SWAT MODEL APPLICATION TO ESTIMATE STREAMFLOW IN ATTANAGALU OYA BASIN FOR SUSTAINABLE WATER RESOURCE MANAGEMENT

Choki Zam

(189252T)

Degree of Master of Science

Department of Civil Engineering

University of Moratuwa
Sri Lanka

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Choki Zam

(189252T)

Supervised by
Professor N.T.S. Wijesekera

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

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

Department of Civil Engineering

University of Moratuwa
Sri Lanka

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SWAT MODEL APPLICATION TO ESTIMATE STREAMFLOW IN ATTANAGALU OYA BASIN FOR SUSTAINABLE WATER RESOURCE MANAGEMENT

ABSTRACT

Water crisis is prevailing as a result of the ever increasing population across the globe with advances in society and economy which significantly affects the ecosystems, environment and economy. Water resources are limited and needs to be efficiently managed by estimating streamflow. The Soil and Water Assessment Tool (SWAT) model is a physically based, continuous, computationally efficient, and distributed model considering similar slope, landuse and soil conditions as its smallest unit in the basin. It has been effectively applied at a wide range of watershed scales under different circumstances around the globe to estimate streamflow. Therefore, a process-based distributed model has to be defined and evaluated to estimate the streamflow in order to meet water demands for efficient watershed management.The objective is to evaluate the potential of process based distributed SWAT model for the estimation of streamflow in Attanagalu Oya Basin for sustainable water resource management.

In this study, the SWAT model has been applied over Dunamale watershed in Attanagalu Oya basin for a period of 10 years from 2008 to 2018 on a daily time scale basis. SWAT-CUP was used as calibration and validation tool with SUFI-2 as the optimization algorithm. The model was semi auto calibrated from 2008 to 2012 and validated from 2013 to 2018. Nine parameters were selected from literature review for calibration and validation. The calibrated and validated results are plotted in flow duration curve. A total of 34 iterations were carried out with each iteration having a total simulation of 200 numbers.

The process based distributed SWAT model can be developed for Attanagalu Oya Basin in Dunamale watershed to estimate streamflow with R^2 value of 0.77 during calibration and 0.58 during validation with hydrograph matching pattern. The model gives a better matching for medium flow when compared to high flow and low flow and hence it can be used for sustainable water resource management. Daily model results when accumulated into monthly time frame has higher accuracy in the outcome when compared to daily and can be used in efficient decision making for water planning and management. SWAT model has more parameters and is complex when applied but the results are generated in a detailed manner with HRU as its basic unit and can be used for a better understanding of the watershed.

Keywords: Process based hydrologic model, Water Crisis, HRU

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LIST OF ABRREVIATION

Abbreviation	Description
ALPHA_BF	Groundwater baseflow alpha factor
CN2	SCS runoff curve number
EPCO	Plant uptake compensation factor
ESCO	Soil Evaporation Compensation factor
FDC	Flow Duration Curve
GW_DELAY	Groundwater delay
GW_REVAP	Groundwater “revap” coefficient
R^2	The coefficient of determination
REVAPMN	Threshold depth of water in shallow aquifer required for return flow to occur
SOL_AWC	Available water capacity of the soil layer
SUFI-2	Sequential Uncertainty Fitting
SWAT	Soil Water and Assessment Tool
SWAT-CUP	SWAT Calibration and Uncertainty
Procedures	
SWRM	Sustainable Water Resource Management

1 INTRODUCTION

1.1 General

1.1.1 Water crisis

It is an inevitable fact that water resource is a necessity for human survival. Of the 71% of water surface on earth only about 2% is found to be freshwater and from that 0.5% is available for human consumption because the remaining freshwater is frozen as ice caps and glaciers. Approximately 70% of the freshwater found on earth is often used to produce food and at least 20% is used for industrial uses. For residential consumption, just about 10% of water is utilized. Hence we can understand how precious and limited water resources are on earth.

It is alarming that the growing dependency on already limited water resources has increased exponentially over the recent years due to the ever increasing population and the current patterns of advancement in society like urbanization, expansion of industries, more energy consumption, degrading water quality, modern irrigation for better productivity in agriculture and global warming. As a result water crisis is prevailing across the globe (Kallen, 2015).

Water crisis is greatly associated with alterations in landuse and climate, which are the two primary reasons that disturb water resources around the world (Kim, Choi, Choi, & Park, 2013; R. Wang, Kalin, Kuang, & Tian, 2013; L. Zhang, Nan, Xu, & Li, 2016). Changes in patterns of landuse and climate are the main parameters that affect streamflow (L. Zhang et al., 2016). Understanding the adverse effects of variation in climate and patterns of landuse which disturbs streamflow plays a vital role for long term water resource planning and management (Kim et al., 2013). Alterations in landuse and climate are capable to change the hydrologic conditions in the watershed which significantly affects the ecosystems, environment and economy (Guo, Su, Singh, & Jin, 2016).

Landuse change are majorly caused by human exercises such as modifications in landuse practices, vegetation types and their spatial pattern variations (Wickramagamage, 1998). Landuse change affects evapotranspiration, interception, infiltration and ground water recharge that results in variation of surface and subsurface flows (Anand, Gosain, & Khosa, 2018; Baker & Miller, 2013; L. Zhang et al., 2016). Urbanization is the most commonly observed driver for landuse change highly contributing to rise in impermeable areas in watershed that reduce the quantity of water infiltrating into the soil (R. Wang et al., 2013). Owing to landuse change, the consequences on water resources is one of the most delicate ones (Shrestha, Shrestha, & Shrestha, 2019). Climate change which mainly refers to variations in rainfall and temperature disturbs the water cycle and hence water availability (Khoi & Suetsugi, 2014). Variations in landuse patterns and changes observed in the climatic conditions over the years are a result of the human activities with population rising exponentially leading to water crisis across the globe.

1.1.2 Water Demand

The considerable increase in population over the recent years have resulted in the overall increase in number of water users and water demand. Water is used by many sectors in Sri Lanka such as, domestic water supply, agriculture, recreation, hydropower, navigation, industries, etc. It is a challenge for water managers to meet all these multiple water demands within the available limited water resources. Further water managers have to take into accounts the uncertainties associated with the natural water supplies and demand due to aftermath of alterations in climate and landuse patterns prevailing in Sri Lanka which alter the water quantity and hydrological processes associated. Anticipated challenges from climate change and landuse change being mainly the changes in precipitation and its pattern and changes in temperature will result in adverse impacts on the livelihood of water users. These impact include changes in natural water supply, changes in irrigation condition, fluctuations in soil moisture as a consequence to temperature change, increased evaporation from irrigated lands and reservoirs (Wijesekera, 2010). Population around the world is only expanding day by day and so is the demand associated with the need of water. Thus, the main role of water managers is to take into account water crisis and develop water resources management systems to deliver to the water needs (Loucks, Beek, & Stedinger, 2005).

1.1.3 Importance of process based distributed models

Water resources need to be managed to fulfill demand of water need for all the users in the present and future times to come. Water resources are efficiently managed at basin level by estimating streamflow using a watershed model which is a simplified representation of reality of the world (Daniel et al., 2011). Distributed hydrological models as the name suggest can diverge a basin into various other hydrological response units with respect to the topography, soil, and land use in the basin. Distributed hydrological model can incorporate spatial variation in landuse patterns with streamflow simulation and is globally applied to study the effects of alterations in landuse on streamflow (Fu et al., 2018). Distributed models give prediction with higher resolution than lumped models (Carpenter & Georgakakos, 2006).

Process based watershed model quantifies hydrological processes such as infiltration for irrigation, surface runoff for flood and evaporation and soil moisture for drought. Process based models are necessary to build realism into simulating complex hydrological processes to comprehend how environment and human systems perform and link with each other (Peters-Lidard et al., 2017). Increased awareness and analysis of human impacts on hydrology related processes such as vairations in climate and landuse patterns is also a powerful stimulus to the implementation of a proces based distributed models (Fatichi et al., 2016). Process based distributed models are increasingly used to evaluate the interconnections of anthropogenic with natural system at a basin scale to utilize water sustainably.

1.1.4 Sustainable Water resource management

With the ever increasing population leading to rise in water usage and thus, water demand owing to urbanization and changes in landuse pattern with variations in climatic conditions has resulted in water crisis across the globe. Water being a limited resource needs to be dealt with utmost attention by water managers. Water managers thus, need to manage water by estimating streamflow with watershed models. Therefore, sustainable water resource management is the answer to water crisis across the globe to meet the water requirement of ever increasing population (Loucks et al., 2005).

1.2 Problem Identification

After reviewing literature it can be noted that water crisis is prevailing across the globe as a result of population growing exponentially and so are the demands associated with water owing to human activities leading to urbanization and abnormal changes in climatic conditions. But there are no established models readily available to manage water resources in a detailed manner considering the complexities in a basin (Ball et al., 2015). Therefore, a process-based distributed model has to be defined and evaluated to estimate the streamflow in order to meet water demands for SWRM.

1.3 Study area selection and justification

Attanagalu Oya basin was taken as the reference area to study on due to data availability and its close proximity for field visit. Furthermore, many past studies conducted in the basin suggested water scarcity scale to rise from moderate to severe by 2025 in Gamphana district whose major portion is in Attanagalua Oya basin. Hence it is a necessity to sustainably manage limited water in a distributed manner in the basin as Attanagalu Oya basin plays a vital part in national water supply in Sri Lanka as it has four main national water supply and intake drainage board (NWSDB, 2005) and contributes to Negombo lagoon (Pathirana, Bandara, Jayaweera, & Fonseka, 2013). The study area is shown in the Figure 1-1 below.

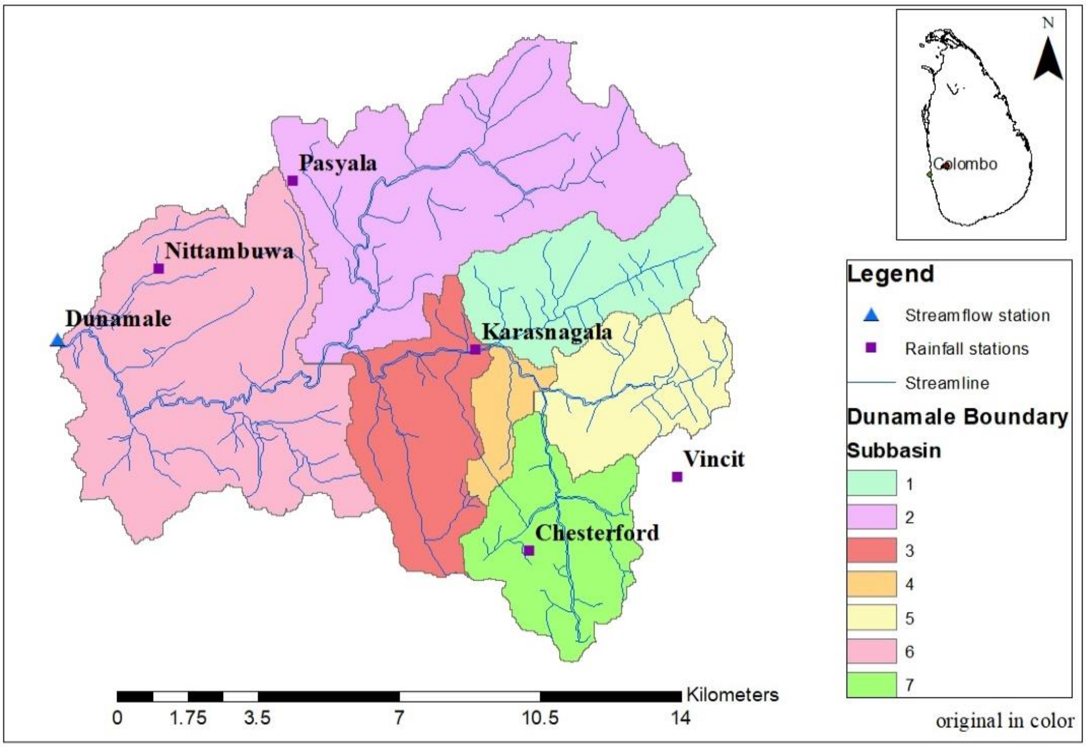


Figure 1-1: Dunamale watershed

Attanagalu Oya lies in the wet zone and is a river in Gampaha district of Sri Lanka. The basin drains into Negombo lagoon as Dandugam Oya. Attanagalu Oya is approximately 76 km with basin size of 727 sq km. The study area is Dunamale watershed which has an area of 153 sq km and five rain gauge stations are considered namely; Chesterford, Nittambuwa, Pasyala, Karasnagala and Vincit. The streamflow station is at Dunamale which is also the outlet in the basin.

1.4 Study Objective

1.4.1 Main Objective

To evaluate the potential of a process based distributed model for estimation of streamflow for sustainable water resource management in Attanagalu Oya Basin.

1.4.2 Specific Objectives

1. To review the state-of-art of process based distributed hydrologic model.
2. To collect data and data checking.
3. To develop a process based distributed model for Attanagalu Oya basin.
4. To calibrate and validate the process based distributed model for Attanagalu Oya basin.
5. To make recommendations for sustainable water resource management in Attanagalu Oya River Basin.

2 LITERATURE REVIEW

2.1 Introduction to hydrologic modelling

Watershed models have been developed, used and are continuously progressing with respect to its applicability, approach, and it's potential to give users a reliable and detailed information to analyze problems and assist in water management decisions for various implications. Prior to 1960 watershed modeling was primarily focused at statistical portrayal of particular hydrological processes. After 1960 with the invention of computer systems, watershed modelling was transformed. Advancement in the computer and other technologies have resulted in introduction to integrated data processing and management tools like Geographic Information Systems (GIS), radar applications, Remote Sensing, database management tools and satellites. All these advancement in technologies have enabled us to perform realistic field measurements and model watersheds around the globe with higher accuracy even for complex mathematical computations in a lesser amount of time. Further computers and watershed models have enabled us to cover up to a large areal extent and temporal resolution up to daily in a watershed (Mirchi, Watkins, Jr., & Madani, 2009).

2.2 The need for watershed modelling.

Modeling a watershed is of prime importance as it can provide valuable information and understanding regarding the problems associated in a watershed at a justifiable cost within a given time. In numerous studies engineers have used watershed models to simulate various hydrological processes for quantitative assessment of hydropower system, irrigation supply, water infrastructure, groundwater quality analysis, flood relief techniques, surface water quality, environmental aspect and design of hydraulic structure. Watershed models help in comprehending the sophisticated processes taking place daily and can also forecast the effects in the years to come. With the help of the prediction from the models, engineers and managers can make well informed policies and build successful projects which results in water resource management that is more sustainable for the years to come resulting in welfare for the society and the environmental aspect (Mirchi et al., 2009).

2.2.1 Classification of models

Watershed models are classified based on process description as empirical, conceptual or physically based model. Conceptual models use broad concepts to explain system and empirical models develop analytical correlation between inputs and outputs of large data sets based purely on observation. Physically-based models are the models which is not based on any concepts but on mathematical equations that define and describe the hydrological processes that occur in a basin for a better understanding (Daniel et al., 2011).

Watershed Models are also classified based on their model input or parameter specification as a stochastic or deterministic approach. Deterministic models are a type of model where the output is mathematically calculated from known relationship between the states and the events. Whereas stochastic models are a kind where the outcome is decided by inputs which mostly if not all are expressed by numerical distributions (Daniel et al., 2011).

Watershed Models can be further classified on the space- related representation for instance lumped and distributed model. Lumped model is a type of model that takes into consideration the entire watershed as one entity. Lumped model calculates the mathematical computations as single unit and its associated parameters and variables are taken as a mean value over the single unit. In comparison to lumped model, distributed models do not consider the entire watershed as one but considers the space-related variations in hydrological processes, precipitation, watershed attributes and boundary conditions.

Models can also be categorized as event based model or continuous models. Event-based models are models having smaller time duration which simulates respective rainfall-runoff events with concern on infiltration and surface runoff. On the other hand continuous process models have longer time duration and indubitably considers entire runoff constituents taking due consideration the soil moisture redistribution between storm events (Daniel et al., 2011).

2.3 Current status of process based hydrologic models

The process-based model is the classical method mentioned in modern books and articles, firstly creating theoretical depiction of our ideas of how the world operates on the basis of logical deductions based on observations, that is, the concepts we are using to describe hydrological behavior and then encoding algorithmic restatement of our conceptual framework in a numerical model (M. P. Clark et al., 2016). From the 1960s onwards people have used process-based models that was built upon principle of observation and scaling physical hydrology related processes (Fatichi et al., 2016).

Some criticize process based models as being over-parameterized, complex model equations and difficult to use (Loague, 1990). That being said, there are several instances where the portrayal of complication is important in comprehending how natural and human processes work as well as interlink (Fatichi et al., 2016).

Complexity does not automatically contribute to an increase in efficiency of the hydrological models, and this efficiency may differ based on the hydrology related variable considered like runoff vs. water content in soil or hydrology related conditions like overflow vs. underflow (Orth, Staudinger, Seneviratne, Seibert, & Zappa, 2015). Instances whereby knowledge of flow direction or distributed model parameters is essential, process-based models are required. Examples of these situations include: spatial and temporal variation of water content in soil, flow of underground water and runoff, sediment and conveyance of pollutant and recognizing the consequences of changes in climate and landuse. The mentioned examples are circumstances in which process-based models perform better whereas rest of the models are unsubstantiated (Fatichi et al., 2016).

Accounting for space-related variability may hinder the recognition of parameters. However, surrogate data like type of soil, land-use as well as geology information can be utilized to combine multiple regions into areas with similar parameters in process-based modeling (Fatichi et al., 2016). In the water sector, the society has achieved notable changes in enhancing mathematical expression of hydrological processes, estimating parameters, as well as recognizing acceptable model simplifications that has allowed the use of available computational power more efficiently (Peters-Lidard et al., 2017).

Despite the complexities, over parametirization and long computational time in process-based model, there is a need to explore the potential of process based model to account for the complexities in the world especailly in the recent changing times for better management of water resources.

2.4 Comparison of process based hydrologic models

Dhami & Pandey had a comparative study on some recently developed, regularly updated and well documented water models known as AnnAGNPS, GSSHA, HYPE, Hec-HMS, MIKE-SHE, PRMS, SWAT, WetSpa and WinSRM (Chourushi, Lodha, & Prakash, 2019). The factors required to assess the models are: (I) The hydrology related processes which the model can simulate, (II) Governing equations used in simulating the hydrology related processes, (III) Number of minimum data necessary to run a model and (IV) spatial and time scale of the model (Dhami & Pandey, 2013). Yang, Herath, & Musiake discussed three distributed models with different treatments of topography namely MIKE-SHE, TOP MODEL and GB model (Devia, Ganasri, & Dwarakish, 2015; Yang, Herath, & Musiake, 2000)

Borah and Bera reviewed eleven watershed scale hydrological and nonpoint source pollution models: AGNPS, HSPF, MIKE SHE, PRMS,ANSWERS, DWSM, ANSWERS-Continuous, AnnAGNPS, CASC2D, KINEROS, and SWAT (Borah & Bera, 2003). Vo, Nguyen, Le and Doan compared four models namely SWAT, MIKE NAM, HEC-HMS, and MIKE SHE based on capacity to accurately describe catchment characteristic, data input criteria, convenience of set up, calibration and time in computing (Vo et al., 2014). It can be noted that hydrological models are compared with range of standards based on the goal of the research.

2.5 Initial Model Selection

The initial model selection for the study was carried out with seven criteria: (1) capacity of water resource management model (2) temporal resolution (3) availability of the model (4) data requirement (5) user friendliness (6) technical support (7) wide range of model applications as shown in Table 2-1.

Each criteria in the initial selection of modes were evaluated and assigned a high, medium or low based as shown in Table 2-2. Each of the criteria facilitates to shortlist models for the intention of the study. Each of the seven criteria and their assessment of high, moderate and low preference so as to select initial water model are explained below.

2.5.1 Capability of model

The capability of a watershed model is an essential factor to select a model. Model that are capable of environment, flood and drought management are highly preferred.

Model capable of any two from the environment, flood or drought management are moderately preferred and model capable of any one from the three management is least preferred.

2.5.2 Temporal Resolution

Temporal resolution of the model refers to the ability to extract output time series that are fit for purpose (Ball et al., 2015). Daily time step model provides a detailed oriented information and while modelling with daily basis data, the results can be accumulated into monthly data with more accuracy. Data on a monthly time frame can be utilized for well-structured design and to better manage the water resource (Wijesekera, 2001). In the case of using daily temporal resolution in a watershed model, the runoff time series shows a detailed and variations in the high, intermediate and low flows (Dissanayake, 2017).

Data with finer resolution always plays a vital role to forecast a good output in a watershed model. The absence of the necessary data resolution for a model can often affect the model's performance amid superior model strength and ability. When using coarse resolution data, streamflow concerning a peculiar precipitation pulse does not always get captured. Therefore, a finer data resolution would provide opportunity for a better result with regard to its accuracy (Thapa, 2014). Model generating daily flow is better preferred in comparison to models with monthly flow when considering flood analysis and flood control simulations to use in mitigation places (Tessema, 2011). Therefore, watershed models that have a minimum daily temporal resolution are highly preferred followed by monthly time frame and seasonally or annually.

2.5.3 Availability of the model

Availability of the model is a crucial factor in selection of model. A model that is freely available is preferred over models with certain versions to be freely available. The least preferred are commercial models as we need to purchase it. So models with no cost are highly preferred, models with some versions as free are moderately preferred and models that cost money are least preferred. Cost plays an important factor for the selection of models.

2.5.4 Data requirement for modelling

Data availability is a key factor in research and more number of data requirement is associated with lesser chance of data availability. Although there are area with sufficient available data but most areas are ungauged around the world. Therefore, less data requirement are highly preferred to moderate data requirement. And models that require intensive data are least preferred when considering the initial selection of water models.

2.5.5 User friendliness

Usually, two forms of manuals are found for every model. One is technical manual and the other is user manual. The former explains fundamental process in a detail oriented manner and later directs and helps users with the development of model. Along with manuals, tutorials and a work group of the model are also available for the models which results in better user friendliness of the model.

The users can easily learn about the models from the two manuals and watch tutorials for further understanding. Users can further clarify their doubts with the user group of the model. Models with both manuals, tutorials and active work group are preferred over models with either of the manuals, tutorials and partially active work groups. Models with poor manuals, tutorial and inactive work group are least preferred as the users have limited help with the model. Thus, more the user friendly a model is, more the users prefer to use the model for their study. Lesser the user friendliness of the model with more difficulty in accessing assistance related to models, lesser is the model adopted for study.

2.5.6 Technical support

Technical support is another criteria for selection of models. Highly responsive or interactive web assistance model is preferred while models with no interactive web based technical support and low indicative of email support is least preferred. Models in between highly responsive and more interactive support and better email support are preferred moderately. Thus, the respective models are given weightage based on their technical support.

2.5.7 Wide range of model applications

Wide range of model applications is an important criteria associated with the initial selection of water model. Models with worldwide applications are highly preferred whereas models with some worldwide applications and a few regional ones are considered as moderately preferred. Models that are applied within certain limitations and in lesser number across the regions are least preferred. Popularity in the use of model ensures the users to select it for their study as more number of models applied assures the success of the model. For initial shortlisting of models wider the use of models leads to more confidence for the user to apply the model for their respective research studies

Table 2-1: Initial model shortlisting criteria

Shortlist criteria	High (5)	Medium (3)	Low (1)
1. Capacity of water resource management model	Capability in environmental, flood and drought management	Capability in any two of the management	Capability in one of the three management
2. Temporal Resolution	Daily	Monthly	Yearly
3. Availability of the model	Freely available	Parts of model free	Commercial
4. Data requirement for modelling	less data requirement	Moderate data requirement	Intensive data requirement
5. User friendliness	User and technical manuals, tutorials available with active group work	Either of the two manuals, Tutorial available and partially active work groups	Poor manuals, Tutorial available and inactive work group
6. Technical support	Highly responsive/interactive web assistance	In between highly responsive and more interactive support and better email support	No interactive web based technical support, low indicative of email support
7. Wide range of model applications	World wide applications	Some worldwide applications and a few regional ones	Restricted applications, less applications in regions

Table 2-2: Initial Model Selection Evaluation

Shortlist criteria	SWAT	WetSpa	MIKE-SHE	HEC-HMS	AnnAGNPS	TOPMODEL
Criteria 1 : Capacity of water resource management model	High (5)	Medium (3)	High (5)	Medium (3)	Medium (3)	Medium (3)
Criteria 2 : Temporal Resolution	High (5)	High (5)	High (5)	High (5)	High (5)	High (5)
Criteria 3: Availability of the model	Medium (3)	High (5)	Low (1)	High (5)	High (5)	High (5)
Criteria 4: Data requirement for modelling	Low	High (5)	Low (1)	Medium (3)	Low (1)	Low (1)
Criteria 5: User friendliness	High (5)	Medium (3)	Medium (3)	High (5)	Medium (3)	Low (1)
Criteria 6: Technical support	High (5)	Medium (3)	Medium (3)	Medium (3)	Medium (3)	Medium (3)
Criteria 7: Wide range of model applications	High (5)	Medium (3)	High (5)	Medium (3)	Medium (3)	Medium (3)
Average Score	**4**	**4**	**4**	**4**	**3**	**3**

2.6 Shortlisted models

SWAT, HEC-HMS, WetSpa and MIKE SHE model are the preliminary shortlisted alternatives after the evaluation. The four models scored the highest and TOPMODEL and AnnAGNPS model were discarded as these two models scored the least upon evaluation. The description of the four models are presented below.

2.6.1 SWAT

The Soil and Water Assessment Tool (SWAT) model is developed by United States Department of Agriculture's Agricultural Research Service dating back upto 40 years. It is a distributed, physically based, computationally efficient and continuous-time scale model. The above model is developed for forecasting the management consequences on water, sediment and farming related chemical yields in basins that do not have gauging stations.

In the selected model, a watershed is branched into various sub-watersheds, that is further sub branched into hydrologic response units (HRUs) which is the basic unit consisting of similar land use, slope and soil attributes. The basic unit in the model are not spatially expressed in SWAT simulation (Gassman, Reyes, Green, & Arnold, 2007).

Versatility in incorporating upland and channel processes together and simulation of land management are the key attributes of the model (Arnold, Moriasis, et al., 2012). The mathematical formulas used in SWAT model are mentioned in the theory documentation of SWAT available from its website (www.tamu.edu) and in the paper by Arnold (Gassman & Yingkuan, 2015).

2.6.2 WetSpa

Originally developed in 1997 by Wang and team, the Water and Energy transfer between Soil, Plants and Atmosphere model known as WetSpa model conceptualizes a hydrological basin as a structure comprising of atmosphere, canopy, root zone, transmission zone and saturation zone layers. The hydrological watershed is branched into numerous grid units that takes heterogeneity into account. Further each grid unit is sub branched into a barren soil and vegetative component (Chourushi, Lodha, & Prakash, 2019; Dhami & Pandey, 2013; Lei et al., 2011; Vo et al., 2014)

2.6.3 MIKE-SHE

MIKE-SHE model is a spatially distributed, physically based model built by Danish Hydraulic Institute in the year 2007. It simulates all processes in surface and subsurface dynamics of water such as precipitation, evapotranspiration, transpiration, infiltration, interception, subsurface and surface flow. Detail descriptions on modeling process and mathematical expressions are mentioned in MIKE-SHE instruction manual (DHI, 2008).

It is widely applied across the world in fields of water supply infrastructure, planning and implementation, irrigation, water and soil monitoring, use of underground water and available water, managing underground water, environment related risk study, variations in land use pattern and climate, floodplain studies. However, the model is a not freely available and needs to be purchased (Dhami & Pandey, 2013; Kumar, Lohani, & Nema, 2019; Pomeroy, 2007).

2.6.4 HEC-HMS

Designed by the United States Army Division of Engineers, Hydrologic Modeling System (HEC-HMS) was developed in the Hydrologic Engineering Center. The model has four model segments; basin model, meteorological model, control specification model, and input data. The first model segment primarily provides the physical details in a watershed.

The second segment also depicts component of a watershed and relevant association. Third model segment includes the evapotranspiration, precipitation and snowmelt information. The last segment comprises the timing for the initiation and termination and computation intermission for the run. It is applied to an extensive variety of issues for instance broad area water supply, overflow hydrographs and runoff, etc. It is freeware software (Dhami & Pandey, 2013; Z. M. Wang, Batelaan, & De Smedt, 1996).

2.7 Detailed Model selection

After initial short listing, the four models selected are further evaluated in a detailed manner to identify the most suitable model for estimating streamflow for sustainable watershed management based on available literature. Nine criteria are identified: (1) Number of process simulated (2) Number of process options (3) Temporal scale (4)

Spatial extend (5) Details of output (6) Spatial distribution of outputs (7) Global popularity of the model (8) Importance of research; number of Sri Lankan applications (9) Ease of modeling as shown in Table 2-3. Model evaluation is carried out by assigning high, medium and low as indicators according to their relevance and performance as shown in Table 2-4 for each of the nine criteria. The nine criteria are discussed in details below.

2.7.1 Number of process simulated

Hydrological processes simulated in a model are necessary to understand the concepts of how the real world functions and incorporating hydrological processes in a model improves model efficiency to better represent the reality and complexity of the world to manage water resources efficiently (Fatichi et al., 2016). Hydrological processes determine whether or not the model is capable of generating the desired outcome (Dhami & Pandey, 2013).

Higher the number of hydrological processes in a model more is the details which adds more realism to a watershed modelling with accurate results and improved water resource management. Therefore, a high preference is given if the model has processes for entre hydrological cycle. A moderate preference is given if the model has partial hydrological cycles and a low preference for the models with lumped hydrological processes.

2.7.2 Number of process options

The efficiency and relevance of the model is established on the use of basic equations available as options to simulate the hydrological processes (Dhami & Pandey, 2013). More than one options for all hydrological processes is highly preferred and a model with at least one option for all hydrological processes is moderately preferred. A model with one option for many hydrological processes is least preferred.

2.7.3 Temporal scale

When considering practical setting, it is essential to address if the models are being applied as continuous or event based. Time based scale model is crucial since hydrology related processes can take place at various time frame. It is essential to acknowledge event based models which runs daily or in an annual time frame.

Event based models simulate storm events of relatively short duration while continuous time hydrologic model can simulate hydrological processes for longer time or seasonal framework (Dhami & Pandey, 2013). Continuous based models with lengthy duration provides a practical portrayal of the runoff process. Models which simulate both event and continuous are strongly favorable when compared to model that simulate continuous simulation. Models with event simulations are least favored.

2.7.4 Spatial extent

The space-related resolution of the hydrologic model will relate to the minimum area of the catchment (Ball et al., 2015). A watershed can be as low as one hectare to thousands of square kilometers. The space-related extend of a watershed is an essential factor in the preference of a model since it serves a vital role in the treatment of individual processes in a model (Dhami & Pandey, 2013). A model with no size restrictions is highly preferred and a limited spatial extend model is least preferred.

2.7.5 Details of output

The output details generated by the model is considered a criteria for model selection as a detailed output gives a clear understanding and results for landuse and climate change. Models that give output details such as soil moisture, evaporation, streamflow subsurface flow and groundwater flow are preferred most. Models which inly generate streamflow as the output is least preferred and models that gives output in between very detailed and only streamflow is moderately preferred.

2.7.6 Spatial distribution of outputs

The outputs are represented spatially either as entire lumped units, sub catchment or hydrologic units. For detail oriented outputs smaller spatial distribution of the outputs is preferred. Hence model with hydrologic unit as spatial output distribution is highly preferred over sub catchment distribution and least preferred for lumped hydrologic unit. Distributed hydrologic models have spatial distribution of outputs as HRUs which are the basic unit in a basin based on combinations of unique topography, landuse and soil type. Lumped models generate results in a lumped manner for a basin and less likely to be selected.

2.7.7 Global popularity of the model

Globally famous model applied for studies related in estimating streamflow across the world is another factor to consider while selecting a model. Model that have worldwide, regional and local applications are most preferred to regional applications and least preferred with local applications.

2.7.8 Importance of research; Number of Sri Lankan application

Importance of research is inversely related to the number of models applied in Sri Lanka. Zero or minimal number of models performed in Sri Lanka indicates a higher importance of research hence the model is highly preferred. Model applications applied within certain areal coverage in Sri Lanka are moderately preferred whereas models applied in all three zones of Sri Lanka is least preferred in terms of importance of research. None or very minimal number of models performed in Sri Lanka but popularity across the globe indicates a necessity to apply the model in Sri Lanka and hence more is the importance of the model. Similarly more applications means the importance of research using the model is less as it is already applied for many studies in Sri Lanka and doesn’t make the study unique.

2.7.9 Ease of modelling

The ease of modeling is important while selecting a model. Highly preferred models are those with optimization tools, easy to understand concepts, not requiring highly trained personnel, versatile graphical outputs and reduced computer processing power. Models with no optimization tools, difficult to conceptualize, specialized expertise required, complex graphical output and requiring high computer processing power are difficult to use and hence preferred low when compared to other models. Models that fall in between the high and low category of ease of modelling are the moderately preferred ones and hence given a medium indicator.

