APPLICABILITY OF ABCD WATER BALANCE MODEL FOR THE ASSESSMENT OF WATER RESOURCES IN KELANI BASIN, SRI LANKA

Ugyen Wangchuk

(158571J)

Degree of Master of Science

Department of Civil Engineering

University of Moratuwa

Sri Lanka

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Ugyen Wangchuk

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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
Dr. R. L. H. L. Rajapakse

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

Department of Civil Engineering

University of Moratuwa
Sri Lanka

June, 2018

DECLARATION

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

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Dr. R. L. H. L. Rajapakse Date

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ABSTRACT

Water resources management in watersheds has become increasingly important due to rapid expansion of human settlements while pollution caused by industrial development has led to the part of the available precious water resources unusable for consumption, thus aggravating scarcity of fresh water resources. The impacts are further exacerbated due to global warming. The use of the multi-parameter, distributed hydrologic models for water resources assessment in the local basins are hindered due to scarcity of data and other resources. The lumped parameter rainfall runoff hydrologic models are widely applied to predict watershed response of small watersheds by simulating rainfall runoff generation and thus useful in water resource management in ungauged basins. This study aims at identifying distinct characteristics of one such widely used model, ABCD Water Balance Model, and studying its applicability to a selected sub basin in Kelani River Basin for simulating catchment response in terms of rainfall runoff. The model was subsequently applied to analyze surface and groundwater resources available in the basin, targeting effective and sustainable water resources development and management.

The data required for the ABCD water balance model were precipitation, evapotranspiration, average temperature and minimum and maximum temperatures. The model was developed in Excel spread-sheet format focusing on the data period from 1994~2011 in the Kelani basin. For model calibration, precipitation and potential evapotranspiration data during the period 1994 to 2001 were used. The generated model streamflow was compared with observed streamflow at Glencorse station for the same period. For the validation of the model, the precipitation and potential evapotranspiration data in the latter 10-year period were used. For estimating the goodness-of-fit, Nash-Sutcliff efficiency coefficient method was used, while model response to four distinct parameters were assessed based on sensitivity analysis and parameter optimization.

The calibrated model has shown that the model is less sensitive to parameters *a* (0.9) and *b* (20) while on the other hand, the model was highly sensitive to parameter *c* (0.68) and *d* (0.01). It was noted that even with the lesser amount of moisture infiltration from the upper soil zone, the aquifer was able to produce runoff. Hence, it proved that in the wet zone, the propensity of the area to produce runoff was largely independent of rainfall intensity. For the model calibration runs, the correlation or coefficient of determination (R^2) between model flow and observed flow was 0.77 with NASH coefficient value of 0.71 and MRAE of 0.27. The model produced a better response to medium flows between 5% ~ 82% with NASH value of 0.78 and good response for high flows below 5% of percent exceedance with acceptable results (NASH = 0.62). The model could not response well for low flows (NASH = 0.45).

This model with four parameters could adequately simulate the rainfall runoff response of the selected sub-watershed area in Kelani Basin (at Glencorse). Hence, this lumped parameter model was deemed suitable for streamflow forecasting and water resources assessment in Kelani basin and it can also be applied in areas elsewhere with similar hydrological characteristics.

Keywords: Lumped parameter model, model applicability, model efficiency and sensitivity

DEDICATION

This thesis is dedicated to all my siblings who stood by me in the time of need and also for their support and encouragement for my further studies. I also would like to dedicate this work to all my relatives, my primary school teachers, especially Madam Kalpana Moktan, who played a key role in molding my education and career.

Last but not the least, I would like to dedicate this especially to my parents, Mom and Dad, who are no longer with me. They would have been very proud over their son accomplishing a Master in Engineering for sure.

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LIST OF ABBREVIATIONS

Abbreviation	Description
ABCD	ABCD Water Balance Model
ANN	Artificial Neutral Network
BFI	Base flow index
CN	Curve Number
DEM	Digital elevation model
DSD	District Secretariat Divisions
E-RCM	Complex Assemble Regional Climate Models
GA	Genetic Algorithm
GCM	Global Climate Model
GCM	General Calculation Model
GCM	General Circulation Model
GIS	Geographic information system
GND	Grama Niladhari Divisions
HEC–HMS	Hydrology Engineering Center's Hydrologic Modelling System
HMLE	Heteroscedastic Maximum Likelihood Estimator
MAE	Mean Absolute Error
MCM	Million Cubic Meter
M-GCM	Multi-General Circulation Model
MM5	Mesoscale Model five
MRAE	Mean Ratio of Absolute Error
MSE	Mean Square-Error Estimator
NSE	Nash-Sutcliffe Efficiency
P-model	Palmer and Alley Model
RCM	Regional Climatic Model
RMSE	Square root of the standard mean square error
SCE	Shuffled Complex Evolution
SCS	Soil Conservation Service
S-RCM	Simple Single Regional Climate Model
SWAT	Soil and Water Assessment Tool
SWB	Simple Water Balance
TM / T-model	Thortnwaite and Mather Model
WMO	World Meteorological Organization

1. INTRODUCTION

1.1. General Backgorund

The application of watershed models has become an indispensable tool for the assessment, and sustainable development and management of water resources since models can provide a mechanism to understand expected behavior of a catchment and evaluate the consequences of natural and human induced changes. Such models are useful for information collection of watershed characteristics and in the evaluation of assumptions and data acquisition for management and decision making. However, the hydrological modeling is still used for forecasting weather, flood, and even for designing of structures and identifying suitable locations for interventions. Moreover, it is also applied for planning, assessment and management of water resources in the watershed areas. For the above purposes, the water balance model technique has been adopted, modified and applied since from Thornthwaite (1948), and later revised by Thornthwaite and Mather (1957), and used for hydrological problem solving by Alley, (1984a), Vandewiele, Xu, and Ni-Lar-Win (1992a) then Xu and Singh (1998a).

Similarly, the ABCD water balance model was developed by Thomas Jr. (1981) where he used the precipitation and potential evapotranspiration as input and streamflow as output. In this research, the ABCD water balance model was used in order to find the suitability of the model for assessment of water resources in wet zone sub-watershed in Kelani basin in Sri Lanka. For model calibration and validation in the selected watershed area, nineteen years of data including temperature minimum and maximum, average temperature, precipitation, evapotranspiration and discharge were used.

For assessing model applicability, the goodness of fit for the model application was analyzed using Nash-Sutcliffe coefficient (Nash & Sutcliffe, 1970). The geographic information system (GIS) tools and digital elevation model (DEM) of 1:50,000 resolution were used for identifying catchment extents and the model calibration and validation were achieved based on collected rainfall and stream flow data following water year system.

Sri Lanka is an island situated near the southern tip of India, located between latitude 6° N and 10° N and longitude 80° E and 82° E. Precipitation in Sri Lanka has multiple origins with monsoonal, convectional and expressional sources while monsoonal rain accounts for a major share of the annual rainfall. According to the rainfall pattern, Sri Lanka is divided into three zones wet zone, dry zone and intermediate zone (Department of Meteorology, 2018). Wet zone which covers south west part of the Island (30% of total land area) receives an average annual rainfall of 2000 – 5000 mm from North East monsoon (November to March) and South West monsoon (May to September). Dry zone covering most of the North East and south west area of the Island (75% of total land area) receives an average rainfall of 1000 – 2000 mm annually from North-East monsoon only; south west monsoonal period is dry in this zone. Intermediate zone receives an annual rainfall of 1300 – 3500 mm. Wet zone is the only water surplus region in the Island. Agricultural activities get affected due to the failure of North East monsoon. Most agricultural and water resources are available in the wet zone basin. Wet zone can face to threats such as flooding, landslides and mud slips due to improper water resource management and sudden climatic changes (Fowse, Gunasekera, Liyanage, & Samarakoon, 2008). Therefore, it is necessary to manage and control flooding events for an efficient and economical water resource management. This is especially important for a developing country like Sri Lanka. Many development projects are being carried out throughout the downstream Kelani basin in wet zone to solve these issues.

In a gauged basins, stream flow series can be measured by the stream flow gauges. For ungauged basins, stream flow series should be derived using models with the parameters established using similar gauged basin results. There are many un gauged river basins all around the world which needs proper hydrological modeling to find reliable stream flow time series which will be needed to take many important decisions related to water resource management like improving reservoir capacities, implementing new projects, predicting disasters and evaluating environmental impact when making improvement programs. The applicability of lumped parameter ABCD model in this case is studied here.

1.2. Problem Statement

The downstream of Kelani Basin has frequently experienced major floods causing catastrophe in the low-lying floodplains while water resources availability in the basin is of major concern as it is the source of drinking water for Metro Colombo area. Based on the recently observed high variability in seasonal rain, the development of additional surface water storage capacity and trans-basin water resources diversions are being are considered. Therefore, proper assessment of water resources availability in the Kelani basin is of utmost importance in consideration of impending variability in seasonal precipitation due to climatic change impact and for the assessment of both surface and groundwater storage in the basins.

1.3. Objectives

1.3.1. Overall objective

The overall objective of the study is to evaluate the performance of ABCD Water Balance Model in the assessment of water resources in a sub-basin of Kelani Basin in the wet zone of Sri Lanka by developing, calibrating, validating and optimization of distinct model for above purpose and compare model parameter sensitivity for varying climate conditions and other catchment specific characteristics.

1.3.2. Specific objectives

1) To conduct comprehensive literature survey to investigate on application and capabilities of ABCD model and identify its strength/weakness.
2) To develop ABCD Water balance model for the selected basin.
3) To calibrate, validate and verify the ABCD model for the selected basin.
4) Identify possible model applications to demonstrate the capacity of ABCD model for water resources assessment in the selected basin.
5) Derive recommendations on the model efficiency, model parameter sensitivity and model applicability based on model application to the selected basin.

2. LITERATURE REVIEW

2.1. Hydrologic Models and Model Applications

2.1.1. General introduction

Water balance models are the most indispensable tool for the assessment, management of water resources, and prediction of runoff volume, flood, and climate change. They also help in finding necessary parameters for structure design and location identification. There are various types of models and Mathematical modeling developed by Mulvany (1850) which was probably the first to introduced and used for stream hydrology as reported in the study of Perspectives in Civil Engineering (Russell, 2003) is in the forefront. In the 1890's, the concept of Mathematical and Empirical Models had conceived an event-based model was introduced but this model came into use only in 1960's and 1970's, yet still no physical link was involved (Abbott, Bathurst, Cunge, O'Connell, & Rasmussen, 1986a).

Models can broadly be classified into four types:, namely Mathematical, Empirical, Physical based and Conceptual Models. Water balance models can also be classified according to the parameters used like One parameter model (1-P), Two parameter model (2-P), Three parameter model (3-P), Four parameter model (4-P) and so on.

The first water balance model was developed Thornthwait (1948) and later revised by Thornthwaite and Mather (1957) where the model inputs were precipitation, temperature and output was streamflow. Since then, water balance techniques have been started to be practiced, modified and applied for identifying the diversity of the hydrological problems.

Similarly ABCD water balance model was introduced by Thomas Jr. (1981). The inputs were monthly precipitation and temperature and output was streamflow compared with observed streamflow. This model was tested various basins and modified (Alley, 1984a; Fernandez et al., 2000; Martinez & Gupta, 2010b; Polebitski et al., 2011) where this model consisted of two main components; i.e. the hydrology (*a*, *b*, *c* and *d* parameters) and snow model (*e*, *f* and *dif* parameters).

The water balance models can be classified based on the variable time scale (hourly, daily, monthly and annually) and depending on the number of parameters used. Accordingly, the ABCD water balance model contains four parameters which govern the model behavior. There are several hydrological water balance models which can be categorized as either Newtonian or Darwinian in nature. The Newtonian model is based on the conservation equation which requires the thorough comprehension of the individual physical processes acting upon a watershed to build a detailed hydrological model. The Darwinian approach tends to explain the behavior of the hydrologic system as a whole by identifying simple and robust temporal nature of the model behavior.

2.1.2. Model objectives

The first water balance model was developed by Thornwaite (1948) and then later modified by Thornwaite and Mather (1955). Water balance models are defined over a variable time scale (hourly, daily, weekly, monthly and annually). Early models were primarily meant to be water balance models for agricultural use. Later, water balance models were also used for evaluating climate change impact (Alley, 1984a; Gleick, 1987) and for weather forecast (Arnell, 1992; Jiang at al., 2007). The models can be categorized as either Newtonian or Darwinian as aforementioned, but the ABCD model was developed by Thomas (1981) based on widely differing principles and assumptions and applied to distinct time scale (Wang & Tang, 2014a).

According to Fernandez et al. (2000), the model parameter *a* was well correlated to explain the soil permeability, which means lower the value of parameter *a*, then lesser the infiltration into upper zone storage hence more the direct runoff. Parameter *b* was strongly related to permeability of soil which means increase in value of parameter *b* will lead to a decrease in evapotranspiration (ETt). Parameter *c* controls the water movement from upper soil to lower soil zone while parameter *d* governs groundwater recharge to stream.

2.1.3. Application of models

According to Xu and Singh (1998b), the relevance of various aspects of the practical application of hydrologic models were introduced originally to evaluate the essential behavior of various hydrologic parameters under different conditions. They also presented the present applications of water balance models along three mainlines: i.e. for Reconstruction of the hydrology of a catchment, Assessment of climatic impact changes, and Evaluation of the seasonal and geographical patterns of water supply and demand.

The research carried out by taking time-series of monthly streamflow, temperature and precipitation for 1337 catchments (Sankarasubramanian & Vogel, 2002b), it was noticed that the basins with low evapotranspiration has poor model performance as introduced (Schreiber 1904; Dekop, 1911; Budyko, 1974). It was improved by integrating their new soil moisture for inter-annual variability of the streamflow which was introduced by Koster and Suarez (1999) and they derived an inter-annual variability as a function of aridity index ($\varphi = \frac{\overline{PE}}{\bar{P}}$) and soil moisture index ($\gamma = b\frac{\bar{P}}{\overline{PE}}$), where b characterizes the soil moisture storage capacity of the catchment without any streamflow observation.

Comparison between the monthly water balance model versus daily water balance model was carried out by Wang et al. (2011) for simulation of monthly runoff using three models, Wapaba model against the ABCD and Budyko model in an Australian catchment. They suggested that daily water balance model was better for the climate change impact assessment than monthly and annual water balance models. However, they also mentioned that the Wapaba model was better than the other two models in the case of seasonal streamflow forecasting in Australia.

2.1.4. Data used in models

The top-down approach was used by Tekleab et al. (2011) for the study of the ABCD water balance modelling for the Upper Blue Nile catchment where monthly precipitation and potential evapotranspiration data of nine years (1995-2004) were used for model calibration and model evaluation. Five years of data for calibration and four years of data for validation were used with the Nash–Sutcliffe efficiency (NSE) as the objective function which derived values of 0.52 ~ 0.95 and Root Mean Square Error (RMSE) for long term mean annual flow with values of 62 minimum and 256 as maximum (mm/yr^{-1}) using available observed stream flow data.

A study was carried out by using ABCD Water Balance Model (Al-Lafta, Al-Tawash, & Al-Baldawi, 2013) in United States with monthly precipitation and potential evapotranspiration data of 17 years. Ten years of data was used for initial simulation and seven years for model evaluation with Mean Square Error (MSE) as the objective function by targeting optimum value as closer to zero.

Water balance model development was begun in 1940s with the introduction of the two parameter model (Thornthwaite, 1948). In a review study on use of monthly water balance models for water resources investigation (Xu & Singh, 1998b), it was discovered the requirement and application of monthly water balance models for the scientific community's development. According to them, the most of the models were capable of sufficient simulating of streamflow using precipitation and potential evapotranspiration data. The ABCD four parameter hydrologic model introduced by Thomas (1981) was a popular model among those class of models. Later Xu and Singh (1998b) also concluded that three to five model parameters were sufficient to model humid regions but that arid and semi-arid regions require more complex models. In the comparison of three water balance models, Alley (1984a) also found that ABCD model was the strongest among the considered three models.

The models containing two to six parameters, i.e. Thornthwaite-Mather model, the Palmer model, and the recent Thomas's ABCD model, were examined by using fifty years data of monthly streamflow at 10 sites in New Jersey by Alley (1984a) in their research. They found out that Thornthwaite-Mather type model has difficulties in finding the correct time lag factor, in the Palmer type model very high correlation between upper and lower storage and for the ABCD model, parameter *a* was largely sensitive to bias in estimating of precipitation and potential evapotranspiration. They advised that in using the state variables of the models in indices of drought and the basin productivity, extreme caution must be taken while attaching physical significance to the model parameters.

2.1.5. Selection of a model

Most of the models have been developed for monthly basis because the smaller time scale models (like daily, hourly, etc.) were more complex and data-intensive (Xu & Singh, 1998b) due to the additional methods required for simulation in greater degree of variability in hydrology methods. However, Schaake, Koren, Duan, Mitchell, & Chen (1996) stated that, need of the simple bucket model with single parameter to multi-parameters like Sacramento model. But in early research by Jakeman and Hornberger (1994), it was mentioned that conceptual and physical based models seem to be over-parameterized which means no useful than simple model with identifiable parameters. Furthermore, Xu & Singh (998b) stated that models with fewer parameters contain more information and were more likely to represent specific catchment characteristics, which facilitates the application of water balance models to the estimation of streamflow at ungagged catchments. In addition, they also suggested that three to five parameters may be sufficient at the monthly time scale for humid regions, while they have also mentioned that a more complex model structure may be necessary for arid and semi-arid environments due to higher climate data and catchment characteristic variability.

The selection of model depends on the objective of the study, data availability, spatial and temporal scale of study as mentioned in the research study in Godavari basin in India (Durga Rao, Rao, & Dadhwal, 2014). Thortnwaite and Mather (TM) model was used with 18 years runoff of monthly resolution data and land use pattern data for runoff estimation.

The study carried out for assessing the annual hydrology in the United States (Sankarasubramanian & Vogel, 2002) noticed that the traditional relationship which predicts the actual evapotranspiration or stream flow from an aridity index $f_4^1 PE = P$ had shown poor performance with low soil moisture storage capacity. They used water balance model with an acceptable performance for the prediction of actual evapotranspiration and inter-annual variability of streamflow by using physics based approach. It was further noted that there exist a requirement of monthly time series of precipitation, potential evapotranspiration and an estimate of maximum soil moisture holding capacity for the model. They also noticed in their comparison that simple Budyko type relationships of the type introduced (Budyko, 1974; Ol'Dekop, 1911; Pike, 1964; Schreiber, 1940) were unable to reproduce the actual evapotranspiration in the watersheds in United States. However, their study has sought for development of physical based models.

Using regional climate models for hydrological impact studies at the catchment scale, a review of the recent modeling strategies was carried out (Teutschbein & Seibert, 2010). It was proposed that hydrologic models can be coupled with simple single regional climate model (S-RCM) simulation and complex assemble regional climate models (E-RCM) for the simulation of climate change impacts on regional or basin scale. It was also suggested that one should be aware of the need for bias correction which adds significantly to uncertainties in modeling climate change impacts when using hydrologic models.

2.2. Model Parameters and Assumptions

2.2.1. Soil moisture assumptions

Initial soil moisture and groundwater level for hydrologic models are usually estimated based on water from soil moisture at the end of the previous month (S_{t-1}) assumption (Griffen, 2014). In his study for identifying a continuous hydrologic model structure for applications at multiple time scales, several different hydrologic models including ABCD model were applied in 71 catchments using daily, monthly and annual data, where the catchment areas ranged from 67 km^2 to 10,375 km^2 with an average of 3,655 km^2 in the United States.

According to Griffen (2014), the models required setting of initial conditions for the soil moisture and groundwater reservoirs. For all models, the initial soil moisture condition was assumed to be at capacity ($= S_{max}\ or\ S = b$ for the ABCD model) and for all groundwater reservoirs were assumed to be initially empty. He assumed that the models could self-correct for the true storage values if model was run for initial warm-up period (i.e. a short time interval at the beginning when the model performance was not evaluated). For monthly time scale, 24 months was set to be the warm-up period.

2.2.2. Number of parameters in hydrologic model

The different water balance models have different number of parameters (Griffen, 2014) like a One-Parameter Budyko model (1974), Manabe bucket model or the Fu equation (Schaake et al., 1996) and Zhang et al. (2008), and two parameter model of Thornthwaite and Mather's (1955), Tα-model (has three parameters) by Alley's (1984), ABCD model (has four parameters) by Thomas's (1981), etc. Schaake et al. (1996) developed the five-parameter "Simple Water Balance" (SWB) model, while an eight parameter model was developed by Krzystofowicz and Diskin (1978). Boughton model (1973) has 10 parameters, while a 12 parameter model was developed by Pitman (1973, 1978). Further, the Sacramento model is known to have 16 parameters whereas the Soil Conservation Service (SCS) developed a water balance model for applications at the event scale (i.e. each rainfall event) (USDA, 1972). The model calculates "rainfall excess" using a proportionality relationship. This model has no parameters (or only one parameter CN) but requires the estimation of "curve numbers" that vary based on the land cover type.

In a review of monthly water balance studies carried out by Xu and Singh (1998b) mentioned that, a variety of models and parameter estimation algorithms have been considered, ranging from relatively complex conceptual models with 10 to 15 parameters for arid regions in Africa (e.g. Pitman, 1973) to very simple models with 2 to 5 parameters for humid regions in temperate zones (e.g. ; Makhlouf & Michel, 1994; Vandewiele *et al*., 1992; Xu *et al*., 1996a).

2.2.3. Models based on time resolution data

The hourly model developed by Krzystofowicz and Diskin (1978), daily model developed by Roberts (1978), monthly water balance model developed by Beken and Byloos (1977), and ABCD Water Balance model originally developed for annual time resolution by Thomas (1981) and later modified for monthly by Alley (1984a) and used with different time resolution data like daily, monthly, etc. were studied. Some models are run at even smaller time scales (Schaake et al., 1996). Models have also been developed for the event time scale (i.e. a single precipitation event) (USDA, 1972).

2.3. Model Sensitivity and Optimization

2.3.1. Sensitivity analysis of hydrologic models

For sensitivity analysis, a model was proposed by coupling an Advanced Land Surface–Hydrology Model with the Penn State–NCAR MM5 Modeling System (Chen & Dudhia, 2001). The model implementation and sensitivity analysis were advanced using the land surface–hydrology model in the Penn State–NCAR Fifth-generation Mesoscale Model (MM5). The concept adopted was that the land surface model to provide not only reasonable diurnal variations of surface heat fluxes as surface boundary conditions for coupled models, but also to correct seasonal evolutions of soil moisture in the context of a long-term data assimilation system. It has shown that the soil thermal and hydraulic conductivities and the surface energy balance were very sensitive to soil moisture changes.

2.3.2. Model parameter optimization

In Northern Belgium, more than 60 catchments ranging in size from 31~60 km^2 have been studied by means of regionalization of physical based water balance model in Belgium. With application to ungauged catchments (Vandewiele, Xu, & Huybrechts, 1991), it was detected that water balance model with three parameters for actual evaporation, slow and fast runoff was capable of either to generate monthly streamflow at ungauged sites or to extend river flows at gauged sites.

2.3.3. Optimization methodology

Most models having multiple parameters which need to be calibrated followed the most commonly used algorithm of Shuffled Complex Evaluation (SCE-UA) algorithm as highlighted by Duan et al. (1994). This method was used for several different models like SWB model (Schaake et al., 1996), the ABCD model (Martinez and Gupta, 2010a; Sankarasubramanian and Vogel, 2002b), and the Wapaba model by Q. J. Wang et al. (2011) whereas genetic algorithm used was based on Matalab 7 where simulation was run continuously for 20 times.

Optimization was performed using VA05A computer package by Hopper (1978) and Vandewiele et al. (1992) where it was supplemented with a program called EOX4F (NAG Fortran Subroutine Library, 1981). According to Xu (1999), parameter estimation in hydrology model can be done either subjective to trial-and-error fitting (e.g. Pitman, 1976) or by using automatic optimization routines (e.g., Ibbitt and O'Donnell, 1971; Kuczera, 1983). As James (1972) argued that only rigid adherence to a standard optimization procedure would enable compilation of a sufficiently comprehensive database for use in regression studies relating model parameters to catchment characteristics.

2.3.4. Model comparison

The study of methodology and comparative study of monthly water balance models in Belgium, China and Burm was carried out (Vandewiele, Xu, & Ni-Lar-Win, 1992b) and compared with the following four models. The first model (T-model consist of two parameters) was developed by Thornwaite and Mather (1955) consist of two storage: 'soil moisture index' m_t and 'water surplus 'v_t. The model has two filter parameters; soil moisture capacity a_1 and storage constant a_2 for v_t. The second model (Tα-model contains three parameters) was developed by Alley (1984) which the model was modified from the preceding model in that a fraction a_3 of the precipitation was immediately converted into direct runoff. Then the rest of the precipitation enters same as before. The third model (ABCD model, it has four parameters) introduced by Thomas Jr. (1981) which was comprised of two storage compounds: groundwater storage and soil moisture storage. The fourth model (P-model consisting of two parameters) was developed by Palmer and Alley (1984). This model uses a 'root constant' concept for calculating evapotranspiration. It also consists of an upper layer roughly equivalent to plough and lower layer as availability capacity which depends on the depth of the effective root zone. They suggested that ABCD Model was always best in terms of quality (Q).

By using top-down approach in upper Blue Nile catchment based on Budyko's hypothesis for understanding for the prediction of direct runoff (Tekleab et al., 2011), the result hinted that annual water balance model was not dominated only by precipitation and potential evaporation. The complexity of model for realistic simulation of the catchment water balance as achieved by including soil moisture with necessary of monthly time scale. It was also mentioned that with only four parameters of the simple model, it has the advantages of minimal equifinality.

A model based on the recent artificial intelligence technology, namely a genetic algorithm (GA) and based artificial neutral network (ANN), was employed in the case study of a flood forecasting neutral network model with genetic algorithm (Wu & Chau, 2006a) in Yangtze River and Han-Kou River in China. An empirical linear regression model, a conventional ANN model and a GA based model were used as benchmark for comparison of model performances. The result revealed that the GA-based ANN algorithm, under the careful handling for avoiding the over fitting, was able to produce the better accuracy performance, although the time taken was long and in expense of additional modeling parameters. Further, it was possible to avoid in particularly the necessity to collect the large amount of the site-specific parameters needed for the traditional physical models.

2.3.5. Modelling approach

There are different types of model approaches in hydrologic modeling for catchments and they are Regionalization approach, Traditional approach, Top-down which is an empirical or data based approach, involving learning about the catchment's hydrologic functioning from patterns in the observed data (Baker, Cullen, Debevec, & Abebe, 2015a) or whereas in bottom-up approach and, etc.

Using the Soil and Water Assessment Tool (SWAT), a research focusing a socio-hydrological approach was conducted for incorporating gender into biophysical models and implications for water resources research (Baker, Cullen, Debevec, & Abebe, 2015b) in Ethiopia by separating the three stakeholder groups as men, women and land scape of 20 km^2. The result indicated that this is a valid strategy that enhances the scientific knowledge in comprehensive landscapes and add ultimate value to the research for identifying development questions.

2.4. Model Calibration and Validation

2.4.1. Calibration and validation of a model

In a study of parameterization, the calibration and validation of a distributed hydrological model is discussed (Refsgaard, 1997). Calibration and validation using a split-sample procedure were carried out for catchment discharge and piezometric heads at seven selected observation well locations. First, the simulation was compared with observed discharge of additional sites but results obtained were poor. Secondly, validated model based on 500 m model grid was used to generate the three additional models with 1000 m, 2000 m and 4000 m grids. Then this result indicated that the maximum size of grid 1000 m should be used for simulations of discharge and groundwater heads.

The result for ABCD model confirmed by Thomas et al. (1983) and Alley (1984) that the value of parameter *a* always exceeded 0.96, with a very high value for parameter *b*, while parameter c and d were statistically non-significant for many catchments whereas results obtained by Alley (1984b) has argued that ABCD model should have been calibrated simply by setting of parameter $a = 0$ and parameter $d = 1$. In another calibration, the parameter d was kept fixed at a value of 0.2 and found there was no significant change in the model quality

Evaluating the use of goodness-of-fit measures in hydrologic and hydro climatic model validation was carried out by using the correlation and correlation-based model (Legates & McCabe, 1999). Their result had advised that correlation-based models should not be used because of limitation of correlation and correlation-based models gave good prediction even when it was not. Thus, they recommended for the use of the coefficient of efficiency (E_1) or agreement (d_1).

Root square (R^2) values of average annual runoff at sub-watersheds were 0.78 and 0.99 for the Ohio and Arkansas Basins. Observed and simulated annual and monthly streamflow for 30 years was used for temporal validation at the gauges and encountered spatial calibration process was helpful in capturing the flow variations from low flow through high flow regimes (Santhi, Kannan, Arnold, & Di Luzio, 2008) in the examination of spatial calibration and temporal validation of flow for regional scale hydrologic modeling in the United States.

Study carried out to analysis of changes in the relationship between precipitation and streamflow in the Yiluo River, China (X. Liu, Dai, Zhong, Li, & Wang, 2013) came up with results indicating changes in streamflow and flows were found to be decreasing in 1980s as due to the influenced by human activities.

2.4.2. Objective function

The probe of model evaluation guideline for systematic quantification of accuracy in watershed by D. N. Moriasi et al. (2007) remarked that there was no such guideline for model evaluation in terms of accuracy of model discharge compared to observed discharge. In general, model simulation can be judged as satisfactory if Nash-Sutcliffe efficiency greater than half (NSE > 0.50) and the ratio of the root mean square error to the standard deviation of measured data less than point seventh (RSR < 0.70). Pearson correlation coefficient (r) and coefficient of determination (r^2) describes the collinearity between simulated and observed data. It ranges -1 to +1 and >0.5 is taken as acceptable.

A procedure for the selection of objective function for hydrological simulation models was carried out (Diskin & Simon, 1977). The calibrated model with generated streamflow was compared with observed streamflow in an optimization procedure using an objective function adopted for the particular purposes. Set of data and objective function to be used for any given model was a subjective decision which influences the model parameter and model performance. The set of data must be comparable with the purpose for which the model was intended.

Evaluation for the effect of objective functions on the model calibration were carried out (Cheng, 2015) with trial and error method and it was mentioned that anyone can judge model performance simply by observation between model discharge and observed discharge. The results of model calibration is said to depend on the objective function.

A research carried out focusing on multi-objective global optimization for hydrologic models used the single objective function for model efficient prediction (Yapo, Gupta, & Sorooshian, 1998) but, however, it was stated that the single objective function was not adequate to find the characteristics of model prediction towards the observed data. The objective functions were Mean Square-error Estimator (MSE) and Heteroscedastic Maximum Likelihood Estimator (HMLE) criterion.

Mean Ratio of Absolute Error (MRAE), which was suggested by World Meteorological Organization (WMO, 1975) is also used widely for model calibration and validation.

2.4.3. Model warm-up period

For estimation of the steady-state parameters in simulating the model, the correct removal of any initialization bias is of an utmost importance. Usually two method is applied (Robinson, 2002), and first, the starting condition of the model can be set such that there was no bias in the output data. This requires the correct setting of the starting condition. Second, the model can be run for a warm-up period and the data are then deleted from that period (the initial transient). This requires the correct estimation of the warm-up period. It is this latter approach upon which this paper focuses. The study has categorized the available methods into five out of 42 warm-up methods.

1. Graphical methods: These involve the visual inspection of time-series of output data.
2. Heuristics approaches: These apply simple rules, with few underlying assumptions.
3. Statistical methods: these rely upon the principles of statistics for determining the warm-up period.
4. Initialization bias tests: These identify whether there is any initialization bias in the data and, therefore, they are not strictly methods for identifying the warm-up period, but they can be used in combination with warm-up methods to determine whether they are working effectively.
5. Hybrid methods: These involve a combination of graphical or heuristic methods with an initialization bias test.

In the study of an automating warm-up length estimation (Hoad, Robinson, & Davies, 2010) mentioned that there are five main methods for dealing with initialization bias according to (Robinson 2004).

The effect of warm-up error can be minimized by (Sheth-Voss et al. 2005):

1). Run the model for a warm-up period until it reaches a realistic condition (steady state for nonterminating simulations). Delete data collected from the warm-up period.

2. Set initial conditions in the model so that the simulation starts in a realistic condition.

3. Set partial initial conditions then warm-up the model and delete warm-up data.

4. Run model for a very long time making the bias effect negligible.

5. Estimate the steady state parameters from a short transient simulation run.

2.5. Model Case Studies in Sri Lanka

The study Modeling of Event and Continuous Flow Hydrographs with HEC–HMS: Case Study in the Kelani River Basin, Sri Lanka (De Silva, Weerakoon, & Herath, 2014) using HEC-HMS hydrology model and Nash-Sutcliff Efficiency for model best-fit efficiency was presented where they achieved a NSE of 0.91 for event–based simulations and 0.88 for continuous simulations.

The research carried out using HEC-HMS Model for Runoff Simulation in a Tropical Catchment with Intra-Basin Diversions – Case Study of the Deduru Oya River Basin, Sri Lanka (Sampath, Weerakoon, & Herath, 2015) indicates that they used HEC-HMS hydrologic model over an area of 2620 km^2, with the result of goodness-of-fit for NSE $(R^2{}_{NS})$ value of 0.76 and RMSE of 25 for data from 1984 to 1985 and Root Mean Square Error (RMSE) of 34 for data period from 1987 to 1989.

2.6. ABCD Water Balance Model

The study conducted using ABCD monthly water balance model by Al-Lafta et al. (2013) used this hydrologic model for three watersheds in United State for identifying the feasibility of the model which almost let to the perfect calibration relation between catchment model parameters and basin characteristics but question remained practicability of the model application due to little snow or no snow. However, they found that model with four parameters (*a*, *b*, *c* and *d*) were sufficient to give the required basin model behavior. They also noticed that the parameter a and b were easy to approximate and parameter *c* and *d* were highly sensitive to the model. The model also achieved the mean square error (MSE) statistic value around eight (8) and main stream flow hydrograph.

To find improvement in the model with different time scales, Wang & Tang (2014b) used Budyko model (1974) at th**e** long-term scale, ABCD model by Thomas (1981) at the monthly scale and Soil Conservation Service (SCS) Curve Number model (SCS, 1972) at the event scale. They reported that the synthesis from the analysis of observed data by

Darwinian approach could provide one component of the hydrological model whereas Newtonian could not due to limitation of observation or knowledge of exact mechanism. Thus, they concluded for the need of improvement in investigation relation to rainfall difference between the event scale and long-term scale by future research.

Use of simple ABCD monthly water balance model in the comparison of uncertainty in multi-parameter and multi-model ensemble hydrologic analysis of climate change (Her et al., 2016) is reported where they demonstrated that the uncertainty in multi-general circuit model ensembles could be an order of magnitude larger than that of multi-parameter ensembles for the prediction of runoff. They used ABCD model (1981) and suggested that selection of the correct general circulation model (GCM) should be much more taken into account than the choosing of a parameter set among the behavioral ones when projecting direct runoff. They noticed during the time of simulating soil moisture and groundwater, the equifinality in hydrologic modeling was more influential than uncertainty in the multi-GCM ensemble. They also observed that the uncertainty in hydrologic calibration of climatic change impact was much more related with uncertainty in ensemble projection of precipitation than that in projected temperature. According to the above facts, this indication shows the need of more attention towards the precipitation data for the reliability of hydrologic predictions.

A study was carried out for the improvement and identification of hydrologic models for the conterminous United States by using monthly ABCD model to 764 catchments and examining diagnostically relevant component of model error (Martinez & Gupta, 2010a). They found that the model parameters and structures are correlated with hydro climatic variables. However, their results indicated that the need of the conventional identification approach to be improved because reported values of NSE or r^2 which did not constraint the model to reproduce important hydrological behavior and could mislead the performance. They suggested that unless suitable hypotheses with appropriate spatiotemporal scale for each hydro-climatic region has not been established then such model could not be used for the identification of inference to the regionalized model structures and model parameters to ungauged basin locations.

To analyze the climate elasticity of streamflow in the United States, a model was used with a nonparametric estimator to construct a map of ε_p (Precipitation Elasticity of a stream) and the results were compared with ten (10) detailed climate change scenarios (Sankarasubramanian, Vogel, & Limbrunner, 2001). They observed that contour map used was providing a validation matric for past and future climate change. Further, they proceeded that ε_p tends to be low with significant snow accumulation and for the basins with the moisture and energy inputs were seasonally in phase with one another. They discovered the importance of both model form and model calibration in determining the sensitive model of streamflow to climate but also noted that it was difficult to estimate the sensitivity of streamflow to climate using a single watershed model. The usefulness of the nonparametric estimator was its low bias and the model was robust which does not require an assumption or a calibration. The models used were Trivariate model, Non-linear ABCD model and ABCD model.

2.7. Literature Review on Data Checking

2.7.1. General

The literature review was carried out for the types of data checking as required for model to predict for future purpose.

2.7.2. Visual checking

Visual data checking was carried out by plotting graph in order to identify any abrupt changes in time series (Wijesekera & Perera, 2016), for study in key issues of data and data checking for hydrological analyses based on a case study of rainfall data in the Attanagalu Oya Basin of Sri Lanka.

2.7.3. Outlier testing

To find the outlier in data, Wijesekera and Perera (2016) carried out outlier data checking for Attanagalu basin using equation given below.

$Y_H = \bar{y} + K_n s_y$ and $Y_L = \bar{y} - K_n s_y$,

where Y_H and Y_L are high and low outlier thresholds in log, $\bar{y}$ is the mean, n is the sample size, s_y is the standard deviation and K_n is the parameter given in Chow et al. (1988).

2.7.4. Review on annual water balance

Water balance gives the part of the basin character according to Budyko (1974) curve method, while if Q/P less than 0.3, then the basin is considered as an arid region, if Q/P is between 0.3 ~ 0.7, then the basin is considered as a semi-arid, and if the ratio is greater than 0.7-1.25, then it is categorized as a humid basin.

As stated by Ghandhari and Moghaddam (2011), the water balance was a perfect way to program and evaluate the scaling of watersheds, applying for water supply, water allocation and waste water management. It is also used for the flood estimation (Anderson *et al*., 2006; Boughton & Hill, 1997) and more importantly for assessments in ungauged basins (Boughton & Chiew, 2007; Boughton, 2004). It is also noted that long-term water storage changes in watersheds, including surface water and groundwater, were expressed in the form of residuals (accumulated or scattered water) in water balance equation (snow and ice amounts can be removed) (Berezovskaya *et al*., 2005).

$$\frac{dS}{dt} = P - Q - ET \quad \text{--- ()}$$

where $\frac{dS}{dt}$ is the total change in storage, P is average precipitation, Q is surface water runoff, and ET is evapotranspiration. This simple expression of water balance was valid where the groundwater output and its withdrawals were negligible. Correct definition for water balance period or hydrological year was a very important factor in the simplification of computations and can be evaluated as a basis for identification about the hydrological watershed (Najjar, 1999).

Using single or multi parametric method, watersheds were classified according to homogeneity characteristics, climatic conditions and physiographical situations (closed or opened watersheds). Thus by comparison methods, it could be evaluated as a basis for using the same equations for similar catchments usually like in closed watersheds where controlling factors were usually level or volume or reservoirs for evaluating water balance equation (Ghandhari & Moghaddam, 2011).

2.7.5. Data gap filling

There are three main techniques for estimating missing meteorological data, namely, Empirical methods, Statistical methods and Function-fitting methods (Xia et al., 1999). According to Gyau-Boakye and Schultz (1994), filling the missing data depends on the length of the gap, climatic region, density of station, and the characteristics of the data archived (Moeletsi, Shabalala, Nysschen, & Walker, 2016) and as mentioned in their studies, an inverse distance weighting method was used for patching daily and decadal rainfall over the Free State Province, South Africa.

There are a number of methods used to estimate missing rainfall values. The widely-used patching methods include: Closest station, Simple arithmetic averaging, Inverse distance weighting, Multiple regression and Normal ratio (Tang et al., 1996; Makhuvha et al., 1997), and neural networks (ANNs) using artificial radial basis function (Nkuna and Odiyo, 2011).

2.7.6. Checking data consistency

Double mass curve is normally used for checking consistency in data time series (Wijesekera & Perera, 2016), where cumulative series of a single station was plotted with the average of others stations. It can also be used for adjustment if there is any significant changes in data. Then, annual values of an earlier portion of the record were adjusted to be consistent with the latter portion, as discussed in their study Attanagalu Oya Basin of Sri Lanka.

3. METHODOLOGY

3.1. General Description of Methodology

Methodology flowchart illustrates a schematic of the methods carried out for project based on main and sub topics. Location and problems (as in Introduction) were identified through literature survey, questionnaires, first hand and secondary information, and through history and background checking about the basins. The research objective is to carry out a research on the Applicability of ABCD Water balance model for the assessment of water resources in Kelani basins, Sri Lanka for the better understanding of basin water resources for future predictions and for the benefit of the people living in the watershed. Literature survey was carried out related to the selected model and the research work and for addressing the objectives and understanding functioning of ABCD Water balance model. Data was collected from the Meteorological Department and Irrigation Department where monthly data for twenty years was used. Data checking and missing data gap filling were achieved using different methods like Visual checking, Single and Double mass curve methods, Annual water balance, etc. as mentioned below. The ABCD Water balance model which consists of four parameters were selected for this research because with appropriate background knowledge about this model and from the literature survey, it was mentioned and deemed that a model with two to four parameter is adequate to give the information of about the hydrological cycle in the watershed (Xu & Singh, 1998b). The Fig. 3-1 shows the schematic representation of the methodology followed where this model was calibrated and validated using input data of 17 years based on monthly precipitation and potential evapotranspiration and the stream flow output was compared with observed streamflow. After calibration, the model parameter optimization and sensitive analysis was carried out. For model validation, 10 years data of monthly basis was used. Depending on the objective function, model performance was assessed for calibration and validation, and parameter adjustment was used to obtain satisfactory results. Further details of data and data types used are mentioned below in the Data and Data Resolution section presented in Chapter 4.

