EVALUATION OF TRANSFERABILITY OF TANK MODEL PARAMETERS FOR UNGAUGED CATCHMENTS IN NILWALA RIVER BASIN

Madhuka Wickramarachchi

(189250K)

Degree of Master of Science

Department of Civil Engineering

University of Moratuwa
Sri Lanka

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

Supervised by
Professor N.T.S. Wijesekera

UNESCO Madanjeet Centre for South Asia Water Management
(UMCSAWM)
Department of Civil Engineering

University of Moratuwa
Sri Lanka

July 2020

DECLARATION

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Abstract

Water is a fundamental requirement for human persistence and one of the essential resources for achieving sustainable development in the country. The growing population and expansion of economic sectors have created an interconnected competitive demand for finite water resources. Thus, a proper water resources management is required where daily rainfall-runoff modeling will be the most fundamental tool for water resource assessment. Though, most of the catchments are ungauged or with limited data, hydrologic modeling is a challenging task for model calibration and validation. Transferring the hydrological model parameters of a gauged catchment to ungauged catchment is generally practiced in such conditions by the hydrologic modelers with a considerable level of uncertainty. Hence, this study has focused to evaluate the accuracy of such regionalization methods of a Tank model parameters in order to quantify the water resource in ungauged catchments in Nilwala River to assist water resource management.

A Tank model with four tanks was developed with MS Excel software for Pitabeddara and Urawa sub-catchments using data from water years 2008/09 to 2017/18. The model was warmed up for five water years to stabilize the soil moisture in the four tanks. Both models for two sub-catchments were calibrated for the first five water years and validated with the remaining five water years. During the process, the models were optimized by using the multi-start GRG-nonlinear search engine of the Solver add-in of MS Excel where the goodness of fit of the model simulations was evaluated by using the Mean Ratio of Absolute Error (MRAE). The optimized Tank model parameters for each catchment were transposed under spatiotemporal, temporal, and spatial transferability approaches to reconstruct the streamflow of each catchment. Model performances in each simulation was evaluated by comparing annual water balance, total flow hydrograph, and flow duration curves.

The MRAE values during model calibration were 0.32 and 0.31 for Pitabeddara and Urawa sub-catchments respectively. Both models were validated with the MRAE values of 0.48 and 0.54 for Pitabeddara and Urawa catchments respectively. The evaluation indicators also illustrated a better matching between estimated and observed flows where annual water balance error percentages were range from 0.7% to 25.1%.

In light of these results, the spatial parameter transferability approach outperformed than other methods for the concerned catchments during study period. Consequently, the lumped Tank model is capable of simulating daily streamflow of concerned catchments in Nilwala River Basin with an accuracy level within 50% - 68%. Most importantly, the best results are in the high and intermediate flow regimes with an average accuracy more than 61% ranges from 53% - 73%. The seasonal-scaled streamflow showed more than 87% of average accuracy with water quantity error of 70 mm/season – 114 mm/season. The monthly-scaled streamflow had an average accuracy level of more than 76% with water quantity error of less than 20.9 mm/month confirming that the Tank model can be satisfactorily utilized for water resources management tasks in the concerned catchments.

Key Words: Parameter Regionalization, Lumped Tank Model, Ungauged Catchment, Water resources Management, Daily data

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Evaluation of Transferability of Tank Model Parameters for Ungauged Catchments in Nilwala River Basin

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LIST OF ABBREVIATIONS

Avg	-	Average
AWB	-	Annual Water Balance
Cal. SF	-	Calculated Streamflow
Evapo.	-	Evaporation
FDC	-	Flow duration curves
MRAE	-	Mean Ratio of Absolute Error
RF	-	Rainfall
SF	-	Streamflow
WMO	-	World Meteorological Organization

1 Introduction

1.1 Water Resources in Sri Lanka

Sri Lanka is blessed with water in the form of a radial network of 103 rivers originating from the central highland and then drains through nearly 90% of the land extent of the country. All these rivers are fed only by the rainfall from monsoons, convections, and depressions (Imbulana, Wijesekera, & Neupane, 2006).

Sri Lanka receives a mean annual rainfall of 1861 mm under five climatic seasons amounting to an approximate volume of 120 billion cubic meters over the entire landmass. Sri Lanka has five climatic seasons in a water year names as the convectional-convergence period from March to mid-April, pre-monsoonal period from mid-April to late May, South-West monsoon period from May to late September, convectional cyclonic period from late September to late November and North-East monsoon from November to February (Imbulana et al., 2006). Annual rainfall varies spatially from 800 mm to over 5,500 mm in the three climatic zones of the dry zone, intermediate zone, and wet zone where the annual runoff coefficient lies between 35% - 40% (Samad, Aheeyar, Royo-Olid, & Arulingam, 2017).

The freshwater which is extracted from rain-fed surface water resources or groundwater resources is an essential resource for the sectors of the economy such as the agricultural sector, industries, and energy sector. Hence the water is a cornerstone of the socio-economic development of the country (Othman, Heydari, Sadeghian, Rashidi, & Parsa, 2014). The economy of Sri Lanka is mainly based on agriculture which consumes more than 80% of available freshwater, and the energy sector also mainly depends on hydropower (Samad et al., 2017). Therefore, water is a fundamental and very important for achieving sustainable development of the country.

1.2 Challenges on Water Resources

The spatial and temporal distribution of rainfall in Sri Lanka shows that the majority of areas in the dry zone experiences water stress conditions which last from a few months to a few years(Amarasinghe, Muthuwatta, & Sakthivadivel, 1999). These conditions would be twisted more by the impacts of climate change which affects the availability of surfacewater and groundwater sources by changing patterns in precipitation and evaporation. Such changes in the hydrological system will also trigger changes in processes such as water quality and soil erosion (Elkaduwa & Sakthivadivel, 1999).

Further, it has been reported that annual precipitation in Sri Lanka will be reduced by 7%, and rainfall during the North-East monsoon season will show a higher reduction. Also research has shown that the dry zone will be drier and expanding; Southwest monsoon rainfall will demonstrate a greater change with increased intensities (Wijesekera, 2011). In an expected climate change situation where the wet zone would become wetter and dry zone would get drier, thereby the water managers will have a greater challenge when managing water in a sustainable manner.

Besides, the quality of available water in many areas of Sri Lanka is being degraded due to natural and anthropogenic activities such as the addition of domestic sewerage, industrial effluents and agricultural runoff to water sources, and natural dilution of highly concentrated different compounds in soil with water sources (Bandara, 2003). The degradation of water quality can critically reduce the amount of water for potable, agriculture, and commercial uses (Radif, 1999; Samad et al., 2017) which will affect the food and water security and, limit national economic development (Jonch-Clausen, 2004).

Presently, the demand for limited freshwater, both as consumptive and non-consumptive use is also being increased with the growth of population and expansion of economic sectors such as agriculture, industry, power, and energy resulting in severe stress on water resources (Radif, 1999). At the same time, economic growth will enforce the changing of consumption pattern of the growing population where demand for goods and services will also be changed and the associated water demands will also become highly affected both spatially and temporally (Amarasinghe et al., 1999; FAO, 2012).

Middelkoop et al. (2001) reported that the uncertainties associated with changing water demands and the future availability of safe water would be aggravated by climate change and, its impacts on hydrological processes thereby creating difficulties for water managers to effectively plan and manage water resource.

1.3 Sustainable Water Resources Management and Challenges

Sustainable water resources management is a concept that directs the management and use of water by considering both present requirements and long-term future needs (Loucks, 2000). Since the water issues are becoming severe and influencing social, economic, environmental and political concerns, at the local and national level, water managers should practice systematic and integrated management practices in water resources management to maintain the sustainability in water (Othman et al., 2014) where failure in planning without proper understanding on hydrological responses will lead to waste of finite resources (Elkaduwa & Sakthivadivel, 1999).

In that context, accurate assessment on the quantity and quality of available water resources in the area of interest is required to identify sustainable management and planning alternatives such as infrastructures development, re-facing of policies, etc. and, monitoring and planning of water resources schemes (Nruthya & Srinivas, 2015; Razavi & Coulibaly, 2013). But we have only a limited range of measurements and measuring techniques on the hydrological systems in both space and time (Beven, 2012). Hence the common option practiced by the water managers or engineers is to use hydrologic models (C. Y. Xu & Singh, 2004) which are mostly developed based on observed rainfall and runoff data (Yokoo, Kazama, Sawamoto, & Nishimura, 2001). These hydrologic models provide a better understanding of the behavior of surfacewater and subsurface water movements which helpful for decision making on water resources, water quality, and related hazard issues (Daniel et al., 2011).

Generally in the developing countries, the water engineers have to perform their engineering designs and other developments mostly in ungauged catchments where there are no or lack of observed data in order to achieve sustainable water resources management (Abeynayake, 2000) thus a direct application of hydrologic models are difficult due to inability of model calibration and verification. Hence the methodologies which can be used in such situations, to estimate water resources need critical evaluation.

1.4 Hydrological Modeling in Ungauged Catchments

In the field of hydrological modeling, there are different types of models w.r.t the model structure such as empirical, conceptual and process-based models; spatial resolution such as lumped and distributed models; and temporal resolution such as event-based models and continuous models (Beven, 2012; Devia, Ganasri, & Dwarakish, 2015; Shaw, 1994). The empirical models such as Rational method, Unit Hydrograph, etc. are capable of estimation of streamflow in ungauged catchments easily due to their simplicity, but they are weak in the estimation of continuous-time series of runoff (Pechlivanidis, Jackson, Mcintyre, & Wheater, 2011; Sitterson et al., 2017) which is the fundamental requirement of water resources management (Razavi & Coulibaly, 2016). Further, the empirical models tend to overestimation of runoff leading to over designing thereby the cost-effectiveness of the design would be decreased (Shaw, 1994). Thus, such models shall not be used in this study since the objective is to sustainable water resources management in ungauged catchments.

Hence considering the facts, simplicity of model structure, and ability to generate continuous time series of streamflow easily by the practicing water engineers or water managers, other combinations of model types would be suitable. Although these models are needed to be calibrated and verified with observed hydrological data prior to use in a particular application (Daggupati et al., 2015) which cannot be performed in ungauged catchment modeling due to unavailability of observed data. Therefore, hydrologists have been attempting to transfer or extrapolate model information or model parameters of a gauged catchment to ungauged catchments for streamflow estimation where the concept is called as regionalization (Oudin, Andréassian, Perrin, Michel, & Le Moine, 2008).

The most widely used method of regionalization is the regression-based method where other common methods are spatial proximity method, arithmetic mean method, scaling relationship, physical similarity approach, etc. (Kokkonen, Jakeman, Young, &

Koivusalo, 2003; Razavi & Coulibaly, 2013; Song, Her, Suh, Kang, & Kim, 2019). Hence, a model with better performance under these conditions is better for the study.

In that context, lumped conceptual models outperform other types of models due to their simple model structure with low data requirements (Perrin, Michel, & Andréassian, 2001; Razavi & Coulibaly, 2013; C. Y. Xu & Singh, 2004).

According to Vaze, Jordan, Beecham, Frost, & Summerell (2011), in general, conceptual models have a number of parameters range from 4 to 20 which might make the model structure simple or complex. Simple model but parsimonious with fewer model parameters that are able to capture hydrological processes have higher performance than complex models with many parameters (Bai, Liu, Liang, & Liu, 2015; Razavi & Coulibaly, 2013). Considering these facts, a lumped conceptual Tank model with four tanks was used in the study because of its simplicity and higher modeling performance as indicated in studies of Basri (2013), Kuok, Harun, & Chiu (2011), Phien & Pradhan (1983) and many other researchers.

Most researchers have indicated that for water resources management concerns, monthly scale rainfall-runoff modeling is sufficient to develop reasonable management alternatives. But for proper and sustainable water resources management, catchment response in extreme events such as peak flows, also should be clearly identified. Further the monthly runoff generated from daily water balance models is more accurate than runoff generated from monthly water balance models (Wang et al., 2011). Hence, the temporal resolution of the model should be in daily for proper quantification of peak flows (Middelkoop et al., 2001) thereby the study has used a daily lumped conceptual model for estimation of streamflow time series.

1.4.1 Modeling of Nilwala River Basin

A limited amount of studies have been done for the basin as examples Abeynayake (2000) and Rathnayake, Sachindra, & Nandalal (2010). Besides, Elkaduwa & Sakthivadivel (1999) has done an analysis for developing proper watershed management. Hence it can be identified that amount of studies in the direction of water resources management are insufficient and modeling of the basin is also not matured.

Therefore, this study is to provide a contribution towards water resources management and hydrologic modeling of Nilwala River basin.

1.5 Problem Statement

Accurate water resources assessment is a requisite for sustainable water resources management in ungauged catchments. The commonly used hydrologic models for water resources assessments cannot be used directly in such situations since they require calibration and verification of model parameters w.r.t. observed data that are not available for ungauged catchments.

In that context, hydrologists, researchers, and water engineers allure to practice the regionalization of model parameters from gauged catchment to an ungauged catchment. Although different types of regionalization methods are practiced, there is no well-established method which is capable in transferring of model parameters to quantify the water resources in ungauged catchments accurately (C. Y. Xu & Singh, 2004) thereby accuracy of transferability of calibrated parameters of lumped conceptual Tank model in daily scale which can be used for modeling of ungauged catchments in Nilwala River basin should be critically evaluated.

1.6 Study Area

The study has focused on two tributaries of Nilwala River basin in the Wet Zone of Sri Lanka. Nilwala River begins near Deniyaya and traverses about 70 km towards sea outfall at Matara to discharge accumulated water through a drain area of 1,073 km^2. The basin receives rainfall from both South-West monsoon and North-East monsoon with an annual average rainfall around 4,000 mm and nearly 40% of total annual rainfall is drained to the sea annually (Abeynayake, 2000).

The terrain of the upstream area of the basin from Bopagoda which is located 36 km upstream of the sea, is hilly terrain with a steep longitudinal slope higher than 0.4 m per km and downstream area has a mild slope with broader valley area (Elkaduwa & Sakthivadivel, 1999). This variation in terrain and the rainfall pattern over the basin have made the Nilwala basin as one of the major flood-prone basins in Sri Lanka

(Imbulana et al., 2006) where downstream area undergoes frequent flooding in last few years.

There are two operational river gauging stations at Pitabeddara and Urawa in upstream of Nilwala river basin under the supervision of the Department of Irrigation, Sri Lanka. The catchments at Pitabeddara and Urawa are shown in Figure 1-1 where the drainage areas are 291 km^2 and 52 km^2 respectively and, these two catchments were considered to achieve the objectives of the study.

1.7 Objectives of the Study

1.7.1 Overall Objective

To critically evaluate the accuracy of transferability of lumped conceptual Tank model parameters for quantification of water resources in the ungauged catchment of Nilwala River Bain in order to assist proper water resource management.

1.7.2 Specific Objectives

Following task are carried out to fulfill the overall objective of the research.

1. Identification of necessity of water resources assessment in ungauged catchments

2. Review the state of art on conceptual models for water resources management

3. Data collection, checking, and verification

4. Develop a Lumped Tank model for Pitabaddara and Urawa catchments

5. Calibrate and validate the Tank model parameters

6. Transfer the calibrated model parameters from the main catchment to sub-catchment and vice versa, and evaluate the model results

7. Propose recommendations on transferability of the Tank model parameters

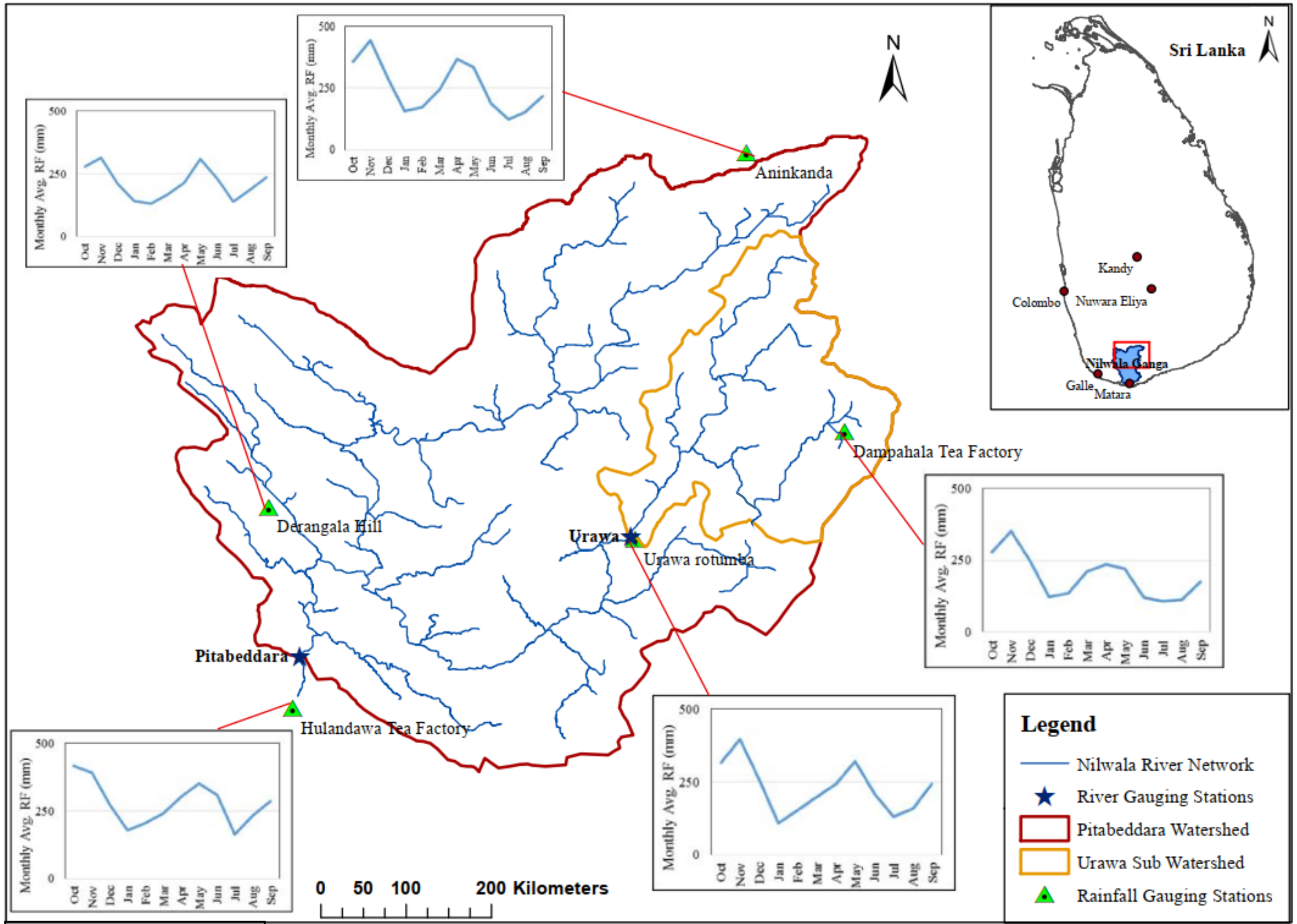

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Figure 1-1: Study Area in Nilwala River Basin

2 Literature Review

2.1 General

Changing of consumption pattern of a growing population with the expansion of production and services sectors such as agriculture, industries, and energy sector, with respect to the economic growth, have pressurized the freshwater availability where the situation is twisted with pronounced climate change impacts on water resources (FAO, 2012; Radif, 1999; UN, 2006). Hence, the proper water resources management and planning strategies based on the quantity and quality of available water resources, have to be practiced by all types of stakeholders. In that context, streamflow is the major input that is taken from gauged data or estimated data through hydrological models. Since the majority of catchments in the world are ungauged, streamflow estimation for such catchments has been hindered thereby compromising the sustainable water resources management in such catchments. Hence a methodology for accurate estimation of streamflow in ungauged catchments should be established where most practicing engineers and modelers are practicing streamflow extrapolation or streamflow transferring methods to quantify the streamflow in ungauged catchments with a considerable level of uncertainty. Therefore, a literature survey was carried out by using hydrological textbooks, scientific search engines, and peer-reviewed researches in the direction of identification of available and recommended methods for streamflow estimation in ungauged catchments. The review has focused on streamflow transferring methods, hydrological modeling, model calibration & validation, and model evaluation.

2.2 Water Crisis and Necessity for Water Resources Management

Water is a renewable but finite resource that is consumed by a variety of stakeholders for their persistence and development (FAO, 2012). Hence growing demand on the water with population growth and expansion of water demanding sectors, creates water scarcity within the country (Radif, 1999; Samad et al., 2017; UN, 2006). Thus, this crisis led the decision-makers and water managers to develop and practice water resources management plans in a sustainable manner (Othman et al., 2014).

2.3 Streamflow Prediction and Transferability

Streamflow is the combination of base flow (return flow from groundwater), interflow (rapid subsurface flow), and saturated overland flow from the surface (Maidment, 1993). An accurate estimation of streamflow is one of the major input for proper planning and management of water resources and their usages by different stakeholders such as drinking water supply, industrial users, irrigation purposes, flood controlling, environment, etc. (Nruthya & Srinivas, 2015; Tamalew & Kemal, 2016). In such situations, continuous streamflow data are used to design critical engineering structures such as reservoirs, drainage systems, and other water controlling structures that enable solving engineering and environmental problems (Kokkonen et al., 2003; Razavi & Coulibaly, 2013). But in the field of hydrology, there is only a limited range of measurement techniques and a limited range of measurements about the hydrological systems (Beven, 2012; Pechlivanidis et al., 2011).

In that context, rainfall-runoff models or watershed models are being used by hydrologists and researchers as a tool for the prediction of catchment streamflow w.r.t. quantity or quality (Patil & Stieglitz, 2014; Singh & Woolhiser, 2002). There are different types of models based on model structure, temporal and spatial scale of analysis, model concept, etc. in the field of hydrological modeling. A detailed literature review on hydrological models and modeling is stated in Section 2.4.

Although, the models enable the prediction of streamflow in a reliable manner, the models involve the calibration of model parameters by using observed data prior to carrying out any predictions (Patil & Stieglitz, 2014). But the majority of the rivers, stream reaches, and tributaries in the world are ungauged or poorly gauged where observed data are limited or not available (Nruthya & Srinivas, 2015; Razavi & Coulibaly, 2013) thereby most hydrological models cannot be directly used for estimation of streamflow in ungauged catchments. Hence estimation of streamflow of ungauged catchments is usually based on transferring or extrapolating information from gauged to ungauged catchments, a process called ‘Regionalization’ (Patil & Stieglitz, 2014; Razavi & Coulibaly, 2013, 2016; Tamalew & Kemal, 2016). In that context to have greater confidence in regionalization, donor, and receiver catchments should form a relatively homogeneous group (Kokkonen et al., 2003; Razavi & Coulibaly, 2013).

In general, the attributes such as catchment area, elevation, slope of basins or channels, and mean annual or daily rainfall and temperature are considered to develop the regionalization approach (Razavi & Coulibaly, 2013). There are several different approaches for regionalization that are used by hydrologists and researchers during streamflow prediction in ungauged catchments. Table 2.1 illustrate such methods used by researchers in their studies.

According to the review study done by Razavi & Coulibaly (2013), following regionalization approaches have been cited.

i. Arithmetic Mean Method
ii. Spatial Proximity (spatial distance) Approach
iii. Physical Similarity Approach
iv. Scaling Relationship
v. Regression-based Methods
vi. Hydrological Similarity Approach

In the arithmetic mean method, the calibrated rainfall-runoff model parameters of surrounding basins are averaged and averaged values will be used in modeling for ungauged catchment (Razavi & Coulibaly, 2013; Tamalew & Kemal, 2016) under the assumption that all basins within the region are similar in hydrological behavior and differences in parameter values arise from random factors (Kokkonen et al., 2003).

The spatial proximity approach refers to the transferring of model parameters based on the spatial distance between gauged catchments and ungauged catchment (Razavi & Coulibaly, 2013). This method assumes that closest catchments are hydrologically similar (Patil & Stieglitz, 2014) thereby spatial interpolation techniques such as inverse distance weighted (IDW) method will be used to find parameters for ungauged catchment w.r.t. gauged catchment (Razavi & Coulibaly, 2016).

Based on the similarity of physical attributes of gauged (donor) and ungauged (receiver) catchments, calibrated model parameters can be transferred which is called as physical similarity approach (Razavi & Coulibaly, 2013).

The scaling approach predicts on the idea that the streamflow contribution from each sub-catchment to the main catchment yield is proportional to a ratio of the catchment area or other attributes which calculate the streamflow in ungauged catchment directly through the ratio (Razavi & Coulibaly, 2013; Tamalew & Kemal, 2016). This is one of the simplest methods for streamflow prediction in ungauged catchments (Nruthya & Srinivas, 2015).

In the regression-based methods of regionalization, a linear or non-linear relationship between hydrological parameters and catchment attributes is developed and it shall be used in modeling for ungauged catchments (Razavi & Coulibaly, 2013; Yokoo et al., 2001). This method is widely used by hydrologists in the context of regionalization (Kokkonen et al., 2003).

All these methods have a different level of performance in regionalization. Although hydrologists confront difficulties in regionalization as uncertainty in model parameters, optimum parameter sets depend on the type of model and objective functions, and availability of different combinations of possible parameter values which can illustrate similar model performance (Bárdossy, 2007).

Table 2-1: Summary of Regionalization Methods

Reference	Location	Regionalization Methods	Data Resolution	Recommendation
Yokoo, Kazama, Sawamoto, & Nishimura, (2001)	Japan	Regression Analysis	Daily Data	The regression method is suitable for streamflow prediction in ungauged catchments
Nepal, Flügel, Krause, Fink, & Fischer (2017)	Glaciated catchments in Nepal	1. Proxy-basin approach 2. Temporal transferability	Daily Data	
Kokkonen et al. (2003)	North Carolina	1. Mean of available parameter values are used for Ungauged catchment 2. Regression Method 3. Transfer parameter directly from a likely similar hydrological catchment	Daily Data	1. Mean of parameters is not suitable for regionalization
Patil, Stieglitz (2015)	756 catchments in the USA	1. Temporal parameter transfer 2. Spatial parameter transfer 3. Spatiotemporal parameter transfer: a combination of temporal and spatial transfer	Daily Data	Temporal transferability is best, but Spatio-temporal transferability has solidity in regionalization.

Razavi & Coulibaly (2016)	90 catchments in Canada	1. Inverse distance weighted method (IDW) 2. Multi-layer perceptron (MLP) 3. Counter propagation neural network (CPNN) 4. Support vector machine (SVM)	Daily Data	MLP technique was very competitive with the IDW, a combination of watershed classification and regionalization give high performance
Oudin, Andreassian, Perrin, Michel & Moine (2008)	913 French catchments	1. Regression approach 2. Spatial proximity	Daily Data	
Song (2019)	49 catchments in Korea	Multiple linear regression method	Daily Data	

2.4 Hydrological Models and Application

Presently, hydrological models are increasingly used as the main tool for water resources assessment, management, planning, and development in the direction of achieving sustainable development in the country (Devia et al., 2015; C. Y. Xu & Singh, 2004). Under those varieties of water resources activities, hydrologic models are capable of analyzing quantity and quality of water, based on spatial and temporal inputs (Singh & Woolhiser, 2002; Sitterson et al., 2017).

According to Devia et al., (2015) a model is used to represent the real-world system in a simple manner where the model is capable of predicting the behavior of the system in different hydrological phenomena. Since the model structure consists of different functions with various parameters to represent the catchment characteristics, the model with the least parameters and less complexity in which predictions are closer to reality is considered as the best model for hydrological modeling (Devia et al., 2015).

Different types of hydrologic models are available in the field of hydrologic modeling based on the model structure, functionality in space and functionality in time (Devia et al., 2015; Sitterson et al., 2017).

The type of models w.r.t the model structure are empirical models, conceptual models and physical process-based models and each type of models can be further categorized as lumped, semi-distributed and distributed models w.r.t consideration of spatial processes of the catchment (Singh & Woolhiser, 2002; Sitterson et al., 2017).

The conceptual models simulate the hydrological system by conceptualizing the catchment as series of interconnected reservoirs with simple equations where the reservoirs receive water as rainfall, infiltration or percolation and discharge water as runoff at the catchment outlet, evaporation, etc. (Singh & Woolhiser, 2002; C. Y. Xu & Singh, 1998). Conceptual models are widely used and very popular in the field of hydrologic modeling due to their ease of use, less time consuming for modeling, and limited data requirements (Sitterson et al., 2017).

The physical process-based models simulate the hydrologic system by using the underline physics of the hydrologic processes incorporating a large number of meteorological and physical characteristics of the catchment (Sitterson et al., 2017). Thus, it requires more data and details of the catchment to predict the streamflow and at the same time deliver a vast range of information on the processes of the catchment (Devia et al., 2015).

2.5 Selection of Hydrologic Model

Different kinds of models with various capabilities are available for hydrological modeling as mentioned in the above section. Many studies and inter-comparisons have been carried by the researchers in a common aim to find the best model for simulation of hydrological processes (Esse et al., 2013). Identification of suitable model from that wide list will be based on the intended purpose such as understanding and identifying hydrological processes, estimation of runoff yield for proper management and planning purposes, identification of frequency of runoff events, etc. while the availability of spatial and temporal data, time, availability of budget for models and previous applications in similar region confine the selection of a suitable model for achieving the relevant objectives (Razavi & Coulibaly, 2013; Sitterson et al., 2017).

Models with simple yet refined methods and with less number of parameters range from two to five to illustrate hydrological processes under low input requirements are the best choices of the researchers (Bai et al., 2015). Perrin, Michel, & Andréassian (2001) have done a study for 429 catchments in France, United States, Australia, Brazil, and the Ivory Coast by using 19 different models to identify the suitable number of parameters to achieve higher model performance where the study illustrated that simple models outperform than models with more parameters. A similar conclusion has been made in the study of Esse et al. (2013) that relatively simple models simulate catchment discharges accurately and increasing model complexity does not always lead to higher performance for a given catchment. Because inadequate complexity in model typically results from over-parameterization and parameter uncertainty which are leading to instability in the model structure in the direction of extracting information available in hydrological time-series (Perrin et al., 2001).

Thus simple model may be able to achieve comparable or even better performance than the complex models (Bai et al., 2015). In the case of regionalization where parameter identification is a difficult task, simple models are very important since a low level of uncertainty incorporated with parameters of such models (Perrin et al., 2001). Hence, simple models are better for this study.

2.5.1 State of Art in Streamflow Prediction in Ungauged Catchments

The main purpose of the study is the prediction of streamflow in an ungauged catchment based on the regionalization concepts which were discussed in Section 2.3. Hence comprehensive literature review on previous regionalization concept applications has been carried out.

Yokoo, Kazama, Sawamoto, & Nishimura (2001) have used a lumped conceptual tank model for modeling 12 catchments in Japan, and the regression method was followed as a regionalization method. A similar type of study has been done by Song, Her, Suh, Kang, & Kim (2019) for 49 catchments in Korea using a three-layer Tank model to evaluate the performance of the Tank model for streamflow predictions in ungauged catchments. Three regionalization methods were evaluated by Kokkonen, Jakeman, Young, & Koivusalo (2003) for 13 catchments in North Carolina using a lumped conceptual model named as IHACRES model in daily temporal resolution.

GR4J and TOPMO continuous lumped rainfall-runoff models on a daily scale were used by Oudin, Andréassian, Perrin, Michel, & Le Moine (2008) and investigated the performance of applicability of regionalization for 913 catchments in French. Patil & Stieglitz (2015) also have evaluated different schemes of parameter transfer for 756 catchments in the USA by using the spatially lumped version of the EXP-HYDRO model in daily temporal scale and concluded that spatiotemporal transferability has solidity in regionalization w.r.t the model used. In the same continent, 90 Canadian catchments were hydrologically modeled on a daily scale by Razavi & Coulibaly (2016) using two lumped conceptual models named as MAC-HBV model and SAC-SMA model and assessed different regionalization techniques for those selected catchments.

Nepal, Flügel, Krause, Fink, & Fischer (2017) have assessed different parameter transferability techniques for daily resolution streamflow predictions in two catchments in Koshi river in Nepal by using process-based J2000 hydrological model and concluded that the J2000 model has the ability to predict streamflow in ungauged catchments in the Himalayan region by transferring the parameters developed for a close-by gauged catchment with similar geophysical characteristics.

2.5.2 Model Comparison

The applications of various models in the direction of regionalization, above mentioned models, and applications were compared towards the objective for identifying available best hydrological model to carrying out this study.

The models were evaluated based on a few criteria that were selected according to the objective of the study. Three qualitative levels as high, medium, and low were considered for each criterion and the respective weights were 5, 3, and 1. The qualitative scale of each criterion w.r.t the characteristics of the model is given in Table 2-2.

Table 2-2: Qualitative scale of criteria for model comparison

Criteria	High	Medium	Low
Spatial scale	Lumped	Semi-distributed	Distributed
Model concept	Conceptual	-	Process-based
No. of parameters	Less than 6	More than 6 but less than 12	More than 12
Temporal resolution	Daily	Hourly or less	Monthly
Data requirement	Less data requirement	Moderate data requirement	More data requirement
Model concept complexity	Simple and easy to understand	-	Complex
Applications on transferability	Worldwide many applications	Few applications in worldwide	Only applications in regional level

The quantitative analysis based on the criteria is given in Table 2-3. Accordingly the second-best available model for fulfilling the objective of this study is the GR4J model.

Table 2-3: Comparison of hydrologic models

No	Reference	Model Name	Spatial Scale	Model Structure	No.of Parameters	Temporal Scale	Data Requirement	Model Concept	Applications on transferability	Total Marks
1	Nepal, Flugel, Krause, Fink & Fscher (2016)	Proces oriented J200	Low(1)	Low(1)	Low(1)	High (5)	Low(1)	Low(1)	Low(1)	11
2	Kokkonen, Jakeman, Young & Koivusalo (2003)	IHACRES	High (5)	High (5)	High (5)	High (5)	Medium (3)	Low(1)	Low(1)	25
3	Patil & Stieglitz (2015)	EXP-HYDRO	High (5)	High (5)	High (5)	High (5)	Medium (3)	High (5)	Low(1)	29
4	Razavi & Coulibaly (2016), Samuel, Coulibaly, & Metcalfe, (2011)	MAC-HBV	High (5)	High (5)	Low(1)	High (5)	Medium (3)	Low(1)	Low(1)	21
5	Razavi & Coulibaly (2016)	SAC-SMA	High (5)	High (5)	Low(1)	High (5)	Medium (3)	Low(1)	Low(1)	21
6	Oudin, Andreassian, Perrin, Michel & Moine (2008)	GR4J	High (5)	High (5)	High (5)	High (5)	High (5)	High (5)	High (5)	35
7	Oudin, Andreassian, Perrin, Michel & Moine (2008)	TOPMO	High (5)	Low(1)	High (5)	High (5)	Low(1)	Low(1)	Low(1)	19
8	Tamalew & Kemal (2016) & Bárdossy (2007)	HBV-96	Medium (3)	High (5)	Medium (3)	High (5)	Medium (3)	Low(1)	High (5)	25
9	Zhu, Zhang, Ma, Gao, & Xu (2016), Heuvelmans, Muys, & Feyen (2004)	SWAT	Low(1)	Low(1)	Low(1)	High (5)	Low(1)	Low(1)	High (5)	15
10	Shrestha et al., 2007	BTOPMC model	Low(1)	Low(1)	High (5)	High (5)	Medium (3)	Low(1)	Low(1)	17
11	Van Der Linde & Woo, 2003	SLURP model	Low(1)	Low(1)	Medium (3)	High (5)	Low(1)	Low(1)	Low(1)	13
12	Goswami, O'Connor, & Bhattarai, 2007	SMAR	High (5)	High (5)	High (5)	High (5)	High (5)	High (5)	Low(1)	31
13	Broderick, Matthews, Wilby, Bastola, & Murphy, 2016	NAM	High (5)	High (5)	High (5)	High (5)	High (5)	High (5)	Low(1)	31
14	De Silva, Weerakoon, & Herath, 2014	HEC-HMS	High (5)	Low(1)	Low(1)	High (5)	Medium (3)	Low(1)	High (5)	21

2.5.3 Lumped Conceptual Tank Model

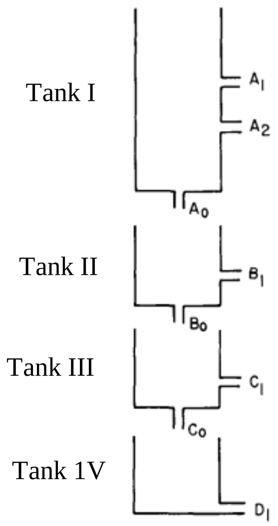
Most practicing engineers and water managers prefer hydrological models to predict streamflow responses which are easy to use with low input data requirements where lumped conceptual models are undoubtedly useful in that context (Perrin et al., 2001; Razavi & Coulibaly, 2013; Singh & Woolhiser, 2002). In the direction of better model performance, distributed models were used by incorporating more physical characteristics into the model structure, but when considering the overall performance of the model, lumped models outperformed the distributed models (Reed et al., 2004). In addition to that, Razavi & Coulibaly (2013) have stated that when modeling ungauged catchments, it is better to use a lumped conceptual model over distributed models which requires more data and human efforts in simulation. (C. Y. Xu & Singh, 2004) have indicated that lumped conceptual models can simulate the hydrological processes and generate catchment outflows at an adequate level of accuracy for practicing engineers in the field. Further the conceptual models have pronounced ability to generate records of runoff for better water resources planning and designing in ungauged catchments (C. Y. Xu & Singh, 1998). In the same time, in regionalization studies, mostly used hydrological models are conceptual models (Razavi & Coulibaly, 2013). Hence based on the objective of the study, it has focused and used a lumped conceptual model for analyzing hydrological processes in the selected catchments.

All the researchers and modelers expect to have a model with a better performance where Bai et al. (2015) have cited that artificial intelligence models which are conceptual models exhibit such performances in some studies. But due to over-parameterization and over-fitting, artificial intelligence models have also been criticized for using in the simulation of hydrological processes (Gaume & Gosset, 2005). Hence, a simple conceptual model is preferred in this study.

This study considered the Tank model which is a popular rainfall-runoff model developed by Sugawara for catchments in Japan, but later it is used by many researchers and hydrologists all over the world because of its simple analytical structure and accurate forecasting of runoff (Devaliya, Tiwari, & Balvanshi, 2017; Kuok et al., 2011). Yokoo, Kazama, Sawamoto, & Nishimura (2001) have also stated that the Tank model has higher performance in runoff simulation with compared to other lumped conceptual models. Further past studies using the Tank model have shown a higher level of accuracy in streamflow predictions for humid and mountainous catchments (Song et al., 2019).

2.5.4 Tank Model Structure

The Tank model concept has been developed by Sugawara followed by continuous enhancements to the model structure. Kuok et al. (2011) have stated that five different types of Tank model structures named as Exponential type, Parallel Exponential type, Overflow type, Storage type, and Series Storage type had been developed by Sugawara in 1957 where the best type of model was the series storage type, Tank model. The successive development of the Tank model structure by Sugawara (1967, 1974 & 1984), four storage tank structure was introduced to illustrate the real-world runoff conditions of a catchment named as surface runoff, intermediate runoff, sub-base runoff and base flow (Kuok et al., 2011). The four storage tank structure is shown in Figure 2-1. Rainfall and evapotranspiration are the main inputs to the model.



A_0 - Infiltration coefficient from Tank I to Tank II
A_1 - Side outlet coefficient No.1 for Tank I
A_2 - Side outlet coefficient No.2 for Tank I
B_0 - Infiltration coefficient from Tank II to Tank III
B_1 - Side outlet coefficient for Tank II
C_0 - Infiltration coefficient from Tank III to Tank IV
C_1 - Side outlet coefficient for Tank III
D_1 - Side outlet coefficient for Tank IV

Figure 2-1: A Simple Tank Model Structure

Source: (Phien & Pradhan, 1983)

The output through side outlets of the top tank is considered as surface runoff, the output through side outlet of the second tank as intermediate runoff, from the third tank as sub-base runoff and output through bottom side outlet of the fourth tank as base flow (Sugawara, 1995). A_0, A_1, A_2, B_0, B_1, C_0, C_1, and D_1 are side and bottom outlet coefficients of storage tanks which are able to control the runoff and infiltration phenomena and HA_1, HA_2, HB_1 and HC_1 are storage heights of outlets from the bottom of the respective tank (Phien & Pradhan, 1983). The total output volume from all side outlets is the total runoff of the catchment.

The researches have defined different ranges for the parameters of the model which is summarized in Table 2-4.

Table 2-4: Defined ranges for Tank model parameters

Parameter	Jaiswal, Ali, & Bharti (2020)	Song, Her, Park, Lee, & Kang (2017)	Setiawan, Fukuda, & Nakano (2003)	Chen, Pi, & Hsieh (2005)
A0	0 - 1.0	0.1 - 0.5	0 - 1.0	0 - 1.0
A1	0 - 1.0	0.08 - 0.5	0 - 1.0	0 - 1.0
A2	0 - 1.0	0.08 - 0.5	0 - 1.0	0 - 1.0
B0	0 - 1.0	0.01 - 0.35	0 - 1.0	0 - 1.0
B1	0 - 1.0	0.03 - 0.5	0 - 1.0	0 - 1.0
C0	0 - 1.0	0 - 0.11	0 - 1.0	0 - 1.0
C1	0 - 1.0	0.003 - 0.03	0 - 1.0	0 - 1.0
D1	0 - 1.0	NA	0 - 1.0	0 - 1.0
HA1 (mm)	0 - 300	5.0 - 60.0	5.0 - 15.0	0 - 150
HA2 (mm)	0 - 500	20.0 - 110.0	25.0 - 60.0	0 - 150
HB1 (mm)	0 - 100	0.0 - 100.0	0.0 - 30.0	0 -100
HC1 (mm)	0 - 100	0.0	0.0 - 60.0	0 - 100

Besides, many researchers and hydrologists have made a different enhancement to the structure w.r.t the physical condition of the catchment and changed the number of storage tanks in the model during rainfall-runoff modeling. Cooper, Nguyen, & Nicell (1997 & 2007) had used two storage tanks for the Tank model structure to simulate runoff. Kuok et al. (2011) have evaluated 3, 4, and 5-Tank series storage type Tank model. Basri (2013) has used 1, 2, 3, and 4-Tank series storage type Tank models in his studies.

In order to incorporate variations in soil moisture content to the model, additional structures were added to the bottom layer of the top tank to represent the effect of the primary and secondary soil moisture storages (Sugawara, 1995).

2.5.5 Advantages and Limitations of Tank Model

The main advantage of the Tank model is that it can be freely and simply developed in MS Excel software to simulate streamflow with satisfactory level of accuracy comparable with other models (Arifjaya, Kusmana, Abdulah, Prasetyo, & Setiawan, 2011; Kuok et al., 2011). Major drawback of this model was the difficulty in optimization of model parameters since the model involve many discrete functions, but with present computer technology, it has been an easier task (Setiawan et al., 2003; Song et al., 2019; Yokoo et al., 2001). Further the model has ability to model vertical and horizontal water distribution through the four tanks (Arifjaya et al., 2011).

Jaiswal, Ali, & Bharti (2020) stated that the accuracy of model simulations depends on the quality of input data since the model strongly rely on observed data which limited the applications of this model in data scares situations. Since the Tank model simulate the catchment as a lump, it is limited to provide streamflow in main outlet and unable calculate flow in each tributaries (Kubo & Don, 2000).

Kubo & Don (2000) have further stated that runoff analysis in low flat areas with tidal effect cannot be carried out with the Tank model because the model is unable to deal with backwater effects in its structure.

2.5.6 Applications of Tank Model

The Tank model has been used by many hydrologists and researchers on achieving different objectives of hydrological studies in different areas of the world, especially in the Asian region.

The Tank model has been used to simulate the streamflow in few basins in Sri Lanka. Wijesekera (1993) has simulated streamflow of Mahaweli River basin at the gauging station Peradeniya by using 3-tank and 4-tank structure Tank models. Further, by using the 3-tank structure Tank model, streamflow of Gin Ganga basin in Sri Lanka was simulated by Wijesekera (2000).

Devaliya et al. (2017) have used the Tank model on a daily scale for water resources assessment in a basin of Central India and they cited many other applications of the model in India for a similar objective. Phien & Pradhan (1983) and Song, Her, Park, Lee, & Kang (2017) have used the Tank model for runoff generation on a daily scale in two basins of Thailand and an hourly scale for a catchment in Korea.

As a tool for preliminary investigation of the potential effect of an increase or a decrease in the imperviousness of urbanizing catchments on both runoff volumes and peak flood flows, the Tank model has been used by Ou, Gharabaghi, Mcbean, & Doherty (2017). Similarly for a flood analysis in a basin of North-Central Vietnam, the Tank model has been used by Phuong, Tien, Chikamori, & Okubo (2018) on a monthly temporal scale. Arifjaya, Kusmana, Abdulah, Prasetyo, & Setiawan (2011) have used the Tank model for water balance calculation of a catchment in West Java.

Setiawan, Fukuda, & Nakano (2003) have applied the Tank model for catchments in Japan and Indonesia to illustrate the applicability of the model in different regions. In order to evaluate the applicability of the Tank model for parameter regionalization, Yokoo et al. (2001) have used the model for catchments in Japan. To incorporate the effect of changes in land use within the catchment, the Tank model has been applied in the studies of Basri (2013) for different catchments in Indonesia.

2.6 Warm-up Period

Although there are various types and concepts of hydrological models and modeling, the most important requirement of the modelers is the accuracy of estimates where removal of any initialization bias become a most critical issue in assuring the accuracy of those estimates from a hydrological model (Hoad, Robinson, & Davies, 2008). But the issue with specifying the correct initial conditions of the catchment to the hydrological model is unaddressed by the modeling community yet (K. B. Kim, Kwon, & Han, 2017).

Hence Hoad et al., (2008) cited that there are few methods to overcome this issue, and following one of them would remove the initialization bias in the hydrological model. The methods which they cited are,

i. Run-in model for a warm-up period until it reaches a realistic condition. Delete data collected from the warm-up period
ii. Set initial condition for realistic value,
iii. Set partial initial condition then run warm-up period and delete warm-up data
iv. Run the model for a long time making bias effect negligible
v. Estimate the steady-state parameters from a short transient simulation run

Similarly, the uncertainty involved with unknown initial conditions of stores shall be minimized either by calibrating the initial conditions or by using a warm-up period (Wagener, Wheater, & Gupta, 2004).

The model warm-up period is used to allow the initial soil moisture to adjust their condition to an optimal state or dynamic equilibrium condition (Daggupati et al., 2015; K. B. Kim et al., 2017). Normally the soil store value in that optimal state is independent of the assumed initial value for soil store (Johnston & Pilgrim, 1976).

However, the optimal soil moisture value is based on in-situ soil moisture data which observations are scarce in most places thereby estimation of the warm-up period becomes difficult (K. B. Kim et al., 2017).

The time period required to reach optimal state will be governed by the temporal and spatial scale of the physical processes of the catchment as well as the complexity of the model structure (Daggupati et al., 2015). The amount of rainfall and the initial wetness of the soil also have a direct impact on the time required for reaching the optimal state (K. B. Kim et al., 2017). Hence the length of the warm-up period may be ranged from months to several years, but one to four years of warm-up period is being commonly used by the hydrological modelers (Daggupati et al., 2015; K. B. Kim et al., 2017). As examples Razavi & Coulibaly (2016), Li et al. (2010) & Oudin, Andréassian, Perrin, Michel, & Le Moine (2008) have used one year period as the warm-up period of their hydrological model. Song, Her, Park, Lee, & Kang (2017) have used two years as a warm-up phase of the Tank model.

Johnston & Pilgrim, (1976) stated that the lower soil stores will need a long period with heavy rainfall to reach an optimal state. Hence the initial value of lower soil store shall be considered as a parameter of the model and the model shall be warmed-up for other stores. Daggupati et al., (2015) stated that the selection of a warm-up period should be done very carefully since it may affect the performance of the model by resulting bias simulated results.

2.7 Model Calibration and Validation

After the selection and development of the hydrologic model to a catchment, the model parameters should be setup w.r.t catchment properties to represent the reality. But in general, it is impossible to estimate the parameters by physical measurements thereby the common practice is to follow parameter calibration which is a systematic methodology of adjusting the values of model parameters to achieve the best fit between model predictions and the observations of catchment responses (Beven, 2012). Comparison of the matching between model predictions and catchment observations through visually is subjective, difficult to reproduce, and dependent on expert judgments thereby objective and reproducible numerical criteria such as objective functions are used (Gracia, Folton, & Oudin, 2017).

There are two basic approaches followed by the modelers in the calibration of hydrologic models namely manual calibration and automatic calibration (Sorooshian & Gupta, 1983). The manual calibration approach is to adjust the model parameters subjectively based on specific characteristics of model predictions and observed data where the modeler should have a comprehensive understanding on model structure and the catchment runoff behavior w.r.t physical and climatic properties (Sorooshian & Gupta, 1983; Wagener et al., 2004). When the number of parameters to be calibrated is higher and the model structure is complex, manual calibration is often time-consuming and requires significant expertise with more skills and experiences in hydrologic modeling (Daggupati et al., 2015; Kumarasamy & Belmont, 2018; Wurbs, 1994).

The automatic calibration approach refers to the utilization of computer software to adjust the model parameters based on the variation of mathematical error function named as objective function with the help of optimization algorithms (Sorooshian & Gupta, 1983).

Since the model calibration is a site-specific process, the model should demonstrate that it is capable of predicting hydrological responses of a different period or situation with an acceptable level of accuracy prior to using it as a forecasting tool (Daggupati et al., 2015; Patil & Stieglitz, 2015). This demonstration process is called model validation. The validation of the model is done under the basic assumption that calibrated model parameters are temporally stable (Patil & Stieglitz, 2015).

2.7.1 Objective Function

An objective function is a numerical relationship between observed data and calculated output of the model which is a quantitative measure of goodness-of-fit of the model calibration (Diskin & Simon, 1977; Shaw, 1994; Sitterson et al., 2017). Pechlivanidis et al. (2011) have stated that most common objective functions are developed based on the least-squares methods and maximum likelihood methods. The development of objective functions aims to a reconstitution of the volume of runoff, restoration of hydrograph dynamics and to achieve no or lesser time lag between observed and estimated streamflow (Servat & Dezetter, 1991).

There are various objective functions available in the field of hydrologic modeling which focus on different aspects of flow regime thereby there may not be a universal function to measure the model performance (Beven, 2012). Hence the selection of an objective function for a study depends on the aim of the study and time step of hydrological modeling (Diskin & Simon, 1977; Gracia et al., 2017).

Hwang, Ham, & Kim (2012) have stated three categories of objective functions named as scale-dependent error measures, measures based on relative errors (scale independent) and relative measures where S. Kim & Kim (2016) have aggregated these three categories into major two categories as scale-dependent and scale-independent measures. The mean square error (MSE), root mean square error (RMSE), mean absolute error (MAE) are few examples to scale-dependent measures which suitable for data with the same scale and not be suitable for data series with different scales (Hwang et al., 2012; Hyndman & Koehler, 2006; S. Kim & Kim, 2016). Commonly used objective functions are,

1. **Nash Sutcliffe efficiency coefficient (NSE)**

   Servat & Dezetter (1991) cited that the NSE was formulated based on regression analysis by Nash & Sutcliffe (1970). The function calculate the percentage of the residual variance compared to the total variance of observed data (Servat & Dezetter, 1991). The formula of the NSE is;

$$NSE = 1 - \frac{\sum_{i=1}^{N}(Q_c - Q_O)^2}{\sum_{i=1}^{N}(Q_O - \bar{Q}_O)^2}$$

   Where, Q_C is calculated streamflow, Q_O is observed streamflow and $\bar{Q}_O$ is mean of observed streamflow. The optimum value for NSE is 1 and it ranges from -∞ to 1.0. Esse et al. (2013) and Song et al. (2019) have mentioned that the NSE is more sensitive for high flows and tends to mislead on other flow conditions.

2. **Root Mean Square Error (RMSE)**

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(Q_C - Q_o)^2}$$

   The optimum value of RMSE is zero and its upper limit is infinity (Hwang et al., 2012). Song et al. (2019) stated that RMSE is more sensitive to high flows.

3. **Mean Ratio Absolute Error (MRAE)**

$$MRAE = \frac{1}{N}\sum_{i=1}^{N}\frac{|Q_C - Q_O|}{Q_O}$$

   Dissanayake (2017), Kamran & Rajapakse (2018), and Wijesekera (1993, 2000) have used the MRAE for their studies to evaluate the error in the overall flow regime. Kamran & Rajapakse (2018) cited that the MRAE is suitable for continuous model simulation evaluations where the optimum value of MRAE is zero.

4. **Coefficient of Determination (R^2)** (M.-X. Jie, Chen, Xu, Zeng, & Tao, 2016; Nepal et al., 2017; Song et al., 2017).

In addition to those commonly used OFs, researchers use a different kind of OFs in their studies such as King-Gupta Efficiency (Bai et al., 2015; Gracia et al., 2017; Patil & Stieglitz, 2015), Relative volume error (Tamalew & Kemal, 2016), Mean Absolute error (Hwang et al., 2012), Relative Absolute error (RAE) and Relative mean absolute error (RMAE).

Single objective functions are unable to capture the most of the aspects of model outputs or biased to individual aspect of model results thereby many studies have pointed out that multi-objective criteria approach facilitate robust evaluation for accuracy of model outputs (M.-X. Jie et al., 2016; Kumarasamy & Belmont, 2018; Mostafaie, Forootan, Safari, & Schumacher, 2018; Pechlivanidis et al., 2011). Similarly sometimes the researchers use common objective functions with appropriate transformations to evaluate different flow regimes (Gracia et al., 2017; Oudin et al., 2008).

2.7.2 Optimization Algorithms

A response surface can be defined by the values of objective function w.r.t different parameter values in the N-dimensional parameter surface. The optimization algorithm swipes over that response surface to find the optimum set of parameter values within the allowable ranges which gives the optimum value (minimum or maximum) for objective function (Beven, 2012; M. X. Jie, Chen, Xu, Zeng, & Tao, 2016; Pechlivanidis et al., 2011). This will assure the optimum matching between model predictions and real-world observations.

There are various types of optimization algorithms to achieve the global optimum for the objective function and they can be categorized into two main categories as deterministic methods based on well-defined mathematical search algorithms and probabilistic methods based on probability (Gill, Kaheil, Khalil, McKee, & Bastidas, 2006). The commonly used global optimization algorithms in the field of hydrologic modeling are Particle Swarm Optimization (PSO) (Bai et al., 2015; Li et al., 2010), Shuffled Complex Evolution (SCE) (M. X. Jie et al., 2016; Razavi & Coulibaly, 2016; Song et al., 2019), Powel Method (R. S. Chen et al., 2005; Yokoo et al., 2001), Genetic Algorithms (GA) (D. M. Xu, Wang, Chau, Cheng, & Chen, 2013), Simulated Annealing method (SA) (Cooper et al., 1997).

Optimization of the conceptual rainfall-runoff model is very complex since the model structure involves a non-linear relationship between the parameters (D. M. Xu et al., 2013). Olofintoye, Adeyemo, & Otieno (2013) have stated that the Evolutionary Algorithms (EA), where GA, PSO, SCE, differential evolution (DE), and genetic programming (GP) are subclasses of EAs are robust and dynamic algorithms to find the global optimum for water resources modeling.

Setiawan, Rudiyanto, Ilstedt, & Malmer (2007) have used the inbuilt optimization algorithm in Solver add-in in MS excel to find the optimum value for MAE objective function in the simulation of the Tank model.

In the Solver Add-in of MS Excel, there are three types of optimization search algorithms named GRG Nonlinear, Simplex LP, and Evolutionary. GRG Nonlinear engine is suitable for smooth nonlinear problems. Simplex LP is suitable for linear problems and the Evolutionary engine based on natural selection is for solving problems that are non-smooth("Excel Solver, Optimization Software, Monte Carlo Simulation, Data Mining - Frontline Systems," n.d.). Accordingly, to optimize the hydrologic model, the Evolutionary engine is better but it takes more computational power and time. Hence Frontline Systems (2020) mentioned that the GRG nonlinear engine with a multi-start option is capable of finding global optimum value for the objective and the process of searching is approximately similar to the process of Evolutionary engine.

2.8 Model Performance Evaluation

By referring to the value of the objective function, it is not sufficient to conclude that the model has simulated reality up to an acceptable level of accuracy and qualitative indications should also be used to evaluate the goodness-of-fit of the model predictions (Houghton-carr, 1999; Servat & Dezetter, 1991). Graphical techniques such as hydrographs and flow duration curves illustrate a visual comparison between estimated and observed streamflow. Hydrographs assist to identify the difference in time of occurrence and magnitude of the streamflow, and the shape of recession curves (Moriasi et al., 2007). In similar literature, they have cited that “the flow duration curves, can illustrate how well the model reproduces the frequency of measured daily flows throughout the calibration and validation periods”.

2.9 Data, Data Checking and Missing Data Estimation

2.9.1 Data

The availability of continuous data for different temporal and spatial scales is preferred for accurate simulation of hydrological models’ responses (Teegavarapu, Tufail, & Ormsbee, 2009). Wijesekera & Perera (2012) stated that the hydrological and meteorological data are the base for water resources development and management. In addition to those data, data on soil properties of the study area also has a greater impact on the performance of the model (Devia et al., 2015). In the same time these data sets should be representative of the catchment processes. In that context, some researchers and modelers had used longer period data sets into the hydrological model for the effective representation of the catchment processes (Ariyasena, 2019). But this will increase the computational efforts of the model and the cost for data acquisition. Li et al. (2010) cited that presently many studies have illustrated that longer data series will not result in better model performance over the other situations thereby they have recommended different lengths of data series based on the study area and type of model used. Typically, the data series is ranging from three months to ten years.

However Li et al. (2010) stated that eight years of data are sufficient for generating accurate daily estimation of catchment responses from the hydrological model with stable parameter values. A similar length of data series had been used for runoff calculation by using the Tank model in the studies done by (Phien & Pradhan, 1983). Generally in the case of conceptual rainfall-runoff modeling, one full hydrological year is the minimum data requirement for proper model calibration (Li et al., 2010). But

Basri (2013) has stated that a minimum of ten-year length data series is essential for accurate estimation of runoff using the Tank model.

Yokoo, Kazama, Sawamoto, & Nishimura (2001) have used three years of daily data for simulating the Tank model. Length of six years data series has been used by Devaliya, Tiwari, & Balvanshi (2017) for runoff estimation by using the Tank Model. In addition to that Setiawan et al. (2003) have used 10 years of daily data to simulate the Tank model for catchments in Indonesia. According to these reviews the length of data series required for better model performance can be identified.

2.9.2 Data Checking

In order to a simulate a hydrological model to represent the catchment responses, the data should be homogeneous and consistent, but due to natural or man-made changes to the gauging environment, the homogeneity and consistency of the data might be influenced and data might contain errors (Wijesekera & Perera, 2012). Hence the datasets should be subjected to an adequate checking process for their accuracy and validity to consider as satisfactory for use on the intended purpose (WMO, 2018).

The researchers follow different kinds of methods and tests to check the datasets. Basically, graphical methods or statistical tests are used in that context (Silva, Dayawansa, & Ratnasiri, 2007). Wijesekera & Perera (2012) stated different tests which are able to identify trends and changes in data set, such as Visual examination of Data, Outlier Testing, Homogeneity Testing with-Test for serial Correlation, Test for Pre-Whitening, Test for Normality, Spearman’s rank correlation test, Standard Normal Homogeneity Test (SNHT), Change point test (Pettitt test), Test for stability of variance (F-test), Test for stability of mean (t-test), Double Mass Analysis, Method of Cumulative Residuals (Ellipse test).

Visual examination of data enables to identify the sudden changes in the data time series (Wijesekera & Perera, 2012).

The Double Mass curve method which is used to check the consistency of data has been developed based on the principle that if each observed data comes from the same parent population, data should be consistent (Subramanya, 2008). The graph of the cumulative of data in one station against cumulative of data in other stations considered during the same period is the Double Mass Curve and it should be a straight line when data are proportional and consistent (Searcy & Hardison, 1960). Any change in the slope of the curve indicates that there is inconsistency in the data series and it can be rectified by adjusting the portion of the data set before inflection point w.r.t the gradient of the latter portion of data set (Wijesekera & Perera, 2012).

2.9.3 Missing Data Estimation

Missing data in a data series of rainfall, streamflow, or in any other input data type to a hydrologic model is a critical issue. For the reason, that availability of a continuous data series at different spatial and temporal scales is crucial for generating accurate catchment responses from the hydrological model (Suhaila, Sayang, & Jemain, 2008; Teegavarapu et al., 2009; Wan Ismail, Wan Zin, & Ibrahim, 2017). Hence estimation of missing values in the data series is the priority among the researchers and modelers where interpolation techniques are the most commonly used methods to fill those gaps in data series (Wan Ismail et al., 2017). In that context simple or complex and temporal or spatial interpolation techniques are available where simple technique refers to estimate missing data by computing the average of observed values on both sides of the gap (WMO, 2018). Spatial interpolation methods are the process of estimating missing data for a point by using available data in nearby stations (Wan Ismail et al., 2017).

Wan Ismail et al. (2017) have stated four interpolation techniques that are Arithmetic Average (AA) method, Normal Ratio (NR) method, Inverse Distance (ID) method and Coefficient of Correlation (CC) method. The Arithmetic mean method refers to obtain missing data in the series by the average of selected nearby stations around the target station. The Normal Ratio method is weighted based on the ratio mean of the available data between the target station and the other neighboring station. This method is used if any neighboring stations have the normal annual rainfall and streamflow data which exceeded more than 10% of the considered station. ID method is based on the fact that correlation between target station and other nearby stations is inversely proportional to the distance between them and in that basis gaps in data series will be estimated.

According to the studies of Wan Ismail et al. (2017), the best method from the above four methods was the Inverse distance method.

In addition to the above four methods Silva et al. (2007) have proposed a new method named Aerial Precipitation Ratio method. In that method it assumes that the contribution of rainfall from nearby stations is proportionate to the Thiessen polygon area covered by each station without considering the target station.

In view of the easy approach, computational efficiency, and the universal applicability of the above methods were used for estimating missing data in Mahaweli basin, Sri Lanka and Normal ratio method was the best method over Aerial Precipitation ratio method (De Silva, 1997).