Table 2-3: Detailed model selection criteria

Criteria	High (5)	Medium (3)	Low (1)
1. Number of process simulated	Entire hydrological cycles	Partial hydrological cycles	Lumped hydrological cycles
2. Number of process options	More than 1 process options for all hydrological processes	At least one process option for all hydrological process	One process option for many process
3. Temporal scale	Event and Continuous	Continuous	Event only
4. Spatial extent	Flexible/no size restrictions	In between no restrictions & limited	Limited extents only
5. Details of output	streamflow, soil moisture,evaporation , subsurface flow, groundwater flow	In between the very detailed and only streamflow	Only streamflow
6. Spatial distribution of outputs	Hydrological units (similar combination of landuse, soil slope)	Sub catchment analysis possible	Lumped hydrologic units
7. Global popularity of the model	Worldwide, regional and local applications	Regional applications	Local applications
8. Importance of research ; No of Sri Lankan application	No/very low number of applications	Only a limited spatial coverage	applications in dry, intermediate zones is more
9. Ease of modelling	Availability of optimization tools, specialized expertise not required, not difficult to understand conceptualization, flexible graphical outputs, low computational requirements	In between high and low categories	No optimization tools, difficult to conceptualize, specialized expertise required, less flexible graphical outputs, high computational requirements

The four shortlisted models are evaluated in a detailed manner and assigned a high, medium and low indicators with a value of 5 for high, 3 for medium and 1 for low. The three indicators are assigned based on the evaluations described in the Table 2-4.

Table 2-4: Detailed Model Selection Evaluation

Shortlist criteria	**SWAT**	**WetSpa**	**MIKE-SHE**	**HEC-HMS**
Criteria 1: Number of process simulated	High (5)	Low (1)	High (5)	High (5)
Criteria 2: Number of process options	High (5)	Medium (3)	Low (1)	High (5)
Criteria 3: Temporal scale	Medium (3)	High (5)	High (5)	High (5)
Criteria 4: Spatial extent	High (5)	Low (1)	High (5)	High (5)
Criteria 5:Details of output	High (5)	Medium (3)	High (5)	High (5)
Criteria 6:Spatial distribution of outputs	High (5)	Medium (3)	Medium (3)	Medium (3)
Criteria 7: Global popularity of the model	High (5)	Medium (3)	High (5)	Medium
Criteria 8: Importance of research ; Number of Sri Lankan application	High (5)	Medium (3)	High (5)	Low (1)
Criteria 9: Ease of modelling	Medium (3)	Medium (3)	Low (1)	Medium (3)
Average Score	**5**	**3**	**4**	**4**

2.8 Discussion

Scientific evaluation is very important for selecting models in estimating streamflow for SWRM. Initial shortlisting suggested that SWAT, WetSpa, MIKE-SHE and HEC-HMS models can be adopted to estimate streamflow for SWRM, leaving out TOPMODEL and AnnAGNPS model. Final evaluation is carried out in a detailed manner and the results strongly recommends SWAT model. SWAT model is preferred from the model comparison as it has the maximum average score when compared to other three models. Among the four models, SWAT model appears to be a better option to estimate streamflow. SWAT model has been successfully calibrated and validated in determining the streamflow at various conditions in a broad spectrum of catchment area across the globe (Chourushi et al., 2019; M. P. Clark et al., 2016; Fatichi et al., 2016; Getachew & Melesse, 2012; Lei et al., 2011; Pomeroy, 2007; Tessema, 2011; Vo et al., 2014)

2.9 Data filling

Wijesekera & Perera noted that data testing allowed confidence limit for data use to be established, thus, delivering the most crucial information to evaluate the relevance of using the corresponding hydrological result for accurate interpretations (Wijesekera & Perera, 2012). The input data processed for simulations in managing water related studies must be homogeneous, stationary and consistent (Hall, 1990). Instances where the set of data are deficient, complications and ambiguity arises in the modeling (Campozano, Sánchez, Avilés, & Samaniego, 2014). The replacement of incomplete data values is always required prior to the realistic use of hydrological time frame (Gyau-Boakye & Schultz, 1994).

Hasanpour and Dinpashoh analyzed eleven cognitive computing and traditional tools to analyze the find the most appropriate method for predicting climatological data for three various climatic scenarios in Iran (Hasanpour Kashani & Dinpashoh, 2012). The findings showed that the approach of multiple regression analysis is the correct tool for classical approaches. Lo, Barca and Passarella implemented four techniques especially in comparison to the filling of incomplete data; simple substitution, classical least squares univariate parametric regression, ranked regression and the Theil (1950) method and the findings demonstrated that the Theil method is by far the most valid technique (Lo Presti, Barca, & Passarella, 2010).

De Silva, Dayawansa and Ratnasiri considered four data filling methods; arithmetic mean, normal ratio, inverse distance and aerial precipitation ratio method. Results indicated that the inverse distance method has been identified as the most reliable approach in Sri Lanka for the dry, intermediate and wet zones (De Silva, Dayawansa, & Ratnasiri, 2007)

The arithmetic-mean approach is the easiest way to calculate areal mean precipitation and this approach is acceptable when the gauges are evenly spread over the region and the specific gauge values do not vary significantly about the mean (Chow, Maidment, & Mays, 1988). Referring to the textbooks for data filling methods, thiessen polygon is suggested to be simple and is widely in use when compared to other methods.

2.10 Model Evaluation

2.10.1 Objective function

The measurement of model output involves a subjective or empirical calculation of its "closeness" of the simulated model performance to observation values usually of streamflow taken within the watershed. Visual examination of the predicted and observed hydrographs is perhaps the most valuable methods when evaluating behavioral model performance. In this study, a hydrologist could device subjective judgment of the model performance that are typically linked to the systematic behavior like over prediction or under prediction and dynamic behavior like timing, rising limb, falling limb, and base flow of the model. In general objective assessment necessitates the use of mathematical approximation of the discrepancy between the predicted and observed hydrological values. Objective function is the statistical calculations of how well the simulations from a model matches the observation values typically of a streamflow (Krause, Boyle, & Bäse, 2005).

In watershed models, the use of objective functions depends on the objective of the study. Peak and low flows are matching moderately while intermediate flows are matching perfectly with the Mean Ratio to Absolute Error (MRAE) (Wijesekera & Perera, 2012). Khandu tested objective functions with a detailed review of literature observing the strong match between low flow, middle flow, peak flow and overall flow. He finally identified MRAE and NSE as appropriate goal functions to match model simulation outputs (Khandu, 2015).

SWAT-CUP provides eleven objective function namely mult, sum, R2, Chi2, NSE, bR2, SSQR, PBIAS, KGE, RSR and MNS (Abbaspour, 2015). Widely used objective function to stimulate streamflow at a daily time scale are regression correlation coefficient (R^2) and the Nash- Sutcliffe model efficiency (NSE) coefficient but both are biased to high flow (Gassman, Sadeghi, & Srinivasan, 2014; Moriasi et al., 2007). In the peer review by Moriasi (2007), NSE, percent bias (PBIAS), and ratio of the root mean square error to the standard deviation of measured data (RSR) was recommended as three quantitative statistics (Khoi & Suetsugi, 2014). In another study by Sevat and Dezetter (1991), the ideal statistic that reflected the best possible fit of hydrograph was NSE (Khoi & Suetsugi, 2014).

The ASABE SWAT 2010 Special Collection assembled twenty research articles, largely selected from 113 papers which used R2, NSE, and PBIAS as objective function in predicting streamflow, sediment load, N and P load and bacterial load contamination across wide variety of watershed conditions (Srinivasan & Arnold, 2010).

2.10.1 Warm up period

The warm up period enables the watershed model to loop several times in an effort to reduce the impact of modeler's prediction of starting parameters like water content in soil and residuals (X. Zhang, Srinivasan, & Hao, 2007). The time period of the warm up duration can differ for types of process in a basin. Model developers usually advise to use two to three years as warm up duration (Abbaspour, 2015).

Hoad, Robinson and Davies listed five key approaches of tackling the initialization bias that is, 1. Making a model run for a warm-up period till a reasonable situation is achieved and information gathered is erased 2. Make initial model scenarios so as the simulation can begin in a practical state 3. Define provisional circumstances then warm up the model and erase the warm up related data 4. To run a model for a long period for making bias trivial 5. Predict the constant parameters from concise simulation runs. The research concentrated on the first method (Hoad, Robinson, & Davies, 2009).

From the warm up methods under the five main categories which are graphical, heuristic, statistical, initialization bias tests and hybrid test, statistical process control (SPC) method is preferred (Robinson, 2002).

2.10.2 Sensitivity Analysis

Sensitivity analysis is the method of evaluating model output transition rate in response to variations in the model parameters. Following the sensitivity testing, the primary parameters can be determined which greatly contributes to the calibration process. Two main ways of sensitivity testing methods typically conducted are: i) local, by varying value one by one, then ii) global, permitting alterations to all values of the parameters. Consequently the two types of sensitivity analysis can deliver varying outcomes. Each parameter's sensitivity generally relies on the other parameters' value; thus, the drawback of local sensitivity analysis is usually that other constant parameters' values are not identified. A major drawback of global sensitivity analysis is the involvement of a significant number of simulations. However, both methods offer information about the sensitivity of all parameters and are mandated actions in calibrating a model (Srinivasan, Santhi, Harmel, & Griensven, 2012).

2.10.3 Model Calibration and validation

Calibration is carried out to better arrange the set of parameters in a model as per a defined set of local environments thus, limiting risk associated with the forecast. Model calibration is evaluated by selectively choosing values for parameters using their relevant ambiguity limits through analyzing outcome forecast accuracy considering specified and assumed conditions using observed data taking the same conditions. Model validation is a method of displaying the applied model is able to generate reasonably precise simulations while reasonable precise simulations can differ according to the aim of the project (Srinivasan et al., 2012). The intent of model validation is to verify if the model can forecast flow for a separate set of duration and environment compared to what the model was tuned for, therefore, the model is relevant outside the calibration sets of environment for instance future time scale as well as other areas (Getachew & Melesse, 2012).

There are two principal methods of calibration: manual and automatic. Traditional manual calibration requires a lot of manual work resulting in more time consumption as it is based on trial and error and depends on the skills of a modeler. Automatic calibration approach is gaining its popularity owing to their capability to utilize the accuracy, speed and potential of computers, while being unbiased and relatively simple to incorporate (X. Zhang et al., 2007).

The two above mentioned methods for model evaluation are usually computed from dividing the accessible measured data as two sets of data. One set is used for initial evaluation and another set is kept for the final evaluation method. The two mentioned datasets are divided by time frames, designed to ensure that the data used for both processes are not distinctly separate. That being said wet, moderate and dry years should be present in both processes over time duration (Thian Yew Gan, 1997).

2.11 SWAT model

2.11.1 Description

The Soil and Water Assessment Tool (SWAT) model is developed by United States Department of Agriculture's Agricultural Research Service dating back upto 40 years. It is a distributed, physically based, computationally efficient and continuous-time scale model. The above model is developed for forecasting the management consequences on water, sediment and farming related chemical yields in basins that do not have gauging stations.

In the selected model, a watershed is branched into various sub-watersheds, that is further sub branched into hydrologic response units (HRUs) which is the basic unit consisting of similar land use, slope and soil attributes. The basic unit in the model are not spatially expressed in SWAT simulation (Gassman et al., 2007).

Versatility in incorporating upland and channel processes together and simulation of land management are the key attributes of the model (Arnold, Moriasis, et al., 2012).

Major model components in SWAT model include weather, hydrology, soil temperature and properties, plant growth, nutrients, pesticides, bacteria and pathogens, and land management. SWAT-simulated hydrological processes comprise canopy storage, surface runoff, infiltration, evapotranspiration, lateral flow, tile drainage, soil profile water redistribution, consumption by pumping (if any), return flow, and surface water, reservoirs, and tributary channels. The mathematical formulas used in SWAT model are mentioned in the theory documentation of SWAT available from its website (www.tamu.edu) and in the paper by Arnold (Arnold & Fohrer, 2005).

Two methods of determining surface runoff are given by the SWAT model: the SCS curve number procedure (USDA-SCS, 1972) and the Green and Ampt infiltration process (Green and Ampt, 1911). Using updated logical method or SCS TR-55 method, SWAT estimates peak runoff rate. The Penman Monteith (Monteith, 1965), Priestley-Taylar methods (Priestley and Taylor, 1972) and Hargreaves methods (Hargreaves, 1985), are used to calculate evapotranspiration. Channel routing is calculated using the method of variable storage coefficient (William, 1969), and the method of Muskingum (Chow, 1959). For HRU, the SWAT model uses the Modified Universal Soil Loss Equation (MUSLE) to calculate sediment yield (Vo et al., 2014).

2.11.2 Data Requirement

Major datasets in SWAT model include DEM, temperature, rainfall, type of soil, usage of land, streamflow and management activities (Philip W. Gassman & Yingkuan, 2015; Krysanova & Arnold, 2008; Krysanova & White, 2015).

2.11.3 SWAT model component selection

SWAT model has major components as surface runoff, infiltration, potential evapotranspiration, lateral flow and channel flood routing. SCS CN system measures surface runoff and infiltration, method, potential evapotranspiration by Hargreaves, Kinematic storage model to simulate lateral flow & Variable storage method for channel flood routing.

The methods were selected for each components owing to lesser number of data requirement. Penman – Monteith, Hargreaves and Taylor approach can, for example, be used to measure possible evapotranspiration. Hargreaves need the minimum data being temperature to calculate potential evapotranspiration. The SCS system was chosen because its calculation is supported by the need to estimate only a few variables and, given its simplicity, results obtained are as good as those of complex designs. A simple Muskingum method was used for channel routing (Gumindoga et al., 2017).

2.11.4 Parameters

Gatachew and Melesse selected nine parameters for calibration in SWAT model. The parameters that primarily impacted surface runoff were ESCO, CANMAX, CN2, BLAI, SOL_Z and REVAPMIN. Whereas, GW_REVAP, ALPHA_BF and GWQMN affects base flow generation (Getachew & Melesse, 2012). Seven parameters were selected for runoff which are SOL AWC, RCHRG DP, CN2, GWQMN, ESCO, SOL K, and CANMX (Lin et al., 2015). Four SWAT parameters have been chosen for measuring surface runoff response sensitivity: the number of curves (CN), the percentage of land coverage, the saturated hydraulic conductivity (KS) and the soil hydrologic (HV) values (Baker & Miller, 2013).

Zhang selected eight parameters for surface runoff to calibrate and they are CN2 (±8), SURLAG(0 to 10), REVAPC(0.00 to 1.00), ESCO(0.00 to 1.00), EPCO(0.00 to 1.00), αgw(0.00 to 1.00), SMFMX(0 to 10), SMFMN(0 to 10) (X. Zhang et al., 2007). Khoi and Suetsugi identified sensitive parameters for hydrology as CN2, ESCO, GQWMN, ALPHA_BF, SOL_Z, SOL_AWC, CH_K2, GW_REVAP, CH_N2 and SOL_K. (Khoi & Suetsugi, 2014). Zhang found eight sensitive parameters for hydrology to be ESCO, ALPHA_BF, GW_DELAY, REVAPMN, TLAPS, PLAPS, SMFMN and SMTMP (L. Zhang et al., 2016). Kim identified sensitive parameters for streamflow as ESCO, CN2, GWQMN, SOL_AWC, SOL_Z, BLAI, and CANMX. (Kim et al., 2013)

There are twenty five major SWAT parameters mentioned in the literature and shown in Table below. (Guo & Su, 2019).

Table 2-5: Major SWAT parameters.

Parameter	Meaning of Parameter	Initial Range	Classification
v_SMFMN	Minimum melt rate for snow during the year (occurs on winter solstice)	0-20	Snow melt
v_SMFMX	Maximum melt rate for snow during the year (occurs on summer solstice)	0-20	Snow melt
v_SMTMP	Base temperature of snow melt	-20-20	Snow melt
v_TIMP	Snow pack temperature la factor	0-1	Snowfall
v_SFTMP	Snowfall temperature	-20-20	Snowfall
r_CN2	SCS runoff curve number for moisture condition II	-0.1-0.1	Surface runoff
v_SURLAG	Surface runoff lag time	0.05-24	Surface runoff
v_ALPHA_BF	Baseflow alpha factor (days)	0-1	Groundwater
v_REVAPMN	Threshold depth of water in the shallow aquifer for 'revap' to occur (mm)	0-500	Groundwater
v_GW_DELAY	Groundwater delay (days)	0-500	Groundwater
v_GW_REVAP	Groundwater 'revap' coefficient	0.002-0.2	Groundwater
v_RCHRG_DP	Deep aquifer percolation fraction	0-1	Groundwater
v_GWQMN	Threshold depth of water in the shallow aquifer required for return flow to occur (mm)	0-1000	Groundwater
v_EPCO	Plant uptake compensation factor	0-1	Evapotranspiration
v_ESCO	soil evaporation compensation factor	0-1	Evapotranspiration
v_SLOPE	Average slope	0-90	Landform
v_SLSUBBSN	Average slope length	10-150	Landform
v_TLAPS	Temperature lapse rate	-10-10	Temperature
v_ALPHA_BNK	Baseflow alpha factor for bank storage	0-1	Channel
v_CH_K2	Effective hydraulic conductivity in main channel alluvium	0.01-500	Channel
v_CH_N2	Manning’s 'n' value for the main channel	0.01-0.3	Channel
v_SOL_AWC	Available water capacity of the soil layer	0-1	Soil
v_SOL_K	Saturated hydraulic conductivity	0-500	Soil
v_CANMX	Maximum canopy storage	0-50	Vegetation
v_BLAI	Max leaf area index	0.5-10	Vegetation

Source: (Guo & Su, 2019)

2.11.5 Calibration and validation

The initial step to evaluate the model performance with initial and final process in SWAT is to determine its most sensible parameters. Users determine what variables to modify based on an expert decision or sensitivity analysis. Sensitivity analysis is the method by which model output variation rates are determined in relation to model input changes. Key parameters and the appropriate calibration accuracy must be established.

In general, there are two types of sensitivity analysis: local, one by one and global, allowing parameter values of all to be changed. However, the two analyzes will produce various results. One parameter's sensitivity is usually dependent on the other parameters' value; thus, the issue with one-time analysis is the appropriate value of the other parameters set is never known. Downside of global analysis of sensitivity is that multiple simulations are required to be run. Nonetheless, both tests give guidance into parameter sensitivity and are essential steps for model calibration (Srinivasan et al., 2012).

The later part is the calibration process that is executed by selectively choosing the values for the parameters within their realistic range for a specified set of time duration. A validation of portion of interest requires a model that uses calibration parameters and contrasts the predictions with the actual specified data not applied in the initial evaluation. SWAT-CUP is a SWAT Sensitivity, Calibration and Validation Tool (Abbaspour, 2015).

2.11.6 Search Algorithm

Sequential Uncertainty Fitting (SUFI2) algorithm is used due to its semi-automated approach in SWAT-CUP (Srinivasan & Arnold, 2010). There is no automated calibration to replace actual physical understanding of the processes in the watershed and manual calibration are complicated and takes a lot of time due to various parameters. Therefore, semi-automated SUF12 is used among the other search algorithm; Parameter Solution (ParaSol), Generalized Likelihood Uncertainty Estimation(GLUE), Markov chain Monte Carlo(MCMC) and Particle Swarm Optimization(PSO) available in SWAT –CUP (Abbaspour, 2015).

3 METHODOLOGY

The methodology flow chart is depicted below in the Figure 3-1. The first and foremost step for the study was to identify a water related problem. Water crisis was identified to be a problem that need attention and solution as it is prevailing across the world owing to ever increasing population leading to urbanization and changes in landuse patterns and changes in climatic conditions. The second step was to establish an objective for the study to solve the problem identified in the first step. To solve water crisis the objective of the study is to evaluate the potential of a process based distributed model for estimation of streamflow for sustainable water resource management.

The third step is literature review which is further divided into catchment selection, model selection and data collection and data checking. From the literature review the study area was selected as Attanagalu Oya Basin owing to data availability, close proximity for site visit and many past studies conducted on the same basin. In the case of model selection an initial model shortlisting was carried out as discussed in Section 2.5 based on seven criteria and its evaluation. From six watershed models initially four models were shortlisted. Further detailed model selection was carried out as described in the Section 2.7 based on nine criteria and its evaluation. The model selected after shortlisting and detailed evaluation is SWAT model. Once study area and model was selected, data collection and data checking was carried out to use for the model as explained in the section 4.

The data collected is divided into two equal datasets, one for calibration and other for validation. The fourth step is to develop the selected model using the selected basin and calibration dataset. After the model is developed the model gives estimated streamflow as a result which is further evaluated. The evaluation is done with the value of objective function and the matching of simulated and observed streamflow plotted in graphs. Upon evaluation if the estimated streamflow is not found to be satisfactory then the user changes the parameters and again develops the model with new parameters until the reasonable results are obtained.

If after evaluating the estimated streamflow shows a good result, the calibrated model is accepted and its parameters are to be used along with the other validation dataset.

After using the same set of calibrated parameters for validation, the estimated streamflow from the model is evaluated. If the estimated streamflow from validation is not satisfactory in terms of the objective function values and matching of simulated and observed streamflow then the constraints are identified. The model is again developed with new parameters for the calibration to proceed for validation unless both calibrate and validated estimated streamflow is reasonable. However, if the estimated streamflow after validation upon evaluating shows good matching with the observed streamflow, then the calibrated and validated model is accepted. The calibration and validation carried out for the study along with the evaluation of the calibrated and validated simulated streamflow result are explained in the Section 5 and Section 6.

The fifth step is the result after calibration and validation is completed. The results from the model which is the estimated streamflow is compared with observed streamflow for both the calibration and validation data period .The sixth step is discussion based on the results plotted in forms of graph and tables on how good the model is and the drawback if any as shown in the Section 7. The last step in the methodology flowchart is the conclusion and recommendation after discussing the results mentioned in the Section 8.

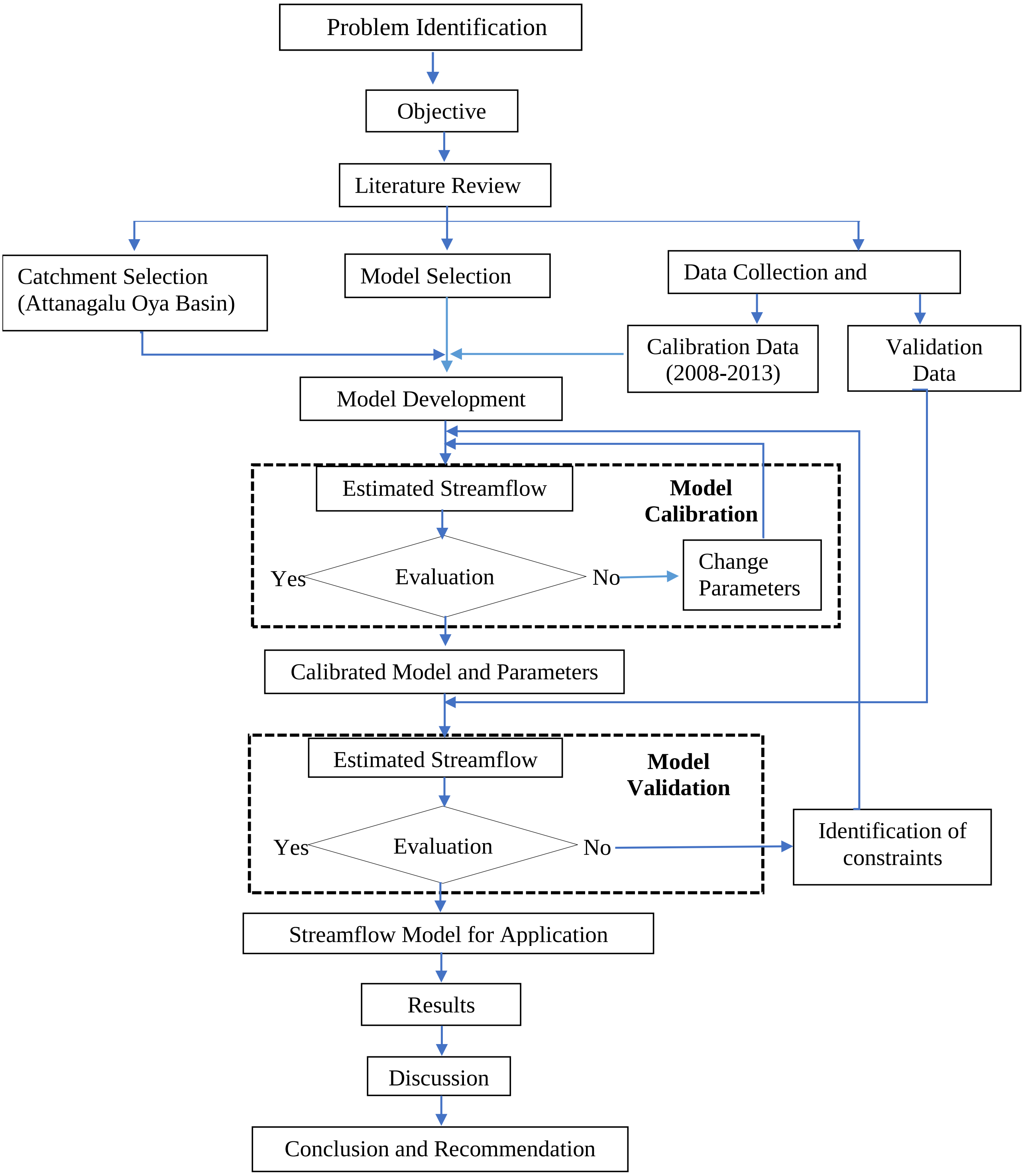


Figure 3- 1: Methodology Flow Chart

4 DATA COLLECTION AND DATA CHECKING

4.1 Study Area

Attanagalu Oya expands over an area of 727 km^2 and the study watershed at gauging station Dunamale is with an area of 157.5 km^2. Five rainfall stations were selected namely Nittambuwa, Pasyala, Karasnagala, Chesterford and Vincit. The location coordinate of the five rainfall stations are given in Table 4-1.

Table 4-1: Rainfall station at Dunamale watershed

Rainfall station	Location coordinate	
Karasnagala	80° 10' 16" E	7° 6' 43.1" N
Nittambuwa	80° 6' 0" E	7° 7' 48" N
Pasyala	80° 7' 48" E	7° 9' 0" N
Vincit	80° 11' 56" E	7° 5' 24" N
Chesterford	80° 10' 60" E	7° 4' 0" N

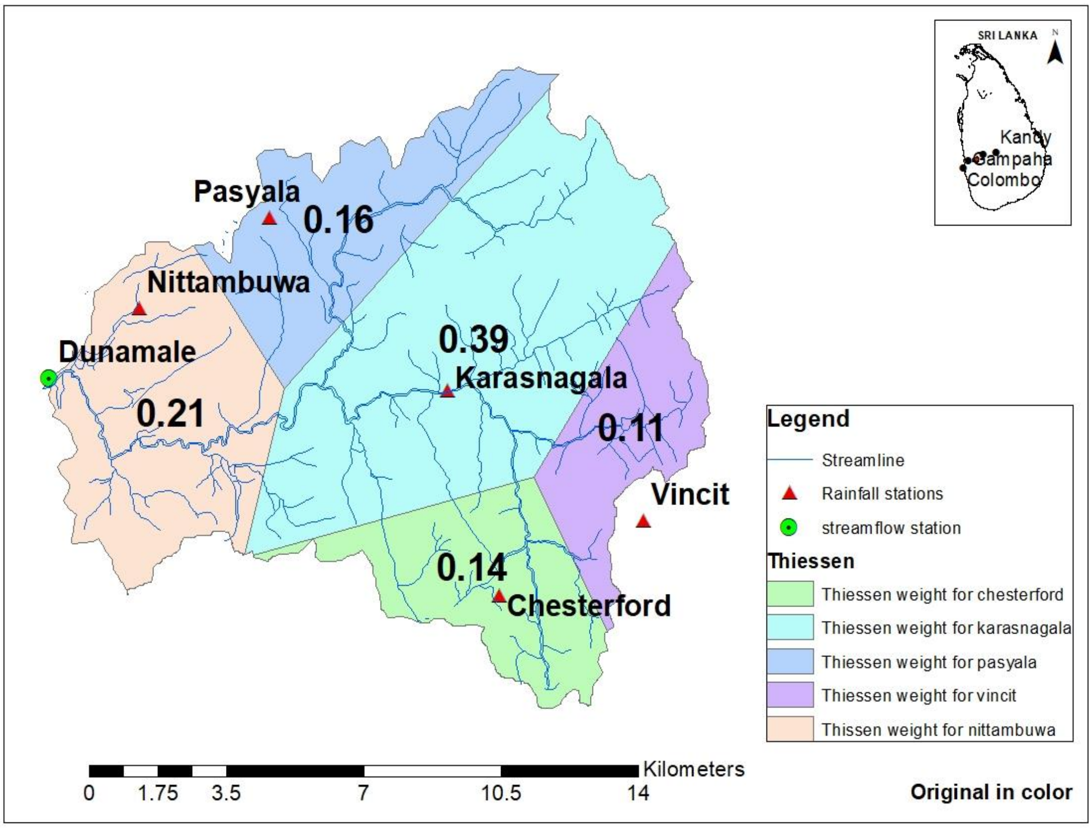


Figure 4-1: Thiessen Polygon- Dunamale

Theissen polygon method was adopted to calculate the mean precipitation for the watershed taking into consideration the spatial and temporal variations as shown in Figure 4-1 above. A 30 m DEM of Sri Lanka was collected from the Survey

Department and utilized in the SWAT model. Further a maskdem of the Attanagalu oya basin was used along with the 30 m DEM of Sri Lanka in SWAT model to reduce the processing time, size of the area and to demarcate the basin.

Maximum and minimum daily temperature of Colombo station was collected from Meteorology department for the year 2008 to 2018 with coordinate 6°55'55" N and 79° 50' 52" E. Daily streamflow data from Dunamale station were received from Irrigation department for the time period from 2008 to 2018. Table 4-2 indicates the location of the river-gauging station.

Table 4-2: Location of Dunamale gauging station

Streamflow station	**Location coordinate**	
Dunamale	80° 4' 50" E	7° 6' 56" N

A data summary table is shown below in the Table 4-3 with spatial and temporal resolution of data, data period and data source.

Table 4-3: Data source and resolution

Data type	**Temporal/spatial resolution**	**Data period**	**Data source**
Rainfall	Daily	October 2008 to September 2018	Department of Irrigation and Department of Meteorology
Streamflow	Daily		Department of Irrigation
Temperature	Daily		Department of Meteorology
Soil map	1:50,000		Soil Science Society of Sri Lanka
Contour	1:50,000		Survey Department
Landuse	1:50,000		Landuse Policy Planning Department

4.1.1 Landuse data

Landuse map of 1:50,000 scale was collected from survey department. Landuse is an essential space-related input used in SWAT. Landuse map showing landuse type and area associated is shown below in the Figure 4-2.

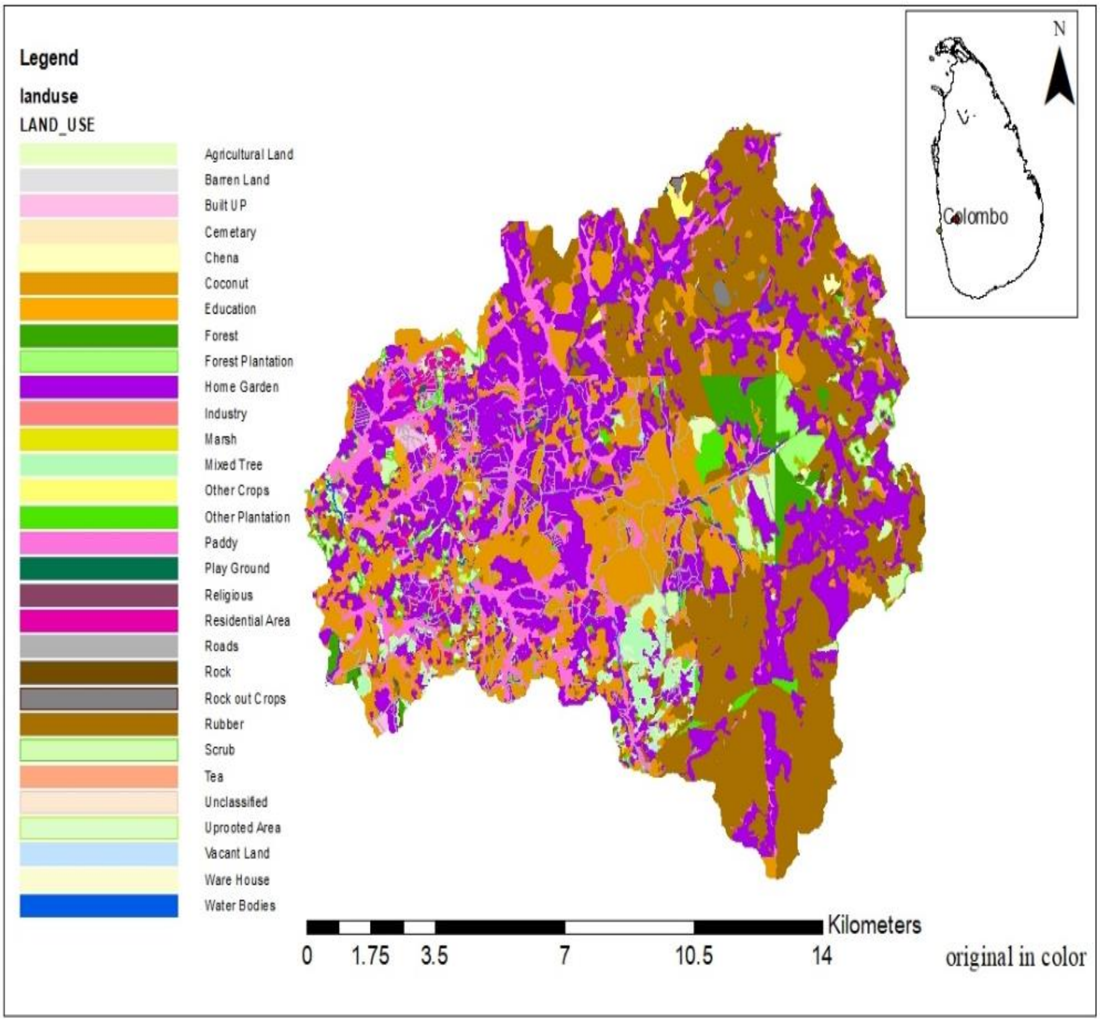


Figure 4-2:Landuse map of Dunamale watershed

4.1.2 Soil data

Soil map with scale of 1:50,000 was collected from Survey Department in Sri Lanka. Soil map is shown in the Figure 4-3 below.

