DEVELOPMENT OF A RAINFALL RUNOFF MODEL FOR KALU GANGA BASIN OF SRI LANKA USING HEC- HMS MODEL

Priyani Mutumala Jayadeera

(138654 A)

Degree of Master of Engineering in Water Resources Engineering and Management

Department of Civil Engineering

University of Moratuwa
Sri Lanka

May 2016

DEVELOPMENT OF A RAINFALL RUNOFF MODEL FOR KALU GANGA BASIN OF SRI LANKA USING HEC- HMS MODEL

Priyani Mutumala Jayadeera

(138654 A)

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

Degree of Master of Engineering in
Water Resources Engineering and Management

Supervised by
Professor N.T.S. Wijesekera

UNESCO Madanjeet Centre for South Asia Water Management (UMCSAWM)

Department of Civil Engineering

University of Moratuwa
Sri Lanka

May 2016

DECLARATION

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

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

………………………………　　　　　　　　　　……………………..

Priyani Mutumala Jayadeera　　　　　　　　　　Date

The above candidate has carried out research for the Masters thesis under my supervision.

……………………………….　　　　　　　　　　……………………..

Professor N.T.S.Wijesekera　　　　　　　　　　Date

ABSTRACT

Water resources management and flood management in a watershed needs identification of the runoff hydrographs and their relationship with the watershed parameters. Sri Lankan Engineering guidelines or literature in Sri Lankan studies do not provide recommendations for a Hydrologic Model or a modeling methodology guideline for a water manager to use for application purposes. In order to fill the gap in knowledge, this research developed a model using Hydrologic Engineering Centre - Hydrologic Modeling System (HEC-HMS) through a case study application on Ellagawa watershed in Kalu Ganga basin of Sri Lanka.

Eight year daily rainfall data from 2006 to 2014 for five rain gauging stations scattered in the Ellagawa watershed with daily streamflow data in Ratnapura and Ellagawa river gauging stations together with eight year monthly evaporation data of Ratnapura station for the same period were used for this study. After a critical evaluation of HEC HMS options, one layer Deficit and Constant loss method in HEC HMS, was used as precipitation loss model which accounts for the soil moisture content in the continuous model. Soil Conservation Service (SCS) unit hydrograph method and recession method were selected for simulation of direct runoff and baseflow respectively. The evaluation identified Muskingam model as the suitable routing model.

Model calibration was done using data from 2006 to 2010 and the calibrated model was verified using the dataset from 2010 to 2014. Both automated parameter optimization in HEC HMS and manual calibration were used in model calibration. The study demonstrates a systematic methodology for the selection of a search algorithm and the appropriate objective function was incorporated. The univariate gradient search method was selected to optimize the parameters by minimizing the Sum of Absolute Residual objective function. Manual calibration was carried out using Mean Ratio of Absolute Error (MRAE) as the objective function. In addition, another two statistical goodness of fit measures such as percent error in volume, and Nash-Sutcliff model efficiency were also checked as an observation.

Evaluation shows that the value of MRAE for Ellagawa and Ratnapura catchments were 0.5406 and 0.5226 respectively during calibration. The MRAE values for Ellagawa and Ratnapura catchments during model verification were 0.6070 and 0.7732 respectively. Model estimated intermediate flows between 17 m^3/s and 31 m^3/s, with a very high accuracy of MRAE 0.326 and flows between 31 m^3/s and 143 m^3/s, estimations was acceptable at a MRAE of 0.5279. Model estimated high flows greater than 143m^3/s with a very high accuracy of MRAE 0.3244, while the low flows which was less than 17 m^3/s, could not be estimated very well. But the magnitude of lowflow errors for both catchments were only 1% of average annual streamflow of Ellagawa and Ratnapura and therefore this model can be used satisfactorily for water resources management. The model matching of time of peakflow occurrence was at an accuracy of 60% while the peak flow magnitude accuracy was 75%. Therefore, this model is acceptable to use in flood management.

ACKNOWLEDGEMENT

I would like to express my sincere gratitude to my research supervisor, professor N.T.S. Wijesekera for the continuous support of my study, for his patience, motivation and immense knowledge. Without his dedicated supervision and continued guidance, this thesis would not have been a in success. I am really grateful to him for spending his valuable time with me towards completing this research.He consistently ensured that this research is my own work by steering me in the right direction whenever I deviated.

I wish to convey my thanks to the course co-ordinator Dr. R.L.H. Lalith Rajapakse for extending all necessary help. His kindness to provide help and amidst support, his busy schedule and sincere and consistent encouragement are greatly appreciated. I am grateful to Ms. Gayani Edirisinghe for her help and support all the way during this research.

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

My sincere thanks also extends to the Director General of Irrigation, Department of Irrigation, Sri Lanka, for giving me this opportunity to follow this Master Degree Programme. I take this opportunity to thank Director of Irrigation (Hydrology), Department of Irrigation for her encouragement to complete this research and the kind assistance when collecting necessary data.

Finally, I must express my very profound gratitude to my husband for providing me unfailing support and continuous encouragement throughout this research leads to my Masters Degree.

CONTENTS

Table of Figures

List of Tables

1 INTRODUCTION

1.1 Rainfall and Water Resources in Sri Lanka

Sri Lanka is an island near the southern tip of India, located between latitude 6° N and 10° N and longitude 80° E and 82° E. Rainfall in Sri Lanka has multiple origins. Monsoonal, Convectional and expressional rain accounts for a major share of the annual rainfall. The mean annual rainfall varies from under 900 mm in the driest parts (southeastern and northwestern) to over 5000 mm in the wettest parts (western slopes of the central highlands) (Department of Meteorology, Rainfall section, para.3).

The Island is subjected to two monsoons; the South West monsoon prevailing from about April to September and the North East monsoon from October to March. On the basis of distribution of rainfall, the island is divided into two distinct areas, the wet zone and the dry zone. The wet zone comprises of the South West area covering about a quarter of the island. The area of the wet zone is about 4 million acres. The wet zone, with its two rainy seasons and an annual average rainfall of 2400 mm, is well developed with economic crops, tea, rubber, coconut, etc. The present economy of the country is largely dependent on development of the wet zone. The rest of the island belongs to the dry zone. The dry zone comprising of over 12 million acres, has only one rainy season, the North East monsoon, from October to March, and the average annual precipitation is about 1400 mm. The dry zone areas are arid and dry and well suited for irrigated agriculture (Arumugam,1969). The volume of water that is annually received from rain is estimated as 118,015 MCM (Wijesekera, 2010).

The rivers of Sri Lanka radiate from the central highlands. These drain from 103 distinct and significant river basins. These cover over 90 % of the island. Apart from these, there are 94 small coastal basins which do not significantly contribute towards the water resources (Central Environmental Authority, 2011).

1.2 Challenges in Water Resources

1.2.1 Challenges in climate change

Wijesekera (2010) quoting Jayatilake et al. (2005) stated that there exists an increasing trend of air temperature particularly during the recent few decades after analyzing long term temperature data and the average annual rainfall has reached below average for the entire study period from 1970 to 2000. Wijesekera (2010) has quoted Sri Lankan Centre for Climate Change Studies for National level modeling and stated that the temperature decrease during Southwest monsoon season is anticipated to be 2.5° C whereas the northeast monsoon season is expected to have a temperature increase of 2.9 ^{0}C and the rainfall change is expected to be greater during the southwest monsoon than northeast monsoon. So, there will be a great challenge for the water resources planners for efficient management of water resources of the country.

1.2.2 Challenges in water demand

During the past few decades, water users have increased and accordingly the demand for water has increased at a considerable rate. In Sri Lanka, water is used by many sectors such as, for agriculture, domestic water supply, hydropower, recreation, urban development, navigation, etc. Water managers have a great challenge to meet these multiple and often conflicting demands.

In addition to all these management challenges, there are uncertainties associated with natural water supplies and demands due to climate change, changes in standards of living, watershed land use changes and due to changes in technology. Hence, the main role of water managers is to develop water resources management systems which can range from small watersheds to large river basins so that changing objectives and goals of the society are met (Locks et al., 2005). To manage water resources in an integrated manner, mathematical models have been found very effective.

1.2.3 Typical watershed models

Typical models used for watershed modeling are HEC HMS (USACE, 2000), Mike Basin (MIKE BASIN, 2012), NAM (Hafezparast, Araghinejad, Fatemi and Bressers, 2013), Tank Model (Wijesekera and Musiake, 1990), Xinanjinag (Ren et al., 2006), SOBEK (Vanderkimpen, Melger and Peeters, 2009) and Soil Water Assessment Tool [SWAT] (Liechti et al., 2014).

Most of these models are expensive and only the models developed at Hydrologic Engineering Centre of US Army Corps of Engineers are available for free use. HEC HMS is a numerical model which includes several methods to simulate watershed, channel and water control structure behavior to predict flow, stage and timing. The model simulation methods represent watershed precipitation and evaporation, runoff volume, direct runoff including overland flow and interflow, base flow and channel flow. The HEC Hydrologic Modeling System is designed to simulate the precipitation –runoff processes of dendritic watershed systems. It is designed to be applicable in a wide range of geographic areas for solving the widest possible range of problems. This includes large river basin water supply, flood hydrology along with small urban or natural watershed runoff. Hydrographs produced by the HEC program are used directly or in conjunction with other software for studies of water availability, urban drainage, flow forecasting, future urbanization impact, reservoir spillway design, flood damage reduction, flood plain regulation and system operation (USACE, 2000).

There had been an enormous interest in the application of hydrological modeling coupled with Geographic Information System [GIS]. Bakir and Xingnan (2008) attempted to critically look at the application of Geospatial Hydrologic Modeling Extension (HEC-GeoHMS) which is an extension of ArcView in HEC HMS. Authors stated that with the topographic information supplied by HEC-GeoHMS, HEC HMS works more readily and exactly. The performance of HEC HMS was compared with that of the Xinanjiang conceptual model (Ren et al., 2006) using historical flood data of the Wanjiabu catchment in China. The results indicated that HEC HMS was more convenient for flood simulation especially in optimizing parameters but not quite accurate as compared with Xinanjiang model. Authors argued that the reason could be due to the fact that the Xinanjiang model has more parameters thereby making it flexible to fit a flood event.