3.2. Methodology Flowchart

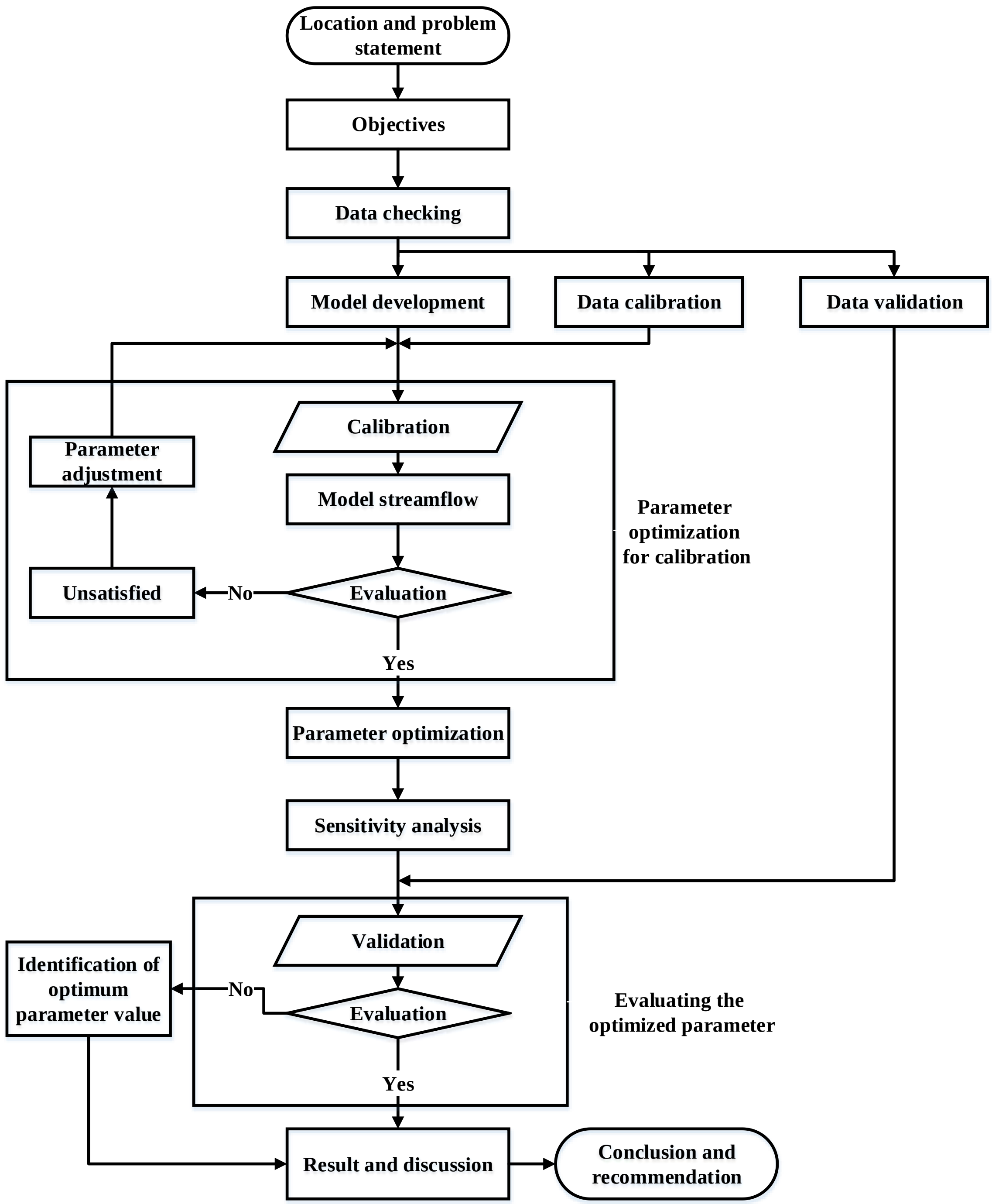


Figure 3-1 Methodology flow chart

3.3. Driving Data for Model Development

Generally, the data needed for watershed models are hydrometeorologic, geomorphologic, agricultural, pedologic, geologic, hydraulic, and hydrologic. Hydrometeorologic data includes rainfall, snowfall, temperature, radiation, humidity, vapor pressure, sunshine hours, wind velocity, and pan evaporation. Agricultural data includes vegetation cover, land use, treatment, and fertilizer application. Pedologic data includes the soil type, texture, and structure; in soil condition soil particle size diameter, porosity, moisture content including capillary and antecedent moisture content. Geologic data includes data on stratigraphy, confined aquifers, hydraulic conductivity, transmissivity, storativity, compressibility, and porosity. For unconfined aquifers, data on specific yield, specific storage, hydraulic conductivity, porosity, water table and recharge are needed. Geomorphologic data includes topographic maps showing elevation contour, river network, drainage areas, slope length and watershed area. Hydraulic data includes roughness, flow stage, river cross section, and river morphology. Hydrologic data includes flow depth, streamflow, discharge base flow, interflow, stream, aquifer interaction potential, water table, and data of associated errors and accuracy.

The data used for this research is twenty years (17 years) of monthly data. The data was basically collected from the Meteorological Department and Irrigation Department. The collected data were temperature, precipitation, stream discharge and evaporation. There are four rainfall stations in the selected Kelani Basin sub-watershed up to Glencorse stream gauging station which was used as watershed outlet.

It is difficult to check data quality very systematically, since data comes from many different sources and due to the error incurred in data during collection process by human and machines. Moreover, the data checking and filled missing data cannot give the accuracy closer to the actual scenario data with inherent basin characteristics. However, it will produce a certain acceptable accuracy which can be used for hydrologic modeling in the basin for forecasting and assessment of water resource management.

Finding of effective rainfall gauging stations in coverage area for the basin can be achieved by Arithmetic mean method or by Isohyetal method or by Thiessen polygon method. In this basin, the Thiessen polygon method was used since the method has been found suitable for flat and low rugged areas. This method is also mechanical and in this method rainfall location at a short distance beyond the boundary of drainage were also used to determine the mean rainfall of the basin, but their influences diminishes as the distances from the boundary increases.

3.4. Study Area Catchment

3.4.1. Location of Glencorse sub basin of Kelani Basin

The study area map illustrating the location of Glencorse sub-watershed in Kelani Basin is presented in Fig. 3-2

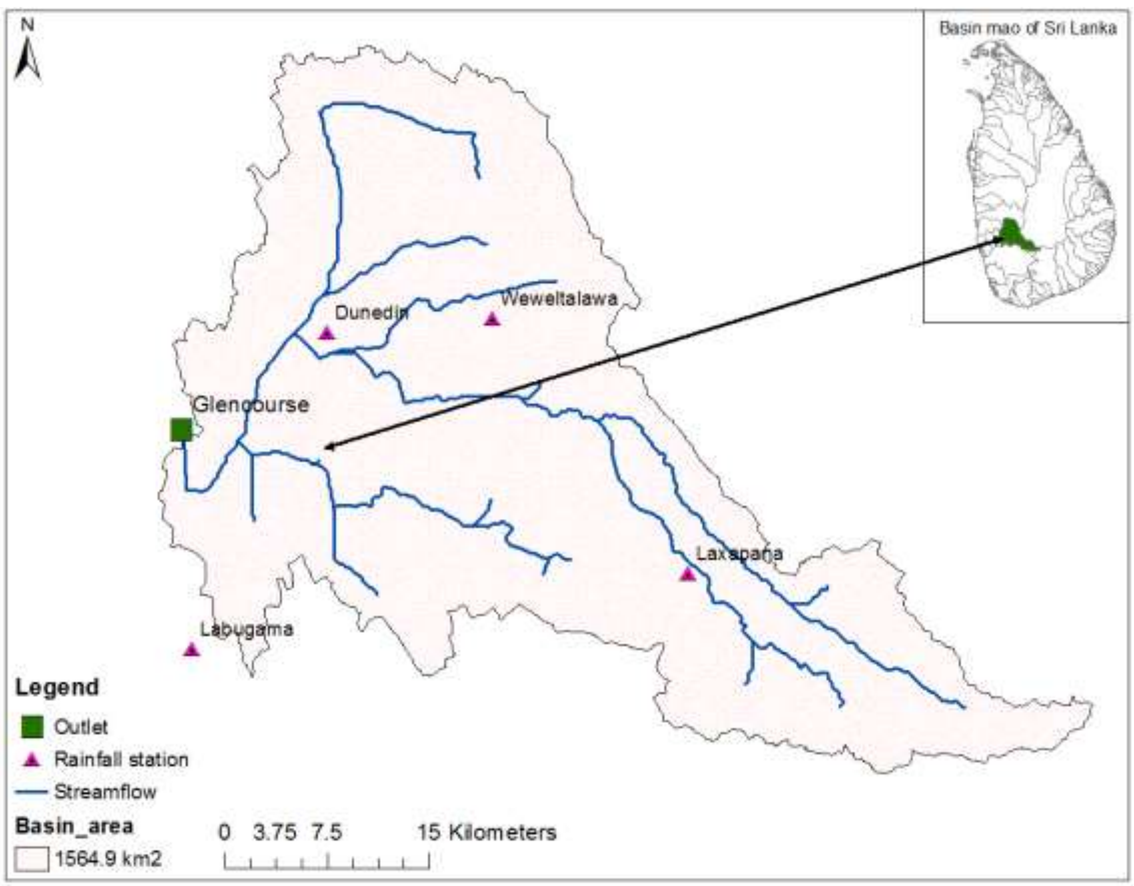


Figure 3-2 Location for Glencorse sub basin of Kelani Basin in Sri Lanka

3.4.2. Basin and sub-watershed characteristics

Sri Lanka is situated south of India and surrounded by Indian Ocean in north and by Pacific Ocean in south. The country population as of 2016 is approximately 21 million. There are three climatic zones, Wet, Intermediate and Dry zone where 103 major natural river basins exist with the longest Mahaweli River with a length of 335 km. Among these basins, the Kelani Basin is located in the wet zone and its catchment area is 2314.46 km^2.

The catchment area demarcation for the study was performed by using the geographic information system (GIS) tools and digital elevation model (DEM) of 1:50,000 resolution and this vector data was used also for generating streamflow network with flow direction and location of outlets.

Kelani basin spans over the provinces of Western, Sabaragamuwa and Central, while flowing from west to east across Nuwara Eliya, Kandy, Ratnapura, Kegalle, Kalutara, Colombo and Gampaha Districts. Kelani Basin is the second largest basin in Sri Lanka. For this research study project, the sub basin area up to Glencorse stream gauge station was considered with a catchment area of 1564.9 km^2. The river is originated at its main source of water in the upstream most Horton Plains National Park (2345 m MSL) and river mouth is located close to the Capital City Colombo, discharging flows to Indian Ocean (0 m MSL). The Kelani River has two main tributaries in its upper reaches. These are; (1) Kehelgamu Oya and (2) Maskeli Oya. These two contributes to a major part of hydro-electric production in Sri Lanka. The length of the river is 145 km and the average river discharge varies from is 20 ~ 25 m^3/s during dry season to 800 ~ 1500 m^3/s during monsoon season. The location of river mouth is 06˚58´44”N and 79˚52´12”E.

3.5. ABCD Water Balance Model and Model Hypothesis

The ABCD Hydrologic Model is a physical based, lumped and nonlinear watershed model that can function as a water balance model initially developed by Thomas (1981) and later revised by Thomas et al. (1984). It is a simple hydrological model for simulating stream flow in response to precipitation and potential evapotranspiration. The ABCD model contains four parameters which govern the behavior of the model. The model consists of two storage compartments, one acting as soil moisture storage and the other as groundwater whereas the soil moisture gains water from the precipitation and losses water as surface runoff, groundwater recharge losses and evapotranspiration. The groundwater storage gains water from the soil moisture as recharge and losses water as discharge. These two losses, surface runoff and groundwater discharge contribute to form the total stream flow which is the main output in the model.

3.5.1. Model parameters and data required

The ABCD Model has basically four governing model parameters.

Parameters a, b, c, and d

- ***a*** controls the amount of runoff and recharge that occurs when the soils are under-saturated.
- ***b*** controls the saturation level of the soils.
- ***c*** defines the ratio of groundwater recharge to surface runoff.
- ***d*** controls the rate of groundwater discharge.

Parameter range

- parameter ***a*** ranges between (0 ~ 1) according to Fernandez et al. (2000)
- parameter ***b*** ranges between (5 ~ 1900) according to Vandewiele et al. (1992)
- parameter ***c*** ranges between (0 ~ 1) according to MOPEX (2010)
- parameter ***d*** ranges between (0 ~ 1) according to Alley (1984)

Data required

i. Monthly rainfall
ii. Potential evapotranspiration (or minimum, maximum, average temperatures)

3.5.2. Model structure and model formula used

The model describes in two state variables as W_t, which is termed as "Water available" and Y_t, termed as "Evapotranspiration opportunity". Thus, available water is defined as:

Soil moisture upper layer

W_t = 'Availability of water' in the current time step and defined as given below

$W_t = S_t + P_t$ it is the sum of soil moisture and precipitation

$W_t = S_t + ET_t + GR_t + DR_t$ ………………………………………...…………… (a)

Y_t= Evapotranspiration opportunity of the system and mathematically defined as,

$Y_t = S_t + ET_t = Y_t = \frac{W_t+b}{2a} - \sqrt{\left(\frac{W_t+b}{2a}\right)^2 - \left(\frac{bW_t}{a}\right)}$ ……………………………………… (b)

P_t= Precipitation

S_t = Soil moisture $S_t = Y_t e^{\frac{-PET_t}{b}}$ ……………………………………..……………. (c)

PET_t = Potential evapotranspiration (mm) that is calculated using an equation such as the following Penman and Hargreaves equation.

$PET_t = e.PET_{EQ}$

where, e is a calibration parameter that is newly introduced to the original ABCD model and PET_{EQ} is the potential.

ET_t = Actual evapotranspiration $ET_t = Y_t(1 - e^{\frac{-PET_t}{b}})$ ………………………..… (d)

DR_t = Direct runoff $DR_t = (1 - c) \times (W_t - Y_t)$ …………………………………… (e)

GR_t = Groundwater recharge $GR_t = c \times (W_t - Y_t)$ ………………………………… (f)

Soil moisture lower layer

G_t = Groundwater storage $G_t = G_t + GD_t$ $= G_t = G_{t-1} + GR_T$

GR_t = Groundwater recharge $GR_t = \frac{1}{1+d}(G_{t-1} + GR_t)$ ……………………..……. (g)

GD_t = Groundwater discharge $GD_t = dG_t$ ……………………………………….... (h)

According to Jeffrey D. Walker, (2014).

$G_t = G_{t-1} + GR_T(1 + d) - 1$

Updated by Al-Latta, Al-Tawash, Al-Baldawi (2013) and Jeffrey D. Walker, (2014).

Thus, total streamflow $Q_t = GD_t + GR_t$ …………………………………………… (i)

3.5.3. Physical structure and mass balance of ABCD Model

The Fig. 3-3 shows the physical structure of ABCD Model which accounts for the soil water for upper and lower groundwater layers where the parameters *a* and *b* pertain to runoff characteristics, and *c* and *d* relate to groundwater storage and discharge to the stream (Y. Liu, Hejazi, Li, Zhang, & Leng, 2018).

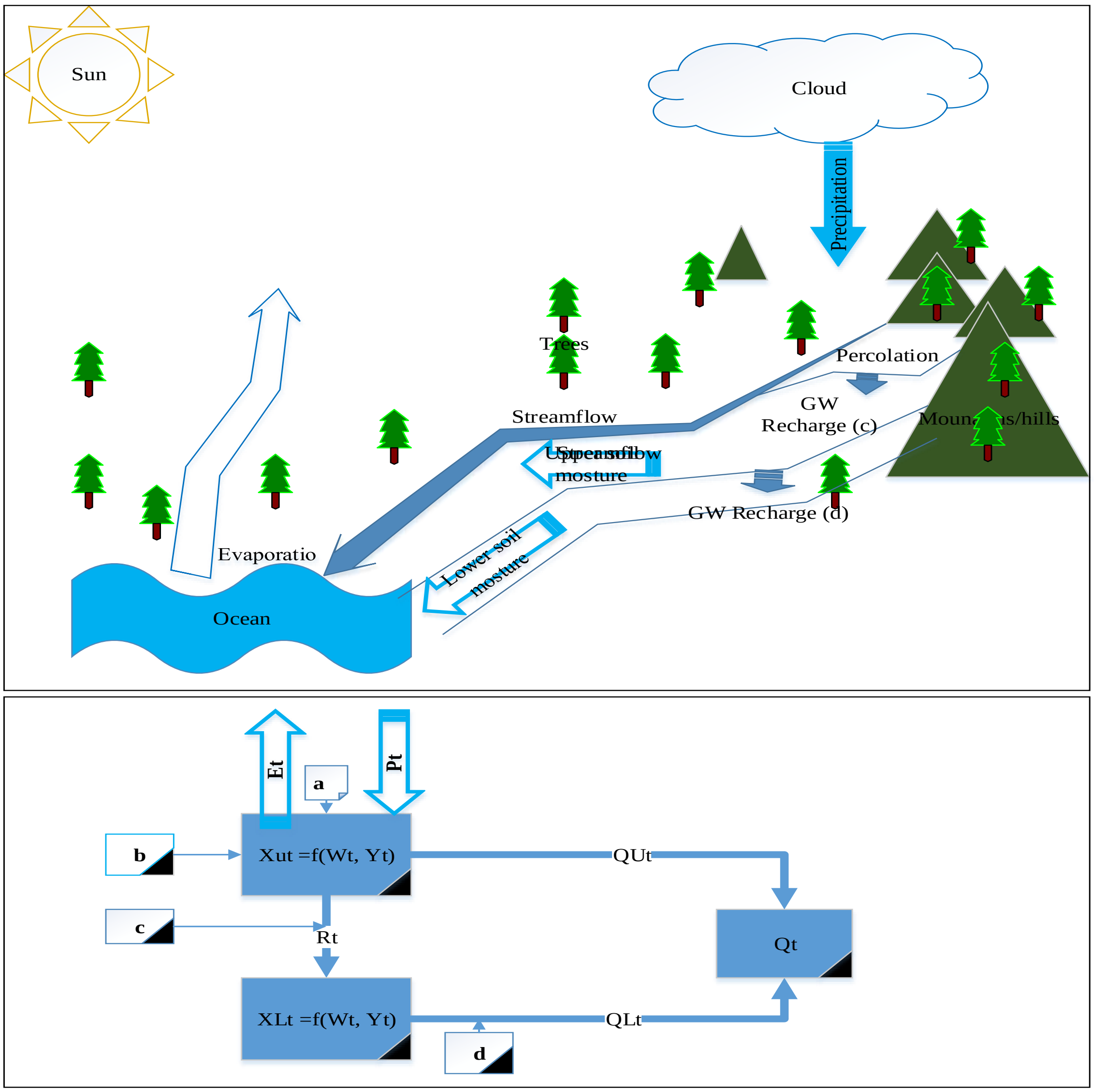


Figure 3-3 Schematic diagram of ABCD Model Structure

3.6. Model Optimization and Sensitivity Analysis

The purpose of the sensitivity analysis is to find the effect of variation in the model parameter on the model output. This also gives the idea of the factor that contributes most strongly to variability and input and output characteristics. This approach was introduced by Nash and Sutcliffe (1970) to build the relative index of agreement or disagreement between observed and computed runoff that was used for comparison of model performance between periods and basins.

They started from the sum of square errors given by Mean Square Error (MSE) which used for evaluating the perturbation and to determine the actual value close to zero (0). The MSE measures the difference between the simulated model streamflow and observed streamflow.

$$F = \sum_{i=1}^{n}(Q_o - Q_m)^2 \quad \text{(I)}$$

where F is the index of disagreement, $Q_{obs,i}$ and $Q_{sim,i}$ are the observed and simulated discharges at time step *i*, the sum being taken over *n* time steps of a pre-selected period. F is analogous to the residual variance of a regression analysis. The initial variance $F_0$is given by.

$$F_0 = \sum_{i=1}^{n}(Q_o - \bar{Q}_m)^2. \quad \text{(II)}$$

where $\bar{Q}_m{}^2$ as a mean of the observed discharge over the pre-selected period by Nash and Sutcliffe (1970).

Square root of the standard mean square error (RMSE) by Legates and McCabe Jr. (1999) measures the absolute fit of the model to the data and checks how close the observed streamflow to the model streamflow. This modeled discharge means, standard deviation and square root of the mean standard error as follows.

Standard Deviation (SD) = $\frac{Q_{o-}Q_m{}^2}{n}\,(Q_o - Q_m)^2$……………………………….…… (III)

$RMSE = \sqrt{\frac{1}{N}\sum_{i-1}^{N}(Q_o - Q_m)^2}$ ………..…………………………………………….. (IV)

Mean absolute error (MAE) given by

$MAE = N^{-1}\sum_{i=1}^{N}|Q_o - Q_m|$ or

Root square (r^2) $\frac{Q_{o-}Q_m{}^2}{n}$

$RSQ = \boldsymbol{r} = \frac{\sum(\boldsymbol{Q_0}-\overrightarrow{\overline{\boldsymbol{Q_o}}})(\boldsymbol{Q_m}-\overleftarrow{\overline{\boldsymbol{Q_m}}})}{\sqrt{\sum(\boldsymbol{Q_o}-\overrightarrow{\overline{\boldsymbol{Q_o}}})^2\sum(\boldsymbol{Q_m}-\overrightarrow{\overline{\boldsymbol{Q_m}}})^2}}$ ………………………………………………… (V)

Modeled monthly discharges were calibrated to maximize the Nash-Sutcliffe efficiency (E). This 'goodness-of-fit' measure was first developed by Nash and Sutcliffe (1970). The value E was a measure of the squared difference of observed and modeled stream flow values divided by variance in the observed data (Nash and Sutcliffe). The E emphasizes large flow volume.

$NASH = E = 1 - \frac{\sum_{t=1}^{T}(Q_0^t - Q_m^t)^2}{\sum_{t=1}^{T}(Q_0^t - \overrightarrow{\overline{Q_o}})^2}$ …………………………………………………… (VI)

where Q_o is the mean of observed discharges, and Q_m is the modeled discharge, and $Q_o{}^t$ is the observed discharge at time t.

4. DATA AND DATA CHECKING

4.1. Data Collection for Selected Area in Kelani Basin

Data collection were done in two ways one by collecting from the Department of Irrigation and from Meteorological Department, and other by generating in the ARC Geographic Information System (ARC-GIS) tool for location, area for basin, Thiessen rainfall and etc. detail data collected has given below.

4.1.1. Rainfall data collection

Data collection were done in two ways, first one data collection were done through geographic information system (Arc GIS) like location of rainfall or gauging stations and size of the basin area in km^2 (square kilometer), and second one data like rainfall, streamflow, temperature and evaporation data were collected either from Irrigation Department or Department of Meteorology, Colombo.

Table 4-1 List of monthly basis data for sub basin in Kelani Basin

No.	Name of the station	Data types	Date/years	Data resolution
1	Labugama	Rainfall (mm)	Oct-1994 to Sep-2011	Monthly
2	Laxapana	Rainfall (mm)	Oct-1994 to Sep-2011	Monthly
3	Weweltalawa	Rainfall (mm)	Oct-1994 to Sep-2011	Monthly
4	Dunedin	Rainfall (mm)	Oct-1994 to Sep-2011	Monthly
6	Glencorse	Discharge (m^3/s)	Oct-1994 to Sep-2011	Monthly

No.	Name of the station	Data types	Date/years	Data resolution
7	Colombo	Temperature Max, & min. (℃)	Oct-1994 to Sep-2011	Monthly
	Colombo	Evaporation (mm)	Oct-1994 to Sep-2011	Monthly
12	Sub-basin	DEM (30 m image)	N/A	1: 50,000

4.1.2. Thiessen area map and location of rainfall and gauging station

The Fig. 4-1 shows the Thiessen polygon and it was done for the effective rainfall distribution for selected project area in Kelani basin in wet zone.

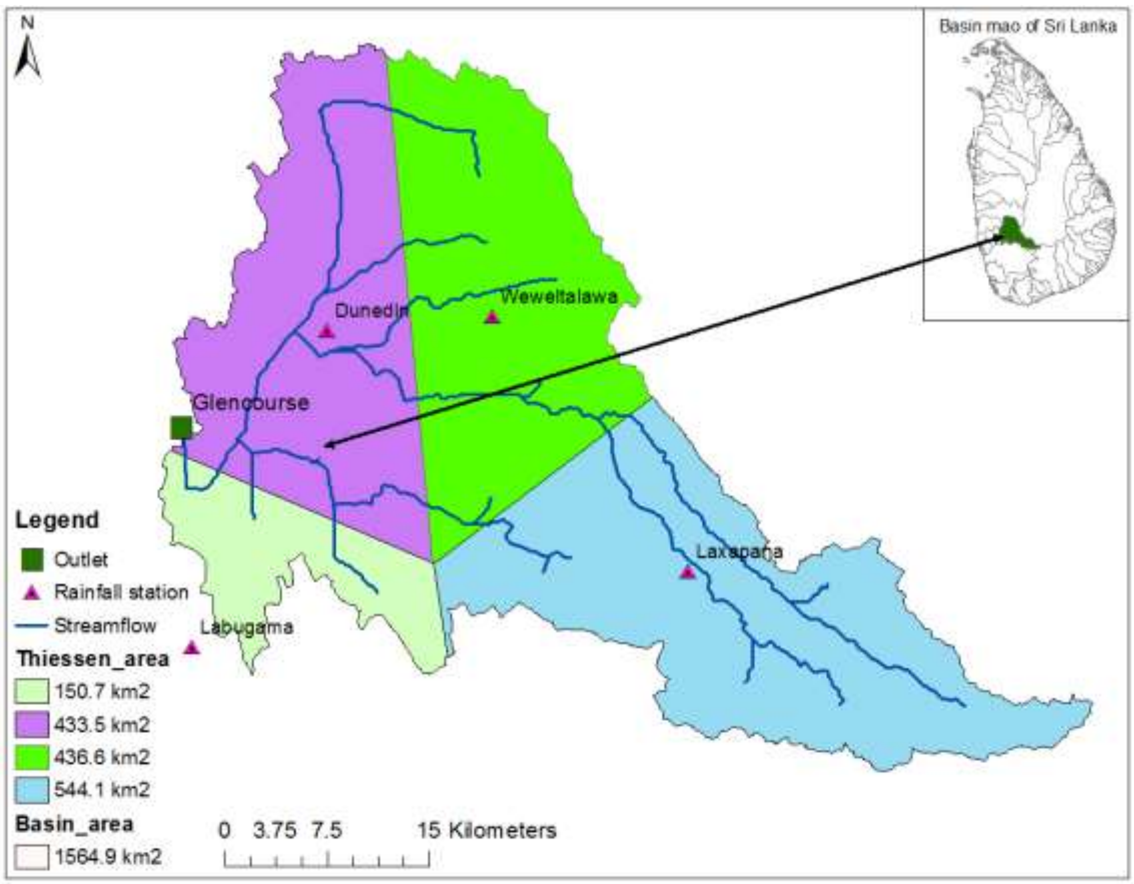


Figure 4-1 Theissen polygon map of selected area in Kelani Basin

There are five rainfall station and they are Labugama, Laxapana, Dunedin and Weweltalawa. The discharge location name is Glencorse. Thiessen rainfall was also carried out for the effective area cover as per the Thiessen area rule (Rainbird, 1967; McGuinness, 1963**)**. The area for individual rainfall station was required in order to calculate Thiessen rainfall for calibration, validation and also to compare with observed discharge. The location of the rainfall station and the discharge location detail has given in the table list below.

Table 4-2 Location detail of rainfall station and discharge station

No.	**Name of station**	**Area (km^2)**	**East (Longitude)**	**North (Latitude)**
1	Labugama	150.7	80º16′13.533″	7º2′31.57″
2	Laxapana	544.1	80º30′28.415″	6º52′41.28″
3	Weweltalawa	436.5	80º22′36.965″	7º2′53.826″
4	Dunedin	433.5	80º31′8.552″	6º54′31.056″
5	Glencorse (Q)	Total area = 1564.8	80º10′47.66″	6º58′10.486″

The above Table 4-2 shows the location of individual rainfall and observed discharge that were obtained from the geographic information system (GIS).

4.1.3. Evapotranspiration calculation for ABCD Model

The detail has given in Appendix-C according to Shuttleworth (1993). Evapotranspiration as the maximum that water can leave the basin as an evaporation and equation as described below by (Shuttleworth, 1993), (Thornthwaite, 1948) and (Penman, 1948).

Relative distance between earth and sun

$d_r = 1 + 0.033\, cos\left(\frac{2\pi}{365}\right)J$ …………………………………...……………….…….. (a)

Solar decline (Radiation)

$\delta = 0.4093 sin\left(\left(\frac{2\pi}{365}\right)J - 1.405\right)$……………………………….………….………….. (b)

Sunset hour angle

$$\omega_S = cos(-tan\phi tan\delta) \ldots \text{(c)}$$

Extraterrestrial solar radiation

$$So = 0.6059 d_r(\omega_s sin\phi sin\delta + cos\phi cos\delta sin\omega_s) \ldots \text{(d)}$$

Potential evapotranspiration

$$PET = 0.0023 S_O \sqrt{(T_{MAX} - T_{MIN})}(T_{MAX} - T_{MIN})(T_{AVE} + 17.8) \ldots \text{(e)}$$

4.2. Data Checking

4.2.1. Annual water balance

The below Fig. 4-3 shows annual water balance. Thiessen area was calculated by generating for all rainfall station in geographic information system (ArcGIS) tool as given above in Fig. 4-1. Then Thiessen weightage was calculated by dividing Thiessen area of a single rainfall station by total area of the catchment. Finally, the Thiessen rainfall was calculated by multiplying the same rainfall station with Thiessen weightage and similarly done with other station. The difference of this annual Thiessen rainfall and the observed discharge as the annual water balance.

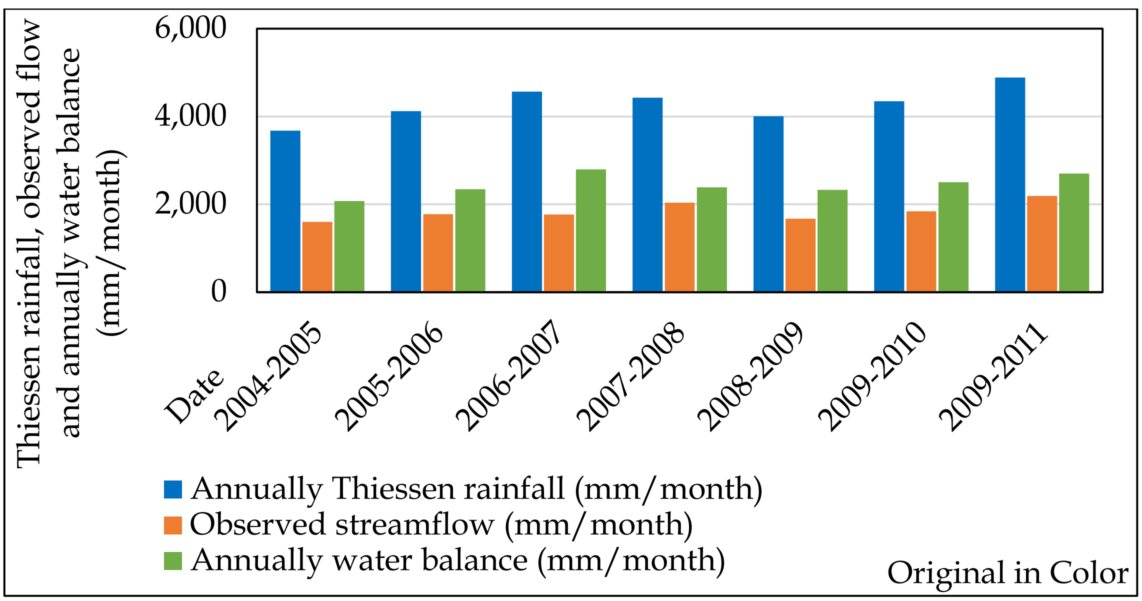


Figure 4-2 Annual water balance checking for sub basin of Kelani Basin

4.2.2. Thiessen rainfall calculation

The Thiessen rainfall calculation was carried out in the excel sheet to find the annual water balance by subtracting observed discharge.

Table 4-3 Thiessen weight calculation for required area in Kelani Basin

Data	**Annually Thiessen rainfall (mm/month)**	**Glencorse streamflow (mm/month)**	**Annually water balance (mm/month)**
1994-1995	863.0	249.7	613.3
1995-1996	680.4	151.9	528.5
1996-1997	625.4	138.5	486.8
1997-1998	843.6	167.4	676.1
1998-1999	828.9	163.9	665.0
1999-2000	682.1	99.8	582.3
2000-2001	541.8	68.3	473.6
2001-2002	561.4	93.4	468.0
2002-2003	734.7	118.1	616.7
2003-2004	641.8	119.2	522.6
2004-2005	607.8	133.4	474.4
2005-2006	700.2	148.0	552.1
2006-2007	754.8	147.3	607.5
2007-2008	753.3	169.6	583.7
2008-2009	672.4	139.6	532.9
2009-2010	698.6	153.3	545.3
2009-2011	739.4	182.5	557.0
Total water balance for 17 years	11929.6	2443.9	9485.6

4.2.3. Visual checking for rainfall data

The visual data checking was carried out by comparing the catchment runoff response to daily rainfall data at individual rainfall gauging stations as shown in Figs. 4-3 to 4-8.

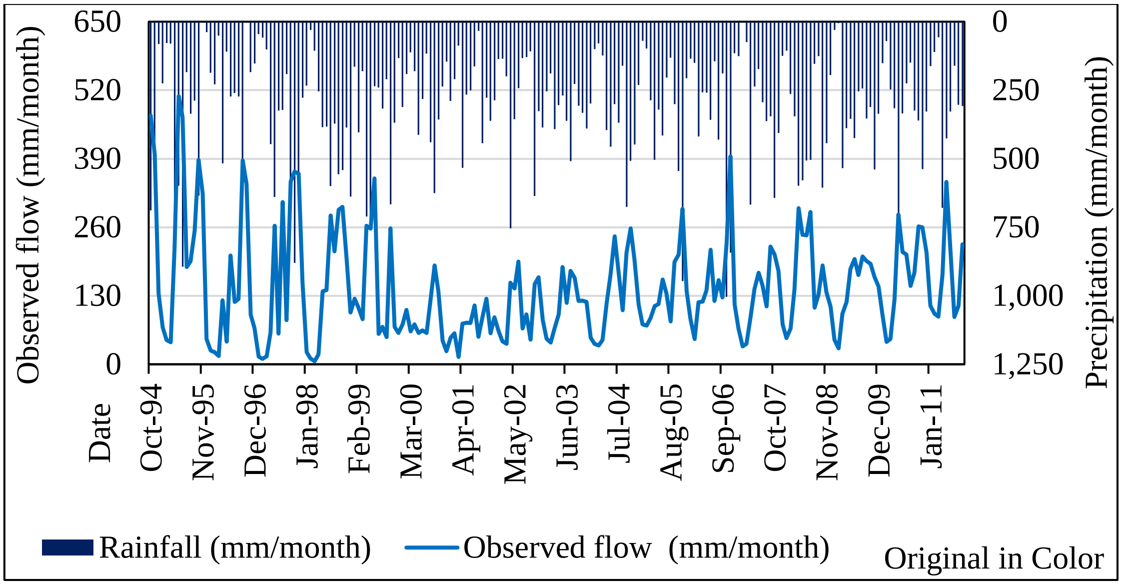


Figure 4-3 Visual checking for observed flow response to Labugama rainfall station

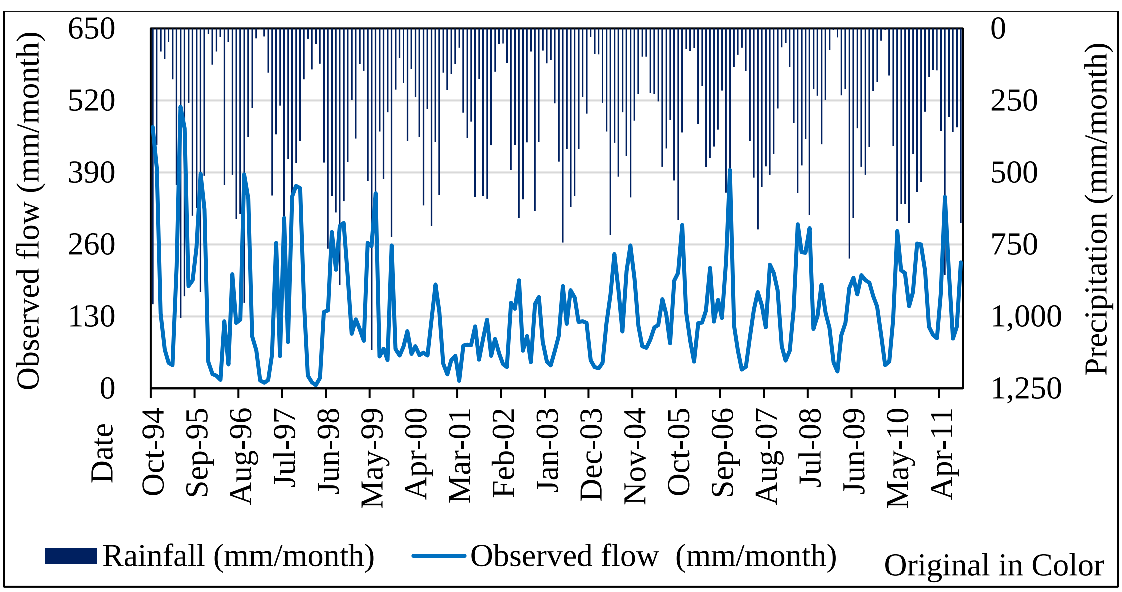


Figure 4-4 Visual checking for Glencorse observed flow response to Laxapana rainfall station

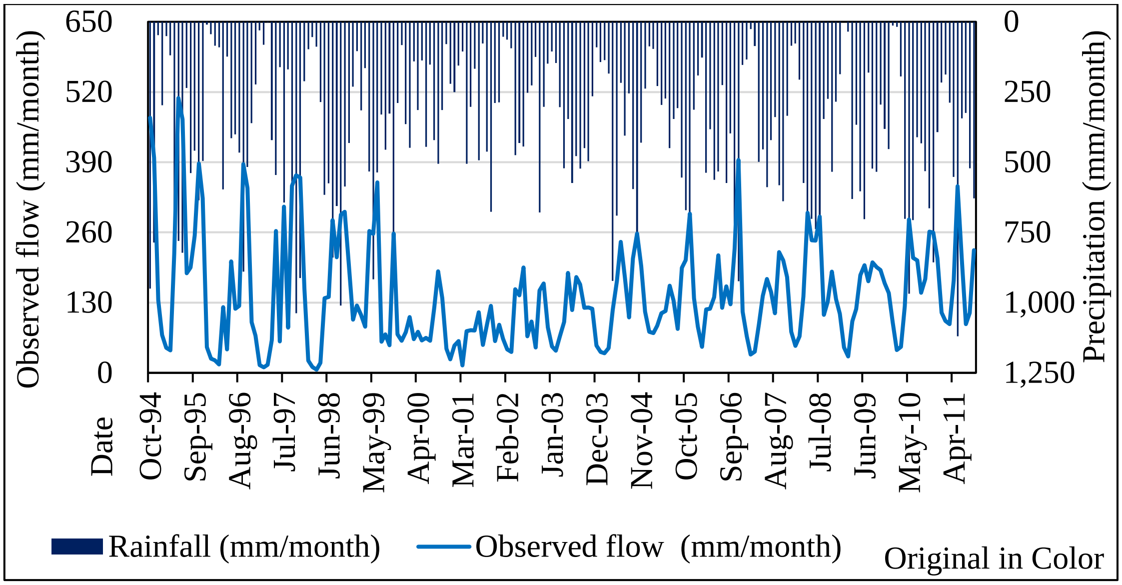


Figure 4-5 Visual checking for Glencorse observed flow response to Weweltalawa rainfall station

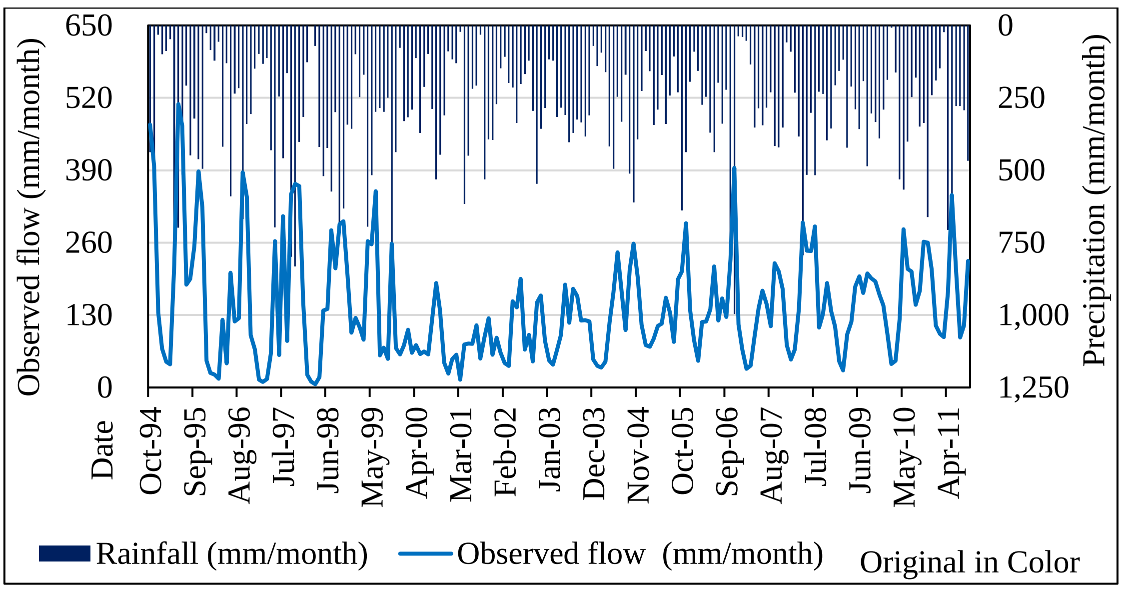


Figure 4-6 Visual checking for Glencorse observed flow response to Dunedin rainfall station

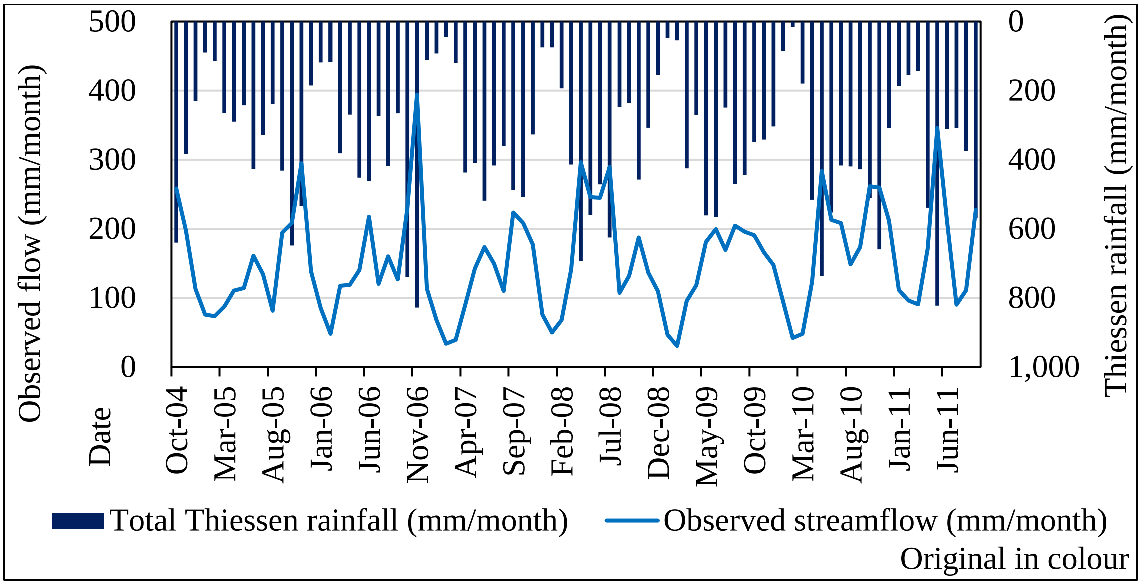


Figure 4-7 Visual checking for streamflow response to total Thiessen rainfall for Calibration period

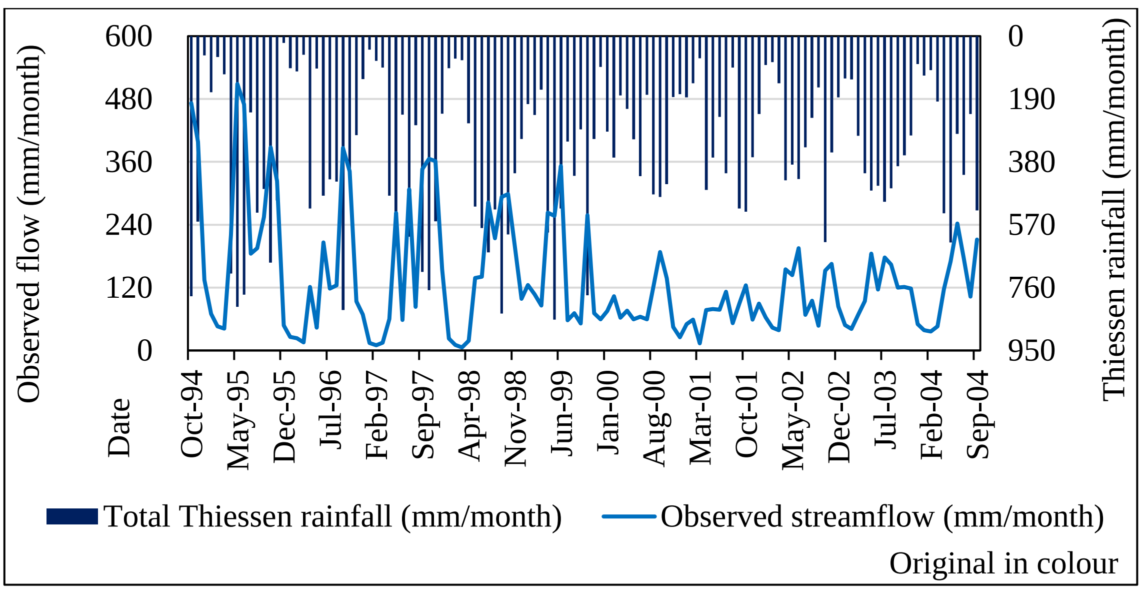


Figure 4-8 Visual checking for streamflow response to total Thiessen rainfall for Validation period

The above graphs were plotted in order to facilitate the visual checking process by comparing observed stream flow and rainfall recorded at individual gauging stations. Visual checking is the first step in data checking which was carried out for finding out missing data gaps and abnormal trends and points (outliers) in data series which could have been erred due to measurement or recording errors. Though the data collected was assumed to be a complete and accurate series, there still could be gaps or erroneous data. This can be due to the human errors or the gaps can be due to machine or equipment failures as well as due to the inconvenience of timely access for data collection. Even if the data collected are initially assumed to be complete and error free (without missing data and outliers), further analysis should be carried out by plotting rainfall versus discharge to see if there exist any data discontinuities and discrepancies.