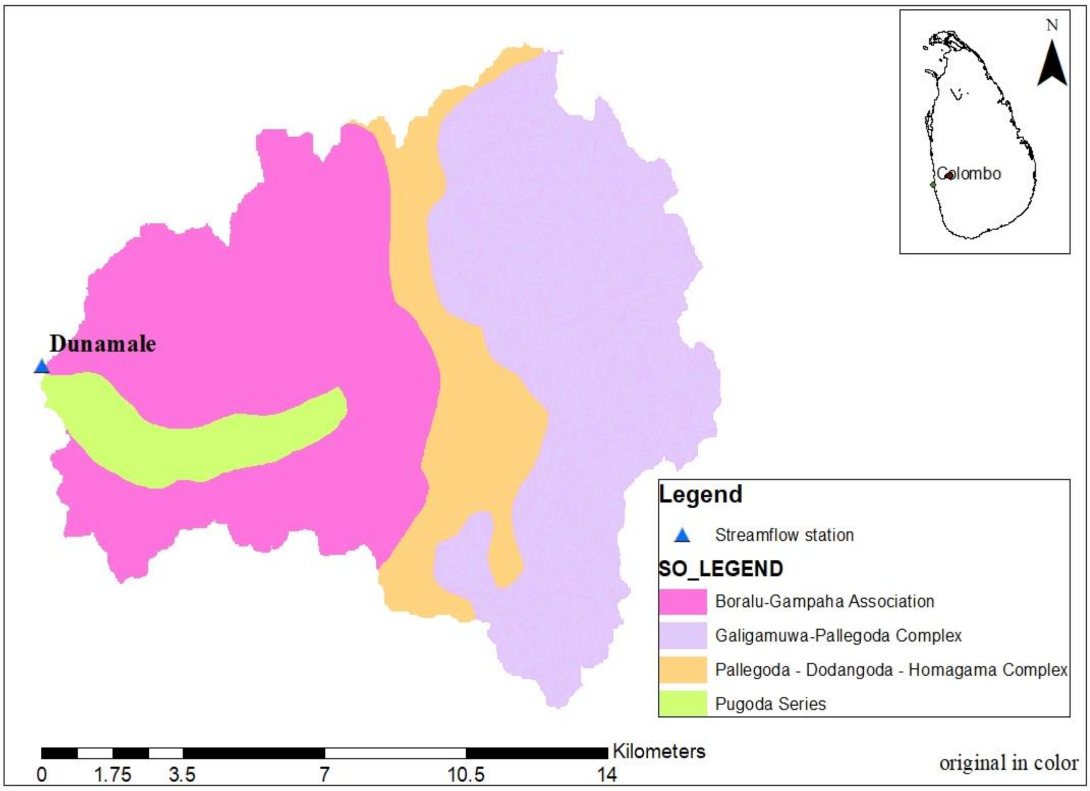


Figure 4-3:Soil map of Dunamale watershed

4.2 Data checking

4.2.1 Station density

The first step in data checking is to check whether the data has sufficient gauging stations for the spatial extend in the catchment area. The allocation of watershed Gauging Stations was aligned with World Meteorological Organization (WMO) standards as shown in the Table 4-4 below. The station density of the study area is found to be sufficient for modeling as the station density is less than that of WMO standards.

Table 4-4: Comparison of Distribution of Gauging Stations of Dunamale Catchment

Gauging Station	Number of Stations at each catchment	Station Density (km^2/station)	WMO Standards (km^2/station)
Rainfall	5	30.6	575
Streamflow	1	153	1875
Temperature	1	153	

4.2.2 Visual checking

Visual data checking have been carried out to identify the inconsistencies in data and the visual precipitation checks correlating to annual streamflow for Dunmale watershed in Attanagula Oya basin was done from 2008 to 2018. Inconsistencies and outliers were identified as shown in Figure 4-4 in rainfall and streamflows with a red circle. The discrepancies in the data is mainly due to the missing rainfall data as there is a value of streamflow present on that same day.

Visual checking of the rainfall and streamflow data of Attanagaly Oya basin from 1970 to 2001 has been carried out and the filling of incomplete data was done with the use of single & multiple regression analysis (Wijesekera & Perera, 2012).

Streamflow responses to each of the five rainfall station namely Karasnagala, Nittambuwa, Pasyala, Vincit and Chesterford were plotted against the streamflow gauging station at Dunamale on a yearly basis for all ten years from 2008 to 2018 in the Appendix A.

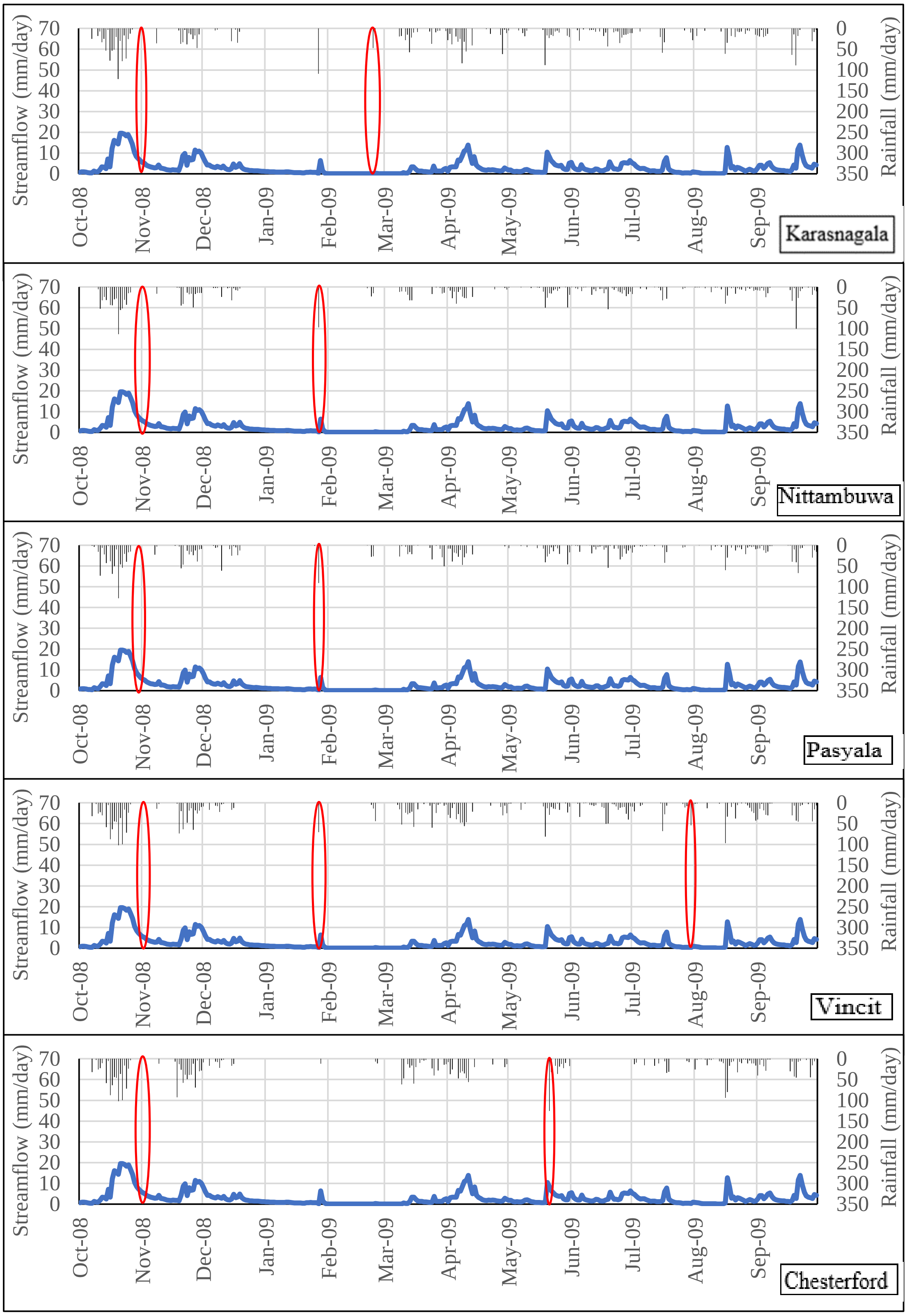


Figure 4-4: Dunamale daily streamflow response with each rainfall station daily data for water year 2008/2009

4.3 Double Mass Curve

Double mass curves are utilized to test uniformity for several hydrological data by comparing results for one station and data from a pattern consisting of data from a variety of different stations from the region. The reliability of precipitation data for each catchment was calculated by double mass curves for total combined precipitation from a single precipitation station with a combined average of adjacent catchment stations. The diagram is a straight line graph in which the rainfall relationship is a fixed proportion. Alterations in the data gathering or the shift in the precipitation station trigger graph breaks. Dunamale catchment double mass curve was plotted against five rainfall stations. Vincit and Pasyala stations shown inconsistency over the time period of 2008-2018 shown in above Appendix C.

4.4 Missing Data

Table 4-5: Missing data

Water Year	**Karasnagala**	**Nittambuwa**	**Pasyala**	**Vincit**	**Chesterford**
2008/09	-	-	-	-	June
2009/10	-	September	April	-	December
2010/11	-	-	-	January, July	November
2011/12	-	-	-	October, November, June, July, September	-
2012/13	-	-	-	November, December	-
2013/14	January, August	September	October, November, December	December, January	February, April
2014/15	November	-	-	-	-
2015/16	-	-	-	-	-
2016/17	February	-	September	-	-
2017/18	-	-	-	December, September	-
Total (months)	6	2	5	13	5
Missing %	**5%**	**2%**	**4%**	**11%**	**4%**

Missing data for the period 2008 to 2018 were noted in Table 10 as below. The maximum missing data is for Vincit station with thirteen months which is about 11%. The percentage of missing information relates directly to the standard of statistical inference, since there exists no fixed literature cut-off on an appropriate percentage of missing information for legitimate statistical inferences. Nonetheless predictive research is likely to be incomplete when over 10% of data is missing. The missing data from the five stations are tabulated in the above Table 4-5.

To fill the missing data thiessen weight was calculated where if one of the rainfall station is missing then the missing station was ignored and other four stations were considered for thiessen weight. In cases where two station data were missing both the station were ignored and other three stations were considered to calculate thiessen weight. Similarly, cases where three rainfall station were missing, the three missing rainfall was ignored for that particular day and thiessen weight was calculated for the two rainfall station. Cases when four rainfall station were missing only one rainfall station was taken into consideration for the thiessen weight to determine the average annual rainfall for the basin. Missing data are filled with thiessen weight considering eight cases including individual missing station and combine missing stations and the thiessen weights are shown in the Table 4-6.

Table 4-6:Thiessen weights for filling data

Rainfall station	**Nittambuwa**	**Pasyala**	**Vincit**	**Karasnagala**	**Chesterford**
Thiessen Weight	0.21	0.16		0.46	0.18
	0.21	0.16	0.18	0.45	
	0.23	0.31	0.22		0.24
		0.33	0.11	0.42	0.14
	0.27		0.11	0.14	0.14
	0.27			0.55	0.18
	0.44		0.30		0.26

4.5 Monthly Rainfall

The rainfall data of all five rainfall stations were plotted on a monthly basis and the overall monthly Theissen rainfall was also plotted below in the Figure 4-5.

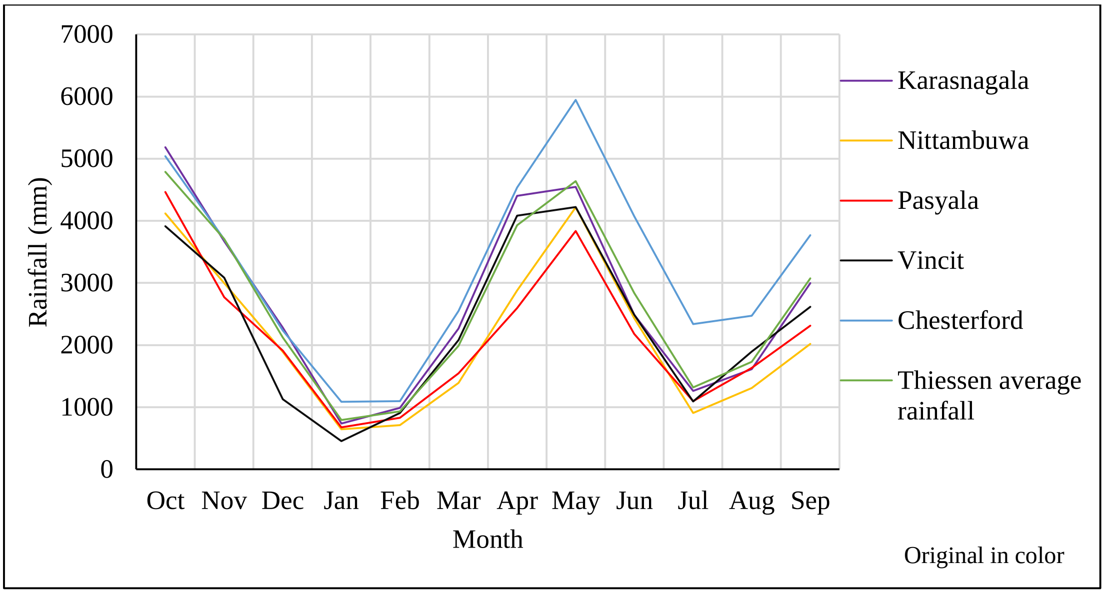


Figure 4-5: Monthly Rainfall data of Dunamale watershed

4.5.1 Annual Water Balance

Table 4-7:Annual water balance of Dunamale catchment

Water year	Thiessen average rainfall (mm/year)	Annual Streamflow (mm/year)	Annual observed pan evaporation (mm/year)	Annual water balance (mm/year)	Runoff coefficient
2008/09	3104	1077.52	1267.52	2026.76	0.35
2009/10	3502	1338.31	1205.61	2163.65	0.38
2010/11	3617	1407.11	1171.05	2209.96	0.39
2011/12	2486	750.00	1269.82	1735.64	0.30
2012/13	3548	1481.67	1207.24	2065.97	0.42
2013/14	2931	1155.46	1317.94	1775.23	0.39
2014/15	3230	1596.78	1198.95	1633.69	0.49
2015/16	3258	827.72	1329.55	2430.00	0.25
2016/17	2862	1226.09	1217.23	1636.19	0.43
2017/18	3322	2088.39	1437.77	1233.66	0.63

Annual water balance was carried out for Dunamale watershed to analyze the annual rainfall, runoff and evaporation. Yearly runoff coefficient differs from 0.25 to 0.63 during the ten year period from 2008 to 2018. The average annual runoff coefficient of Dunamale watershed is 0.41. Annual water balance of the watershed from 2008 to 2018 is as displayed in Table 4-7.

4.5.1.1 Variation of annual rainfall and streamflow

The rise in rainfall results in an increase of streamflow data and corresponding declines in the precipitation results in a fall of streamflow data during the 10-year period from 2008 to 2018. Except for the water year 2015/2016 where a minimal increase in rainfall has resulted in a large decrease of streamflow data leading to low runoff coefficient. Also in the water year 2017/2018 although there is increase in both rainfall and streamflow data but the increase in streamflow data is considerably high when compared to other years. Therefore, the observed flow data may be inconsistent as shown below in Figure 4-6.

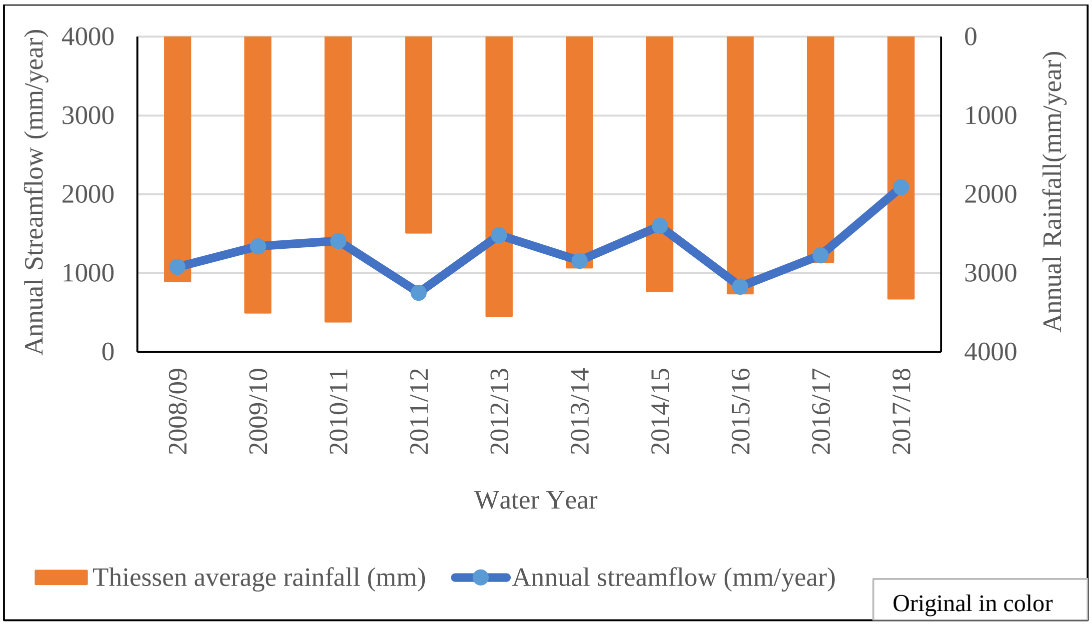


Figure 4-6: Variation of annual rainfall and streamflow of Dunamale watershed

4.5.2 Variation of annual runoff coefficient and evaporation

It can be observed from the Figure 4-7 that in the year 2017/2018 the runoff coefficient is the highest and lowest in the year 2015/2016 when compared to other years. Further it can be noted that evaporation is highest in the year 2017/2018 and lowest in 2010/2011.

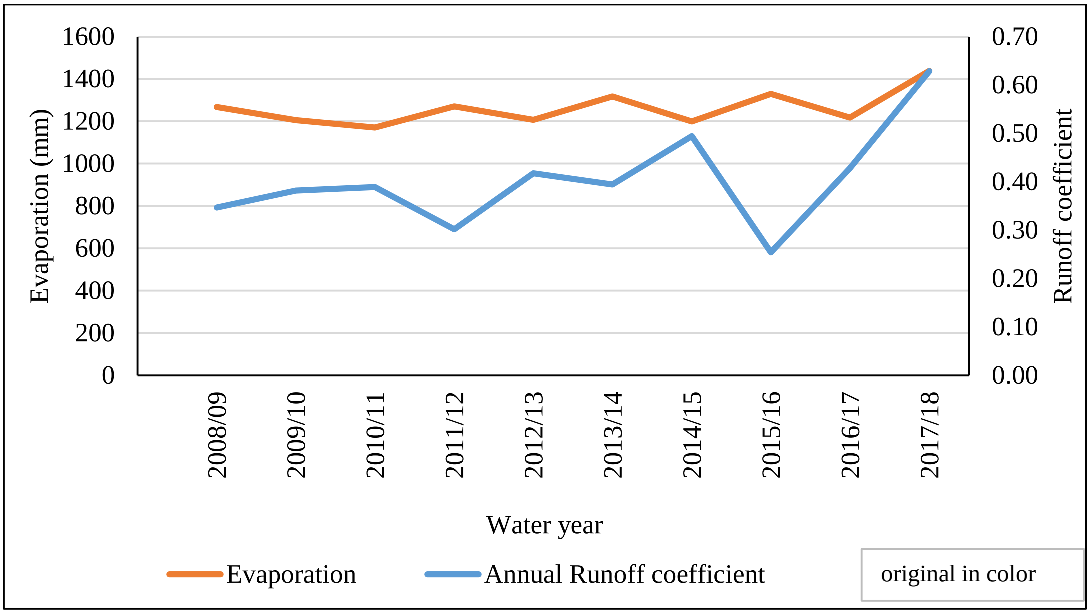


Figure 4-7:Variation of annual evaporation and runoff coefficient of Dunamale watershed

4.6 Flow Duration Curve

Flow duration curve is calculated for the entire data period of 10 years from 2008 to 2018. The streamflow is then distributed as high flow, intermediate flow and low flow based on the slope. Wijesekera, (2018) divided stream flow into 5 regions, including: high flow rates (0–10%), wet conditions (10%–40%), mid-range flows (40%–60%), dry (60%–95%) and low flows (90%–100%).

Watershed hydrology based method is used to capture the high, intermediate and low streamflow thresholds at monthly and daily scales. The method conjunctively evaluates the consistent streamflow segments and average slope of the flow duration curve to capture the thresholds which are watershed signatures for a particular temporal resolution.

Initially an Order of Magnitude FDC (OM FDC) is plotted to capture the slope change points belonging to segments having same order of magnitude. Semi logarithmic FDC enables an easy comparison of gradient change in both high and low flow regions.

Hence, the gradient of streamflow change is computed using the logarithms of observed streamflow. Slope between change points when plotted against the Probability of Exceedance (PoE), highlights the rapid decrease of slope in high flow region, stability of

streamflow magnitude with less varying slope in the intermediate flow region, and again an increase of slope in the low flow region. Slope at the transition between these flows types lead to the identification of streamflow change point (Wijesekera, 2018).
The high flows are up to 17% and low flows are from 73% to 100% after calculations for the study as shown in Figure 4-8 below.

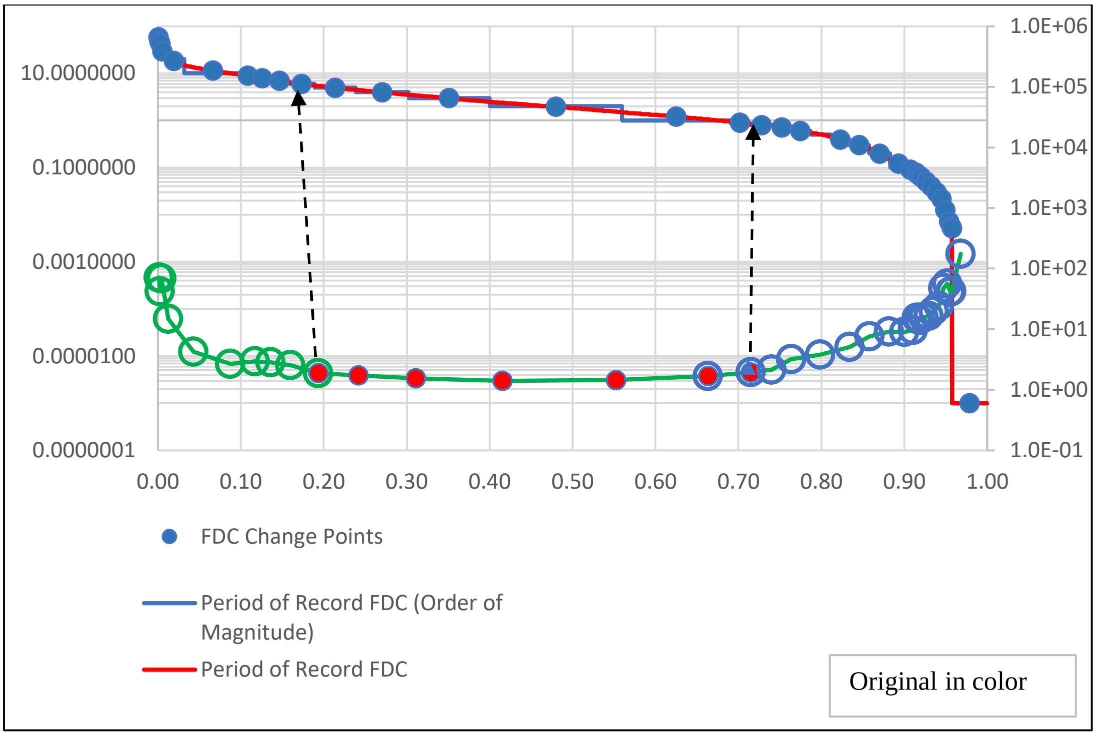


Figure 4-8: Flow duration curve classification of Dunamale watershed

5 SWAT MODEL DEVELOPMENT

5.1 Model Schematic

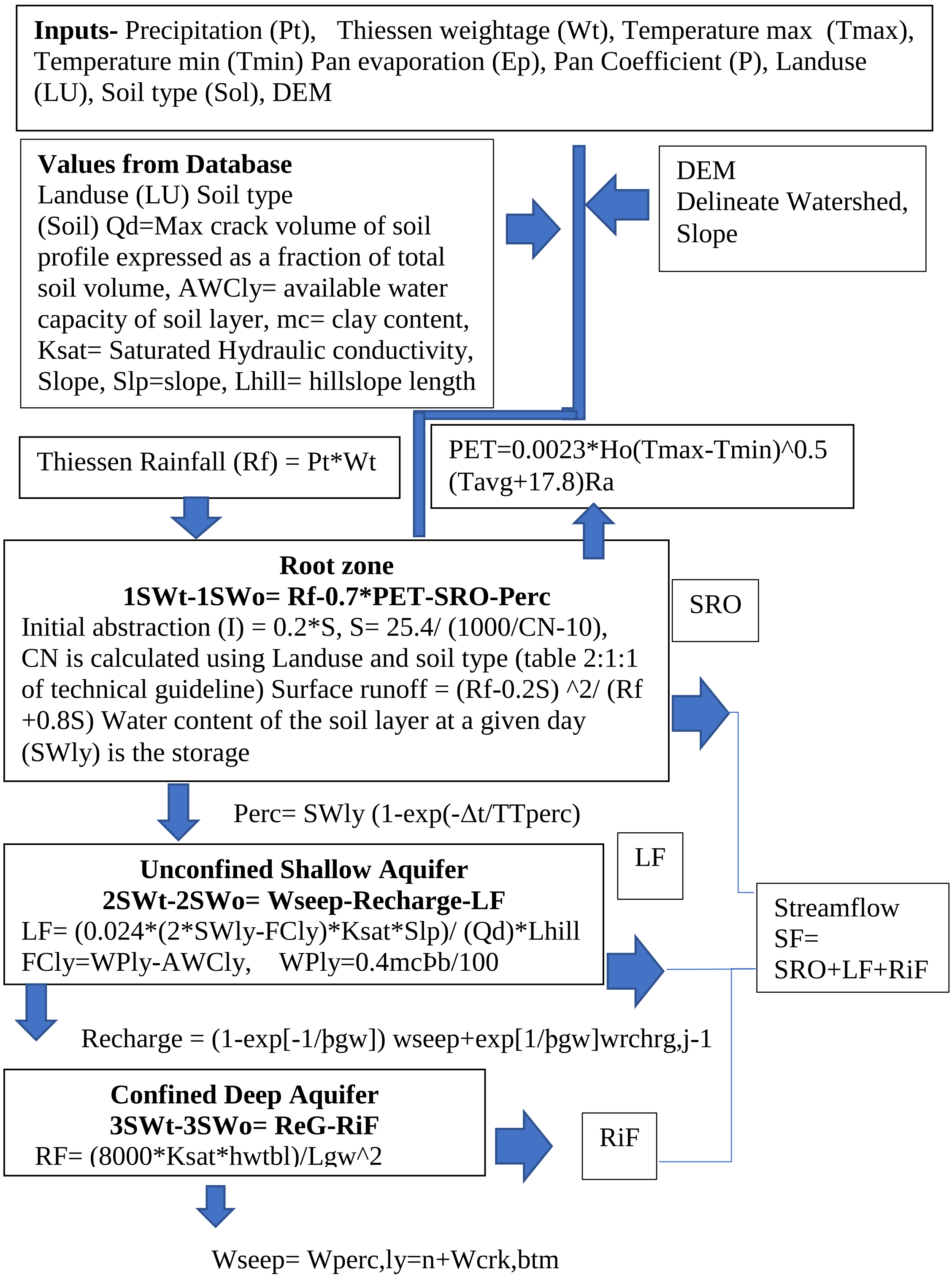


Figure 5-1:Model Schematic Diagram

The Soil and Water Assessment Tool (SWAT) is a physically dependent catchment model that works on a regular time scale. SWAT uses land type, soil and climate data inputs and replicates the hydrological process with the following water balance equation,

Equation 5-1: Water balance equation of SWAT model

$$SW_t = SW_0 + \sum_{i=1}^{t} (R_i - Q_{surf,i} - E_i - W_{seep,i} - Q_{gw,i}) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (1)$$

Where SW_t is soil water quality (mm) on day t, SW_0 is the initial soil moisture content (mm), R_i is the quantity of rainfall on day i (mm), Qsurf is the quantity of surface runoff on day i (mm), E_i is the quantity of evapotranspiration on day i (mm), $W_{seep, i}$ is the volume of water entering the vadose area from the soil profile (percolation) on day i (mm), and $Q_{gw, i}$ is the quantity of return flow on day i (mm).

Rainfall is either collected or flow on land. Surface water either penetrates through soil or outflows as surface run-off. SCS approach is used to measure infiltration. The surface runoff travels to a stream flow path and helps short duration response of the catchment area. For each hydrological response unit (HRU) which is the basic unit of the model, SWAT analyzes surface runoff amount and peak runoff levels. The volume of runoff is determined with the help of varying SCS curve number. With moisture content the curve number changes nonlinearly. The model calculates separately evaporation from plants and soils. The potential evaporation of soil water is determined by the possible evapotranspiration and leaf area index (S.L. Neitsch, J.G. Arnold, J.R. Kiniry, 2009).

Evaporation is determined from exponential functions of soil depth and moisture content. Plant transpiration is simulated as a linear function of potential evapotranspiration and leaf area index. The actual evaporation of soil water is calculated using exponential soil depth and water content functions. Plant transpiration is calculated as a linear function of the evapotranspiration potential and the index of leaf area. There are two approaches in SWAT for estimating surface runoff: 1) the Green and Ampt method for infiltration, and 2) SCS for the process of curve number. The so called Penman-Monteith, Priestley-Taylor and Hargreaves are methods for the assessment of evapotranspiration. Percolation is measured for each soil layer and percolation occurs only when the amount of water is greater than that of that layer's water content.

SWAT will simulate two aquifers within all sub-watershed. The shallow aquifer being an unconfined aquifer leading to the flow of the principal channel of the sub-watershed and deep aquifer. Potential evapotranspiration is calculated using the Hargreaves formula (Hargreaves & Allen, 2003). SWAT's redistribution component uses a storage routing technique to predict the flow across each soil layer in the root zone. The percolation takes place when the soil layer's field capacity is overwhelmed and the lower layer is not saturated. The saturated hydraulic conductivity of the soil layer determines the flow rate. Lateral sub-surface flow in the soil profile (0-2 m) is determined at the same time as redistribution by using kinematic storage model (Arnold, Kiniry, et al., 2012; S.L. Neitsch, J.G. Arnold, J.R. Kiniry, 2009)

The model shows variations in conductivity, slope and soil water content. It also allows the upstream flow to the adjacent layer or to the surface. The return flow (base flow) is the flow from the groundwater. SWAT allows the modeling to be performed separately for two aquifer systems: a shallow, unconfined aquifer that contributes to the flow of streams within the basin and a deep, confined aquifer that contributes to the flow of streams outside the basin.

Water percolating beneath the root zone is divided into two fractions that represent recharges to these aquifers. In addition to the return flow, the water stored in the shallow aquifer may, under very dry conditions, replenish moisture in the soil profile or be removed directly by plant uptake. As a function of the demand for evapotranspiration, SWAT models flow of the water from the shallow aquifer to the surrounding unsaturated layers. The REVAP coefficient is used to determine the maximum water that is extracted from the aquifer through this ("revap") method. Water can also flow into the deep aquifer from the shallow aquifer, or be drained by pumping. Water in the deep aquifer can be cleared by pumping. (S.L. Neitsch, J.G. Arnold, J.R. Kiniry, 2009).

5.2 Database Preparation for SWAT

5.2.1 UserSoil database

Other inputs required by the SWAT Usersoil Database were the physical and chemical attributes of soil. The soil's physical property in each boundary controls the flow of water, air across the soil profile, which has a significant effect on water cycling in the hydrological response unit (HRU), and has been used to assess the soil profile's water budget. Simple physio-chemical attributes of major watershed soil types were gathered from the book titled, Soils of Wet zone of Sri Lanka. The physical attributes of soil require by SWAT is tabulated below in Table 5-1.

Table 5-1:Soil physical properties required by SWAT

Name	**Description**
SNAM	Soil name (optional)
NLAYERS	Number of layers in the soil (min 1 max 10)
HYDGRP	Soil hydrologic group (A,B,C,D)
SOL_ZMX	Maximum rooting depth of soil profile (mm)
ANION_EXCL	Fraction of porosity from which anions are excluded (optional)
SOL_CRK	Potential or maximum crack volume of the soil profile expressed as a fraction of the total soil volume (optional)
TEXTURE	Texture of soil layer (optional)
SOL_Z	Depth from soil surface to bottom of layer (mm)
SOL_BD	Moist bulk density (Mg/m^3 or g/cm^3)
SOL_AWC	Available water capacity of soil layer (mm H_2O/mmsoil)
SOL_K	Saturated hydraulic conductivity (mm/hr)
SOL_CBN	Organic carbon content (% soil weight)
CLAY	Clay content (% soil weight)
SILT	Silt content (% soil weight)
SAND	Sand content (% soil weight)
ROCK	Rock fragment content (% total weight)
SOL_ALB	Moist soil albedo
USLE_K	USLE equation soil erodibility (K) factor (units (metric ton m^3 hr)/(m^3 metric ton cm))

Source: (Arnold, Kiniry, et al., 2012)

5.2.2 Weather generation database

Daily precipitation and daily highest and lowest temperature data were used in the rainfall and temperature database. Elevation of the station and coordinate of the station were entered in the database.

