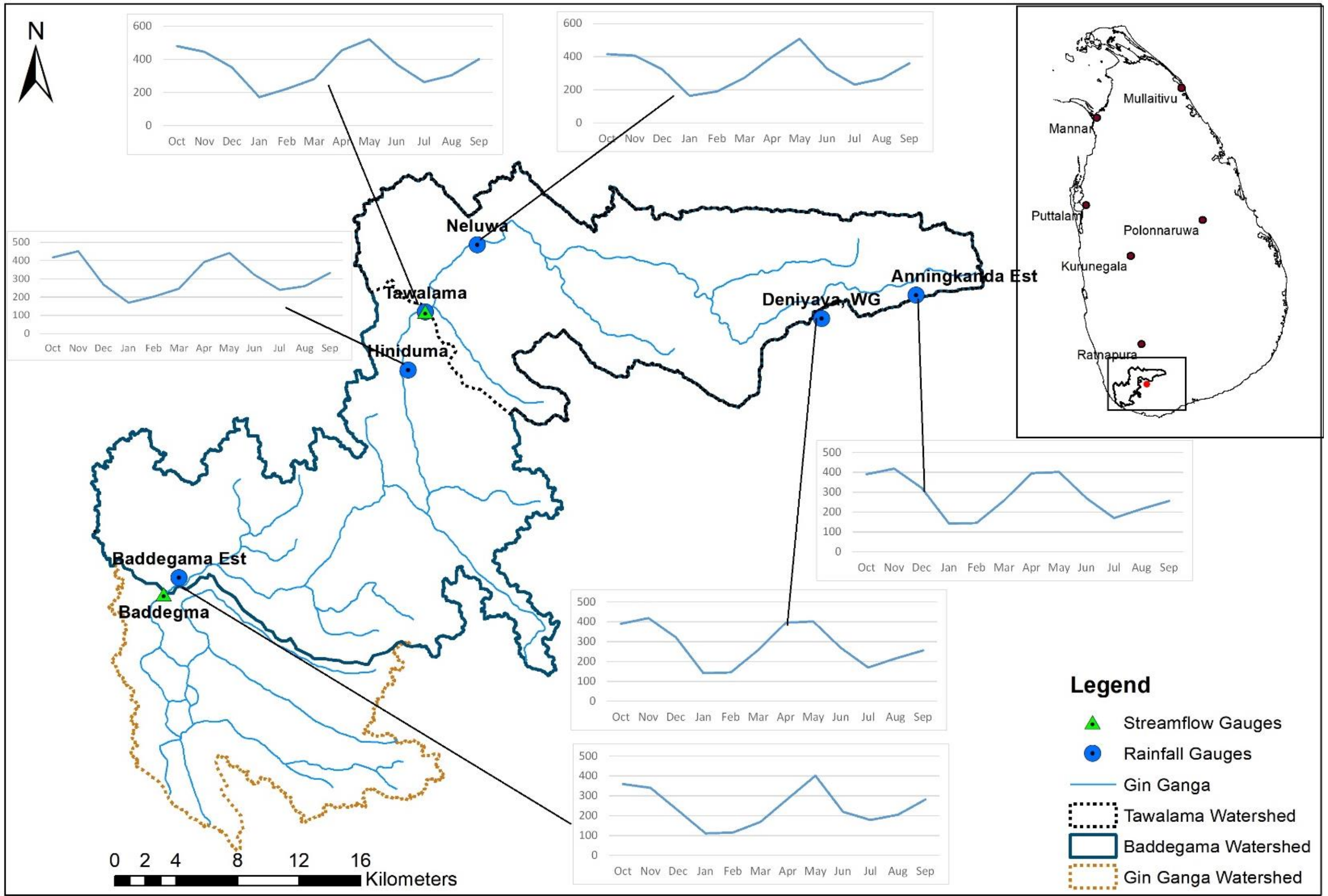
To identify the parameter transferability of the tank model structure in the Gin River Basin of Sri Lanka to estimate the streamflow of ungauged watersheds for sustainable water infrastructure planning design and management.

### 1.6.1 Specific Objectives

1. State of art literature review on application of lumped models for streamflow predictions and parameter transferability.
2. Data collection and model development for Baddegama and Tawalama catchments in Gin River.
3. Model calibration and verification for both catchments.
4. Evaluation of model parameter transferability from main catchment to sub catchments and vice versa.
5. Conclusion on effectiveness of model parameter transferability for predicting ungauged basins.

## 1.7 Study Area

The Gin Ganga basin is located roughly between longitudes of $80^0$ 08" E and $80^0$ 40" E and latitudes of $6^0$ 04" N and $6^0$ 30" N. Basin has an area of 943 $km^2$. The length of the river is typically quoted as 113 km, originating near Gonagala Kanda which has elevation over 1300 m. Over 80% basin is located in Galle district and Matara, Ratnapura, Kalutara district share the remaining. Land use of the area is dominated by agriculture while considerable area in mid and upper catchment has forest cover. Agriculture, homestead/ home gardens occur throughout the basin. Rainfall in the area varies with altitude with mean annual rainfall ranges between 2500 and 3500 mm. Meanwhile the temperature varies between $24^{0}$C to 32 $^{0}$C with high humidity levels. Annual discharge is 1268 Million $m^3$. Rainfall pattern is bimodal falling from May to September and November to February (Wickramaarachchi et al., 2012). Since the most low-lying area of the basin is flooded during rainy seasons it considered to be main hazard in the region. Most recent flood has been reported in year 2017, 2018 and 2019. As complete basin is situated on wet zone significant amount of water available for water usage but water shortage is reported in dry seasons and there is a need for water resources development in the area.




Original in Color

Figure 1-1: Study Area

# 2 Literature Review

Streamflow predictions in a watershed has become the best available information for water resources managers to plan sustainable development of the water resources. Often this can be a tedious task in ungauged watersheds due to unavailability of gauged streamflow measurements. Hence it is utmost important to identify the methods available to model ungauged watersheds successfully when the main watershed is gauged and modelled accurately. This has been identified as a research gap as the proper guidance on how the transferring of streamflow measurements, model or model parameters for many popular hydrological models are not covered in detail and yet to be fully understood.

Main objective of this literature review is to identify a lumped conceptual model to effectively analyze the hydrologic model transferability for the purpose of streamflow predictions in ungauged watersheds. In this regard, a literature review using scientific search engines and peer reviewed researches were carried out and summarized to capture the state of art streamflow transfer methods available for lumped conceptual models. Thereafter focused review on how the tank model has been used in estimating ungauged watersheds streamflow within the basin or nearby watersheds is carried out for identifying the research gap for tank model or model parameter transferability.

## 2.1 Hydrological (Runoff) Modelling

In reality all hydrologic systems are approximation of the actual system which combine its hydrological inputs and outputs by the use of concept of system transformation. Broadly speaking hydrological models are classified as physical and abstract model. Physical models represent the system in a reduced physical form while abstract models represent the systems in mathematical form (Chow et al., 1988). Chow, Maidment, & Mays (1988) has pointed out in their "Applied Hydrology" book that abstract models can be categorized according to how they treat randomness of variables, their behavior in space and time. Models can be deterministic if it does not account for randomness of the variables and if it does it is called stochastic models. Models can be differentiated according to the way they determined the runoff. Categorization according to this separates models as empirical, conceptual and physics based. Model can be further divided as lumped, semi distributed and distributed according to spatial interpretation of the hydrologic system (Sitterson et al., 2017).

Empirical models are called date driven models or black box models as they use non-linear statistical relationships to estimate runoff (Sitterson et al., 2017). These models include mathematical equations which has no relation to physical processes of catchment. Unit Hydrograph, Artificial neural network, and fuzzy regression are some example of empirical models (Devia et al., 2015).

Conceptual rainfall runoff model uses simple mathematical equations to represent conversion of rainfall to runoff, evapotranspiration and other water movements. these models based on the concept of reservoir storages (tanks or buckets) that represent water held in various forms such as soil moisture, groundwater etc. Most of the time these models are example of lumped model as well and their complexity vary according to number of catchment processes they try to simulate (Vaze et al., 2011). It is noted model parameters not always have a physical relationship hence at least some parameters have to be estimated through calibration against observed data (Pechlivanidis et al., 2011). Tank model, XINANJIANG model, HBV model, TOP model, IHACRES, and SACRAMENTO model are some examples of conceptual models (Cao Don et al., 2005).

Physics-based models represent hydrological processes using the governing equations of motion which based on continuum mechanics. These equations are solved numerical methods. Conservation of mass and energy, momentum, and kinematics. St. Venant, Boussinesq's, Darcy, and Richard's are some of the equations adopted by these models (Pechlivanidis et al., 2011). Physics based methods take in to consideration of spatial and temporal variations within the catchment. They are desired when precise data are available and hydrological process are accurately understood. They use fine scales of computation. The large requirement of data often limits their usage. VELMA, VIC, MIKE SHE, PIHM are example of some physics-based models (Sitterson et al., 2017).

Lumped models consider the whole watershed as a single unit. All the variables are averaged over entire basin, while disregarding spatial variability of processes, inputs, boundary conditions, geometric characteristics. In contrast distributed models considers spatial variability and average parameters values at grid scale while producing outputs for every grid (Pechlivanidis et al., 2011). Unlike lumped model distributed model can estimate variables at different points of catchment whereas lumped model produce estimates at outlet only (Orellana et al., 2008).

Meanwhile semi-distributed models combine advantages of both types of spatial representation while dividing the catchment at discrete of the modeler as he thinks it may be useful thus enabling representing important features of the catchment. It conceptualize the catchment through network of sub units and a parsimonious model can be applied to each sub unit (Orellana et al., 2008). In Semi-distributed model watershed is divided into smaller sub-watershed, elevation bands, or hydrologically homogeneous units, thus avoiding averaging parameter values over a larger heterogeneous areas (Bourdin et al., 2012). UBCWM (which based one area –elevation zones), HBV-EC (is an extend version of HBV which discretization of climate zones) and SWAT and TOPMODEL based on HRU (hydrological response units) are some example of semi-distributed models (Bourdin et al., 2012).

## 2.2 Model Selection

The availability of many models as cited above, increase the complexity of model selection by a modeler. Though there are many models no single model can be considered as universal. With availability of many model and no clear guidelines modelers always face the problems of determining the perfect model for their watershed (Marshall et al., 2005). Gan, Dlamini, & Biftu (1997) noted three issues to be addressed when selecting conceptual rainfall runoff models. First issue is that model should capture the major hydrological processes of the catchments, secondly the time steps used in model should be small enough to represent the rate of change of the processes under consideration, and thirdly model calibration should be done properly to avoid erroneous results.

Methodologies have been developed by researches to select best parsimonious model for a catchment considering the uncertainty of a model. Marshall et al. (2005) developed Bayesian framework which use Bayes factors to select best version of Australian Water balance model (AWBM) for Murray Darlin basin in Australia. Bai et al. (2009) suggest a fuzzy top-down model evaluation and selection method by comparing 12 US catchments with conceptual models of different complexities. Even in these studies the methods described tend to stick with the simplest models which estimated the streamflow adequately.

Perrin et al. (2001) analyze the 19 lumped models with varying complexity to 429 catchments in US, Australia, Ivory Coast and Brazil and concluded that complex model outperformed simple one in calibration and not in verification mode and argue that complex model lack the stability and tend to over-parameterization and parameter uncertainty. Study reveals that parsimonious models can yield promising results hence should be preferred in further developments.

Often it is suggested that model selection should be based on project objective, data availability, catchment characteristics, output requirement, simplicity desired, user friendliness, and computational cost etc. (Pechlivanidis et al., 2011; Sitterson et al., 2017).

Also, it is noted that for predictions of streamflow in ungauged basin through conceptual models has been preferred as less complex conceptual lumped models are equally reliable for predictions of streamflow. Whereas physically based model results high uncertainty in ungauged catchments due to demand for physical catchments attributes for derivation of parameters and sometimes cause over parameterization as well. Also, such models require considerable data and human effort compared to conceptual or semi-distributed model. Therefore non-distributed models preferred in ungauged basins (Goswami et al., 2007; Razavi et al., 2012; Shu & Ouarda, 2012).

Hence it is decided that simple lumped conceptual model which can pick streamflow response to the precipitation would be good enough to achieve the objective of the study i.e. parameter transferability for determination of streamflow at ungauged basin.

### 2.2.1 Status of Lumped Conceptual Model

As cited above lumped conceptual model considers area under study as a single unit and conceptualize the watershed as series of tanks. Often these models are preferred by the researches due to its simplicity, understandability and less data requirements. Majority of these models need rainfall and evaporation as input data. Often lumped models compute the results for single outlet as contrast to physics-based method in which results can be obtain for interior points of catchment. This often lead to fast computation times (Sitterson et al., 2017).

The simpler the structure is, the less the number of parameters becomes. This is helpful when calibrating parameters, but less general to accommodating various elements. On the other hand, a more complicated structure may be closer to the real watershed structure, but makes parameter calibration more difficult (Paik et al., 2005).

Through the literature review it has been identified among other objectives, lumped conceptual model has been used for streamflow regionalization extensively due to its simplicity and less data requirement for estimation of streamflow in ungauged basin(e.g. Broderick et al., 2016; Goswami, O'Connor, & Bhattarai, 2007; Samuel, Coulibaly, & Metcalfe, 2011; Van Der Linden & Woo, 2003; Young, 2006). This identification has led to selecting of conceptual model for analyzing parameter transferability in Sri Lankan context.

### 2.2.2 Tank Model

Tank model originally developed by M. Sugawara is well known lumped conceptual model. It is developed contemplating conditions of Japan's humid watersheds and hence well accepted within Japan (Singh & Frevert, 2001).

Standard tank model is a simple linear storage system which consist with 04 tanks vertically. Precipitation is put into top of the tank. The evaporation is subtracted from the top tank and if water is absent for complete deduction it will be deducted from subsequent second, third or fourth tanks. Each tank has side outlets and bottom outlets which shows runoff and infiltration from each tank respectively. The output from side outlet of top tank considers to be surface runoff, output from second tank considers to be intermediate runoff and outputs from third and fourth tanks are considered to be sub-base flow and baseflow respectively (Sugawara, 1995).

Tank model with four tanks structure is used to analyze daily discharge from daily precipitation and evaporation inputs. Here the concept of initial loss is included in the non-linear structure of the model. When used for flood analysis the third and fourth tanks are replaced by constant discharge as the flows from lower tanks are negligible part in large flood discharges (Paik et al., 2005; Sugawara, 1995)

Tank model was extensively developed by M. Sugawara during the period of 1957-1984 where he analyzed the application of tank model to several Japanese watersheds, developing tank model with snow component, accommodating soil moisture and irrigation intake on tank model and automatic calibration of the tank model (Sugawara, M. (1957, 1967, 1979, 1984) Sugawara, M., et al. (1974)).

Tank model has been applied in wide range of watersheds around the globe for estimating streamflow (e.g.: Japan (Fukuda *et al.*, 1999, Sugawara, M., et al. 1974); Vietnam (Phien & Pradhan, 1983); Korea (Paik et al., 2005; Song et al., 2017) ; Indonesia (Basri, 2013; Setiawan et al., 2003); India ((Devaliya et al., 2017; Ramasastri, 1990); Malaysia (Kuok et al., 2010); Sri Lanka (Musiake & Wijesekera, 1990); Canada (Ou et al., 2017) USA, Ivory Coast, Brazil (Perrin et al., 2001). It can be clearly seen that tank model is popular among the researchers of the Asian countries and its usage in western countries is commendable.

Tank model structure which is used for this study is described in Section 3.3.

### 2.2.3 Tank Model Applications for Different Objectives

Tank model has been applied to analysis of urban storm water management by Ou et al. (2017) for Canada. Two types of tank model (two tanks to represent permeable zone and one tank to represent impermeable zone) has been developed using daily data to assess the impacts of imperviousness.

Similarly Basri (2013) suggested using different number of tanks to represent different land uses to avoid uncertainty cause by different soil, land cover. This paper has identified the different tanks namely garden tank, forest tank, paddy tank, and vacant tank which comprise different land use, soil combinations.

Paik et al. (2005) have developed a seasonal tank with 40 parameters as opposed to standard 12 parameters in which it allows varying of parameters seasonally. Concluded that though this will increase model complexity, it is more reliable in predicting seasonal variation in continuous modelling.

In Sri Lankan context, Musiake & Wijesekera (1990) applied the tank model with four tanks to part of Mahaweli basin and observed that introduction of spatial variability of rainfall and optimizing using Powell’s method improved the prediction results.

Often studies used different number of tanks while developing tank model. Kuok, Harun, & Chiu (2011) studied the watershed in Malaysia to identify the best number of tanks model for humid regions. This study cited that many researchers often resort to four tank model and concluded that tank model with four tanks are suitable for humid region either for daily or hourly simulation.

Tank model has been used in effort of regionalization with multiple regression models. Regionalization using tank model is assessed through changes in landscape metrics including mean shape index, mean perimeter-area ratio, mean patch size and patch density of land use/ land cover over 30 catchments in Germany. This has been done through multiple regression model and has been successful in estimating six parameters hence researcher concluded that regionalization of conceptual model should not be substitute for modeling practices since reliable regionalized models were not achieved for all the parameters of the tank model (Amiri et al., 2016). Similarly Yokoo, Kazama, Sawamoto, & Nishimura (2001) evaluates a method of linear regression which compare tank model parameters to basin geographical characteristics and having being success on two watersheds, suggested that parameters of the tank model can be directly attributed to basin characteristics.

### 2.2.4 Tank Model Optimization

Earlier tank model was optimized using trial and error method which needed good experience of using the model. It is understood that calibration of tank model is difficult due to its non-linear structure and difficulty in input/output analysis. Trial and error method utilize the shape and volume of the hydrograph for optimum calibration. To adjust high discharge, parameters of first tank will be adjusted, then by studying transient or intermediate flow that follow peak discharge, parameters of second tank will be adjusted. Finally by observing baseflow section of hydrograph parameters of third and fourth tank will be adjusted (Sugawara, 1979).

First initiative of automatic calibration is presented by Mr. Sugawara in his study of "Automatic Calibration of the Tank Model" in 1979. Phien & Pradhan (1983) pointed out this method is not based on standard optimization methods instead it relies trial and error method which carried out automatically by computer which use criteria of discharge volume and hydrograph shape as discussed earlier.

Later with the advancement of computers and algorithm many studies have been conducted towards the optimization of tank model parameters using various software and algorithms.

In its simplest form tool called solver in MS Excel is used with objective function of RMSE by Ou et al. (2017) for parameter optimization. Song et al. (2017) used Simulink extension of Matlab for developing the model and optimized through simplest forms such as Graphical analyses, such as scatter and time-series plots, errors in water balance and $R^2$, NSE, NSEInv, PBIAS.

In its advance form search/ optimizing algorithms has been applied for obtaining optimized calibrated parameters of tank model. Successful results obtained by applying Powell's method by Musiake & Wijesekera (1990) for the Mahaweli basin, Sri Lanka. Setiawan et al. (2003) applied Marquardt algorithm for two watersheds in Japan and Indonesia for estimating Tank model parameters and showed the effectiveness of the said algorithm. Paik et al. (2005) applied Powell's method and meta-heuristic algorithms, i.e. a genetic algorithm and harmony search for optimization in Daecheong dam basin, Korea and concluded that meta-heuristic algorithms outperformed the Powell's method owing to less erroneous parameter calibration, needlessness of setting initial parameter values, and freedom from numerical dispersions. Further, this study considered the development of modified harmony research and shows that it results in better optimization than GA, HS, and Powell. Global Optimization methods namely Genetic Algorithm (GA), Shuffle Complex Evolution (SCE) and Particle Swarm Optimization (PSO) are applied to storm event modelling using Tank model by Kuok et al. (2010) in Malaysia and concluded that PSO method outperformed the GA and SCE methods.

In summary it can be seen that no general agreement between researches on which optimization method should be used and hence it is decided that optimization methods are determined at researches discretion depending study objectives, previous studies in same region, availability, time and cost etc. In this study MS Excel Solver based GRG non-linear method is used as the optimization method. GRG stands for "Generalized reduced gradient" and it looks at the slope of the objective function as the input values to determine that it has yield an optimum value (Excel Solver: Which Solving Method Should I Choose? | EngineerExcel, n.d.).

## 2.3 Model Regionalization

Lack of adequate hydro- meteorological data at suitable spatial temporal scale often seen as a major problem in ungauged basins faced by hydrologists. This was highlighted by International Association of Hydrological Sciences (IAHS) in their declaration of decade (2003-2012) for predictions of ungauged basins and emphasized on necessity of improved regionalization or other methods to predict ungauged basin more accurately as the most of the basin around the globe are ungauged (Sivapalan et al., 2003).

Regionalization could be understood as the process of transformation or transferring hydrological model information from gauged to ungauged or poorly gauged basin to estimate streamflow (Razavi et al., 2012; Samuel et al., 2011; Young, 2006). Usually this incorporates either model or model parameter transfers between donor and receiver basins. Goswami et al. (2007) showed that many of ungauged catchments are located in areas (headwater of rivers in mountain regions) where they needed most. Inaccessibility, rugged and inhospitable terrain or not knowing the real value causes these to be poorly gauged. Hence there are many examples of studies where researches' sole objective is to find out whether a rainfall- runoff model can be regionalized for predicting the variation of daily streamflows.

Various regionalization methods are referred in literature including arithmetic mean method, spatial- proximity method, physical similarity method, scaling relationships, and regression-based methods. Arithmetic mean method involves averaging model parameters of surrounding basins, spatial proximity method transfer parameters based on spatial distance (using technique such as IDW, Kriging) between catchments, physical similarity approach is based on similarity of physical aspects (such as area, slope, elevation, permeability, imperviousness) of gauged and ungauged catchments, regression based method developed relationships between model parameters and catchment attributes taking model parameter as dependent variable and catchment attributes as independent variables and scaling relationships such as drainage area ratio method involve basin size and physiographic properties for regionalization (Razavi et al., 2012).

Razavi et al. (2012) in the article of *"Streamflow Prediction in Ungauged Basins: Review of Regionalization Methods"* identified that physical similarity & spatial proximity methods are suitable for Arid to warm temperature, regression-based methods are for warm temperature and scaling relationships technique are for warm humid climates by referring to various literatures.

Various researches have been carried out on regionalization by selecting basins with sufficient information to predict streamflow adequately across various hydrological conditions. Thereafter some of these catchments are considered to be ungauged (pseudo- ungauged basin) and applied regionalization methods to assess the effectiveness of streamflow transfer from donor basin to receiver basin.

Samuel et al. (2011) studied 94 basins in Ontario, Canada using MAC-HBV conceptual model and compare arithmetic mean method, spatial proximity (IDW, kriging), physical similarity and regression method. Proposed a novel method of coupling spatial proximity IDW with physical similarity and found out that that spatial proximity methods and coupled method significantly outperformed the regressions method. Hence concluded that catchment attributes are less important than the spatial proximity between gauged and ungauged basins. Similar findings are reported by Merz & Blöschl (2004) in his study on Austria catchments.

Young (2006) used regression-based method and nearest neighbor approach (based on spatial proximity) for assessing regionalization in basins in UK. This study cited that Transposing gauged data from a similar nearby gauged catchment is the low-cost solution to predict flows at ungauged locations but may often lead produce unreliable results especially if the analogue catchment is not nested with the target catchment. Conclusion of this study finding is in contradict with Merz & Blöschl (2004); Samuel et al. (2011). It says the multi-variate regression was more successful than the use of a nearest neighbor approach based on catchment characteristics. Further, it is pointed out uncertainty assessment using the results of regression-based models is problematic as the information about the interrelationships between model parameters related to model structure has been lost in the regionalization process.

Shu & Ouarda (2012) studied single/multiple source site flow duration curve (FDC) method and single/multiple source site area ratio (AR) methods for predicting flow in ungauged basins. Three weighting schemes (geographical distance weighted, drainage area weighted, and physiographical descriptor weighted) were used and found out that geographical distance weighted FDC and AR method outperformed other weighting schemes. And from the two methods FDC generate better results when using single or multiple source sites. This study suggested AR based methods are not suitable for large catchments.

In the assessment of regionalization in Liard basin Canada, Van Der Linden & Woo (2003) directly transfer the model parameters from basin to sub-basin and sub-basin to sub-basin. According to his findings, sub-basins parameters can be transferred to sub-basin of similar characteristics (hydrologically and physiologically) while parameters calibrated to a larger catchment at outlet are less suitable for the simulation of runoff for its sub-basins.

Meanwhile Goswami et al. (2007) studied methods which does not involve in transferring model parameter from gauged basin to ungauged basin for regionalization. These include regional averaging of discharge for model calibration, regional pooling of data for model calibration with observed hydrological data are combined and Transposition of nearest neighbor discharge data for model. The study concluded that in general method of pooling works best. And noted that results are comparable between regional averaging and pooling methods applied for homogeneous region having few gauged catchments.

Last paragraph of Section 2.2.3 has shown literature on regionalization of Tank model's parameters using statistical regression models with respect to basin characteristics. No effort on transferring parameters directly or some similar simple method has been identified.

In this study, direct transfer of the parameter from main catchment to sub catchment and vice versa is applied as it is one of the easiest ways to utilize parameter transferability by the water manager. Further, it is noted that study area consists of mid and upper part (less developed area) of Gin Ganga basin which has more or less the same hydrological and physical characteristics.

## 2.4 Model Calibration and Validation

In rainfall runoff modelling, purpose of the calibration is to optimize or systematically adjust model parameters to achieve best values for set of parameters which explained the observed flow. Meanwhile validation is applied as a confirmation of the calibration. In this context calibrated parameters are used to simulate flows outside the calibration period which assess the model applicability for flow predication over any period apart from calibrated period (Vaze et al., 2011).

Even careful selection of a hydrology model by the modeler, is often challenged by the problem of calibration as there is no universal way of estimating parameters of the models by either measurement of prior estimation. This due to either non availability of measurement techniques at a scale required by model parameters or variables of the model has not direct physical relationships which can be measured(K. Beven, 2012).

Parameter calibration is carried out through trial and error by adjusting the model parameters. This is done either by manually or automated way by incorporating optimization algorithms and sometimes it is an effort of the combination (Bourdin et al., 2012; Song et al., 2017; Vaze et al., 2011). Typical automatic parameter estimation requires objective function, optimization algorithm, termination criteria and calibration data (Singh & Woolhiser, 2003), further it depends on calibration data, model structure and identifiability of model parameters (Gan et al., 1997). Calibration is required for reducing the prediction uncertainty of the model (Song et al., 2017). It is noted that ideal calibration should be incorporated wet, dry and intermediate periods (Song et al., 2017).

The purpose of validation is to objectively seek the suitability of optimal parameters obtained during calibration for different input and observations data periods and ensure that it will provide best fit between observed and simulated flows (Kuok et al., 2011). If the verification results are poor, parameter value adjustments may require to produce reasonable modifications. If the modifications could be made without major degradation of calibration, the modification can be adopted. Otherwise redoing calibration with incorporation of the verification events will be required (Flood-Runoff Analysis, 1994). Kuok et al. (2011) in their study of best number of tanks in Tank model has opted to use manual trial and error calibration method.

It is the normal practice to divide the data period into calibration and validation data period (split sample process). But, Vaze et al. (2011) identifies this method may lead to uncertainties if a model demonstrate acceptable level performance in calibration but not in validation. This is due to split sample method assume both catchment and climatic conditions are stationary for the entire data period. Hence alternative calibration-validation methods have been developed. Use of entire data period for calibration and showing model is satisfactory for different sub periods within the same data period and repeated calibration and validation procedure with different starting and ending points are some examples (Vaze et al., 2011).

The quality of the calibration and validation may incorporate the judgements based on both visual and statistical comparison of observed and simulated streamflows. Time series plots, flow duration curves, statistical means (such as bias, absolute deviation, $R^2$) can be used for determination of these judgements (Hansen et al., 1996).

Calibration through optimization process often lead to problem of equifinality i.e. existing of plausible parameters set yielding acceptable results. Hence various approaches from visual inspection of observed and predicted parameters to various number of qualitative measures of goodness of fit known as objective functions are used for better identifying parameter values (K. Beven, 2012). LEE et al. (2008) studied seven different plausible parameter sets for a distributed model and concluded that those parameter sets provide similar results with respects to OFs and hydrographs but careful look at internal responses of the catchment gives insights for narrowing down more reliable range of parameter sets. Uncertainty with respect to input data, constraint conditions and overparameterization could be the sources of equifinality (Lu et al., 2009).

### 2.4.1 Objective Function

The goodness of fit of parameter optimization or calibration is appreciated through use of objective function. It is often noted that careful matching of objective function according to study being carried is utmost important as different objective functions may sensitive to different parts of the flow hydrograph (Ex: Nash-Sutcliffe Efficiency (NSE) best match the peak flow whereas log transformed NSE matches the low or recession flow). Hence nowadays use of multiple objective functions has attracted more popularity as  use of single objective function being criticized as they lead to bias results (Bourdin et al., 2012). Meanwhile response surface, which is consisted with peaks and troughs, is the surface which is defined by the objective function values for varying model parameters. Conceptually peaks in this surface represents good fits as troughs shows poor fits (K. Beven, 2012).

Objective function (OF) may depend on the purpose of the study or simulation and on the time step of hydrological modeling. The objective of continuous modelling is to properly assess the water budget over a long duration whereas event modelling focus on simulation of peak flows during single event (Green & Stephenson, 2009). It is noted that most objective function based on least square errors are in favor of high flows of the hydrograph (Fowler et al., 2018; Garcia et al., 2017). For the low flow simulation use of appropriate transformation on common objective function (Ex: modified NSE), OF based on FDC and use of multi objective functions are proposed (Garcia et al., 2017).

Garcia et al. (2017) studied the several discharge transformation of Kling Gupta efficiency (KGE) such as KGE (Q), KEG ($Q^{0.5}$), KGE (1/Q) & KGE ($Q_{sort}$). They tested single objective function as well as combined objective functions and found out that mean of the KGE (Q) which put more weight on high flows and KGE (1/Q) which put more weight on low flows produce the better results in simulating low flow indices.

Song et al. (2017) has selected NSE and root squared NSE as objective function while emphasizing the tendency of NSE for high flow due to its squared form and $NSE_{sqrt}$ which offers more balanced form between high and low flows due to root squared transformed flow. The formula for NSE and $NSE_{sqrt}$ is shown below (Eqn. 2-1 & 2-2).

$$NSE = 1 - \frac{\sum_{i=1}^{N}(Q_c - Q_o)^2}{\sum_{i=1}^{N}\left(Q_c - \overline{Q}_o\right)^2} \qquad ...Eqn. 2-1$$

$$NSE = 1 - \frac{\sum_{i=1}^{N}\left(\sqrt{Q_c} - \sqrt{Q_o}\right)^2}{\sum_{i=1}^{N}\left(\sqrt{Q_c} - \sqrt{\overline{Q}_o}\right)^2} \qquad ...\ Eqn. 2-2$$

$Q_c$ is calculated streamflow, $Q_o$ is observed streamflow and $\overline{Q}_o$ is mean of observed flow. The NSE ranges from -∞ to 1 while optimum values is considered to be 1.

Paik et al. (2005) use sum of squares as the objective function for his study of development of tank model with seasonally varied model parameters (Eqn. 2-3). GA and HS optimization algorithms were used for calibration. Further, present error in volume has used as a check for adequacy of the calibrated parameters. Formula for sum of squares is shown below (Eqn. 2-4).

$$\text{SSQ} = \sum_{t=1}^{n} [Q_c - Q_o]^2 \qquad \ldots Eqn. 2-3$$

$$PEV\ (\%) = \left| \frac{Total\ simulated\ runoff\ volume - Total\ observed\ runoff\ volum}{Total\ observed\ runoff\ volume} \right|\ x\ 100. Eqn. 2-4$$

Ou et al. (2017) has used the tank model for urban water modelling with two tanks. Root mean square error (RMSE) is used as the objective function (Eqn. 2-5). Song et al. (2019) stated that RMSE is more sensitive to high flows.

$$RMSE = \left(\frac{1}{n}\sum_{i=1}^{n}(Q_o - Q_c\right)^{1/2} \ \ldots \text{ Eqn. 2-5}$$

MRAE has been used by Dissanayake (2017), Kamran & Rajapakse (2018), and Wijesekera (1993, 2000) for evaluating goodness of fit of the parameters. It is noted that optimum values for the MRAE is zero and it is more sensitive to the prominent flow which is intermediate flow most of the time (Eqn. 2-6).

$$MRAE = \frac{1}{n}\sum_{i=1}^{n} \frac{|Q_o - Q_c|}{Q_o} \ldots . Eqn. 2-6$$

Table 2-1 shows the different objective functions used in studies relating to Tank model while Table 2-2 shows the objective functions used in regionalization

Table 2-1: Objective Functions Used in Tank Model Development

| Objective Function | Type of simulation | Reference |
|---|---|---|
| RMSE | Continuous – daily data | Ou et al. (2017) |
| SSQ | Continuous – daily data | Paik et al. (2005) |
| NSE | Continuous –Hourly data | Song et al. (2017) |
| | Event- Hourly | Kuok et al. (2010) |
| $NSE_{sqrt}$ | Continuous –Hourly data | Song et al. (2017) |
| Coefficient of correlation (R) | Event- Hourly | Kuok et al. (2010); Setiawan et al. (2003) |

Table 2-2: Objective Functions Used in Regionalization

| Objective Function | Type of simulation | Reference |
|---|---|---|
| RMSE | Continuous –Daily | Shu & Ouarda (2012) |
| Volume error and Nash-volume error | Continuous –Daily | Samuel et al. (2011) |
| NSE | Continuous –Daily | Broderick et al. (2016); Goswami et al. (2007); Shu & Ouarda (2012); Van Der Linden & Woo (2003); Young (2006) |
| sLog NSE | | Nepal et al. (2017) |
| Coefficient of determination | | Nepal et al. (2017) |
| BIAS Error | Continuous –Daily | Young (2006) |
| Mean sum of Squared error | Continuous –Daily | Young (2006) |
| Kling Gupata Efficiency (KGE) | Continuous –Daily | Patil & Stieglitz (2015) |

### 2.4.2 Model Warm-up

In Hydrological models, model warm-up is used for bringing the model to stable optimal state in terms of their internal store such as soil moistures (Kim et al., 2018). When properly done this step helps to yield better model results which match to observations.

Kim et al. (2018) in their "Exploration of warm-up period in conceptual hydrological modelling" noted there are only a handful researches available on the subject of warm-up period. Initial conditions and warm-up periods are very crucial in the event of catchments with short records of hydrological data as this will require shot warm-up periods. They assess the impact of initial soil moisture conditions, rainfall amount, and effect of simulation start point on selecting warm-up period and concluded that determination of warm-up period depends on structure of hydrological model. Rainfall amount has no effect and less time is required when initial conditions are near to the optimal conditions.

### 2.4.3 Parameter Optimization

Parameter optimization is carried out for minimizing or maximizing the magnitude of objective function (Flood-Runoff Analysis, 1994) or find the peak in the response surface in the parameter space as defined by one or more objective functions (K. Beven, 2012). Calibration may not results in global minimum always, re-optimization with different initial conditions or constraints may improve the suboptimal parameter values (Flood-Runoff Analysis, 1994).

Optimization should not be confined to comparison of observed and simulated flows only; it should involve other forms of comparison such as hydrographs for better optimization. This is needed since the in optimization it is assumed that observations are error free and that the model is true representation of data which is not the case in hydrological modelling (K. Beven, 2012).

Various methods of optimization with relating tank model has been discussed in Section 2.2.4. For the purpose of this study optimization coupled with objective function MRAE, Non-linear GRG algorithm & visual examination of hydrographs & flow duration curves were carried out.

## 2.5 Flow Regimes - Flow Duration Curve

The choice of model always depends on the purpose of modelling being done for (ex: to assess the low flow, catchment yield, flood etc.). Model selection, data requirement and calibration should reflect this purpose and if the same model is used for several purposes the necessity of calibration on a number of different flow regimes on flow duration curve may arise (Vaze et al., 2011).

It is pointed out that rather than only using statistical means as discussed above, the goodness of fit should be inquired by reviewing visual means such as flow hydrographs, flow duration curves and rainfall excess hyetographs as it is the best judgement we have (Flood-Runoff Analysis, 1994).

Essentially flow duration curves are exceedance probability vs streamflow during period of record. Flow duration curves may construct at various temporal scale such as daily, monthly, yearly. Identification of different flow regimes, such as high, medium and low often pose a challenge to water practitioners and it essential for every water related infrastructure development. Identification of high flows are necessary for planning for floods, whereas medium flows are essential for essential for planning water infrastructure and low flows are necessary to maintain environmental flows (Ali, 2017). Ambiguity in identification of flow regimes, often hinders correct water management practices being applied, and to overcome this Wijesekera (2020) has suggested a method of capturing flow segments based on order of magnitude of the flows. And this study uses this method for identification of different flow thresholds for Baddegama and Tawalama catchments in Gin Ganga basin.

## 2.6 Data Requirement, Data Checking and Infilling of Missing Data

Climate data is the most important input for rainfall runoff modelling and at the same time it has been the major cause of difficulty in model calibration. Hence checks should be performed on both input and comparison data sets prior to any modelling or calibration. The main objective of data checking is to check the integrity and consistency of the data. These checks are normally intend to evaluate stationarity of the data time series, spatial coherence of data, accuracy of spatial location of gauge site, consistency of data collection (if it provided by different agencies) and procedures use for spatial interpolation of point data (Vaze et al., 2011).

### 2.6.1 Data Requirement

The temporal resolution for both managing and regulating water resource is commonly between a week and a month. However, for the yield assessment for many run-of-river resource schemes and the assessment of water use impacts on stream ecology a daily time step is most appropriate (Young, 2006).

Data resolution is an important consideration when mathematically modelling watershed. Daily data are considered more important for flood simulation and flood protection works while monthly data are recommended for water allocation and planning works such as irrigation, hydropower (Tessema, 2011). Kavetski, Fenicia, & Clark (2011) compared sub-daily and daily data impact on modelling and found out that mostly slow dynamics are invariant for data scale while fast dynamics are predicted with increase precision as data resolution is increased. Moreover, daily variations of the streamflow of a watershed can be easily comprehend when attempting to verify the modelling accuracies. However, monthly data are easily accessible, and less costly when compared with daily data of same data duration (Meterological Department, n.d.). Monthly data are the most commonly used temporal resolution for water resources planning in Sri Lanka (Ponrajah, 1984). Even though for water resources applications daily data would be preferred if available.

### 2.6.2 Data Duration

Gan et al. (1997) noted that availability of 3 to 5 years of data which includes wet, dry, medium years for activating all models' parameters during calibration is ideal. In his study, different data duration with wet only, dry only, mixed years were studied. This study lead to conclusion of that generally data length is not crucial if it is not less than one hydrological cycle as long as the data used contain enough information for calibrating the parameters. This idea is confirmed by Li et al. (2010) in his study of estimation calibration data length required.

Various researchers have used different length of data for simulation purposes. Eight years of data is used by Li et al. (2010) & Phien & Pradhan (1983). Basri (2013) has stated that 10 years of data series is essential for modelling Tank model. Setiawan et al. (2003) has used 10 years of daily data to simulate Tank model while three years of daily data were used by Yokoo et al. (2001).

### 2.6.3 Infilling of Missing Data

Missing data hinders the efficient modelling of streamflow simulation and hence it is essential of having continuous series of data to accurately predict catchment responses. For this very reason estimating of missing data is a crucial task among the researchers (Norliyana Wan Ismail et al., 2017).

Norliyana Wan Ismail et al. (2017) has experimented with four different approaches to estimate missing data. They used, Arithmetic Average (AA) method, Normal Ratio (NR) method, Inverse Distance (ID) method and Coefficient of Correlation (CC) method for these estimations. They concluded that no one method can yield best results for every basin they tested and stated that if no data is available from neighboring stations, mean values of different years for same period could be useful.

Premalal, Silva, & Dayawansa (2007) tested AR, NR, ID and Aerial precipitation method based on Thiessen polygon area method over different agrological zones of Sri Lanka using monthly data. This research concluded that different methods are appropriate for different part of the country. They expressed that ID method is suitable for low country zones (for dry, mid and wet), NR method is suitable for mid and up-country intermediate zones, AA method is suitable for upcountry wet zones and aerial precipitation method is suitable for mid-country wet zones.

# 3 Methodology

The Figure 3-1 has shown the methodology flow chart followed in this study. Details specific to each step has been discussed in Section 4 and 5 wherever appropriate.

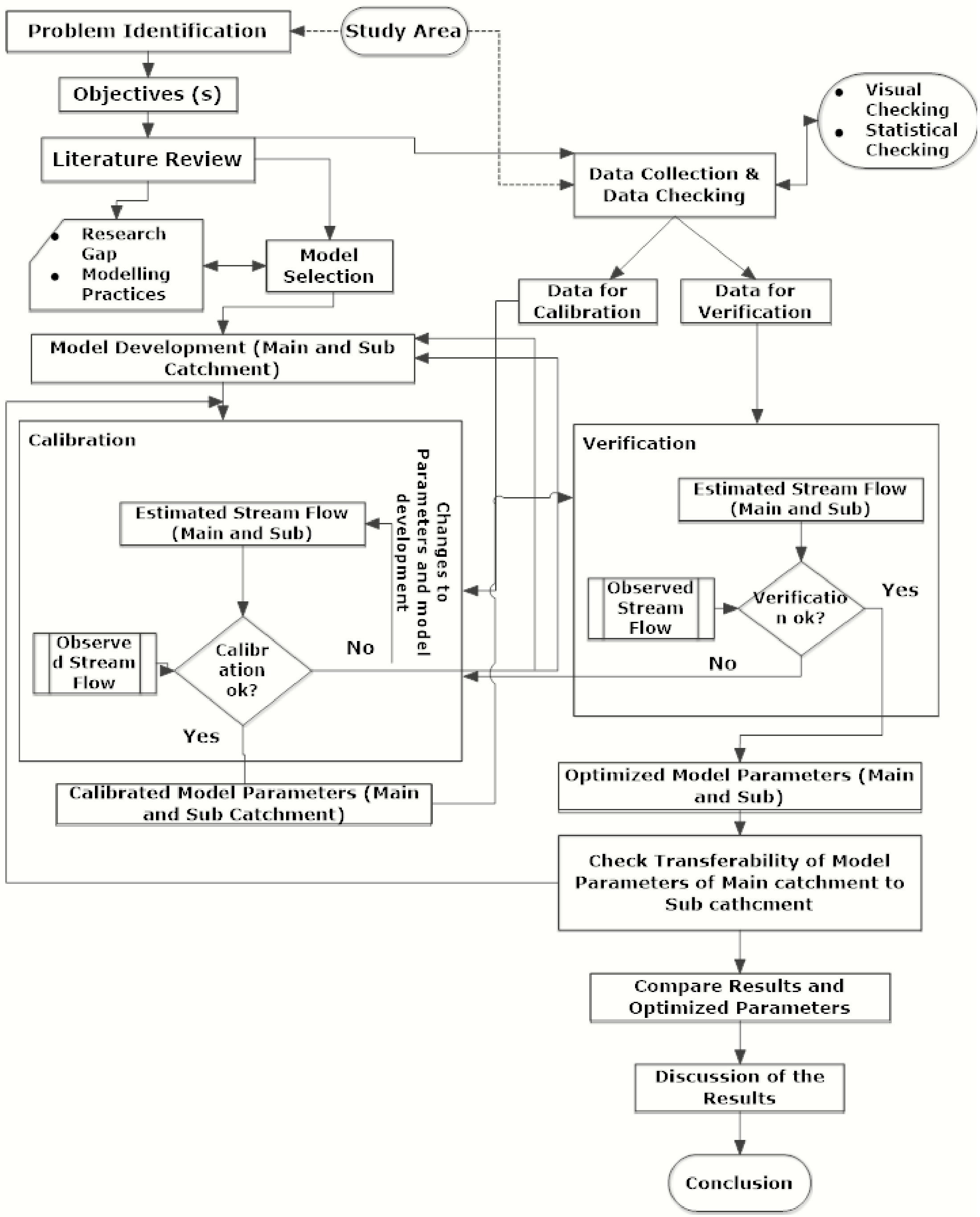



Figure 3-1: Methodology Flowchart

## 3.1 Selection of Watersheds

With respect to the data availability two catchments at Baddegama (as main catchment) and Tawalama (as sub catchment) in Gin Ganga basin were selected for model development. Both catchments are in same region hence presume same hydrological features prevails such that parameter transferability can be checked. Both rainfall and stream flow data were available sufficiently for these locations for carrying out the objective this study.

## 3.2 Selection of Model

After reviewing available models for rainfall runoff modelling in Chapter 2.0, it is decided that Tank model is appropriated for modelling of streamflow with the aim of observing applicability of parameter transferability in model simulation. The model itself a conceptual lumped model with simple representation of the streamflow prediction of the catchment without complex parameters. Even though model is simple its behavior is non- linear and it has proven for its capability for successfully capturing rainfall runoff response of the catchments in Asian region.

## 3.3 Tank Model Structure, Inputs and Parameters

Tank model can have one or more storage reservoirs and associated number of parameters. In this study, according to literature review it was decided to apply tank model with four storages with following parameter configuration as this is well suited for continuous simulation. All together it has 12 parameters of which A1, A2, B1, C1, and D1 constants which control the runoff. While A0, B0, C0, D0 are the infiltration coefficients. The heights shown from HA1, HA2, HB1, HC1 are the constants which shows the storage requirement in “mm” which should be met before occurring runoff from each outlet. YA0, YB0, YC0 represents the infiltration occurs through each tank. Finally, YA1, YA2, YB1, YC1 and YD1 shows runoff generate in each tank of which total would be equal to the runoff generate at particular day. Figure 3-2 shows the graphical representation of the adapted tank model structure for this study.

Following equations depicts the relation between each parameter.

$$Ya1 = A1 * (HA - HA1)\ , given\ (H0 - HA1) > 0\ otherwise = 0 \ldots Eqn. 3 - 1$$

$$Ya2 = A2 * \ (HA - HA2), given\ (H0 - HA2) > 0\ otherwise = 0 \ldots Eqn. 3 - 2$$

$$Yb1 = B1 * \ (HB - HB1), given \ (HB - HB1) > 0 \ otherwise = 0 \ldots Eqn. 3-3$$

$$Yc1 = C1 * \ (HC - HC1), given \ (HC - HC1) > 0 \ otherwise = 0 \ldots Eqn. 3-4$$

$$Yc1 = D1 * \ (HD - HD1), given \ (HD - HD2) > 0 \ otherwise = 0 \ldots Eqn. 3-5$$

$$HA = P - E + Ha \qquad \ldots Eqn. 3-6$$

$$HB = YA0 - YB1 + Hb \quad \ldots Eqn. 3-7$$

$$HC = YB0 - YC1 + Hc \quad \ldots Eqn. 3-8$$

$$HD = YC0 - YD1 + Hd \quad \ldots Eqn. 3-9$$

Ha, Hb, Hc, Hd = storage at previous day in respective tank, HA, HB, HC, HD = storage at present day in respective tanks, P = precipitation at previous day,

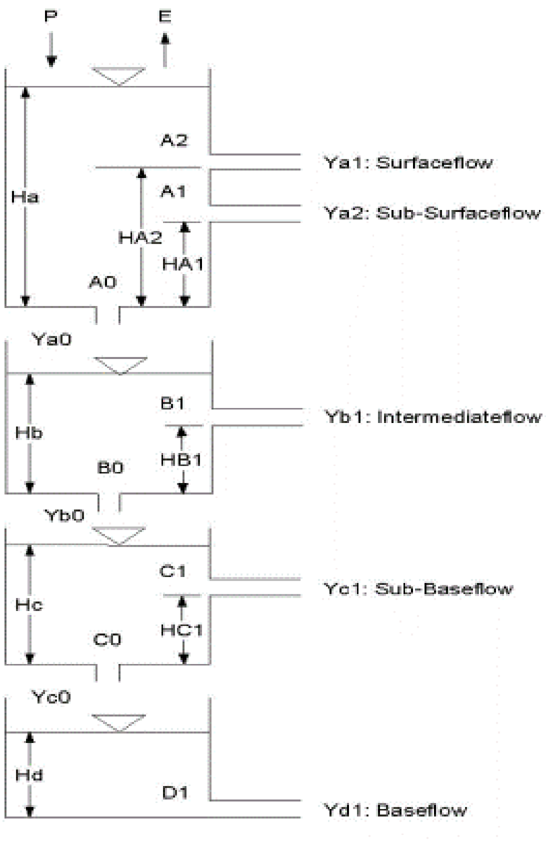



Figure 3-2: Tank Model Structure (Source: Amiri et al., 2016

E = evaporation at present day. If the evaporation is not completely deducted from upper tank it is deducted from lower tanks accordingly.

$$Ya0 \ = \ Ha \ * \ A0 \ldots Eqn. 3-10$$

$$Yb0 = Hb * B0 \ldots Eqn. 3 - 11$$

$$Yc0 = Hc * C0 \ldots Eqn. 3 - 12$$

Then total runoff generated at any given time will be equal to;

$$Y(t) = Ya1(t) + Yb1(t) + Yb1(t) + Yd1(t) \cdots Eqn. 3 - 13$$

The whole process in tank model is based on water balance principal but the model becomes non-linear due to its interconnectivity and other constraints as mentioned in above equations.

For this study MS Excel was used to develop the model in computer environment and in-built solver tools were used to optimization of the model results. The model developed for Baddegama catchment is shown in Figure 5-1.

## 3.4 Tank Model Calibration

As describe earlier model calibration is performed for both catchments in order to find the optimal parameter set. Five year Observed streamflow record from 2008/2009 to 2012/2013 is used for calibration. Semi-automatic calibration method is employed during calibration as slight change of parameters obtained thorough automatic optimization using Solver, is required. This enables further matching of simulated results to the observed streamflow. Automatic calibration mainly focuses on minimizing error function values for achieving statistical goodness of fit. As this may not yield best results with respect to matching of hydrographs, flow duration curves, and annual water balance errors, the parameters derived from Solver tool are slightly adjusted. The parameters were adjusted considering the impact on order of magnitude of parameters and soil moisture behavior in each tank in order to achieve best model performance.

As described earlier, apart from objective function, visual and numerical indicators such as total hydrographs, annual water balance and flow duration curves (sorted and unsorted) were used in each trial for analyzing the goodness of fit of the results. In this sense, MRAE: objective function act as statistical measure of goodness of fit and other visual and numerical indicators described above are used as model performance evaluation criteria.

Selection of objective function and selection of optimization method is carried out according to the findings in the literature review and are described in below sections.

### 3.4.1 Selection of Objective Function

There are different objective functions were available which are well suited for various objectives and more sensitive on specific flow regimes such as high flows. It is found out squared error functions more tend to define fittings of high flow segments and absolute error functions suited for overall more prominent flow segment, usually medium to low flow segments. As the objective this study to simulated continuous period of record for the purpose of identifying applicability of parameter transferability in Tank model, Mean Relative Absolute error (MRAE) function is selected.

### 3.4.2 Selection of Optimization Method

As seen in literature review though there were many optimization methods for dealing with optimization of hydrological model, there were no common ground or consent as to which optimization method is best suited. Since the model is developed in MS Excel it is decided to implement the in-built optimization method using Solver Tools in MS Excel. Under Solver Tool three optimization methods are available. The three methods are Simplex LP, GRG Non-Linear, Evolutionary. The Simplex LP method is not suitable for these type analyses as the data which is subjected to this study shows nonlinear behavior. Hence GRG non-linear method with multi-start option was used

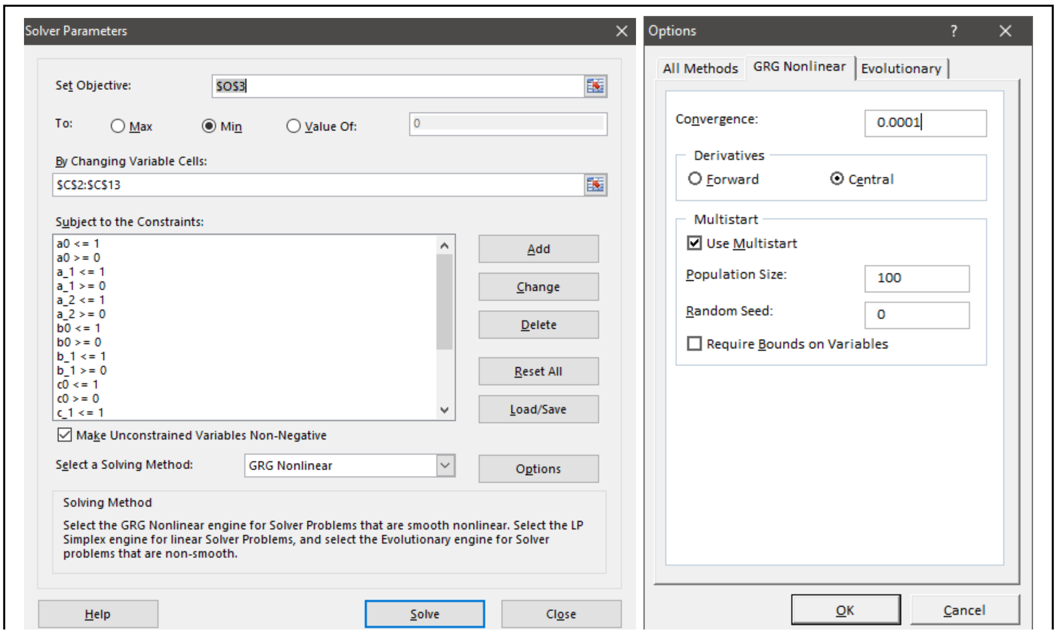



Figure 3-3: Setting Up of Solver in MS Excel

as optimization algorithm. Multi start option will run optimization repeatedly at different start point which automatically chosen according to given population size. Population size of 20, 50, and 100 were tested in this analysis. This results in up to 100 sub problems and each sub problem contain many trials as results are converged (usually more than 10 trails).

# 4 Data Collection and Checking

## 4.1 Study Area & Data

Data collected from Irrigation Department and Meteorological Department in Sri Lanka for years of 2007/08 to 2017/18. There are two catchments in the study area namely Baddegama and Tawalama. These are based on the streamflow gauges available in Irrigation Department. The area of Tawalama catchments and Baddegama catchments are 359 km$^2$ and 736 km$^2$ respectively. There are six rainfall station, namely Aninngkanda Estate, Deniyaya Willey Group, Neluwa, Tawalama and Baddegama. All are within the study area except Deniyaya WG station which lies little away from the boundaries. Two streamflow gauges, Baddegama and Tawalama are within the study area. Evaporation data from Kottawa station is used for the study. Table 4-1 and Table 4-2 shows the sources of the above data and the location details of gauging stations. Table 4-3 shows the station density at Baddegama and Tawalama station against WMO recommendations.

Table 4-1: Details of Data Used for the Study

| Data Type | Temporal/ Spatial Resolution | Data Period | Data Source |
|---|---|---|---|
| Rainfall | Daily | October 2007 to September 2018 | Department of Meteorology & Irrigation Department |
| Streamflow | Daily | | Irrigation Department |
| Pan Evaporation | Daily | | |
| Land Use Map | 1:50000 | | Department of Survey |
| Topographic | 1:50000 | | Department of Survey |

Table 4-2: Locations of Gauging Stations

| **Gauging Station** | **Coordinates (Decimal Degrees)** | |
|---|---|---|
| | Longitude | Latitude |
| Anningkanda Estate | 80.61 | 6.35 |
| Tawalama | 80.33 | 6.33 |
| Deniyaya | 80.56 | 6.33 |
| Neluwa | 80.35 | 6.38 |
| Hiniduma | 80.32 | 6.30 |
| Baddegama Estate | 80.18 | 6.18 |
| Tawalama River Gauging | 80.33 | 6.34 |
| Baddegama River Gauging | 80.18 | 6.17 |
| Kottawa Evaporation Gauging | 80.31 | 6.08 |

Table 4-3: Distribution of Gauging Stations at Two Catchments

| Type of Gauging Station | Number of Stations | | Station Density ($km^2$/station) | | Station Density as WMO standard ($km^2$/station) |
|---|---|---|---|---|---|
| | Baddegama | Tawalama | Baddegama | Tawalama | |
| Rainfall | 5 | 4 | 123 | 90 | 575 |
| Streamflow | 1 | 1 | 736 | 359 | 1875 |
| Evaporation | 1 | 1 | 736 | 359 | - |

## 4.2 Rainfall Stations and Missing Data

The Table 4-4 shows the number of missing rainfall data for the selected data period and percentage of missing data.

### 4.2.1 Infilling of Missing Data

For infilling missing data Thiessen polygon method (an average areal precipitation method) is used (Chow et al., 1988). This method assumes the contribution of rainfall from surrounding stations is proportionate to Thiessen polygon area claimed by each

Table 4-4: Details of Missing Rainfall Data

| Name of Station | No of Missing Days from 2007-2018 | Percentage of Missing Data |
|---|---|---|
| Anningkanda Estate | 1 | 0.02% |
| Tawalama | 0 | 0% |
| Deniyaya | 155 | 3.86% |
| Neluwa | 183 | 4.55% |
| Hiniduma | 93 | 2.31% |
| Baddegama Estate | 123 | 8.31% |

station without considering the missing gauge. And the resulting weights are used to calculate areal average rainfall for missing data records. The weights used in each missing data scenario for Baddegama catchment and Tawalama catchment are shown in Table 4-5 and Table 4-6. Here "NA" shows the station which data are missing.

Table 4-5: Thiessen Weights for Baddegama Catchment Missing Data Estimation

| Anningkanda | Deniyaya | Neluwa | Tawalama | Hiniduma | Baddegama |
|---|---|---|---|---|---|
| NA | 0.23 | 0.18 | 0.07 | 0.28 | 0.24 |
| 0.19 | NA | 0.22 | 0.07 | 0.28 | 0.24 |
| 0.05 | 0.23 | NA | 0.23 | 0.28 | 0.24 |
| 0.06 | 0.17 | 0.3 | 0.18 | NA | 0.29 |
| 0.05 | 0.17 | 0.07 | 0.18 | 0.53 | NA |

Table 4-6: Thiessen Weights for Tawalama Catchment Missing Data Estimation

| Anningkanda | Deniyaya | Neluwa | Tawalama |
|---|---|---|---|
| NA | 0.47 | 0.37 | 0.16 |
| 0.38 | NA | 0.46 | 0.16 |
| 0.11 | 0.4 | NA | 0.49 |

## 4.3 Thiessen Rainfall

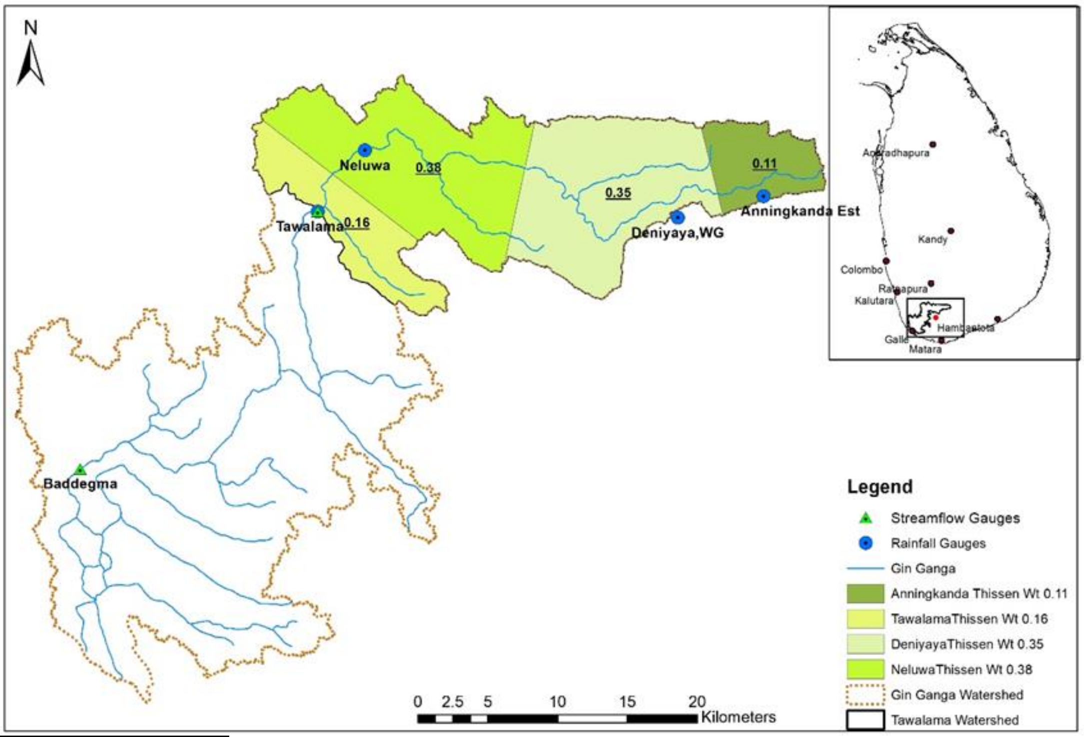
After infilling of missing data, average rainfall for each catchment is calculated using Thiessen polygon method. Stationarity of data series is assumed here.

### 4.3.1 Tawalama Watershed

Thiessen polygon developed for the Tawalama watershed is shown in Figure 4-1 and respective Thiessen weights are shown in Table 4-7.

Table 4-7: Thiessen Weights for Tawalama Watershed

| Rainfall Station | Thiessen Weight |
|---|---|
| Tawalama | 0.16 |
| Neluwa | 0.38 |
| Deniaya, WG | 0.35 |
| Anningkanda Estate | 0.11 |




Original in Color

Figure 4-1: Thiessen Polygon of Tawalama Watershed

### 4.3.2 Baddegama Watershed

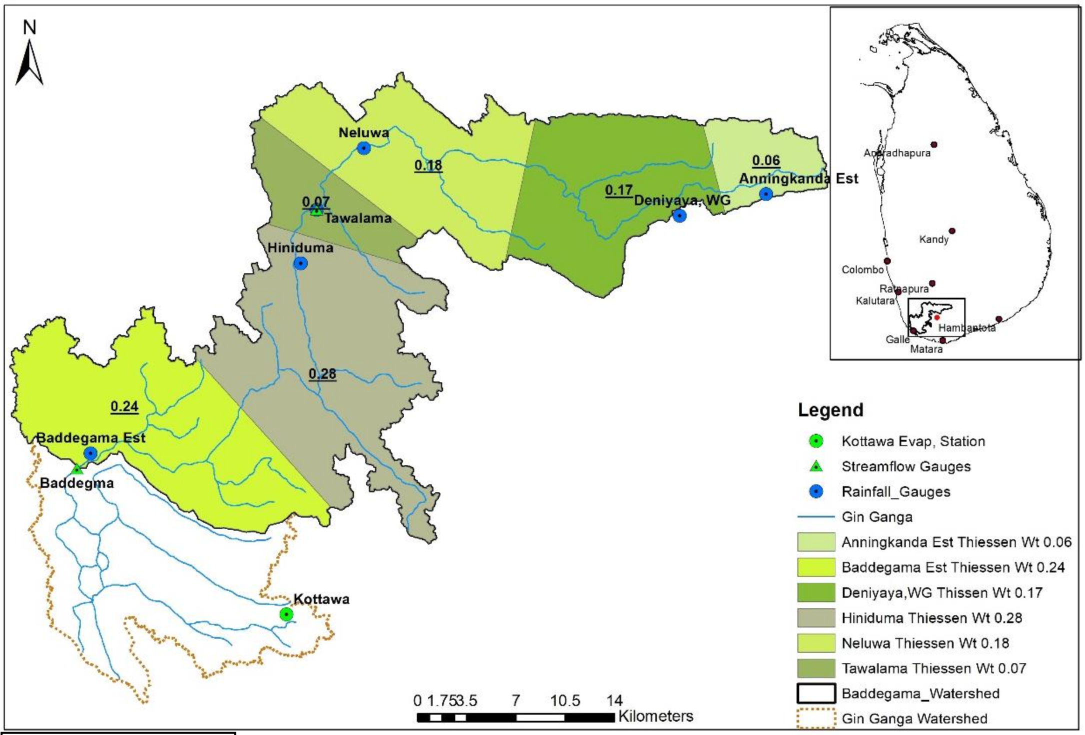
Thiessen polygon developed for the Baddegama watershed is shown in Figure 4-2 and respective Thiessen weights are shown in Table 4-8.

## 4.4 Data checking

Data checking is carried out with annual water balance checking, double mass consistency checking and visual checking. Visual checking is used to find out data outliers, inconsistencies and correlations of average Thiessen rainfall/ individual station rainfall to streamflow. Last step identifies the relevancy of a rainfall station to

Table 4-8: Thiessen Weights for Baddegama Watershed

| Rainfall Station | Thiessen Weight |
|---|---|
| Tawalama | 0.07 |
| Neluwa | 0.18 |
| Deniaya, WG | 0.17 |
| Anningkanda Estate | 0.06 |
| Hiniduma | 0.28 |
| Baddegama Estate | 0.24 |




Original in Color

Figure 4-2: Thiessen Polygon of Baddegama Watershed

the catchment outflow hence can identify as representative rainfall station for analysis. Further, double mass curve is used to check the consistency of the data.