The Fig. 4-4 shows the data checking in May, 2002 with a monthly precipitation value of 754 mm but a very low discharge of mere 154 mm. Missing data gaps identified in this Labugama station data series were in November, 1995 and 1996. All the Figs. 4-4, 4-5, 4-6, 4-7 are showing reasonable agreement between rainfall and runoff except minor deviations in March, 2001 and February, 2002, for all stations.

The visual checking was further extended to include Thiessen precipitation and observed discharge. The Fig. 4-7 shows for the calibration period and the Fig. 4-8 shows the validation period. Both the graphs show only minor discrepancies so that respective data sets can be used for model runs. Moreover, the correlation between Thiessen rainfall and observed streamflow has shown 0.6 and 0.7. This linear regression has also shown that the relation between observed flow and precipitation is valid and acceptable.

4.2.4. Temperature data checking and filling missing data

There were no missing values in temperature data series for both maximum and minimum temperatures in 2009. The data was used from 1991 to 2010 (Table 4-4).

Table 4-4 Maximum temperature for selected area in Kelani Basin in degree Celsius (Tmax. (℃))

Months	**Mean for max. temperature for 17years**	**Standard deviation for max. Temp.**	**Mean for min. temperature for 17 years**	**Standard deviation max. Temp.**
Oct	30.7	1.0	24.2	0.9
Nov	30.8	0.8	23.7	0.5
Dec	31.0	0.7	23.2	0.5
Jan	31.5	1.0	22.9	0.7
Feb	31.9	1.2	23.4	0.8
Mar	32.4	1.1	24.1	1.1
Apr	32.2	1.0	24.6	1.1
May	31.6	0.6	25.6	1.1
Jun	30.7	0.4	25.4	1.0
Jul	30.3	0.4	25.3	0.9
Aug	30.4	0.5	25.2	1.1
Sep	30.6	0.6	24.8	1.1

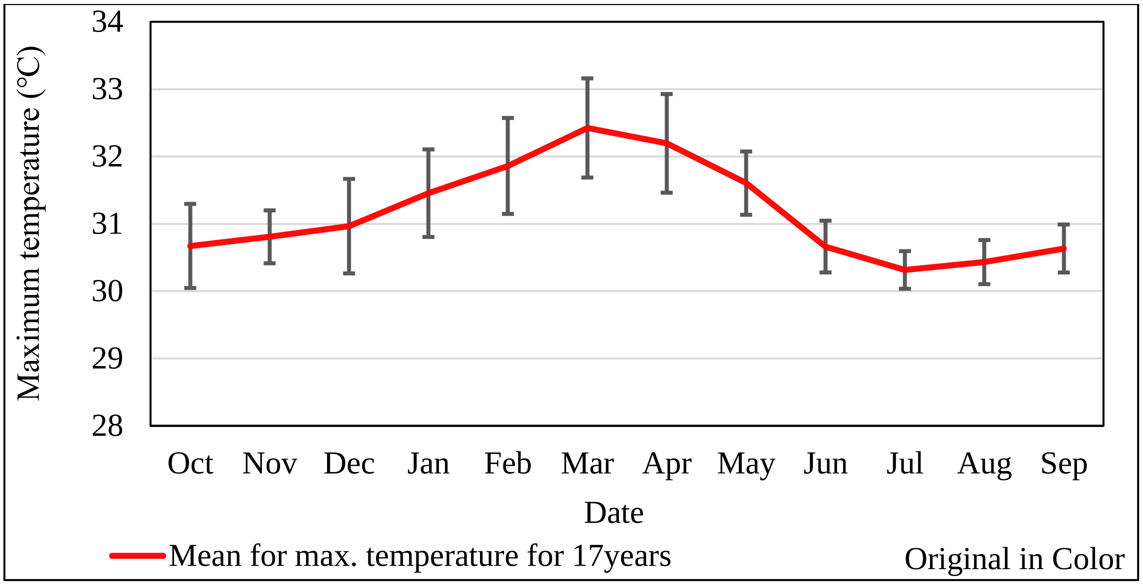


Figure 4-9 Maximum monthly temperature graph with standard deviation for project area in Kelani Basin

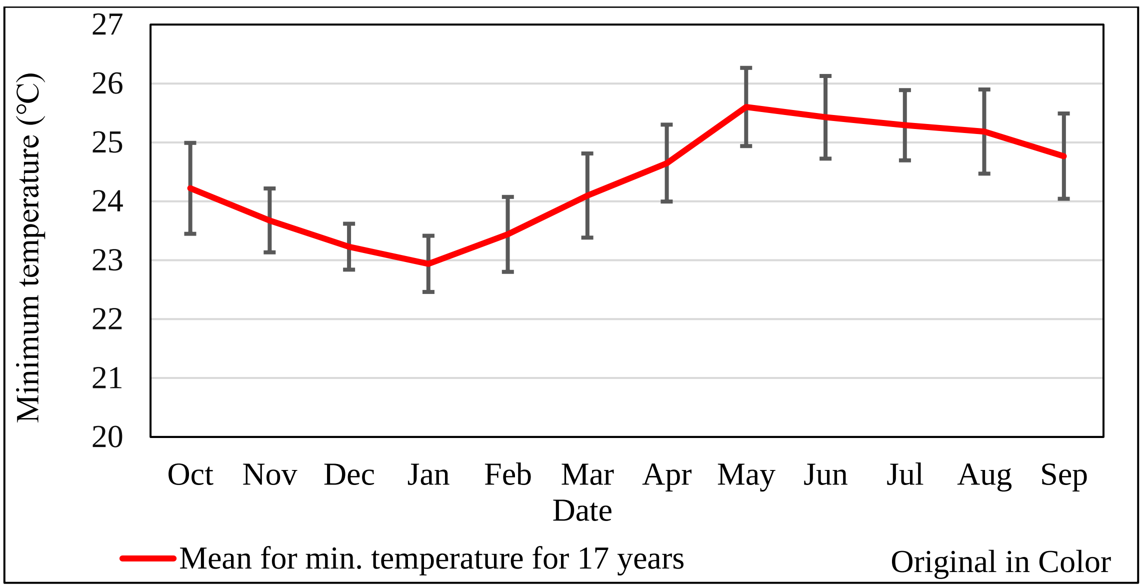


Figure 4-10 Minimum monthly temperature with standard deviation for sub basin of Kelani Basin in degree Celsius (Tmin. (°C))

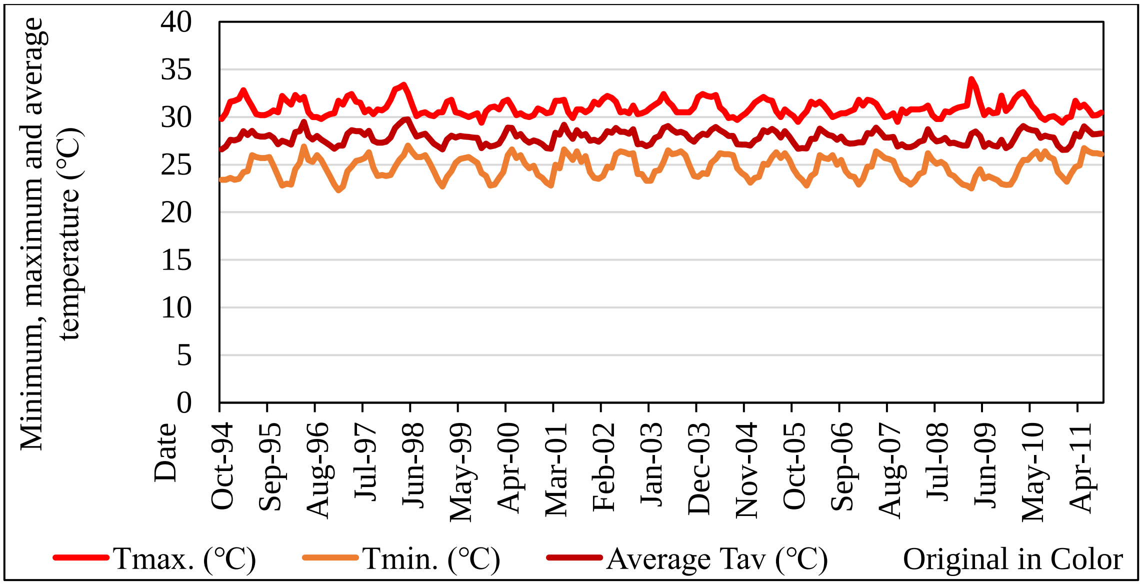


Figure 4-11 Minimum, maximum and average temperature from 1994~2011

The data checking for maximum and minimum temperature was carried out for temperature data for the entire period of 17 years on monthly bases. This monthly temperature data of 17 years was rearranged in annual order and the mean annual average temperature, standard deviation and other associated general statistics were estimated by omitting missing data sections of the particular year. The estimated standard deviation values were relatively low, indicating lesser data variability and thus the missing temperature data points can be replaced by using the estimated annual average data calculated as above. The calculation was separately carried out in excel spreadsheets for the maximum and minimum temperature. The data used extended over a period of 17 years with monthly resolution from October 1994 to September 2011. There were no missing data gaps in the minimum and maximum temperature series for Kelani basin. Still, data checking was carried out to see how the average values are deviating from the mean average value (Figs. 4-9 ~ 4-11).

4.2.5. Single mass curve for all rainfall station data for Kelani basin

The Fig. 4-12 shows the single mass curve for all rainfall gauging stations. This graph was plotted in order to visually compare and verify the relations in cumulative rainfall among the several nearby stations, so that data anomalies can be identified and in case of missing data, the data gaps can be filled data from the nearest station with nonempty data records. The figure shows Dunedin and Labugama rainfall stations having similar relation in their cumulating data series and similarly the stations Weweltalawa and Laxapana rainfall stations having slightly higher annual rainfall with similar relation between the two series.

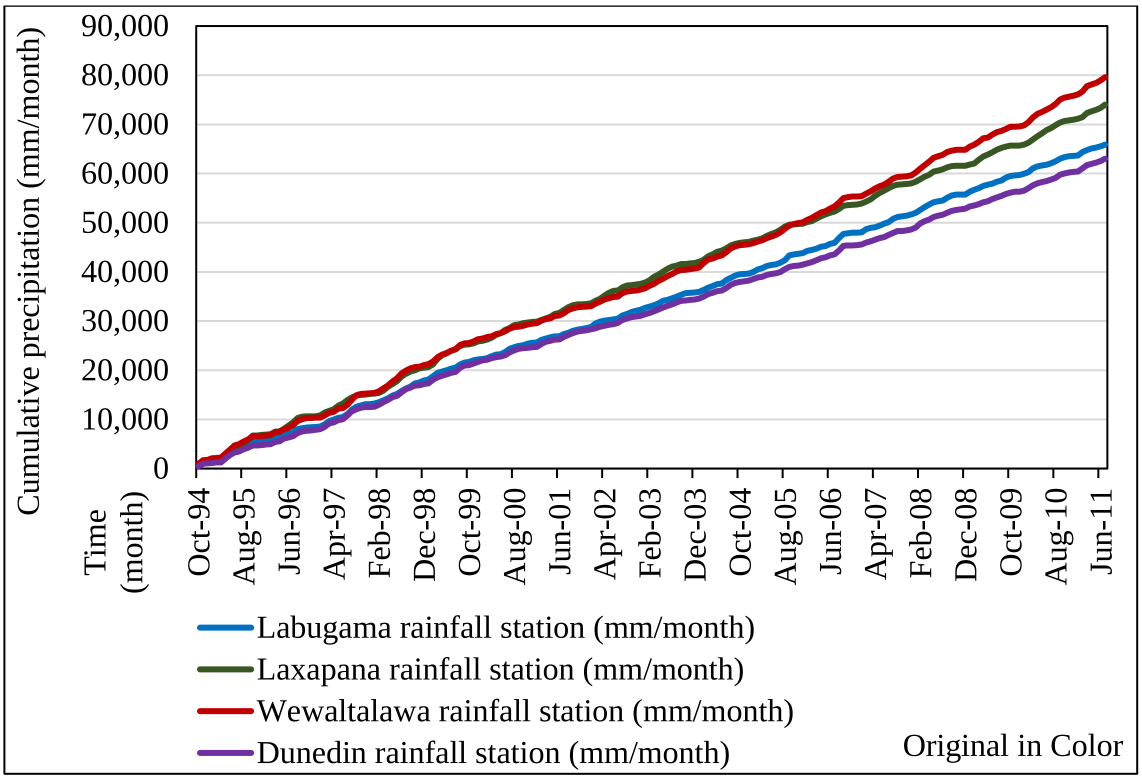


Fig. 4-12 Single mass curves of rainfall data of four selected stations in Kelani basin

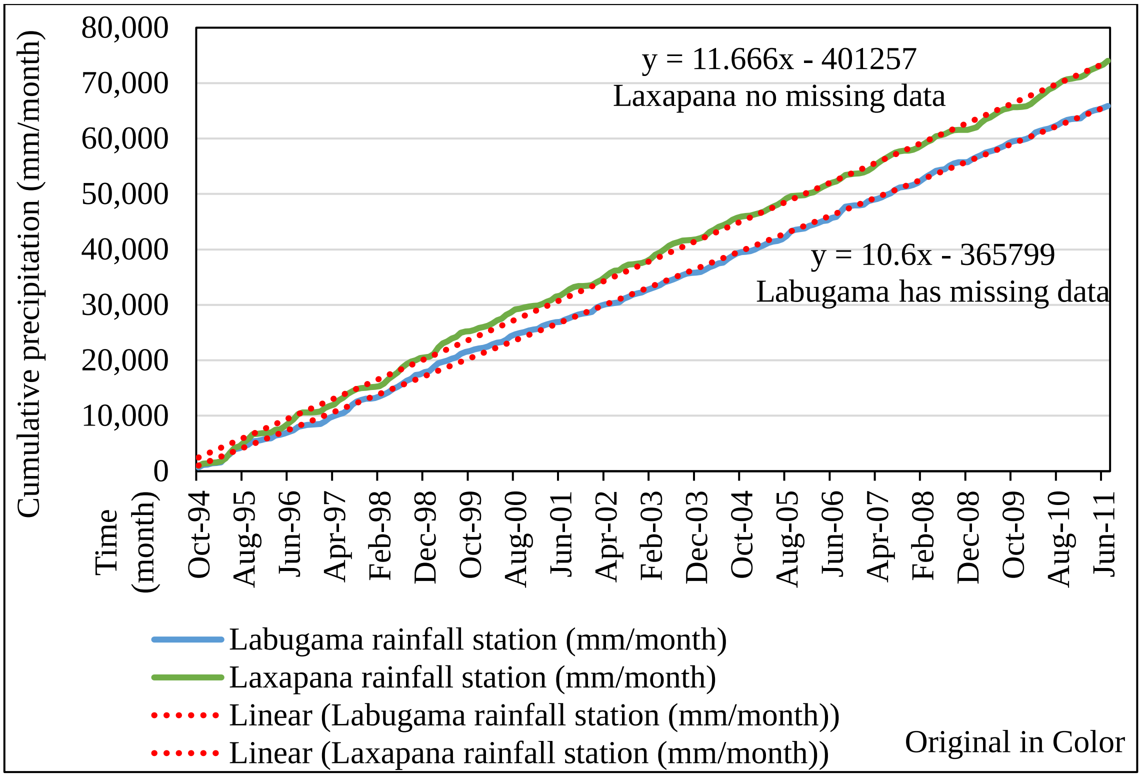


Fig. 4-13 Single mass curve for missing data filling for project area in Kelani Basin

The Fig. 4-13 graph shows the linear relation between two stations Labugama and Laxapana. The data sets were rearranged by omitting the missing data across the data series from other rainfall stations as well so that the same period of data will be removed from all data series in row wise order. Subsequently, the cumulative data series for each rainfall station was plotted. The resultant five cumulative plots help identifying similar trends or slope for curves without missing data. The curve with no missing data but located nearest to the rainfall station with missing data (in actual ground location) was identified. Then the ratio of slopes between the two curves with and without missing data was estimated and used in missing data gap filling by multiplying it with the rainfall data of the nearest rainfall station with no missing data (this data is selected from the series before rearrangement). After multiplication, this data was used in filling in missing data of that particular period from the multiplied data of that same period (Moeletsi et al., 2016).

The, $The\ slope\ ratio\ (S) = \frac{m_1}{m_2}$, $m_2 =$ 366.3 and m_1= 323.68

$S = \frac{323.68}{366.3} = 0.9$, therefore $Missing\ data = 0.9\ \times Pt$

where, Pt is precipitation from nearest station with no missing data, m_1 is the slope for the missing data station and m_2 is the slope for the nearest station with no missing data.

4.2.6. Double mass curve

Double mass curve was the second step in data checking carried out after the filling of the missing data. The data was arranged in annual order for all rainfall stations and the monthly average for all rainfall stations of the particular basin was estimated. Double mass curve is usually applied for consistency checking and even used for data filling (Wijesekera & Perera, 2016). The resultant graph below (Fig. 4-14) shows that there is no significant difference or deviation after filling in the missing rainfall data for Labugama station in the project area, confirming that the gap filling to replace missing data has not affected the inherent characteristics of the data series.

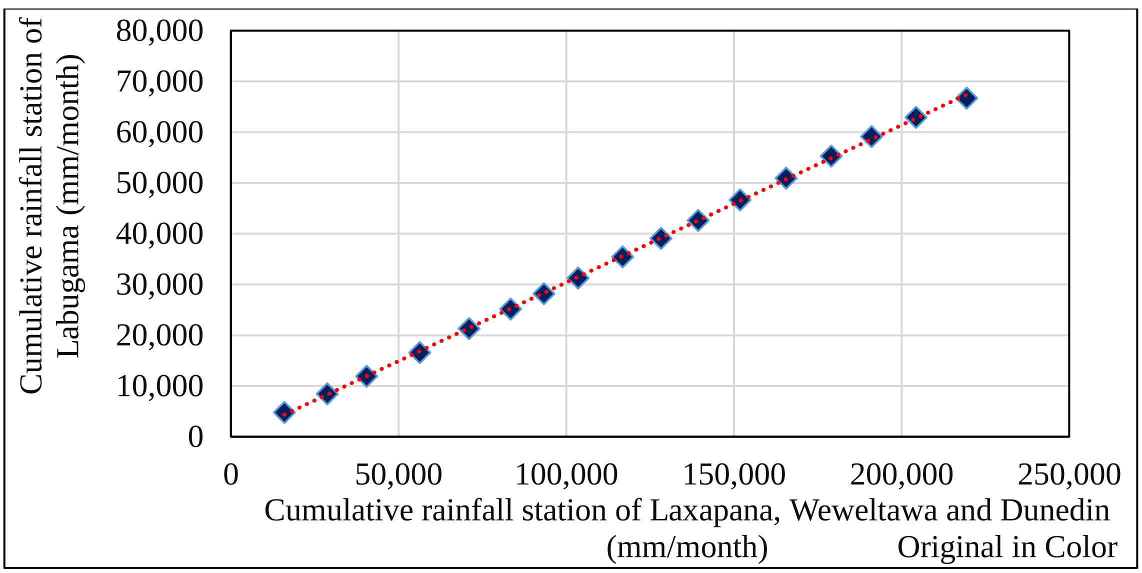


Fig. 4-14 Double mass curve of Labugama station in Kelani Basin

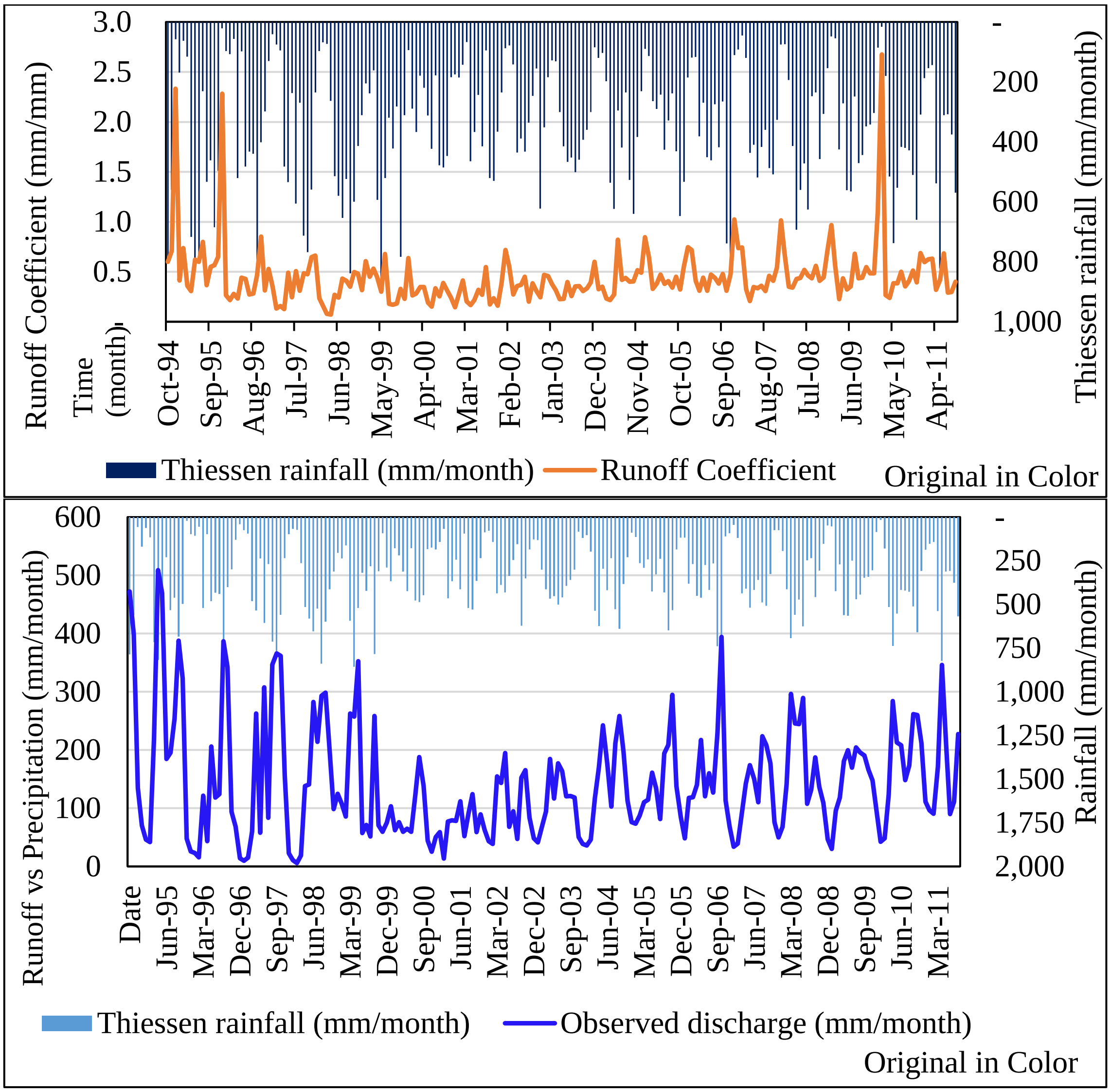
Table 4-5 Cumulative rainfall for project area in Kelani Basin

Date	Annual sum for 3 rainfall data	Cumulative for average rainfall data	Cumulative for single rainfall data
1994-1995	15935.3	15935.3	4776.9
1995-1996	12795.8	28731.1	8459.3
1996-1997	11773.8	40504.9	11877.6
1997-1998	15800.6	56305.5	16549.1
1998-1999	14677.0	70982.5	21289.8
1999-2000	12399.1	83381.6	25127.8
2000-2001	9942.1	93323.7	28143.2
2001-2002	10267.3	103591.0	31260.7
2002-2003	13190.8	116781.8	35424.0
2003-2004	11460.0	128241.8	39106.0
2004-2005	11069.8	139311.5	42622.7
2005-2006	12504.8	151816.3	46661.3
2006-2007	13751.1	165567.4	50902.9
2007-2008	13447.7	179015.1	55259.1
2008-2009	12081.7	191096.8	59092.7
2009-2010	13193.1	204289.9	62904.3
2009-2011	15087.1	219376.9	66664.9

In the selected sub-watershed in Kelani Basin, there are four rain gauge stations and the Table 4-5 shows the calculation of total annual average for the three rainfall stations Dunedin, Laxapana, Weweltalawa, and similar calculation was performed for the Labugama station data, separately. The cumulative sum for average rainfall was then calculated for the two respective data series. The double mass curve was then plotted between cumulative annual average of three stations versus the total annual average of the selected principal single station (Labugama rainfall station).

4.2.7. Runoff coefficient

The runoff coefficient (i.e. the ratio of stream flow/precipitation) is calculated from the observed rainfall and streamflow and it varies from month to month and year to year (Fig. 4-15). Effects of regulation, diversion and land use changes can be manifested as trends or significant shifts in the ratio, which is an important state variable for the sub region. The vector of runoff coefficients provides a macro-measure of the state of the aquatic environment, and the soil moisture vector provide an analogous state parameter for the related land resources and hence the environmental quality (Thomas Jr., 1981).



Fig, 4-15 Runoff coefficient vs. Precipitation and Runoff for monthly data

5. ANALYSIS AND RESULTS

5.1. Data Preparation for Model Input

Table 5-1 presents the respective areas falling under each rainfall gauging stations in sub-watershed in Kelani basin up to Glencorse stream gauge station and World Meteorological Organization (WMO) has recommended area coverage per rain gauge station in similar terrain. The total area of the Glencorse sub-watershed is 1564.8 km^2.

Table 5-1 Thiessen rainfall calculation for project area in Kelani Basin

No.	Name of stations	Area density (km^2)	WMO standard km^2 (area/station)
1	Labugama	150.7	575
2	Laxapana	544.1	575
3	Weweltalawa	436.5	575
4	Dunedin	433.5	575
5	Glencorse (Qo)	Total area = 1564.8	1875

The Thiessen weights for individual rainfall gauging station were estimated based on their area coverage as follows:

Thiessen weightage = Thiessen area / Total area

Thiessen weighted rainfall = Thiessen weightage x Pt (Precipitation of individual station)

Total Thiessen weighted rainfall = Total of all four rainfall stations of same monthly date

This Thiessen weighted rainfall is the input rainfall for the model calibration and validation which led to the model output as the simulated streamflow. Overall correlation for this Thiessen weighted rainfall and observed discharge was around 0.68. However the data was divided into two parts for calibration and validation period.

5.2. Model Selection and Model Development

The ABCD Water balance model was selected and the model was developed as an Excel spreadsheet model according to the governing equations given below. The model was verified by comparing between manual calculations and spreadsheet model calculations. The specimen calculation has been given in Appendix-B which also shows the remaining part for the model development method carried out in the study. The ABCD Water Balance Model contains two (2) storage compartments, namely Upper soil storage and Lower soil storage components which are controlled by two parameters b and c, respectively, although the model altogether contains four (4) parameters.

5.2.1. Soil moisture upper layer

Upper soil storage (QUt) which contributes to direct runoff is controlled by parameter b. Therefore, QU_t = (1 - c) * (W_t - Y_t) where W_t is available water and Y_t is evapotranspiration opportunity. During the calibration, the initial upper soil storage was 338.2 mm.

W_t = 'Availability of water' is the current time step and defined as,

$$W_t = S_t + P_t \quad = S_t + ET_t \quad + GR_t \quad + DR_t \quad \ldots\ldots\ldots\ldots\ldots\ldots \text{(1)}$$

Y_t= Evapotranspiration opportunity of the system and mathematically defined as,

$$Y_t = S_t + ET_t = Y_t = \frac{W_t + b}{2a} - \sqrt{\left(\frac{W_t + b}{2a}\right)^2 - \left(\frac{bW_t}{a}\right)} \quad \ldots\ldots\ldots\ldots\ldots\ldots \text{(2)}$$

P_t= Precipitation

$$S_t = \text{Soil moisture } S_t = Y_t e^{\frac{-PET_t}{b}} \quad \ldots\ldots\ldots\ldots\ldots\ldots \text{(3)}$$

PET_t = Potential evapotranspiration (mm) that was calculated using an equation such as the following Penman and Hargreaves equation.

$PET_t = e.PET_{EQ}$,

where e is a calibration parameter that was newly introduced to the original ABCD model, and PET_{EQ} as potential evapotranspiration.

ET_t = Actual evapotranspiration $ET_t = Y_t(1 - e^{\frac{-PET_t}{b}})$ ……….……….….……… (4)

DR_t = Direct runoff DR_t = $DR_t = (1 - c)(W_t - Y_t)$ …………….……..…………….. (5)

GR_t = Groundwater recharge $GR_t = c \times (W_t - Y_t)$ ……………...………………… (6)

5.2.2. Soil moisture lower layer

Lower soil zone is controlled by parameter c, while the lower soil storage (XL_t) contributes to direct runoff. Where $R_t = c*(W_t - Y_t)$, where W_t is available water and Y_t is evapotranspiration opportunity. During the calibration period, the lower soil storage at the end of the period was 199.9 mm

G_t = Groundwater storage $G_t = G_t + GD_t = G_{t-1} + GR_t$ ……………...…………… (7)

GR_t = Groundwater recharge $G_t = \frac{1}{1+d}(G_{t-1}GR_t)$ …………………………………. (8)

GD_t = Groundwater discharge $GD_t = dG_t$ ………………………………………….. (9)

By Jeffrey D. Walker, 2014.

$G_t = G_{t-1} + GR_t(1 + d) - 1$ Updated by Al-Latta, Al-Tawash, Al-Baldawi (2013)

Thus, Total streamflow $Q_t = GD_t + DR_t$ By Jeffrey D. Walker (2014).

5.3. Selection of Objective Function for Calibration and Validation

Though the primary objective functions are Nash–Sutcliffe Efficiency coefficient (NSE) and Mean Ratio of Absolute Error (MREA), still Pearson correlation coefficient (*r*) and Coefficient of determination (r^2) were also used, to describe the collinearity between simulated and observed data. It ranges from -1 to +1 and >0.5 is considered as an acceptable range.

$$Pearson\ R = \frac{\sum(\boldsymbol{Q_O}-\bar{\boldsymbol{Q}}_{\boldsymbol{O}})(\boldsymbol{Q_M}-\bar{\boldsymbol{Q}}_{\boldsymbol{M}})}{\sqrt{\sum(\boldsymbol{Q_O}-\bar{\boldsymbol{Q}}_{\boldsymbol{O}})^2(\boldsymbol{Q_M}-\bar{\boldsymbol{Q}}_{\boldsymbol{M}})^2}} \quad \ldots\ldots \textbf{(i)}$$

$$RSQ = R^2 = \left(\frac{\sum(\boldsymbol{Q_O}-\bar{\boldsymbol{Q}}_{\boldsymbol{O}})(\boldsymbol{Q_M}-\bar{\boldsymbol{Q}}_{\boldsymbol{M}})}{\sqrt{\sum(\boldsymbol{Q_O}-\bar{\boldsymbol{Q}}_{\boldsymbol{O}})^2(\boldsymbol{Q_M}-\bar{\boldsymbol{Q}}_{\boldsymbol{M}})^2}}\right)^{\boldsymbol{2}} \quad \ldots\ldots \textbf{(ii)}$$

The Nash-Sutcliffe efficiency NSE close to 1 being the optimal and value obtained between (0 to 1) as an acceptable performance and less than zero (<0) as observed discharge is better than model (D. N. Moriasi et al., 2007)

$$NSE = 1 - \frac{\sum_{i=1}^{n}(Q_O - Q_M)^2}{\sum_{i=1}^{n}(Q_O - \overline{Q_O})^2} \quad \ldots\ldots \textbf{(iii)}$$

$$MREA = \frac{1}{N} \times \frac{\sum(Q_O - Q_M)}{\sum Q_O} \quad \ldots\ldots \textbf{(iv)}$$

By using ABCD monthly water balance model in 764 catchments in United State for Toward improved identification of hydrological models: A diagnostic evaluation of the "*ABCD*" monthly water balance model for the conterminous United States (Martinez & Gupta, 2010b). They discovered that the model performance, parameter, and structure were correlated with hydro-climatic variable. However, they suggested that NSE or r^2

reported value can be misleading for future forecast due to lack of constraint model. Overall model calibration did not improve though the performance of calibration result has a given good results. They mentioned that problem cannot be only with data but also can be in model due to inability of the model structural hypothesis to represent the hydrological behavior across the United State.

5.4. Results for Model Calibration (Simulated vs. Observed Discharge)

The model calibration was carried out using Thiessen rainfall and potential evapotranspiration as input data. As described earlier, the model contains four parameters where parameter '*a*' is propensity to generate runoff, '*b*' is upper soil moisture, '*c*' is groundwater recharge and '*d*' is lower soil moisture contribution to runoff. The individual parameter adjustments to optimize the objective function was carried out using the manual operation as well as Solver and Goal Seek functions in Excel.

The model simulated discharge versus observed discharge for Thiessen rainfall series in Glencorse watershed is presented in Figs. 5-1 and 5-2 while the scatter plot and flow duration curve are shown in Figs. 5-3 and 5-4, respectively.

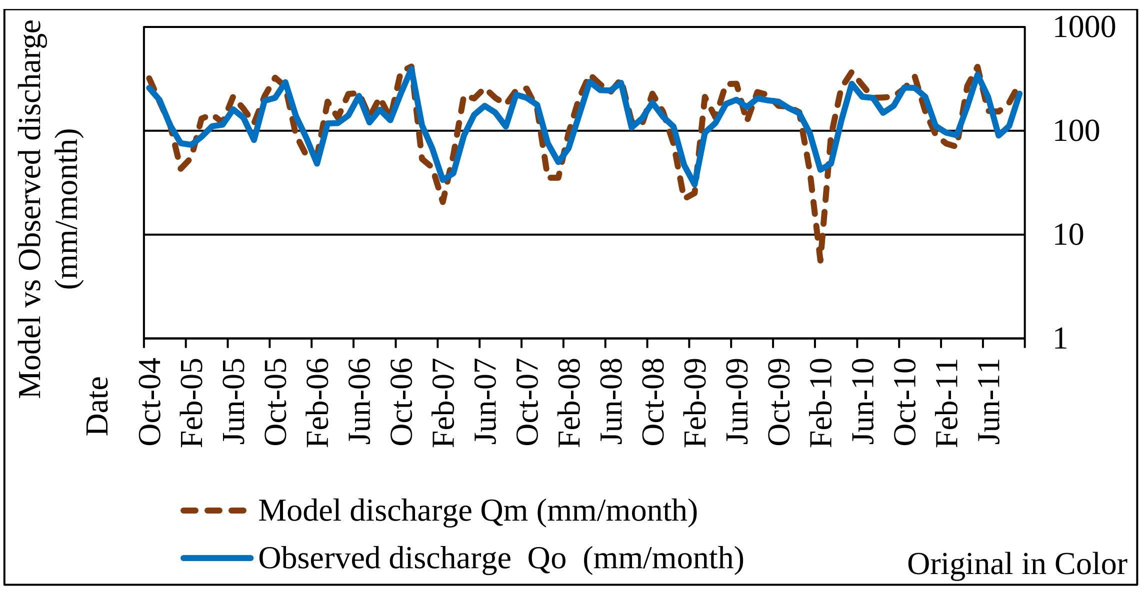


Figure 5-1 Simulated vs. observed discharge (for calibration)

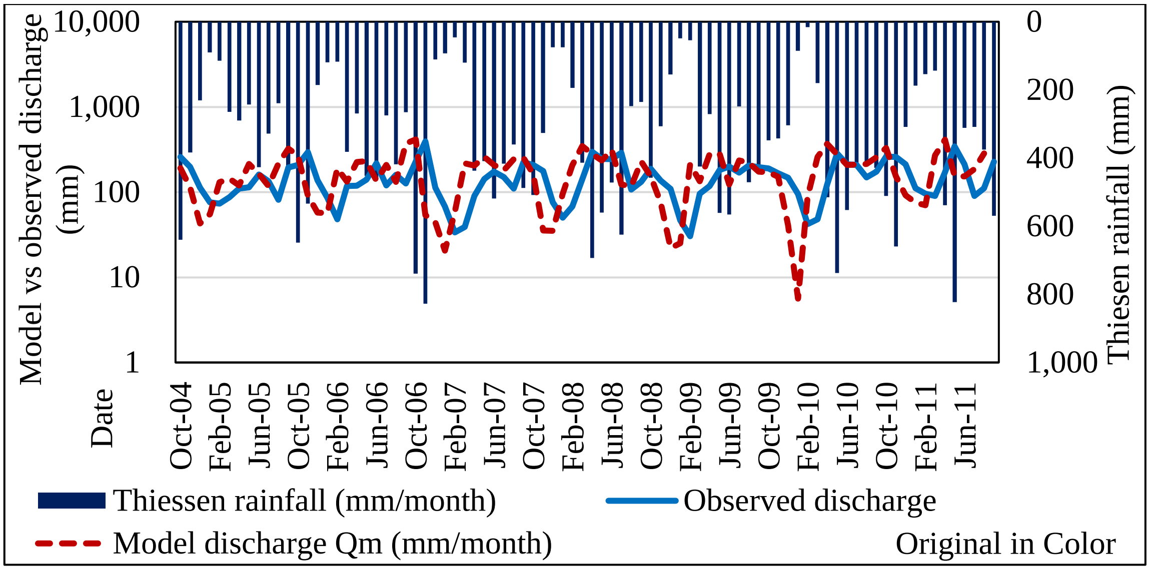


Figure 5-2 Model vs. observed discharge (with Thiessen rainfall for calibration)

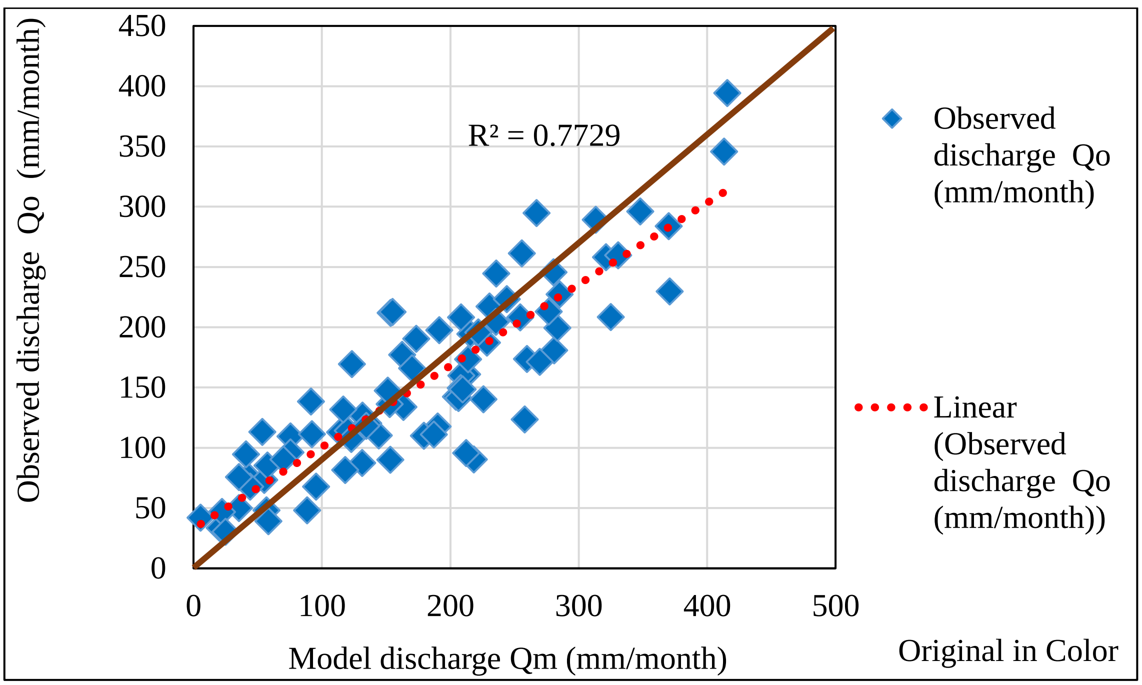


Figure 5-3 Scattered plot graph for calibration period

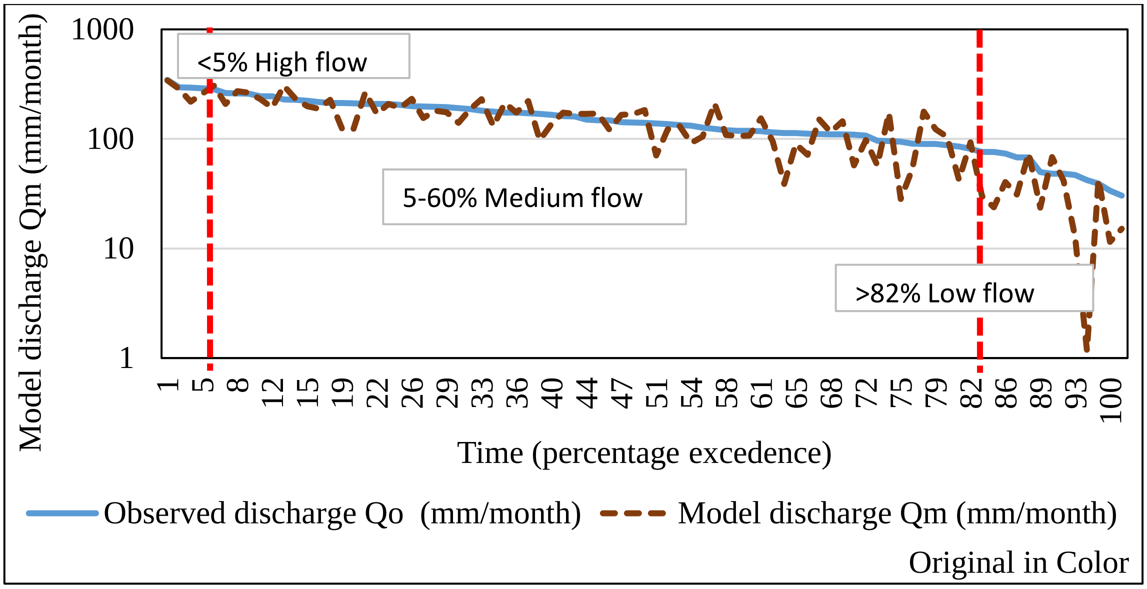


Figure 5-4 Flow duration curve for calibration period

Table 5-2 Water balance for calibration period

Date	Annual Thiessen rainfall (mm)	Glencorse stream flow (mm)	Model discharge (mm)	Annual observed water balance (mm)	Simulated water balance (mm)	Annual water balance difference (mm)
2004-2005	3680.2	1601.4	1468.1	2078.8	2212.1	-133.3
2005-2006	4123.5	1776.1	1656.4	2347.4	2467.1	-119.7
2006-2007	4564.4	1767.7	1844.7	2796.8	2719.7	77.1
2007-2008	4425.3	2035.6	1785.1	2389.7	2640.2	-250.4
2008-2009	4007.8	1674.6	1607.8	2333.1	2400.0	-66.9
2009-2010	4345.3	1839.6	1753.5	2505.7	2591.7	-86.1
2010-2011	4889.2	2189.6	1982.4	2699.6	2906.8	-207.2
Total =	30035.7	12884.5	12098.1	17151.2	17937.6	-786.5

The above Table 5-2 shows the annual water balance calculated with observed and simulated discharges. The highest annual rainfall was 4889.2 mm/month and the lowest was 3680.2 mm/month in the year of 2010/2011 and 2004/2005, respectively.