1.3 Hydrological Modeling in Sri Lanka

Wijesekera (2010) identified and assessed the research work that had been conducted on surface water resources and climate change of Sri Lanka through a review of selected 91 publications related to water resources in Sri Lanka. It had been identified that only 58% of the water themes had been covered by research. Out of 91 publications reviewed, Wijesekera (2010) summarised that with respect to basins, there were 13 studies for Mahaweli river, 10 for Walawe, 8 for Kelani, 5 each for Kalu and Nilwala, 2 for Deduru oya and Gin ganga, 1 each for Bolgoda and Menik ganga. Further, the author mentioned that there were limited number of modeling efforts in surface runoff, water resource modeling, flood modeling, etc., which indicated the use of models for prediction of surface water flow in streams and flood runoff hydrographs and such literature only present the case studies which demonstrates the suitability of a model, its application potential, etc. It was difficult to assess which models would satisfactorily lead to the estimation of Sri Lanka’s surface water resources within a desired level of accuracy. Among the publications, this review noted only one abstract describing the comparison of a lumped and a distributed model as the only work done towards distributed basin scale modeling. Therefore, the author stated that the importance of such studies increases when making suitable interventions through the intervention of physical changes within a watershed and the low modeling efforts may be either due to lack of data, non availability of modeling tools, lack of expertise or lack of encouragement from those who manage surface water.

1.4 The Role of the Irrigation Department

Sri Lanka is endowed with a hydraulic civilization natured by a rich irrigation heritage. The main role of Irrigation Department of Sri Lanka is to keep these traditions alive by development and management of water and land resources for sustainable use. While providing water for paddy cultivation to ascertain food security of the nation, all other water needs have to be fulfilled. The policies, plans and programs of the Irrigation Department are geared to achieve these targets (Department of Irrigation, Para 1). To fulfill the need of flood protection in river basins, it is very important to have reliable hydrologic models to evaluate the water in the watersheds.

Water Resource Planning Division of Irrigation Department has carried out feasibility / pre feasibility studies for water resource development projects in various river basins of Sri Lanka including Mundeni Aru, Heda Oya and Kumbukkan Oya.

A feasibility study has been carried out for Heda Oya basin which is located in Ampara and Monaragala administrative districts using NAM model (Hafezparast et al., 2013). In the study, flows of Siyambalanduwa from 1991- 2005 and monthly rainfall of Siyambalanduwa, Moneragala, Kehallanda and Baduluwela for the Siyambalanduwa catchment were used in the NAM Model to find catchment parameters. In addition, Evapotranspiration rates (ET) of Batticalloa based on calculation using CROPWAT Model (CropWat, 1998) was used as input in the NAM model. As the long term continuous flow data were not available at the proposed dam site at Ritigala, flow data of Siyambalanduwa was used in model calibration. Coefficient of determination was used as the statistical performance measure to evaluate the model performances during calibration and verification. Calibration was carried out for 1991 to 2000 period and verification was carried out for the balance period 2000 to 2005. After optimizing the parameters for Siyambaladuwa catchment, using these parameters, monthly runoff were generated for Ritigala dam site for the period of 1980 – 2005 (Department of Irrigation, 2006).

A pre- feasibility study was carried out for the Mundeni Aru basin which is located in Baticaloa and Ampara administrative districts in the Eastern province. As long term observed runoff data was available at Maha Oya gauging station located across Maha Oya, the model was calibrated for the Maha Oya catchment. Observed daily flows during 1946/47 – 1950/51 period and the catchment rainfall based on the Thiessen weighted daily rainfall of Maha Oya and Ekiriyankumbura were used in the NAM model to determine catchment parameters. In addition, daily evaporation at Padiyathalawa was used as an input in the NAM model. Verification of the model was done for available data for the period 1951/52-1953/54. NAM model was also calibrated using the observed daily flows at Weragoda gauging station location across Galodei Aru. Observed daily flows at Weragoda for the period 1945/46 – 1988/89 and the catchment rainfall based on the Thiessen weighted daily rainfall of Ekiriyankumbura and Maha Oya was used in the NAM model to determine the catchment parameters. Verification of model parameters was done for the available data for the period 1968/69 -1970/71 period. Similarly, NAM model was calibrated using the observed daily runoff data at Pollebedda gauging station located across Rumbukkan Oya, for the period 1980/81 – 1983/84). Verification of the model was done for 1985/86 – 1987/88 periods (Department of Irrigation, 2014).

A feasibility study has been carried out for the Kumbukkan Oya basin using the same NAM model. As the long term observed runoff is available at Nakkala gauging station, the model was calibrated for the Nakkala catchment. Nakkala daily flows during 1975-1994 period and the catchment rainfall based on Thiessen weighted daily rainfall of Mahadowa, Debedda and Okkampitiya for the Nakkala catchment was used in the NAM model to determine the catchment parameters. In addition, daily evaporation at Nakkala was used as input in the NAM model. Verification of model parameters was done for available data for the period 1979-1980 (Department of Irrigation, 2013).

Although these models are calibrated and verified, there are no reviewed publications on any of these studies.

1.5 Development of a Model for Kalu Ganga Basin

1.5.1 General

Kalu Ganga basin consisting of 2690 km^2 is situated in the wet zone. Measuring 129 km in length, the river originates from Adam’s Peak, flows through Ratnapura and Kalutara districts and reaches the sea at Kalutara. The mountainous forests in the central province and the Sinharaja Forest Reserve are the main sources of water for the river. Although the Kalu River, the third longest river in Sri Lanka, discharges the largest amount of water into the ocean while causing floods along its route from the most upstream major town, Ratnapura, to the most downstream town, Kalutara, Nandalal and Ratnayake (2010) stated that Kalu Ganga is still an untamed river.

A map of the basin of the Kalu Ganga is presented in Figure 1-1.

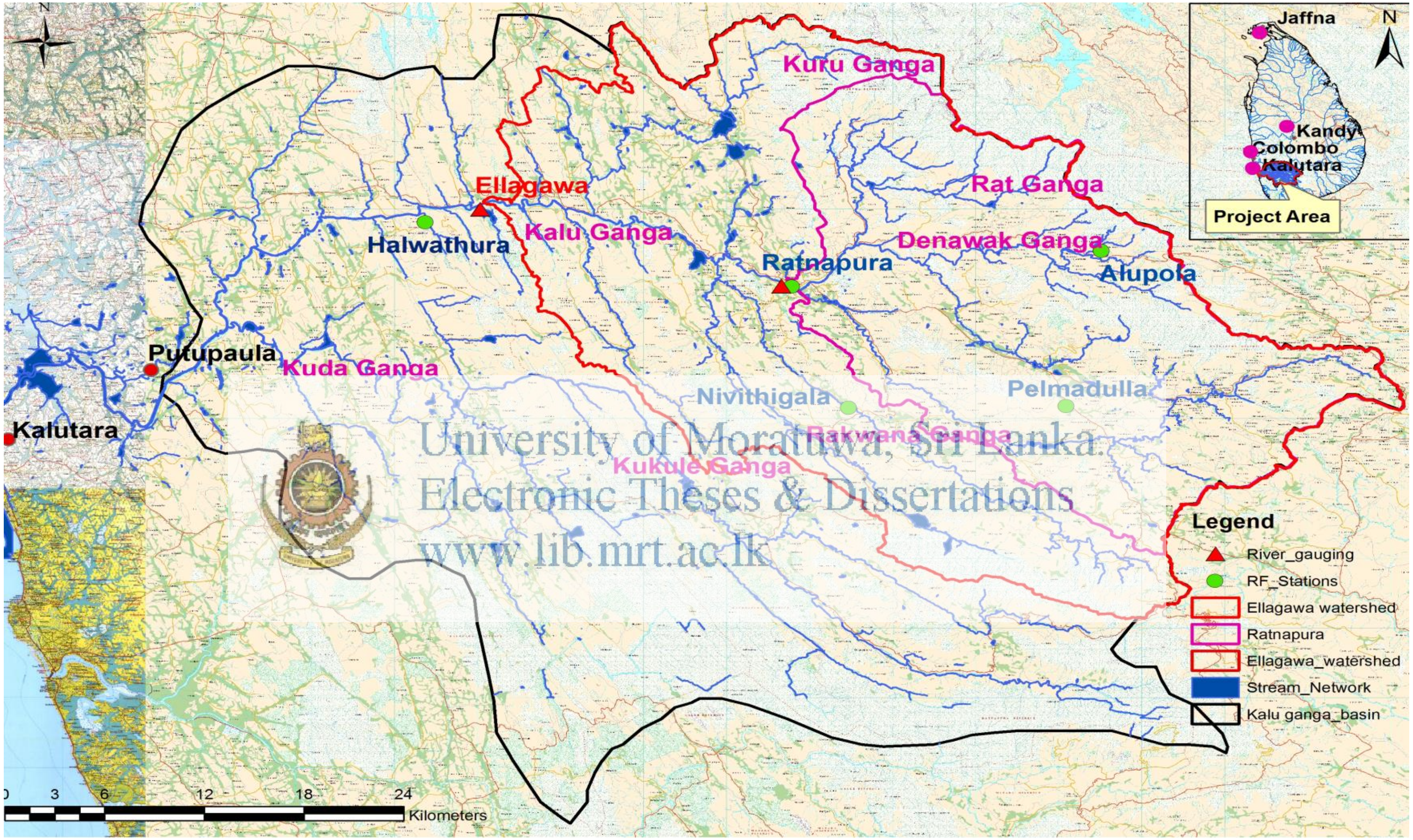

Figure 1-1 Map of Kalu Ganga basin with Ellagawa and Ratnapura catchments

1.5.2 Vulnerability to floods in Kalu Ganga basin

Disaster Profile of Sri Lanka says that floods destroyed 49891 houses and damages caused to crops and paddy is 444216 ha in the country during the period 1974 – 2006 (Disaster Profile, Sri Lanka). The largest number of people (3,329,806) has been affected by various hazard events in Ratnapura and that for Kalutara is 809,017 (Disaster and Risk Profile, Sri Lanka). The flood occurred in 2003 caused severe damages to many parts of the country including Gampaha, Kalutara, Ratnapura, Kegalle districts with rising of water levels of Kelani River, Kalu River and Gin Ganga. According to the statistics of Disaster Management Centre of Sri Lanka, 88,344 people belonging to 20,569 families were affected in Kalutara district. Many roads in Kalutara district went under water (Disaster Management Centre, 2011).