### 4.4.1 Variation of Annual Rainfall and Streamflow at Tawalama

Figure 4-4 shows the variation of annual rainfall and streamflow at Tawalama. Here it is observed that from 2008-2011 streamflow has increased, from 2015-2017 discharge has been decreased. Further, it can be seen that variation of discharge to rainfall doesn't quite agreeing in year 2014/15 while it seems rainfall response is little off in year 2012/13 causing higher runoff coefficient.

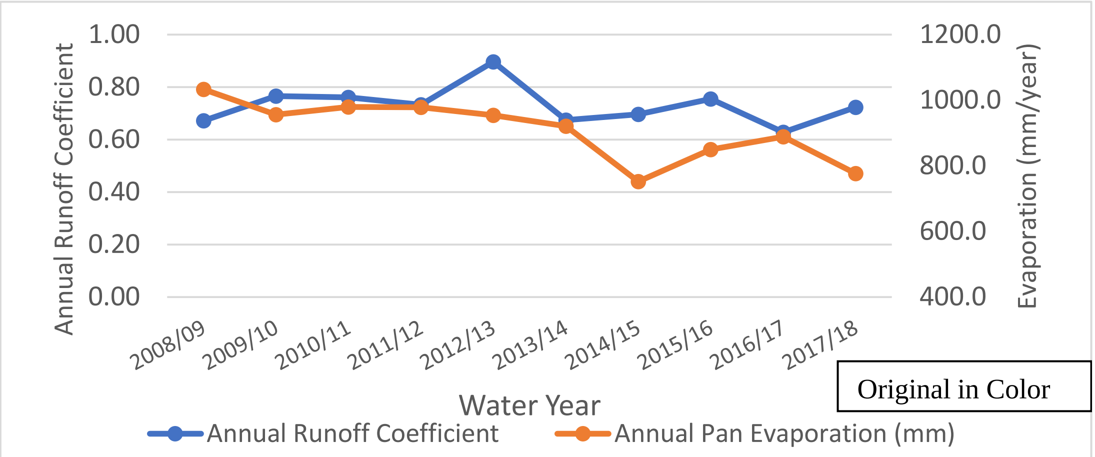



Figure 4-3: Variation of Annual Runoff Coefficient and Pan Evaporation of Tawalama

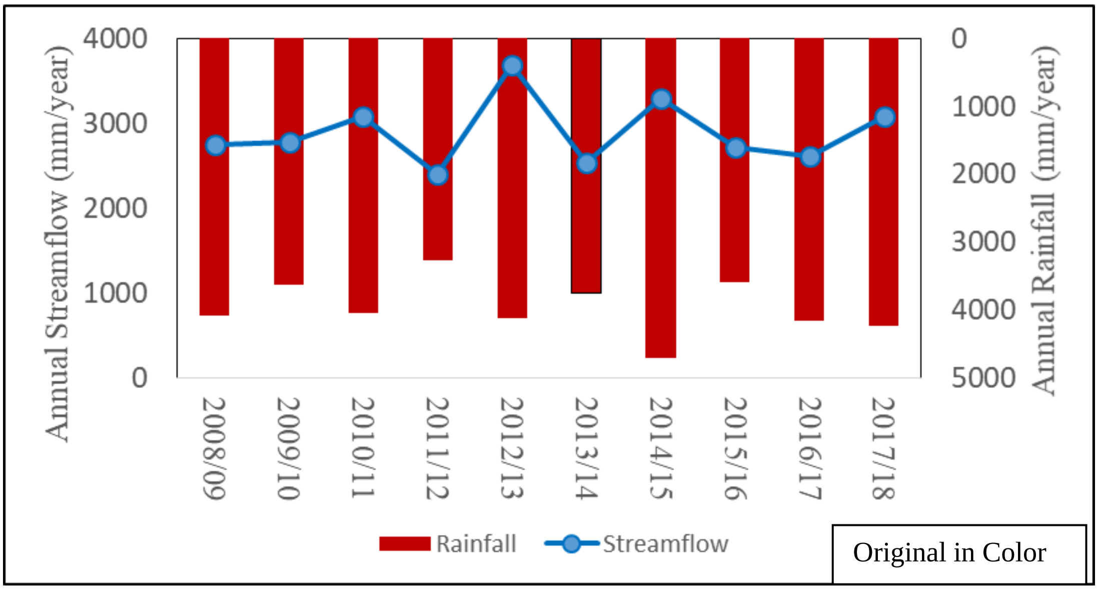



Figure 4-4: Variation of Annual Rainfall and Streamflow at Tawalama

### 4.4.2 Annual Water Balance

Annual water balance checking considers comparison of rainfall to streamflow to evaporation. The calculation of annual runoff coefficients gives insights to the catchment behavior for precipitation. Annual water balance is carried using Thiessen average rainfall for both catchments.

#### 4.4.2.1 Annual Water Balance at Tawalama

Table 4-9 shows the results of the annual water balance at Tawalama which compares the Thiessen average rainfall to streamflow at Tawalama river gauge and to pan evaporation at Kottawa. Figure 4-3 shows the variation of annual runoff coefficient and annual pan evaporation.

It can be seen that annual runoff coefficient vary from 0.63 to 0.77 except for year 2012/2013 where it is 0.9 which shows some data inconsistency in either rainfall or streamflow measurements. But, there were no observed missing data for this year. According to Hydrological Annual prepared by Irrigation Department long term average annual runoff coefficient 0.71 at Tawlama which shows good compatible to the analysis. And for the year 2017/18 it is 0.68 in Hydrological Annual at Tawalam station where as comparison of Thiessen rainfall to streamflow shows it as 0.72. Further, the evaporation shows decreasing trending from 2008 to 2018.

Table 4-9: Annual Water Balance at Tawalama

| Water Year | Average Annual Rainfall (mm/year) | Annual Stream flow (mm/year) | Annual Pan Evaporation (mm/year) | Annual Water Balance (mm/year) | Annual Runoff Coefficient |
|---|---|---|---|---|---|
| 2008/09 | 4086.4 | 2745.6 | 1033.1 | 1340.9 | 0.67 |
| 2009/10 | 3631.4 | 2784.6 | 956.1 | 846.8 | 0.77 |
| 2010/11 | 4050.5 | 3083.3 | 979.6 | 967.3 | 0.76 |
| 2011/12 | 3278.2 | 2404.4 | 978.2 | 873.9 | 0.73 |
| 2012/13 | 4123.8 | 3694.4 | 954.2 | 429.4 | 0.90 |
| 2013/14 | 3761.9 | 2535.9 | 920.7 | 1226.0 | 0.67 |
| 2014/15 | 4721.0 | 3287.1 | 751.8 | 1433.8 | 0.70 |
| 2015/16 | 3589.1 | 2711.0 | 849.2 | 878.1 | 0.76 |
| 2016/17 | 4155.1 | 2606.5 | 888.4 | 1548.6 | 0.63 |
| 2017/18 | 4245.1 | 3074.0 | 776.8 | 1171.1 | 0.72 |
| Average | 3964.3 | 2892.7 | 908.8 | 1071.6 | 0.7 |

### 4.4.3 Annual Water Balance at Baddegama

Similar study is carried out for Baddegam station and results are shown in Table 4-10. The annual runoff coefficient varies from 0.68 to 0.81 while the Hydrological Annual at Irrigation Department shows long term annual runoff/rainfall ratio of 0.75. For the 2008-2018 average of 0.7 is shown in this analysis.

Figure 4-5 shows the variation of annual runoff coefficient and annual evaporation. And the variations of two are quite compatible and no inconsistency is shown as for Tawalama watershed.

Table 4-10: Annual Water Balance at Baddegama

| Water Year | Average Annual Rainfall (mm/year) | Annual Stream flow (mm/year) | Annual Pan Evaporation (mm/year) | Annual Water Balance (mm/year) | Annual Runoff Coefficient |
|---|---|---|---|---|---|
| 2008/09 | 3743.6 | 2732.1 | 1033.1 | 1011.5 | 0.73 |
| 2009/10 | 3798.1 | 2793.5 | 956.1 | 1004.7 | 0.74 |
| 2010/11 | 4022.2 | 3050.2 | 979.6 | 972.0 | 0.76 |
| 2011/12 | 3293.8 | 2472.5 | 978.2 | 821.4 | 0.75 |
| 2012/13 | 4031.7 | 3141.7 | 954.2 | 890.0 | 0.78 |
| 2013/14 | 3570.5 | 2417.6 | 920.7 | 1152.8 | 0.68 |
| 2014/15 | 4481.6 | 3053.6 | 751.8 | 1428.1 | 0.68 |
| 2015/16 | 3567.1 | 2901.1 | 849.2 | 666.0 | 0.81 |
| 2016/17 | 3841.0 | 2621.4 | 888.4 | 1219.6 | 0.68 |
| 2017/18 | 4260.8 | 2887.5 | 776.8 | 1373.3 | 0.68 |
| Average | 3861.1 | 2807.1 | 908.8 | 1053.9 | 0.7 |

### 4.4.4 Variation of Annual Rainfall and Streamflow of Baddegama

Similar results can be observed by plotting annual streamflow and annual Thiessen rainfall at Baddegama. The stream discharge is shown consistent response to the rainfall received by the watershed (Figure 4-6).

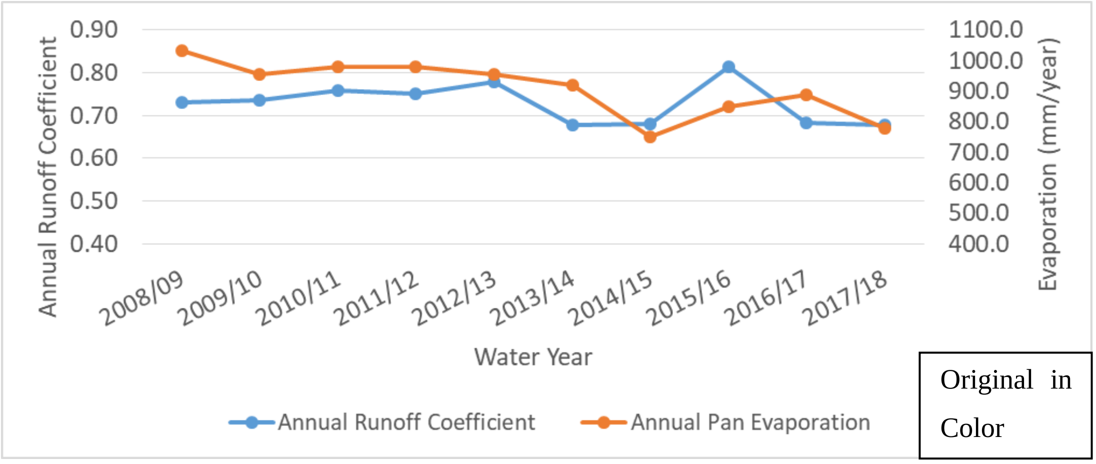



Figure 4-5: Variation of Annual Runoff Coefficients and Evaporation of Baddegama

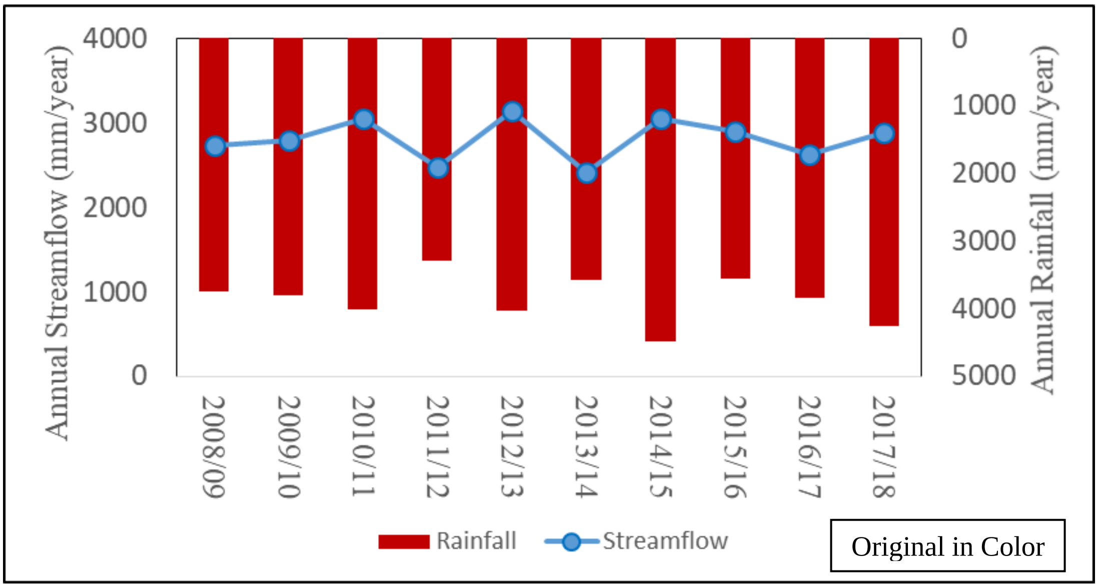



Figure 4-6: Variation of Annual Rainfall and Streamflow at Baddegama

## 4.5 Monthly average rainfall

Monthly average rainfall of the Aninnigknada, Deniyaya, Neluwa, Tawalama, Hiniduma, Baddegama for the year 2008-2018 is shown Table 4-11 and Figure 4-7 shows rainfall variations in the graph. This shows that there are two distinct season namely north-east monsoon (October to March) and south-west monsoon (April to September). Similar variations also show these are representative rainfall stations for the study area.

Table 4-11: Monthly Average Rainfall in Study Area

| | Rainfall Station | | | | | |
|---|---|---|---|---|---|---|
| Month | Aninnigknada | Deniyaya | Neluwa | Tawalama | Hiniduma | Baddegama |
| Oct | 388.8 | 306.5 | 414.9 | 479.1 | 418.0 | 359.5 |
| Nov | 489.5 | 332.9 | 407.0 | 444.1 | 450.6 | 340.3 |
| Dec | 312.8 | 263.9 | 323.5 | 350.5 | 268.5 | 227.3 |
| Jan | 146.1 | 128.3 | 163.5 | 171.4 | 169.4 | 111.8 |
| Feb | 163.2 | 126.1 | 190.1 | 221.4 | 202.5 | 115.8 |
| Mar | 221.5 | 152.3 | 273.8 | 281.0 | 246.4 | 168.8 |
| Apr | 367.6 | 214.9 | 398.3 | 453.3 | 392.2 | 286.4 |
| May | 345.3 | 327.3 | 508.8 | 519.8 | 441.6 | 401.6 |
| Jun | 194.9 | 258.0 | 327.5 | 369.5 | 322.1 | 219.6 |
| Jul | 118.6 | 162.9 | 231.8 | 261.3 | 239.9 | 179.1 |
| Aug | 157.8 | 146.8 | 267.1 | 303.1 | 260.3 | 205.3 |
| Sep | 221.4 | 228.3 | 361.4 | 400.7 | 332.7 | 281.5 |

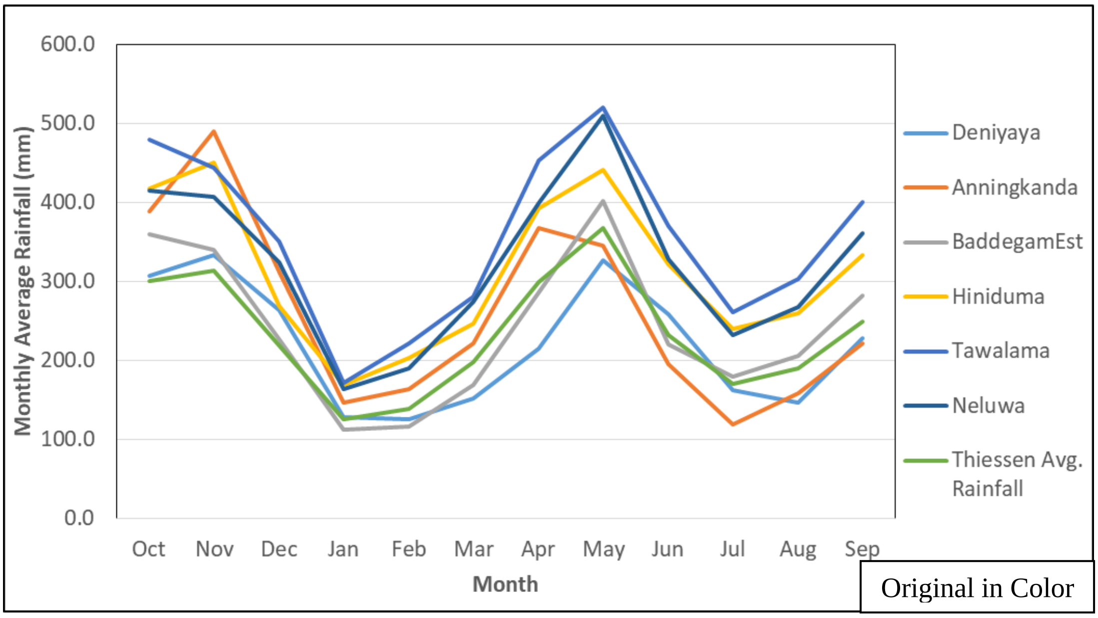



Figure 4-7: Monthly Average Rainfall Variation of Each Station

## 4.6 Visual Data Checking

Visual data checking is incorporated to identify the inconsistencies in the streamflow responses to rainfall or/and data outliers or missing data. The streamflow against each rainfall station and Thiessen rainfall of two watershed is produced for each water year considered for analysis. The daily streamflow vs daily rainfall is plotted in semi log plot which enables clear identification of inconsistencies.

### 4.6.1 Tawalama Watershed

Semi log plots for each station for the water year of 2017/18 is shown in Figure 4-8 and it can clearly be seen that streamflow response to the rainfall is quite consistent except for few locations. And these locations of inconsistencies are marked with red circles.

### 4.6.2 Baddegama Watershed

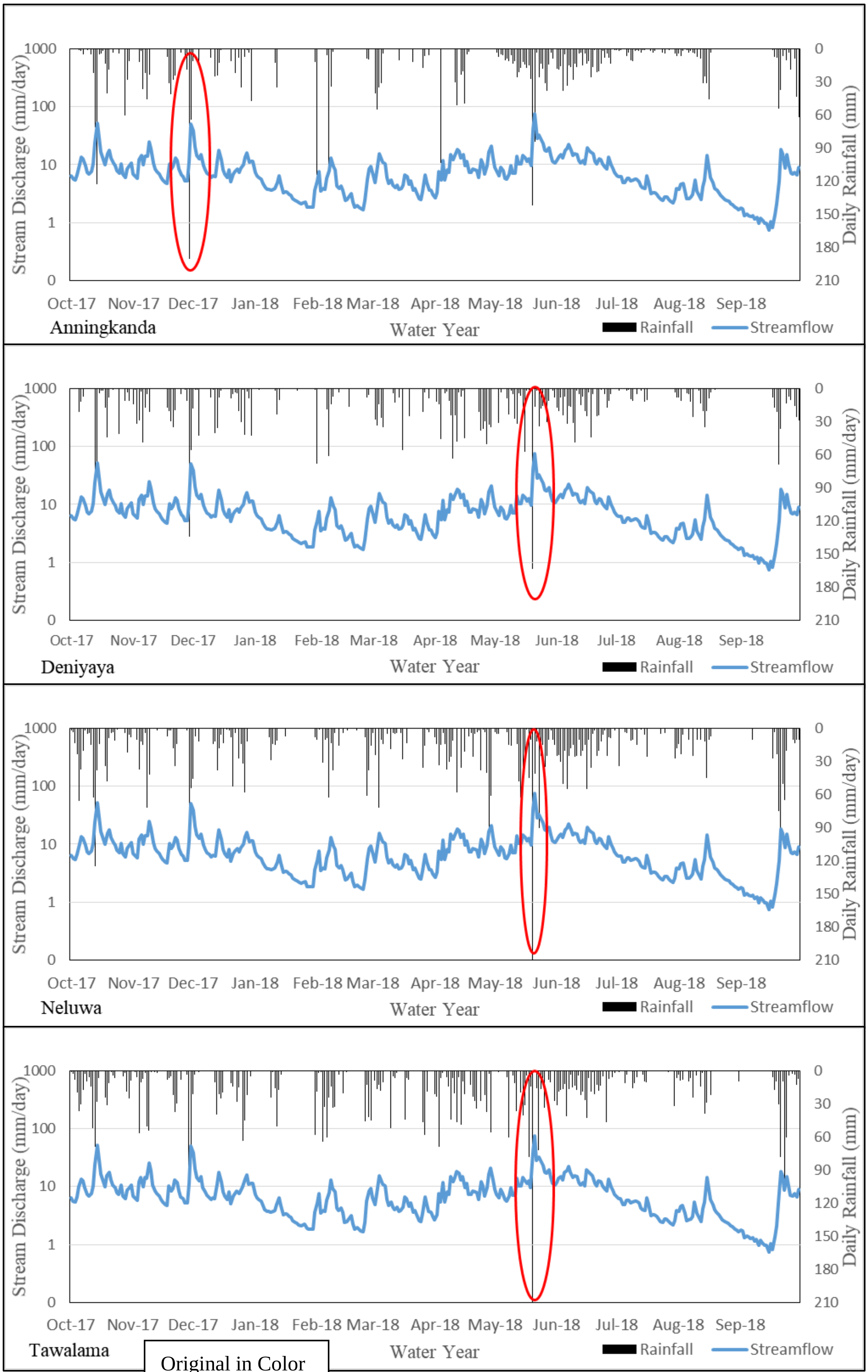
Similarly, semi log plot for Baddegama is shown in Figure 4-9 & Figure 4-10 and it shows more inconsistencies than the Tawalama watershed for the year 2017/18 at each station.

Baddegam streamflow vs Thiessen Rainfall for the study data period (2007/08-2017/18) is shown in Figure 4-12 to Figure 4-13.

Semi log plots for other individual station and Tawalama SF vs Thiessen Rainfall are shown in Annexure A. It is considered that overall streamflow response to the rainfall is quite consistent and adequate for the present study.

## 4.7 Double Mass Curve

Double mass curve checks the data consistency of one station to others by plotting them in single graph. Cumulative rainfall of one station is plotted against cumulative average rainfall of other stations. Double mass curve of each station is plotted together in Figure 4-14 and separate double mass curve analysis is presented in Annexure B 1. It was observed that no significant inconsistency which may need applying correction factor is presented in the data collected. Hence data was used as it is for the present study while only infilling missing data.




Original in Color

Figure 4-8:Streamflow vs Rainfall at Each Station in Tawalama Watershed- 2017/18

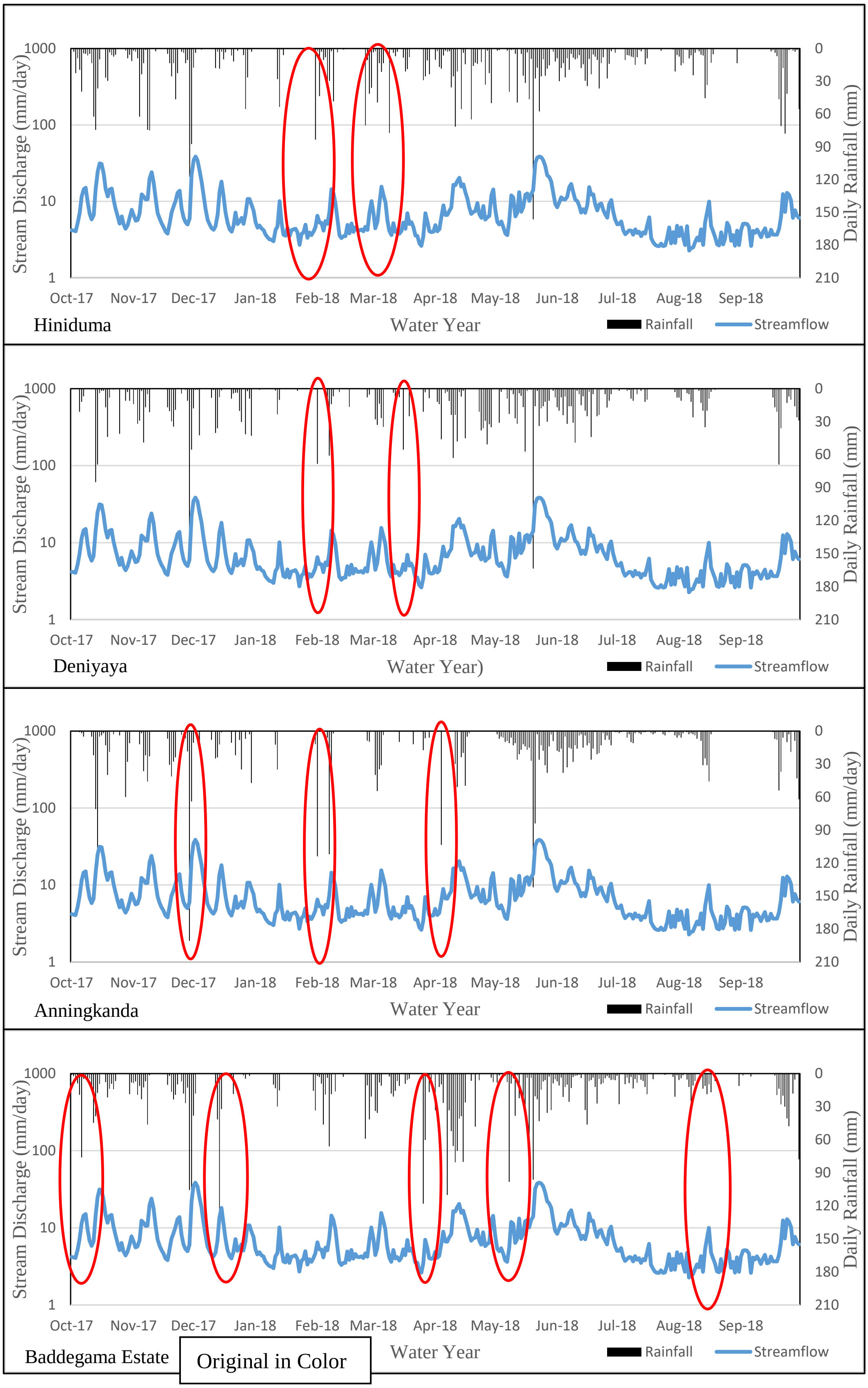



Figure 4-9: Streamflow vs Rainfall at Each Station in Baddegama Watershed-2017/18

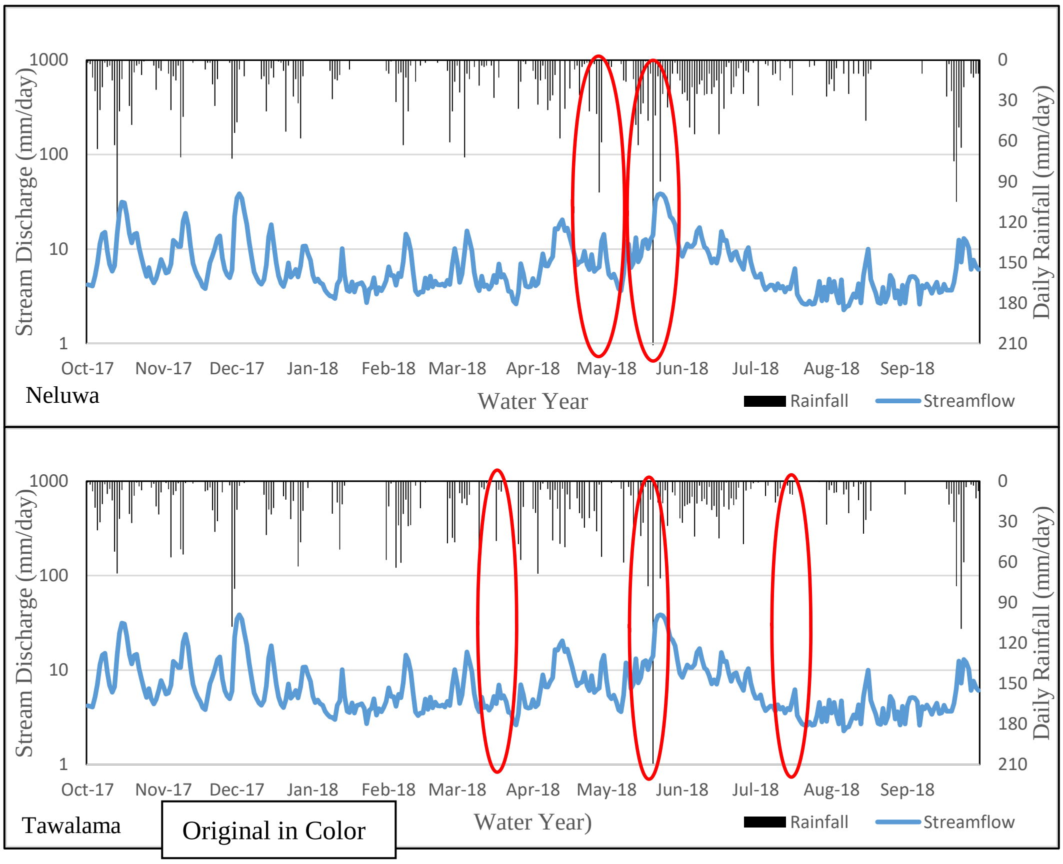
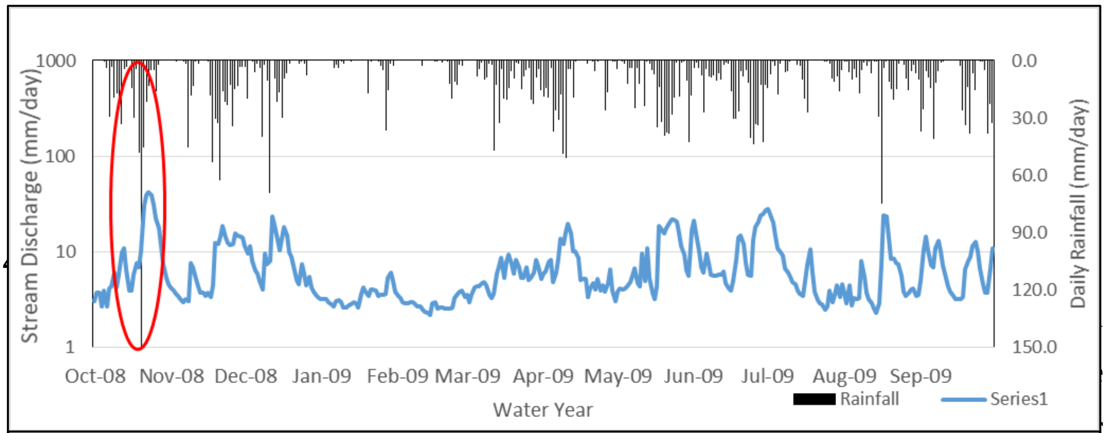
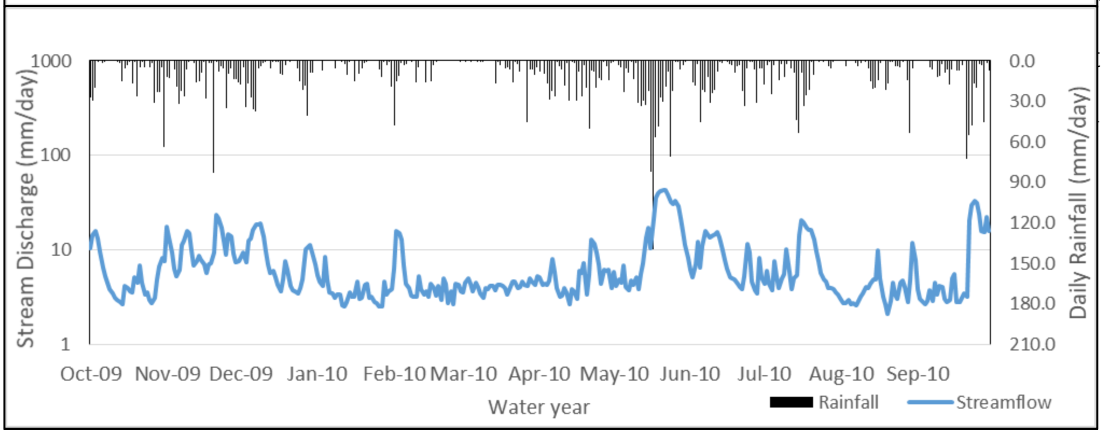
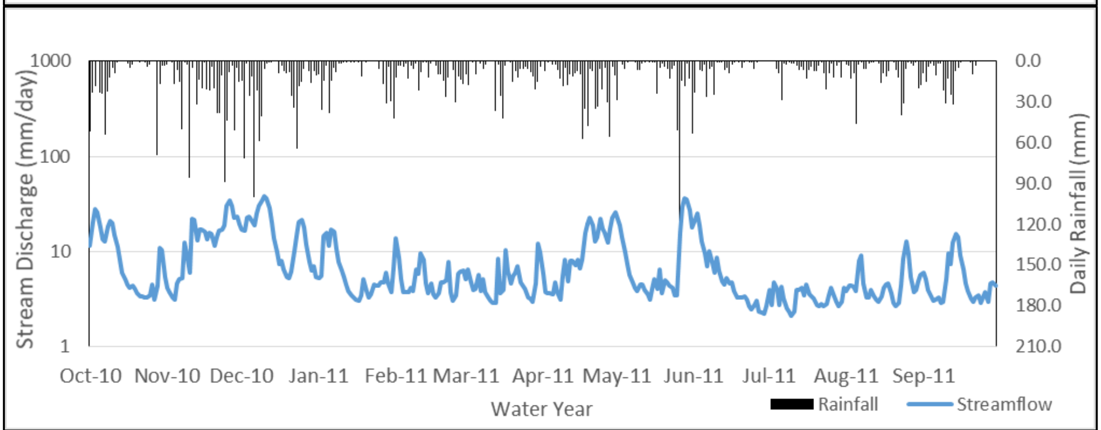



Figure 4-10: Streamflow vs Rainfall at each Station in Baddegama Watershed-2017/18



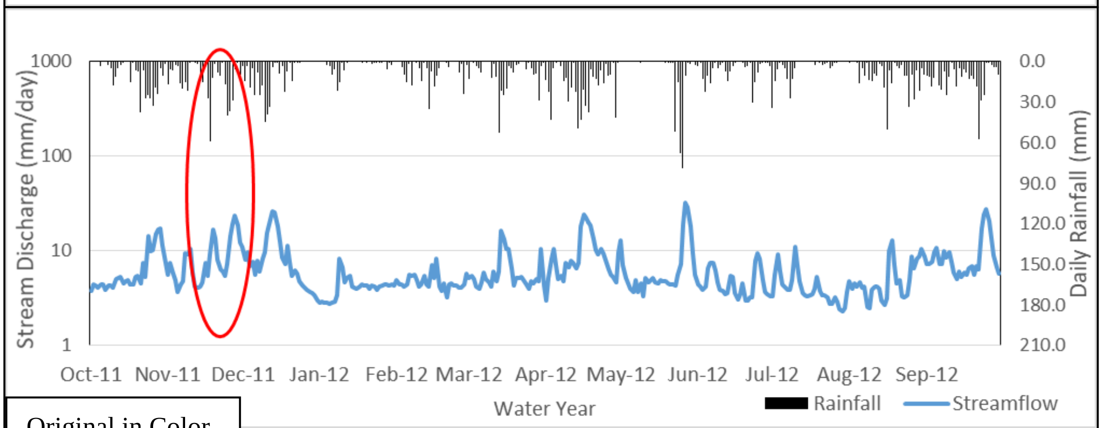




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Figure 4-11: Baddegama SF vs Thiessen Rainfall - 2008/09 to 2011/12

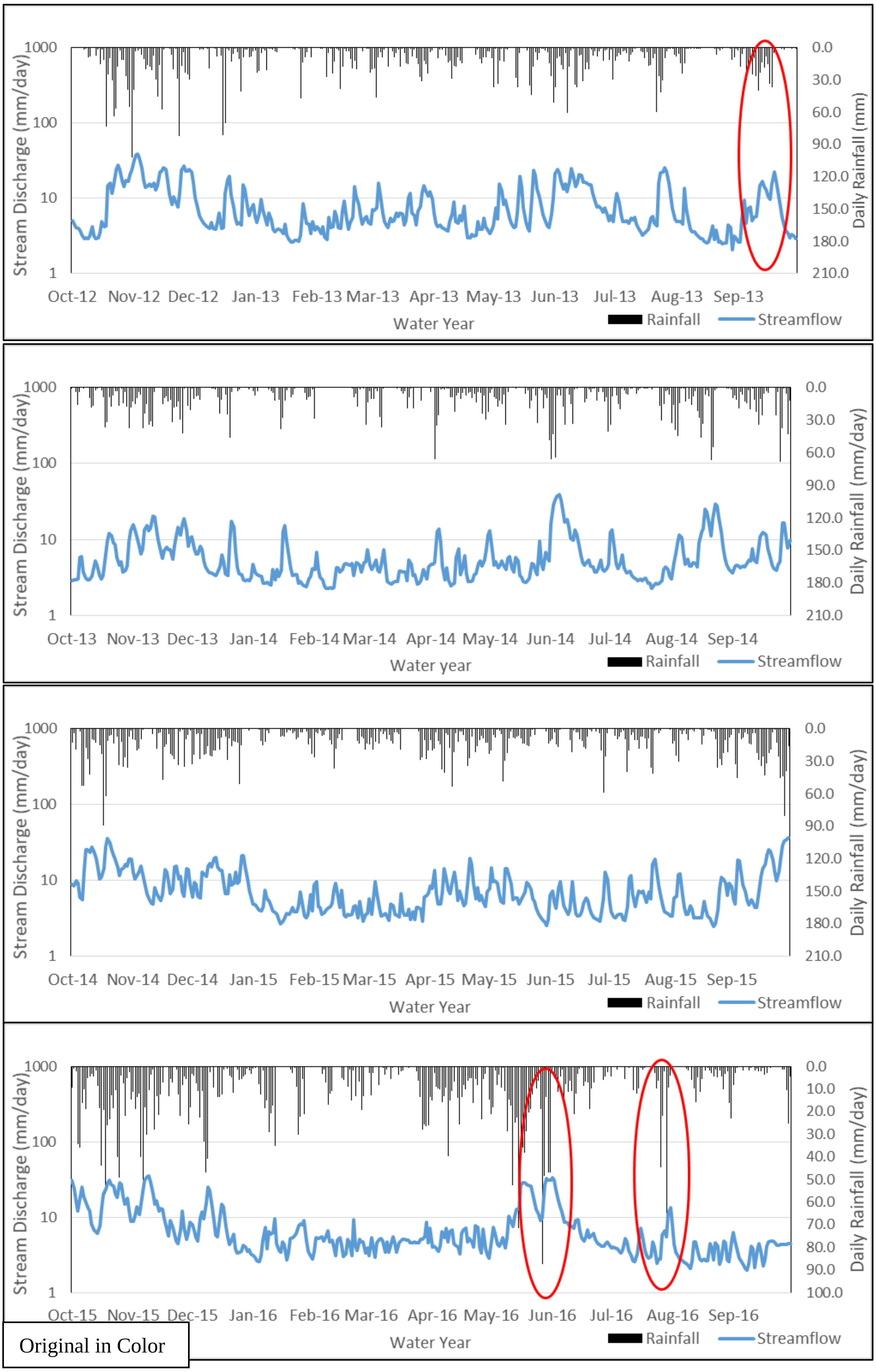



Figure 4-12: Baddegama SF vs Thiessen Rainfall - 2012/13 to 2015/16

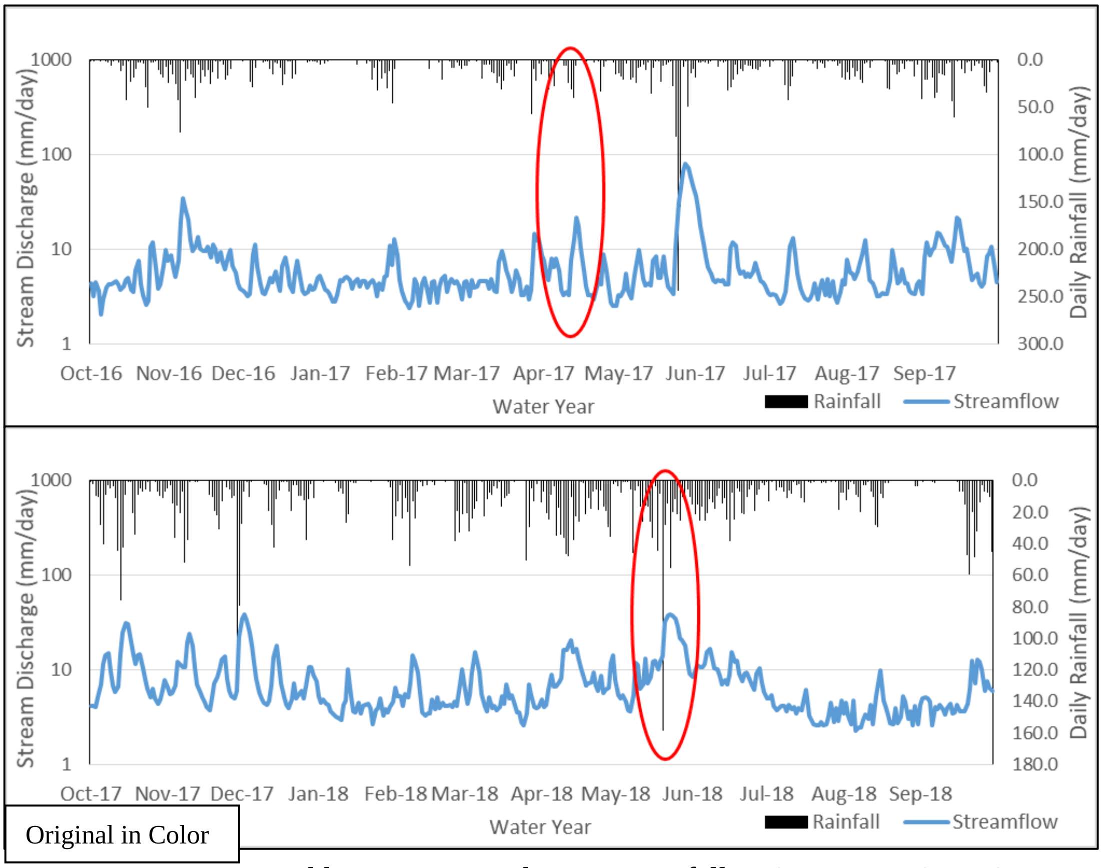



Figure 4-13: Baddegama SF vs Thiessen Rainfall - 2016/17 to 2017/18

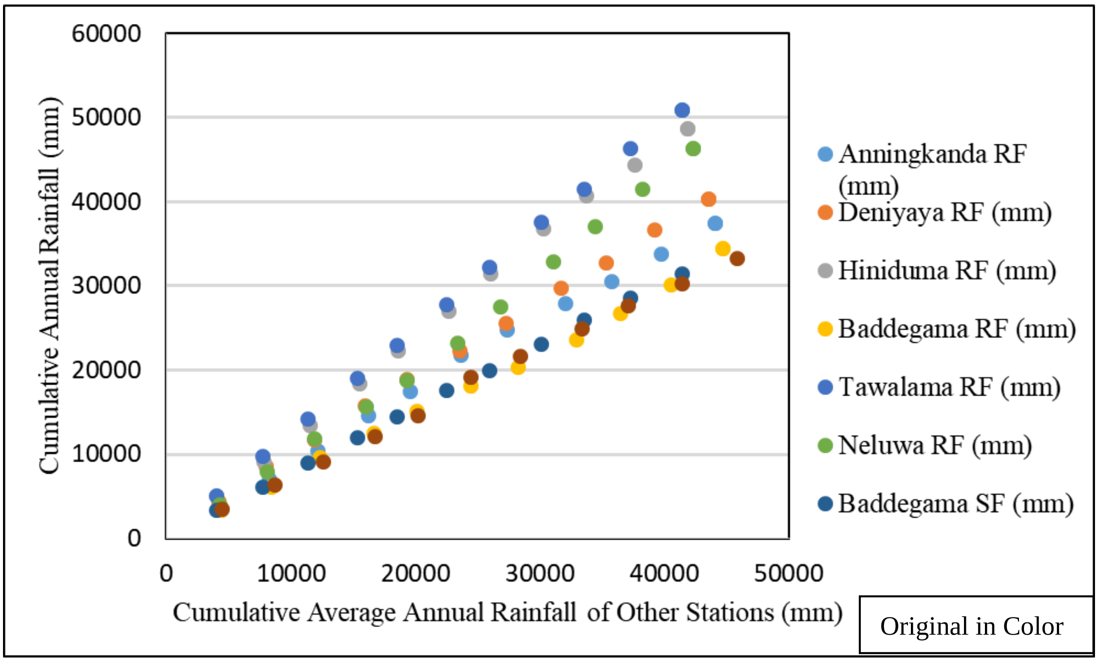



Figure 4-14: Double Mass Curves of Rainfall Stations

# 5 Results and Analysis

The following section describe obtained results through analysis in detail.

## 5.1 Tank Model Initial Parameters & Model Development

Various research results were observed for identifying the initial parameter values and it is observed that A0 to D1 can have min valued 0 and max value of 1(Devaliya et al., 2017; Setiawan et al., 2003). Summary of optimized parameter values referred when defining initial parameters as the start of simulation is shown Table 5-1. Further, to that parameter ranges proposed by Sugawara are shown in Table 5-2 (Setiawan et al., 2003).

Table 5-1: Tank Model Initial Parameters

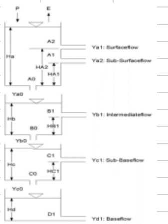
| | (Phien & Pradhan, 1983) | | (Kuok et al., 2011) | (Basri et al., 2002) | (Arifjaya et al., 2011) | (Setiawan et al., 2003) | | (Wijesekera, 1993) (Musiake & Wijesekera, 1990) | |
|---|---|---|---|---|---|---|---|---|---|
| A0 | 0.05 | 0.14 | 0.42 | 0.375 | 0.14349 | 0.285 | 0.028 | 0.2339 | 0.1326 |
| A1 | 0.035 | 0.045 | 0.002 | 0.1 | 0.14343 | 0.05 | 0.001 | 0.0947 | 0.2315 |
| A2 | 0.035 | 0.045 | 0.001 | 0.015 | 0.91407 | 0.061 | 0.022 | 0.2418 | 0.1682 |
| B0 | 0.05 | 0.115 | 0.6 | 0.1 | 0.0166 | 0.216 | 0.001 | 0.0183 | 0.0441 |
| B1 | 0.04 | 0.057 | 0.055 | 0.17 | 0.001 | 0.471 | 0.005 | 0.0402 | 0.0650 |
| C0 | 0.005 | 0.005 | 0.83 | 0.025 | 0.00099 | 0.051 | 0.004 | 0.0149 | 0.0172 |
| C1 | 0.005 | 0.005 | 0.055 | 0.05 | 0.42396 | 0.293 | 0.006 | 0.0321 | 0.0077 |
| D1 | 0.0002 | 0.0002 | 0.000001 | 0.005 | 0.00033 | 0.001 | 0.001 | 0.0001 | 0.00097 |
| HA1 | 30 | 40 | 10 | 10 | 14.4055 | 5 | 5.893 | 2.89 | 14.28 |
| HA2 | 35 | 45 | 20 | 30 | 198.628 | 50.741 | 60 | 38.77 | 41.38 |
| HB1 | 10 | 6.5 | 0 | 30 | 0.49431 | 30 | 30 | 78.38 | 24.75 |
| HC1 | 10 | 6.5 | 0 | 25 | 0.00033 | 60 | 0.003 | 1.89 | 0 |
| Region | Thailand | | Malaysia | Indonesia | West Java | Japan | Indonesia | SL - Mahaweli | SL- Kalu |

Table 5-2: Initial Values and Min-Max Values for Tank Model

| | (Setiawan et al., 2003) by Sugawara | | |
|---|---|---|---|
| Parameter | Initial | Min value | Max value |
| A0 | 0.2 | 0 | 1 |
| A1 | 0.1 | 0 | 1 |
| A2 | 0.1 | 0 | 1 |
| B0 | 0.06 | 0 | 1 |
| B1 | 0.03 | 0 | 1 |
| C0 | 0.012 | 0 | 1 |
| C1 | 0.006 | 0 | 1 |
| D1 | 0.001 | 0 | 1 |
| HA1 | 15 | 5 | 15 |
| HA2 | 25 | 25 | 60 |
| HB1 | 15 | 0 | 30 |
| HC1 | 15 | 0 | 60 |

Original in Color

| Intial | Parameter | Optimezed |
|---|---|---|
| 0.130274764 | A0 | 0.130274764 |
| 0.042772076 | A1 | 0.042772076 |
| 0.096027645 | A2 | 0.096027645 |
| 0.173714179 | B0 | 0.173714179 |
| 0.829377967 | B1 | 0.829377967 |
| 0.072856569 | C0 | 0.072856569 |
| 0.012431601 | C1 | 0.032431601 |
| 0.00095 | D1 | 0.00095 |
| 4.908709463 | HA1 | 4.908709463 |
| 22.10751261 | HA2 | 22.10751261 |
| 28.10482904 | HB1 | 28.10482904 |
| 5.049134811 | HC1 | 5.049134811 |




| | |
|---|---|
| MRAE | 0.2329 |
| Nash-Suct | 0.8381 |
| NSE log | 0.8209 |

| | | 1st Tank | | | | 2nd Tank | | | | | | 3rd Tank | | | | 4th Tank | | | | Runoff | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Date | Daily Precipitation (mm) | Storage of Previous day (mm) | Runoff (Lower outlet ) (mm) | Infiltration (mm) | Storage Balance (mm) | Storage of Previous day (mm) | Infiltration from 1st Tank (mm) | Remaining Daily Evapo-transpiration (same day) (mm) | Storage (mm) | Infiltration (mm) | Storage Balance (mm) | Storage of Previous day (mm) | Infiltration from 2nd Tank (mm) | Infiltration (mm) | Storage Balance (mm) | Storage of Previous day (mm) | Infiltration from 3rd Tank (mm) | Runoff from outlet (mm) | Storage Balance (mm) | Total Runoff (mm) | Discharge Observed | \|Qc - Qo\|/ Qo | |
| 9/30/2008 | 0.0 | | | | | | | | | | | | | | | | | | | | | | |
| 10/1/2008 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 3.3 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.00 | 3.09 | 1.0 | Warm Up 1 |
| 9/30/2013 | 1.4 | 0.7 | 0.0 | 0.0 | 0.0 | 10.7 | 0.0 | 2.8 | 7.9 | 1.4 | 6.5 | 35.3 | 1.4 | 2.7 | 33.0 | 2173.9 | 2.7 | 2.1 | 2174.5 | 3.09 | 2.91 | 0.1 | |
| 9/30/2008 | 0.0 | | | | | | | | | | | | | | | | | | | | | | |
| 10/1/2008 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 6.5 | 0.0 | 3.3 | 3.3 | 0.6 | 2.7 | 33.0 | 0.6 | 2.4 | 30.2 | 2174.5 | 2.4 | 2.1 | 2174.9 | 2.99 | 3.09 | 0.0 | Warm Up 2 |
| 9/30/2013 | 1.4 | 0.7 | 0.0 | 0.0 | 0.0 | 10.7 | 0.0 | 2.8 | 7.9 | 1.4 | 6.5 | 35.3 | 1.4 | 2.7 | 33.0 | 2560.1 | 2.7 | 2.4 | 2560.3 | 3.46 | 2.91 | 0.2 | |
| 9/30/2008 | 0.0 | | | | | | | | | | | | | | | | | | | | | | |
| 10/1/2008 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 6.5 | 0.0 | 3.3 | 3.3 | 0.6 | 2.7 | 33.0 | 0.6 | 2.4 | 30.2 | 2560.3 | 2.4 | 2.4 | 2560.3 | 3.36 | 3.09 | 0.1 | Warm Up 3 |
| 9/30/2013 | 1.4 | 0.7 | 0.0 | 0.0 | 0.0 | 10.7 | 0.0 | 2.8 | 7.9 | 1.4 | 6.5 | 35.3 | 1.4 | 2.7 | 33.0 | 2628.2 | 2.7 | 2.5 | 2628.4 | 3.53 | 2.91 | 0.2 | |
| 9/30/2008 | 0.0 | | | | | | | | | | | | | | | | | | | | | | |
| 10/1/2008 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 6.5 | 0.0 | 3.3 | 3.3 | 0.6 | 2.7 | 33.0 | 0.6 | 2.4 | 30.2 | 2628.4 | 2.4 | 2.5 | 2628.3 | 3.42 | 3.09 | 0.1 | Warm Up 4 |
| 9/30/2013 | 1.4 | 0.7 | 0.0 | 0.0 | 0.0 | 10.7 | 0.0 | 2.8 | 7.9 | 1.4 | 6.5 | 35.3 | 1.4 | 2.7 | 33.0 | 2640.2 | 2.7 | 2.5 | 2640.4 | 3.54 | 2.91 | 0.2 | |
| 9/30/2008 | 0.0 | | | | | | | | | | | | | | | | | | | | | | |
| 10/1/2008 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 6.5 | 0.0 | 3.3 | 3.3 | 0.6 | 2.7 | 33.0 | 0.6 | 2.4 | 30.2 | 2640.4 | 2.4 | 2.5 | 2640.3 | 3.43 | 3.09 | 0.1 | Warm Up 5 |
| 9/30/2013 | 1.4 | 0.7 | 0.0 | 0.0 | 0.0 | 10.7 | 0.0 | 2.8 | 7.9 | 1.4 | 6.5 | 35.3 | 1.4 | 2.7 | 33.0 | 2642.3 | 2.7 | 2.5 | 2642.5 | 3.54 | 2.91 | 0.2 | |
| 9/30/2008 | 0.0 | | | | | | | | | | | | | | | | | | | | | | |
| 10/1/2008 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 6.5 | 0.0 | 3.3 | 3.3 | 0.6 | 2.7 | 33.0 | 0.6 | 2.4 | 30.2 | 2642.5 | 2.4 | 2.5 | 2642.4 | 3.44 | 3.09 | 0.1 | Calibration |
| 10/2/2008 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 2.7 | 0.0 | 4.0 | 0.0 | 0.0 | 0.0 | 30.2 | 0.0 | 2.1 | 26.1 | 2642.4 | 2.1 | 2.5 | 2642.0 | 3.29 | 3.72 | 0.1 | |
| 10/3/2008 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 2.7 | 0.0 | 0.0 | 0.0 | 26.1 | 0.0 | 1.7 | 21.1 | 2642.0 | 1.7 | 2.5 | 2641.2 | 3.11 | 3.74 | 0.2 | |
| 10/4/2008 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 4.1 | 0.0 | 0.0 | 0.0 | 21.1 | 0.0 | 1.2 | 15.4 | 2641.2 | 1.2 | 2.5 | 2639.9 | 2.90 | 2.70 | 0.1 | |
| 10/5/2008 | 0.4 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 3.7 | 0.0 | 0.0 | 0.0 | 15.4 | 0.0 | 0.9 | 10.7 | 2639.9 | 0.9 | 2.5 | 2638.3 | 2.73 | 3.95 | 0.3 | |
| 10/6/2008 | 4.1 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 3.2 | 0.0 | 0.0 | 0.0 | 10.7 | 0.0 | 0.5 | 6.8 | 2638.3 | 0.5 | 2.5 | 2636.3 | 2.58 | 2.66 | 0.0 | |
| 10/7/2008 | 29.2 | 0.0 | 0.0 | 0.1 | 0.9 | 0.0 | 0.1 | 0.0 | 0.1 | 0.0 | 0.1 | 6.8 | 0.0 | 0.5 | 6.3 | 2636.3 | 0.5 | 2.5 | 2634.3 | 2.56 | 4.16 | 0.4 | |
| 10/8/2008 | 3.5 | 0.9 | 1.0 | 3.6 | 22.6 | 0.1 | 3.6 | 0.0 | 3.7 | 0.6 | 3.1 | 6.3 | 0.6 | 0.5 | 6.4 | 2634.3 | 0.5 | 2.5 | 2632.3 | 4.08 | 4.37 | 0.1 | |
| 10/9/2008 | 19.6 | 22.6 | 0.8 | 3.2 | 20.1 | 3.1 | 3.2 | 0.0 | 6.2 | 1.1 | 5.2 | 6.4 | 1.1 | 0.5 | 6.8 | 2632.3 | 0.5 | 2.5 | 2630.3 | 3.62 | 6.02 | 0.4 | |
| 10/10/2008 | 17.5 | 20.1 | 1.4 | 4.9 | 30.0 | 5.2 | 4.9 | 0.0 | 10.1 | 1.8 | 8.3 | 6.8 | 1.8 | 0.6 | 7.8 | 2630.3 | 0.6 | 2.5 | 2628.5 | 5.54 | 4.29 | 0.3 | |
| 10/11/2008 | 25.5 | 30.0 | 1.7 | 5.9 | 35.6 | 8.3 | 5.9 | 0.0 | 14.3 | 2.5 | 11.8 | 7.8 | 2.5 | 0.8 | 9.4 | 2628.5 | 0.8 | 2.5 | 2626.7 | 6.65 | 5.79 | 0.1 | |
| 10/12/2008 | 33.3 | 35.6 | 2.3 | 7.7 | 45.3 | 11.8 | 7.7 | 0.0 | 19.4 | 3.4 | 16.1 | 9.4 | 3.4 | 0.9 | 11.6 | 2626.7 | 0.9 | 2.5 | 2625.1 | 8.57 | 9.81 | 0.1 | |
| 10/13/2008 | 4.2 | 45.3 | 3.0 | 9.8 | 57.2 | 16.1 | 9.8 | 0.0 | 25.8 | 4.5 | 21.4 | 11.6 | 4.5 | 1.2 | 14.5 | 2625.1 | 1.2 | 2.5 | 2623.8 | 10.94 | 10.91 | 0.0 | |
| 10/14/2008 | 3.5 | 57.2 | 2.4 | 7.9 | 46.6 | 21.4 | 7.9 | 0.0 | 29.3 | 5.1 | 23.2 | 14.5 | 5.1 | 1.4 | 17.7 | 2623.8 | 1.4 | 2.5 | 2622.8 | 9.99 | 6.57 | 0.5 | |
| 10/15/2008 | 0.0 | 46.6 | 1.9 | 6.3 | 37.6 | 23.2 | 6.3 | 0.0 | 29.5 | 5.1 | 23.2 | 17.7 | 5.1 | 1.7 | 20.6 | 2622.8 | 1.7 | 2.5 | 2621.9 | 8.59 | 3.89 | 1.2 | |
| 10/16/2008 | 14.6 | 37.6 | 1.3 | 4.5 | 27.6 | 23.2 | 4.5 | 0.0 | 27.7 | 4.8 | 22.9 | 20.6 | 4.8 | 1.9 | 22.9 | 2621.9 | 1.9 | 2.5 | 2621.3 | 5.63 | 3.96 | 0.4 | |

Figure 5-1: Tank Model Development for Baddegama Catchment

## 5.2 Model Warmup

To stabilize model internal processes including soil moisture storage a five-year warm up period is utilized. The model was setup in such way in each simulation it is warmed up for the given calibration or validation data for period of five water year cycles so that it has stabilized its internal processes.

The model was always initialized with zero soil moisture and during simulation it freely adjusted the soil moisture in each tank. Table 5-3 shows the variation of soil moistures during warm up (for calibration). Figure 5-2 and Figure 5-3 show their behavior and stabilization during the simulation graphically.

Table 5-3: Soil Moisture Stabilization During Model Warmup

| Catchment | Warm up Cycle No. | Soil moisture content Tank 1 (mm/day) | Soil moisture content Tank 2 (mm/day) | Soil moisture content Tank 3 (mm/day) | Soil moisture content Tank 4 (mm/day) |
|---|---|---|---|---|---|
| Baddegama | 1 | 0.0 | 6.5 | 33.0 | 2174.5 |
| | 2 | 0.0 | 6.5 | 33.0 | 2560.3 |
| | 3 | 0.0 | 6.5 | 33.0 | 2628.4 |
| | 4 | 0.0 | 6.5 | 33.0 | 2640.4 |
| | 5 | 0.0 | 6.5 | 33.0 | 2642.6 |
| Tawalama | 1 | 0.0 | 26.3 | 75.3 | 857.0 |
| | 2 | 0.0 | 26.3 | 75.3 | 1013.2 |
| | 3 | 0.0 | 26.3 | 75.3 | 1040.7 |
| | 4 | 0.0 | 26.3 | 75.3 | 1045.5 |
| | 5 | 0.0 | 26.3 | 75.3 | 1046.4 |

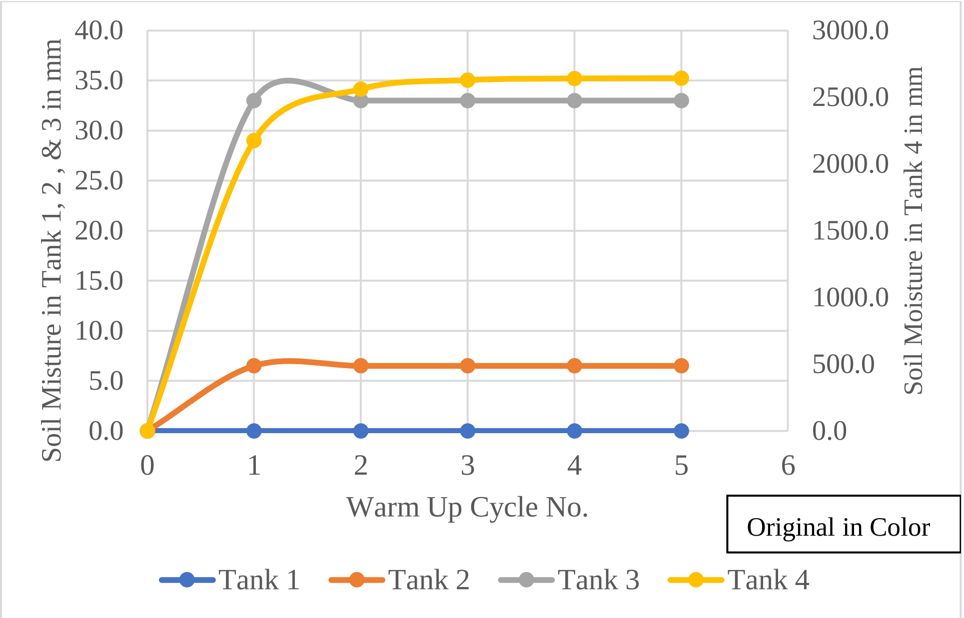



Figure 5-2: Soil Moisture Variations in Each Tank for Warm Up Period at Baddegama Catchment

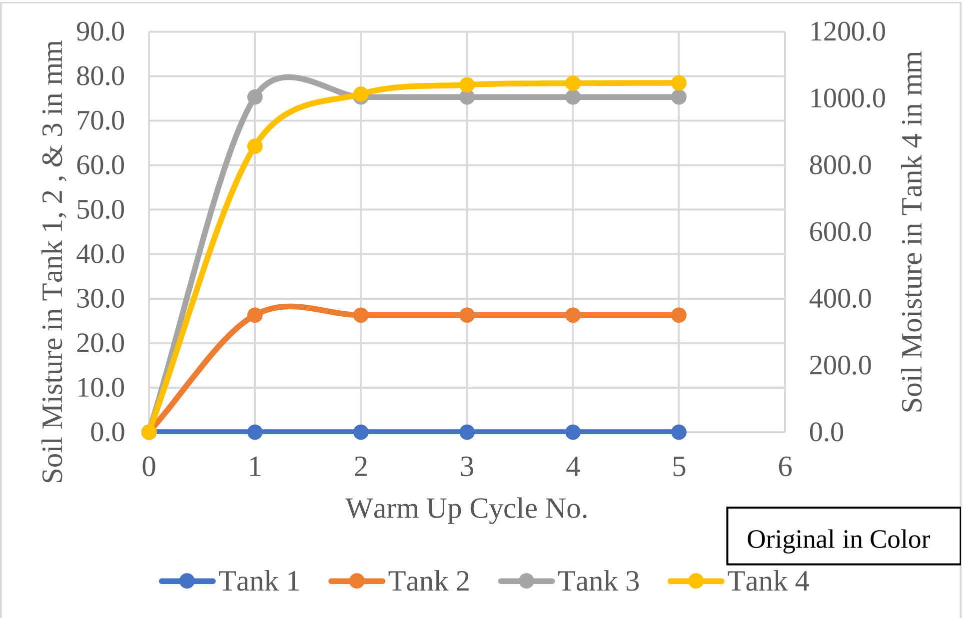



Figure 5-3: Soil Moisture Variations in Each Tank for Warm Up Period at Baddegama Catchment

## 5.3 High, Intermediate, & Low flow classification

For the purpose of evaluating model performance, one of recognized method used is analysis of fitting of the model results for different flow regimes (Wijesekera, 2020). As describe in literature review this will enable evaluating the model for intended objective and it will give more insight as to how the model is performing.