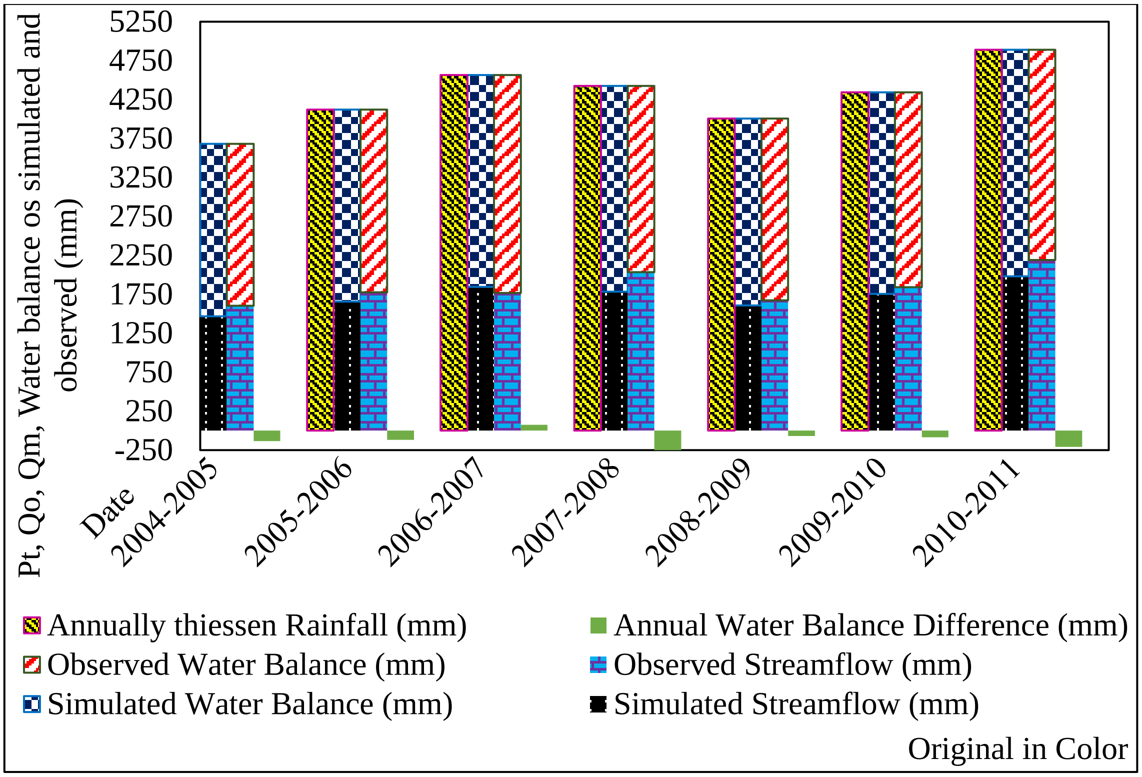


Figure 5-5 Water balance graph for calibration period

The Fig. 5-5 shows the water balance for observed and simulated stream discharge series and annual water balance difference in the sub-basin. The highest observed water balance was 2699.6 mm in the year 2010/2011 and the lowest was 2078.8 mm in 1994/1995. For the model simulated discharge series, the highest water balance was 2906.8 mm in 2010/2011 and the lowest was 2212.1mm in the year 1994/1995.

However, the water balance here has been estimated disregarding the evapotranspiration component and for a better understanding of available water resources, it is crucial to include this into consideration, especially in dry zone basins.

5.5. Results for Model Validation (Model vs. Observed Discharge)

Similarly, the results for the validation period are illustrated in Figs. 5-6 to 5-10 and Table 5-3 and almost identical behavior as that of calibration period was observed.

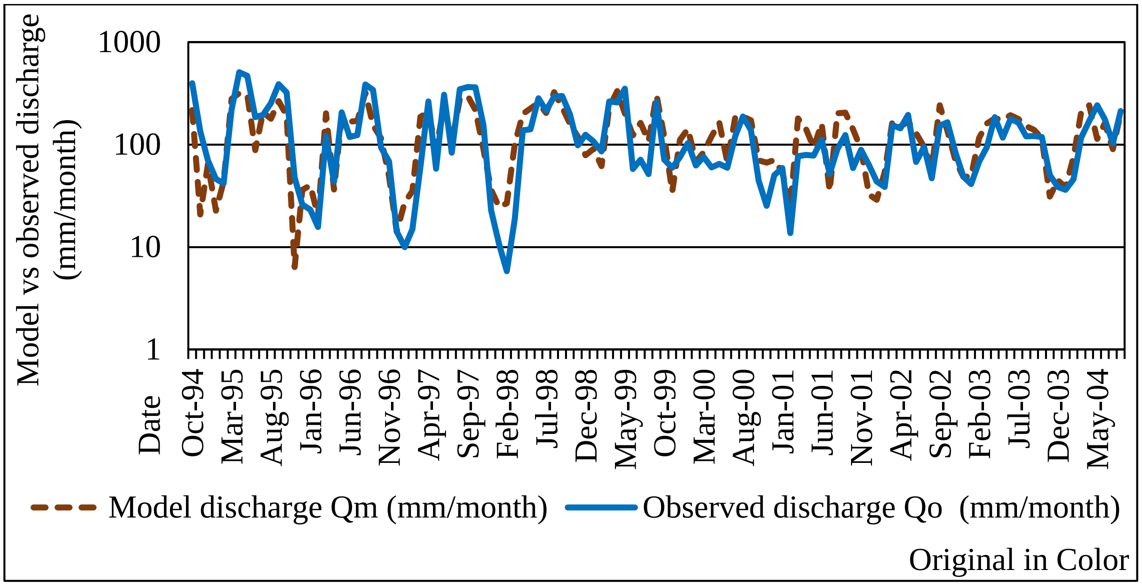


Figure 5-6 Model vs. observed discharge (for validation)

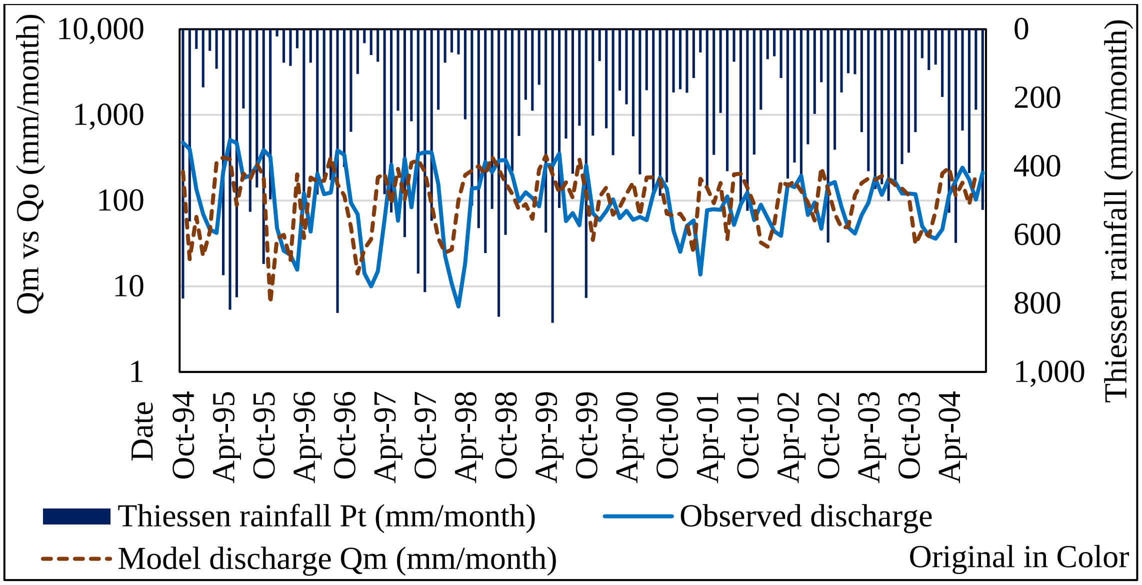


Figure 5-7 Model vs. observed discharge (with Thiessen rainfall for validation)

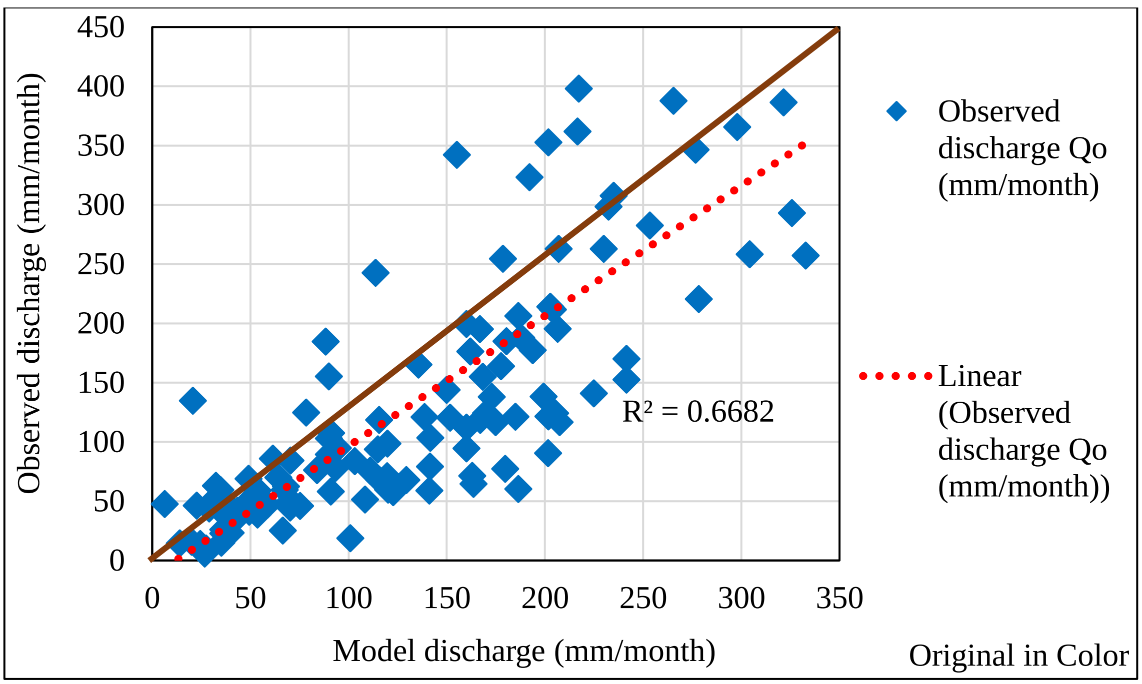


Figure 5-8 Scattered plot graph for validation period

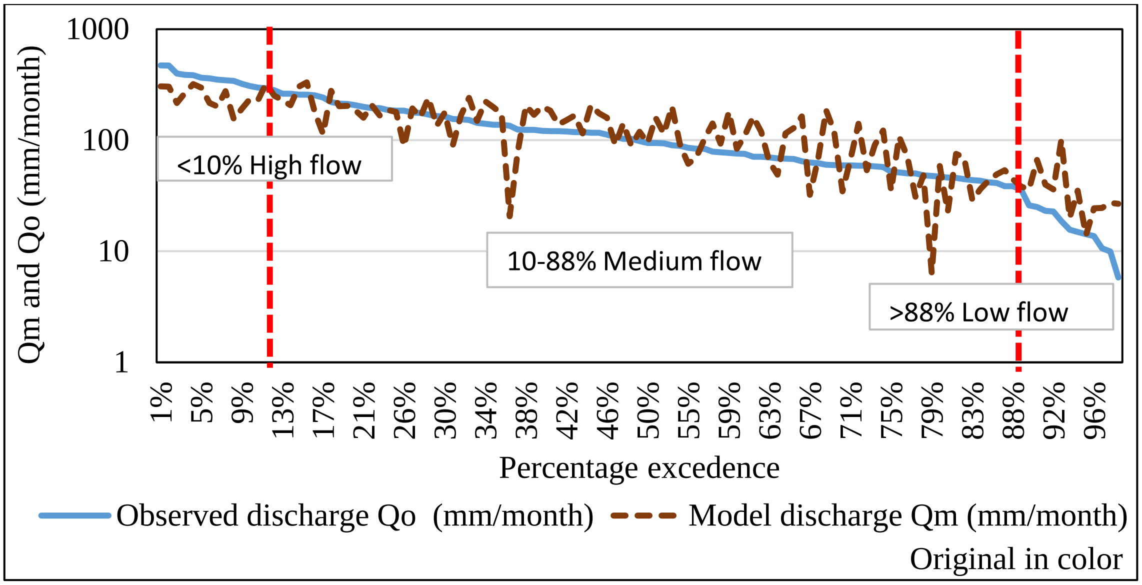


Figure 5-9 Flow duration curve for validation period

Table 5-3 Water balance for validation

Date	Annually Thiessen rainfall (mm)	Glencorse streamflow (mm)	Model discharge (mm)	Annually observed water balance (mm)	Simulated water balance (mm)	Annual water balance difference (mm)
1994-1995	5294.9	2995.9	2046.6	2299.1	3248.4	-949.3
1995-1996	4263.7	1823.3	1643.6	2440.5	2620.2	-179.7
1996-1997	3882.9	1662.6	1494.8	2220.3	2388.1	-167.8
1997-1998	5173.8	2009.3	1999.0	3164.6	3174.8	-10.3
1998-1999	4924.3	1966.7	1901.5	2957.6	3022.8	-65.2
1999-2000	4119.9	1198.2	1587.3	2921.7	2532.6	389.1
2000-2001	3307.6	819.2	1270.0	2488.4	2037.6	450.9
2001-2002	3433.8	1120.5	1319.3	2313.2	2114.4	198.8
2002-2003	4406.1	1416.7	1699.1	2989.5	2707.0	282.4
2003-2004	3800.9	1430.3	1462.7	2370.6	2338.2	32.4
Total =	42608.1	16442.6	16424.0	26165.4	26184.1	-18.7

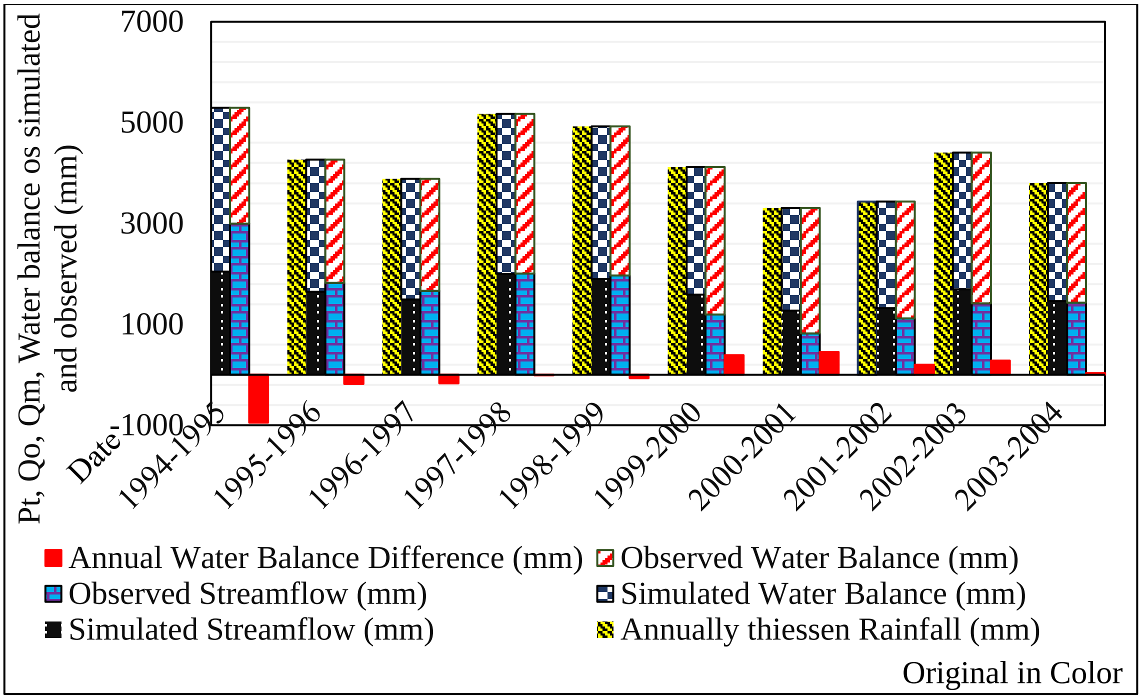


Figure 5-10 Water balance graph for validation

5.6. Parameter Sensitivity Analysis and Model Optimization

The model parameter sensitivity analysis was carried out to identify the model response to its governing parameters in order to facilitate model calibration, validation and optimization procedures. The model optimization was the carried out to find the optimum value for the ABCD parameters *a*, *b*, *c*, and *d* for the selected sub basin up to Gelncorse stream gauging station in Kelani Basin. Objective functions used for the parameter optimization were Pearson, RMSE, RSQ and NSE (Nash & Sutcliffe (1970)).

The NSE ranges between $-\infty$ and 1.0 (1 inclusive), with NSE = 1 being the optimal value. Values between 0.0 and 1.0 were generally viewed as acceptable levels of performance, whereas values $\leq$0.0 indicating that the mean observed value as a better predictor than the simulated value, which shows unacceptable model performance.

Pearson's correlation coefficient (r) and coefficient of determination (R^2) describe the degree of collinearity between simulated and observed data. The correlation coefficient, which ranges from −1 to 1, is used as an index of the degree of linear relationship between observed and simulated data. If $r = 0$, no linear relationship exists. If $r = 1$ or -1, a perfect positive or negative linear relationship exists. Similarly, R^2 describes the proportion of the variance in measured data as explained by the model. The R^2 ranges from 0 to 1, with higher values indicating less error variance, and typically values greater than 0.5 were considered as an acceptable according to Santhi et al. (2001) and Van Liew et al. (2003). The RMSE, MAE, and MSE values of 0 is indicated as a perfect fit.

The following Tables 5-4 to 5-7 and Figs. 5-11 to 5-14 depict the results of the model sensitivity analysis and model optimization procedures carried out for the selected sub basin up to Gelncorse stream gauging station in Kelani Basin.

Table 5-4 Parameter a optimization for sub basin of Kelani Basin

With only Parameter *a* changed				**Best-fit-of model**			
a	**b**	**c**	**d**	**PEARSON**	**RSQ**	**NSE**	**MRAE**
0.50	20	0.58	0.01	0.90	0.773	0.71	0.271
0.55	20	0.58	0.01	0.90	0.773	0.71	0.271
0.60	20	0.58	0.01	0.90	0.773	0.71	0.271
0.65	20	0.58	0.01	0.90	0.773	0.71	0.271
0.70	20	0.58	0.01	0.90	0.773	0.71	0.272
0.75	20	0.58	0.01	0.90	0.773	0.71	0.272
0.80	20	0.58	0.01	0.90	0.773	0.71	0.272
0.85	20	0.58	0.01	0.90	0.773	0.71	0.273
0.90	20	0.58	0.01	0.90	0.773	0.71	0.273
0.95	20	0.58	0.01	0.90	0.773	0.71	0.274
0.98	20	0.58	0.01	0.90	0.773	0.71	0.274
1.00	20	0.58	0.01	0.90	0.773	0.71	0.274

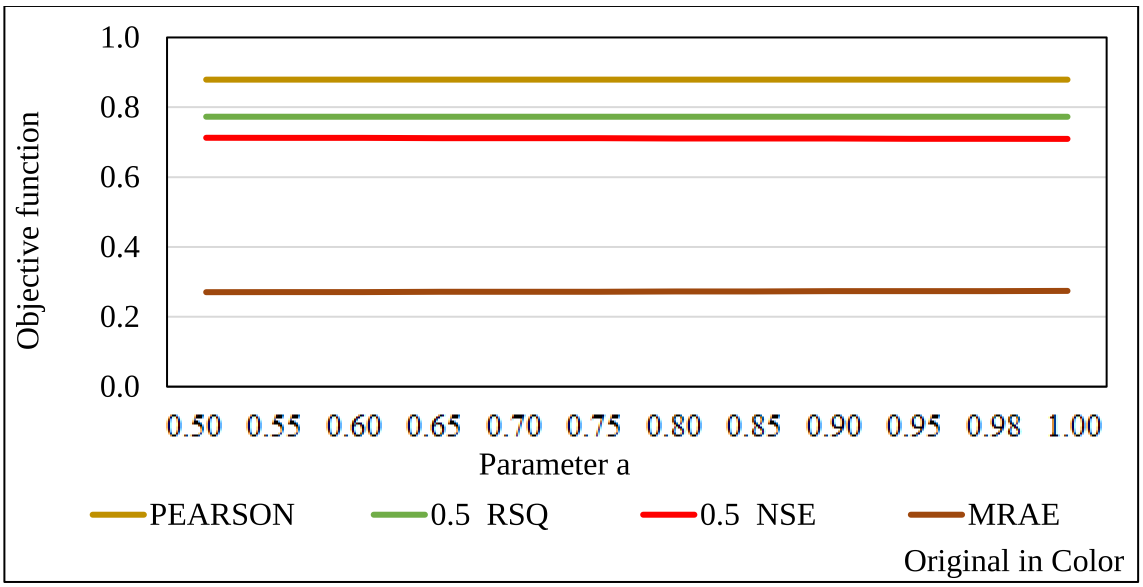


Figure 5-11 Parameter *a* optimization graph for best-fit

Table 5-5 Parameter a optimization for project area in Kelani Basin

With only Parameter *b* changed				**Best-fit-of model**			
a	**b**	**c**	**d**	**PEARSON**	**RSQ**	**NSE**	**MRAE**
0.99	5.00	0.58	0.01	0.90	0.773	0.72	0.261
0.99	10.00	0.58	0.01	0.90	0.773	0.72	0.265
0.99	15.00	0.58	0.01	0.90	0.773	0.72	0.270
0.99	20.00	0.58	0.01	0.90	0.773	0.71	0.274
0.99	25.00	0.58	0.01	0.90	0.773	0.70	0.279
0.99	30.00	0.58	0.01	0.90	0.773	0.69	0.284
0.99	35.00	0.58	0.01	0.90	0.773	0.68	0.291
0.99	40.00	0.58	0.01	0.90	0.773	0.67	0.298
0.99	45.00	0.58	0.01	0.90	0.773	0.66	0.305
0.99	50.00	0.58	0.01	0.90	0.773	0.64	0.313
0.99	55.00	0.58	0.01	0.90	0.773	0.63	0.321
0.99	60.00	0.58	0.01	0.90	0.772	0.61	0.329

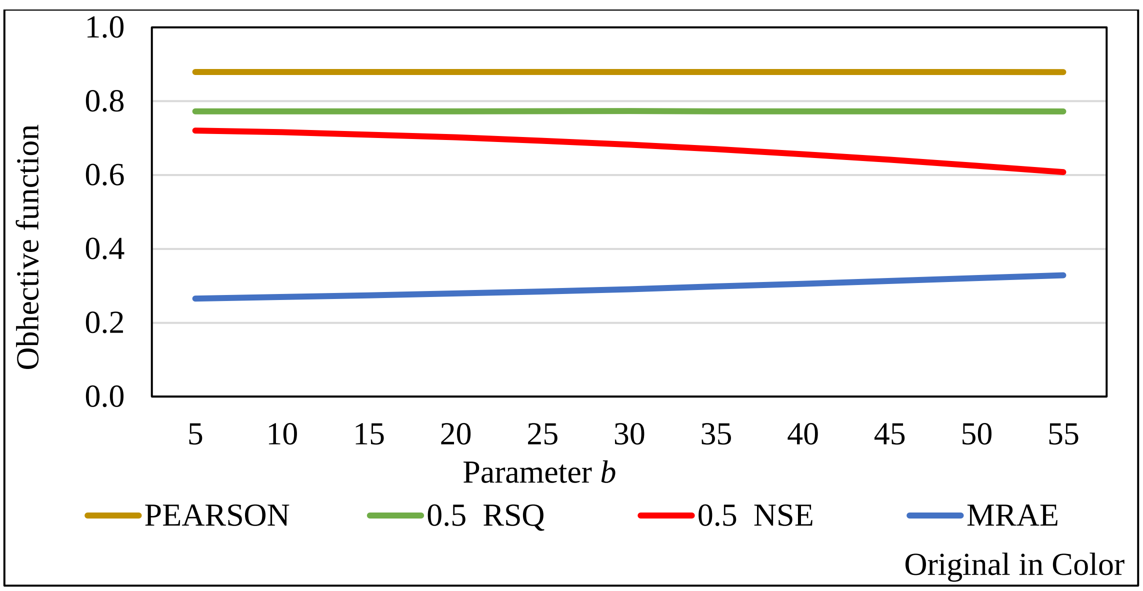


Figure 5-12 Parameter *b* optimization graph for best-fit

Table 5-6 Parameter *c* optimization for selected area in Kelani Basin

With only Parameter *c* changed				Best-fit-of model			
a	**b**	**c**	**d**	**PEARSON**	**RSQ**	**NSE**	**MRAE**
0.99	10	0.10	0.01	0.90	0.773	-5.89	1.048
0.99	10	0.15	0.01	0.90	0.773	-4.60	0.945
0.99	10	0.20	0.01	0.90	0.773	-3.46	0.842
0.99	10	0.25	0.01	0.90	0.773	-2.45	0.743
0.99	10	0.30	0.01	0.90	0.773	-1.58	0.648
0.99	10	0.35	0.01	0.90	0.773	-0.85	0.561
0.99	10	0.40	0.01	0.90	0.773	-0.26	0.478
0.99	10	0.45	0.01	0.90	0.773	0.19	0.398
0.99	10	0.50	0.01	0.90	0.773	0.51	0.327
0.99	10	0.60	0.01	0.90	0.773	0.72	0.264
0.99	10	0.65	0.01	0.90	0.773	0.62	0.284
0.99	10	0.70	0.01	0.90	0.773	0.38	0.345

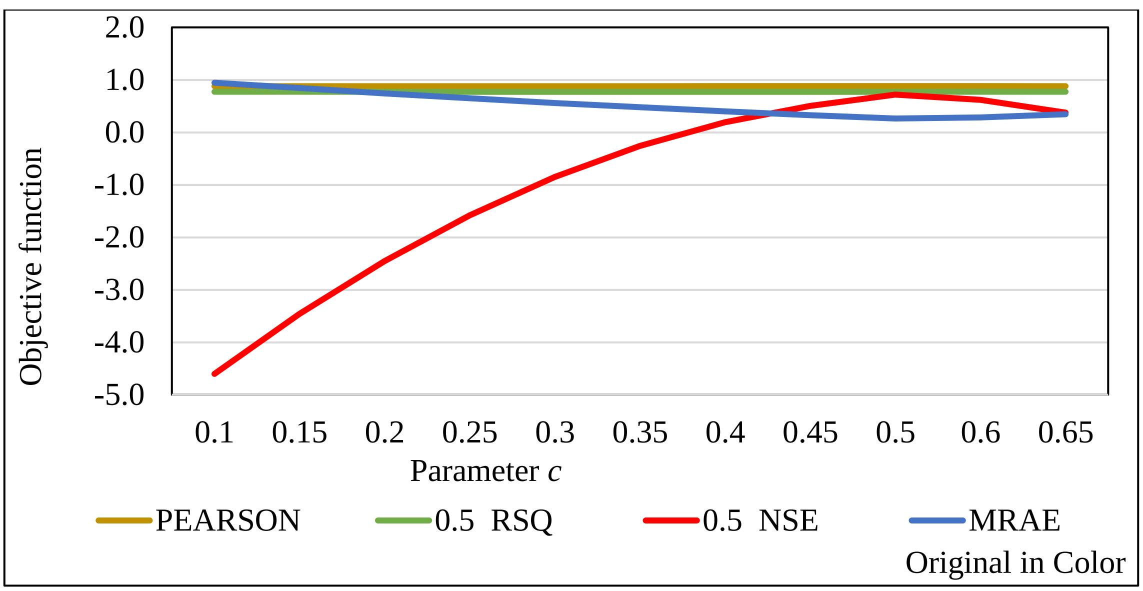


Figure 5-13 Parameter *c* optimization graph for best-fit

Table 5-7 Parameter d optimization for Kelani basin

With only Parameter *d* changed				**Best-fit-of model**			
a	**b**	**c**	**d**	**PEARSON**	**RSQ**	**NSE**	**MRAE**
0.99	10	0.65	0.001	0.90	0.773	0.60	0.290
0.99	10	0.65	0.005	0.90	0.773	0.61	0.287
0.99	10	0.65	0.002	0.90	0.773	0.60	0.289
0.99	10	0.65	0.004	0.90	0.773	0.60	0.288
0.99	10	0.65	0.006	0.90	0.773	0.61	0.286
0.99	10	0.65	0.008	0.90	0.773	0.61	0.285
0.99	10	0.65	0.010	0.90	0.773	0.62	0.284
0.99	10	0.65	0.020	0.90	0.773	0.64	0.280
0.99	10	0.65	0.040	0.90	0.773	0.68	0.272
0.99	10	0.65	0.080	0.90	0.773	0.72	0.263
0.99	10	0.65	0.090	0.90	0.773	0.72	0.263
0.99	10	0.65	0.100	0.90	0.773	0.72	0.264

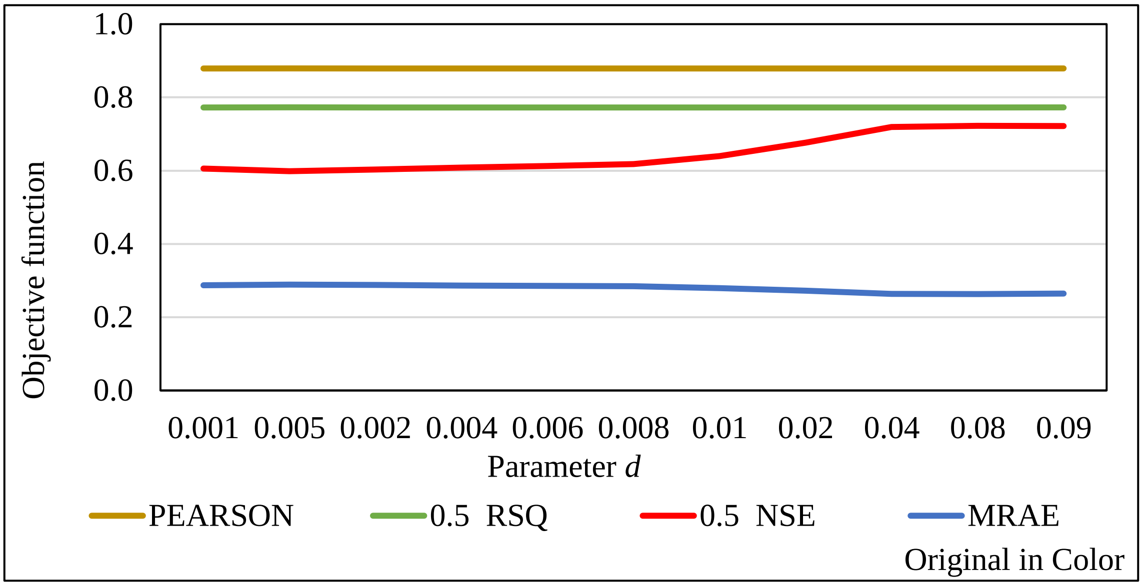


Figure 5-14 Parameter *d* optimization graph for best-fit

Parameter optimization was carried out in two different ways, one by using a procedure similar to auto-calibration using Excel Solver function in the Excel spreadsheets and the other, by manually changing the parameter values systematically within identified range and monitoring the effected variation in model output through the objective function.

The above Fig. 6-11 shows the variation observed in the objective functions when only parameter '*a*' was changed from the lowest 0.5 to the largest value 1 (one) within the allowable range of 0-1 (zero to one). The all other parameter values were fixed and the parameters *b* was kept at 20.0, *c* at 0.58 and *d* at 0.01 during the entire sensitivity analysis procedure for parameter *a*. Similarly, this method was carried out for all four parameters and it was noticed that the using of automatic solver function did not produce satisfactory results up to the required level of acceptance. However, it is always better to be used first by maintaining the parameters within the standard range to understand the response of objective functions to the incorporated changes in model parameters.

6. DISCUSSION

6.1. Discussion

The comprehensive literature survey, data collection and data checking, model selection and model formulation, model calibration/validation/sensitivity analysis and model optimization led to the better insight and understanding of the ABCD model and its applicability to the selected sub-basin up to Glencorse stream gauging station in Kelani Basin and the findings and their implications are discussed herein in this section.

It was noted that identification of initial moisture storage and fixing it at a reasonable value could increase the model results for the initial period significantly. Otherwise, a significantly long (up to about 3 months) data set from model warming up period led to reduction in optimum objective function values and was required to be removed from the data set. This has earlier been discussed under the weakness of model and it was claimed that the assumption of soil moisture storage led to unrealistic simulation values as mentioned by Alley (1984) and later confirmed by Vandewiele et al. (1992). This otherwise requires detailed information on land use and antecedent moisture conditions to estimate pre-estimate initial soil moisture storage values, yet no exact procedure to do so is elaborated. However question also remains practicability of such model inputs due to little snow or no snow cover (not applicable to the context of tropics) as mentioned by Al-Lafta et al. (2013).

Among the major strengths of the model, its simplicity and convenience in parameter estimation, simulation, linkage to physical phenomenon, availability of literature and detail parameter information and the broad application range of different time resolutions based on annual, monthly or daily data have been highlighted while the model applications using annual, daily by Thomas Jr. (1981) and monthly basis data by Alley et al. (1984) have been reported.

The model contains four (4) parameters *a*, *b*, *c*, and *d*, which ranges from zero to one (0 ~ 1) except parameter *b* which ca vary from 0 ~ 7000. While calibrating the model, it produced better results, when parameter *a* was 0.9 and parameter *b* was 10 (ten), parameter *c* was 0.58 and parameter *d* was 0.01 which is closer to zero (0). The other objective functions were also found to produce acceptable ranges with NSE of 0.72 and MRAE of 0.27 while the observed correlation (*r*) was 0.77 between the observed and the simulated. The model output was highly sensitive to the parameters *c* and *d* while parameters *a* and *b* were not that much sensitive as observed based on objective functions. However, this can vary from catchment to catchment as well as used objective function and opted management procedures depending on whether the catchments flows are dominated by runoff or baseflow conditions, and whether the interest is of water resources (governed by low flow conditions) or flood management (governed by high flow conditions).

Although up to fifty percent of soil moisture contribution was observed from the upper soil zone to lower soil zone, the model was able to perform reasonably and produce acceptable simulated stream discharge. This proves that the upper soil zone was acting as a saturated soil bed with a monthly average upper soil storage of 142.03 mm while the lower soil storage was 2.0 mm. The results also give an indication that the nature of sub basin to produce discharge was largely independent of the intensity of rainfall.

On the other hand, according to Fernandez et al. (2000), parameter *a* was well correlated with the soil permeability, which means if lower the value of parameter *a*, then lesser the infiltration into upper zone storage hence more the direct runoff. While parameter *b* was more related to permeability of soil and storage which means an increase in value of parameter *b* will decrease losses due to evapotranspiration (ETt). Parameter *c* controls the water movement from upper soil to lower soil zone while parameter *d* controls the recharge of groundwater to stream flow.

Hence, the selected ABCD model with four parameters (*a*, *b*, *c* and *d*) was deemed capable of representing the catchment conditions with sufficient accuracy as per the observed model behavior (Al-Lafta et al., 2013). Moreover, (Xu & Singh, 1998b) also concluded that three to five model parameters were sufficient to model catchment behavior or response (runoff) of basins in humid regions. Furthermore, comparing three different water balance models, Alley (1984a) commented that ABCD model was the strongest among the three models considered.

For the calibration run, the correlation between the simulated flow and observed flow was 0.77 with a NASH value of 0.72 and MRAE of 0.27. The model produced better response for medium flows in the range between 5% ~ 82% percent exceedance and reasonably good results for high flows below 5% percent exceedance. The model could not simulate well the low flow component and it was observed to be less than 18% of total flows.

For the validation period, the model parameter a remained the same at a value of 0.9, as established during the calibration. The parameter b and c were slightly adjusted to five (5) and 0.61, respectively, and with the parameter d at 0.001 which is closer to zero (0), the best fir was obtained with NSE of 0.66, MRAE of 0.5 while the correlation was 0.67.

The values of parameters *a*, *c* and *d* almost remained the same for both calibration and validation runs but slight change in parameter *b* allowed the validation run to achieve the same correlation value which was around 0.7 for observed and simulated flows. Hence, this further confirms the applicability of the model for this selected sub basin.

The model also proved as an acceptable tool for this basin with a NSE value of 0.72 and 0.71 for calibration and validation, respectively where it is mentioned that model is considered as acceptable if the NSE value obtained is greater than half (>0.5).

The model was highly sensitive to parameters *c* and *d*, however, this may vary from basin to basin depending on availability of soil moisture storage to sustain strong flow conditions under dry weather. This model with four parameters adequately reproduced the hydrological characteristics of the selected sub basin and hence suitable for streamflow forecasting and water resources management in the basin. The observed NASH value was 0.72 and MRAE value was 0.26 for parameter optimization.

The simulated Average monthly upper soil zone storage was 205.5 mm and its contribution to direct runoff was 146.1 mm while the simulated average monthly lower soil zone storage was 201.8 mm and its contribution to direct runoff was 2.1 mm. However, the average monthly total soil storage was 409.3 mm for calibration period. Further, the total simulated inflow was 30,035.70 mm, outflow was 12,445.97 mm, with a water balance of17,589.74 mm for calibration period of seven years.

The Figs. 5-4 and 5-9 show the flow duration curve for the simulated stream flow. The model has indicated good performance for medium flows in the range of 5% ~ 60% according to percent exceedance during calibration and range 10% ~ 88% during validation period with net storage of 786.48 mm and 44.54 mm, respectively.

Optimized parameter values during the calibration run were used for the model validation and no signification variation in optimized parameters was required for the model validation. Hence, it is proven that the model can be used for the water resources assessment in this sub basin of Kelani Basin.

According to Table 5-5, a decrease in NSE value is observed when parameter *b* is increased from minimum to maximum while keeping all the other parameters *a*, *c* and *d* at their optimized values. Similarly, the Table 5-6 shows a decrease in NSE when parameter *c* is increased from lower to higher value by setting the other parameters *a*, *b* and *d* at validated/standard values. Hence, these two parameters were affecting quite inversely to the NSE values and subsequently to the model efficiency at optimized level. The observed effect may be justified as when the soil moisture storage is higher, the groundwater conveyance to the lower soil compartment and recharge to the stream flow may also be influenced in positive direction.

Overall, the research study has helped better understanding and insight into the watershed characteristics, model behavior and its applicability to the selected sub basin while the research findings verify that model can be applied to basins with similar hydro-morphological attributes in the same region or elsewhere.

7. CONCLUSIONS AND RECOMMANDATIONS

7.1. Conclusions

1. The four-parameter monthly water balance model was developed and applied to the sub basin up to Glencorse stream gauging station in Kelani Basin and has been proven to be quite efficient in simulating the monthly runoff despite its simple structure and only four parameters.

2. The model output was highly sensitive to the parameters *c* and *d* while the model did not show much sensitivity to the parameters *a* and *b*.

3. Four parameter ABCD monthly water balance showed satisfactory performance while using Mean Relative Absolute Error (MRAE) and Nash–Sutcliffe Efficiency (NSE) coefficient as objective functions.

4. Four parameter ABCD monthly water balance model was successfully calibrated and verified. The MRAE value for calibration period was 0.26 while for verification period, the MRAE value was found as 0.50. The NSE value for calibration and validation were 0.72 and 0.61, respectively.

5. The four-parameter ABCD monthly water balance model has been proven to be quite efficient in simulating the monthly runoff with despite its simple structure and only four parameters, hence for its simplicity and high efficiency of performance, the model can easily and efficiently be incorporated in the water resource management in the selected basin or any other basin with similar hydro-morphological characteristics.

7.2. Recommendations

1. It is suitable to apply this model and its parameters to another basin location and to perform additional trials to check whether the same parameters would reproduce good results.

2. It is better to have sufficient and accurate data for more accuracy of model prediction of the result.

3. In the present study, it was found that the model output was highly sensitive to the parameters *c* and *d* while the model did not show much sensitivity to the parameters *a* and *b*. However, this may depend on whether the basin has an adequate soil moisture storage capacity and for the latter, parameter b and may become sensitive. This should be investigated further by using basins with and without sufficient soil moisture storage capacity (i.e. sub-watersheds in extreme upstream ends of a basin)

4. For its simplicity and high efficiency of performance, this four-parameter monthly water balance model can easily and efficiently be incorporated in the water resources management to simulate monthly runoff. However, further generalization of the results is recommended before using the model for any design or management purpose.

5. The sub basin water balance in the present study has been estimated disregarding the evapotranspiration component and for a better understanding of available water resources, it is crucial to include this into consideration, especially in dry zone basins.

6. The four parameter ABCD monthly water balance model may be a suitable option under data scarce situations for generating basin stream flow data in ungauged basins though model simulation simulation.