1.5.3 Water use sectors in Kalu Ganga basin

The water in Kalu Ganga is used for supplying domestic water to Colombo and suburbs, Irrigation and generation of hydro power. At present, there are flood protection dykes along the river at critical locations of the lower catchment and are maintained by the Irrigation Department. In order to meet these conflicting multiple demand, it is essential to study and evaluate the behavior of rainfall – runoff processes in the Kalu ganga basin and to develop an efficient water management technique to determine the floods resulting from major storm events and propose mitigatory measures for flood problem for Kalu ganga basin for the use of Irrigation Department.

In the present work, HEC HMS model was selected, developed, calibrated and verified for Kalu Ganga basin as it is one of the presently used free softwares for modeling watersheds. This research attempts to develop a model for Kalu Ganga basin upto Ellagawa gauging station (1250 km^2), which covers approximately 46% of Kalu ganga basin.

1.6 Problem Statement

After reviewing literature on hydrological modeling in Sri Lanka, it can be identified that there is a need for an established tool for a watershed to manage water resources in a catchment. Hence, this research demonstrates the methodology of developing a tool for a watershed for water resource management by a case study application for Kalu Ganga basin at Ratnapura and Ellagawa. The reasons for selecting Kalu ganga basin are, availability of data at finer resolution, the possibility of comparison of performance in two catchments and the nature of the basin with respect to the vulnerability to floods and the existence of multiple water demands.

HEC HMS Model is selected for the study as it is a freely available and flexible software for watershed modeling.

1.7 Main Objective

The main objective is to develop a model for a watershed to manage water resources in a catchment efficiently.

1.8 Specific Objectives

1. Review of the performance of rainfall – runoff models with respect to inputs, objective functions and optimization criteria
2. Development of a HEC HMS model for Kalu Ganga basin
3. Calibration and verification of the hydrologic model for the Kalu Ganga basin
4. Comparison of model performance with respect to two catchments at Ratnapura and Ellagawa
5. Making recommendations for better water resources and flood management

2 LITERATURE REVIEW

2.1 Hydrological Models

Hydrological models are important for a wide range of applications, including water resources planning, development and management, flood prediction and design and coupled systems modeling including, for example, water quality, hydro-ecology and climate (Pechlivanidis, Jackson, Mcintyre and Wheater, 2001).

Application of mathematical models in water resource planning and forecasting has become increasingly popular during the last decade of Sri Lanka, with the introduction of micro computers. Numerical models in simulating of river flows are used in planning of water resources projects and real time flood forecasting (Dharmasena, 1997).

2.1.1 Types of hydrological models

Hydrological models are categorized as physically based or conceptual. Pechlivanidis et al. (2001) described that the conceptual models will be based on two criteria, the structure of the model is specified prior to any modeling being undertaken and not all the model parameters have a direct physical interpretation or not measurable and have to be estimated through calibration against observed data. Physically based models may be defined by wholly measurable parameters using basic mathematical equations such as St. Venant equations, Green-Ampt. equations etc.

Models can be categorized as lumped (all parameters and variables represent average values over the entire area) or distributed (spatial variation of input parameters and variables is accounted for), when the spatial description of processes are considered (Bronstert and Wohlfeil, 1999). When the number of model parameters are increased with the degree of spatial discretization, distributed models easily becomes over parameterized and subsequently ill-posed with respect to the input output data. Thus uncertainty in estimation of parameters and hence uncertainty in identification of model is a common problem (Madsen, Wilson and Ammentorp, 2002). Therefore, semi-distributed models are proposed to combine the advantages of both lumped and distributed approaches (Orellana et al., 2008). This kind of model does not pretend to represent a spatially continuous distribution of state variables, rather it discretizes the catchment to a degree thought to be useful by the modeler using a set of lumped models.

Rainfall-runoff models can be classified as continuous simulation models or event based models. Event hydrologic modeling may be useful for better understanding the underlying hydrologic processes and identifying the relevant parameters. Event modeling requires intensive fine scale hydrologic monitoring data for calibration of the event model. In contrast, continuous hydrologic modeling synthesizes hydrologic processes and phenomena (synthetic responses of the basin to a number of rainfall events and their cumulative effects) over a longer time period which includes both wet and dry conditions (Xuefeng and Steinman, 2009).

McEnroe (2010) stated that continuous simulation of streamflow is useful to predict the streamflow impacts of land use changes and storm water management practices on stream stability and ecology. Continuous simulation models account for hydrologic processes such as evapotranspiration, canopy interception, depression storage, percolation, shallow sub surface flow etc. that are neglected in single event flood models.

In a review of model types, calibration approaches and uncertainty analysis methods, Pechlivanidis et al. (2001) summarized the different classification of hydrological model types and discussed relative advantages and disadvantages of each type of model, established model calibration processes and discussed the sources of uncertainty that affected model predictions.

2.1.2 Modeling objectives

Hydrological modeling applications have a variety of objectives which depends on the problem that needs to be investigated (Pechlivanidis et al., 2001). By quoting Singh and Woolhiser (2002), Pechlivanidis et al. (2001) summarized the different objectives of hydrological modeling as follows. (1) Extrapolation of point measurements in both spatial and temporal (2) Improving the fundamental understanding of existing hydrological systems and assessing the impact of changes due to climate and land use on water resources (3) Developing new models or improving existing models for management decisions on current and future catchment hydrology such as irrigation water management, flood forecasting and management, streamflow restoration, water quality evaluation and wetland restoration etc.

2.1.3 Application of hydrological models

Bronstert and Wohlfeil (1999) had applied three versions of HBV model, Nordic HBV model characterized as a lumped model, HBV-96 and HBV-D models characterized as semi-distributed models to German part of the Elbe drainage basin and inter comparison of lumped and distributed versions of the model were done. The authors concluded that the models had performed well in all cases, but distributed model versions were more data intensive and enabled better results.

Orellana et al. (2008) had carried out a case study on upper Lee catchment in United kingdom to show the potential of the Semi-Distributed Rainfall –Runoff Modeling Toolbox (RRMT-SD). Also, the case study had shown the potential of the toolbox for developing regional equations for a priori estimation of model parameters and subsequent optimization using multipliers, hence maintaining spatial variations which are consistent with catchment characteristics.

Ajami, Gupta, Wagener and Sorooshian (2004) compared lumped, semi-lumped and semi-distributed versions of the SAC-SMA (Sacremento Soil Moisture Accounting) model for the Illinois River basin at Watts. The results were evaluated visually and statistically for the calibration and validation periods. These evaluations showed that for homogeneous basin like Illinosis River basin at Watts, overall flow predictions did not improve with increased spatial complexity. However, it can be seen the following improvements during specific periods. (1) semi-distributed model can match parts of the recession more accurately than lumpled model (2) semi-distributed model can capture small peaks during recession where as in lumped model, those small peaks are missed (3) lumped model over estimates the high flows while semi-distributed model under estimates high flows (4) high and medium flows in flow duration curve could be matched in semi-distributed model. But, finally authors highlighted that although semi-distributed model is preferred as it can provide information about flow condition at interior points of a basin, the resulting improvement in simulation capability at the outlet, compared to the lumped model is not yet significant to justify adaptation of semi-distributed model.

Khakbaz, Imam, Hsu and Sorooshian (2012) developed and calibrated a semi distributed model for Illinosis River Basin at Siloam Springs, Akransas and discussed the advantages of using semi distributed modeling structure. The study tested four different calibration strategies that consider input forcing and basin characteristics having various degrees of spatial homogeneity. Among those calibration strategies, those based on lumped calibration applied to semi-distributed model structure performed better than distributed calibration strategies. Finally, Khakbaz et al. (2012) suggested that the semi-distributed models can be constructed by dividing the larger basin at locations where even a short historical record may be available. The improvement of model performance, while not very large in terms of statistical measures, were significant in terms of producing better simulations at the outlet for spatially variable storms.

Xuefeng and Steinman (2009) developed both event and continuous models using HEC HMS for Mona Lake watershed in Left Michigan. Authors had used same transform and baseflow methods for both event and continuous models. The relevant parameters calibrated in the event model were used in continuous modeling. But for rainfall loss model, two different methods were used in event and continuous models. This study suggested that a combination of event and continuous modeling can be an effective way that not only take the full advantage of the characteristics of distinct modeling approaches and availability of data, but also enhances the modeling capabilities.

McEnroe (2010) had provided guidance for continuous simulation of streamflow in Johnson County in Kansas, America with HEC HMS hydrologic modeling system. The author examined the hydrologic characteristics of USGS gauged streams in Johnson County and explained how HEC HMS models the hydrologic processes in continuous simulation. Further, the study demonstrated some practical applications of continuous simulation for Indian Creek Tributary 4. The author concluded that in continuous simulation, it should be focused on to the low end of streamflow spectrum and future improvements were suggested.

2.1.4 Data used for modeling

In this work, Bronstert and Wohlfeil (1999) had used a digital elevation model with 1 km resolution and national land use map for Germany. A subbasin map was created delineating 44 subbasins within Elbe drainage basin with corresponding gauging stations. Temperature and precipitation data from 25 stations were used in the study. In addition, daily precipitation data from 663 precipitation stations in the area were used for the distributed modeling. Potential evapotranspiration rates were pre- processed as regionally specific monthly values.

In the study of applying the Rainfall-Runoff Modeling Toolbox (RRMT-SD), Orellana et al. (2008) had used 8 years of historical hourly flow and rainfall data, monthly and mean potential evapotranspiration data for the period of 1991-1998 of upper Lee catchment in United Kingdom for model calibration. Four year data from 1998-2002 were used for model verification.

Ajami et al. (2004) in their study for Illinosis river basin at Watts, a mesh of NEXRAD cells was created using the Hydrologic Rainfall Analysis Project (HRAP) grid to define the mean average precipitation over each subbasin. Seven year period of hourly rainfall and streamflow data from 1993-1999 were used for calibration.