In this study the high, intermediate and low flow thresholds are established considering the break in gradient in flow duration curve, identified as a function of order of magnitude of streamflow.

The results of method utilized are presented in Figure B 2 and Figure B 3 for Baddegama and Tawalama respectively. According to that high flow threshold is 18% for both catchments whereas Baddegama and Tawalama low flow threshold is 70% and 79% respectively.

## 5.4 Tank Model Calibration

### 5.4.1 Calibration of Baddegama Catchment

The results of calibration for Baddegama catchment is illustrated here. The statistical goodness of fit, visual and graphical evaluation results is shown in respective sections.

MRAE is used as measure of statistical goodness of fit. Flow duration curves and total hydrographs are developed for evaluation of model performance graphically and annual water balance showcase the model performance numerically.

#### 5.4.1.1 Statistical Measure of Goodness of Fit- Baddegama

The Table 5-4 shows the objective function values obtained for entire calibration flow series and its behavior in different regimes in sorted and unsorted flow duration curves.

Table 5-4: MRAE Results - Calibration Baddegama

| **Gauging Station** | **MRAE for Overall Flow** | **MRAE w.r.t FDC (Sorted)** | | | **MRAE w.r.t FDC (Unsorted)** | | |
|---|---|---|---|---|---|---|---|
| | | **High** | **Medium** | **Low** | **High** | **Medium** | **Low** |
| Baddegama | 0.233 | 0.028 | 0.069 | 0.056 | 0.179 | 0.254 | 0.229 |

#### 5.4.1.2 Comparison of Flow Duration Curves - Baddegama

Figure 5-4 and Figure 5-5 shows the sorted FDC and unsorted FDC graphs respectively. These are developed from the observed and calculated streamflow during calibration. Overall, it could be noted that model is overestimating medium flows and underestimating low flows. It shows how the results are matching with different flow regimes under consideration.

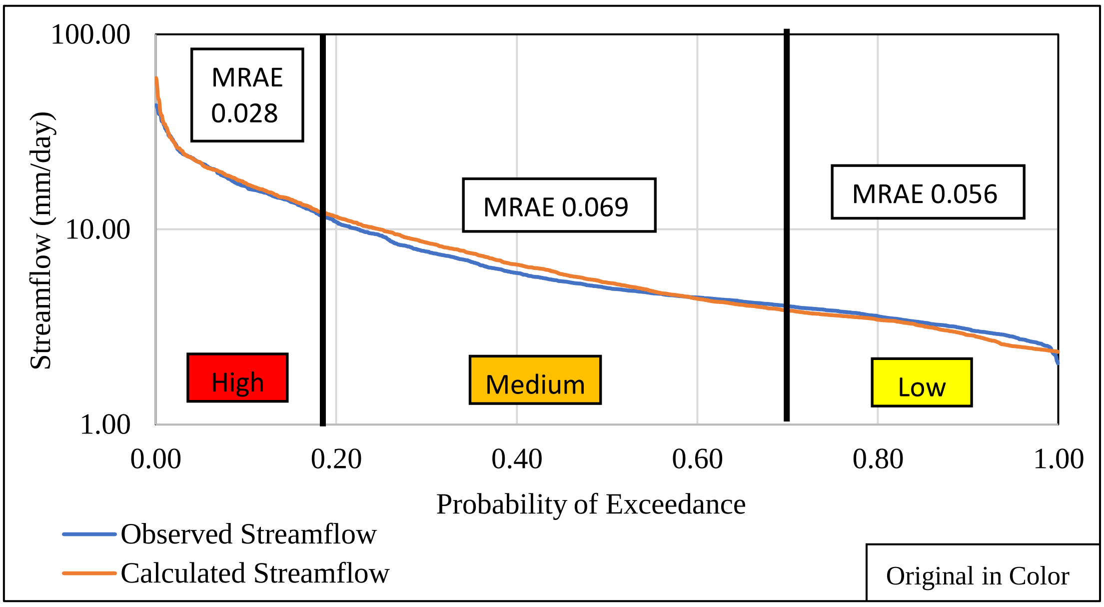



Figure 5-4: FDC (Sorted) - Calibration Baddegama

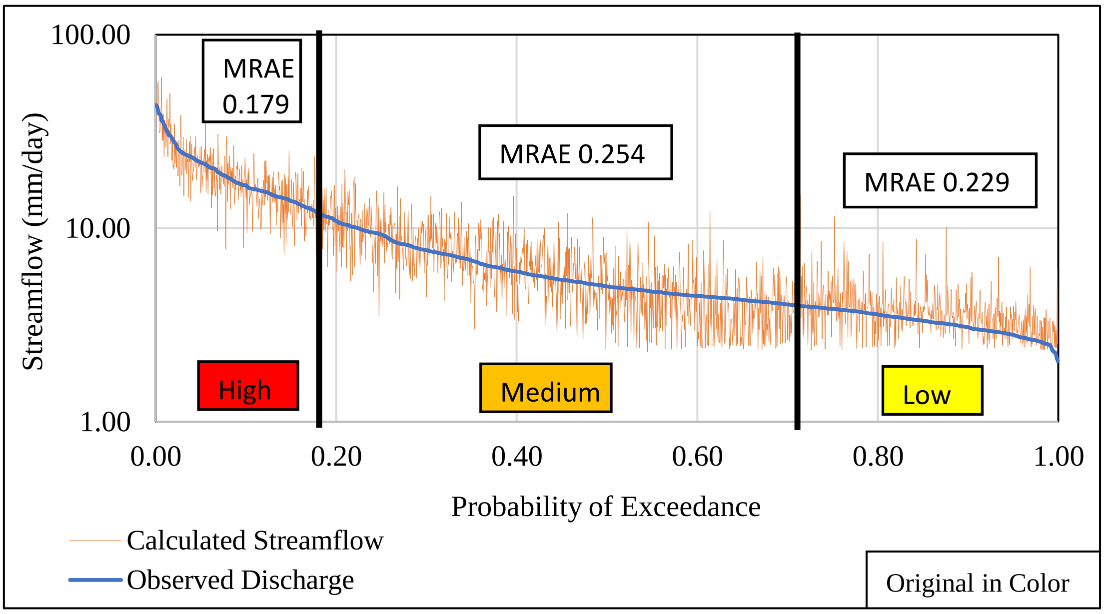
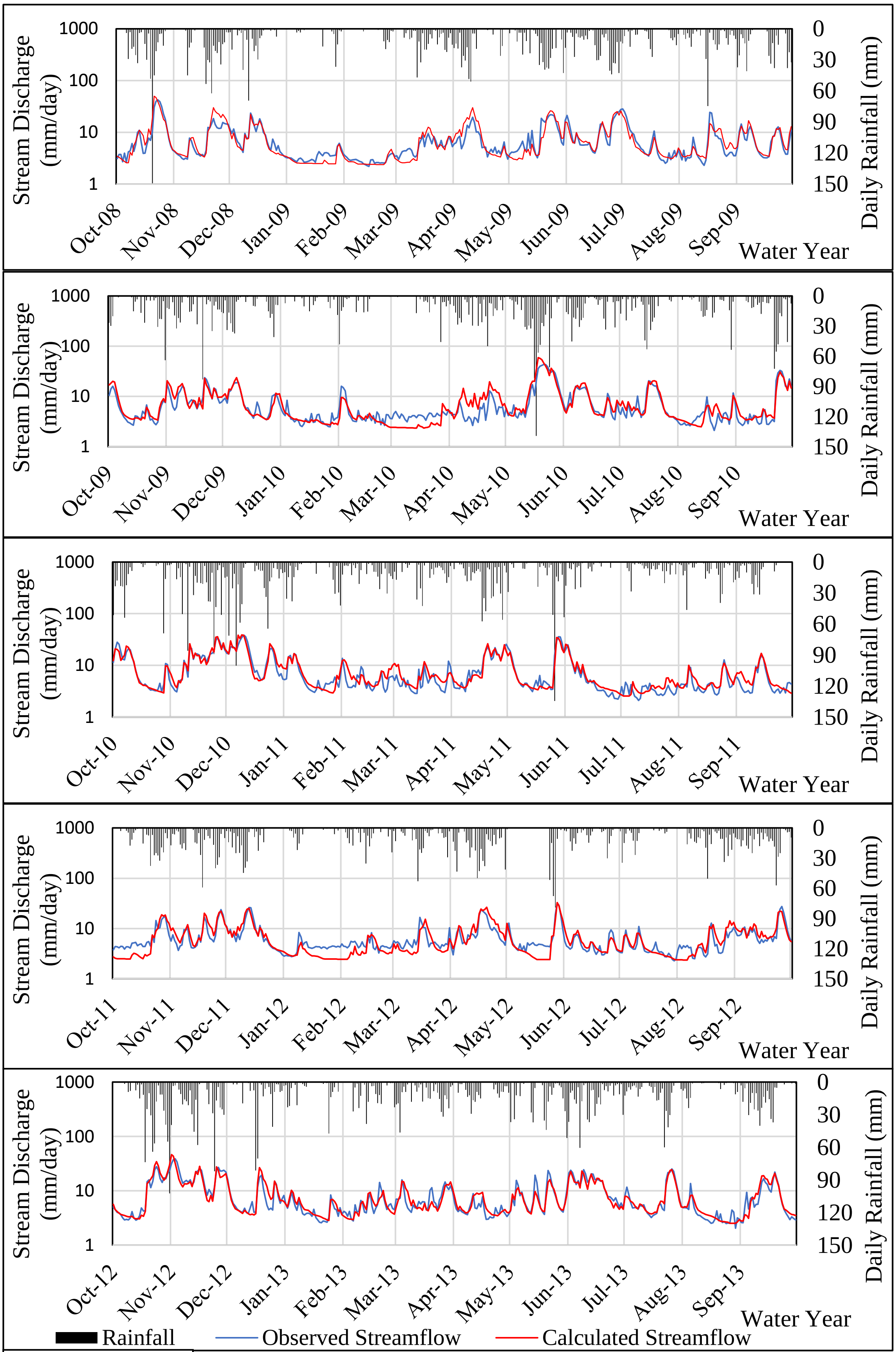



Figure 5-5: FDC (Unsorted) - Calibration Baddegama

#### 5.4.1.3 Comparison of Hydrographs of Observed and Estimated streamflow - Baddegama

Figure 5-6 shows the hydrographs for the calibration period of Baddegama catchment. It can be seen that overall hydrograph matching is acceptable. Model is arguably catch high flow responses well and where adequate data are not present it tends to underestimate low flows.




Original in Color

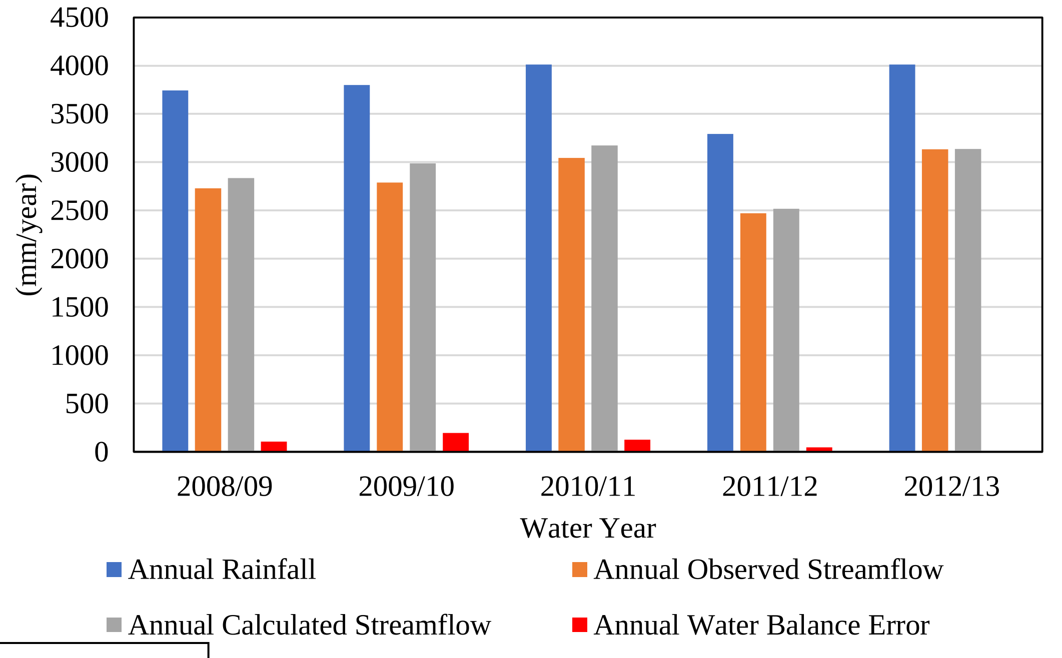
Figure 5-6: Hydrographs for Observed and Estimated Streamflow in Baddegama for Calibration

#### 5.4.1.4 Annual Water Balance - Baddegama

Annual water balance is calculated as difference between annual rainfall and annual streamflow. This value can be calculated for both observed and estimated streamflow and error of mismatching can be found as shown in Table 5-5 and Figure 5-7. This stands for mass error of model. It can be seen that annual water balance error positive for each year and hence model is overestimating the streamflow as a whole.

Table 5-5: Annual Water Balance - Baddegama Calibration

| Water Year | Annual RF (mm) | Annual Observe SF (mm) | Annual cal. SF (mm) | AWB Observed (mm) | AWB Simulated (mm) | AWB Error | AWB Error (%) |
|---|---|---|---|---|---|---|---|
| 2008/09 | 3743.6 | 2728.6 | 2835.6 | 1015.0 | 908.0 | 107.0 | 3.9 |
| 2009/10 | 3798.1 | 2789.9 | 2987.0 | 1008.3 | 811.1 | 197.2 | 7.1 |
| 2010/11 | 4012.7 | 3045.1 | 3172.6 | 967.6 | 840.1 | 127.5 | 4.2 |
| 2011/12 | 3293.8 | 2472.5 | 2519.0 | 821.4 | 774.9 | 46.5 | 1.9 |
| 2012/13 | 4011.3 | 3134.7 | 3136.8 | 876.6 | 874.5 | 2.1 | 0.1 |
| Average | 3771.9 | 2834.2 | 2930.2 | 937.8 | 841.7 | 96.1 | 3.4 |




Original in Color

Figure 5-7: Annual Water Balance- Baddegama Calibration

### 5.4.2 Calibration of Tawalama Sub-catchment

The results of calibration of Tawalama sub-catchment is shown below.

#### 5.4.2.1 Statistical Measure of Goodness of Fit- Tawalama

The Table 5-6 shows the MRAE values obtained for entire calibration flow series and its behavior in different regimes in sorted and unsorted flow duration curves for Tawalama sub catchment.

Table 5-6: MRAE Results – Calibration Tawalama

| Gauging Station | MRAE for Overall Flow | MRAE w.r.t FDC (Sorted) | | | MRAE w.r.t FDC (Unsorted) | | |
|---|---|---|---|---|---|---|---|
| | | High | Medium | Low | High | Medium | Low |
| Tawalama | 0.246 | 0.082 | 0.024 | 0.039 | 0.238 | 0.257 | 0.223 |

#### 5.4.2.2 Comparison of Flow Duration Curves – Tawalama

Similar to Baddegama, Flow duration curves are developed for Tawalama sub catchment and are shown in Figure 5-8 and Figure 5-9. Overall fitting of the FDC is better than Baddegama and unsorted FDC shows less fluctuations than unsorted FDC for Baddegama.

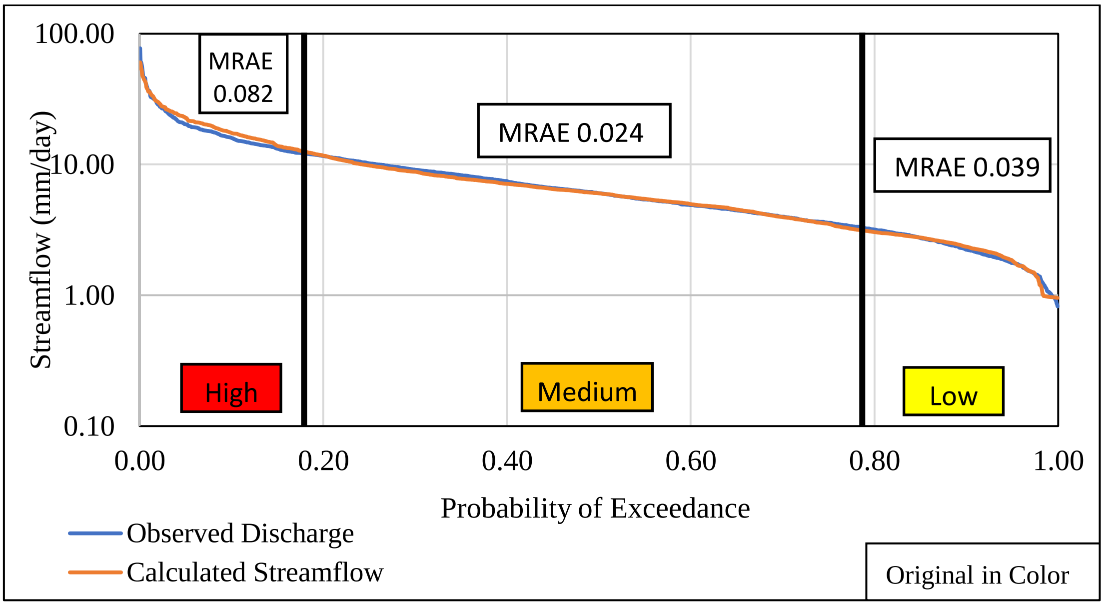



Figure 5-8: FDC (Sorted) - Calibration Tawalama

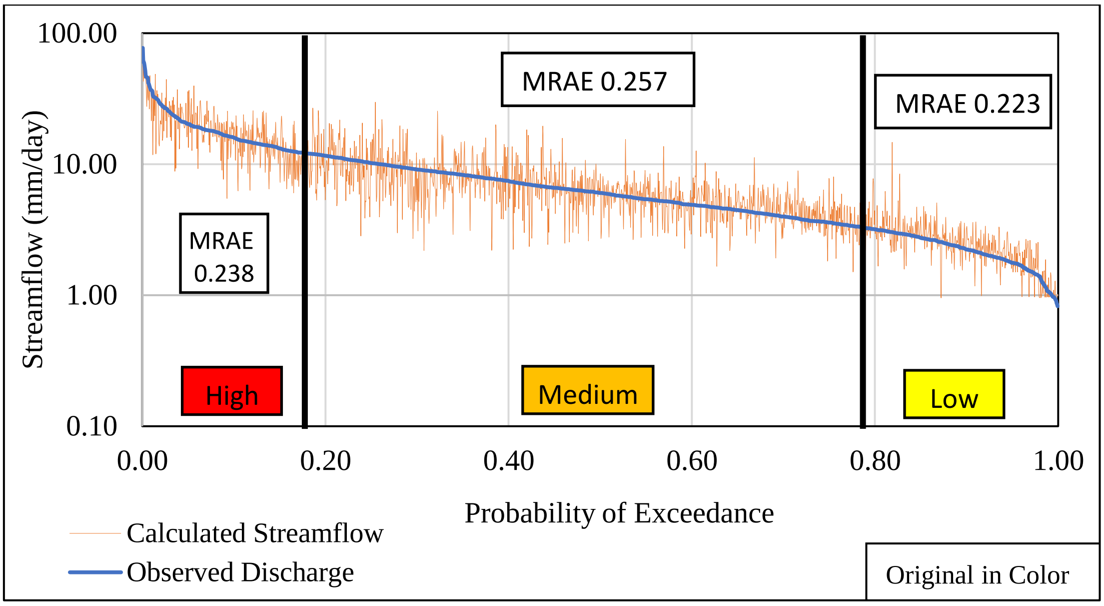



Figure 5-9: FDC (Unsorted) - Calibration Tawalama

#### 5.4.2.3 Comparison of Hydrographs of Observed and Estimated streamflow – Tawalama

Figure 5-10 shows the hydrographs of simulated and observed streamflow for the calibration data period. It can be seen that apart from water year 2012/13 other years are well matching in all flow regimes.

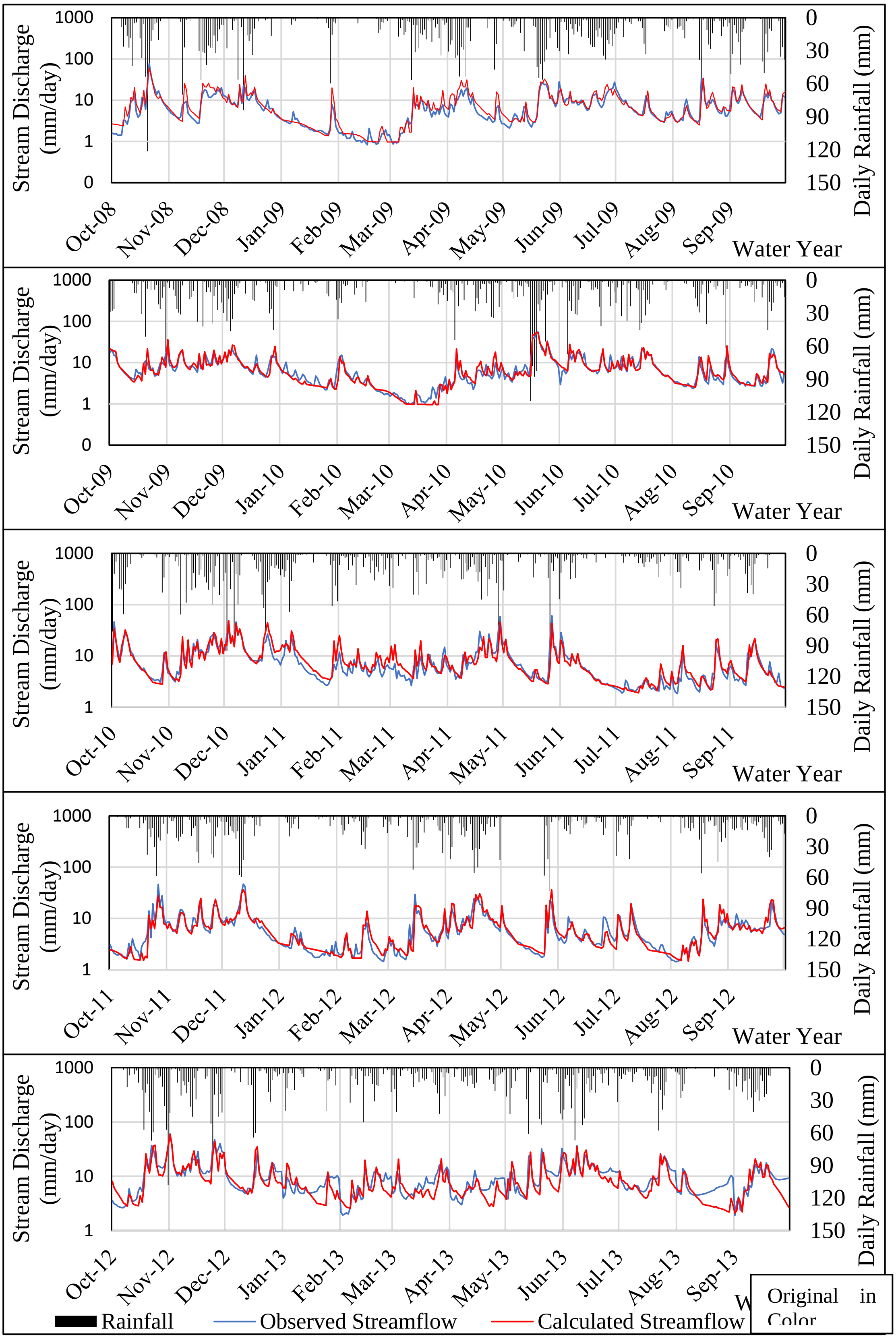



Figure 5-10: Hydrographs for Observed and Estimated streamflow in Tawalama for Calibration

#### 5.4.2.4 Annual Water Balance - Tawalama

Annual water balance calculated for Tawalama sub catchment is shown in Table 5-7 and Figure 5-11. It can be seen that water balance error is greater for year 2008/09 and 2012/13. Further, it is noted that except for year 2012/13, for all other years, model is overestimating hence average AWB error is positive.

Table 5-7: Annual Water Balance - Tawalama Calibration

| Water Year | Annual RF(mm) | Annual Observed SF (mm) | Annual cal. SF (mm) | AWB Observed | AWB Simulated | AWB Error (mm) | AWB Error (%) |
|---|---|---|---|---|---|---|---|
| 2008/09 | 4086.4 | 2744.5 | 3093.5 | 1341.9 | 993.0 | 349.0 | 12.7 |
| 2009/10 | 3631.4 | 2783.1 | 2886.0 | 848.3 | 745.3 | 103.0 | 3.7 |
| 2010/11 | 4045.8 | 3077.6 | 3230.3 | 968.3 | 815.6 | 152.7 | 5.0 |
| 2011/12 | 3278.2 | 2404.4 | 2413.1 | 873.9 | 865.1 | 8.7 | 0.4 |
| 2012/13 | 4116.8 | 3689.6 | 3328.0 | 427.2 | 788.8 | -361.6 | -9.8 |
| Average | 3831.7 | 2939.8 | 2990.2 | 891.9 | 841.6 | 50.3 | 1.7 |

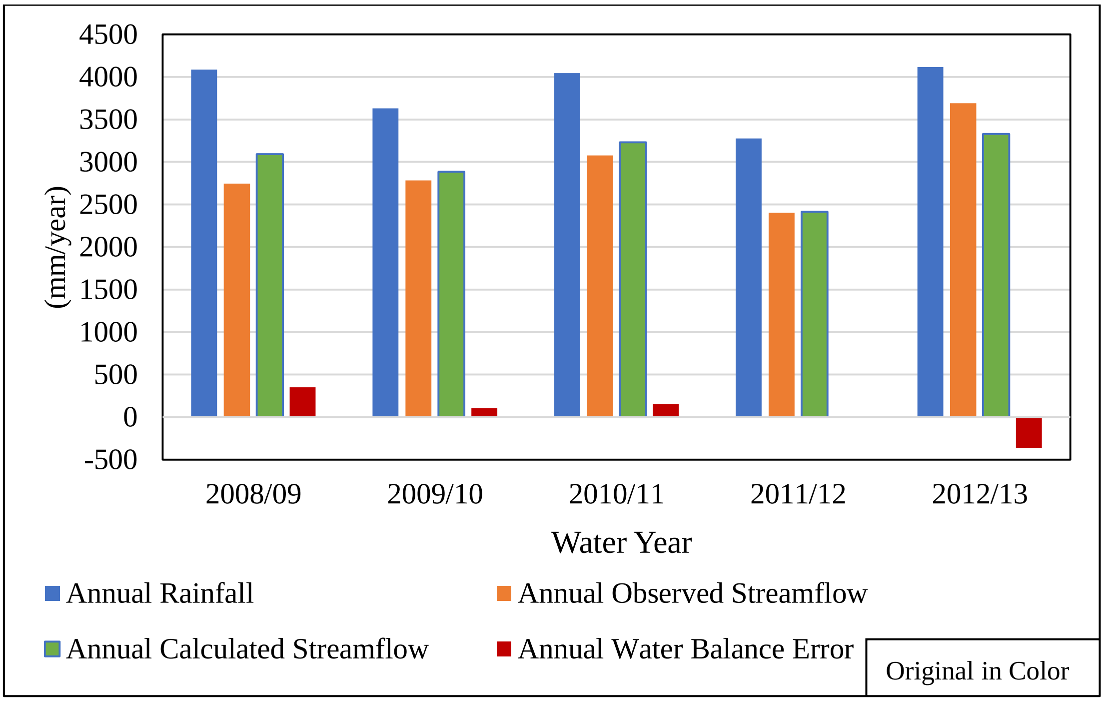



Figure 5-11: Annual Water Balance - Tawalama Calibration

## 5.5 Tank Model Validation

For the validation of calibrated parameters of the tank model period of record from 2013/14 water year to 2017/18 water year is used. Streamflow data for both catchments were collected at the station and used for validation.

### 5.5.1 Validation of Baddegama Catchment

#### 5.5.1.1 Statistical Measure of Goodness of Fit- Baddegama Validation

Statistical goodness of fit observed through MRAE values for validation flow series is presented in Table 5-8.

Table 5-8: MRAE Results - Validation Baddegama

| Gauging Station | MRAE for Overall Flow | MRAE w.r.t FDC (Sorted) | | | MRAE w.r.t FDC (Unsorted) | | |
|---|---|---|---|---|---|---|---|
| | | High | Medium | Low | High | Medium | Low |
| Baddegama | 0.298 | 0.102 | 0.148 | 0.013 | 0.194 | 0.324 | 0.315 |

#### 5.5.1.2 Comparison of Flow Duration Curves – Baddegama Validation

Sorted and unsorted FDC graphs are shown in Figure 5-12 and Figure 5-13 respectively. It is seen that medium flows and part of high flows are over predicted in the validation.

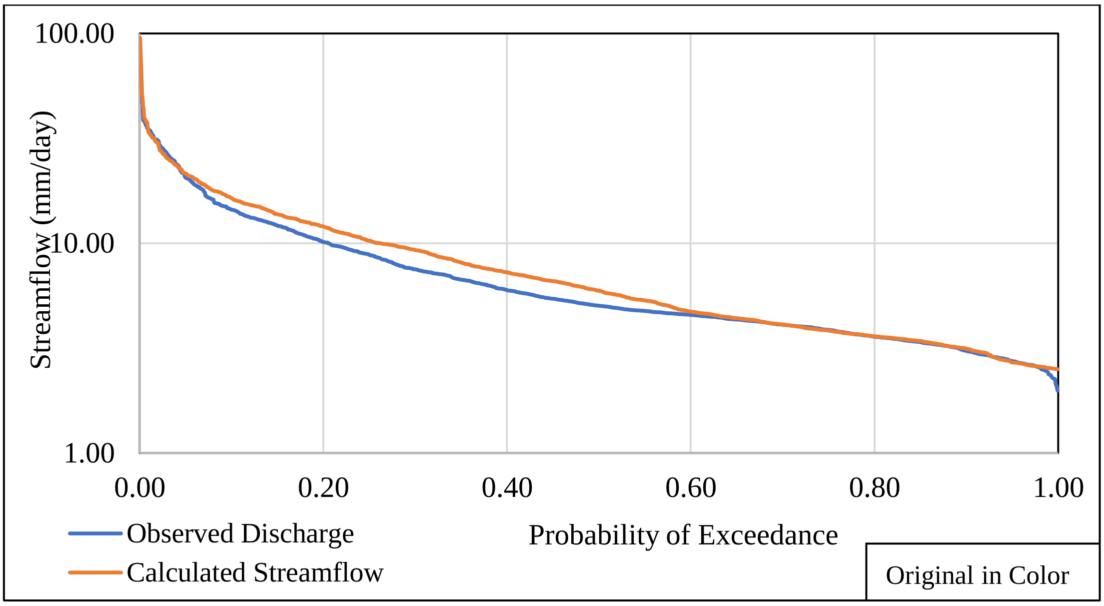



Figure 5-12: FDC (Sorted) - Validation Baddegama

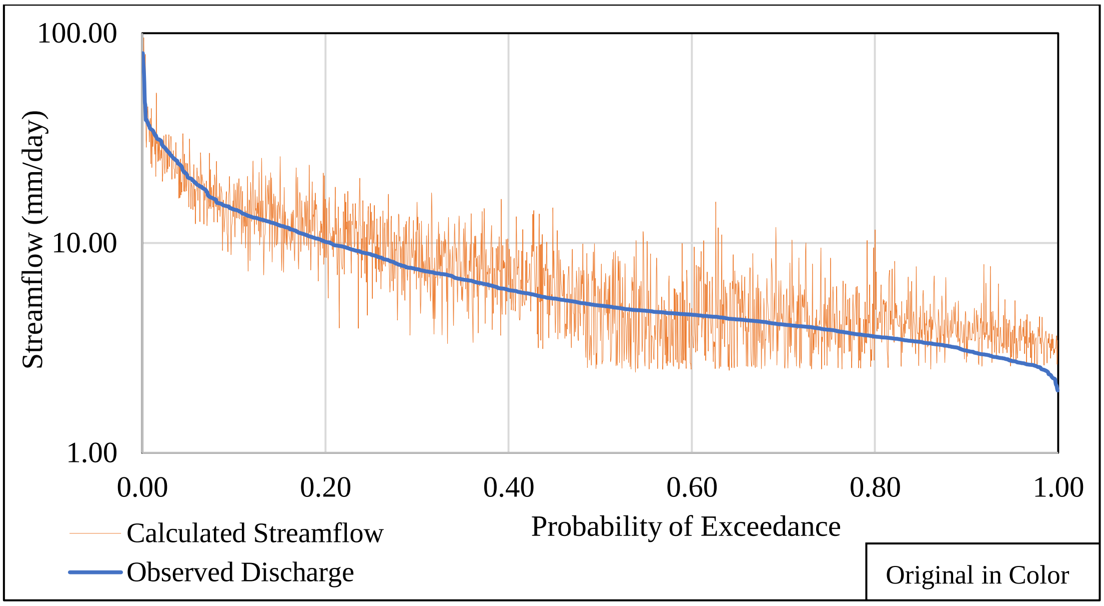



Figure 5-13: FDC (Unsorted) - Validation Baddegama

#### 5.5.1.3 Comparison of Hydrographs of Observed and Estimated streamflow – Baddegama Validation

Figure 5-14 shows the hydrographs of simulated and observed streamflow for the validation data period of 2013/14 to 2017/18.

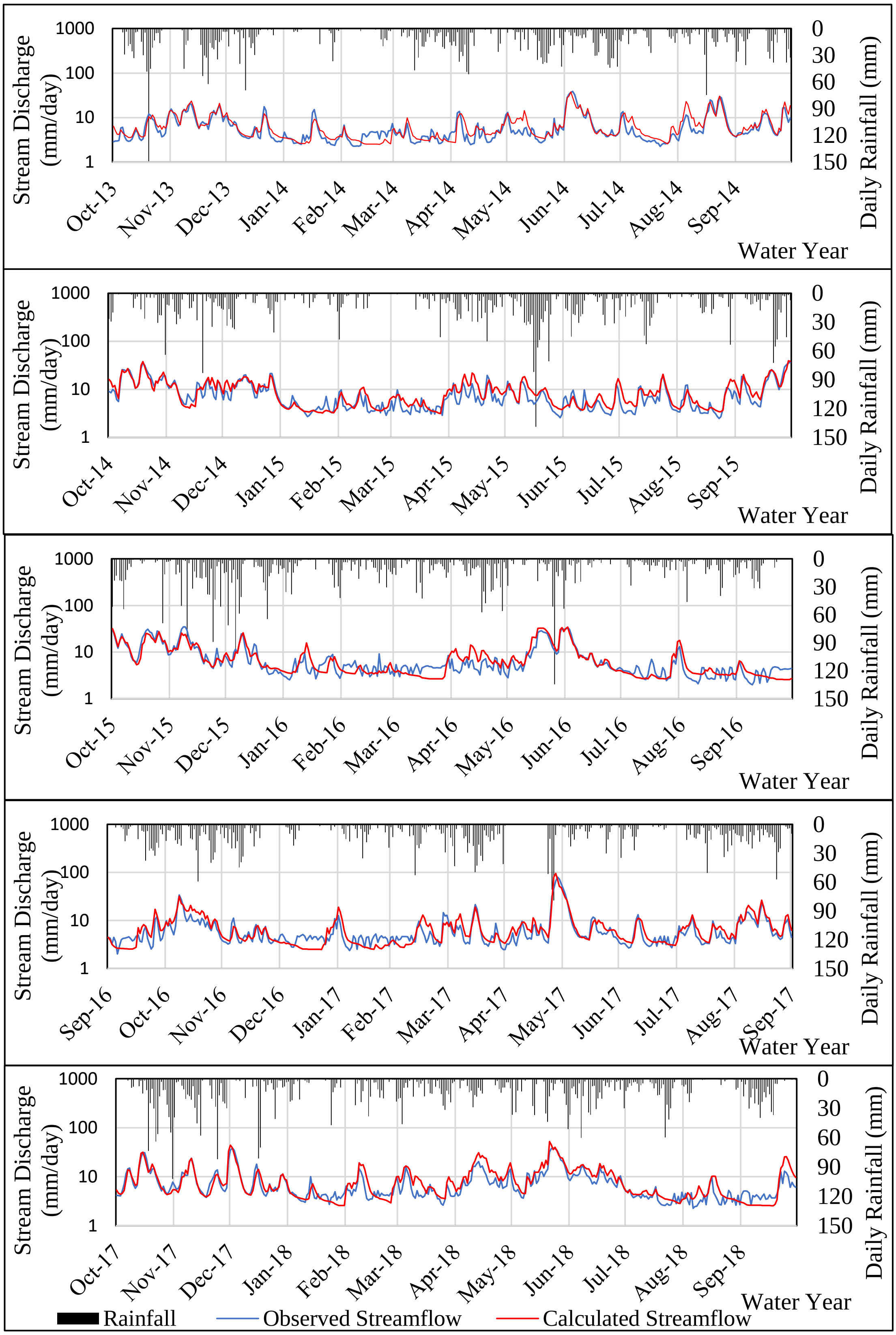



Figure 5-14: Hydrographs for Observed and Estimated streamflow in Baddegama for Validation

#### 5.5.1.4 Annual Water Balance – Baddegama Validation

Table 5-9 shows the annual water balance of Baddegama for validation period. It can be seen that overall average water balance error is positive i.e. overestimation and error is under 10%.

Table 5-9: Annual Water Balance - Baddegama Validation

| Water Year | Annual RF (mm) | Annual Observe SF (mm) | Annual cal. SF (mm) | AWB Observed (mm) | AWB Simulated (mm) | AWB Error | AWB Error (%) |
|---|---|---|---|---|---|---|---|
| 2013/14 | 3743.6 | 2413.0 | 2600.3 | 1330.6 | 1143.3 | 187.3 | 7.8 |
| 2014/15 | 3798.1 | 3047.8 | 3408.2 | 750.3 | 389.9 | 360.4 | 11.8 |
| 2015/16 | 4012.7 | 2896.6 | 2964.2 | 1116.1 | 1048.5 | 67.6 | 2.3 |
| 2016/17 | 3293.8 | 2621.2 | 2882.5 | 672.6 | 411.3 | 261.3 | 10.0 |
| 2017/18 | 4011.3 | 2880.4 | 3368.5 | 1130.9 | 642.8 | 488.2 | 16.9 |
| Average | 3771.9 | 2771.8 | 3044.8 | 1000.1 | 727.2 | 272.9 | 9.8 |

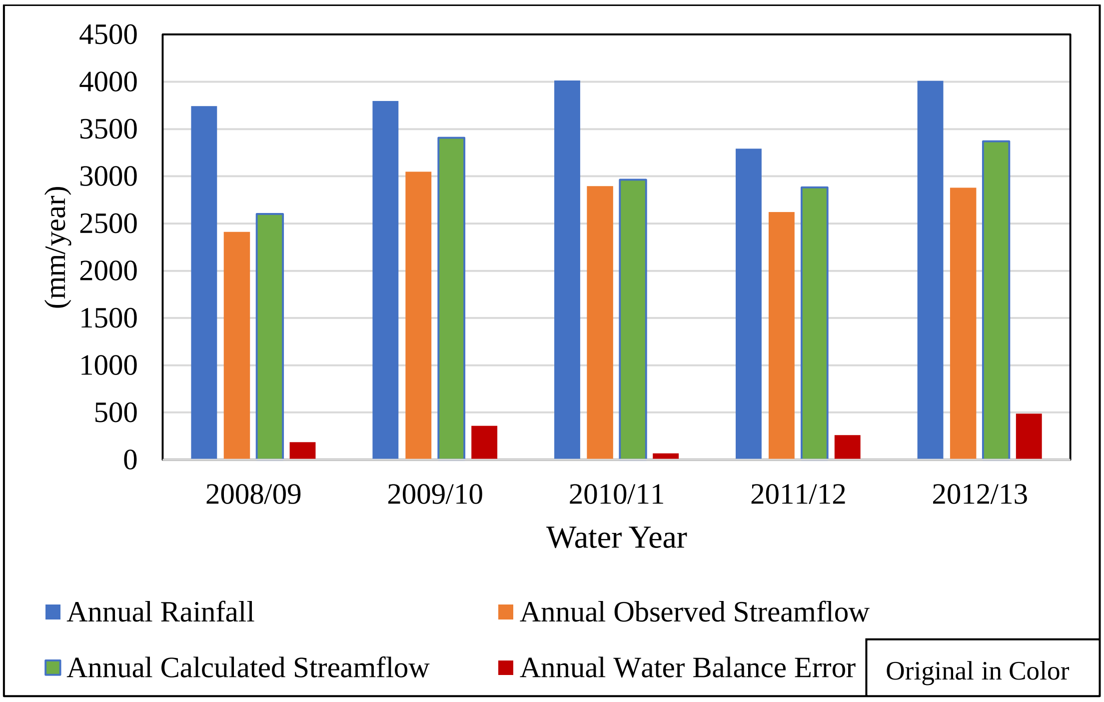



Figure 5-15: Annual Water Balance- Baddegama Validation

### 5.5.2 Validation of Tawalama Sub-Watershed

#### 5.5.2.1 Statistical Measure of Goodness of Fit- Tawalama Validation

Table 5-10: MRAE Results - Validation Tawalama

| Gauging Station | MRAE for Overall Flow | MRAE w.r.t FDC (Sorted) | | | MRAE w.r.t FDC (Unsorted) | | |
|---|---|---|---|---|---|---|---|
| | | High | Medium | Low | High | Medium | Low |
| Tawalama | 0.364 | 0.209 | 0.202 | 0.403 | 0.282 | 0.338 | 0.510 |

#### 5.5.2.2 Comparison of Flow Duration Curves – Tawalama Validation

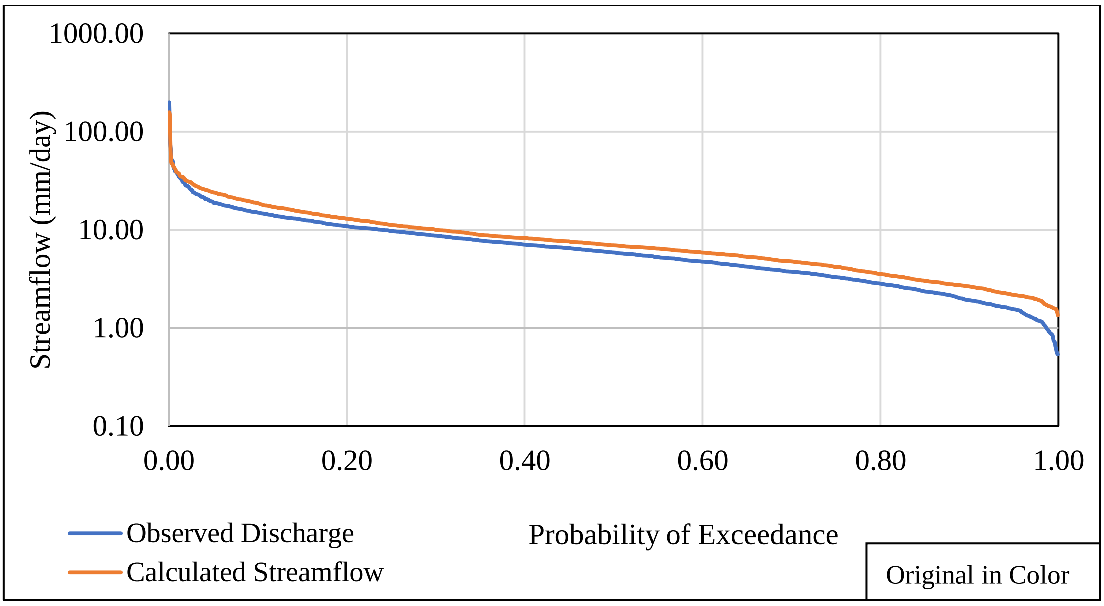



Figure 5-16: FDC (Sorted) - Validation Tawalama

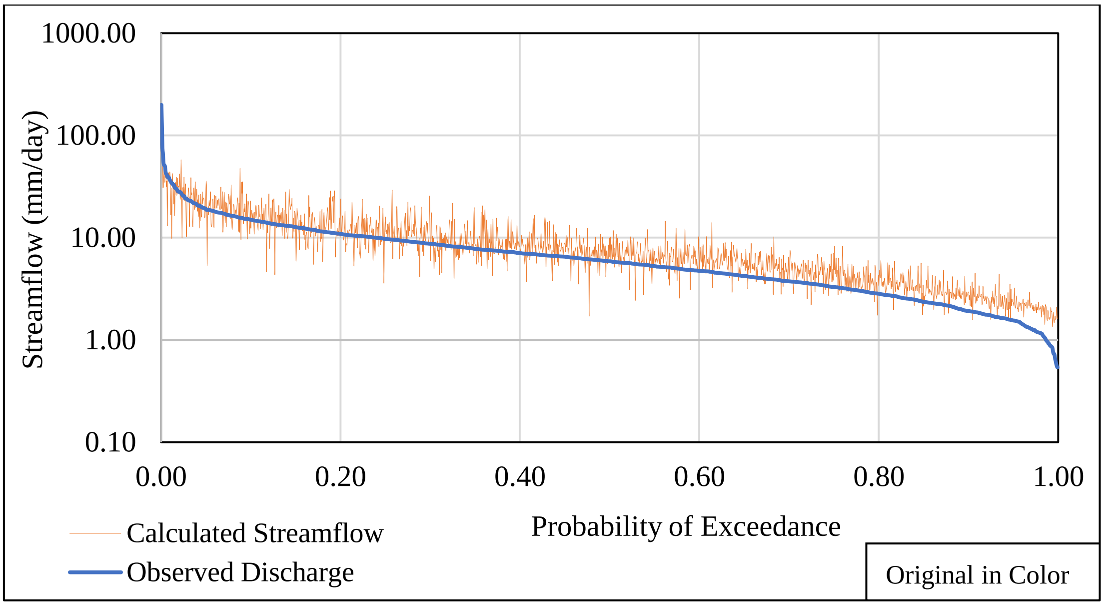



Figure 5-17: FDC (Unsorted) - Validation Tawalama

#### 5.5.2.3 Comparison of Hydrographs of Observed and Estimated streamflow – Tawalama Validation

Figure 5-18 shows the hydrographs of simulated and observed streamflow for the validation data period for Tawalama catchment. Better simulation of total hydrographs could be observed during validation.

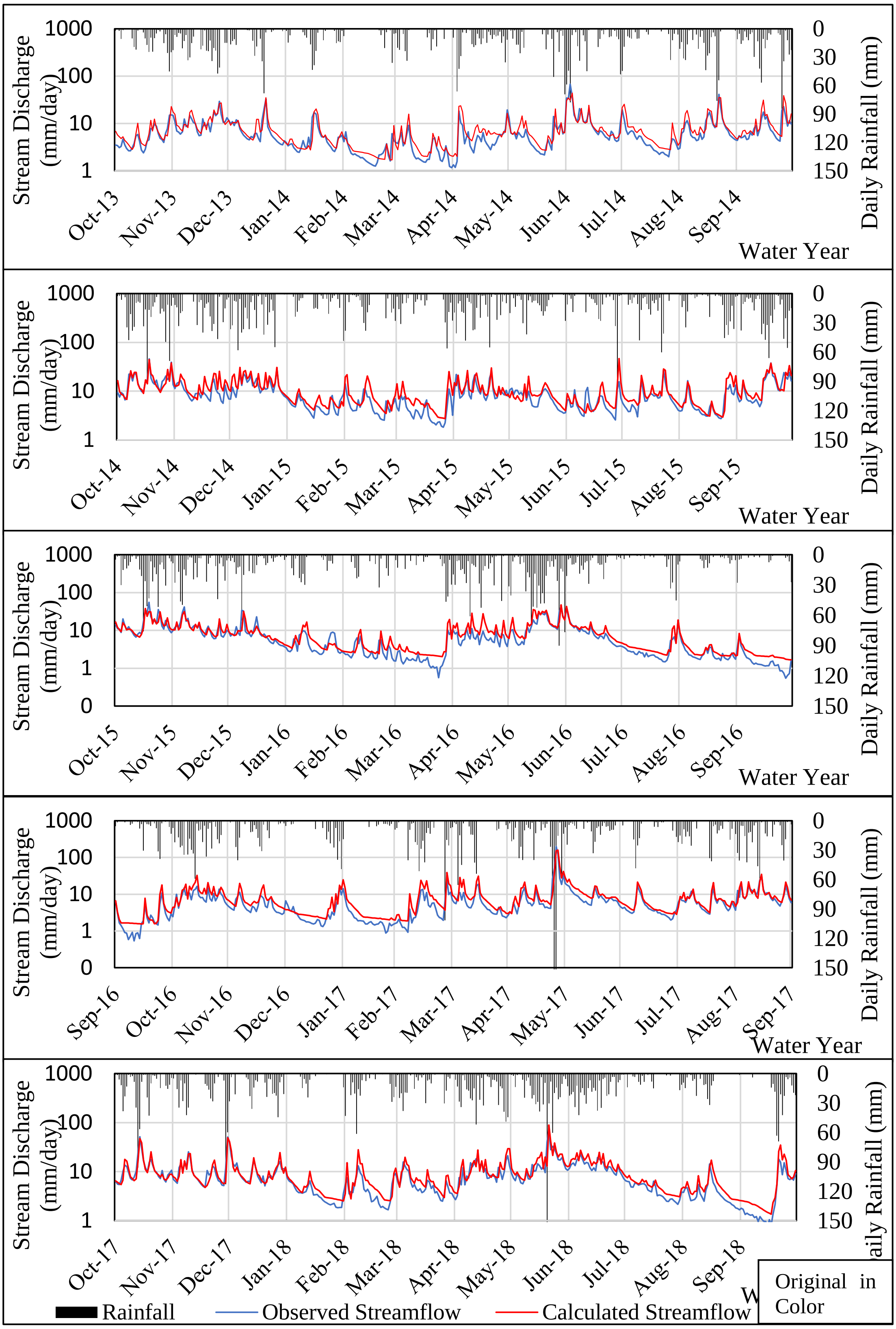



Figure 5-18: Hydrographs for Observed and Estimated Streamflow in Tawalama for Validation

#### 5.5.2.4 Annual Water Balance – Tawalama Validation

Table 5-11: Annual Water Balance- Tawalama Validation

| Water Year | Annual RF (mm) | Annual Observe SF (mm) | Annual cal. SF (mm) | AWB Observed (mm) | AWB Simulated (mm) | AWB Error | AWB Error (%) |
|---|---|---|---|---|---|---|---|
| 2013/14 | 3757.0 | 2531.9 | 2935.8 | 1225.2 | 821.2 | 403.9 | 16.0 |
| 2014/15 | 4717.8 | 3282.5 | 3961.6 | 1435.3 | 756.2 | 679.1 | 20.7 |
| 2015/16 | 3589.1 | 2711.0 | 3108.2 | 878.1 | 480.9 | 397.2 | 14.7 |
| 2016/17 | 4147.6 | 2604.8 | 3315.3 | 1542.8 | 832.3 | 710.4 | 27.3 |
| 2017/18 | 4243.6 | 3067.7 | 3571.6 | 1176.0 | 672.0 | 503.9 | 16.4 |
| Average | 4091.0 | 2839.6 | 3378.5 | 1251.5 | 712.5 | 538.9 | 19.0 |

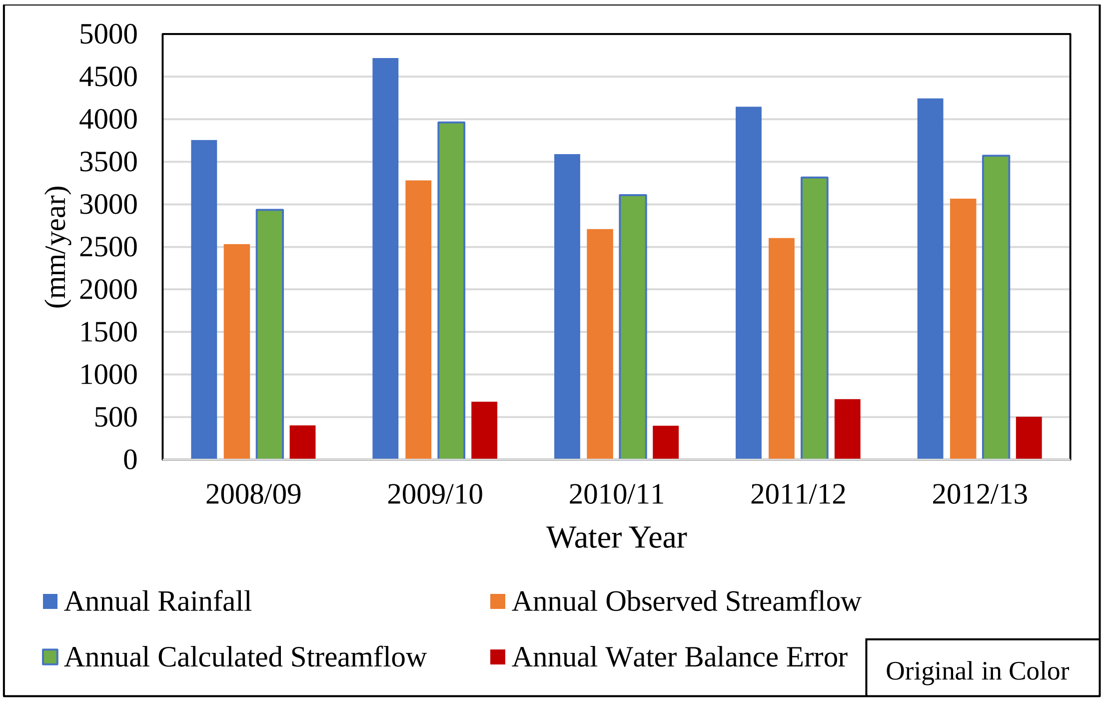



Figure 5-19: Annual Water Balance- Tawalama Validation

## 5.6 Optimized Parameters

Optimized parameters with respect to above results are shown in Table 5-12. These results were obtained after several optimization trials in MS Excel Solver environment. Each trial at least consists with 20 or more starting points and trials were run till designated convergence limits were met (i.e. convergence of 0.0001). This optimization was conducted in a systematic manner until best solution is observed.

Table 5-12: Optimized Tank Model Parameters

| Parameter | Optimized Value for Baddegama Catchment | Optimized Value for Tawalama Sub Catchment |
|---|---|---|
| A0 (1/day) | 0.13027 | 0.36556 |
| A1 (1/day) | 0.04277 | 0.13710 |
| A2 (1/day) | 0.09602 | 0.26299 |
| B0 (1/day) | 0.17371 | 0.04879 |
| B1 (1/day) | 0.82937 | 0.07033 |
| C0 (1/day) | 0.07285 | 0.01216 |
| C1 (1/day) | 0.03243 | 0.02339 |
| D1 (1/day) | 0.00095 | 0.00095 |
| HA1 (mm) | 4.90870 | 4.99135 |
| HA2 (mm) | 22.10751 | 22.00424 |
| HB1 (mm) | 28.10482 | 28.00280 |
| HC1 (mm) | 5.04913 | 5.00095 |

## 5.7 Tank Model Parameter Transferability

The optimized parameters were utilized for assessing model parameter transferability. Essentially three type of parameter transferability were tested, i.e. spatiotemporal transferability, temporal and spatial transferability.

To assess the spatiotemporal transferability of optimized parameters, the optimized parameters were transferred from main catchment to sub catchment i.e. from Baddegama catchment to Tawalama sub catchment for time period of 2008/09 to 2017/18 and vice versa. To assess the temporal transferability of the parameters, optimized parameters for each catchment is applied for whole time duration utilized in this study for the same catchment i.e. from 2008/09 to 2017/18. To assess the spatial transferability, the optimized parameters for each catchment are interchange spatially i.e. optimized parameter of Baddegama for the period of 2008/09 to 2012/13 is applied to Tawalama for same period and vice versa. Here the optimized parameters were subjected to direct transfer without any modification. This approach is considered since in ungauged catchment simplistic methods are preferred by water managers.

### 5.7.1 Results of Spatiotemporal Transferability

#### 5.7.1.1 Spatiotemporal Transferability from Main catchment (Baddegama) to Sub catchment (Tawalama)

Optimized parameters of Baddegama main catchment shown in Table 5-12 is transferred to Tawalama 2007/08 – 2017/18 data period. And respective results are shown in below sections.

##### 5.7.1.1.1 Statistical Measure of Goodness of Fit

Statistical goodness of fit observed through MRAE values for spatiotemporal transferability for whole data period is presented in table.