According to the study by Silva et al. (2007), they have recommended different estimation methods for the different regions in Sri Lanka. Those are,

- The inverse distance method is suitable for all three low-country zones (wet, intermediate, and dry).
- The Normal ratio method is suitable for Mid-country and Up-country intermediate zones
- Arithmetic mean method is suitable for Up-country Wet zone area
- Aerial precipitation ratio method is appropriate for Mid-country wet zone area

3 Methodology

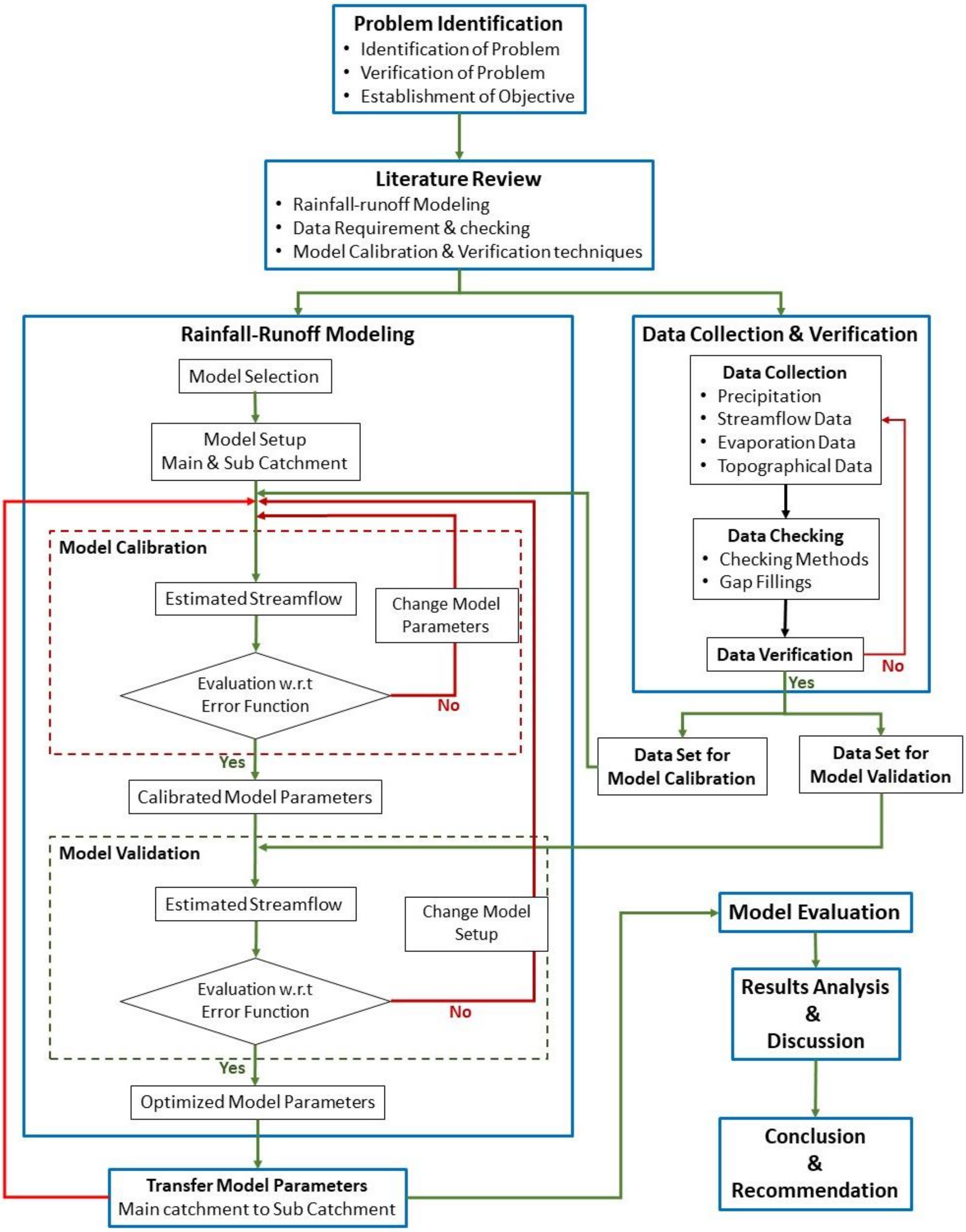


Figure 3-1: Methodology Flowchart of the Study

3.1 Selection of Catchments

In order to achieve the objectives of the study for evaluation of transferability of Tank model parameters, two catchments were selected in the same hydrological region where one catchment was a sub-catchment of the other selected catchment. Considering the availability of daily rainfall data and daily streamflow data within the study period (2008/09 water year to 2017/18 water year) in Nilwala Basin, Pitabeddara catchment, and Urawa sub-catchment were selected for the study.

3.2 Hydrologic Model Selection

Based on the comprehensive review of hydrological models performance and applications of models for regionalization in the past studies around the globe especially in Asia region, Tank Model was selected for this study by considering its simplicity in the model structure. According to the literature review, it was identified that many researchers and hydrologists in Asia region as well as in other regions around the world have proposed and used the Tank model as a conceptual model in the direction of water resources assessment and parameter regionalization for modeling ungauged catchments.

3.2.1 Tank Model Structure and Parameters

The Tank model is a conceptual hydrological model that consists few or more storage tanks with outlets arranged vertically/horizontally to represent both vertical and lateral flows of water in the catchment (Arifjaya et al., 2011). The Tank model structure which is developed by Sugawara 1967, with four tanks is capable of simulating daily streamflow due to daily rainfall and evaporation.

Based on the requirement and land use types in the catchment, different Tank model structures comprising a different number of storage tanks are used by hydrologists and researchers for their hydrological studies. In this study, four tank structure model was used as shown in Figure 3-2 with 12 number of parameters.

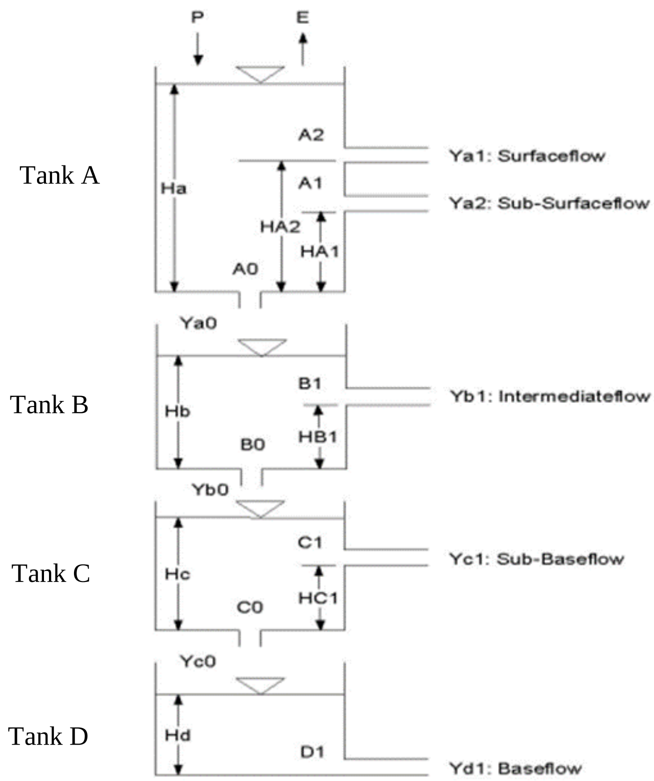


Figure 3-2: Structure of Tank Model

A1, A2, B1, C1, and *D1* are constants that control the runoff from each storage tank. Infiltration will be controlled by constant coefficients named *A0, B0,* and *C0* in the upper three tanks. *HA1, HA2, HB1* and *HC1* are height to the side outlets which named as storage parameters. All these parameters should be found by following an accurate calibration process where the model is more likely able to predict the real streamflow in the catchment. *Ha, Hb, Hc,* and *Hd* are considered as variables in the system.

The whole process of the model structure is simply based on the Water Balance concept which is mentioned as follows by (Chow, Maidment, 1988).

$$\frac{dH}{dt} = P(t) - ET(t) - Y(t) \cdots\cdots\cdots\cdots\cdots\cdots Equation\ 1$$

Where, *H* is storage of tank (mm), *P(t)* is daily rainfall (mm/day), *ET(t)* is daily evapo-transpiration (mm/day) and *Y(t)* is daily outflow (mm/day).

Hence, the water balance of the individual tank can be written as in following Equation 2 to Equation 5.

Tank A

$$\frac{dHa}{dt} = P(t) - ET(t) - Ya_{0,1}(t) \cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots \, Equation\ 2$$

Tank B

$$\frac{dHb}{dt} = Ya0(t) - Yb_{0,1}(t) \cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots \, Equation\ 3$$

Tank C

$$\frac{dHc}{dt} = Yb0(t) - Yc_{0,1}(t) \cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots \, Equation\ 4$$

Tank D

$$\frac{dHd}{dt} = Yc0(t) - Yd1(t) \cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots \, Equation\ 5$$

The total streamflow in the catchment will be a total of all lateral outflows from each tank and it can be determined using Equation 6.

$$Y(t) = Ya1(t) + Yb1(t) + Yb1(t) + Yd1(t) \cdots\cdots\cdots\cdots\cdots \, Equation\ 6$$

3.2.2 Schematic Diagram of Tank Model

Based on the above equations and hydrological processes in the Tank model structure, the schematic diagram has been shown in Figure 3-3.

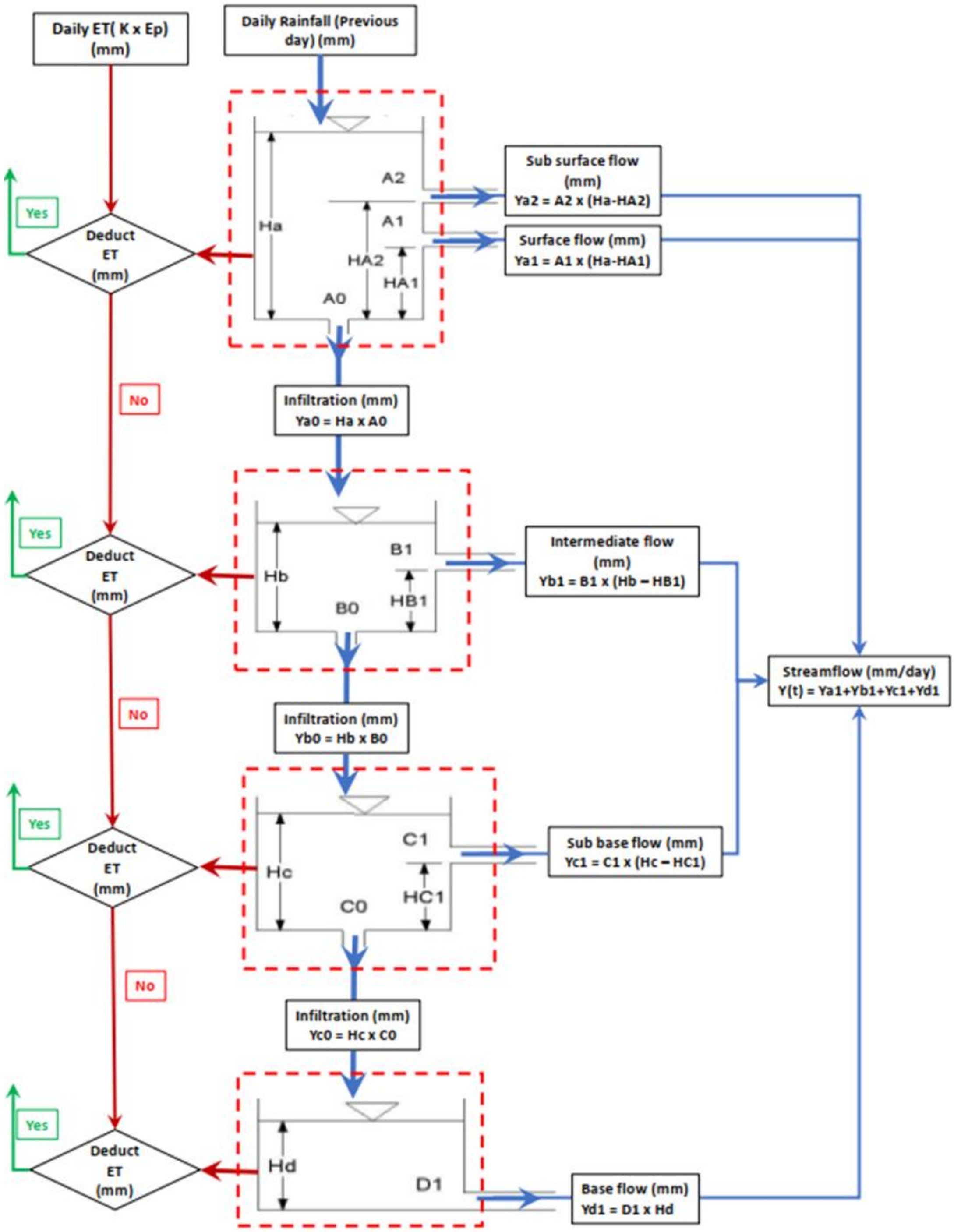


Figure 3-3: Schematic Diagram for Tank Model

4 Data and Data Checking

4.1 Data and Data Collection

Pitabeddara catchment in Pitabeddara river gauging station and Urawa catchment in Urawa river gauging station are sub-catchments in the Nilwala River Basin with having a catchment area of 291.4 km^2 and 52.4 km^2 respectively. Five rain gauging stations and one evaporation station as shown in Figure 1-1 were selected for the study considering their data availability within the studying period. The collected data types, data sources, and data resolution are given in Table 4-1. The locations of the gauging stations are given in Table 4-2.

Table 4-1: Data Sources and Resolutions

Data Type	Data Resolution	Data Period	Data Source
Rainfall	Daily	October 2008 to September 2018	Department of Irrigation and Department of Meteorology
Streamflow	Daily		Department of Irrigation
Evaporation	Daily		Department of Meteorology
Contour	1:50,000	2001	Survey Department of Sri Lanka
Topo sheet	1:50,000	2001	

The digital Topo sheets of tile no. 81 and 87 were used to delineate the two catchments.

Table 4-2: Locations of the Gauging Stations

Gauging Station	Coordinates of the Station	
Anningkanda	80° 36' 20"E	6° 20' 51"N
Derangala Hill	80° 27' 58"E	6° 14' 41"N
Dampahala Tea Factory	80° 38' 03"E	6° 16' 0.3"N
Hulandawa	80° 28' 23"E	6° 11' 11"N
Urawa Rotumba	80° 34' 23"E	6° 14' 07"N
Pitabeddara River Gauge	80° 28' 31"E	6° 12' 47"N
Urawa River Gauge	80° 34' 19"E	6° 14' 10"N

The densities of selected streamflow gauging stations and rainfall gauging stations are shown in Table 4-3 with a comparison of WMO standards.

Table 4-3: Densities of Gauging Stations in Two Catchments

Type of Gauging Station	**Number of Stations**		**Station Density (km^2/station)**		**Station Density as WMO standard (km^2/station)**
	Pitabeddara	Urawa	Pitabeddara	Urawa	
Rainfall	5	2	58.3	26.2	575
Streamflow	1	1	291.4	52.4	1875
Evaporation	1	1	291.4	52.4	-

4.2 Thiessen Average Rainfall

In the direction of runoff analysis, usage of weighted mean rainfall as an input to the model is more effective (Sugawara, Watanabe, Ozaki, & Katsuyama, 1984). Over different rainfall averaging methods such as Arithmetic-mean method and Iso-hyetal method, Thiessen method has been used for determining areal average rainfall for both catchments (Chow, Maidment, & Mays, 1988).

Figure 4-1 and Figure 4-2 illustrate the Thiessen polygons developed for Pitabeddara catchment and Urawa sub-catchment respectively. The respective Thiessen weights of each gauging station for estimation of areal average rainfall is given in Table 4-4.

Table 4-4: Thiessen Weights of Rainfall Gauging Stations

Rainfall Station	**Thiessen Weight**	
	Pitabeddara Catchment	**Urawa Sub-catchment**
Anningkanda	0.16	-
Derangala Hill	0.25	-
Dampahala Tea Factory	0.13	0.76
Hulanduwa	0.09	-
Urawa Rotumba	0.37	0.24

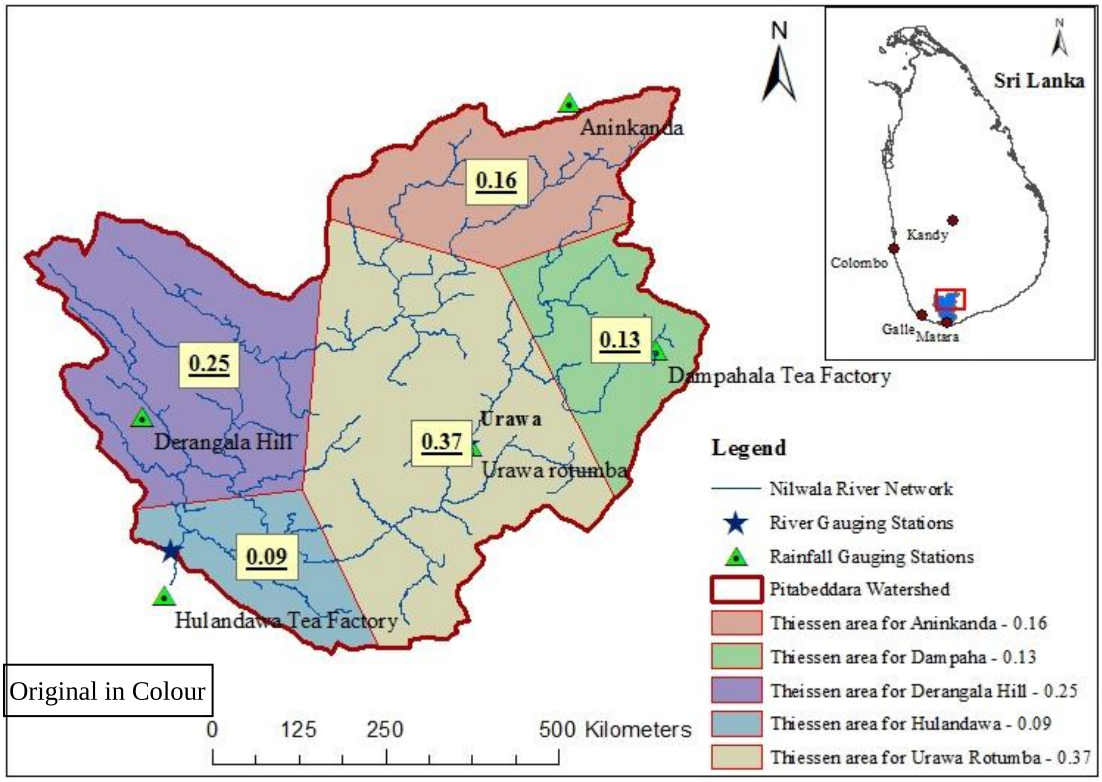


Figure 4-1: Thiessen Polygons for Pitabeddara Watershed

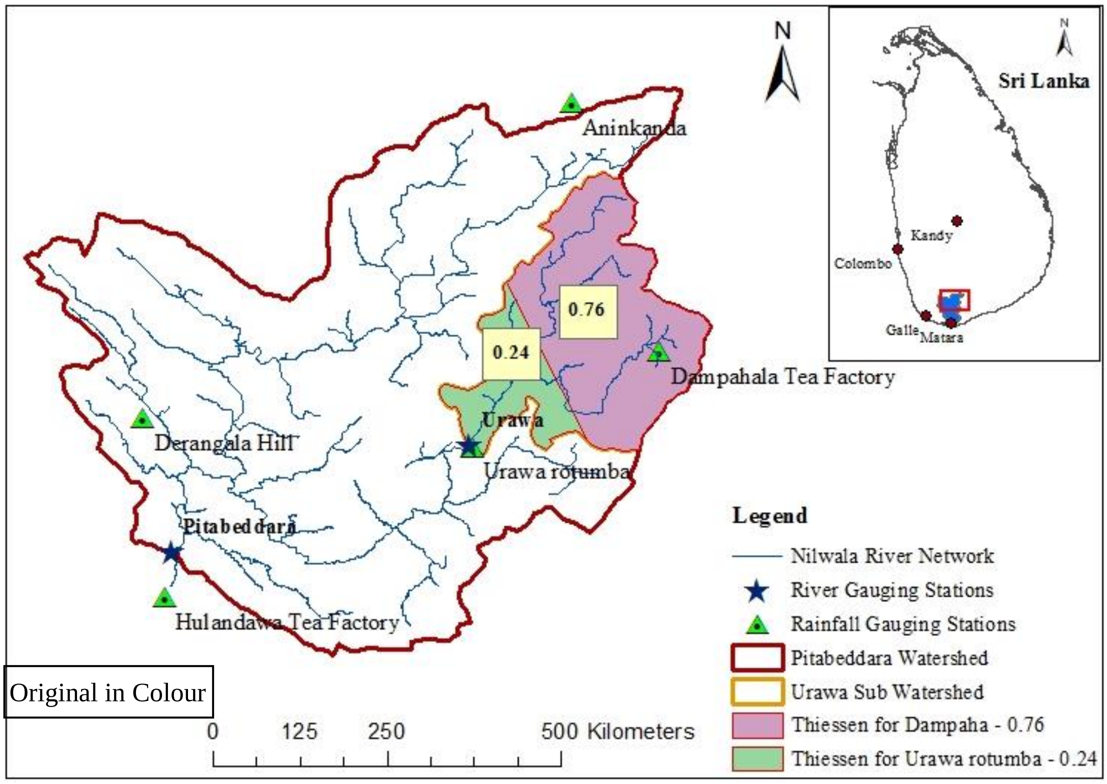


Figure 4-2: Thiessen Polygons for Urawa sub-watershed

4.3 Data Checking

The level of confidence where a hydrological modeler able to use data in modeling, could be identified through the data checking process. In the same time, it enables the modeler to identify the validity of the hydrologic output of the model which will be used for decision making (Wijesekera & Perera, 2012). For the data checking process, different types of statistical and non-statistical tests are available and in this study, Visual Data checking, Annual Water Balance checking, and Double Mass Curve Analysis have been carried out.

The missing data in the rainfall series were identified and filled based on the Thiessen average method which is one of the spatial estimation methods stated in the WMO guideline: Guide to Climatological Practices (2018).

4.3.1 Annual Water Balance

Checking of annual water balance in the catchment will enable to compare rainfall, streamflow, evaporation data, and annual runoff coefficient thereby illustrating the behavior of the catchment over the study period. The calculations have been carried out for both Pitabeddara and Urawa catchments. Thiessen averaged rainfall has been considered in the calculation for both catchments.

4.3.1.1 Annual Water Balance at Pitabeddara Catchment

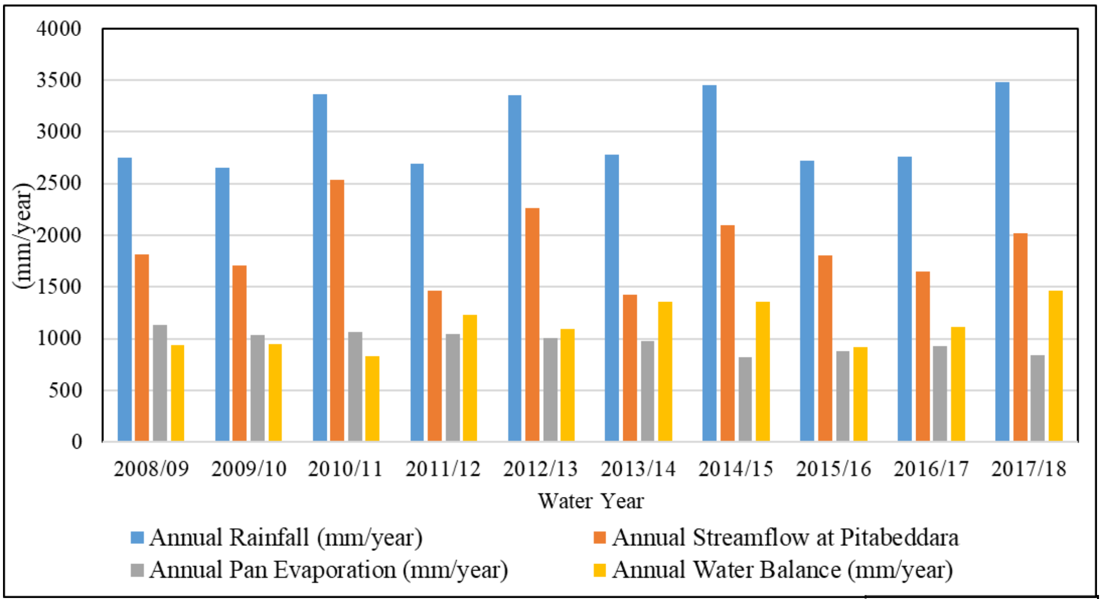
The annual variation of the water balance in the catchment is shown in Table 4-5 and Figure 4-3 for the study time period.

According to the calculations, it was identified that the annual runoff coefficient varies within 0.50 to 0.75. The Hydrological Annual- 2017/18 prepared by the Irrigation Department has stated long term averaged annual runoff coefficient as 0.59 for Pitabeddara catchment where the calculated average annual runoff coefficient within the study period is 0.62 in this study.

The highest streamflow was observed in the 2010/11 water year but the highest rainfall was observed in the 2017/18 water year.

Table 4-5: Annual Water Balance at Pitabeddara

Water Year	Annual Rainfall (mm/year)	Annual Streamflow (mm/year)	Annual Pan Evaporation (mm/year)	Annual Water Balance (mm/year)	Annual Runoff Coefficient
2008/09	2750.4	1818.3	1128.6	932.1	0.66
2009/10	2653.7	1706.3	1034.7	947.4	0.64
2010/11	3371.6	2538.7	1067.6	832.9	0.75
2011/12	2691.5	1460.6	1040.2	1230.9	0.54
2012/13	3357.4	2271.4	1000.7	1086.0	0.68
2013/14	2778.0	1425.2	972.7	1352.8	0.51
2014/15	3454.1	2098.0	818.7	1356.1	0.61
2015/16	2718.3	1802.5	883.1	915.7	0.66
2016/17	2770.3	1647.5	926.5	1122.8	0.59
2017/18	3481.6	2018.7	836.7	1462.9	0.58
Average	**3002.7**	**1878.7**	**971.0**	**1124.0**	**0.62**



Original in Colour

Figure 4-3: Annual Water Balance at Pitabeddara

According to Figure 4-3, in water years 2013/14, 2014/15, and 2017/18, the difference between pan evaporation and annual water balance is considerably higher.

4.3.1.2 Variation of Annual Rainfall and Annual Streamflow at Pitabeddara

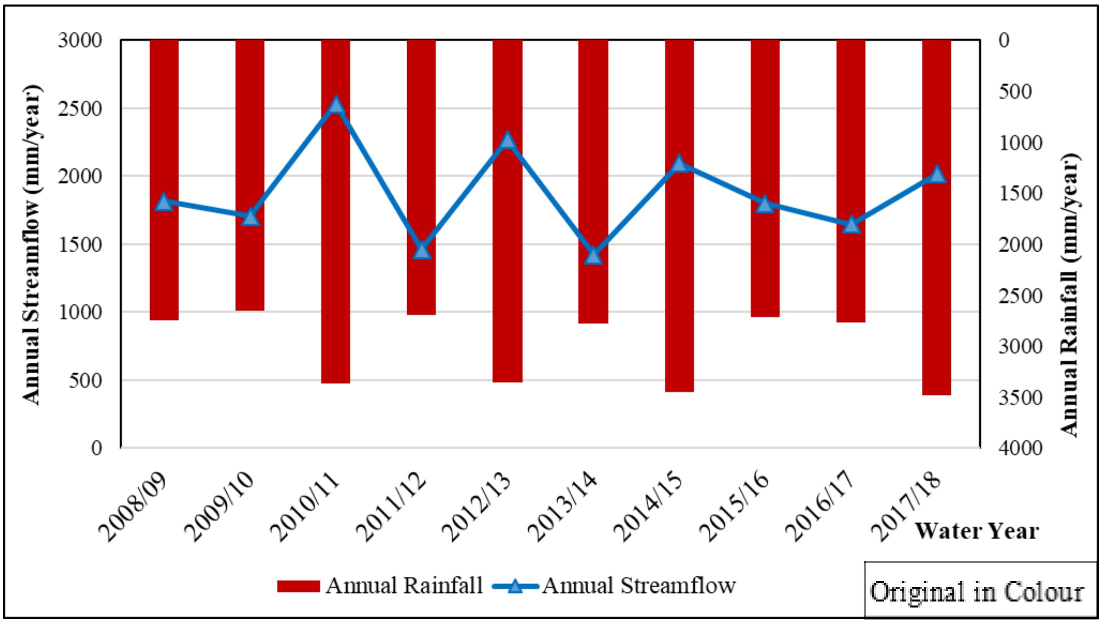


Figure 4-4: Variation of Annual Rainfall and Annual Streamflow of Pitabeddara catchment

Annual streamflow in the water year 2010/2011 is comparatively high w.r.t water years with approximately similar annual rainfall which can be clearly identified in Figure 4-4. Consequently, during that water year, the annual runoff coefficient is also comparatively higher than the other water years.

In water years 2011/2012 and 2013/2014, the stream has discharged less flow compared to approximately similar rainy water years.

4.3.1.3 Annual Water Balance at Urawa Catchment

The annual variation of the water balance in the catchment is shown in Table 4-6 and Figure 4-5 for the study time period. The estimated annual runoff coefficient for Urawa sub-catchment within the selected time period ranges from 0.40 to 0.65 wherein the Hydrological Annual 2017/18 has stated long term averaged runoff coefficient value as 0.44.

In water years 2009/10 and 2015/16, annual water balance is considerably less than annual pan evaporation, and the annual runoff coefficient is also at its highest value during the study period.

Table 4-6: Annual Water Balance at Urawa

Water Year	Annual Rainfall (mm/year)	Annual Streamflow (mm/year)	Annual Pan Evaporation (mm/year)	Annual Water Balance (mm/year)	Annual Runoff Coefficient
2008/09	2525.3	1574.6	1128.6	950.7	0.62
2009/10	1968.1	1284.6	1034.7	683.5	0.65
2010/11	2950.5	1828.1	1067.6	1122.5	0.62
2011/12	2111.5	1070.1	1040.2	1041.4	0.51
2012/13	2715.1	1697.4	1000.7	1017.8	0.63
2013/14	2028.9	984.4	972.7	1044.5	0.49
2014/15	2624.2	1409.8	818.7	1214.4	0.54
2015/16	2253.2	1458.6	883.1	794.6	0.65
2016/17	2784.2	1109.1	926.5	1675.1	0.40
2017/18	2847.7	1781.6	836.7	1066.1	0.63
Average	**2480.9**	**1419.8**	**971.0**	**1061.1**	**0.57**

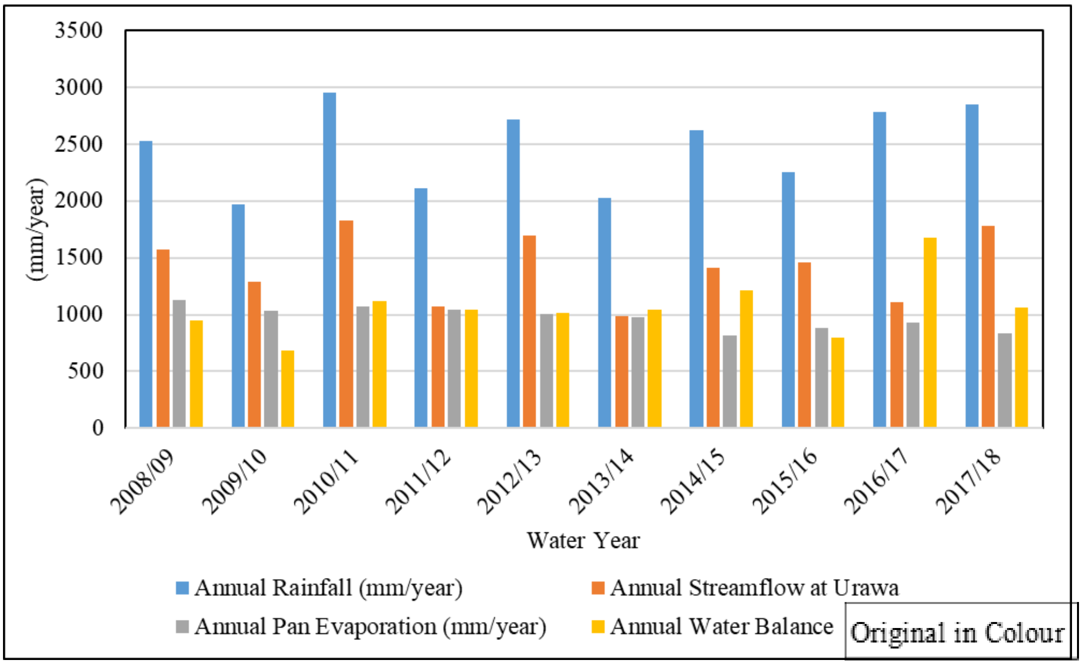


Figure 4-5: Annual Water Balance at Urawa

Considerably higher difference between annual pan evaporation and annual water balance can be observed during water year 2014/15 and water year 2016/17 according to Figure 4-5.

4.3.1.4 Variation of Annual Rainfall and Annual Streamflow at Urawa

From the rainiest water years 2010/11, 2012/13, 2016/17 and 2017/18, the annual streamflow in water year 2016/17 is lesser with compared to the other water years which can be clearly observed in the Figure 4-6. In addition to that, the Figure 4-6 illustrates that the driest water year 2009/10 between the study period has a comparatively higher stream discharge w.r.t similarly drier water year 2013/14.

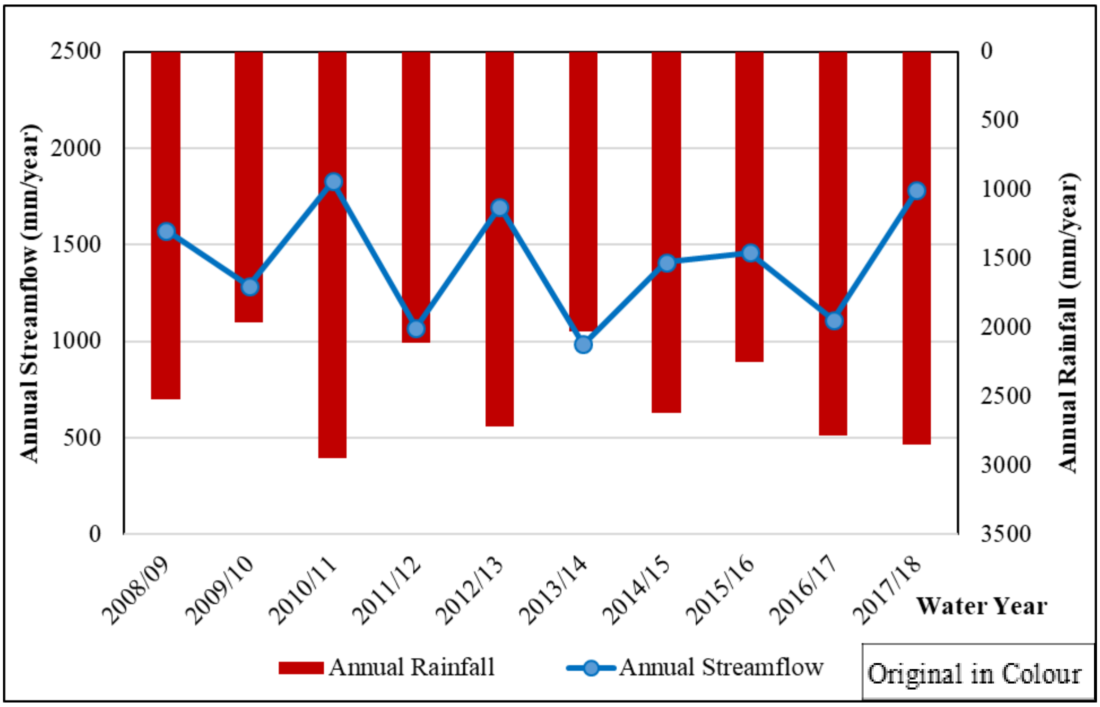


Figure 4-6: Variation of Annual Rainfall and Annual Streamflow of Urawa catchment

4.3.2 Visual Data Checking

Visual data checking is done to identify any sudden changes in the data time series and, any inconsistencies between the rainfall and streamflow relationship within the period. Streamflow responses to rainfall for each rainfall gauging station and for Thiessen average rainfall over the catchment were plotted for each water year to identify such changes and inconsistencies in data.

4.3.2.1 Visual Data Checking for Pitabeddara Catchment

Daily streamflow responses to the daily rainfall were plotted in a semi-log plot for each water year in the study period and Figure 4-8 shows the semi-log plots of streamflow and rainfalls for the 2010/2011 water year for each rainfall gauging station. The visual data examination for other water years in semi-log plots are attached in the Annexure A. Only in few days, unrealistic responses of streamflow and non-representative rainfall events were identified which locations are shown by red circles thereby it can be identified that all the selected rain gauging stations influence the streamflow in Pitabddara catchment.

The Thiessen averaged rainfall and streamflow for Pitabeddara catchment in the 2010/2011 water year is shown in Figure 4-7. Non-representative rainfall events for the streamflow were visually identified which are highlighted in red circles in the figure. Since the non-representative rainfall events are insignificant, this Thiessen averaged rainfall will be used as input for the modeling.

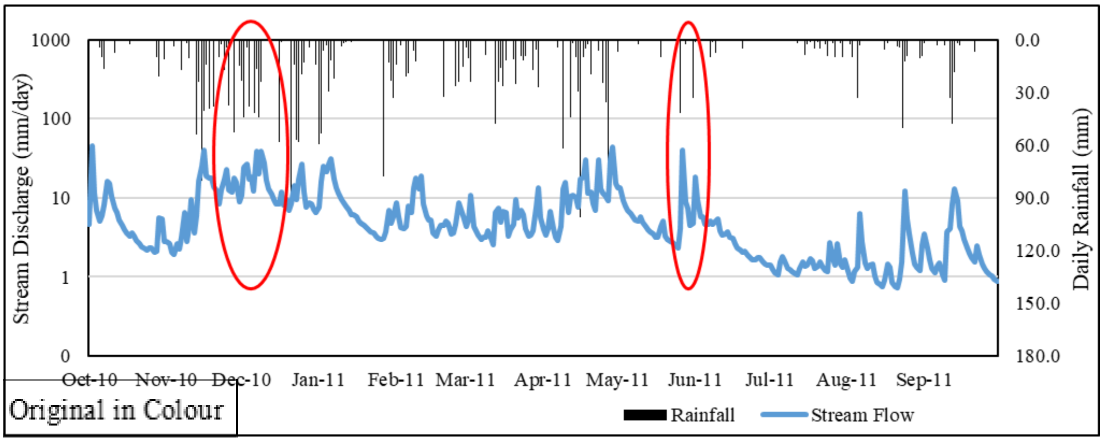


Figure 4-7: Thiessen Averaged Rainfall and Streamflow at Pitabeddara in water year 2010/2011

In Annexure A, Thiessen averaged rainfall and streamflow hydrographs of Pitabeddara for the whole period are attached with identified non-representative rainfall events.

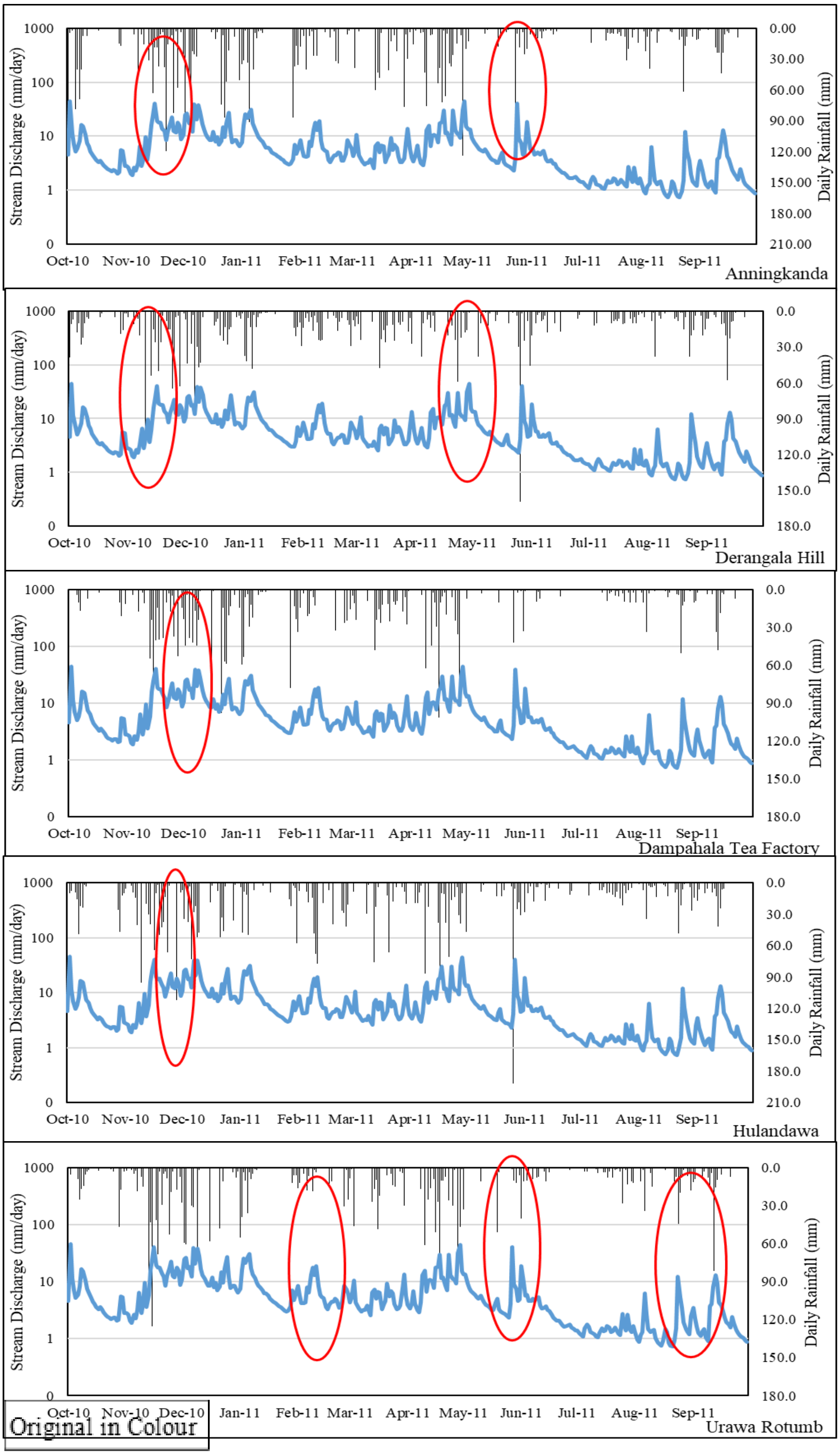


Figure 4-8: Streamflow at Pitabeddara vs Rainfall in each Rainfall Gauging Station in water year 2010/2011

4.3.2.2 Visual Data Checking for Urawa Catchment

Similar visual checking has been done for rainfall and streamflow data for Urawa catchment and non-representative rainfall events have been identified which are shown by red circles in Figure 4-9. The identified non-representative rainfall events are insignificant w.r.t the whole data series thereby it was assumed that the selected rain gauging stations are suitable and Thiessen averaged rainfall can be used as input for the modeling.

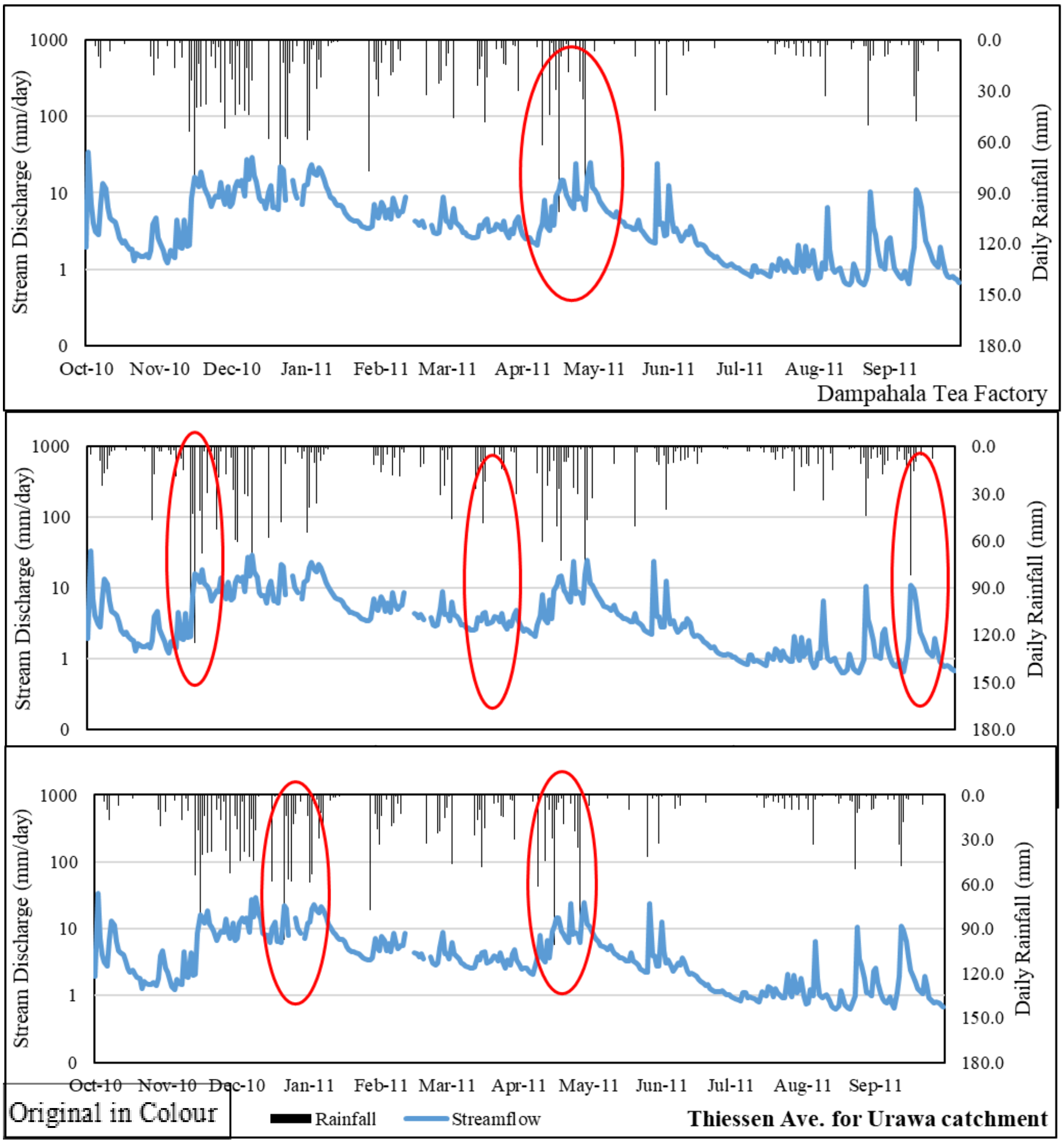


Figure 4-9: Streamflow at Urawa vs Rainfall of each station and Thiessen Rainfall

4.3.3 Double Mass Curve method

Cumulative hydrological data of one station with a cumulative average of nearby stations in the catchment were plotted to identify the consistency of rainfall data and streamflow data in each station. All the plots as shown in Figure 4-10 are in a straight line without any significant break in straightness. Thus, the rainfall data and streamflow data are assumed to be not having significant inconsistencies.

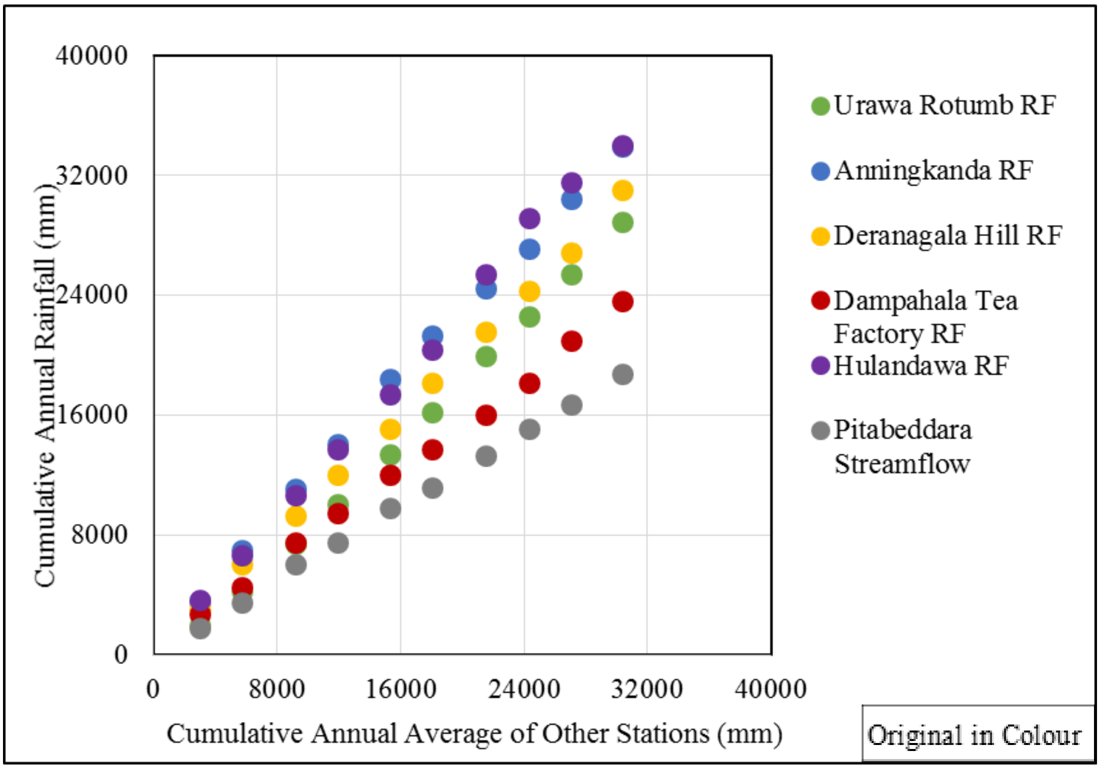


Figure 4-10: Double Mass Curve for each Rainfall Stations

4.4 Monthly Averaged Rainfall

Monthly average rainfall for each station has been calculated and is presented in Table 4-7 and Figure 4-11. This represents the two seasons correspond to North-East Monsoon (October to March) and Southwest monsoon (April to September).

Table 4-7: Monthly Averaged Rainfall of Five Stations

Rain gauge station	Monthly Average Rainfall (mm)											
	Oct	**Nov**	**Dec**	**Jan**	**Feb**	**Mar**	**Apr**	**May**	**Jun**	**Jul**	**Aug**	**Sep**
Aningkanda	356.1	444.4	287.1	157.8	171.4	242.1	367.4	333.6	186.1	121.6	155.0	218.2
Derangala	278.9	313.0	208.9	141.7	130.8	165.2	213.1	308.4	231.7	137.8	186.6	236.9
Dampahala	278.4	349.6	246.0	123.1	134.2	209.3	236.5	219.2	119.1	108.1	111.7	174.4
Hulandawa	417.5	391.3	272.4	179.4	207.0	239.9	302.8	351.6	309.4	163.8	233.7	287.2
Urawa Rotumb	316.4	396.2	256.0	109.3	152.6	198.6	243.5	320.2	208.8	129.9	157.2	244.7

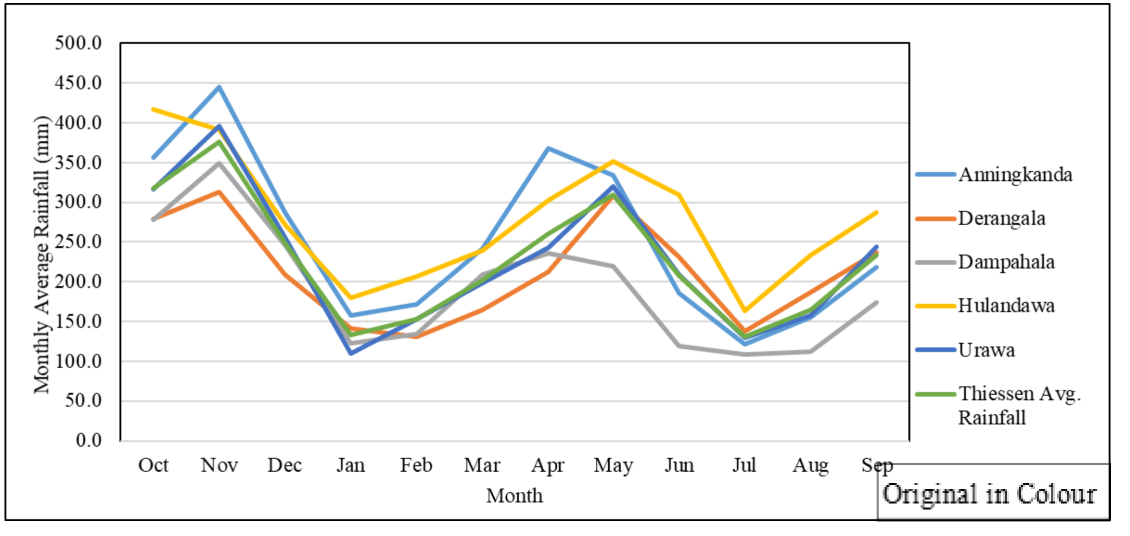


Figure 4-11: Variation of Monthly Average Rainfall for the Five Stations

5 Analysis and Results

5.1 Classification of Flow Regime – High, Intermediate and Low Flows

As discussed in the literature review, a well-established flow classification is not available. This study has determined the high and low flow thresholds of the flow regime by considering the variation of the gradient in flow duration curve which was identified based on changing in order of magnitude of streamflow. The graphical representations of identification are shown in Figure 5-1 and Figure 5-2.

The high flow thresholds are 8% and 8.2%, and low flow thresholds are 87% and 82% for Pitabeddara and Urawa catchments respectively.

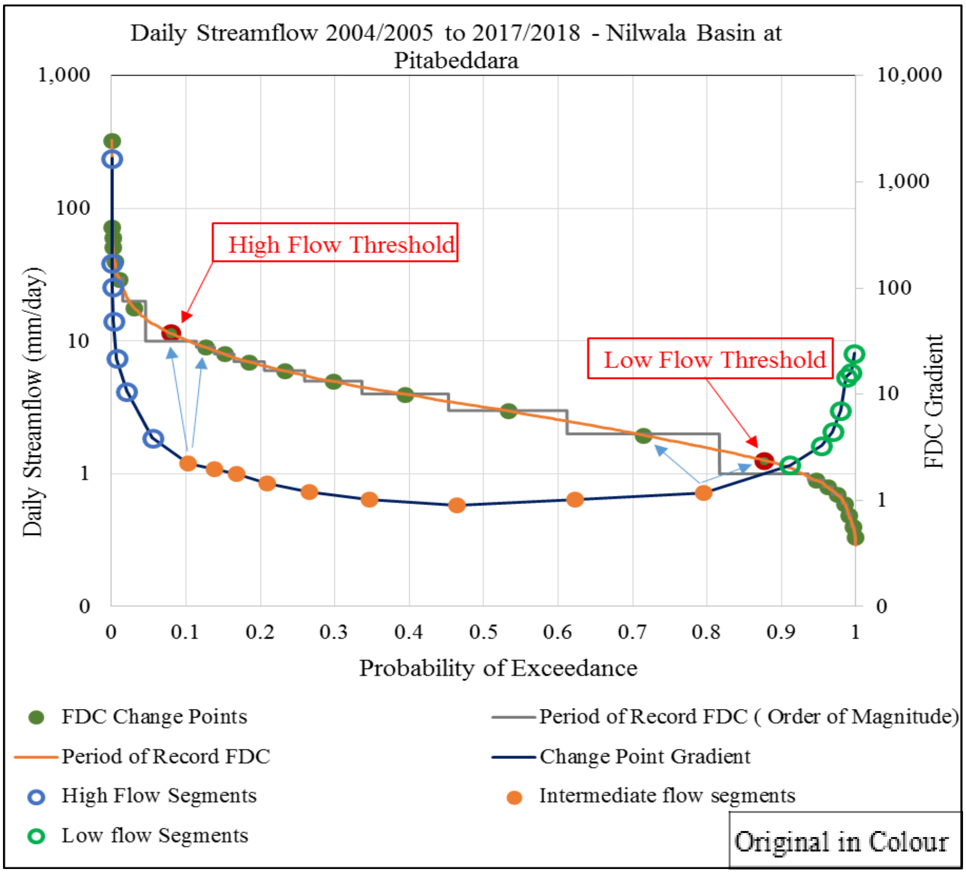


Figure 5-1: Flow Classification for Pitabeddara Catchment

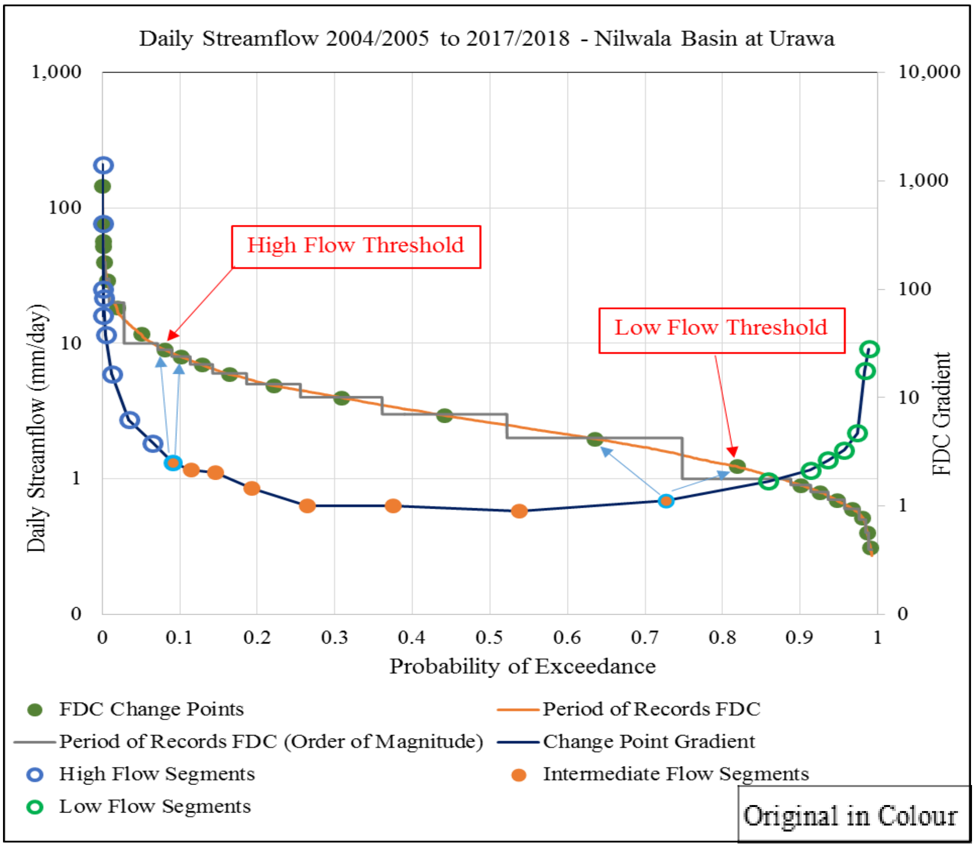


Figure 5-2: Flow Classification for Urawa Catchment

5.2 Tank Model Development for Catchments

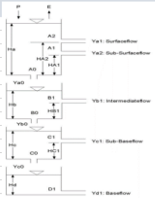
The Tank model for two catchments was developed using Microsoft Excel software package w.r.t. the model concept described in Section 3.2. Figure 5-3 shows the model setup for Pitabeddara catchment. Few sample calculations as done in the following subsection were done to evaluate and understand the process in the structure.

5.2.1 Sample Calculation for Streamflow w.r.t Process of Tank Model

Considering the representation of the hydrological processes within the Tank model structure, a sample calculation for Pitabeddara catchment has been done to illustrate the streamflow estimation steps in the model. The following assumptions have been made for the model parameters and initial storages of each tank. Table 5-1 shows the data and assumed values in the sample calculation.