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LIST OF APPENDICES

APPENDIX A: DATA CHECKING

Appendix A1: Water Balance Checking

Table 6-1 Annual water balance in mm for data checking

Date	Annually Thiessen rainfall (mm/month)	Glencorse streamflow (mm/month)	Annually water balance (mm/month)
1994-1995	5294.9	2995.9	2299.1
1995-1996	4263.7	1823.3	2440.5
1996-1997	3882.9	1662.6	2220.3
1997-1998	5173.8	2009.3	3164.6
1998-1999	4924.3	1966.7	2957.6
1999-2000	4119.9	1198.2	2921.7
2000-2001	3307.6	819.2	2488.4
2001-2002	3433.8	1120.5	2313.2
2002-2003	4406.1	1416.7	2989.5
2003-2004	3800.9	1430.3	2370.6
2004-2005	3680.2	1601.4	2078.8
2005-2006	4123.5	1776.1	2347.4
2006-2007	4564.4	1767.7	2796.8
2007-2008	4425.3	2035.6	2389.7
2008-2009	4007.8	1674.6	2333.1
2009-2010	4345.3	1839.6	2505.7
2009-2011	4889.2	2189.6	2699.6
Total	72643.8	29327.2	43316.6

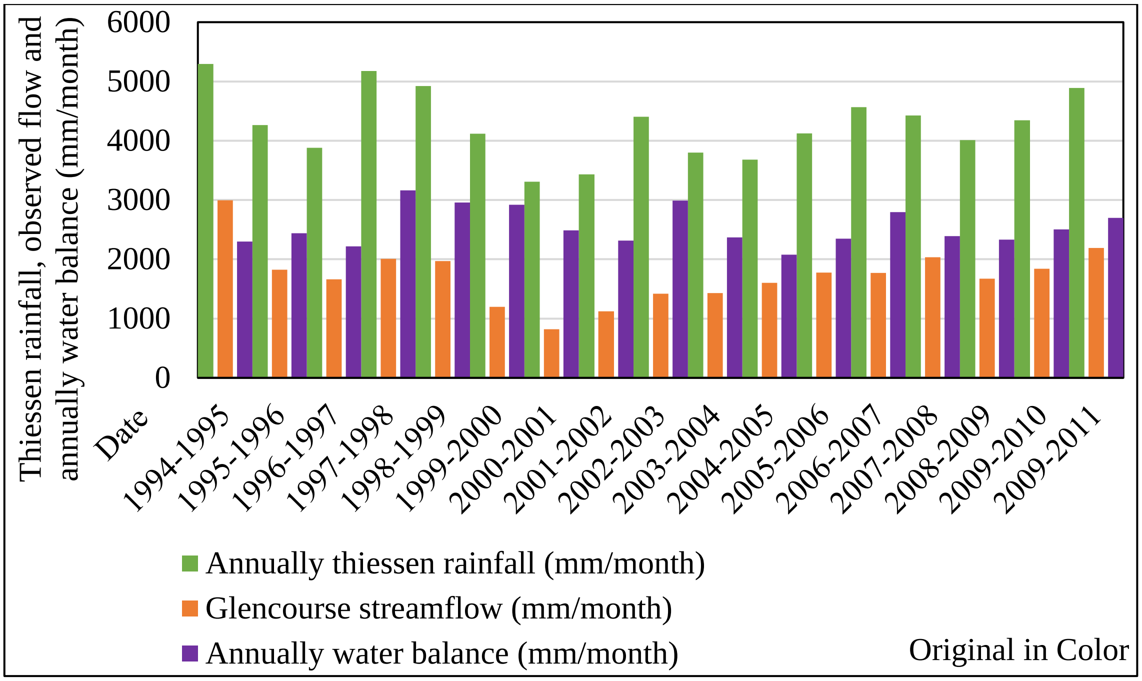
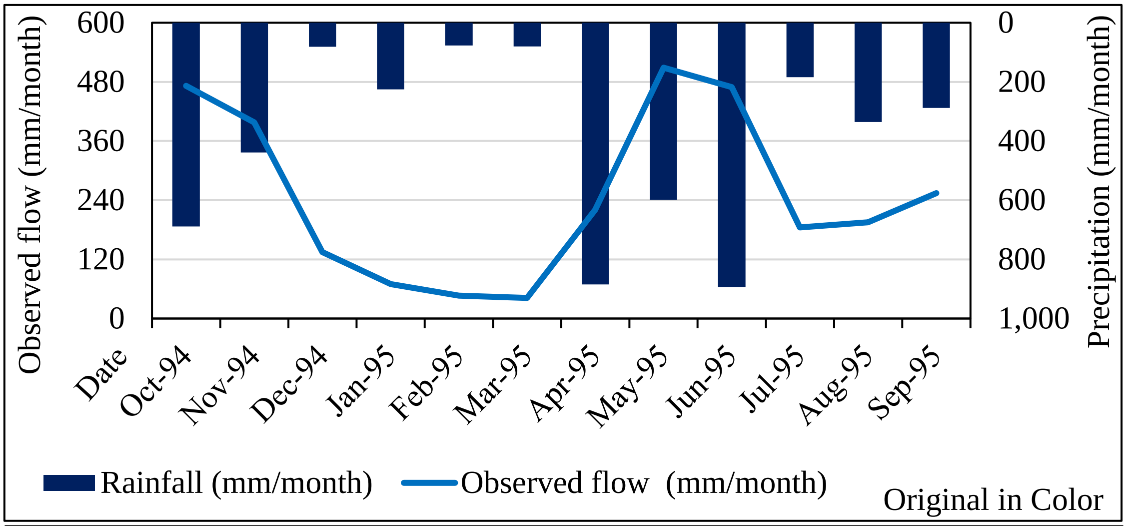
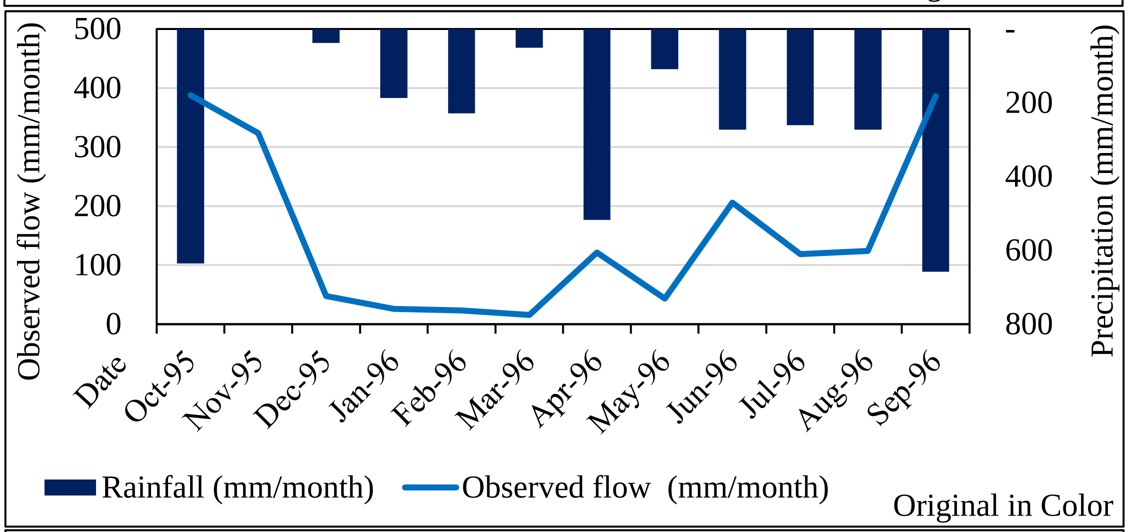
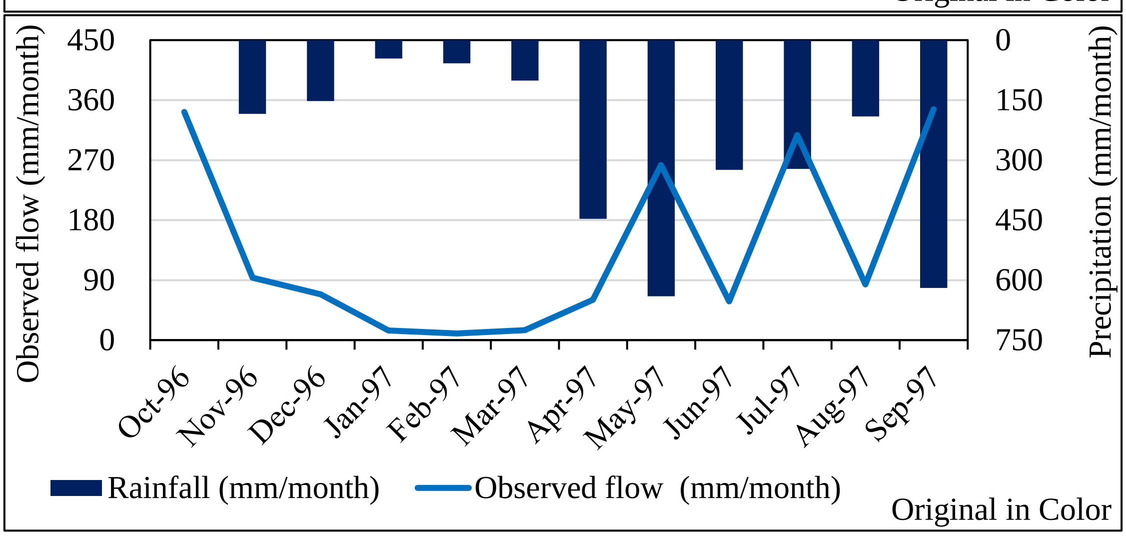


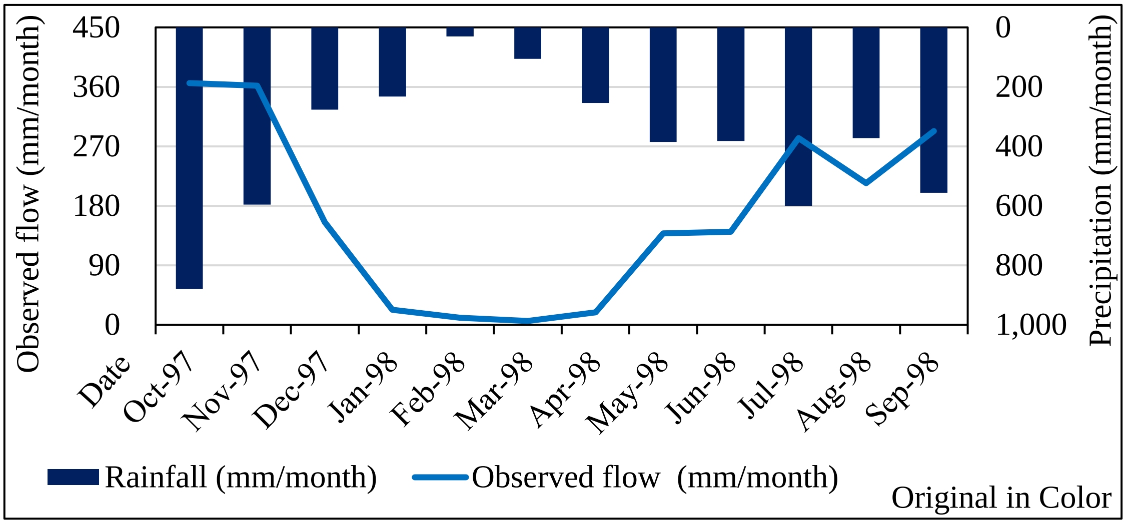
Figure 7-1 Annual water balance graph for 17 years

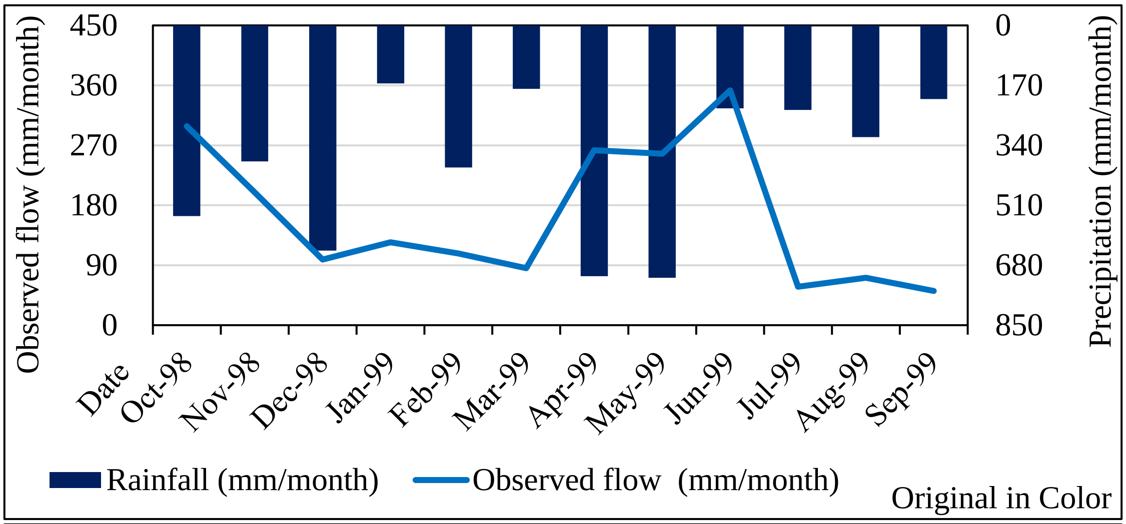
Appendix A2: Visual Data Checking

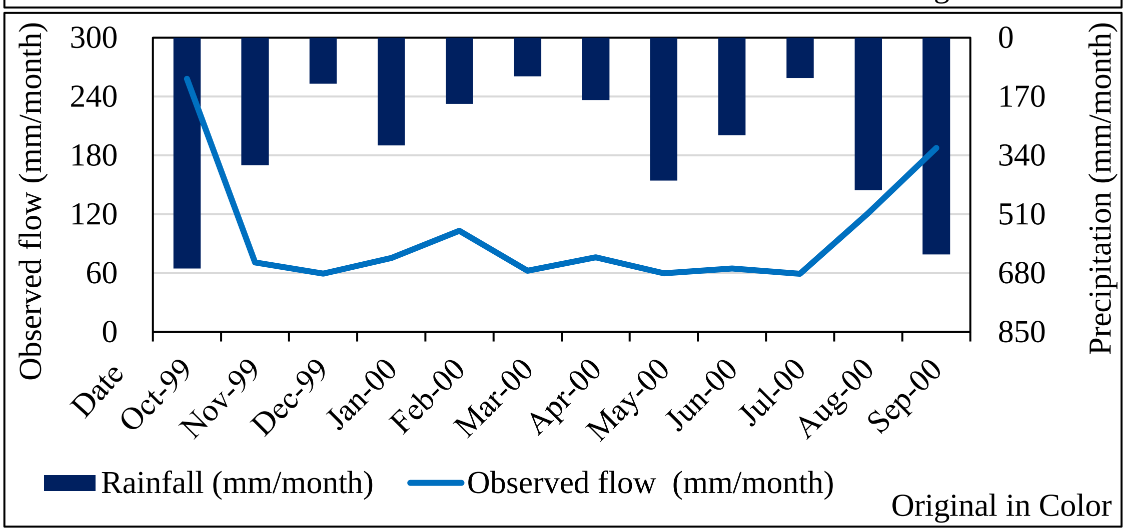

Observed flow (mm/month)
600
480
360
240
120
0
Precipitation (mm/month)
0
200
400
600
800
1,000
Date
Oct-94
Nov-94
Dec-94
Jan-95
Feb-95
Mar-95
Apr-95
May-95
Jun-95
Jul-95
Aug-95
Sep-95
Rainfall (mm/month)
Observed flow (mm/month)
Original in Color

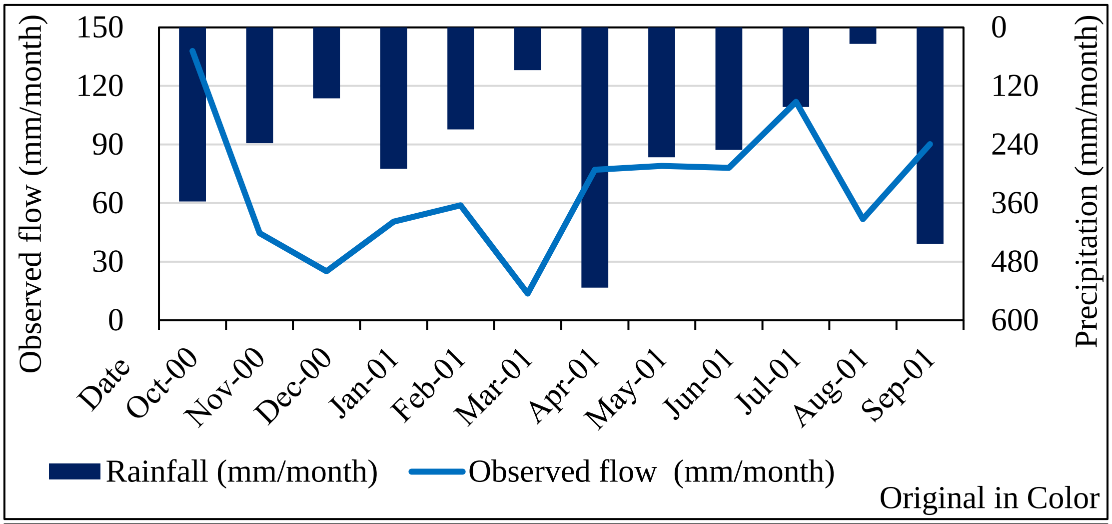

Observed flow (mm/month)
500
400
300
200
100
0
Precipitation (mm/month)
-
200
400
600
800
Date
Oct-95
Nov-95
Dec-95
Jan-96
Feb-96
Mar-96
Apr-96
May-96
Jun-96
Jul-96
Aug-96
Sep-96
Rainfall (mm/month)
Observed flow (mm/month)
Original in Color

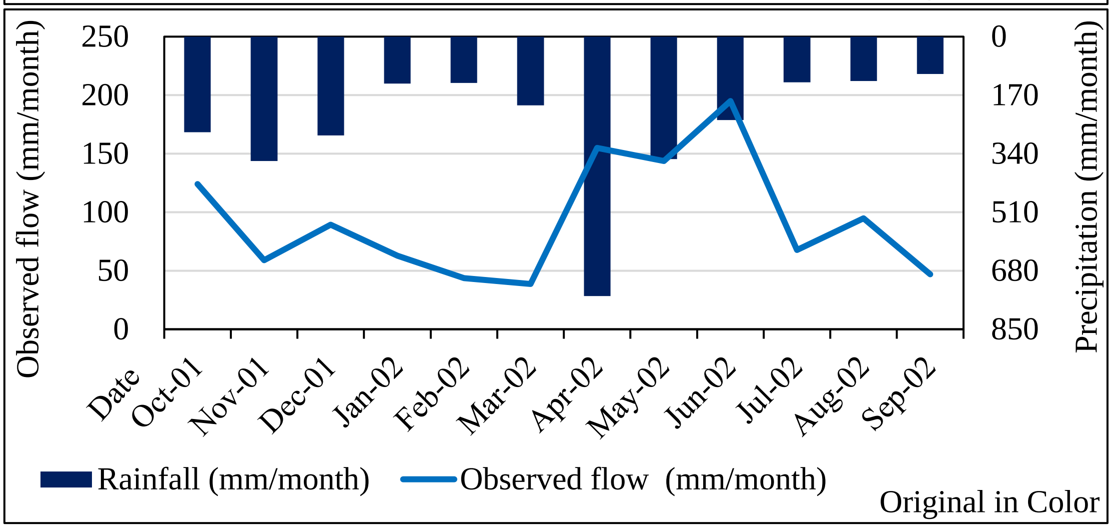

Observed flow (mm/month)
450
360
270
180
90
0
Precipitation (mm/month)
0
150
300
450
600
750
Oct-96
Nov-96
Dec-96
Jan-97
Feb-97
Mar-97
Apr-97
May-97
Jun-97
Jul-97
Aug-97
Sep-97
Rainfall (mm/month)
Observed flow (mm/month)
Original in Color

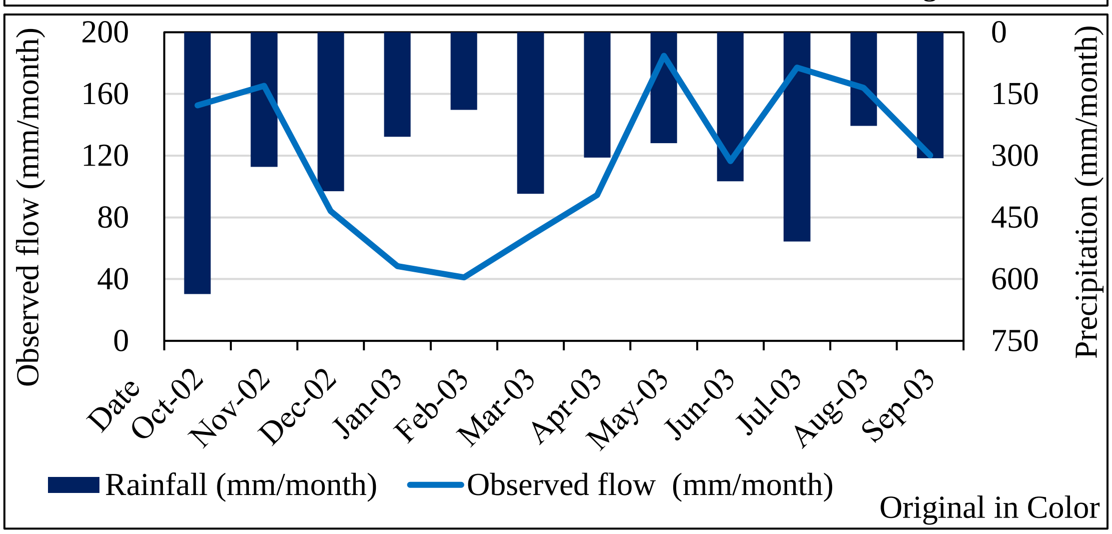

Observed flow (mm/month)
450
360
270
180
90
0
Precipitation (mm/month)
0
200
400
600
800
1,000
Date
Oct-97
Nov-97
Dec-97
Jan-98
Feb-98
Mar-98
Apr-98
May-98
Jun-98
Jul-98
Aug-98
Sep-98
Rainfall (mm/month)
Observed flow (mm/month)
Original in Color

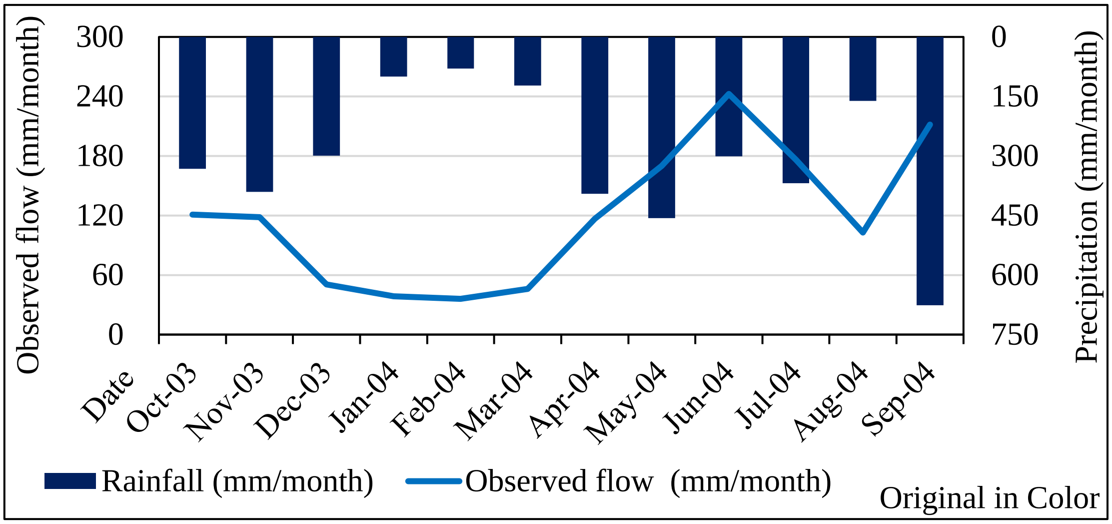

Observed flow (mm/month)
450
360
270
180
90
0
Precipitation (mm/month)
0
170
340
510
680
850
Date
Oct-98
Nov-98
Dec-98
Jan-99
Feb-99
Mar-99
Apr-99
May-99
Jun-99
Jul-99
Aug-99
Sep-99
Rainfall (mm/month)
Observed flow (mm/month)
Original in Color

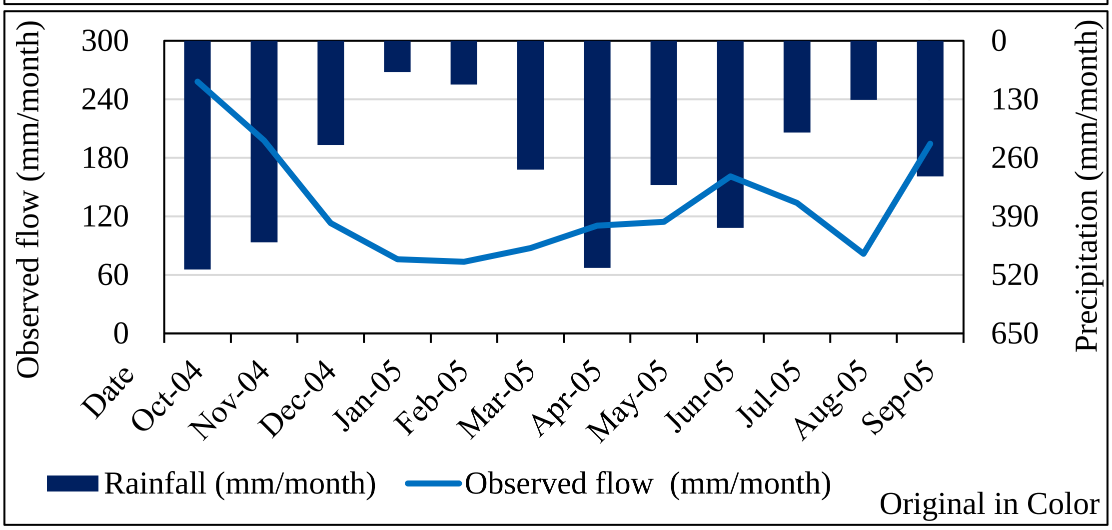

Observed flow (mm/month)
300
240
180
120
60
0
Precipitation (mm/month)
0
170
340
510
680
850
Date
Oct-99
Nov-99
Dec-99
Jan-00
Feb-00
Mar-00
Apr-00
May-00
Jun-00
Jul-00
Aug-00
Sep-00
Rainfall (mm/month)
Observed flow (mm/month)
Original in Color

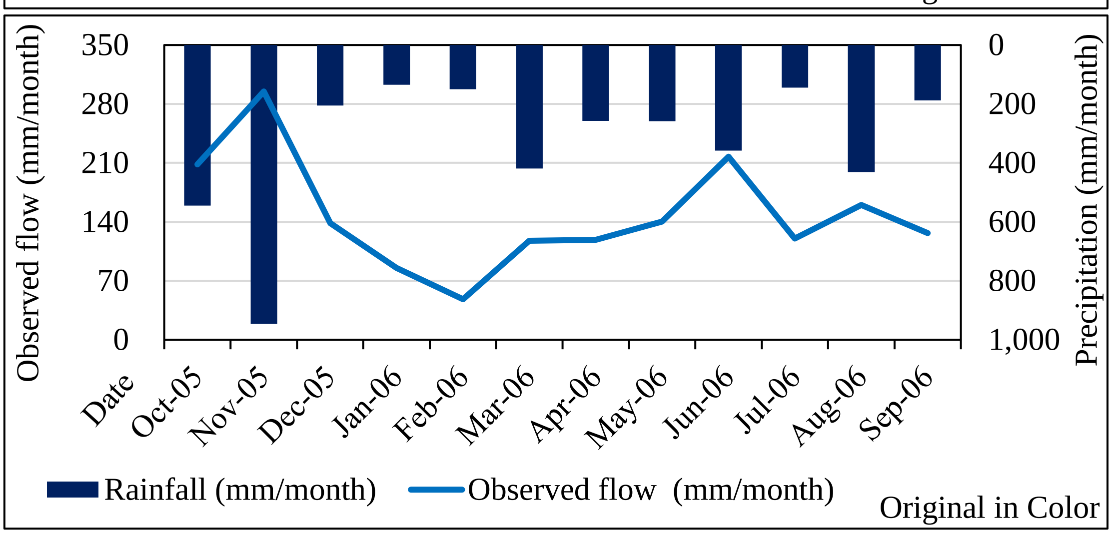

Observed flow (mm/month)
150
120
90
60
30
0
Precipitation (mm/month)
0
120
240
360
480
600
Date
Oct-00
Nov-00
Dec-00
Jan-01
Feb-01
Mar-01
Apr-01
May-01
Jun-01
Jul-01
Aug-01
Sep-01
Rainfall (mm/month)
Observed flow (mm/month)
Original in Color

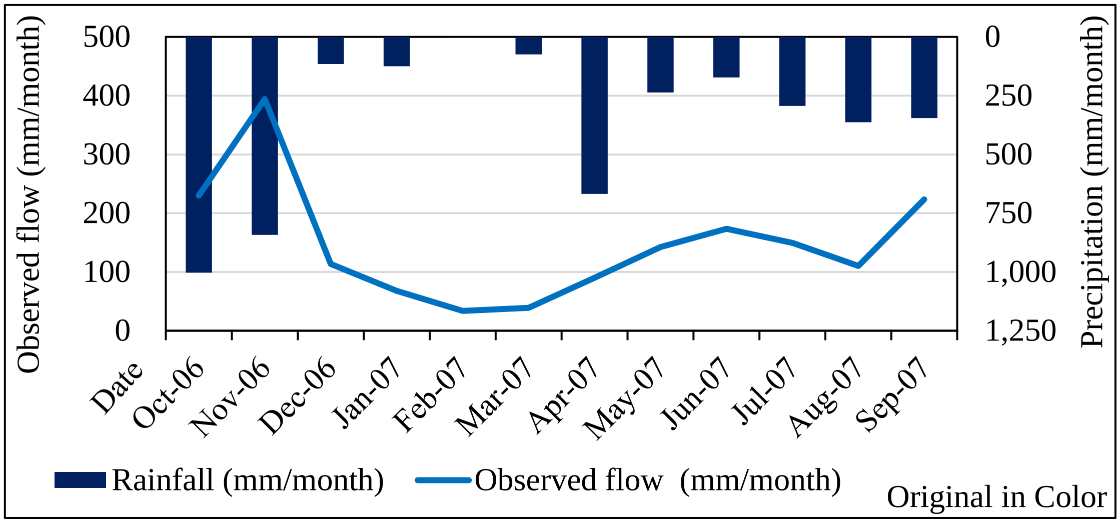

Observed flow (mm/month)
250
200
150
100
50
0
Precipitation (mm/month)
0
170
340
510
680
850
Date
Oct-01
Nov-01
Dec-01
Jan-02
Feb-02
Mar-02
Apr-02
May-02
Jun-02
Jul-02
Aug-02
Sep-02
Rainfall (mm/month)
Observed flow (mm/month)
Original in Color

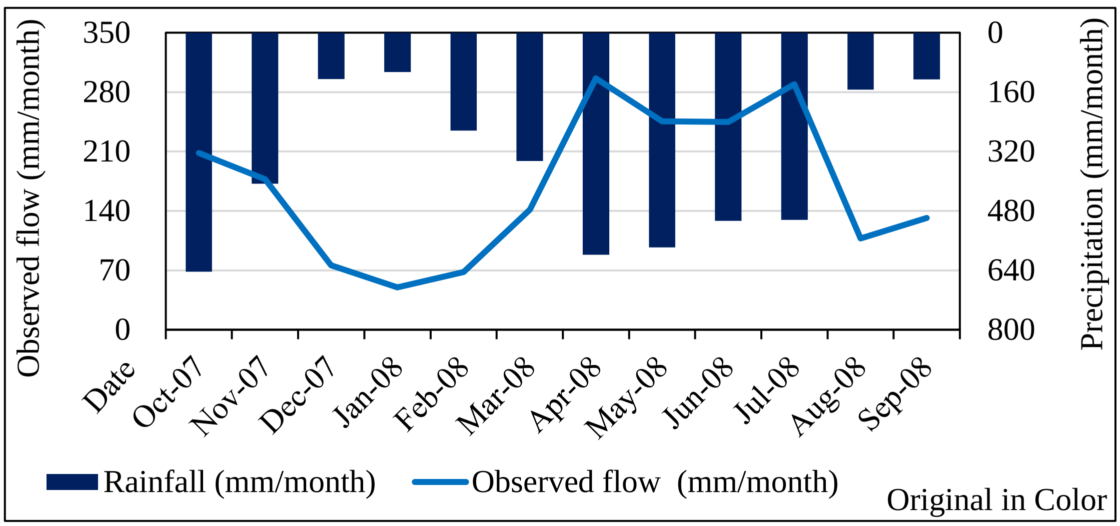

Observed flow (mm/month)
200
160
120
80
40
0
Precipitation (mm/month)
0
150
300
450
600
750
Date
Oct-02
Nov-02
Dec-02
Jan-03
Feb-03
Mar-03
Apr-03
May-03
Jun-03
Jul-03
Aug-03
Sep-03
Rainfall (mm/month)
Observed flow (mm/month)
Original in Color

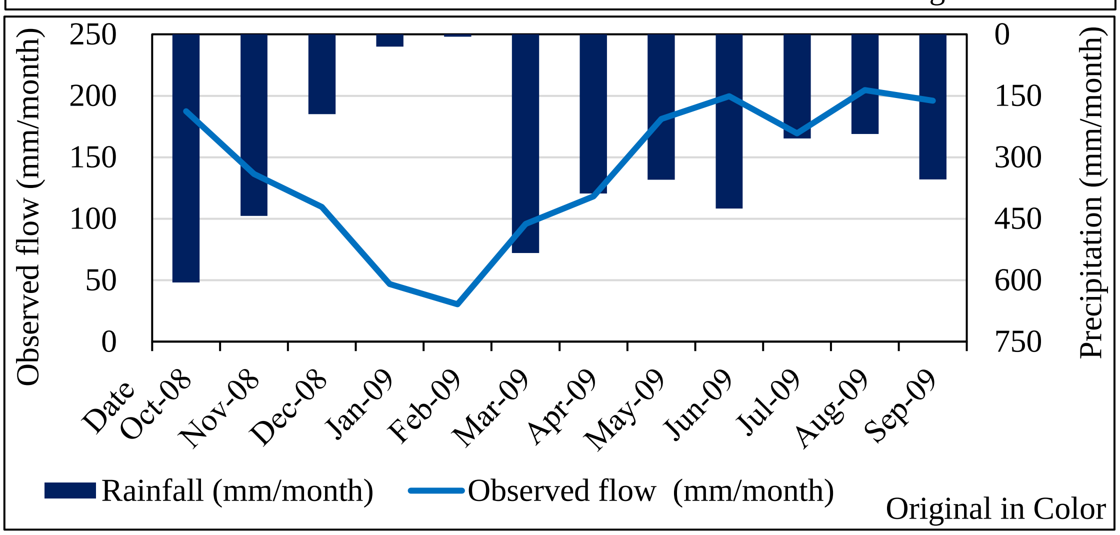

Observed flow (mm/month)
300
240
180
120
60
0
Precipitation (mm/month)
0
150
300
450
600
750
Date
Oct-03
Nov-03
Dec-03
Jan-04
Feb-04
Mar-04
Apr-04
May-04
Jun-04
Jul-04
Aug-04
Sep-04
Rainfall (mm/month)
Observed flow (mm/month)
Original in Color


Observed flow (mm/month)
300
240
180
120
60
0
Precipitation (mm/month)
0
130
260
390
520
650
Date
Oct-04
Nov-04
Dec-04
Jan-05
Feb-05
Mar-05
Apr-05
May-05
Jun-05
Jul-05
Aug-05
Sep-05
Rainfall (mm/month)
Observed flow (mm/month)
Original in Color


Observed flow (mm/month)
350
280
210
140
70
0
Precipitation (mm/month)
0
200
400
600
800
1,000
Date
Oct-05
Nov-05
Dec-05
Jan-06
Feb-06
Mar-06
Apr-06
May-06
Jun-06
Jul-06
Aug-06
Sep-06
Rainfall (mm/month)
Observed flow (mm/month)
Original in Color


Observed flow (mm/month)
500
400
300
200
100
0
Precipitation (mm/month)
0
250
500
750
1,000
1,250
Date
Oct-06
Nov-06
Dec-06
Jan-07
Feb-07
Mar-07
Apr-07
May-07
Jun-07
Jul-07
Aug-07
Sep-07
Rainfall (mm/month)
Observed flow (mm/month)
Original in Color


Observed flow (mm/month)
350
280
210
140
70
0
Precipitation (mm/month)
0
160
320
480
640
800
Date
Oct-07
Nov-07
Dec-07
Jan-08
Feb-08
Mar-08
Apr-08
May-08
Jun-08
Jul-08
Aug-08
Sep-08
Rainfall (mm/month)
Observed flow (mm/month)
Original in Color


Observed flow (mm/month)
250
200
150
100
50
0
Precipitation (mm/month)
0
150
300
450
600
750
Date
Oct-08
Nov-08
Dec-08
Jan-09
Feb-09
Mar-09
Apr-09
May-09
Jun-09
Jul-09
Aug-09
Sep-09
Rainfall (mm/month)
Observed flow (mm/month)
Original in Color

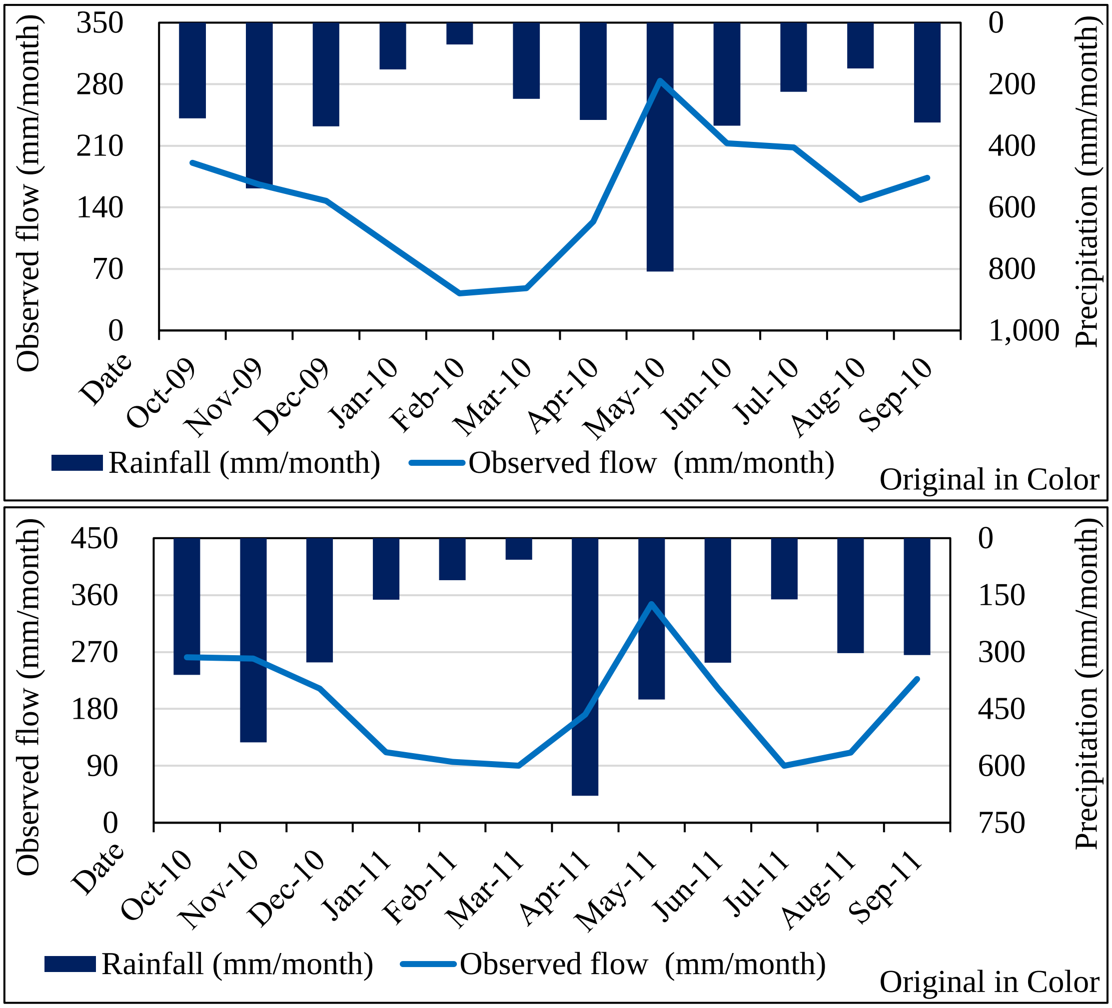
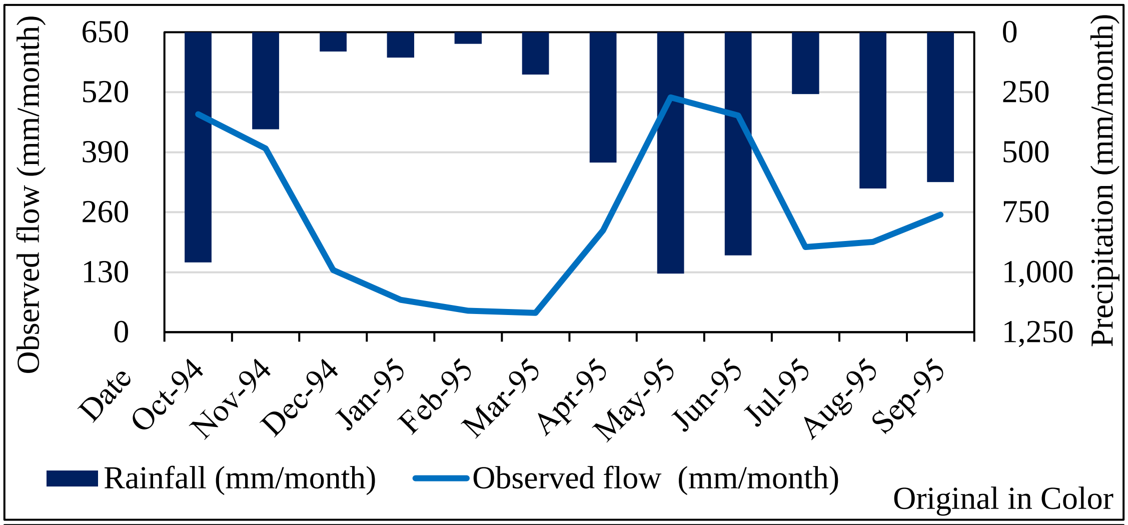
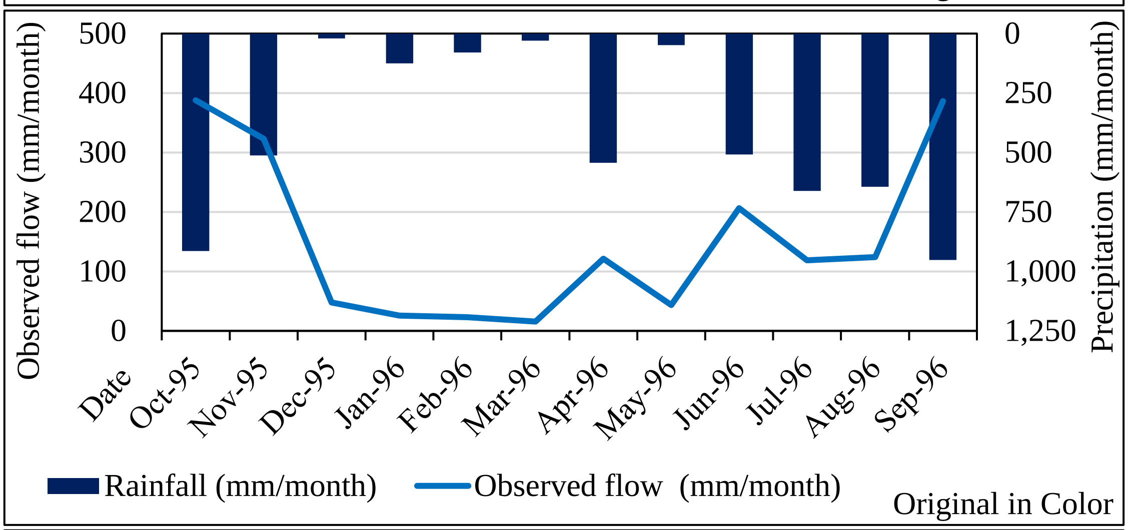
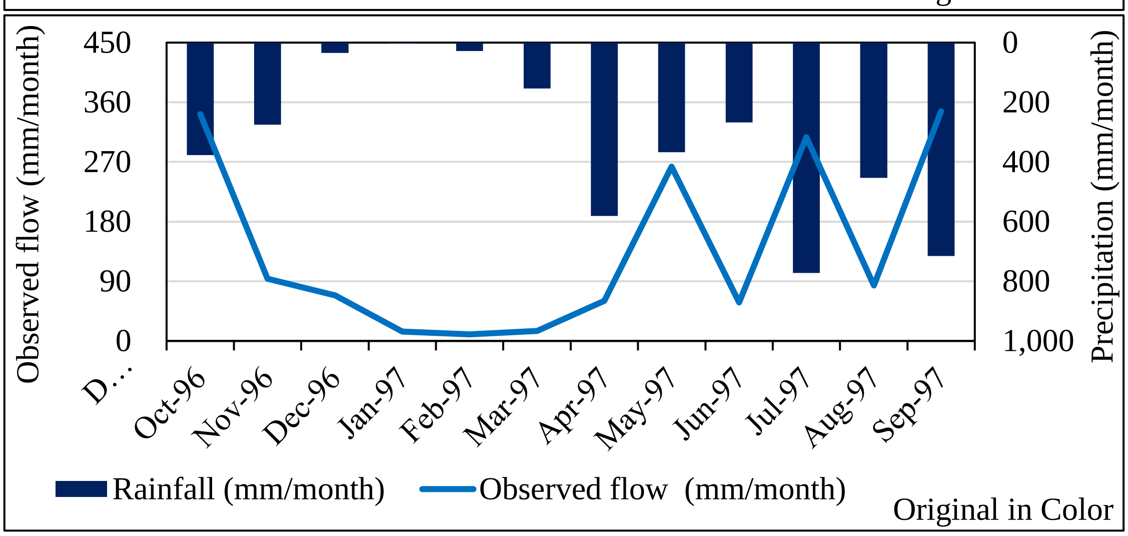
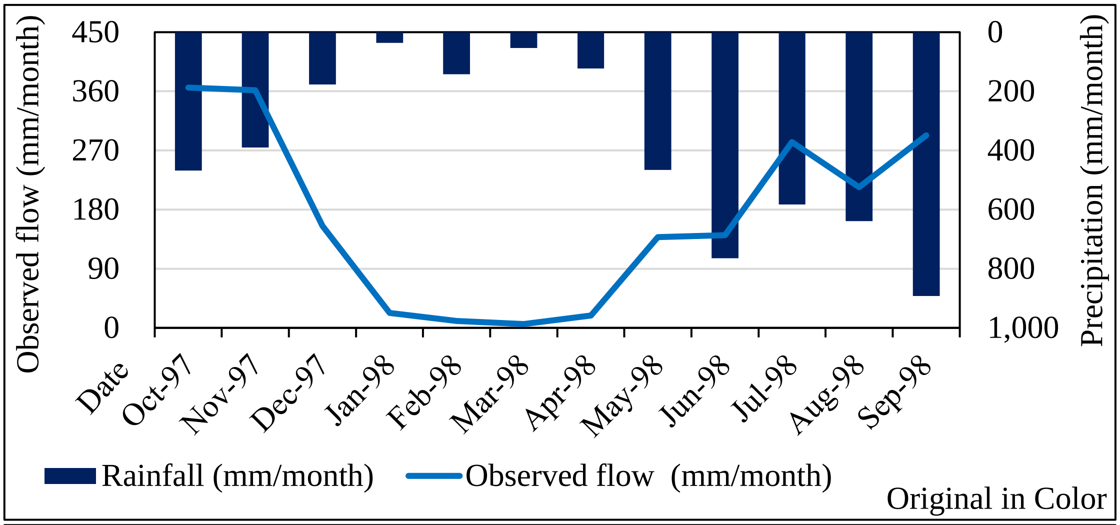