Table 5-13: Measure of Goodness of Fit of Model for Tawalama with Spatiotemporally Transferred Parameters

| Gauging Station | MRAE for Overall Flow | MRAE w.r.t FDC (Sorted) | | | MRAE w.r.t FDC (Unsorted) | | |
|---|---|---|---|---|---|---|---|
| | | High | Medium | Low | High | Medium | Low |
| Tawalama | 0.412 | 0.144 | 0.058 | 0.584 | 0.322 | 0.336 | 0.715 |

#### 5.7.1.1.2 Comparison of Flow Duration Curves

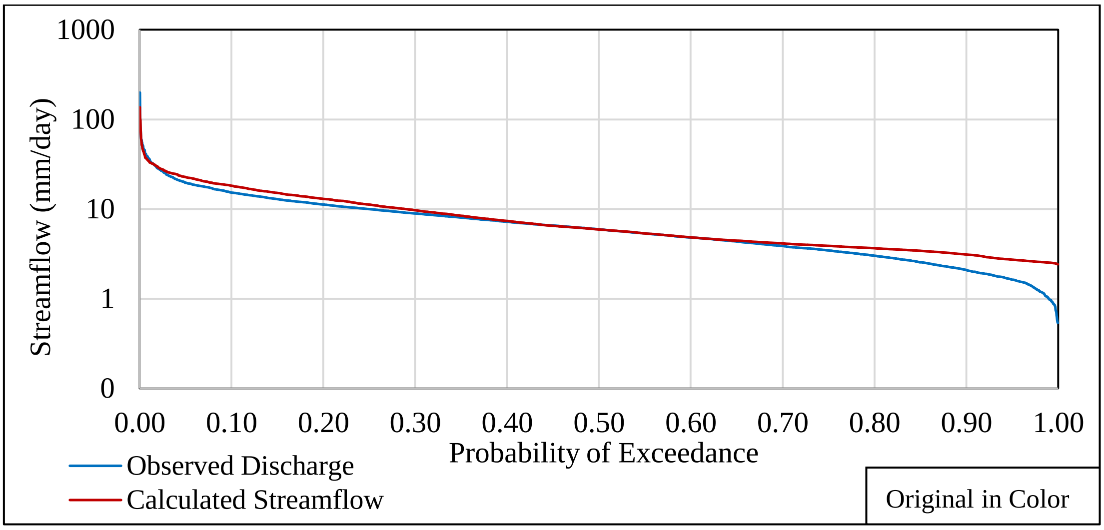



Figure 5-20: FDC (Sorted) for Tawalama with Spatiotemporally Transferred Parameters from Baddegama

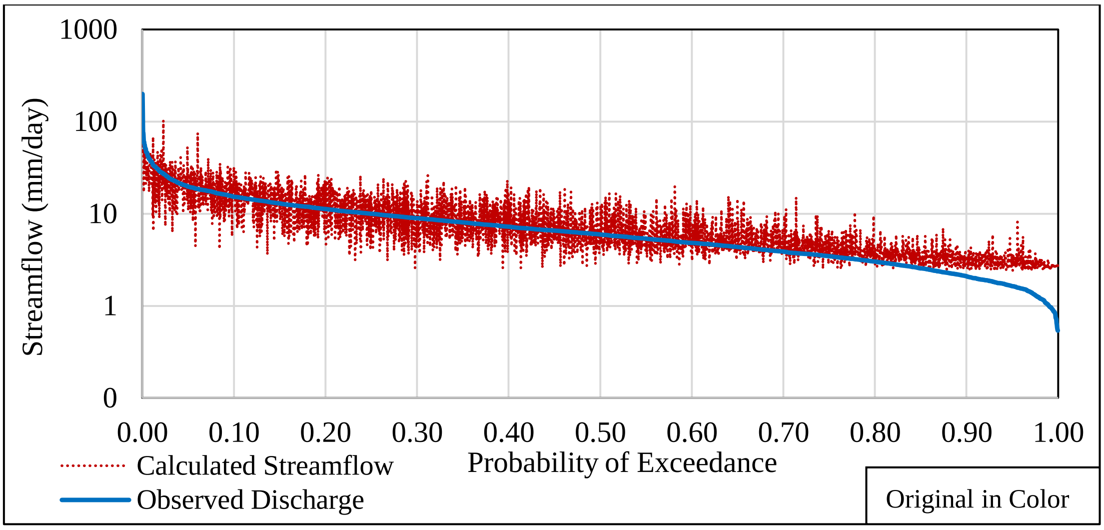



Figure 5-21: FDC (Unsorted) for Tawalama with Spatiotemporally Transferred Parameters from Baddegama

### 5.7.1.1.3 Comparison of Hydrographs of Observed and Estimated streamflow

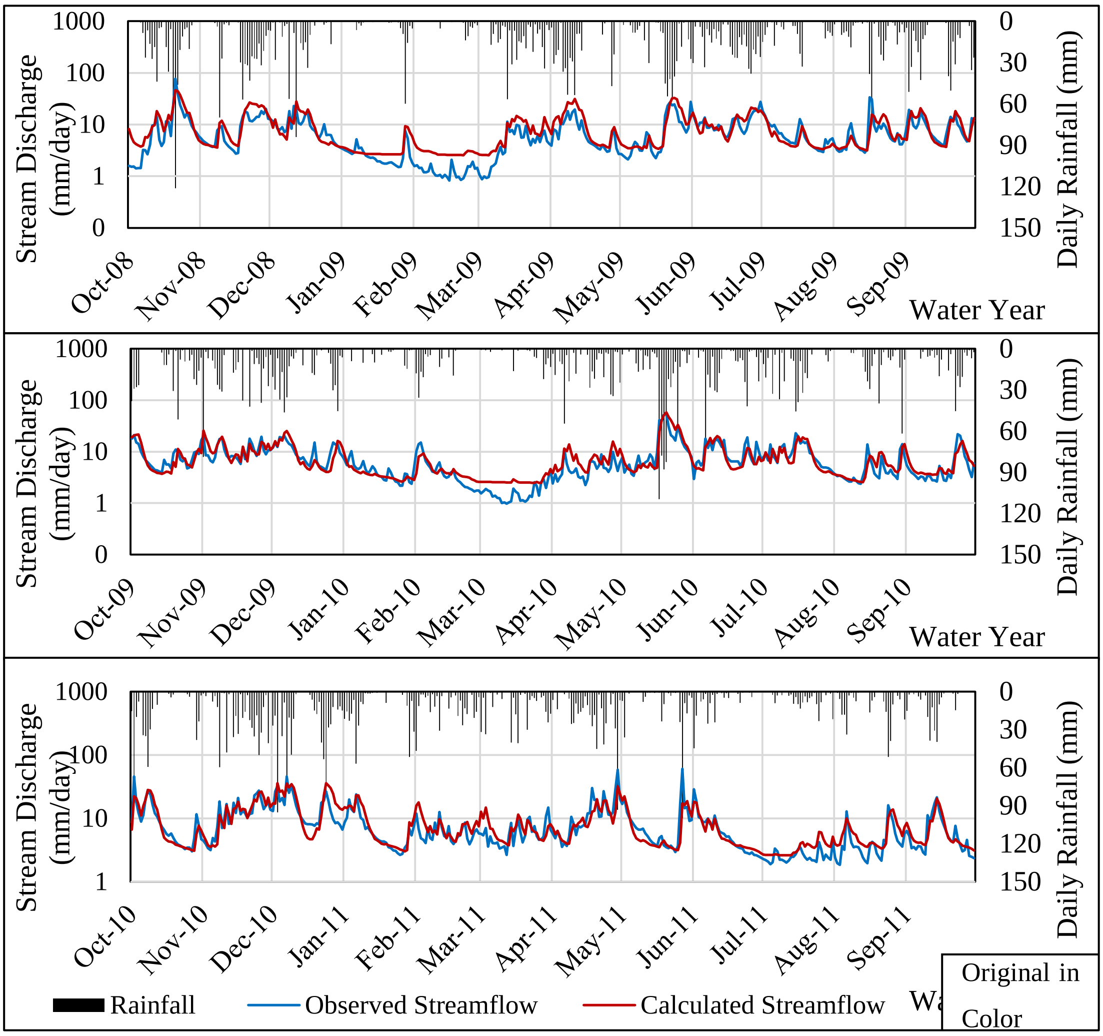
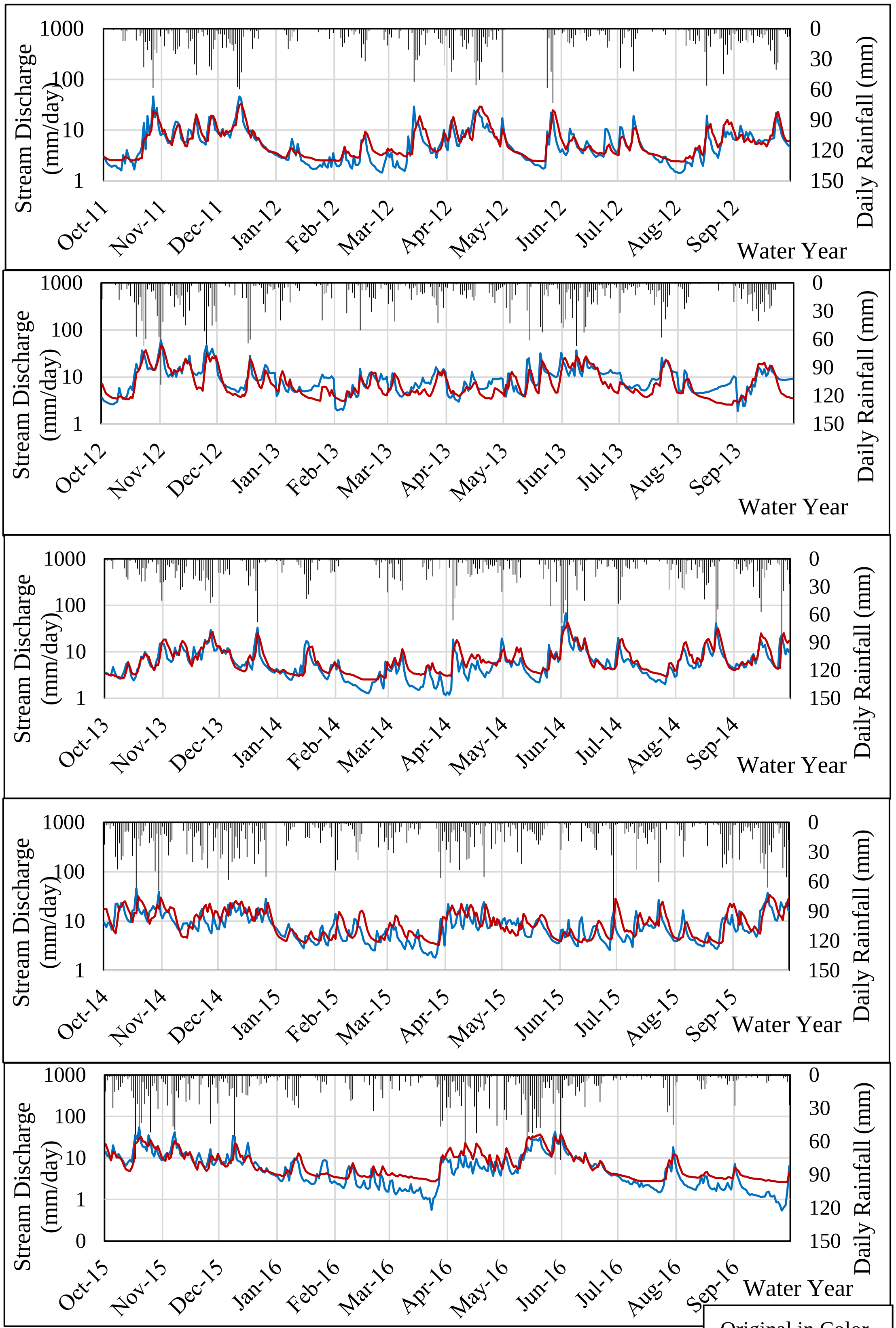



Figure 5-22: Flow Hydrographs for Tawalama with Spatiotemporally Transferred Parameters




Original in Color

Figure 5-23: Flow Hydrographs for Tawalama with Spatiotemporally Transferred Parameters

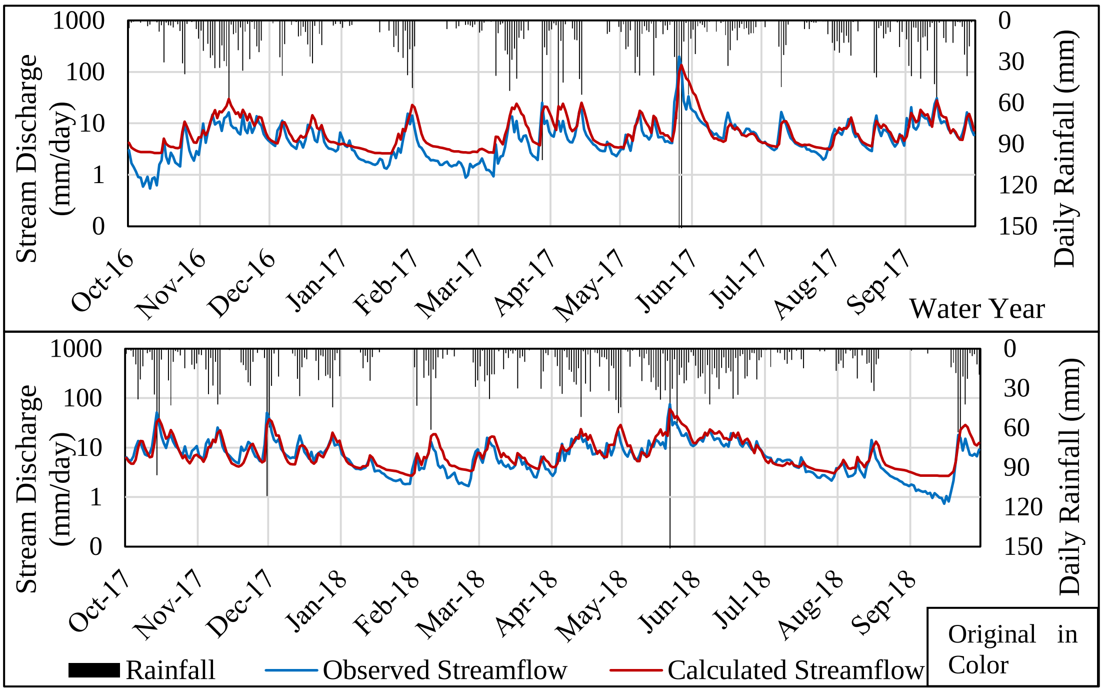



Figure 5-24: Flow Hydrographs for Tawalama with Spatiotemporally Transferred Parameters

#### 5.7.1.1.4 Annual Water Balance

Table 5-14: Annual Water Balance of Tawalama with Transferred Parameters

| Water Year | Annual RF (mm) | Annual Observe SF (mm) | Annual cal. SF (mm) | AWB Observed (mm) | AWB Simulated (mm) | AWB Error | AWB Error (%) |
|---|---|---|---|---|---|---|---|
| 2008/09 | 4048.3 | 2744.5 | 3216.5 | 1126.1 | 1303.8 | 831.8 | 17.2% |
| 2009/10 | 3654.0 | 2783.1 | 2921.1 | 1029.5 | 871.0 | 732.9 | 5.0% |
| 2010/11 | 4061.3 | 3077.6 | 3217.6 | 1065.4 | 983.7 | 843.7 | 4.6% |
| 2011/12 | 3260.8 | 2404.4 | 2521.5 | 1040.2 | 856.4 | 739.3 | 4.9% |
| 2012/13 | 4133.3 | 3689.6 | 3256.3 | 997.3 | 443.7 | 877.0 | -11.7% |
| 2013/14 | 3735.5 | 2531.9 | 2859.3 | 969.0 | 1203.6 | 876.2 | 12.9% |
| 2014/15 | 4725.3 | 3282.5 | 3834.0 | 816.2 | 1442.8 | 891.3 | 16.8% |
| 2015/16 | 3598.5 | 2711.0 | 3125.9 | 883.1 | 887.5 | 472.6 | 15.3% |
| 2016/17 | 4149.3 | 2604.8 | 3353.4 | 926.3 | 1544.5 | 795.9 | 28.7% |
| 2017/18 | 4225.5 | 3067.7 | 3537.9 | 832.3 | 1157.9 | 687.6 | 15.3% |
| Average | 3959.2 | 2889.7 | 3184.4 | 968.5 | 1069.5 | 774.8 | 10.2% |

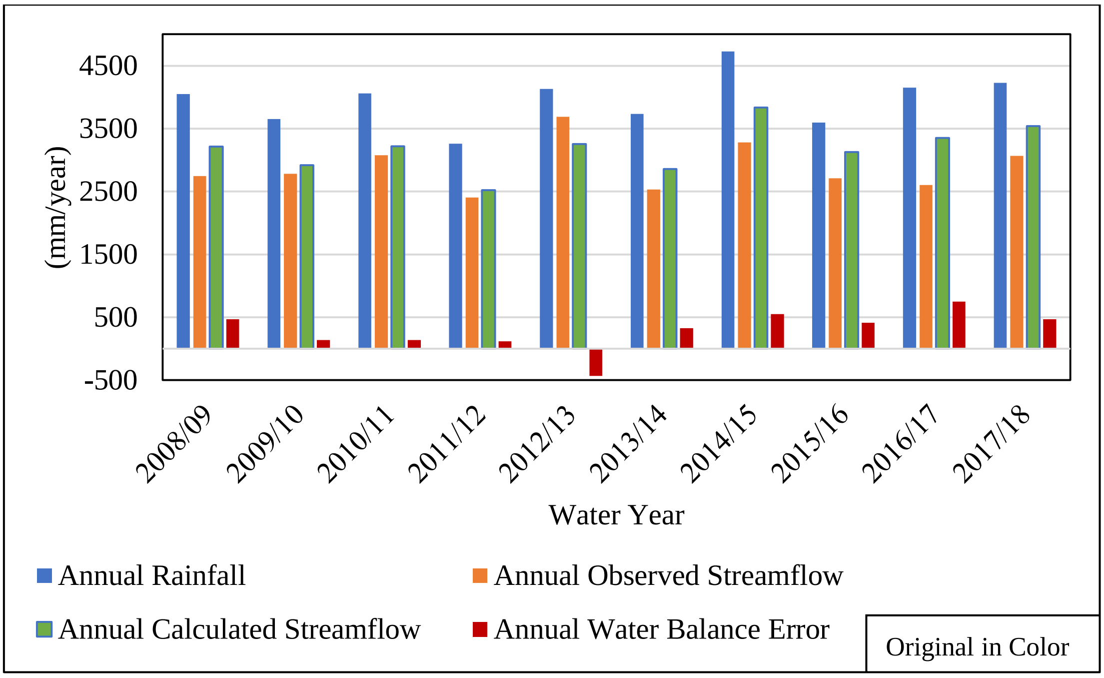



Figure 5-25: Annual Water balance of Tawalama with transferred parameters

#### 5.7.1.2 Model Parameter Transferability from Sub catchment to Main catchment

Optimized parameters of Tawalama sub catchment shown in Table 5-12 is transferred to Baddegama 2007/08 – 2017/18 data period. And respective results are shown in below sections.

##### 5.7.1.2.1 Statistical Measure of Goodness of Fit

Table 5-15: Measure of Goodness of Fit of Model for Baddegama with Spatiotemporally Transferred Parameters

| Gauging Station | MRAE for Overall Flow | MRAE w.r.t FDC (Sorted) | | | MRAE w.r.t FDC (Unsorted) | | |
|---|---|---|---|---|---|---|---|
| | | High | Medium | Low | High | Medium | Low |
| Baddegama | 0.346 | 0.064 | 0.201 | 0.034 | 0.302 | 0.366 | 0.380 |

#### 5.7.1.2.2 Comparison of Flow Duration Curves

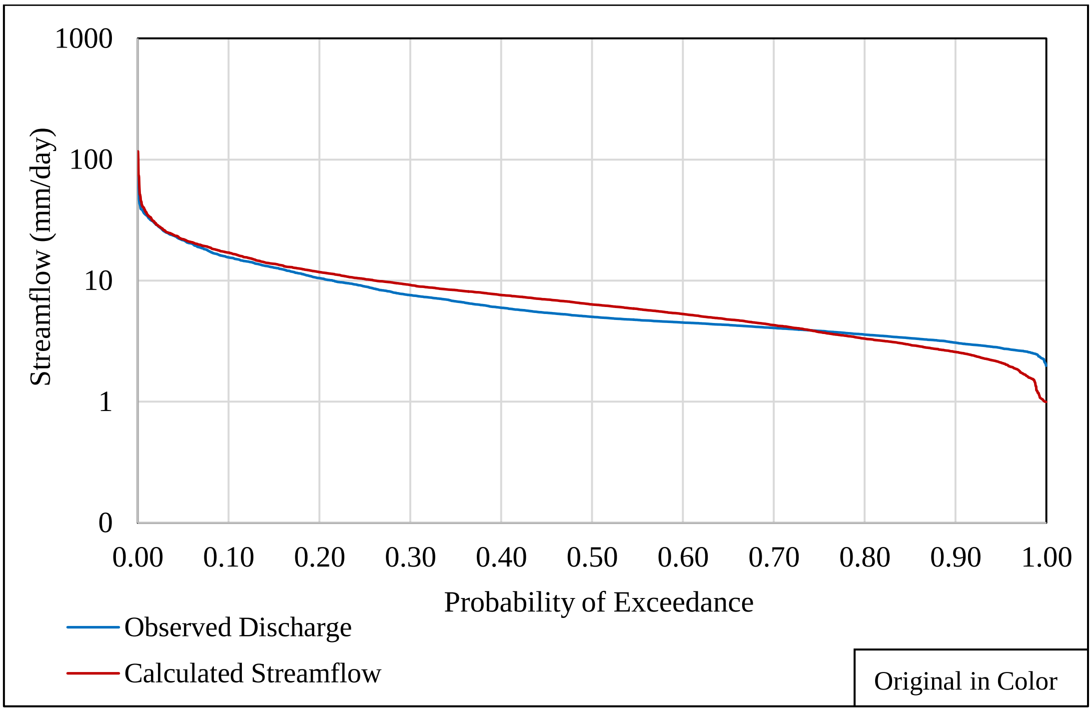



Figure 5-26: FDC (Sorted) for Baddegama with Spatiotemporally Transferred Parameters from Tawalama

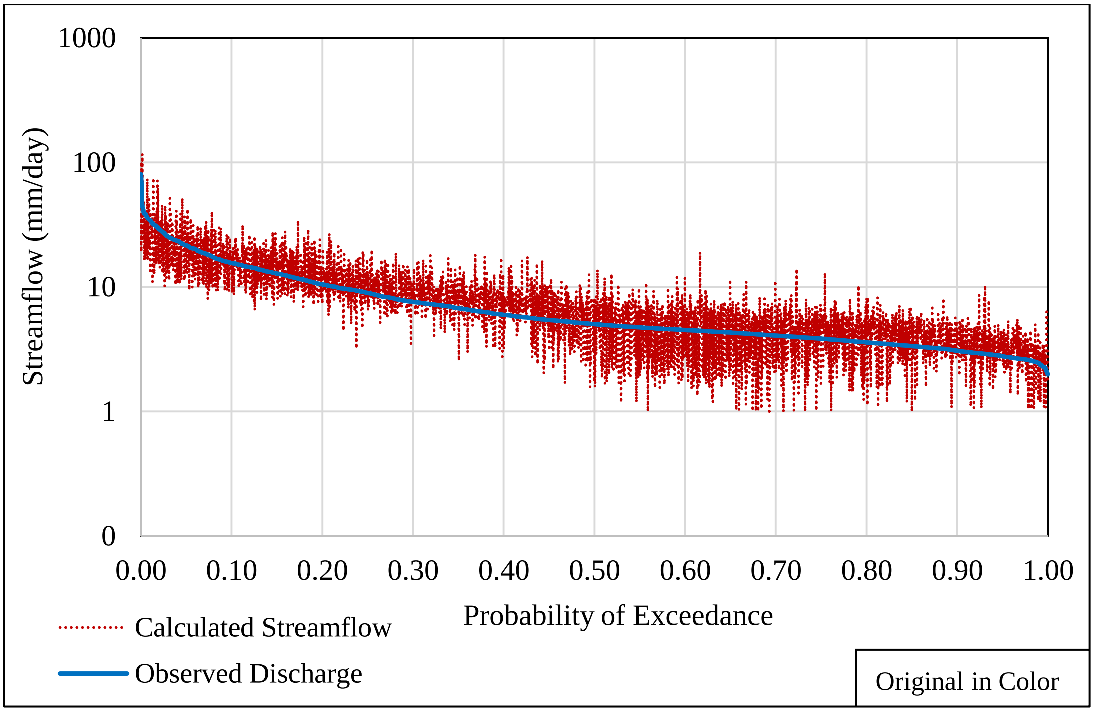



Figure 5-27: FDC (Unsorted) for Baddegama with Spatiotemporally Transferred Parameters from Tawalama

#### 5.7.1.2.3 Comparison of Hydrographs of Observed and Estimated streamflow

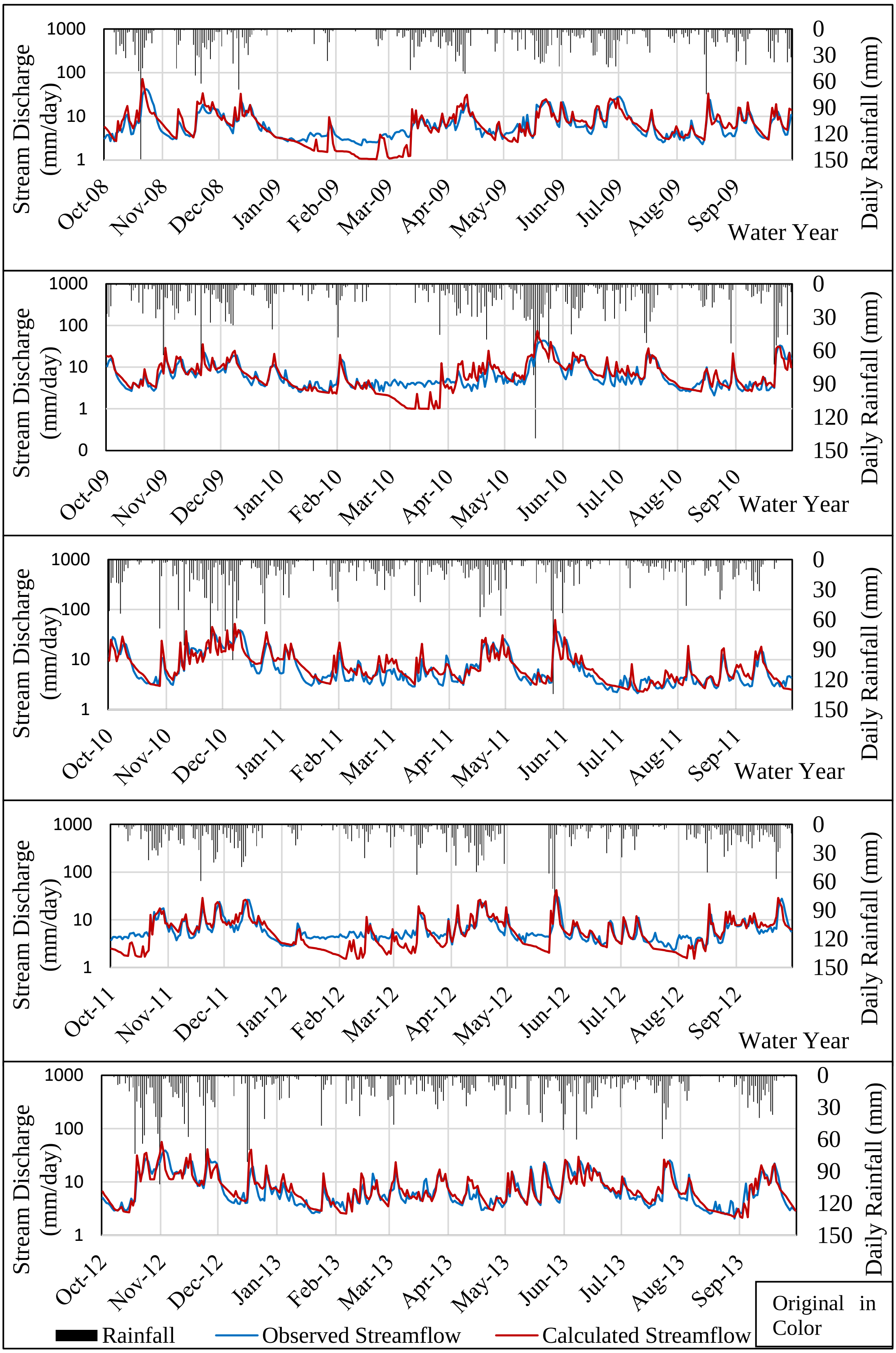



Figure 5-28: Flow Hydrographs for Baddegama with Spatiotemporally Transferred Parameters

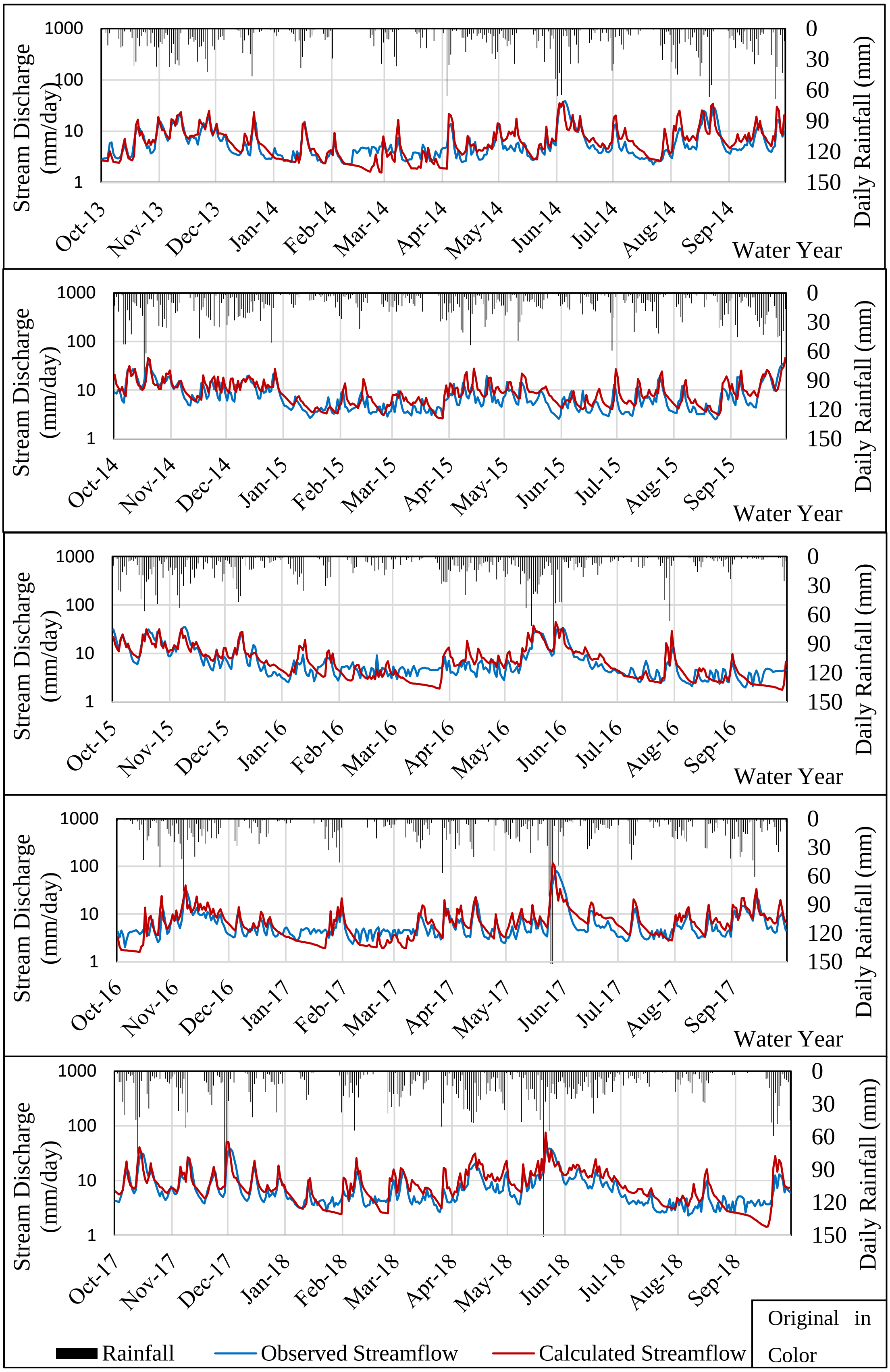



Figure 5-29: Flow Hydrographs for Baddegama with Spatiotemporally Transferred Parameters

#### 5.7.1.2.4 Annual Water Balance

Table 5-16: Annual Water balance of Baddegama with Spatiotemporally Transferred Parameters

| Water Year | Annual RF (mm) | Annual Observe SF (mm) | Annual cal. SF (mm) | AWB Observed (mm) | AWB Simulated (mm) | AWB Error | AWB Error (%) |
|---|---|---|---|---|---|---|---|
| 2008/09 | 3743.6 | 2728.6 | 2850.0 | 1015.0 | 893.6 | 121.4 | 4.4% |
| 2009/10 | 3798.1 | 2789.9 | 2995.8 | 1008.3 | 802.3 | 205.9 | 7.4% |
| 2010/11 | 4012.7 | 3045.1 | 3245.4 | 967.6 | 767.3 | 200.3 | 6.6% |
| 2011/12 | 3293.8 | 2472.5 | 2437.5 | 821.4 | 856.4 | -35.0 | -1.4% |
| 2012/13 | 4011.3 | 3134.7 | 3234.4 | 876.6 | 776.9 | 99.7 | 3.2% |
| 2013/14 | 3566.8 | 2413.0 | 2701.0 | 1153.7 | 865.8 | 287.9 | 11.9% |
| 2014/15 | 4466.9 | 3047.8 | 3653.6 | 1419.0 | 813.2 | 605.8 | 19.9% |
| 2015/16 | 3567.1 | 2901.1 | 3082.2 | 666.0 | 484.8 | 181.1 | 6.2% |
| 2016/17 | 3835.0 | 2616.7 | 3007.0 | 1218.3 | 828.1 | 390.2 | 14.9% |
| 2017/18 | 4259.1 | 2880.4 | 3554.1 | 1378.7 | 704.9 | 673.8 | 23.4% |
| Average | 3855.4 | 2803.0 | 3076.1 | 1052.5 | 779.3 | 273.1 | 9.7% |

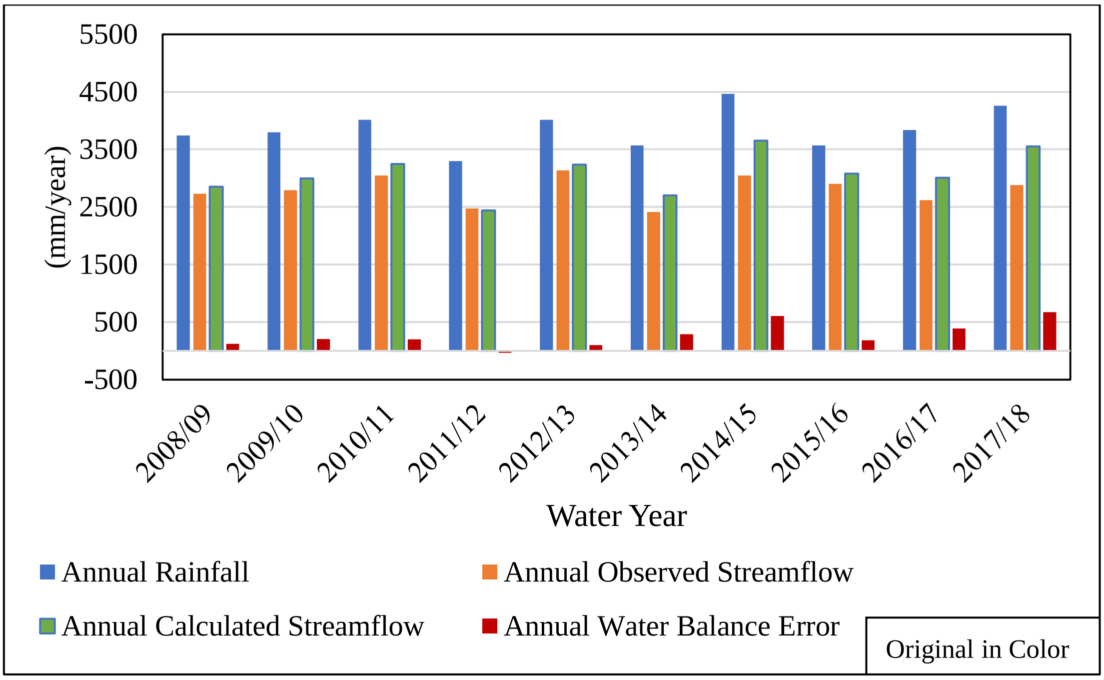



Figure 5-30: Annual Water balance of Baddegama with Transferred Parameters

### 5.7.2 Results of Temporal Transferability

The calibrated and optimized parameters of the same catchment is applied to itself for a time period different than calibration. Here the calibrated time period for both the catchment is 2008/09 to 2012/13 and it is transferred to time period of 2008/09 to 2017/18.

#### 5.7.2.1 Temporal Transferability of Baddemgama Main catchment

The optimized set of parameters of Baddegama is applied through 2008/09 to 2017/18 to Baddegama catchment itself and results obtained are shown below.

##### 5.7.2.1.1 Statistical Measure of Goodness of Fit

Table 5-17: Measure of Goodness of Fit of Model for Baddegama with Temporally Transferred Parameters

| **Gauging Station** | **MRAE for Overall Flow** | **MRAE w.r.t FDC (Sorted)** | | | **MRAE w.r.t FDC (Unsorted)** | | |
|---|---|---|---|---|---|---|---|
| | | **High** | **Medium** | **Low** | **High** | **Medium** | **Low** |
| Baddegama | 0.284 | 0.076 | 0.147 | 0.011 | 0.186 | 0.305 | 0.284 |

##### 5.7.2.1.2 Comparison of Flow Duration Curves

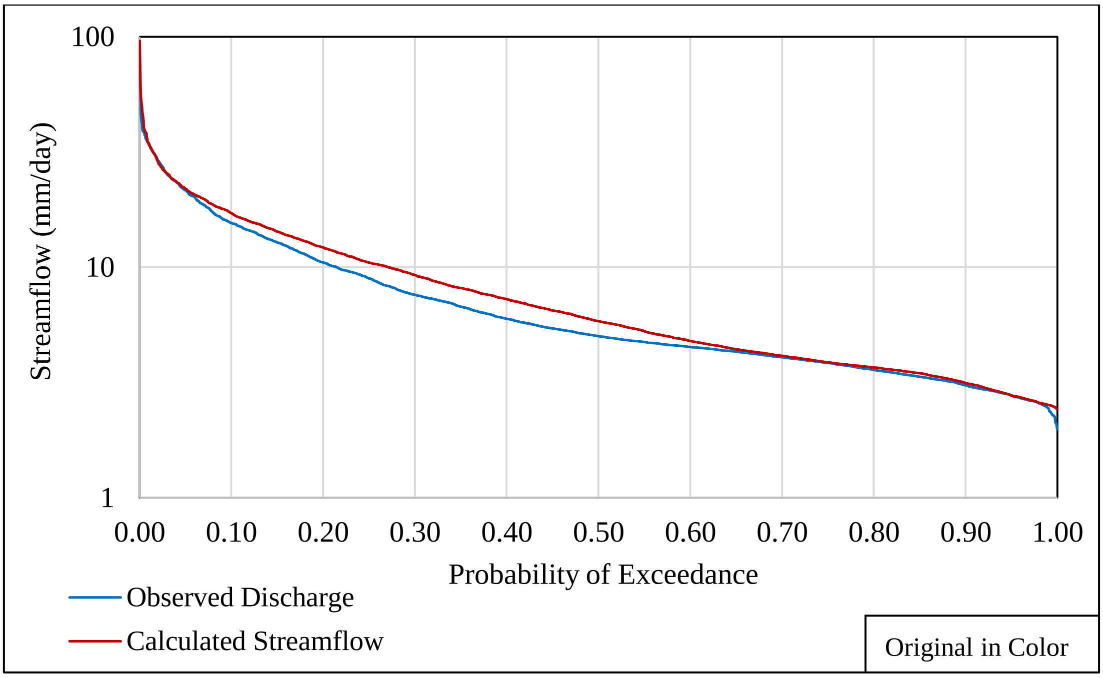



Figure 5-31: FDC (Sorted) for Baddegama with Temporally Transferred Parameters

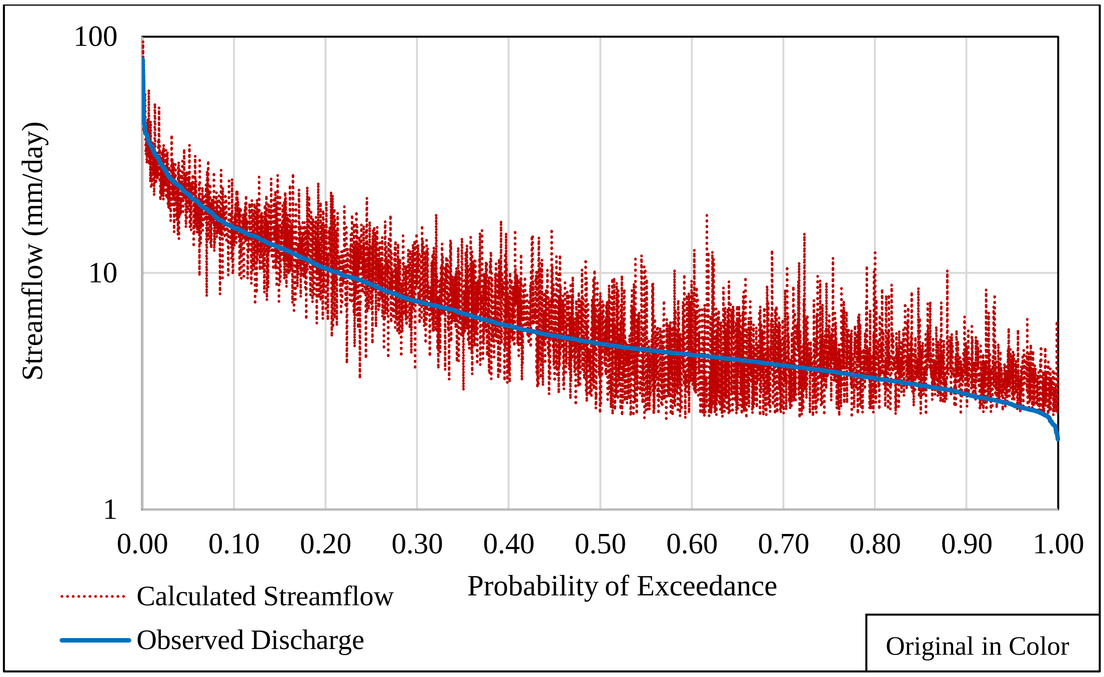
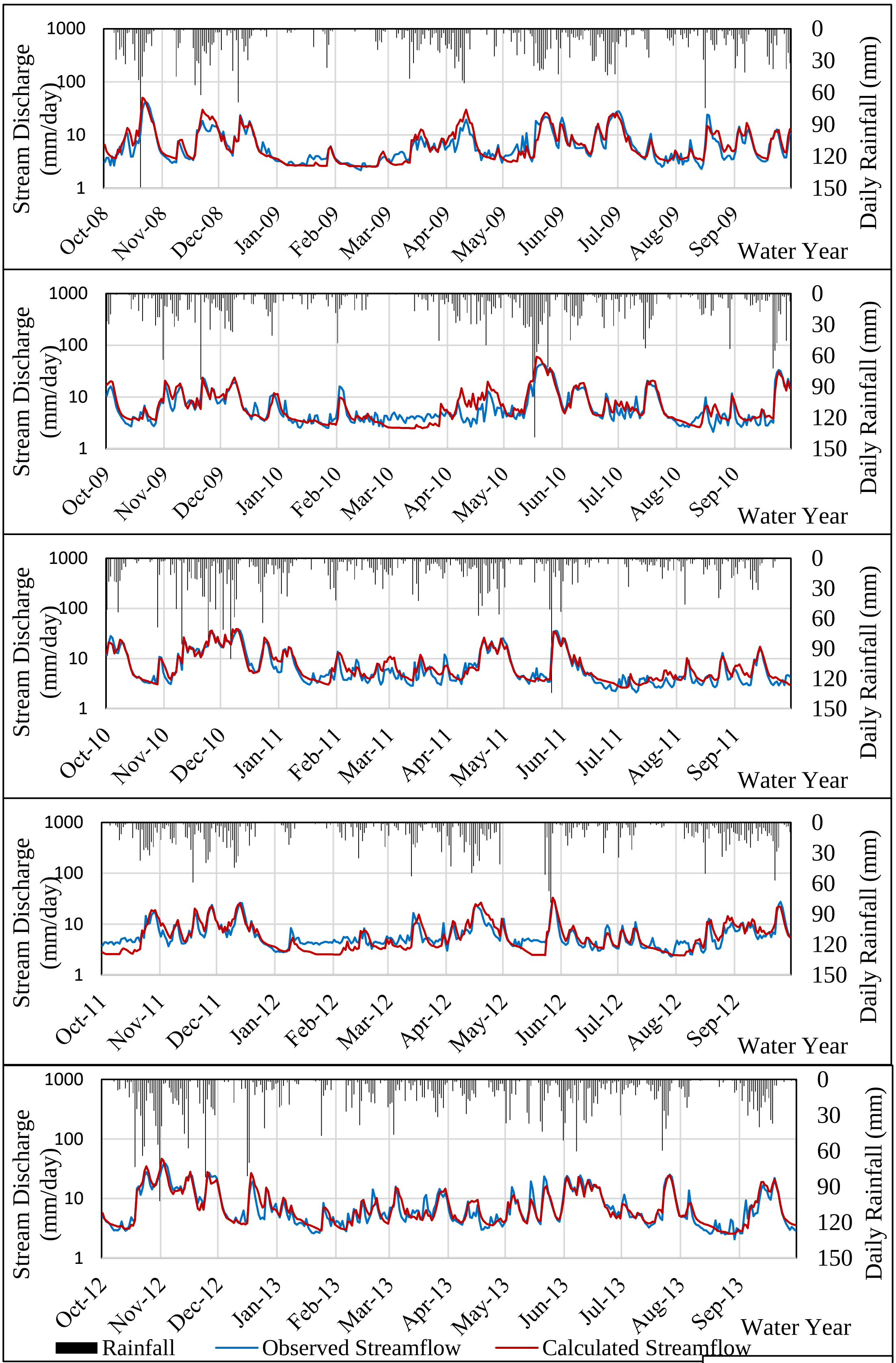



Figure 5-32: FDC (Unsorted) for Baddegama with Temporally Transferred Parameters

#### 5.7.2.1.3 Comparison of Hydrographs of Observed and Estimated streamflow

Figure 5-33 and Figure 5-34 shows the results of flow hydrographs comparison of Baddegama catchment with temporally transferred parameters.

This shows that there is quite compatibility with respect to predicting of high and medium flows.




Original in Color

Figure 5-33: Flow Hydrographs for Baddegama with Temporally Transferred parameters

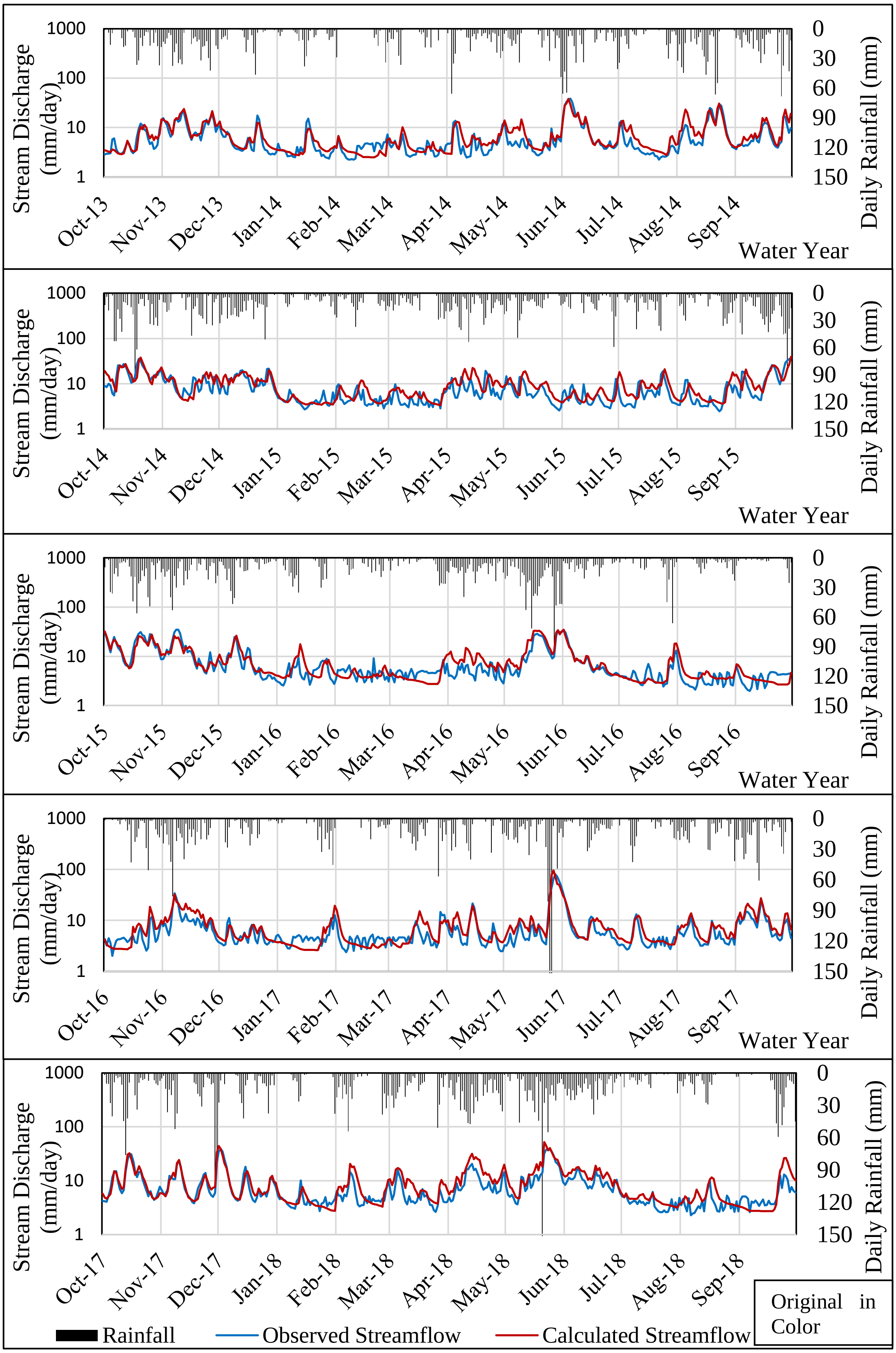



Figure 5-34: Flow Hydrographs for Baddegama with Temporally Transferred Parameters

#### 5.7.2.1.4 Annual Water Balance

Table 5-18: Annual Water balance of Baddegama with Temporally Transferred Parameters

| Water Year | Annual RF (mm) | Annual Observe SF (mm) | Annual cal. SF (mm) | AWB Observed (mm) | AWB Simulated (mm) | AWB Error | AWB Error (%) |
|---|---|---|---|---|---|---|---|
| 2008/09 | 3743.6 | 2728.6 | 2921.7 | 1015.0 | 821.9 | 193.1 | 7.1% |
| 2009/10 | 3798.1 | 2789.9 | 3031.4 | 1008.3 | 766.8 | 241.5 | 8.7% |
| 2010/11 | 4012.7 | 3045.1 | 3203.9 | 967.6 | 808.8 | 158.8 | 5.2% |
| 2011/12 | 3293.8 | 2472.5 | 2541.2 | 821.4 | 752.7 | 68.7 | 2.8% |
| 2012/13 | 4011.3 | 3134.7 | 3152.5 | 876.6 | 858.8 | 17.8 | 0.6% |
| 2013/14 | 3566.8 | 2413.0 | 2698.9 | 1153.7 | 867.9 | 285.9 | 11.8% |
| 2014/15 | 4466.9 | 3047.8 | 3550.3 | 1419.0 | 916.6 | 502.5 | 16.5% |
| 2015/16 | 3567.1 | 2901.1 | 3097.7 | 666.0 | 469.4 | 196.6 | 6.8% |
| 2016/17 | 3835.0 | 2616.7 | 3042.0 | 1218.3 | 793.0 | 425.3 | 16.3% |
| 2017/18 | 4259.1 | 2880.4 | 3521.4 | 1378.7 | 737.7 | 641.0 | 22.3% |
| Average | 3855.4 | 2803.0 | 3076.1 | 1052.5 | 779.3 | 273.1 | 9.7% |

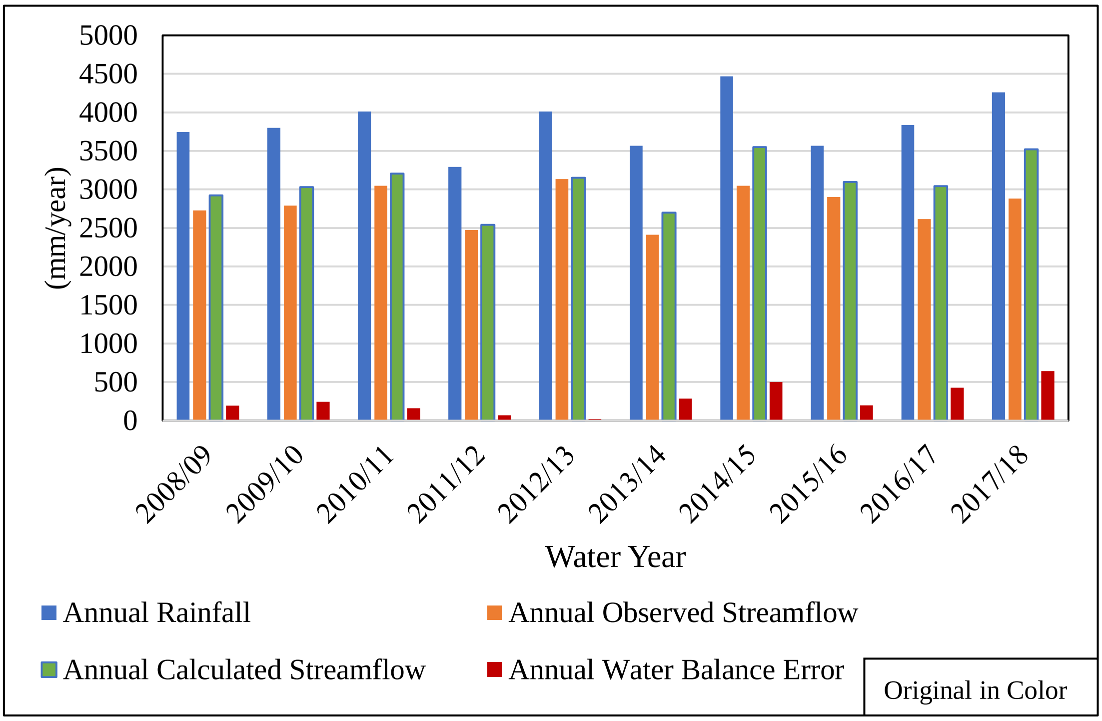



Figure 5-35: Annual Water balance of Baddegama with Temporally Transferred Parameters

### 5.7.2.2 Temporal Transferability of Tawalama sub catchment

The optimized set of parameters for Tawalama sub catchment is applied to itself through 2008/09 to 2017/18 and results obtained are shown below.

#### 5.7.2.2.1 Statistical Measure of Goodness of Fit

Table 5-19: Measure of Goodness of Fit of Model for Tawalama with Temporally Transferred Parameters

| Gauging Station | MRAE for Overall Flow | MRAE w.r.t FDC (Sorted) | | | MRAE w.r.t FDC (Unsorted) | | |
|---|---|---|---|---|---|---|---|
| | | High | Medium | Low | High | Medium | Low |
| Tawalama | 0.305 | 0.145 | 0.088 | 0.186 | 0.264 | 0.294 | 0.373 |

#### 5.7.2.2.2 Comparison of Flow Duration Curves

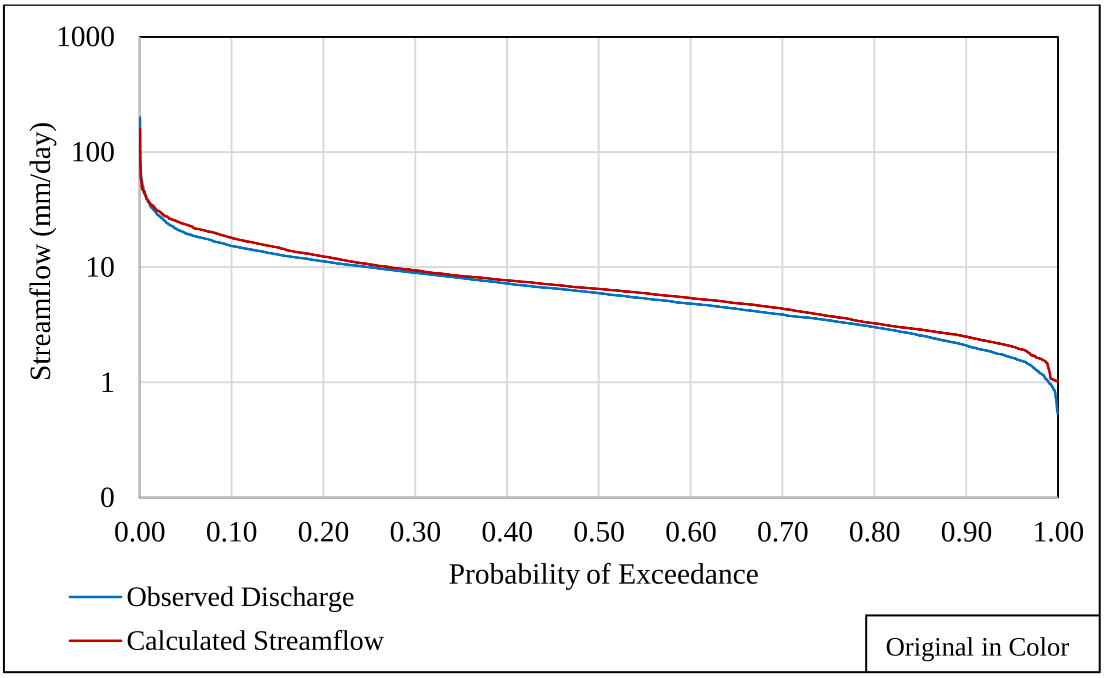



Figure 5-36: FDC (Sorted) for Tawalama with Temporally Transferred Parameters

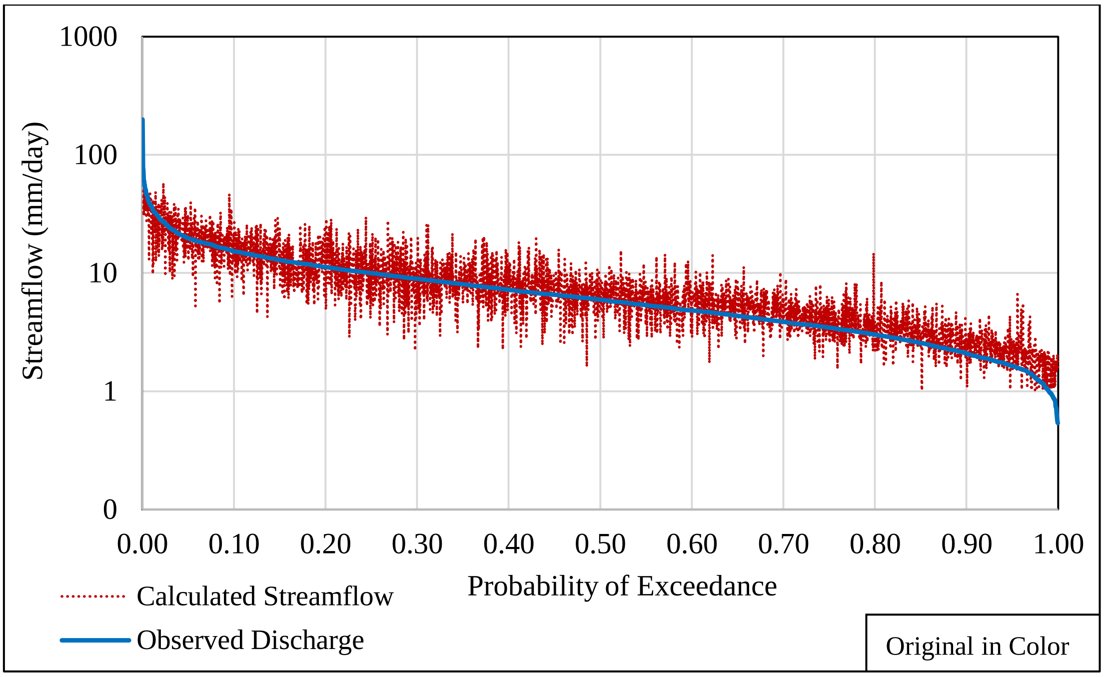
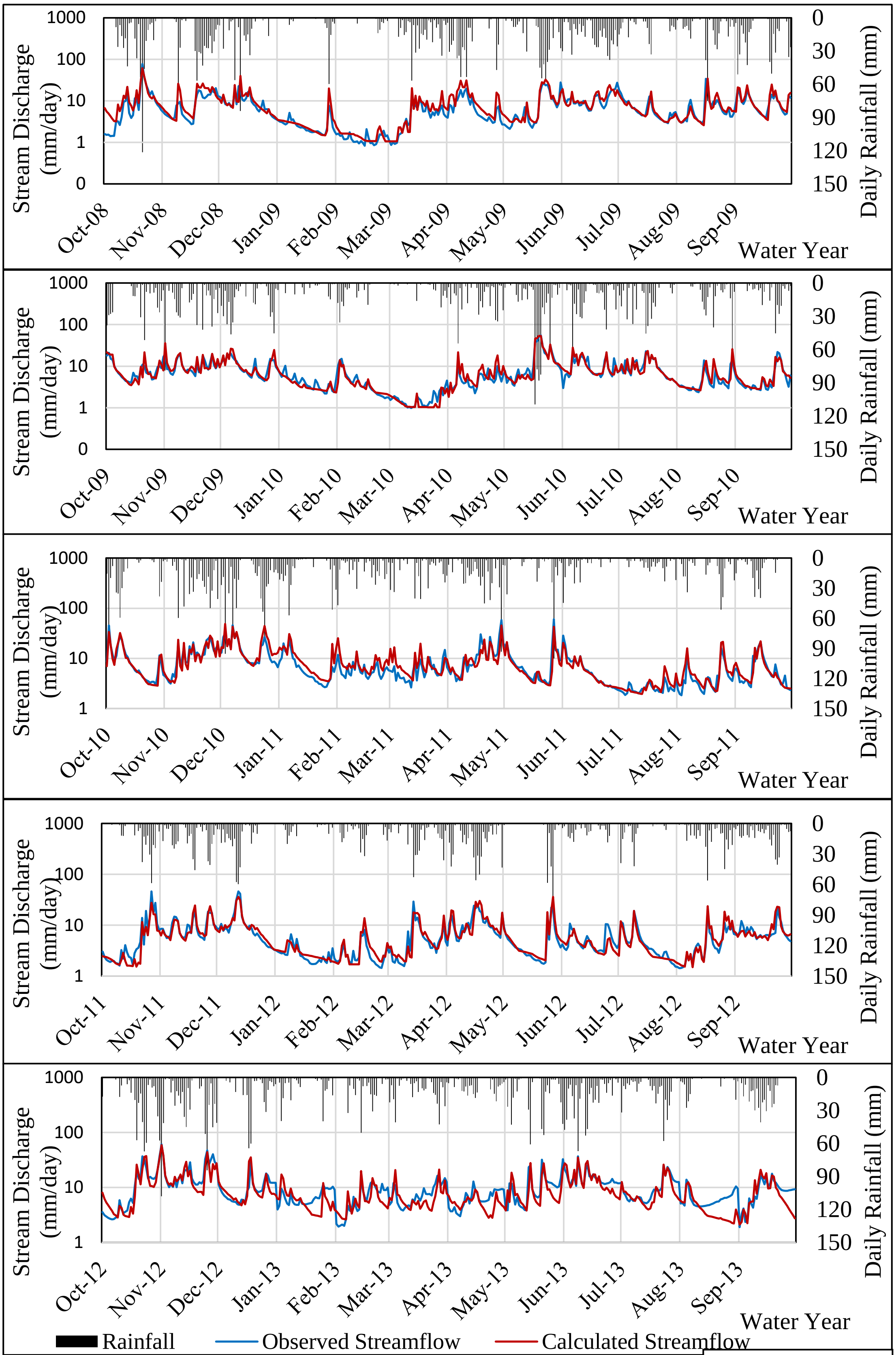



Figure 5-37: FDC (Unsorted) for Tawalama with Temporally Transferred Parameters

**5.7.2.2.3 Comparison of Hydrographs of Observed and Estimated streamflow**

Similarly, to Baddegama, temporally transferred parameters of Tawalama has also shown promising results with good matching in total flow hydrographs as shown in Figure 5-38 and

Figure 5-39.




Original in Color

Figure 5-38: Flow Hydrographs for Tawalama with Temporally Transferred Parameters

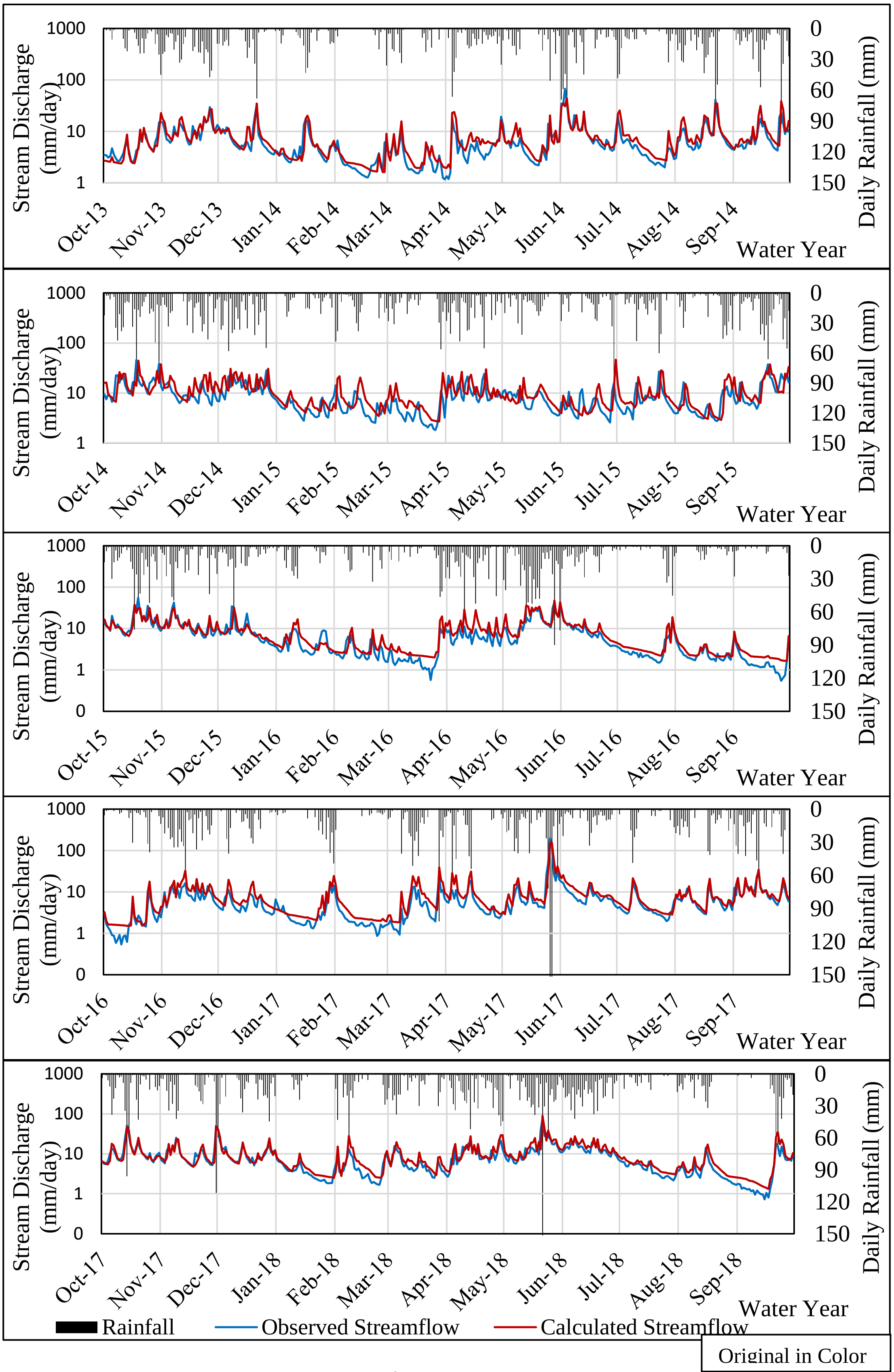



Figure 5-39: Flow Hydrographs for Tawalama with Temporally Transferred Parameters

#### 5.7.2.2.4 Annual Water Balance

Table 5-20: Annual Water Balance of Tawalama with Temporally Transferred Parameters

| Water Year | Annual RF (mm) | Annual Observe SF (mm) | Annual cal. SF (mm) | AWB Observed (mm) | AWB Simulated (mm) | AWB Error | AWB Error (%) |
|---|---|---|---|---|---|---|---|
| 2008/09 | 4048.3 | 2744.5 | 3162.7 | 1303.8 | 885.6 | 418.2 | 15.2% |
| 2009/10 | 3654.0 | 2783.1 | 2909.3 | 871.0 | 744.7 | 126.3 | 4.5% |
| 2010/11 | 4061.3 | 3077.6 | 3246.7 | 983.7 | 814.6 | 169.1 | 5.5% |
| 2011/12 | 3260.8 | 2404.4 | 2424.8 | 856.4 | 836.0 | 20.4 | 0.8% |
| 2012/13 | 4133.3 | 3689.6 | 3336.2 | 443.7 | 797.1 | -353.4 | -9.6% |
| 2013/14 | 3735.5 | 2531.9 | 2866.6 | 1203.6 | 868.9 | 334.7 | 13.2% |
| 2014/15 | 4725.3 | 3282.5 | 3938.4 | 1442.8 | 786.9 | 655.9 | 20.0% |
| 2015/16 | 3598.5 | 2711.0 | 3091.8 | 887.5 | 506.7 | 380.8 | 14.0% |
| 2016/17 | 4149.3 | 2604.8 | 3303.7 | 1544.5 | 845.6 | 698.9 | 26.8% |
| 2017/18 | 4225.5 | 3067.7 | 3563.4 | 1157.9 | 662.1 | 495.8 | 16.2% |
| Average | 3959.2 | 2889.7 | 3184.4 | 1069.5 | 774.8 | 294.7 | 10.2% |

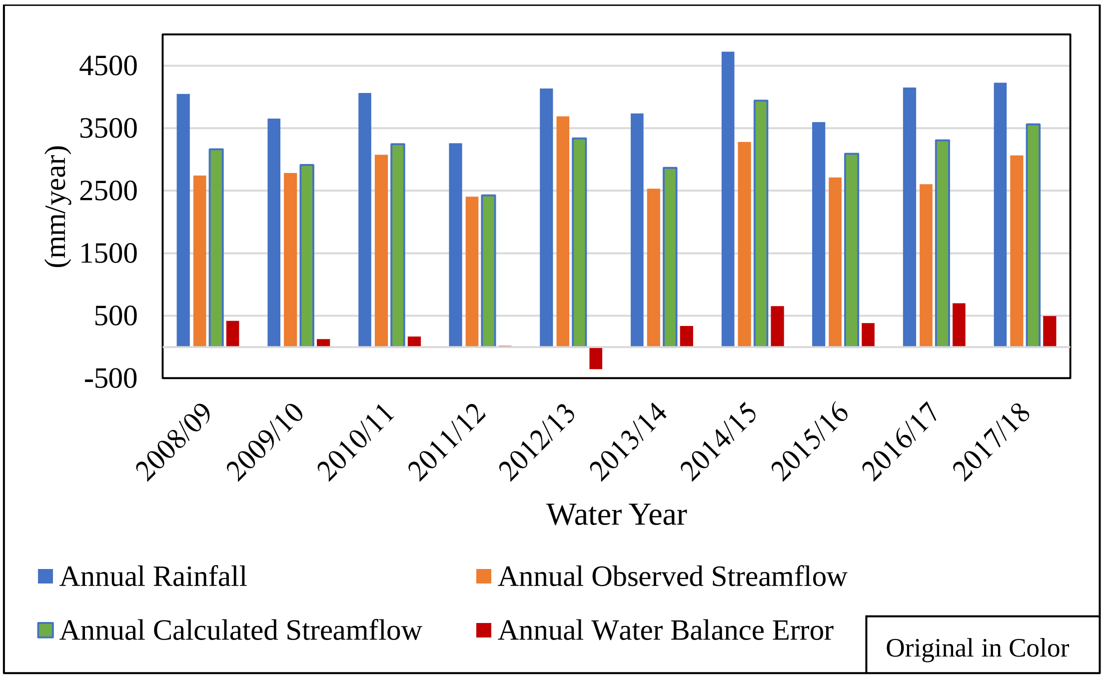



Figure 5-40: Annual Water Balance of Tawalma with Temporally Transferred Parameters

### 5.7.3 Results of Spatial Transferability

This approach utilizes the transferring optimized parameters from main catchment to sub catchment for the same time period and vice versa.