Tank Model - Pitabeddara Catchment

A0	0.2988967
A1	0.10572
A2	0.5392821
B0	0.0336176
B1	0.0416021
C0	0.0060743
C1	0.0254613
D1	0.00009
HA1	2.1012461
HA2	28.448693
HB1	41.622616
HC1	81.008246



MRAE	0.3282

Date	Daily Precipitation (mm)	1st Tank: Storage of Previous day (mm)	Precipitation of Previous day (mm)	Daily Evapo-transpiration (same day) (mm)	Storage (mm)	Runoff (upper outlet) (mm)	Runoff (Lower outlet) (mm)	Infiltration (mm)	Storage Balance (mm)	2nd Tank: Storage of Previous day (mm)	Infiltration from 1st Tank (mm)	Remaining Daily Evapo-transpiration (same day) (mm)	Storage (mm)	Runoff from outlet (mm)	Infiltration (mm)	Storage Balance (mm)	3rd Tank: Storage of Previous day (mm)	Infiltration from 2nd Tank (mm)	Remaining Daily Evapo-transpiration (same day) (mm)	Storage (mm)	Runoff from outlet (mm)	Infiltration (mm)	Storage Balance (mm)	4th Tank: Storage of Previous day (mm)	Infiltration from 3rd Tank (mm)	Storage (mm)	Runoff from outlet (mm)	Storage Balance (mm)	Runoff: Total Runoff (mm)	Observed Discharge	|Qc - Qo|/ Qo	
9/30/2008	0.0																															Warm-Up 1
10/1/2008	0.0	0.0	0.0	3.3	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	3.3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.00	1.0	1.0	
9/30/2013	0.0	0.0	0.0	3.4	0.0	0.0	0.0	0.0	0.0	55.6	0.0	3.4	52.2	0.4	1.8	50.0	124.9	1.8	0.0	126.7	1.2	0.8	124.8	1313.7	0.8	1314.5	0.1	1314.4	1.72	2.0	0.1	
9/30/2008	0.0																															Warm-Up 2
10/1/2008	0.0	0.0	0.0	3.3	0.0	0.0	0.0	0.0	0.0	50.0	0.0	3.3	46.7	0.2	1.6	45.0	124.8	1.6	0.0	126.3	1.2	0.8	124.4	1314.4	0.8	1315.1	0.1	1315.0	1.49	1.0	0.5	
9/30/2013	0.0	0.0	0.0	3.4	0.0	0.0	0.0	0.0	0.0	55.6	0.0	3.4	52.2	0.4	1.8	50.0	124.9	1.8	0.0	126.7	1.2	0.8	124.8	2463.0	0.8	2463.8	0.2	2463.6	1.83	2.0	0.1	
9/30/2008	0.0																															Warm-Up 3
10/1/2008	0.0	0.0	0.0	3.3	0.0	0.0	0.0	0.0	0.0	50.0	0.0	3.3	46.7	0.2	1.6	45.0	124.8	1.6	0.0	126.3	1.2	0.8	124.4	2463.6	0.8	2464.3	0.2	2464.1	1.59	1.0	0.6	
9/30/2013	0.0	0.0	0.0	3.4	0.0	0.0	0.0	0.0	0.0	55.6	0.0	3.4	52.2	0.4	1.8	50.0	124.9	1.8	0.0	126.7	1.2	0.8	124.8	3438.2	0.8	3438.9	0.3	3438.6	1.91	2.0	0.0	
9/30/2008	0.0																															Warm-Up 4
10/1/2008	0.0	0.0	0.0	3.3	0.0	0.0	0.0	0.0	0.0	50.0	0.0	3.3	46.7	0.2	1.6	45.0	124.8	1.6	0.0	126.3	1.2	0.8	124.4	3438.6	0.8	3439.4	0.3	3439.1	1.68	1.0	0.7	
9/30/2013	0.0	0.0	0.0	3.4	0.0	0.0	0.0	0.0	0.0	55.6	0.0	3.4	52.2	0.4	1.8	50.0	124.9	1.8	0.0	126.7	1.2	0.8	124.8	4265.5	0.8	4266.3	0.4	4265.9	1.99	2.0	0.0	
9/30/2008	0.0																															Warm-Up 5
10/1/2008	0.0	0.0	0.0	3.3	0.0	0.0	0.0	0.0	0.0	50.0	0.0	3.3	46.7	0.2	1.6	45.0	124.8	1.6	0.0	126.3	1.2	0.8	124.4	4265.9	0.8	4266.7	0.4	4266.3	1.75	1.0	0.8	
9/30/2013	0.0	0.0	0.0	3.4	0.0	0.0	0.0	0.0	0.0	55.6	0.0	3.4	52.2	0.4	1.8	50.0	124.9	1.8	0.0	126.7	1.2	0.8	124.8	4967.5	0.8	4968.3	0.4	4967.8	2.05	2.0	0.0	
9/30/2008	0.0																															Calibration
10/1/2008	0.0	0.0	0.0	3.3	0.0	0.0	0.0	0.0	0.0	50.0	0.0	3.3	46.7	0.2	1.6	45.0	124.8	1.6	0.0	126.3	1.2	0.8	124.4	4967.8	0.8	4968.6	0.4	4968.1	1.81	1.0	0.8	
10/2/2008	0.0	0.0	0.0	4.0	0.0	0.0	0.0	0.0	0.0	45.0	0.0	4.0	41.0	0.0	1.4	39.6	124.4	1.4	0.0	125.8	1.1	0.8	123.9	4968.1	0.8	4968.9	0.4	4968.5	1.59	0.9	0.8	
10/3/2008	0.0	0.0	0.0	2.7	0.0	0.0	0.0	0.0	0.0	39.6	0.0	2.7	37.0	0.0	1.2	35.7	123.9	1.2	0.0	125.1	1.1	0.8	123.2	4968.5	0.8	4969.2	0.4	4968.8	1.57	0.8	0.9	
10/4/2008	2.8	0.0	0.0	4.1	0.0	0.0	0.0	0.0	0.0	35.7	0.0	4.1	31.6	0.0	1.1	30.6	123.2	1.1	0.0	124.3	1.1	0.8	122.5	4968.8	0.8	4969.5	0.4	4969.1	1.55	0.8	0.9	
10/5/2008	3.8	0.0	2.8	3.7	0.0	0.0	0.0	0.0	0.0	30.6	0.0	0.9	29.7	0.0	1.0	28.7	122.5	1.0	0.0	123.5	1.1	0.7	121.6	4969.1	0.7	4969.8	0.4	4969.4	1.53	1.1	0.4	
10/6/2008	6.4	0.0	3.8	3.6	0.2	0.0	0.0	0.1	0.1	28.7	0.1	0.0	28.8	0.0	1.0	27.8	121.6	1.0	0.0	122.6	1.1	0.7	120.8	4969.4	0.7	4970.1	0.4	4969.7	1.51	1.6	0.0	
10/7/2008	3.6	0.1	6.4	3.1	3.4	0.0	0.1	1.0	2.3	27.8	1.0	0.0	28.8	0.0	1.0	27.9	120.8	1.0	0.0	121.8	1.0	0.7	120.0	4969.7	0.7	4970.4	0.4	4970.0	1.63	1.8	0.1	
10/8/2008	10.5	2.3	3.6	2.3	3.6	0.0	0.2	1.1	2.4	27.9	1.1	0.0	28.9	0.0	1.0	28.0	120.0	1.0	0.0	121.0	1.0	0.7	119.2	4970.0	0.7	4970.7	0.4	4970.3	1.62	1.6	0.0	
10/9/2008	7.9	2.4	10.5	1.8	11.0	0.0	0.9	3.3	6.8	28.0	3.3	0.0	31.3	0.0	1.1	30.2	119.2	1.1	0.0	120.2	1.0	0.7	118.5	4970.3	0.7	4971.0	0.4	4970.5	2.39	2.9	0.2	
10/10/2008	26.5	6.8	7.9	1.7	12.9	0.0	1.1	3.9	7.9	30.2	3.9	0.0	34.1	0.0	1.1	32.9	118.5	1.1	0.0	119.7	1.0	0.7	118.0	4970.5	0.7	4971.3	0.4	4970.8	2.58	3.4	0.2	
10/11/2008	14.5	7.9	26.5	2.0	32.3	2.1	3.2	9.7	17.4	32.9	9.7	0.0	42.6	0.0	1.4	41.1	118.0	1.4	0.0	119.4	1.0	0.7	117.7	4970.8	0.7	4971.5	0.4	4971.1	6.76	5.0	0.4	
10/12/2008	48.1	17.4	14.5	2.3	29.6	0.6	2.9	8.8	17.2	41.1	8.8	0.0	50.0	0.3	1.7	47.9	117.7	1.7	0.0	119.4	1.0	0.7	117.7	4971.1	0.7	4971.8	0.4	4971.4	5.29	5.7	0.1	
10/13/2008	1.7	17.2	48.1	3.5	61.8	18.0	6.3	18.5	19.0	47.9	18.5	0.0	66.4	1.0	2.2	63.2	117.7	2.2	0.0	119.9	1.0	0.7	118.2	4971.4	0.7	4972.1	0.4	4971.6	26.79	13.2	1.0	
10/14/2008	4.9	19.0	1.7	0.8	19.9	0.0	1.9	6.0	12.1	63.2	6.0	0.0	69.1	1.1	2.3	65.6	118.2	2.3	0.0	120.5	1.0	0.7	118.8	4971.6	0.7	4972.4	0.4	4971.9	4.48	3.6	0.2	
10/15/2008	3.9	12.1	4.9	1.8	15.2	0.0	1.4	4.5	9.2	65.6	4.5	0.0	70.2	1.2	2.4	66.6	118.8	2.4	0.0	121.1	1.0	0.7	119.4	4971.9	0.7	4972.7	0.4	4972.2	4.04	3.0	0.3	
10/16/2008	12.5	9.2	3.9	3.0	10.1	0.0	0.8	3.0	6.3	66.6	3.0	0.0	69.7	1.2	2.3	66.1	119.4	2.3	0.0	121.7	1.0	0.7	119.9	4972.2	0.7	4973.0	0.4	4972.5	3.50	2.3	0.5	
10/17/2008	16.4	6.3	12.5	1.3	17.4	0.0	1.6	5.2	10.6	66.1	5.2	0.0	71.4	1.2	2.4	67.7	119.9	2.4	0.0	122.3	1.1	0.7	120.5	4972.5	0.7	4973.3	0.4	4972.8	4.36	2.7	0.6	
10/18/2008	0.8	10.6	16.4	2.8	24.3	0.0	2.3	7.3	14.7	67.7	7.3	0.0	75.0	1.4	2.5	71.1	120.5	2.5	0.0	123.1	1.1	0.7	121.2	4972.8	0.7	4973.6	0.4	4973.1	5.25	4.7	0.1	
10/19/2008	24.8	14.7	0.8	1.6	13.9	0.0	1.2	4.2	8.5	71.1	4.2	0.0	75.2	1.4	2.5	71.3	121.2	2.5	0.0	123.8	1.1	0.8	121.9	4973.1	0.8	4973.9	0.4	4973.4	4.18	3.6	0.2	

Figure 5-3: Tank Model Set-up in MS Excel for Pitabeddara Catchment

Table 5-1 Assumed Values of Model Parameters and Storages for Sample Calculation

Parameters	Pan coefficient	0.8
	A0 (1/day)	0.25
	A1 (1/day)	0.2
	A2 (1/day)	0.4
	B0 (1/day)	0.06
	B1 (1/day)	0.08
	C0 (1/day)	0.02
	C1 (1/day)	0.01
	D1 (1/day)	0.003
	HA1 (mm)	11
	HA2 (mm)	50
	HB1 (mm)	30
	HC1 (mm)	4
Initial Storages (mm)	Ha	16.1
	Hb	40.0
	Hc	66.0
	Hd	406.8

Since the daily precipitation is measured from 09:00 hrs of a day to 09:00 hrs of the next day and the daily streamflow is the average value of the discharges at 06:00 hrs to 18:00 hrs of a day, calculation of streamflow of a day is done by using the precipitation of the preceding day.

The sample streamflow calculation on 01st October 2009 is required rainfall on 30th September 2009 (12.4 mm), evapotranspiration on 01st October 2009 (0.8 x 2.44 mm), and storages of each tank (initial storages as mentioned in Table 5-1) on 01st October 2009.

Calculation for Tank A

Storage = (Storage of Previous day) + (Precipitation of previous day) – (Evapotranspiration)

= 16.1 mm + 12.4 mm – (0.8 x 2.44) mm = 26.5 mm

Hence infiltration and runoff from lower side outlet (A1) only occur (Ya2 = 0).

Runoff (Ya1) = (26.5 – 11) x 0.2 = 3.1 mm

Infiltration (Ya0) = 26.5 x 0.25 = 6 .6 mm

Storage balance = (Storage) – {(Runoff) + (Infiltration)} = 26.5 – (3.1 + 6.6) =16.8 mm

Calculation for Tank B

Storage = (Storage of Previous day) + (Infiltration from Tank A) – (Evapotranspiration)

= 40 mm + 6.6 mm – (0) mm = 46.6 mm

Runoff (Yb1) = (46.6 – 30) x 0.08 = 1.3 mm

Infiltration (Yb0) = 46.6 x 0.06 = 2.8 mm

Storage balance = (Storage) – {(Runoff) + (Infiltration)} = 46.6 – (1.3 + 2.8) = 42.5 mm

Calculation for Tank C

Storage = (Storage of Previous day) + (Infiltration from Tank B) – (Evapotranspiration)

= 66 mm + 2.8 mm – (0) mm = 68.8 mm

Runoff (Yc1) = (68.8 – 4) x 0.01 = 0.6 mm

Infiltration (Yc0) = 68.8 x 0.02 = 1.4 mm

Storage balance = (Storage) – {(Runoff) + (Infiltration)} = 68.8 – (0.6 + 1.4) = 66.8 mm

Calculation for Tank D

Storage = (Storage of Previous day) + (Infiltration from Tank C) – (Evapotranspiration)

= 406.8 mm + 1.4 mm – (0) mm = 408.2 mm

Runoff (Yd1) = 408.2 x 0.003 = 1.2 mm

Storage balance = (Storage) – (Runoff) = 408.2 –1.2 = 407 mm

Stream Discharge = Sum of Runoff from each tank

= 3.1 + 0 + 1.3 + 0.6 + 1.2

= 6.2 mm/day

Observed Discharge = 6.6 mm/day

5.3 Warm-up of Tank Model

As discussed in the literature review, the model should be warmed up to eliminate any error propagation due to the initial conditions of the model parameters especially in soil moisture conditions of the four tanks. Hence a cyclic period of five water years was used to warm up the Tank model which lead to stabilizing the soil moisture content in tanks. Table 5- 2, Figure 5-4 and Figure 5-5 illustrate the behavior of soil moisture content in each tank. The model was initiated with zero soil moisture conditions for all tanks and the values given in Table 5-2 are soil moisture content at the end of the simulation.

Table 5-2: The behavior of soil moisture content in each tank of the model

Catchment	Simulation 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)
Urawa	1	0.0	43.0	54.8	393.5
	2	0.0	43.0	54.8	460.8
	3	0.0	43.0	54.8	471.7
	4	0.0	43.0	54.8	473.4
	5	0.0	43.0	54.8	473.7
Pitabeddara	1	0.0	38.4	51.3	325.7
	2	0.0	38.4	51.3	597.8
	3	0.0	38.4	51.3	718.2
	4	0.0	38.4	51.3	786.5
	5	0.0	38.4	51.3	825.3

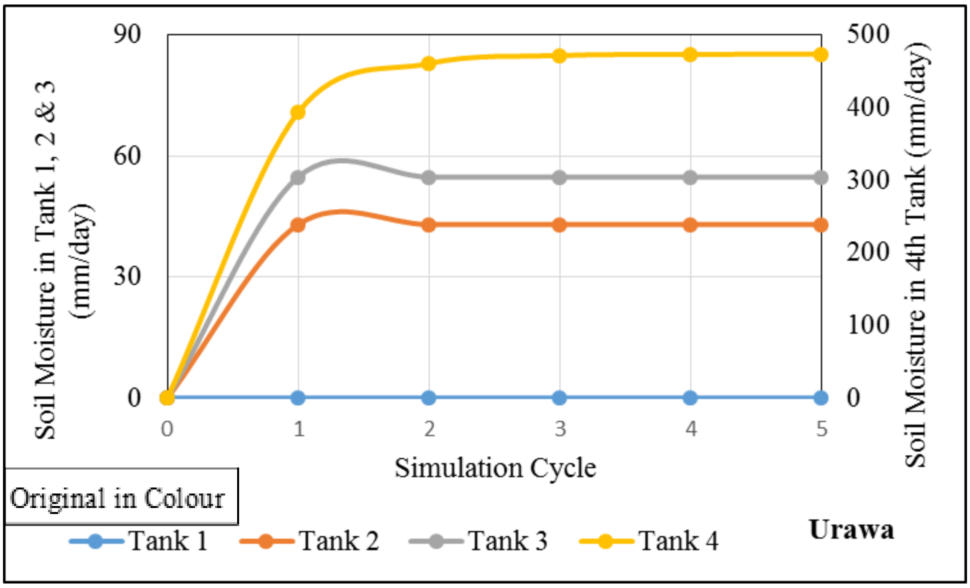


Figure 5-4: Soil moisture content variation in each tank for warm-up period - Urawa

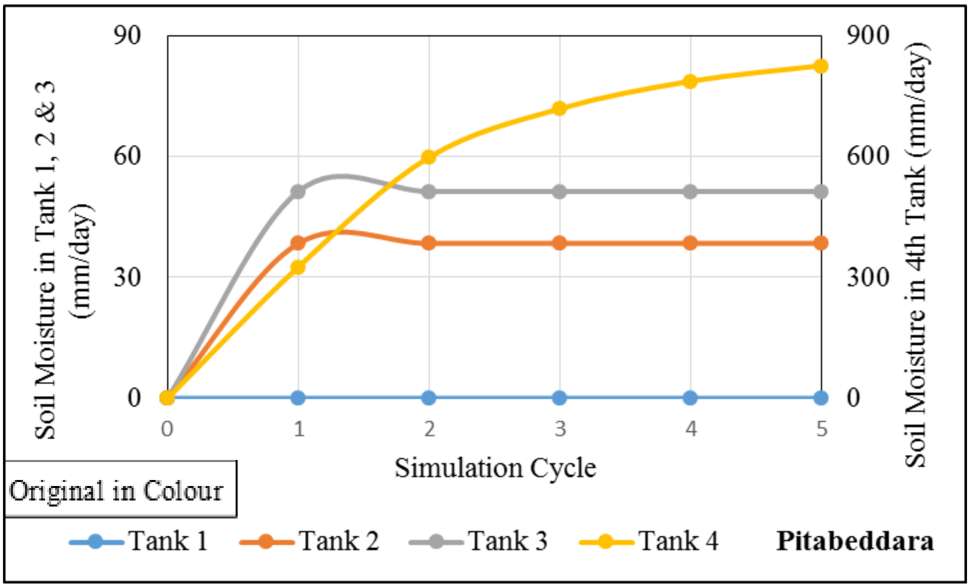


Figure 5-5: Soil moisture content variation in each tank for warm-up period - Pitabeddara

5.4 Optimization of Tank Model

5.4.1 Selection of Initial Parameters

Sugawara et al. (1984) stated that the initial values for the model parameters can be found based on the descending rate of the peak flows in hydrograph in logarithm scale. Since this is a conceptual model, initial value for parameters cannot be directly found w.r.t the catchment properties. Hence considering these concepts and reviewing the parameter values in past studies which have used the Tank model for runoff simulation, initial values for parameters were selected within the defined range as given in Table 2-4.

5.4.2 Selection of Optimization Algorithm

According to the literature review, different kinds of optimization algorithms are used to optimize the model parameters in order to achieve a high level of performance in modeling. Since in this study, the model is developed by using Microsoft Excel software, the inbuilt optimization algorithm in Solver Add-in of MS Excel is used. Considering the nonlinearity of the hydrological cycle and computational timing, GRG nonlinear method with a multi-start option was used as an optimization algorithm in this study.

5.4.3 Selection of Objective Function

According to the objective of the study for water resources management, the model should simulate the overall flow regime at an acceptable accuracy level. Hence the evaluation objective function should be sensitive for the overall flow regime of the catchment. Since the Mean Ratio of Absolute Error (MRAE) calculate the error in each observed data point, MRAE is sensitive for most available flow condition. Similarly Jayadeera (2016), Kamran & Rajapakse (2018), and Wijesekera (2000) have stated that the MRAE is suitable to evaluate the goodness-of-fit of model predictions which focus on water resources management. Hence this study has used the MRAE as the objective function.

5.5 Calibration of Tank Model

In order to calibrate the Tank model, five years of observed streamflow data range from 2008/2009 water year to 2012/2013 water year were used. The semi-automatic calibration procedure has been followed to get a minimum value for MRAE in parallel with the best matching of observed and estimated streamflow. The parameter values w.r.t. minimum MRAE value which is optimized through the Solver tool were slightly adjusted by considering the order of magnitude of parameters, stabilization of soil moisture in each tank and especially matching of high and low flow peaks between observed and estimated streamflow. The process has been followed for a number of calibration trials until the improvement in the objective function and the matching of hydrographs are insignificant within two trials. In each trial, the model has been run for 75 – 100 of sub problems with evaluating 10 -15 of trial solutions by using the Solver tool. During each trial different initial parameter values were applied in order to search the minimum of error surface in different directions.

Besides, outliers in the observed streamflow have not been considered in the calculation of goodness of fit during the calibration process. The performance of the model in each calibration trial was evaluated graphically and numerically by using evaluation indicators namely annual water balance, total hydrograph (in semi-log), and high, medium, and low flows in flow duration curve (sorted and unsorted).

5.5.1 Model Calibration for Urawa Sub-catchment

5.5.1.1 Statistical Measure of Goodness of Fit

Quantitative measures of model performance for overall flow series and different flow regimes are given in Table 5-3.

Table 5-3: Measure of goodness of fit of model for Urawa – 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**
Urawa	0.31	0.03	0.05	0.05	0.34	0.30	0.33

5.5.1.2 Comparison of Observed and Estimated Streamflow Hydrograph

Figure 5-6 illustrates the hydrograph with observed streamflow and estimated streamflow from the model. This facilitates clear identification of the matching of observed streamflow and estimated streamflow. The estimated streamflow shows mismatching with observed streamflow from February to April in most water years where the transition of major monsoon seasons is taking place.

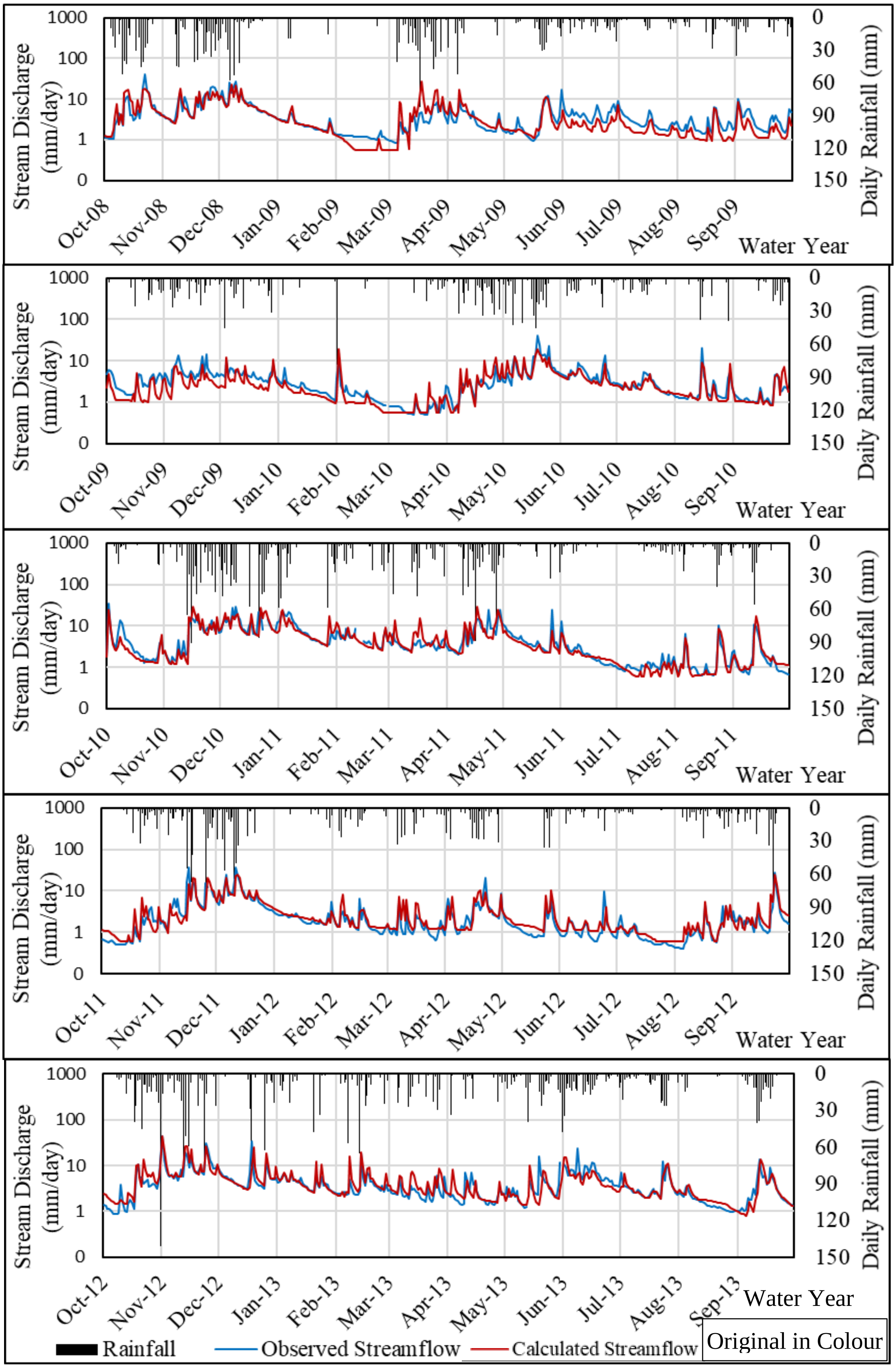


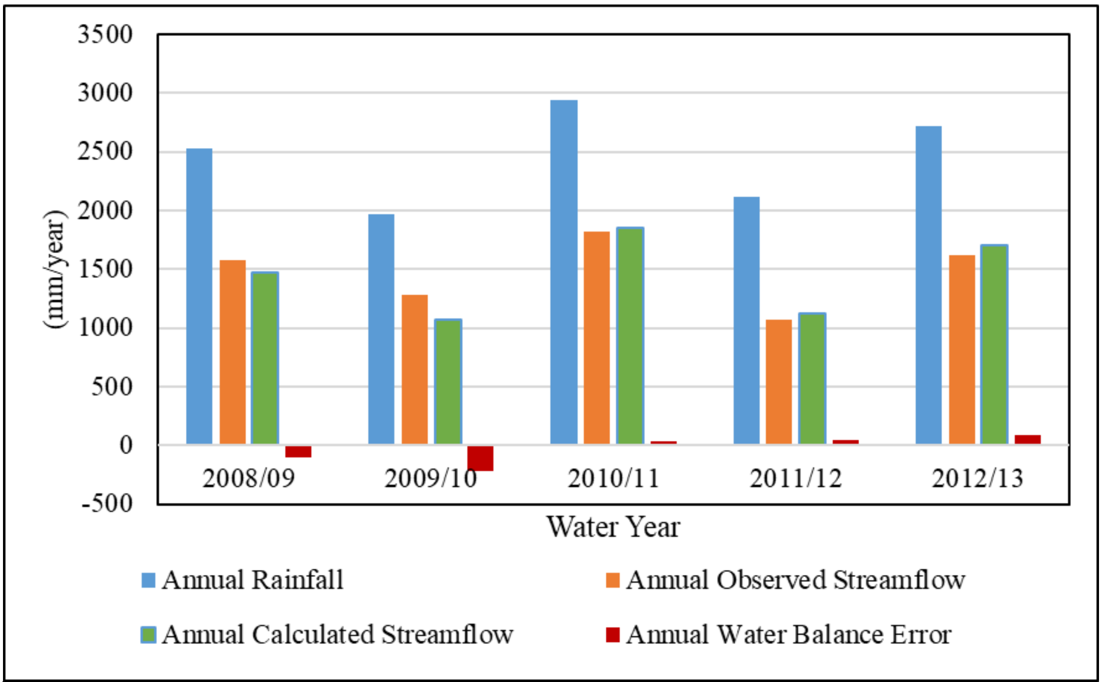
Figure 5-6: Observed and Estimated Flow Hydrograph in Urawa for Calibration

5.5.1.3 Annual Water Balance Error

The difference of annual water balances between observed streamflow series and estimated streamflow series within the calibration period is calculated and given in Table 5-4 and Figure 5-7. Accordingly, it can be identified that the model discharges less water as runoff compared to real conditions. The model has underestimated the streamflow averagely by about 2.4%.

Table 5-4: Annual Water Balance for Urawa - Calibration Period

Water Year	Annual RF (mm)	Annual Observe SF (mm)	Annual cal. SF (mm)	Annual Pan Evpo. (mm)	AWB for Observe Data	AWB for Cal.	AWB Error %
2008/09	2525.3	1573.6	1467.6	1126.1	951.7	1057.7	-6.7%
2009/10	1968.1	1283.8	1066.5	1029.5	684.3	901.6	-16.9%
2010/11	2942.1	1823.9	1854.4	1065.4	1118.2	1087.7	1.7%
2011/12	2111.5	1070.1	1117.9	1040.2	1041.4	993.6	4.5%
2012/13	2715.1	1616.9	1703.9	997.3	1098.2	1011.3	5.4%
Average	**2452.4**	**1473.7**	**1442.0**	**1051.7**	**978.8**	**1010.4**	**-2.4%**



Original in Colour

Figure 5-7: Annual Water Balance for Calibration Period in Urawa Catchment

5.5.1.4 Comparison of Flow Duration Curves

Flow duration curves (FDC) were developed for observed streamflow series and estimated streamflow series in calibration data period to observe the goodness of fit graphically. The FDC facilitates the identification of matching in different flow regimes namely high, medium, and low flows. Figure 5-8 and Figure 5-9 illustrate sorted and unsorted FDC respectively.

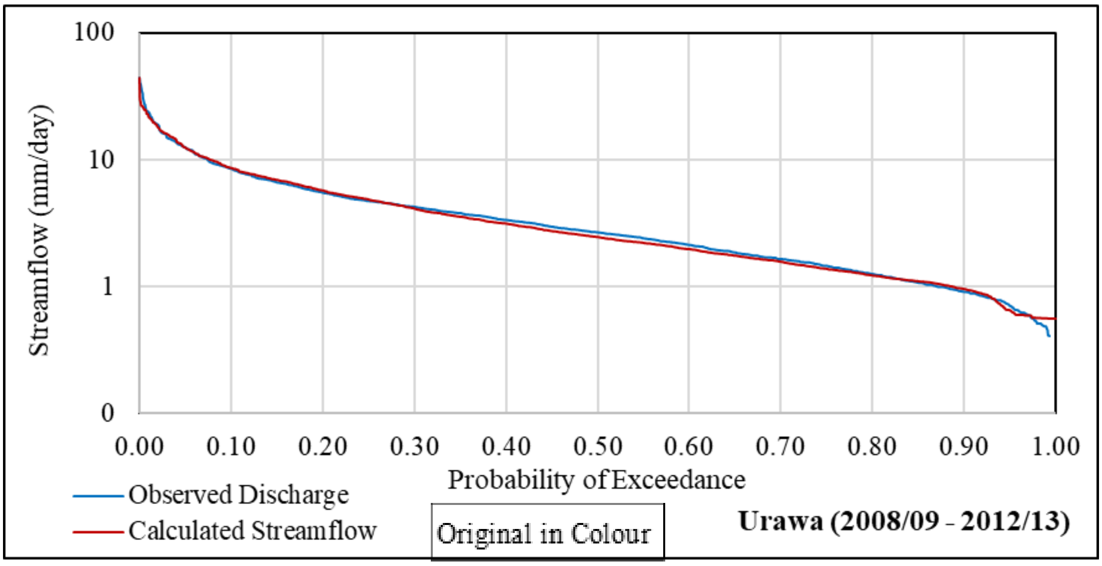


Figure 5-8: FDC (sorted) for Urawa Catchment in Calibration Period

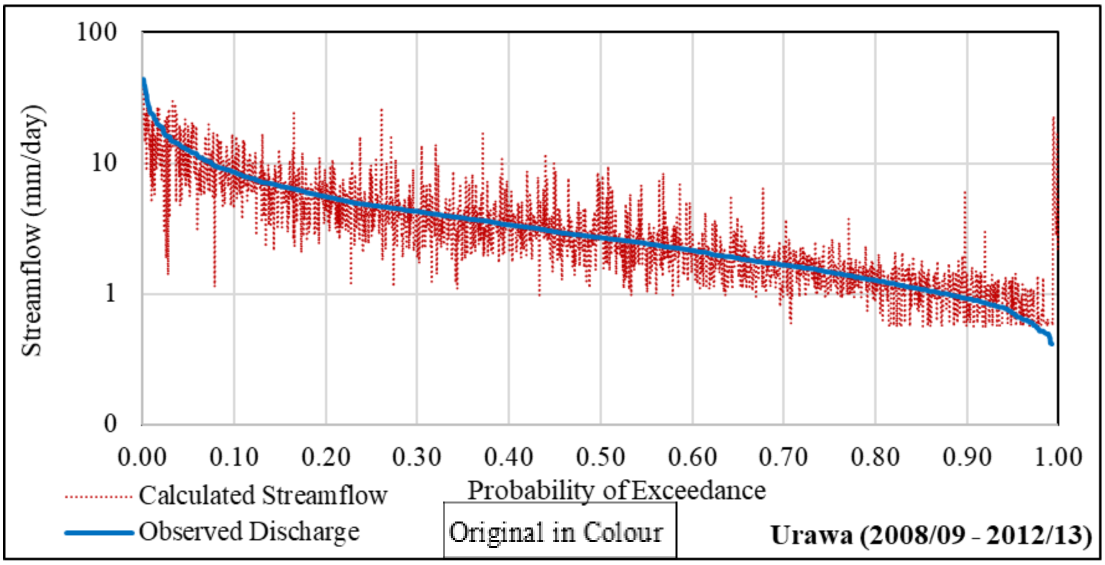


Figure 5-9: FDC (Unsorted) for Urawa in Calibration Period

5.5.2 Model Calibration for Pitabeddara Catchment

A similar procedure was followed with a similar data period to calibrate the Tank model for Pitabeddara catchment also.

5.5.2.1 Statistical Measure of Goodness of Fit

After a few calibration trials, considering the criteria mentioned in Section 5.8, following goodness of fit measure which was given in Table 5-5 was observed.

Table 5-5: Measure of goodness of fit of the model for Pitabeddara - 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**
Pitabeddara	0.32	0.07	0.04	0.13	0.38	0.30	0.43

5.5.2.2 Comparison of Observed and Estimated Streamflow Hydrograph

The semi-log hydrograph for observed and estimated streamflow for Pitabeddara catchment is given in Figure 5-10. Slight overestimation of streamflow can be identified in a few months.

5.5.2.3 Annual Water Balance Error

According to the annual water balance difference between observed and estimated streamflow as shown in Table 5-6 and Figure 5-11, averagely about 3.2% of less runoff is generated by the model.

Table 5-6: Annual Water Balance for Pitabeddara - Calibration Period

Water Year	Annual RF (mm)	Annual Observe SF (mm)	Annual cal. SF (mm)	Annual Pan Evpo. (mm)	AWB for Observe	AWB for Cal.	AWB Error %
2008/09	2750.4	1817.6	1682.3	1126.1	932.8	1068.1	-7.4%
2009/10	2653.7	1705.6	1695.5	1029.5	948.1	958.2	-0.6%
2010/11	3366.8	2534.4	2329.6	1065.4	832.4	1037.2	-8.1%
2011/12	2691.5	1460.6	1644.2	1040.2	1230.9	1047.3	12.6%
2012/13	3357.4	2267.9	2366.2	997.3	1089.5	991.2	4.3%
Average	**2964.0**	**1957.2**	**1943.6**	**1051.7**	**1006.7**	**1020.4**	**0.2%**

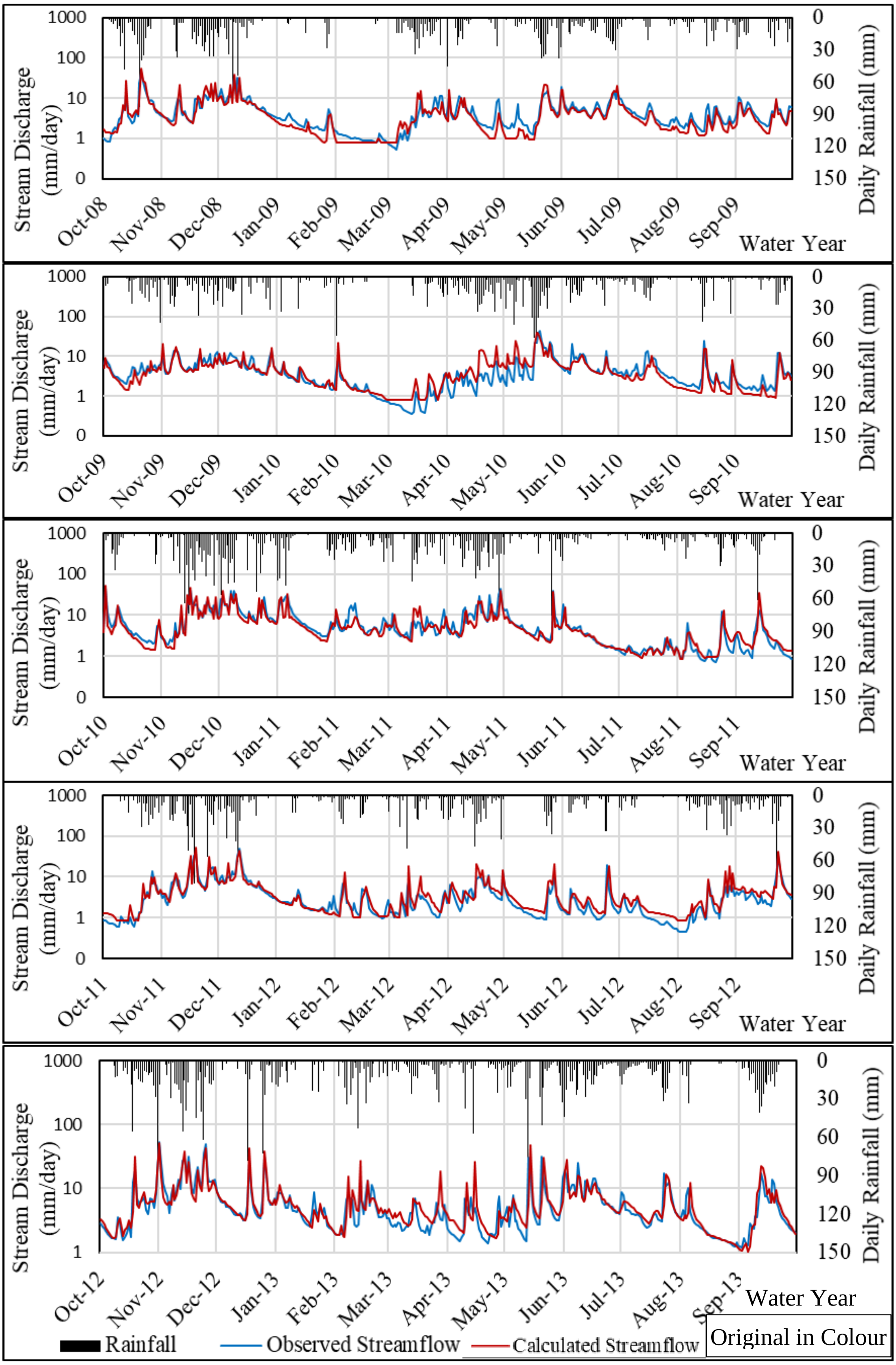


Figure 5-10: Observed and Estimated Flow Hydrograph for Pitabeddara – Calibration Period

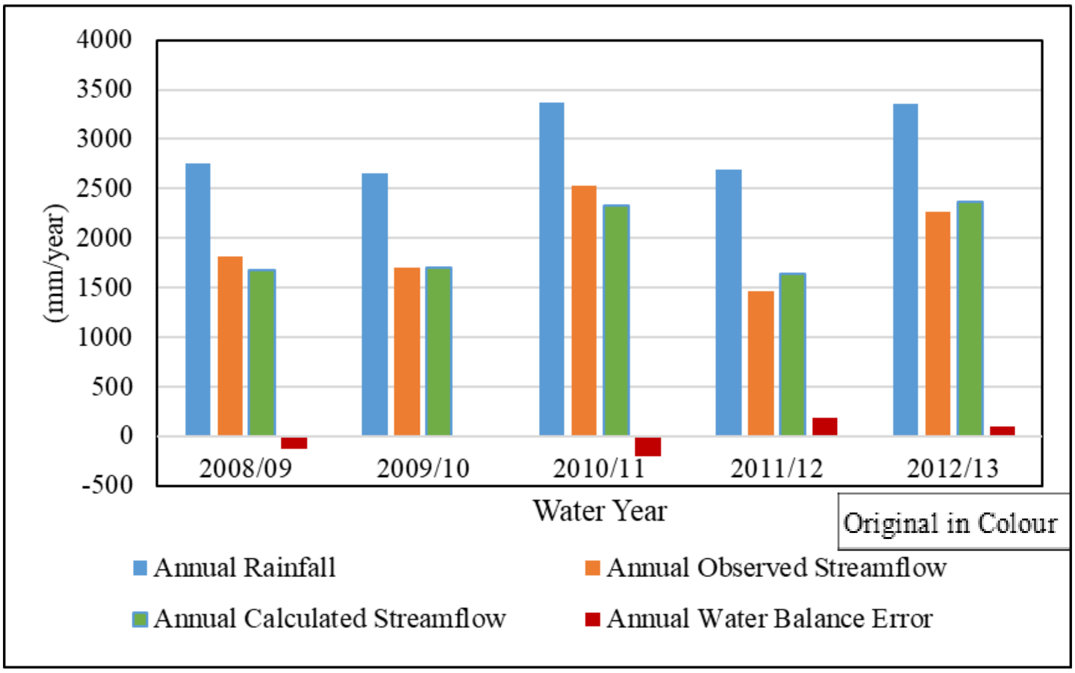


Figure 5-11: Annual Water Balance for Pitabeddara - Calibration Period

5.5.2.4 Comparison of Flow Duration Curves

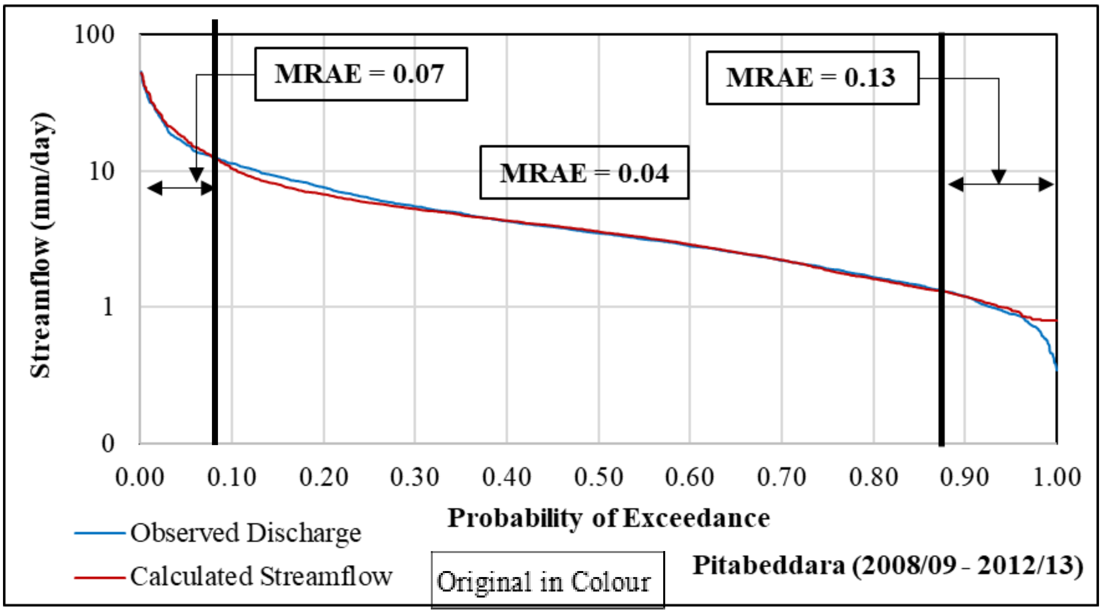


Figure 5-12: FDC (sorted) for Pitabeddara in Calibration period

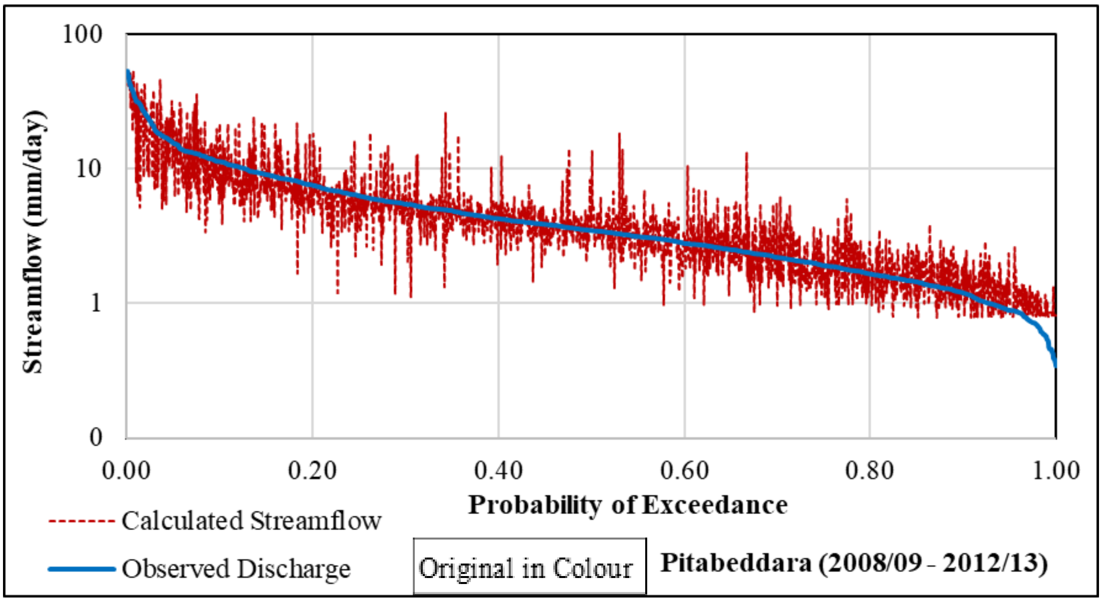


Figure 5-13: FDC (unsorted) for Pitabeddara catchment in Calibration period

5.6 Validation of Tank Model

In order to validate the calibrated model parameters, observed data ranges from 2013/2014 to 2017/2018 were used. The results are given in the following subsections.

5.6.1 Model Validation for Urawa Sub-catchment

5.6.1.1 Statistical Measure of Goodness of Fit

Quantitative measures of model performance for overall flow series and different flow regimes are given in Table 5-7 for the validation data period.

Table 5-7: Measure of goodness of fit of model for Urawa – Validation

Gauging Station	MRAE for Overall Flow	MRAE w.r.t FDC (Sorted)			MRAE w.r.t FDC (Unsorted)		
		High	Medium	Low	High	Medium	Low
Urawa	0.54	0.14	0.26	0.62	0.31	0.47	0.99

5.6.1.2 Comparison of Observed and Estimated Streamflow Hydrograph

Figure 5-14 illustrates the hydrograph with observed streamflow and estimated streamflow from the model in the validation period.

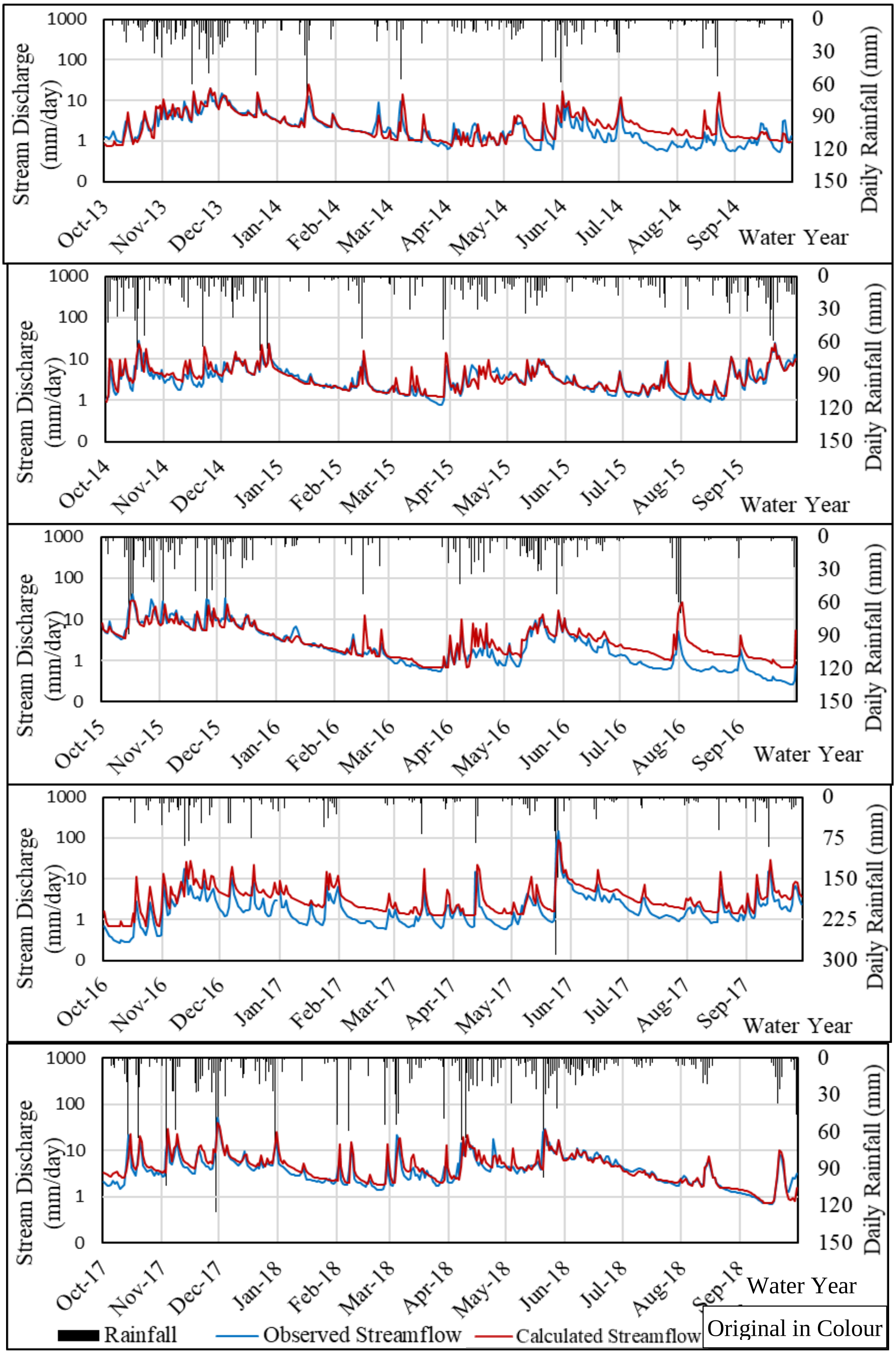


Figure 5-14: Observed and Estimated Flow Hydrograph for Urawa – Validation Period

5.6.1.3 Annual Water Balance Error

The difference of annual water balances between observed streamflow series and estimated streamflow series within the validation period is calculated and given in Table 5-8 and Figure 5-15. According to the results, it can be identified that the model overestimates the runoff by averagely about 20% for the validation period.

In addition to that, it has to be noted that the average runoff coefficient during the calibration period is comparatively high w.r.t the average runoff coefficient during the validation period for the Urawa catchment.

Table 5-8: Annual Water Balance for Urawa - Validation Period

Water Year	Annual RF (mm)	Annual Observe SF (mm)	Annual cal. SF (mm)	Annual Pan Evpo. (mm)	AWB for Observe	AWB for Cal.	AWB Error %
2013/14	2028.9	982.3	1165.6	969.0	1046.6	863.3	18.7%
2014/15	2624.2	1407.6	1552.8	816.2	1216.6	1071.4	10.3%
2015/16	2253.2	1458.6	1585.0	883.1	794.6	668.2	8.7%
2016/17	2771.6	1108.0	1966.5	926.3	1663.6	805.0	77.5%
2017/18	2847.7	1779.7	1962.8	832.3	1068.0	884.9	10.3%
Average	**2505.1**	**1347.2**	**1646.5**	**885.4**	**1157.9**	**858.6**	**25.1%**

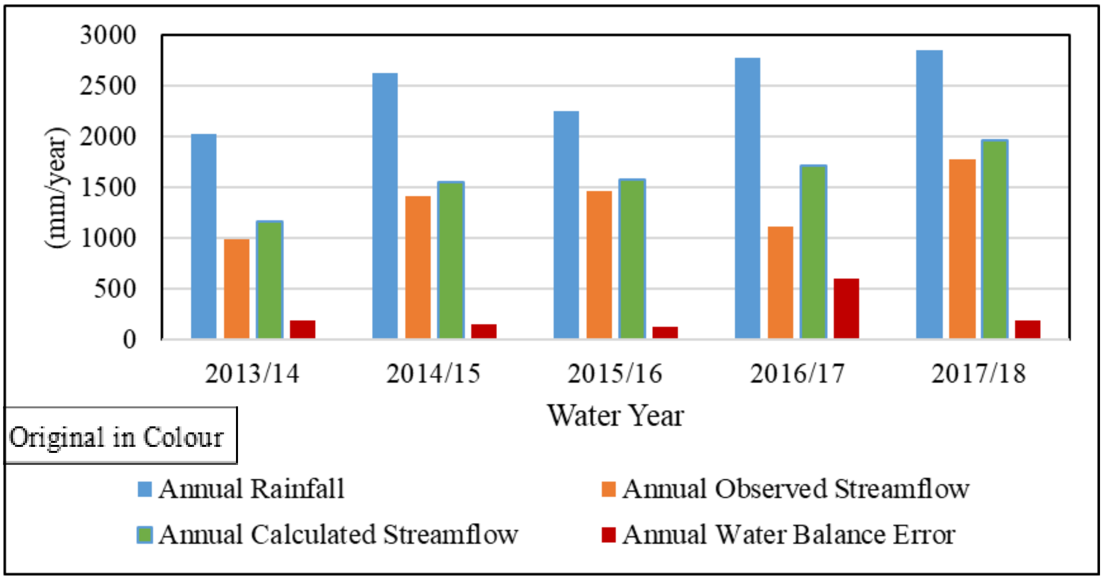


Figure 5-15: Annual Water Balance for Validation Period in Urawa Catchment

5.6.1.4 Comparison of Flow Duration Curves

Figure 5-16 and Figure 5-17 illustrate sorted and unsorted FDC respectively for validation data period. The overestimation of runoff by the model can be clearly identified through these graphs. The margin of overestimation of medium and low flows are comparatively large w.r.t high flow predictions from the model.

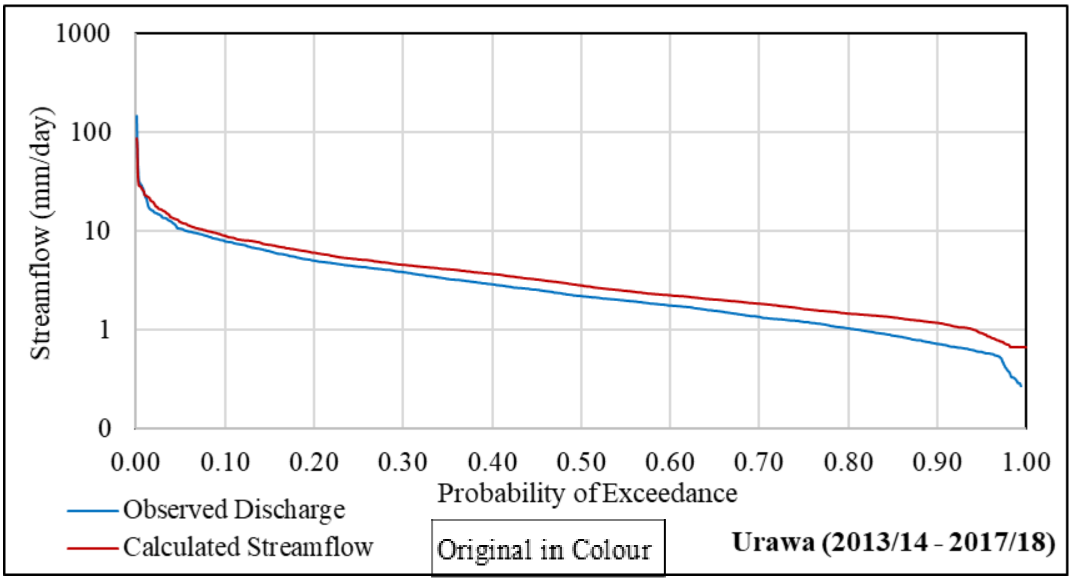


Figure 5-16: FDC (Sorted) for Urawa in Validation Period

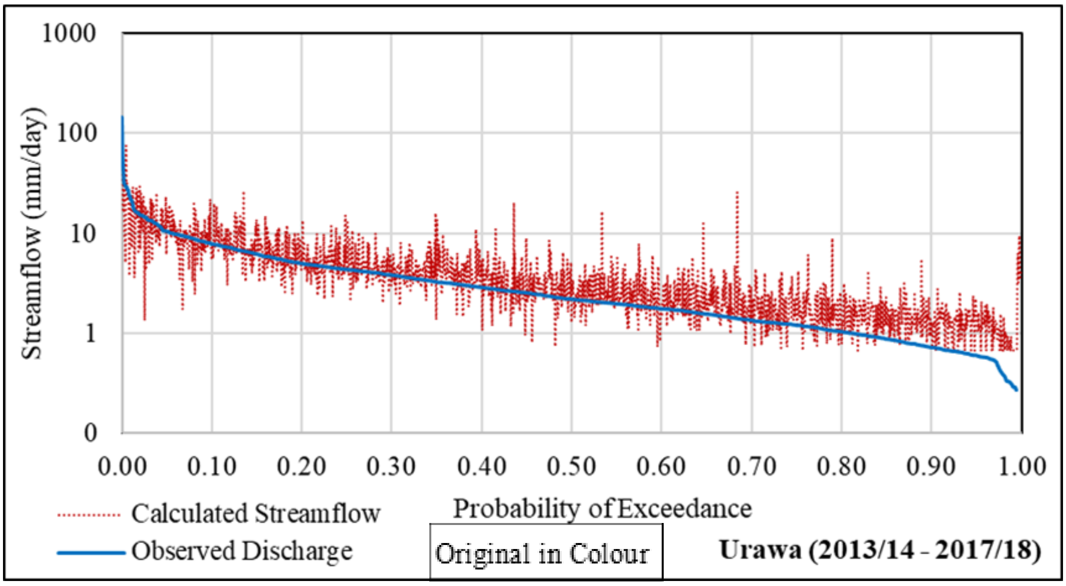


Figure 5-17: FDC (Unsorted) for Urawa Catchment in Validation Period

5.6.2 Model Validation for Pitabeddara Catchment

A similar data period was used to evaluate the validity of the model for simulation of Pitabeddara catchment. The results are given in the following subsections.

5.6.2.1 Statistical Measure of Goodness of Fit

Quantitative measures of model performance for overall flow series and different flow regimes are given in Table 5-9 for the validation data period.

Table 5-9: Measure of goodness of fit of model for Pitabeddara – Validation

Gauging Station	**MRAE for Overall Flow**	**MRAE w.r.t FDC (Sorted)**			**MRAE w.r.t FDC (Unsorted)**		
		High	**Medium**	**Low**	**High**	**Medium**	**Low**
Pitabeddara	0.48	0.21	0.29	0.56	0.39	0.45	0.77

5.6.2.2 Comparison of Observed and Estimated Streamflow Hydrograph

Figure 5-18 illustrates the hydrograph with observed streamflow and estimated streamflow from the model in the validation period.

5.6.2.3 Annual Water Balance Error

The difference of annual water balances between observed streamflow series and estimated streamflow series within the validation period is calculated and given in Table 5-10 and Figure 5-19.

Table 5-10: Annual Water Balance for Pitabeddara - Validation Period

Water Year	Annual RF (mm)	Annual Observe SF (mm)	Annual cal. SF (mm)	Annual Pan Evpo. (mm)	AWB for Observe	AWB for Cal.	AWB Error %
2013/14	2776.3	1421.4	1772.9	969.0	1354.9	1003.4	25%
2014/15	3454.1	2095.0	2441.4	816.2	1359.1	1012.8	17%
2015/16	2718.3	1802.5	2067.2	883.1	915.7	651.1	15%
2016/17	2761.8	1646.4	1773.9	926.3	1115.4	987.9	8%
2017/18	3481.6	2017.0	2618.7	832.3	1464.6	862.9	30%
Average	**3038.4**	**1796.4**	**2134.8**	**885.4**	**1242.0**	**903.6**	**18.7%**

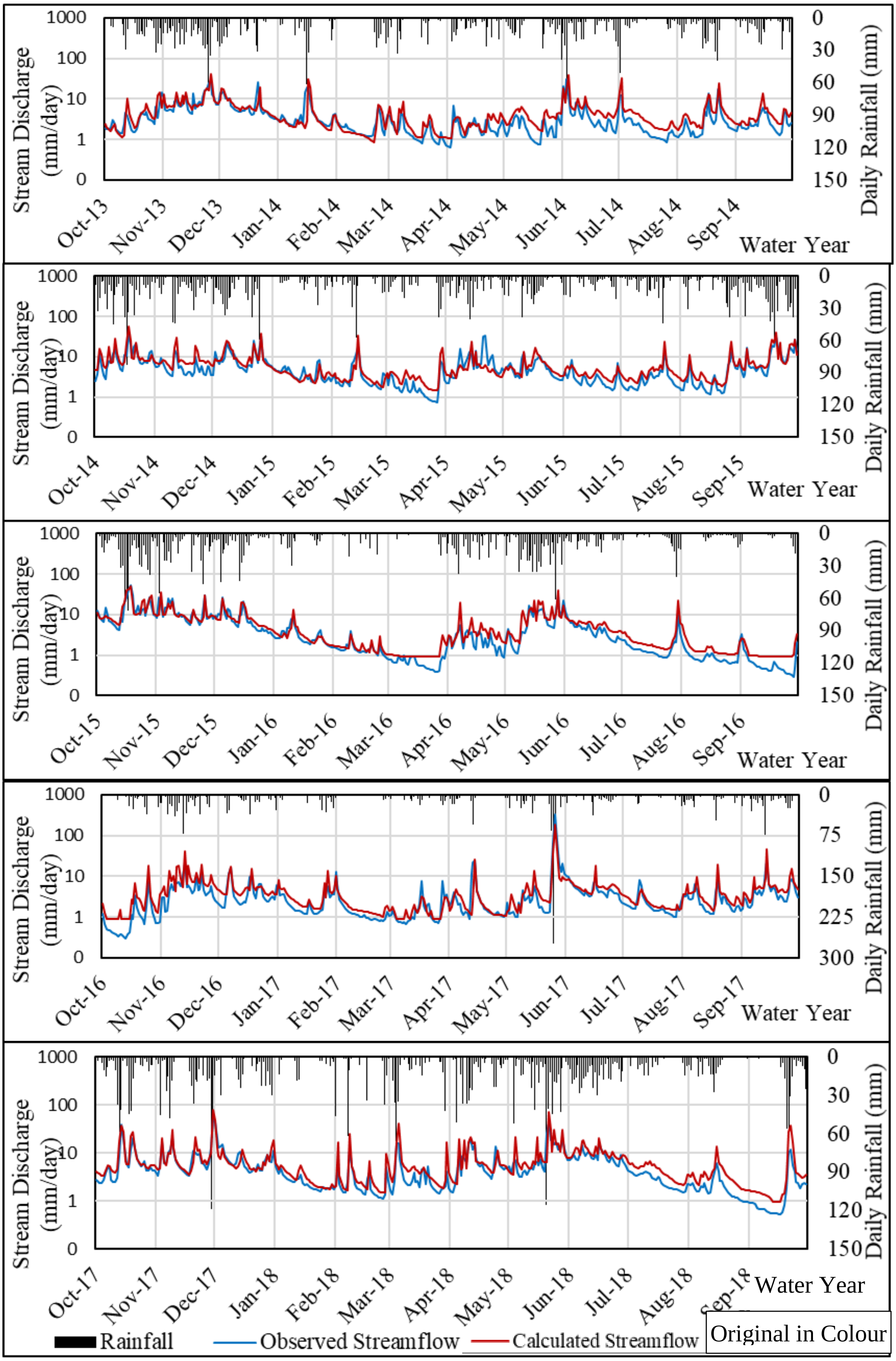


Figure 5-18: Observed and Estimated Flow Hydrograph for Pitabeddara – Validation Period

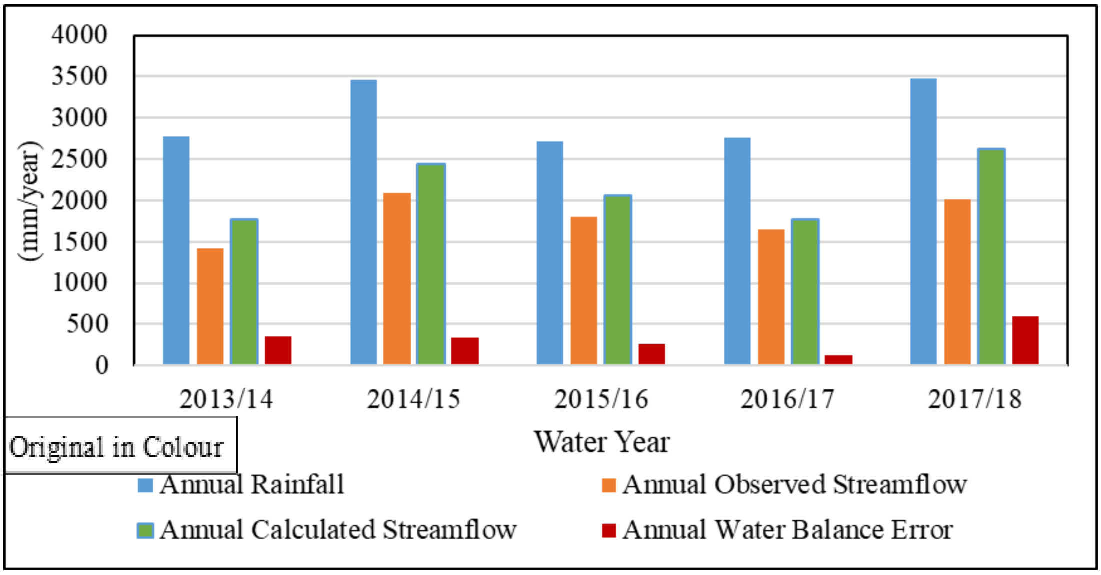


Figure 5-19: Annual Water Balance for Validation Period in Pitabeddara Catchment

5.6.2.4 Comparison of Flow Duration Curves

Figure 5-20 and Figure 5-21 illustrate sorted and unsorted FDC respectively for validation data period.