5.3 Watershed Delineation

In SWAT watershed is delineated with a 30 m DEM from survey department and a applying a maskDEM of Attanagalu oya basin to demarcate the study area. SWAT delineates the watershed and seven sub watershed is formed along with streamline after watershed delineation by ArcSWAT along with the monitoring points and outlet at the Dunamale station as shown in Figure 5-2.

Further the landuse is reclassified into 10 groups, soil into 7 types and slope into two classes. The landuse, soil type and slope are overlaid with each other. After overlaying the soil, landuse and slope and defining threshold of landuse and slope as 20% and soil as 10%, a total of 40 HRUs were demarcated in the basin. The basin outlet is situated in the sixth sub-basin and the flow from the sixth sub basin is considered as the modelled streamflow as flows from other sub basins accumulates and contribute to the sixth sub basin.

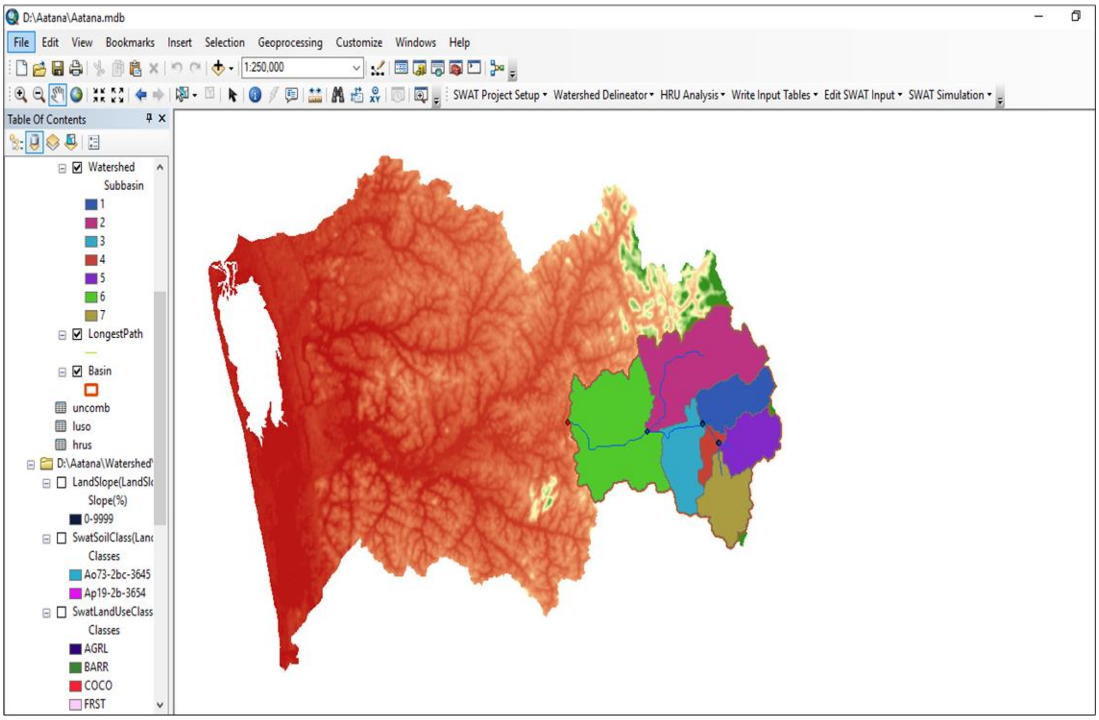


Figure 5-2:SWAT watershed delineation

5.4 Weather Data

In the SWAT model, daily rainfall and temperature data of Sri Lanka from Meteorology and Irrigation Department are used to produce the streamflow model. Daily precipitation and input data for peak and lowest temperature were compiled in the plain text format that included the warm-up time for the model. The input tables are built after the weather inputs are incorporated in the model. Processes and the methods are selected based on literature, SWAT model is then set up and run for initial model results.

5.5 Initial Model Results

5.5.1 Warm up period

Before the model run, warming up of the model for three cycles were performed for stabilizing the soil moisture so that the model gives accurate results. The model was run for a warm up period of three cycles, each cycle consisting of five years as the same duration for calibration dataset. The results of running the model three cycles prior to running the data is shown in the Figure 5-3 and soil moisture is found to be stabilized after the model is warmed up.

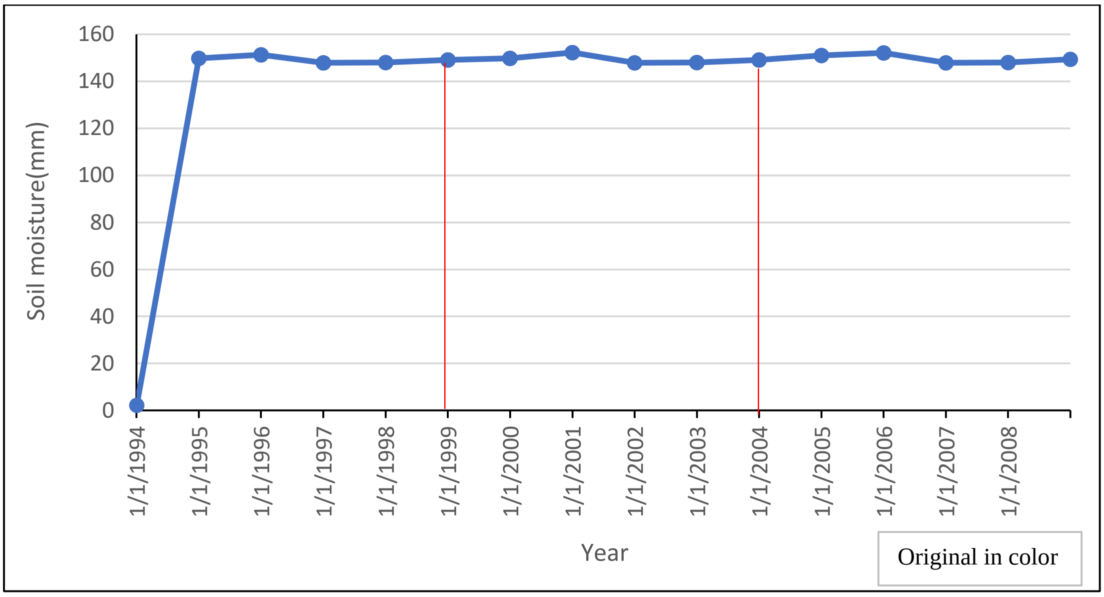


Figure 5-3:Model Warm Up

5.6 Model Streamflow and Observed Streamflow

The initial modeled streamflow from the SWAT model and observed streamflow is compared in the Figure 5-4 below.

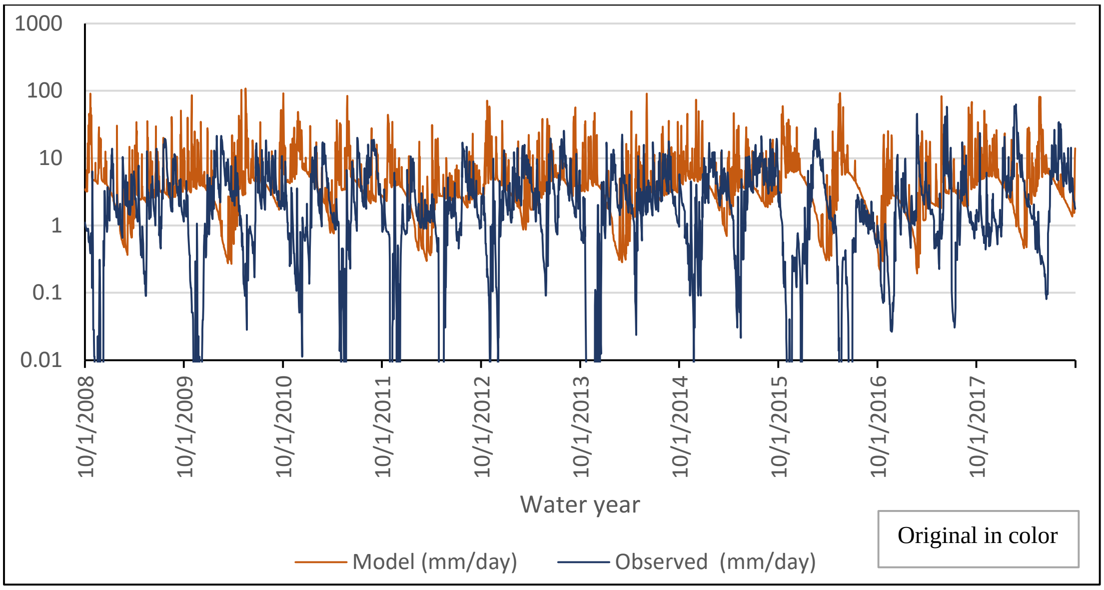


Figure 5-4:Observed and modelled streamflow daily

The modeled flow was computed on a monthly basis to compare the measured and modeled streamflow and it was noted that the pattern persisted even though there was variability in hydrograph matching as shown in Figure 5-5.

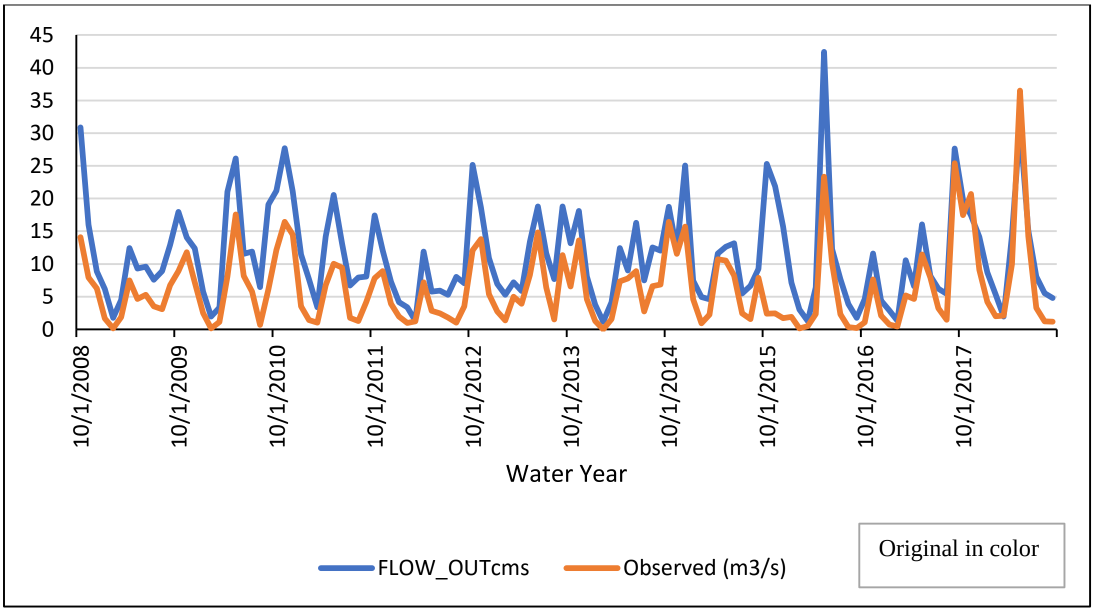


Figure 5-5:Observed and modelled streamflow monthly

The SWAT check was performed to cross check the results and in the message box SWAT check suggested that the surface runoff was excessive as illustrated in Figure 5-6.

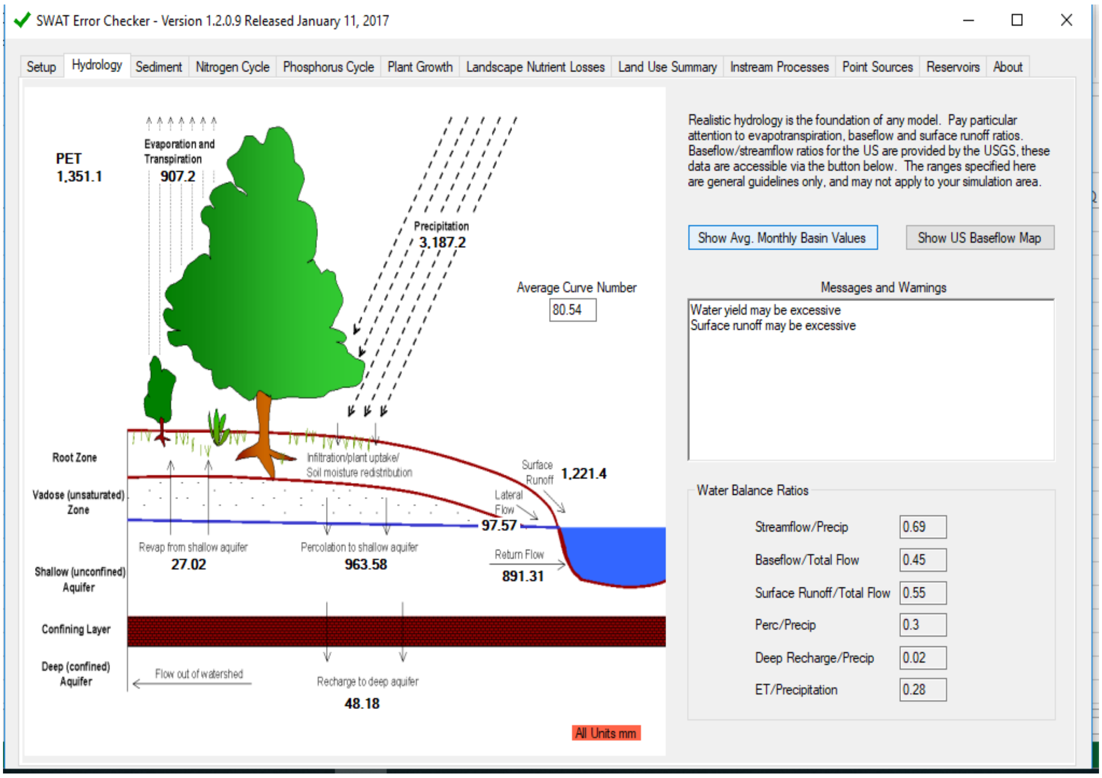


Figure 5-6:Model process result

5.7 Flow components

Flow components for the water year 2008/2009 is plotted for the initial results in the Figure 5-7 below.

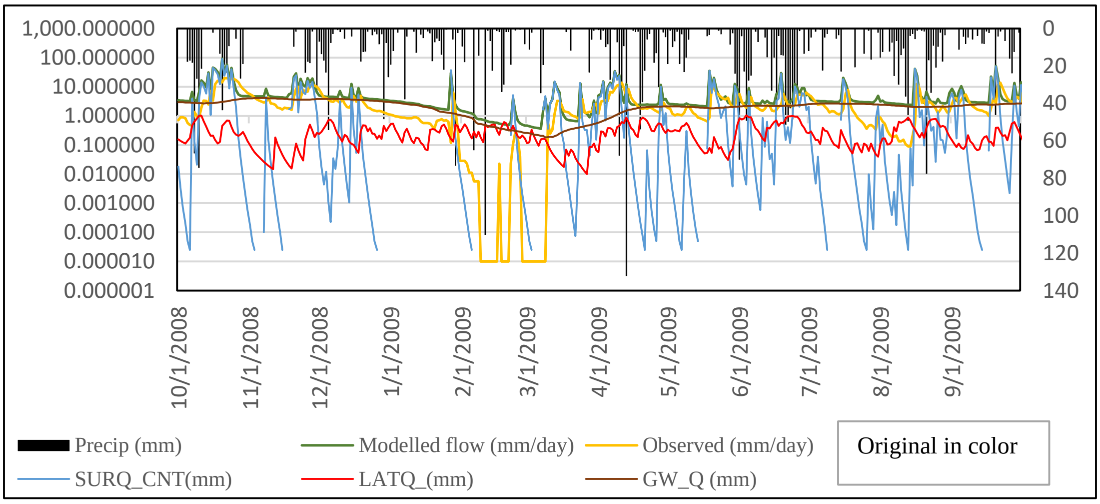


Figure 5-7:Flow components for the water year 2008/2009

From the model components it was observed that surface runoff was excessive and the runoff coefficient with the initial model results comes out to be 0.71 when the actual runoff coefficient is 0.41.

5.8 Calibration Dataset

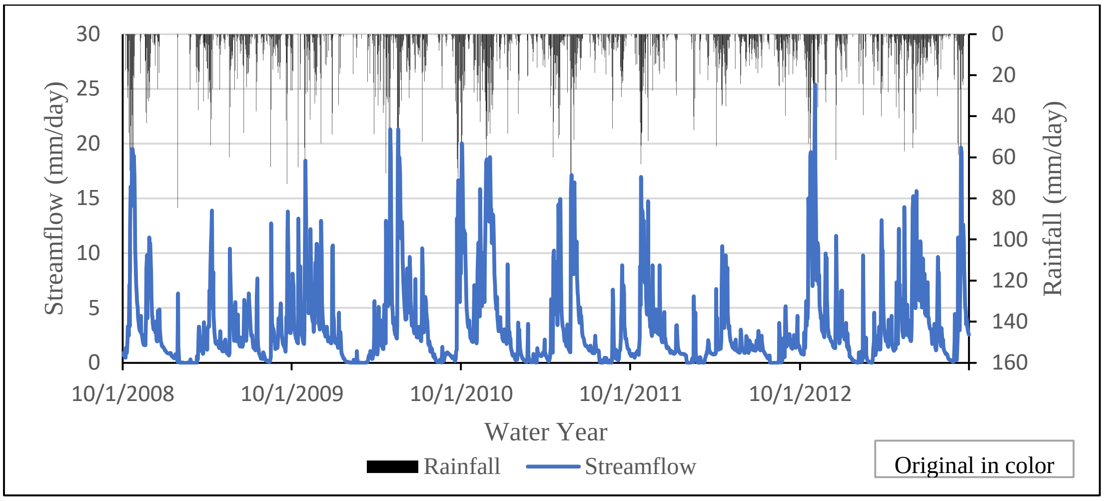


Figure 5-8:Calibration dataset

For calibration, streamflow and rainfall daily data of five years from October 2008 to September 2013 is considered.

5.9 Validation Dataset

For validation streamflow and rainfall daily data of five years from October 2013 to September 2018 is considered.

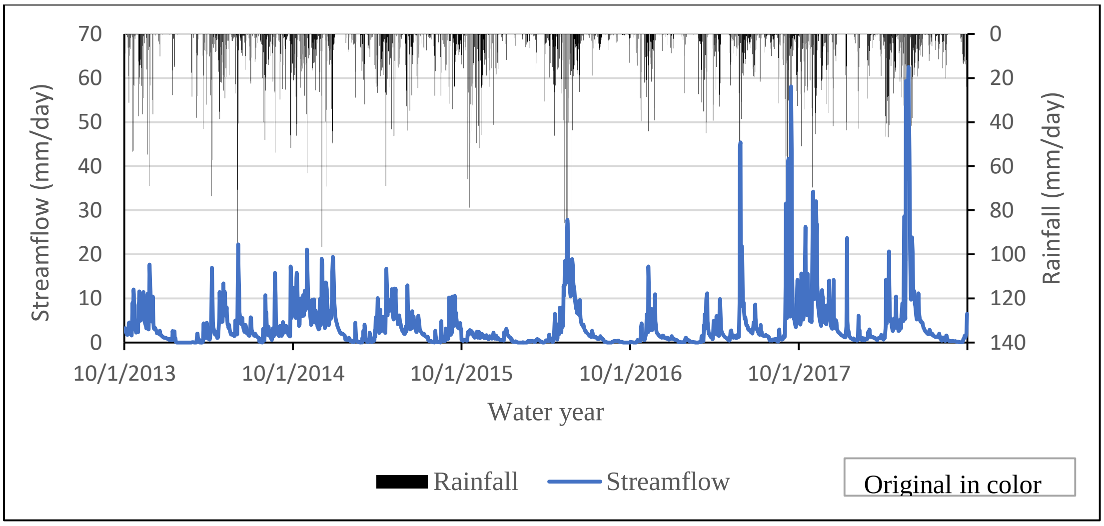


Figure 5-9:Validation dataset

5.10 Model Iterations for Calibration

For calibration of SWAT model, SWAT-CUP was adopted with semi automation technique using nine parameters that were selected from the literature. In SWAT-CUP for this study, SUFI-2 was selected as an optimization algorithm also from literature. Firstly the range mentioned from SWAT user manual for each parameter was set as shown in Table 5-2 and then number of simulation to be performed for each iteration was set as 200. In the SWAT file named File.cio, number of years to be simulated along with number of warm up years and the specific year to be used was specified. Further the observed streamflow values of the calibration period was fed specifying the main outlet in the basin which was sub basin 6 and the objective function was selected as R^2. Following the instructions from SWAT-CUP user guide, SWAT model was calibrated for the first iteration.

From the first iteration which was automatic as no initial specific range was specified for the parameters, the best simulation for the modeled streamflow came out to be 124th simulation with the value of R^2 as 0.63. Further in the calibration result of first iteration, the best parameter set for next iteration is suggested as shown in Table 5-3. The modeled streamflow from first iteration was plotted with the observed streamflow for hydrograph matching and high, medium and low flow matching. The modeled streamflow was evaluated for the best result.

Table 5-2:SWAT parameter and their range

Sl No	Parameter_Name	Min_value	Max_value
1	R__CN2.mgt	-0.2	0.2
2	V__ALPHA_BF.gw	0	1.0
3	V__GW_DELAY.gw	0	500
4	V__GWQMN.gw	0	1000
5	V__ESCO.hru	0	1.0
6	V__EPCO.hru	0	1.0
7	V__GW_REVAP.gw	0.02	0.2
8	R__SOL_AWC(..).sol	-0.1	0.1
9	V__REVAPMN.gw	0	300

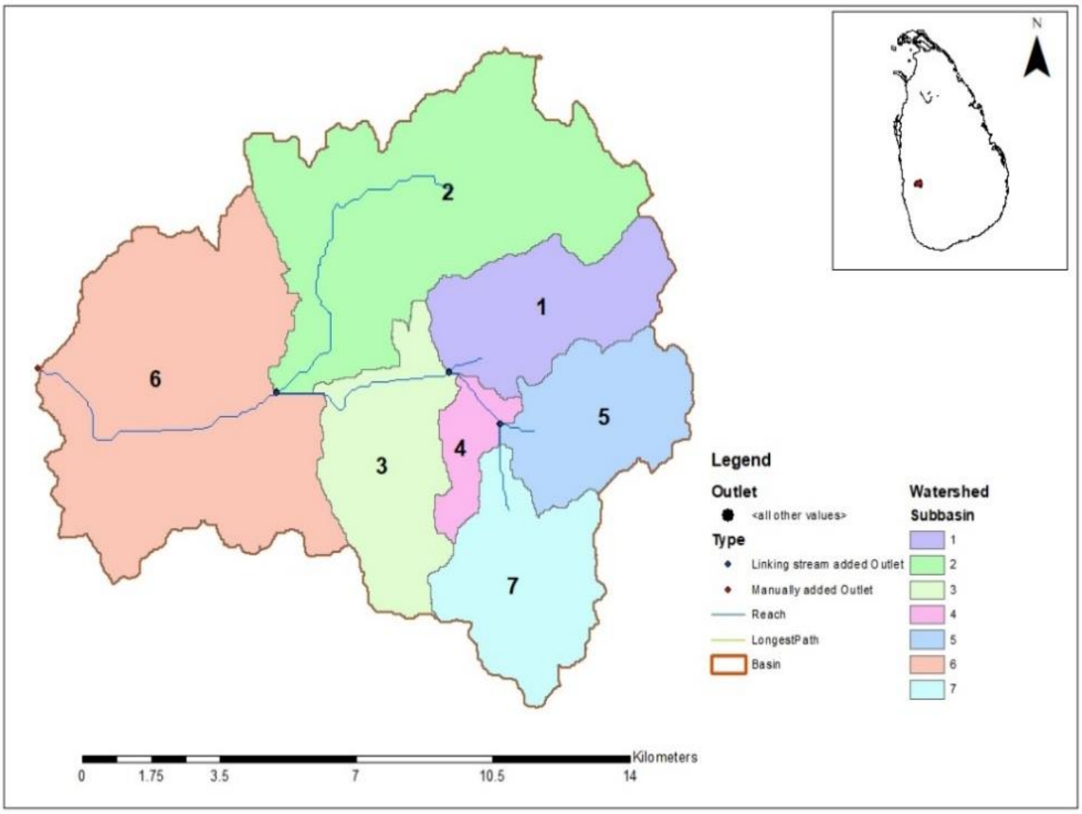
Table 5-3:Best parameter range from 1st iteration

SL No	Par_name	New_min	New_max
1	r__CN2.mgt	-0.689	-0.513
2	v__ALPHA_BF.gw	0.063	0.190
3	v__GW_DELAY.gw	-388.533	-180.962
4	v__GWQMN.gw	536.279	788.374
5	v__ESCO.hru	0.712	0.993
6	v__EPCO.hru	0.637	0.726
7	v__GW_REVAP.gw	61.152	113.586
8	r__SOL_AWC(1).sol	-0.121	-0.059
9	v__REVAPMN.gw	-76.012	-3.086

6 ANALYSIS AND RESULTS

6.1 ANALYSIS

6.1.1 Watershed delineation



. Figure 6-1:Sub basin delineation by SWAT model

ArcSWAT tool is used to delineate Attanagalu Oya watershed. As a result, a total of seven sub-basins with an area of 153 km^2 is delineated as shown in Figure 6-1 below. Each sub basin was demarcated with streamline and outlets. Further sub basins were divided into HRUs by ArcSWAT using similar types of soil, landuse and slope. A total of 60 HRUs were identified in seven sub- basin

6.1.2 Landuse map

A summary of land use and its area along with code used for each type is shown below in Table 6-1. The maximum area of 29.92% is found to be home garden and minimum area of 0.05% is pasture from the Table 6-1. A landuse map from the model is shown in the below Figure 6-2.

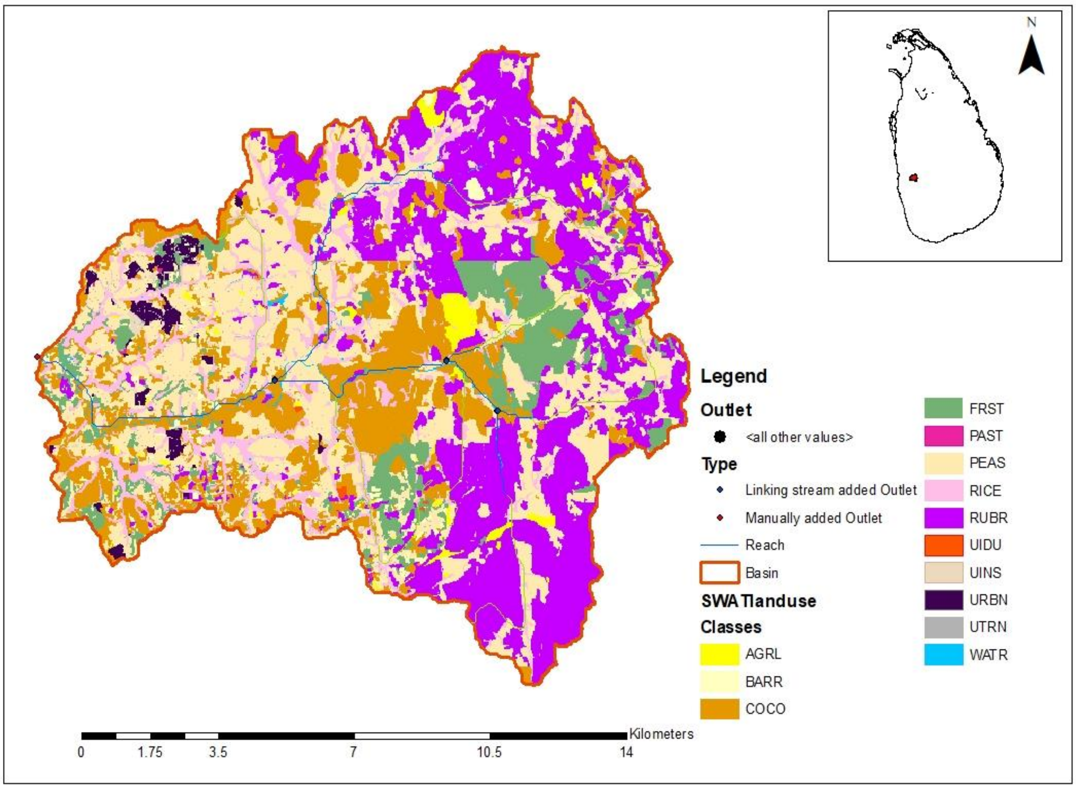


Figure 6-2:Landuse map of the watershed

Table 6-1:Land use, SWAT codes and their areal coverage in the watershed

SWAT code	Landuse	Area (km2)	Area (%)
AGRL	Agricultural land	2.58417	1.69
BARR	Barren land	2.22156	1.45
COCO	Coconut	27.95616	18.27
FRST	Forest	12.54753	8.20
PAST	Pasture	0.07038	0.05
PEAS	Home garden	45.78372	29.92
RICE	Paddy	14.27031	9.33
RUBR	Rubber	43.36632	28.34
UIDU	Industrial	0.11781	0.08
UINS	Institutional	0.30447	0.20
URBN	Residential	2.08233	1.36
UTRN	Transportation	0.90729	0.59
WATR	Water	0.78948	0.52

6.1.3 Soil map

Soil map representing the types of soil in the Attangalu Oya watershed is shown below in the Figure 6-3. Further the details of swat code for soil and its area Is tabulated in the Table 6-2.

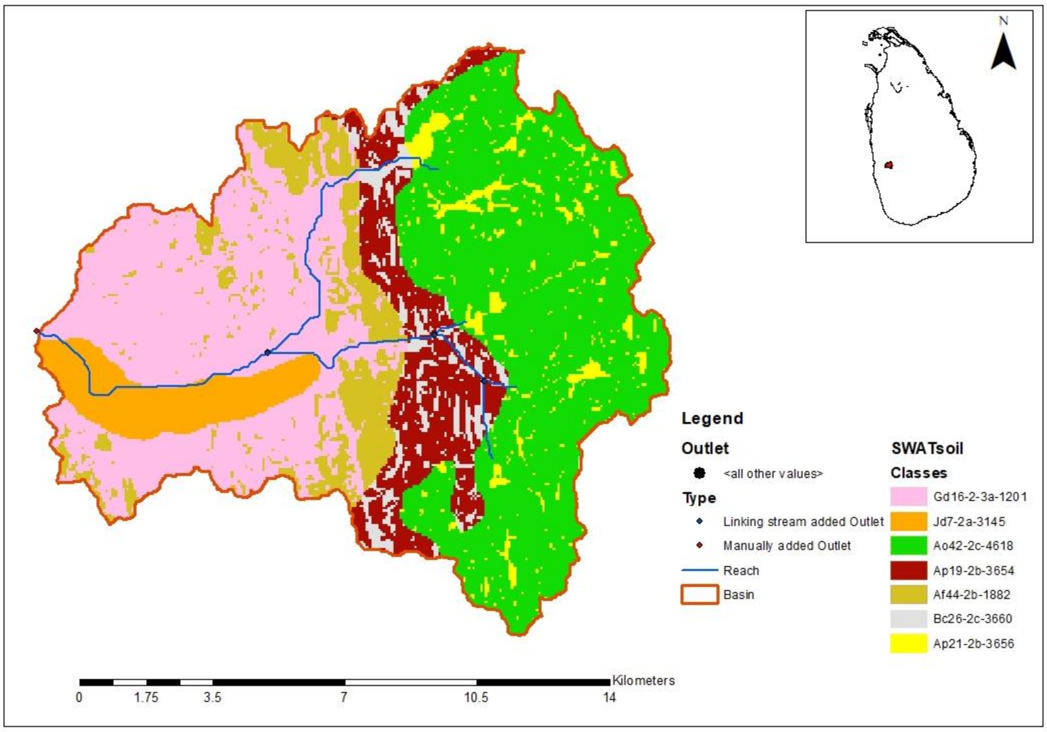


Figure 6-3: Soil map of the watershed

Table 6-2:Major soil classes of watershed and their areal coverage

SWAT code	Area (km2)	Area (%)
Gd16-2-3a-1201	45.68733	29.861
Jd7-2a-3145	9.68796	6.332
Ao42-2c-4618	56.15253	36.701
Ap19-2b-3654	14.95575	9.775
Af44-2b-1882	14.18616	9.272
Bc26-2c-3660	6.27912	4.104
Ap21-2b-3656	6.04962	3.954

6.1.4 Slope map

The slope in the watershed was categorized on the basis of natural break and two slope classes were classified as: category 1: 0 to 9 percent, category 2: 9 to 9999 percent. By default, the highest slope value was 9999 percent. Figure 6-4 illustrates the slope distribution and shows that there are higher slopes at the upstream of the watershed portion.