#### 5.7.3.1 Spatial Transferability of Parameters from Baddegama to Tawalama sub catchment

The results of spatially transferring optimized parameters from Baddegama main catchment to Tawalama sub catchment is shown in following sections.

##### 5.7.3.1.1 Statistical Measure of Goodness of Fit

Table 5-21: Measure of Goodness of Fit of Model for Tawalama with Spatially Transferred Parameters

| Gauging Station | MRAE for Overall Flow | MRAE w.r.t FDC (Sorted) | | | MRAE w.r.t FDC (Unsorted) | | |
|---|---|---|---|---|---|---|---|
| | | High | Medium | Low | High | Medium | Low |
| Tawalama | 0.338 | 0.085 | 0.059 | 0.363 | 0.292 | 0.303 | 0.478 |

##### 5.7.3.1.2 Comparison of Flow Duration Curves

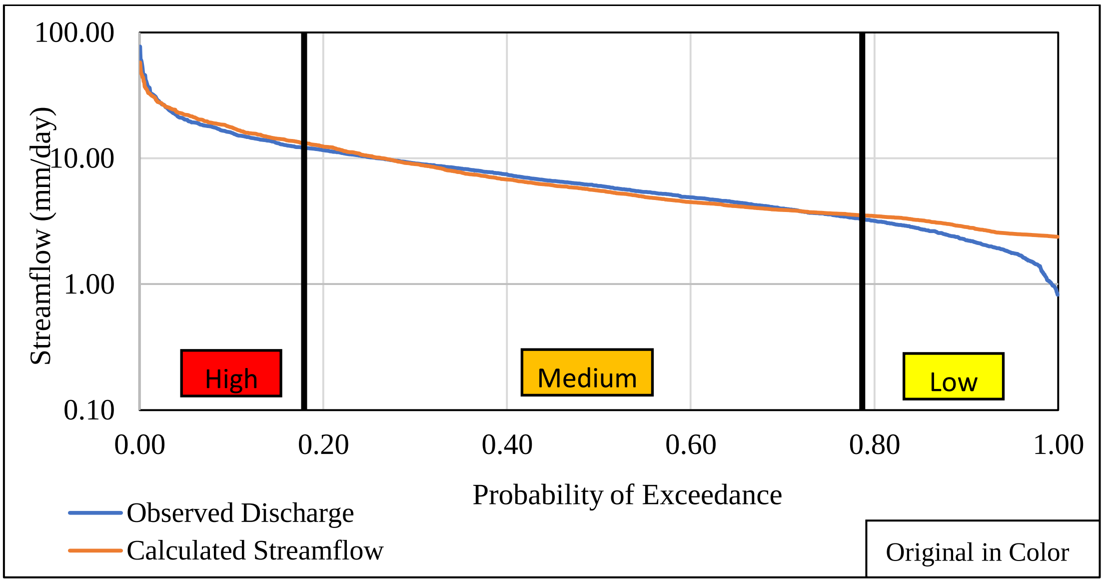



Figure 5-41: FDC (Sorted) for Tawalama with Spatially Transferred Parameters from Baddegama

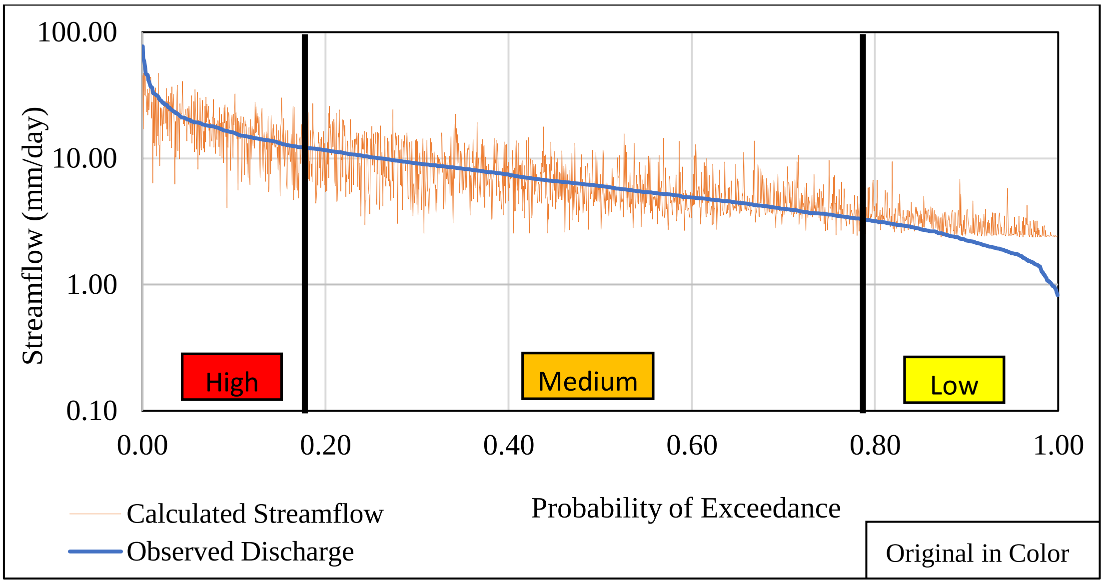



Figure 5-42: FDC (Unsorted) for Tawalama with Spatially Transferred Parameters from Baddegama

#### 5.7.3.1.3 Comparison of Hydrographs of Observed and Estimated streamflow

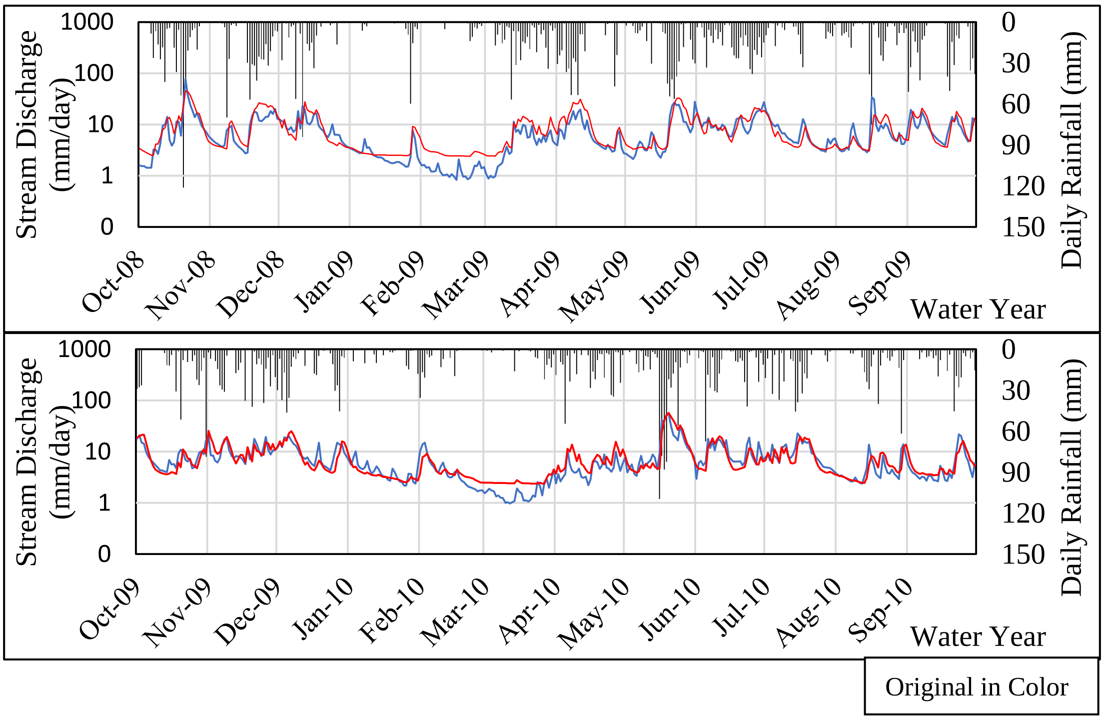



Figure 5-43: Flow Hydrographs for Tawalama with Spatially Transferred Parameters

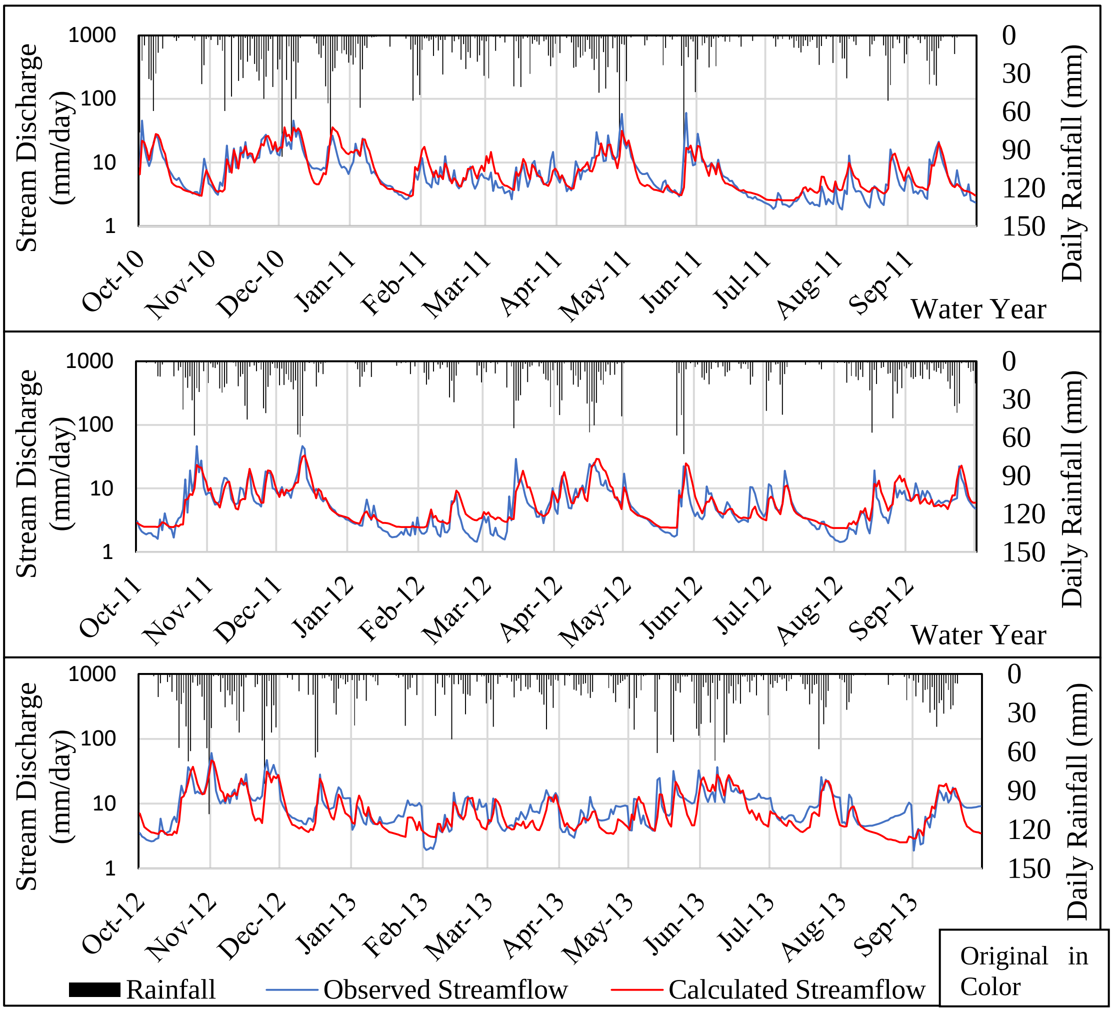



Figure 5-44: Flow Hydrographs for Tawalama with Spatially Transferred Parameters

#### 5.7.3.1.4 Annual Water Balance

Table 5-22: Annual Water Balance of Tawalama with Spatially Transferred Parameters

| Water Year | Annual RF (mm) | Annual Observe SF (mm) | Annual cal. SF (mm) | AWB Observed (mm) | AWB Simulated (mm) | AWB Error | AWB Error (%) |
|---|---|---|---|---|---|---|---|
| 2008/09 | 4086.4 | 2744.5 | 3132.0 | 1341.9 | 954.5 | 387.5 | 14.1 |
| 2009/10 | 3631.4 | 2783.1 | 2882.9 | 848.3 | 748.5 | 99.8 | 3.6 |
| 2010/11 | 4045.8 | 3077.6 | 3190.6 | 968.3 | 855.3 | 113.0 | 3.7 |
| 2011/12 | 3278.2 | 2404.4 | 2502.4 | 873.9 | 775.9 | 98.0 | 4.1 |
| 2012/13 | 4116.8 | 3689.6 | 3242.8 | 427.2 | 873.9 | -446.7 | -12.1 |
| Average | 3831.7 | 2939.8 | 2990.1 | 891.9 | 841.6 | 50.3 | 1.7 |

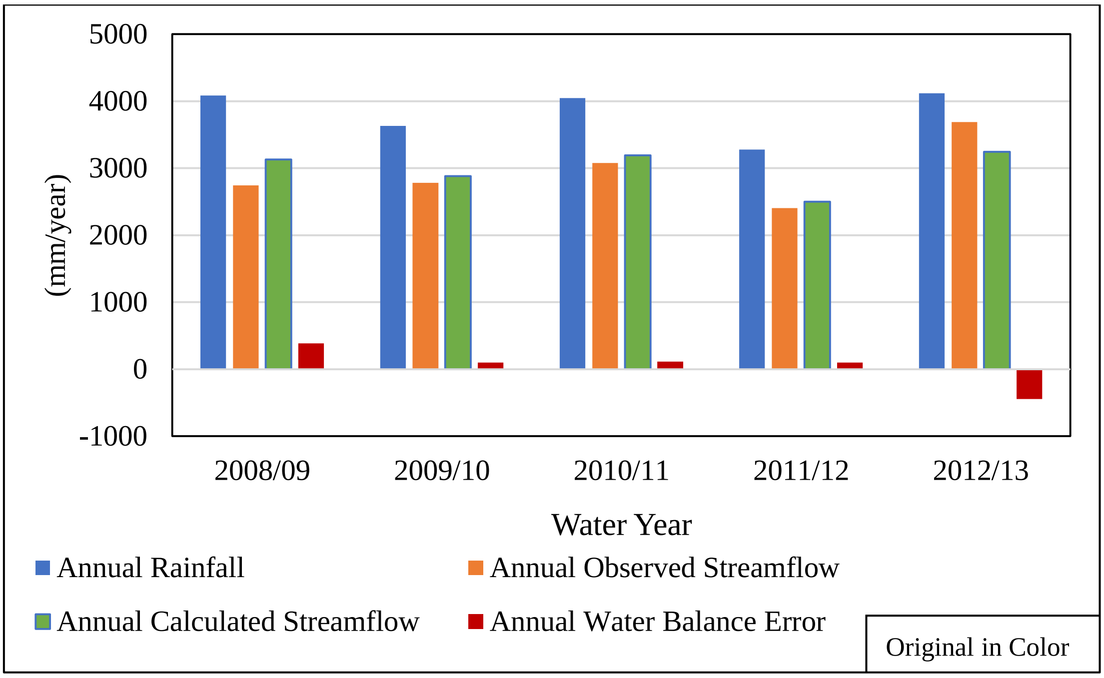



Figure 5-45: Annual Water Balance of Tawalama with Spatially Transferred Parameters

#### 5.7.3.2 Spatial Transferability of Parameters from Tawalama to Baddegama main catchment

The results of spatially transferring optimized parameters from Tawalama sub catchment to Baddegama main catchment is shown in following sections.

##### 5.7.3.2.1 Statistical Measure of Goodness of Fit

Table 5-23: Measure of Goodness of Fit of Model for Baddegama with Spatially Transferred Parameters

| Gauging Station | MRAE for Overall Flow | MRAE w.r.t FDC (Sorted) | | | MRAE w.r.t FDC (Unsorted) | | |
|---|---|---|---|---|---|---|---|
| | | High | Medium | Low | High | Medium | Low |
| Baddegama | 0.308 | 0.039 | 0.112 | 0.211 | 0.309 | 0.318 | 0.289 |

#### 5.7.3.2.2 Comparison of Flow Duration Curves

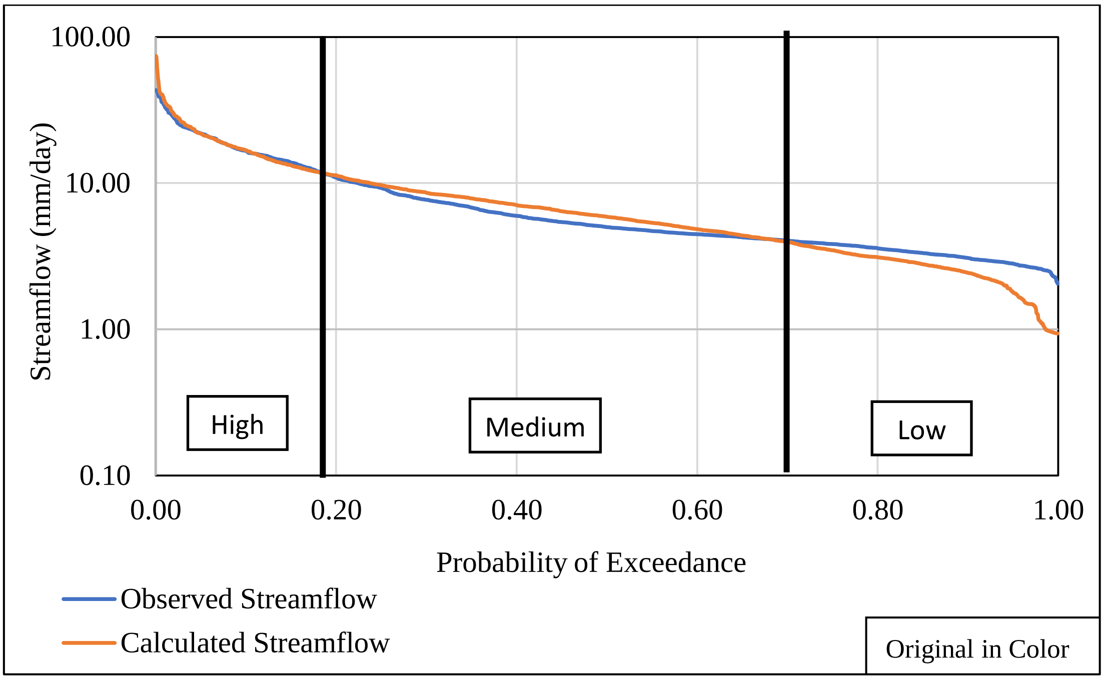



Figure 5-46: FDC (Sorted) for Baddegama with Spatially Transferred Parameters from Tawalama

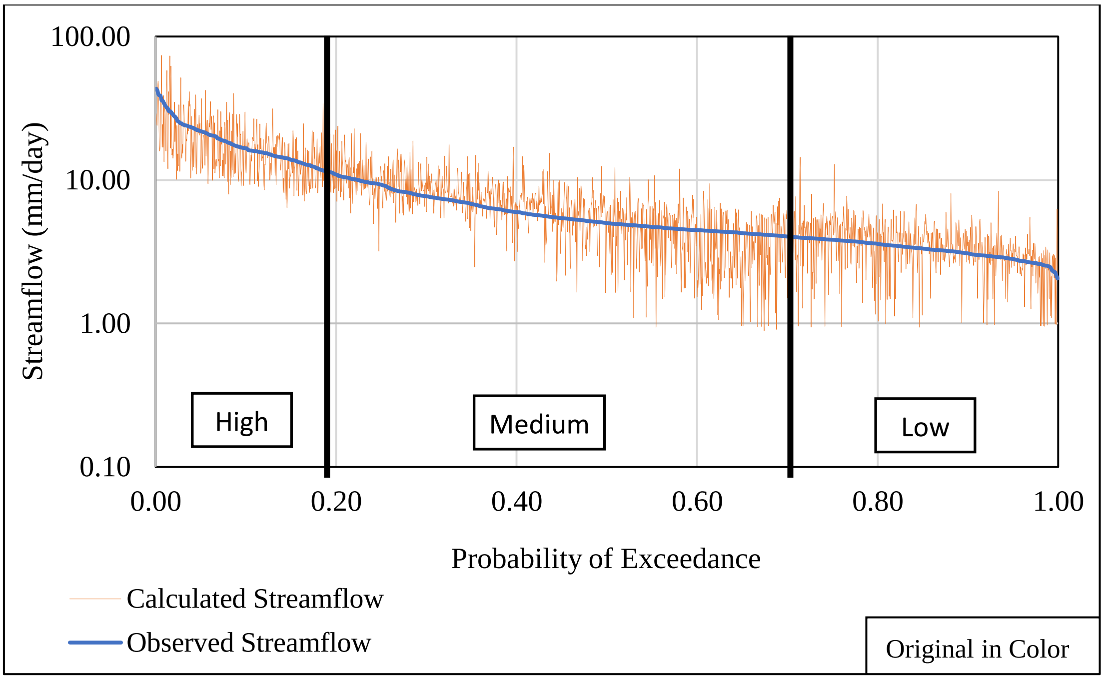



Figure 5-47: FDC (Sorted) for Baddegama with Spatially Transferred Parameters from Tawalama

#### 5.7.3.2.3 Comparison of Hydrographs of Observed and Estimated streamflow

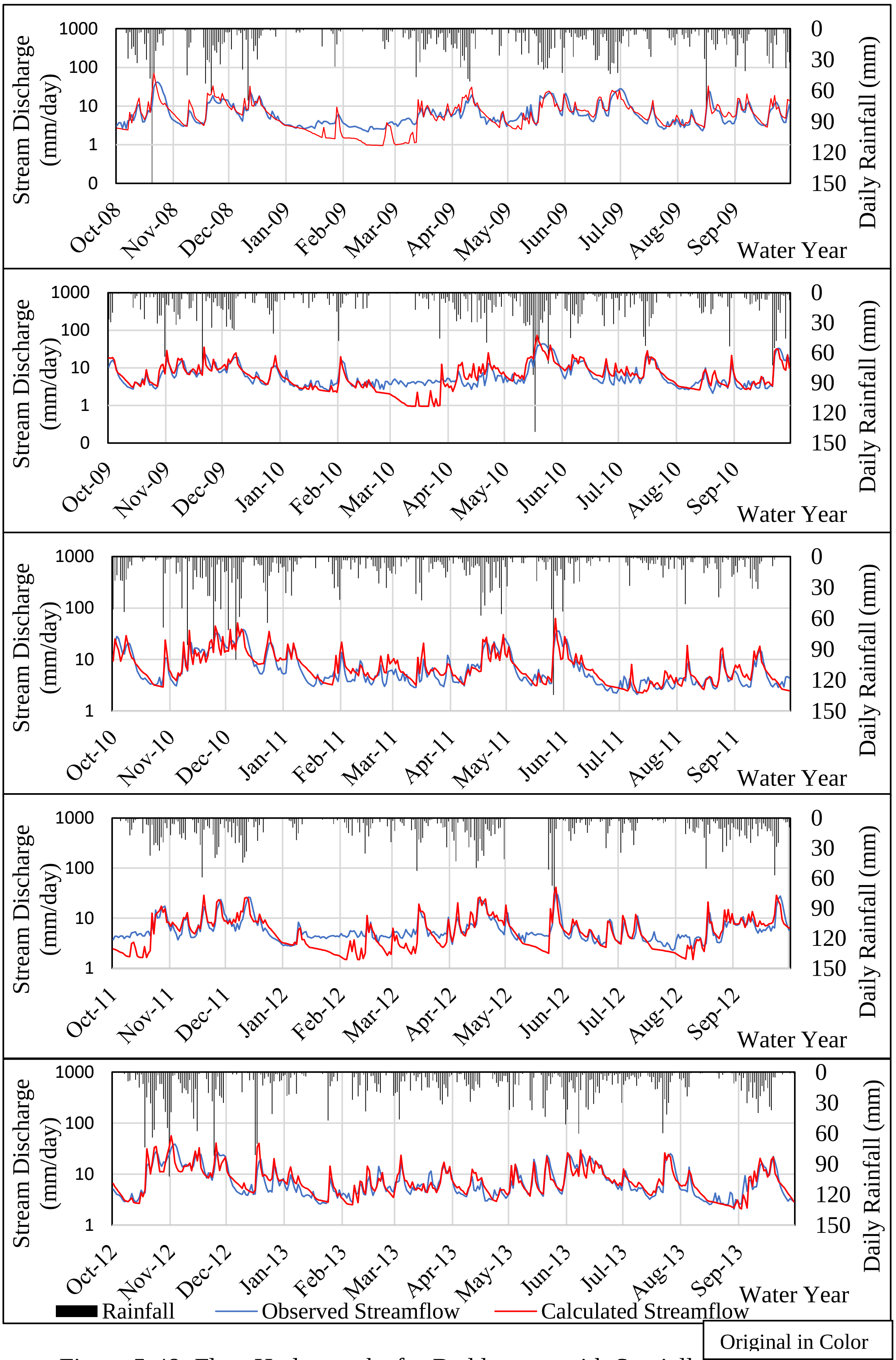



Figure 5-48: Flow Hydrographs for Baddegama with Spatially Transferred Parameters

#### 5.7.3.2.4 Annual Water Balance

Table 5-24: Annual Water Balance of Baddegama with Spatially Transferred Parameters

| Water Year | Annual RF (mm) | Annual Observe SF (mm) | Annual cal. SF (mm) | AWB Observed (mm) | AWB Simulated (mm) | AWB Error | AWB Error (%) |
|---|---|---|---|---|---|---|---|
| 2008/09 | 3743.6 | 2728.6 | 2793.2 | 1015.0 | 950.4 | 64.6 | 2.4 |
| 2009/10 | 3798.1 | 2789.9 | 2974.3 | 1008.3 | 823.8 | 184.5 | 6.6 |
| 2010/11 | 4012.7 | 3045.1 | 3230.2 | 967.6 | 782.5 | 185.1 | 6.1 |
| 2011/12 | 3293.8 | 2472.5 | 2426.7 | 821.4 | 867.1 | -45.8 | -1.9 |
| 2012/13 | 4011.3 | 3134.7 | 3226.8 | 876.6 | 784.5 | 92.1 | 2.9 |
| **Average** | **3771.9** | **2834.2** | **2930.3** | **937.8** | **841.7** | **96.1** | **3.4** |

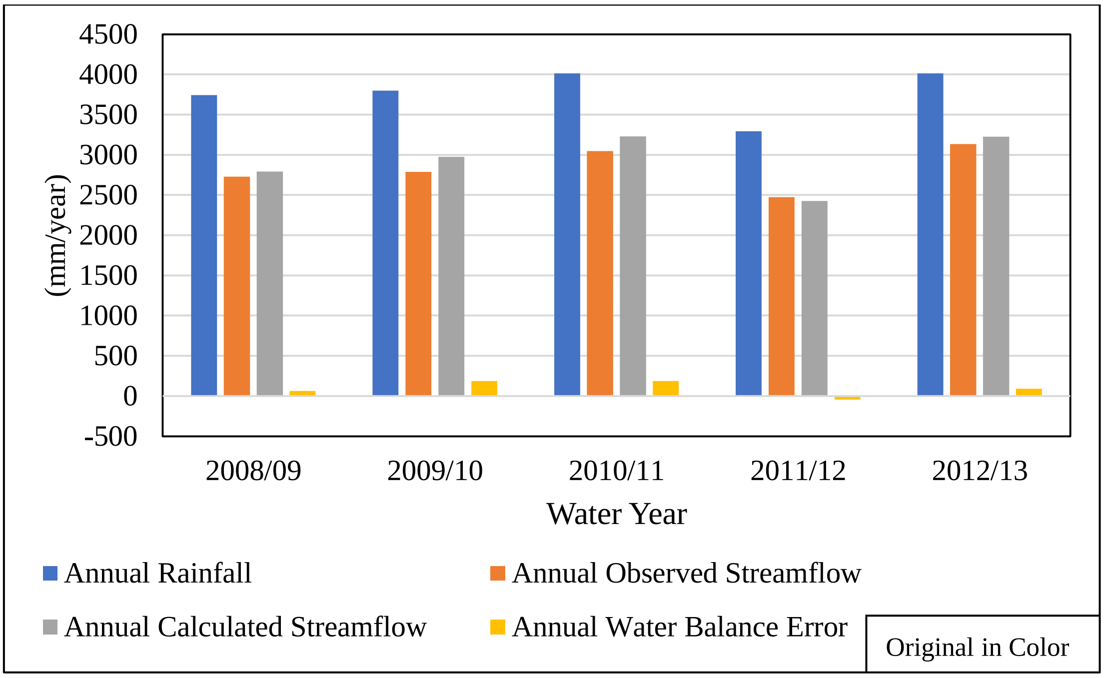



Figure 5-49: Annual Water Balance of Baddegama with Spatially Transferred Parameters

# 6 Discussion

## 6.1 Selection of Data, Data analysis and errors

Rainfall, streamflow and evaporation data of 10 water years (from October 2007 to September 2018) were selected. This is done as per the suggestion of literature review so that having five years of data for calibration and validation is good enough for continuous simulation. These gauging station and rainfall stations were selected considering that they have the most consistent data with accuracy. As an example, "Udugama" rainfall station within the basin was not considered due to inconsistent data availability. It was missing data from 2013 to 2016. So, considering the quality of data availability only rainfall stations at Aninkanda, Neluwa, Baddegama Estate, Deniyaya, Tawalama and Hinuduma were selected. Two gauging stations at Tawalama and Baddegama of Irrigation department were selected as they were the only available gauging station with continuous daily streamflow data. Similarly, the Kottawa station was the only evaporation station in the region of study.

In literature review it was noted that ideal calibration should be incorporated wet, dry and intermediate periods. In these catchments during the period of study it can be seen that year 2009/2010 and 2011/12 being relatively drier, and year 2014/15 and 2017/2018 being relatively wetter while other years being intermediate as shown in Figure 4-4 and Figure 4-6. Also Figure 4-7 shows that data undergoes long sequence of seasonal pattern in each year, rendering dry and wet periods in the catchments.

Less missing data were observed for the period of study (Table 4-4). Tawalama station didn't had any missing records while others had less than 10% of missing records for the entire period. Infilling of missing data was carried out using Thiessen aerial averaging method as described in Section 4.2.1. Here Thiessen polygon area claimed by each station without considering the station with missing data is used for determining average rainfall for modelling purpose.

Representative of rainfall stations to streamflow were checked using hydrographs, water balance and using double mass curve as described in Section 4.6, 4.4.1 & 4.7. As shown in Figure 4-8 to Figure 4-13 and in Appendix A there were few places in each water year where the responses of streamflow to the rainfall were not compatible such as high rainfall not yielding high streamflow and during period of no raining much larger streamflow variations is seen. This could be due to baseflow variations in the region or error in measurements. But, in overall the response in hydrographs are quite acceptable and hence concluded that representativeness of each stations were upheld. Annual water balance assumes that soil moisture at the beginning and ending of each water year is same. Hence annual water balance should be in compatible with annual evaporation and it should not be less than annual evaporation since it includes the water share for infiltration and percolation which was neglected initially. Careful observation shows in Tawalama for water year 2012/13 and in Baddegama for 2015/16, the annual water balance is significantly lesser than the evaporation (Table 4-9 and Table 4-10). This indicates errors or inconsistencies in measured data.

As stationarity of a time series is so important for any modelling and daily hydrographs and monthly rainfall averages has shown data in this study are stationary. Monthly rainfall averages of each station for data period were plotted for catchments as in Figure 4-7 to identify this aspect. There it can be clearly seen the two seasons of maha and yala (long sequence of parallel diurnal data) and hence it is decided the principle of stationary was upheld.

Double mass curves as shown in Figure 4-14 and Appendix B show slight gradient changings without larger breakings or changing in gradient so that overall data set can be considered as consistent and could be effectively used in modelling efforts.

According to above analysis it is decide that the station selected were representative of streamflow and consist of errors to a lesser degree hence can be used in time series modelling.

## 6.2 Model Selection

Extensive research in Section 2.2 shows that model selection can be done at discretion of the researcher giving more emphasize on project or research objectives. Often it is suggested that model selection should be based on project objective, data availability, catchment characteristics, output requirement, simplicity desired, user friendliness, and computational cost etc. (Pechlivanidis et al., 2011; Sitterson et al., 2017).

It is noted that for predictions of streamflow in ungauged basin through conceptual models has been preferred as less complex conceptual lumped models are equally reliable for predictions of streamflow. Whereas physically based model results high uncertainty in ungauged catchments due to demand for physical catchments attributes for derivation of parameters and sometimes cause over parameterization as well. Also, such models require considerable data and human effort compared to conceptual or semi-distributed model. Therefore non-distributed models preferred in ungauged basins (Goswami et al., 2007; Razavi et al., 2012; Shu & Ouarda, 2012).

### 6.2.1 Selection of Tank Model with Four Storage Reservoirs

Tank model originally developed by M. Sugawara is a lumped conceptual model which accepts rainfall and evaporations as inputs. Standard tank model consists with four tanks though many variations of tank arrangement has been applied by researchers depending on the situations (Section 2.2.3). Although it is noted that four storage tank model is the most common used one. (Kuok et al., 2011) determined that four tank model four tanks are suitable for humid region either for daily or hourly simulation.

Hence, tank model with four storage reservoirs is being used in this study.

### 6.2.2 Selection of Objective function

Objective function (OF) may depend on the purpose of the study or simulation and on the time step of hydrological modeling. The objective of continuous modelling is to properly assess the water budget over a long duration whereas event modelling focus on simulation of peak flows during single event (Green & Stephenson, 2009). As opposed to selecting objective function based on least square errors which favor high flows, absolute error functions tend to predict intermediate to low flows better. As this study spans over calibration and validation of five-year continuous data set, MRAE is used as OF as discussed in Section 2.4.1. MRAE is sensitive to more prominent flow segments, usually medium flow regime.

### 6.2.3 Selection of Initial Parameters

The initial parameters were selected with the assistance of literature values in Table 5-1. Specially parameter values for Tank model in Asian region (Phien & Pradhan, 1983; Setiawan et al., 2003) and in Sri Lanka (Musiake & Wijesekera, 1990; Wijesekera, 1993) were looked at for defining initial values. It is noted that such a method was resorted since the Tank model is a lumped conceptual model in which its parameters could not be directly compared to catchment properties such as land use, soil as the tank model is sensitive to overall catchment response to precipitation (Sugawara, 1984,1995). In contrary to this Basri,(2013) has mentioned the use of different tank structures for different land use but limited number of researches in this regard hinders applicability of such method. Additionally Dr. Sugawara has mentioned initial selection of parameter values according to descending rates of discharge after peaks as founded in hydrographs in logarithmic scale (Sugawara, 1995).

The results of the study show that selection of initial parameters with respect to hydrologically similar basins as discussed above may be adequate for purpose of simulation.

## 6.3 Model performance

Model performance was evaluated quantitatively and qualitatively using different type of criteria. Quantitative performance is evaluated using objective function- MRAE and qualitative performance is observed through use of hydrographs, annual water balance and flow duration curves. This approach is taken as Hansen et al. (1996); Phien & Pradhan (1983) stated that quality of the calibration and validation may incorporate the judgements based on both visual and statistical comparison of observed and simulated streamflows and more concerns should be given on those visual examination such as flow hydrographs, annual water balance during hydrologic modelling for water resources management and planning. Further, this may help with avoiding problem of equifinality i.e. existing of many parameters set yielding acceptable results (K. Beven, 2012).

### 6.3.1 Model Performance in Calibration

Model was set up in MS Excel and Solver GRG non-linear optimization method was used to optimize objective function i.e. MRAE for achieving minimal value. As described in Section 5.3.1 set of different initial parameters were looked at and several attempts were made to obtain global parameter sets by starting with different initial values. Further, obtained results were examined visually as described above.

During model warm up as per Table 5-3 it is observed that storage level in 4$^{th}$ tank was not stabilized easily as in other tanks. That may cause due to non-linear nature of the tank model and due to the fact that order of magnitude of coefficient D1 in fourth tank is directly affecting this nature. When D1 values are high its storage level stabilizes quickly but it will lower the low flows to extreme end while putting model calibration is in vein.

Results of calibration for both Baddegama and Tawalama catchment is shown in Table 6-1. Overall MRAE values for Baddegama and Tawalama catchments are 0.233 and 0.246 respectively. This shows that model predicted the streamflow in both catchments with accuracy level of greater than 75%.

Table 6-1: Comparison of MRAE Values for Both Catchments in Calibration

| **Gauging Station** | **MRAE for Overall Flow** | **MRAE w.r.t FDC (Sorted)** | | | **MRAE w.r.t FDC (Unsorted)** | | |
|---|---|---|---|---|---|---|---|
| | | **High** | **Medium** | **Low** | **High** | **Medium** | **Low** |
| Baddegama | 0.233 | 0.028 | 0.069 | 0.056 | 0.179 | 0.254 | 0.229 |
| Tawalama | 0.246 | 0.082 | 0.024 | 0.039 | 0.238 | 0.257 | 0.223 |

When comparing MRAE values of sorted FDC which compares the observed high to calculated high and vice versa, it could safely say the water quantity has been estimated accurately. In Baddegama there is slight over estimating of medium flows and low flows than Tawalama (Figure 5-4 and Figure 5-8 respectively).

But, things get more complicated with MRAE values of unsorted FDC for different flow regimes which compares the observed values to its direct simulated values. In all cases higher MRAE values can be observed, showing more fluctuation in the graphs which are resulted by mismatch of observed and simulated values (Figure 5-5 and Figure 5-9). Nevertheless, in any case the accuracy level of 75% has been held which shows better simulation of Tank model. Ultimately the incompatibility in FDC unsorted and compatibility in FDC sorted state that model is capable of estimating streamflow magnitudes adequately though its time of occurrence is varying.

The annual water balance error for Baddegama (Table 5-5) shows that on average 3.4% overestimation in water quantity. While this has maximum value in water year 2009/10 (7.1%) and minimum value in water year 2012/13 (0.1%). When compared with the hydrographs (Figure 5-6) it can be clearly seen that there is under estimation of low flows and over estimation of high flows generally. Further, it can be seen model is struggling to capture the low flows in the absence of rainfall, usually in the months of January to April in each water year.

Similarly, when comparing the annual water balance error of Tawalama catchment (Table 5-7) it is seen that average WB error is 1.7% while maximum over estimating is 12.7% in 2008/09 and unlike in Baddegama, it is observed underestimation of -9.8% in 2012/13. For year 2008/09, from the hydrographs it can be seen that even low flows are overestimated while for year 2012/13 there are greater underestimations in low flows or flow in no rain period which show result of data inconsistencies. This is confirmed as the annual runoff coefficient of 0.9 is quite high on contrary to long term average is 0.71 from Hydrological Annual of ID (Section 4.4.1.1).

Further, it is noted that mismatch of low flows may occur due to inconsistency of the model concepts as lumped models tend to aggregate heterogeneous parameters. And this may cause the factors affecting sub- base and base flows such as infiltration and percolation to be neglected while causing overestimation of low flows. Furthermore, underestimation of low flows could be seen as clear data inconsistency as shown in March-April 2010, Jan-Feb 2012 in Baddegama (Figure 5-6) and Jan-Feb 2013, Aug-Sep 2013 (Figure 5-10).

Table 6-2 shows that higher MRAE values are observed in Baddegama for 2009/10 & 2011/12 water years. Careful examination of both the hydrographs shows that there is significant mismatching due to under estimation as well as over estimation. Similar behavior is observed for year 2012/13 in Tawalama catchment.

Through Table 6-3, it is noted that model is matching the flows quite good in wet months for both catchments showing smaller MRAE values while showing larger MRAE in dry months. Here January to April is considered to be relatively drier in wet zone and other months could be think as intermediate months except May to September which are the North-west monsoon months.

Table 6-2: Comparison of Annual MRAE Values for Both Catchments in Calibration Period

| Water Year | MRAE Value | |
|---|---|---|
| | Baddegama | Tawalama |
| *overall* | *0.233* | *0.246* |
| 2008/09 | 0.212 | 0.269 |
| 2009/10 | 0.274 | 0.212 |
| 2010/11 | 0.234 | 0.243 |
| 2011/12 | 0.262 | 0.213 |
| 2012/13 | 0.182 | 0.295 |

Table 6-3: Comparison of Annual Wet and Dry Period MRAE Variations for Both Catchments in Calibration Period

| Water Year | MRAE Value of Baddegama | | MRAE Value of Tawalama | |
|---|---|---|---|---|
| | Jan - April | May - Sep | Jan - April | May - Sep |
| 2008/09 | 0.220 | 0.203 | 0.332 | 0.269 |
| 2009/10 | 0.392 | 0.232 | 0.240 | 0.212 |
| 2010/11 | 0.293 | 0.232 | 0.367 | 0.243 |
| 2011/12 | 0.297 | 0.234 | 0.250 | 0.213 |
| 2012/13 | 0.215 | 0.156 | 0.338 | 0.295 |

In general, model performance indicators have shown that both models for Baddegama and Tawalama have adequately calibrated and optimized parameters have been obtained and incapability to simulate the low flows, which has less impact on water management, is not considered to be bigger issue of the model.

### 6.3.2 Model Performance in Validation

In the validation of optimized parameters, it is seen that overall MRAE of 0.298 is achieved in Baddegama catchment whereas MRAE of 0.364 is achieved in Tawalama catchment. In the calibration MRAE results were 0.233 and 0.246 respectively. Further, it is noted that difference in MRAE values are 0.065 for Baddegama and 0.118 Tawalama. Overall accuracy of 70% and 64% has been achieved for Baddegama and Tawalama catchments respectively in validation. The results of MRAE in different flow regime in validation is shown in Table 6-4. Table 6-5 shows variations of MRAE in validation for each validated year.

Table 6-4: Comparison of MRAE Values in Validation for Both Catchments

| **Gauging Station** | **MRAE for Overall Flow** | **MRAE w.r.t FDC (Sorted)** | | | **MRAE w.r.t FDC (Unsorted)** | | |
|---|---|---|---|---|---|---|---|
| | | **High** | **Medium** | **Low** | **High** | **Medium** | **Low** |
| Baddegama | 0.298 | 0.102 | 0.148 | 0.013 | 0.194 | 0.324 | 0.315 |
| Tawalama | 0.364 | 0.209 | 0.202 | 0.403 | 0.282 | 0.338 | 0.510 |

Table 6-5: Comparison of Annual MRAE Values for Both Catchments in Validation Period

| Water Year | MRAE Value | |
|---|---|---|
| | Baddegama | Tawalama |
| *overall* | *0.298* | *0.364* |
| 2013/14 | 0.268 | 0.321 |
| 2014/15 | 0.296 | 0.358 |
| 2015/16 | 0.305 | 0.409 |
| 2016/17 | 0.305 | 0.428 |
| 2017/18 | 0.315 | 0.307 |

Overall higher MRAE values have been reported due to the fact that model has been incapable of predicting low and intermediate flows with greater accuracy as shown in above table. Tawalama has shown larger inaccuracy level when compared to Baddegama catchment though hydrographs behavior is smoother than Baddegama (Figure 5-18).

This could be further observed through FDC curves in Figure 5-12, 5-13, 5-16 & 5-17. Figure 5-13, FDC unsorted for Baddegama shows larger fluctuation in intermediate flows and over estimation in low flows. FDC sorted shows intermediate flow values has been over predicted. This may be due to the fact that model has been calibrated to a period with higher runoff coefficient than in validation hence model tend to overestimate intermediate flows. Average runoff coefficient of Baddegama in calibration period 0.75 while for validation period it is 0.68, except for year 2015/16 which is 0.81, resulting average valued of 0.71. Apart from that it is noted the underestimation of low flows may results with respect to model structure and its parameters of C1, D1 which directly affects the low flow simulation. In hydrographs, Feb- March 2014, Feb- April 2016, Sep 2016, & Sep 2018 (Figure. 5-14) there are flat projections in low flow areas, this is direct results of C1 & D1. It seems C1 and D1 calibrated values are not optimum for validation period hence could not capture streamflow variations even with the presence of rainfall. This shows the initial assumption of the sample data has come from representative sample population may have not been true hence the model excitation in validation incomplete. Because of this model can't predict low flows beyond the values in calibration adequately. In Table 5-9 annual water balance for the validation in Baddegama is shown. Average overestimation is 9.8% while it ranges from 2.3% in 2015/16 to 16.9% in 2017/18. Table 6-6 shows, similarly in calibration, the dry period MRAE values are higher than wetter period thus showing model inability to capture intermediate to low flows due to effect of optimized parameters. But, contrary to that hydrographs and FDC shows that total water balancing is being undertaken by the model.

Analyzing of Tawalama hydrographs and FDCs shows following. Hydrographs, FDC sorted and unsorted show that streamflow has been overestimated in intermediate and low flows, while it shows good predictability with relating to high flows (Table 6-6). The model has been able to capture high flows with respect to flooding in both catchments (May -2017 in Figure 5-14 & 5-18). When comparing FDC unsorted it could be clearly seen less fluctuations than in Baddegama and clear over estimation of low flow. This is proved from Table 6-6 values. Looking at dry period of hydrographs (Figure 5-18) overestimation could be easily identified and, in both catchments, it is noted that low flow curves of simulation follows the gradient of observed flows. As in Baddegama, here also, runoff coefficient which model is calibrated is higher (0.77) than the runoff coefficient which model is validated (0.69). This may lead to higher estimation of overall flows. The effect of C1 and D1 has caused the model not to pick low flow variations and rather resulting straight lines.

Table 6-6: Comparison of Annual Wet and Dry Period MRAE Variations for Both Catchments in Validation Period

| Water Year | MRAE Value of Baddegama | | MRAE Value of Tawalama | |
|---|---|---|---|---|
| | Jan - April | May - Sep | Jan - April | May - Sep |
| 2013/14 | 0.285 | 0.289 | 0.379 | 0.311 |
| 2014/15 | 0.340 | 0.314 | 0.461 | 0.306 |
| 2015/16 | 0.448 | 0.266 | 0.612 | 0.380 |
| 2016/17 | 0.343 | 0.264 | 0.574 | 0.272 |
| 2017/18 | 0.403 | 0.344 | 0.366 | 0.360 |

When comparing annual water balance of validation of Tawalama catchment it is observed that its percentage error is greater than that of Baddegama. On average, error is 19.0% while it ranges from 14.7% (2015/16) to 27.3% (2016/17). This is clearly the results of overestimation of intermediate to low flows as shown by hydrographs.

### 6.3.3 Model Performance in Monthly Scale for Calibration and Validation.

On average water balance error is less than 20% for both catchments annually and this shows that model has been able to predict water quantity adequately even in validation showing its suitability for water management. In this section the results are further aggregated to find out the suitability of predictions for water resource management as this study endeavors to find out how a model can be helpful in water management of ungauged catchment.

Table C1 shows Baddegama average monthly water simulation error is 2.93% (overestimated) and it shows 24.75% overestimating anomaly for April month. This also can be seen in validation which shows 35.48% for April Month. This may be due to the fact April being driest month and the model is not performing very well in low flows due to presence of data inconsistency. For validation average error is 10.0% which shows better predictability than annual values. It is noted that errors are maximize for the dry period. Similarly, Table C2 shows, Tawalama has an improved water balance error of 2.3% overestimation in calibration though it has much estimation error in validation which shows larger error than annual values. Average error in validation is 22.51% overestimation. Further, it is noted larger errors has been occurred during month of February, March & April. This shows there may be data inconsistencies of daily data, especially in dry months which contribute larger errors when aggregating.

Scatter plot in Figure C3, C4, C7 & C8 shows monthly data correlation in calibration and validation for Baddegama and Tawalama. In both cases it can be seen that overestimation occurs in validation. Except for validation of Tawalama, daily data aggregation into monthly scale has shown improved results as the point in scatter plotter are grouped around optimum line i.e. $R^2$ =1. In overall the accuracy level of 90% for Baddegama and 77% for Tawalama has been achieved considering both calibration and validation. This shows the model build on daily basis, could be successfully reconstructed for monthly data resolution for water resources management purposes.

### 6.3.4 Model Optimization and Evaluation of Parameters of Tank Model

Initial parameters were selected as described in Section 5.3.1 and initial parameters were selected as for Table 5-1 and Table 5-2. Different starting points were employed during optimization using Solver in MS Excel as this contain $12^{th}$ dimension error surface, which cause difficulty in achieving global minimum.

Hence, Semi-automatic calibration is used here, i.e. parameters given by Solver is adjusted while evaluating the performance in hydrographs, FDCs and annual water balances. In this regard the parameter D1 was fixed to 0.00095 after several observations for both catchments. Further, C1 in Tank model for Baddegama was changes to 0.01243 to 0.03243 to match with subsurface flow patterns and to minimize annual water balance error. It is noted that observing whether the global minimum value has been obtained for an objective function is difficult. Hence employing different optimization methods and use of ensemble of objective function is suggested with availability of better resources.

During optimization it is noted that effect of sample representativeness has greater effect of model calibration and validation. It is better if raw data (Rainfall, evaporation & streamflow) representativeness of the population could be evaluated carefully using statistical methods other than the methods depicted here as the model tend to stick to minimum flows depicted by calibrated model parameters and they may act as boundary values when no rain is presented. This may be avoided having more parameters or another storage at the bottom. Hence this regard efficacy of inclusion of different tank model structures according to different hydro-physical conditions (such as land use, soil type, and slope) and performing conceptual semi-distributed modelling, could result improved predictability.

When comparing parameter values for both catchments, it can be seen that their difference is within one order of magnitude for A1, A2, B0 and B1. The order of magnitude of the other parameters are same. Also, it is noted that optimized storage constant values (HA1, HA2, HB1, and HC1) won’t be much different from the initial given values. And it is noted that both catchments will retain similar values when started with same values and hence the optimized parameters are much similar as shown in Table 5-12.

For the parameters from A0 to D1, differences between two catchments are under 0.23 except for B1 in which difference is 0.75. This may be due to the fact that difference in land use, soil type and area between two catchment as stated in Yokoo et al. (2001). It is noted that Baddegama catchment area is twice as large as Tawalama. Apart from that there are no greater difference of parameters and their effect on both catchments are similar in nature as shown in sections related to Transferability. This may be due to the fact that both catchment inherent the similar hydrological and physical features while Tawalama being nested in larger Baddegama catchment.

### 6.3.5 Model performance Against Other Error Functions

During the calibration and validation two other error functions namely, NSE and $NSE_{sqrt}$ were used as indicators of model performance. The overall results of these functions are shown in Table 6-7. The results show that good agreement between the error functions which indicate good performance of the model in both calibration and validation.

Table 6-7: Model Performance with Respect to Other Error Functions

| | **Baddegama** | | **Tawalama** | |
|---|---|---|---|---|
| **Error function** | **Calibration** | **Validation** | **Calibration** | **Validation** |
| MRAE (best value = 0) | 0.233 | 0.298 | 0.246 | 0.364 |
| NSE (best value =1) | 0.838 | 0.806 | 0.766 | 0.760 |
| $NSE_{sqrt}$ (best value =1) | 0.844 | 0.789 | 0.798 | 0.768 |

## 6.4 Model Parameter Transferability Performance

As discussed in Section 2.3, there were no general consent among which regionalization method is better, only the different approaches which suits for different scenarios are presented. Hence in this study it is decided available simplest method could be used and assumed that it will yield better results given that catchments are more or less similar in hydrological conditions. Hence direct transfer of optimized parameters is used as this is the simplest method of transferability which is best suited for water managers in their day to day estimations. This approach has been supported by the fact that two catchments are based on mid and upper part of the Gin Ganga basin which are having more or less similar hydrological characteristics and Tawalama is nested in within Baddegama catchment.

Three simple parameter transferability approaches were considered with above assumptions. Spatiotemporal, temporal and spatial are the three approaches tested. The results are shown in below sections.

### 6.4.1 Model Performance under Spatiotemporal Transferability of Parameters

Under this approach, the optimized parameters of Baddegama catchment were transferred for simulating streamflow of Tawalama catchment and optimized parameters of Tawalama is transferred to Baddegama for duration of 2008/09 to 2017/18.

Transfer of Baddegama parameters to Tawalama has shown overall 59.0% accuracy as per Table 5-13. Though accuracy of estimating low flows has been dire effort showing lesser than 30% accuracy level but medium and high flow accuracy is above 65% which shows better usability of the model by water managers. It can be seen from the FDC charts, high and medium flows have been fairly predicted from the transferred parameters (Figure 5-20 & 5-21).

The flow hydrographs (Figure 5-22 to 5-24) has shown that high to medium flows are matching quite well while showing some shift in time axis. With respect to low flows it is seen that mostly the low flows are over estimated (generally in months of January to April). This is mainly due to absence of rainfall (Feb – March 2014, Jan – Apr 2016, Aug-Sep 2016 & Aug- Sep 2018) and due to the transferred parameters of C1 and D1 are not able to pick up the variation of low flows under no rainy days because of the sample data may not being representative of population. The C1 and D1 values has already predetermined the smallest streamflow values that can be predicted, during its calibration period, such that it cannot go beyond certain level and it clearly cause overestimation of low flows as seen in hydrographs (Figure 5-22 to 5-24). This may be the main cause rather than not having rainfall.

Average water balance error is 10.2% as shown in Table 5-14 while it ranges from 28.7% (2016/17) to -11.7% (2012/13). Underestimation is clearly the data inconsistency as discussed in earlier, may be owing to incorrect measure of streamflow (shows higher runoff coefficient of 0.9 rather unusual for the catchment).

Similarly transfer of Tawalama parameters to Baddegama has resulted in followings. It has shown overall accuracy of 66%. And it has shown similar results for high, medium and low flows (Table -15). Thus, it can be seen that transfer from Tawalama to Baddegama has shown improved results. FDC (sorted and unsorted) also shown that transfer of sub to main is follow along the observed FDCs (Figure 5-26 & 5-27) unlikely in transfer from main to sub. From the hydrographs it can be clearly seen underestimation of low flow whereas in transferability from main to sub has shown overestimation of underflows (Figure 5-28 & 5-29). This is due to the fact model calibrated for Tawalama has higher high flows and lower low flows than in Baddegama and whenever data inconsistency or no rainy days occurs, model is arriving at said minimum values (Jan-Feb 2012, March-April 2016 in Figure 5-28).

Average water balance error for Baddegama with spatiotemporally transferred parameters, is 9.7% as shown in Table 5-16 while it ranges from overestimation of 23.4% (2017/18) to underestimation of -1.4% (2011/12). The overall results of water balance are improved to the results for transfer from main to sub catchment.

### 6.4.2 Model Performance under Spatial Transferability of Parameters

Here the optimized parameters for 2008/09 to 2012/13 of Baddegama Main catchment is transferred spatially for Tawalama sub catchment for same time duration. Similarly, Tawalama parameters are transferred to Baddegama. Applicability of this approach is greatly affected by the assumption of similarity of hydrological features of the basin (Van Der Linden & Woo, 2003). The discussion on the results of this approach is illustrated here.

From Table 5-21 it is seen that spatially transferring of parameters has improved MRAE values than spatiotemporal transferability for Tawalama. Overall accuracy of 66% has been achieved and low simulation accuracy level has been improved by about 23%. Accuracy of high and medium flow has been retained in similar levels. This has been reflected in FDC sorted (Figure 5-41) while FDC unsorted shows variability of the values along observed FDC, it shows that low flow has been cut off at the minimum value predicted by model for Baddegama calibration. As discussed in previous sections this issue can be also observed from flow hydrographs (Figure 5-43 & 5-44). Hence when in the presence of no rain period or data inconsistencies the low values predicted is cut off ex: Jan-Mar 2009, Mar-Apr 2010, in Figure 5-43.

Average annual water balance error is only 1.7%, but 2008/09 shows 14.4% overestimation and 2012/13 shows underestimation of 12.1% which is clearly data inconsistency as discussed in previous sections (Table 5-22).

The spatial transferability for Baddegama from Tawalama has also shown improved results. The overall accuracy of 69% can be observed for period of 2008/09 to 2012/13. It is noted accuracy level of high, medium and low flow also within the same level (Table 5-23). FDC sorted show over estimation in medium flow and underestimation of low flows (Figure 5-46). FDC unsorted shows larger fluctuations in medium to lower part of the flow regimes showing that there are major disturbances in the simulation thus we could see offset in medium to low flows in hydrographs as shown in Figure 5-42. Further, it is noted that as discussed in spatiotemporal transferability, the model predicting low flows lower than actual, in no rain periods (because the model has been calibrated to a range of values which expand beyond max and min flows of Baddegama (Feb-Mar 2009, Mar-Apr 2010, Jan-Feb 2012 –Figure 5-48).

Average water balance is 3.4% while it ranges from 6.6% (in 2009/10) to -1.9% (in 2011/12) which shows that annual variations are considerably smaller. This shows that water balance performance of spatial transfer of Tawalama parameters to Baddegama has outperformed vice versa transfer.

### 6.4.3 Model Performance under Temporal Transferability of Parameters

Temporal transferability seeks the applicability of the model parameter of same catchment for different period that of calibration and validation. But, considering data availability, the optimize parameters for each catchment is applied for whole period of 2008/09 to 2017/18 (which include both calibration and validation data period) and its performance were observed.

The application of this method to Baddegama catchment shows accuracy of 72% and in all flow regimes it has shown above 69% accuracy level (Table 5-17). These results show little improvement that of validation. FDC charts shows the overestimation of medium flows and much variations of medium flows in FDC unsorted (Figure 5-31 & 5-34). The observation of hydrographs (Figure 5-33 & 5-34) shows that flow pattern is simulated adequately except where absence of rainfall, but exaggeration is quite low, this can be confirmed using MRAEs with respect to FDC – unsorted. Average annual water balance error is 9.7% and it ranges from 0.6% (2012/13) to 22.3% (2017/18) showing overestimation for full duration. In general, higher overestimation could be identified as calibrated parameters are for a period with high runoff coefficient than later years (2013-2018).

Temporal transferability of Tawalama catchment shows accuracy level 69% and similar to Baddegama, this is improved result with respect to validation. Apart from that it is seen over 70% accuracy level is shown for both high and medium flows and for low flows it is 63% (Table 5-19). FDC sorted and unsorted both shows smooth transitions and fluctuations in FDC unsorted (Figure 5-37) is minimum when compared to other diagrams (Figure 5-32) showing smaller differences in observed and simulated values.

Except for year 2012/13, all other hydrographs show better matching with respect to peaks and medium flows. Main shortcoming in those graphs is, the model could not show the fluctuations in lower flow region. It may be the reason of model structure itself (behavior of C1 and D1) as discussed earlier. Average water balance error is 10.2% which shows max overestimation of 26.8% (2016/17) and max underestimation of 9.6% (2012/13). This represent that data inconsistency in year 2012/13 has been affected overall results in every approaches. Even though, Tawalama temporal transfer shows better FDCs and hydrographs' shapes than Baddegama its water balance errors are comparatively higher.

### 6.4.4 Model Performance in Monthly Scale for Parameter Transferability.

Similarly, to calibration and validation, daily scale results were aggregated into monthly scale for different transferability approaches and results were examined for its suitability for water management.

Comparison of Table C 3 and Table C 6, shows the monthly scale performance of spatiotemporal transferability for both catchments. Tawalama, average monthly scale flow estimation error is 12.08% while its 9.72% for Baddegama. It shows that transfer from sub catchment to main has improved results while showing max error has happened in March for Tawalama and April for Baddegama, both are dry months, which shows model instability in predicting dry months as discussed earlier. Scatter plots Figure C9 and Figure C 16 shows how the model has overestimated the monthly water simulation. In both cases around 70% monthly water simulation accuracy level has been maintained for any month.

Table C 4 and Table C 7 shows water estimation errors with spatially transferred parameters. It clearly shows the improved results over spatiotemporal transferability. Spatial transfer of parameter to Tawalama has shown average monthly WB error of 2.44% overestimation while for Baddegama it is 2.89% overestimation. Considering each month, it is shown over 86% water estimation accuracy for any month considered for spatial transfer of Tawalama whereas accuracy level for Baddegama is over 80%. Scatter plots in Figure C 12 & Figure C 18 have shown that better agreement between observed and simulated values while grouping them around $R^2$ =1 line.

The comparison of monthly water simulation for temporal transferability is shown in Table C 5 & Table C 8. It shows that Tawalama resulted average flow simulation error of 11.91% and Baddegama resulted average flow simulation error of 9.82%. Further to that Tawalama shows higher overestimation in months of February, March and April (more than 20% over estimation) while for Baddegama, only March shows flow simulation error greater than 20%. In general, it can be stated that Tawalama shows over 73% accuracy level and for Baddegama it is over 80% except for April which has accuracy of 65%. The scatter plots in Figure C 13 & Figure C 20 shows that results are overestimated but not vary much from observed ones.

In any transfer method it seen that accuracy levels are within acceptable range while spatial transferability shows the best results. Summary of model performance of the study is shown in Table 6-8. Here it is noted that Baddegama temporal transferability has shown an error of 28% while transferring its parameter to Tawalama (spatiotemporal) has shown 49% error level, which amounts to average 38.5% error. Similarly, Tawalama temporal transferability has shown an error of 31% while transferring its parameter to Baddegama has shown an error of 35%, altogether which amounts to 33%. So, it can safely assume that transferring of optimized parameters in either way will cause an average error of 32% in which one could expect 68% accuracy level. The above is on daily basis, but as the water resources managers greatly concerns on monthly flow simulation. Hence, if we aggregate the daily results in to monthly basis, much improved accuracy level can be observed. In fact, the error, on average, vary between 9.72% to 12.08%, rendering accuracy level well over 89%.

Furthermore, by looking at MRAE values and water balances error in Table 6-7 and respective hydrographs as discussed earlier, it is decided that spatial transfer of the optimized parameter has outperformed other transfer methods. Further, it is noted that spatially transferring parameter from Tawalama (Sub- catchment) to Baddegama (Main catchment) has shown the best result.

## 6.5 Model Optimization, Model Parameters and Catchment Behavior

This study used the solver tool in excel to optimize the model through GRG-Nonlinear optimization method. This is one of the optimization methods which used in tank model optimization as identified in Section 2.2.4. Solver is used as this is powerful freely available tool which can be developed using spreadsheet("Excel Solver," n.d.; Ou et al., 2017). But, calibration via optimization may not results in global minimum always, re-optimization with different initial conditions or constraints may improve the suboptimal parameter values (Flood-Runoff Analysis, 1994). Optimization should not be confined to comparison of mathematical output only, proper identification of catchment behavior through comparison of hydrographs and total flow duration curve are required (K. Beven, 2012).

When considering the catchment characteristics implementation in Tank model, Dr. Sugawara has mentioned that outlets of different tank represent different component of catchment response to precipitation. Top tank's outlets are analogues to surface discharge and 2nd tank outlet represent intermediate discharge while third and fourth represent sub-base and base discharges. Further, infiltration coefficient simulates infiltration and percolation & deep percolation. He indicates that this representation shows the zonal structure of ground water (Sugawara,1995).

While, explaining physical meaning of the tank model Dr. Sugawara explained that runoff and infiltration coefficient show the total response of the basin which cannot be explained from point data or point experiments even if the number of points were large. Such phenomena occurs as larger portion of water is carried out relatively less area of stream network compared to basin area, and existence of discontinues factors such as faults, fissures, gaps in permeable or impermeable layers (Sugawara, 1984). Hence careful selection of parameter ranges considering catchment characteristics such as land use, soil, and slope is very essential in hydrological modelling using Tank model.

### 6.5.1 Model Parameter Attribution to Catchment Characteristics

During the study trial and error is used to identify the catchment response time through hydrographs. These are governed by model parameters and it is observed that values for parameters tallying with concept of time constant of each tank explained by Dr. Sugawara (Sugawara, 1984) which directly relates to catchment characteristics. The values are in reducing order of magnitude.

With initial parameters, warm up period is used for soil moisture establishment and initial catchment wetness condition is achieved. The model parameters show that recession of peaks is controlled by 2nd and 3rd tank parameters and better simulation of intermediate flows observed through hydrographs and total flow duration curves with optimized parameters. It is observed that ground water recession is best matched in wet periods and the recovery is little off during dry periods but nevertheless the impact is minimum as shown in water balances.