Khakbaz et al. (2012) had used eleven years of hourly mean areal precipitation time series data from NEXRAD data set. Also, monthly mean evaporation data were used. It was assumed that spatial and diurnal variability of potential evapotranspiration over the subbasins and during the day was uniform.

In the comparison of event and continuous hydrological modeling, Xuefeng and Steinman (2009) had used observed flow data at eight monitoring sites in the Mona Lake watershed for model calibration and verification. An Odyssey pressure and temperature recording system had been installed for collecting stream water level and temperature data at each site. Streamflow was manually measured and processed by using the Window-based hydrologic software, HYDROL-INF. Then rating curves were developed and observed hydrographs were computed for all monitoring sites, which were further used for model calibration.

In the continuous simulation of HEC HMS model applied to Indian Creek Tributary 4, McEnroe (2010) had converted the gage data from the original fixed depth interval format to the required fixed time interval format with a computer program written for this task and generated the incremental precipitation for the decade 1997-206 with time interval of 5 minutes, 15 minutes and 1 hour. The model was calibrated for this period with above precipitation data and monthly average values of potential evapotranspiration.

2.2 Hydrological Modeling in Sri Lanka

Dharmasena (1997) reviewing five hydrological models and one hydrodynamic model with case study applications to river basins in Sri Lanka stated that while using hydrological models for representing head basins, hydrodynamic models are interfaced to represent the lower parts of the rivers. Application of different hydrological models indicated that a wide variety of models can be successfully applied to Sri Lankan rivers, instead of a particular model. Further author suggested that the conceptual models would provide superior results especially for rivers subject to prolonged droughts.

Nandalal and Ratnayake (2010) developed an event based modeling using HEC HMS lumped conceptual hydrologic model for Kalu Ganga basin. Two different models, having four sub basins and ten sub basins were developed. They were calibrated using four historical flood events. The results showed the suitability of the HEC HMS software in the modeling of Kalu Ganga river basin. Further, the results of the two models indicated that there is no impact of the number of sub basins considered in the modeling of the basin on the prediction of floods. But, this study was mainly focused on high flows and model performance only in high flows were discussed where as the representativeness of model for medium and low flows has not been analyzed.

Halwathura and Najim (2013) developed three different approaches to calibrate and validate HEC HMS 3.4 model for Attanagalu oya. Dunamale sub catchment was calibrated with three different methods such as SCS curve number loss method, deficit constant loss method with clark unit hydrograph and Snyder unit hydrograph transform method in order to determine the most suitable simulation method for this catchment. The authors concluded that the Snyder unit hydrograph transform method simulates the flows more reliably than Clark unit hydrograph method. They also concluded that SCS CN loss method did not perform well but deficit constant loss method was a good option of continuous simulation of Attanagalu Oya catchment.

Costa (1995) investigated the storage characteristics of Kalu Ganga catchment in order to identify the temporal variation of response characteristics of this catchment and obtained a relationship between the temporal variation and the response function of the catchment using a lumped system model for flood forecasting. The author found that the response characteristics of subbasins did not show any appreciable change from subbasin to subbasin and all the subbasins of Kalu ganga catchment possess an evapotranspiration rate of 525 mm/year.

Samarasinghe et al. (2010) have done a study of application of remote sensing and GIS for flood risk analysis for Kalu Ganga basin. In this study, flood event extracted from satellite images were compared with the flood extent obtained using HEC HMS and HEC RAS. The study produced flood hazard maps of 10 year, 20 year, 50 year and 100 year return period flood events.

Wijesekera and Musiake (1990) had carried out streamflow modeling for two Sri Lankan catchments namely Kalu Ganga basin at Putupaula and Mahaweli Ganga basin at Peradeniya. A simple tank model with four tanks was used to simulate streamflow and the powel search technique considering spatial variability of rainfall was incorporated to optimize the model parameters. In this study rain gauge weights were also considered as parameters and were optimized. Data from 1969-1973 were used for model calibration while data from 1976-1980 were used for model verification. Results of Mahaweli basin showed that the average annual water balance values provided better results than when yearly values were used which implied that the evaporation values were not very critical in the model outputs. In models of both basins, inclusion of non uniformity of rainfall improved the model predictions but very marginally. The authors concluded that the optimized parameters were acceptable with the rainfall distributions and the location of rainfall stations.

2.3 Objective Function

Objective Function is the function used to match the model results with reality. The objective function depends on the modeling objectives such as modeling for flood control, water resources planning and management, etc. The objective function use has differed from researcher to researcher even with the same objective.

This function measures the degree of matching the relevant component of computed and observed hydrographs. Calibration process can find the optimal parameters which minimize the objective function. Further, calibration process estimates some model parameters which cannot be estimated by observation or measurement or have no direct physical meaning. Calibration may be either manual or automated where manual calibration relies on user's knowledge of basin physical properties and expertise in hydrologic modeling (Cunderlik and Simonovic, 2004).

Green and Stephenson (2009) discussed twenty one objective functions and stated that the method of assessing a model depends on the objective of modeling. For example, if the modeler is interested only in peak flows, there is a little point in investigating low flows or even the hydrograph shape. Also, if routing effects are concerned, they said that the rising and falling limbs of hydrographs are important. Authors recommended to use percent error in peak, percent error in volume and sum of squares / sum of absolute residuals objective functions in single event modeling. When more general dimensionless ordinate independent measure of fit is required to assess the performance of a model over a number of different events and authors suggested to use the coefficient of efficiency or Nash-Sutcliff objective function as it is a reasonable choice. The objective functions recommended by Green and Stephenson (2009) are listed below.

i. Percent Error in Peak (PEP)

$$PEP = \frac{Q_{op} - Q_{cp}}{Q_{op}} \times 100 \tag{1}$$

ii. Percent Error in Volume (PEV)

$$PEV = \frac{V_o - V_c}{V_o} \times 100 \tag{2}$$

iii. Sum of Squared Residuals (SSR)

$$SSR = \Sigma\,(Qobs - Qcal)^2 \tag{3}$$

iv. Sum of Absolute Residuals (SAR)

$$SAR = \Sigma\,ABS(Qobs - Qcal) \tag{4}$$

v. Coefficient of Efficiency (CE) or Nash – Sutcliff

$$CE = 1 - \frac{\sum\left(Q_{obs} - Q_{cal}\right)^2}{\sum\left(Q_{obs} - \overline{Q}_{obs}\right)^2} \tag{5}$$

Madsen (2000) applied the MIKE 11/NAM continuous model to the Danish Tryggevaelde catchment and the model was calibrated for 5 year period. Overall Volume Error, Overall Root Mean Square Error [RMSE], Average RMSE of peak flow events and Average RMSE of low flow events were used as objective functions.

Giang and Phuong (2010) developed, calibrated and verified a model for Gia Vong river basin in Vietnam using MIKE NAM model for five flood events. They had used correlation coefficient, Peak error, wave error type 1 and wave error type 2 and volume error as objective functions.

Cunderlik and Simonovic (2004) have quoted Sorooshian et al. (1983) who gives a comprehensive summary of statistical performance measures used for evaluation of performance of a hydrologic model. Finally, Cunderlik and Simonovic (2004) had used the same six statistical measures for both event and continuous models. These include percent error in peak, percent error in volume, linear zero lag cross correlation coefficient, relative BIAS, relative RMSE and relative peak weighted RMSE.

World Meteorological Organization (1975) in its publication compares conceptual models used for operational hydrological forecasting and recommends several objective functions. One of them are Ratio of Absolute Error to Mean (RAEM) which is given below.

$$RAEM = \frac{\sum \left| Q_{obs} - Q_{cal} \right|}{n\overline{Q}_{obs}} \qquad (6)$$

Q_{obs} is the observed streamflow , Q_{cal} is the calculated streamflow and n is the number of observations used for comparison. This objective function indicates the ratio between observed and calculated discharge with respect to the mean of observed discharges. It compares the error values with respect to the mean of the observed flows. This objective function depends on the characteristics of the observed flow series. When there are big and small peaks, the error values may not enable for easy comparison and mean of observed flow does not reflect the real mean value of the flow series.

Wijesekera and Abeynayake (2003) defined that Mean Ratio of Absolute Error (MRAE) is the difference between calculated and observed flow with respect to that particular observation and it is defined as,

$$MRAE = \frac{1}{n}\sum \frac{\left| Q_{obs} - Q_{cal} \right|}{Q_{obs}} \qquad (7)$$

In this objective functions too, Q_{obs} is the observed streamflow and Q_{cal} is the calculated streamflow, and n is the number of observations used for comparison.

This objective function compares the errors with respect to each observed flow. Therefore, this gives better representation when contrasting data are present in the observed data set.

Wu, Chau and Fan (2010) stated by quoting Legates and McCabe (1999), that the pearson's Correlation coefficient (r) or the coefficient of determination (R^2), have been identified as inappropriate measures in hydrologic model evaluation. In addition to the various performance measures discussed in the above literature, Wu et al. (2010) recommended a new objective function named as Persistence Index [PI] as given below, which can be used to check the prediction lag effect.

$$\text{PI} = \quad 1 - \frac{\sum \left(Q_i - Q_{cal} \right)^2}{\sum \left(Q_i - Qi - l \right)^2} \qquad (8)$$

Where, Q_{i-l} represents the flow from a so-called persistence model that basically takes last flow observation (at time i minus the lead time, l) as a prediction.

USACE (2000) recommends the following five objective functions to be used in automatic parameter optimization.

i. Peak-Weighted Root Mean Square Error (PWRMSE)

$$PWRMSE = \sqrt{\frac{\sum_{t=1}^{N}\left(Q_0(t)-Q_M(t)\right)^2 \frac{Q_o(t)+Q_A}{2Q_A}}{N}}; Q_A = \frac{1}{N}\sum_{t=1}^{N} Q_o(t) \tag{9}$$

Using a weighting factor, the PWRMSE measure gives greater weight to error values near the peaks.

ii. Sum of Squared Residuals (SSR)

$$SSR = \sum_{t=1}^{N}\left(Q_o(t)-Q_M(t)\right)^2 \tag{10}$$

The SSR measure gives greater weight to large errors and lesser weight to small errors.

iii. Sum of Absolute Residuals (SAR)

$$SAR = \sum_{t=1}^{N}\left|Q_o(t)-Q_M(t)\right| \tag{11}$$

The SAR function gives equal weights to both large and small errors.

iv. Percent Error in Peak flow(PEPF)

$$PEPF = 100\left|\frac{Q_o(peak)-Q_M(peak)}{Q_o(peak)}\right| \tag{12}$$

PEPF measure only considers the magnitude of computed peak flow and does not for total volume or timing of the peak.

v. Percent Error in Volume (PEV)

$$PEV = 100\left|\frac{V_o - V_M}{V_o}\right| \tag{13}$$

PEV function only considers the computed volume and does not account for the magnitude or timing of the peak flow.