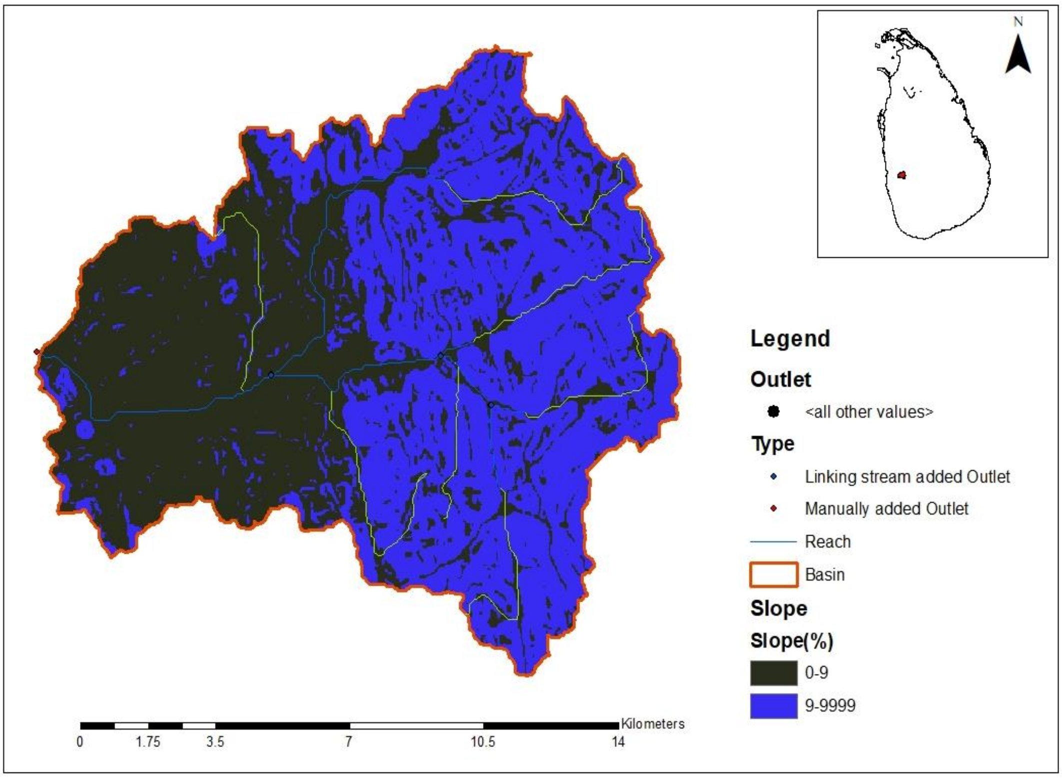


Figure 6-4:Slope map of the watershed

The Table 6-3 and Table 6-4 below shows the calibration hydrograph tips with four issues from the SWAT official website to correct the calibration process and perform calibration in a more effective way. The calibration results show the issue number 2 and hence the solutions and the reasons can be identified to calibrate the model and get more realistic simulated streamflow.

6.2 Calibration Results

6.2.1 Statistical goodness of fit measures

The calibration results of Dunamale model has shown in Table 6-3 by statistical measure of R^2. A total of 34 iterations were performed, the results were evaluated based on hydrograph matching, R^2 value from the model, annual water balance, hydrograph matching with R^2 value of high, low and medium flow. 200 number of simulations were done for each iteration and best fit is given at 124th simulation of the 8th iterations.

Table 6-3:Dunamale model calibration results

Gauging Station	Hydrograph Matching R^2	Annual Water Balance Error(mm)	FDC			
			Whole	High	Medium	Low
			R^2	R^2	R^2	R^2
Dunamale	0.77	845	0.77	0.49	0.51	0.03

6.2.2 Calibrated parameters range of Dunamale model

The calibrated parameters of Dunamale watershed are tabulated in Table 6-4. In SWAT model, semi-automated calibration was performed using SWAT-CUP with SUFI-2 as optimization algorithm whereby it gives output of fitted value of parameters with the range of minimum and maximum set as follows.

Table 6-4:Optimized parameter's ranges of dunamale

Sl No	Parameter_Name	Fitted_Value	Min_value	Max_value
1	R__CN2.mgt	-0.601	-0.777	-0.450
2	V__ALPHA_BF.gw	0.127	0.001	0.128
3	V__GW_DELAY.gw	-284.747	-319.210	-77.369
4	V__GWQMN.gw	662.327	410.586	874.624
5	V__ESCO.hru	0.852	0.571	0.870
6	V__EPCO.hru	0.682	0.593	0.750
7	V__GW_REVAP.gw	87.369	35.008	130.645
8	R__SOL_AWC(..).sol	-0.090	-0.092	-0.027
9	V__REVAPMN.gw	-39.549	-89.634	33.274

6.2.3 Observed and simulated hydrograph comparison

The following Figure 6-5 and Figure 6-6 shows the observed and simulated hydrographs at Dunamale in semi-log and normal scale.

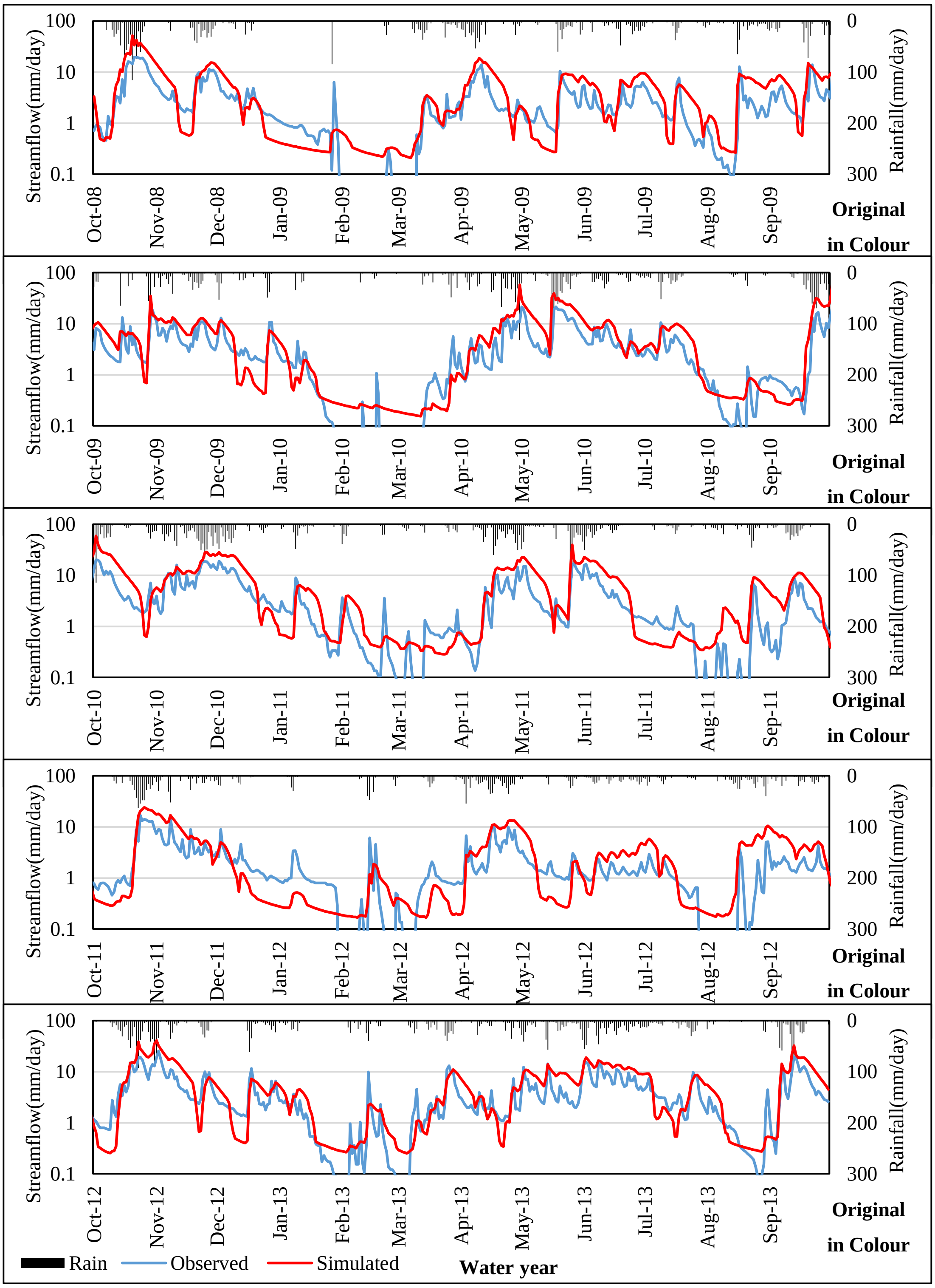


Figure 6-5:Simulated vs observed hydrograph (semi-log)

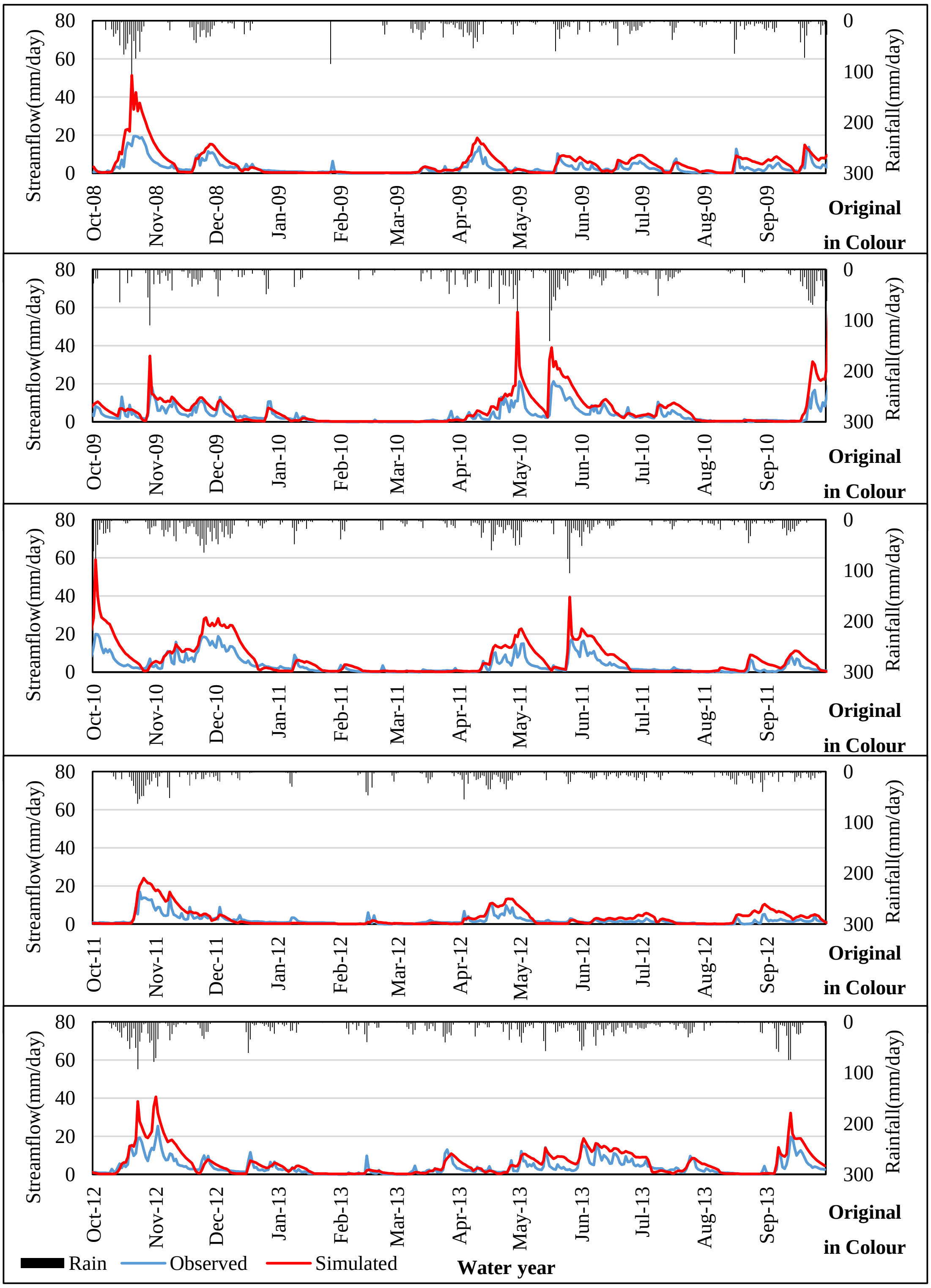


Figure 6-6:Simulated vs observed hydrograph (normal plot)

6.2.4 Flow Duration Curve Matching

Flow duration curves for Dunalame watershed was calculated and plotted in two ways as following Figure 6-7 and Figure 6-8.

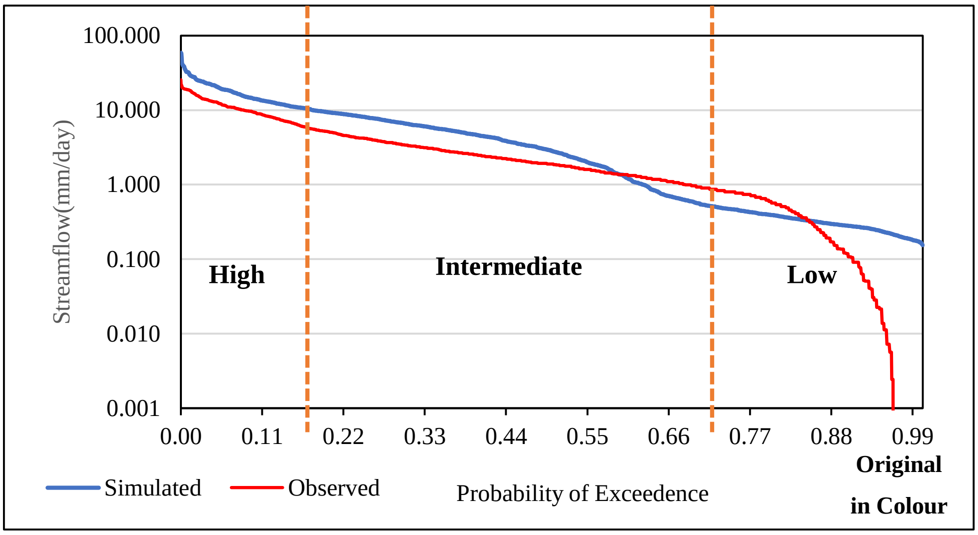


Figure 6-7:FDC at Dunamale (both sorted)

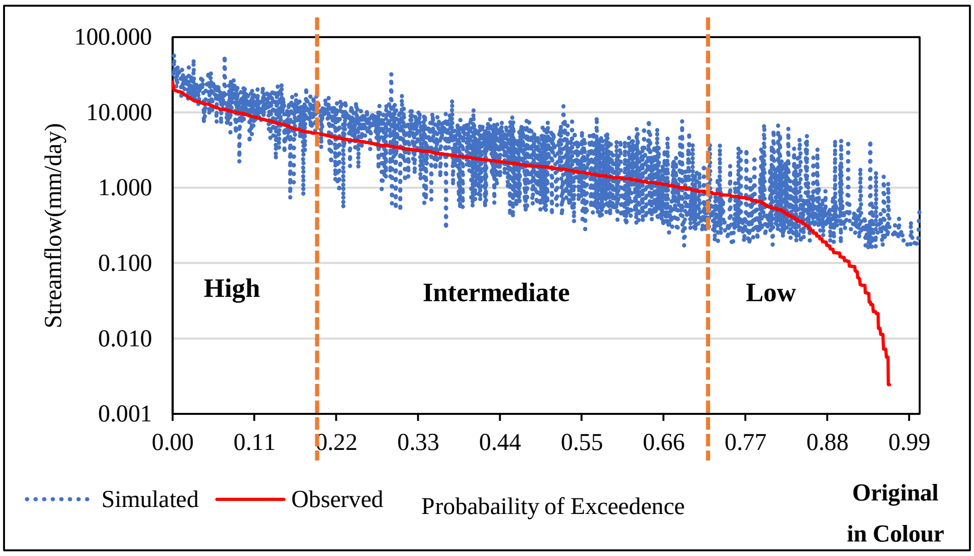


Figure 6-8:FDC at Dunamale(sorted only observed)

6.2.5 Annual water balance error

Annual water balance error for Dunamale catchment is plotted in bar chart as follows in Figure 6-9.

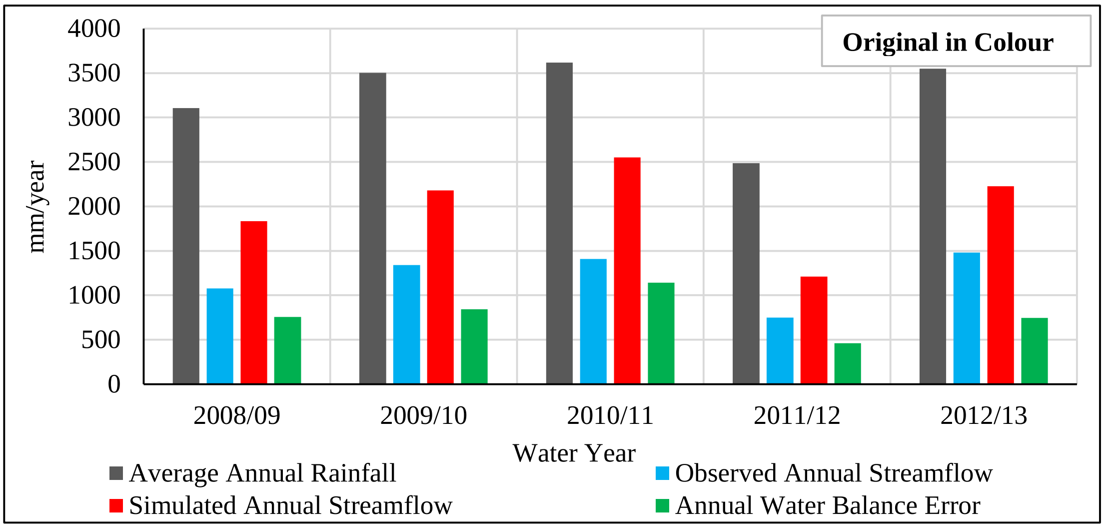


Figure 6-9:Annual water Balance error at Dunamale

6.3 Monthly Comparison

6.3.1 Monthly Observed and Calculated Hydrograph

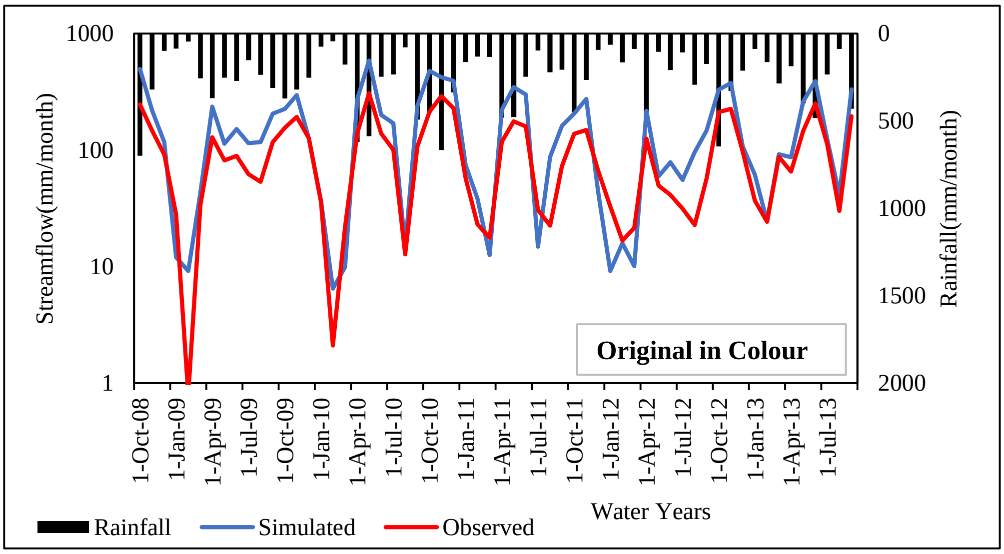


Figure 6-10:Monthly hydrograph in semi-log plot

The monthly observed and modeled streamflow from the model is plotted for monthly comparison and is found to be matching in behavior.

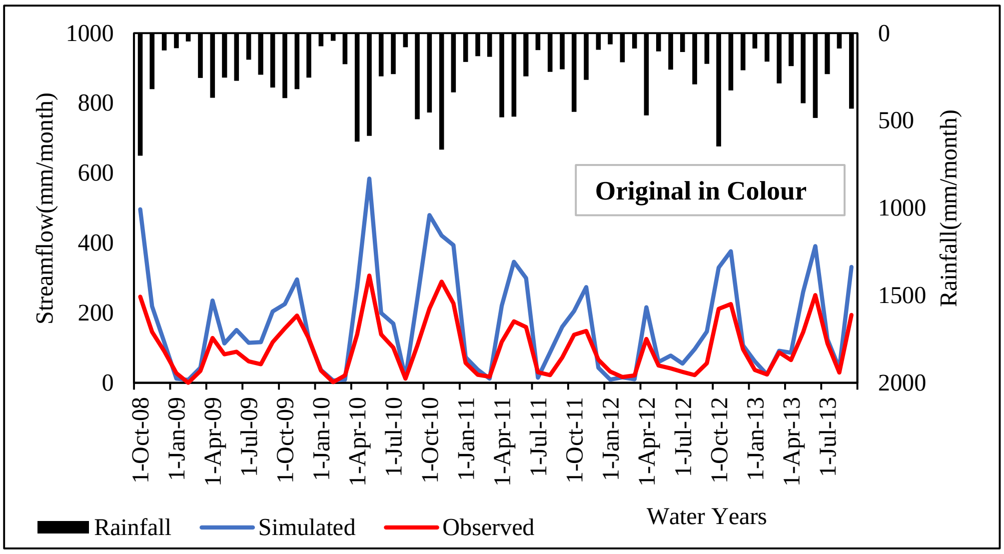


Figure 6-11:Monthly hydrograph in normal plot

Monthly observed and modelled streamflow from model is plotted in normal plot in the above Figure 6-7 for better comparison on a monthly scale.

6.3.2 Monthly Correlation of Observed and Calculated Streamflow

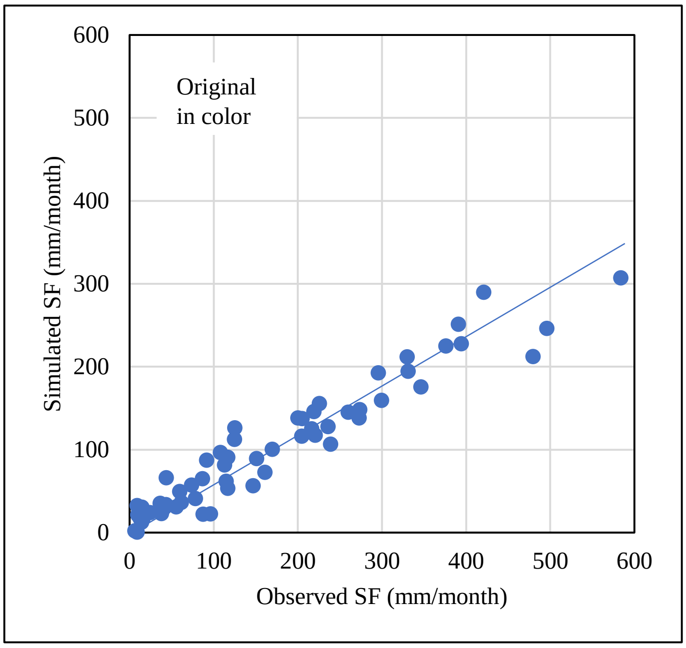


Figure 6-12:Monthly observed vs simulated streamflow

6.4 Model Verification

6.4.1 Statistical goodness of fit measures

The validation results of Dunamale model has shown in Table 6-13 by statistical measure of R^2. Calibrated parameters were set to unchanged option during validation process. During validation process R^2 error indicate lesser value than calibration in flow hydrograph matching. However, all three flows in the flow duration curve show good fitting with observed streamflow while indicating higher R^2 error near to best fit value.

Table 6-5:Comparison of model validation results

Gauging Station	Hydrograph Matching R^2	Annual Water Balance Error(mm)	FDC			
			Whole	High	Medium	Low
			R^2	R^2	R^2	R^2
Dunamale	0.58	718.19	0.58	0.32	0.41	0.20

6.4.2 Observed and simulated hydrograph comparison

The following Figure 5-14 and Figure 5-15 indicated that observed and simulated hydrographs at Dunamale in semi-log and normal scale. During validation period the simulated streamflow shows considerably good response to feed rainfall data. However, only 2015/16 water year on October to January months indicated drastically raise of simulated streamflow compared to observed streamflow. Although in duration (2015-October to 2016-January) the simulated and observed streamflow shows similar pattern. Therefore, human misreading of observed streamflow may be the reason for this abnormal situation.

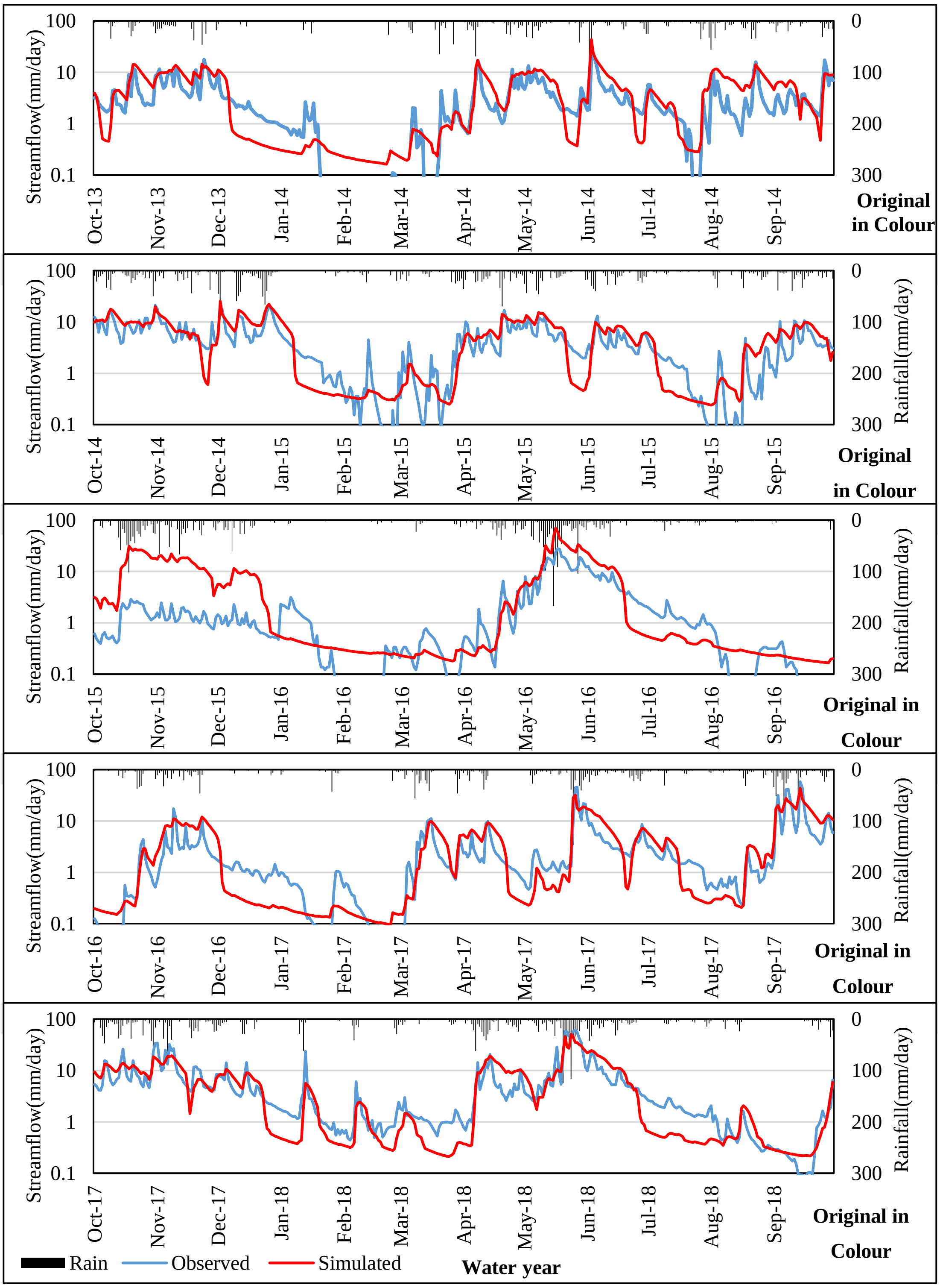


Figure 6-13:Simulated vs observed hydrograph (semi-log)

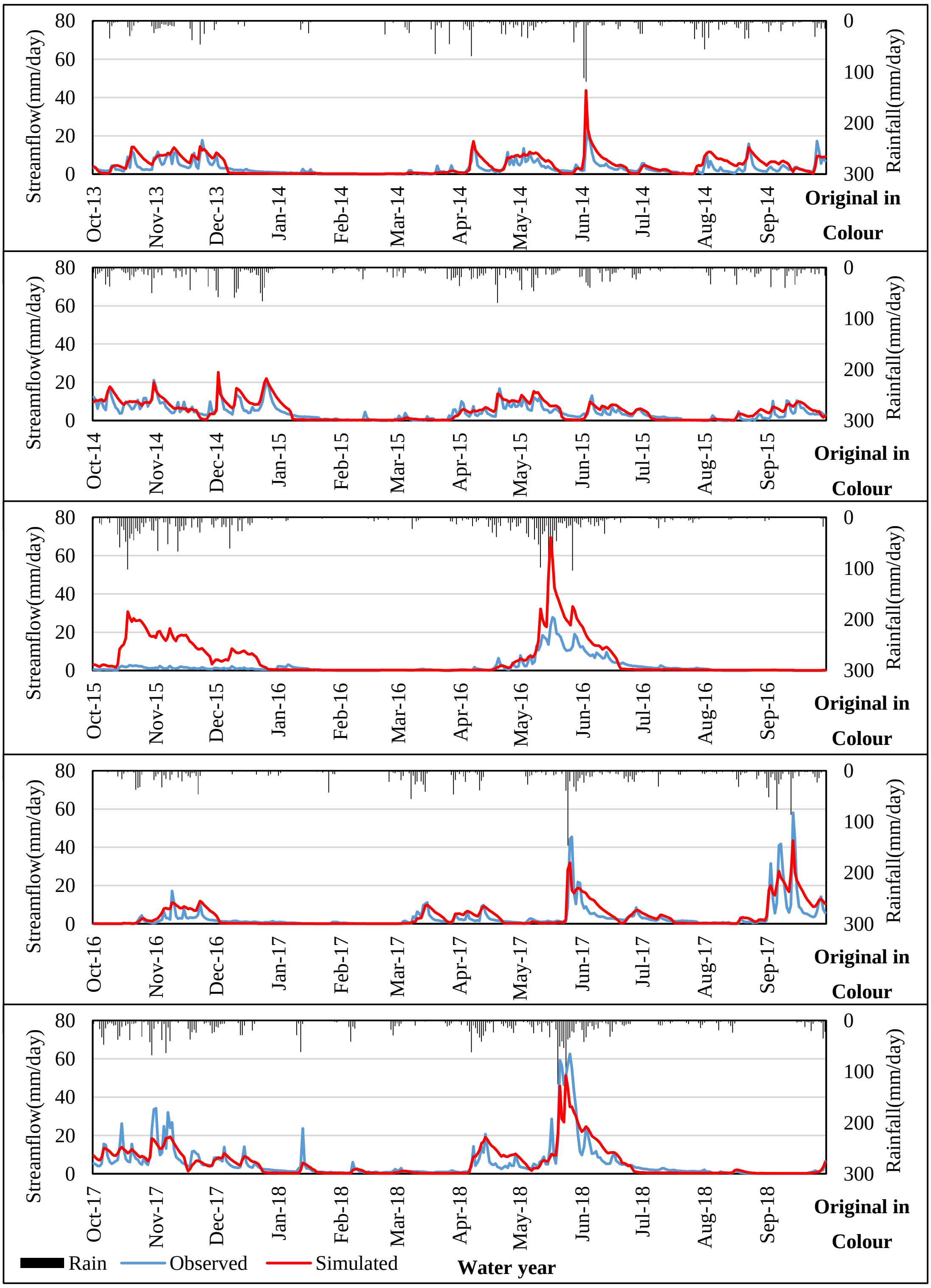


Figure 6-14:Simulated vs observed hydrograph (normal plot)

6.4.3 Flow Duration Curve Matching

Flow duration curves for Dunalame model were plotted in two ways as following Figure 6-16 and Figure 6-17.