Various studies have shown how tank model parameter or its configurations relate to catchment characteristics such as land use, soil etc.(Amiri et al., 2016; Basri, 2013; Yokoo et al., 2001). With respect these studies, following can be noted through maps in Appendix D. Appendix D shows the maps of Land use, Soil and slope of the study area. Table D-1 shows the greater forest cover in both catchment and less development area. Twice paddy area in Baddegama with respect to Tawalama may attribute to the low infiltration of top tank while increase infiltration of other tanks comparatively to the Tawalama may show variance of the soil structures underlying. Figure D 3 shows that Tawalama is dominant with one type of soil with high conductivity so the rate of infiltration in top tank is higher. High runoff coefficient in top tank may attribute to presence of high slope in Tawalama sub catchment area as shown in Figure D 4. Similar tank storage levels and C1 and D 1 parameters for both catchments may indicate that similarity of zonal structure of groundwater. Comparatively Baddegama has most of vegetation cover including forest and hence it shows reduce runoff coefficients except in second tank. Hence it may assume that second tank runoff coefficient is more sensitive to underlying soils.

Careful examining of catchment characteristics may result in better understanding of the behavior of the model parameters and it is recommended this should be further assessed so the model can be used in instances of changing of catchment characteristics, especially in changing of land use due to urbanization.

Table 6-8: Summary Performance of Tank Model with Optimized Parameters

| Station Name | Analysis Type | MRAE | MRAE (Unsorted) | | | Annual WB Error (%) | | | Monthly WB Error (%) | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | High | Mid | Low | Avg. | Min | Max | Avg. | Min | Max |
| Baddegama | Calibration | 0.233 | 0.179 | 0.254 | 0.229 | 3.4 | 0.1 | 7.1 | 2.93 | -2.35 | 24.75 |
| | Validation | 0.298 | 0.194 | 0.324 | 0.315 | 9.8 | 2.3 | 16.9 | 10.00 | 0.06 | 35.48 |
| Baddegama Transferability | Spatiotemporal | 0.346 | 0.302 | 0.366 | 0.380 | 9.7 | -1.4 | 23.4 | 9.72 | 1.07 | 29.08 |
| | Spatial Transfer | 0.308 | 0.309 | 0.318 | 0.289 | 3.4 | -1.4 | 6.6 | 2.89 | 0.47 | 20.05 |
| | Temporal | 0.284 | 0.186 | 0.305 | 0.284 | 9.7 | 0.6 | 22.3 | 9.82 | -0.30 | 34.28 |
| | | | | | | | | | | | |
| Tawalama | Calibration | 0.246 | 0.238 | 0.257 | 0.223 | 1.7 | 0.4 | 12.7 | 2.32 | -1.62 | 7.95 |
| | Validation | 0.346 | 0.282 | 0.338 | 0.510 | 19.0 | 14.7 | 27.3 | 22.51 | 2.44 | 51.06 |
| Tawalama Transferability | Spatiotemporal | 0.412 | 0.322 | 0.336 | 0.715 | 10.2 | 4.6 | 28.7 | 12.08 | 1.90 | 31.80 |
| | Spatial Transfer | 0.338 | 0.292 | 0.303 | 0.478 | 1.7 | 3.6 | 14.1 | 2.44 | 0.26 | 13.84 |
| | Temporal | 0.305 | 0.264 | 0.294 | 0.373 | 10.2 | 0.8 | 26.8 | 11.91 | -0.73 | 26.75 |

*Note: in WB error positive values show overestimation and negative values show underestimation.*

# 7 Conclusion

1. The lumped conceptual Tank model is able to simulate daily streamflow of Baddegama and Tawalama with an accuracy of 77% and 75% during calibration and 70% and 65% in validation period respectively, showing model is capable of successfully predict the streamflow in these catchments.

2. High flows in daily streamflow simulation are predicted with an accuracy of 82% and 76% in calibration for Baddegama and Tawalama respectively. During validation accuracy is reduced to 70% and 66% respectively.

3. Medium flows in daily streamflow simulation, are predicted with an accuracy of 75% and 74% in calibration for Baddegama and Tawalama respectively. During validation accuracy is reduced to 68% and 66% respectively.

4. Low flows in daily streamflow simulation are predicted with an accuracy of 73% and 78% in calibration for Baddegama and Tawalama respectively. During validation accuracy is reduced to 68% and 49% respectively.

5. High accuracy level for total flow and for different flow regimes shows that model can safely reconstruct the daily streamflows for purpose of water planning & management.

6. Model predicts daily streamflow with an accuracy ranges from 59% to 72% when applied any transferability method and model predicts annual water balance with an average accuracy over 81% and it shows 77% average accuracy for monthly scale flow estimations with respect to any transferability method, thus showing model and selected parameter transferability methods are applicable for regionalization.

7. Present study shows that spatial transferability is the best regionalization approach with an accuracy of 66%-69% and with lowest water balance errors. Average annual water balance error is ranges from 1.7% to 3.4% while average monthly scale simulation error is ranges from 2.44% to 2.89%.

8. Application of any transferability method shows that accuracy over 65% for monthly scale flow estimations could be expected for any given month by

aggregating daily streamflows simulated under this study. This shows suitability of tested parameter transferability methods for water resources management.

9. The results of the present study show that daily streamflow could be predicted with an accuracy of 68% and average monthly scale flow estimations could be predicted with an average accuracy of 89% by applying optimized parameters of the either catchment.

10. These results show the model could be used successfully for predicting daily streamflow of ungauged catchments in the Gin Ganga basin with greater confidence hence indicates Tank model suitability for parameter transferability and water management in ungauged catchments.

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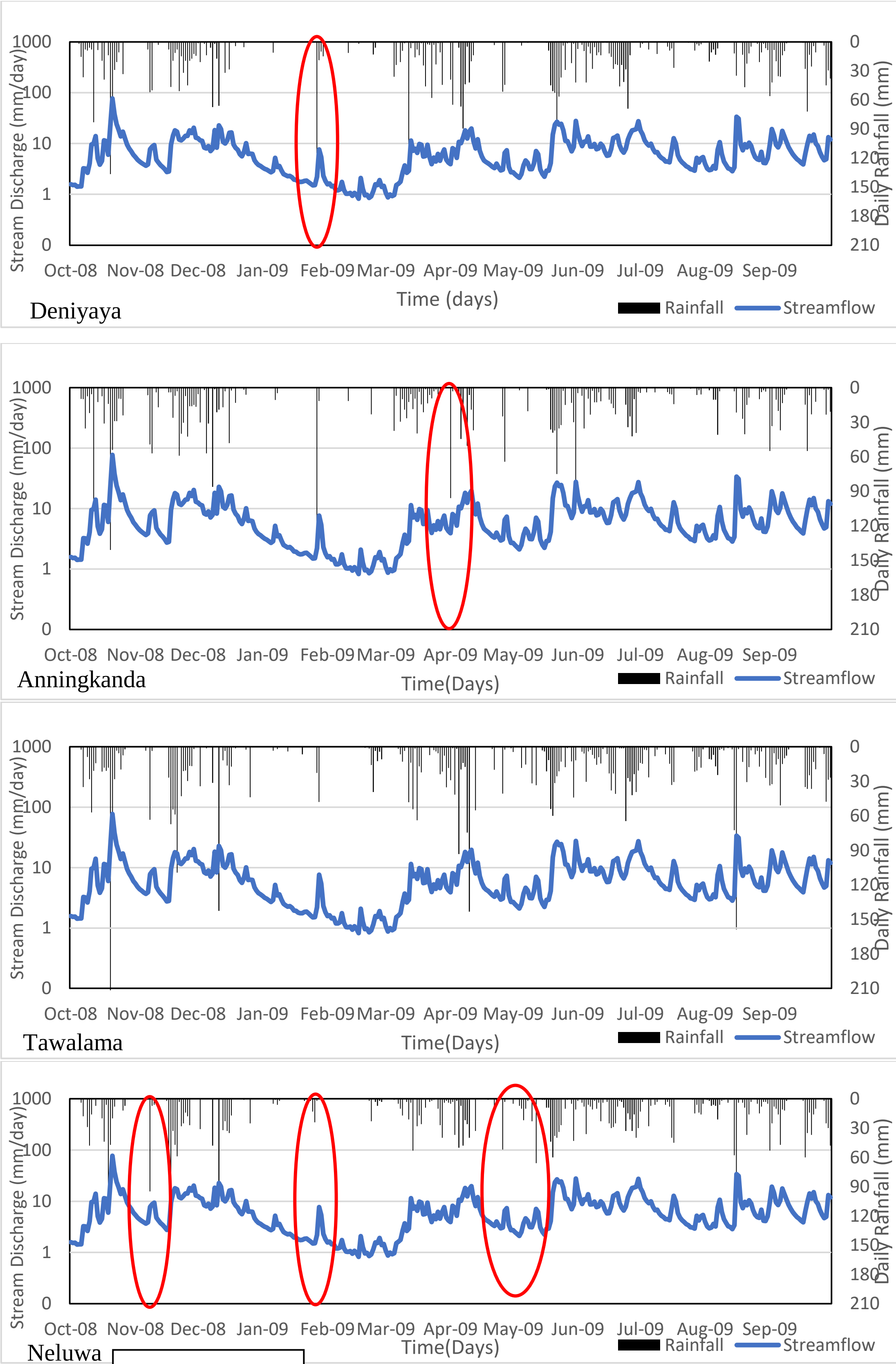
# Appendix A: Representativeness of Rainfall to Streamflow




Original in Color

Figure A 1: Tawalama SF vs Rainfall for Water Year 2008/09

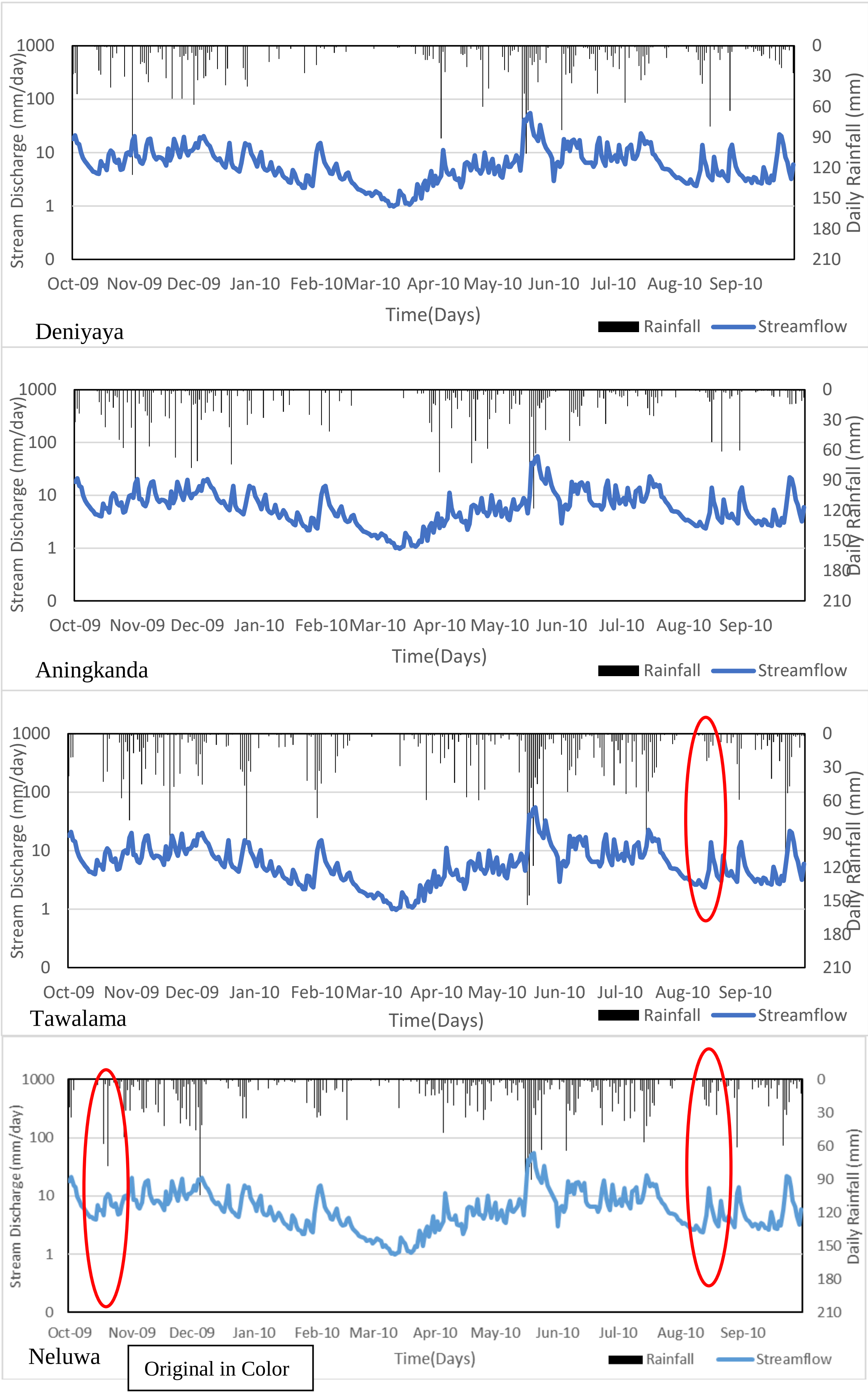
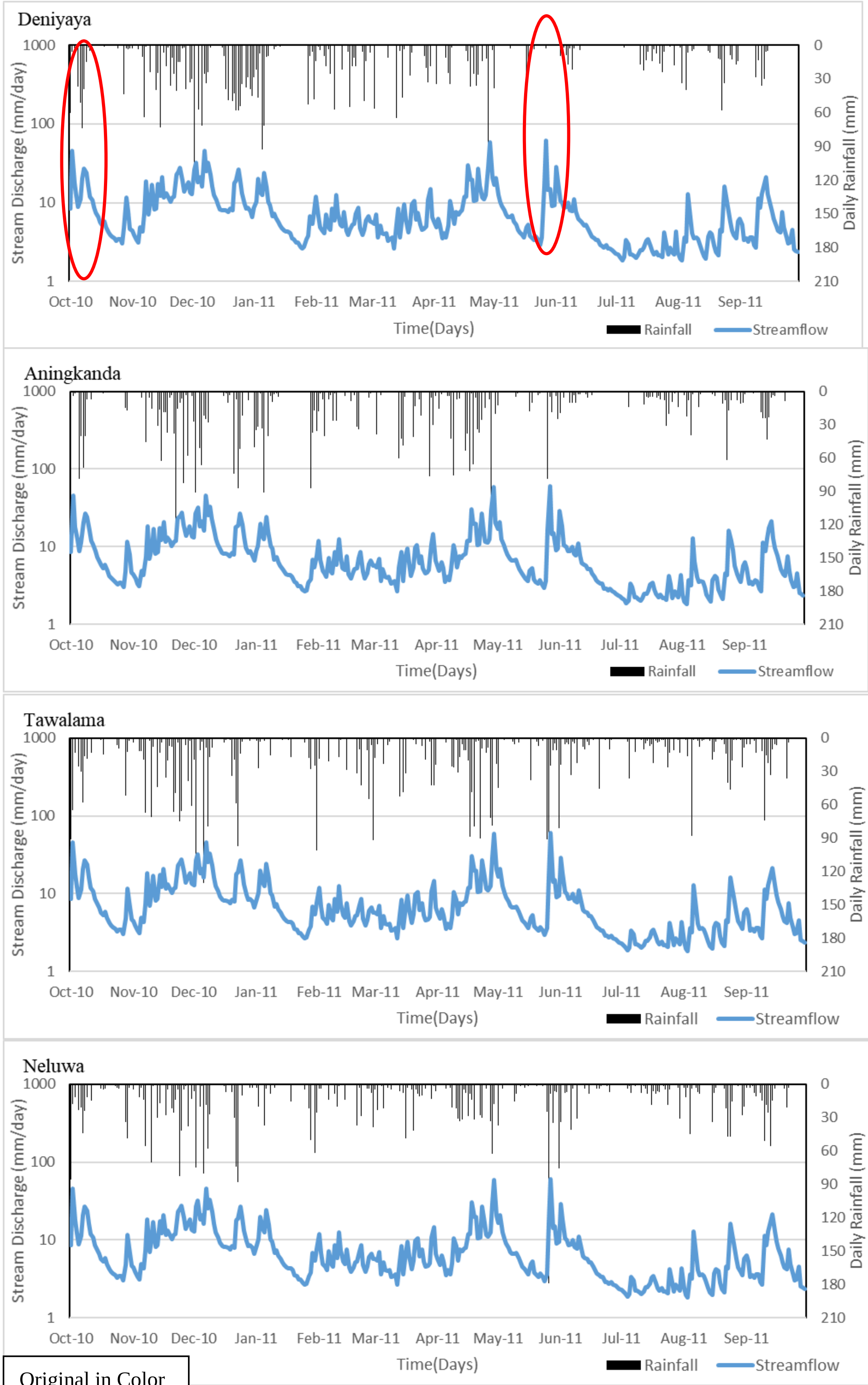



Figure A 2: Tawalama SF vs Rainfall for Water Year 2009/10




Original in Color

Figure A 3: Tawalama SF vs Rainfall for Water Year 2010/11

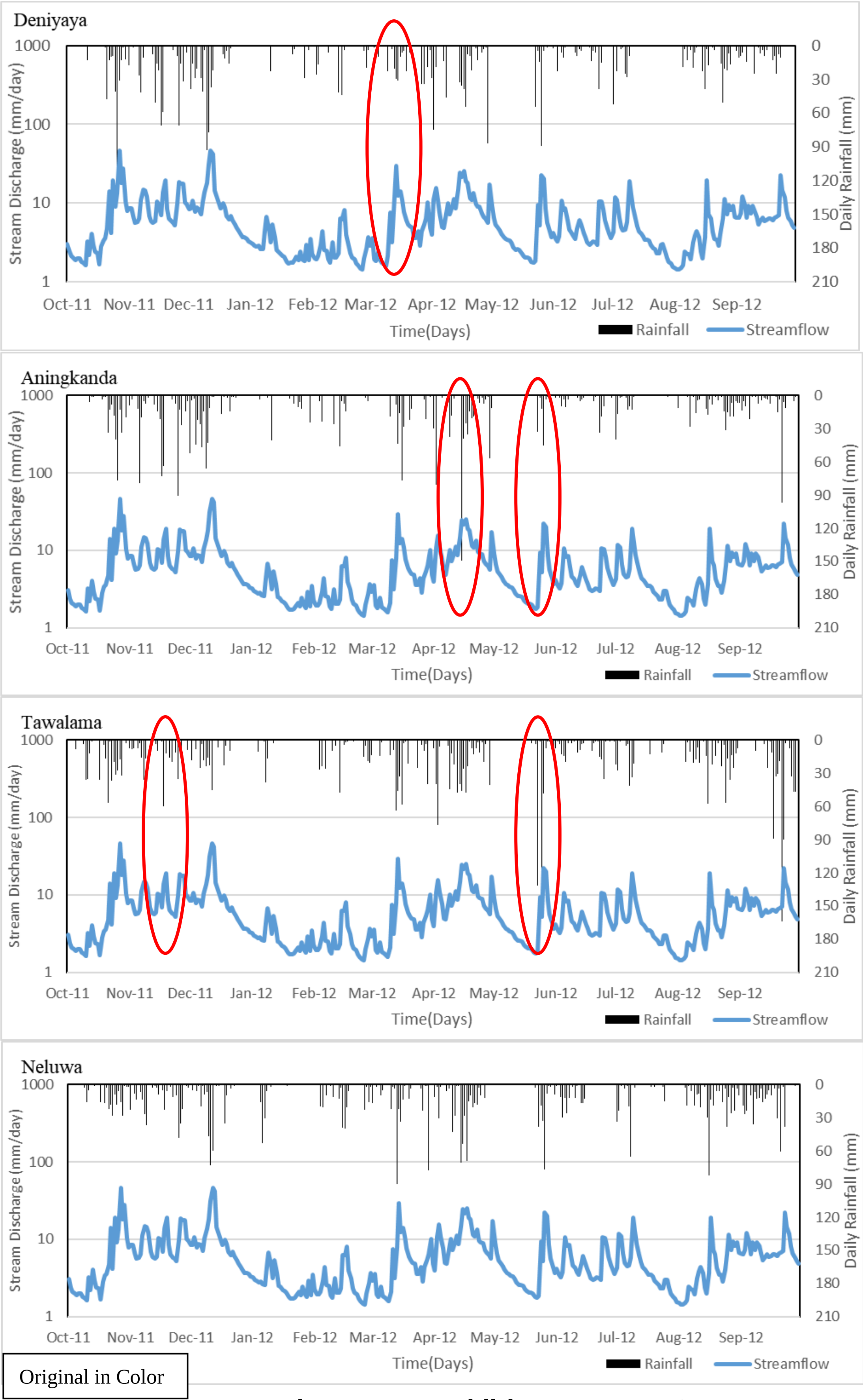
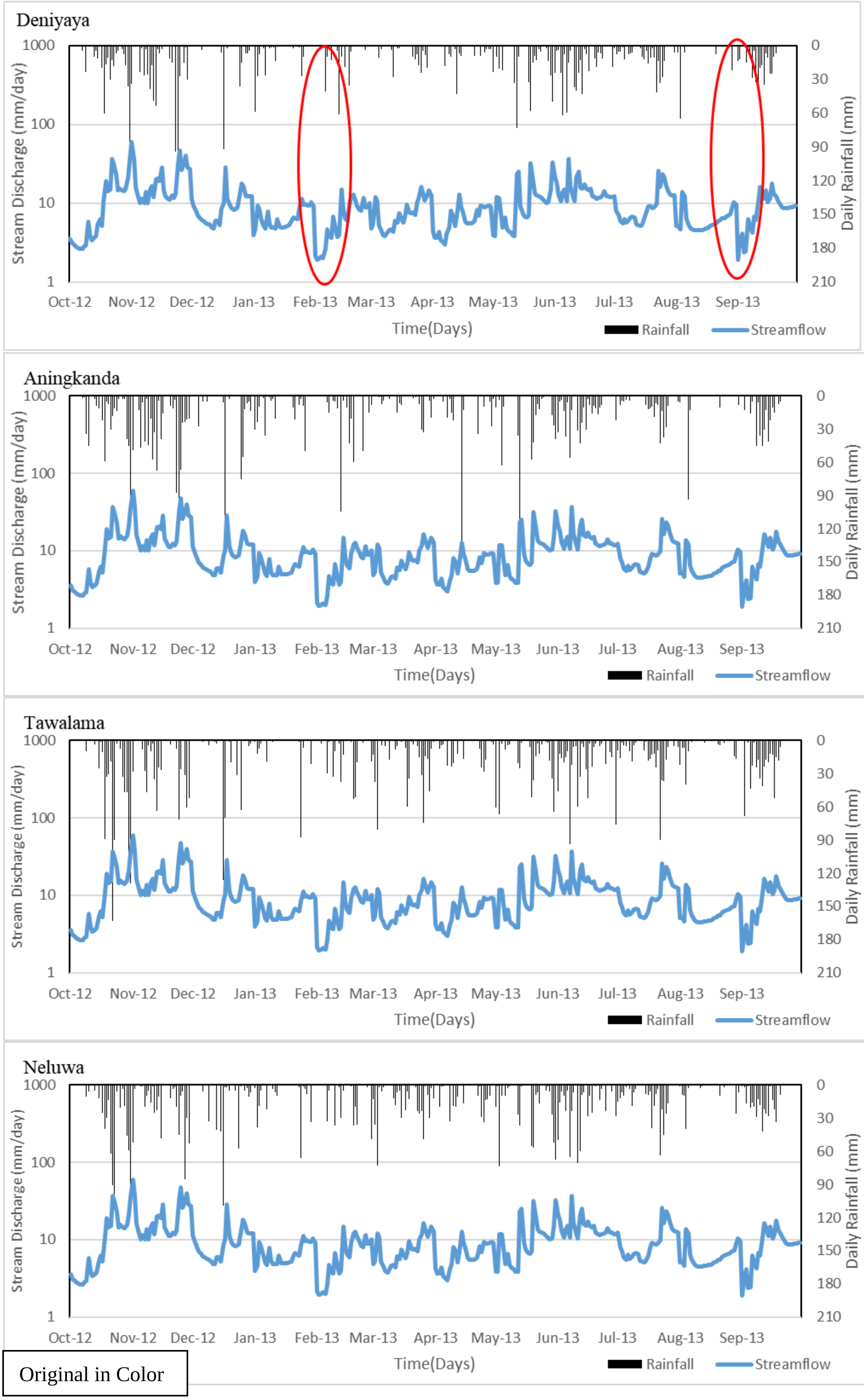



Figure A 4: Tawalama SF vs Rainfall for Water Year 2011/12




Original in Color

Figure A 5: Tawalama SF vs Rainfall for Water Year 2012/13

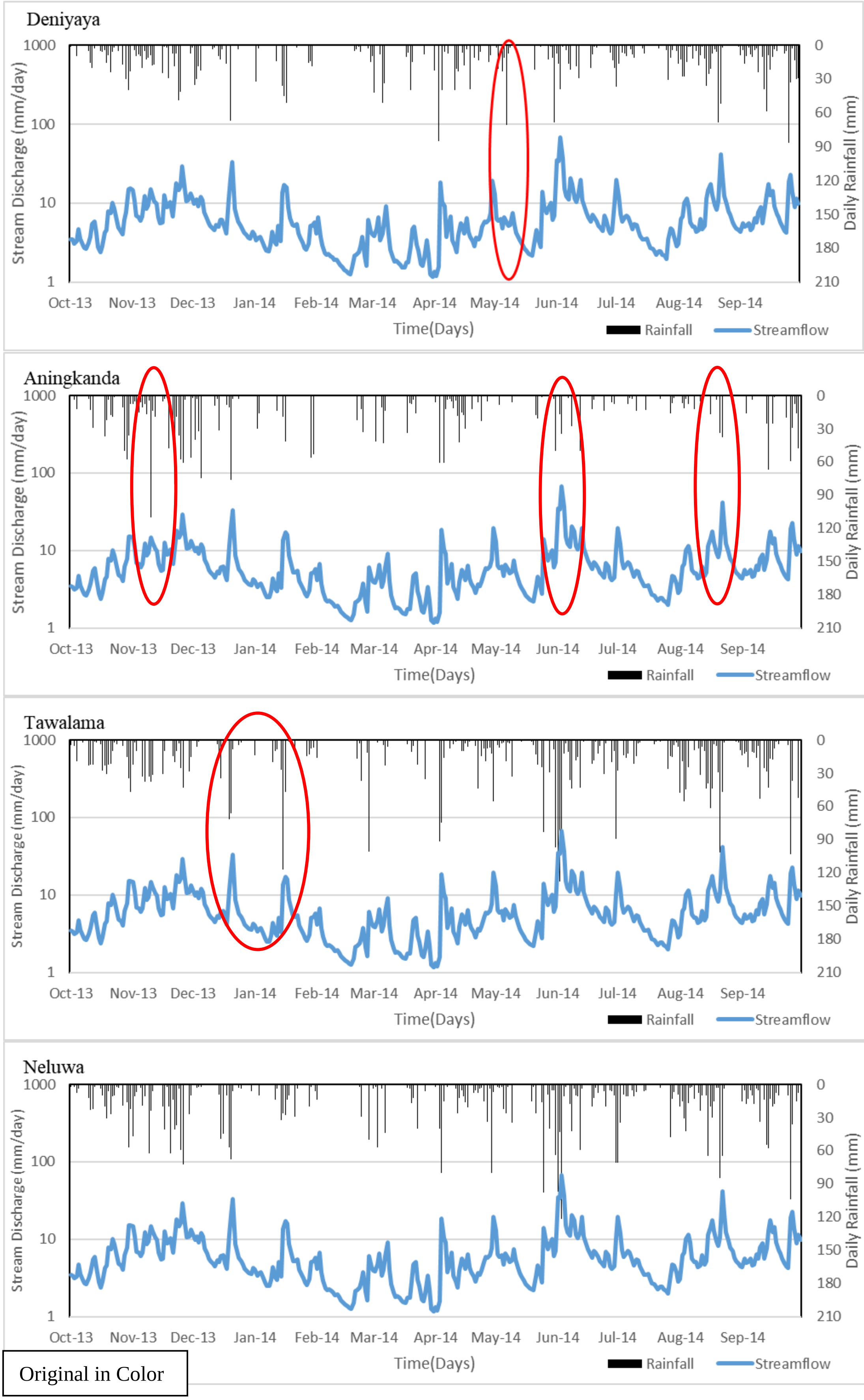



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Figure A 6: Tawalama SF vs Rainfall for Water Year 2013/14

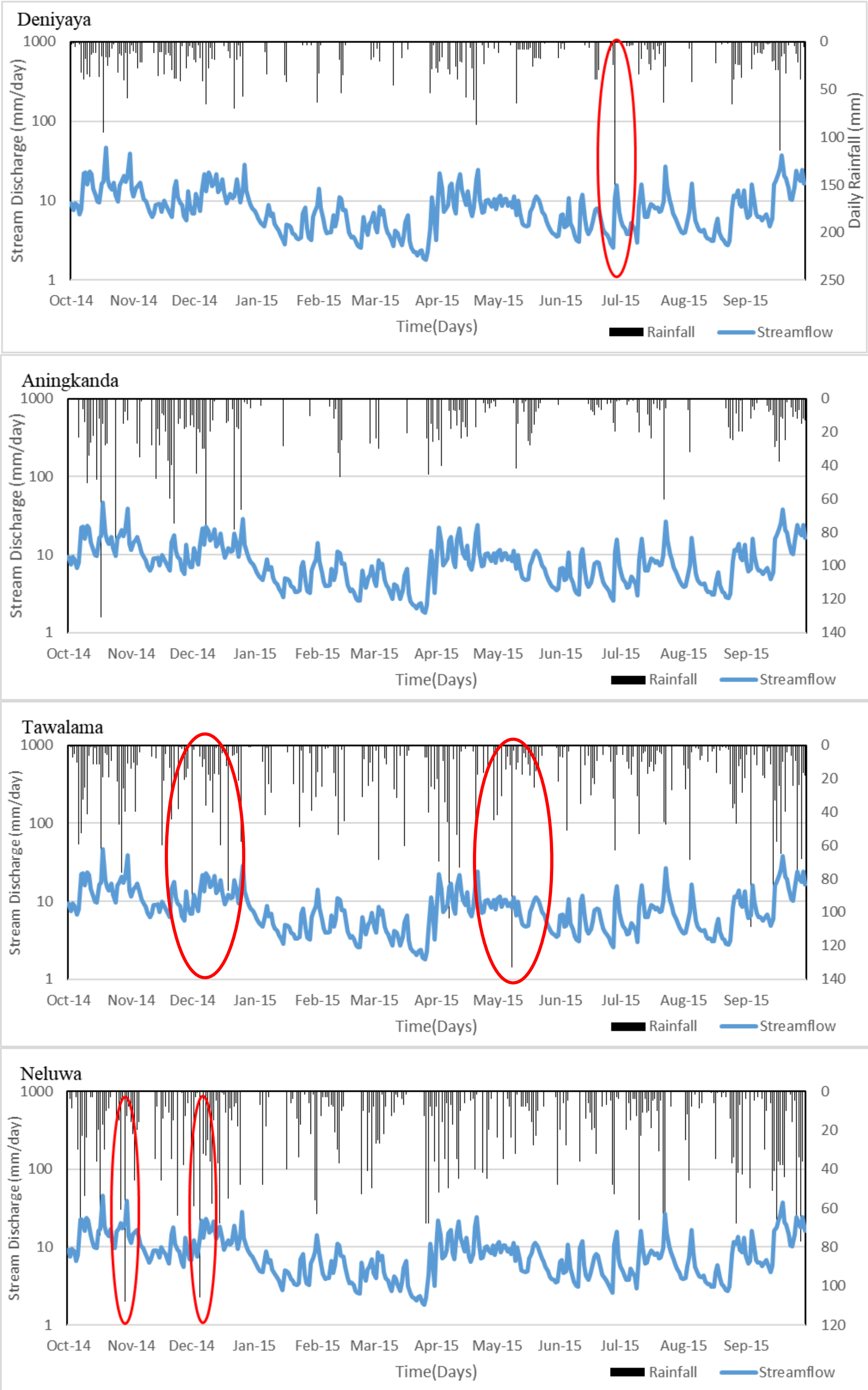
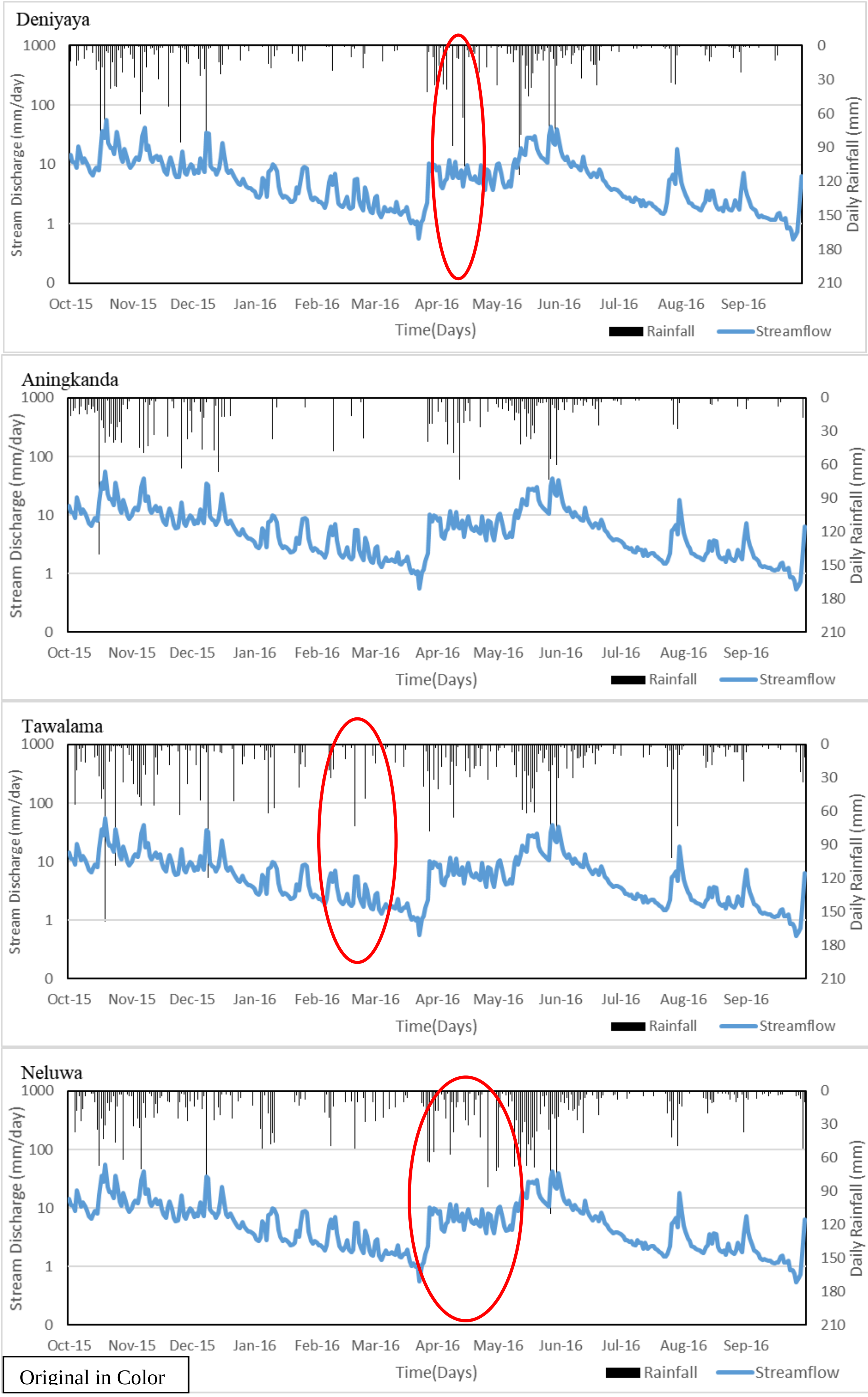
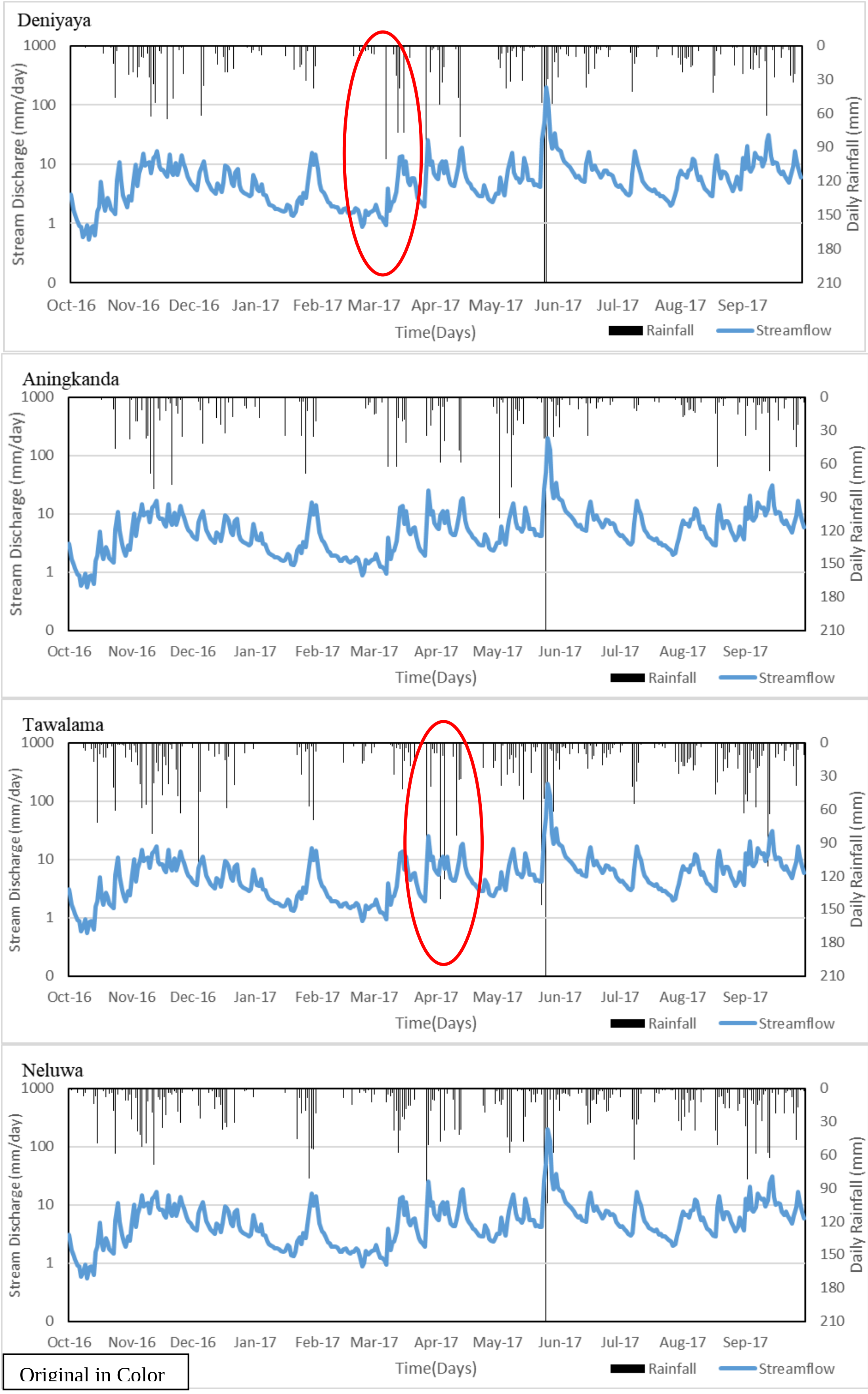



Figure A 7: Tawalama SF vs Rainfall for Water Year 2014/15



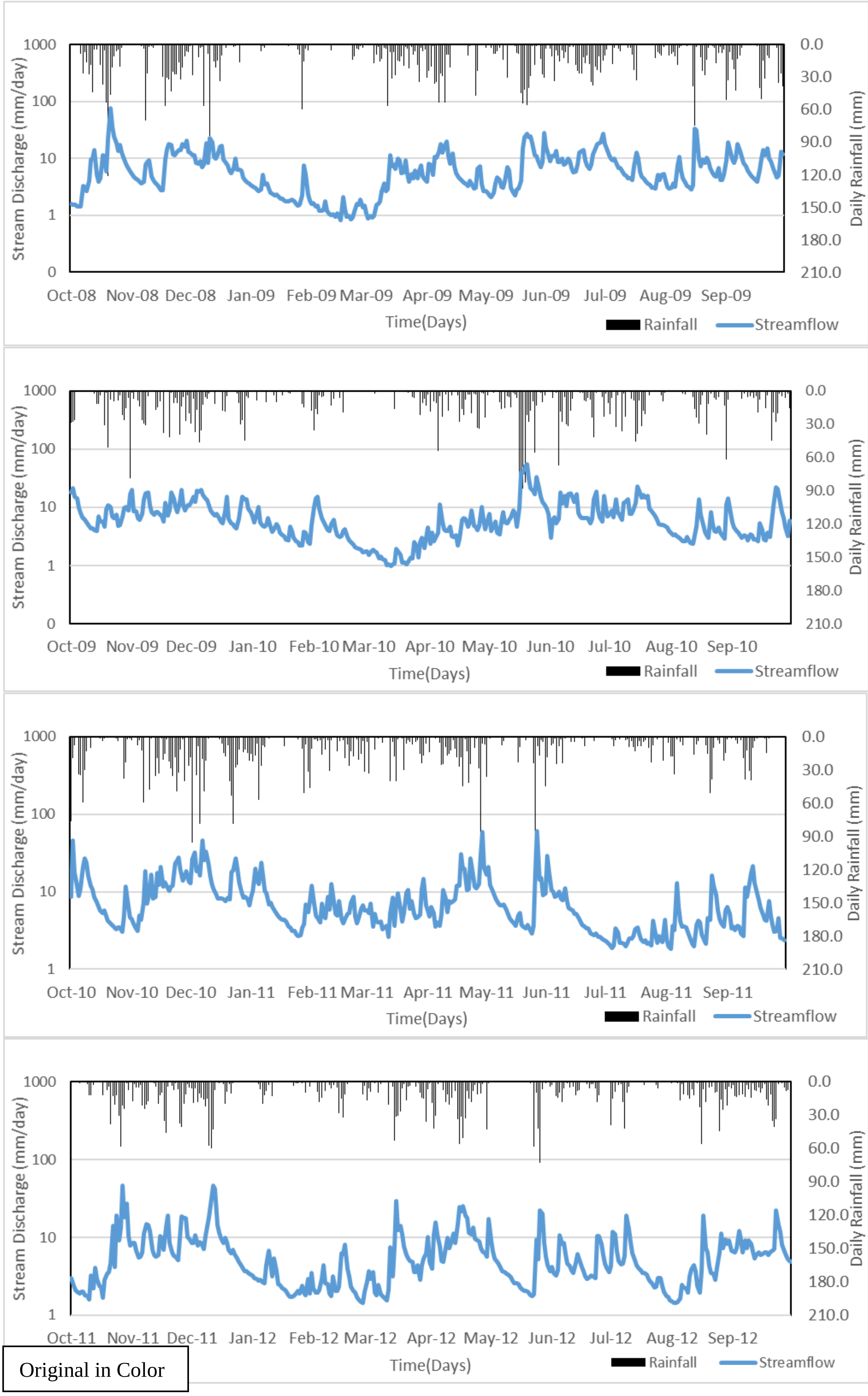

Original in Color

Figure A 8: Tawalama SF vs Rainfall for Water Year 2015/16




Original in Color

Figure A 9: Tawalama SF vs Rainfall for Water Year 2016/17




Original in Color

Figure A 10: Tawalama SF vs Thiessen Rainfall for 2008/09 to 2017/18 (1 of 3)

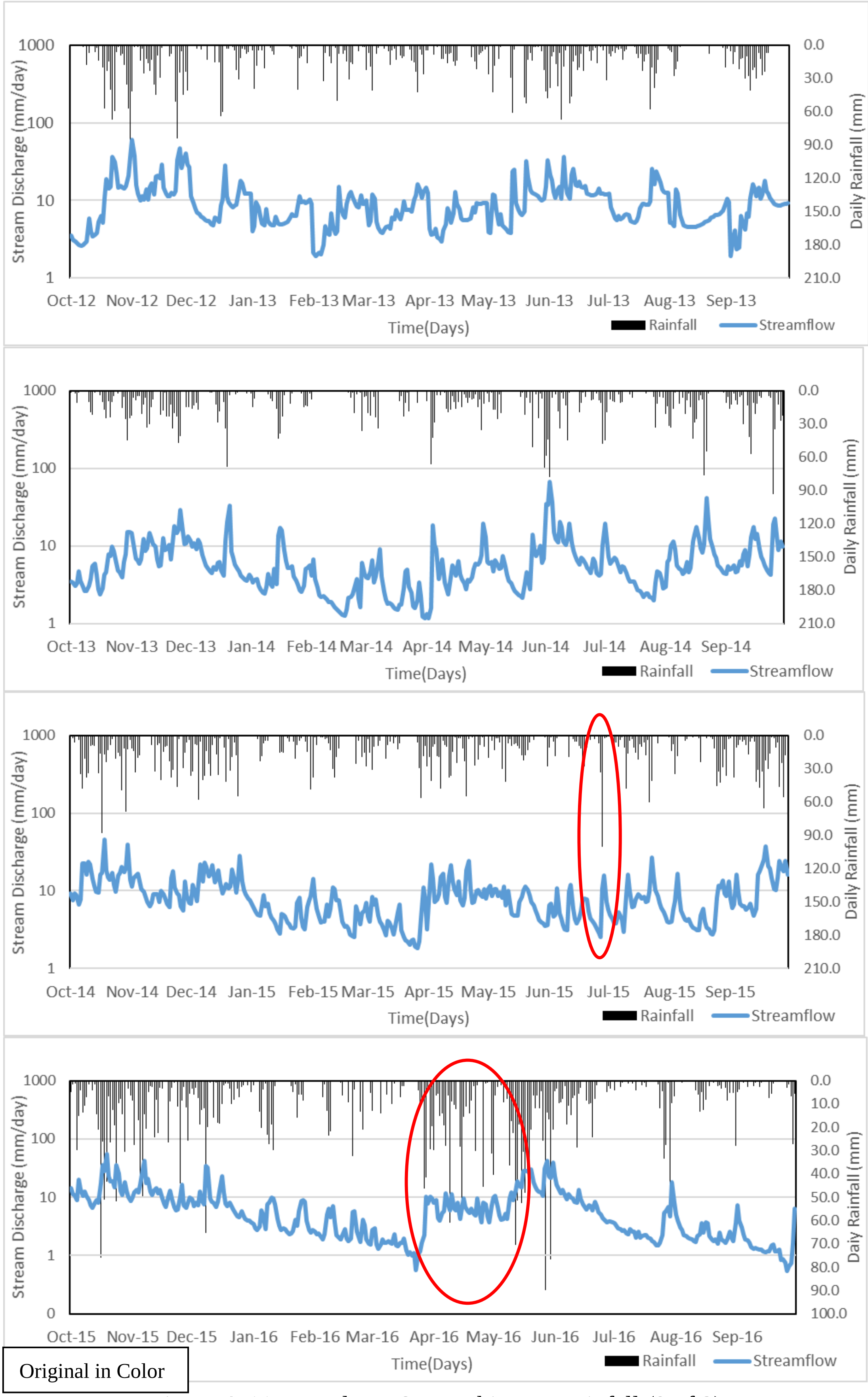
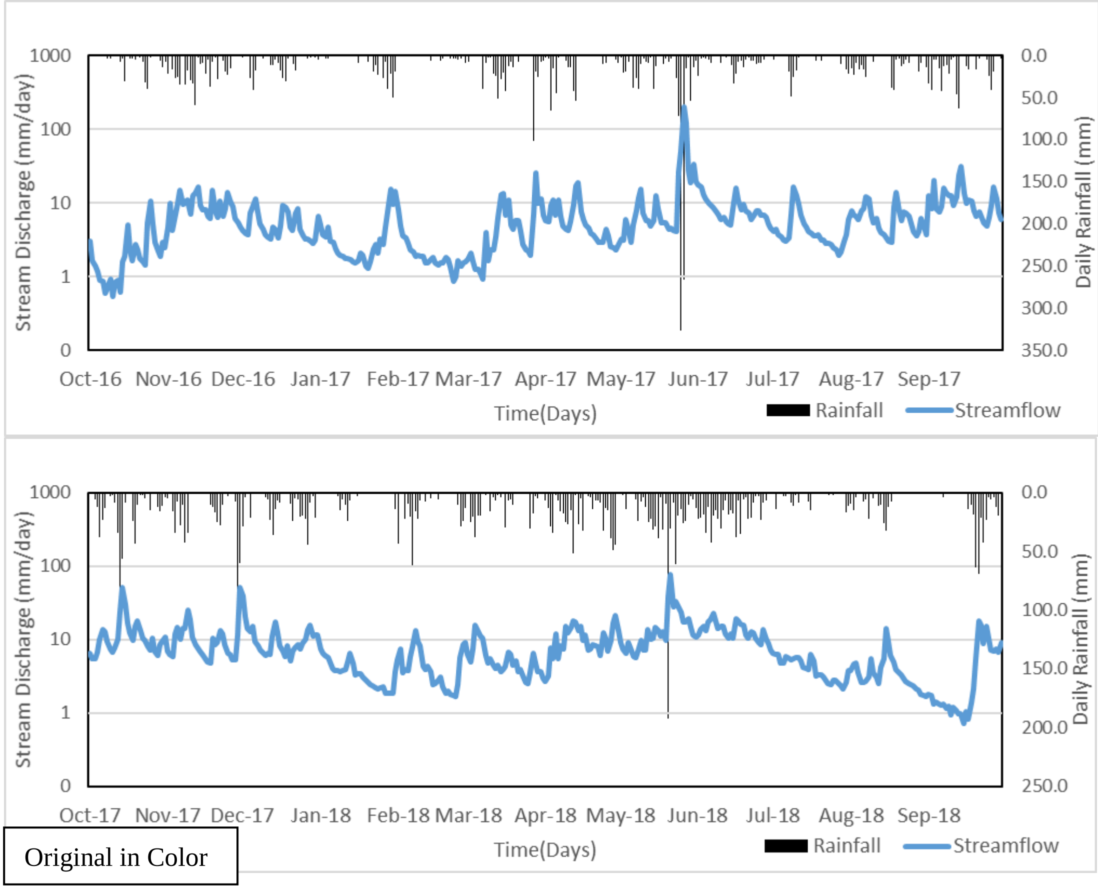
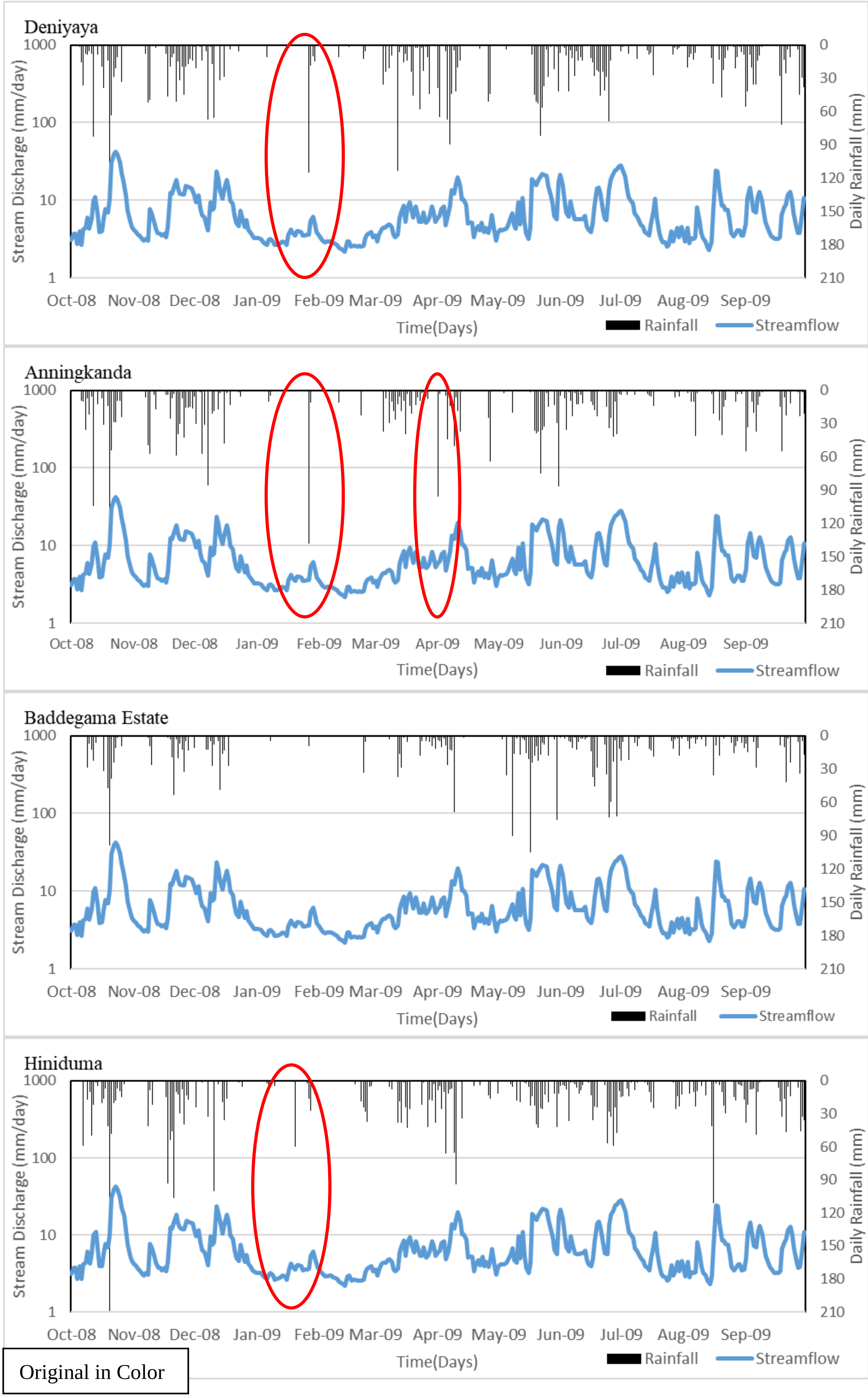



Figure A 11: Tawalama SF vs Thiessen Rainfall (2 of 3)




Original in Color

Figure A 12: Tawalama SF vs Thiessen Rainfall (3 of 3)




Original in Color

Figure A 13: Baddegama SF vs Rainfall for Water Year 2008/09 (1 of 2)

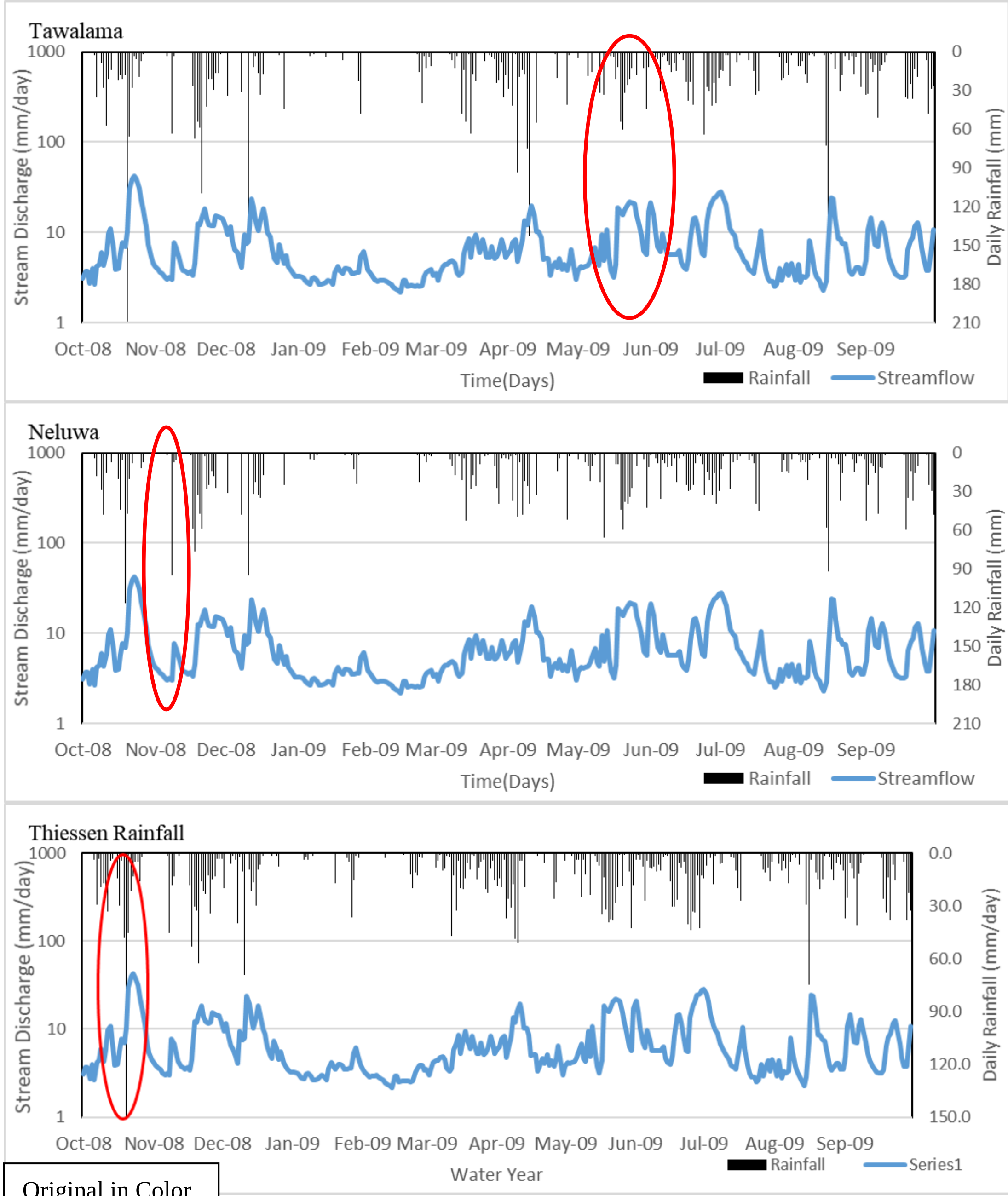



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Figure A 14: Baddegama SF vs Rainfall for Water Year 2008/09 (2 of 2)

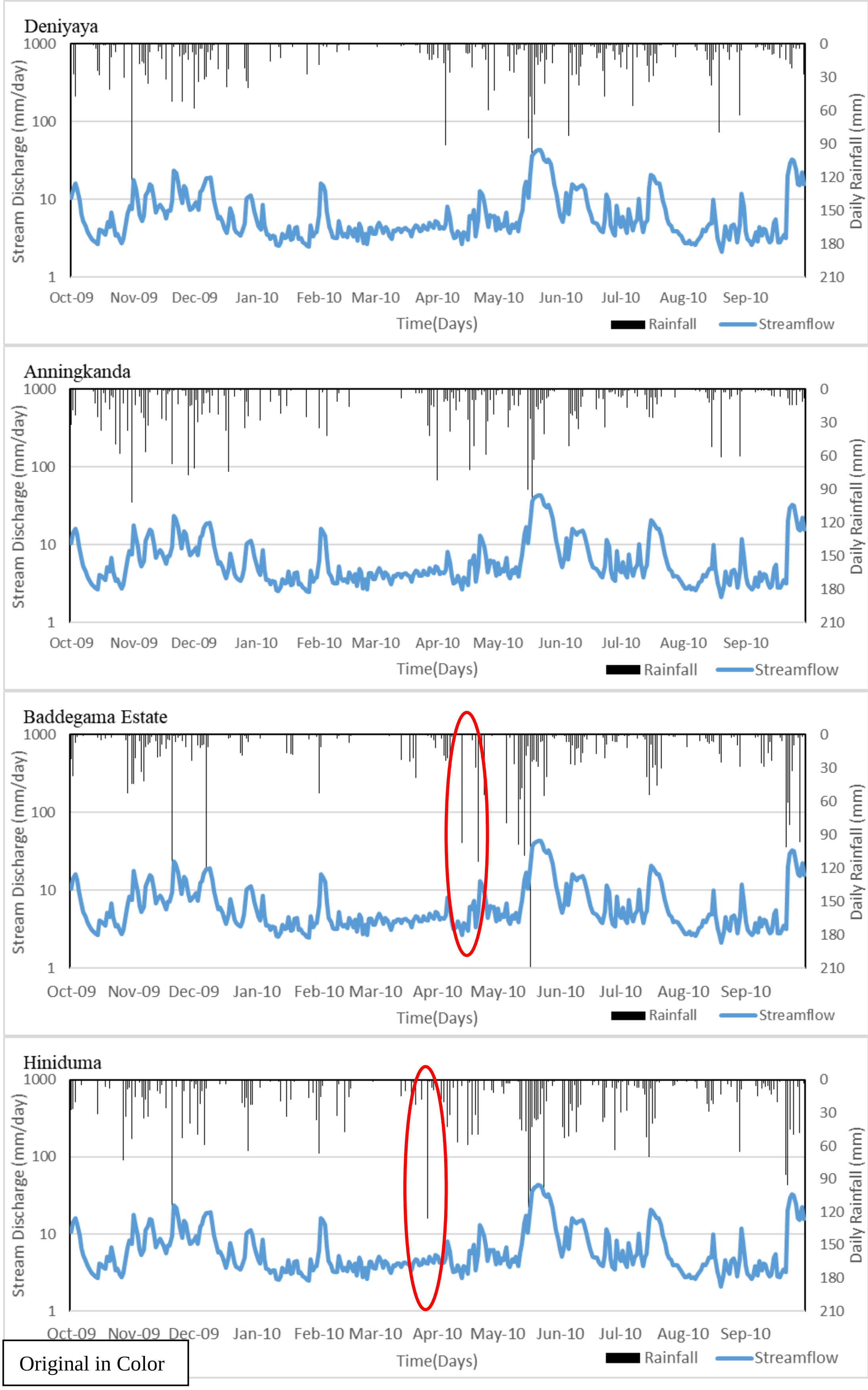


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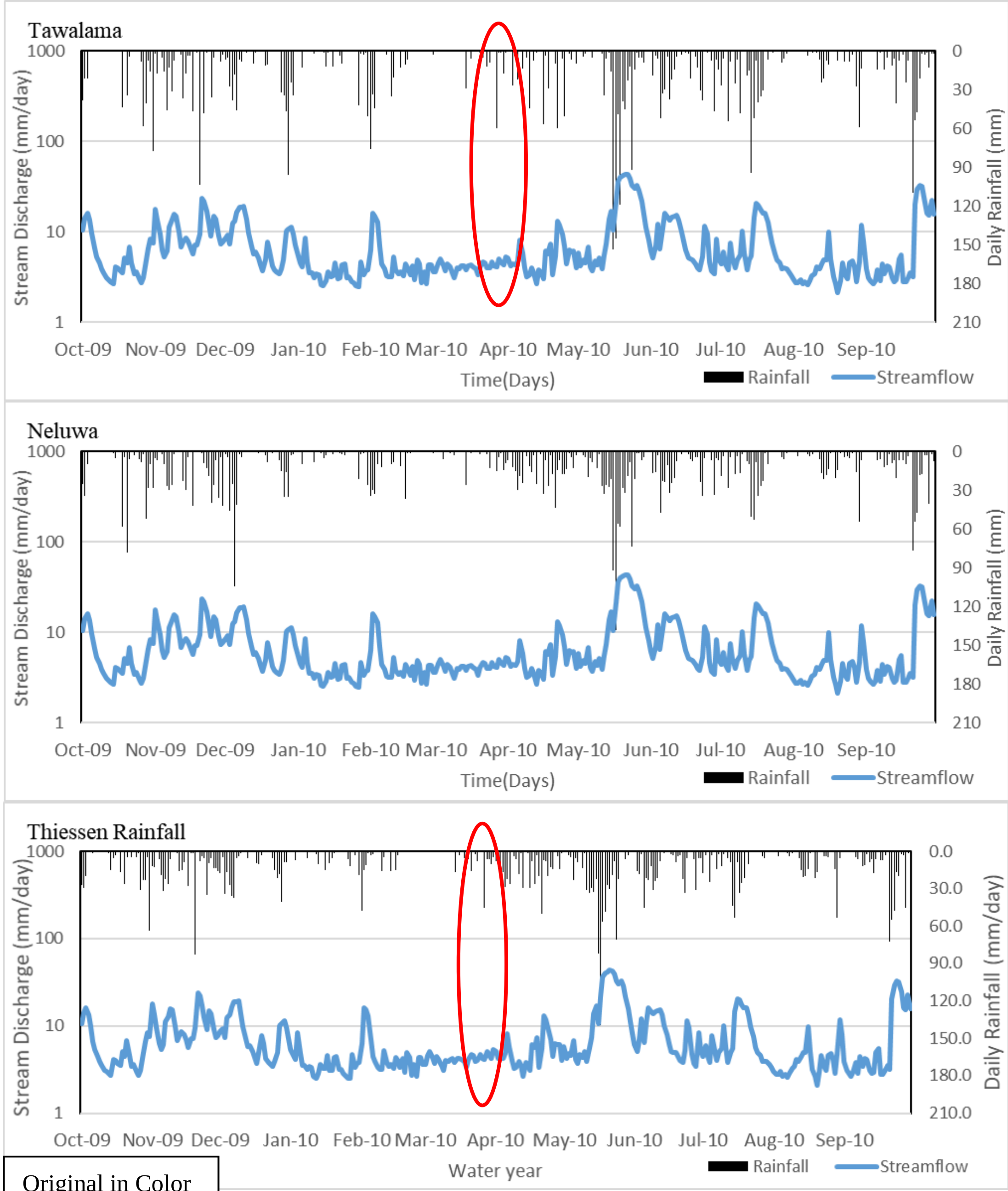
Figure A 15: Baddegama SF vs Rainfall for Water Year 2009/10 (1 of 2)