2.4 Model Calibration and Verification

When a hydrologic model is selected and developed, representativeness of the model depends on its parameters. The representativeness is achieved only by optimizing these parameters for the best fit with reality. This process is called model calibration and verification. The quantitative measure of the parameter optimization is described by the objective function. Calibration uses observed hydro meteorological data in a systematic search for parameters that yield the best fit of the computed results to the observed runoff (USACE, 2000). The model calibration can be done in two ways, either manual calibration or by using computer based automatic calibration procedure. In manual calibration, a trial and error parameter adjustment is made. In this case, the goodness of fit of the calibrated model is basically based on a visual judgment by comparing the simulated and observed hydrographs (Madsen, 2000).

Model verification is in reality an extension of the calibration process. The purpose of verification is to assure that the calibrated model adequately assesses the range of variables and conditions that are expected within the simulation. Although there are several methods for verification, the most effective method is to use different data set of the available record of observed values. Once the calibration parameters are developed, simulation is performed for the remaining period of observed data and the goodness of fit is reassessed (Alagmand et al., 2010).

In an event based modeling study carried out for Gia Vong river basin in Vietnam, Giang and Phuong (2010) mentioned that the objective of calibration is to select model parameters so the model simulates the hydrological behavior as closely as possible and verification is done by selecting new set of observed data and the parameters which have been calibrated. In this study, having used five flood events, Giang and Phuong (2010) stated that although there are many discussions on calibration and verification, there is no consensus on a particular methodology. Authors further stated that there has been much attention given to specify the procedure for parameter calibration and verification using the continuous simulation while a very limited attention has been so far devoted to solve the same problem with interrupted (event) data.

After calibration and verification of the event and continuous models in Upper Thames River Basin (UTRB), Cunderlik and Simonovic (2004) found that the continuous model systematically under estimates the total streamflow volume by 10 – 15% and they recommended a correction factor to be applied for this.

Sudheer, Chaubey, Garg and Migliaccio (2006) evaluated the impact of the calibration time resolution on model predictive ability. Authors applied Soil and Water Assessment Tool (SWAT) and it was calibrated at monthly and daily time scales for the War Eagle Creek watershed in the USA. Sudheer et al. (2006) mentioned that a general assessment of the model performance merely based on goodness of fit statistics may mislead the modeler on the behavior of model simulations. The results implied that evaluation of models should be conducted considering their behavior in various aspects of simulation, such as predictive uncertainty, hydrograph characteristics, ability to preserve statistical properties of the historic flow series etc. Authors suggested that watershed model calibrations should be completed on a daily time step in order to preserve the hydrological behavior of the watershed accurately and enlightens the scope for improving/ developing effective auto calibration procedures at daily time step for watershed models.

2.5 HEC HMS Model Structure

HEC HMS model computes the runoff volumes by computing and subtracting from precipitation, the volume of water that is intercepted, infiltrated, stored, evaporated or transpired (USACE, 2000). HEC HMS has three main components. These are (1) Basin Model (2) Precipitation Model (3) Control Specification. The main components of the basin model are precipitation loss model, transform model, baseflow model and routing model.

2.5.1 Precipitation loss model

The graph of excess rainfall versus time or excess rainfall hyetograph is the key component of the study of rainfall runoff relationships. Chow, Maidment and Mays (1988) defined the abstractions or losses as the difference between the observed total rainfall hyetograph and the excess rainfall hyetograph. There are many methods of separating effective component from the total rainfall. These include Phi Index method, Horton method, Green Ampt method, Average storm method, NRCS (SCS) Curve Number method (Chow et al., 1988).

Chow et al. (1988) describes that Phi index is the constant rate of abstraction that will yield an excess rainfall hyetograph with a total depth which equals to the depth of direct runoff over the watershed and it is determined by trial and error.

Wijesekera (2010) in a review of water related studies done in Sri Lanka mentioned that there is only one reported study on rainfall losses in Sri Lankan catchments.

Manchanayake, Sumanaweera and Jayaratne (1985) in their study evaluated the loss rates for few Sri Lankan catchments by using two methods named as Horton method and Average storm method for few selected storm periods and compared the results. The study concluded that the average storm method gives considerable differences with Horton method and if temporal and aerial distribution of rainfall are uniform over the catchment, the average storm method would give quite satisfactory results.

El-Kafagee and Rahman (2011) in the study to derive improved initial and continuing loss values using data from selected catchments in New South Wales (NSW) with the use of 253 rainfall runoff events from five NSW catchments, had found that the median initial loss value was 17 mm and the median continuing loss value was 0.94 mm/h .

Halwathura and Najim (2013) in their study done for Attanagalu oya basin concluded that SCS CN loss method did not perform well but deficit constant loss method was a good option.

USACE (2000) provides advantages and disadvantages of precipitation loss models in HEC HMS.

Among the nine different loss methods available in HEC HMS to simulate precipitation losses, only the deficit and constant method and the soil moisture accounting method can be used for continuous hydrologic modeling (Cunderlik and Simonovic, 2004). In deficit and constant loss method, there are three parameters. They are (1) Initial Deficit (2) Maximum Storage and (3) Constanta Loss.

Initial deficit indicates the amount of water required to saturate the soil layer to the maximum storage (USACE, 2000). Maximum Storage is the amount of water the soil layer can hold specified as a depth. The upper bound would be the depth of active soil layer multiplied by porosity (USACE, 2000). There are no typical values found for maximum storage. But, this is similar to maximum potential retention (S) defined by SCS Curve Number method. Maximum potential retention, S can be calculated using SCS method (Chow et al., 2010).Composite CN value is calculated as described by Chow et al. (2010).

The constant rate defines the infiltration rate when the soil layer is saturated (USACE, 2000).

2.5.2 Transform model

There are seven transform methods in HEC HMS model. Halwathura and Najim (2013) in their study done for Attanagalu oya basin, concluded that Snyder unit hydrograph method simulated flows more reliably than Clark unit hydrograph method.

Lag time is the only parameter in SCS transform model. Lag time is proportional to the time of concentration, T_c which is calculated using Kirpich formula (Chow et al., 1998).

2.5.3 Baseflow model

There are 4 methods of baseflow modeling in HEC HMS such as, bounded recession baseflow, constant monthly baseflow, linear reservoir baseflow and recession baseflow. Recession baseflow model is designed to approximate the typical behavior observed in watersheds when channel flow recedes exponentially after an event. Although this method is intended primarily for event simulation, it has the ability to automatically reset after each storm event and consequently may be used for continuous simulation (USACE, 2000).

There are three parameters of recession baseflow model. These are (1) Initial flow (2) Recession Constant and (3) Recession Threshold Flow/Ratio.

2.5.4 Routing model

There are six routing methods in HEC HMS to compute river routing named as lag, kinematic wave, modified pulse, Muskingam, Muskingm Cunge and straddle stagger routing method. USACE (2000) discuss the applicability and limitations of routing models and provides guidelines for selecting routing model. Various issues such as back water effects, flood plain storage, interaction of channel slope, configuration of flow network, occurrence of sub critical and super critical flow and availability of data are discussed. The kinematic wave and Muskingam models cannot account for the influence of backwater on the flood wave, because these are based on uniform flow assumptions and only modified pulse model can simulate backwater effects (USACE, 2000). Further, it says that flood flows through extremely flat and wide flood plains may not be modeled accurately as one dimensional flow.

By quoting Birkhead and James (2002), Nandalal and Ratnayake (2010) mentioned that Muskingam model accounts explicitly for channel storage only and not total storage along a river reach which may include lateral inflows or outflows, losses and temporal changes in bank storage and hence the model may generate unrealistic values for Muskingam parameters. In their study for Kalu Ganga basin, as the lower reaches of basin bear such characteristics mentioned above, authors stated that Muskingam model was able to successfully model the lower reaches where as the Lag model which is suitable to steeper channel lengths was used to route the upper reaches of the river.

2.6 Automatic Parameter Optimization in HEC HMS

In automatic parameter optimization, HEC HMS model has default constraints that limit the ranges of optimized values. USACE (2000) describes that out of two search methods in HEC HMS, Univariate Gradient search method evaluates one parameter at a time while holding others constant where as Nelder and Mead method uses a downhill simplex to evaluate all parameters simultaneously and determine which parameter to adjust.

Skahill (2006) pointed out some limitations associated with the existing HEC HMS automatic parameter optimization capabilities and proposed some improvements. As potential improvements to existing HEC HMS automatic parameter optimization, Gauss-Marqardt-Levenberg (GML) method of computer based parameter estimation method was introduced. The author recommended two algorithmic enhancements to the GML method that retains its strengths, but overcomes its weaknesses in the face of local optima. Skahill (2006) developed a model for Goodwin Creek Experimental watershed in United States using HEC HMS. After calibrating the model using automated parameter optimization, author concluded that the ability to find the global objective function minimum was an insufficient requirement to attain a hydrologically acceptable model.