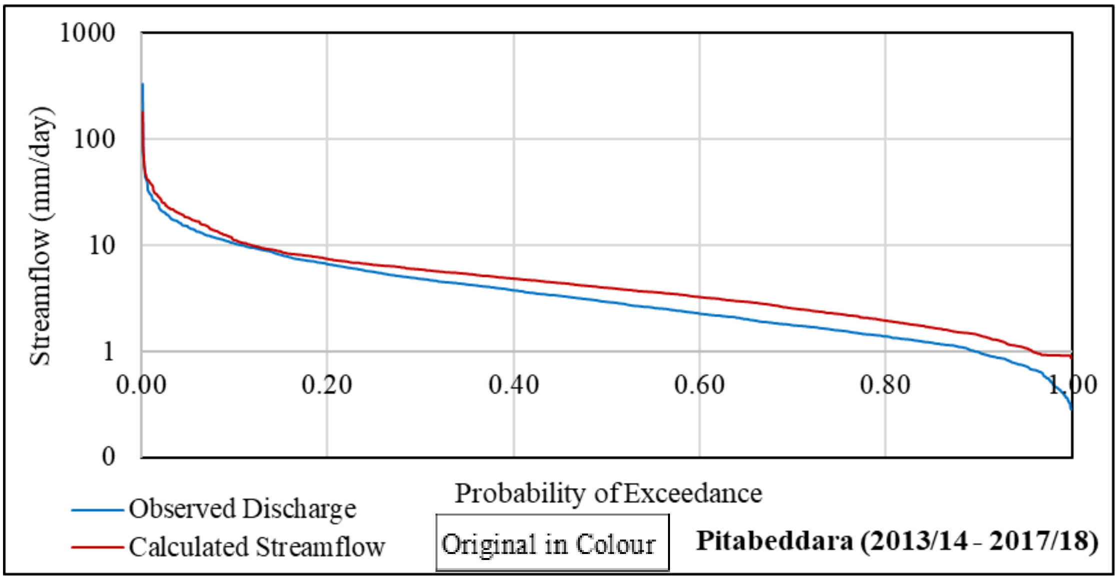


Figure 5-20: FDC (Sorted) for Pitabeddara in Validation Period

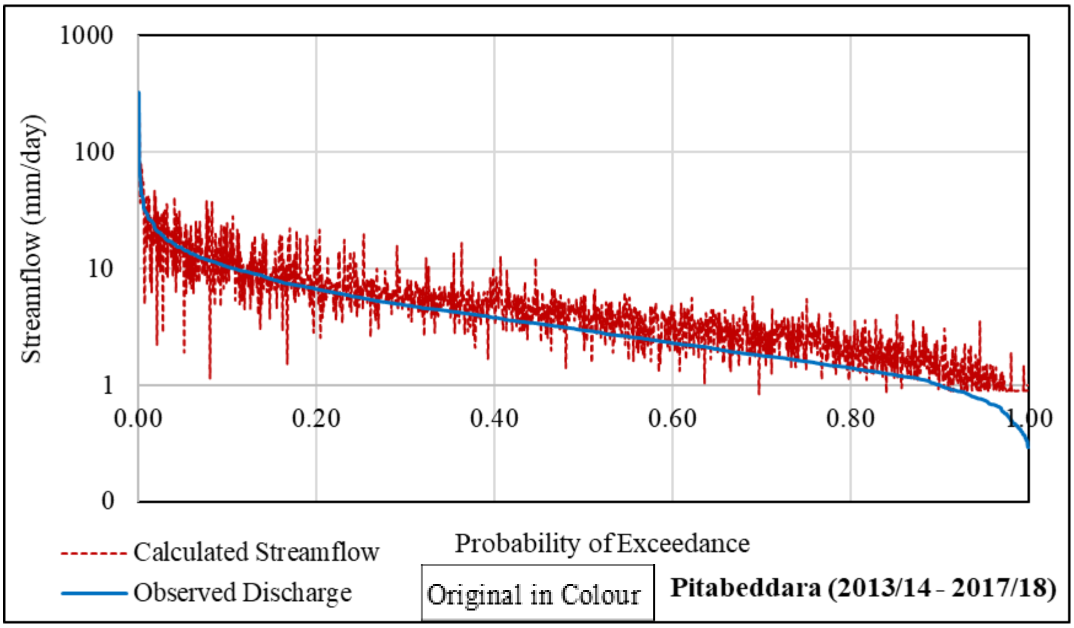


Figure 5-21: FDC (Unsorted) for Pitabeddara in Validation Period

5.7 Optimized Tank Model Parameters

After the comprehensive systematic calibration and validation trails, the model performance described in the above sections was accepted as the best performance of the model for the respective catchments. Hence the optimized parameters for both catchments are as given in Table 5-11.

Table 5-11: Optimized Tank Model Parameters for both catchments

Parameter	Optimized Value for Urawa Catchment	Optimized Value for Pitabeddara Catchment
A0 (1/day)	0.4009	0.2988
A1 (1/day)	0.0935	0.1060
A2 (1/day)	0.1736	0.5393
B0 (1/day)	0.0386	0.0334
B1 (1/day)	0.0288	0.0422
C0 (1/day)	0.0124	0.0123
C1 (1/day)	0.0181	0.0260
D1 (1/day)	0.000082	0.0001
HA1 (mm)	0.11	2.10
HA2 (mm)	13.57	28.45
HB1 (mm)	42.99	41.62
HC1 (mm)	33.00	81.00

5.8 Model Parameter Transferability

The optimized parameters of the Tank model for both catchments were transferred from the main catchment to sub-catchment (Pitabeddara catchment to Urawa catchment) and from sub-catchment to main catchment (Urawa catchment to Pitabeddara catchment). Following transferability approaches have been used,

1. Spatiotemporal transferability approach
2. Temporal transferability approach
3. Spatial transferability approach

Since the study has mainly focused on water resources management, transferability modeling in the temporal axis was done for data period ranges from 2008/09 water year to 2017/18 water year.

Since simple and convenient methodologies are preferred by the water engineers for use in water resources assessment in ungauged catchments, the parameters were directly transferred according to the above three approaches.

5.8.1 Model Performance in Spatiotemporal Transferability Approach

This approach contains both spatial and temporal parameter transfer methodologies. The total study period ranges from 2008/09 water year to 2017/18 water year has been considered in the temporal axis to evaluate the models' performances.

5.8.1.1 Spatiotemporal Parameter Transferability from Main catchment to Sub-catchment

The optimized model parameters for Pitabeddara catchment were directly transferred to the model for Urawa sub-catchment. The results are given in the following subsections.

5.8.1.1.1 Statistical Measure of Goodness of Fit

Quantitative measures of model performance for overall flow series and different flow regimes are given in Table 5-12 for the whole data period.

Table 5-12: Measure of goodness of fit of model for Urawa 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
Urawa	0.46	0.38	0.02	0.38	0.60	0.39	0.64

5.8.1.1.2 Comparison of Observed and Estimated Streamflow Hydrograph

Figure 5-22 and Figure 5-23 illustrate the hydrograph with observed streamflow and estimated streamflow from the model with spatiotemporally transferred parameters.

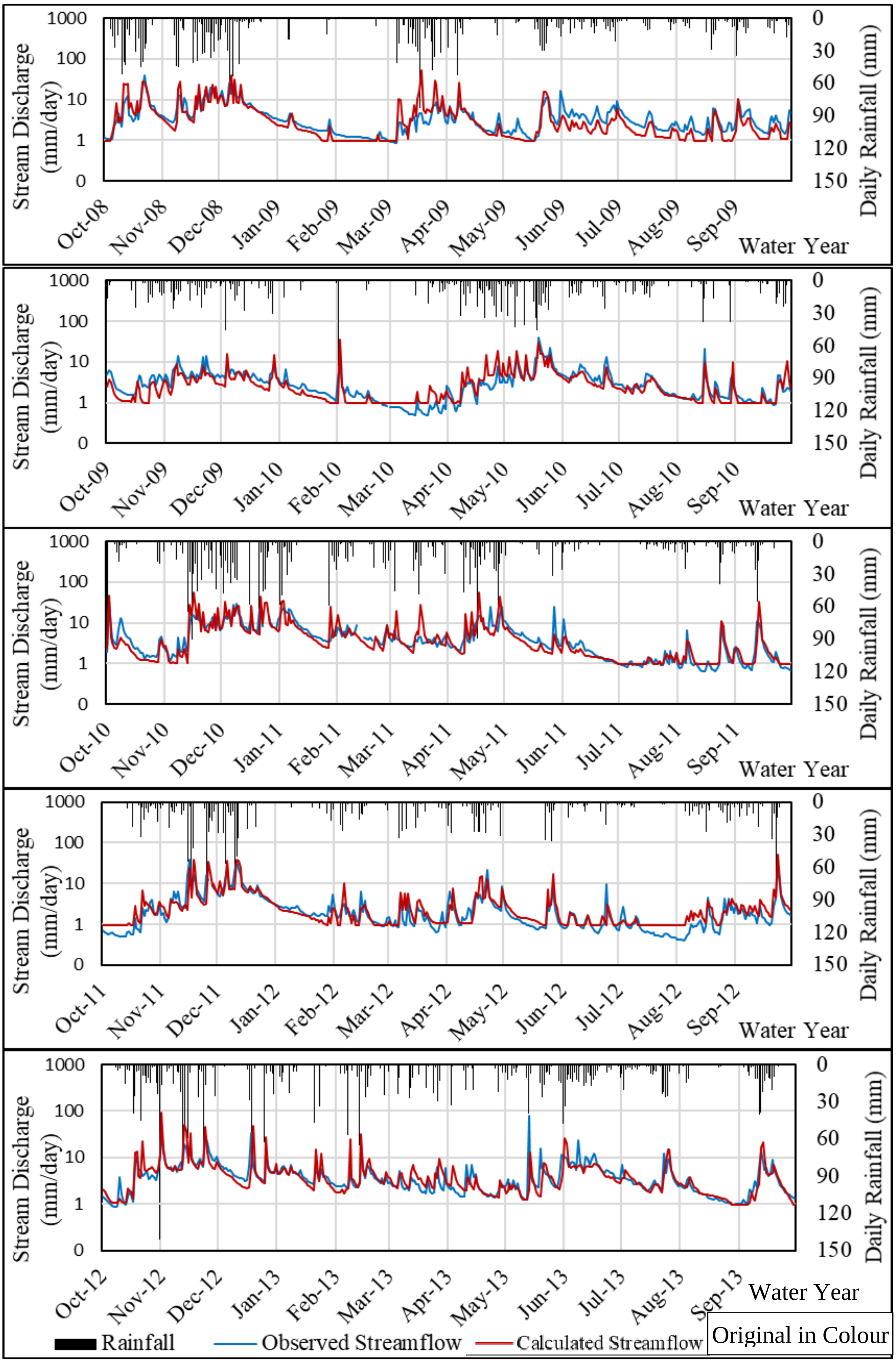


Figure 5-22: Flow Hydrograph for Urawa with spatiotemporally transferred parameters – 2008/09-2012/13

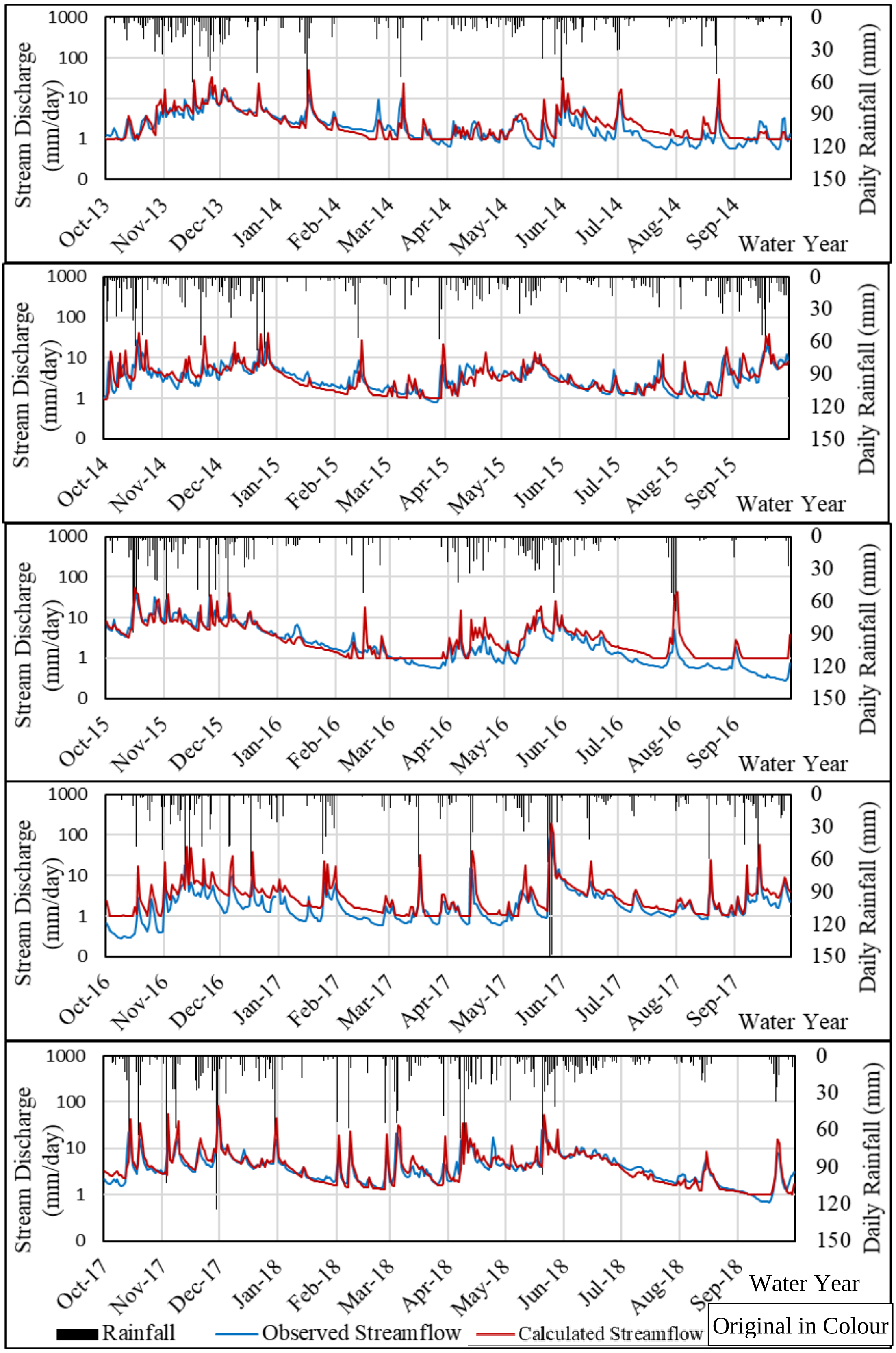


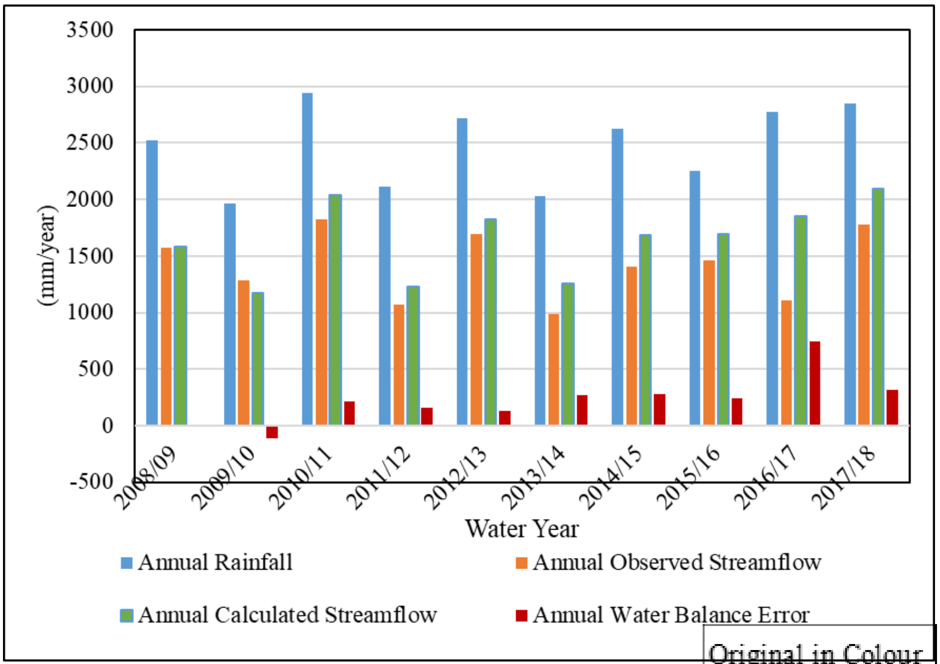
Figure 5-23: Flow Hydrograph for Urawa with spatiotemporally transferred parameters – 2013/14-2017/18

5.8.1.1.3 Annual Water Balance Error

The difference of annual water balances between observed streamflow series and estimated streamflow series within 2008/09 water year to 2017/18 water year are calculated and given in Table 5-13 and Figure 5-24.

Table 5-13: Annual Water Balance for Urawa with spatiotemporally transferred parameters

Water Year	Annual RF (mm)	Annual Observe SF (mm)	Annual cal. SF (mm)	Annual Pan Evpo. (mm)	AWB for Observe	AWB for Cal.	AWB Error %
2008/09	2525.3	1573.6	1587.0	1126.1	951.7	938.2	0.9%
2009/10	1968.1	1283.8	1170.5	1029.5	684.3	797.7	-8.8%
2010/11	2942.1	1823.9	2039.2	1065.4	1118.2	903.0	11.8%
2011/12	2111.5	1070.1	1227.4	1040.2	1041.4	884.1	14.7%
2012/13	2715.1	1694.4	1825.3	997.3	1020.8	889.8	7.7%
2013/14	2028.9	982.3	1255.7	969.0	1046.6	773.2	27.8%
2014/15	2624.2	1407.6	1683.2	816.2	1216.6	941.0	19.6%
2015/16	2253.2	1458.6	1697.7	883.1	794.6	555.4	16.4%
2016/17	2771.6	1108.0	1852.0	926.3	1663.6	919.6	67.1%
2017/18	2847.7	1779.7	2093.9	832.3	1068.0	753.8	17.7%
Average	**2478.8**	**1418.2**	**1643.2**	**968.5**	**1060.6**	**835.6**	**15.9%**



Original in Colour

Figure 5-24: Annual Water Balance Error for spatiotemporal transferability condition - Urawa

5.8.1.1.4 Comparison of Flow Duration Curves

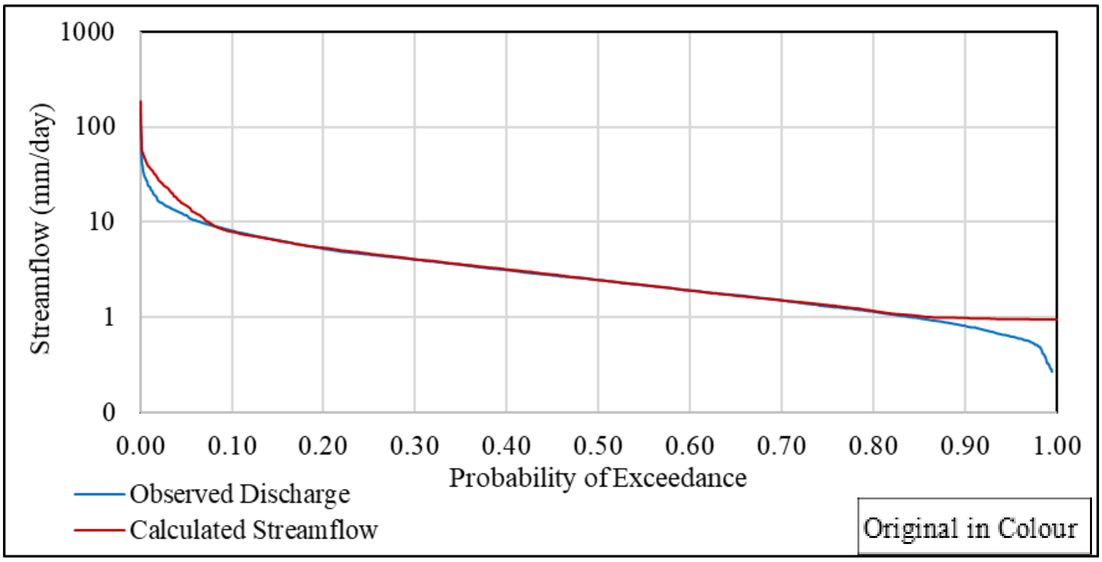


Figure 5-25: FDC (Sorted) for Urawa with spatiotemporally transferred parameters from Pitabeddara

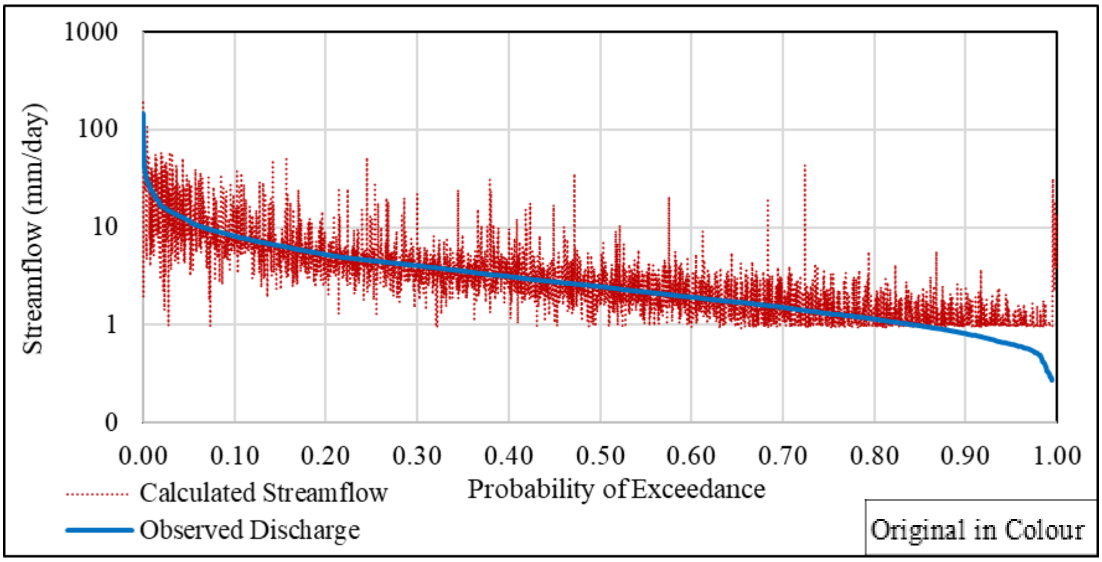


Figure 5-26: FDC (Unsorted) for Urawa with spatiotemporally transferred parameters from Pitabeddara

5.8.1.2 Parameter Transferability from Sub-catchment to Main catchment

The optimized model parameters for Urawa sub-catchment were directly transferred to the model for Pitabeddara catchment and the model simulated the streamflow from 2008/09 water year to 2017/18 water year.

5.8.1.2.1 Statistical Measure of Goodness of Fit

Quantitative measures of model performance for overall flow series and different flow regimes are given in Table 5-14 for the whole data period for parameter transferability condition.

Table 5-14: Measure of goodness of fit of model for Pitabeddara 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**
Pitabeddara	0.61	0.12	0.39	1.24	0.27	0.51	1.49

5.8.1.2.2 Comparison of Observed and Estimated Streamflow Hydrograph

Figure 5-27 and Figure 5-28 illustrate the hydrograph with observed streamflow and estimated streamflow from the model with transferred parameters from Urawa sub-catchment.

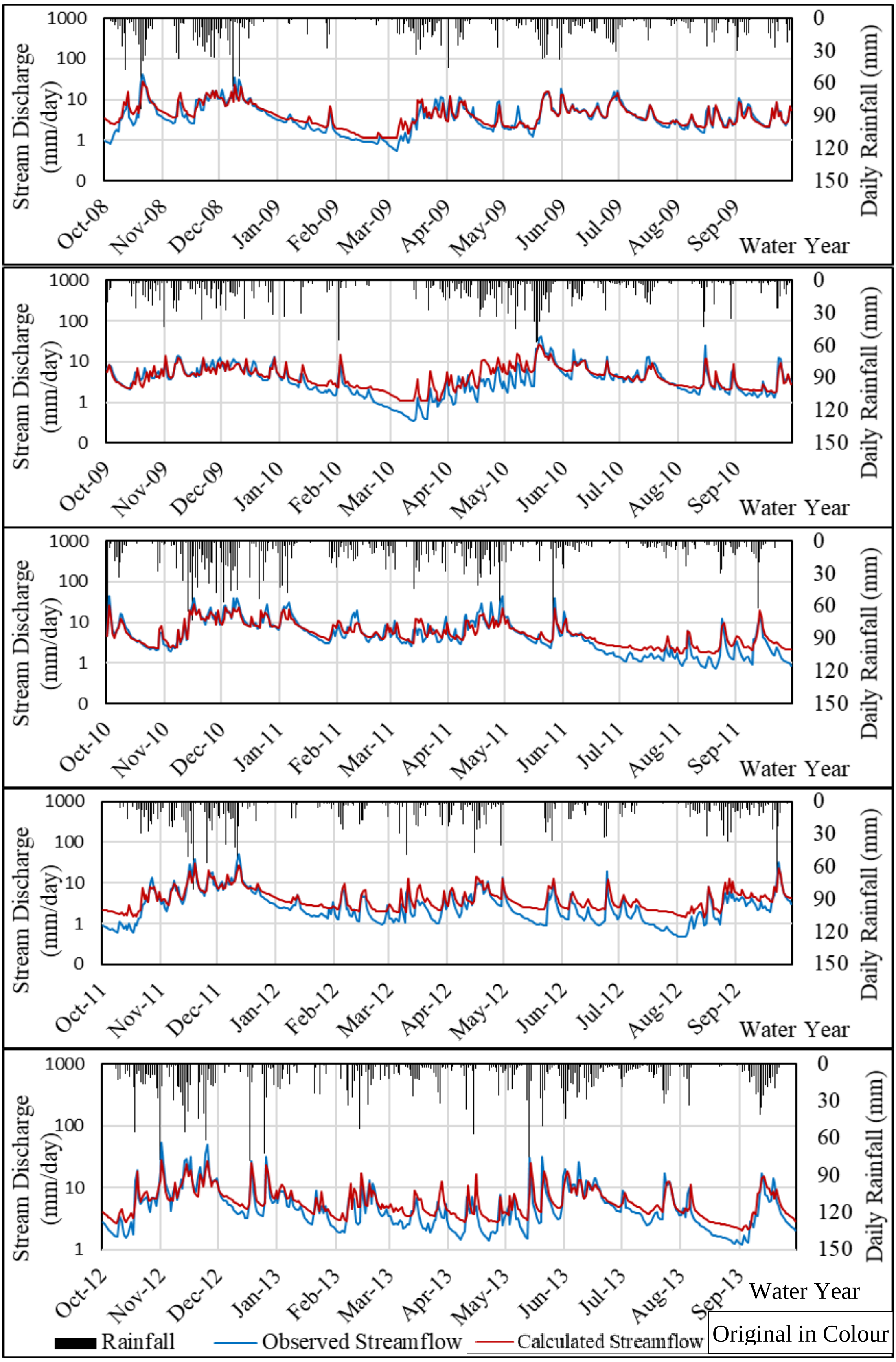


Figure 5-27: Flow Hydrograph for Pitabeddara with spatiotemporally transferred parameters – 2008/09-2012/13

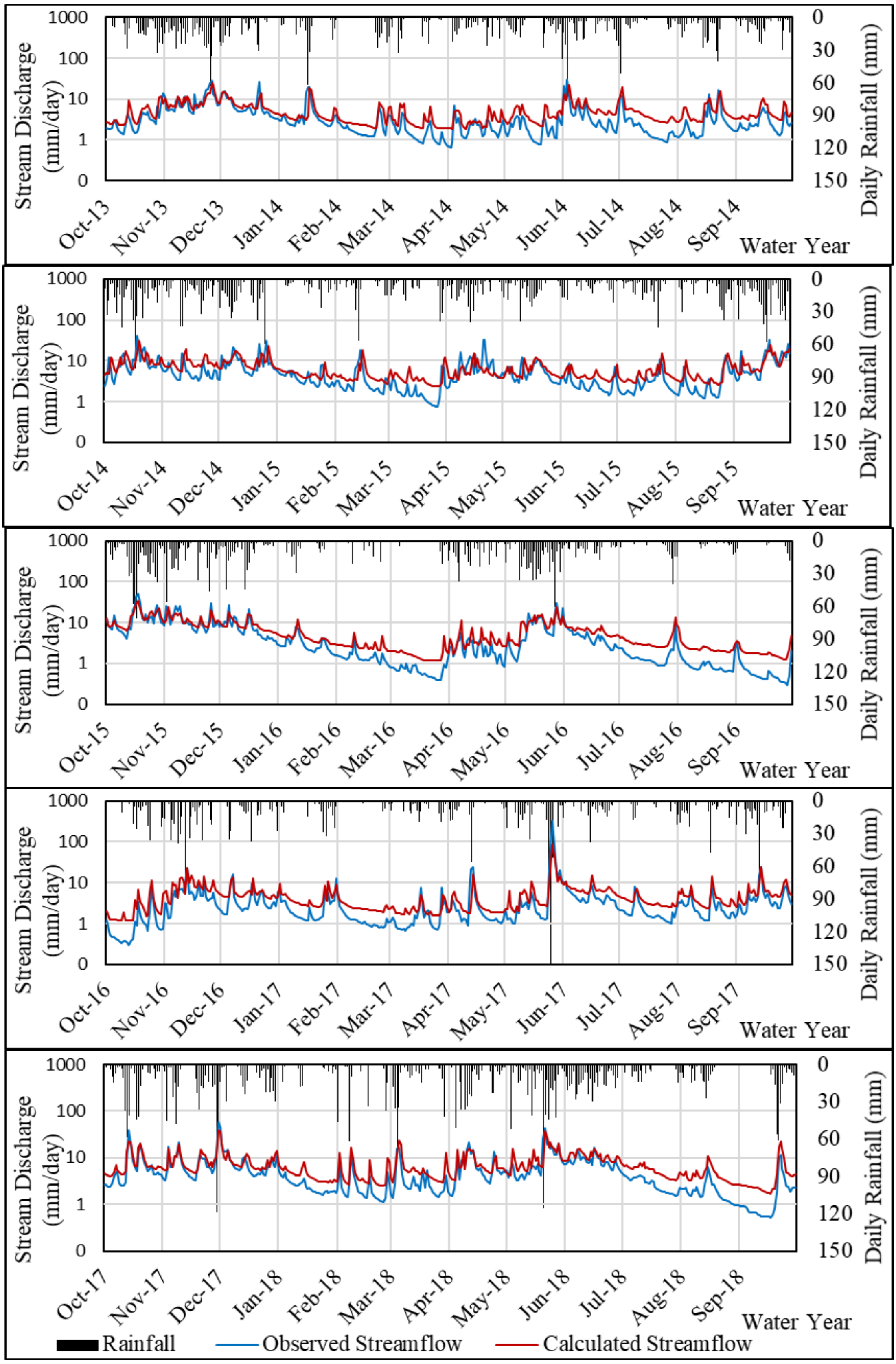


Figure 5-28: Flow Hydrograph for Pitabeddara with spatiotemporally transferred parameters –2013/14-2017/18

5.8.1.2.3 Annual Water Balance Error

The difference of annual water balances between observed streamflow series and estimated streamflow series within 2008/09 water year to 2017/18 water year are calculated and given in Table 5-15 and Figure 5-29.

Table 5-15: Annual Water Balance for Pitabeddara with spatiotemporally transferred parameters

Water Year	Annual RF (mm)	Annual Observe SF (mm)	Annual cal. SF (mm)	Annual Pan Evpo. (mm)	AWB for Observed flow	AWB for Cal.	AWB Error %
2008/09	2750.4	1817.6	1825.2	1126.1	932.8	925.3	0.4%
2009/10	2653.7	1705.6	1809.1	1029.5	948.1	844.6	6.1%
2010/11	3366.8	2534.4	2383.2	1065.4	832.4	983.6	-6.0%
2011/12	2691.5	1460.6	1749.1	1040.2	1230.9	942.4	19.8%
2012/13	3357.4	2267.9	2421.8	997.3	1089.5	935.6	6.8%
2013/14	2776.3	1421.4	1891.6	969.0	1354.9	884.6	33.1%
2014/15	3454.1	2095.0	2454.7	816.2	1359.1	999.4	17.2%
2015/16	2718.3	1802.5	2189.3	883.1	915.7	529.0	21.5%
2016/17	2761.8	1646.4	1850.3	926.3	1115.4	911.5	12.4%
2017/18	3481.6	2017.0	2639.8	832.3	1464.6	841.8	30.9%
Average	**3001.2**	**1876.8**	**2121.4**	**968.5**	**1124.4**	**879.8**	**13.0%**

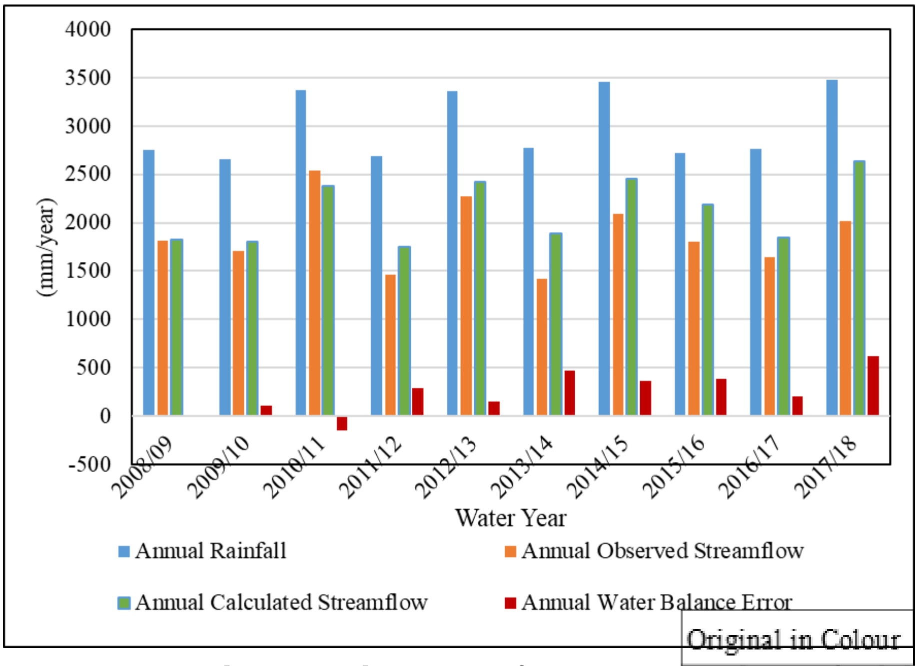


Figure 5-29: Annual Water Balance Error for spatiotemporal Transferability Condition - Pitabeddara

5.8.1.2.4 Comparison of Flow Duration Curves

Figure 5-30 and Figure 5-31 illustrate sorted and unsorted FDC respectively for Pitabeddara catchment model results with transferred parameters from Urawa sub-catchment.

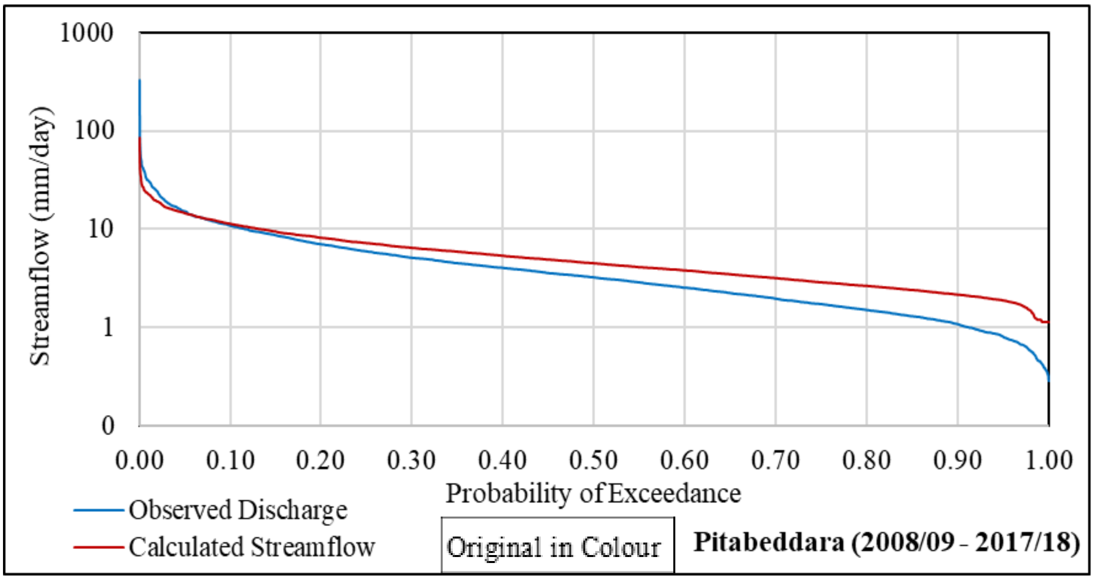


Figure 5-30: FDC (Sorted) for Pitabeddara with spatiotemporally transferred parameters from Urawa

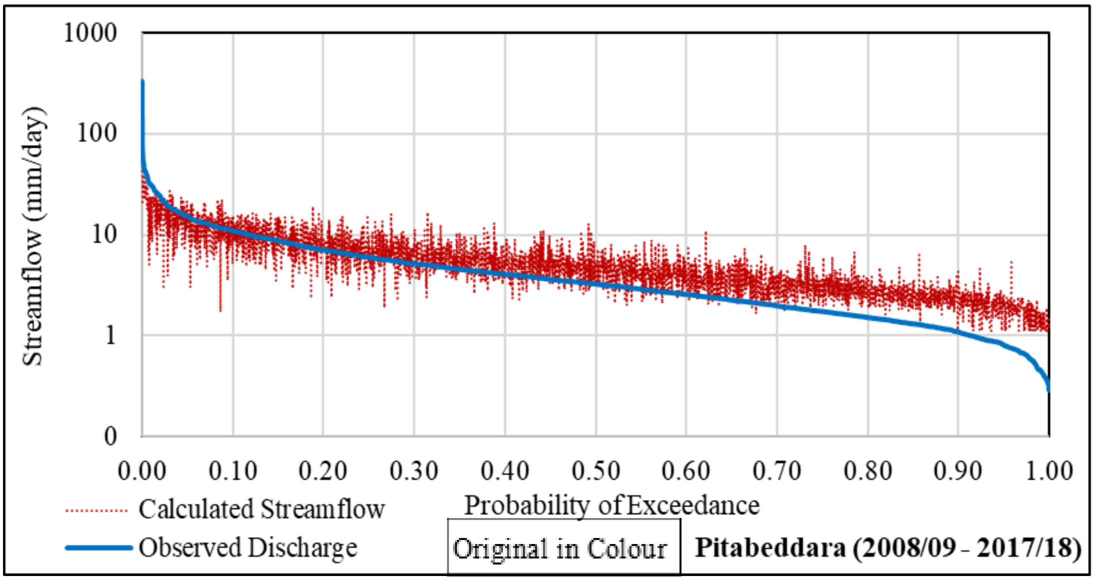


Figure 5-31: FDC (Unsorted) for Pitabeddara with spatiotemporally transferred parameters from Urawa

5.8.2 Model Performance in Temporal Transferability Approach

The optimized parameters were transferred in the temporal axis ranges from 2008/09 water year to 2017/18 water year within the same spatial extent. The approach has been followed for both catchments and results are as following sections.

5.8.2.1 Temporal Parameter Transferability in Urawa Sub-catchment

The calibrated Tank model parameters for water year 2008/09 to 2012/13 were transferred to simulate the streamflow within the period ranges from water year 2008/09 to 2017/18.

5.8.2.1.1 Statistical Measure of Goodness of Fit

The MRAE values for the transferability approach are given in the following Table 5-16.

Table 5-16: Measure of goodness of fit of model for Urawa in temporal transferability

Gauging Station	MRAE for Overall Flow	MRAE w.r.t FDC (Sorted)			MRAE w.r.t FDC (Unsorted)		
		High	Medium	Low	High	Medium	Low
Urawa	0.51	0.10	0.21	0.69	0.34	0.41	1.02

5.8.2.1.2 Comparison of Observed and Estimated Streamflow Hydrograph

Figure 5-32 and Figure 5-33 illustrate the behavior of streamflow hydrographs with observed and estimated streamflows.

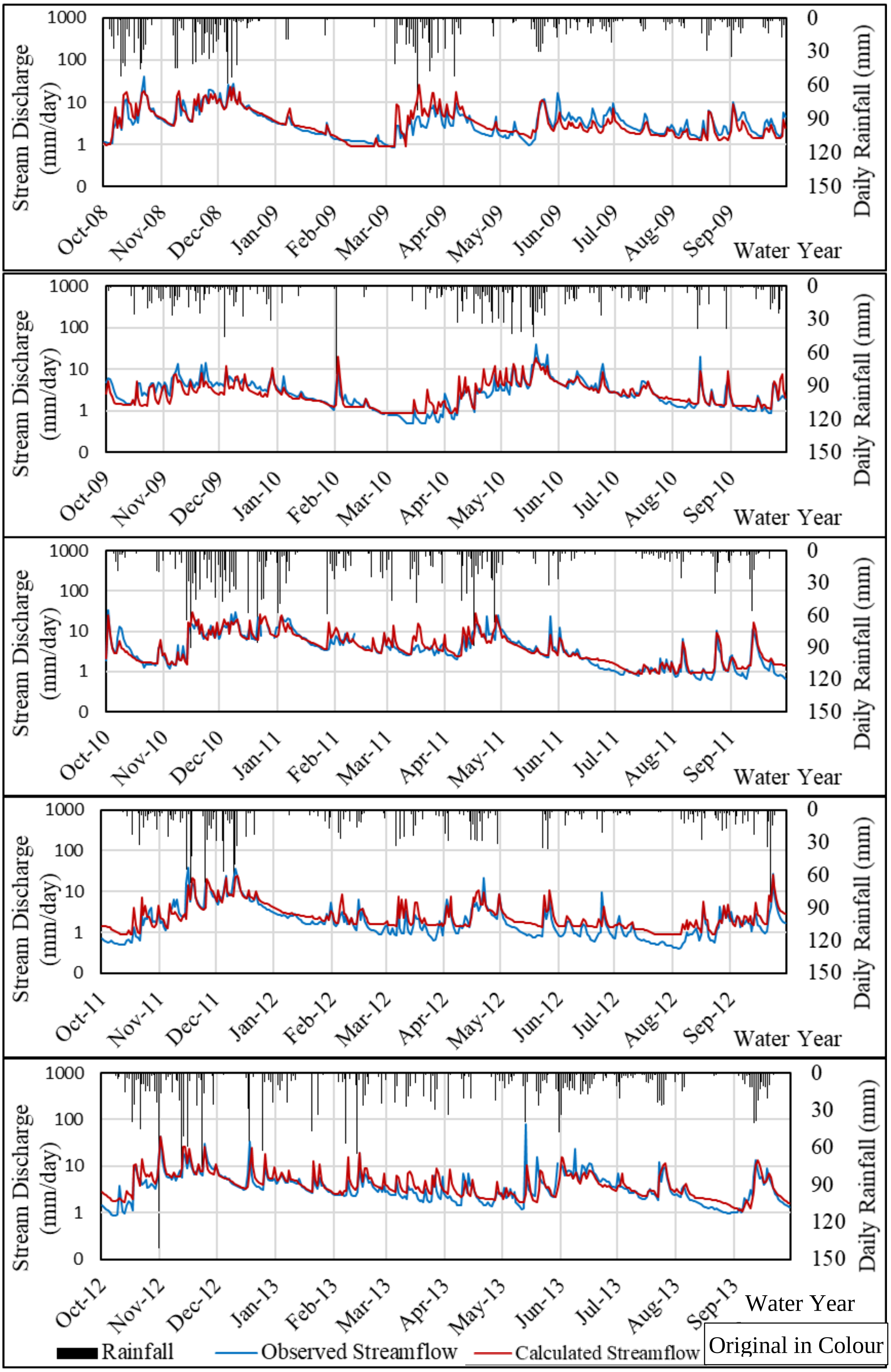


Figure 5-32: Flow Hydrograph of Urawa for Temporal transferability - 2008/09-2012/13

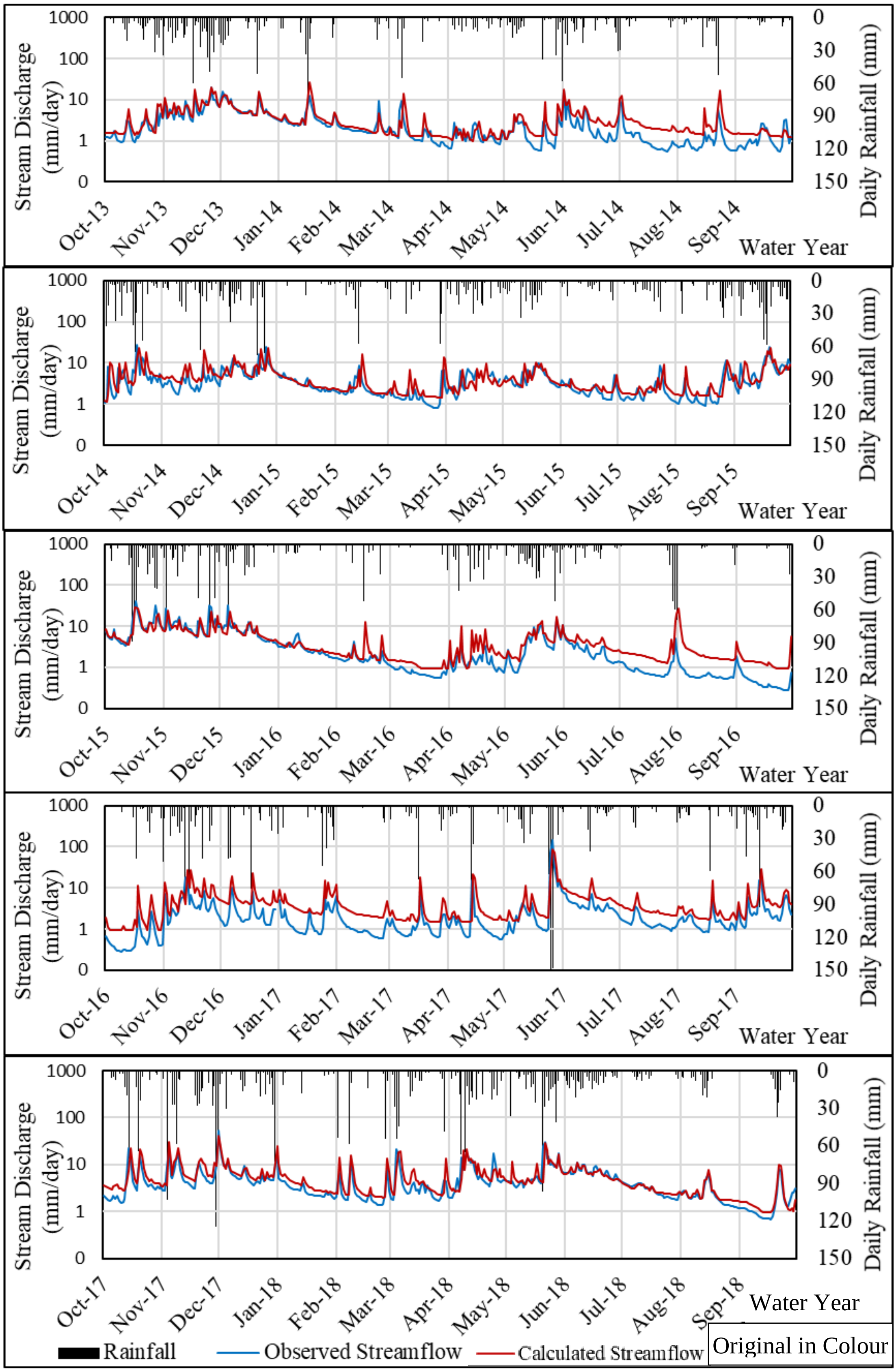


Figure 5-33: Flow Hydrograph of Urawa for Temporal transferability - 2013/14-2017/18

5.8.2.1.3 Annual Water Balance Error

Error in annual water balances from observed data and estimated data are given in Table 5-17 and Figure 5-34.

Table 5-17: Annual Water Balance for Urawa with Temporally transferred parameters

Water Year	Annual RF (mm)	Annual Observe SF (mm)	Annual cal. SF (mm)	Annual Pan Evpo. (mm)	AWB for Observe flow	AWB for Cal.	AWB Error %
2008/09	2525.3	1573.6	1572.6	1126.1	951.7	952.6	-0.1%
2009/10	1968.1	1283.8	1180.1	1029.5	684.3	788.0	-8.1%
2010/11	2942.1	1823.9	1965.0	1065.4	1118.2	977.1	7.7%
2011/12	2111.5	1070.1	1225.2	1040.2	1041.4	886.3	14.5%
2012/13	2715.1	1694.4	1808.1	997.3	1020.8	907.1	6.7%
2013/14	2028.9	982.3	1275.6	969.0	1046.6	753.3	29.9%
2014/15	2624.2	1407.6	1647.1	816.2	1216.6	977.1	17.0%
2015/16	2253.2	1458.6	1676.8	883.1	794.6	576.4	15.0%
2016/17	2771.6	1108.0	1794.4	926.3	1663.6	977.1	62.0%
2017/18	2847.7	1779.7	2049.2	832.3	1068.0	798.5	15.1%
Average	**2478.8**	**1418.2**	**1619.4**	**968.5**	**1060.6**	**859.4**	**14.2%**

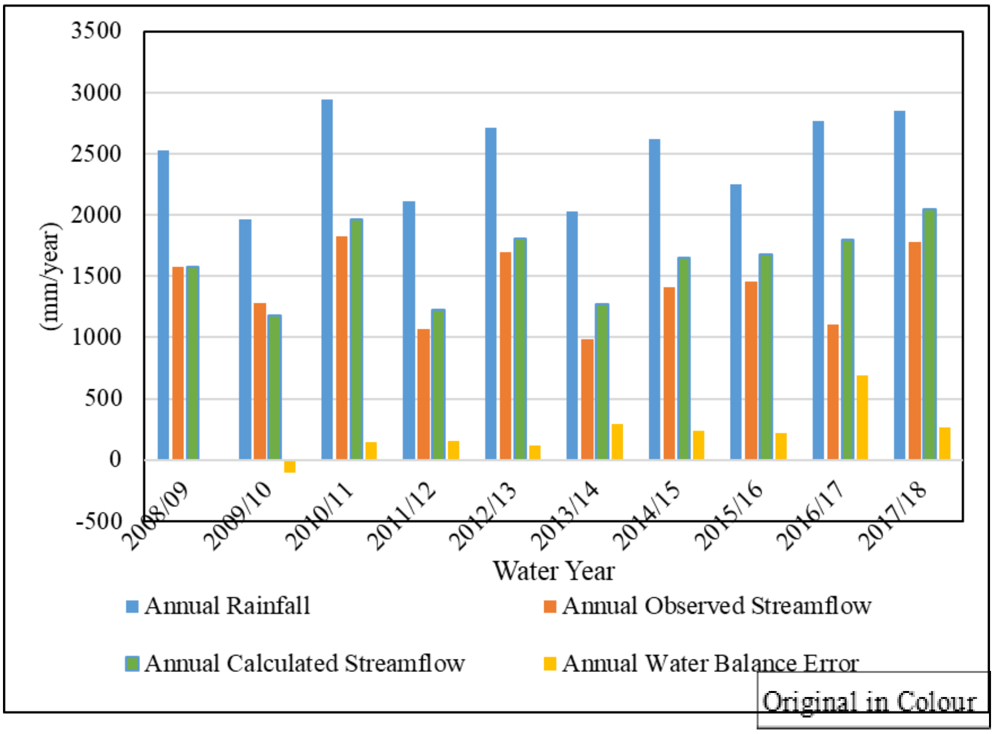


Figure 5-34: Annual Water Balance Error for Temporal Transferability Condition - Urawa

5.8.2.1.4 Comparison of Flow Duration Curves

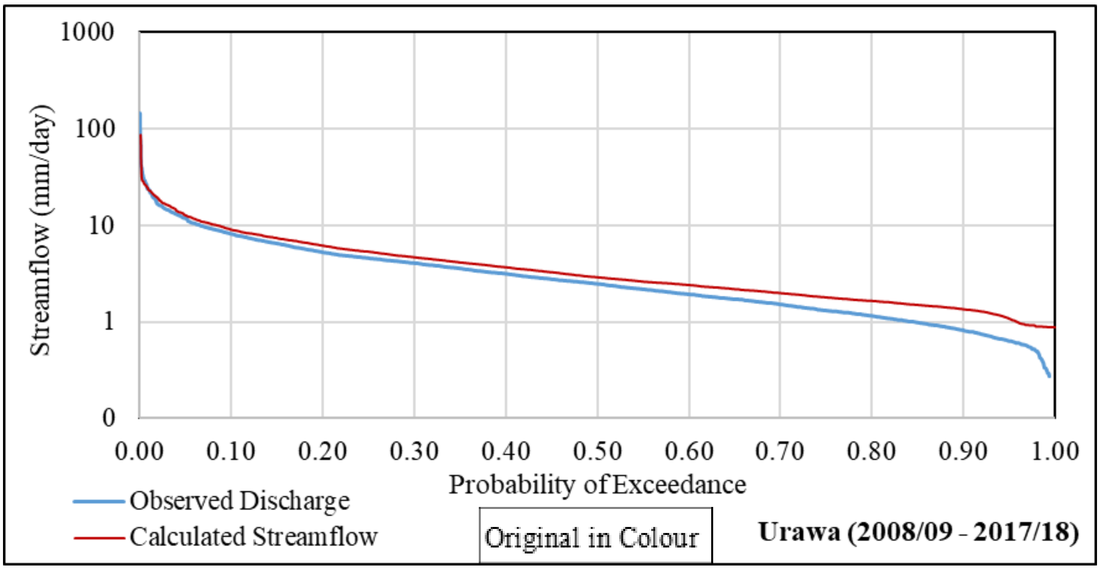


Figure 5-35: FDC (Sorted) for Urawa with temporally transferred parameters

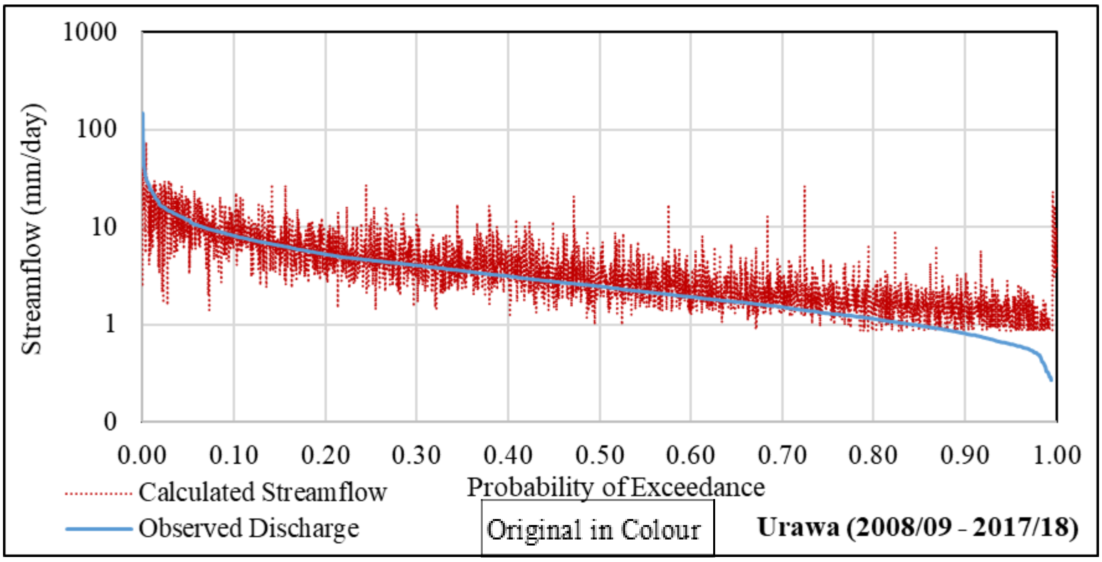


Figure 5-36: FDC (Unsorted) for Urawa with temporally transferred parameters

5.8.2.2 Temporal Parameter Transferability in Pitabeddara Catchment

The calibrated and optimized parameters of the Tank model for the catchment are temporally transferred to water year 2008/09 to water year 2017/18. The model performances under this condition are given in the following subsections.

5.8.2.2.1 Statistical Measure of Goodness of Fit

Quantitative measures of model performance for overall flow series and different flow regimes are given in the following Table 5-18.

Table 5-18: Measure of goodness of fit of model for Pitabeddara in temporal transferability

Gauging Station	MRAE for Overall Flow	MRAE w.r.t FDC (Sorted)			MRAE w.r.t FDC (Unsorted)		
		High	Medium	Low	High	Medium	Low
Pitabeddara	0.49	0.15	0.23	0.75	0.37	0.42	1.02

5.8.2.2.2 Comparison of Observed and Estimated Streamflow Hydrograph

Figure 5-37 and Figure 5-38 illustrate the hydrograph with observed streamflow and estimated streamflow from the model with temporally transferred parameters.

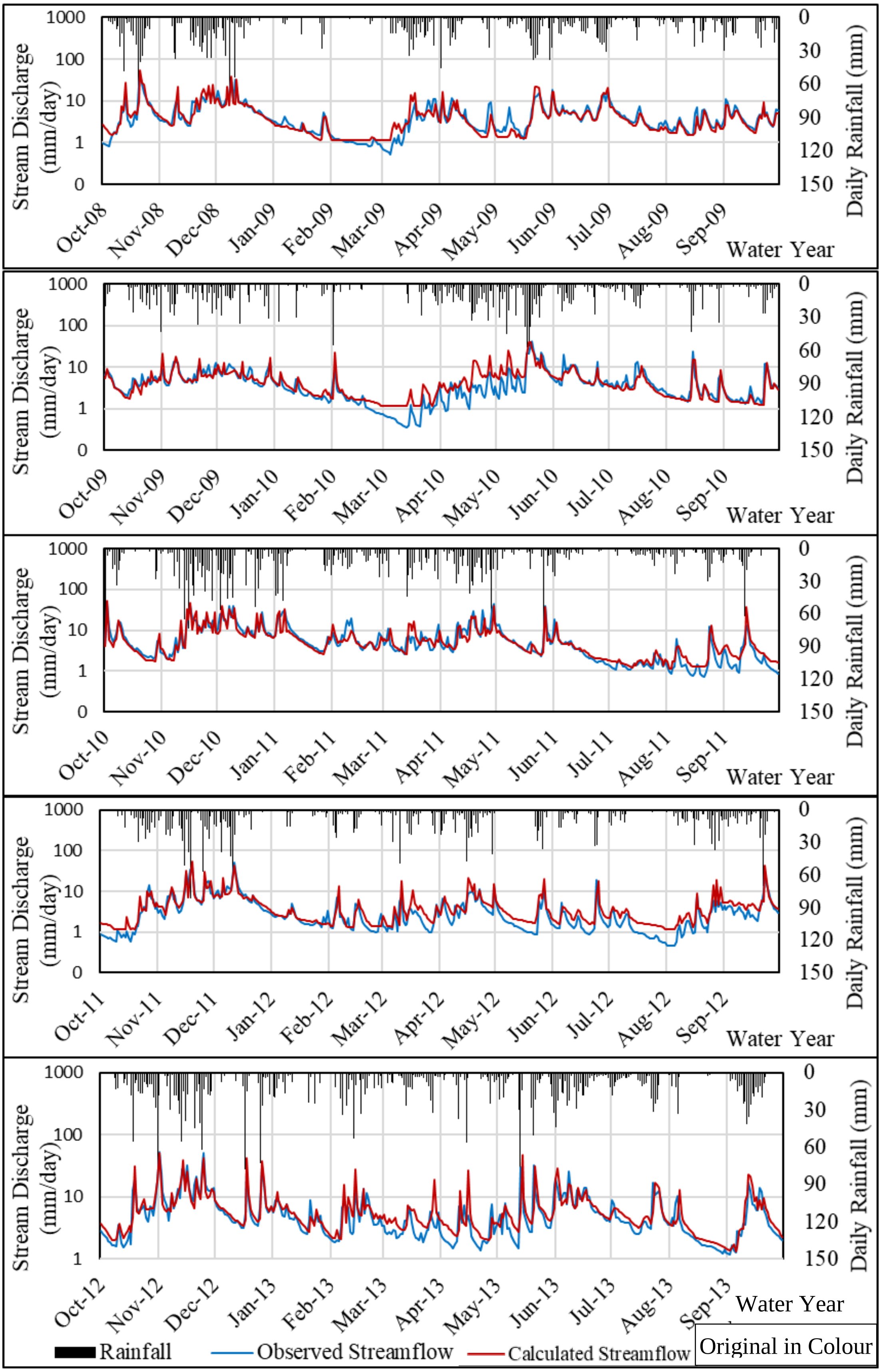


Figure 5-37: Flow Hydrograph of Pitabeddara in Temporal transferability - 2008/09-2012/13

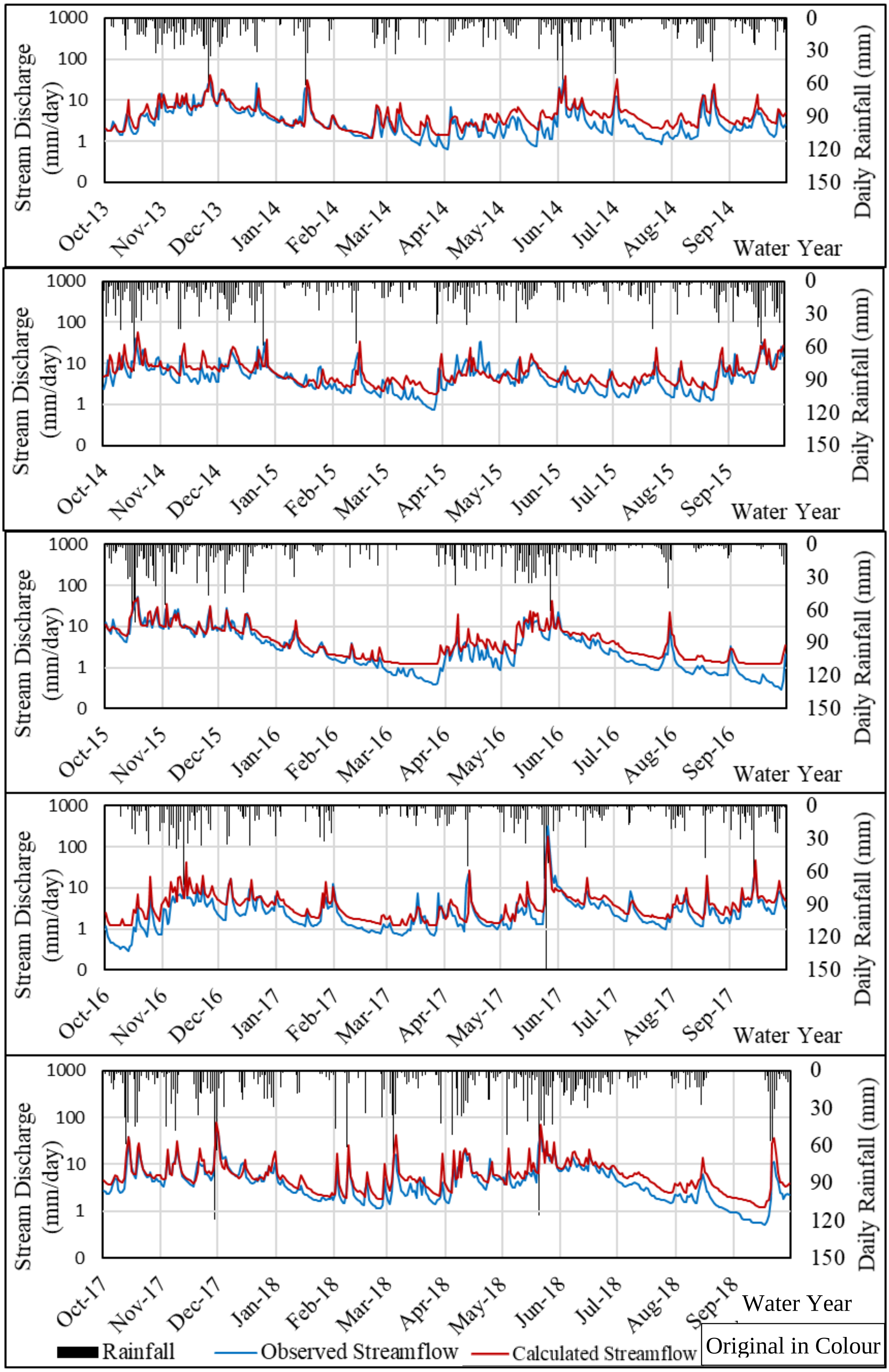


Figure 5-38: Flow Hydrograph of Pitabeddara in Temporal transferability - 2013/14-2017/18

5.8.2.2.3 Annual Water Balance Error

Under temporally transferred parameters, the following annual water balance error was observed in the estimation of the model for Pitabeddara catchment.