Original in Color

Figure A 16: Baddegama SF vs Rainfall for Water Year 2009/10 (2 of 2)

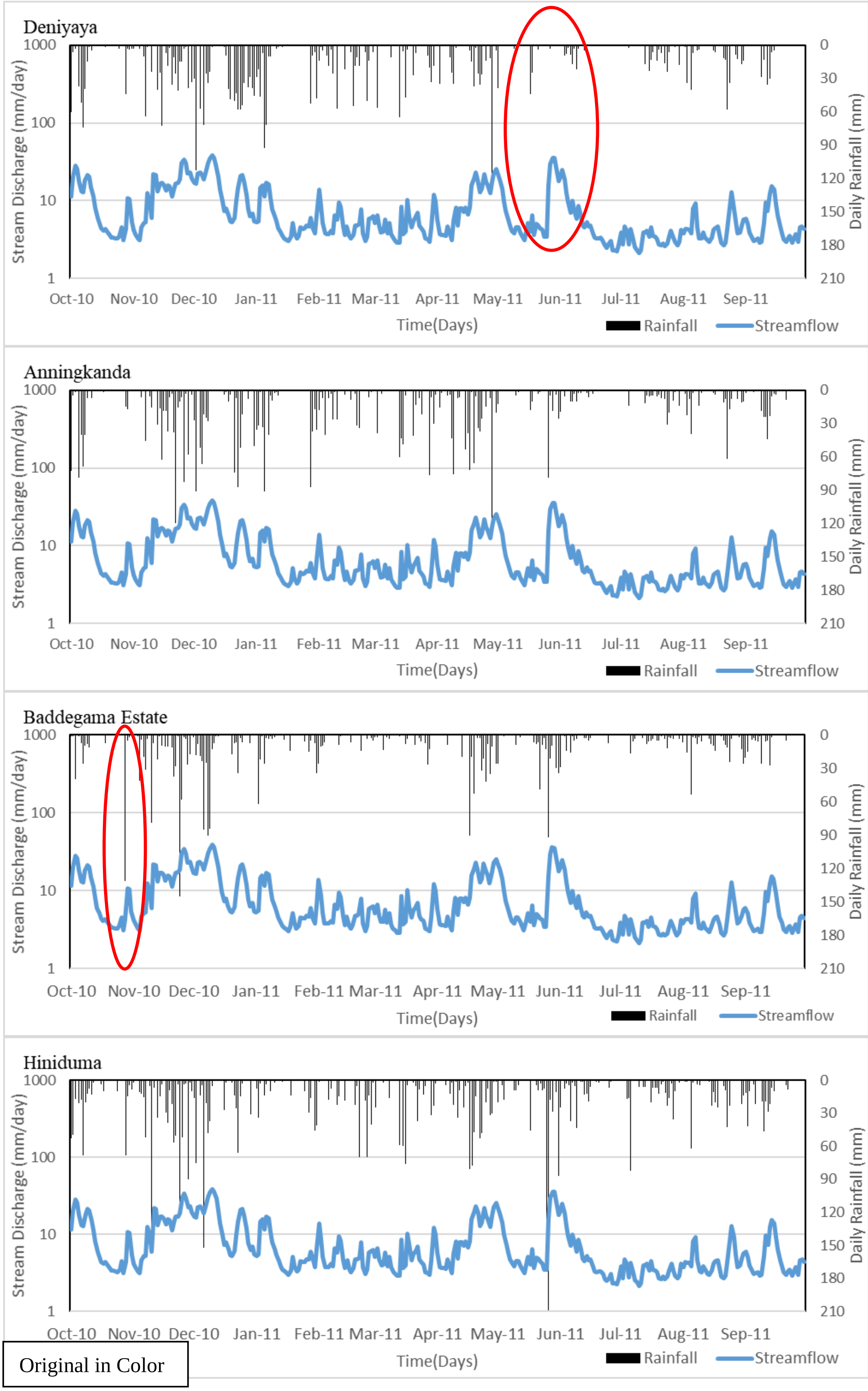



Figure A 17: Baddegama SF vs Rainfall for Water Year 2010/11 (1 of 2)

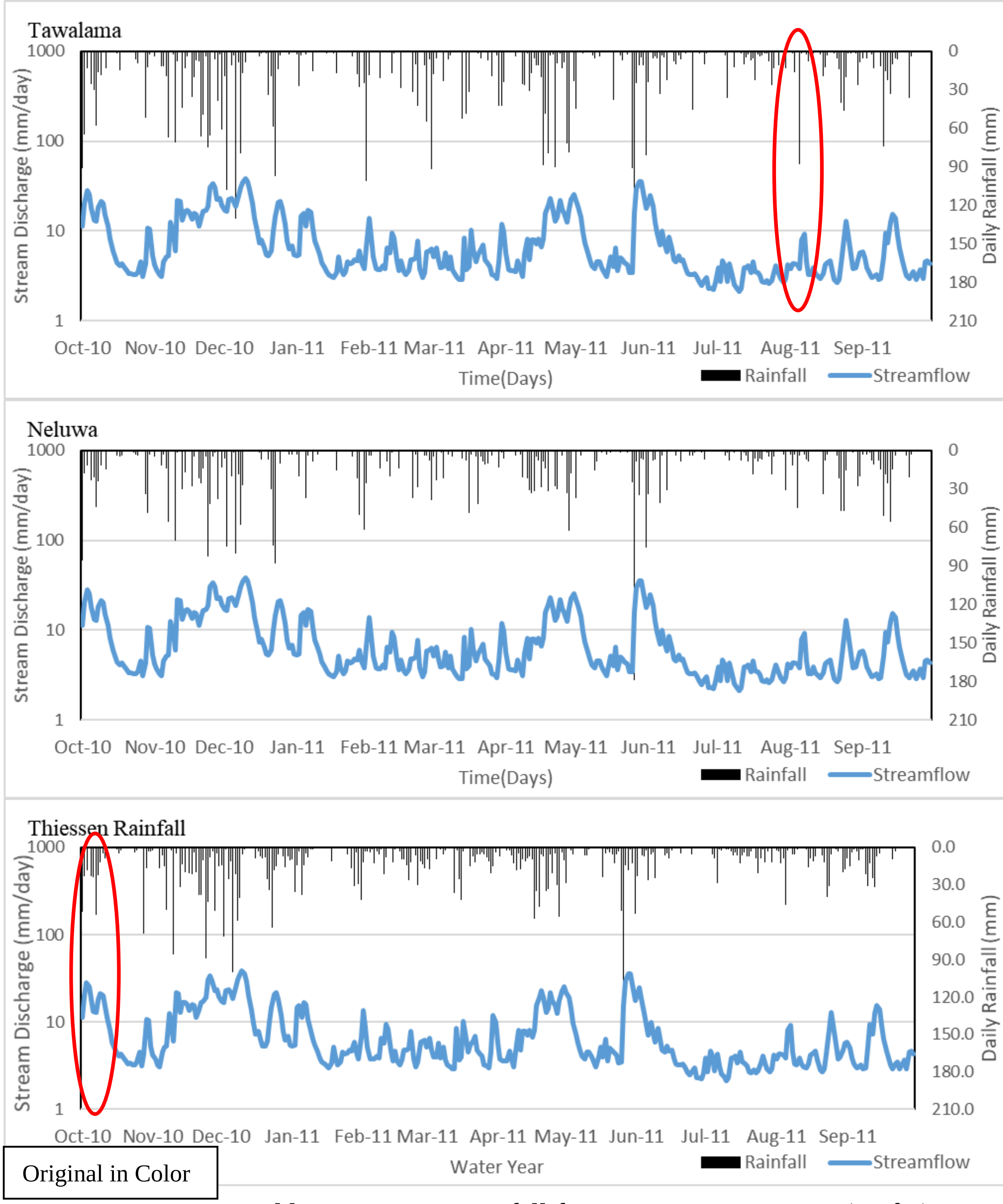



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Figure A 18: Baddegama SF vs Rainfall for Water Year 2010/11 (2 of 2)

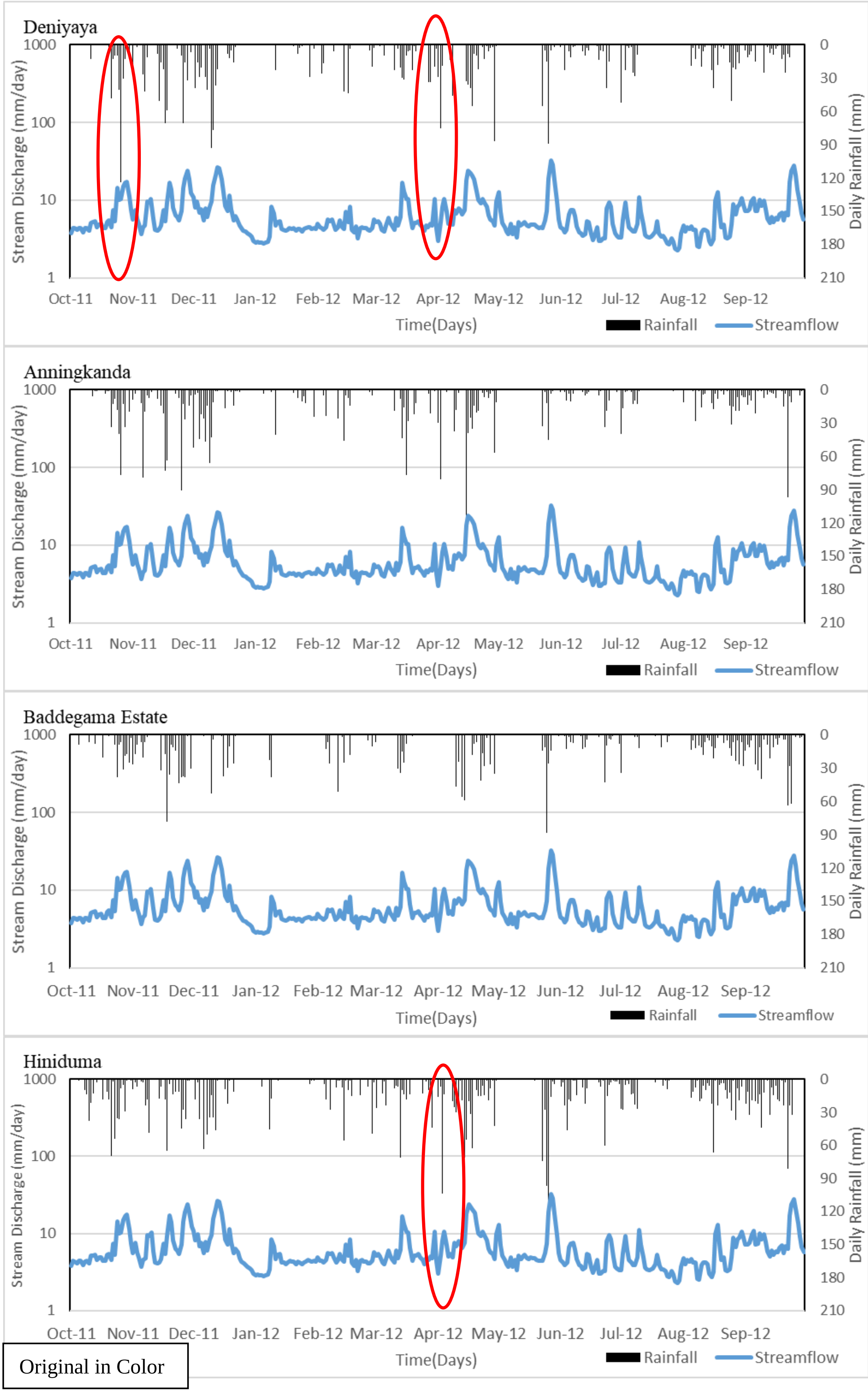


Figure A 19: Baddegama SF vs Rainfall for Water Year 2011/12 (1 of 2)

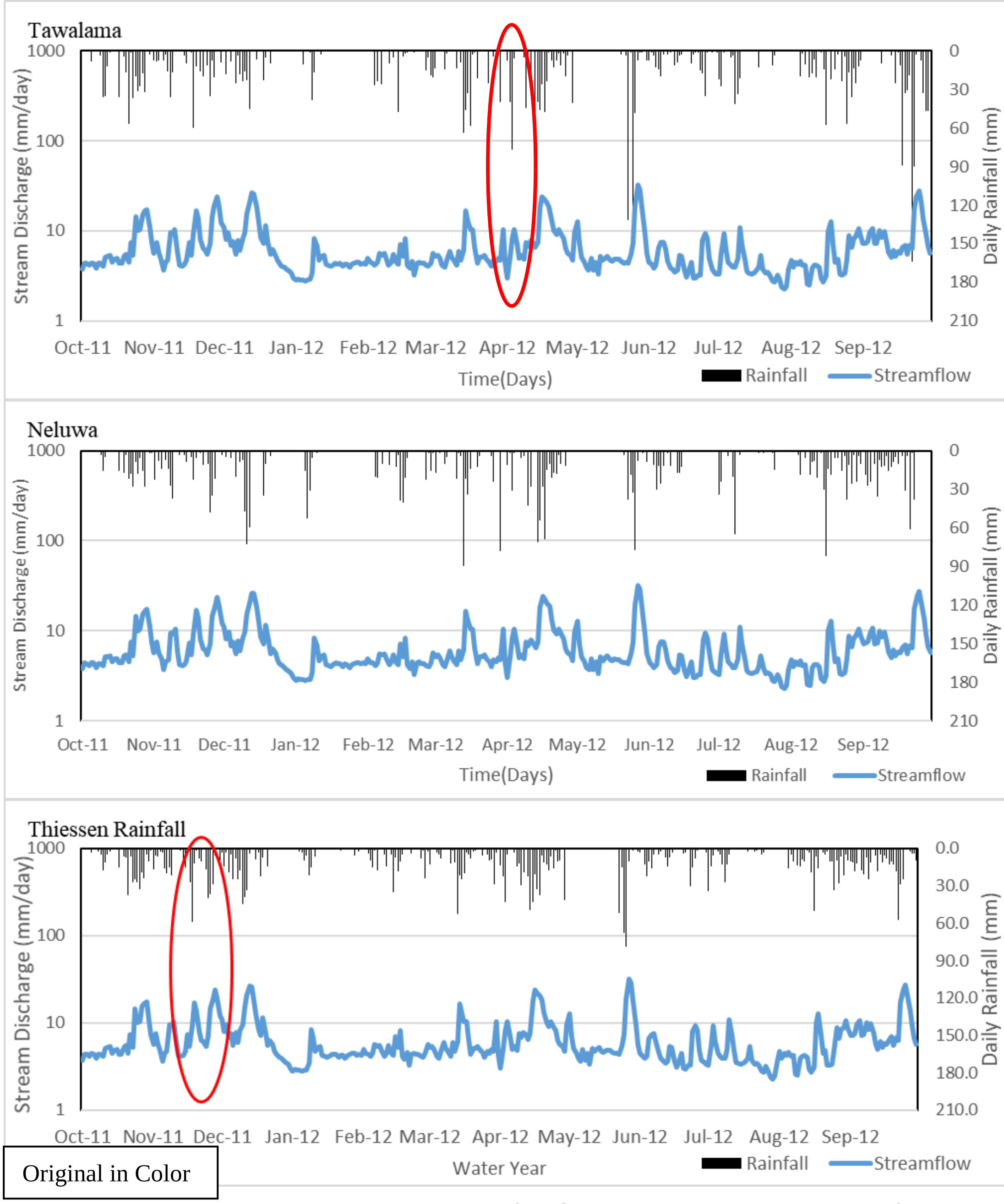


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Figure A 20: Baddegama SF vs Rainfall for Water Year 2011/12 (2 of 2)

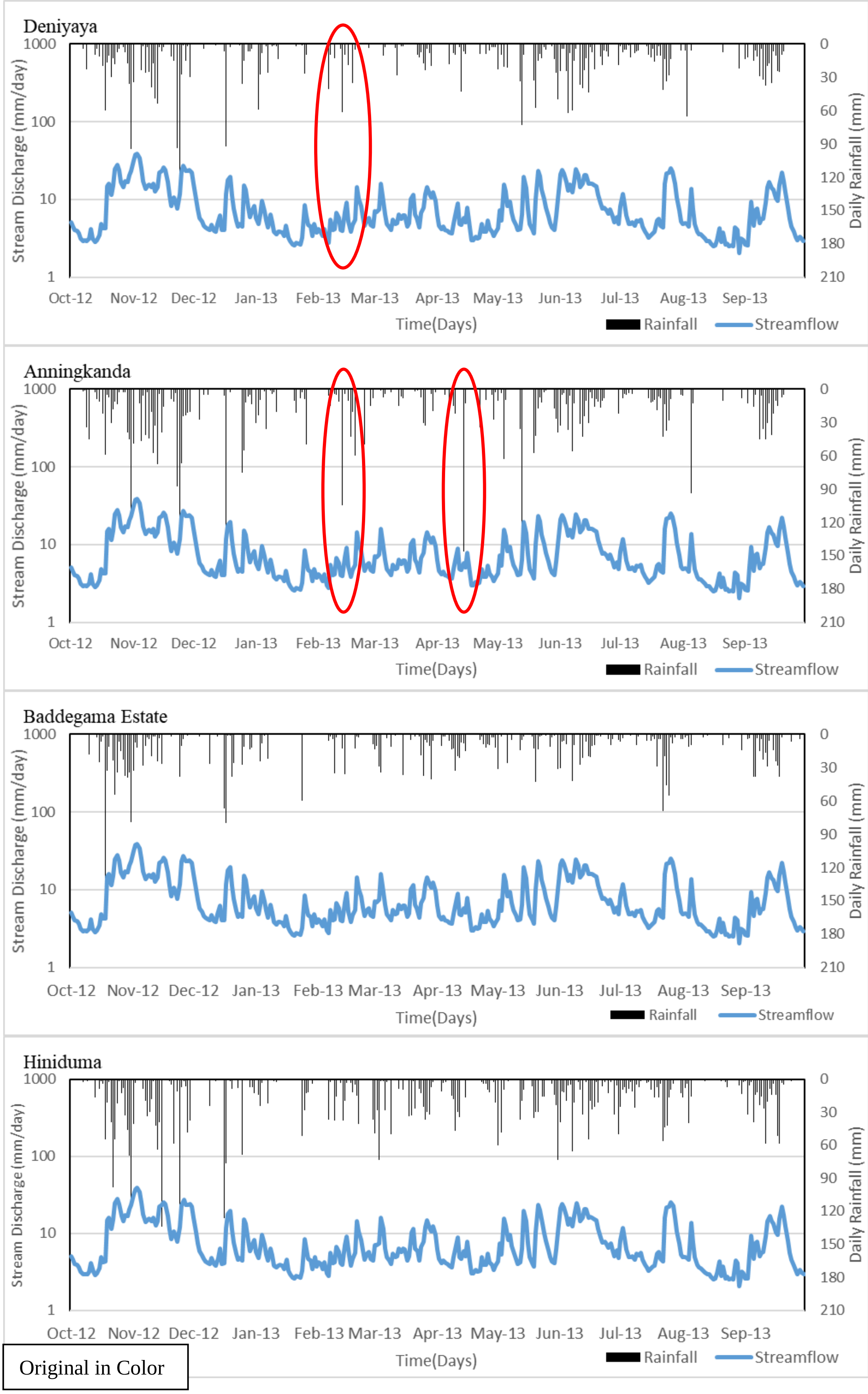


Figure A 21: Baddegama SF vs Rainfall for Water Year 2012/13 (1 of 2)

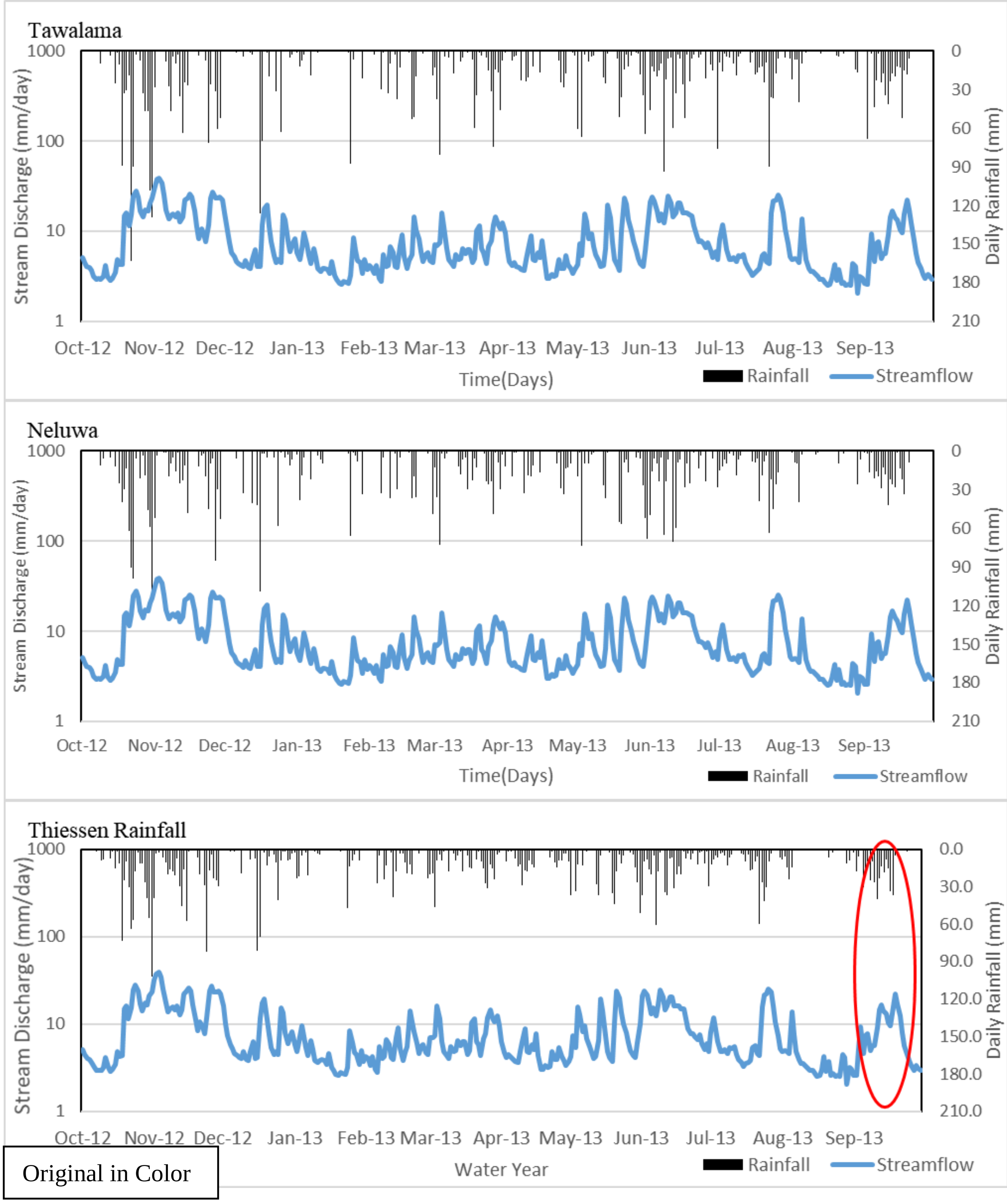


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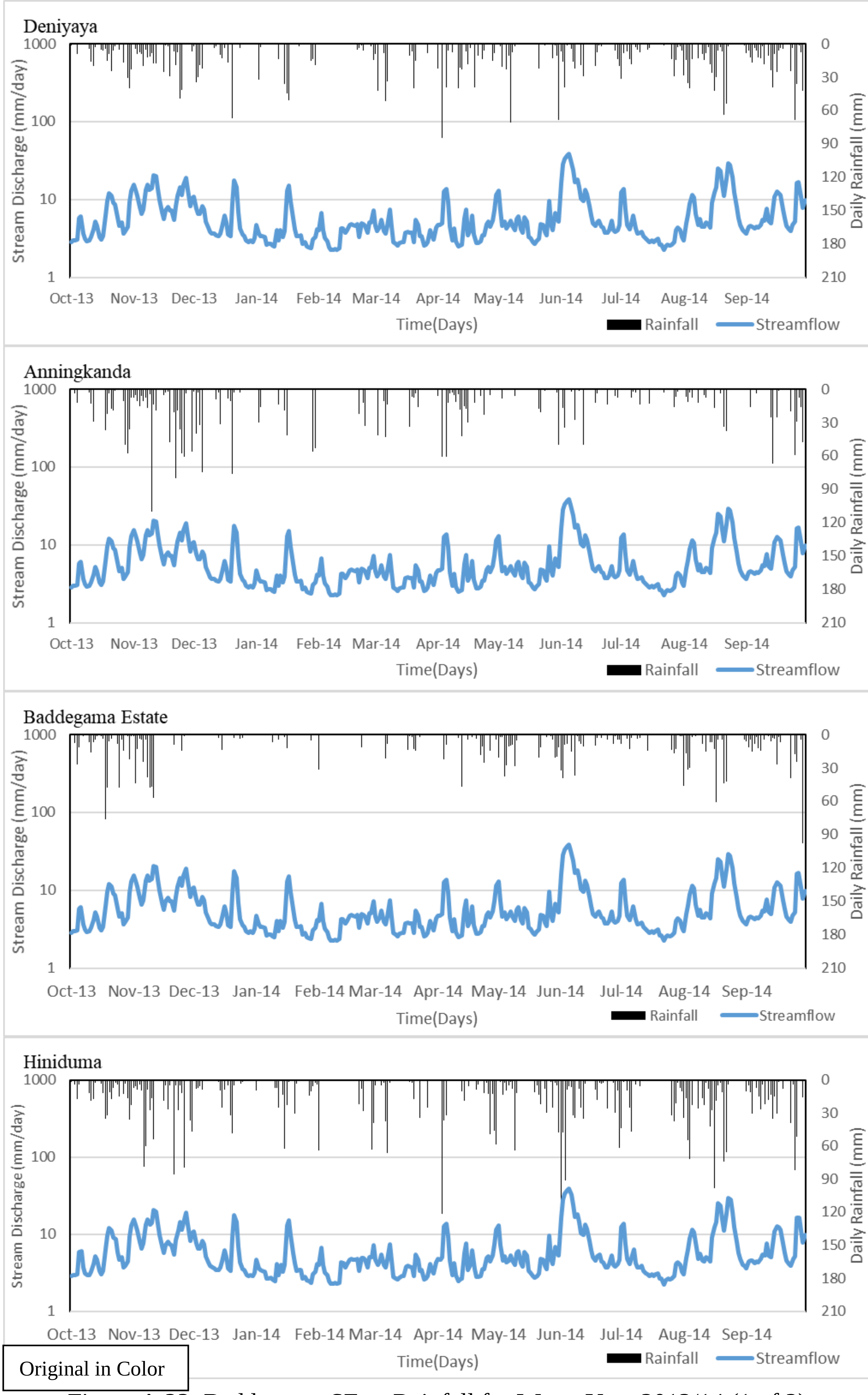
Figure A 22: Baddegama SF vs Rainfall for Water Year 2012/13 (2 of 2)




Original in Color

Figure A 23: Baddegama SF vs Rainfall for Water Year 2013/14 (1 of 2)

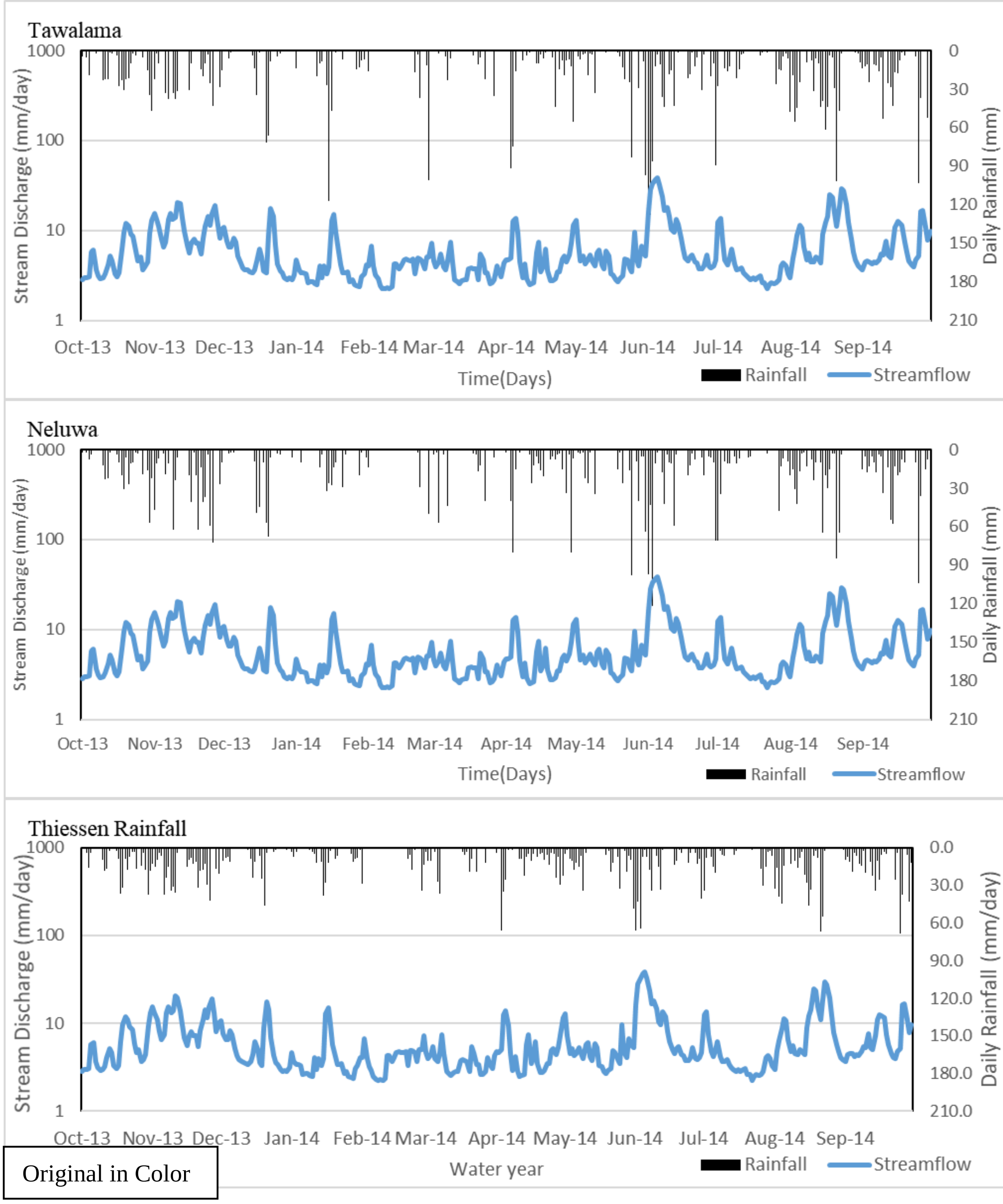



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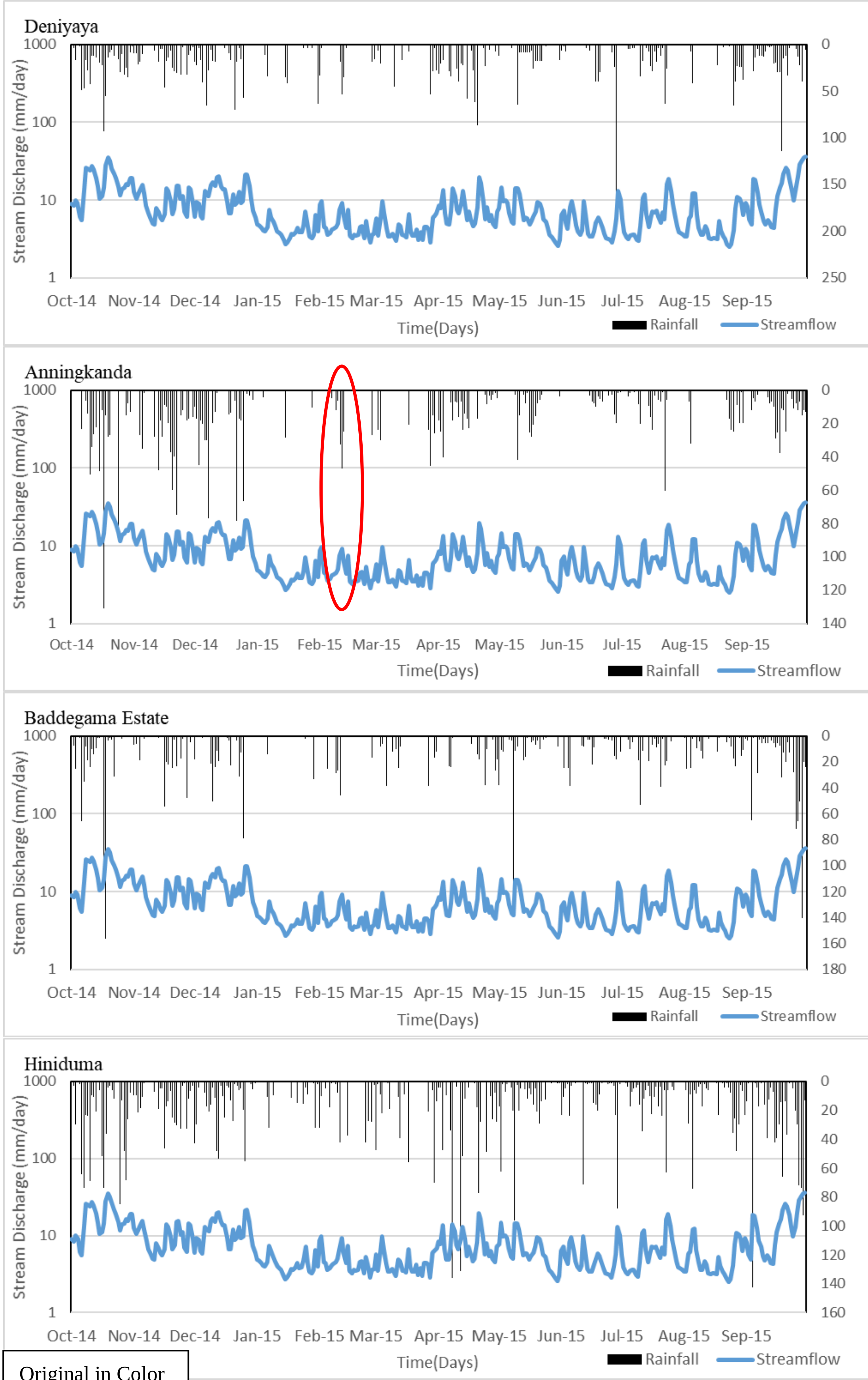
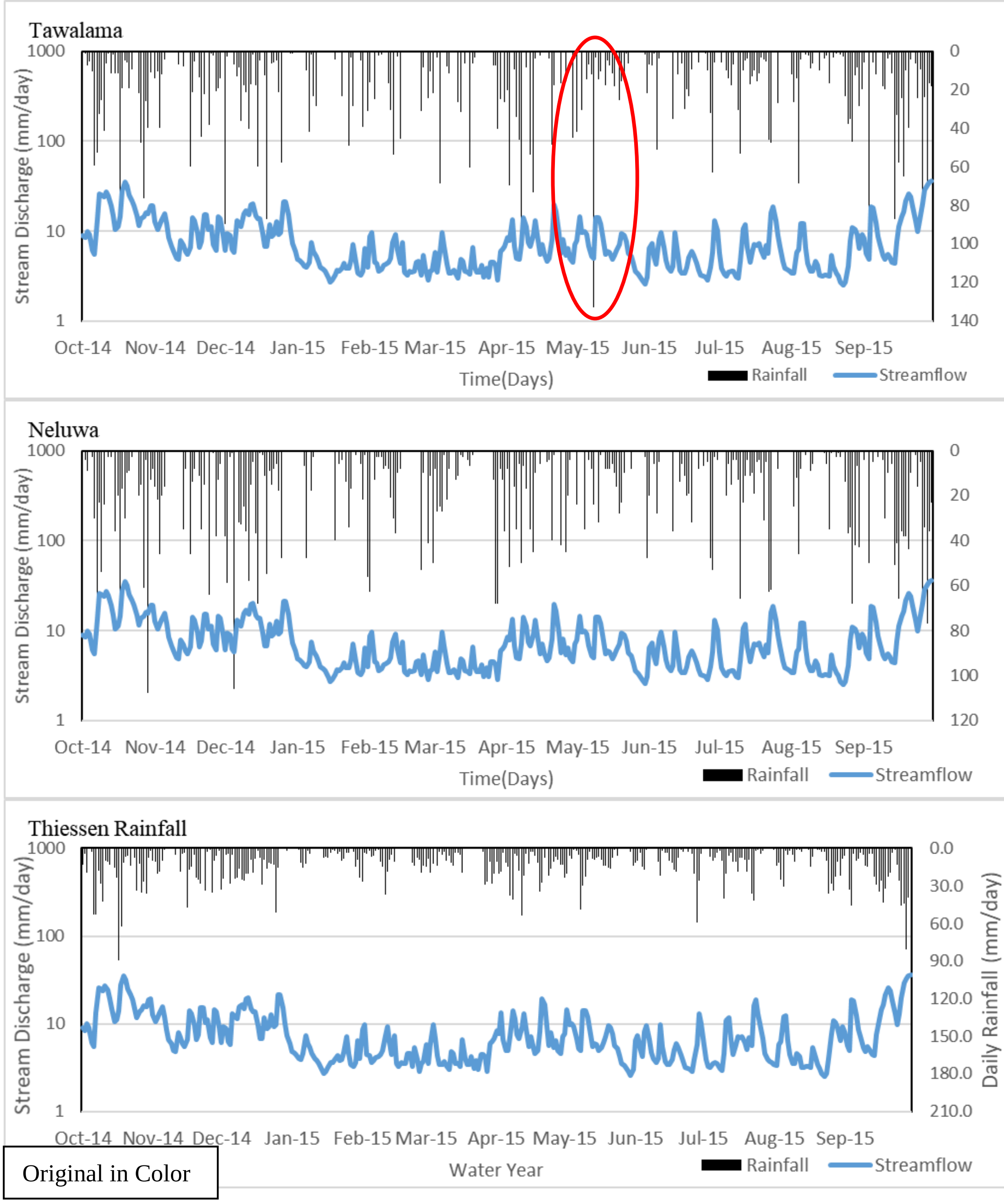
Figure A 24: Baddegama SF vs Rainfall for Water Year 2013/14 (2 of 2)




Original in Color

Figure A 25: Baddegama SF vs Rainfall for Water Year 2014/15 (1 of 2)




Original in Color

Figure A 26: Baddegama SF vs Rainfall for Water Year 2014/15 (2 of 2)

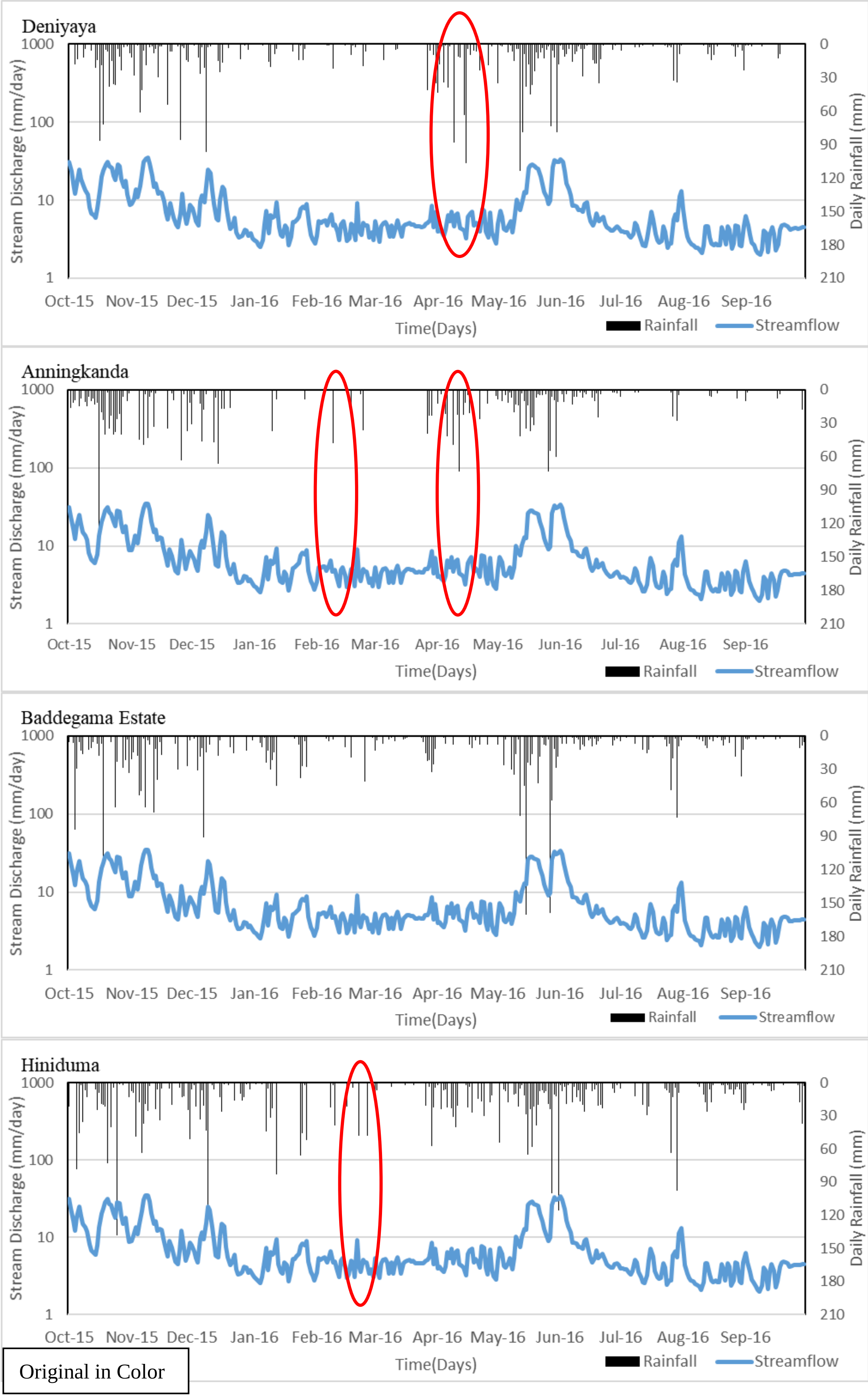



Figure A 27: Baddegama SF vs Rainfall for Water Year 2015/16 (1 of 2)

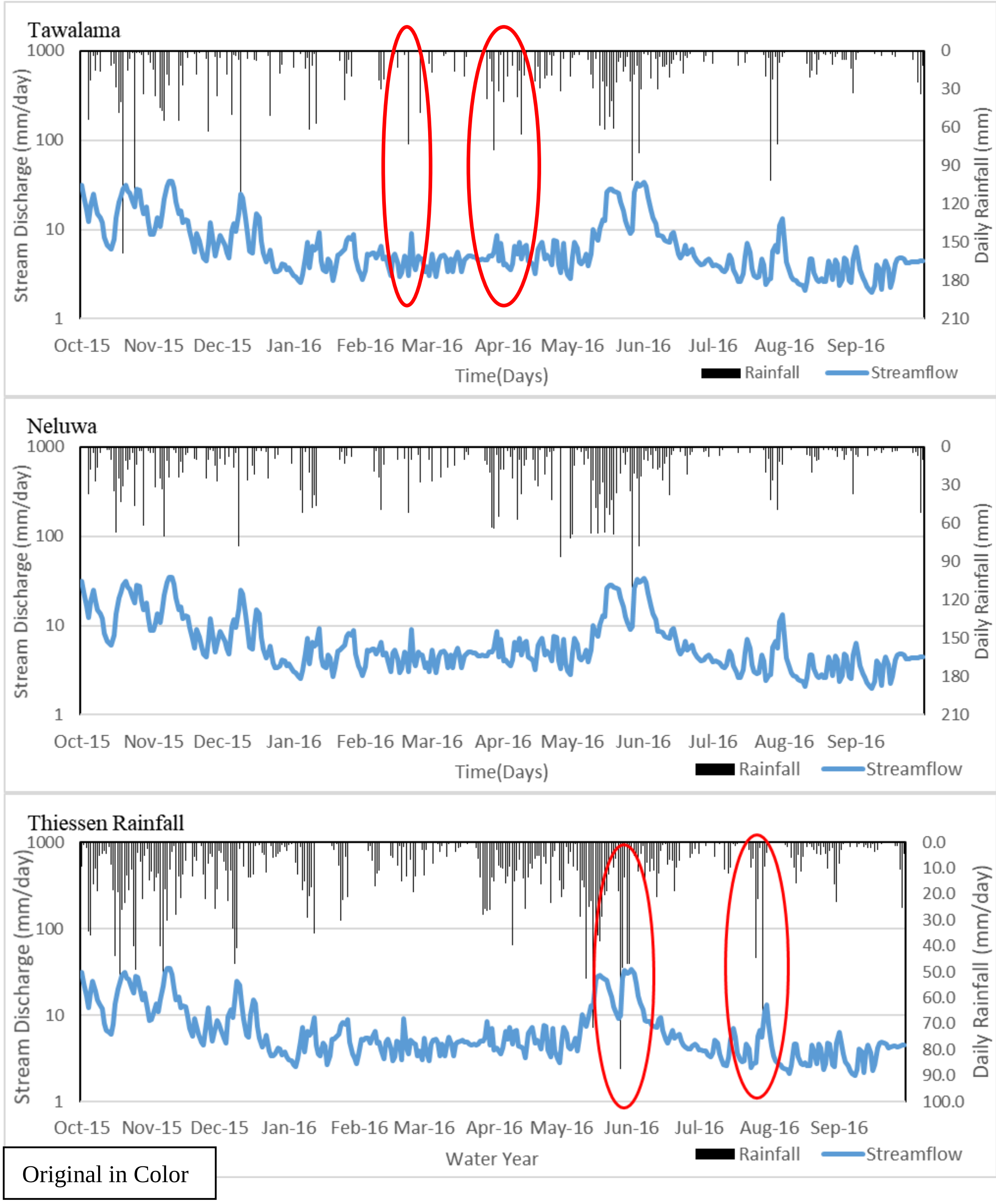
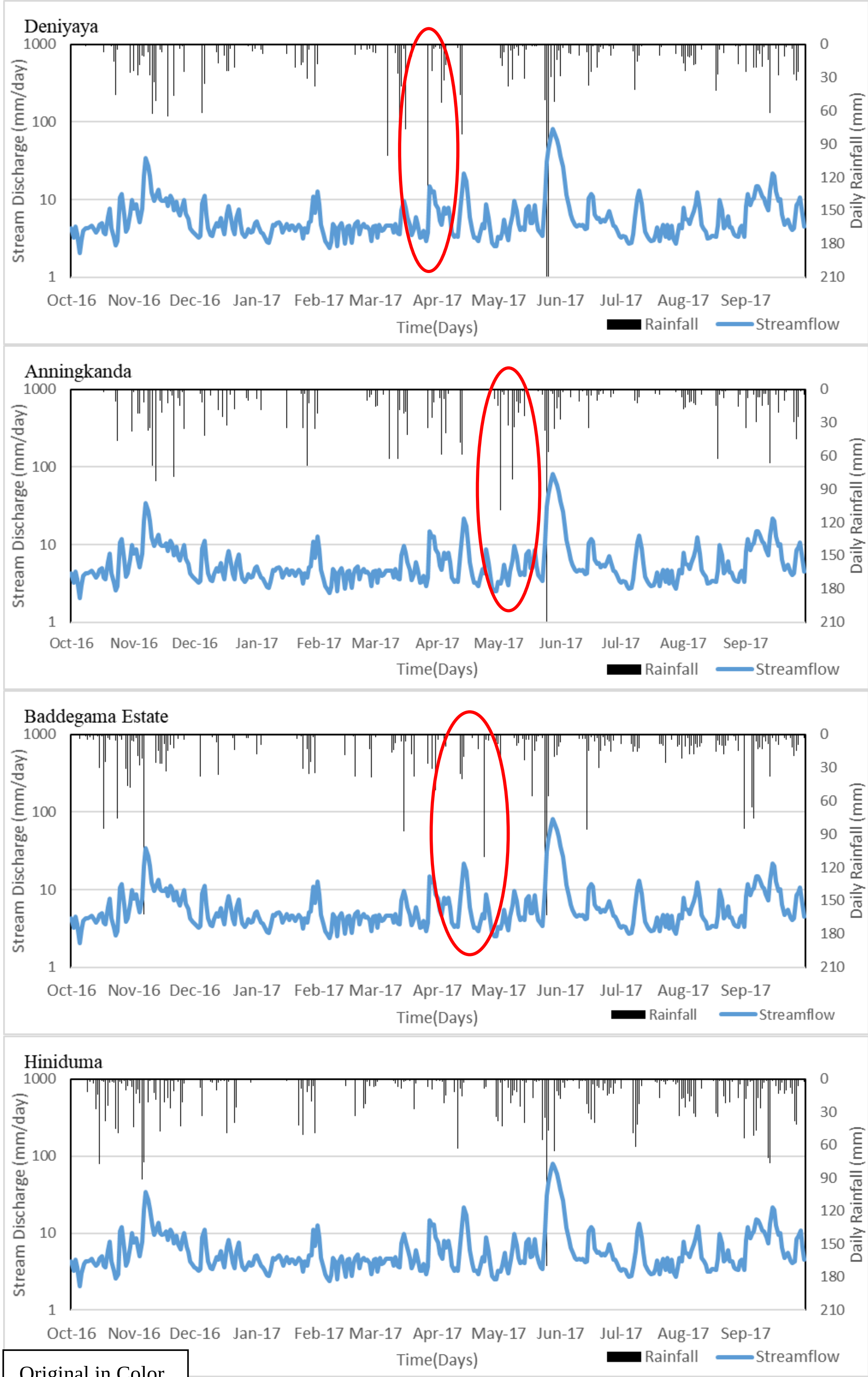



Figure A 28: Baddegama SF vs Rainfall for Water Year 2015/16 (2 of 2)




Original in Color

Figure A 29: Baddegama SF vs Rainfall for Water Year 2016/17 (1 of 2)

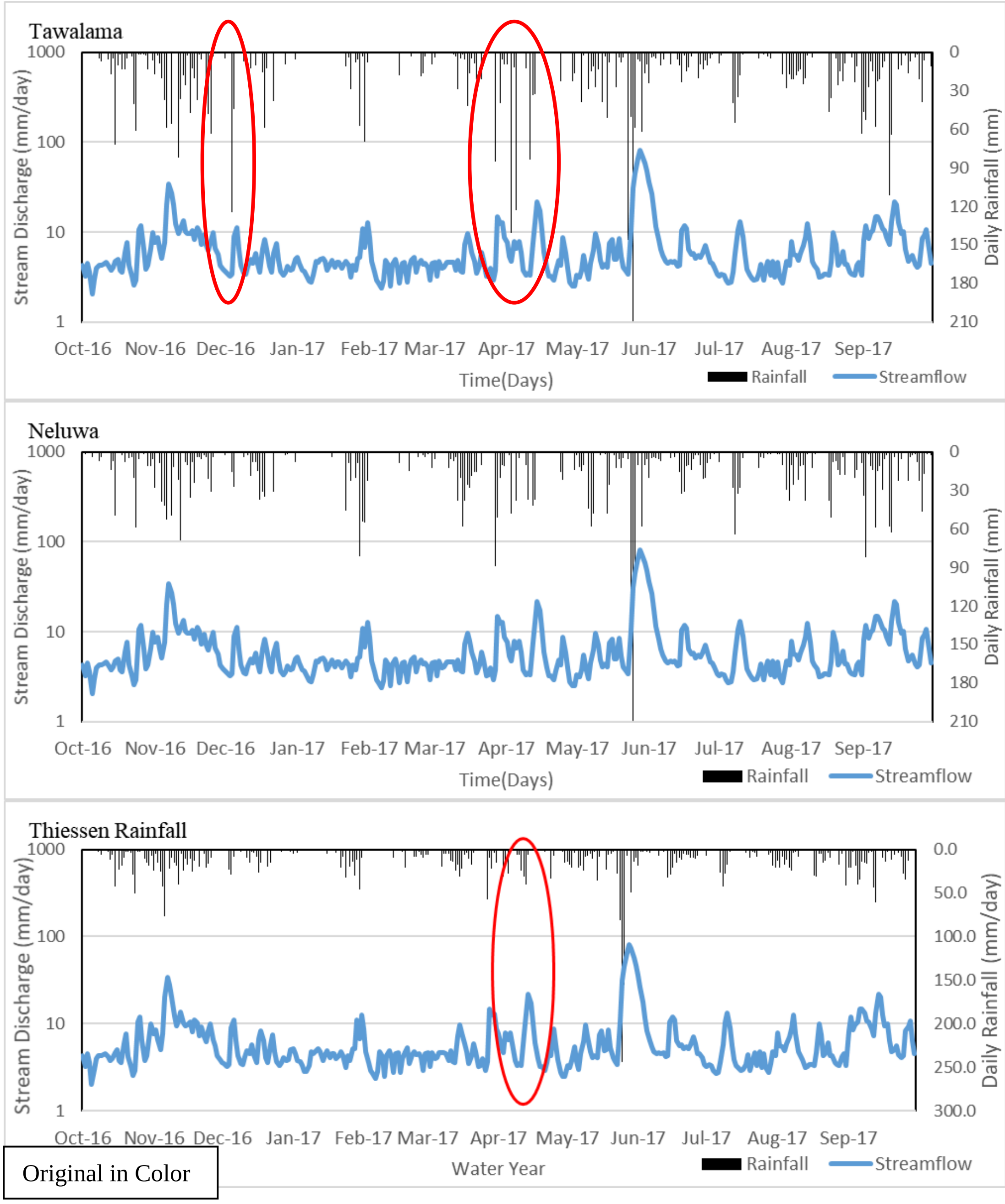
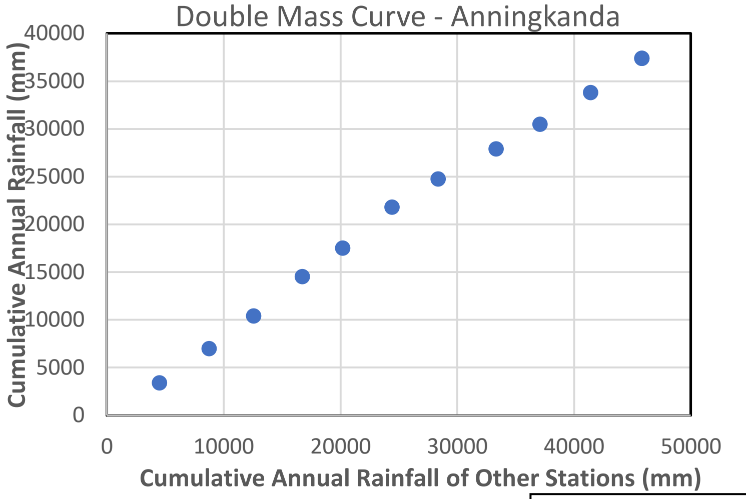



Figure A 30: Baddegama SF vs Rainfall for Water Year 2016/17 (2 of 2)

## Appendix B1: Double Mass curve

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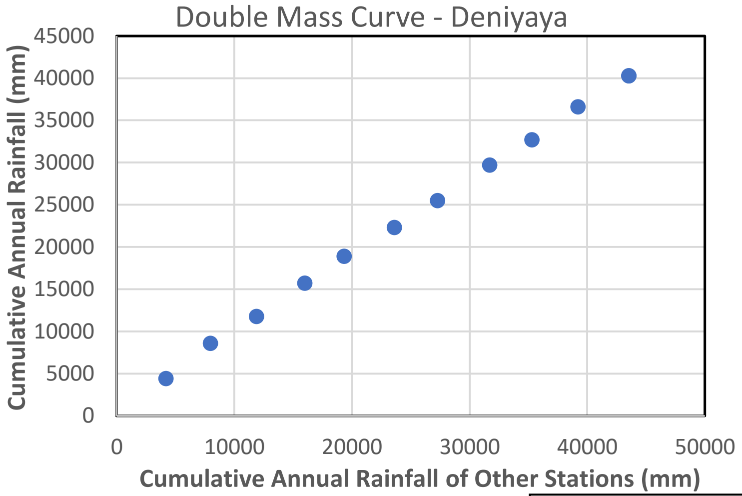


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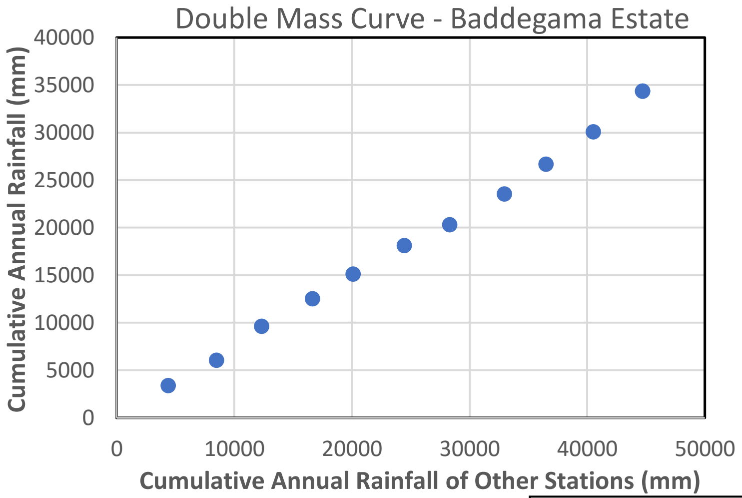


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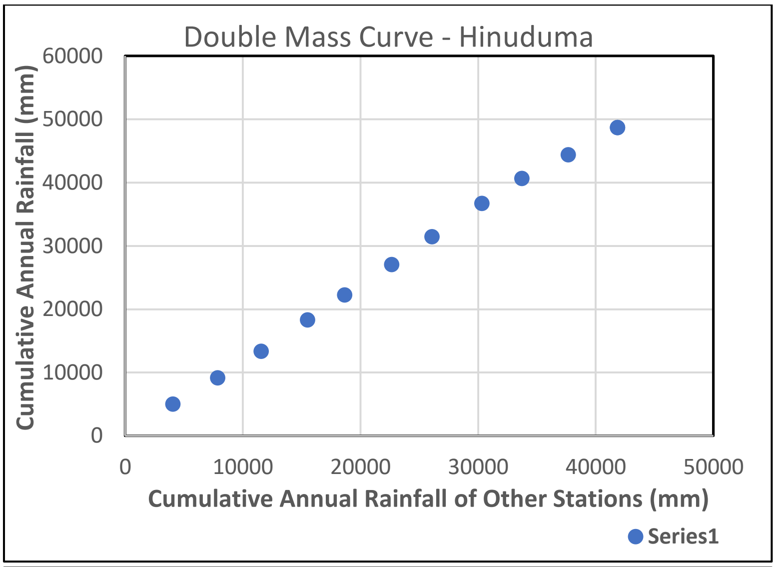


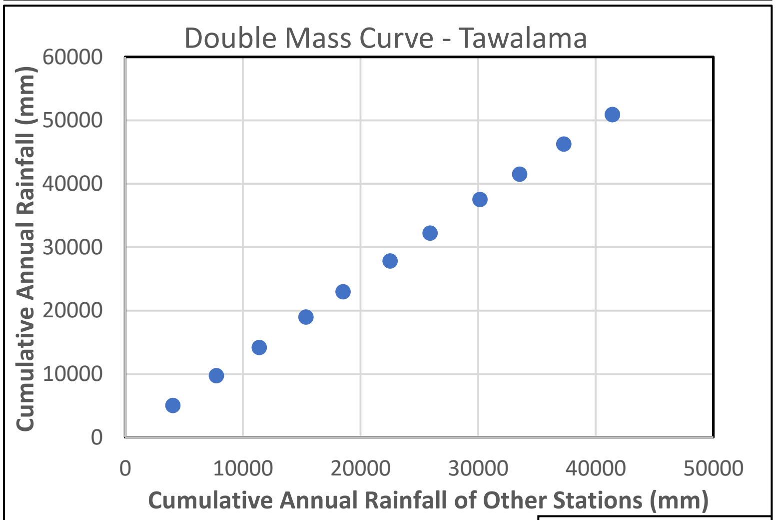


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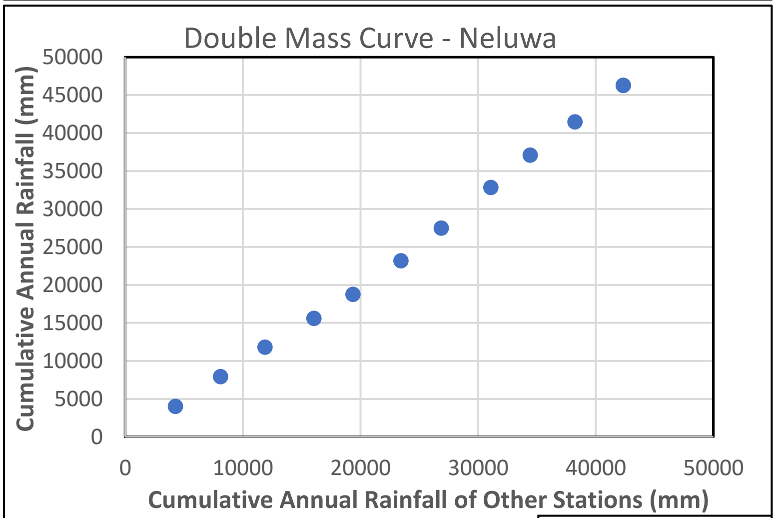



Original in Color

Figure B 1: Double Mass Curves for Rainfall Stations

## Appendix B2: Flow Classification

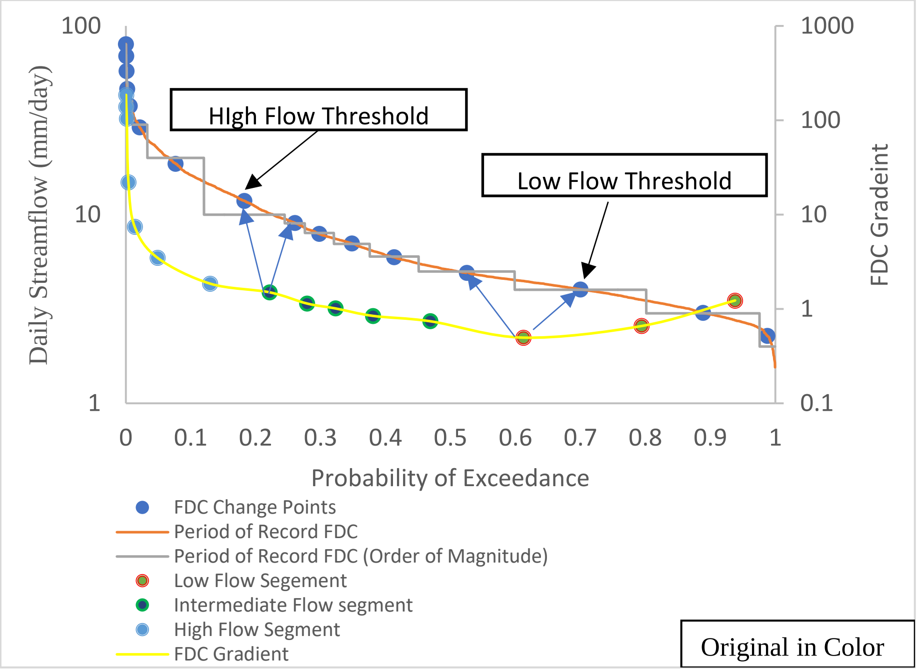



Figure B 2: Flow Classification for Baddegama

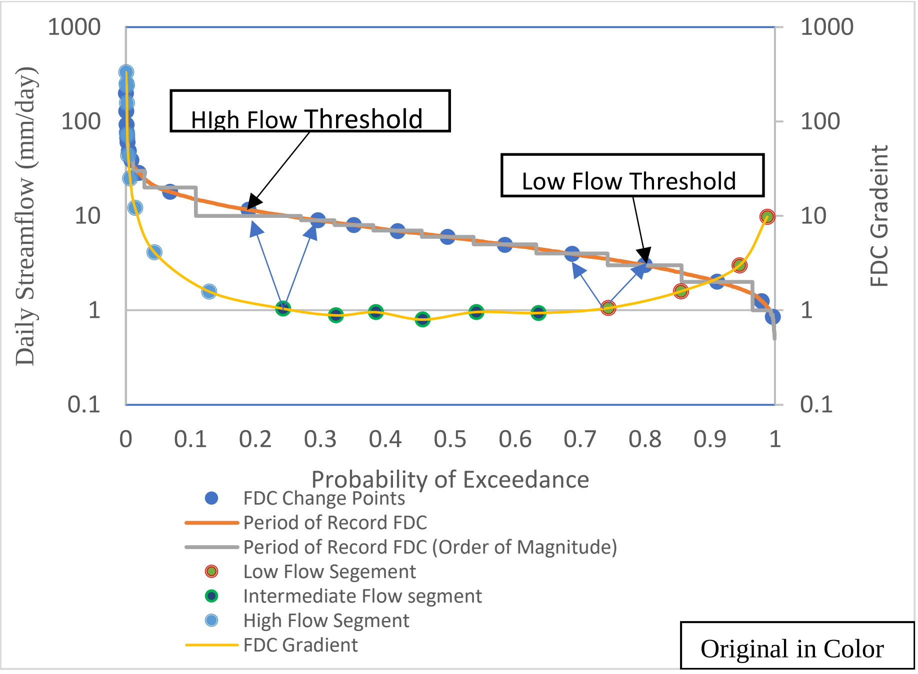



Figure B 3: Flow Classification for Tawalama

# Appendix C: Comparison of Results in Monthly Scale

Comparison of Monthly average streamflow results for Baddegama main catchment for calibration and validation.