3 METHODOLOGY

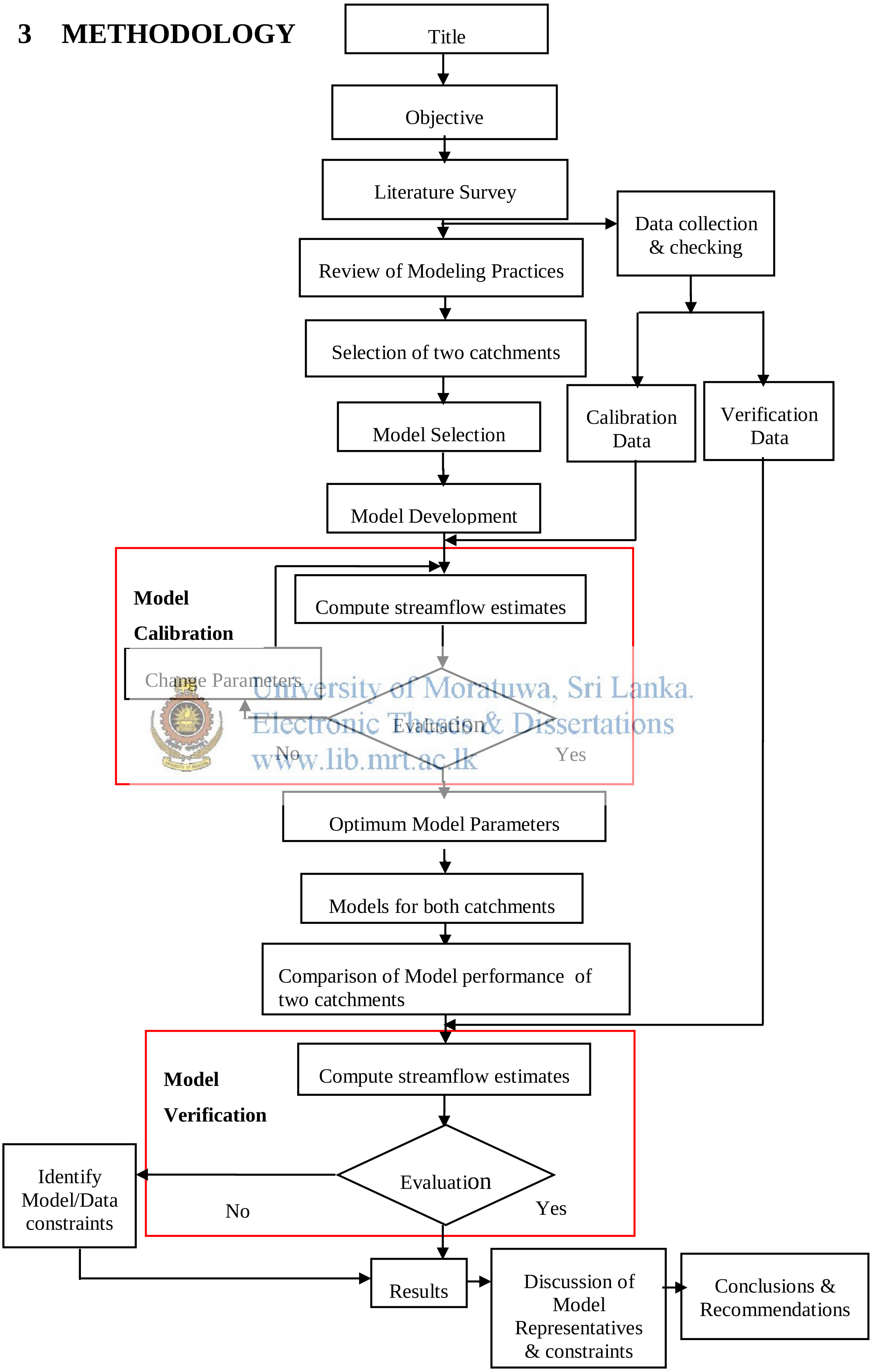

Figure 3-1 Methodology flow chart of the study

The methodology used in this research is shown in Figure 3-1. After identifying the objective and specific objectives, literature survey was carried out to identify the commonly used hydrological models and their applications and various objective functions. After reviewing various models which have been applied to many river basins, by considering model availability and flexibility, HEC HMS model is selected for Kalu Ganga basin as it is the only software freely available. Two catchments are selected for the purpose of comparison of parameters and model performances. Model development is carried out by considering three main components, basin model, precipitation model and control specification. There are several sub models in the basin model itself for rainfall loss, direct runoff, baseflow and channel routing and selection of sub models are done by considering several criterion. Three models developed are Ratnapura and Ellagawa Lumped models and Ellagawa distributed model. Model development, calculation of initial parameters and selection of objective functions is described in Chapter 5.3. Four year data from October 2006 to September 2007 were used for model calibration and the balance four year data from October 2010 to September 2014 were used for model verification. The model performances are evaluated for the minimum value of Mean Ratio of Absolute Error (MRAE) as the objective function. In addition, percent error in volume (also referred as mass balance error) and Nash-Sutcliff were also checked for observation. All three models, Ellagawa lumped, Ratnapura lumped and Ellagawa distributed models are calibrated and verified. Objective function values corresponding to model calibration and verification and graphical presentations are given in Chapter 5.4 for all three models.

4 DATA COLLECTION AND DATA CHECKING

4.1 Study Area

Ellagawa watershed is a sub watershed of Kalu Ganga basin and the drainage area of Ellagawa watershed is 1358 km^2. In the study area there are two river gauging stations at Ratnapura and at Ellagawa. Four rain gauging stations namely, Ratnapura, Alupola, Pelmadulla and Nivithigala which are located within the study area and one station namely Halwathura which lies little away from the boundary were selected. The locations of river gauging / rain gauging stations, Ellagawa and Ratnapura watershed boundaries are shown in Figure 1-1 and Table 4-1. Data sources and resolutions are given in Table 4-2. Land use details of the Ellagawa study area is in Table 4-3 and Figure 4-1.

Table 4-1 Location of gauging stations

Gauging station	Location
Hawathura	80° 21′ 36″ E 60° 48′ 0″ N
Ratnapura	80° 24′ 0″ E 60° 5′ 30″ N
Alupola	80° 34′ 48″ E 60° 43′ 12″ N
Pelmadulla	80° 31′ 48″ E 60° 37′ 12″ N
Nivithigala	80° 15′ 36″ E 60° 21′ 36″ N
Ratnapura River gauging	80° 27′ 10″ E 60° 37′ 20″ N
Ellagawa River gauging	80° 13′ 0″ E 60° 43′ 53″ N

Table 4-2 Data sources and resolutions

Data type	Temporal resolution	Data period	Data source
Rainfall	Daily	October 2006 to September 2014	Department of Irrigation and Department of Meteorology
Streamflow	Daily		Department of Irrigation
Evaporation	Monthly		Dept. of Irrigation
Topographic	1:50,000		Dept. of Survey
Contour	1:10,000		Dept. of Survey
Land use	1 : 50,000		Dept. of Survey

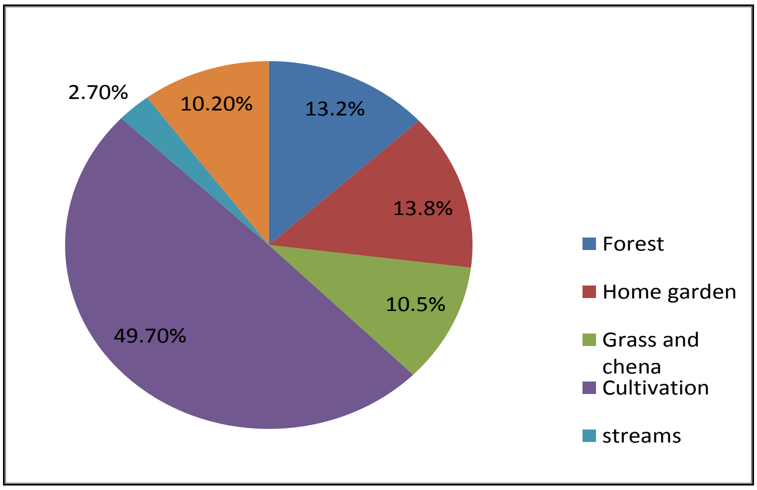

Figure 4-1 Land use for Ellagawa study area

It is observed that about 49.7% of the study area is under cultivation. Forest area is 13.2% and grass and chena land is 10.5%.

Table 4-3 Land use types of Ellagawa catchment

Land use type	Area (%)	Area (km^2)
Forest	13.2	385
Home garden	13.8	403
Grass and chena	10.5	307
Cultivation	49.8	1456
streams	2.7	78.83

4.2 Data and Data Checking

The main types of data used in this study are daily rainfall, daily streamflow, monthly evaporation, 1 : 50,000 topographic data and 1 : 10,000 terrain data.

4.2.1 Annual water balance

Annual water balance was carried out for both Ellagawa and Ratnapura watersheds in order to compare the annual volume of rainfall, streamflow, evaporation and annual runoff coefficients. Annual water balance of Ellagawa watershed is shown in Table 4-4.

Table 4-4 Annual water balance calculation of Ellagawa watershed

Year	Annual rainfall (mm/year)	Annual streamflow (mm/year)	Annual evaporation (mm/year)	Annual runoff coefficient
2006/2007	2721	1531	1191	0.6
2007/2008	2716	2287	429	0.8
2008/2009	2831	1540	1291	0.5
2009/2010	3279	1780	1499	0.5
2010/2011	3193	1943	1250	0.6
2011/2012	2509	820	1690	0.3
2012/2013	3856	1934	1923	0.5
2013/2014	3381	1487	1894	0.4
Average	**3061**	**1665**	**1396**	**0.5**

4.2.1.1 Variation of annual runoff coefficients and evaporation of Ellagawa

Annual runoff coefficient varies from 0.3 to 0.8 during the 8 year period. It can be observed that in year 2007/2008, runoff coefficient is very high compared to other years where as it is very low in year 2011/2012 (Figure 4-2). The runoff coefficient value of Kalu Ganga basin was verified with the values recommended by literature. Annual runoff coefficient values were again compared with those given in the Hydrological Annuals prepared by the Hydrology Division of Irrigation Department. In 2011/2012, runoff coefficient given in the Annual report is 0.29. In 2007/2008, evaporation also has a very low value compared with other years. The reason is that the streamflow does not respond to the rainfall in this year. If this data point is disregarded, there is a slight increasing trend (Figure 4-2). The maximum evaporation can be seen in year 2012/2013. This is because the highest rainfall is observed in that year but corresponding streamflow is not that high.