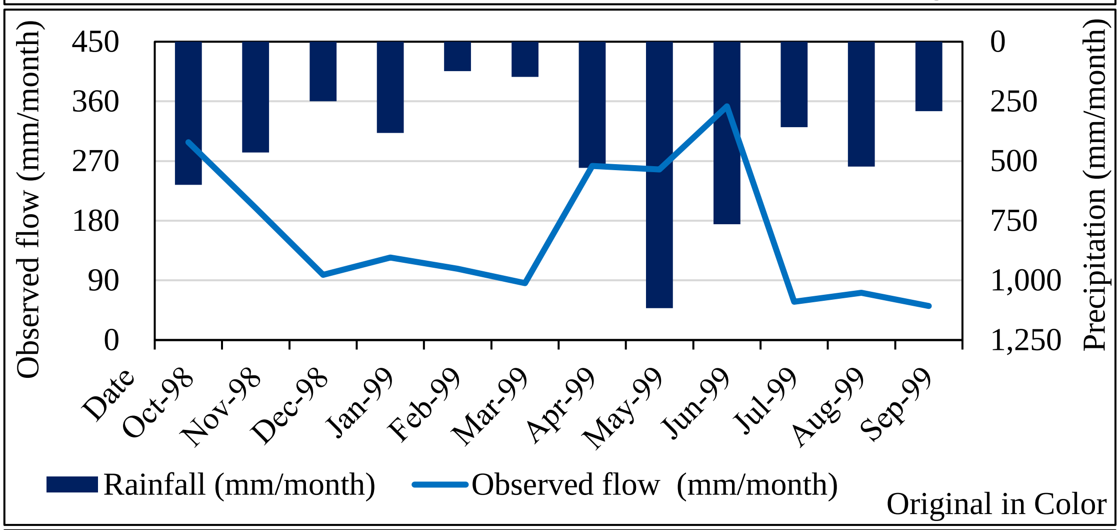
Figure 7-2 Visual checking for Glencorse streamflow response to Labugama rainfall

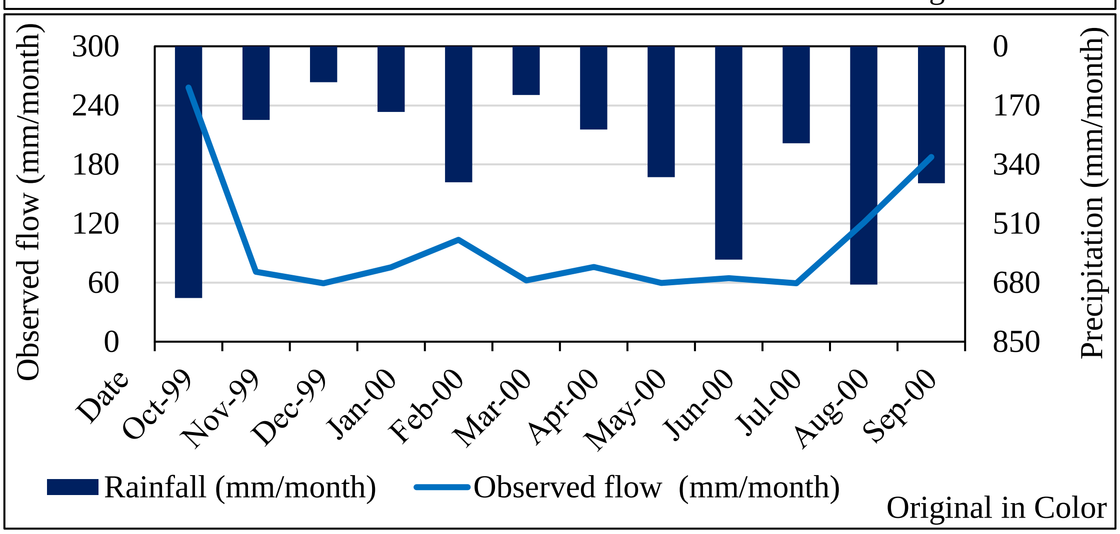

Observed flow (mm/month)
650
520
390
260
130
0
Precipitation (mm/month)
0
250
500
750
1,000
1,250
Date
Oct-94
Nov-94
Dec-94
Jan-95
Feb-95
Mar-95
Apr-95
May-95
Jun-95
Jul-95
Aug-95
Sep-95
Rainfall (mm/month)
Observed flow (mm/month)
Original in Color

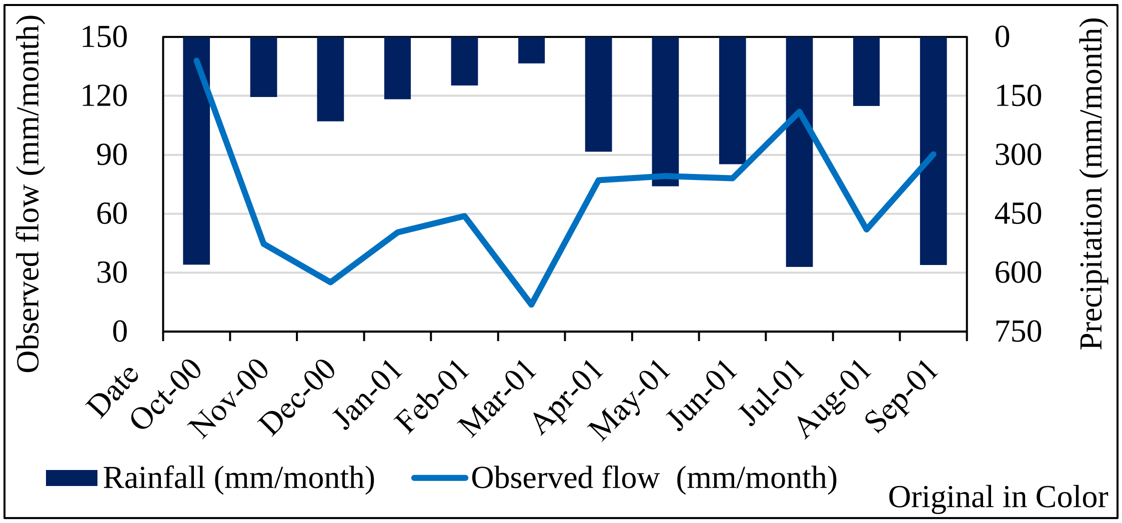

Observed flow (mm/month)
500
400
300
200
100
0
Precipitation (mm/month)
0
250
500
750
1,000
1,250
Date
Oct-95
Nov-95
Dec-95
Jan-96
Feb-96
Mar-96
Apr-96
May-96
Jun-96
Jul-96
Aug-96
Sep-96
Rainfall (mm/month)
Observed flow (mm/month)
Original in Color


Observed flow (mm/month)
450
360
270
180
90
0
Precipitation (mm/month)
0
200
400
600
800
1,000
D…
Oct-96
Nov-96
Dec-96
Jan-97
Feb-97
Mar-97
Apr-97
May-97
Jun-97
Jul-97
Aug-97
Sep-97
Rainfall (mm/month)
Observed flow (mm/month)
Original in Color

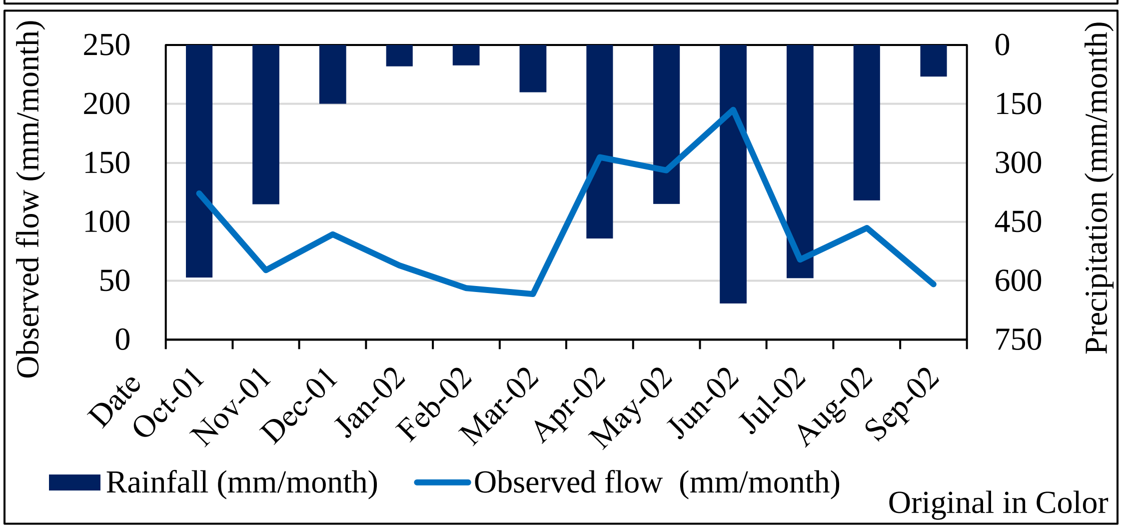

450
360
270
180
90
0
0
200
400
600
800
1,000
Observed flow (mm/month)
Precipitation (mm/month)
Date
Oct-97
Nov-97
Dec-97
Jan-98
Feb-98
Mar-98
Apr-98
May-98
Jun-98
Jul-98
Aug-98
Sep-98
Rainfall (mm/month)
Observed flow (mm/month)
Original in Color


450
360
270
180
90
0
0
250
500
750
1,000
1,250
Observed flow (mm/month)
Precipitation (mm/month)
Date
Oct-98
Nov-98
Dec-98
Jan-99
Feb-99
Mar-99
Apr-99
May-99
Jun-99
Jul-99
Aug-99
Sep-99
Rainfall (mm/month)
Observed flow (mm/month)
Original in Color

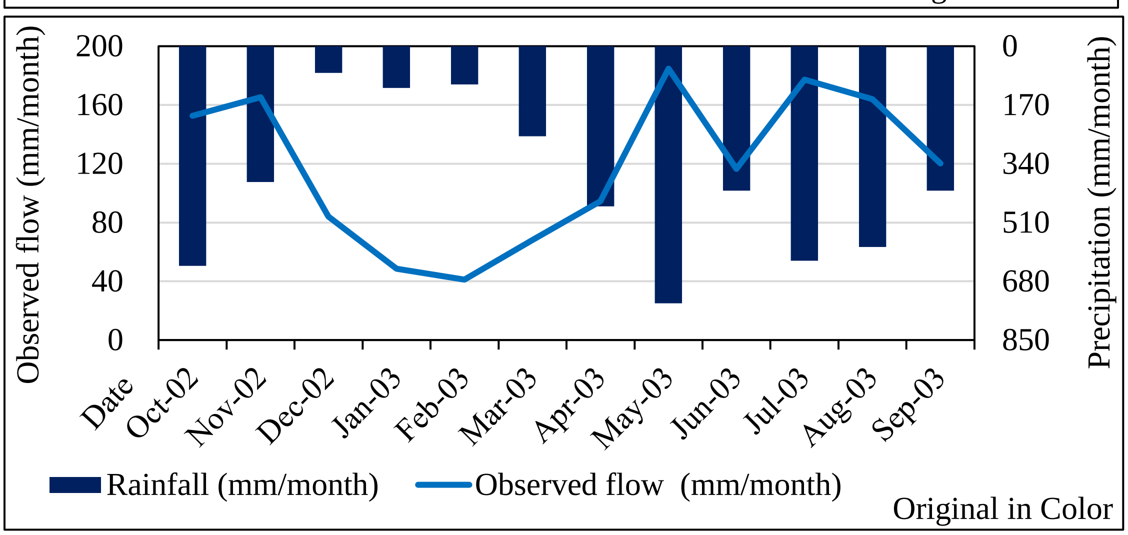

300
240
180
120
60
0
0
170
340
510
680
850
Observed flow (mm/month)
Precipitation (mm/month)
Date
Oct-99
Nov-99
Dec-99
Jan-00
Feb-00
Mar-00
Apr-00
May-00
Jun-00
Jul-00
Aug-00
Sep-00
Rainfall (mm/month)
Observed flow (mm/month)
Original in Color



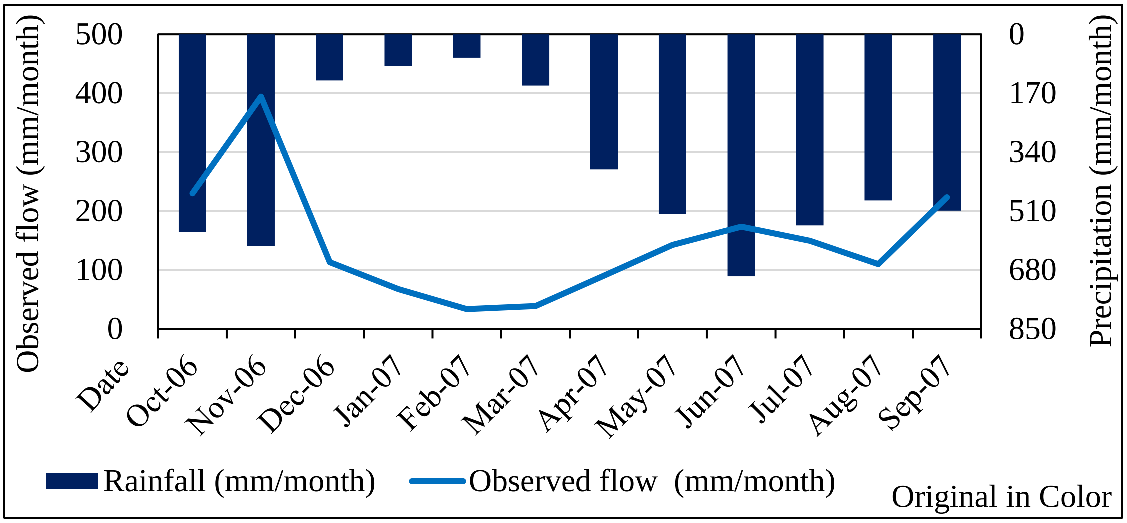
Observed flow (mm/month)
150
120
90
60
30
0
0
150
300
450
600
750
Precipitation (mm/month)
Date
Oct-00
Nov-00
Dec-00
Jan-01
Feb-01
Mar-01
Apr-01
May-01
Jun-01
Jul-01
Aug-01
Sep-01
Rainfall (mm/month)
Observed flow (mm/month)
Original in Color



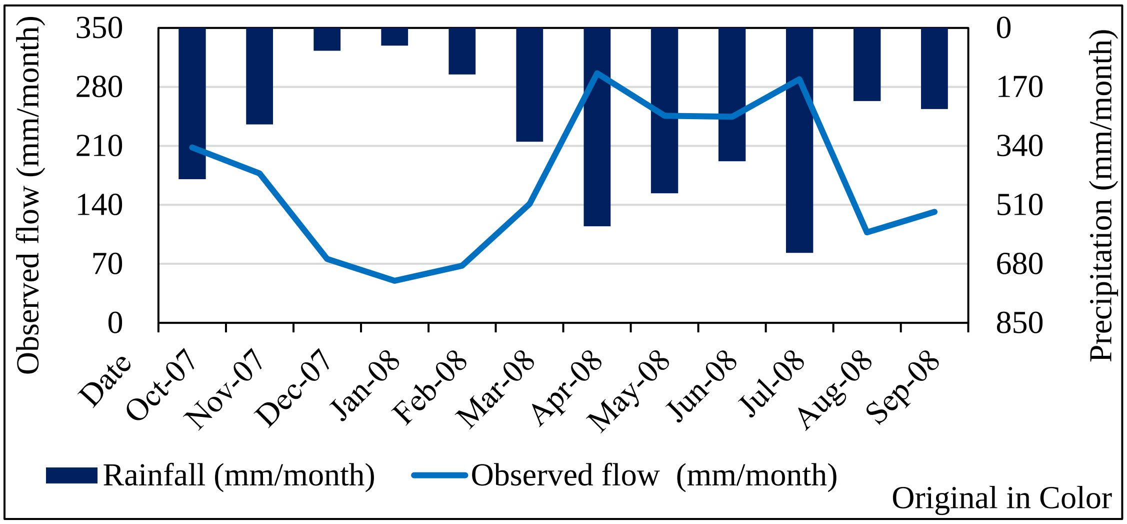
Observed flow (mm/month)
250
200
150
100
50
0
0
150
300
450
600
750
Precipitation (mm/month)
Date
Oct-01
Nov-01
Dec-01
Jan-02
Feb-02
Mar-02
Apr-02
May-02
Jun-02
Jul-02
Aug-02
Sep-02
Rainfall (mm/month)
Observed flow (mm/month)
Original in Color



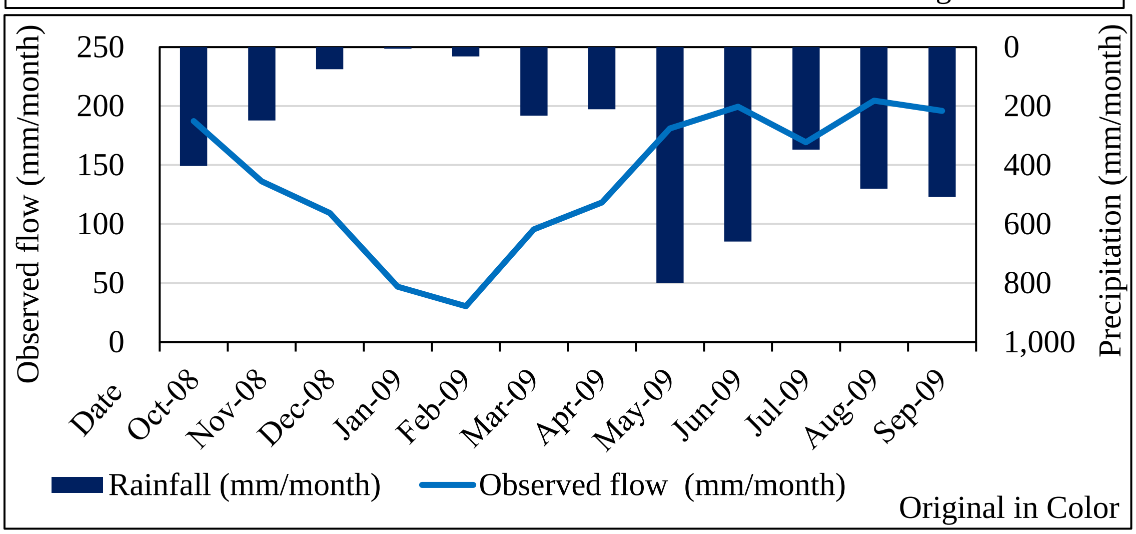
Observed flow (mm/month)
200
160
120
80
40
0
0
170
340
510
680
850
Precipitation (mm/month)
Date
Oct-02
Nov-02
Dec-02
Jan-03
Feb-03
Mar-03
Apr-03
May-03
Jun-03
Jul-03
Aug-03
Sep-03
Rainfall (mm/month)
Observed flow (mm/month)
Original in Color



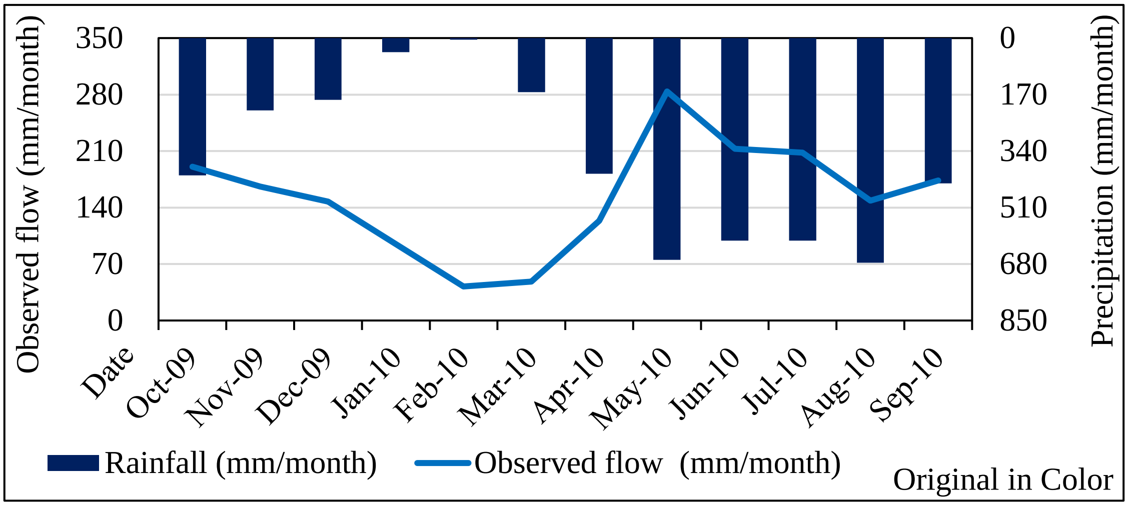
Observed flow (mm/month)
Precipitation (mm/month)
500
400
300
200
100
0
170
340
510
680
850
Date
Oct-06
Nov-06
Dec-06
Jan-07
Feb-07
Mar-07
Apr-07
May-07
Jun-07
Jul-07
Aug-07
Sep-07
Rainfall (mm/month)
Observed flow (mm/month)
Original in Color



Observed flow (mm/month)
Precipitation (mm/month)
350
280
210
140
70
0
170
340
510
680
850
Date
Oct-07
Nov-07
Dec-07
Jan-08
Feb-08
Mar-08
Apr-08
May-08
Jun-08
Jul-08
Aug-08
Sep-08
Rainfall (mm/month)
Observed flow (mm/month)
Original in Color



Observed flow (mm/month)
Precipitation (mm/month)
250
200
150
100
50
0
200
400
600
800
1,000
Date
Oct-08
Nov-08
Dec-08
Jan-09
Feb-09
Mar-09
Apr-09
May-09
Jun-09
Jul-09
Aug-09
Sep-09
Rainfall (mm/month)
Observed flow (mm/month)
Original in Color



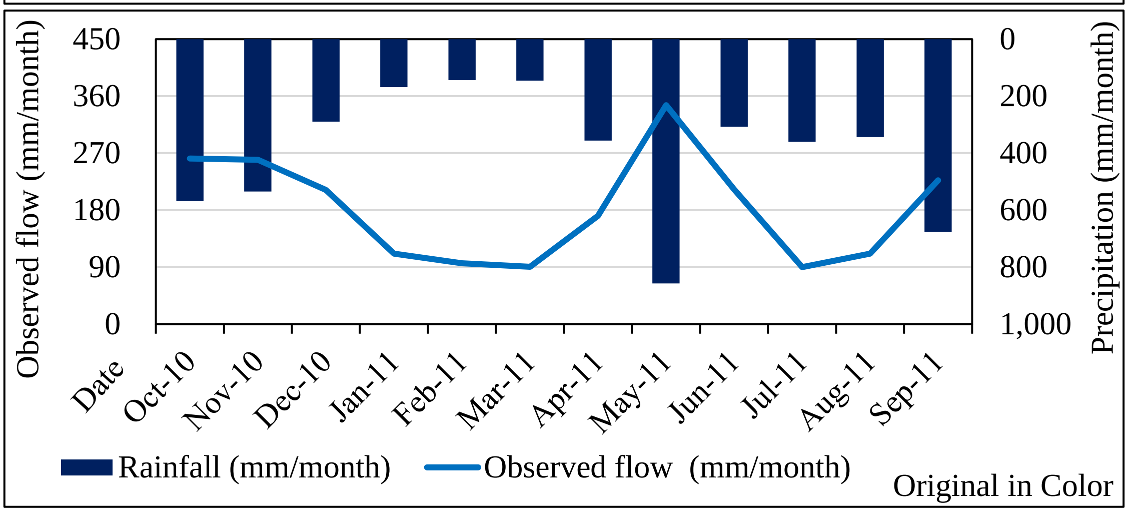
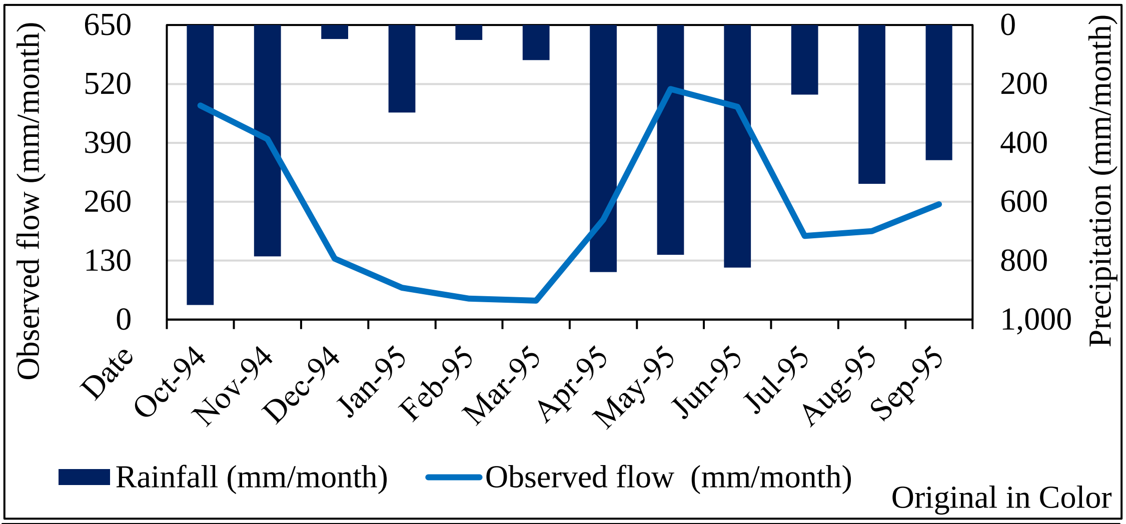
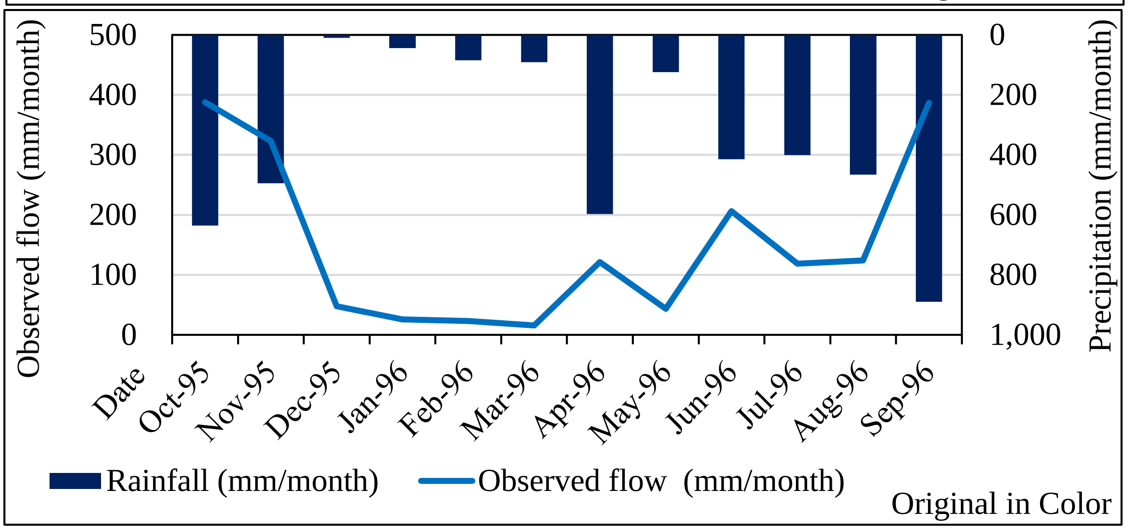
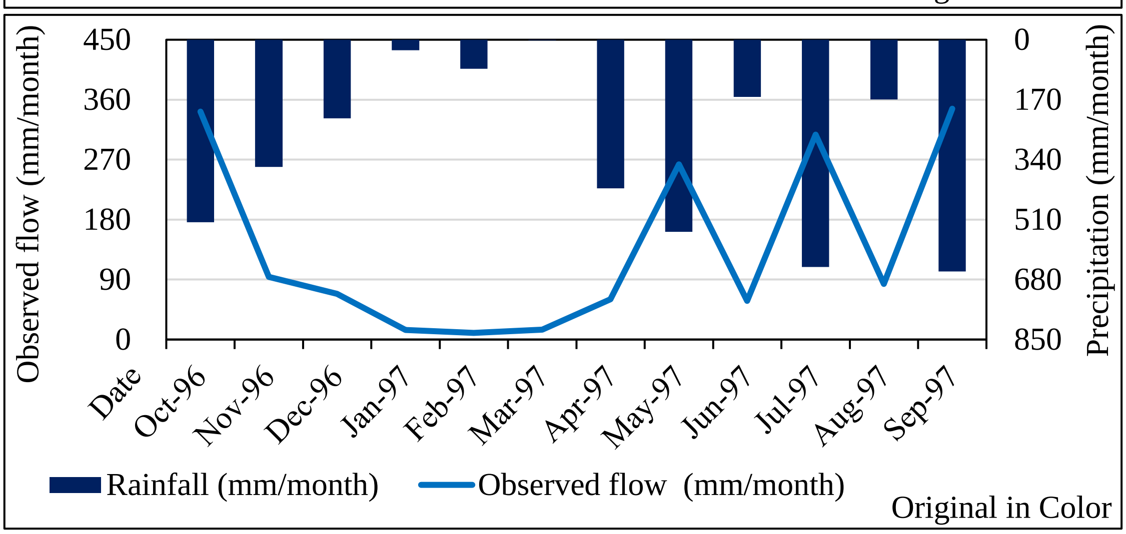
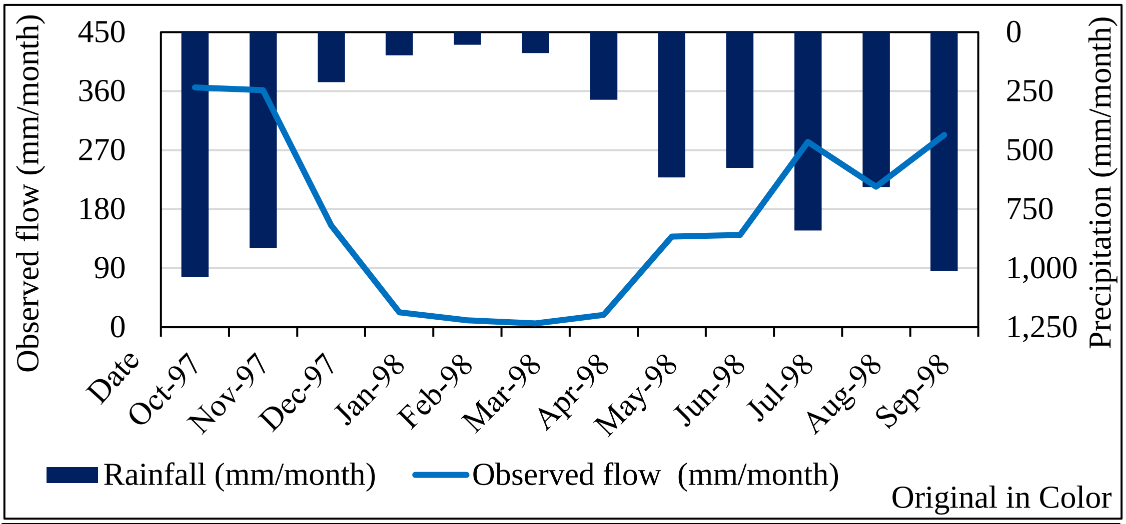


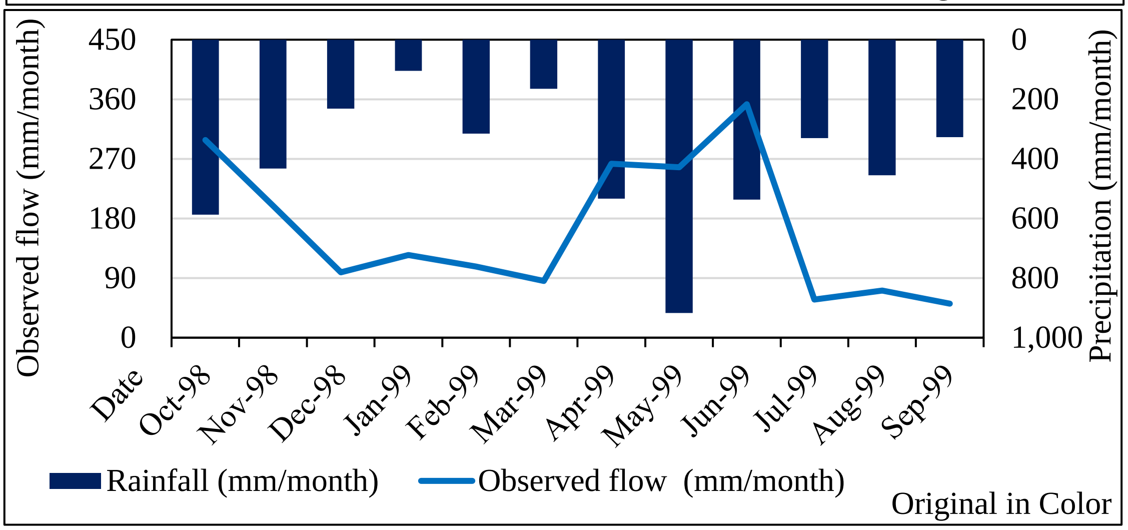
Figure 7-3 Visual checking Glencorse streamflow response to Laxapana rainfall

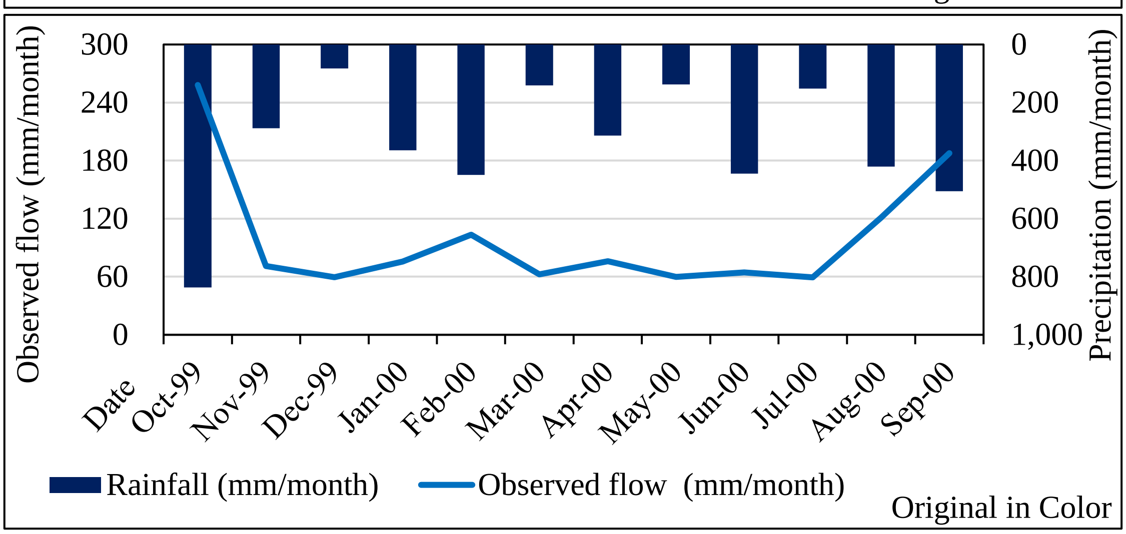

Observed flow (mm/month)
650
520
390
260
130
0
0
200
400
600
800
1,000
Precipitation (mm/month)
Date
Oct-94
Nov-94
Dec-94
Jan-95
Feb-95
Mar-95
Apr-95
May-95
Jun-95
Jul-95
Aug-95
Sep-95
Rainfall (mm/month)
Observed flow (mm/month)
Original in Color

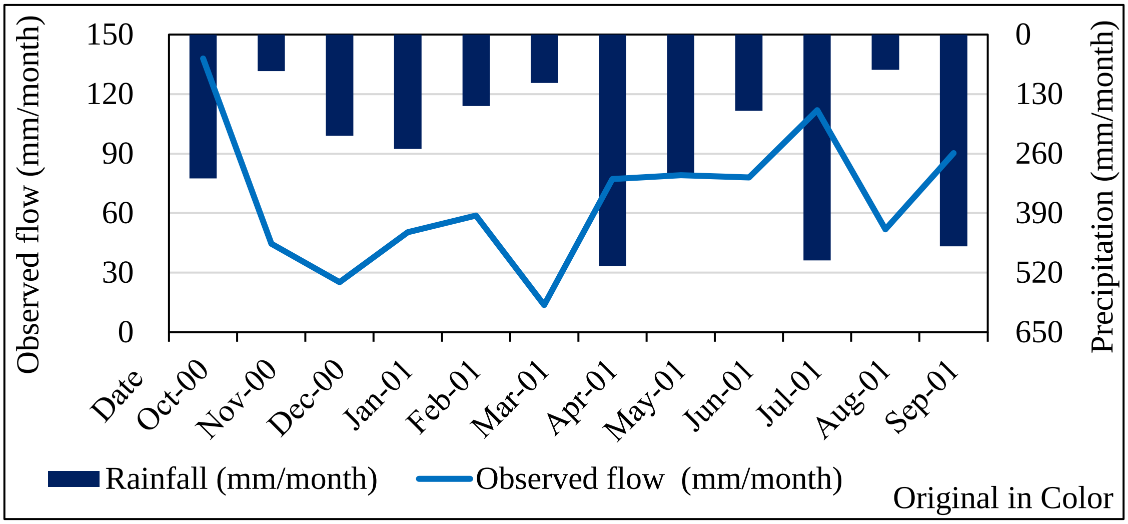

Observed flow (mm/month)
500
400
300
200
100
0
0
200
400
600
800
1,000
Precipitation (mm/month)
Date
Oct-95
Nov-95
Dec-95
Jan-96
Feb-96
Mar-96
Apr-96
May-96
Jun-96
Jul-96
Aug-96
Sep-96
Rainfall (mm/month)
Observed flow (mm/month)
Original in Color


Observed flow (mm/month)
450
360
270
180
90
0
0
170
340
510
680
850
Precipitation (mm/month)
Date
Oct-96
Nov-96
Dec-96
Jan-97
Feb-97
Mar-97
Apr-97
May-97
Jun-97
Jul-97
Aug-97
Sep-97
Rainfall (mm/month)
Observed flow (mm/month)
Original in Color

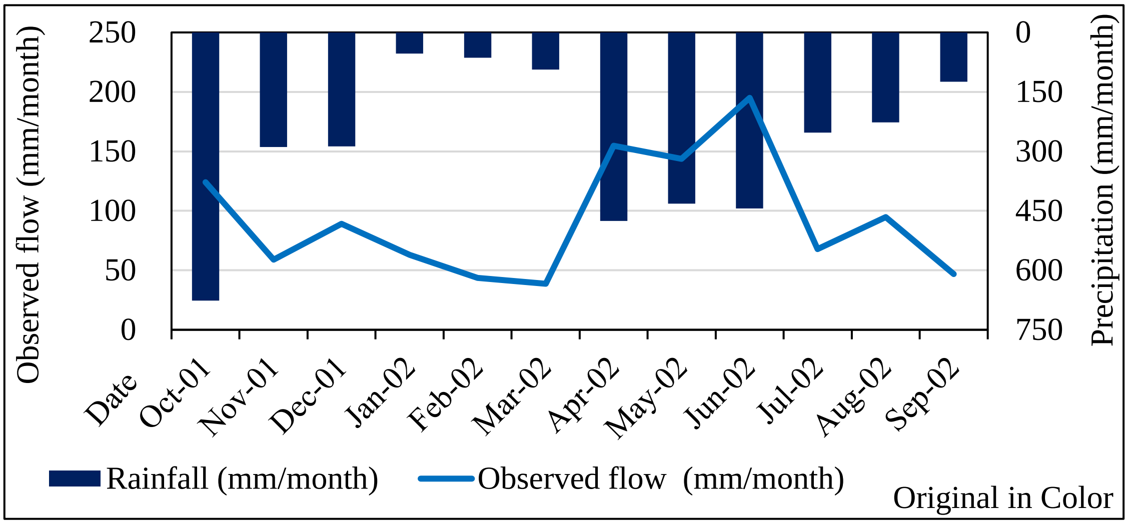

Observed flow (mm/month)
450
360
270
180
90
0
0
250
500
750
1,000
1,250
Precipitation (mm/month)
Date
Oct-97
Nov-97
Dec-97
Jan-98
Feb-98
Mar-98
Apr-98
May-98
Jun-98
Jul-98
Aug-98
Sep-98
Rainfall (mm/month)
Observed flow (mm/month)
Original in Color


Observed flow (mm/month)
450
360
270
180
90
0
0
200
400
600
800
1,000
Precipitation (mm/month)
Date
Oct-98
Nov-98
Dec-98
Jan-99
Feb-99
Mar-99
Apr-99
May-99
Jun-99
Jul-99
Aug-99
Sep-99
Rainfall (mm/month)
Observed flow (mm/month)
Original in Color

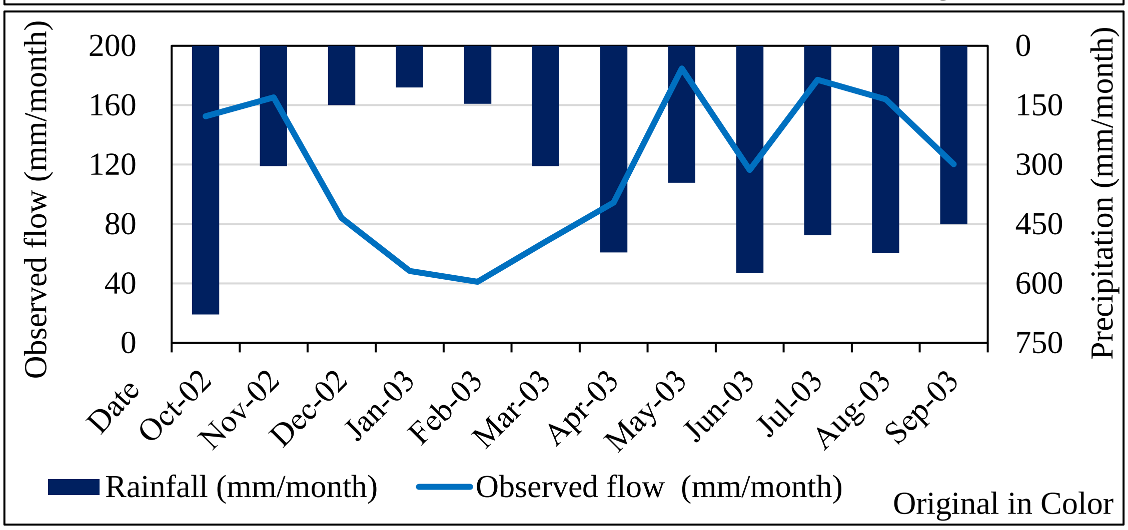

Observed flow (mm/month)
300
240
180
120
60
0
0
200
400
600
800
1,000
Precipitation (mm/month)
Date
Oct-99
Nov-99
Dec-99
Jan-00
Feb-00
Mar-00
Apr-00
May-00
Jun-00
Jul-00
Aug-00
Sep-00
Rainfall (mm/month)
Observed flow (mm/month)
Original in Color