Table 5-19: Annual Water Balance for Pitabeddara with Temporally transferred parameters

Water Year	Annual RF (mm)	Annual Observe SF (mm)	Annual cal. SF (mm)	Annual Pan Evpo. (mm)	AWB for Observe flow	AWB for Cal.	AWB Error %
2008/09	2750.4	1817.6	1817.8	1126.1	932.8	932.6	0.0%
2009/10	2653.7	1705.6	1819.7	1029.5	948.1	834.0	6.7%
2010/11	3366.8	2534.4	2449.4	1065.4	832.4	917.4	-3.4%
2011/12	2691.5	1460.6	1760.0	1040.2	1230.9	931.5	20.5%
2012/13	3357.4	2267.9	2477.6	997.3	1089.5	879.8	9.2%
2013/14	2776.3	1421.4	1887.6	969.0	1354.9	888.7	32.8%
2014/15	3454.1	2095.0	2558.4	816.2	1359.1	895.7	22.1%
2015/16	2718.3	1802.5	2180.4	883.1	915.7	537.9	21.0%
2016/17	2761.8	1646.4	1882.7	926.3	1115.4	879.1	14.4%
2017/18	3481.6	2017.0	2723.6	832.3	1464.6	758.0	35.0%
Average	**3001.2**	**1876.8**	**2155.7**	**968.5**	**1124.4**	**845.5**	**14.9%**

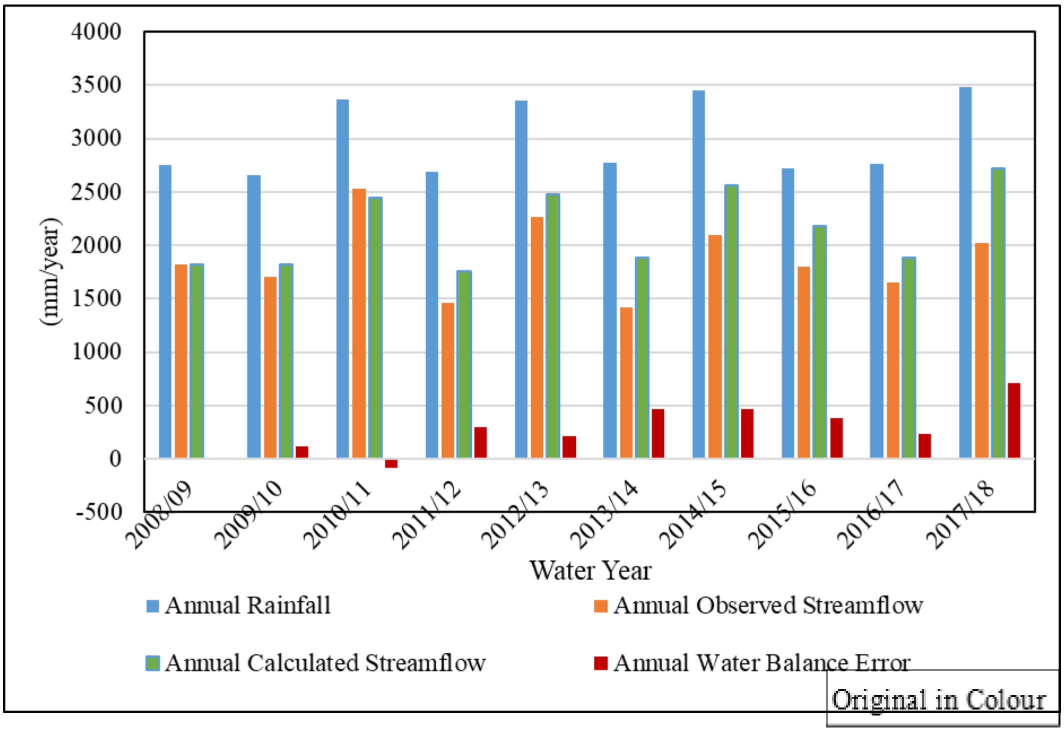


Figure 5-39: Annual Water Balance Error for Temporal Transferability Condition - Pitabeddara

5.8.2.2.4 Comparison of Flow Duration Curves

The respective flow duration curves with observed and estimated flows for temporal transferability simulation are given in Figure 5-40 and Figure 5-41.

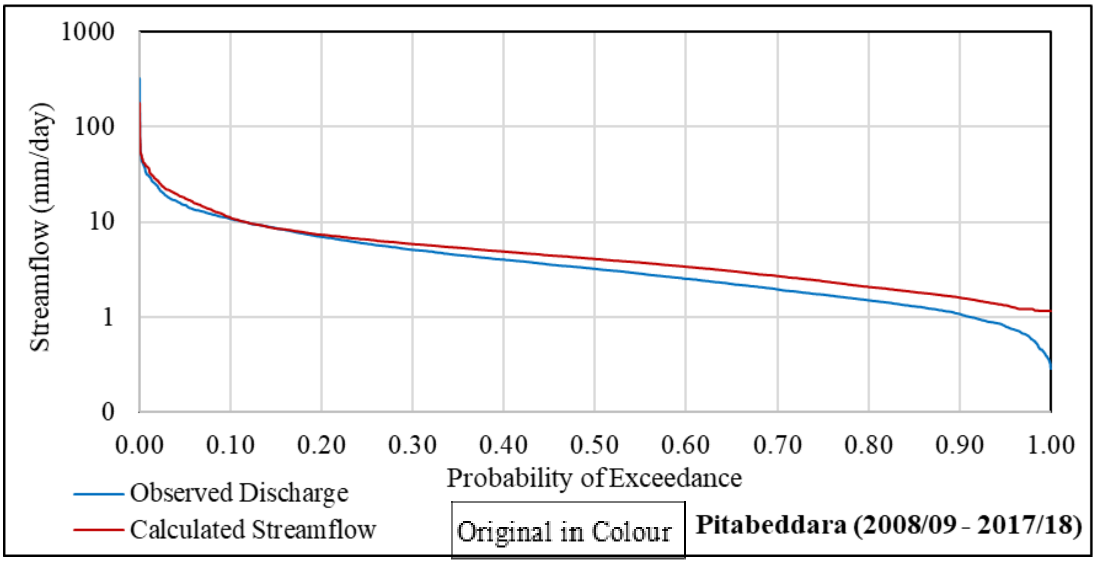


Figure 5-40: FDC (Sorted) for Pitabeddara with temporally transferred parameters

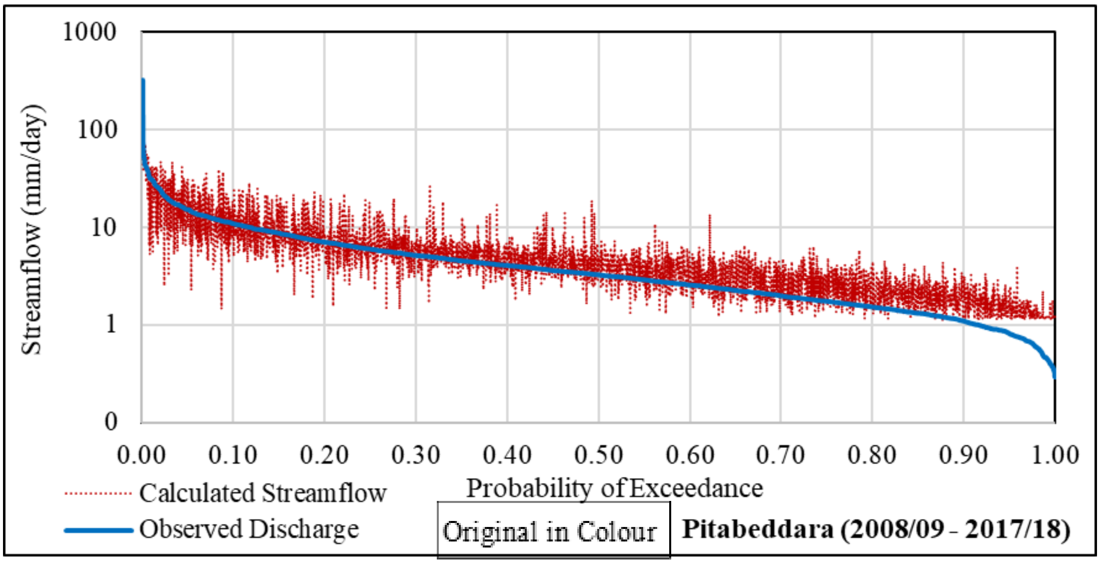


Figure 5-41: FDC (Unsorted) for Pitabeddara with temporally transferred parameters

5.8.3 Model Performance in Spatial Transferability Approach

In this approach, the optimized parameters for both models were transferred from one catchment to other catchment in the same time period.

5.8.3.1 Spatial Parameter Transferability from Main catchment to Sub-catchment

The optimized parameters of Pitabeddara catchment are transferred to the model of Urawa catchment and simulate the model for water year 2008/09 to water year 2012/13. The model results are given in the following sections.

5.8.3.1.1 Statistical Measure of Goodness of Fit

The MRAE values calculated for the model simulation under spatial transferability condition are given in Table 5-20.

Table 5-20: Measure of goodness of fit of model for Urawa 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
Urawa	0.39	0.28	0.20	0.25	0.59	0.39	0.29

5.8.3.1.2 Comparison of Observed and Estimated Streamflow Hydrograph

Streamflow hydrographs with the observed flow and estimated flow during water years 2008/09 to 2012/13 are given Figure 5-42.

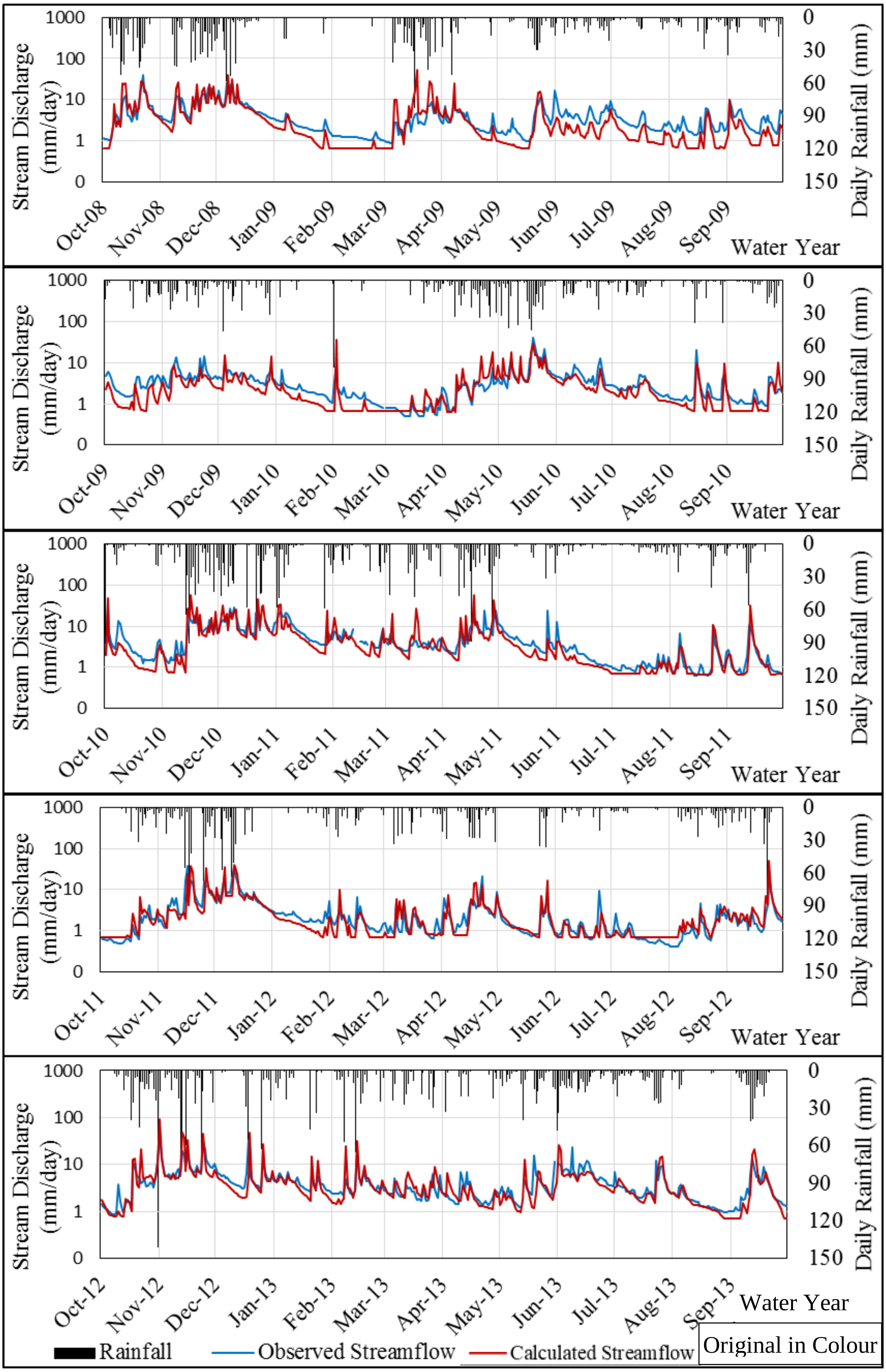


Figure 5-42: Flow Hydrograph of Urawa in spatial transferability - 2008/09-2012/13

5.8.3.1.3 Annual Water Balance Error

According to the model simulation for Urawa catchment with spatially transferred parameters, comparison in annual water balance w.r.t both observed streamflow and estimated streamflow is given in Table 5-21 and Figure 5-43.

Table 5-21: Annual Water Balance for Urawa with spatially transferred parameters

Water Year	Annual RF (mm)	Annual Observe SF (mm)	Annual cal. SF (mm)	Annual Pan Evpo. (mm)	AWB for Observe Data	AWB for Cal.	AWB Error %
2008/09	2525.3	1573.6	1483.3	1126.1	951.7	1041.9	-5.7%
2009/10	1968.1	1283.8	1062.2	1029.5	684.3	905.9	-17.3%
2010/11	2942.1	1823.9	1934.8	1065.4	1118.2	1007.3	6.1%
2011/12	2111.5	1070.1	1126.5	1040.2	1041.4	985.0	5.3%
2012/13	2715.1	1616.9	1728.3	997.3	1098.2	986.8	6.9%
Average	**2452.4**	**1473.7**	**1467.0**	**1051.7**	**978.8**	**985.4**	**-1.0%**

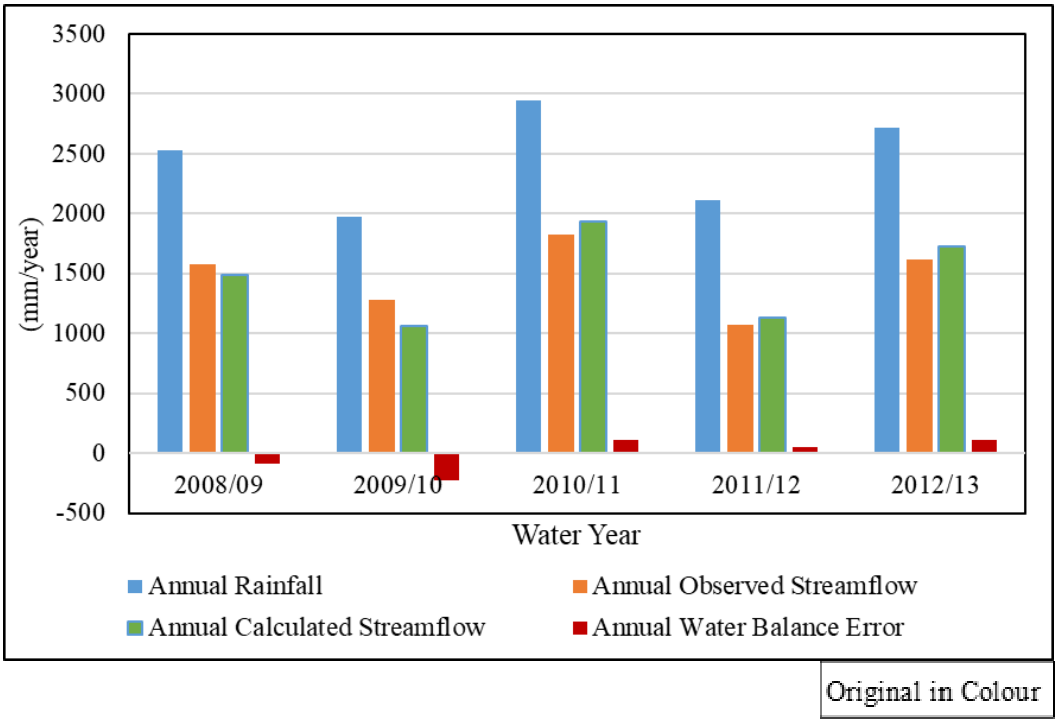


Figure 5-43: Annual Water Balance for Urawa with spatially transferred parameters

5.8.3.1.4 Comparison of Flow Duration Curves

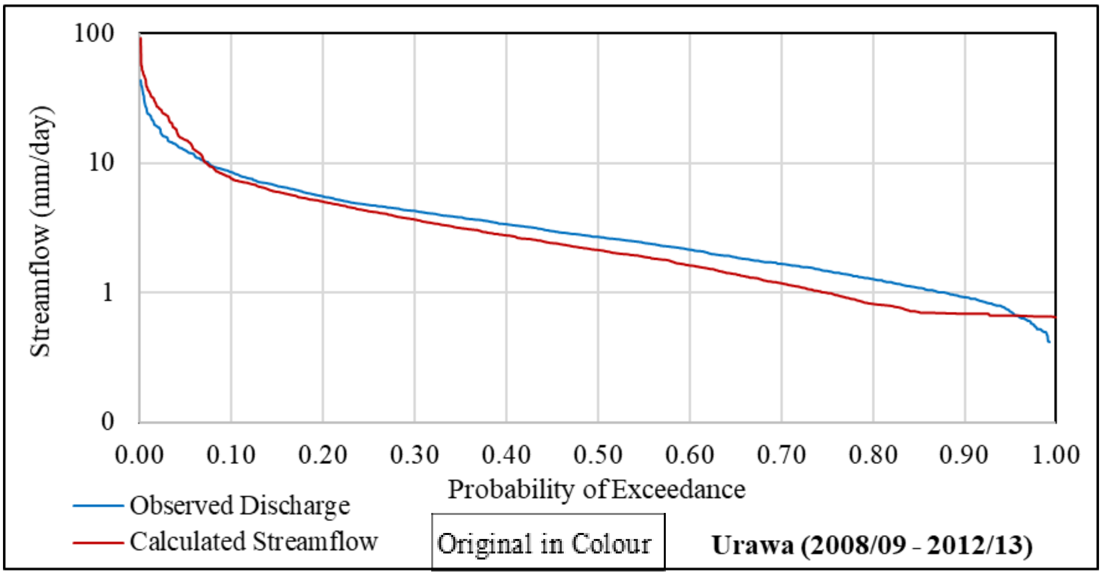


Figure 5-44: FDC (Sorted) for Urawa with spatially transferred parameters

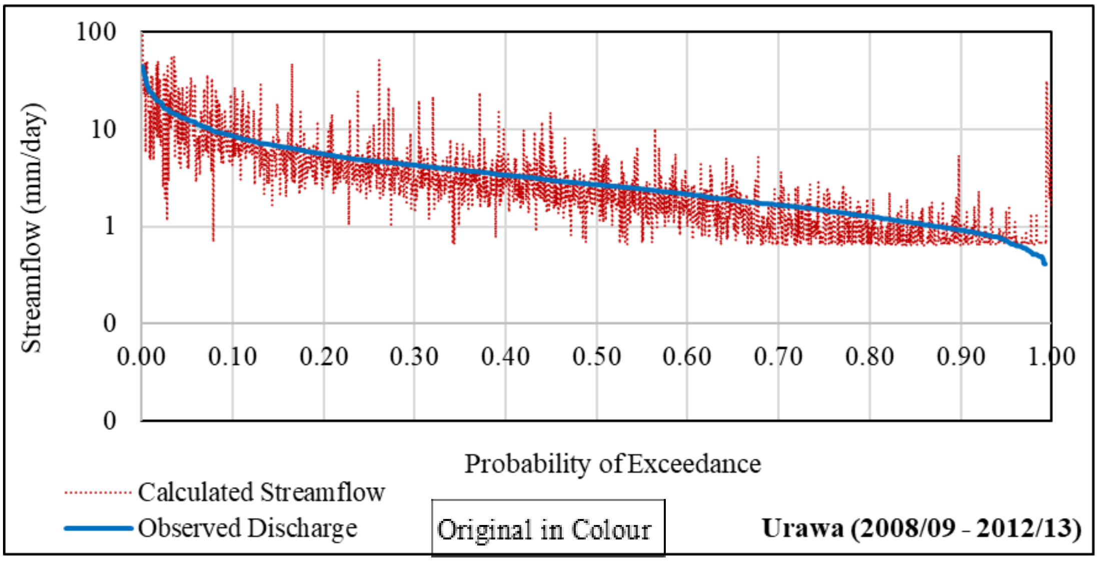


Figure 5-45: FDC (Unsorted) for Urawa with spatially transferred parameters

5.8.3.2 Spatial Parameter Transferability from Sub-catchment to Main catchment

The optimized parameters of Urawa catchment have transferred to simulate the Tank model for Pitabeddara catchment within the water year 2008/09 to 2012/13. The results are elaborated in the following subsections.

5.8.3.2.1 Statistical Measure of Goodness of Fit

The goodness of fit of the model simulations with spatially transferred parameters is given in the following Table 5-22.

Table 5-22: Measure of goodness of fit of model for Pitabeddara 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
Pitabeddara	0.35	0.19	0.12	0.53	0.31	0.30	0.71

5.8.3.2.2 Comparison of Observed and Estimated Streamflow Hydrograph

The flow hydrographs which are developed with observed streamflow and estimated streamflow during the water year 2008/09 to 2012/13 are given in Figure 5-46 below.

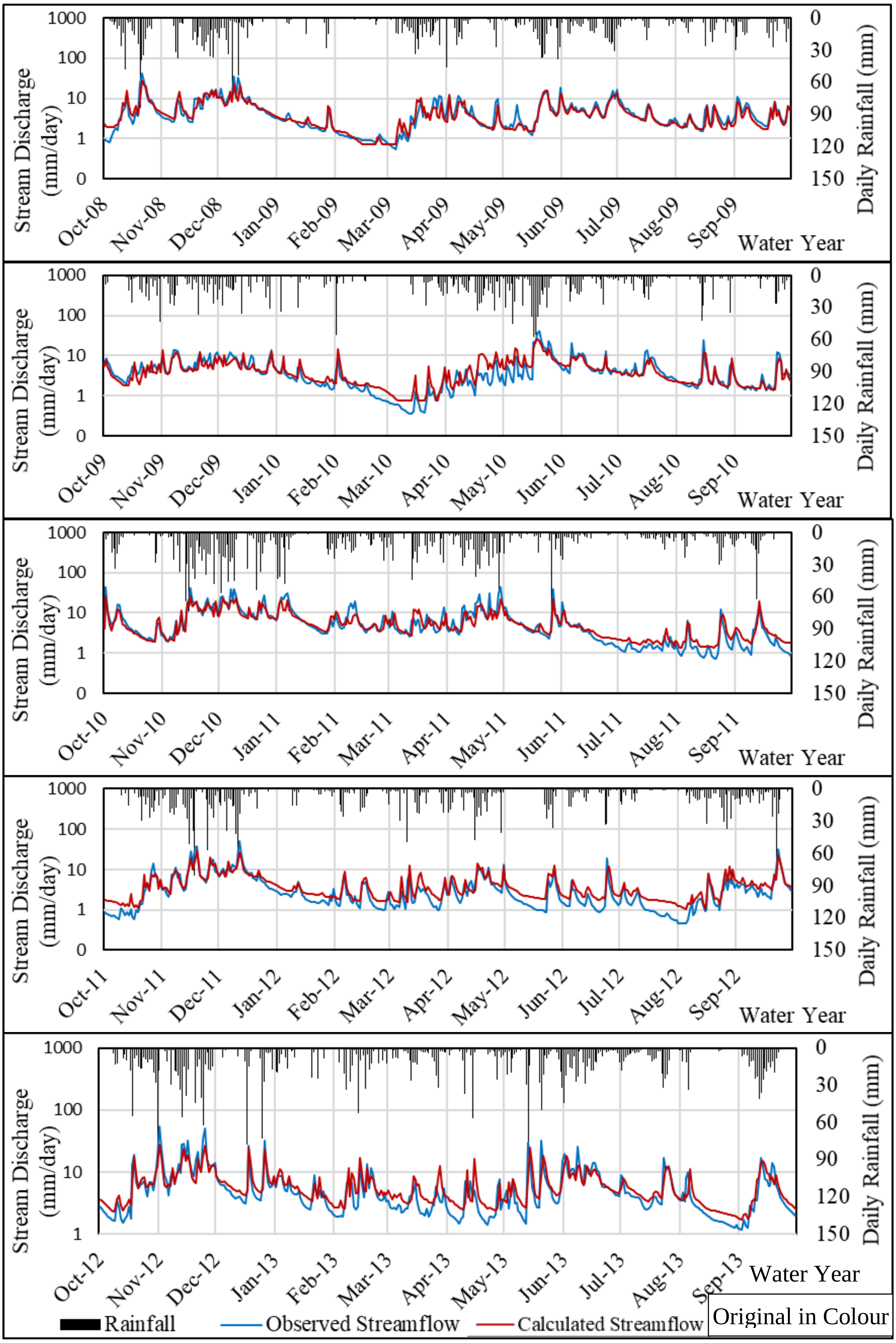


Figure 5-46: Flow Hydrograph of Pitabeddara in spatial transferability - 2008/09-2012/13

5.8.3.2.3 Annual Water Balance Error

In order to evaluate the model performance, error in annual water balances under observed streamflow condition and estimated streamflow condition were calculated and the results were given in Table 5- and Figure 5-47 below.

Table 5-23: Annual Water Balance for Pitabeddara with spatially transferred parameters

Water Year	Annual RF (mm)	Annual Observe SF (mm)	Annual cal. SF (mm)	Annual Pan Evpo. (mm)	AWB for Observe Data	AWB for Cal.	AWB Error %
2008/09	2750.4	1817.6	1671.0	1126.1	932.8	1079.4	-8.1%
2009/10	2653.7	1705.6	1670.4	1029.5	948.1	983.3	-2.1%
2010/11	3366.8	2534.4	2248.7	1065.4	832.4	1118.2	-11.3%
2011/12	2691.5	1460.6	1618.2	1040.2	1230.9	1073.3	10.8%
2012/13	3357.4	2267.9	2295.1	997.3	1089.5	1062.4	1.2%
Average	**2964.0**	**1957.2**	**1900.7**	**1051.7**	**1006.7**	**1063.3**	**-1.9%**

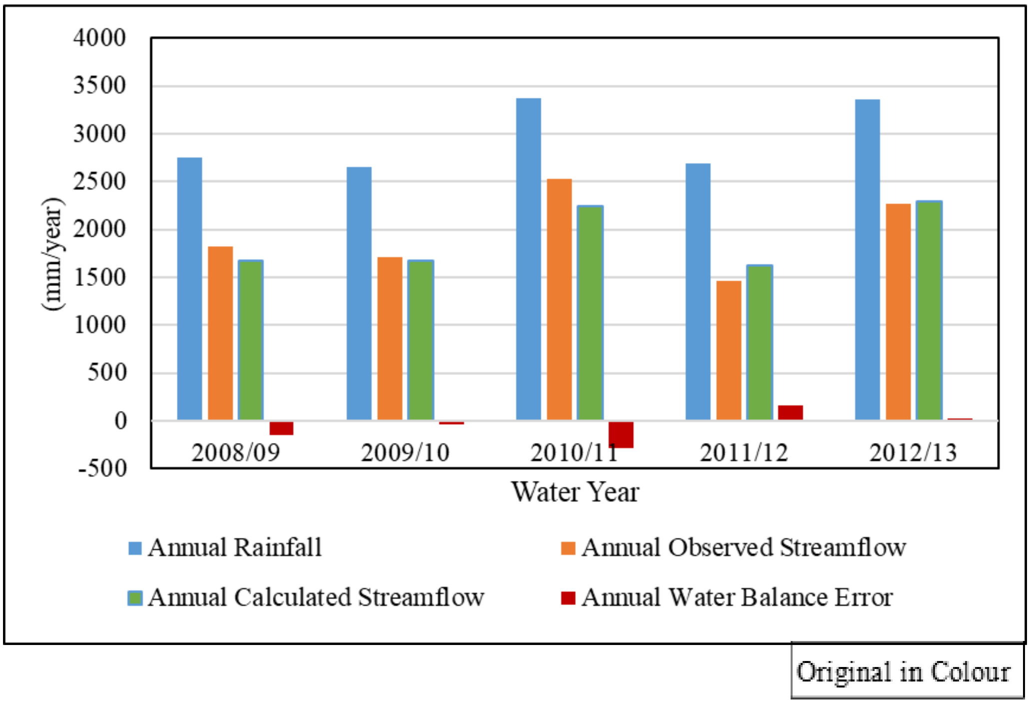


Figure 5-47: Annual Water Balance for Pitabeddara with spatially transferred parameters

5.8.3.2.4 Comparison of Flow Duration Curves

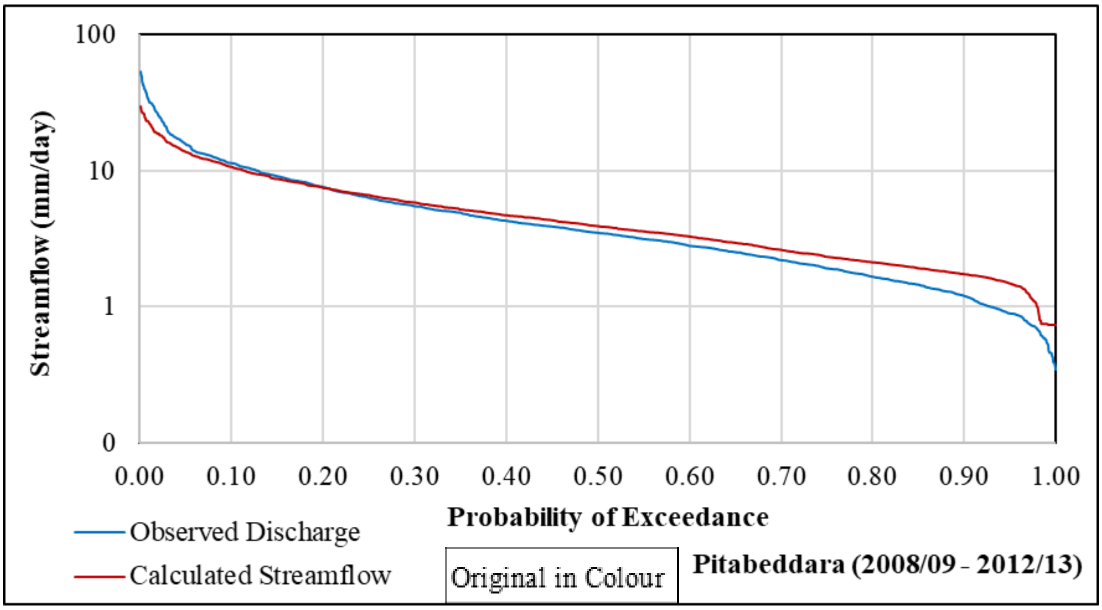


Figure 5-48: FDC (Sorted) for Pitabeddara with spatially transferred parameters

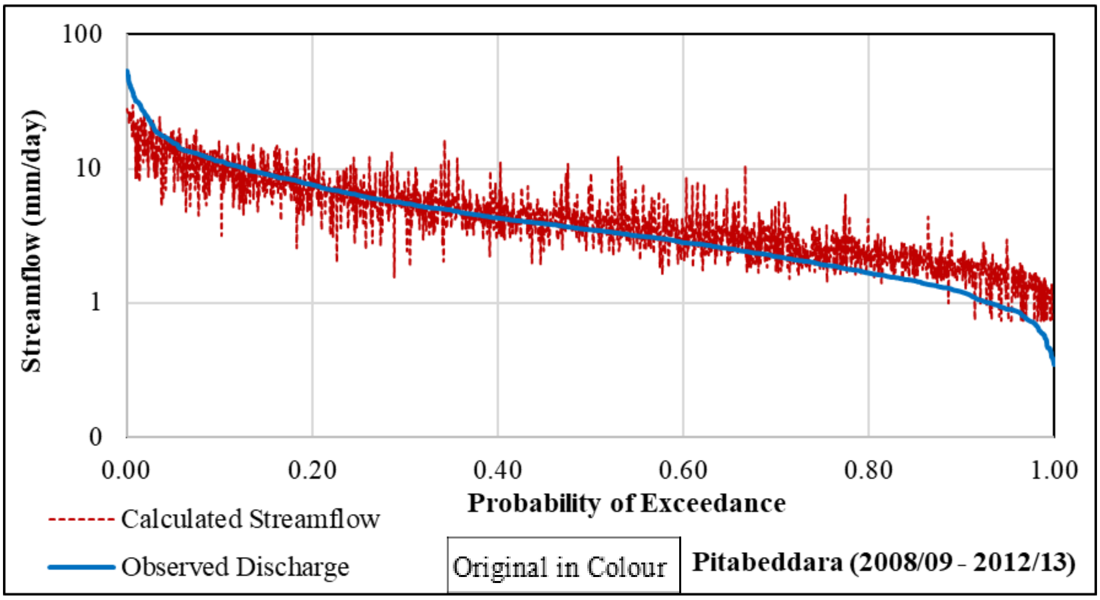


Figure 5-49: FDC (Unsorted) for Pitabeddara with spatially transferred parameters

6 Discussion

6.1 Data and Data Errors

6.1.1 Selection of Data Period and Gauging Stations

Based on the comprehensive literature review, a representative continuous data series ranges from a five to ten years period is sufficient for accurate simulation of daily lumped hydrological models. Although there are four river gauging stations in Nilwala River Basin, only two stations are functionally well and having reliable data. Hence, considering the reliability of data and accuracy of model simulation towards the objective of the study, Pitabeddara and Urawa river gauging stations were selected with 10 years of data period ranges from 2008/2009 water year to 2017/2018 water year. At the same time, during this period the catchment was undergone for extreme weather conditions such as drier in 2009/10 and 2011/12 water years and, wetter in 2010/11 and 2017/18 water years which can be observed in Figure 4-4 and Figure 4-6. Hence, the model might be able to simulate both low flow and high flow conditions of the catchment when it set up for such data series.

According to Sugawara et al. (1984), the use of weighted mean rainfall from several representative rain gauging stations as an input for the model is more effective for accurate runoff analysis. Thus a visual data checking process as mentioned in Section 4.3.2 was carried out to evaluate the representativeness of the selected rain gauging stations. The process of visual checking of data revealed that only a few rainfall events are non-representative to the streamflow at both river gauges thereby the selected rain gauging stations could be considered very likely representative to the selected sub-catchments of Nilwala River basin. In the same time, selected gauging stations have a very low percentage of no data days (less than 10%) which can be identified in Table 6-1.

Although the selected rain gauging stations were having a considerably low correlation with the streamflow as mentioned in Table 6-1 which can affect the accuracy of hydrologic model simulation.

Table 6-1: Correlation between rainfall data and streamflow data

Data Type	Station	Missing Data		Correlation	
		No. of Missing Data	Missing Data %	with Pitabeddara streamflow	with Urawa streamflow
Rainfall	Dampahala Tea Factory	61	1.7%	0.38	0.43
	Derangala Hill	273	7.5%	0.25	-
	Anningkanda	0	0.0%	0.30	-
	Hulandawa	182	5.0%	0.34	-
	Urawa Rotumba	1	0.0%	0.31	0.39
River Discharge	Pitabeddara	0	0.0%	-	-
	Urawa	19	0.5%	-	-

6.1.2 Data Errors

Generally, in annual water balance where it assumes that soil moisture levels at the beginning of the water year and end of water year are the same and, the share of water for ground infiltration and percolation is insignificant and most of the time it is negligible. But it was observed that in water years 2013/14, 2014/15 and 2017/18 in Pitabeddara catchment as per Figure 4-3 and, in water years 2014/15 and 2016/17 in Urawa catchment as per Figure 4-5 the water shares remained for infiltration and percolation are comparatively large since the difference between annual pan evaporation and annual water balance is higher. Hence, during those periods the data can consist of errors and it can affect the accuracy of the rainfall-runoff analysis. But such errors were not corrected assuming that the impact on model accuracy might be insignificant.

Although the double mass curves in Figure 4-10 showed straight and constant ratio between two quantities. Hence data can be considered as consistent since there are no observable breaks in the graphs in Figure 4-10.

6.2 Model Selection

According to Table 2-2, there are various types of hydrologic models that are used in parameter transferability for streamflow predictions in ungauged catchments. But most researchers and water managers prefer hydrologic models with a simple concept and with less number of parameters under low input requirement (Bai et al., 2015).

Tank model is also a simple conceptual model that requires only rainfall and evapotranspiration as input data. and the model has been used for various hydrological applications around the world plus locally. Similarly the literature review has revealed that lumped conceptual models are outperformed than other types of models in the modeling of ungauged catchments. Further the Tank model is capable of modeling water distribution in both horizontal and vertical directions i.e. surface runoff, sub-surface runoff, intermediate flow, sub-base flow, and base flow (Arifjaya et al., 2011). Hence this study has used a lumped conceptual Tank model rather than using complex distributed models where the water managers can conveniently use the model on their water management and planning requirements with minimum data availability.

Although the Tank model has a simple concept, it has various types of structure arrangements w.r.t number of tanks. The best number of tanks for the model will ensure the best fit between observed and simulated flow hydrographs (Kuok et al., 2011). According to the literature review, the number of tanks in the Tank model is varied with the purpose of modeling and land use of the area. Since the study has mainly focused on water resources management which requires a total spectrum of flow regime and the modeling is done as lumped catchment which consists of various types of land uses, four tank structure has been used for the study.

6.3 Validity of Model Performance

The study has evaluated the model performance qualitatively and quantitatively w.r.t different types of criteria such as goodness of fit with MRAE value, annual water balance, matching of flow hydrographs, and matching of flow duration curves.

Achieving a model simulation where all those indicators are on their optimum condition, is a very difficult task thereby a compromise of all these indicators was considered to achieve better accuracy in model simulations. As Phien & Pradhan, (1983) stated more concern should be given for annual water balance and matching of flow hydrographs during hydrologic modeling for water resources management and planning. Thus, the study has given more concerns on those indicators during model calibration and validation processes.

6.3.1 Model Performance in Calibration Period

As per Table 5-3 and Table 5-5, the overall MRAE values for both models for Urawa and Pitabeddara catchments are 0.31 and 0.32 respectively which indicate that the models predicted the streamflow in both catchments up to an acceptable level of accuracy about 70%. But the MRAE vales for annual streamflow in a few water years are comparatively higher as observed in Table 6-2.

Table 6-2: Comparison of annual MRAE values for both catchments' models on calibration period

Water Year	MRAE Value	
	Pitabeddara	Urawa
2008/09	0.28	0.34
2009/10	0.39	0.31
2010/11	0.28	0.28
2011/12	0.37	0.34
2012/13	0.29	0.29

According to Table 4-6, during water year 2011/2012, Urawa catchment has considerably lower annual runoff coefficient compared to in other water years of the calibration period. Since model parameters were optimized for the total calibration period where the average annual runoff coefficient is higher, the model might predict the streamflow with a higher annual runoff coefficient. Thus during the water year 2011/2012, estimated streamflow and observed streamflow might not be matched and tends to higher MRAE value. Similar phenomena might affect to Pitabeddara catchment also since during water year 2011/2012, the catchment's annual runoff coefficient is very low w.r.t in other water years as observed in Table 4-5. Hence the model overestimated streamflow during water year 2011/2012 which can be observed in Figure 5-10 and the MRAE value become higher during the period.

In the visual data checking process as per Figure A-2, it was observed that Thiessen averaged rainfall might not be representative for the observed streamflow from March to June in the water year 2009/2010 and the averaged rainfall is comparatively high. Thus the model tends to overestimate the streamflow during that period and cause to higher MRAE value.

The shapes of the estimated streamflow hydrographs have fairly good matching with the observed streamflow of both catchments as observed in Figure 5-6 and Figure 5-10. However, the magnitudes of most low flows are not matching. At the same time, it can be observed that during low or no rain conditions, the Tank model is unable to predict the streamflow at a satisfactory level of accuracy. Hence, the involvement of primary and secondary soil moisture compartments to the model might enhance the model performance where it controls the infiltration rates.

The sorted and unsorted flow duration curves for observed and estimated streamflow are better indicators of model performance which give a clear illustration of the variation of estimated streamflow w.r.t the observed streamflow (Wagener et al., 2004). The estimated streamflow for Urawa catchment showed a better matching in sorted flow duration curve according to Figure 5-8, but the unsorted flow duration curve shown in Figure 5-9 indicates a considerable variation in estimated streamflow w.r.t the observed streamflow. Hence, this indicates that the model is capable of estimating streamflow in a similar range of magnitude as observed streamflow, but the time of occurrence of estimated streamflow has a deviation w.r.t observed streamflow.

According to Figure 5-9, approximately 50% of the high flows of both Urawa and Pitabeddara catchments during the calibration period have been simulated with accuracy of 80% or more where the average accuracy of prediction was more than 60%. This contradict the statement of Phien & Pradhan (1983) that the Tank model is incapable to simulate high flows. But S. Chen, Chen, & Yang (2014) have used Tank model for flood analysis which confirm that the model is capable for high flow simulations also.

Further Nepal et al. (2017) have explained that underestimation of peaks might be occurred due to underestimation of rainfall, failure of model concept in flood processes, the nonlinearity of catchment, and especially uncertainty in discharge rating curves during the high flows. These might have an impact on the high flow estimation through both models.

Further, more than 50% of low flows in both Urawa and Pitabeddara catchments are overestimated according to Figure 5-9. Since the modeling was done as a lumped catchment, it was assumed that the heterogeneity of soil types and land uses are negligible and have similar characteristics. But as Basri (2013) stated, these characteristics have a direct impact on infiltration rates over the catchment. Since the low flows are dominated by sub-base flows and base flows created from infiltrated water, negligence of heterogeneity might cause to overestimation of low flows.

However when these daily predictions are aggregated to an annual scale, it can be observed that the models' predictions are having higher accuracy. This can be identified through the annual water balance error between observed data and estimated data. On average, the model for Urawa catchment has underestimated the streamflow annually only by 2.4% according to Table 5-4 and Figure 5-7. Similarly, the model of Pitabeddara catchment has underestimated the streamflow only by 0.2% on average during the calibration period when it aggregated to an annual scale as observed in Table 5-6. Hence, both models for Urawa and Pitabeddara catchments have a very higher accuracy level in predictions on the annual scale during the calibration period.

In general, overall indications of performance evaluation criteria have proven that both models for Urawa and Pitabeddara catchments have calibrated up to a satisfactory level of accuracy.

6.3.2 Model Performance in Validation Period

Although both models for two catchments showed better results in the calibration period, the MRAE values are increased to 0.54 and 0.48 for Urawa and Pitabeddara catchments respectively in the validation period as observed in Table 5-7 and Table 5-9. This is due to the overestimation of streamflow by the models as observed in Figure 5-14 and Figure 5-18. Both models for two catchments are having a very higher inaccuracy in their predictions for low flows such as 99% of inaccuracy for Urawa and 77% of inaccuracy for Pitabeddara catchment as observed in Table 5-7 and Table 5-9.

When we consider the modeling of Urawa catchment during validation period, in water year 2014/2015 and water year 2017/2018 have a higher accuracy level and according to Figure 5-14 also a better matching of estimated streamflow and observed streamflow can be observed. But in water year 2015/2016 and 2016/2017, inaccuracy of model predictions is very high which can be clearly understood from Figure 5-14 since it illustrates significant mismatching between model predictions and observed streamflow. In water year 2016/2015, the shape of the estimated streamflow hydrograph is approximately similar to observed streamflow but the magnitudes of the estimated streamflow are high. These mismatching might be due to data error observed in water year 2016/2017 in Section 4.3.1.4 as observed streamflow during that water year is comparatively low w.r.t approximately similar rainy water years. Hence, the assumption made on the impacts of data errors is invalid. Thus, proper improvements to data errors should be done to achieve higher accuracy in modeling.

Table 6-3: Comparison of annual MRAE values for both catchments' models on validation period

Water Year	MRAE Value	
	Pitabeddara	Urawa
2013/14	0.53	0.49
2014/15	0.42	0.25
2015/16	0.48	0.71
2016/17	0.52	0.98
2017/18	0.47	0.27

Although the high flow region in both Urawa and Pitabeddara catchments have been predicted at a considerably good accuracy level as observed in the flow duration curves in Figure 5-16 and Figure 5-20.

When the model predictions are aggregated to the annual scale in the validation period, similar overestimation of streamflow by both models for two catchments can be observed as in Table 5-8 and Table 5-10.

According to Table 6-4, it can be identified that both models of two catchments have been calibrated to higher runoff conditions compared to the validation period since the annual runoff coefficients have considerable variation. Hence model parameters might be adjusted to generate more runoff from the receiving rainfall thereby both models might overestimate the streamflow during the validation period as discussed previously.

Table 6-4: Comparison of avg. annual runoff coefficient for both catchments

Time Period	Annual Avg. Rainfall (mm)		Annual Runoff Coefficient	
	Pitabeddara	Urawa	Pitabeddara	Urawa
Calibration Period (2008/09 – 2012/13)	2964.0	2454.1	0.65	0.61
Validation Period (2013/14 – 2017/18)	3038.4	2507.6	0.59	0.54
Total Study Period (2008/09 – 2017/18)	3002.7	2480.9	0.62	0.57

Although, on average, both models have predicted the streamflow during the validation period with an accuracy level of around 50% and the other evaluation indicators showed an acceptable level of accuracy in simulation. Hence, it was considered that both models for Urawa catchment and Pitabeddara catchments are validated.

6.3.3 Model Performance for Water Resources Management

The water resource managers and engineers are mostly carrying out their water resources management practices on a monthly scale or a seasonal scale. Hence, the model results were aggregated to monthly scale and seasonal scale to evaluate the performance of models towards water resources management and planning.

6.3.3.1 Model Performance in Monthly scale

According to Table C-1 in Annexure C, when the daily estimations of the model for Urawa catchment are aggregated to monthly scale, the monthly averaged estimations have nearly about 90% of accuracy level in most of the months of the calibration period, but during March the model has overestimated the streamflow by more than 50%. According to Figure 4-11, the beginning of a rainfall season after a dry period is taken place during March. Thus during this period, the soil moisture of the model moves from unsaturated condition to saturated condition which might lead to instability in the model structure producing inaccurate streamflow.

Considering the scatter plot given in Figure C-1, it can be observed that the points are much closed to the optimum line ($R^2 = 1$). Hence, it can be considered that monthly scale predictions for Urawa catchment during the calibration period are having a higher accuracy level.

Although during the validation period, similar phenomena can be observed as in the daily scale since the streamflow of Urawa catchment has been overestimated in all the months, but the inaccuracy in the estimations is lesser than on daily scale results according to Figure C-2 and Table C-1. According to Table C-1, in most of the months other than March, July, and August, the model estimations are having 75% or more accuracy level when aggregated to the monthly scale.

When the daily estimations of the model for Pitabeddara catchment are aggregated to monthly scale during the calibration period, the model estimations have lesser accuracy with near to 75% only in March and in all other months, the accuracy of model estimations are higher than 90% which can be identified in Table C-2 and Figure C-4. The better matching in the scatter plot given in Figure C-6 also proves this as its points are clustered to the optimum line ($R^2 = 1$). Similar model instability might be impacted to reduce the accuracy as discussed earlier. However, during the validation period, the monthly scaled streamflow of Pitabeddara catchment are overestimated confirming a similar scenario as in the daily scale results. Hence, monthly scale estimations which are developed base on daily resolution estimations, are having better accuracy for both catchments.

6.3.3.2 Seasonal Comparison of Model Performance

Maha season and Yala season are the main two seasons that are considered during the planning and management of water resources by the water resource managers and engineers. Hence, the daily estimations were aggregated to the seasonal scale resolution to observe the model performance.

Errors in seasonal scaled streamflow are given in the above Table 6-5 for both catchments during model calibration and validation periods. Further details are given in Annexure D also. Accordingly, both models for two catchments have achieved a greater accuracy of around 90% in the models' predictions during Maha seasons in the calibration period. This can be confirmed through the scatter plots given in Figure D-1 and Figure D-6 as all the points are on the optimum line or very close to the optimum line. During the Yala seasons of the calibration period, both models for two catchments have simulated streamflow up to a satisfactory level of accuracy.

Table 6-5: Seasonal comparison of streamflow of both catchments

	Water Year	Error in Estimation for Urawa		Error in Estimation for Pitabeddara	
		Maha Season	Yala Season	Maha Season	Yala Season
Calibration Period	2008/09	-4.4%	24.2%	0.9%	14.9%
	2009/10	27.9%	8.3%	3.0%	-1.2%
	2010/11	-5.7%	6.3%	7.9%	8.4%
	2011/12	-1.5%	-10.0%	-1.7%	-29.8%
	2012/13	-14.5%	7.6%	-2.6%	-6.6%
	Average	**-2.3%**	**8.7%**	**2.0%**	**-1.0%**
Validation Period	2013/14	-7.1%	-45.5%	-8.3%	-50.7%
	2014/15	-15.3%	-4.7%	-22.0%	-10.7%
	2015/16	9.8%	-69.9%	-4.0%	-37.3%
	2016/17	-103.6%	-27.5%	-44.7%	8.9%
	2017/18	-22.0%	1.8%	-23.7%	-36.4%
	Average	**-16.9%**	**-20.2%**	**-17.7%**	**-20.1%**

According to Table 6-5, the seasonally scaled estimated streamflow for both catchments during the validation period have a lesser level of accuracy. Although the seasonally scaled streamflow for both catchments from daily scale estimated streamflow, have averagely better accuracy near to 80% or more which can be used in water resource management and planning.

6.3.4 Model Parameter Evaluation

The initial parameter values were selected as described in sub section 5.4.1. Since the error surface for this simulation during the parameter optimization is an n-dimensional (n-number of parameters – 12) surface, finding global minimum is difficult. Hence, different initial parameter values in each calibration trial was given in order to search global minimum in different directions over the error surface.

The optimized parameter values given in Table 5-11 are within the defined ranges by the researchers which was given in Table 2-4. In the same time the summation of outflow and infiltration parameter values in each storage tank should be less than one (S. Chen et al., 2014). The optimized parameters for both catchments have fulfilled this constraint in each tank. Besides that the runoff coefficients in all four tanks are followed the order of magnitude defined for those coefficients. Hence the optimized parameters can be acceptable.

However it can be observed in Table 5-11 that there is considerable difference between values of same parameter (in *A2*, *D1*, *HC1*) in both catchments although they are adjacent catchments. Yokoo et al. (2001) have stated that there is a huge impact of basin area to the value of *A2* parameter. Since Pitabeddara catchment is nearly five times larger than Urawa catchment, such higher difference in value of *A2* between two catchments might occurred.

Both catchment slope and stream density have influence in contribution of base flow to the streamflow (Yokoo et al., 2001). Urawa catchment is having higher slope with compared to in Pitabeddara catchment due to existence of hilly areas. As observed in Figure 1-1 stream density in Pitabeddara catchment is comparatively high. Therefore, since Urawa catchment has high slope with less stream density, the contribution of base flow to the streamflow might be comparatively low which lead to smaller value in *D1* with compared to in Pitabeddara catchment.

6.4 Model Performance in Parameter Transferability

6.4.1 Selection of Parameter Transferability Approaches

The literature review revealed that there are different types of parameter transferability approaches that are being practiced by the hydrologic modelers and engineers to estimate the streamflow in ungauged catchments. Table 2.1 illustrated such approaches. All these methods are having different levels of complexities and performance in simulating streamflow. Hence there is no best approach that can be applied all over the world thereby a suitable approach can only be identified based on site-specific studies and comparative studies (Razavi & Coulibaly, 2013). Similarly, a method that is easily understandable and usable would be better for the water managers in their regular water resource estimations. Therefore, the study has considered three simple approaches such as the spatiotemporal transferability approach, temporal transferability approach, and spatial transferability approach.

Further the parameters were transferred by assuming that both catchments are likely having similar hydrological behavior since they are located in the same region (Kokkonen et al., 2003).

6.4.2 Model Estimations under Spatiotemporal Transferability Approach

In the spatiotemporal transferability approach, the optimized parameters for Urawa catchment have been used to reconstruct the streamflow of Pitabeddara catchment and the optimized parameters for the Pitabeddara catchment have been used to simulate streamflow of Urawa catchment for the period ranges from water year 2008/09 to 2017/18.

The model for Urawa with transferred parameters has simulated the streamflow with an accuracy level of 54% where medium flows have been simulated more accurately as observed in Table 5-12. According to Figure 5-22, Figure 5-23, Figure 5-25, and Figure 5-26, most of the high flows and lows of the Urawa catchment have been overestimated by the model with spatiotemporally transferred parameters. Nearly about 40% of high flow events and 72% of low flow events were overestimated by 20%. This might be due to higher variation in runoff coefficients of the two catchments within the period as mentioned in Table 6-4. The optimized parameters of Pitabeddara catchment have been calibrated for more streamflow conditions with a higher annual runoff coefficient value of 0.65 where the annual runoff coefficient during water year 2008/09 to 2017/18 of Urawa catchment is 0.57, which is considerably low w.r.t Pitabeddara catchment. This might affect the overestimation of streamflow in Urawa catchment.

The fixing of low flow values in no rainfall period observed in Figure 5-23 and Figure 5-26 are due to the variation in *D1* parameter value between two catchments where it was high in Pitabeddara catchment. The *D1* value of Pitabeddara catchment was calibrated to simulate minimum flow of 0.95 mm/day during zero rainfall period in Pitabeddara catchment. Hence, when this parameter value is used in Urawa catchment, it tend to generate constant minimum flow of 0.95 mm/day during no rainfall period which lead to fixing of low flow values in the hydrograph.

According to Table 5-11, it can be observed that the values of runoff coefficients for side outlets in the top tank of the Tank model for Pitabeddara catchment are comparatively high w.r.t the values for similar factor in the Tank model of Urawa catchment. Further, the infiltration coefficient of the top tank in the Tank model for Pitabeddara catchment is relatively small compared to the respective factor in the model for Urawa catchment. Hence, with the low infiltration and higher side outlet coefficients, the Tank model for Urawa might generate more surface runoff than expected as well as a very higher runoff with higher rainfall events that can lead to overestimation of high flows.

When considering the annual water balance in Urawa catchment according to Table 5-13, only two water years (2013/14 and 2016/17) have a very higher inaccuracy where other water years are within the error limit of 20%. Therefore, on average the annual water balance of estimated streamflow has an accuracy level of about 85%. But in monthly averaged flow comparison in Table C-3 and seasonal flow comparison in

Table D-5 for Urawa catchment illustrate very higher overestimation of streamflow w.r.t the observed streamflow.

The estimations of the model for Pitabeddara catchment with the optimized parameters of Urawa catchment that were spatiotemporally transferred to Pitabeddara catchment, are having considerably low accuracy level as the MRAE value is 0.61 and the flow hydrographs in Figure 5-27 and Figure 5-28 illustrate clear mismatching in estimated and observed streamflow in most of the water years. In addition to this figures, Figure 5-30 and Figure 5-31 illustrate that the model with transferred parameters have overestimated the intermediate flow events (nearly about 65%) and all low flow events, and underestimated the high flow events (about 50% of events) of Pitabeddara catchment causing higher inaccuracy in estimation of overall flow regime. This might be due to the high infiltration coefficient value in the top tank and less runoff coefficient values in the side outlets of the top tank according to Table 5-11. Consequently almost all the monthly and seasonal scaled streamflow are also overestimated drastically as observed in Table C-4 and Table D-6.

The annual water balances for reconstructed streamflow of Pitabeddara catchment with spatiotemporally transferred parameters have greater accuracy about 80% in all the water years other than in water years 2013/14 and 2017/18.

Hence, the spatiotemporal transferability approach is more accurate when model parameters are transferred from the main catchment to its sub-catchment rather than vice versa. The optimized parameters for the Pitabeddara catchment are better for both catchment in this type of transferability approach. However, using this method in water resources management planning processes is less beneficial.

6.4.3 Model Estimations under Temporal Transferability Approach

In this approach, the optimized parameters of each catchment have been applied to the same model to simulate the streamflow for a period of ten years ranges from water year 2008/09 to 2017/18.

Both models have simulated the streamflow up to a satisfactory level of accuracy since the MRAE values are 0.51 and 0.49 for models of Urawa and Pitabeddara respectively.

But both models were unable to simulate the low flows up to a considerable level of accuracy as the MRAE values are more than 1.0 in both models. Hence, according to the MRAE values in Table 5-16 and Table 5-18, and the flow duration curves in Figure 5-35, Figure 5-36, Figure 5-40, and Figure 5-41, it can be observed that both models are better in the simulation of high and intermediate flows with the temporally transferred parameters.

When considering the annual water balance error of both models according to Table 5-17 and Table 5-19, both models showed only about 20% or lesser inaccuracy during all water years except in one or two water years wherein water years 2013/14 and 2016/17 of Urawa catchment, and water year 2013/14 and 2017/18 of Pitabeddara catchment. These inaccuracies might be occurred due to the data errors that were identified during the data checking process. Hence, the identified data errors are having a significant effect on the model accuracy confirming the failure of assumption where it needs to be corrected as discussed earlier.

The flow comparison in monthly scale in Table C-5, Table C-6, Figure C-13, and Figure C-15 illustrate that both models have overestimated the monthly averaged flows in all months. Further, in March, July, and August, the accuracies of monthly averaged estimated flows are very low in both models, but in the remaining months, both models have considerably better accuracy more than 60% in the predictions. The reason for such inaccuracy in model predictions might be a result of the model instability due to soil moisture variation from unsaturated condition to saturated condition during these months since the beginnings of another rainfall monsoon are occurred during these months that can be observed in Figure 4-11.

Although in seasonal scale, the predictions of the model for Urawa catchment with temporally transferred parameters are having lesser accuracy in both Maha and Yala seasons that can be identified in scatter plots in Figure D-14. But the model for Pitabeddara catchment has simulated the flows in Maha season with better accuracy as indicated in the scatter plots in Figure D-16.

Hence the model with the optimized parameter set for Pitabeddara catchment has outperformed than the other model in the temporal transferability approach.

6.4.4 Model Estimations under Spatial Transferability Approach

The optimized parameters of Pitabeddara catchment have used to model the Urawa catchment during water year 2008/09 to 2012/13 period and vice versa.

The model of Urawa catchment with spatially transferred parameters has simulated the streamflow with the MRAE value of 0.39 where intermediate flows and low flows have very low MRAE values according to Table 5-20. But Figure 5-44 and Figure 5-45 indicated that most of the intermediate flows and low flows are underestimated by the model. Similarly, the comparison of flow hydrographs in Figure 5-42 indicates that the time of occurrence of the estimated flow hydrograph of the Urawa model and observed flow hydrographs are similar, but the magnitudes of estimated low flows have significant variation with observed data. Although this variation might be considered as insignificant since the annual water balance error in each water year is very low where the averaged error is about 1% according to Table 5-21.

When the predictions of the model of Urawa with transferred parameters are aggregated to a monthly scale, the monthly averaged estimated streamflow has an accuracy level of 80% or more as per Table C-7 except in March and June. On the contrary, according to Table D-9, the seasonally scaled predictions of the model of Urawa with spatially transferred parameters have an accuracy of 85% or more except in two seasons as Yala in 2008/09 water year and Maha in 2009/10 water year. During these two seasons it can be observed that the seasonal rainfalls are comparatively low but the runoff coefficient values are higher than 0.70 which is comparatively very higher w.r.t other water years. Hence during this period, observed data might include some errors. These errors or the model instability in low rainfall conditions might cause such errors in the model simulation.

The estimated streamflow from the model for Pitabeddara catchment with spatially transferred parameters has the MRAE value of 0.35 and, high flows and intermediate flows were simulated with an accuracy level of 70% or more as per Table 5-22. Further the comparison of flow hydrographs in Figure 5-46 also illustrates a better matching in estimated and observed streamflow. Consequently, this matching is further proven in the annual water balance error calculations where average error within five year period is about 2% according to Table 5-23. Similarly, the flow duration curves in Figure 5-48 and Figure 5-49 also show a considerably good matching in high and intermediate flows where the variation of estimated flow w.r.t observed flow is comparatively low in the unsorted flow duration curve. But most of the low flows were overestimated and high flows were underestimated by the model according to Figure 5-49.

The monthly averaged estimated streamflow of the Pitabeddara model show a higher accuracy in most of the months but comparatively low accuracy in March according to Table C-8. The scatter plot in Figure C-19 also indicates a better matching between observed streamflow and estimated streamflow as almost all the points are very closed to the optimum line (R^2=1). In addition to that, the seasonal flow comparison in Figure D-20 also indicates a better matching in both Maha and Yala seasons.