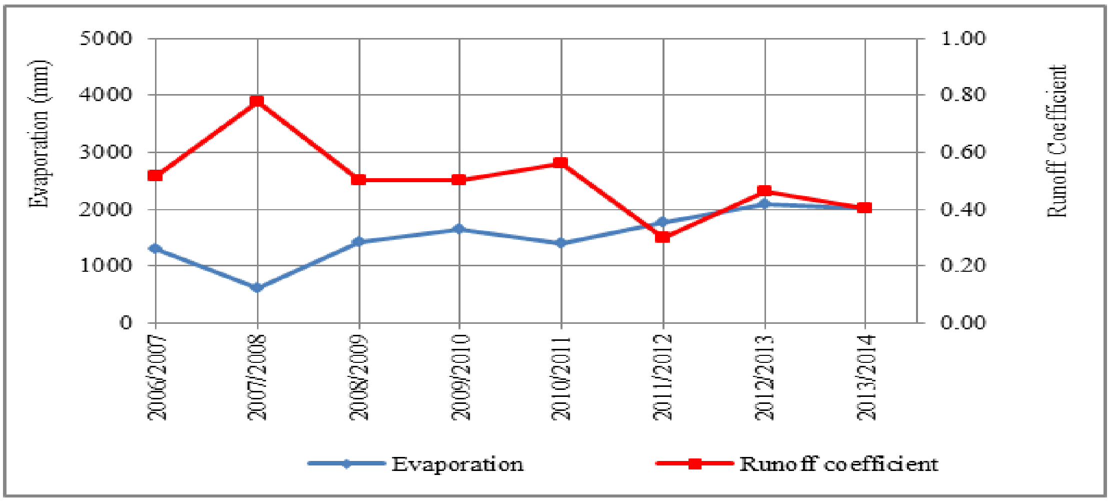

Figure 4-2 Variation of annual evaporation and runoff coefficient of Ellagawa catchment

4.2.1.2 Variation of annual rainfall and streamflow of Ellagawa

Although rainfall values in first three years are almost same, streamflow in year 2007/2008 is comparatively very high. It can be observed in Figure 4-3 that although rainfall in 2006/2007 and 2007/2008 are almost the same, streamflow had increased from 2006/2007 to 2007/2008 by 756 mm and this is unexpected. In contrast, the streamflow in 2011/2012 has decreased up to 820 mm which is the lowest streamflow value during the period which shows that streamflow in this year does not respond to rainfall. Year 2011/2012 can be observed as the driest year, but the streamflow is much smaller leading to a value of high evaporation and low runoff coefficient. This reveals that there may be inconsistencies in streamflow data.

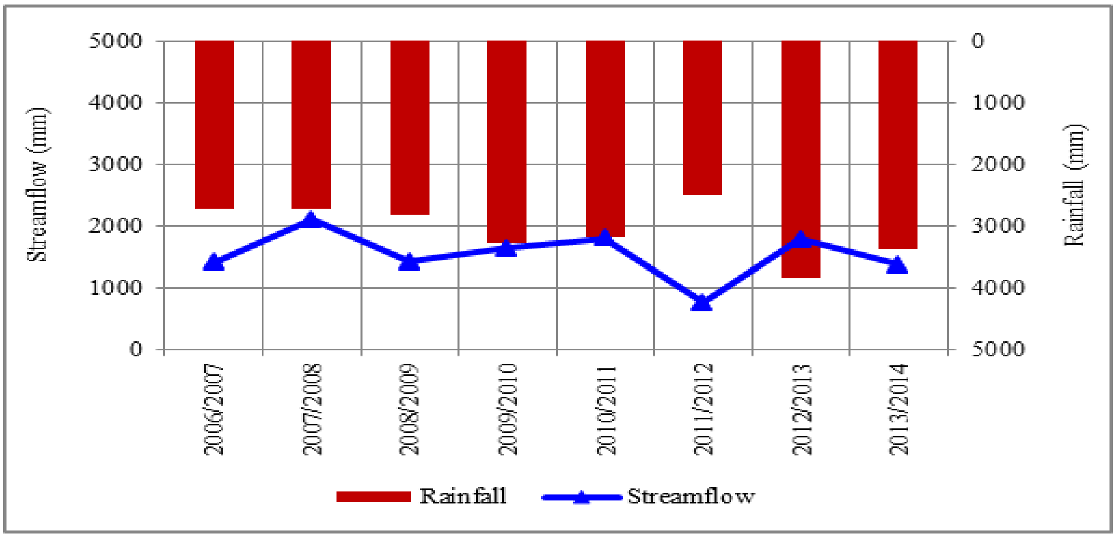

Figure 4-3 Variation of annual rainfall and annual streamflow of Ellagawa catchment

Annual water balance of Ratnapura watershed is given in Table 4-5, Figure 4-4 and Figure 4-5.

Table 4-5 Annual water balance of Ratnapura watershed

Year	Annual rainfall (mm/year)	Annual streamflow (mm/year)	Annual evaporation (mm/year)	Annual runoff coefficient
2006/2007	2634	1630	1004	0.6
2007/2008	3045	2016	1028	0.7
2008/2009	2918	1707	1210	0.6
2009/2010	3417	1716	1701	0.5
2010/2011	3514	1854	1660	0.5
2011/2012	2040	871	1170	0.4
2012/2013	4348	1964	2385	0.5
2013/2014	3391	1311	2080	0.4
Average	**3164**	**1634**	**1530**	**0.5**

4.2.1.3 Variation of annual runoff coefficient and evaporation of Ratnapura

While observing annual volumes of rainfall, streamflow, evaporation and runoff coefficients, similar to Ellagawa watershed, runoff coefficient in year 2007/2008 is very high compared to other years. It can be observed in Figure 4-4 that there is a decreasing trend in runoff coefficient resulting evaporation to have an increasing trend. In 2011/2012 and 2012/2013 years, runoff coefficients are small. In 2012/2013 and 2013/2014 years, annual evaporation are high.

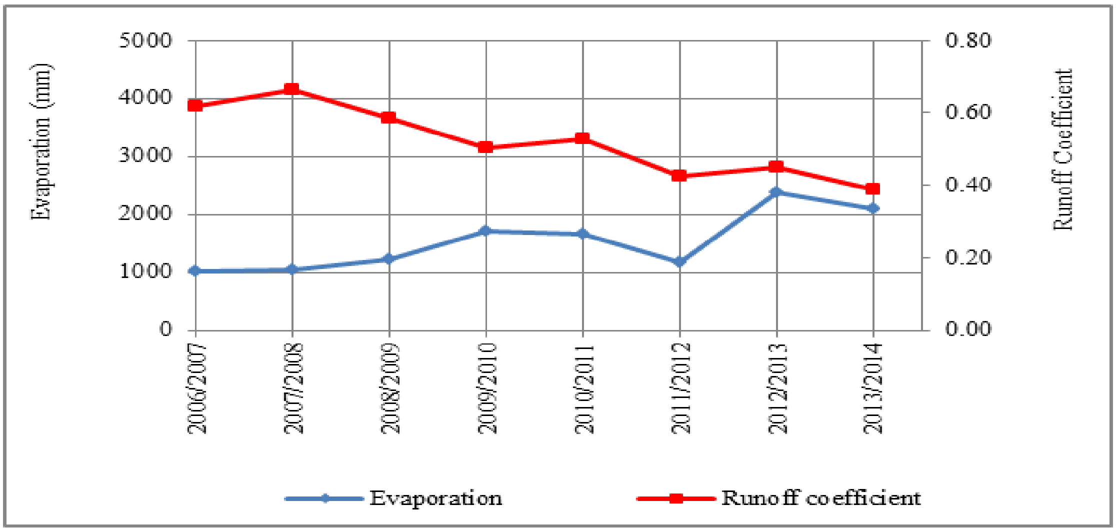

Figure 4-4 Variation of annual evaporation and runoff coefficient of Ratnapura catchment

4.2.1.4 Variation of annual rainfall and streamflow of Ratnapura

Similar to Ellagawa watershed, 2011/2012 year is the driest year in Ratnapura watershed and streamflow responses to rainfall is very poor there by resulting a very low streamflow volume with a low runoff coefficient (Figure 4-5). In the years 2012/2013 and 2013/2014, although rainfall is very high, streamflow values are not comparative. This again shows the non responsiveness of streamflow to rainfall during these years.

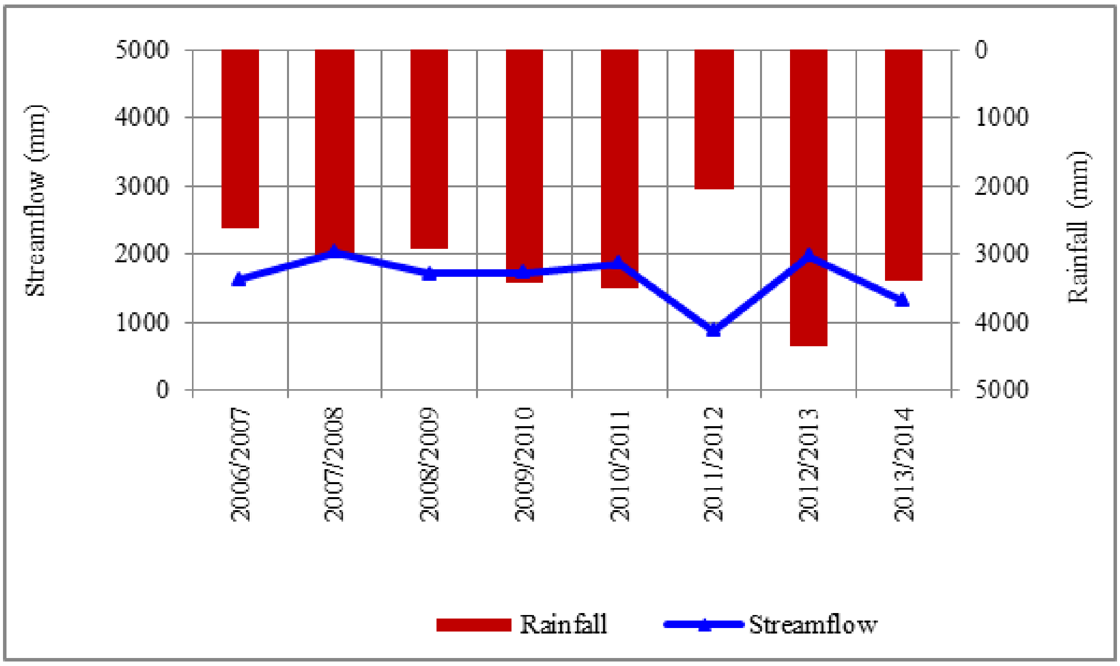

Figure 4-5 Variation of annual rainfall and annual streamflow of Ratnapura catchment

4.2.2 Visual data checking

Visual checks were also carried out to find whether there are inconsistencies in data. Streamflow responses to rainfall were plotted for each rain gauging station and for each year. Figure 4-6 presents streamflow responses of Ellagawa river gauging station with rainfall for each rain gauging station in year 2007/2008. The plots of Ellagawa streamflow with rainfall in each station for 2011/2012 are in Figure 4-7.