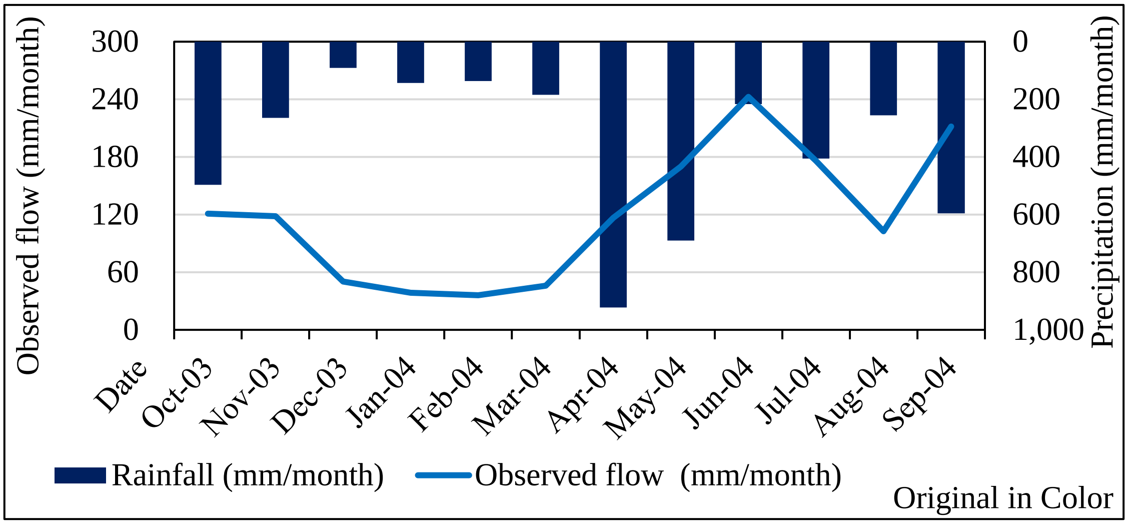
Observed flow (mm/month)
150
120
90
60
30
0
0
130
260
390
520
650
Precipitation (mm/month)
Date
Oct-00
Nov-00
Dec-00
Jan-01
Feb-01
Mar-01
Apr-01
May-01
Jun-01
Jul-01
Aug-01
Sep-01
Rainfall (mm/month)
Observed flow (mm/month)
Original in Color



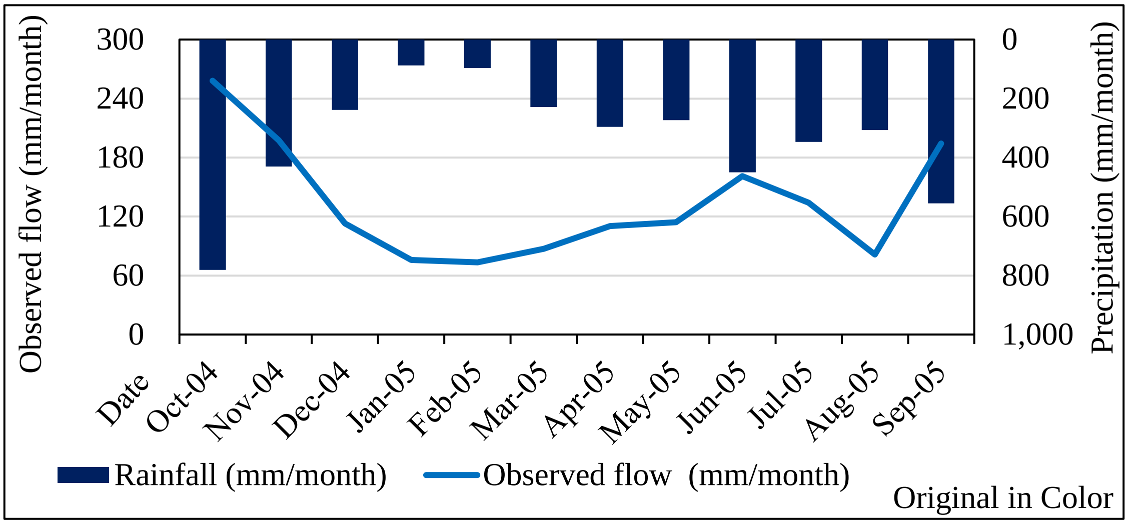
Observed flow (mm/month)
250
200
150
100
50
0
0
150
300
450
600
750
Precipitation (mm/month)
Date
Oct-01
Nov-01
Dec-01
Jan-02
Feb-02
Mar-02
Apr-02
May-02
Jun-02
Jul-02
Aug-02
Sep-02
Rainfall (mm/month)
Observed flow (mm/month)
Original in Color



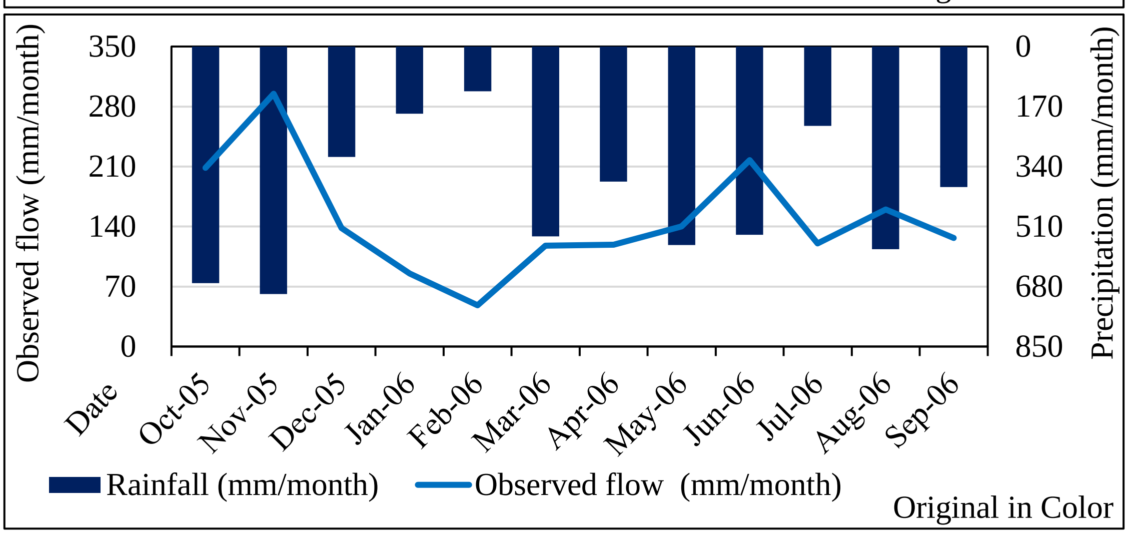
Observed flow (mm/month)
200
160
120
80
40
0
0
150
300
450
600
750
Precipitation (mm/month)
Date
Oct-02
Nov-02
Dec-02
Jan-03
Feb-03
Mar-03
Apr-03
May-03
Jun-03
Jul-03
Aug-03
Sep-03
Rainfall (mm/month)
Observed flow (mm/month)
Original in Color



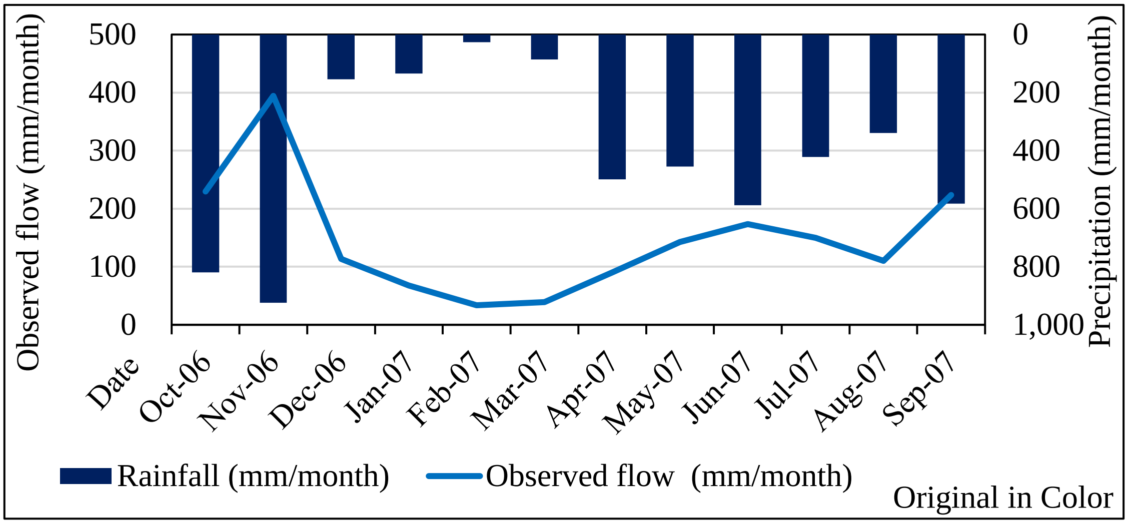
Observed flow (mm/month)
300
240
180
120
60
0
Precipitation (mm/month)
0
200
400
600
800
1,000
Date
Oct-03
Nov-03
Dec-03
Jan-04
Feb-04
Mar-04
Apr-04
May-04
Jun-04
Jul-04
Aug-04
Sep-04
Rainfall (mm/month)
Observed flow (mm/month)
Original in Color

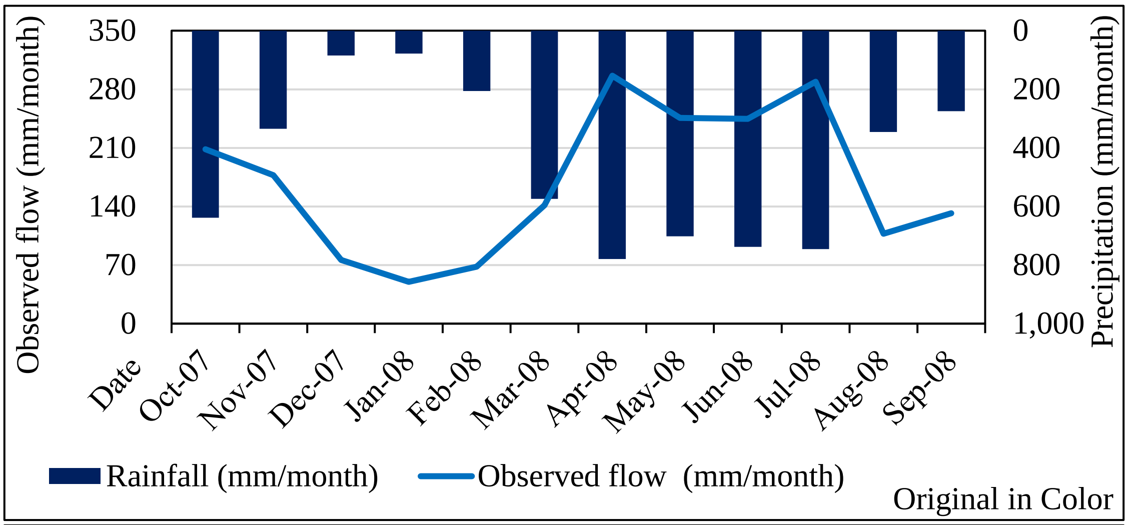


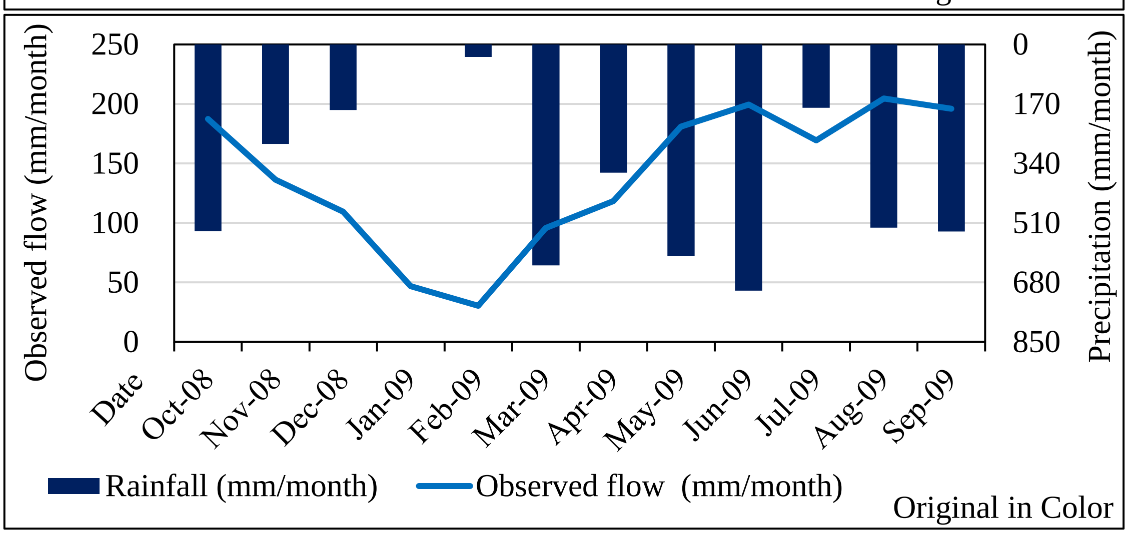
Observed flow (mm/month)
300
240
180
120
60
0
Precipitation (mm/month)
0
200
400
600
800
1,000
Date
Oct-04
Nov-04
Dec-04
Jan-05
Feb-05
Mar-05
Apr-05
May-05
Jun-05
Jul-05
Aug-05
Sep-05
Rainfall (mm/month)
Observed flow (mm/month)
Original in Color

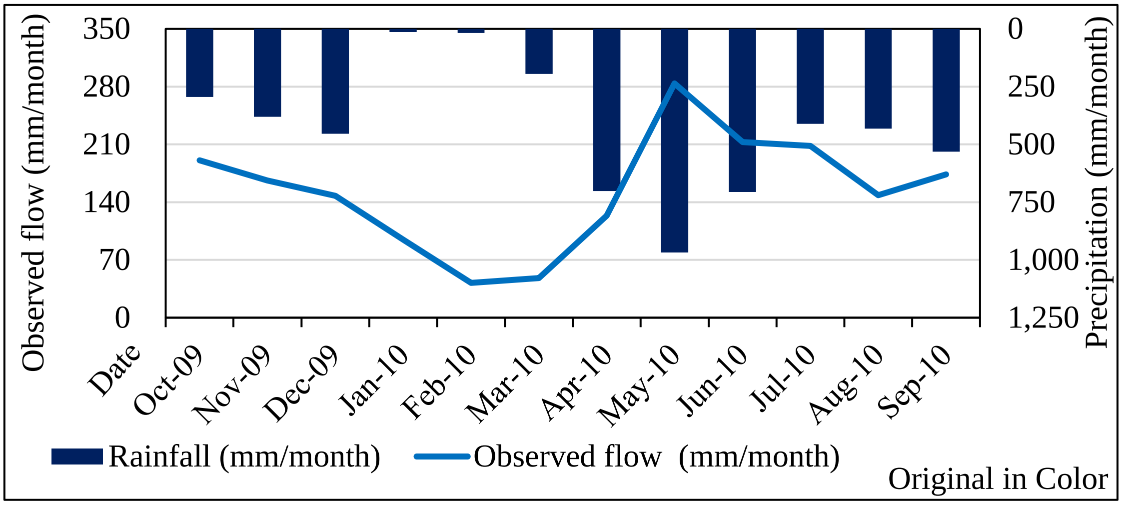


Observed flow (mm/month)
350
280
210
140
70
0
Precipitation (mm/month)
0
170
340
510
680
850
Date
Oct-05
Nov-05
Dec-05
Jan-06
Feb-06
Mar-06
Apr-06
May-06
Jun-06
Jul-06
Aug-06
Sep-06
Rainfall (mm/month)
Observed flow (mm/month)
Original in Color


Observed flow (mm/month)
500
400
300
200
100
0
0
200
400
600
800
1,000
Precipitation (mm/month)
Date
Oct-06
Nov-06
Dec-06
Jan-07
Feb-07
Mar-07
Apr-07
May-07
Jun-07
Jul-07
Aug-07
Sep-07
Rainfall (mm/month)
Observed flow (mm/month)
Original in Color


Observed flow (mm/month)
350
280
210
140
70
0
0
200
400
600
800
1,000
Precipitation (mm/month)
Date
Oct-07
Nov-07
Dec-07
Jan-08
Feb-08
Mar-08
Apr-08
May-08
Jun-08
Jul-08
Aug-08
Sep-08
Rainfall (mm/month)
Observed flow (mm/month)
Original in Color


Observed flow (mm/month)
250
200
150
100
50
0
0
170
340
510
680
850
Precipitation (mm/month)
Date
Oct-08
Nov-08
Dec-08
Jan-09
Feb-09
Mar-09
Apr-09
May-09
Jun-09
Jul-09
Aug-09
Sep-09
Rainfall (mm/month)
Observed flow (mm/month)
Original in Color



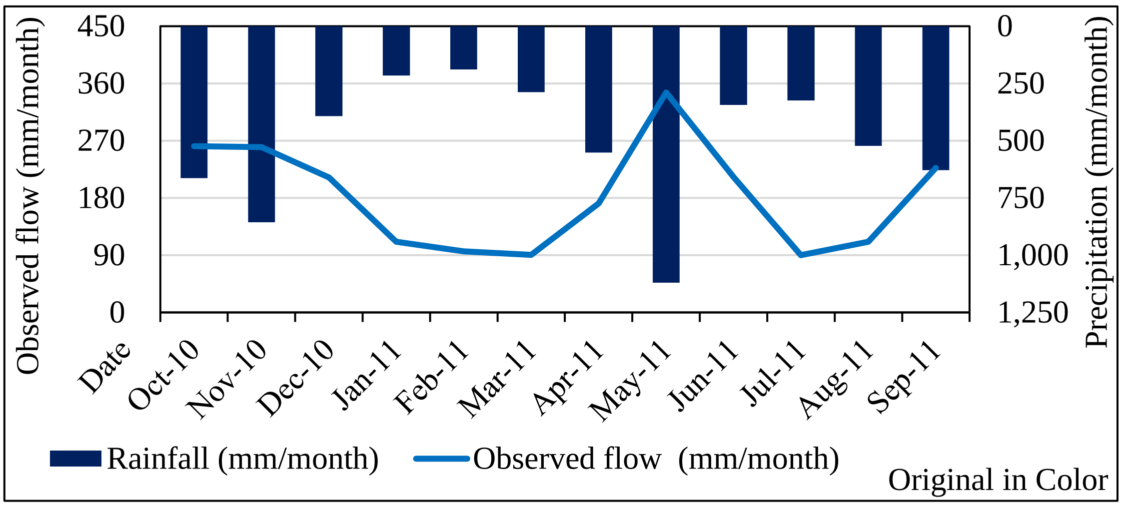
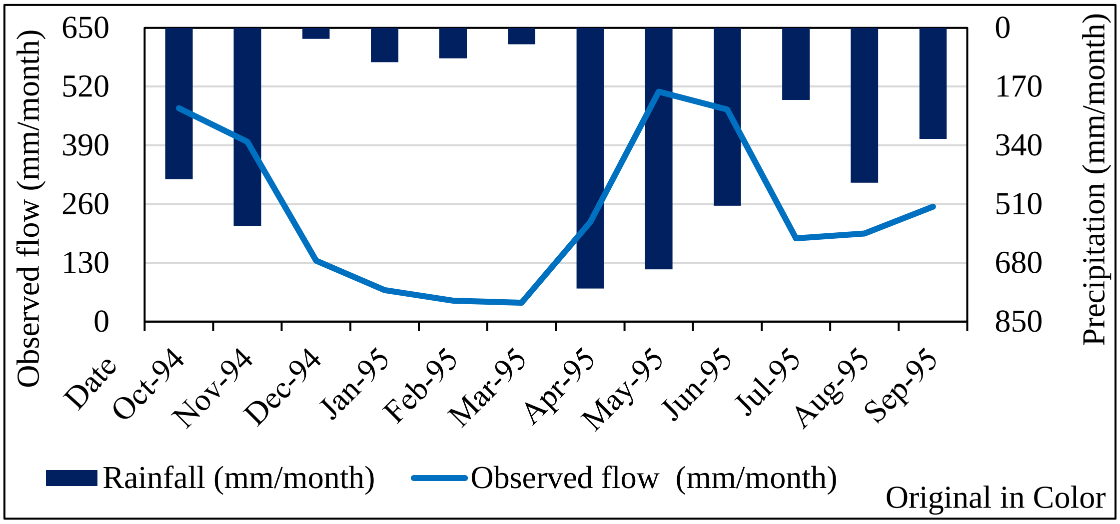
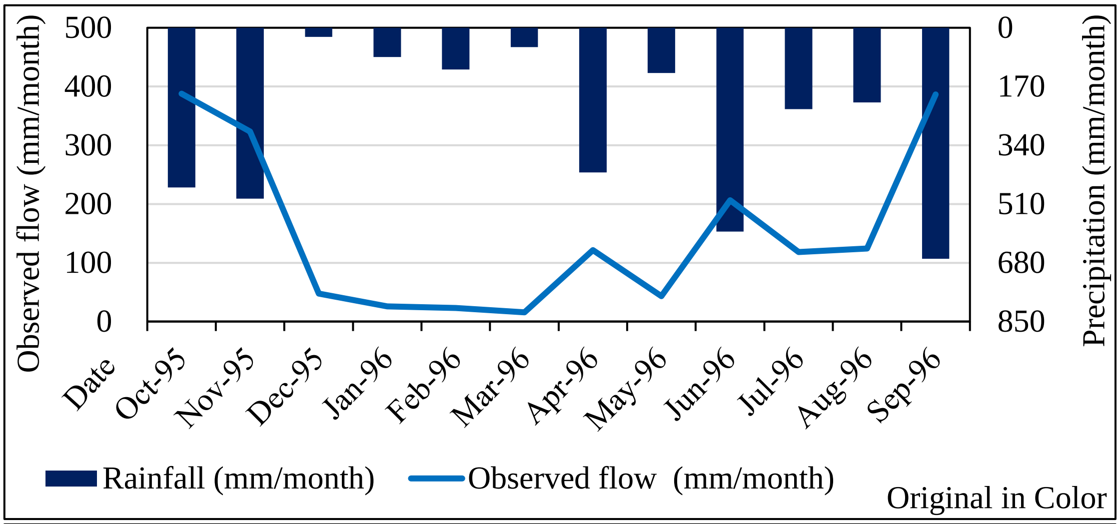
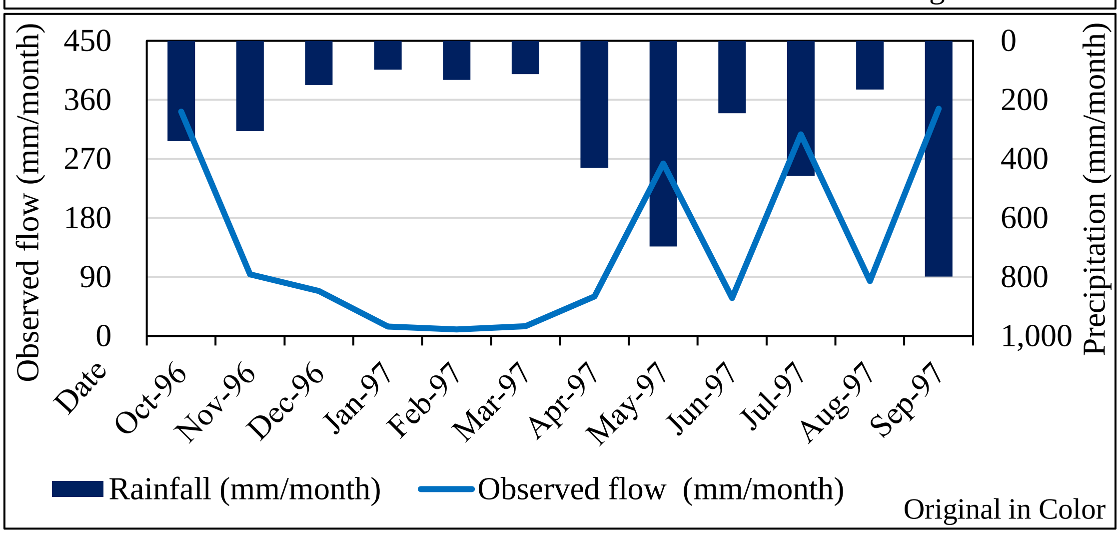
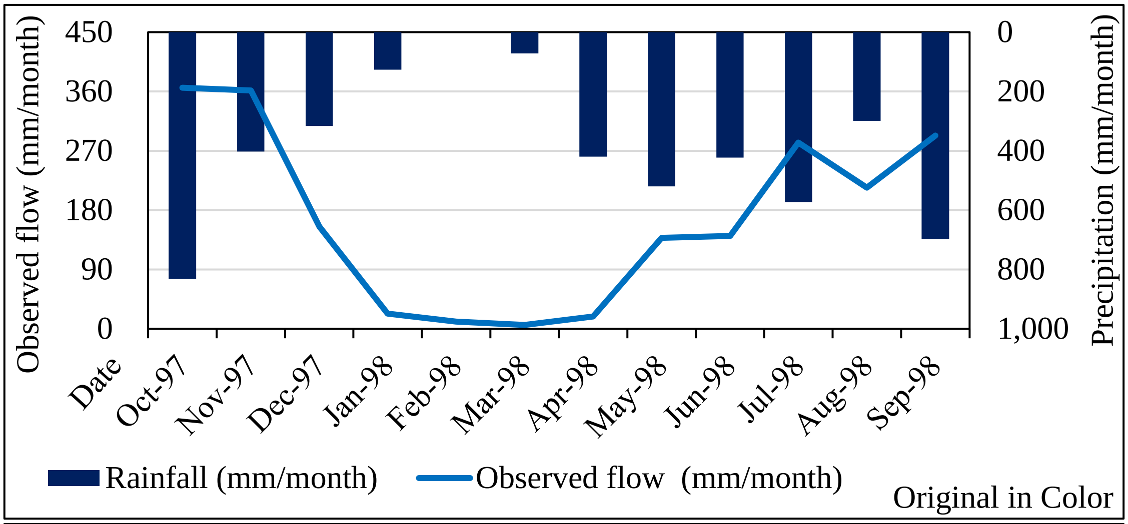


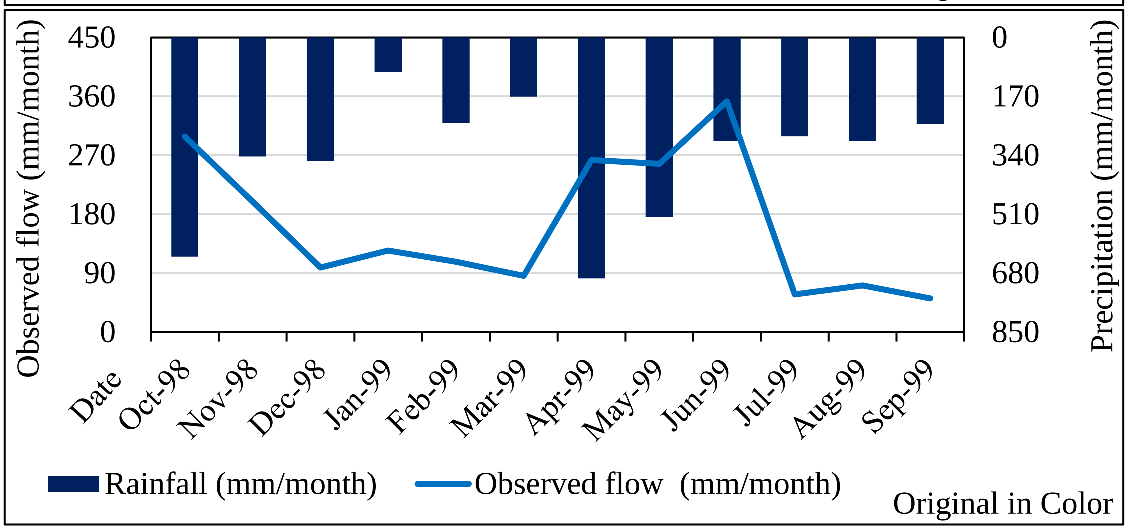
Figure 7-4 Visual checking Glencorse streamflow response to Weweltalawa rainfall

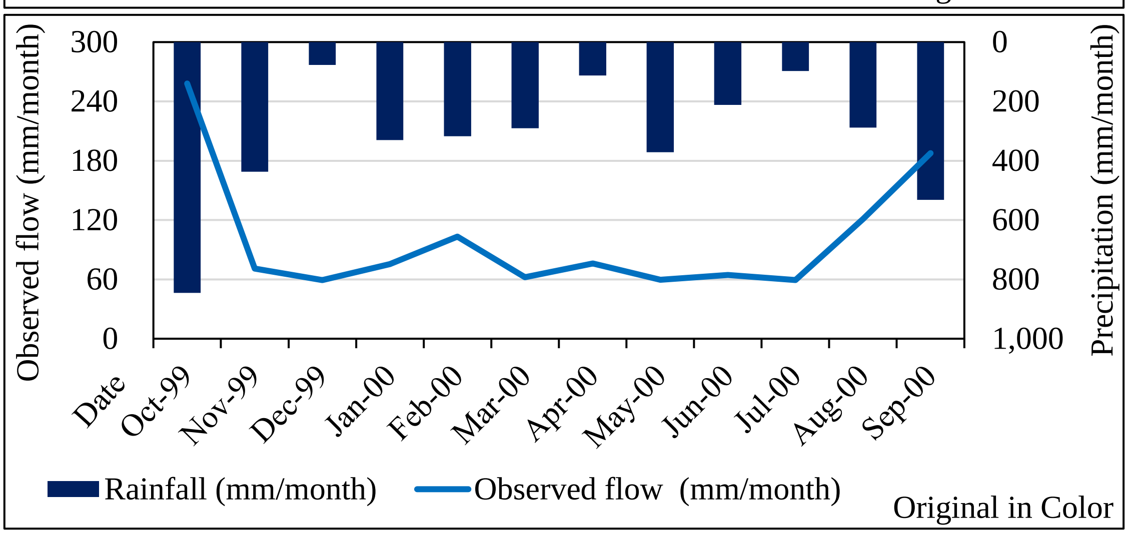

Observed flow (mm/month)
650
520
390
260
130
0
0
170
340
510
680
850
Precipitation (mm/month)
Date
Oct-94
Nov-94
Dec-94
Jan-95
Feb-95
Mar-95
Apr-95
May-95
Jun-95
Jul-95
Aug-95
Sep-95
Rainfall (mm/month)
Observed flow (mm/month)
Original in Color

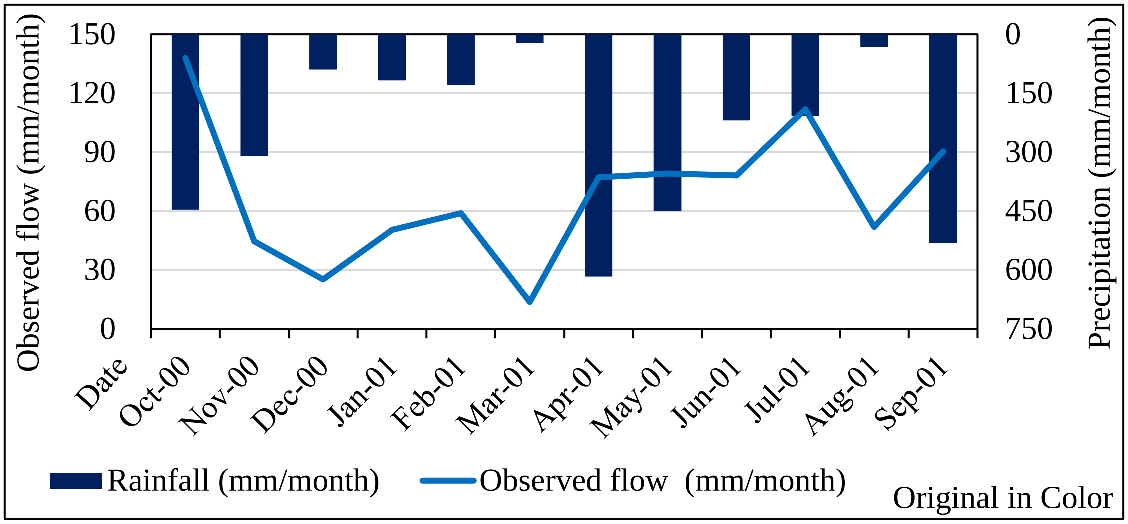

Observed flow (mm/month)
500
400
300
200
100
0
0
170
340
510
680
850
Precipitation (mm/month)
Date
Oct-95
Nov-95
Dec-95
Jan-96
Feb-96
Mar-96
Apr-96
May-96
Jun-96
Jul-96
Aug-96
Sep-96
Rainfall (mm/month)
Observed flow (mm/month)
Original in Color

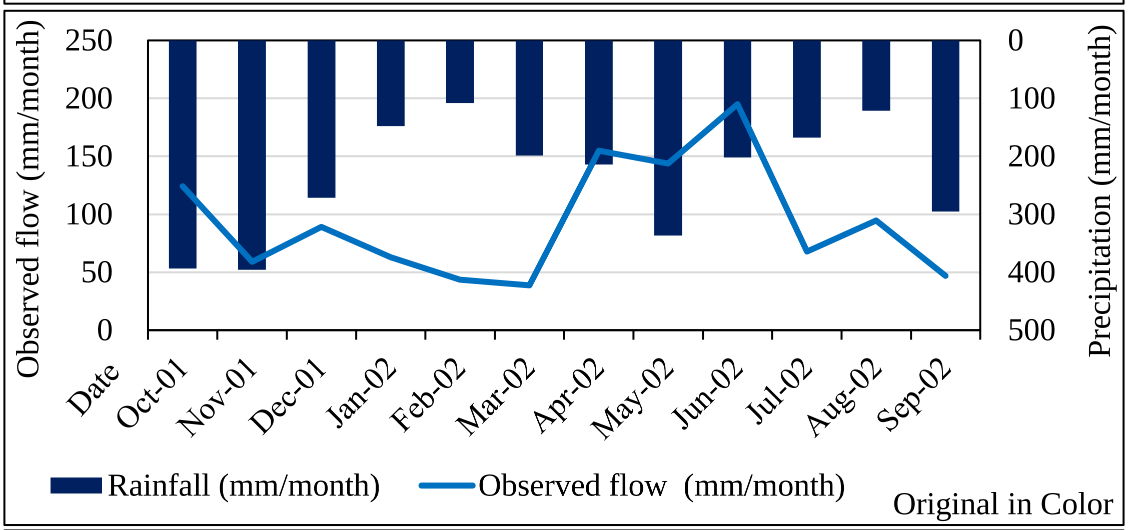

Observed flow (mm/month)
450
360
270
180
90
0
0
200
400
600
800
1,000
Precipitation (mm/month)
Date
Oct-96
Nov-96
Dec-96
Jan-97
Feb-97
Mar-97
Apr-97
May-97
Jun-97
Jul-97
Aug-97
Sep-97
Rainfall (mm/month)
Observed flow (mm/month)
Original in Color

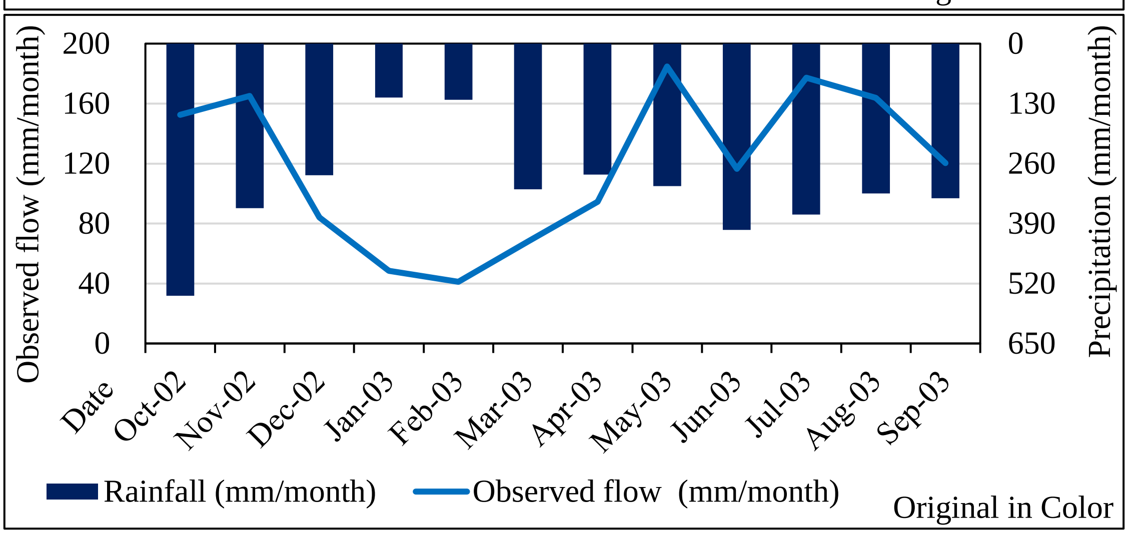

Observed flow (mm/month)
450
360
270
180
90
0
0
200
400
600
800
1,000
Precipitation (mm/month)
Date
Oct-97
Nov-97
Dec-97
Jan-98
Feb-98
Mar-98
Apr-98
May-98
Jun-98
Jul-98
Aug-98
Sep-98
Rainfall (mm/month)
Observed flow (mm/month)
Original in Color

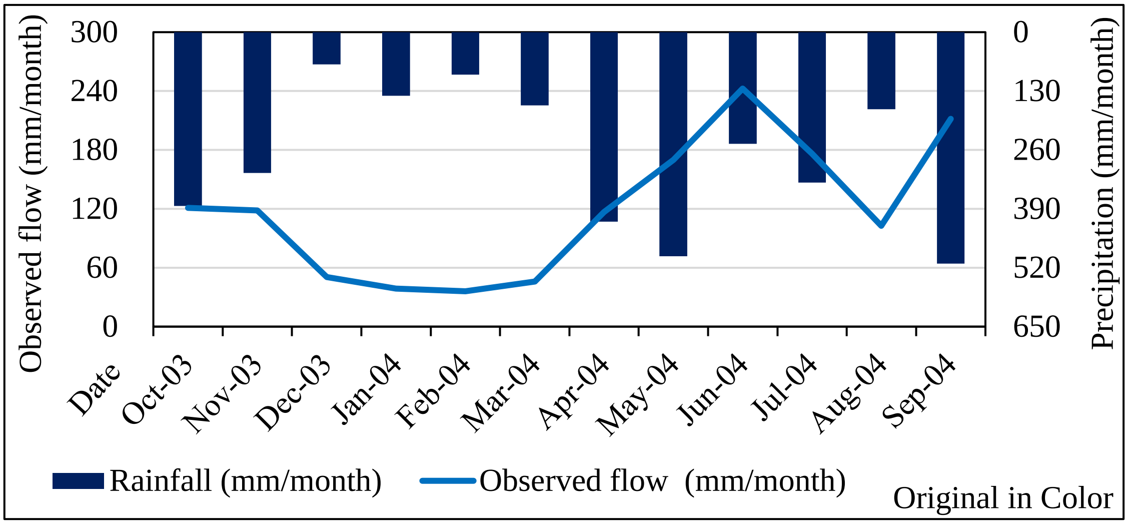

Observed flow (mm/month)
450
360
270
180
90
0
0
170
340
510
680
850
Precipitation (mm/month)
Date
Oct-98
Nov-98
Dec-98
Jan-99
Feb-99
Mar-99
Apr-99
May-99
Jun-99
Jul-99
Aug-99
Sep-99
Rainfall (mm/month)
Observed flow (mm/month)
Original in Color

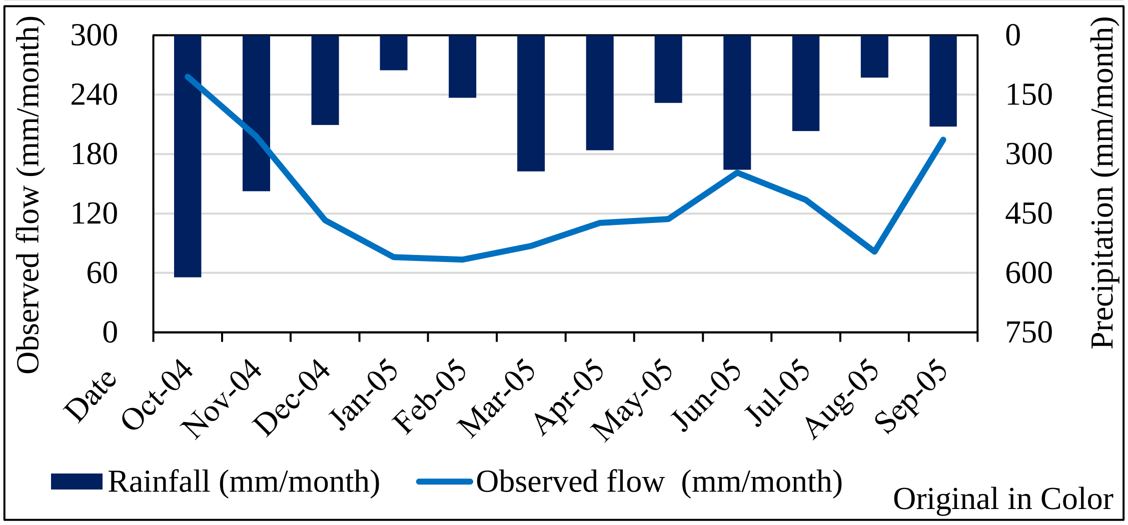

Observed flow (mm/month)
300
240
180
120
60
0
0
200
400
600
800
1,000
Precipitation (mm/month)
Date
Oct-99
Nov-99
Dec-99
Jan-00
Feb-00
Mar-00
Apr-00
May-00
Jun-00
Jul-00
Aug-00
Sep-00
Rainfall (mm/month)
Observed flow (mm/month)
Original in Color

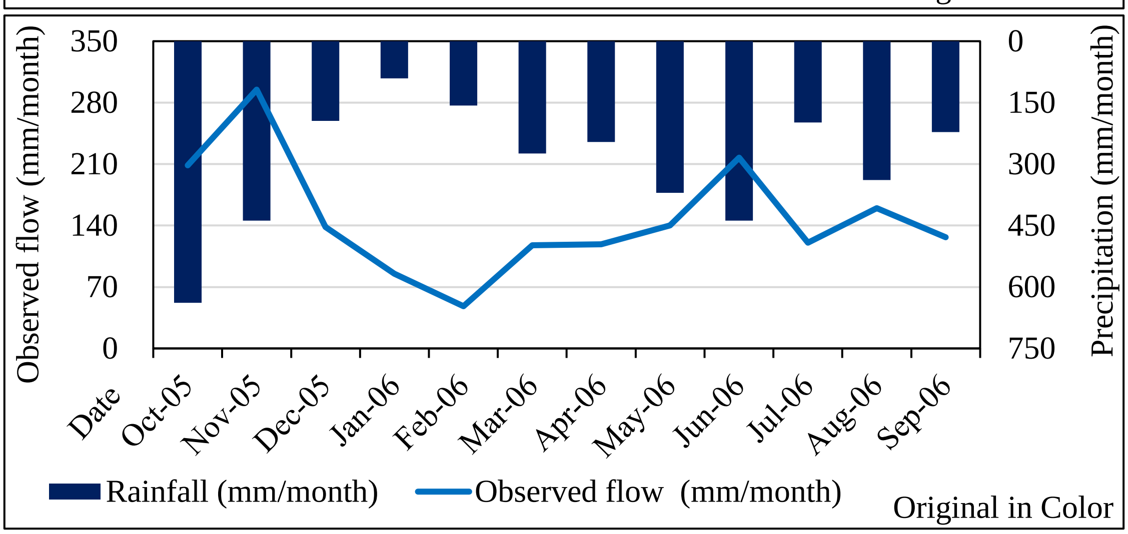

Observed flow (mm/month)
150
120
90
60
30
0
Precipitation (mm/month)
0
150
300
450
600
750
Date
Oct-00
Nov-00
Dec-00
Jan-01
Feb-01
Mar-01
Apr-01
May-01
Jun-01
Jul-01
Aug-01
Sep-01
Rainfall (mm/month)
Observed flow (mm/month)
Original in Color