Accordingly, it can be observed that the model for Pitabeddara with spatially transferred parameters is outperformed than the model for Urawa with optimized parameters of Pitabeddara catchment.

The summary of the model performances with optimized parameters is given in Table 6-6 below. Although, these performances of the models might be varied due to the uncertainty of meteorological data and model parameters (Jayadeera, 2016; Song et al., 2019). Hence further studies have to be done for conclusiveness.

Table 6-6: Summary of model performance under optimized parameters

		Calibration Period		Validation Period		With spatiotemporally transferred parameters		With temporally transferred parameters		With spatially transferred parameters	
		Urawa	Pitabeddara	Urawa	Pitabeddara	Urawa	Pitabeddara	Urawa	Pitabeddara	Urawa	Pitabeddara
MRAE		0.31	0.32	0.54	0.48	0.46	0.61	0.51	0.49	0.39	0.35
Best flow segment		Intermediate	Intermediate	High & intermediate	High & intermediate	Intermediate	High	High & intermediate	High & intermediate	Intermediate & low	High & intermediate
AWB error		2.4%	0.7%	-25.1%	-18.7%	-15.9%	-13.0%	-14.2%	-14.9%	1.0%	1.9%
MWB error		2.1%	1.0%	-24.0%	-25.1%	-29.5%	-36.1%	-32.7%	-33.3%	0.5%	2.9%
SWB error	Maha	-2.3%	2.0%	-16.9%	-17.7%	-18.9%	-10.8%	-15.3%	-12.7%	-6.9%	5.2%
	Yala	8.7%	-1.0%	-20.2%	-20.1%	-11.6%	-15.8%	-12.6%	-17.4%	11.3%	-0.2%

Error % = 100*(Observed flow – Calculated flow)/ Observed flow

7 Conclusions

1. Based on the results of the present study, the spatial transferability approach is the best regionalization approach for daily streamflow simulation in concerned catchments with an accuracy level of 61% - 65%.

2. The spatiotemporal transferability approach is the second-best approach with an accuracy level of 54% for parameter regionalization between the concerned two catchments during 2008/09 – 2017/18 water years.

3. Monthly scaled flow estimations in Urawa and Pitabeddara catchments can be reconstructed up to an average accuracy of 80% and 76%, and average error in water quantity of 15.9 mm/month and 20.9 mm/month respectively under the parameter transferability approaches.

4. The seasonal scaled streamflow under the parameter transferability approaches in Urawa catchment are simulated with average accuracy of 87% in Maha season and 89% in Yala season together with water quantity error of 114.2 mm/ Maha season and 70.6 mm/Yala season.

5. In Pitabeddara catchment, seasonal scaled streamflow are simulated with an average accuracy of 90% in Maha and 89% in Yala, and errors in water quantity are 99.9mm/Maha season and 94.5 mm/Yala season during 2008/09 – 2017/18 water years.

6. The lumped conceptual Tank model can simulate the daily streamflow of Urawa and Pitabeddara catchments with an accuracy of 69% and 68% during the calibration period, and 46% and 52% during the validation period respectively.

7. In daily simulation of Urawa catchment, the best results were shown in intermediate flow regime during 2008/09 – 2017/18 water years with an average accuracy level of 61%, which varies between 53% to 69%.

8. In Pitabeddara catchment, most accurate daily simulations during 2008/09 – 2017/18 water years were in high flow regime with an accuracy range of 61% - 73% together with an average accuracy of 66%.

9. With the optimized parameter values of Pitabeddara catchment, the four tanks structured Tank model will be able to simulate the daily streamflow of ungauged catchments in Nilwala River basin up to an accuracy level of 58%.

10. The Tank model would be able to reconstruct the monthly and seasonal scaled streamflow of ungauged catchments in Nilwala River basin with an accuracy range of 67% - 99% and 80% - 93% respectively by using the optimized parameter values of Pitabeddara catchment.

8 Recommendations

1. Precipitation data from a rainfall gauging station which has a better correlation coefficient with streamflow, are recommended to use for simulation in order to get higher accuracy in modeling.
2. If a high-performance computer is available for modeling, it is better to use the Evolutionary search engine in optimization to find the global optimum for the objective function.
3. Efficacy of inclusion of primary and secondary soil moisture components to the Tank model for streamflow reconstruction within Nilwala River basin should be evaluated.

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APPENDIX A: REPRESENTATIVENESS OF RAINFALL TO STREAMFLOW

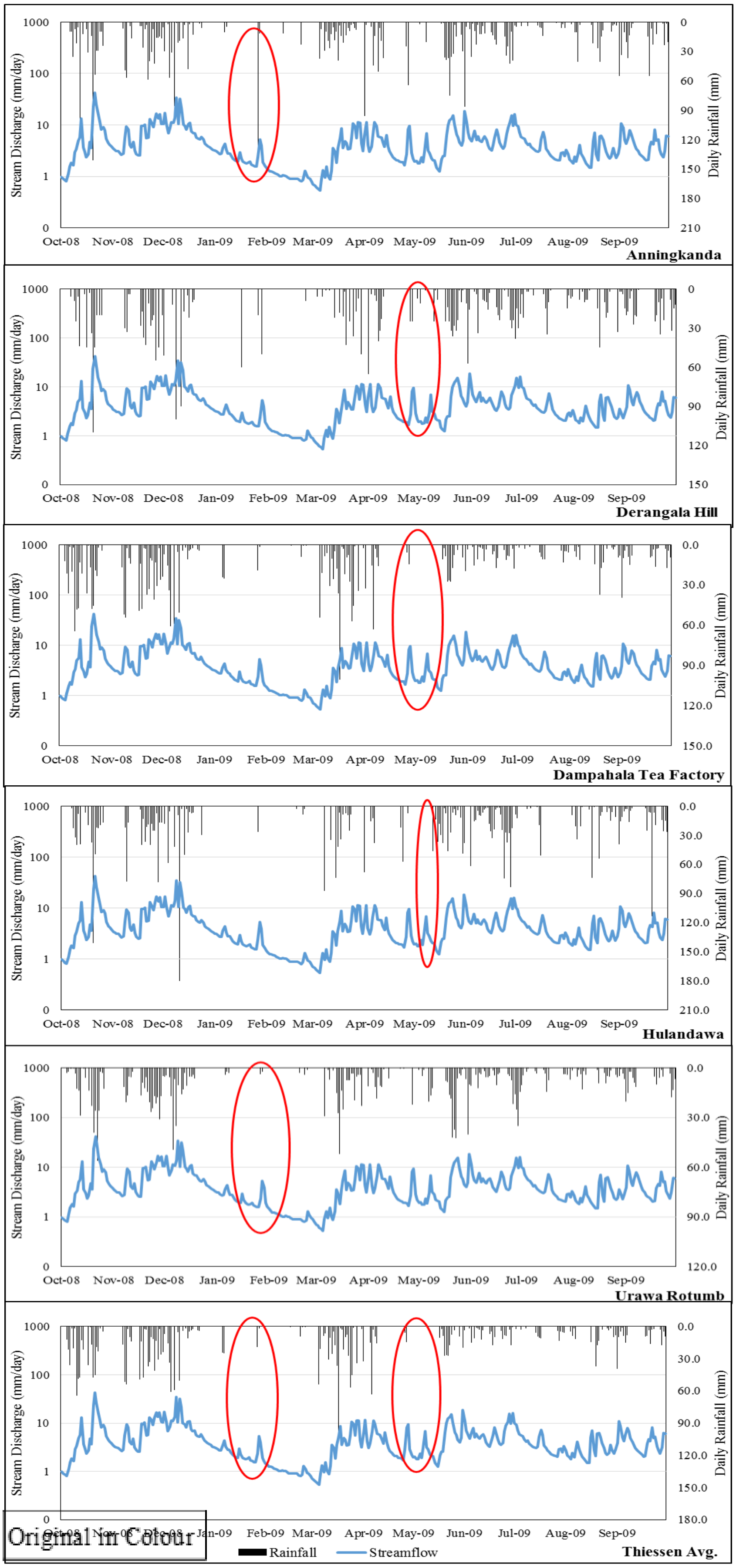


Figure A - 1: Streamflow at Pitabeddara vs Rainfall in water year 2008/2009

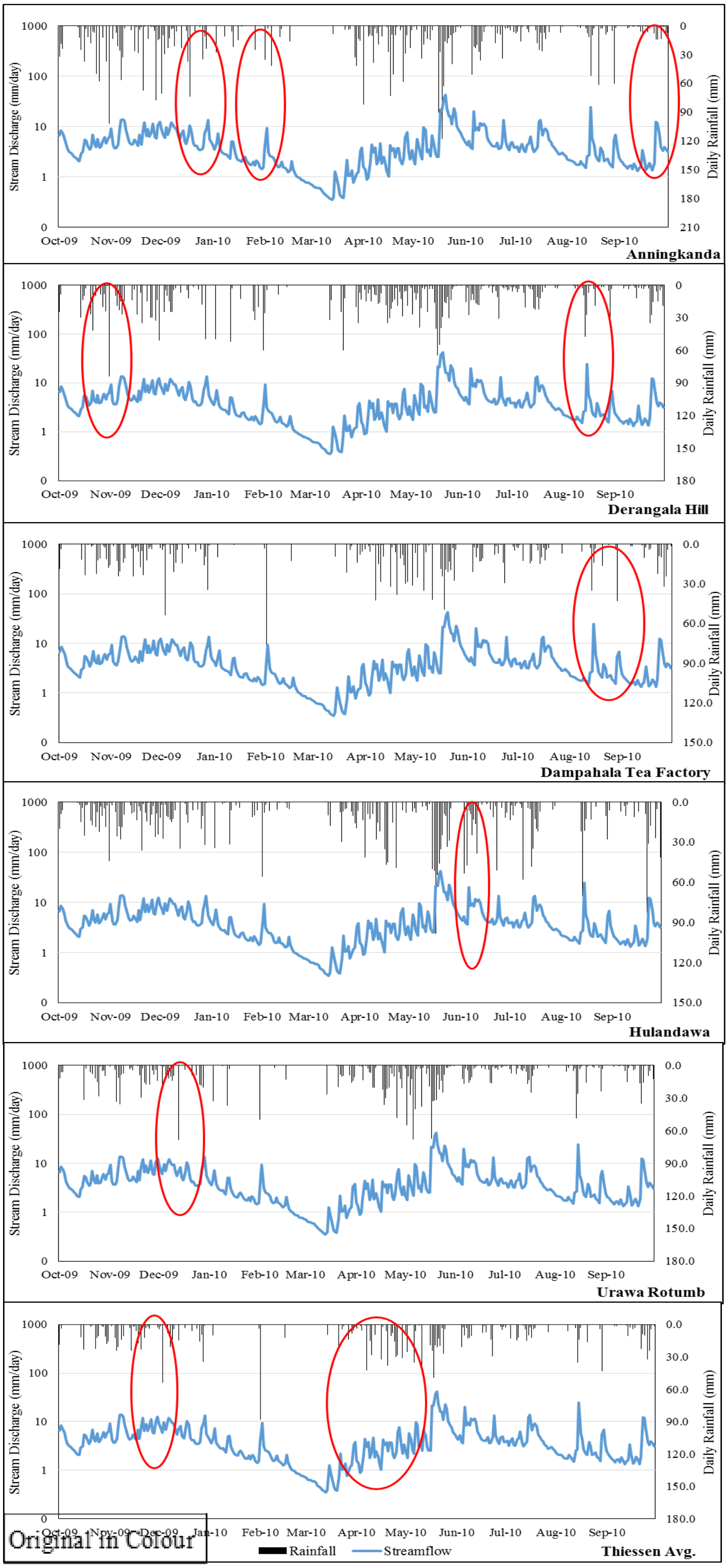


Figure A - 2: Streamflow at Pitabeddara vs Rainfall in water year 2009/2010

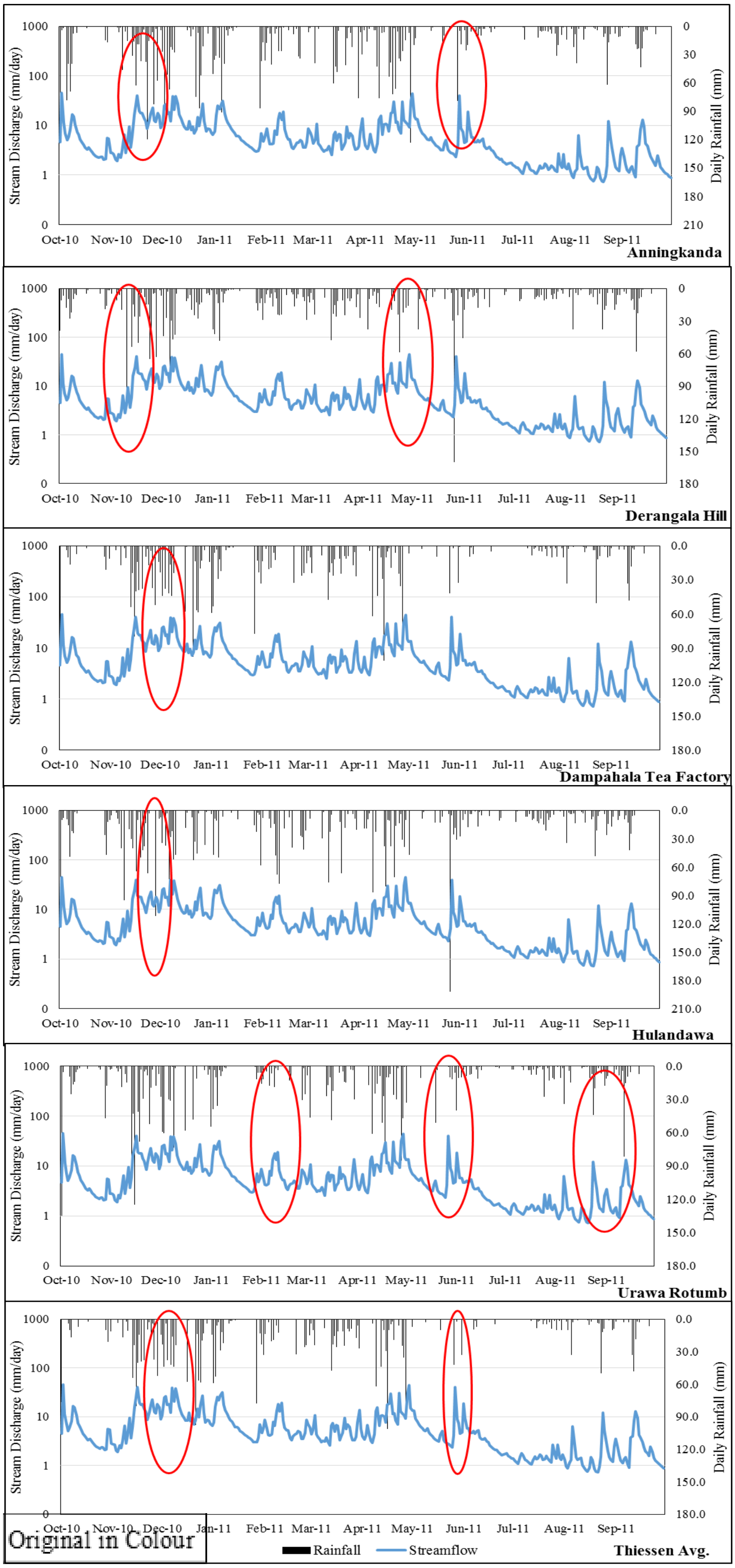


Figure A - 3: Streamflow at Pitabeddara vs Rainfall in water year 2010/2011

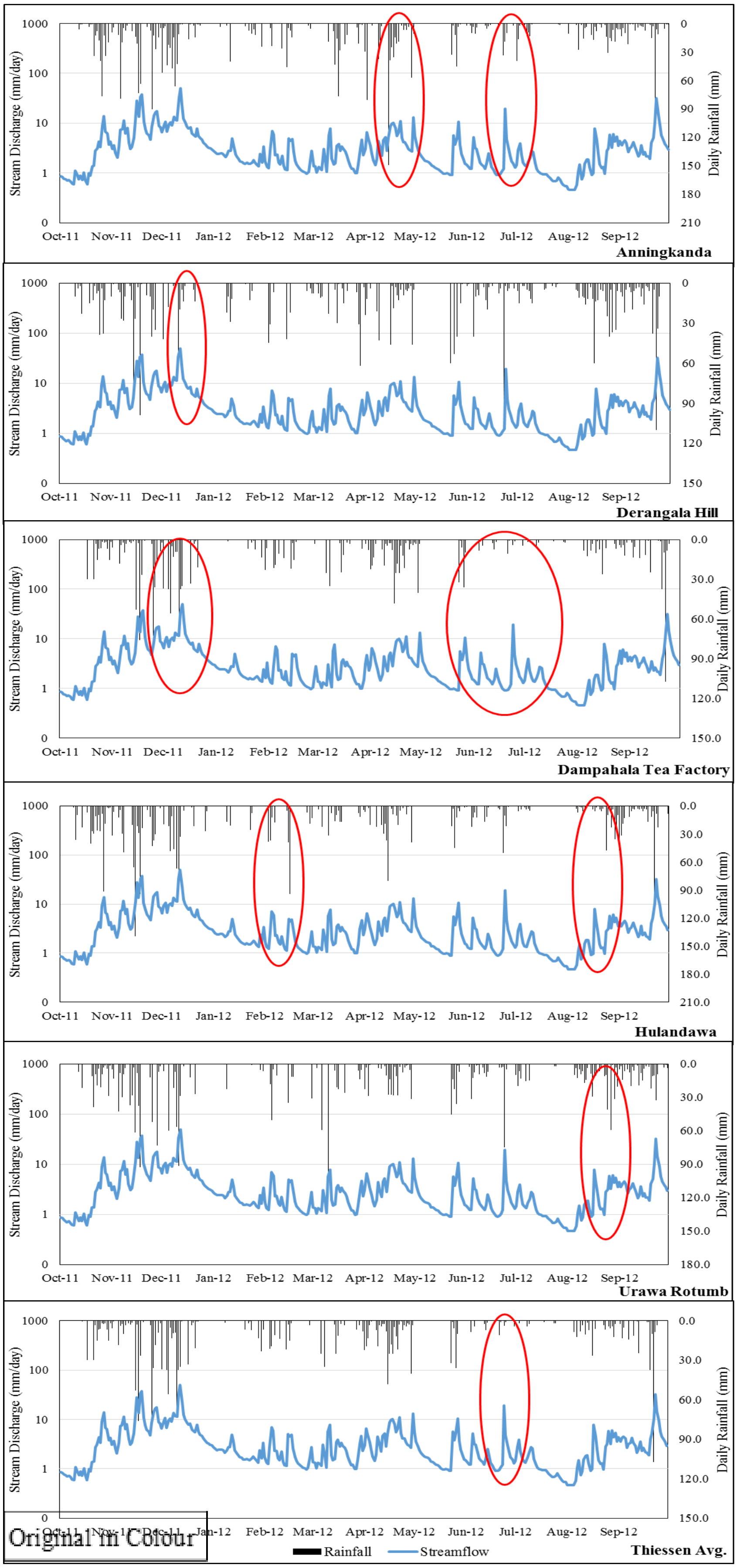


Figure A - 4: Streamflow at Pitabeddara vs Rainfall in water year 2011/2012

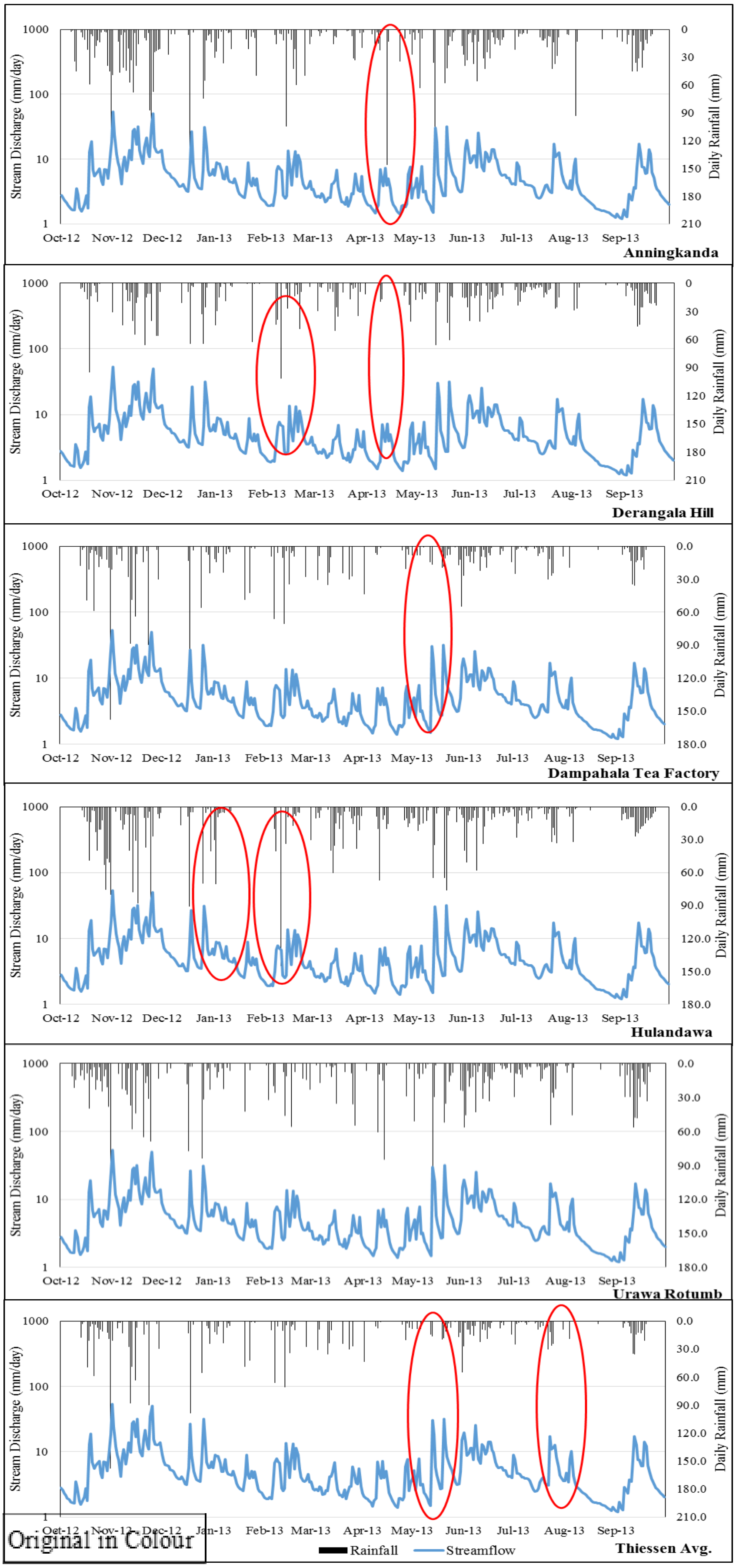


Figure A - 5: Streamflow at Pitabeddara vs Rainfall in water year 2012/2013

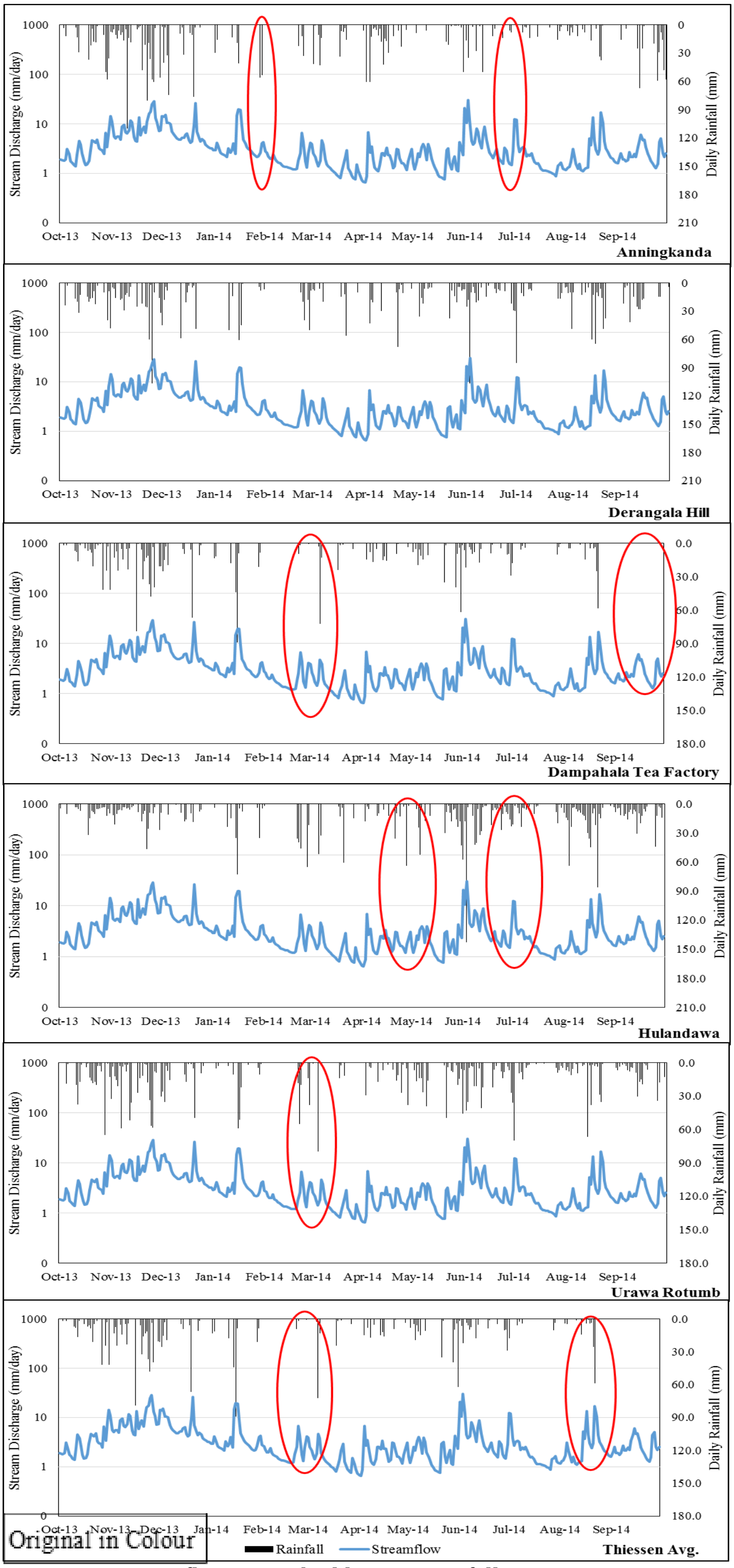


Figure A - 6: Streamflow at Pitabeddara vs Rainfall in water year 2013/2014

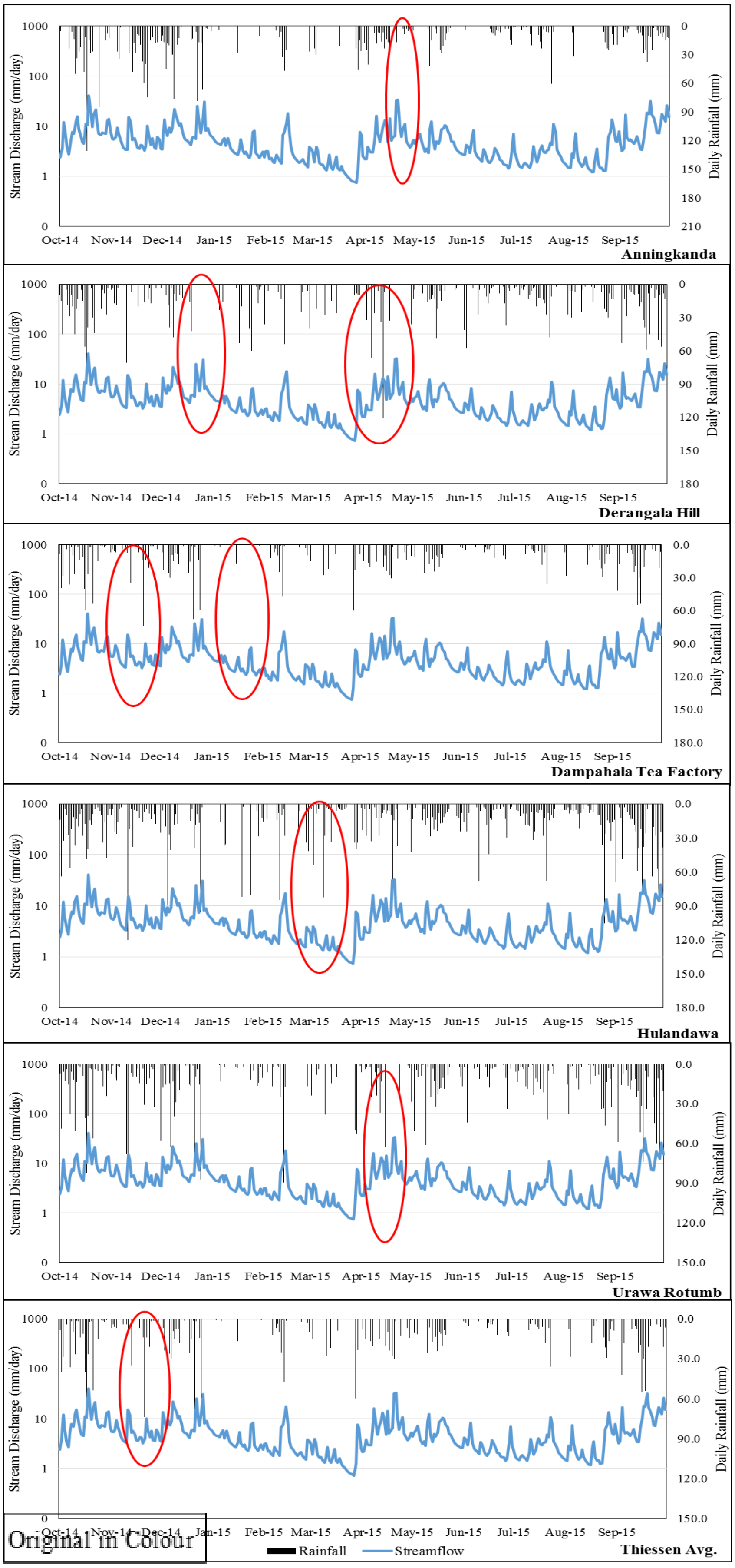


Figure A - 7: Streamflow at Pitabeddara vs Rainfall in water year 2014/2015

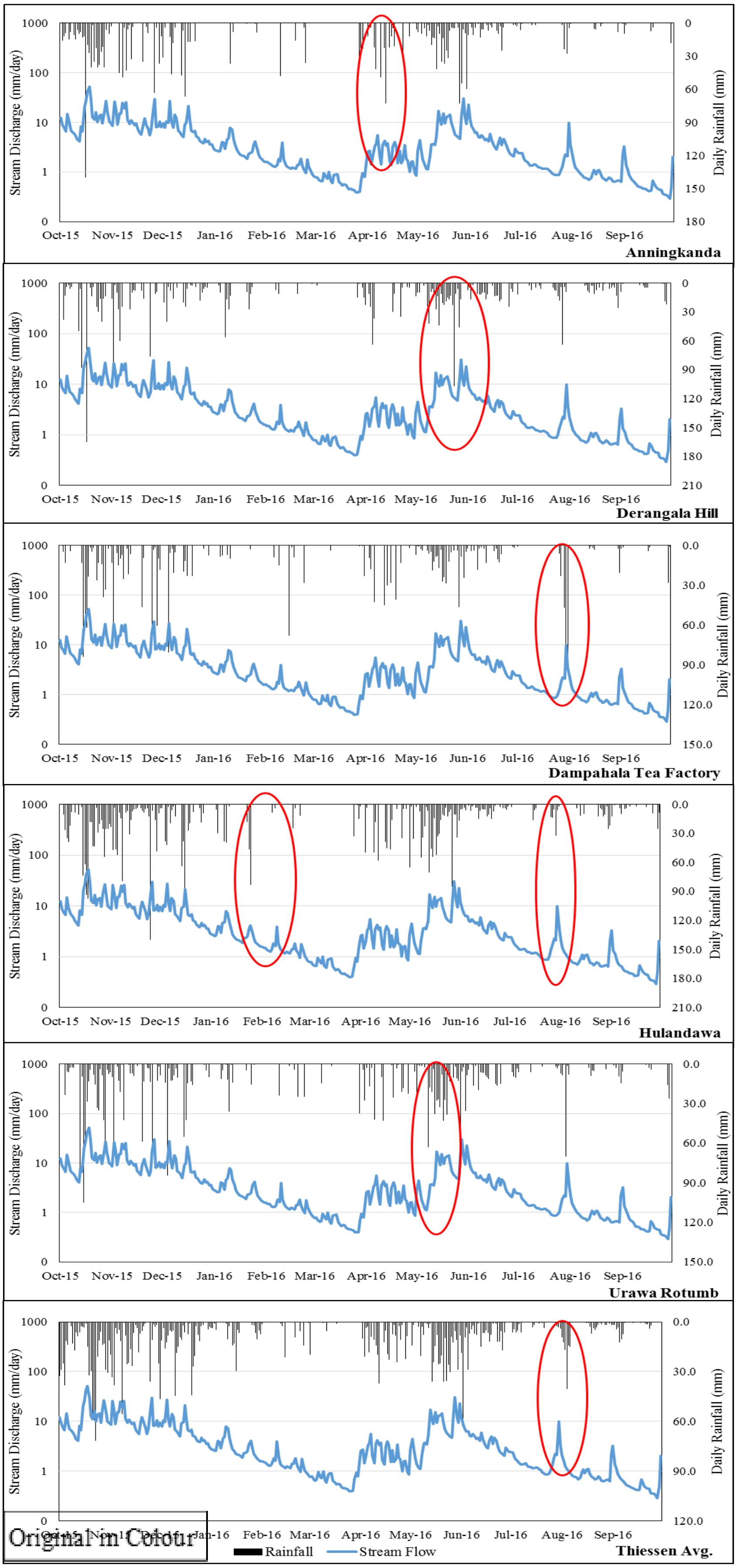


Figure A - 8: Streamflow at Pitabeddara vs Rainfall in water year 2015/2016

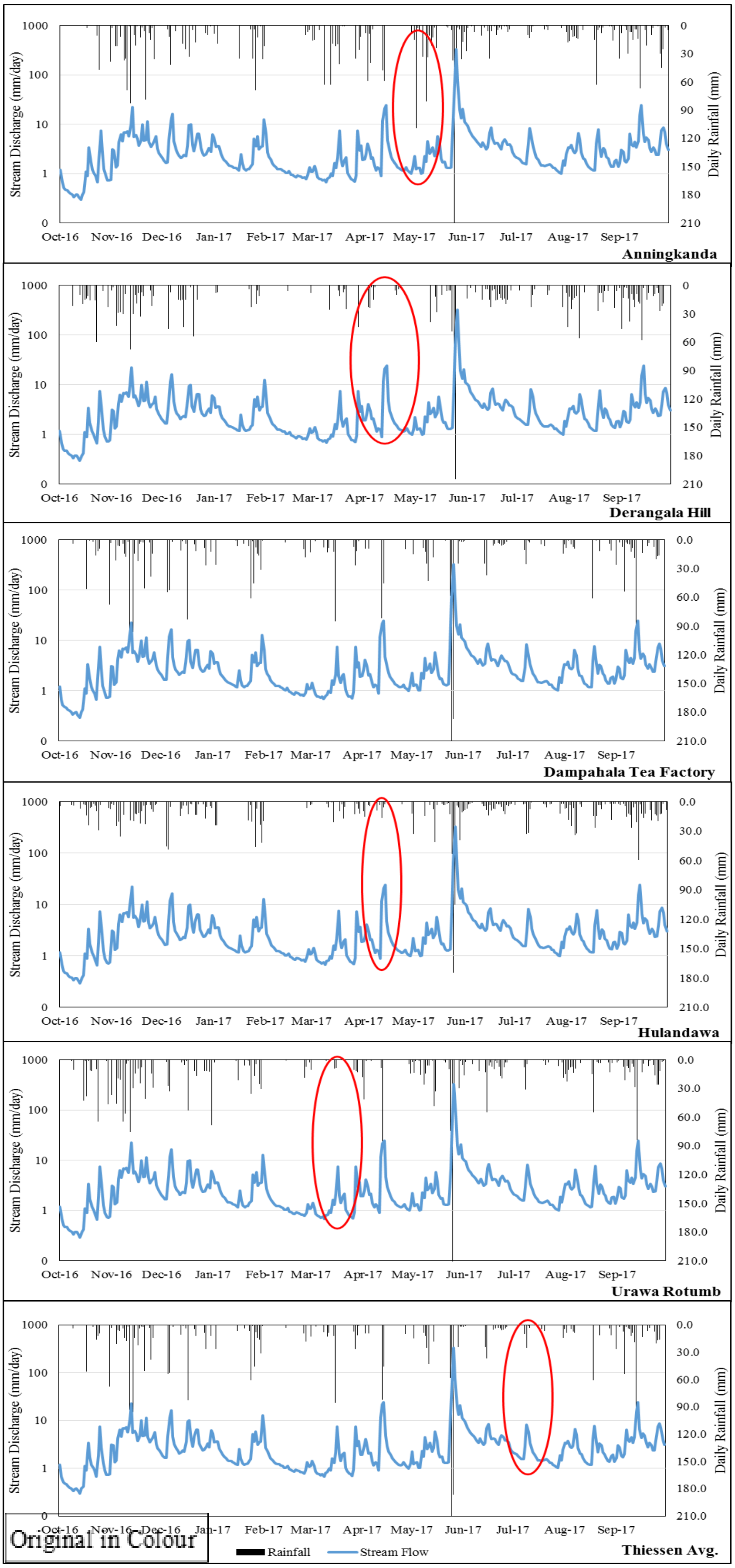


Figure A - 9: Streamflow at Pitabeddara vs Rainfall in water year 2016/2017

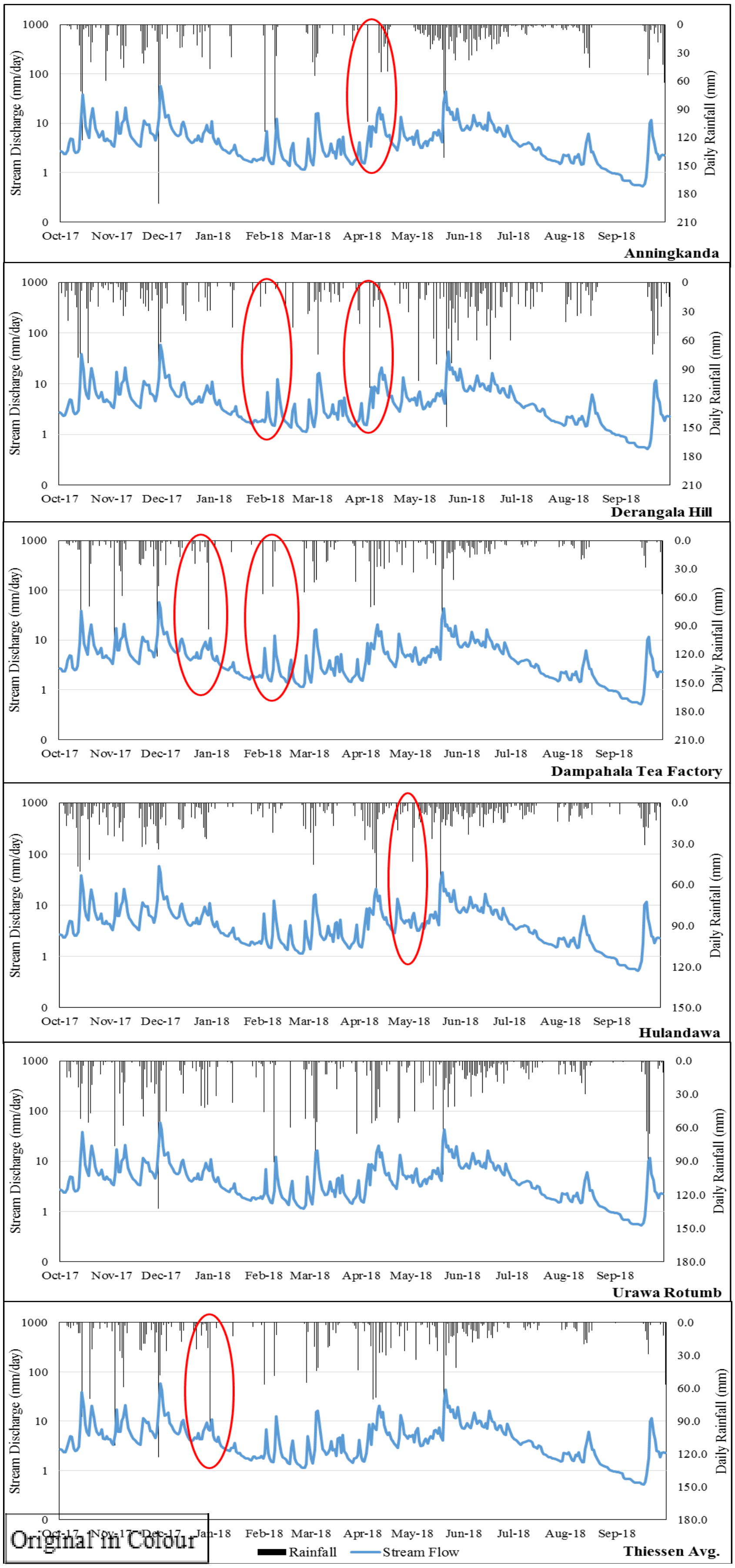
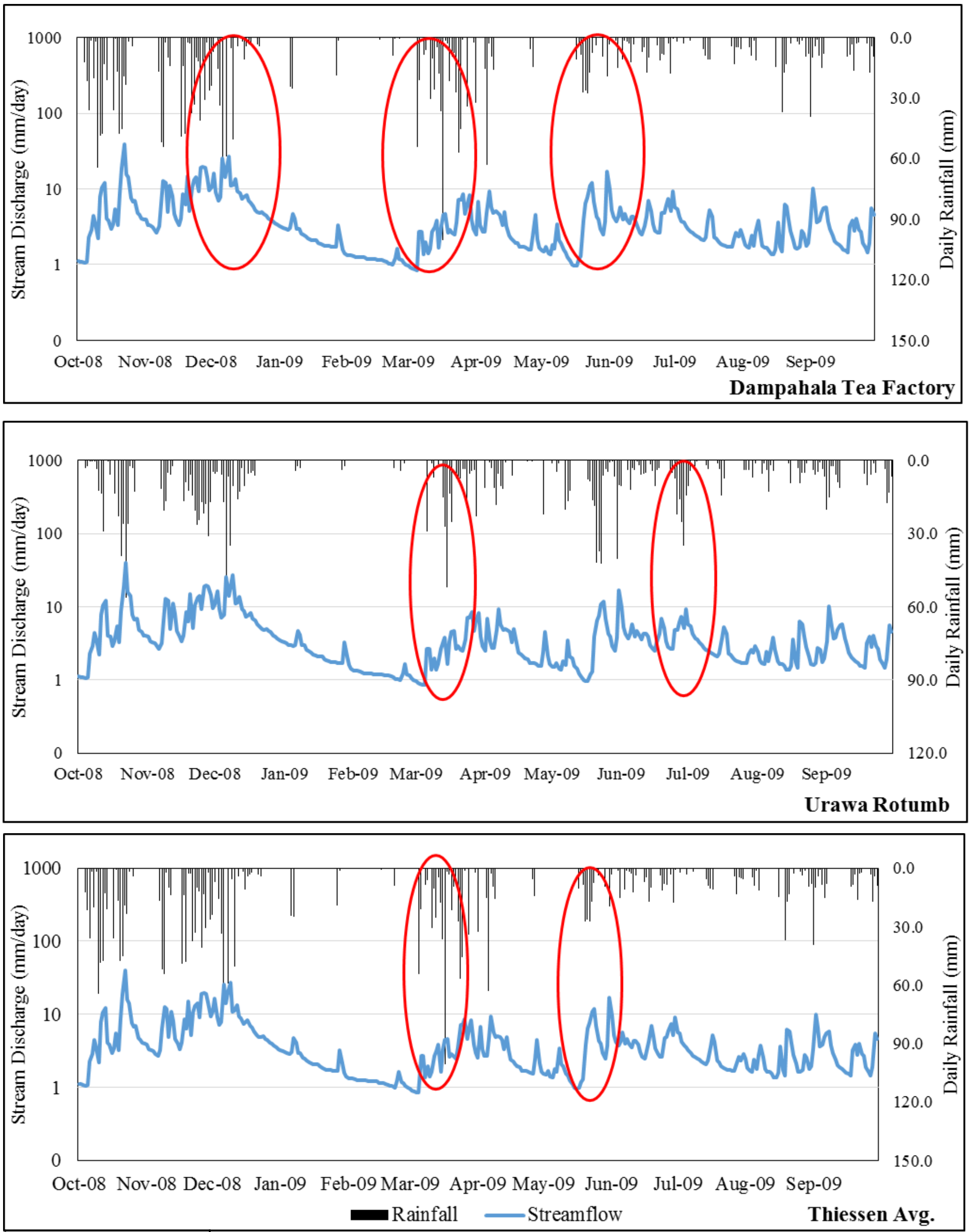
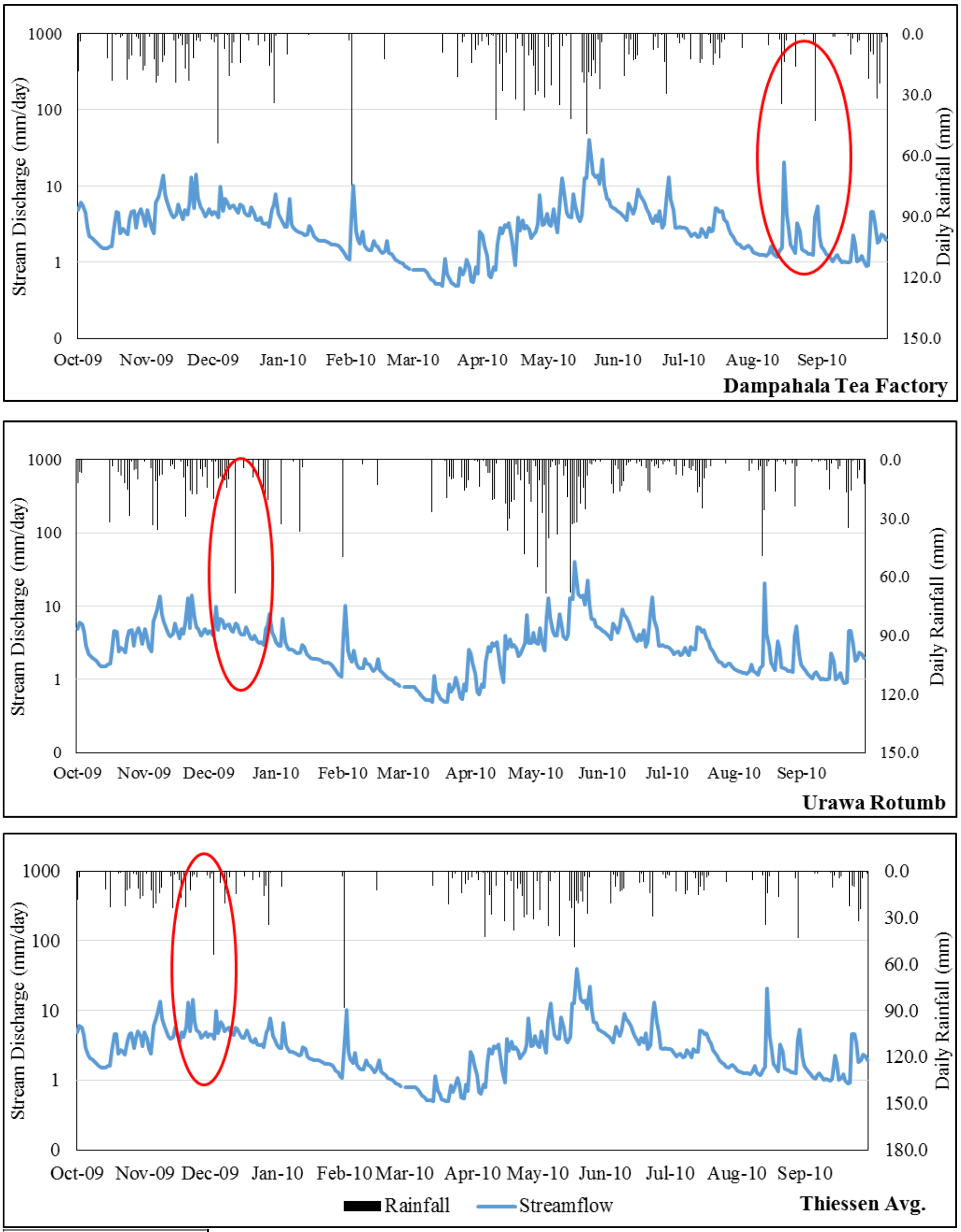


Figure A - 10: Streamflow at Pitabeddara vs Rainfall in water year 2017/2018



Original in Colour

Figure A - 11: Streamflow at Urawa vs Rainfall in water year 2008/2009



Original in Colour

Figure A - 12: Streamflow at Urawa vs Rainfall in water year 2009/2010

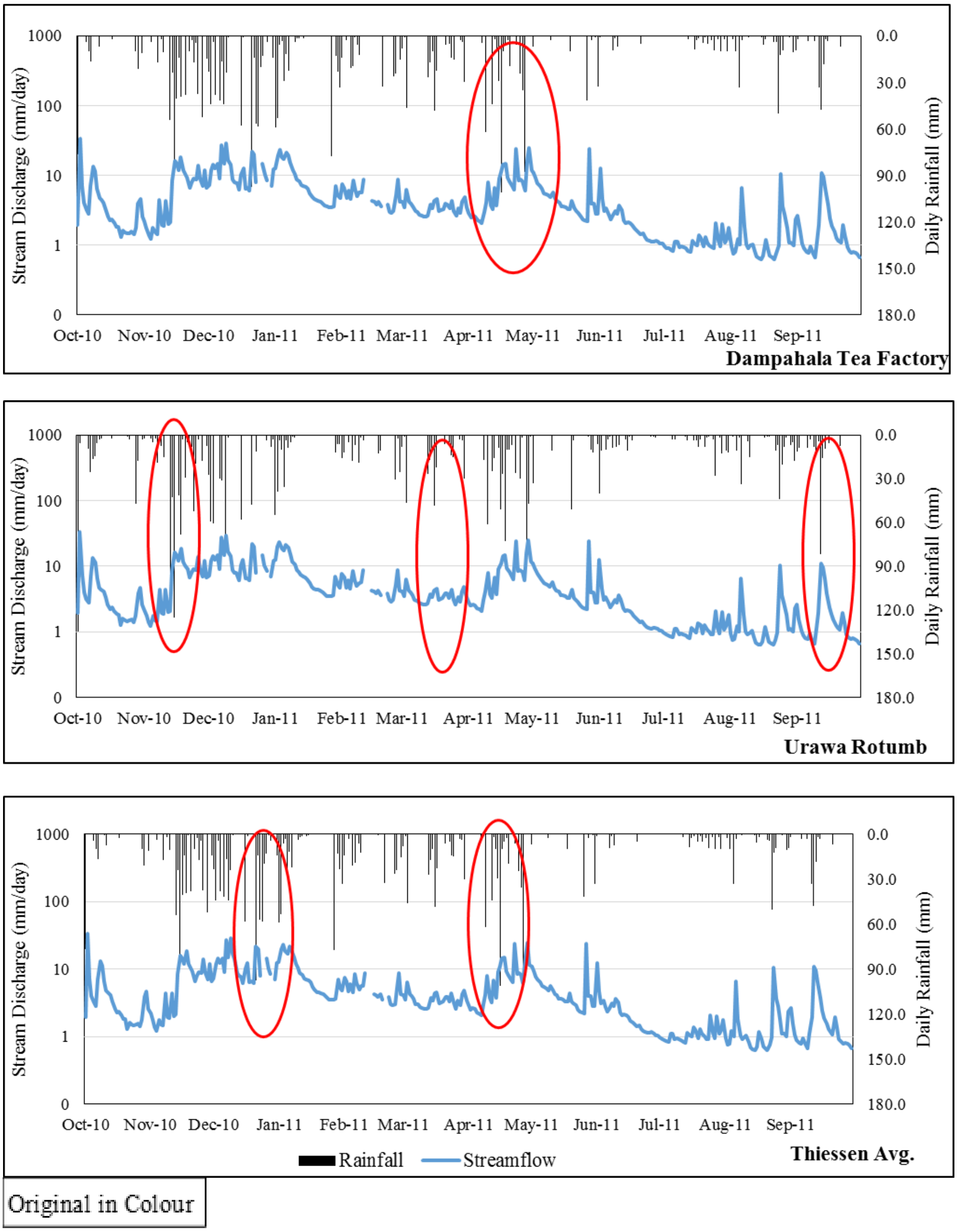
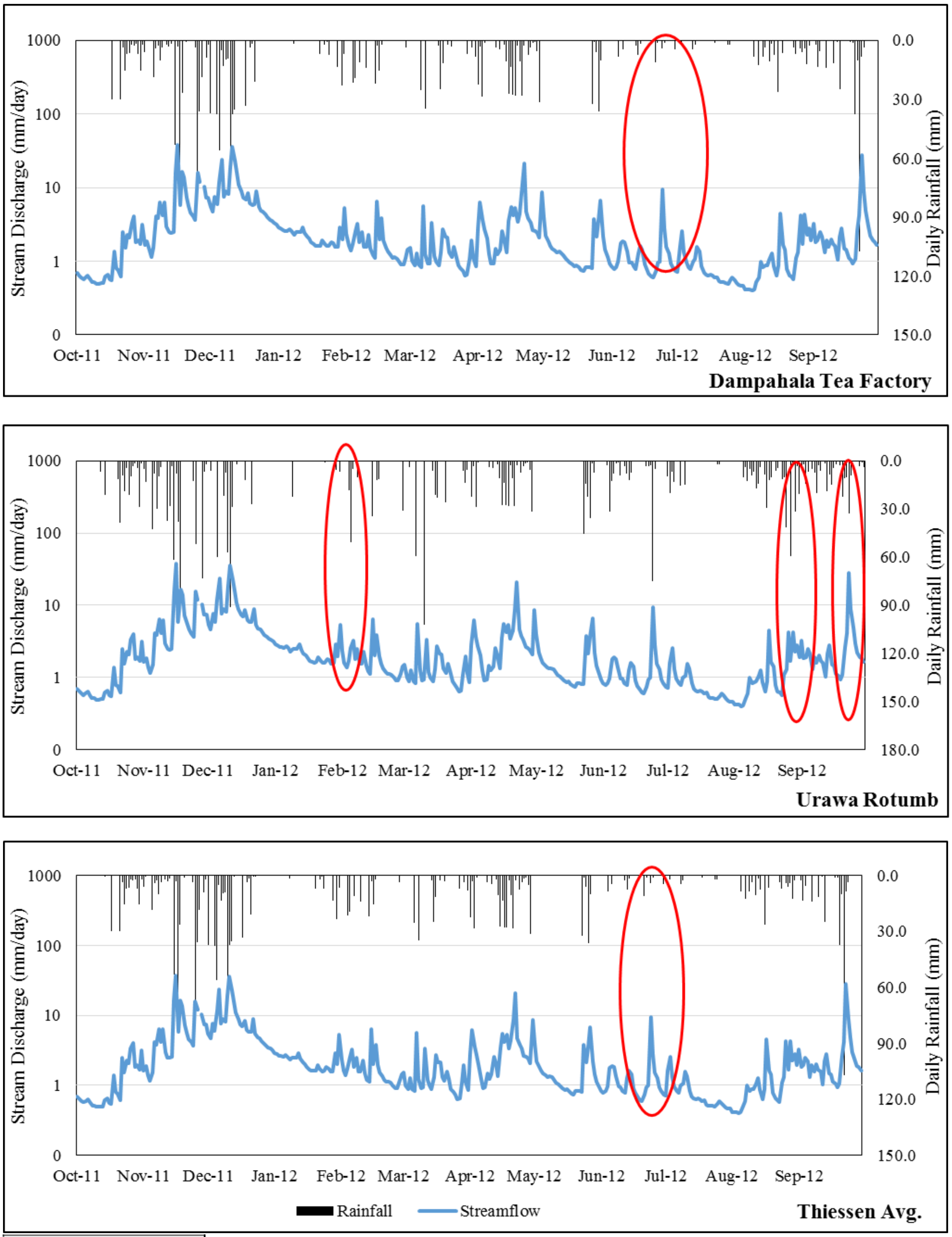
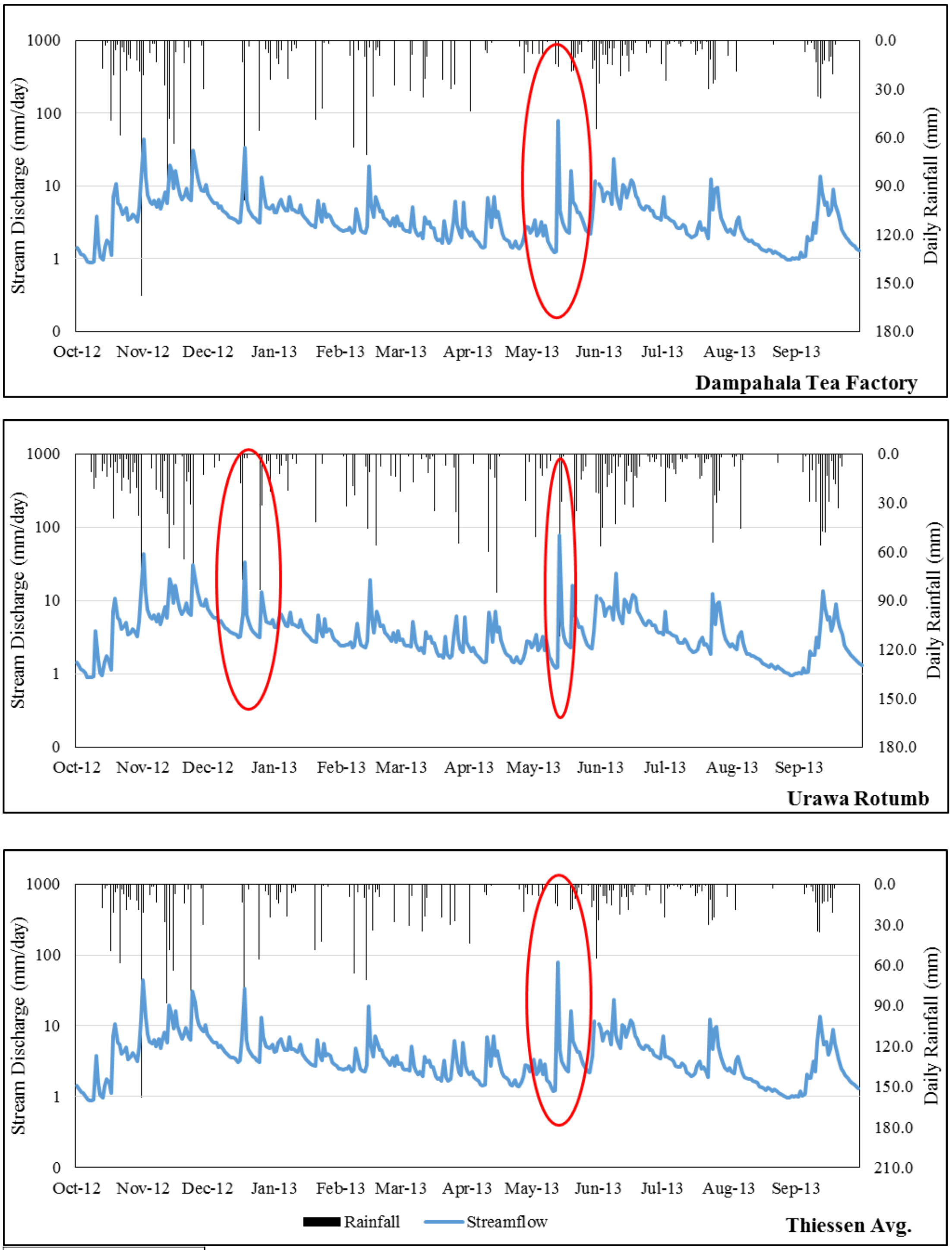