Table C 1: Comparison of Monthly Average Streamflow for Baddegama for Calibration and Validation

| | Calibration | | | Validation | | |
|---|---|---|---|---|---|---|
| **Month** | **Observed streamflow (mm)** | **Simulated streamflow (mm)** | **Water Balance Error %** | **Observed streamflow (mm)** | **Simulated streamflow (mm)** | **Water Balance Error %** |
| Oct | 274.17 | 286.26 | 4.41 | 350.81 | 351.02 | 0.06 |
| Nov | 375.35 | 397.59 | 5.93 | 328.87 | 343.46 | 4.44 |
| Dec | 316.53 | 326.02 | 3.00 | 257.61 | 267.13 | 3.69 |
| Jan | 138.64 | 131.37 | -5.24 | 138.09 | 131.26 | -4.95 |
| Feb | 134.06 | 129.19 | -3.63 | 133.54 | 136.73 | 2.39 |
| Mar | 179.01 | 174.38 | -2.58 | 149.33 | 164.45 | 10.13 |
| Apr | 228.53 | 285.10 | 24.75 | 207.42 | 281.01 | 35.48 |
| May | 338.04 | 326.78 | -3.33 | 360.56 | 424.59 | 17.76 |
| Jun | 266.61 | 269.61 | 1.12 | 277.90 | 289.60 | 4.21 |
| Jul | 193.76 | 189.21 | -2.35 | 143.28 | 164.14 | 14.56 |
| Aug | 150.46 | 160.80 | 6.87 | 178.58 | 211.24 | 18.29 |
| Sep | 239.00 | 253.91 | 6.24 | 245.84 | 280.15 | 13.96 |
| | | Average | 2.93 | | Average | 10.00 |

*Water balance error % = (Simulated – Observed)/Observed *100*

*Positive percentages errors show overestimation while negative percentages show underestimation.*

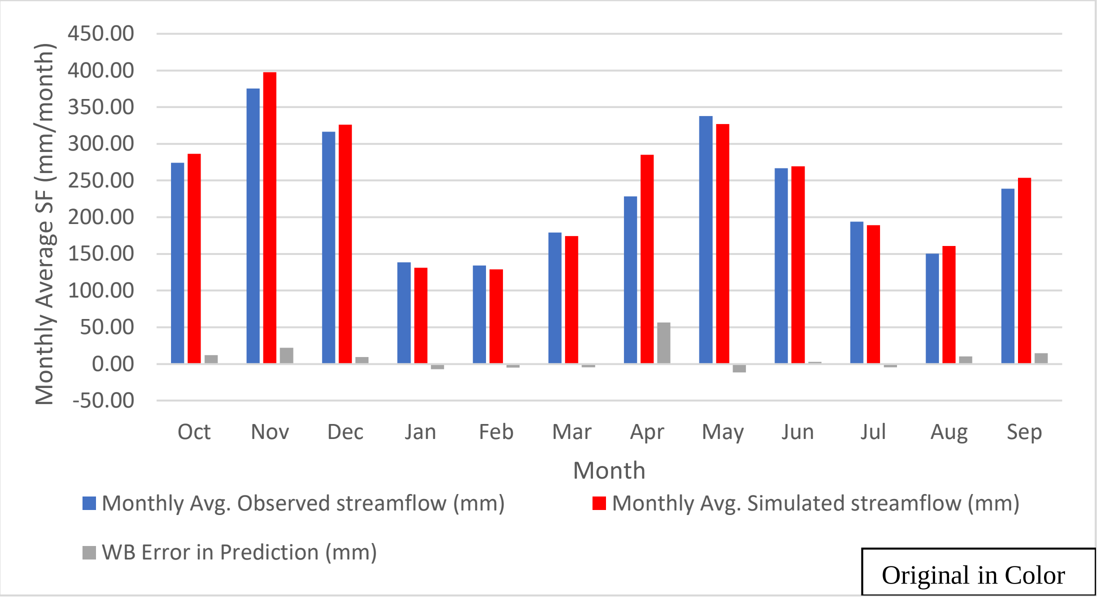



Figure C 1: Comparison of Monthly Average Streamflow for Baddegama for Calibration

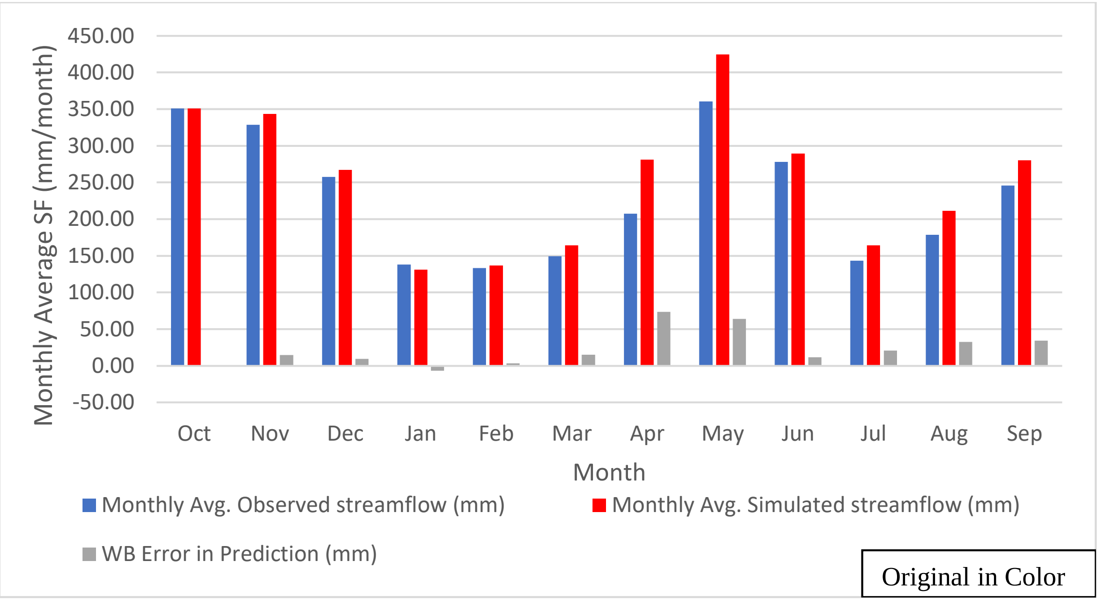



Figure C 2: Comparison of Monthly Average Streamflow for Baddegama for Validation

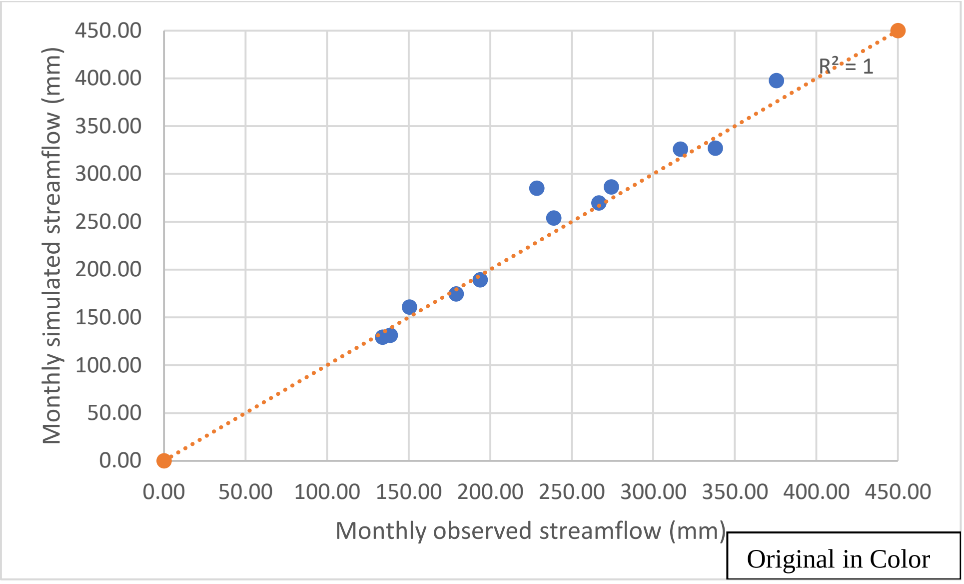



Figure C 3: Scatter Plot for Baddegama Monthly Average Streamflow for Calibration

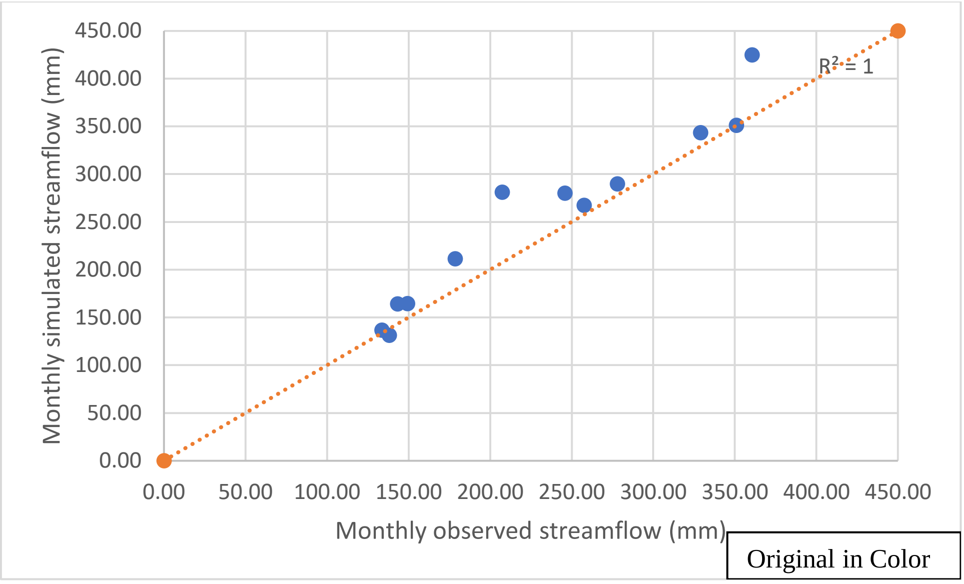



Figure C 4: Scatter Plot for Baddegama Monthly Average Streamflow for Validation

Comparison of Monthly average streamflow results for Tawalama sub catchment for calibration and validation

Table C 2: Comparison of Monthly Average Streamflow for Tawalama for Calibration and Validation

| | **Calibration** | | | **Validation** | | |
|---|---|---|---|---|---|---|
| **Month** | **Observed streamflow (mm)** | **Simulated streamflow (mm)** | **Water Balance Error %** | **Observed streamflow (mm)** | **Simulated streamflow (mm)** | **Water Balance Error %** |
| Oct | 299.74 | 286.81 | -4.31 | 327.81 | 335.80 | 2.44 |
| Nov | 379.24 | 385.03 | 1.53 | 323.15 | 371.56 | 14.98 |
| Dec | 351.83 | 375.82 | 6.82 | 293.39 | 329.80 | 12.41 |
| Jan | 147.84 | 159.59 | 7.95 | 137.16 | 158.67 | 15.68 |
| Feb | 122.20 | 131.24 | 7.40 | 104.59 | 146.30 | 39.88 |
| Mar | 163.26 | 175.83 | 7.69 | 127.89 | 193.19 | 51.06 |
| Apr | 261.15 | 281.35 | 7.74 | 241.76 | 325.41 | 34.60 |
| May | 310.08 | 299.47 | -3.42 | 406.76 | 463.22 | 13.88 |
| Jun | 290.35 | 285.64 | -1.62 | 309.68 | 360.11 | 16.29 |
| Jul | 212.09 | 198.39 | -6.46 | 153.02 | 194.27 | 26.96 |
| Aug | 173.08 | 177.86 | 2.76 | 175.44 | 214.98 | 22.54 |
| Sep | 228.95 | 233.14 | 1.83 | 238.93 | 285.19 | 19.36 |
| | | Average | 2.32 | | Average | 22.51 |

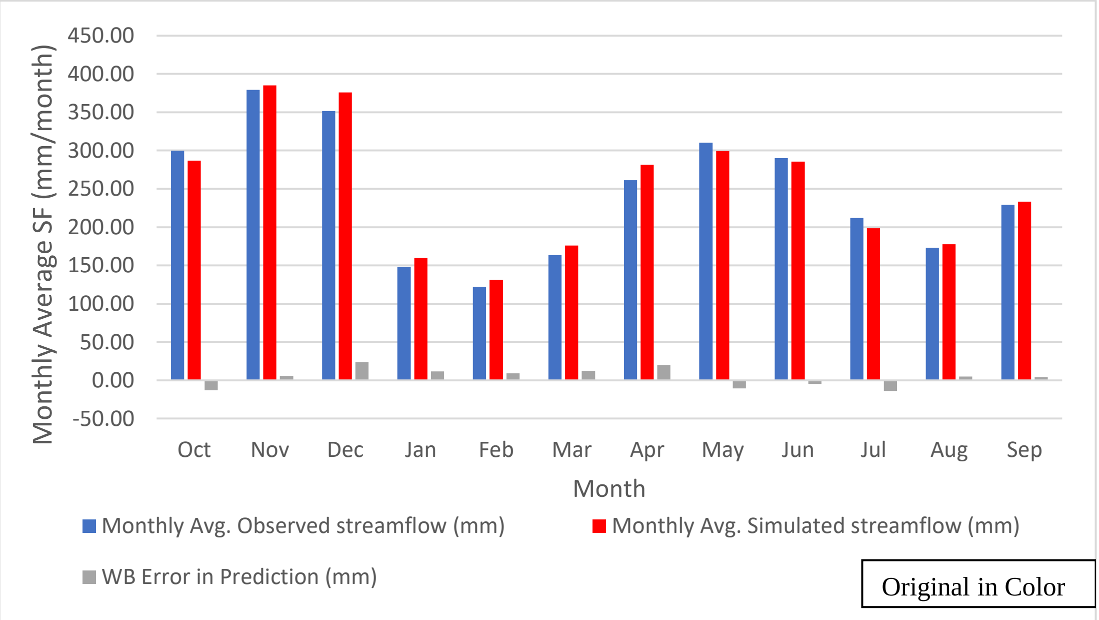



Figure C 5: Comparison of Monthly Average Streamflow for Tawalama for Calibration

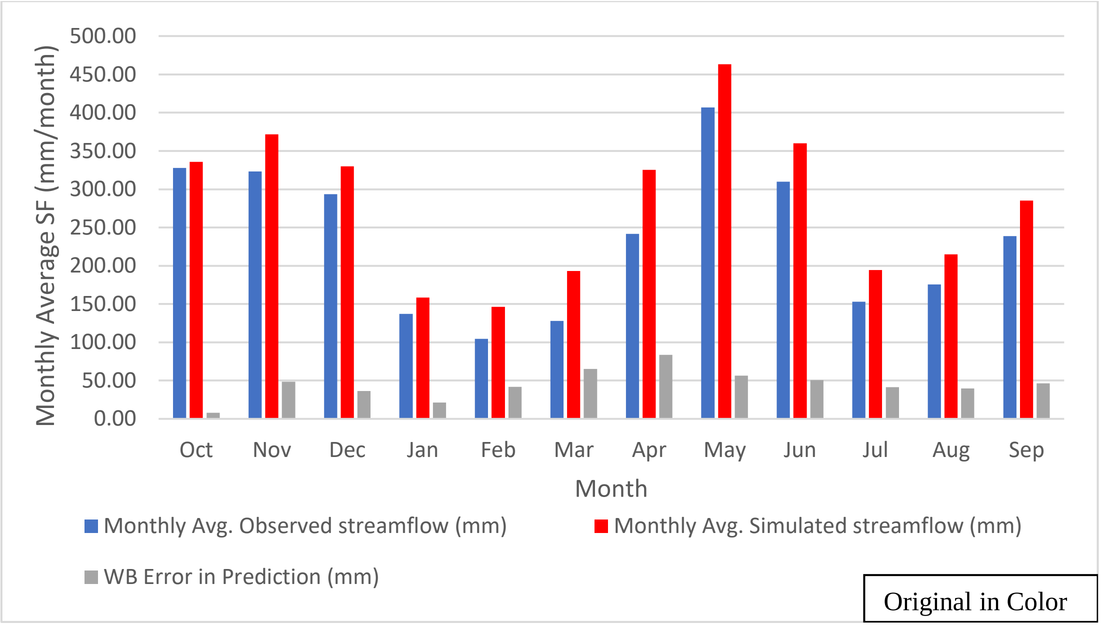



Figure C 6: Comparison of Monthly Average Streamflow for Tawalama for Validation

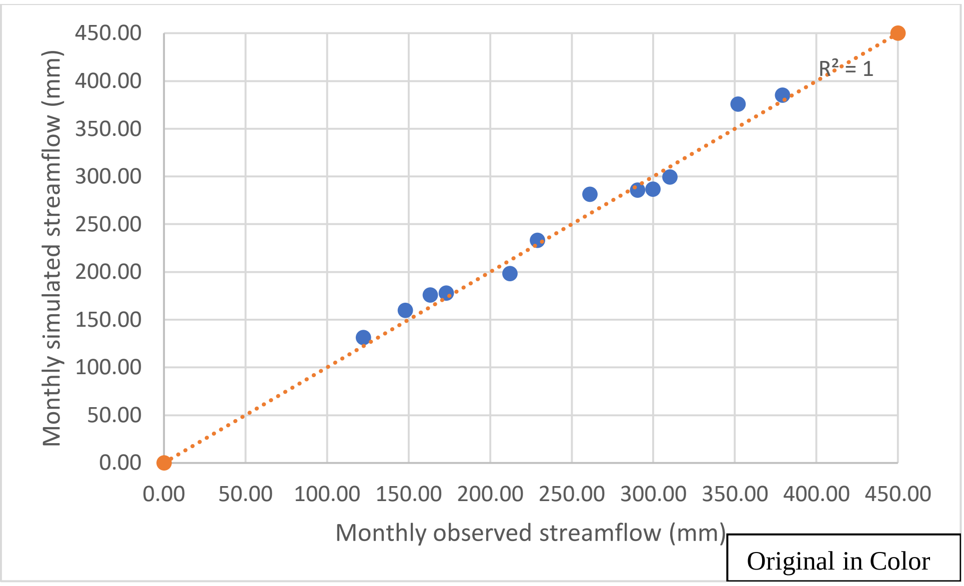
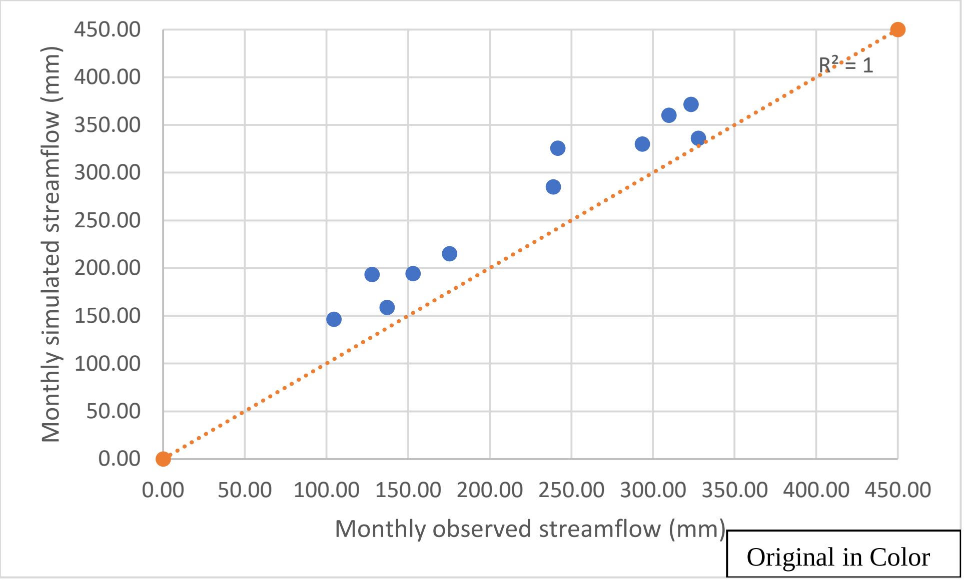



Figure C 7: Scatter Plot for Tawalama Monthly Average Streamflow for Calibration



Original in Color

Figure C 8: Scatter Plot of Tawalama Monthly Average Streamflow for Validation

Comparison of Monthly average streamflow results for Tawalama sub catchment with spatiotemporally transferred parameters.

Table C 3: Comparison of Monthly Average Streamflow for Tawalama with Spatiotemporally Transferred Parameters

| **Month** | **Observed streamflow (mm)** | **Simulated streamflow (mm)** | **WB Error** | **WB Error %** |
|---|---|---|---|---|
| Oct | 313.38 | 319.34 | 5.96 | 1.90 |
| Nov | 351.42 | 376.24 | 24.81 | 7.06 |
| Dec | 322.81 | 338.47 | 15.66 | 4.85 |
| Jan | 143.27 | 150.22 | 6.95 | 4.85 |
| Feb | 112.12 | 145.31 | 33.18 | 29.59 |
| Mar | 146.39 | 192.94 | 46.55 | 31.80 |
| Apr | 251.21 | 310.98 | 59.76 | 23.79 |
| May | 361.60 | 397.12 | 35.52 | 9.82 |
| Jun | 296.48 | 303.87 | 7.39 | 2.49 |
| Jul | 182.99 | 185.98 | 3.00 | 1.64 |
| Aug | 173.80 | 195.73 | 21.92 | 12.61 |
| Sep | 234.22 | 268.19 | 33.97 | 14.50 |
| | | Average | 24.56 | 12.08 |

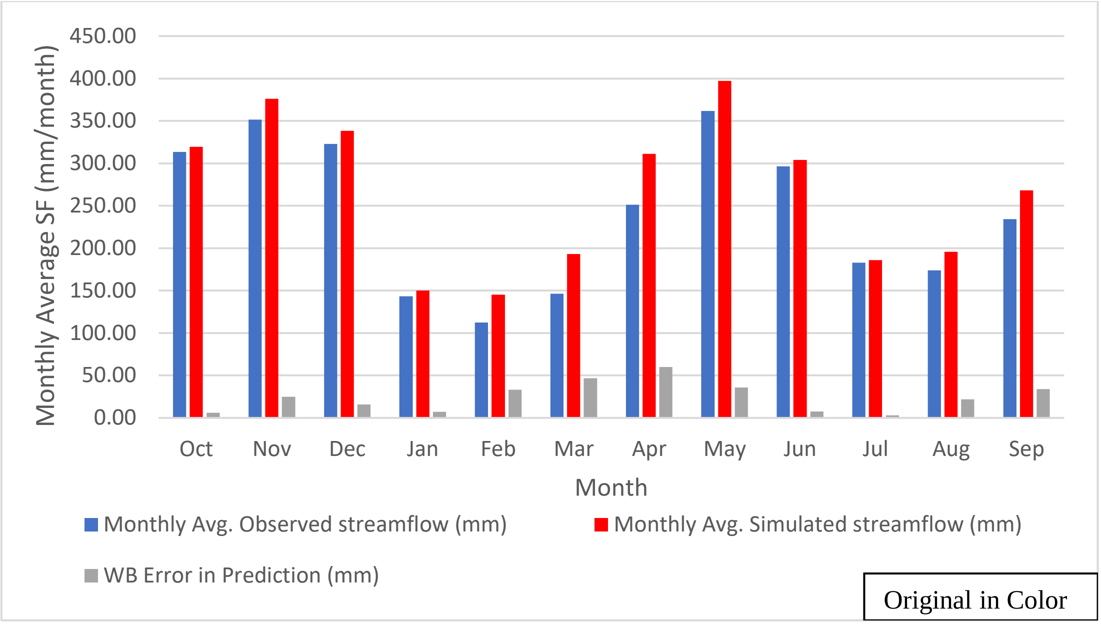



Figure C 9: Comparison of Monthly Average Streamflow for Tawalama with Spatiotemporally Transferred Parameters

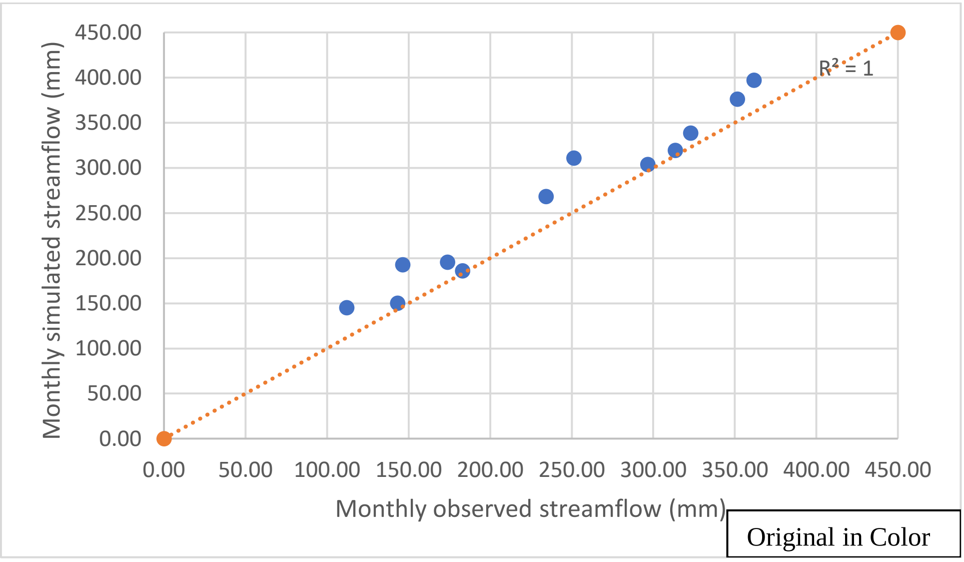



Figure C 10: Scatter Plot for Tawalama Monthly Average Streamflow with Spatiotemporally Transferred Parameters

Comparison of Monthly average streamflow results for Tawalama sub catchment with spatially transferred parameters.

Table C 4: Comparison of Monthly Average Streamflow for Tawalama with Spatially Transferred Parameters

| **Month** | **Observed streamflow (mm)** | **Simulated streamflow (mm)** | **WB Error** | **WB Error %** |
|---|---|---|---|---|
| Oct | 299.74 | 297.31 | -2.43 | -0.81 |
| Nov | 379.24 | 388.79 | 9.55 | 2.52 |
| Dec | 351.83 | 361.31 | 9.47 | 2.69 |
| Jan | 147.84 | 148.23 | 0.39 | 0.26 |
| Feb | 122.20 | 139.12 | 16.92 | 13.84 |
| Mar | 163.26 | 184.59 | 21.32 | 13.06 |
| Apr | 261.15 | 285.78 | 24.63 | 9.43 |
| May | 310.08 | 305.45 | -4.63 | -1.49 |
| Jun | 290.35 | 278.54 | -11.81 | -4.07 |
| Jul | 212.09 | 189.01 | -23.08 | -10.88 |
| Aug | 173.08 | 175.73 | 2.65 | 1.53 |
| Sep | 228.95 | 236.26 | 7.31 | 3.19 |
| | | Average | 4.19 | 2.44 |

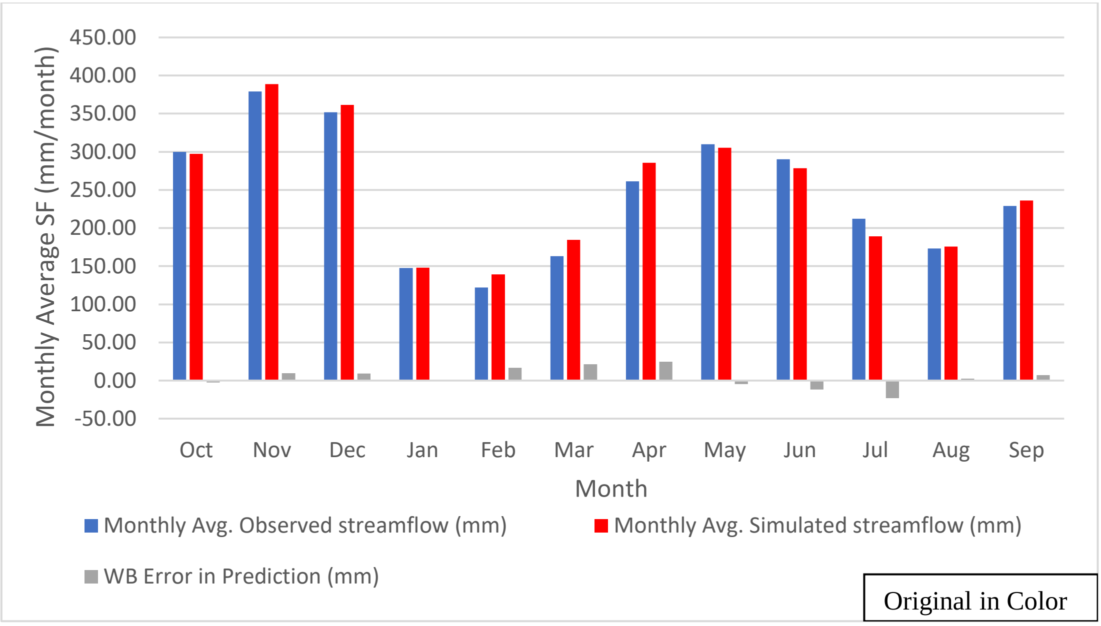



Figure C 11: Comparison of Monthly Average Streamflow for Tawalama with Spatially Transferred Parameters

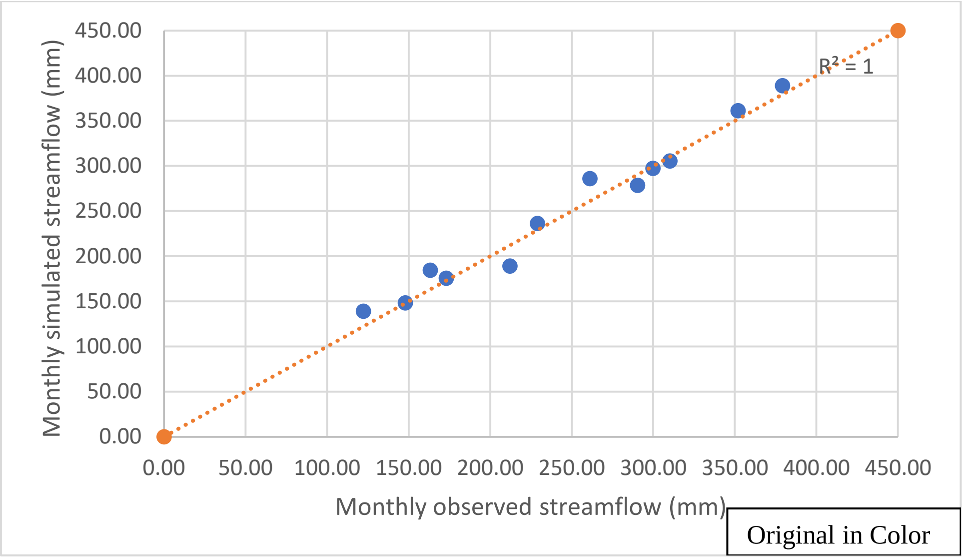



Figure C 12: Scatter Plot for Tawalama Monthly Average Streamflow with Spatially Transferred Parameters

Comparison of Monthly average streamflow results for Tawalama sub catchment with temporally transferred parameters.

Table C 5: Comparison of Monthly Average Streamflow for Tawalama with Temporally Transferred Parameters

| **Month** | **Observed streamflow (mm)** | **Simulated streamflow (mm)** | **WB Error** | **WB Error %** |
|---|---|---|---|---|
| Oct | 313.38 | 311.08 | -2.30 | -0.73 |
| Nov | 351.42 | 378.53 | 27.11 | 7.71 |
| Dec | 322.81 | 352.52 | 29.71 | 9.20 |
| Jan | 143.27 | 161.21 | 17.94 | 12.52 |
| Feb | 112.12 | 136.64 | 24.52 | 21.87 |
| Mar | 146.39 | 185.55 | 39.16 | 26.75 |
| Apr | 251.21 | 302.64 | 51.43 | 20.47 |
| May | 361.60 | 385.06 | 23.46 | 6.49 |
| Jun | 296.48 | 319.02 | 22.54 | 7.60 |
| Jul | 182.99 | 196.76 | 13.78 | 7.53 |
| Aug | 173.80 | 195.75 | 21.95 | 12.63 |
| Sep | 234.22 | 259.61 | 25.39 | 10.84 |
| | | Average | 24.56 | 11.91 |

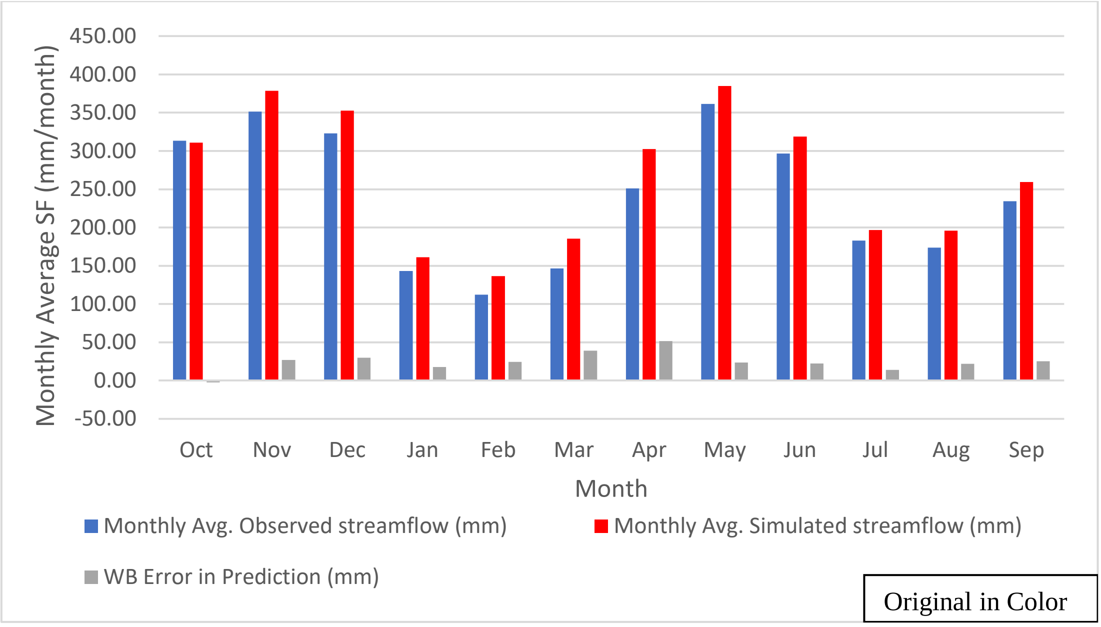



Figure C 13: Comparison of Monthly Average Streamflow for Tawalama with Temporally Transferred Parameters

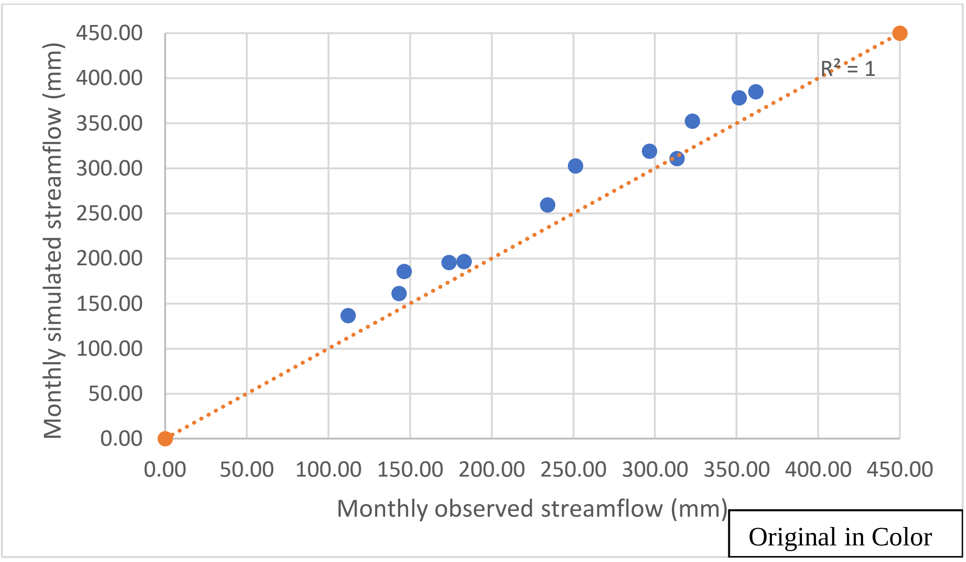



Figure C 14: Scatter Plot for Tawalama Monthly Average Streamflow with Temporally Transferred Parameters

Comparison of Monthly average streamflow results for Baddegama main catchment with spatiotemporally transferred parameters.

Table C 6: Comparison of Monthly Average Streamflow for Baddegama with Spatiotemporally Transferred Parameters

| **Month** | **Observed streamflow (mm)** | **Simulated streamflow (mm)** | **WB Error** | **WB Error %** |
|---|---|---|---|---|
| Oct | 313.03 | 316.37 | 3.34 | 1.07 |
| Nov | 351.50 | 380.01 | 28.51 | 8.11 |
| Dec | 287.19 | 321.07 | 33.88 | 11.80 |
| Jan | 139.14 | 144.87 | 5.73 | 4.12 |
| Feb | 132.84 | 128.82 | -4.01 | -3.02 |
| Mar | 164.57 | 169.87 | 5.30 | 3.22 |
| Apr | 217.55 | 280.80 | 63.26 | 29.08 |
| May | 352.13 | 376.31 | 24.18 | 6.87 |
| Jun | 269.58 | 303.14 | 33.57 | 12.45 |
| Jul | 169.41 | 194.99 | 25.58 | 15.10 |
| Aug | 163.67 | 192.24 | 28.57 | 17.45 |
| Sep | 242.40 | 267.60 | 25.20 | 10.40 |
| | | Average | 22.76 | 9.72 |

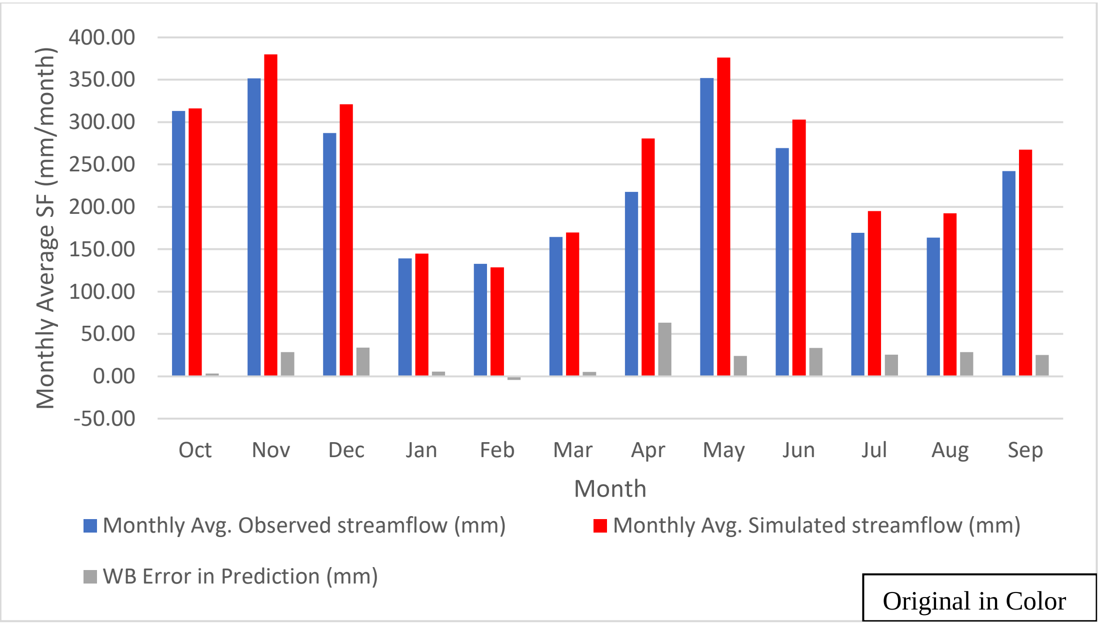



Figure C 15: Comparison of Monthly Average Streamflow for Baddegama with Spatiotemporally Transferred Parameters

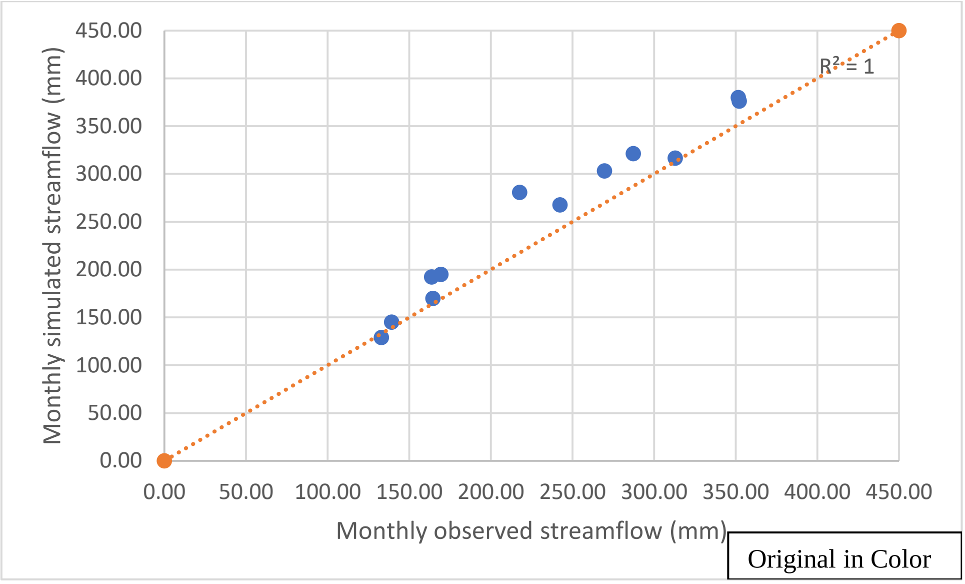



Figure C 16: Scatter Plot for Baddegama Monthly Average Streamflow with Spatiotemporally Transferred Parameters

Comparison of Monthly average streamflow results for Baddegama main catchment with spatially transferred parameters.

Table C 7: Comparison of Monthly Average Streamflow for Baddegama with Spatially Transferred Parameters

| Month | Observed streamflow (mm) | Simulated streamflow (mm) | WB Error | WB Error % |
|---|---|---|---|---|
| Oct | 274.17 | 277.83 | 3.66 | 1.34 |
| Nov | 375.35 | 389.31 | 13.96 | 3.72 |
| Dec | 316.53 | 346.05 | 29.52 | 9.33 |
| Jan | 138.64 | 139.29 | 0.65 | 0.47 |
| Feb | 134.06 | 121.40 | -12.66 | -9.44 |
| Mar | 179.01 | 165.50 | -13.50 | -7.54 |
| Apr | 228.53 | 274.34 | 45.82 | 20.05 |
| May | 338.04 | 321.70 | -16.33 | -4.83 |
| Jun | 266.61 | 284.79 | 18.18 | 6.82 |
| Jul | 193.76 | 197.32 | 3.56 | 1.84 |
| Aug | 150.46 | 163.66 | 13.20 | 8.77 |
| Sep | 239.00 | 249.08 | 10.08 | 4.22 |
| | | Average | 8.01 | 2.89 |

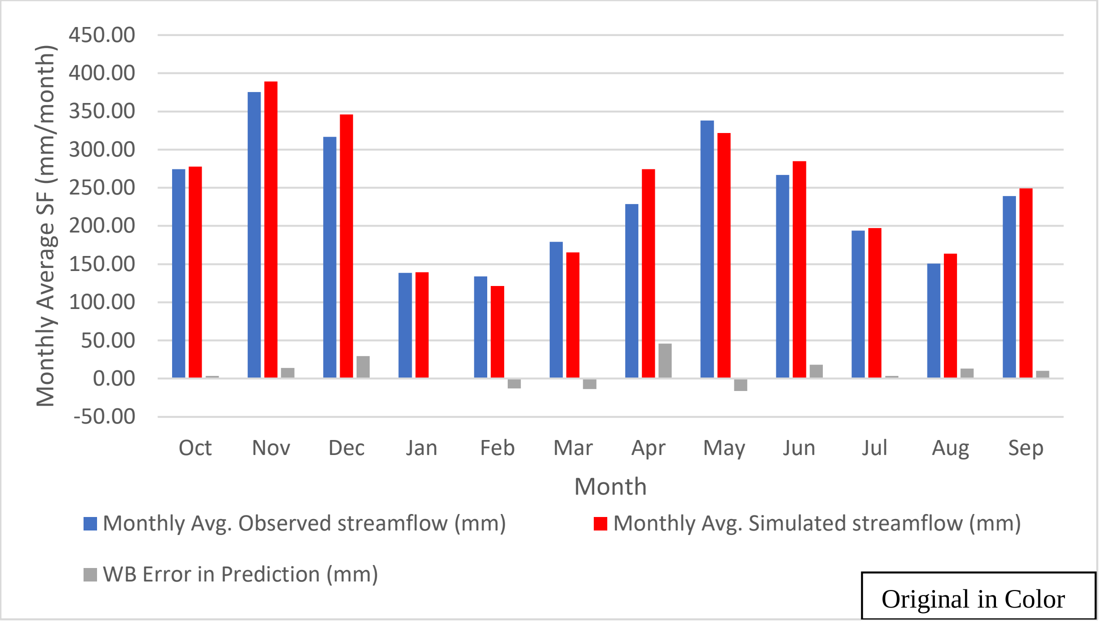



Figure C 17: Comparison of Monthly Average Streamflow for Baddegama with Spatially Transferred Parameters

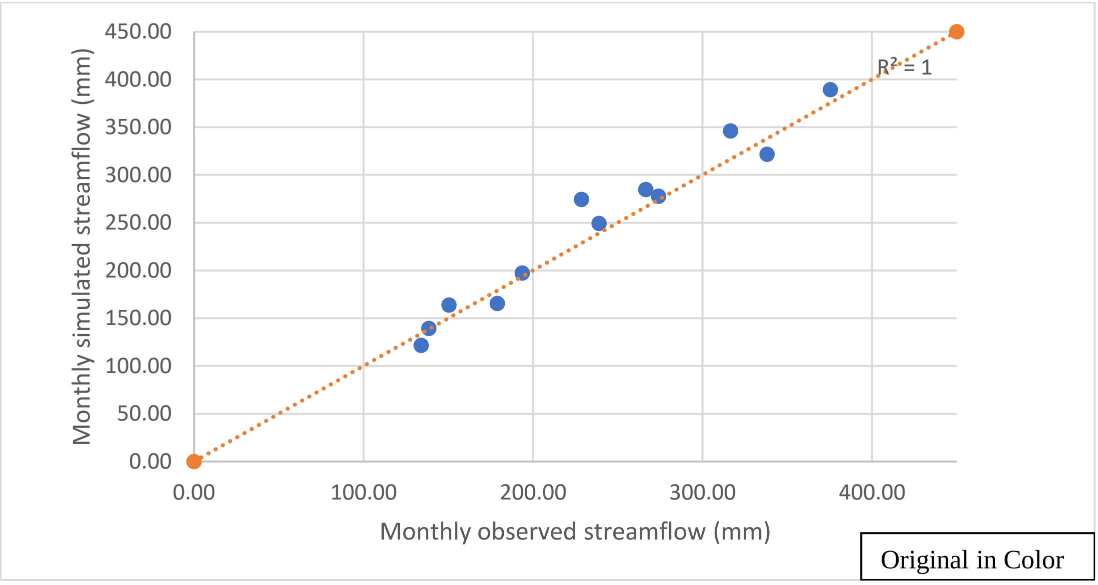



Figure C 18: Scatter Plot for Baddegama Monthly Average Streamflow with Spatially Transferred Parameters

Comparison of Monthly average streamflow results for Baddegama main catchment with temporally transferred parameters.

Table C 8: Comparison of Monthly Average Streamflow for Baddegama with Temporally Transferred Parameters

| Month | Observed streamflow (mm) | Simulated streamflow (mm) | WB Error | WB Error % |
|---|---|---|---|---|
| Oct | 313.03 | 326.98 | 13.95 | 4.46 |
| Nov | 351.50 | 377.68 | 26.17 | 7.45 |
| Dec | 287.19 | 303.62 | 16.44 | 5.72 |
| Jan | 139.14 | 138.72 | -0.42 | -0.30 |
| Feb | 132.84 | 137.42 | 4.58 | 3.45 |
| Mar | 164.57 | 177.66 | 13.09 | 7.96 |
| Apr | 217.55 | 292.13 | 74.58 | 34.28 |
| May | 352.13 | 386.57 | 34.44 | 9.78 |
| Jun | 269.58 | 284.23 | 14.65 | 5.44 |
| Jul | 169.41 | 184.75 | 15.34 | 9.06 |
| Aug | 163.67 | 192.02 | 28.35 | 17.32 |
| Sep | 242.40 | 274.33 | 31.93 | 13.17 |
| | | Average | 22.76 | 9.82 |

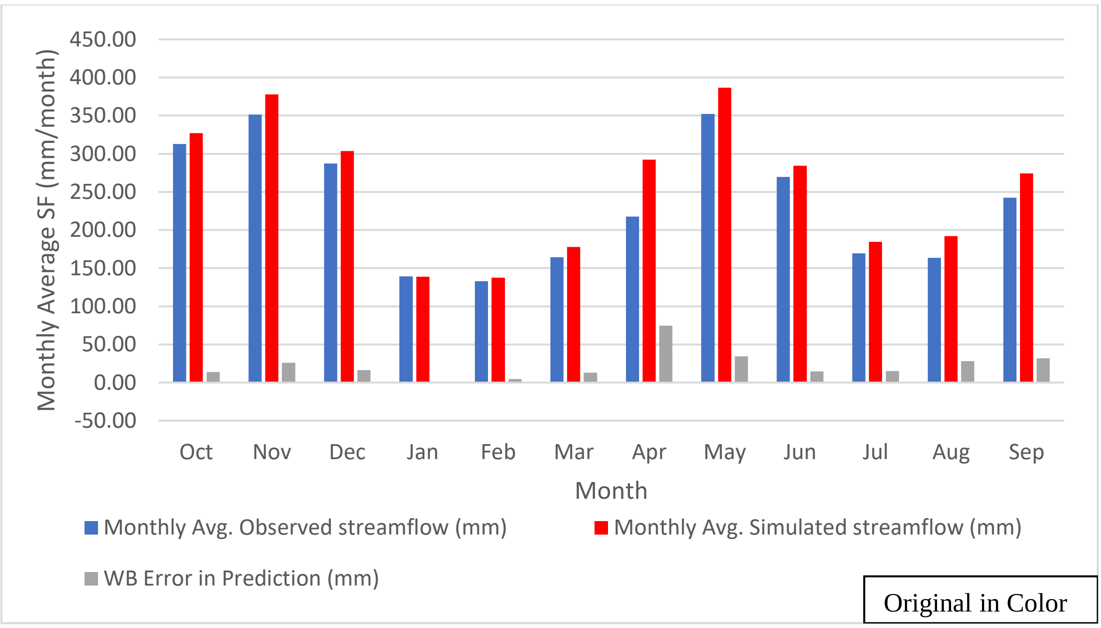



Figure C 19: Comparison of Monthly Average Streamflow for Baddegama with Temporally Transferred Parameters

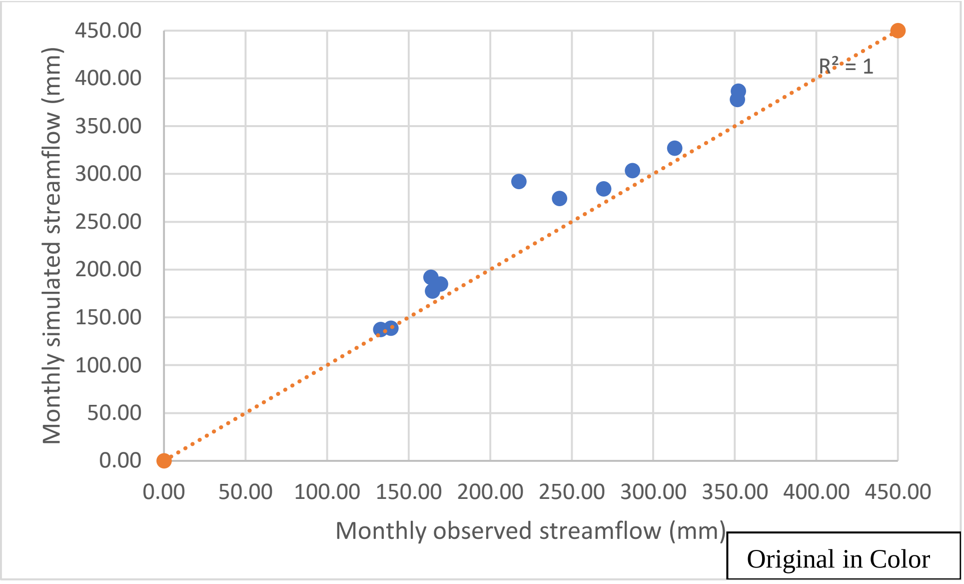



Figure C 20: Scatter Plot for Baddegama Monthly Average Streamflow with Temporally Transferred Parameters

## Appendix D: Land use, Soil and Slope Map

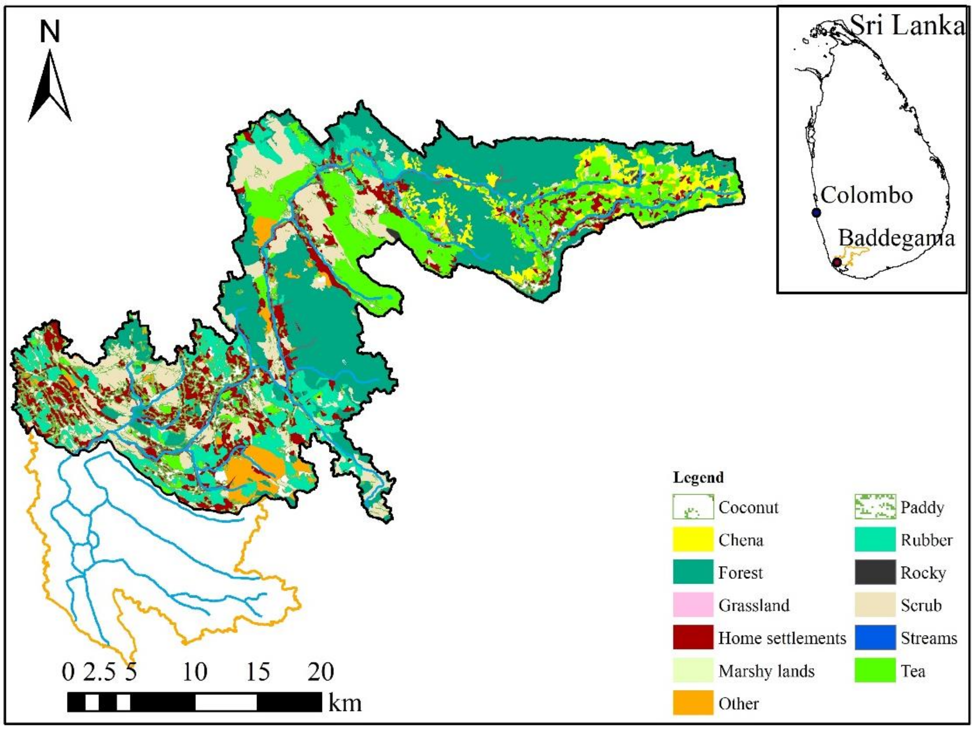



Figure D 2: Land Use map of Baddegama (source: LUPPD 2016)

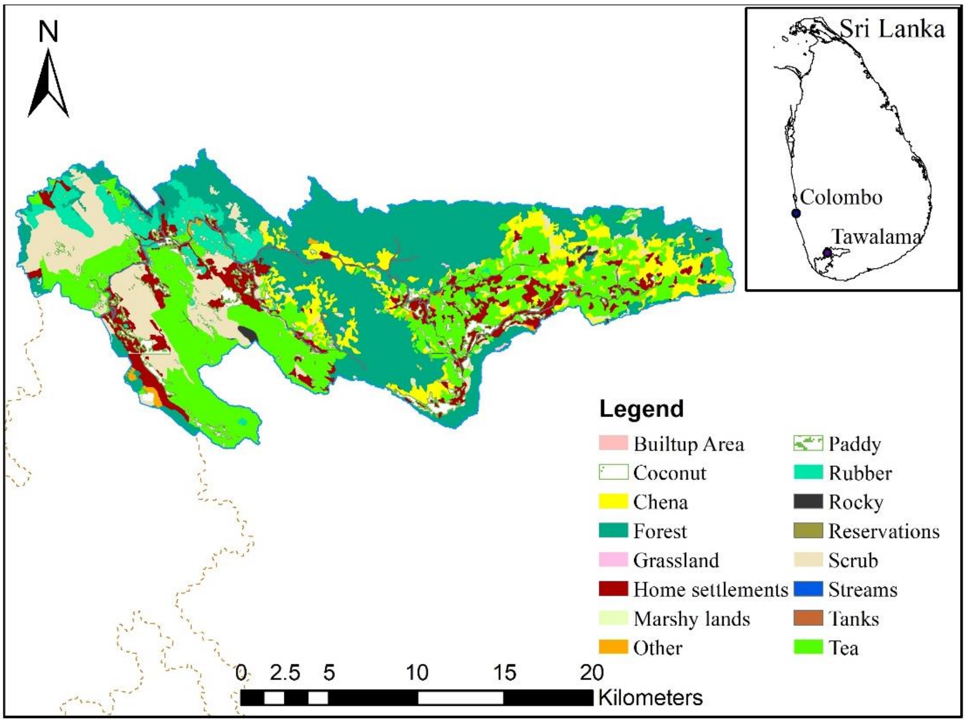



Figure D 1: Land Use Map of Tawalama (LUPPD Sri Lanka 2016)

Table D 1: Land Use Percentages in Study Area

| Land Use Type | Land Use area % | |
|---|---|---|
| | Baddegama | Tawalama |
| Coconut | 0.66 | 0.06 |
| Chena | 4.35 | 8.80 |
| Forest | 30.32 | 32.56 |
| Grass Land | 0.07 | |
| Homestead | 13.95 | 8.86 |
| Marshy | 0.01 | 0.02 |
| Other | 3.23 | 0.56 |
| Paddy | 8.93 | 4.54 |
| Rubber | 10.40 | 5.69 |
| Rock Area | 0.25 | 0.49 |
| Scrub jungle | 13.13 | 12.15 |
| Stream | 1.06 | 1.17 |
| Tea | 13.61 | 25.10 |
| Water Area | 0.03 | |
| | 100.00 | 100.00 |

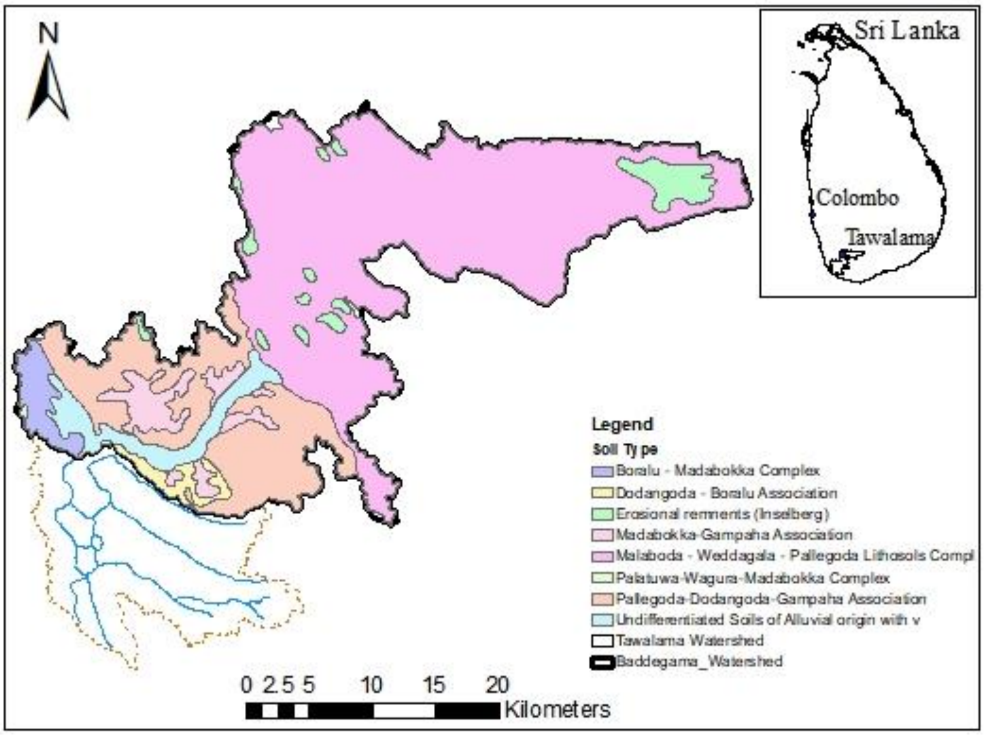



Figure D 3: Soil Map of Study Area

(Source: Soil Science Society of Sri Lanka 2016)

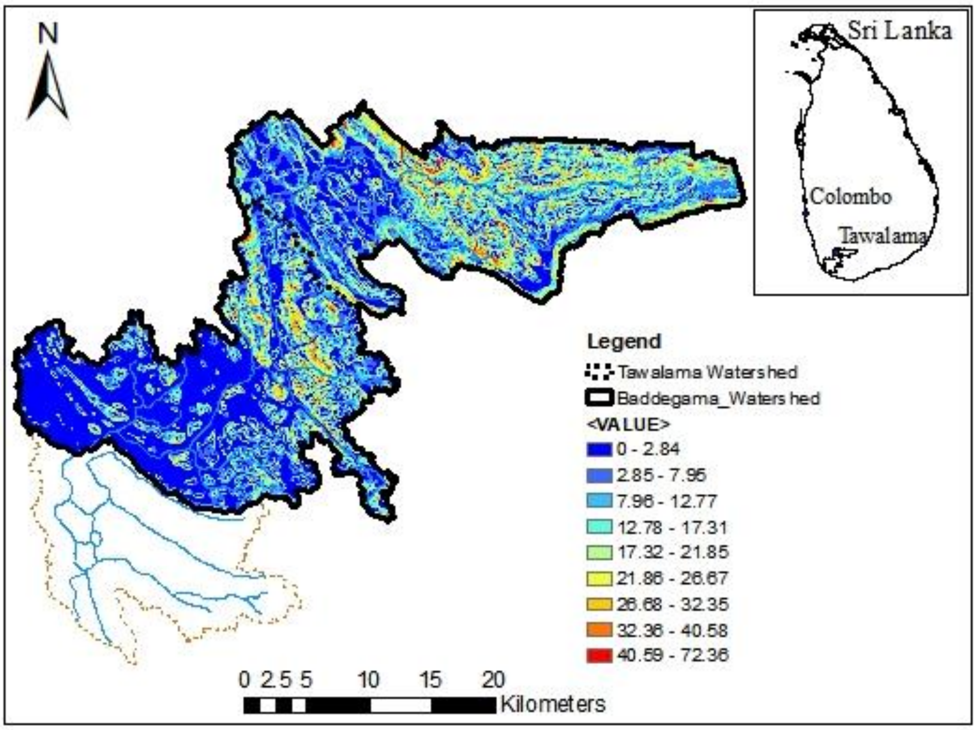



Figure D 4: Slope Map of Study Area

(Derived using Contours provided by Survey Department of Sri Lanka)