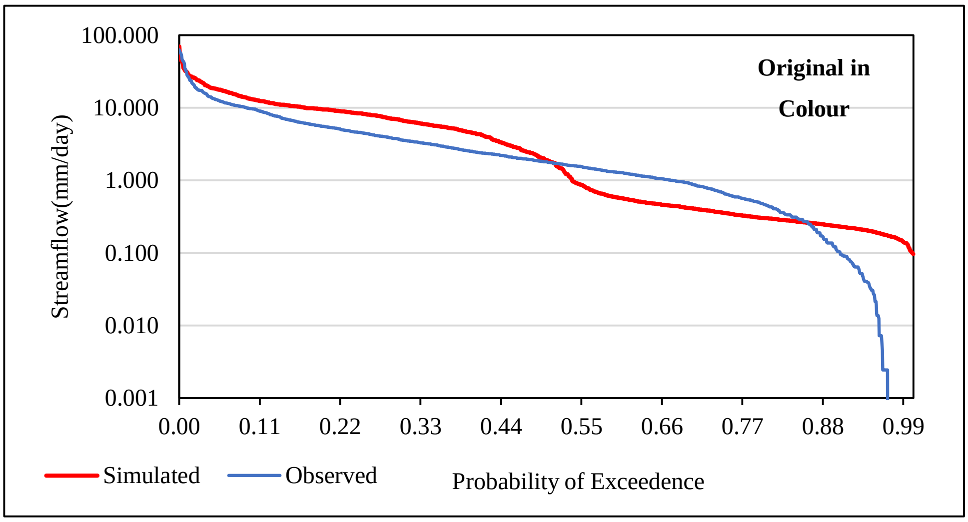


Figure 6-15:FDC at Dunamale (both sorted

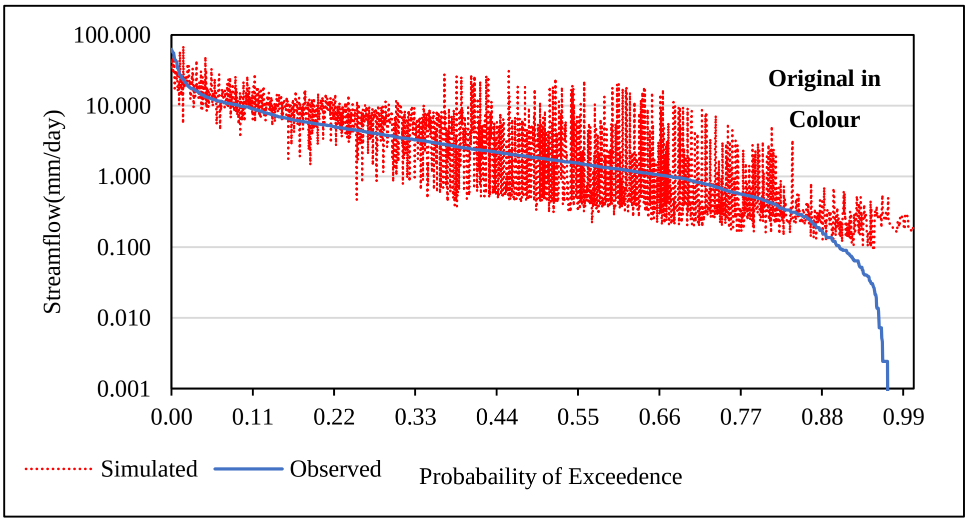


Figure 6-16:FDC at Dunamale (sorted only observed streamflow)

6.4.4 Annual Water Balance Error

Annual water balance error for Dunamale catchment is plotted in bar chart as follows in Figure 6-18. According to the values Dunamale model shows 45% of annual water balance error during validation period. With compared to calibration period annual water balance is not showing high variation.

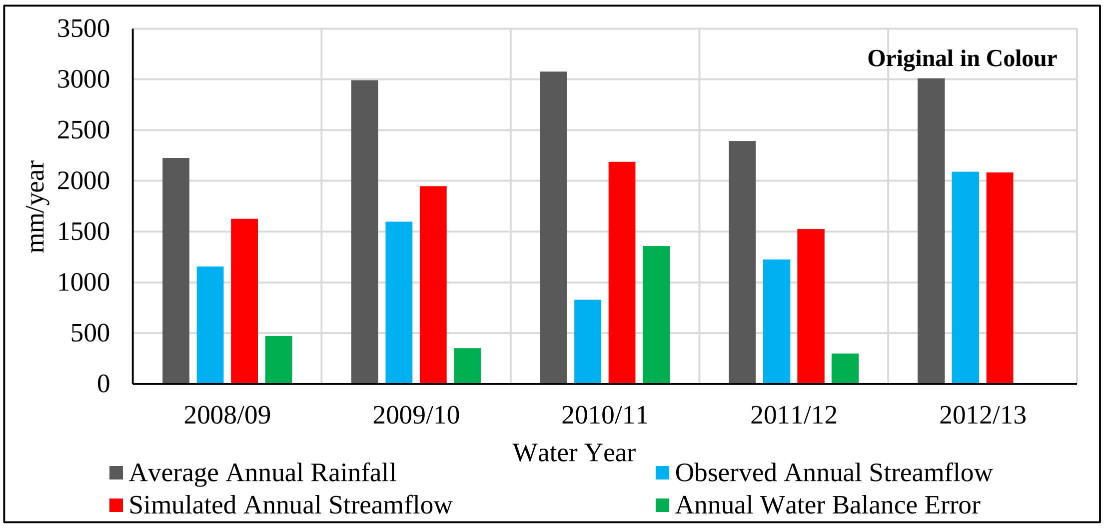


Figure 6-17:Annual water balance error at dunamale

6.5 Monthly Comparison

6.5.1 Monthly observed and calculated hydrograph

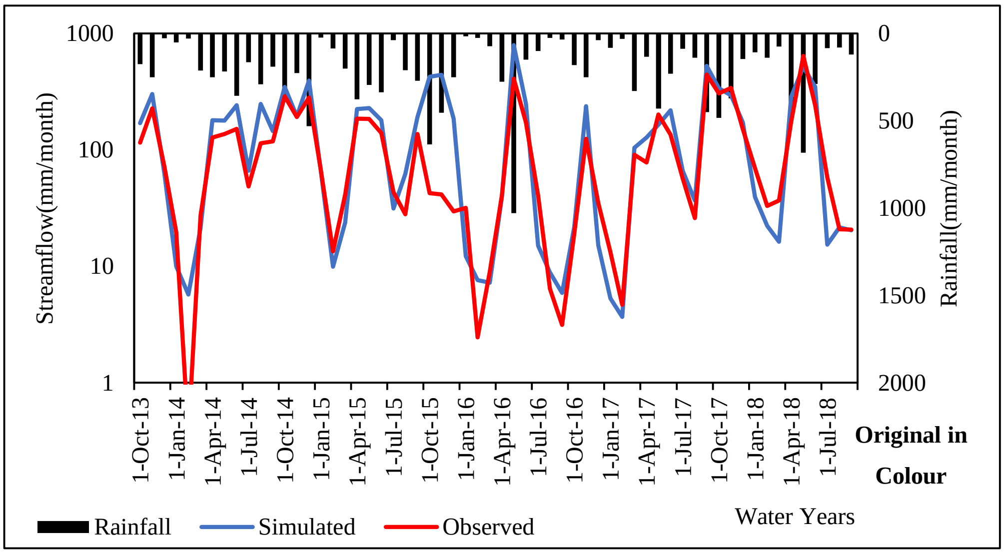


Figure 6-18:Monthly hydrograph in semi-log plot

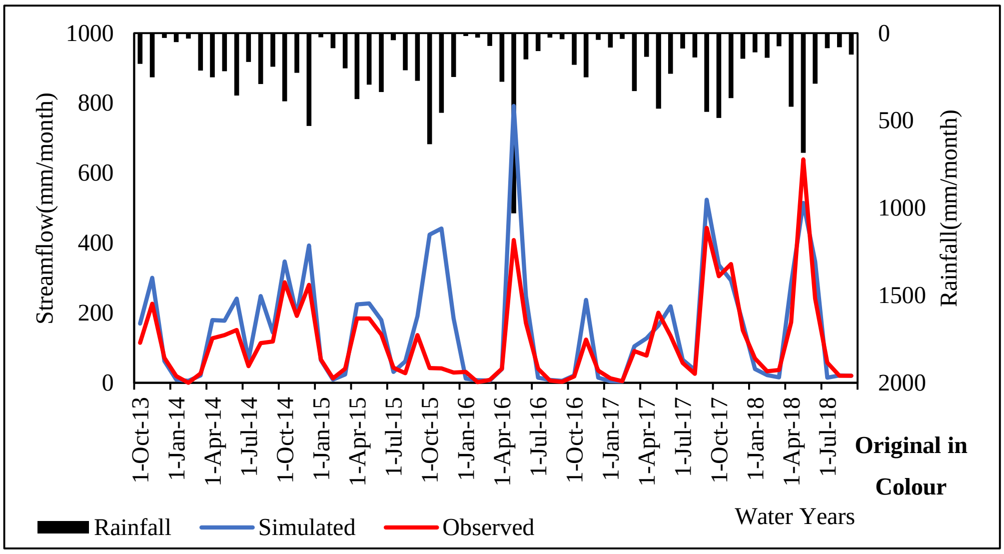


Figure 6-19:Monthly hydrograph in normal plot

6.5.2 Monthly Correlation of Observed and Calculated Streamflow

Figure 6-20 represented monthly observed streamflow vs simulated streamflow during validation process. With compared to calibration period, here simulated streamflow is correlated better with observed streamflow.

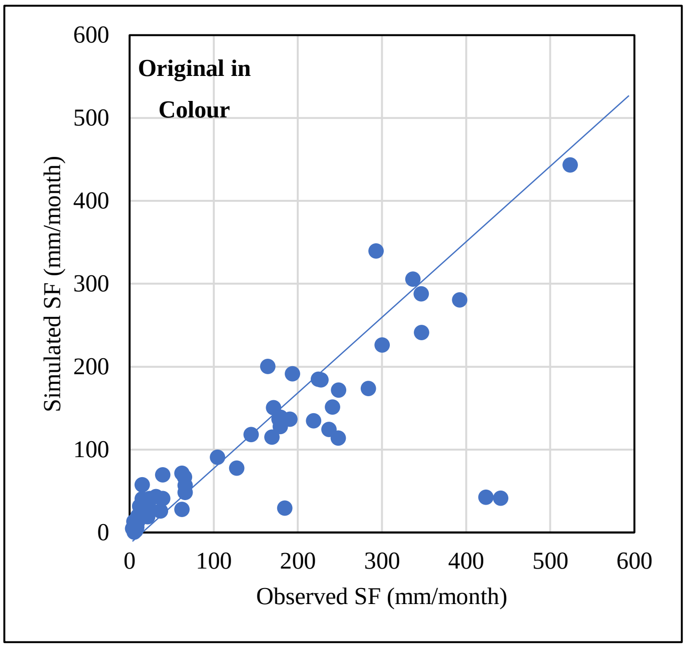


Figure 6-20:Monthly observed vs simulated streamflow

7 DISCUSSION

7.1 SWAT Model application in water resource management

SWAT model was selected as the process based distributed model to estimate streamflow for sustainable water resource management after shortlisting and evaluating as mentioned in Section 2.5, 2.6, 2.7 and 2.8. SWAT model is developed, calibrated and validated. SWAT model has more parameters when compared to other models which results in model complexities and is not easy to apply. On contrary SWAT model gives result in a detailed manner with its basic unit as HRU and SWAT model can be used to manage water resources as the results indicate better matching for intermediate flows which is necessary when managing water resources.

7.2 Watershed Demarcation

30 m DEM was used for watershed delineation. Seven sub watersheds are formed along with streamline after watershed delineation by ArcSWAT along with the monitoring points and outlet at the Dunamale station as shown in Figure 6-1. The watershed area and shape were found to be same when compared to other studies carried out on same basin. Landuse map of Sri Lanka was reclassified assuming the best possible match of SWAT landuse code as shown in table.

Slope was classified assuming two slope classes as shown in Figure 6-4. Thus, landuse is reclassified into 10 groups, soil into 7 types and slope into two classes. After overlaying the soil, landuse and slope and assuming threshold of landuse and slope as 20% and soil as 10%, a total of 40 HRUs were demarcated in the basin. The basin outlet is situated in the sixth sub-basin and the flow from the sixth sub basin is considered as the modeled streamflow as flows from other sub basins accumulates and contribute to the sixth sub basin.

7.3 Model Component Selection

Section 2.11.4 on model component tells SWAT model has major components as surface runoff, infiltration, potential evapotranspiration, lateral flow and channel flood routing. For each model component there are options or methods to be selected in the model by the user. The methods which require minimum data is selected for each model component.

For potential evapotranspiration three methods are available in the SWAT model component and Hargreaves method is selected as it needs minimum data being temperature to calculate potential evapotranspiration. The SCS CN method was chosen to estimate surface runoff and infiltration given its simplicity with only few variables. Kinematic storage model to simulate lateral flow. The selection of the method for each model component was based on minimum data requirement.

7.4 Objective Function Selection

From the Section 2.10.1 most widely used objective function in SWAT model based on literature review is R^2 and NSE for water resource management but NSE is biased to high flows which is good for flood management. Although MRAE is found to be perfectly matching for intermediate flows as mentioned in the Section 2.10.1 which is good for water resource management. However, MRAE is not present among the eleven objective function listed in SWAT-CUP user manual.

Multi objective function mostly used in the literature further complicates the model calibration and validation hence only one objective function is used. Objective function R^2 gives better matching of the pattern. R^2 is used as the objective function for the study in Attanagalu Oya watershed.

7.5 Model Warm up Period

The warm up period is a time frame where the model is run for a duration specified by the user to simulate results to the closest observed outcomes. During the warm up period, model doesn't collect or simulate any results. Model warm up is necessary to minimize errors as soil moisture is stabilized after a model is warmed up as shown in the Figure 5-3. The model warm up period was taken as three cycles with each cycle consisting of five years. The calibration period was for five years and hence a model warm up period of fifteen years was taken and as shown in Figure 5-3, the soil moisture was found to be stabilized after warming up for three cycles.

7.6 Data and Data Period

7.6.1 Selection of data period

The study data period was selected as 10 water years from October 2008 to September 2018 selecting a daily time frame. To update the latest data values with more accuracy the water year 2018 data was chosen. The data period was divided into calibration data period for 5 years from October 2008 to September 2013 and similarly validation period for another 5 years from October 2013 to September 2018.

From Table 4-7, it is clearly seen that water year 2010/2011 and 2017/2018 have the wettest period and water year 2011/2012 and 2016/2017 have the driest period. Thus, both the datasets consist of dry and wet extreme events and the model is assumed to be excited and independent of the data period when developing the model.

7.6.2 Error in dataset

From Table 4-7 it can be noted that the water year 2015/2016, streamflow has decreased drastically when compared to a small increase in thiessen rainfall leading to low runoff coefficient. Overall thiessen rainfall in Attanagalu Oya shows comparatively high rainfall and low values of streamflow. The raw data of streamflow for some cases were very low which can be due to data error. Also, in the water year 2017/2018, there was an increase in both rainfall and streamflow but the increase in streamflow data is considerably high when compared to other years.

It is clear that out of five rainfall stations, Vincit and Pasyala stations are showing inconsistency from the double mass curve figures in Appendix B. Discrepancy in data has been shown in the appendix with red circles in all the five rainfall stations, mainly due to missing of rainfall data when there was a value of streamflow for that particular day. However, missing rainfall data were filled using thiessen average owing to its simplicity and spatial area coverage.

7.7 Selection of Initial Model Parameters

The initial model parameter selection was based from the Section 2.11.1 where nine parameters were selected from the major twenty five parameters. The nine parameters; (1) SCS runoff curve number (2) Groundwater baseflow alpha factor (3) Groundwater delay (4) Threshold depth of water in shallow aquifer required for return flow to occur (5) Soil Evaporation Compensation factor (6) Plant uptake compensation factor (7) Groundwater “revap” coefficient (8) Available water capacity of the soil layer (9) Threshold depth of water in shallow aquifer for “revap”. Parameter (2), (3), (4), (7) and (9) belong to groundwater, (5) and (6) for evapotranspiration, (8) for soil and (1) for surface runoff. The parameters were set to their range and then calibrated.

7.8 Model Performance

7.8.1 Calibration and validation results

In calibration the R^2 value is 0.77 and in validation R^2 value as 0.58 which indicates a good result. Moreover the objective function R^2 is purely driven by the pattern and not the values and thus, the error related to R^2 is the flow volume. Therefore, the results have not focused on values rather the pattern. However, the overall R^2 value is acceptable for both the calibration and validation of the model.

7.8.2 Hydrograph matching

The hydrograph matching is plotted in the Figure 6-5 as semi-log pot and Figure 6-6 as normal plot for calibration results and Figure 6-14 as semi-log plot and Figure 6-15 as normal plot for validation results. From the figures mentioned above it was shown that the overall hydrograph is matching with the pattern when simulated and observed streamflow is compared.

7.8.3 Matching of Flow Duration Curve

The matching of flow duration curve taking into consideration low, medium and high flows is depicted in Figure 6-7 and Figure 6-16 with calibrated and validated simulation results. It is noted from the figures mentioned above that the medium flow shows best matching when compared with high flow and low flow. The high flow has better matching when compared to low flow. The low flows are found to be least in matching as the observed streamflow is having very low values due to error in dataset as mentioned in Section 7.5.2.

7.8.4 Annual water balance error

From the Table 6-3 and Table 6-5 it can be observed that the annual water balance error value is 845mm during calibration and 718 during validation. The annual water balance for both the period is found to be high as a result in the least matching of low flows. The observed streamflow is noted to have very low values resulting in high differences between the observed and simulated low flows owing to the error in dataset as mentioned in Section 7.5.2.

7.8.5 Monthly Performance

The daily model results when accumulated into monthly results as illustrated with the Figure 6-10 and Figure 6-19 can be noted that the hydrograph behavior is matching with higher accuracy and can be used in making better decisions for water resource planning and management.

7.9 Reliability of Results

7.9.1 Uncertainty in meteorological data

Often the reliability of the results is associated with uncertainty with the data. As data errors could result in change of the output values. The data mainly referring to input data such as precipitation and temperature. In a model the uncertainty related to the precipitation data mainly occurs due to the space related and time scale variation of precipitation value within the same catchment area. In Dunamale watershed data from five rainfall stations were collected. Further there could be data error related to collection and reading as human error since some of the rainfall data were missing which had streamflow data at the same day as discussed in the Section 4.2. All these could result in variations of the results simulated by the model in the study.

7.9.2 Uncertainty in parameters

While simulating results in a model there is uncertainty with parameters as well. In SWAT there are about 25 major parameters, and 9 parameters were assumed to be fit and selected for the study from the Section 7.5. Calibrating the model on a daily scale with 9 parameters with semi automation is complex when trying to best fit results with the hydrographs matching.

8 CONCLUSIONS AND RECOMMENDATIONS

8.1 CONCLUSIONS

1. The process based distributed SWAT model can be developed for Attanagalu Oya Basin in Dunamale watershed to estimate streamflow with R^2 value of 0.77 during calibration and 0.58 during validation with hydrograph matching pattern to manage water resource efficiently.
2. The model gives a better matching for medium flow when compared to high flow and low flow and hence it can be used for sustainable water resource management.
3. Daily model results when accumulated into monthly time frame has higher accuracy in the outcome when compared to daily and can be used for irrigation and water reservoir resulting in better decision for water planning and management.
4. SWAT model has more parameters and is complex when applied but the results are generated in a detailed manner and can be used for a better understanding of the watershed.

8.2 RECOMMENDATION

Further need to analyze the impacts of individual and combined climate and landuse change impact on the water resources with increasing population and modernization across the globe.

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APPENDIX A: STREAMFLOW RESPONSE WITH RAINFALL

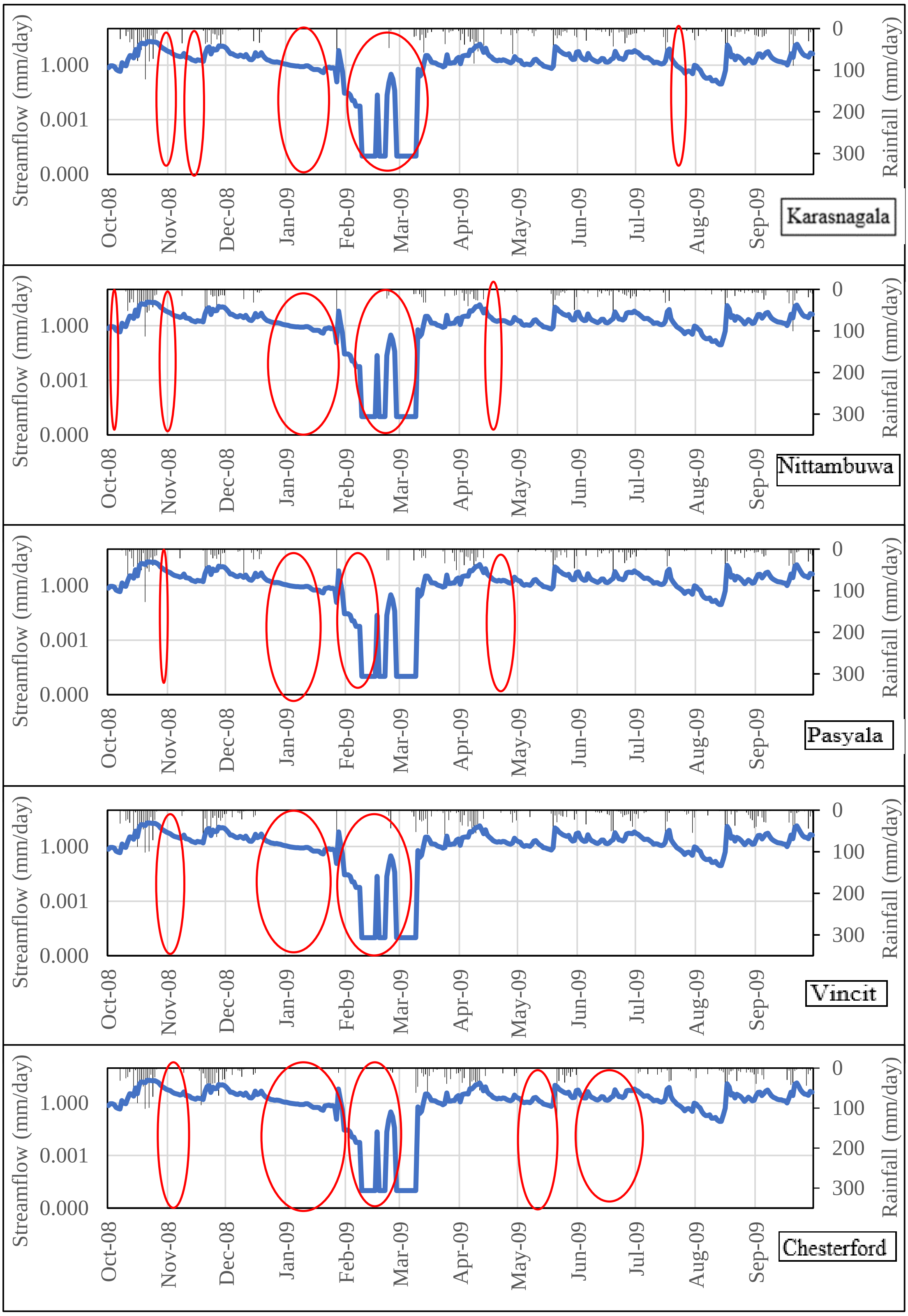


Figure A 1:Dunamale daily streamflow response with each rainfall station data for water year 2008/2009 log graph

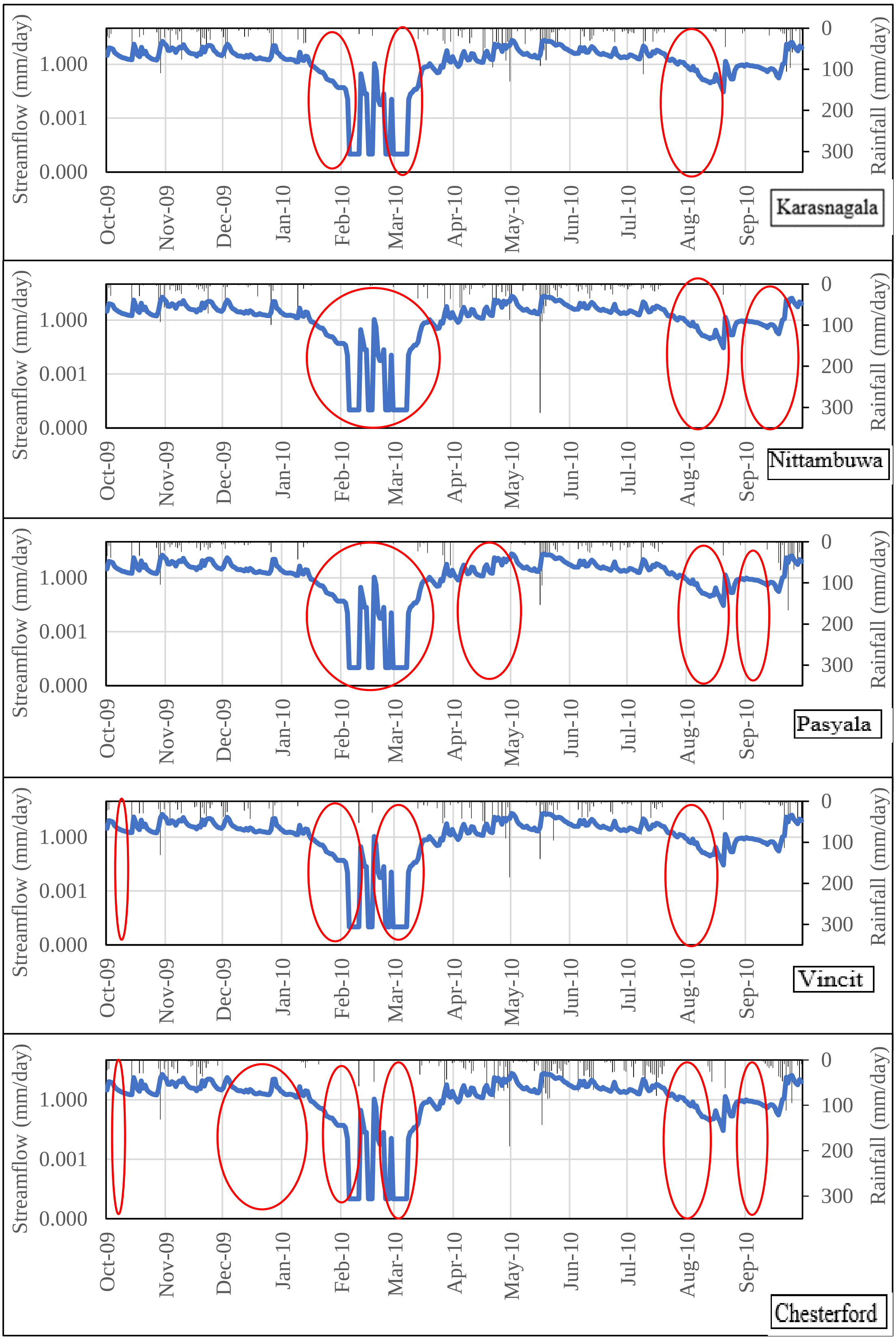


Figure A 2:Dunamale daily stream flow response with each rainfall station data for water year 2009/2010 log graph

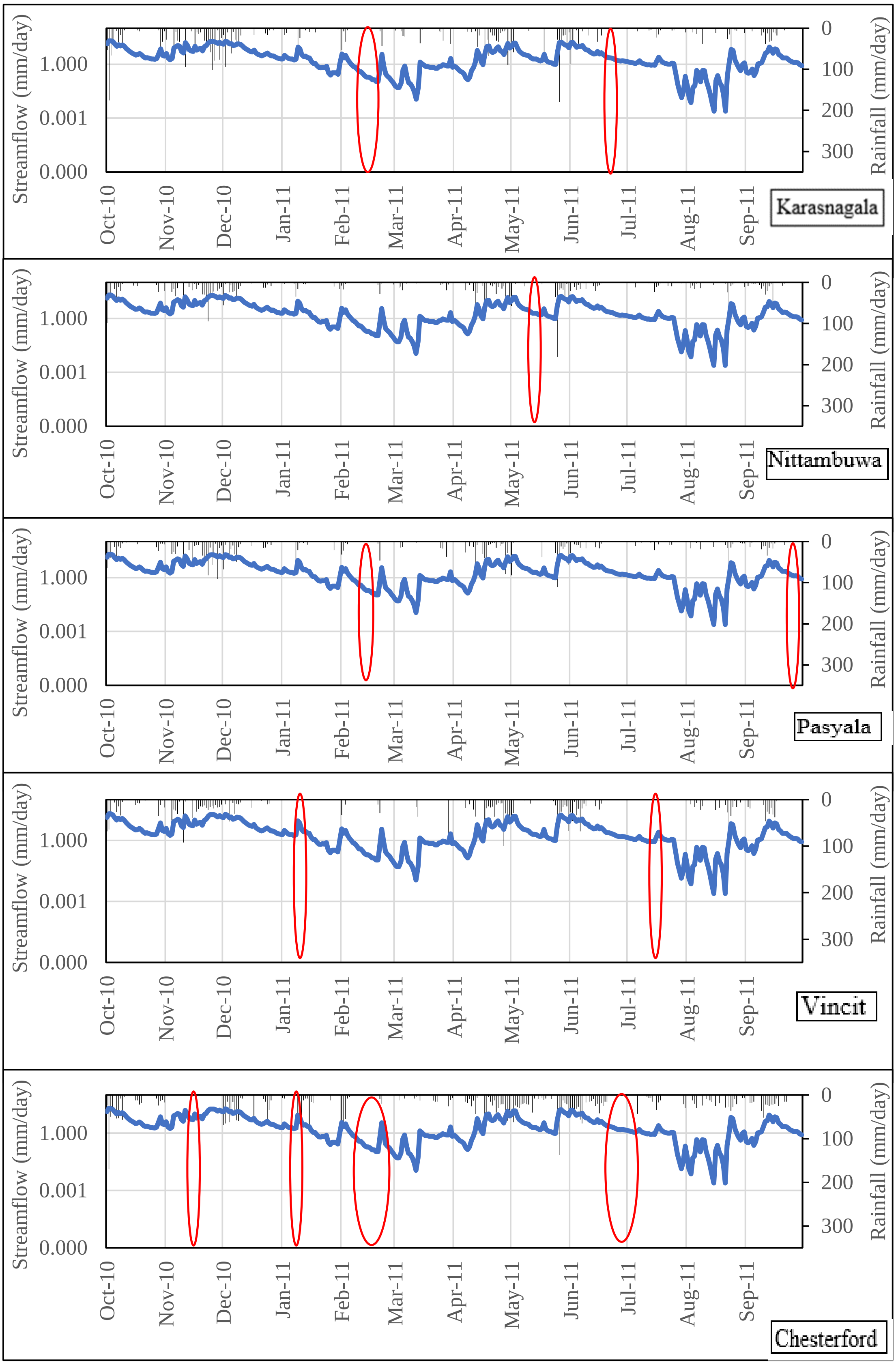


Figure A 3:Dunamale daily streamflow response with each rainfall station data for water year 2010/2011 log graph

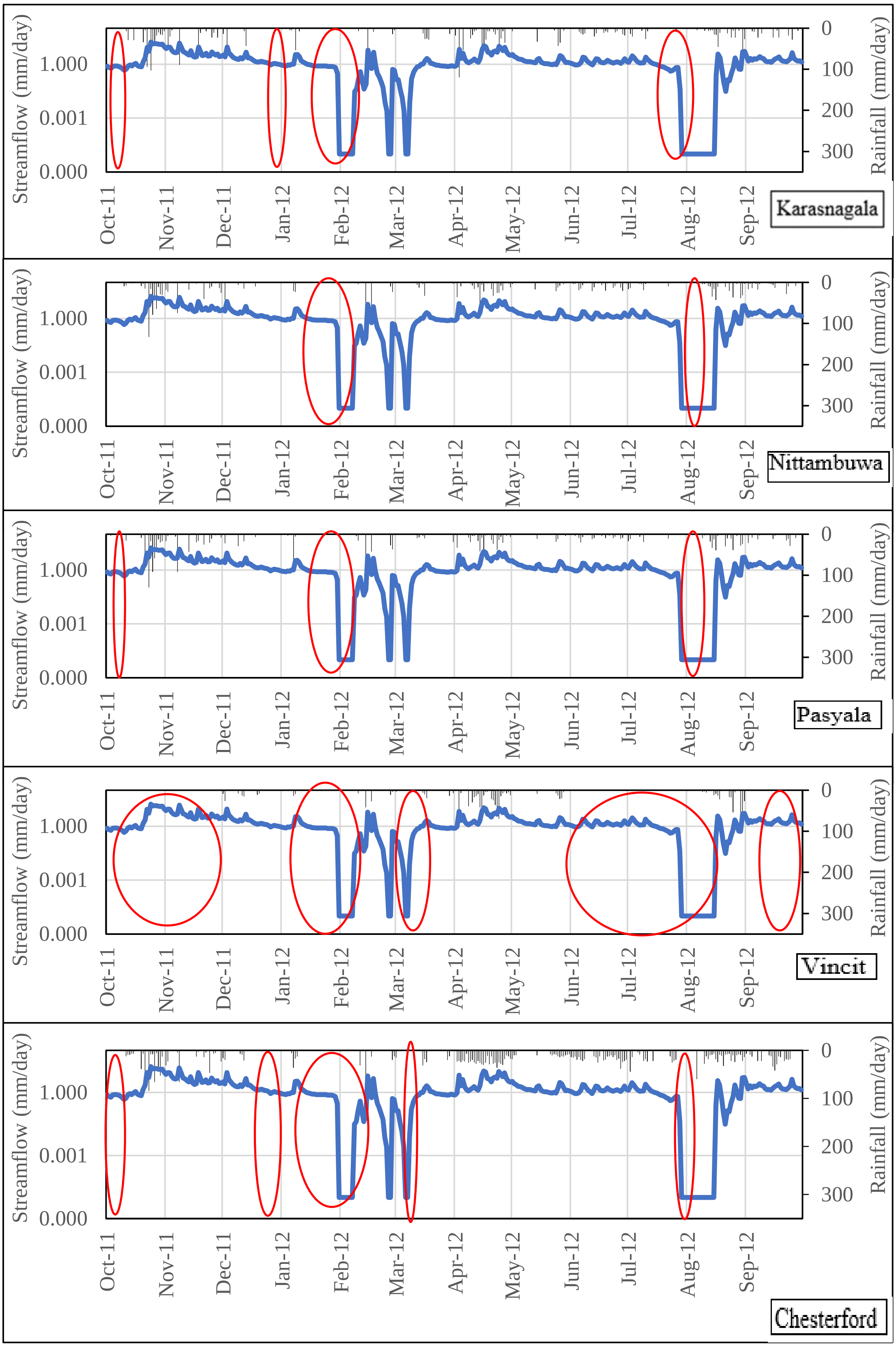


Figure A 4:Dunamale daily streamflow response with each rainfall station data for water year 2011/2012 log graph