Figure A - 13: Streamflow at Urawa vs Rainfall in water year 2010/2011



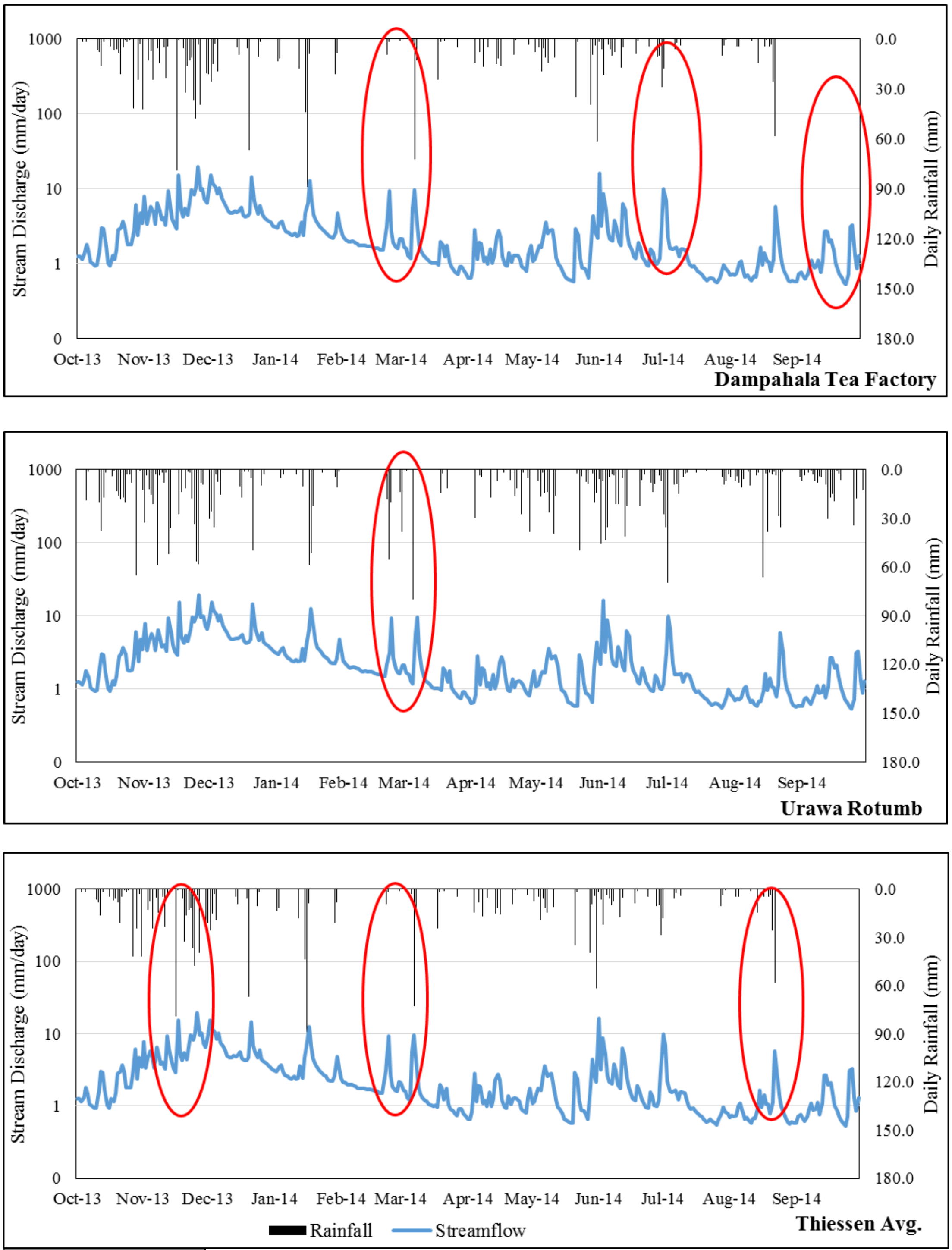
Original in Colour

Figure A - 14: Streamflow at Urawa vs Rainfall in water year 2011/2012



Original in Colour

Figure A - 15: Streamflow at Urawa vs Rainfall in water year 2012/2013



Original in Colour

Figure A - 16: Streamflow at Urawa vs Rainfall in water year 2013/2014

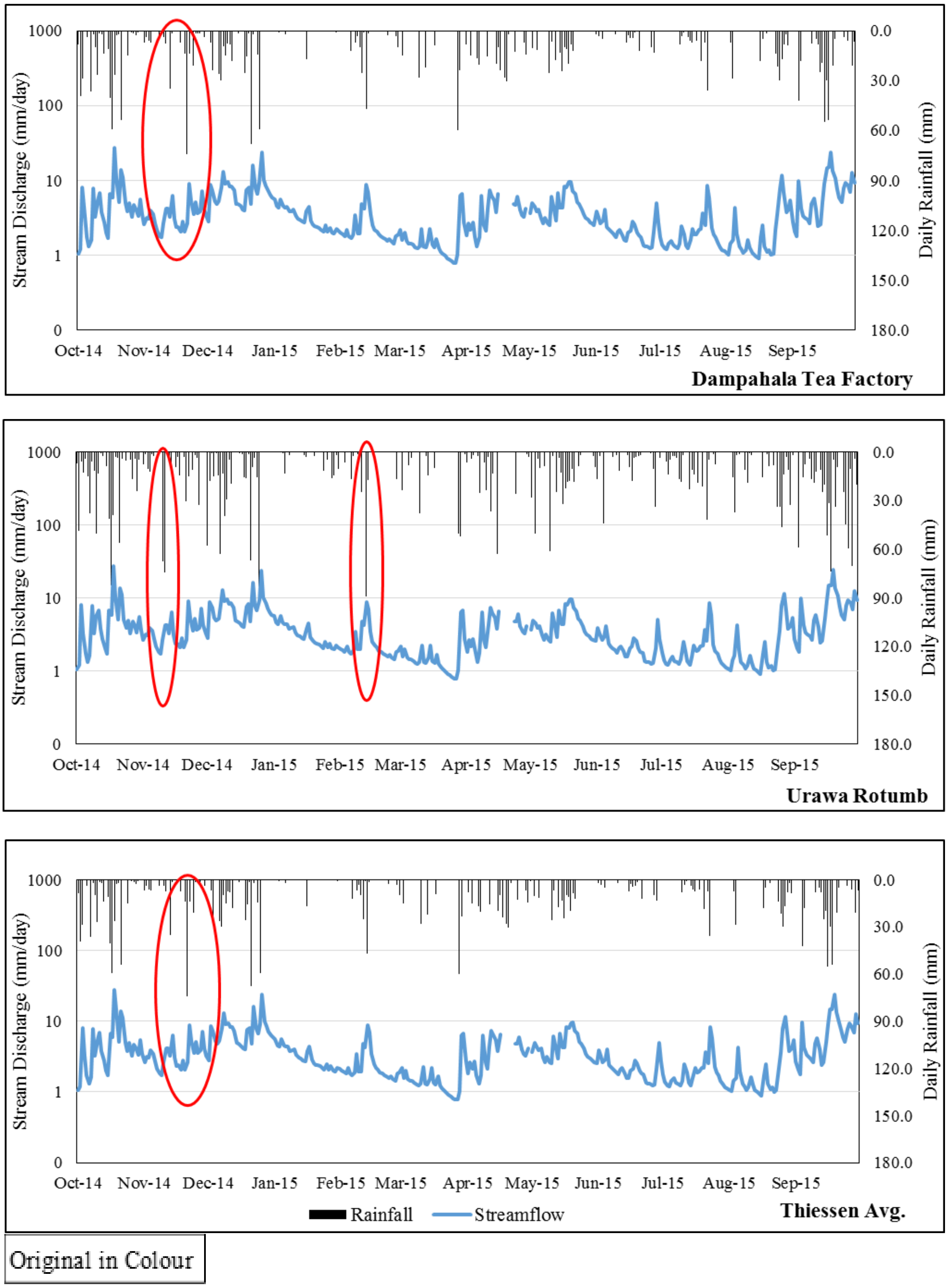
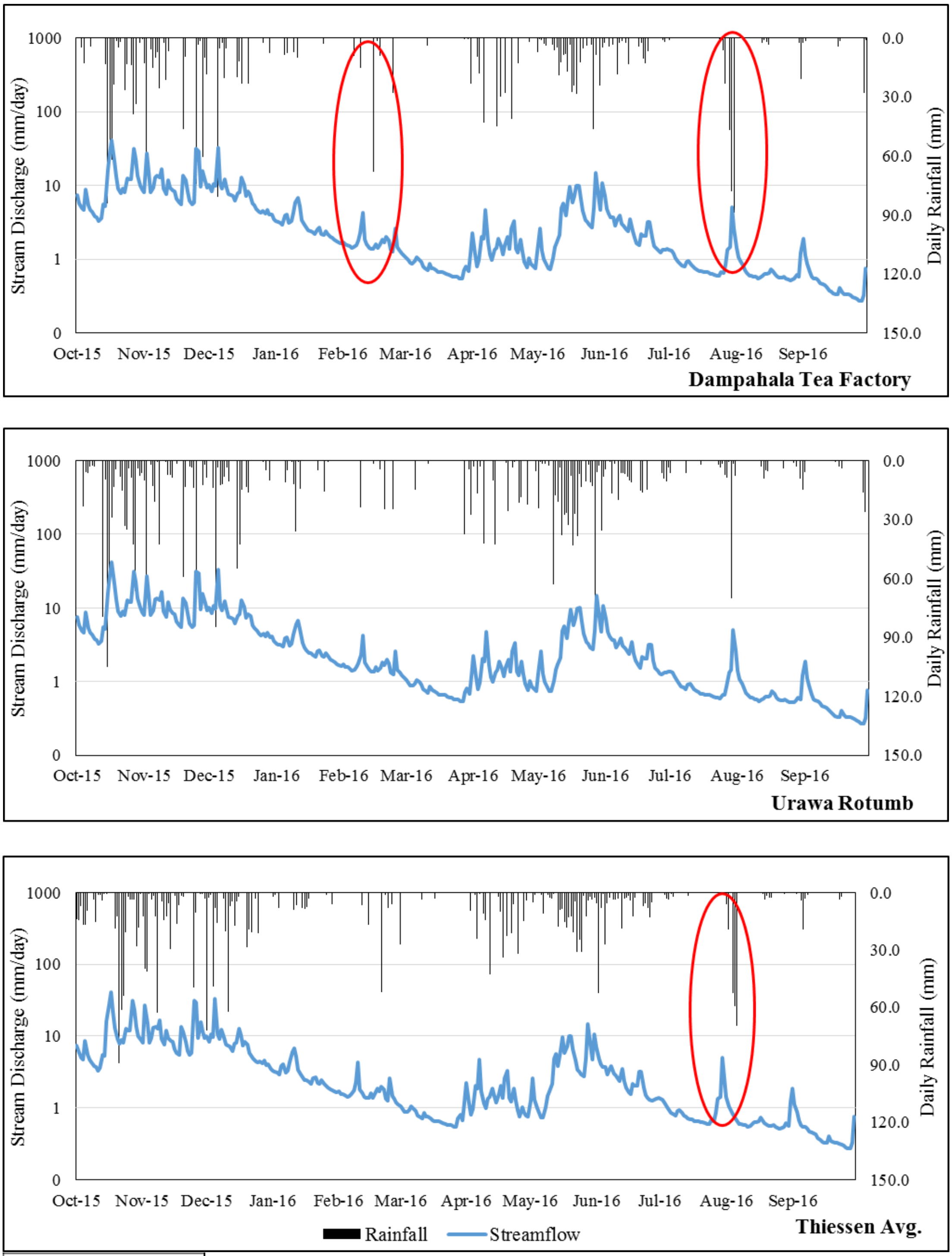


Figure A - 17: Streamflow at Urawa vs Rainfall in water year 2014/2015



Original in Colour

Figure A - 18: Streamflow at Urawa vs Rainfall in water year 2015/2016

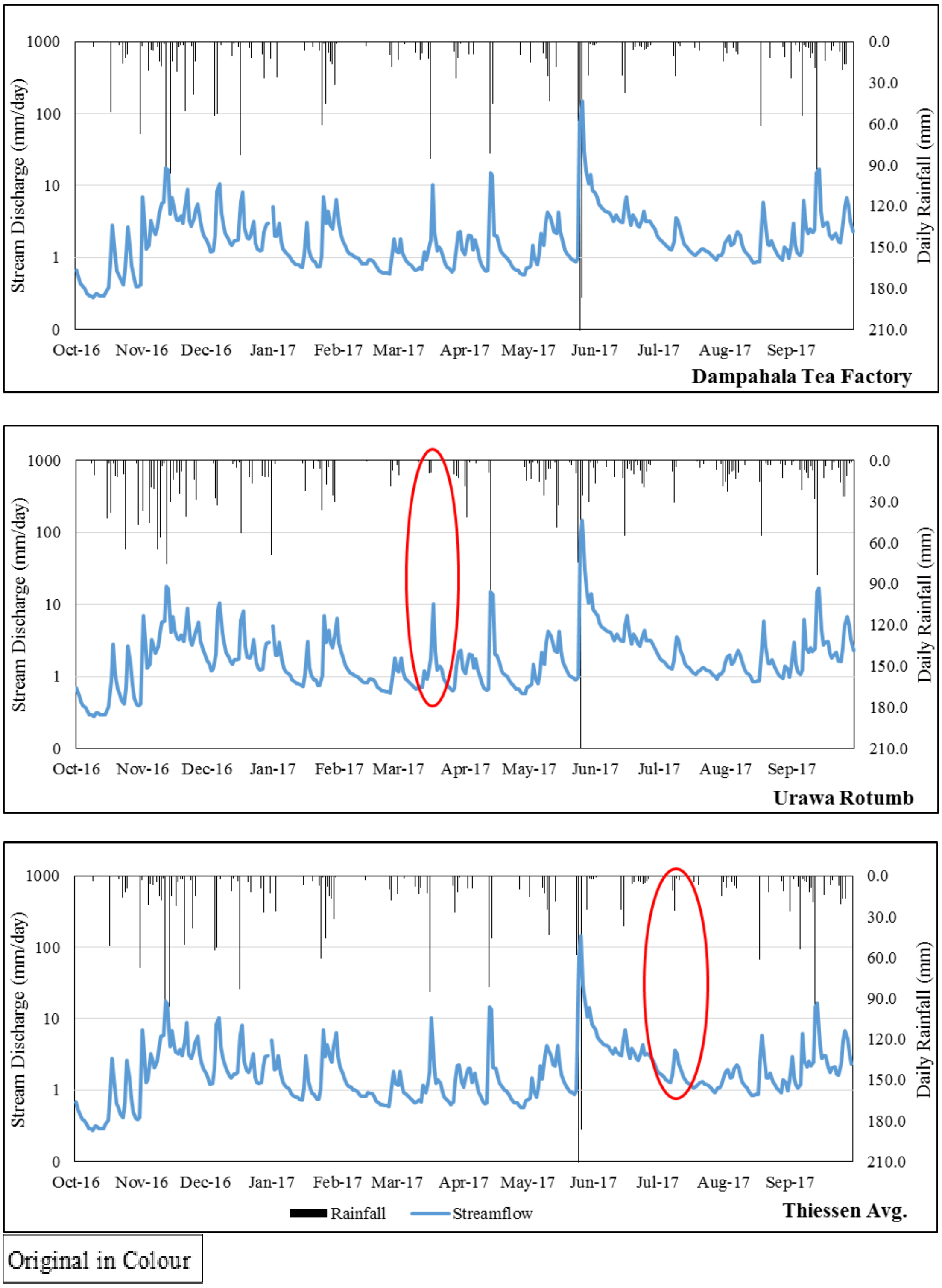
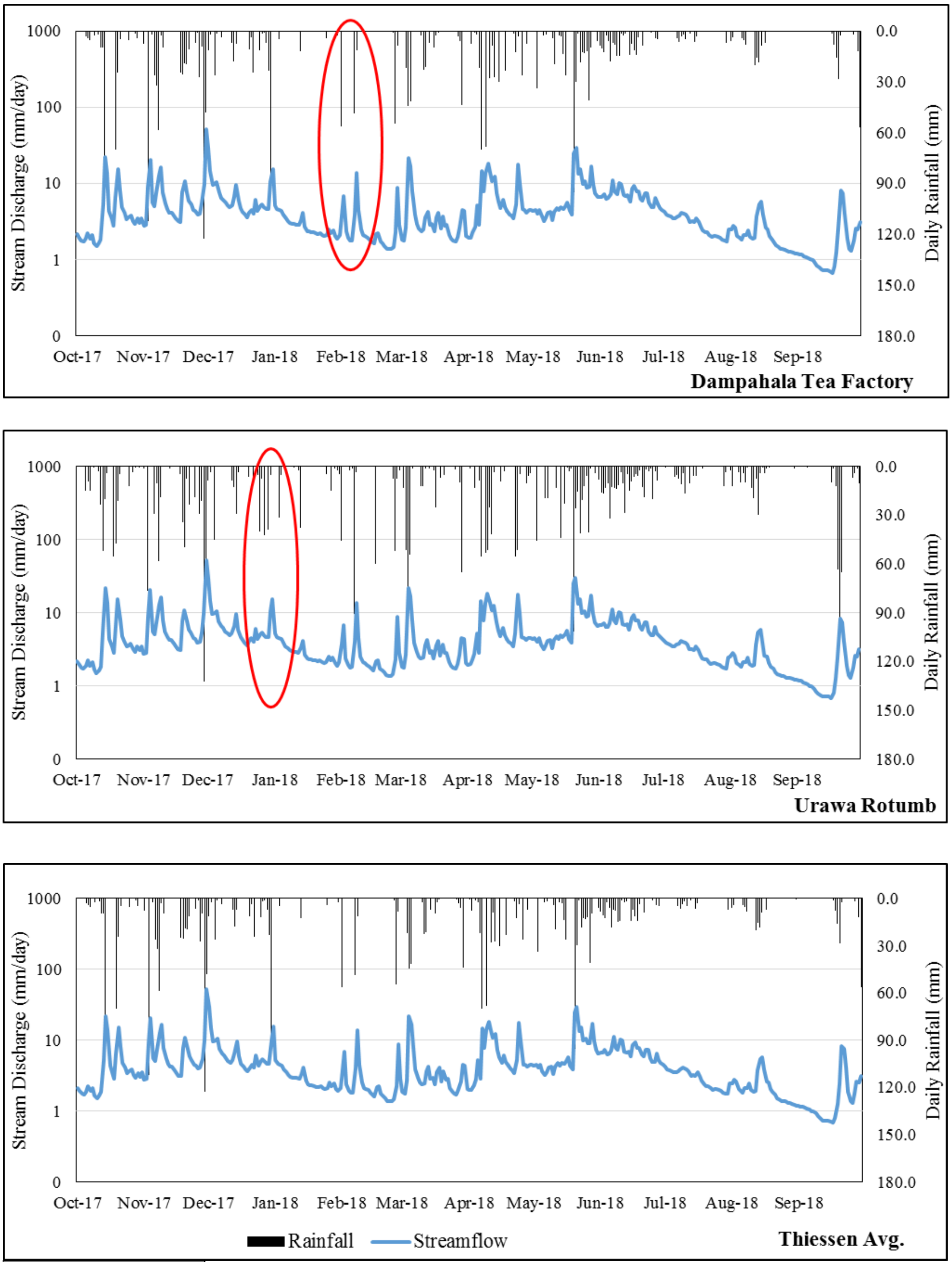


Figure A - 19: Streamflow at Urawa vs Rainfall in water year 2016/2017



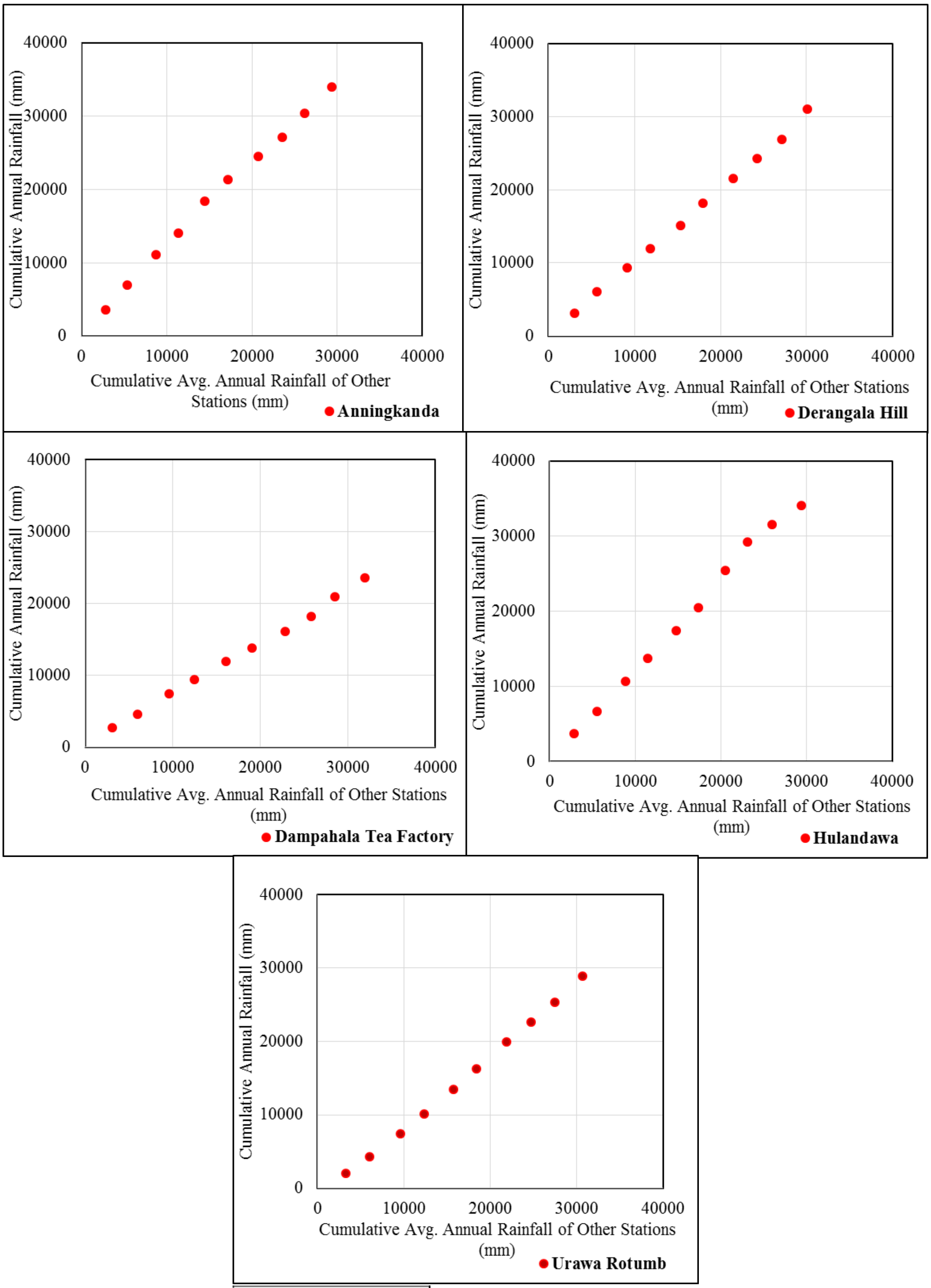
Original in Colour

Figure A - 20: Streamflow at Urawa vs Rainfall in water year 2017/2018

APPENDIX B: DOUBLE MASS CURVES

Table B - 1: Cumulative Rainfall of each station for Double Mass Curves

Water Year	Anningkanda		Derangala Hill		Dampahala Tea Factory		Hulandawa		Urawa Rotumba	
	Annual Cuml. Rainfall (mm)	Avg. Annual Cuml. Rainfall of other stns. (mm)	Annual Cuml. Rainfall (mm)	Avg. Annual Cuml. Rainfall of other stns. (mm)	Annual Cuml. Rainfall (mm)	Avg. Annual Cuml. Rainfall of other stns. (mm)	Annual Cuml. Rainfall (mm)	Avg. Annual Cuml. Rainfall of other stns. (mm)	Annual Cuml. Rainfall (mm)	Avg. Annual Cuml. Rainfall of other stns. (mm)
2008/09	3575.3	2854.9	3085.0	2977.5	2703.7	3072.8	3670.8	2831.0	1960.2	3258.7
2009/10	7009.0	5388.1	6051.7	5627.4	4568.0	5998.3	6675.5	5471.4	4257.1	6076.1
2010/11	11130.6	8711.1	9308.0	9166.7	7488.3	9621.7	10655.1	8830.0	7392.9	9645.5
2011/12	14101.8	11339.1	12005.0	11863.3	9474.3	12496.0	13773.1	11421.3	10103.9	12338.6
2012/13	18419.8	14487.1	15124.0	15311.0	11994.1	16093.5	17392.5	14743.9	13437.6	15732.6
2013/14	21361.1	17158.0	18188.0	17951.3	13779.3	19053.5	20426.5	17391.7	16238.3	18438.7
2014/15	24490.9	20735.2	21561.0	21467.6	16065.5	22841.5	25381.3	20512.6	19932.8	21874.7
2015/16	27092.0	23580.8	24327.0	24272.0	18183.9	25807.8	29199.4	23053.9	22612.7	24700.6
2016/17	30413.6	26201.3	26866.5	27088.1	20970.3	28562.2	31578.5	25910.1	25390.0	27457.2
2017/18	33984.0	29396.0	31018.5	30137.4	23599.9	31992.0	34037.3	29382.7	28928.3	30659.9



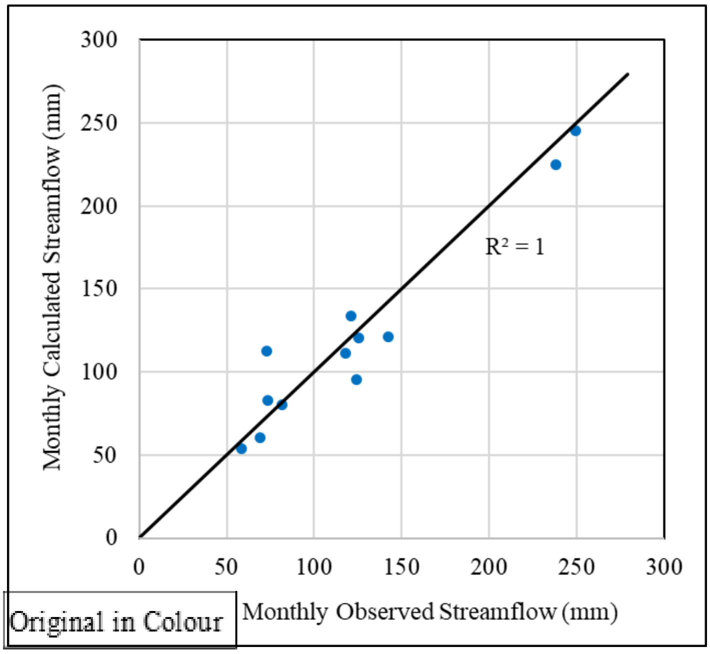
Original in Colour

Figure B - 1: Double Mass Curves for Rainfall Stations

APPENDIX C: COMPARISON OF RESULTS IN MONTHLY SCALE

Table C - 1: Monthly flow comparison for Urawa catchment in model calibration & validation

Month	Calibration Period			Validation Period		
	Monthly Avg. Observed Flow (mm)	Monthly Avg. Calculated Flow (mm)	Error %	Monthly Avg. Observed Flow (mm)	Monthly Avg. Calculated Flow (mm)	Error %
October	117.9	111.6	5.3%	148.4	158.5	-6.8%
November	238.1	224.9	5.6%	209.4	246.9	-17.9%
December	249.3	245.3	1.6%	201.1	226.0	-12.4%
January	125.4	120.6	3.8%	91.2	114.3	-25.3%
February	73.7	83.0	-12.6%	59.0	74.0	-25.4%
March	73.1	112.4	-53.7%	59.7	79.3	-32.7%
April	120.8	133.5	-10.5%	88.5	106.0	-19.7%
May	142.0	121.2	14.7%	185.2	187.2	-1.1%
June	124.3	95.4	23.2%	112.5	139.3	-23.8%
July	69.0	60.3	12.5%	55.9	81.0	-44.8%
August	58.4	53.6	8.1%	50.1	79.6	-58.9%
September	81.8	80.1	2.0%	86.2	102.4	-18.8%



Original in Colour

Figure C - 1: Scatter plot with monthly avg. flow of Urawa catchment - Calibration period

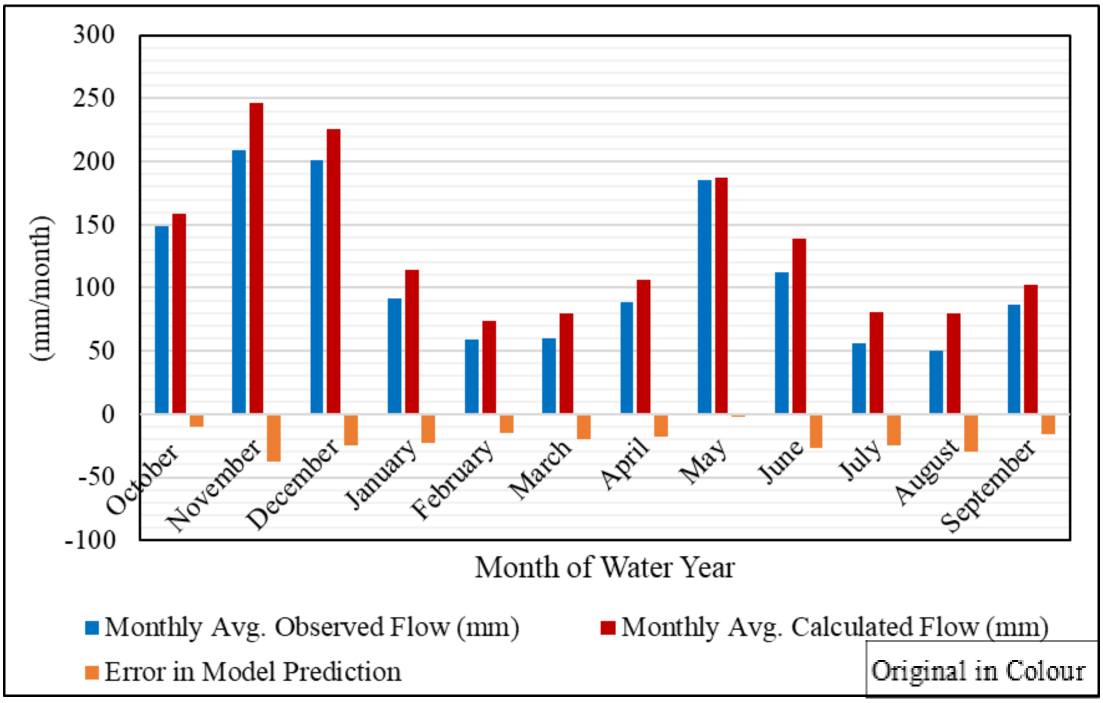
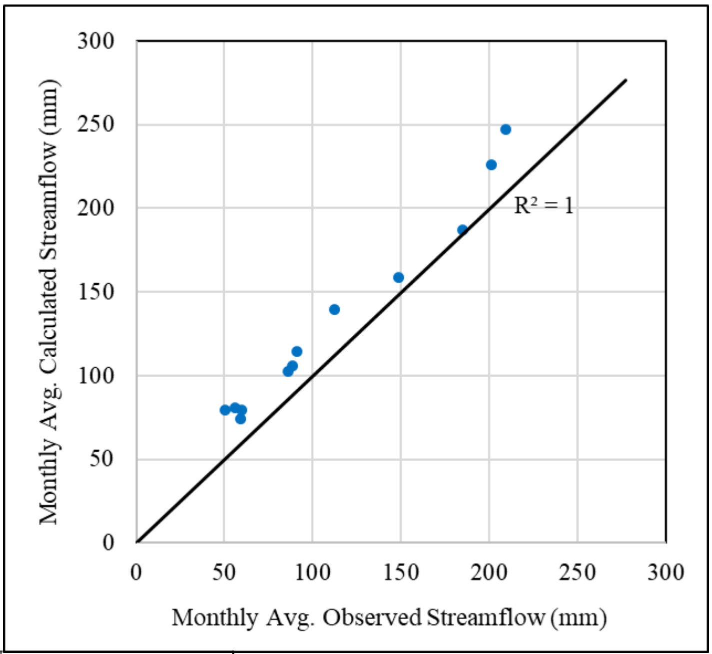


Figure C - 2: Monthly flow comparison for Urawa catchment - Validation period



Original in Colour

Figure C - 3: Scatter plot with monthly avg. flow of Urawa catchment - Validation period

Table C - 2: Monthly flow comparison for Pitabeddara catchment in calibration & validation

Month	Calibration Period			Validation Period		
	Monthly Avg. Observed Flow (mm)	Monthly Avg. Calculated Flow (mm)	Error %	Monthly Avg. Observed Flow (mm)	Monthly Avg. Calculated Flow (mm)	Error %
October	159.2	156.6	1.6%	222.9	264.4	-18.6%
November	318.9	314.8	1.3%	256.2	310.6	-21.2%
December	304.9	286.3	6.1%	237.5	255.1	-7.4%
January	132.7	116.8	12.0%	105.2	111.5	-6.0%
February	97.5	94.0	3.6%	64.0	77.7	-21.4%
March	96.5	118.9	-23.2%	59.8	93.1	-55.7%
April	168.2	176.2	-4.7%	139.1	136.8	1.6%
May	195.1	205.7	-5.4%	277.9	280.8	-1.1%
June	173.3	165.9	4.3%	157.9	201.8	-27.8%
July	106.5	94.9	10.9%	74.8	114.8	-53.4%
August	81.9	83.0	-1.5%	76.2	116.4	-52.8%
September	122.6	130.5	-6.4%	125.1	171.9	-37.4%

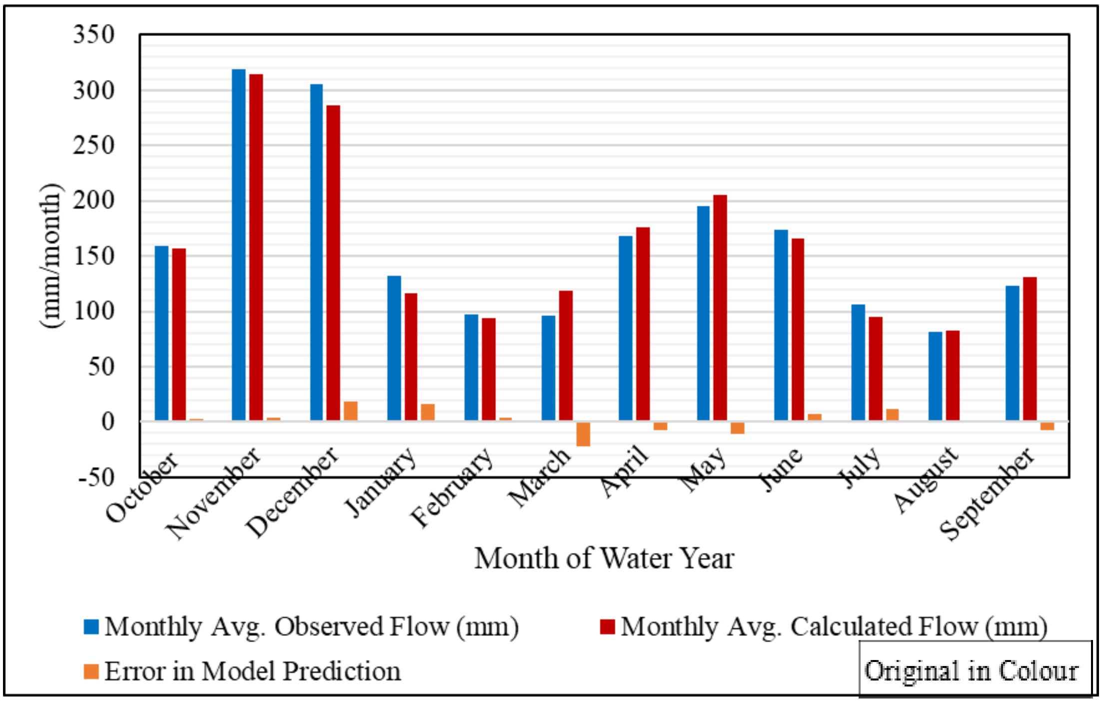


Figure C - 4: Monthly flow comparison for Pitabeddara catchment - Calibration period

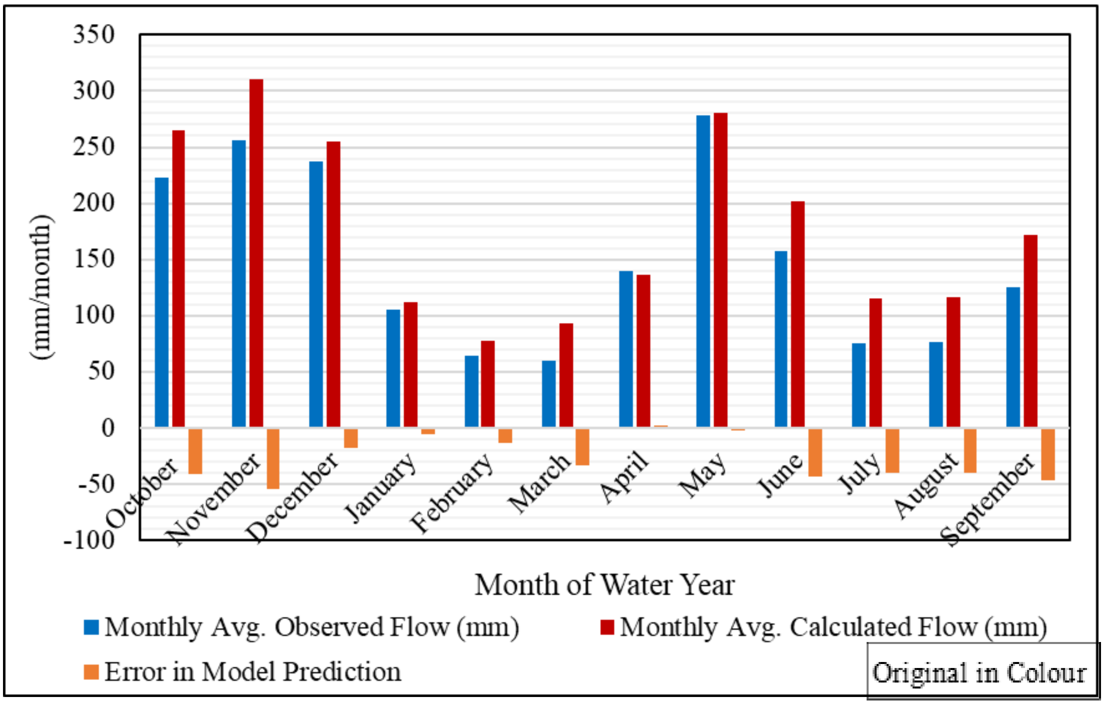


Figure C - 5: Monthly flow comparison for Pitabeddara catchment - Validation period

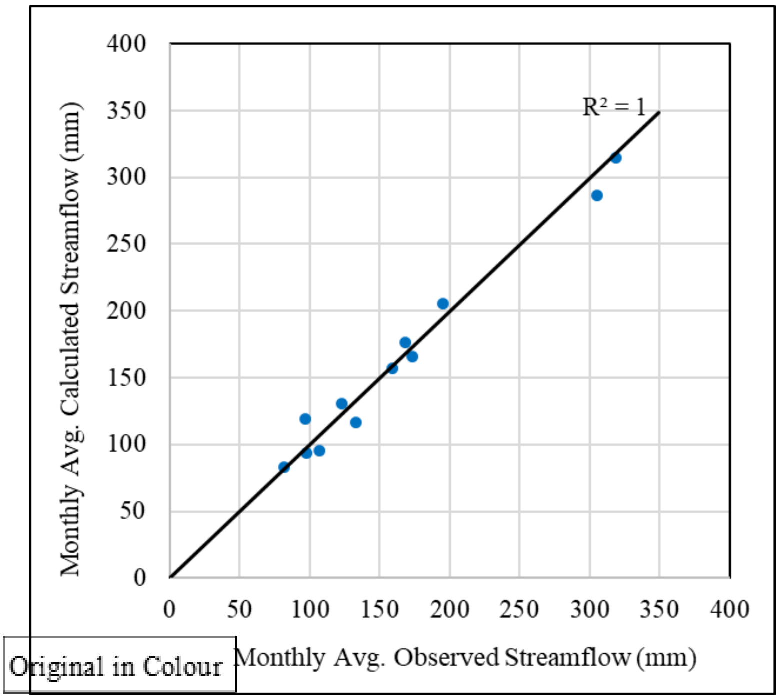


Figure C - 6: Scatter plot with monthly avg. flow of Pitabeddara catchment – Calibration period

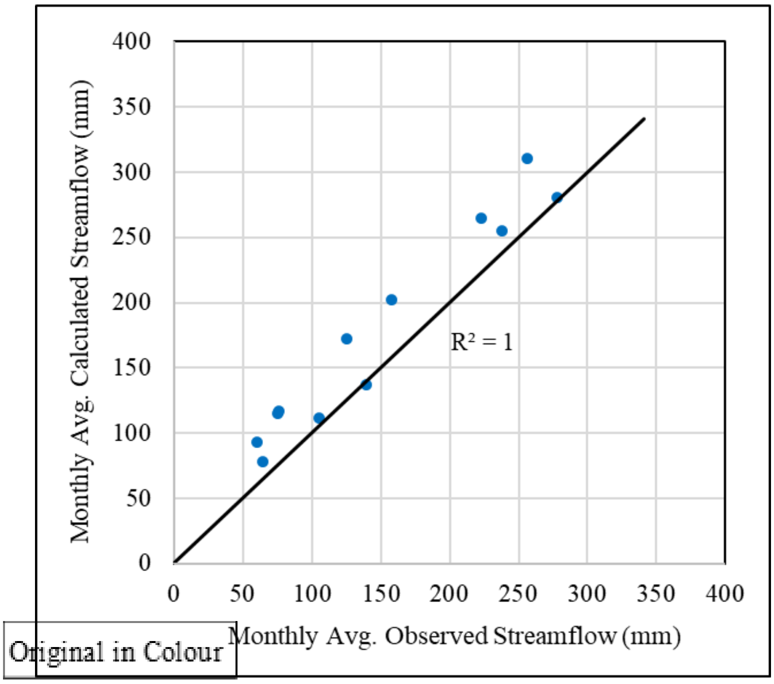


Figure C - 7: Scatter plot with monthly avg. flow of Pitabeddara catchment – Validation period

Table C - 3: Monthly flow comparison for Urawa catchment with spatiotemporally transferred parameters

Month	Monthly Avg. Observed Flow (mm)	Monthly Avg. Calculated Flow (mm)	Error %
October	148.4	187.7	-26.5%
November	209.4	287.8	-37.4%
December	201.1	237.2	-17.9%
January	91.2	104.5	-14.5%
February	59.0	67.9	-15.1%
March	59.7	83.5	-39.9%
April	88.5	118.2	-33.5%
May	185.2	224.2	-21.1%
June	112.5	133.9	-19.0%
July	55.9	78.0	-39.4%
August	50.1	77.7	-55.1%
September	86.2	116.0	-34.6%

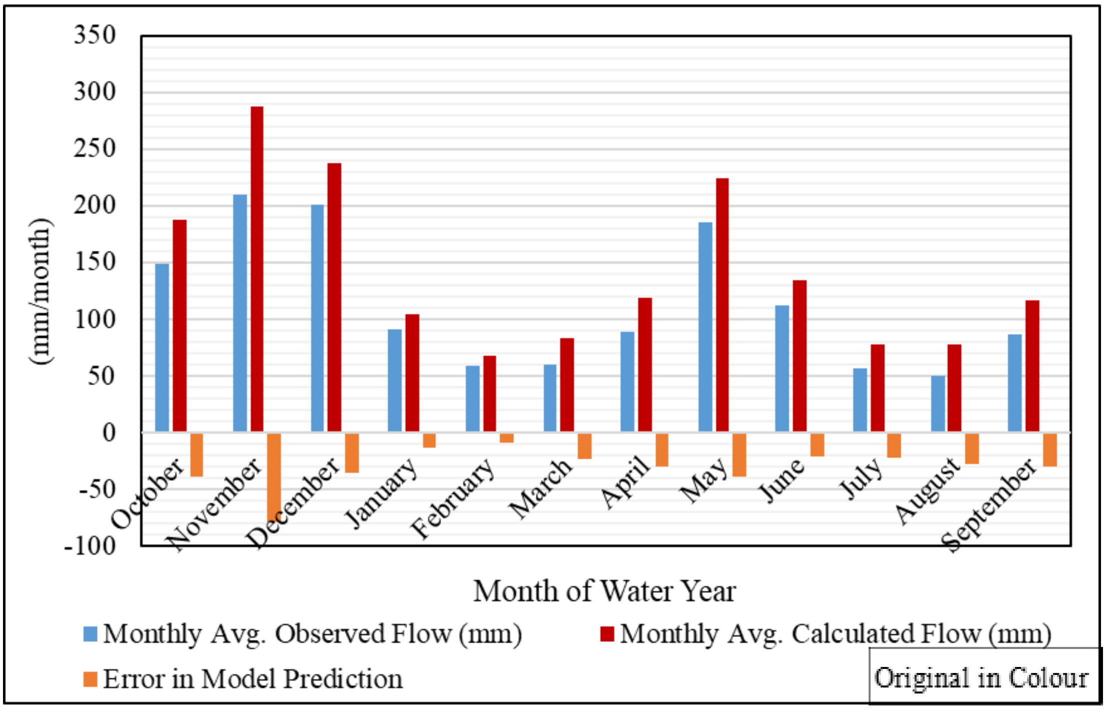


Figure C - 8: Monthly flow comparison for Urawa catchment with spatiotemporally transferred parameters

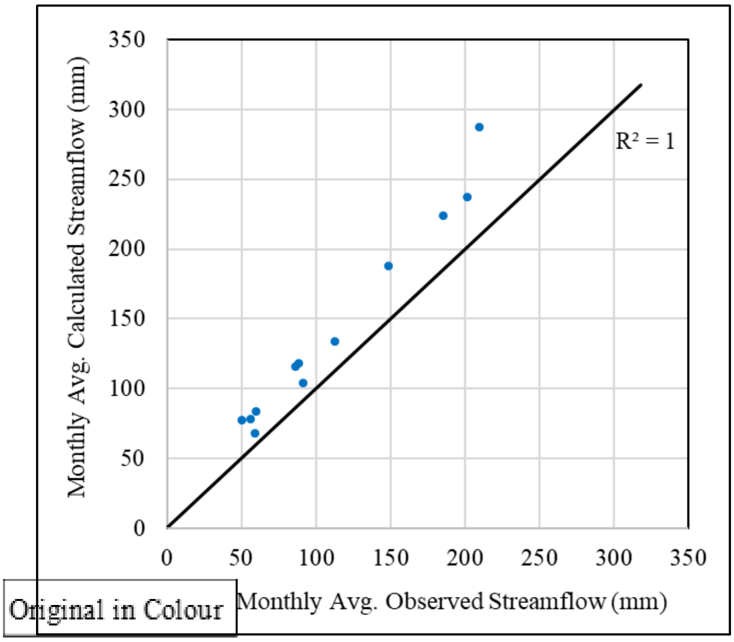


Figure C - 9: Scatter plot with monthly avg. flow of Urawa catchment with spatiotemporally transferred parameters

Table C - 4: Monthly flow comparison for Pitabeddara catchment with spatiotemporally transferred parameters

Month	Monthly Avg. Observed Flow (mm)	Monthly Avg. Calculated Flow (mm)	Error %
October	222.9	246.9	-10.8%
November	256.2	293.8	-14.7%
December	237.5	263.5	-10.9%
January	105.2	141.1	-34.2%
February	64.0	100.8	-57.5%
March	59.8	108.8	-82.0%
April	139.1	141.8	-1.9%
May	277.9	252.6	9.1%
June	157.9	216.4	-37.1%
July	74.8	136.4	-82.3%
August	76.2	133.2	-74.8%
September	125.1	169.8	-35.7%

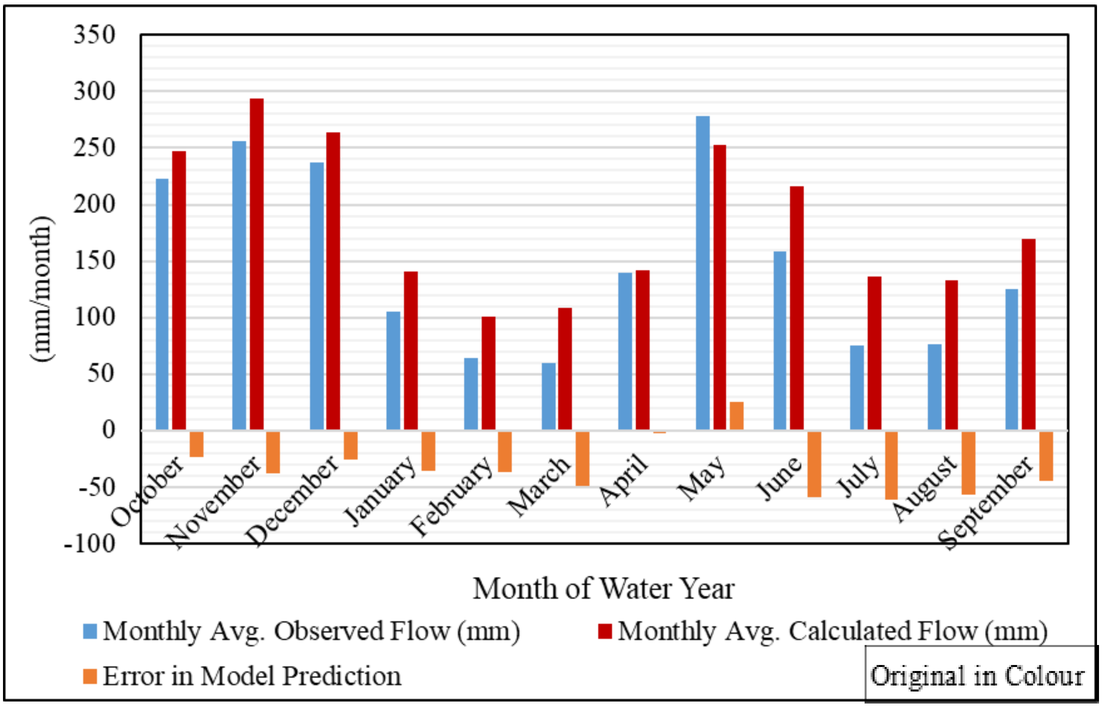


Figure C - 10: Monthly flow comparison for Pitabeddara catchment with spatiotemporally transferred parameters

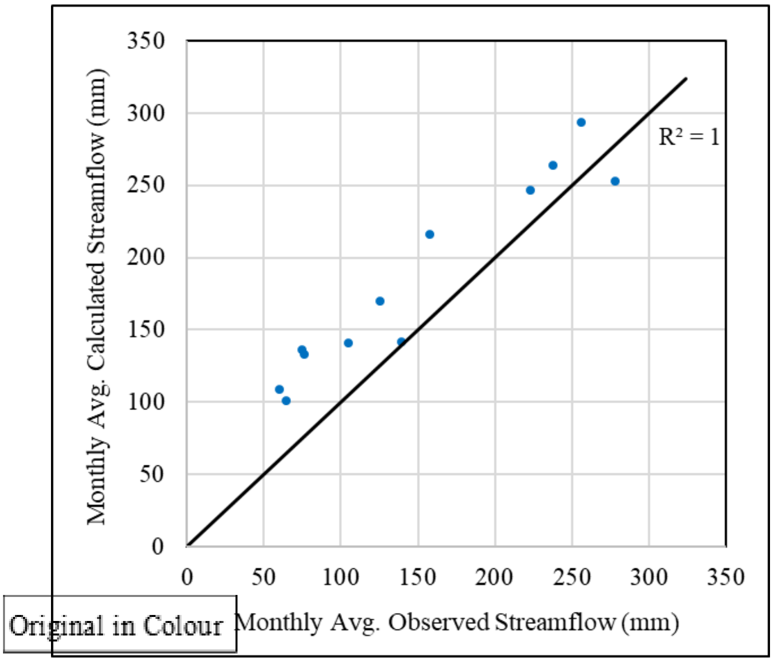


Figure C - 11: Scatter plot with monthly avg. flow of Pitabeddara catchment with spatiotemporally transferred parameters

Table C - 5: Monthly flow comparison for Urawa catchment with temporally transferred parameters

Month	Monthly Avg. Observed Flow (mm)	Monthly Avg. Calculated Flow (mm)	Error %
October	148.4	168.3	-13.4%
November	209.4	254.9	-21.8%
December	201.1	234.1	-16.4%
January	91.2	122.2	-34.0%
February	59.0	81.1	-37.5%
March	59.7	87.1	-45.7%
April	88.5	113.5	-28.2%
May	185.2	195.0	-5.3%
June	112.5	146.8	-30.4%
July	55.9	88.7	-58.6%
August	50.1	87.2	-74.2%
September	86.2	109.8	-27.4%

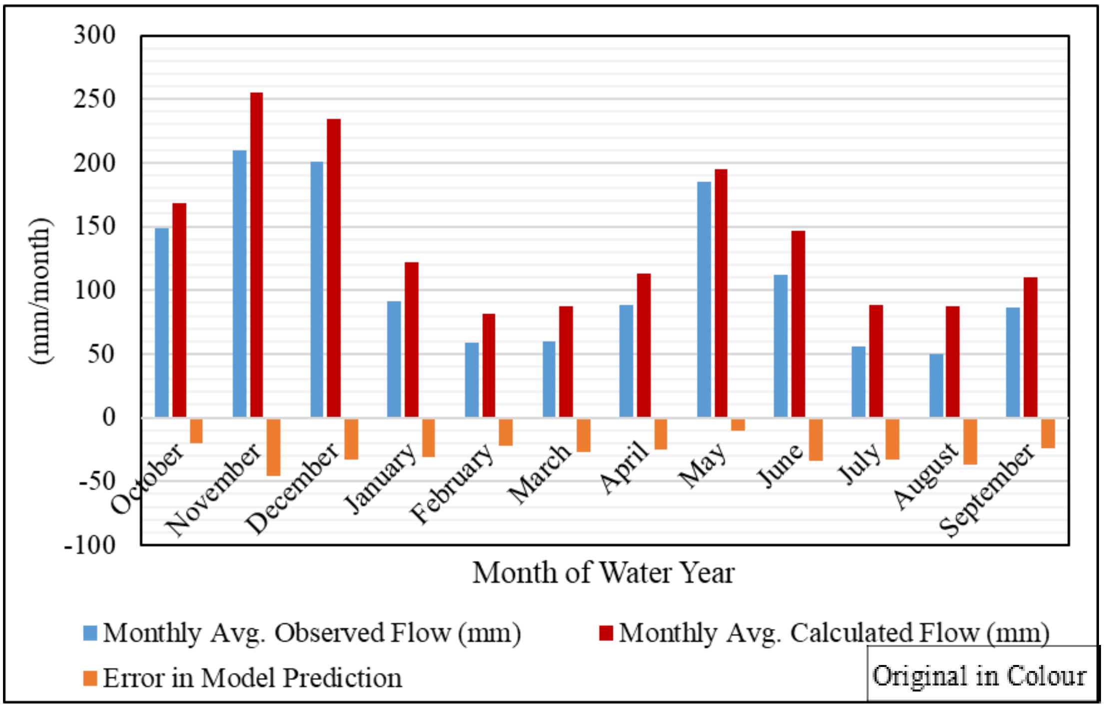


Figure C - 12: Monthly flow comparison for Urawa catchment with temporally transferred parameters

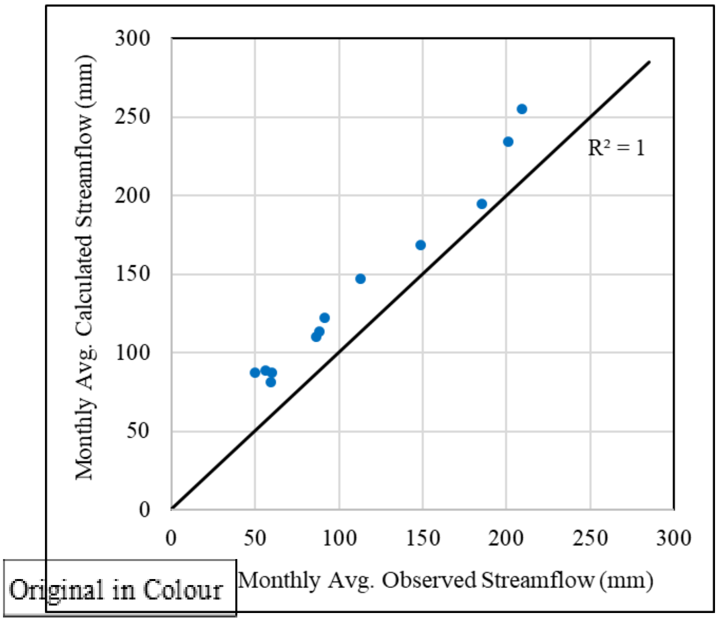


Figure C - 13: Scatter plot with monthly avg. flow of Urawa catchment with temporally transferred parameters

Table C - 6: Monthly flow comparison for Pitabeddara catchment with temporally transferred parameters

Month	Monthly Avg. Observed Flow (mm)	Monthly Avg. Calculated Flow (mm)	Error %
October	222.9	273.1	-22.5%
November	256.2	319.8	-24.8%
December	237.5	264.7	-11.4%
January	105.2	121.1	-15.2%
February	64.0	86.5	-35.1%
March	59.8	102.7	-71.8%
April	139.1	146.1	-5.0%
May	277.9	290.4	-4.5%
June	157.9	211.0	-33.6%
July	74.8	124.3	-66.1%
August	76.2	125.9	-65.2%
September	125.1	181.0	-44.7%

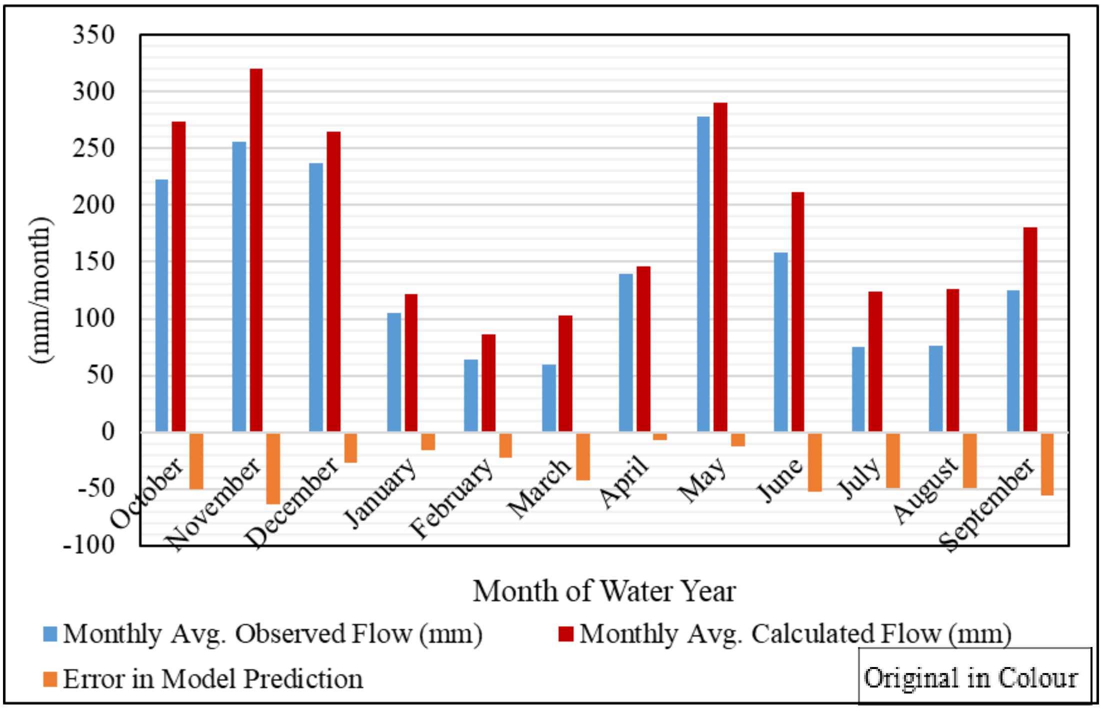


Figure C - 14: Monthly flow comparison for Pitabeddara catchment with temporally transferred parameters

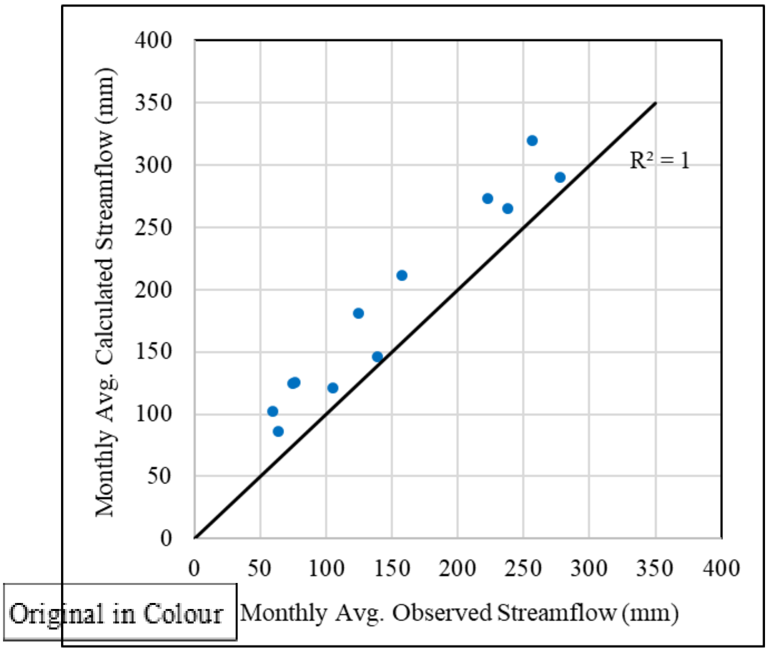


Figure C - 15: Scatter plot with monthly avg. flow of Pitabeddara catchment with temporally transferred parameters

Table C - 7: Monthly flow comparison for Urawa catchment with spatially transferred parameters

Month	Monthly Avg. Observed Flow (mm)	Monthly Avg. Calculated Flow (mm)	Error %
October	117.9	116.0	1.5%
November	238.1	263.0	-10.5%
December	249.3	262.1	-5.2%
January	125.4	102.7	18.1%
February	73.7	77.5	-5.1%
March	73.1	116.8	-59.8%
April	120.8	139.2	-15.3%
May	142.0	118.6	16.5%
June	124.3	85.6	31.1%
July	69.0	54.3	21.3%
August	58.4	47.4	18.8%
September	81.8	83.8	-2.5%

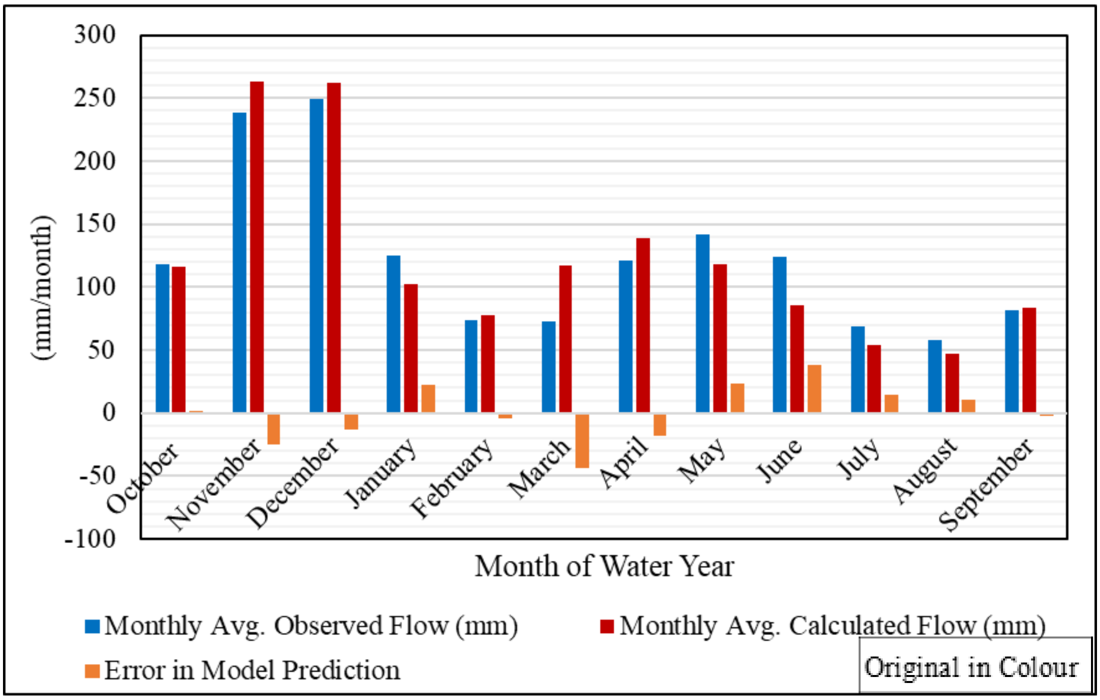


Figure C - 16: Monthly flow comparison for Urawa catchment with spatially transferred parameters

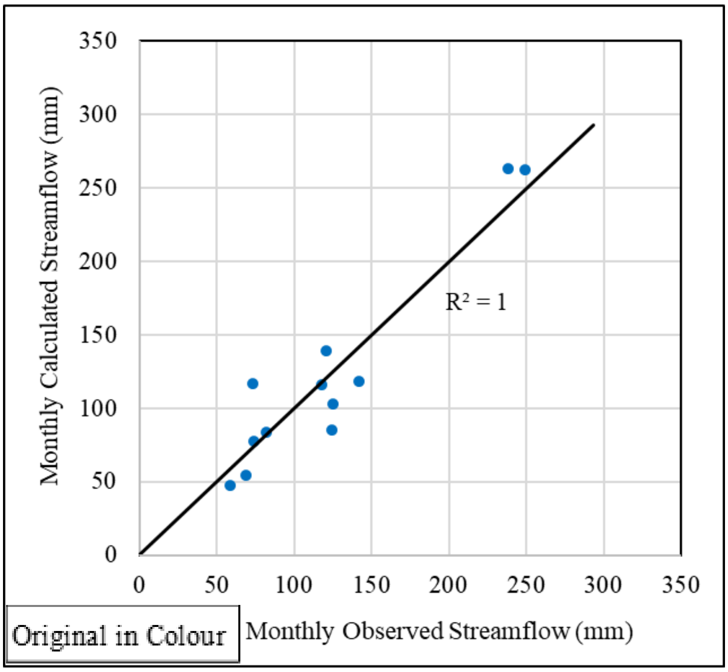


Figure C - 17: Scatter plot with monthly avg. flow of Urawa catchment with spatially transferred parameters