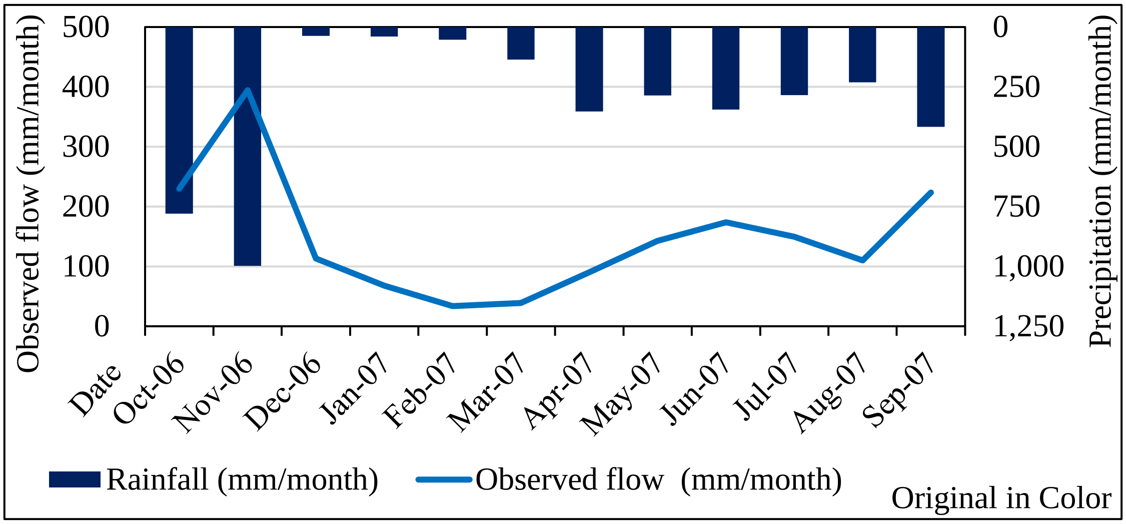

Observed flow (mm/month)
250
200
150
100
50
0
Precipitation (mm/month)
0
100
200
300
400
500
Date
Oct-01
Nov-01
Dec-01
Jan-02
Feb-02
Mar-02
Apr-02
May-02
Jun-02
Jul-02
Aug-02
Sep-02
Rainfall (mm/month)
Observed flow (mm/month)
Original in Color


Observed flow (mm/month)
200
160
120
80
40
0
Precipitation (mm/month)
0
130
260
390
520
650
Date
Oct-02
Nov-02
Dec-02
Jan-03
Feb-03
Mar-03
Apr-03
May-03
Jun-03
Jul-03
Aug-03
Sep-03
Rainfall (mm/month)
Observed flow (mm/month)
Original in Color

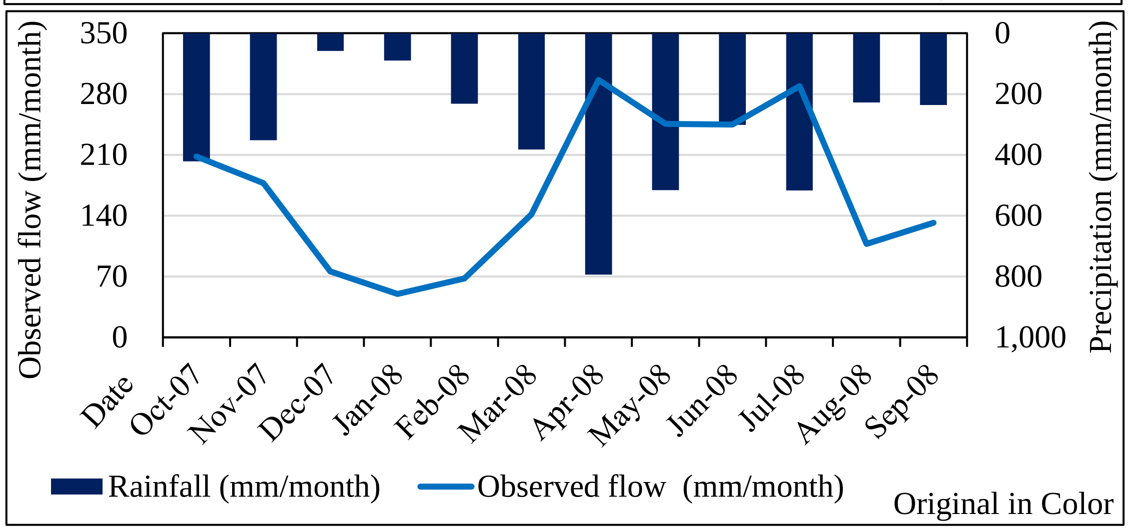

Observed flow (mm/month)
Precipitation (mm/month)
Date
Oct-03
Nov-03
Dec-03
Jan-04
Feb-04
Mar-04
Apr-04
May-04
Jun-04
Jul-04
Aug-04
Sep-04
Rainfall (mm/month)
Observed flow (mm/month)
Original in Color


Observed flow (mm/month)
Precipitation (mm/month)
Date
Oct-04
Nov-04
Dec-04
Jan-05
Feb-05
Mar-05
Apr-05
May-05
Jun-05
Jul-05
Aug-05
Sep-05
Rainfall (mm/month)
Observed flow (mm/month)
Original in Color

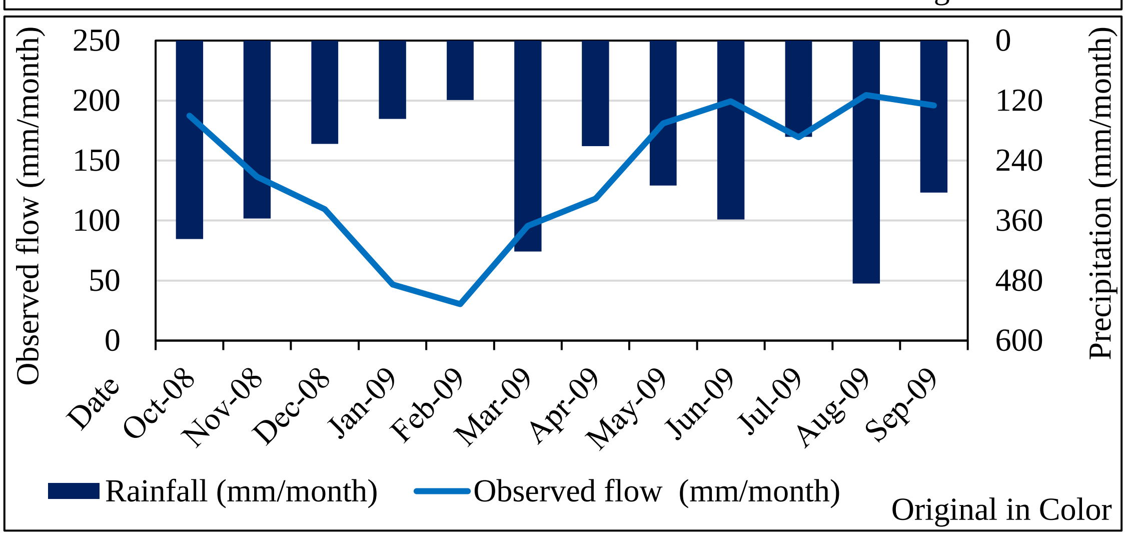

Observed flow (mm/month)
Precipitation (mm/month)
Date
Oct-05
Nov-05
Dec-05
Jan-06
Feb-06
Mar-06
Apr-06
May-06
Jun-06
Jul-06
Aug-06
Sep-06
Rainfall (mm/month)
Observed flow (mm/month)
Original in Color



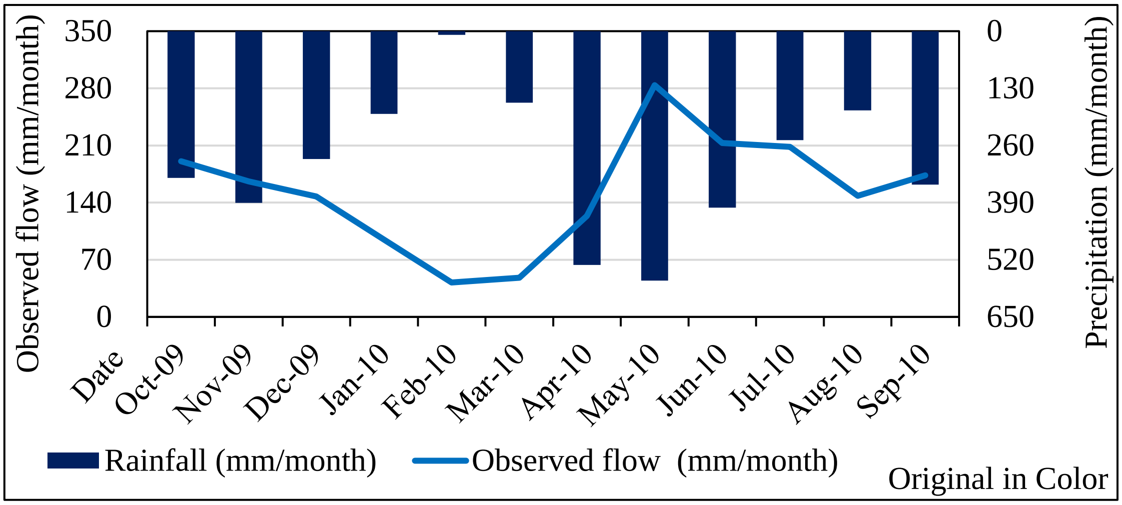
Observed flow (mm/month)
Precipitation (mm/month)
500
400
300
200
100
0
0
250
500
750
1,000
1,250
Date
Oct-06
Nov-06
Dec-06
Jan-07
Feb-07
Mar-07
Apr-07
May-07
Jun-07
Jul-07
Aug-07
Sep-07
Rainfall (mm/month)
Observed flow (mm/month)
Original in Color



Observed flow (mm/month)
Precipitation (mm/month)
350
280
210
140
70
0
0
200
400
600
800
1,000
Date
Oct-07
Nov-07
Dec-07
Jan-08
Feb-08
Mar-08
Apr-08
May-08
Jun-08
Jul-08
Aug-08
Sep-08
Rainfall (mm/month)
Observed flow (mm/month)
Original in Color



Observed flow (mm/month)
Precipitation (mm/month)
250
200
150
100
50
0
0
120
240
360
480
600
Date
Oct-08
Nov-08
Dec-08
Jan-09
Feb-09
Mar-09
Apr-09
May-09
Jun-09
Jul-09
Aug-09
Sep-09
Rainfall (mm/month)
Observed flow (mm/month)
Original in Color



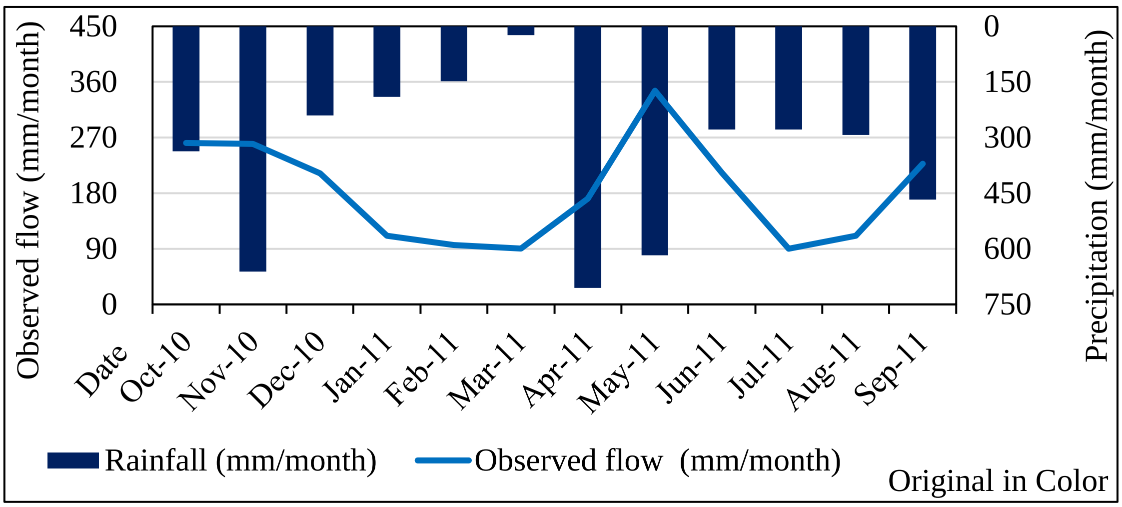
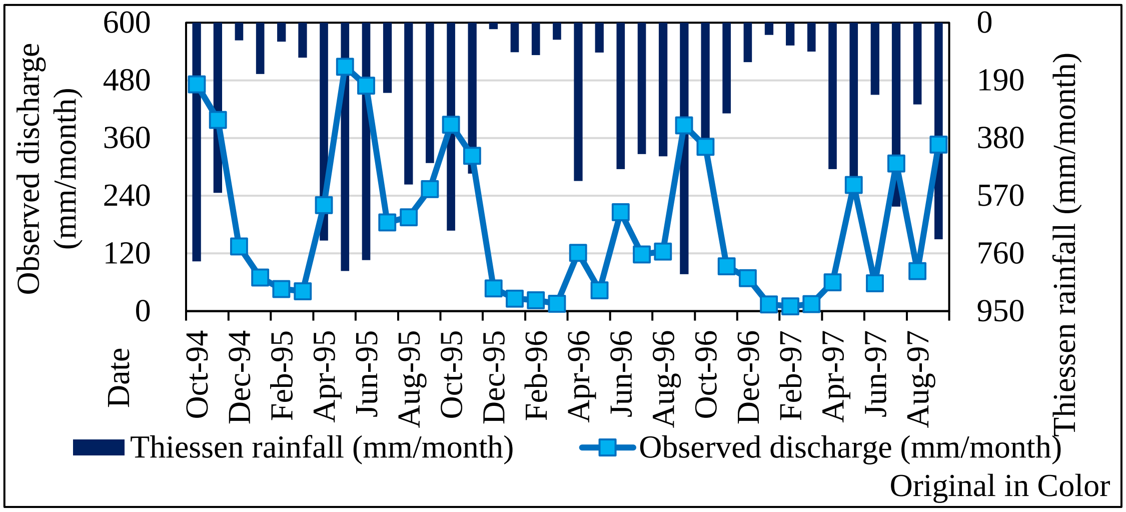
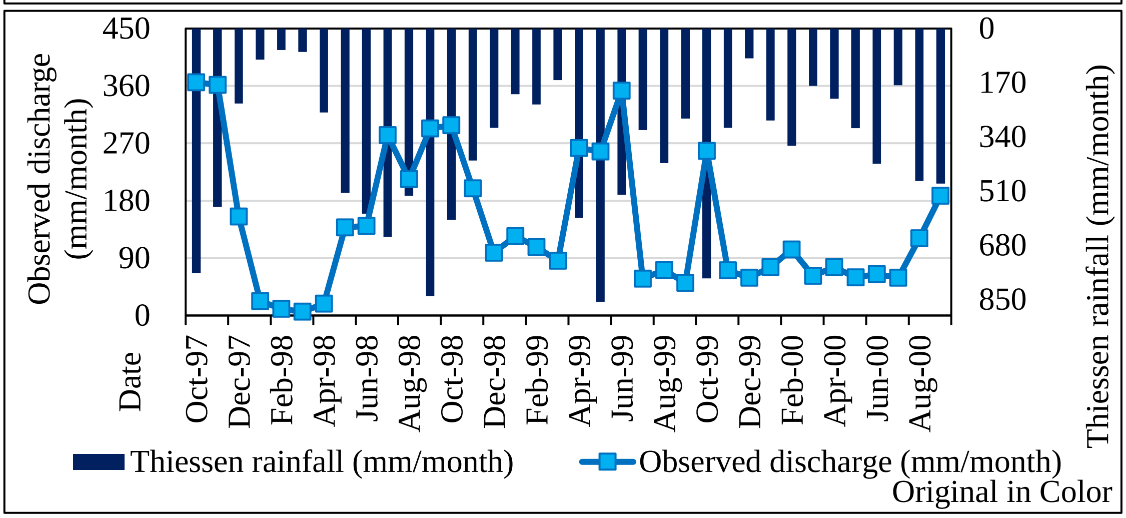


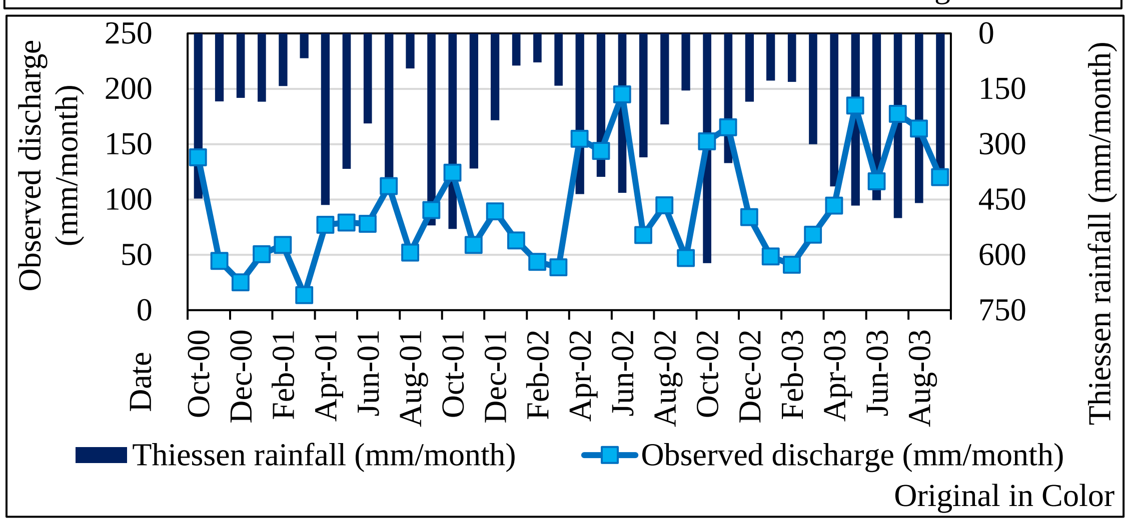
Figure 7-5 Visual checking Glencorse streamflow response to Dunedin rainfall



Observed discharge (mm/month)
600
480
360
240
120
0
0
190
380
570
760
950
Thiessen rainfall (mm/month)
Date
Oct-94 Dec-94 Feb-95 Apr-95 Jun-95 Aug-95 Oct-95 Dec-95 Feb-96 Apr-96 Jun-96 Aug-96 Oct-96 Dec-96 Feb-97 Apr-97 Jun-97 Aug-97
Thiessen rainfall (mm/month)
Observed discharge (mm/month)
Original in Color



Observed discharge (mm/month)
450
360
270
180
90
0
0
170
340
510
680
850
Thiessen rainfall (mm/month)
Date
Oct-97 Dec-97 Feb-98 Apr-98 Jun-98 Aug-98 Oct-98 Dec-98 Feb-99 Apr-99 Jun-99 Aug-99 Oct-99 Dec-99 Feb-00 Apr-00 Jun-00 Aug-00
Thiessen rainfall (mm/month)
Observed discharge (mm/month)
Original in Color



Observed discharge (mm/month)
250
200
150
100
50
0
0
150
300
450
600
750
Thiessen rainfall (mm/month)
Date
Oct-00 Dec-00 Feb-01 Apr-01 Jun-01 Aug-01 Oct-01 Dec-01 Feb-02 Apr-02 Jun-02 Aug-02 Oct-02 Dec-02 Feb-03 Apr-03 Jun-03 Aug-03
Thiessen rainfall (mm/month)
Observed discharge (mm/month)
Original in Color

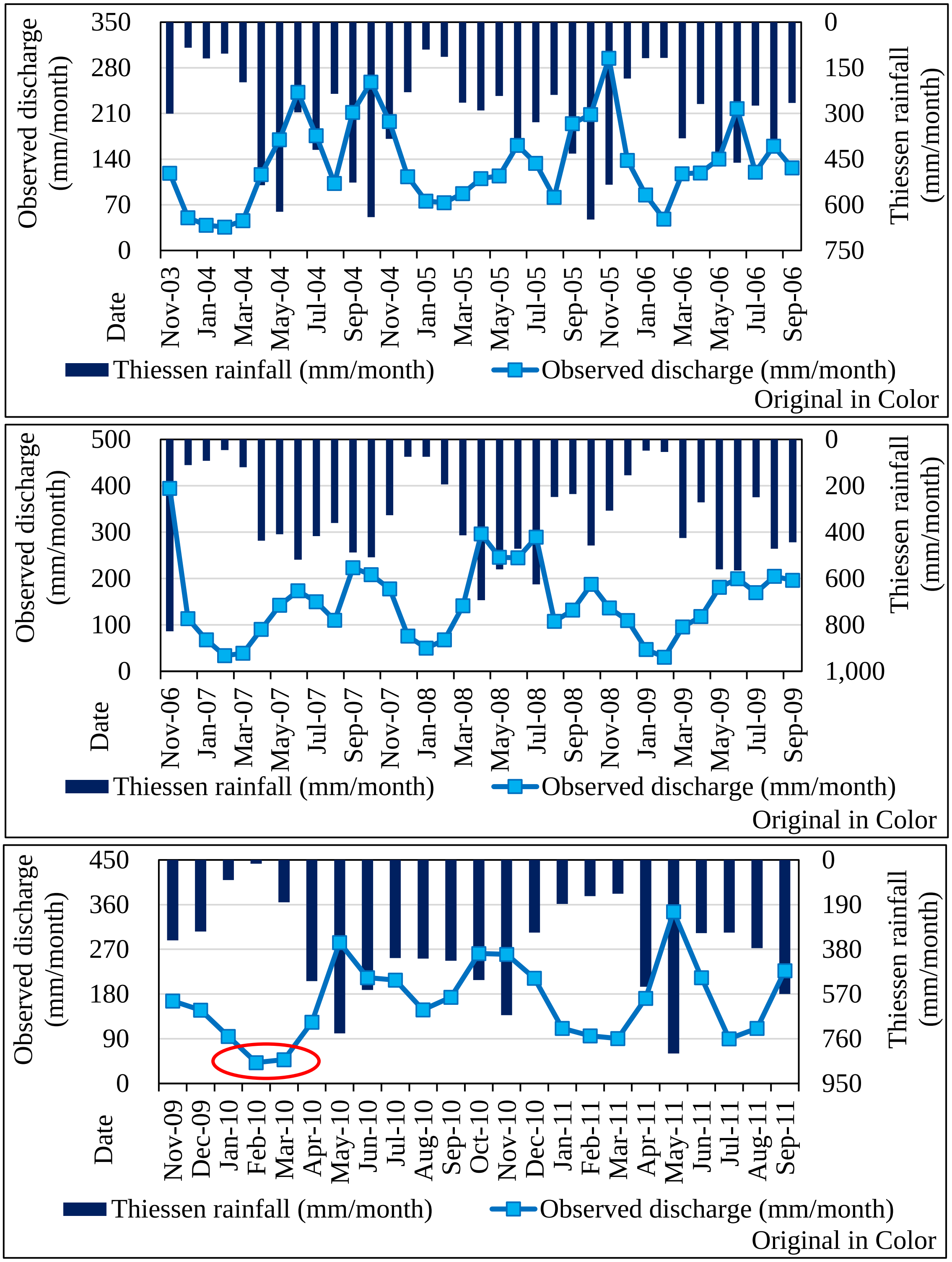
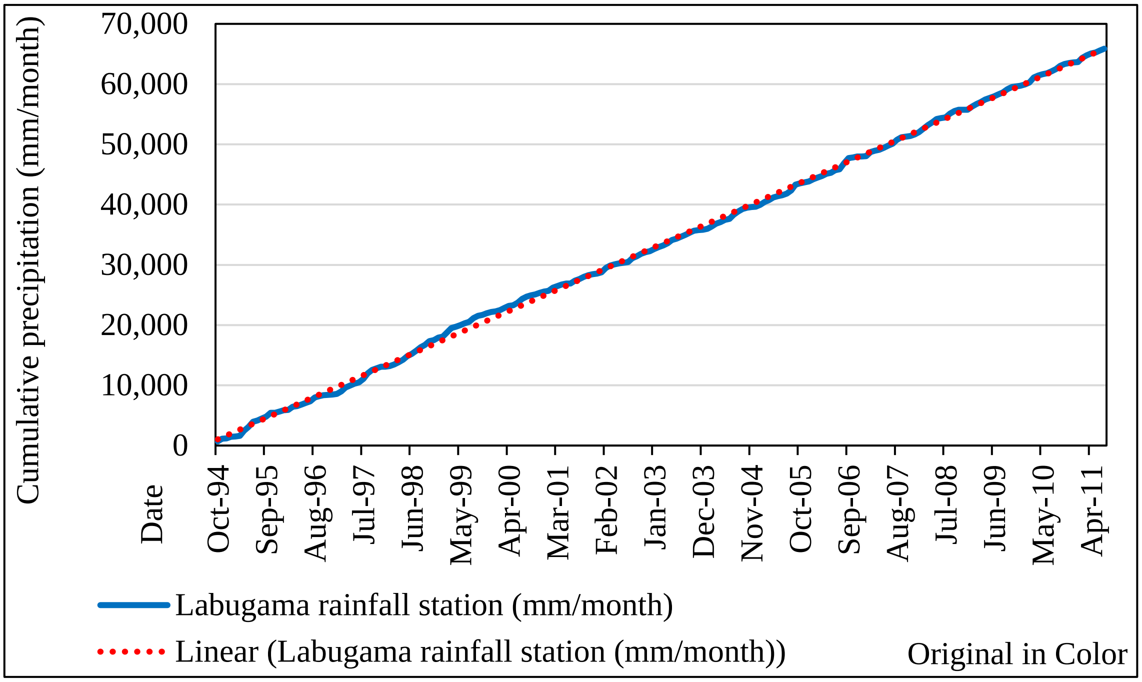
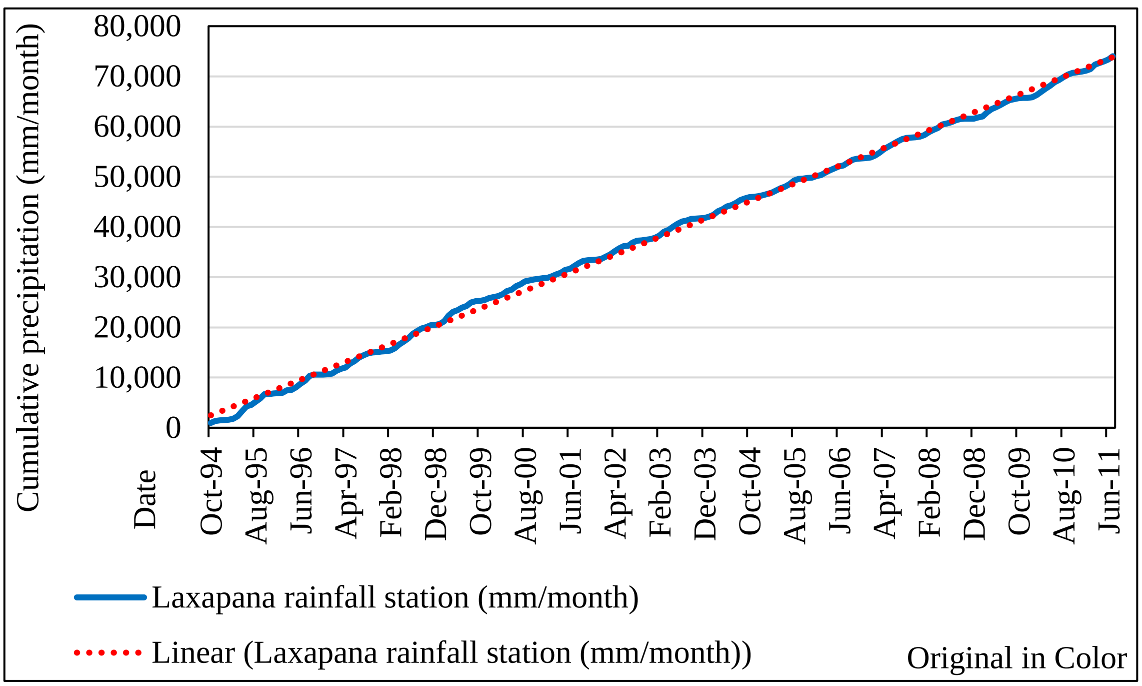
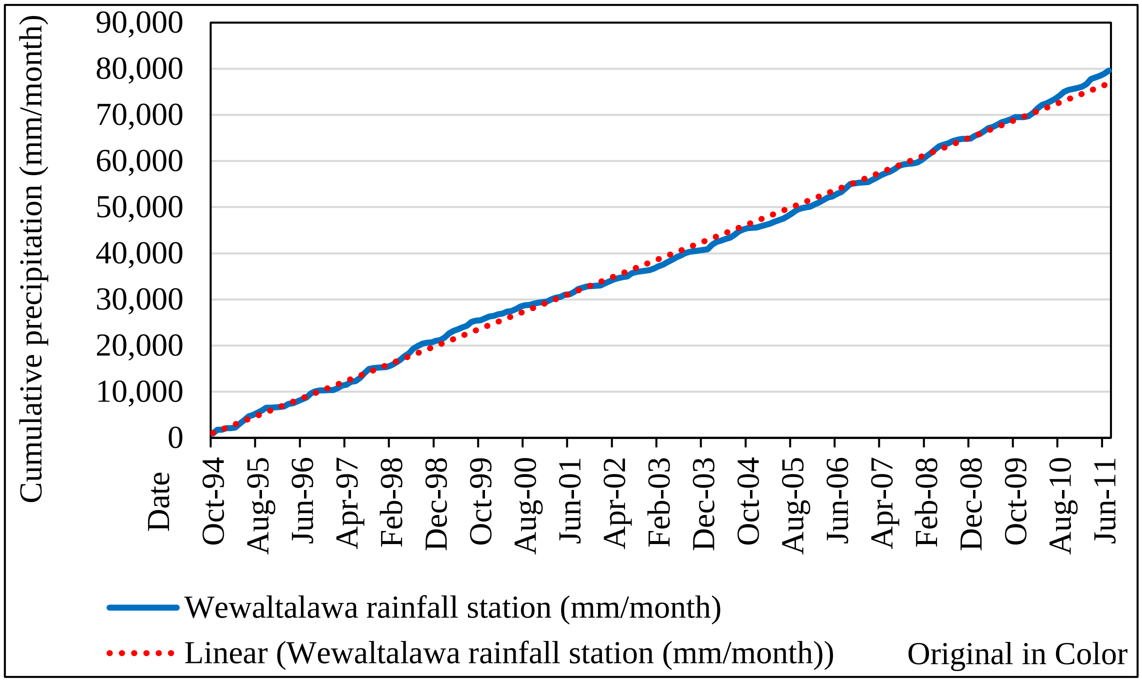


Figure 7-6 Visual checking Thiessen rainfall with Glencorse streamflow

Appendix A3: Single Mass Curve


70,000
60,000
50,000
40,000
30,000
20,000
10,000
0
Cumulative precipitation (mm/month)
Date
Oct-94
Sep-95
Aug-96
Jul-97
Jun-98
May-99
Apr-00
Mar-01
Feb-02
Jan-03
Dec-03
Nov-04
Oct-05
Sep-06
Aug-07
Jul-08
Jun-09
May-10
Apr-11
Labugama rainfall station (mm/month)
Linear (Labugama rainfall station (mm/month))
Original in Color


80,000
70,000
60,000
50,000
40,000
30,000
20,000
10,000
0
Cumulative precipitation (mm/month)
Date
Oct-94
Aug-95
Jun-96
Apr-97
Feb-98
Dec-98
Oct-99
Aug-00
Jun-01
Apr-02
Feb-03
Dec-03
Oct-04
Aug-05
Jun-06
Apr-07
Feb-08
Dec-08
Oct-09
Aug-10
Jun-11
Laxapana rainfall station (mm/month)
Linear (Laxapana rainfall station (mm/month))
Original in Color



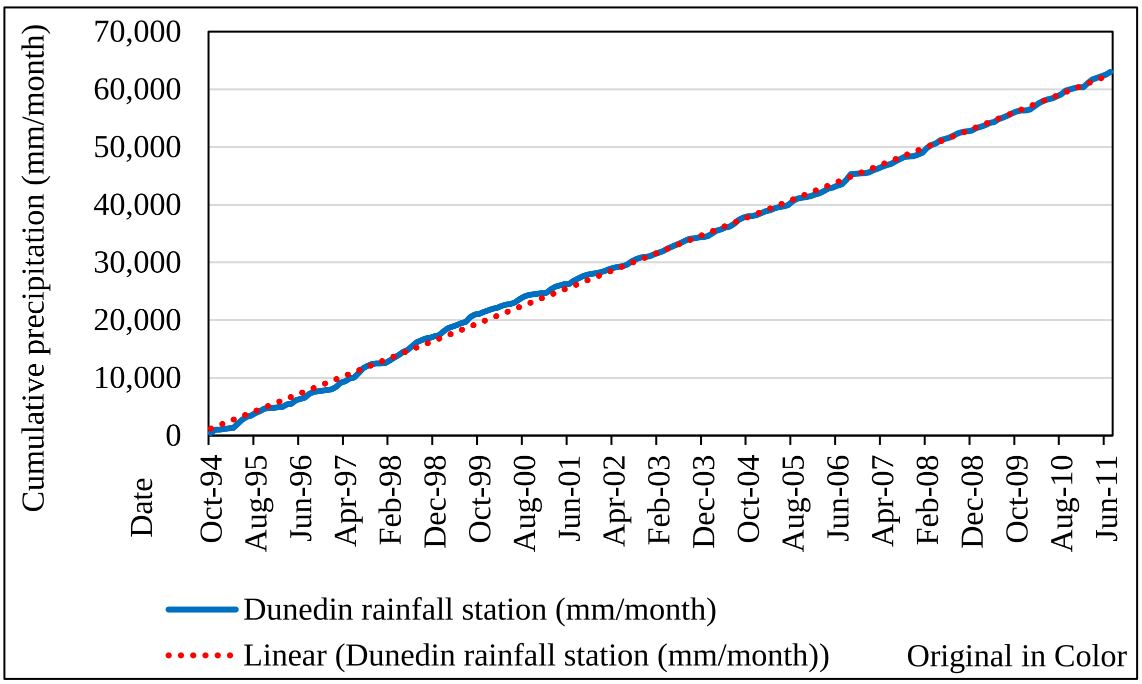


Figure 7-7 Single mass curve for all rainfall data

Appendix A4: Double Mass Curve

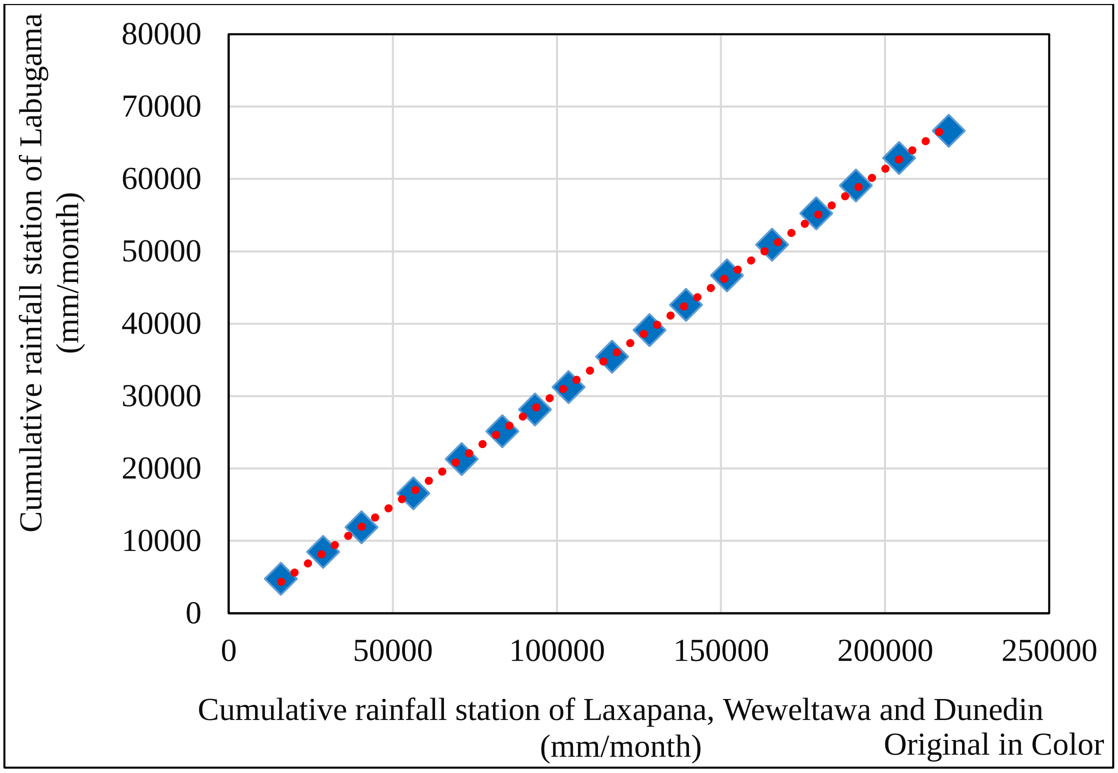


Figure 7-8 Double mass curve for consistency checking

APPENDIX B: SPECIMEN CALCULATION

Potential evapotranspiration calculation

Table 7-1 Basin location in longitude and latitude and in decimal

Kelani basin	Discharge location	Kirindi discharge location
(Latitude)	6º58′10.486″	6º27′34.151″
Latitude (in decimal), ϕ =	6.9696	6.4595
π =	3.141	

Table 7-2 Temperature in degree celcius

Year	Months	Months	Tmin. (℃)	Tmax. (℃)	Average Tav (℃)
Jan, 1990	31	1	14.8	31.1	22.95

Relative distance between earth& sun

$dr =$ 1+0.033 cos ((2π/365) J), where J is number of days in a month

= 1+0.033*cos (2*π/365)*31)

= 2.02

Solar decline (radiation)

$$\boldsymbol{\delta} = 0.4093\sin(\frac{2\pi}{365}J - 1.405)$$

= 0.4093*sin (2*π/365)*31

= -0.313

Sunset hour angle

$\boldsymbol{\omega_s} = \cos(-tan\emptyset tan\delta)$

= cos (-tan (6.9696)*tan (-0.313)

= 1.00

Extraterrestrial solar radiation

$\boldsymbol{S_0} = 0.6059dr(\omega_s sin\phi sin\delta + cos\phi cos\delta sin\omega_s)$

= 0.6059*2.02*(1*sin (6.9696)*sin (-0.313) +cos (6.9696)*cos (-0.313)*sin (1)

= 0.52

Potential evapotranspiration

$\boldsymbol{PET} = 0.0023S_0(T_{max} - T_{min})(T_{ave} + 17.8)$

= 0.0023*0.52(31.1-14.8)*(22.95+17.8)

= 0.35 mm

Table 7-3 Thiessen rainfall and observe flow (mm)

Thiessen rainfall Pt (mm)	**Pan evapotranspiration (mm)**	**Observed discharge Qo (mm)**
155.22	1.93	71.50

Table 7-4 Parameter ranges and input value

Parameter a (0.8-0.99)	0.99
Parameter b (0-1900)	50
Parameter c (0-0.5)	0.5
Parameter d (closer to 0)	0.8

Residual soil moisture storage

$\boldsymbol{XU_t} = E_t - PET$

= 1.93+0.35

= 1.58 mm

Available water

$\boldsymbol{W_t} = P_t + XU_{t-1}$

Wt. = Pt+XUt-1, where XUt-1 is upper soil moisture previous time (assumption 0.3)

= 155.22+0.3

= 155.52 mm

Evapotranspiration opportunity

$$\boldsymbol{Y_t} = \frac{W_t + b}{2a} - \sqrt{\left(\frac{W_t + b}{2a}\right)^2 - \frac{bW_t}{a}}$$

$\boldsymbol{Y_t}$ = (Wt +b)/2a - (√ ((Wt +b/2a) ^{2}- (dWt/a))

= (155.52+50)/2*0.99-(√(155.52+50/2*0.99)^2 -(0.8*155.52/0.99)

= 124.42 mm

Actual evapotranspiration computed in model as

$$\boldsymbol{E_t} = Y_t(1 - exp\left(-\frac{PE_t}{b}\right)$$

$\boldsymbol{E_t}$ = Yt*(1-exp (-PEt/b)

= 124.42*(1-exp (-1.93/50)

= 0.867 mm

Water available for runoff

(Wt - Yt) = 155.52-124.42

= 31.10 mm

Recharge to groundwater

Rt. = c*(Wt -Yt)

= 0.5*(31.1)

= 15.55 mm

Lower soil zone

$$\boldsymbol{XL_t} = (XL_{t-1} + R_{year})(1 + d) - 1$$

XLt = (XLt -1 +RYeart)*(1+d)-1, (where XLt -1 is pan evaporation)

= (1.93+15.55)*(1+0.8)-1

= 28.9 mm

Upper zone to runoff contribution.

$$\boldsymbol{QU_t} = (1 - c)(W_t - Y_t)$$

QUt = (1-0.5)*(31.1)

= 15.55 mm

Lower zone to runoff contribution

$\boldsymbol{QL_t} = dXL_{\boldsymbol{t}}$

QLt = 0.8*28.9

= 23.14 mm

Total streamflow

$\boldsymbol{Q_t} = (QU_t + QL_t)$

Qt = 15.55+23.14

= 38.69 mm

APPENDIX C: EVAPOTRANSPIRATION CALCULATION

Potential evapotranspiration is estimated from observed air temperature and latitude using the method described by Shuttleworth (1993).

Required data were Latitude 6º58′10.486″ and Latitude, ϕ =6.9696, pi (π)= 3.1414 and Julian number (J)= 30.

Relative distance between earth and sun

$d_r = 1 + 0.033\, cos\left(\frac{2\pi}{365}\right)J$ …………………………………...…………….…….. (a)

Where J is the Julian day (number of days since January 1 of a given year)

Solar decline (Radiation)

$\delta = 0.4093 sin\left(\left(\frac{2\pi}{365}\right)J - 1.405\right)$ ……………………………….……….……………. (b)

Sunset hour angle

$\omega_S = cos(-tan\phi tan\delta)$ ……………………………..…………….…….………. (c)

The extraterrestrial solar radiation depends on the time of year and latitude:

$So = 0.6059 d_r(\omega_s sin\phi sin\delta + cos\phi cos\delta sin\omega_s)$ ……………..………………….. (d)

Where d_r is the relative distance between the earth and sun, ω_s is the sunset hour angle (radians), ϕ is the latitude (radians), and δ is the solar declination (radians).

Potential evapotranspiration

$PET = 0.0023 S_O \sqrt{(T_{MAX} - T_{MIN})}(T_{MAX} - T_{MIN})(T_{AVE} + 17.8)$ …………………... (e)

Where PET is daily potential evapotranspiration (in/day), S_o is the water equivalent of extraterrestrial solar radiation (in/day), T_{MIN} and T_{MAX} are the daily minimum and maximum air temperature (degC), and T_{AVE} is the average daily temperature computed as the mean of T_{MIN} and T_{MAX}