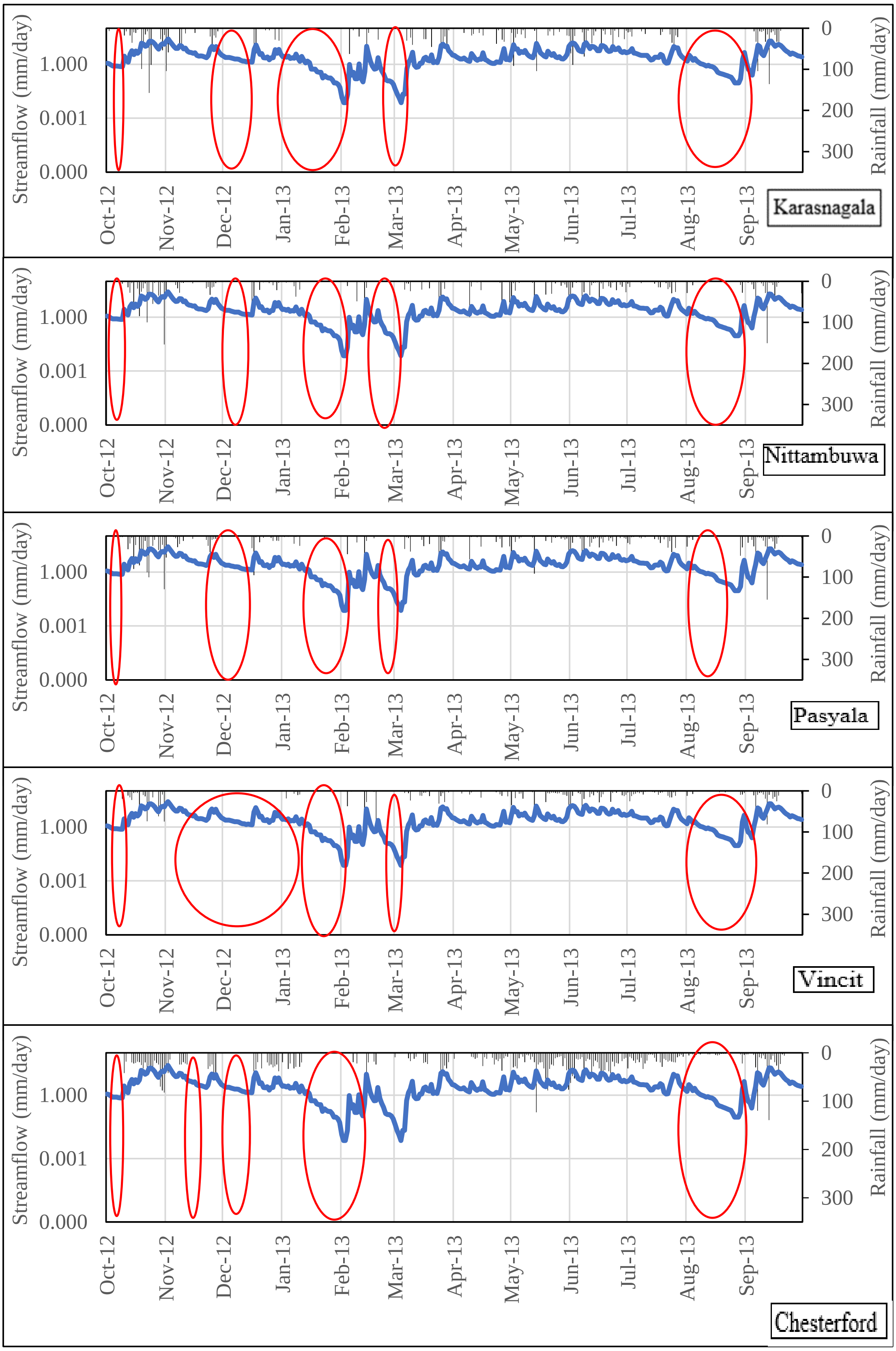


Figure A 5:Dunamale daily streamflow response with each rainfall station data for water year 2012/2013 log graph

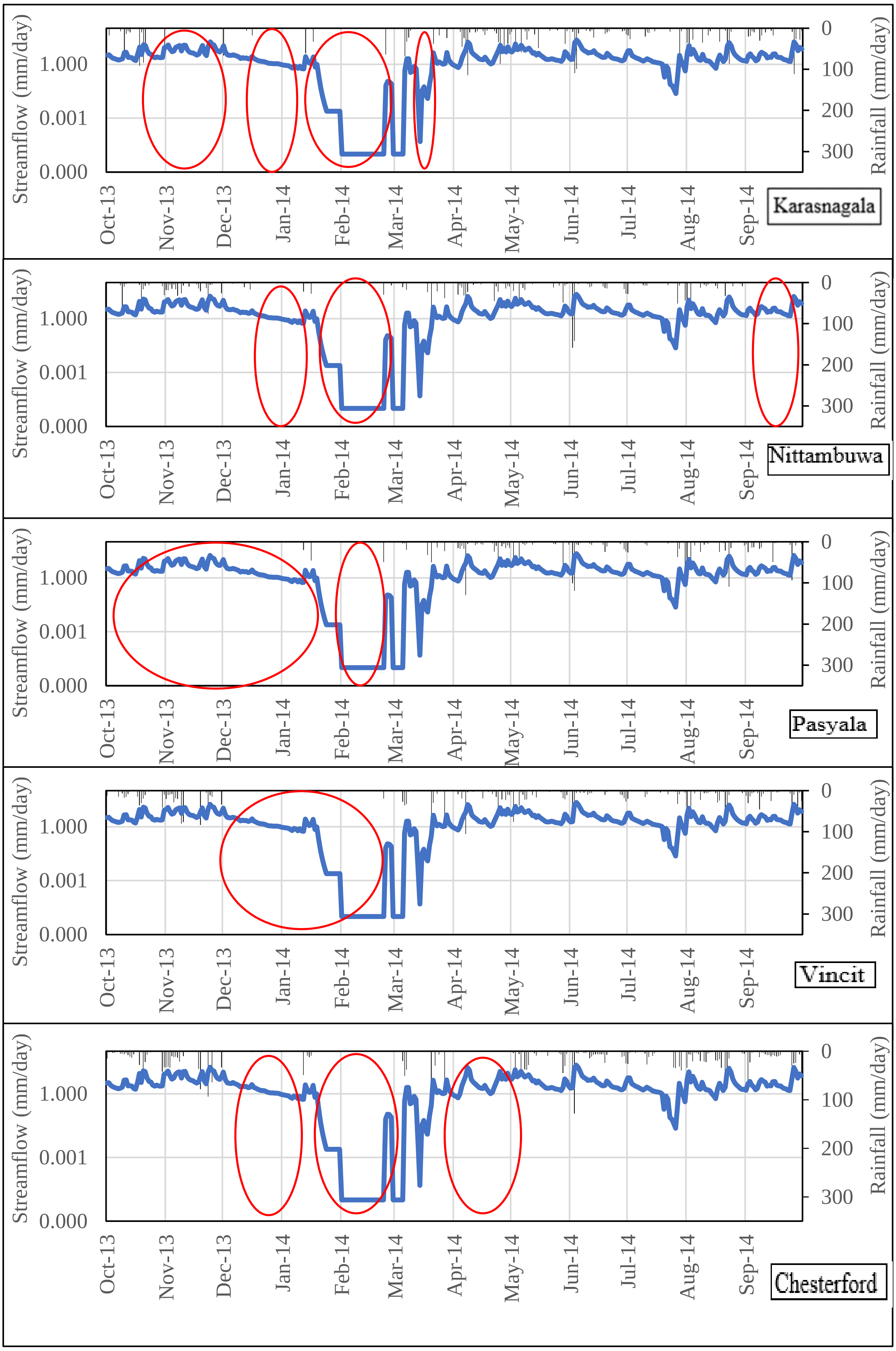


Figure A 6:Dunamale daily streamflow response with each rainfall station data for water year 2013/2014 log graph

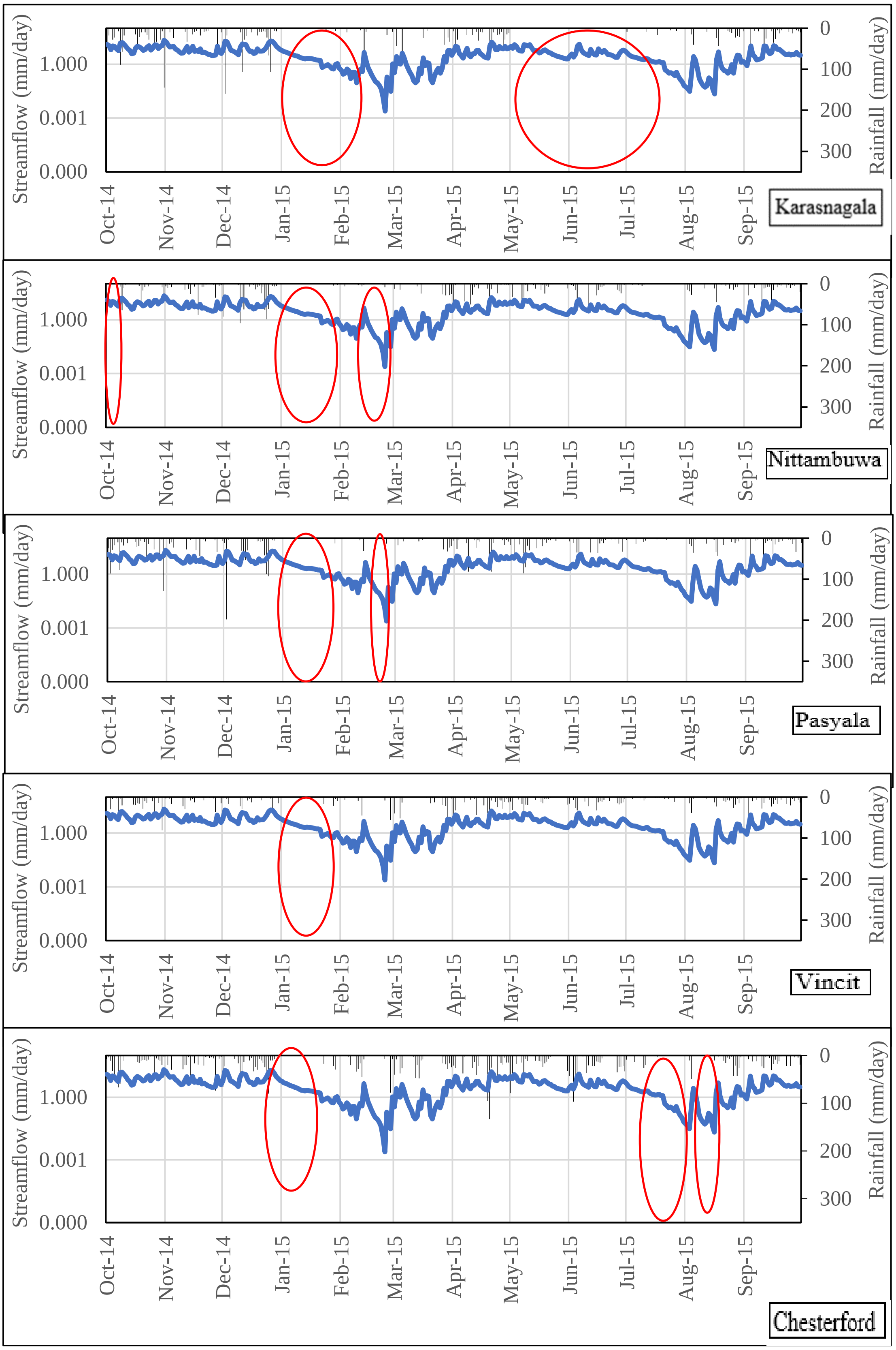


Figure A 7:Dunamale daily streamflow response with each rainfall station data for water year 2014/2015 log graph

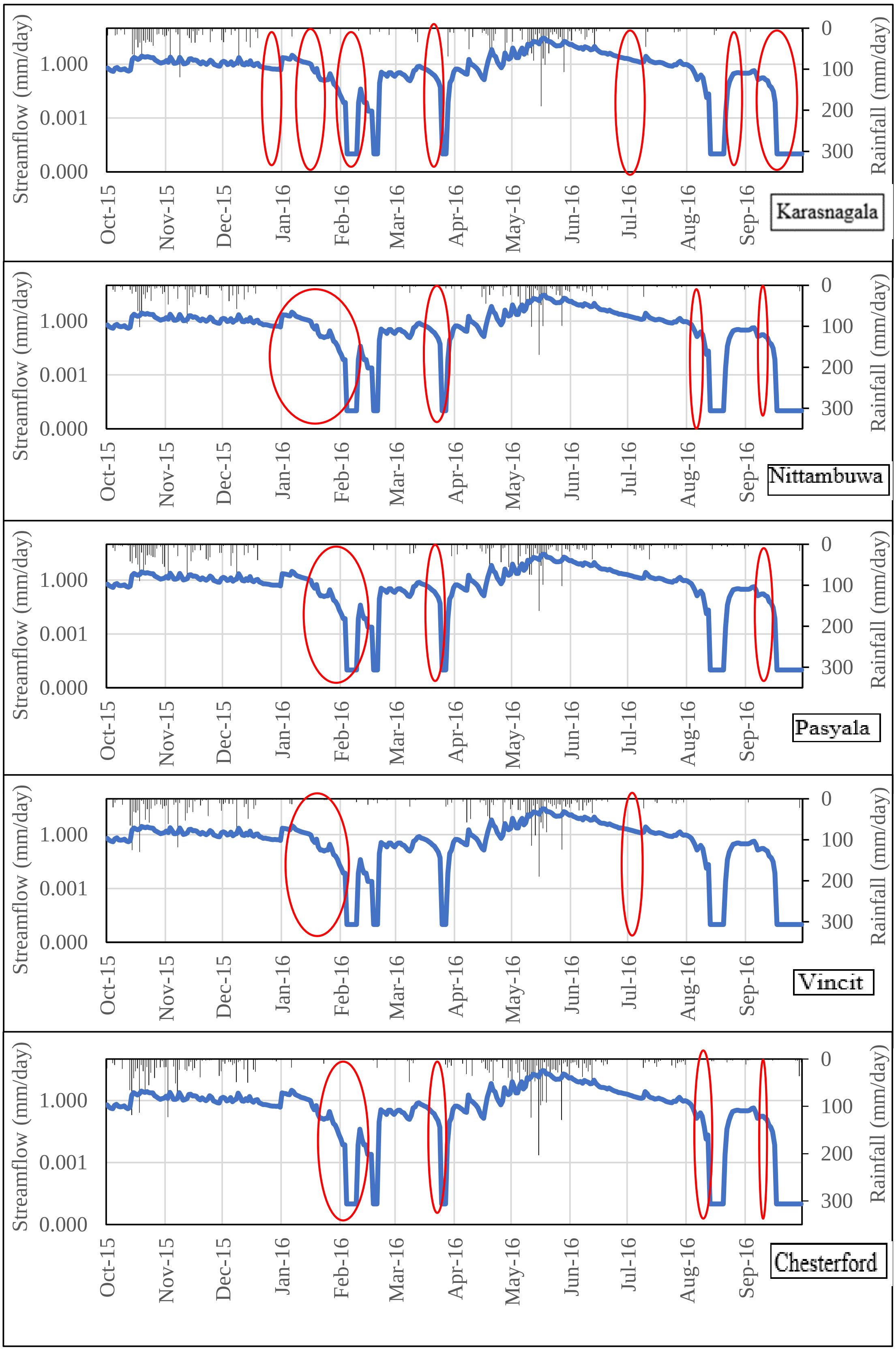


Figure A 8:Dunamale daily streamflow response with each rainfall station data for water year 2015/2016 lo graph

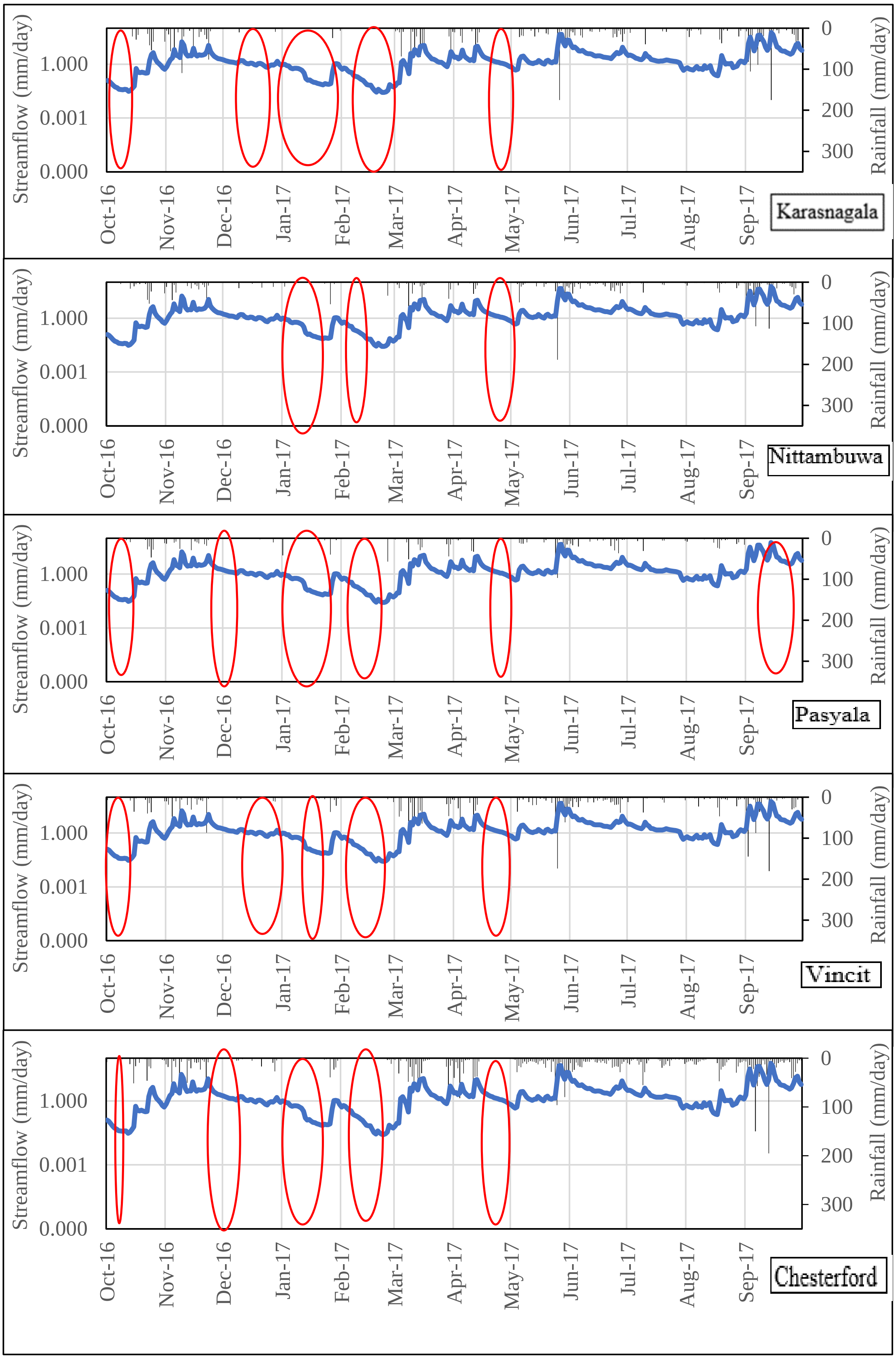


Figure A 9:Dunamale daily streamflow response with each rainfall station data for water year 2016/2017 log graph

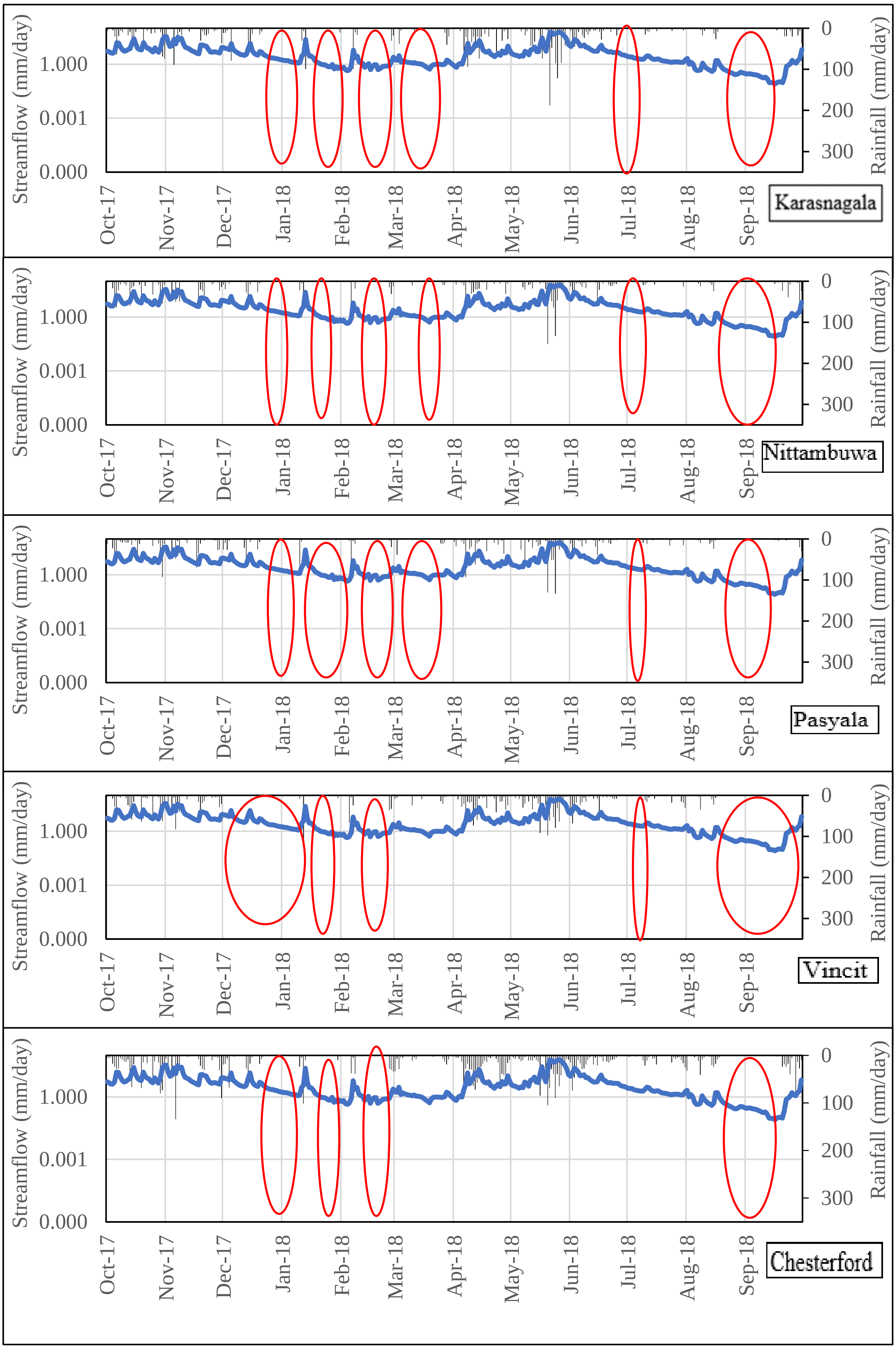


Figure A 10:Dunamale daily streamflow response with each rainfall station data for water year 2017/2018 log graph