Table C - 8: Monthly flow comparison for Pitabeddara catchment with spatially transferred parameters

Month	Monthly Avg. Observed Flow (mm)	Monthly Avg. Calculated Flow (mm)	Error %
October	159.2	149.4	6.2%
November	318.9	272.9	14.4%
December	304.9	271.2	11.0%
January	132.7	137.9	-3.9%
February	97.5	102.1	-4.8%
March	96.5	117.9	-22.2%
April	168.2	163.9	2.6%
May	195.1	191.7	1.7%
June	173.3	167.7	3.2%
July	106.5	107.4	-0.8%
August	81.9	91.8	-12.2%
September	122.6	126.7	-3.4%

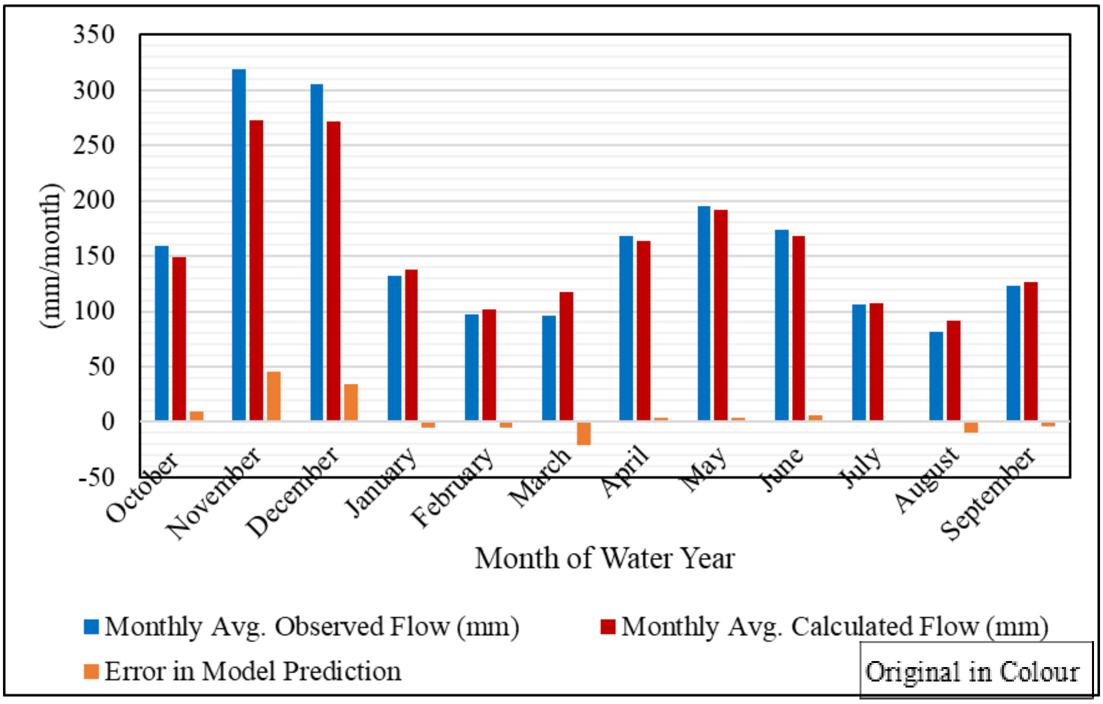


Figure C - 18: Monthly flow comparison for Pitabeddara catchment with spatially transferred parameters

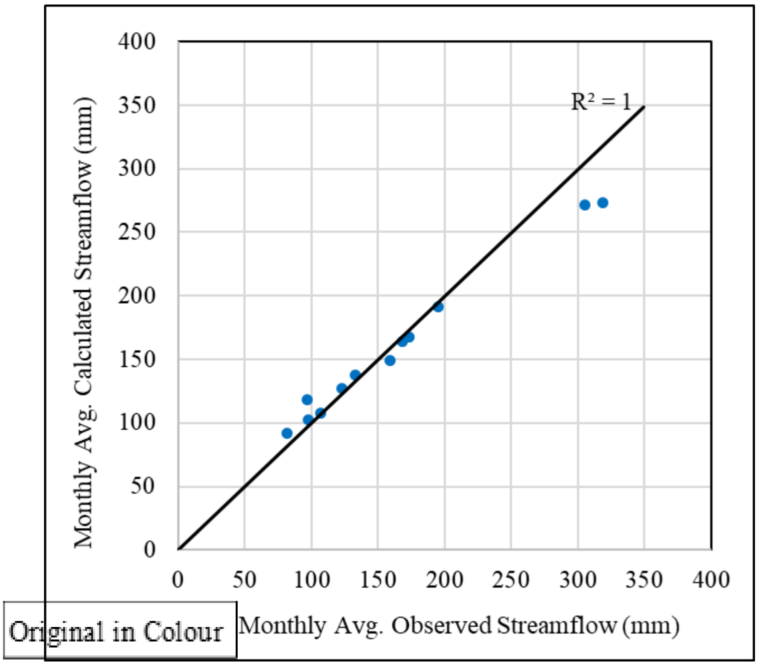


Figure C - 19: Scatter plot with monthly avg. flow of Pitabeddara catchment with spatially transferred parameters

APPENDIX D: SEASONAL COMPARISON OF RESULTS

Table D- 1: Seasonal flow comparison for Urawa catchment – Calibration period

Water Yr	Season	Seasonal RF(mm)	Seasonal Obs. SF	Seasonal cal. SF	Seasonal Pan Evpo	SWB Observed	SWB Simulated	SWB Error
2008/09	Maha	1666.2	961.3	1003.4	588.9	704.9	662.8	4.4%
	Yala	859.1	612.3	464.2	537.2	246.7	394.9	-24.2%
2009/10	Maha	767.0	568.2	409.9	546.9	198.8	357.1	-27.9%
	Yala	1201.1	715.6	656.6	482.6	485.4	544.5	-8.3%
2010/11	Maha	1957.4	1208.9	1277.9	491.8	748.5	679.5	5.7%
	Yala	984.8	615.0	576.5	573.6	369.7	408.3	-6.3%
2011/12	Maha	1227.0	699.7	710.4	532.6	527.2	516.5	1.5%
	Yala	884.6	370.4	407.5	507.6	514.2	477.1	10.0%
2012/13	Maha	1647.0	949.5	1087.5	468.4	697.4	559.4	14.5%
	Yala	1068.2	667.4	616.3	528.9	400.8	451.8	-7.6%

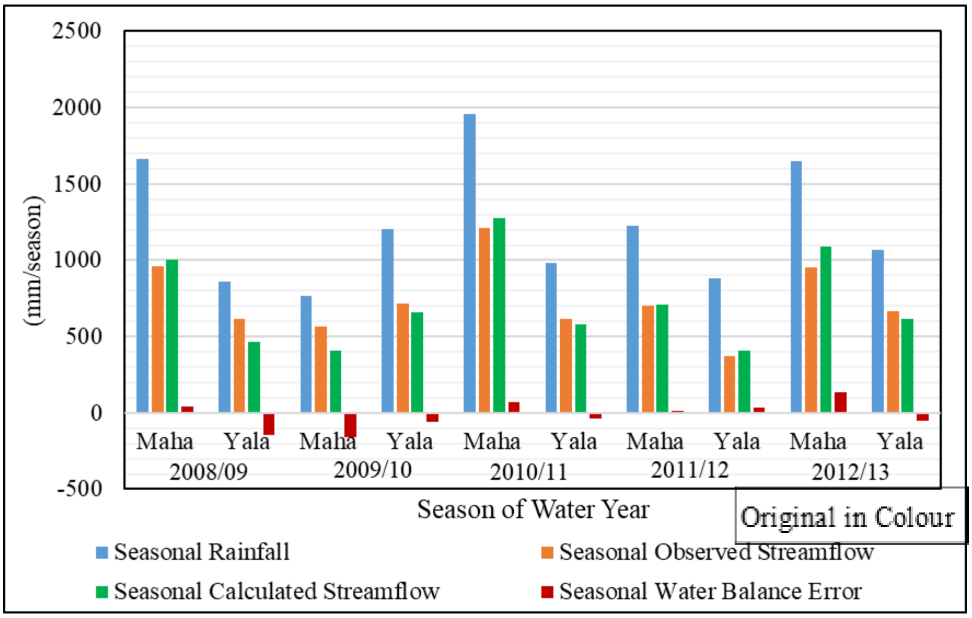


Figure D- 2: Seasonal flow comparison for Urawa catchment – Calibration period

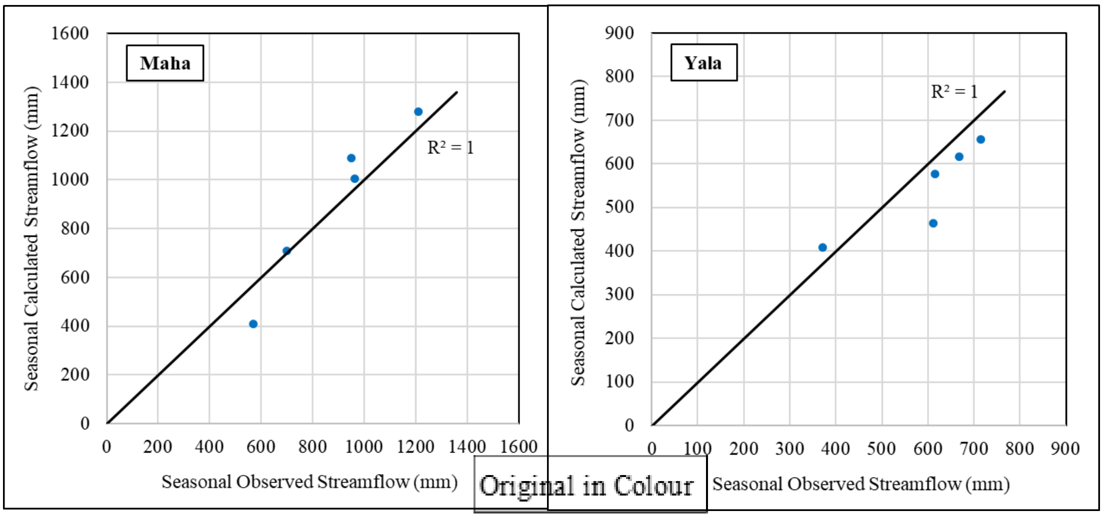


Figure D- 1: Scatter plot with seasonal flow of Urawa catchment – Calibration period

Table D- 2: Seasonal flow comparison for Urawa catchment – Validation period

Water Yr	Season	Seasonal RF(mm)	Seasonal Obs. SF (mm)	Seasonal cal. SF (mm)	Seasonal Pan Evpo (mm)	SWB Observed	SWB Simulated	SWB Error
2013/14	Maha	1206.8	686.6	735.3	520.8	520.2	471.5	7.1%
	Yala	822.2	295.7	430.3	448.1	526.4	391.9	45.5%
2014/15	Maha	1372.8	746.9	860.8	409.5	625.9	512.0	15.3%
	Yala	1251.4	660.7	692.0	406.7	590.7	559.4	4.7%
2015/16	Maha	1271.5	1120.5	1010.8	426.2	151.0	260.7	-9.8%
	Yala	981.6	338.1	574.2	456.9	643.6	407.4	69.9%
2016/17	Maha	1289.2	384.6	783.0	468.6	904.6	506.3	103.6%
	Yala	1482.3	723.4	922.6	457.7	759.0	559.7	27.5%
2017/18	Maha	1587.6	905.4	1104.5	436.3	682.2	483.1	22.0%
	Yala	1260.1	874.3	858.2	396.1	385.8	401.8	-1.8%

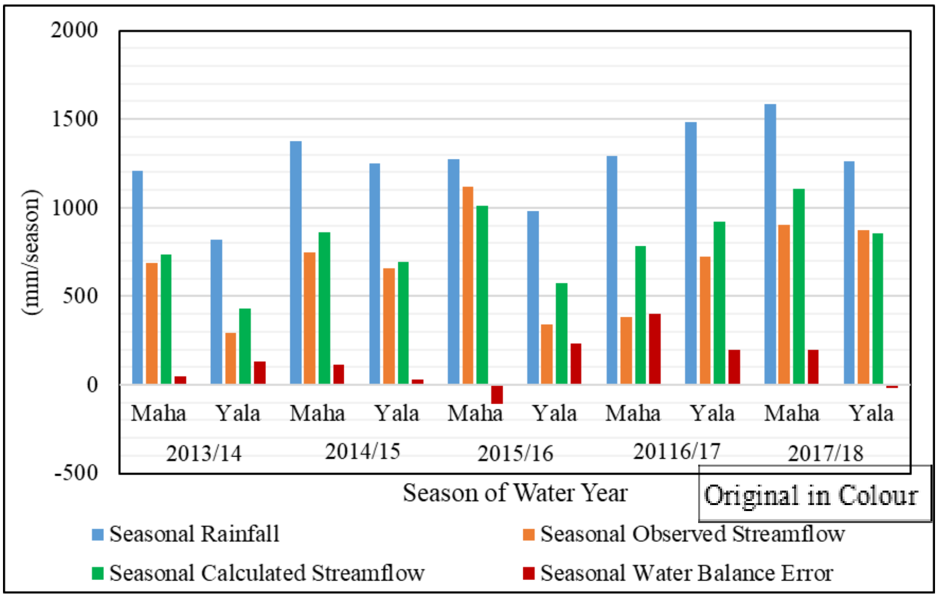


Figure D- 4: Seasonal flow comparison for Urawa catchment – Validation period

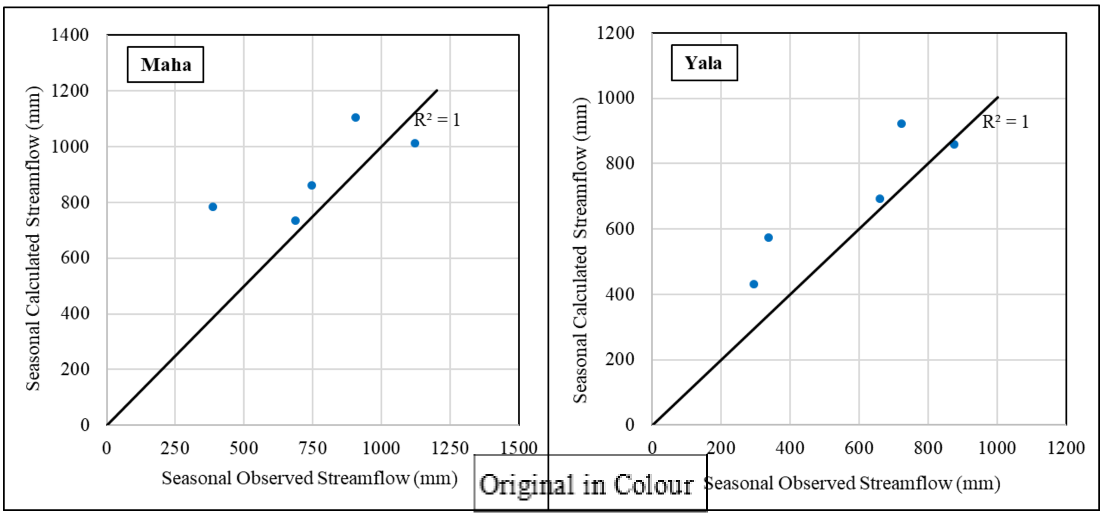


Figure D- 3: Scatter plot with seasonal flow of Urawa catchment – Validation period

Table D- 3: Seasonal flow comparison for Pitabeddara catchment – Calibration period

Water Yr	Season	Seasonal RF(mm)	Seasonal Obs. SF (mm)	Seasonal cal. SF (mm)	Seasonal Pan Evpo (mm)	SWB Observed	SWB Simulated	SWB Error
2008/09	Maha	1460.0	965.2	956.8	588.9	494.8	503.2	-0.9%
	Yala	1290.4	852.4	725.6	537.2	438.0	564.8	-14.9%
2009/10	Maha	1137.6	748.4	726.3	546.9	389.2	411.3	-3.0%
	Yala	1516.1	957.2	969.1	482.6	558.9	546.9	1.2%
2010/11	Maha	2112.5	1651.7	1521.3	491.8	460.8	591.2	-7.9%
	Yala	1254.4	882.7	808.3	573.6	371.6	446.1	-8.4%
2011/12	Maha	1455.5	897.3	912.9	532.6	558.1	542.6	1.7%
	Yala	1236.0	563.3	731.3	507.6	672.8	504.7	29.8%
2012/13	Maha	1829.3	1285.9	1319.2	468.4	543.4	510.1	2.6%
	Yala	1528.1	982.1	1047.0	528.9	546.1	481.1	6.6%

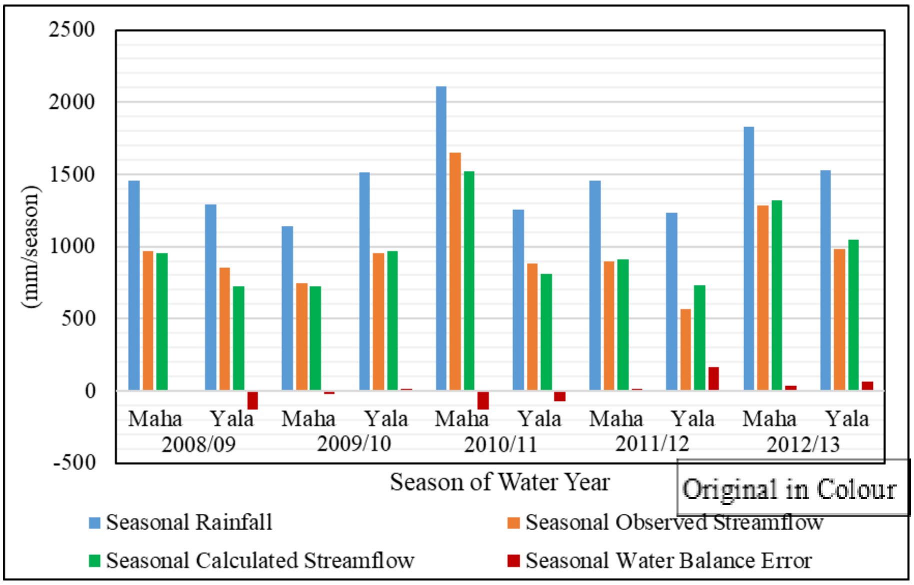


Figure D- 5: Seasonal flow comparison for Pitabeddara catchment – Calibration period

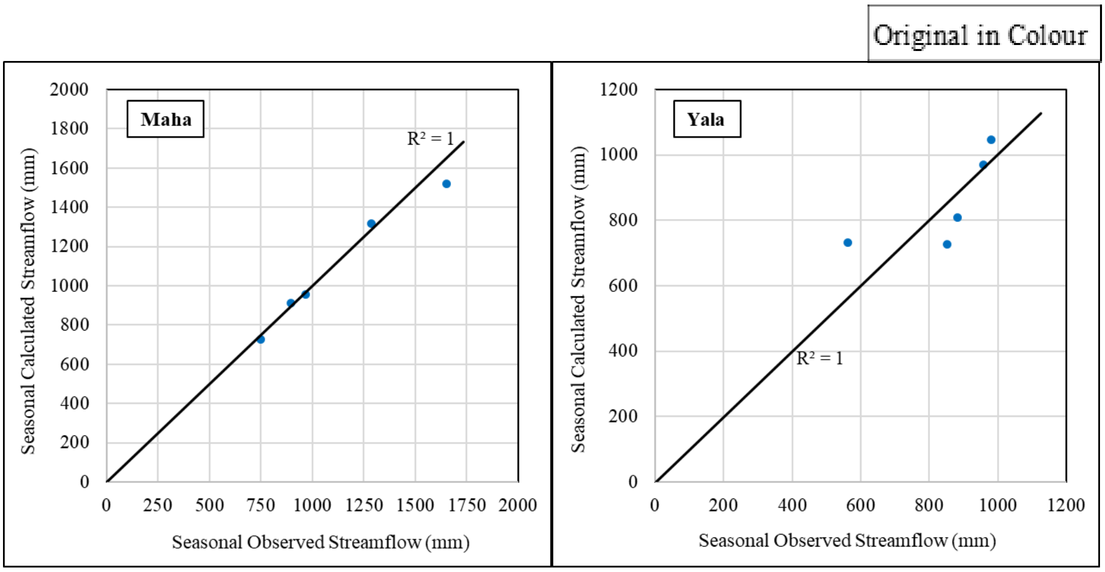


Figure D- 6: Scatter plot with seasonal flow of Pitabeddara catchment – Calibration period

Table D- 4: Seasonal flow comparison for Pitabeddara catchment – Validation period

Water Yr	Season	Seasonal RF(mm)	Seasonal Obs. SF (mm)	Seasonal cal. SF (mm)	Seasonal Pan Evpo (mm)	SWB Observed	SWB Simulated	SWB Error
2013/14	Maha	1414.4	869.5	941.4	520.8	544.9	473.0	8.3%
	Yala	1361.9	551.9	831.5	448.1	810.0	530.4	50.7%
2014/15	Maha	1751.4	1075.9	1312.9	409.5	675.6	438.5	22.0%
	Yala	1702.7	1019.1	1128.5	406.7	683.6	574.2	10.7%
2015/16	Maha	1478.7	1226.4	1275.7	424.0	252.3	203.1	4.0%
	Yala	1238.7	574.0	788.3	456.9	664.6	450.3	37.3%
2016/17	Maha	1191.7	514.0	743.7	470.8	677.7	448.0	44.7%
	Yala	1570.9	1134.4	1033.4	457.7	436.5	537.5	-8.9%
2017/18	Maha	1715.6	1042.5	1289.5	436.3	673.1	426.1	23.7%
	Yala	1766.0	974.5	1329.2	396.1	791.5	436.7	36.4%

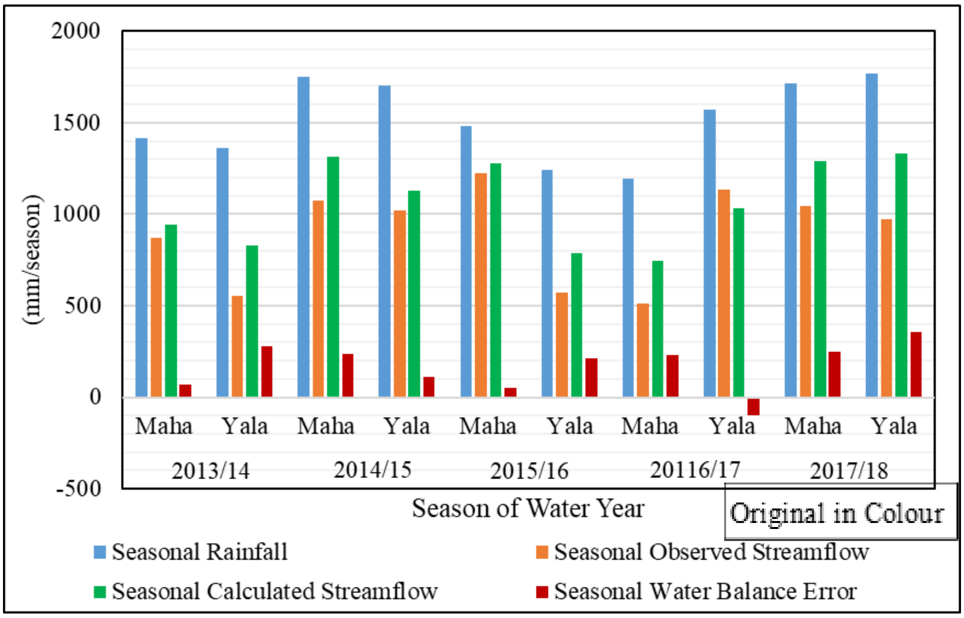


Figure D- 7: Seasonal flow comparison for Pitabeddara catchment – Validation period

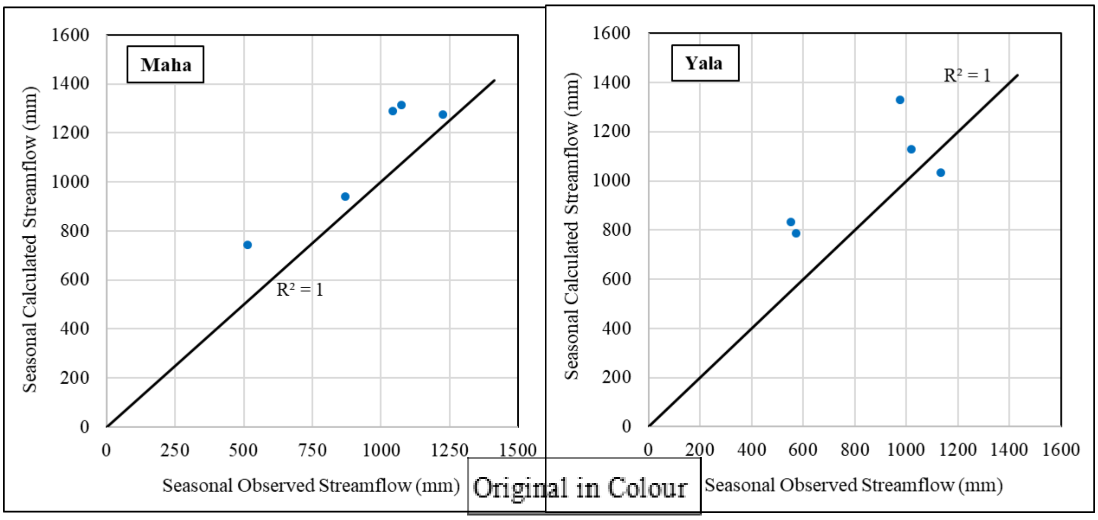
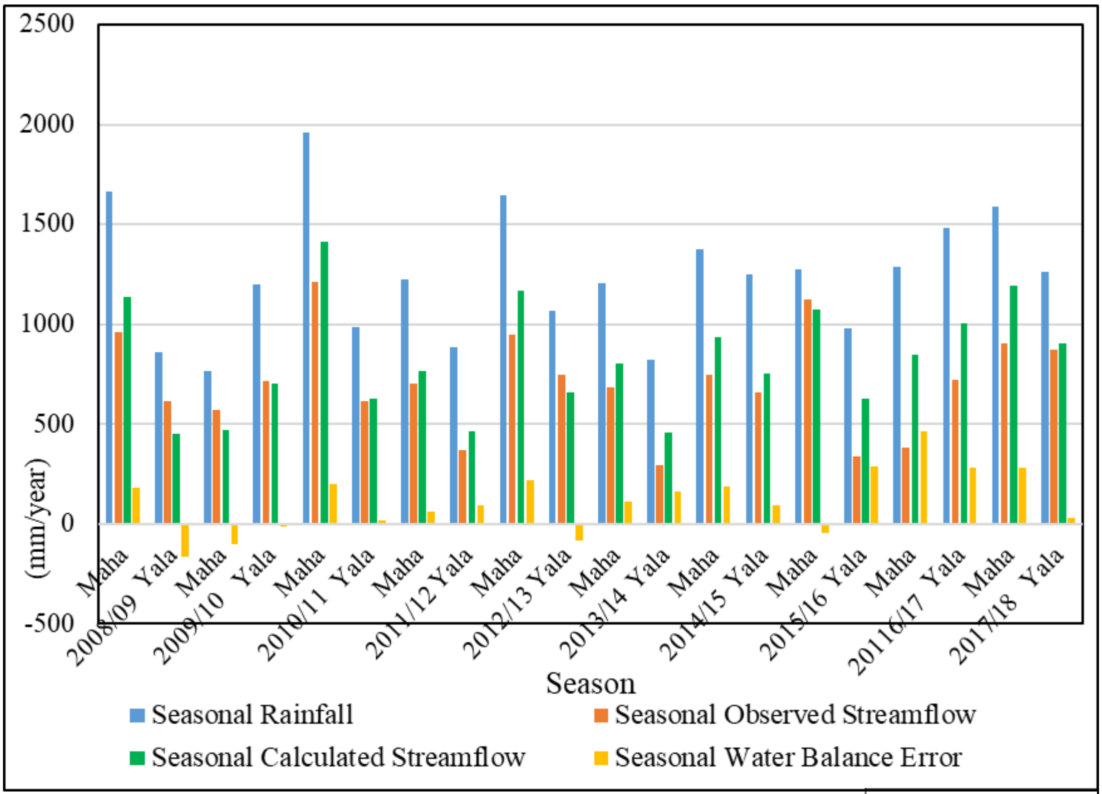


Figure D- 8: Scatter plot with seasonal flow of Pitabeddara catchment – Validation period

Table D- 5: Seasonal flow comparison for Urawa catchment with spatiotemporally transferred parameters

Water Yr	Season	Seasonal RF(mm)	Seasonal Observed SF (mm)	Seasonal calculated SF (mm)	Seasonal Pan Evpo (mm)	SWB Observed	SWB Simulated	SWB Error
2008/09	Maha	1666.2	961.3	1138.9	588.9	704.9	527.3	18.5%
	Yala	859.1	612.3	448.1	537.2	246.7	410.9	-26.8%
2009/10	Maha	767.0	568.2	467.2	546.9	198.8	299.9	-17.8%
	Yala	1201.1	715.6	703.3	482.6	485.4	497.8	-1.7%
2010/11	Maha	1957.4	1208.9	1409.5	491.8	748.5	547.9	16.6%
	Yala	984.8	615.0	629.7	573.6	369.7	355.1	2.4%
2011/12	Maha	1227.0	699.7	763.4	532.6	527.2	463.5	9.1%
	Yala	884.6	370.4	463.9	507.6	514.2	420.6	25.3%
2012/13	Maha	1647.0	949.5	1166.6	468.4	697.4	480.4	22.9%
	Yala	1068.2	744.8	658.7	528.9	323.3	409.4	-11.6%
2013/14	Maha	1206.8	686.6	800.8	520.8	520.2	406.0	16.6%
	Yala	822.2	295.7	455.0	448.1	526.4	367.2	53.8%
2014/15	Maha	1372.8	746.9	932.5	409.5	625.9	440.3	24.9%
	Yala	1251.4	660.7	750.7	406.7	590.7	500.7	13.6%
2015/16	Maha	1271.5	1120.5	1072.0	426.2	151.0	199.5	-4.3%
	Yala	981.6	338.1	625.7	456.9	643.6	355.9	85.1%
2016/17	Maha	1289.2	384.6	848.0	468.6	904.6	441.3	120.5%
	Yala	1482.3	723.4	1004.0	457.7	759.0	478.3	38.8%
2017/18	Maha	1587.6	905.4	1189.5	436.3	682.2	398.1	31.4%
	Yala	1260.1	874.3	904.4	396.1	385.8	355.7	3.4%



Original in Colour

Figure D- 9: Seasonal flow comparison for Urawa catchment with spatiotemporally transferred parameters

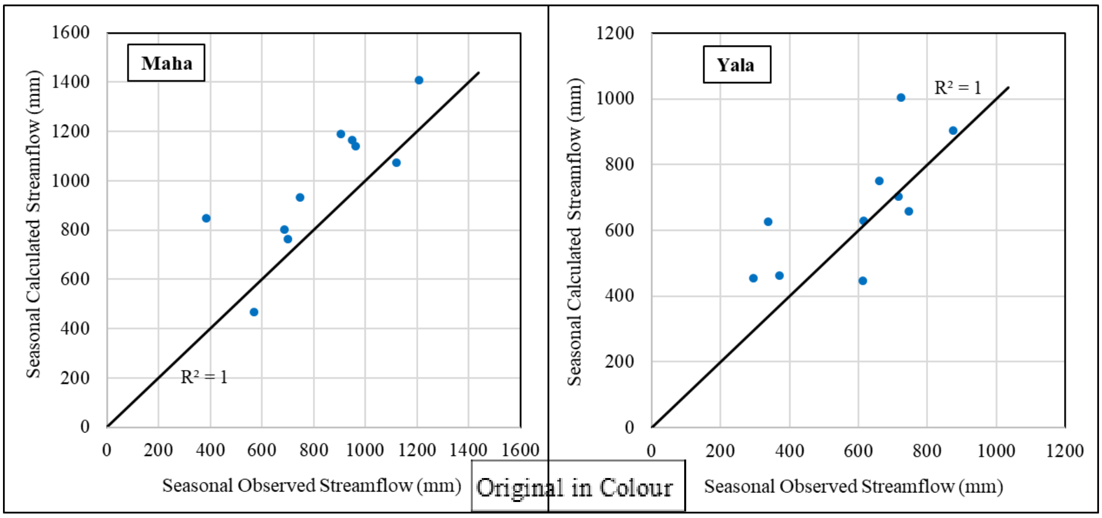


Figure D- 10: Scatter plot with seasonal flow of Urawa catchment with spatiotemporally transferred parameters

Table D- 6: Seasonal flow comparison for Pitabeddara catchment with spatiotemporally transferred parameters

Water Yr	Season	Seasonal RF(mm)	Seasonal Observed SF (mm)	Seasonal calculated SF (mm)	Seasonal Pan Evpo (mm)	SWB Observed	SWB Simulated	SWB Error
2008/09	Maha	1460.0	965.2	1006.0	588.9	494.8	454.0	4.2%
	Yala	1290.4	852.4	819.2	537.2	438.0	471.2	-3.9%
2009/10	Maha	1137.6	748.4	790.6	546.9	389.2	347.0	5.6%
	Yala	1516.1	957.2	1018.4	482.6	558.9	497.6	6.4%
2010/11	Maha	2112.5	1651.7	1503.8	491.8	460.8	608.7	-9.0%
	Yala	1254.4	882.7	879.5	573.6	371.6	374.9	-0.4%
2011/12	Maha	1455.5	897.3	969.5	532.6	558.1	485.9	8.0%
	Yala	1236.0	563.3	779.6	507.6	672.8	456.5	38.4%
2012/13	Maha	1829.3	1285.9	1337.4	468.4	543.4	491.9	4.0%
	Yala	1528.1	982.1	1084.4	528.9	546.1	443.7	10.4%
2013/14	Maha	1414.4	869.5	1005.9	520.8	544.9	408.4	15.7%
	Yala	1361.9	551.9	885.7	448.1	810.0	476.2	60.5%
2014/15	Maha	1751.4	1075.9	1328.6	409.5	675.6	422.8	23.5%
	Yala	1702.7	1019.1	1126.1	406.7	683.6	576.6	10.5%
2015/16	Maha	1497.1	1227.9	1337.6	426.2	269.3	159.5	8.9%
	Yala	1221.1	574.6	851.7	456.9	646.5	369.5	48.2%
2016/17	Maha	1190.9	512.0	801.0	468.6	678.9	389.8	56.5%
	Yala	1570.9	1134.4	1049.3	457.7	436.5	521.6	-7.5%
2017/18	Maha	1715.6	1042.5	1301.4	436.3	673.1	414.2	24.8%
	Yala	1766.0	974.5	1338.3	396.1	791.5	427.6	37.3%

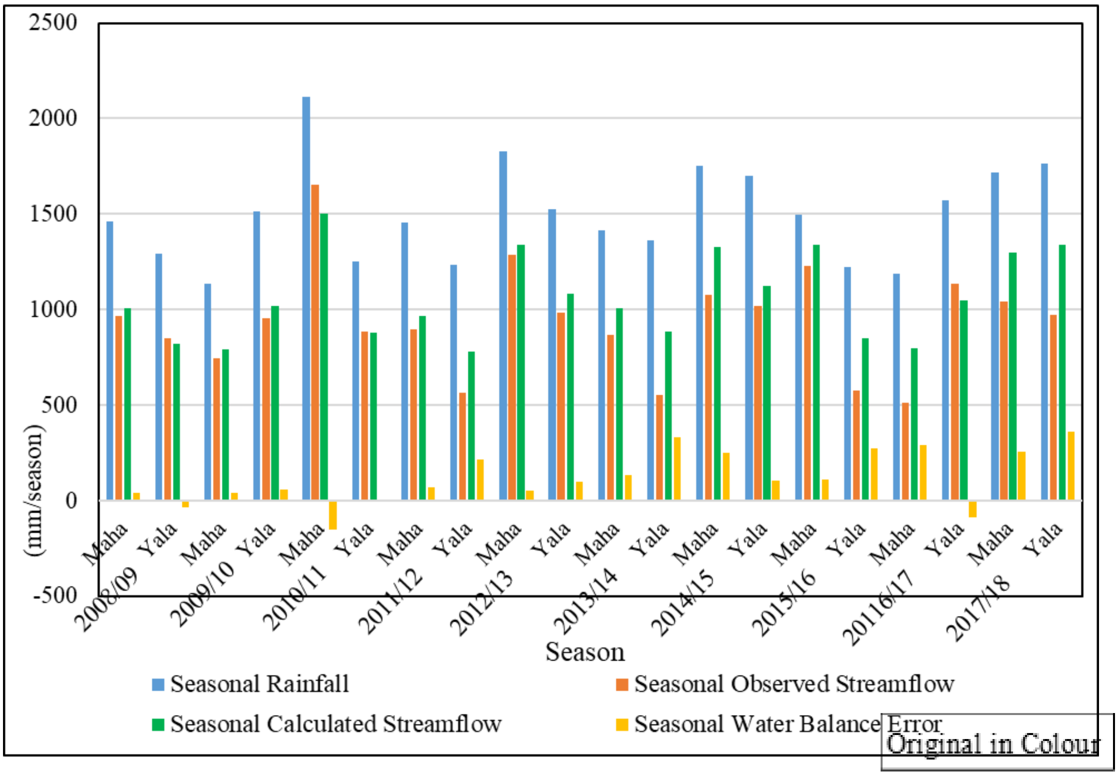


Figure D- 11:Seasonal flow comparison for Pitabeddara catchment with spatiotemporally transferred parameters

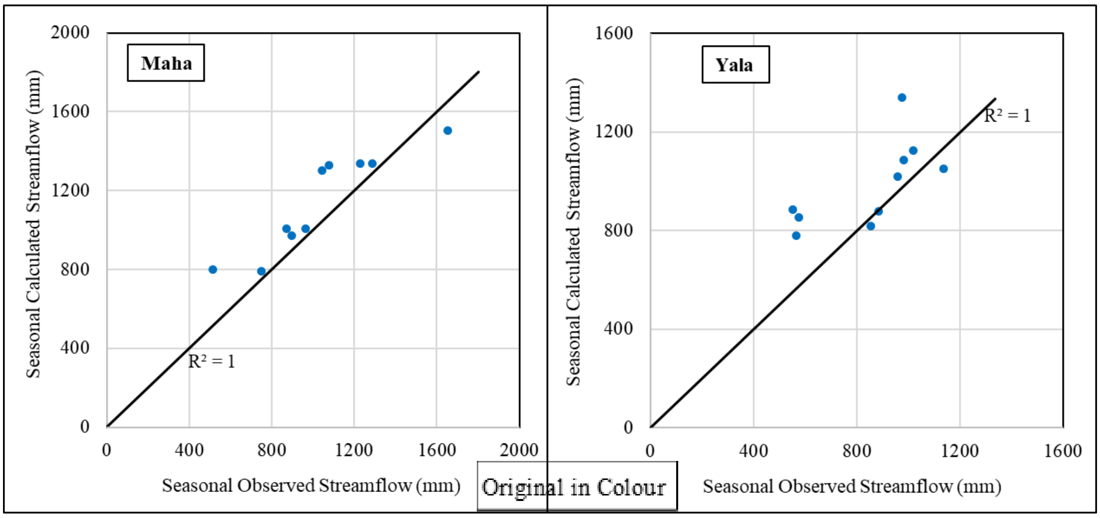


Figure D- 12: Scatter plot with seasonal flow of Pitabeddara catchment with spatiotemporally transferred parameters

Table D- 7: Seasonal flow comparison for Urawa catchment with temporally transferred parameters

Water Yr	Season	Seasonal RF(mm)	Seasonal Observed SF (mm)	Seasonal calculated SF (mm)	Seasonal Pan Evpo (mm)	SWB Observed	SWB Simulated	SWB Error
2008/09	Maha	1666.2	961.3	1050.1	588.9	704.9	616.1	9.2%
	Yala	859.1	612.3	522.5	537.2	246.7	336.6	-14.7%
2009/10	Maha	767.0	568.2	466.9	546.9	198.8	300.1	-17.8%
	Yala	1201.1	715.6	713.2	482.6	485.4	487.9	-0.3%
2010/11	Maha	1957.4	1208.9	1333.6	491.8	748.5	623.8	10.3%
	Yala	984.8	615.0	631.4	573.6	369.7	353.4	2.7%
2011/12	Maha	1227.0	699.7	764.5	532.6	527.2	462.4	9.3%
	Yala	884.6	370.4	460.6	507.6	514.2	423.9	24.4%
2012/13	Maha	1647.0	949.5	1140.0	468.4	697.4	507.0	20.1%
	Yala	1068.2	744.8	668.1	528.9	323.3	400.1	-10.3%
2013/14	Maha	1206.8	686.6	797.0	520.8	520.2	409.7	16.1%
	Yala	822.2	295.7	478.5	448.1	526.4	343.6	61.8%
2014/15	Maha	1372.8	746.9	908.2	409.5	625.9	464.5	21.6%
	Yala	1251.4	660.7	738.9	406.7	590.7	512.5	11.8%
2015/16	Maha	1271.5	1120.5	1057.2	426.2	151.0	214.3	-5.7%
	Yala	981.6	338.1	619.6	456.9	643.6	362.0	83.3%
2016/17	Maha	1289.2	384.6	827.6	468.6	904.6	461.7	115.2%
	Yala	1482.3	723.4	966.9	457.7	759.0	515.5	33.7%
2017/18	Maha	1587.6	905.4	1148.0	436.3	682.2	439.6	26.8%
	Yala	1260.1	874.3	901.2	396.1	385.8	358.9	3.1%

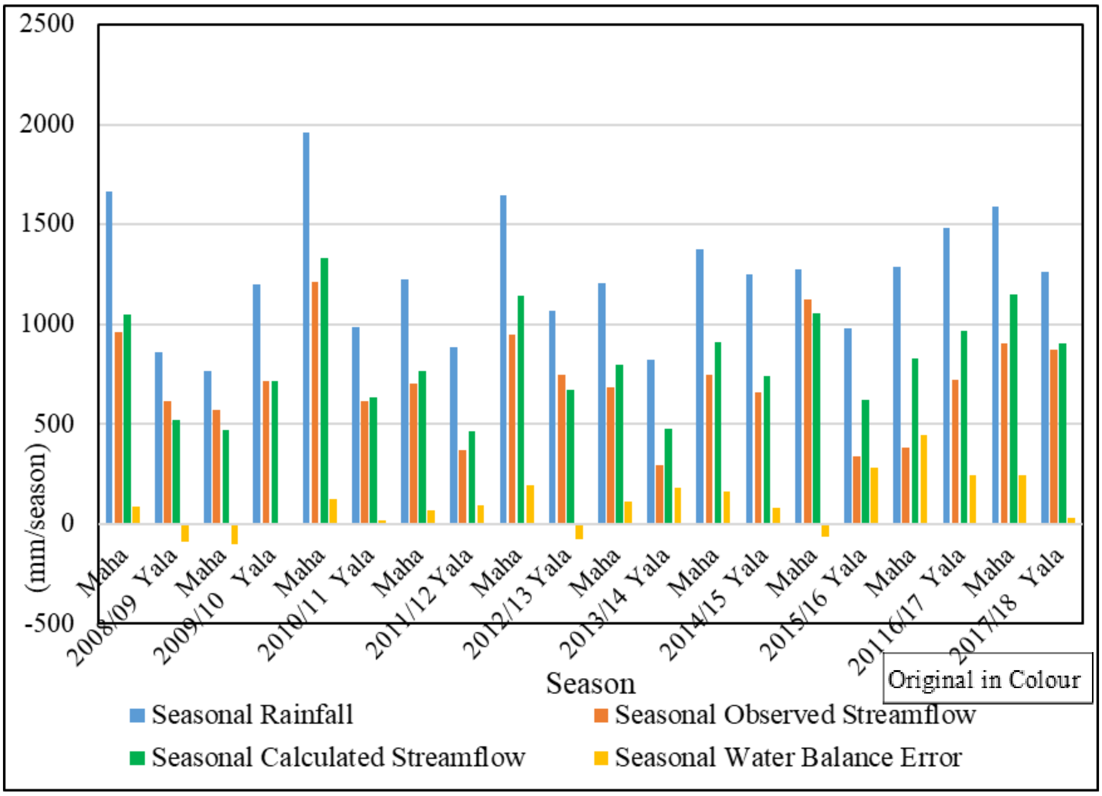


Figure D- 13: Seasonal flow comparison for Urawa catchment with temporally transferred parameters

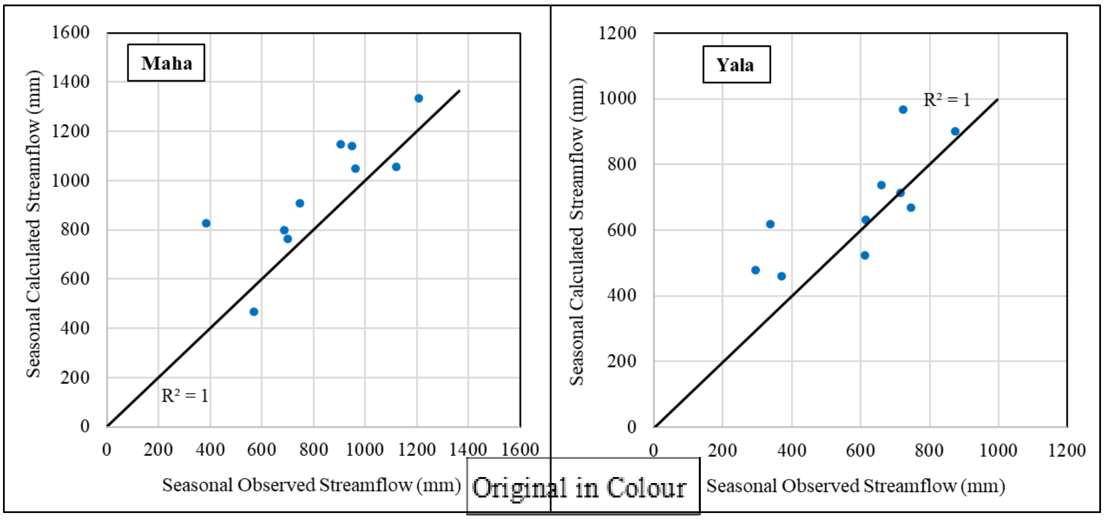


Figure D- 14: Scatter plot with seasonal flow of Urawa catchment with temporally transferred parameters

Table D- 8: Seasonal flow comparison for Pitabeddara catchment with temporally transferred parameters

Water Yr	Season	Seasonal RF(mm)	Seasonal Observed SF (mm)	Seasonal calculated SF (mm)	Seasonal Pan Evpo (mm)	SWB Observed	SWB Simulated	SWB Error
	Maha	1460.0	965.2	1028.2	588.9	494.8	431.8	6.5%
2008/09	Yala	1290.4	852.4	789.6	537.2	438.0	500.8	-7.4%
	Maha	1137.6	748.4	788.9	546.9	389.2	348.8	5.4%
2009/10	Yala	1516.1	957.2	1030.9	482.6	558.9	485.2	7.7%
	Maha	2112.5	1651.7	1581.6	491.8	460.8	530.9	-4.2%
2010/11	Yala	1254.4	882.7	867.8	573.6	371.6	386.6	-1.7%
	Maha	1455.5	897.3	971.3	532.6	558.1	484.1	8.2%
2011/12	Yala	1236.0	563.3	788.7	507.6	672.8	447.3	40.0%
	Maha	1829.3	1285.9	1375.2	468.4	543.4	454.1	6.9%
2012/13	Yala	1528.1	982.1	1102.4	528.9	546.1	425.8	12.3%
	Maha	1414.4	869.5	995.8	520.8	544.9	418.6	14.5%
2013/14	Yala	1361.9	551.9	891.8	448.1	810.0	470.1	61.6%
	Maha	1751.4	1075.9	1371.8	409.5	675.6	379.6	27.5%
2014/15	Yala	1702.7	1019.1	1186.6	406.7	683.6	516.1	16.4%
	Maha	1497.1	1227.9	1334.5	426.2	269.3	162.6	8.7%
2015/16	Yala	1221.1	574.6	845.9	456.9	646.5	375.3	47.2%
	Maha	1190.9	512.0	795.2	468.6	678.9	395.7	55.3%
2016/17	Yala	1570.9	1134.4	1087.5	457.7	436.5	483.4	-4.1%
	Maha	1715.6	1042.5	1342.3	436.3	673.1	373.3	28.8%
2017/18	Yala	1766.0	974.5	1381.3	396.1	791.5	384.6	41.8%

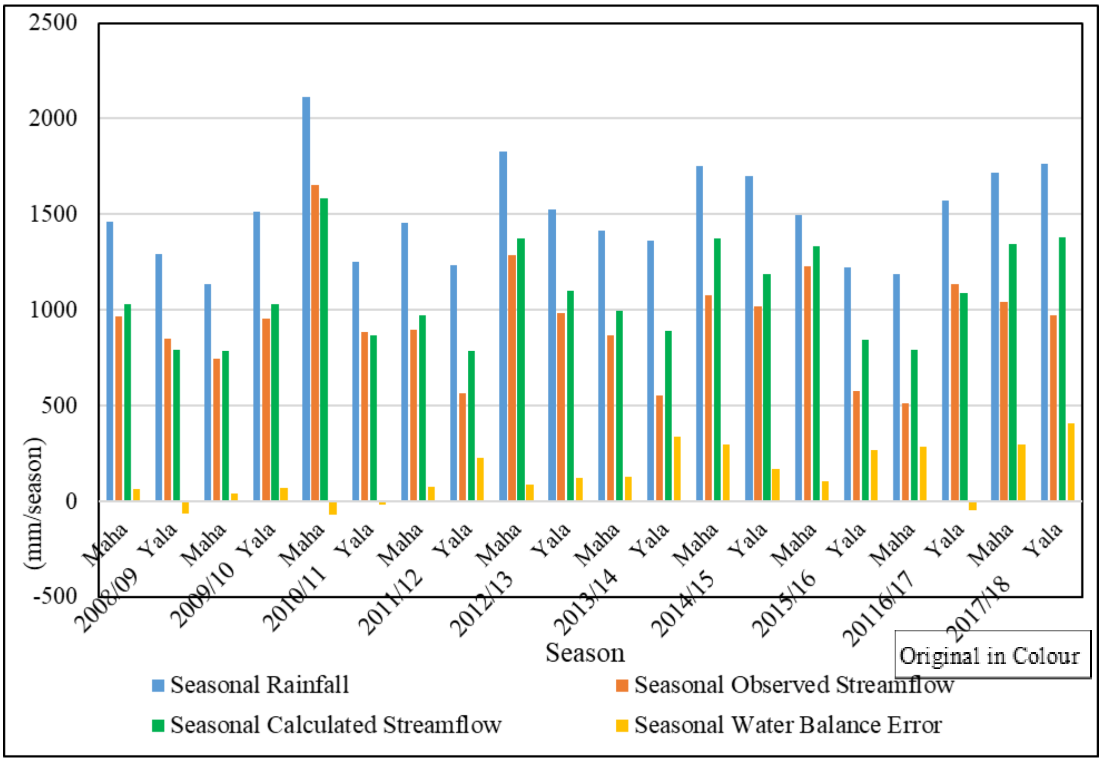


Figure D- 15: Seasonal flow comparison for Pitabeddara catchment with temporally transferred parameters

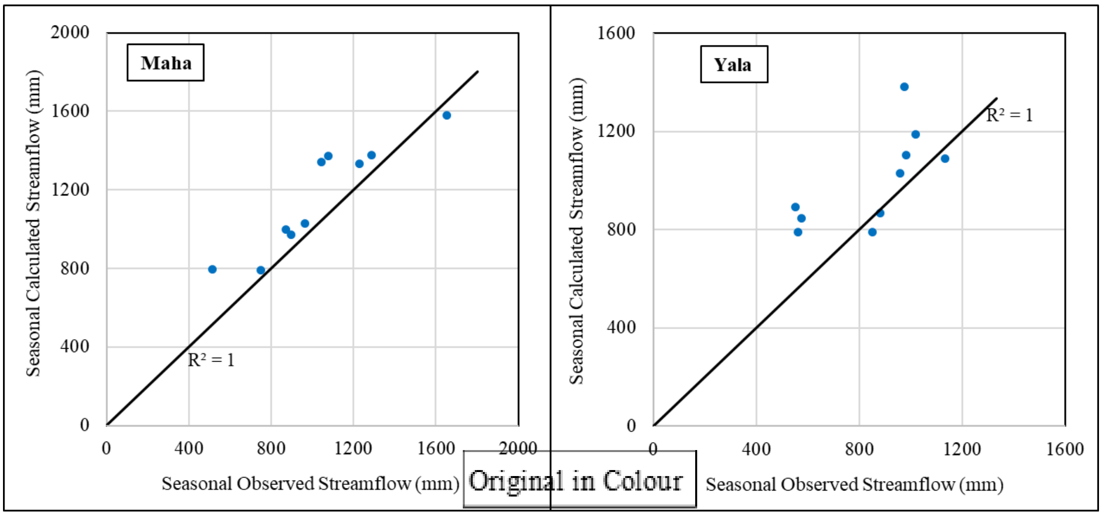


Figure D- 16: Scatter plot with seasonal flow of Pitabeddara catchment with temporally transferred parameters

Table D- 9: Seasonal flow comparison for Urawa catchment with spatially transferred parameters

Water Yr	Season	Seasonal RF(mm)	Seasonal Obs. SF (mm)	Seasonal cal. SF (mm)	Seasonal Pan Evpo (mm)	SWB Observed	SWB Simulated	SWB Error
2008/09	Maha	1666.2	961.3	1091.0	588.9	704.9	575.2	13.5%
	Yala	859.1	612.3	392.4	537.2	246.7	466.7	-35.9%
2009/10	Maha	767.0	568.2	412.7	546.9	198.8	354.3	-27.4%
	Yala	1201.1	715.6	649.5	482.6	485.4	551.6	-9.2%
2010/11	Maha	1957.4	1208.9	1357.0	491.8	748.5	600.4	12.3%
	Yala	984.8	615.0	577.8	573.6	369.7	406.9	-6.0%
2011/12	Maha	1227.0	699.7	712.5	532.6	527.2	514.4	1.8%
	Yala	884.6	370.4	414.0	507.6	514.2	470.6	11.8%
2012/13	Maha	1647.0	949.5	1117.8	468.4	697.4	529.2	17.7%
	Yala	1068.2	667.4	610.5	528.9	400.8	457.6	-8.5%

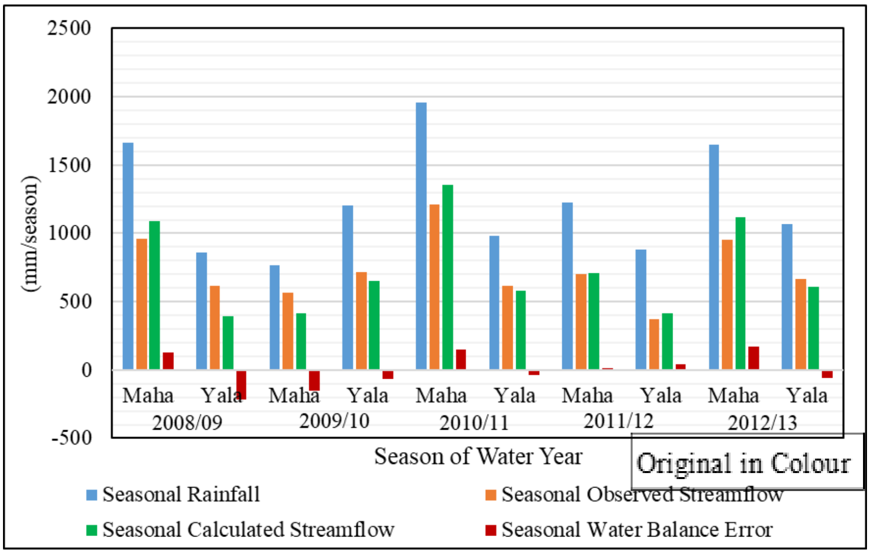


Figure D- 17: Seasonal flow comparison for Urawa catchment with spatially transferred parameters

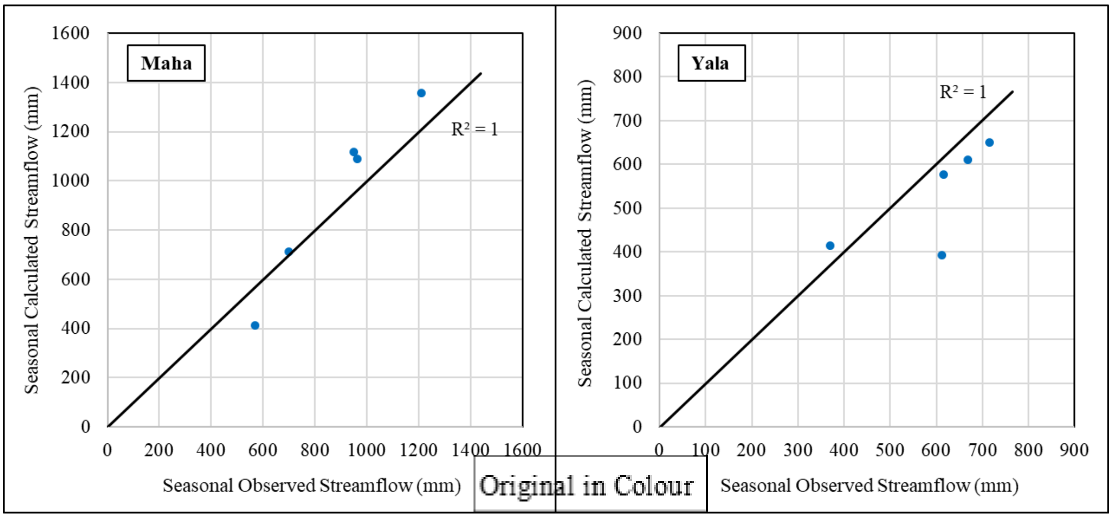


Figure D- 18: Scatter plot with seasonal flow of Urawa catchment with spatially transferred parameters

Table D- 10: Seasonal flow comparison for Pitabeddara catchment with spatially transferred parameters

Water Yr	Season	Seasonal RF(mm)	Seasonal Obs. SF (mm)	Seasonal cal. SF (mm)	Seasonal Pan Evpo (mm)	SWB Observed	SWB Simulated	SWB Error
2008/09	Maha	1460.0	965.2	922.9	588.9	494.8	537.1	-4.4%
	Yala	1290.4	852.4	748.1	537.2	438.0	542.3	-12.2%
2009/10	Maha	1137.6	748.4	721.0	546.9	389.2	416.7	-3.7%
	Yala	1516.1	957.2	949.4	482.6	558.9	566.6	-0.8%
2010/11	Maha	2112.5	1651.7	1436.2	491.8	460.8	676.3	-13.0%
	Yala	1254.4	882.7	812.5	573.6	371.6	441.8	-8.0%
2011/12	Maha	1455.5	897.3	903.6	532.6	558.1	551.9	0.7%
	Yala	1236.0	563.3	714.6	507.6	672.8	521.5	26.9%
2012/13	Maha	1829.3	1285.9	1273.7	468.4	543.4	555.5	-0.9%
	Yala	1528.1	982.1	1021.3	528.9	546.1	506.8	4.0%

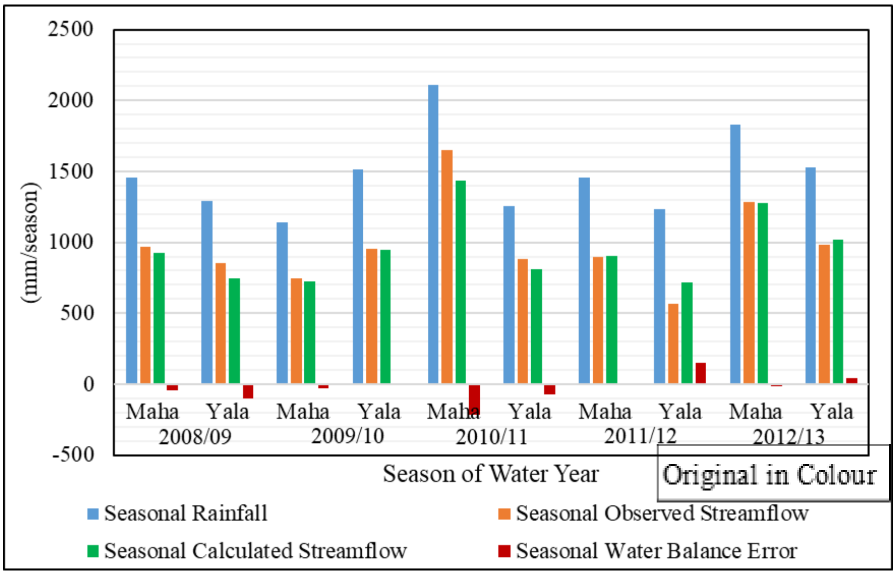


Figure D- 19: Seasonal flow comparison for Pitabeddara catchment with spatially transferred parameters

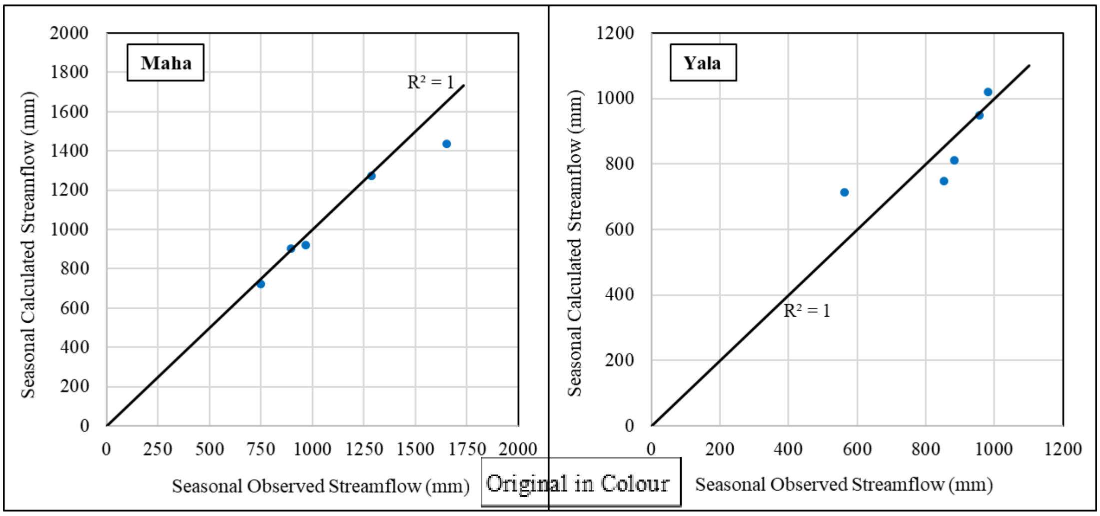


Figure D- 20: Scatter plot with seasonal flow of Pitabeddara catchment with spatially transferred parameters