APPENDIX B: THIESSEN WEIGHTAGES TO FILL MISSING DATA

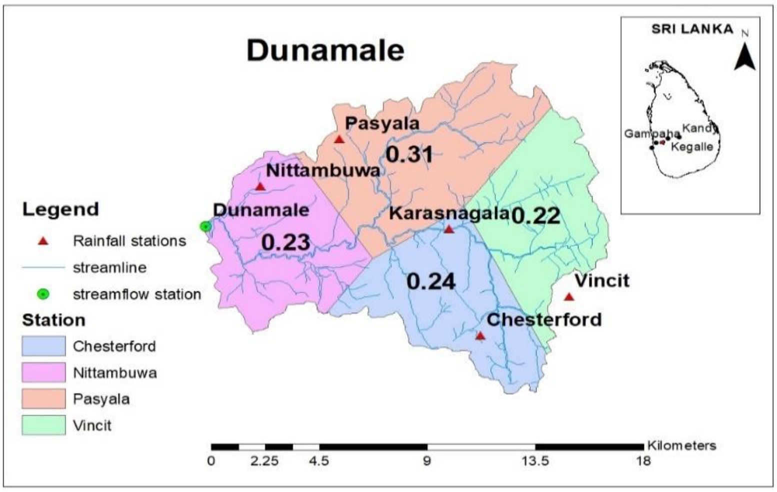


Figure B 1:Thiessen weight of Dunamale except Karasnagala station

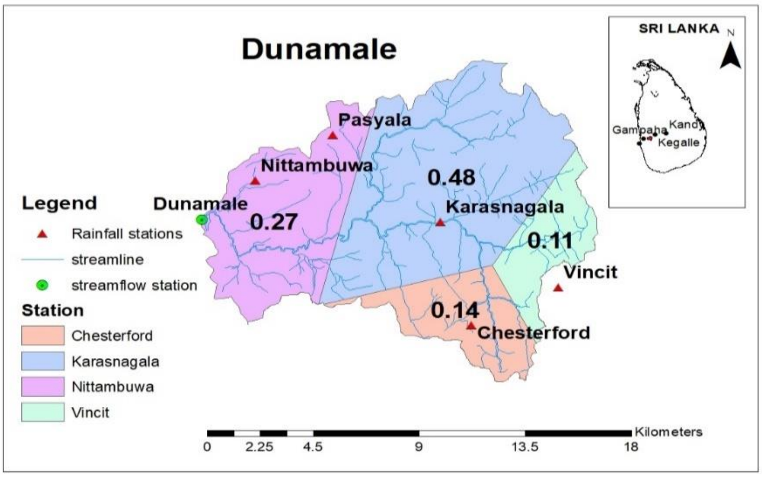


Figure B 2:Thiessen weight of Dunamale except for Pasyala station

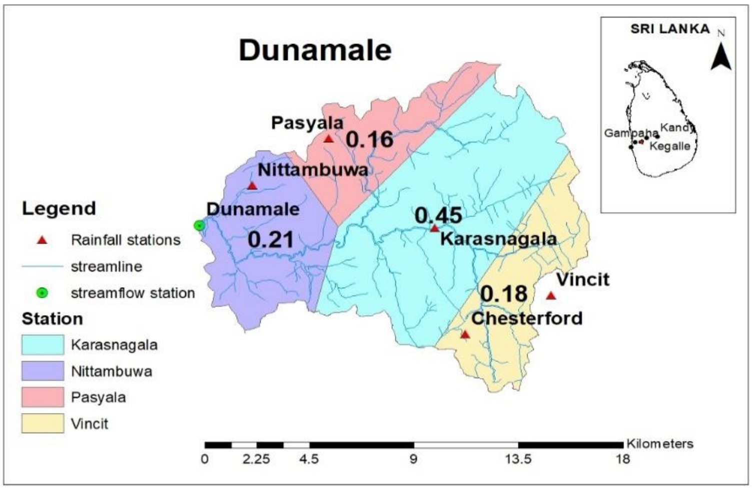


Figure B 3:Thiessen weight of Dunamale except for Vincit station

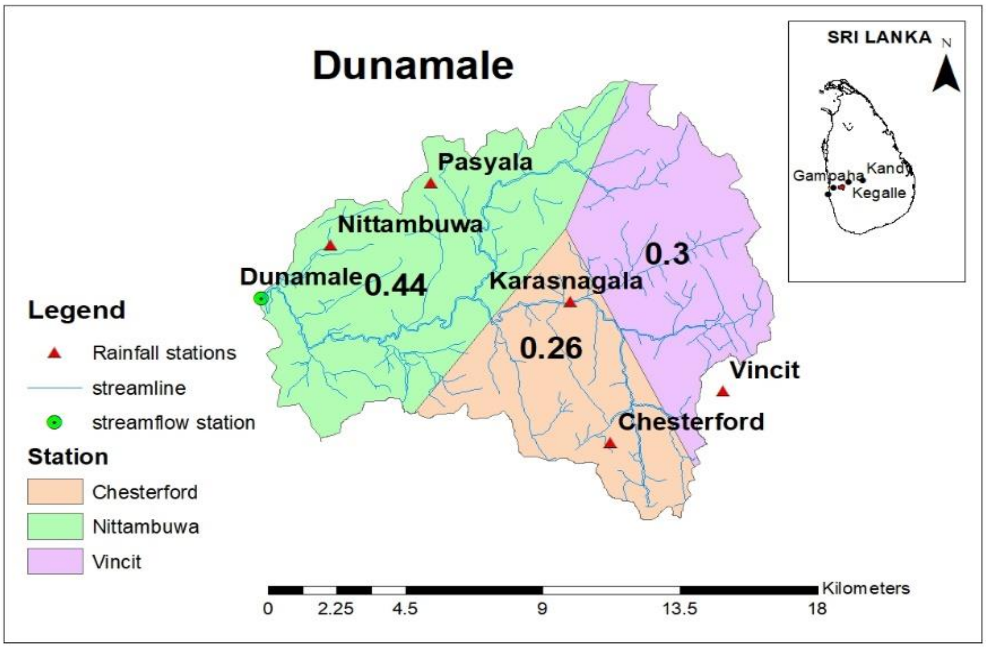


Figure B 4:Thiessen weight of Dunamale except for Chesterford station

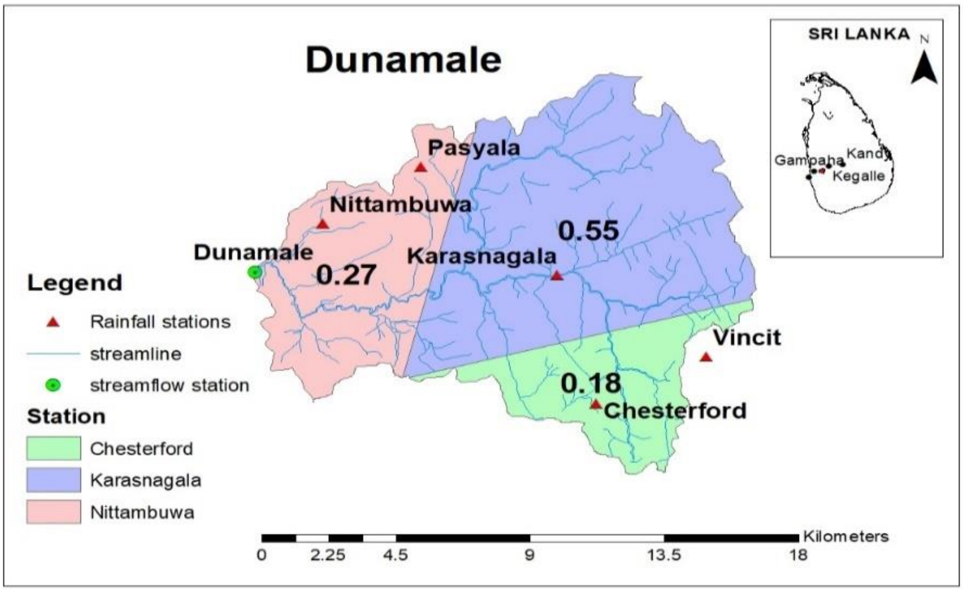


Figure B 5:Thiessen weight of Dunamale except for Nittambuwa and Pasyala station

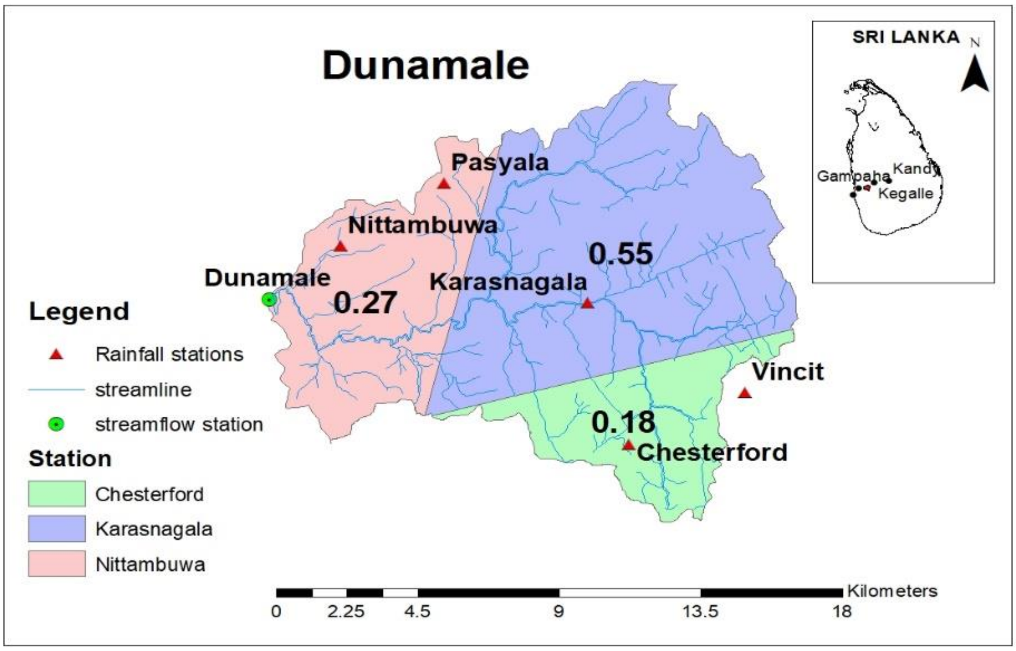


Figure B 6:Thiessen weight of Dunamale except for Vincit and Pasyala station

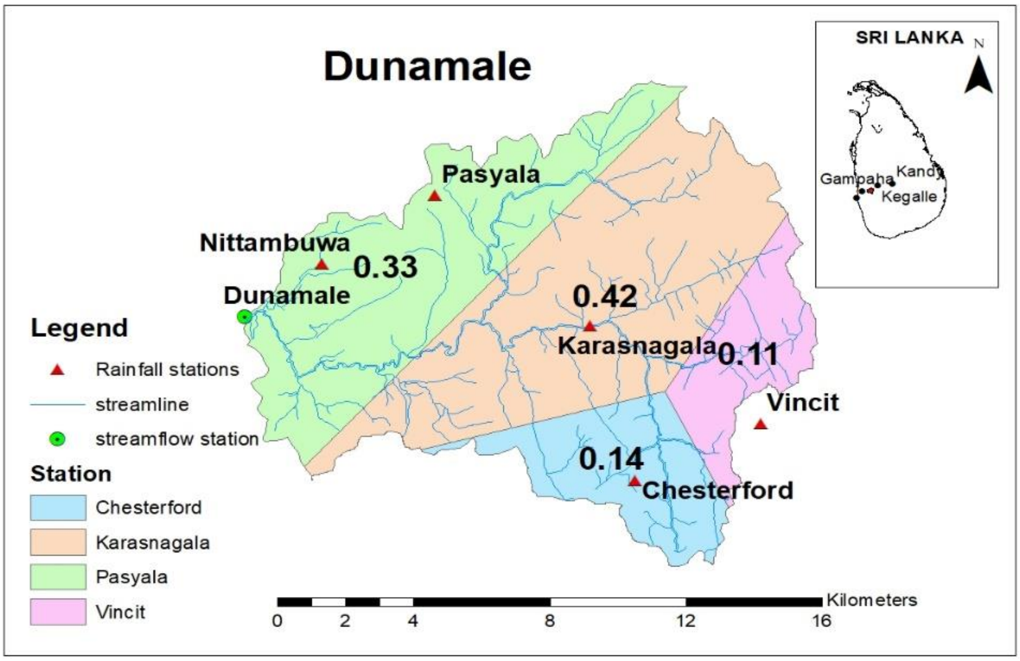


Figure B 7:Thiessen weight of Dunamale except for Nittambuwa station

APPENDIX C: DOUBLE MASS CURVE AFTER FILLING MISSING DATA

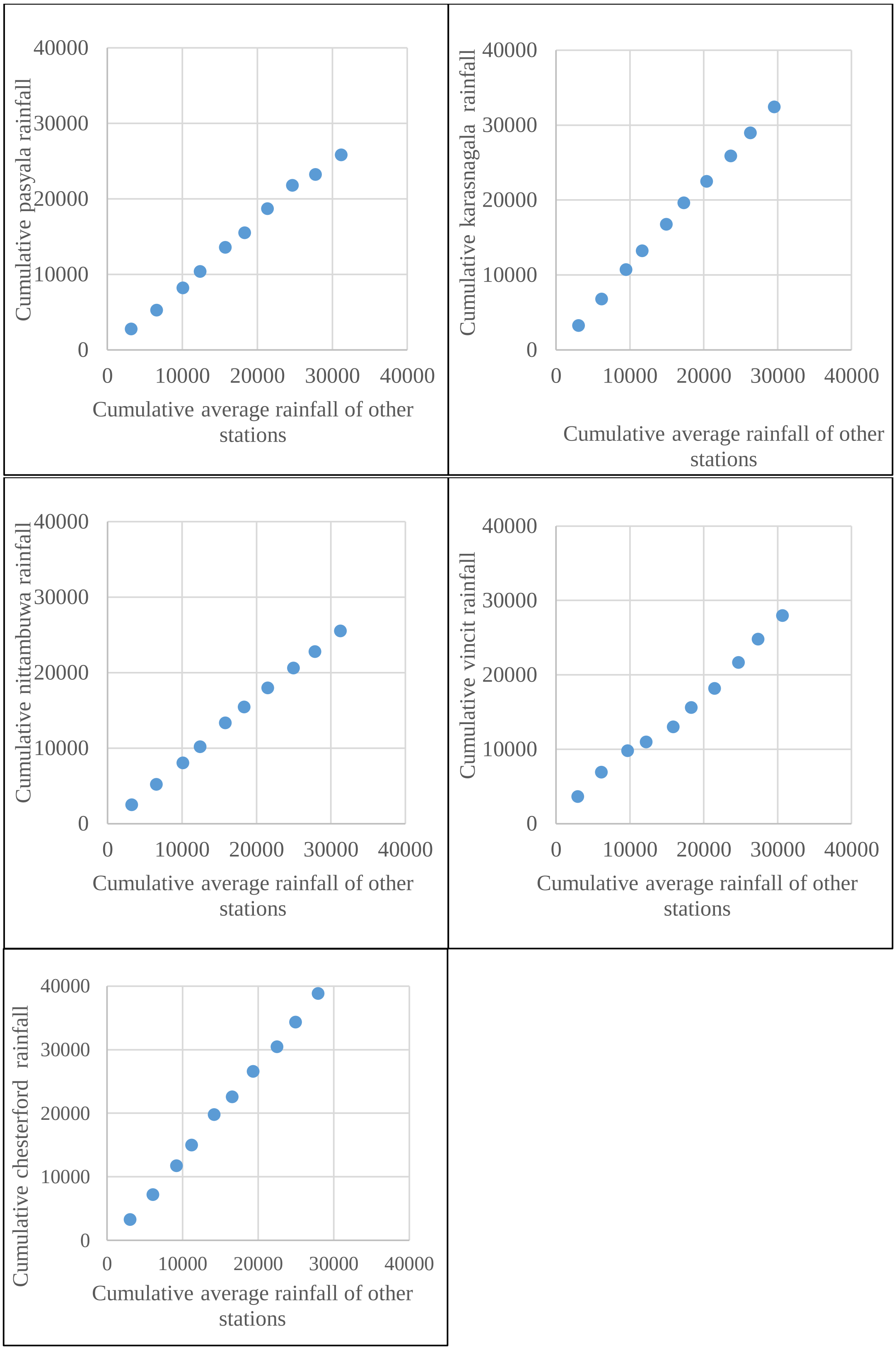


Figure C 1:Double mass curve

APPENDIX D: FLOW COMPONENT FOR EACH WATER YEAR

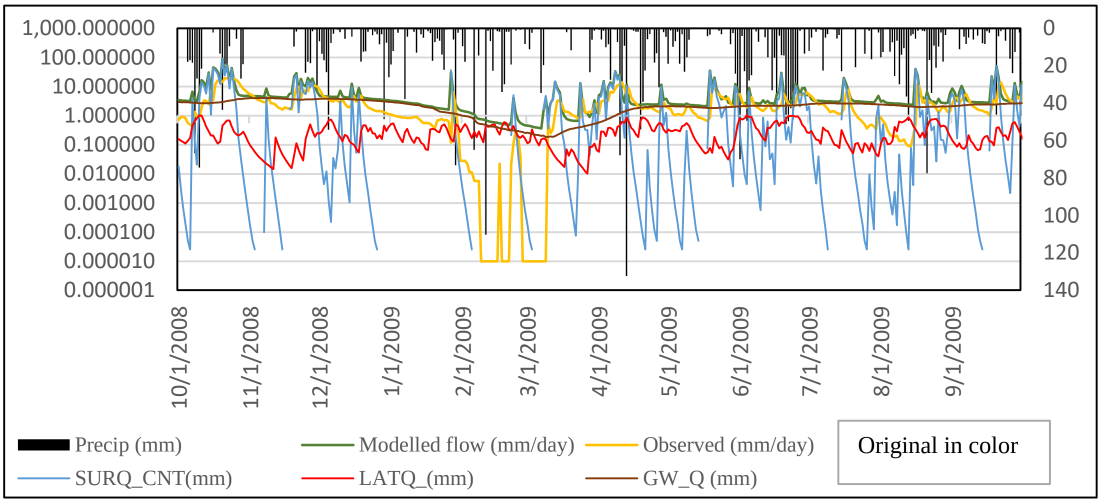


Figure D 1:Flow components for the water year 2008/2009

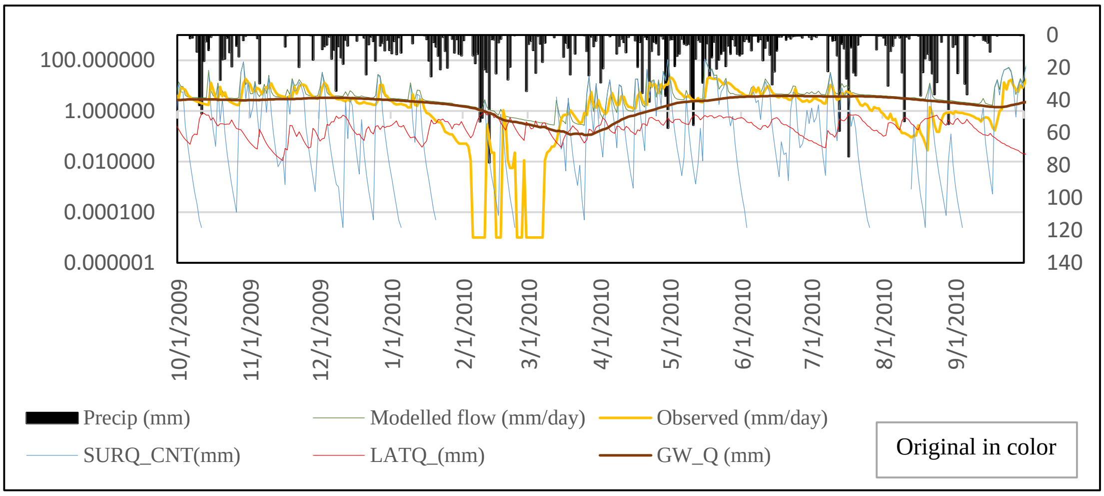


Figure D 2:Flow components for the water year 2009/2010

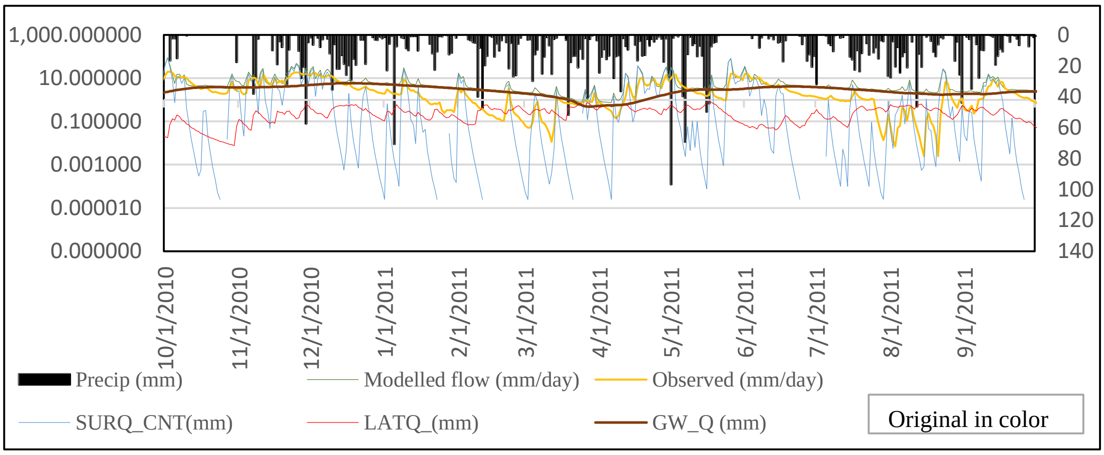


Figure D 3:Flow components for the water year 2010/2011

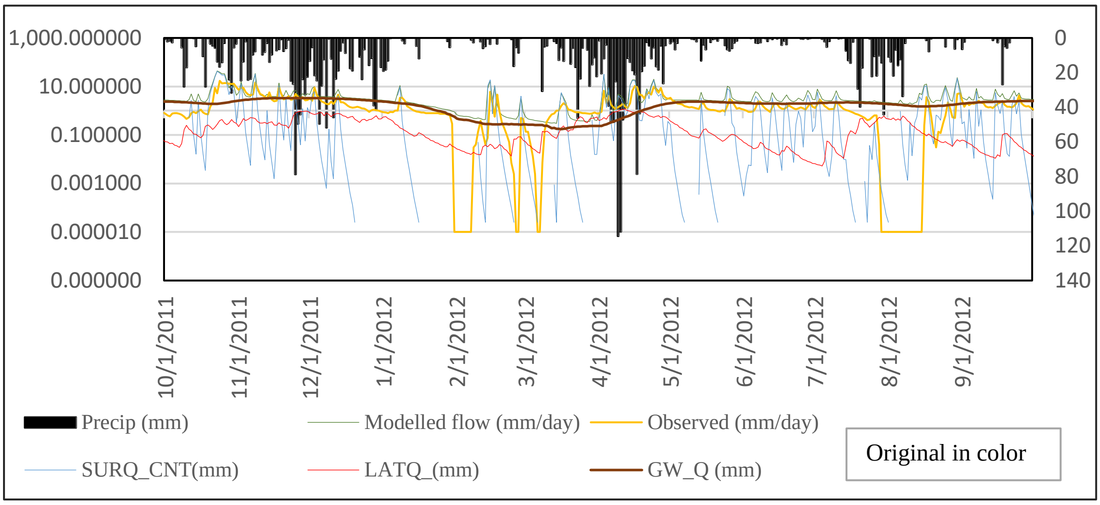


Figure D 4:Flow components for the water year 2011/2012

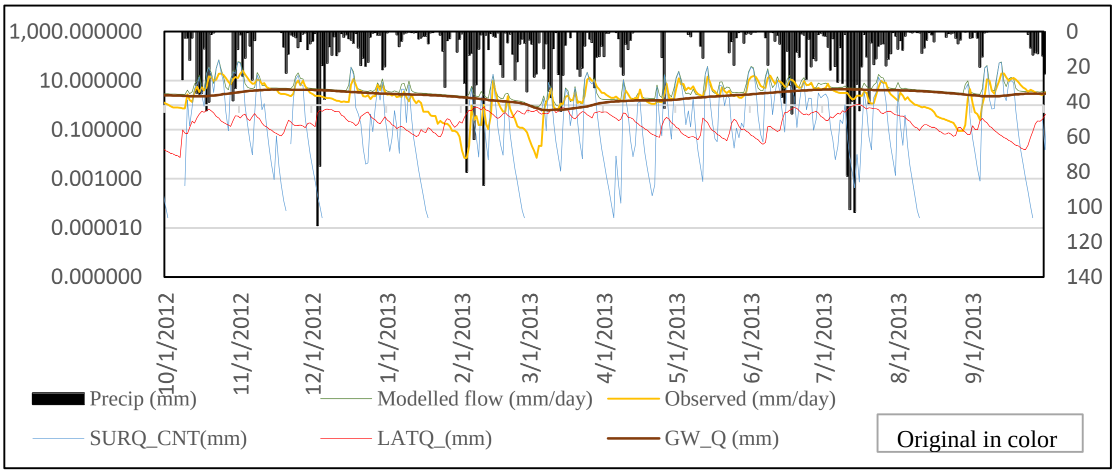


Figure D 5:Flow components for the water year 2012/2013

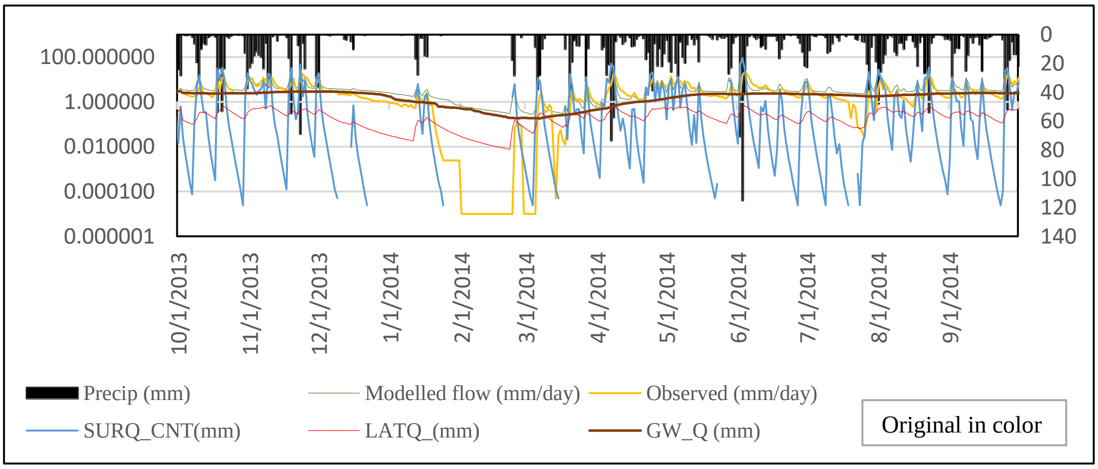


Figure D 6:Flow components for the water year 2013/2014

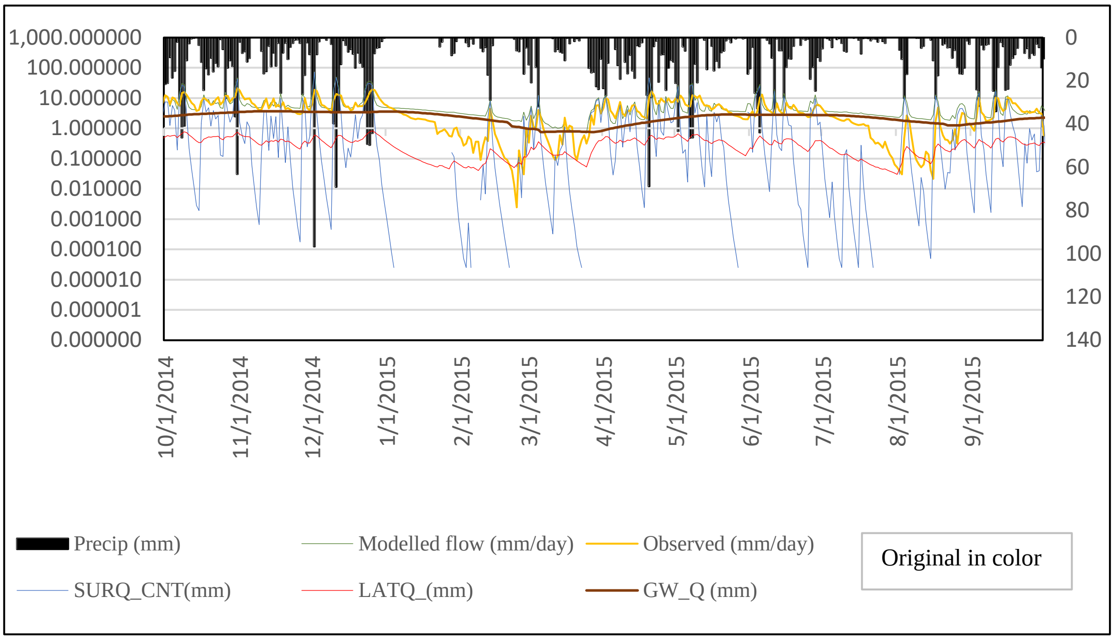


Figure D 7:Flow components for the water year 2014/2015

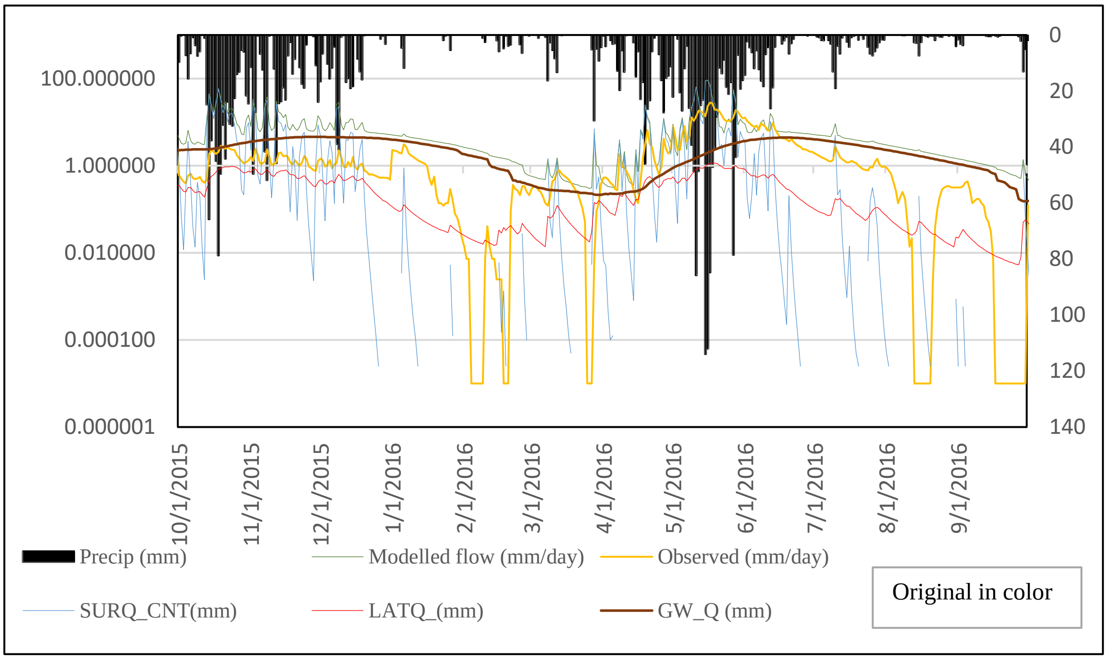


Figure D 8:Flow components for the water year 2015/2016

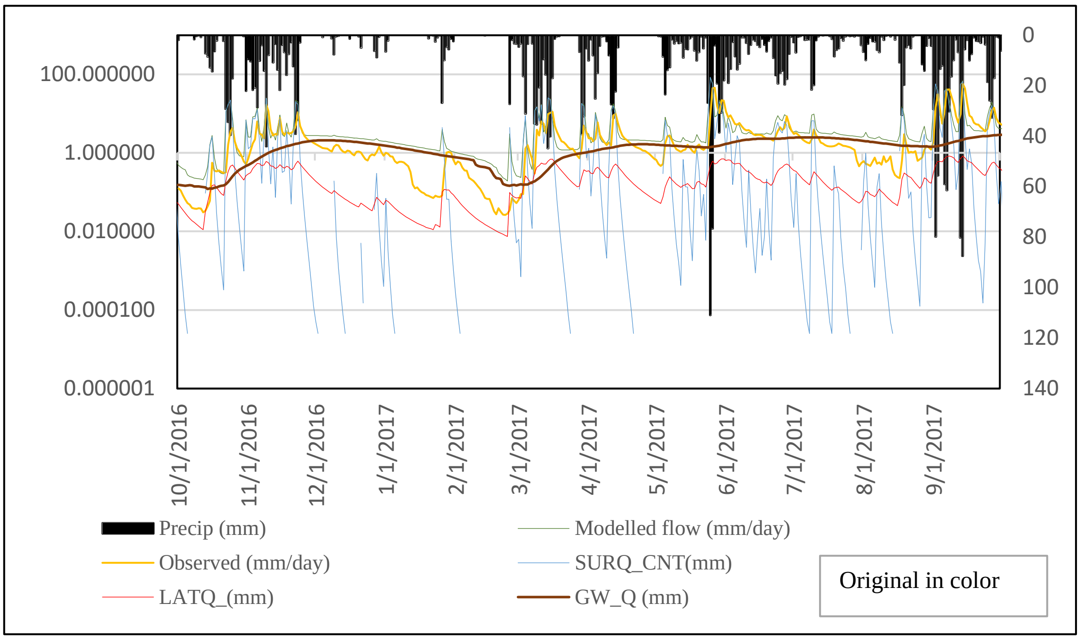


Figure D 9:Flow components for the water year 2016/2017

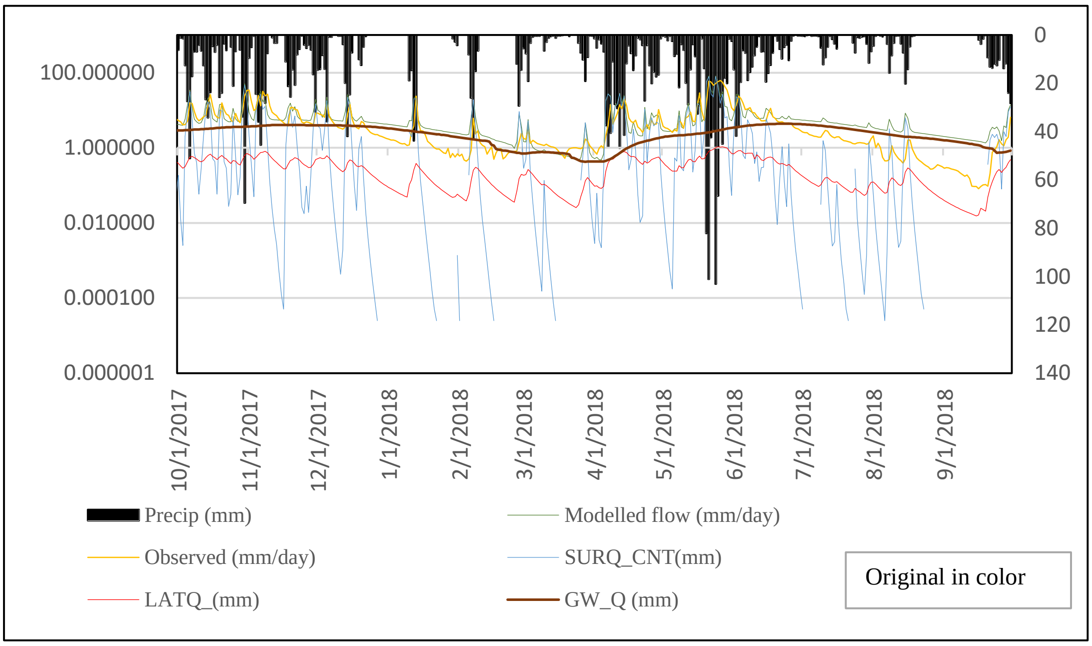


Figure D 10: Flow components for the water year 2017/2018

APPENDIX E: CALIBRATION HYDROGRAPH TIPS AND CALIBRATION STATISTICS TIP

Table E 1:Calibration hydrograph tips for issue 1 and 2

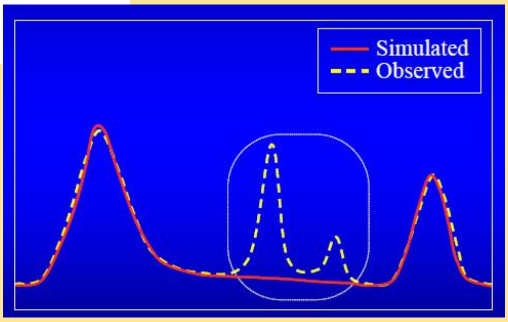
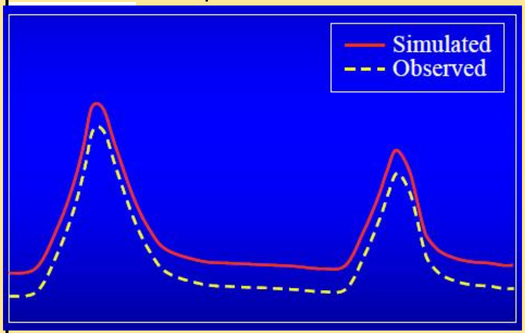
Tips for Hydrograph Calibration (source: swat.tamu.edu)	
Issue 1: Model fails to simulate some peak flows	**Issue 2:** Over prediction of flow
	
Causes:	**Causes:**
1.1 The rainfall station/s is not representative. Such system shows no response to localized storms	2.1 High Surface flow than reality 2.2 Higher Baseflow than reality
1.2 OR, some gages (rainfall or discharge) might be malfunctioning	2.3 Less evapotranspiration losses than reality
Solutions: (1.1)	**Solutions:** (2.1)
Use precipitation data from representative stations	Decrease curve number (CN_2) for land use types
Solutions: (1.2)	**Solutions:** (2.2)
Careful review of rainfall and discharge data for the model duration	Increase deep percolation loss (GWQMN)
	Increase groundwater revap coefficient (GW_REVAP)
	Decrease threshold depth of water in shallow aquifer for revap to occur (REVAPMIN)
	Solutions: (2.3)
	Check hydrograph's response for the parameters - Soil available water (SOL_AWC) and Soil Evaporation Compensation factor (ESCO)

Table E 2:Calibration hydrograph tips for issue 3 and 4

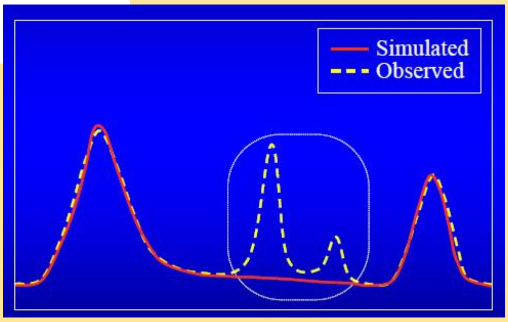
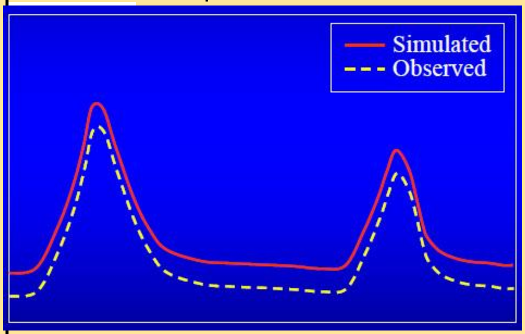
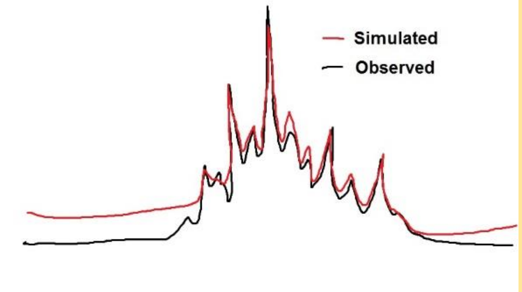
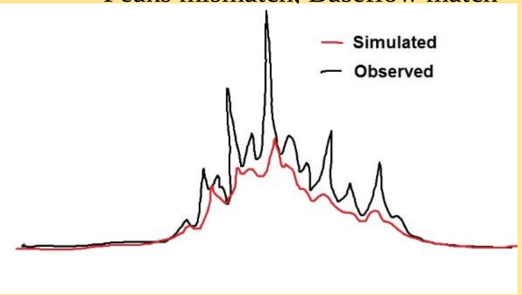
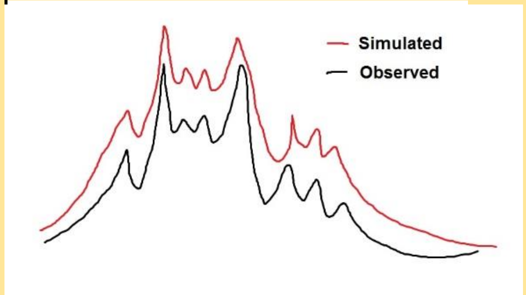
Tips for Hydrograph Calibration (source: swat.tamu.edu)	
Issue 1: Model fails to simulate some peak flows 	**Issue 2:** Over prediction of flow 
Causes:	**Causes:**
1.1 The rainfall station/s is not representative. Such system shows no response to localized storms	2.1 High Surface flow than reality 2.2 Higher Baseflow than reality
1.2 OR, some gages (rainfall or discharge) might be malfunctioning	2.3 Less evapotranspiration losses than reality
Solutions: (1.1)	**Solutions:** (2.1)
Use precipitation data from representative stations	Decrease curve number (CN_2) for land use types
Solutions: (1.2)	**Solutions:** (2.2)
Careful review of rainfall and discharge data for the model duration	Increase deep percolation loss (GWQMN)
	Increase groundwater revap coefficient (GW_REVAP)
	Decrease threshold depth of water in shallow aquifer for revap to occur (REVAPMIN)
	Solutions: (2.3)
	Check hydrograph's response for the parameters - Soil available water (SOL_AWC) and Soil Evaporation Compensation factor (ESCO)

Table E 3:Calibration statistic tips for hydrograph

Tips for Using Statistics (Source: Krause et al. 2005. Comparison of different efficiency criteria for hydrological model assessment)		
Case 1 Peaks match, Baseflow mismatch  **Match Indicator:** Peak values	**Case 2** Peaks mismatch, Baseflow match  **Match Indicator:** Base Flow	**Case 3** Overall Under-/Over estimation  **Match Indicator:** Pattern
NSE, RSR **NSE** quantifies via absolute values due to which, in general, the high values have greater influence than lower values. Thus, its high in case 1. **RSR** also gives good values.	**NSE_{rel}** **NSE_{rel}** is sensitive on low flows only and not reactive on peak flows. Thus, its an ideal statistic to evaluate base flow and high in case 2.	**R^2** Value of R^2 is purely driven by the pattern and not the values. Although this behavior is useful in terms of achieving the "disturbances" in the hydrograph it will overlook the volume problem
Error Indicator: Base flow	**Error Indicator:** Peak Values	**Error Indicator:** Flow Volume
NSE_{rel} Due to normalized expression, **NSE_{rel}** is not reactive on peak flows. Any poor performance in base flow is promptly noticed. Understandably its low in case 1.	**NSE, RSR** Since **NSE** is sensitive to high values, in case 2 it will show a low value. **RSR** also gives similar indication.	**wR^2, PBIAS** wR^2 takes into account the gradient b of the regression on which R^2 is based enabling it to check magnitude along with pattern. Along with R^2, **PBIAS** also indicates a low success value in this case as it checks the water volume.