It can be observed that in Figure 4-6, Ellagawa streamflow does not respond to the rainfall of Ratnapura during December 2007 and January 2008. These points are marked as red circles. Streamflow responds well with the Alupola rainfall. It is not responding to Pelmadulla rainfall too in January 2008. Responsiveness with Nivithigala rainfall is also satisfactory. Streamflow does not respond with Halwathura rainfall at all in February 2008. This shows that there are abnormalities in rainfall and streamflow in December, January and February months of 2007/2008 and these periods can be identified as mismatching periods and the accuracy of results of the study for this period may require careful study. Streamflow responses of Ellagawa to rainfall in other years are shown in Appendix A.

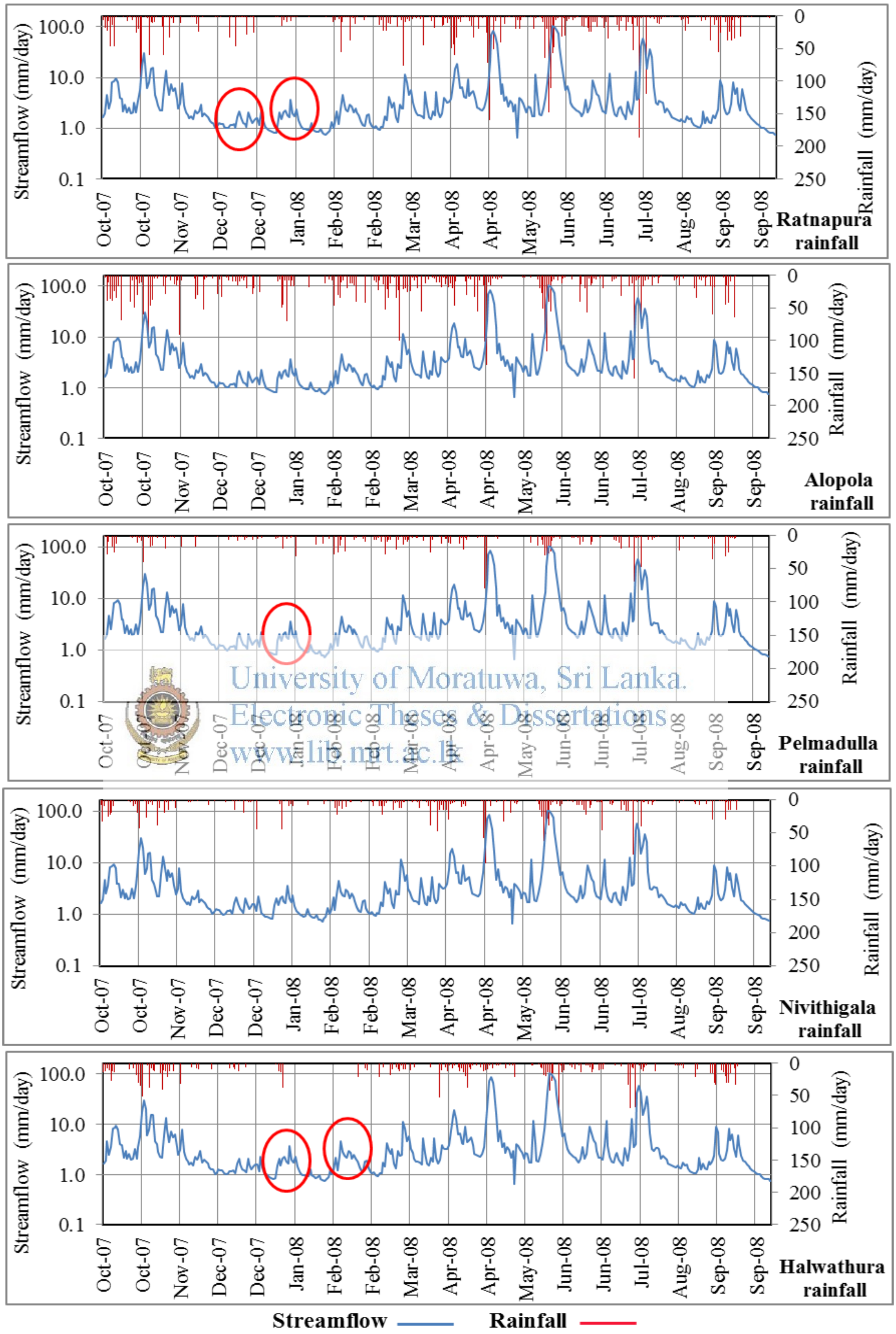

Figure 4-6 Ellagawa streamflow response with rainfall in 2007/2008

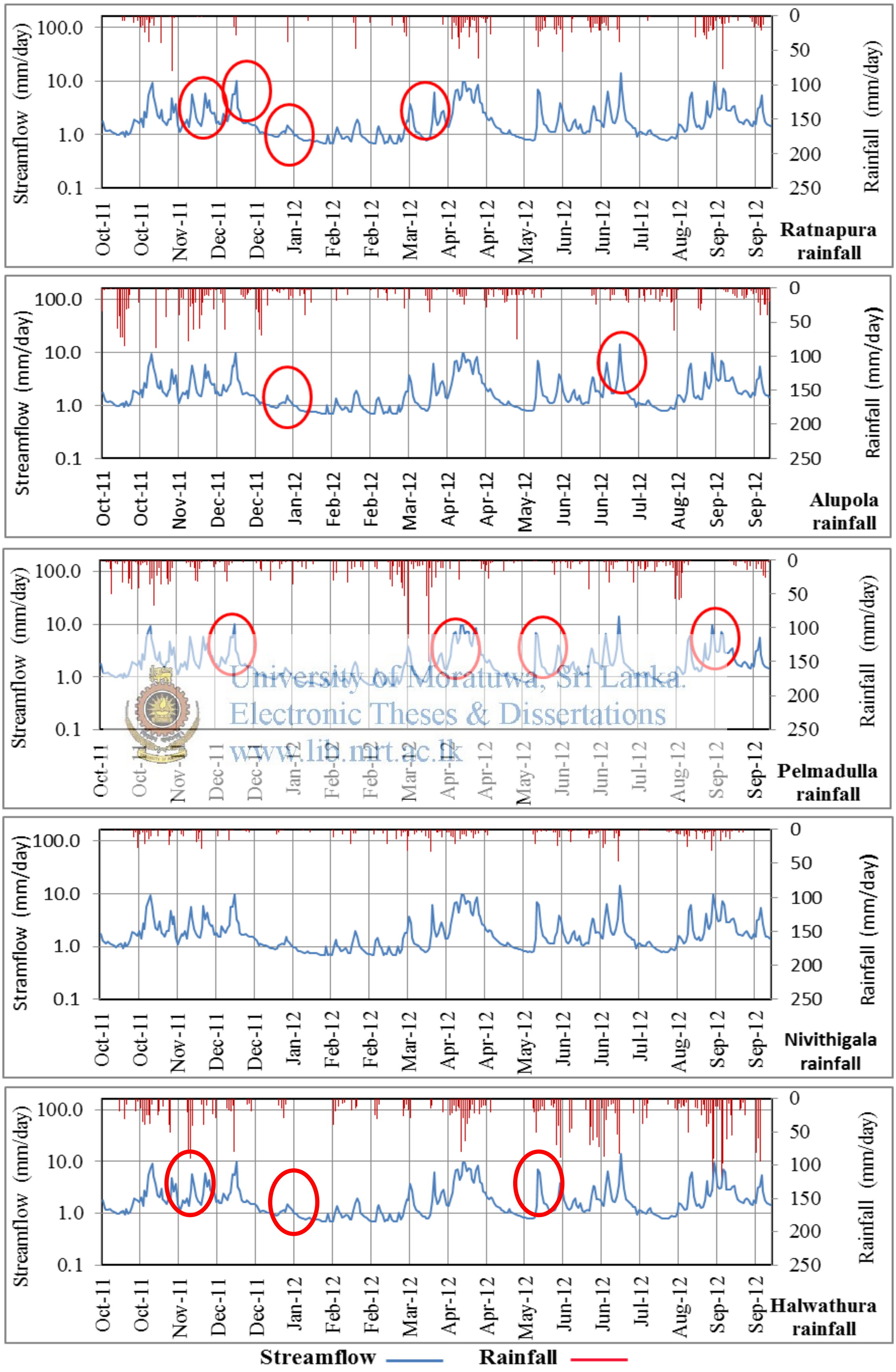

Figure 4-7 Ellagawa streamflow response with rainfall in 2011/2012

In Figure 4-7, Ellagawa streamflow response with Ratnapura rainfall, it can be observed that there are streamflow peaks without rainfall pulses during November and December of 2011 and April of 2012 too. There is a high peak in July 2012 with Alupola rainfall, but the rainfall is not comparative. There are high peaks during December of 2011 and April, May and September of 2012 without any rainfall pulse in Pelmadulla rainfall.

Similar to Ellagawa, rainfall responsiveness of Ratnapura with rainfalls in rain gauging stations are plotted and given in Appendix A.

4.2.3 Theissen average rainfall

Theissen polygon method (Chow, 2010) was used to calculate the catchment average rainfall. Theissen polygons were developed for both Ellagawa and Ratnapura catchments. Theissen polygons are shown in Figure 4-8 and Figure 4-9. Theissen average for Ellagawa and Ratnapura catchments are in Table 4-6 and Table 4-7 respectively.

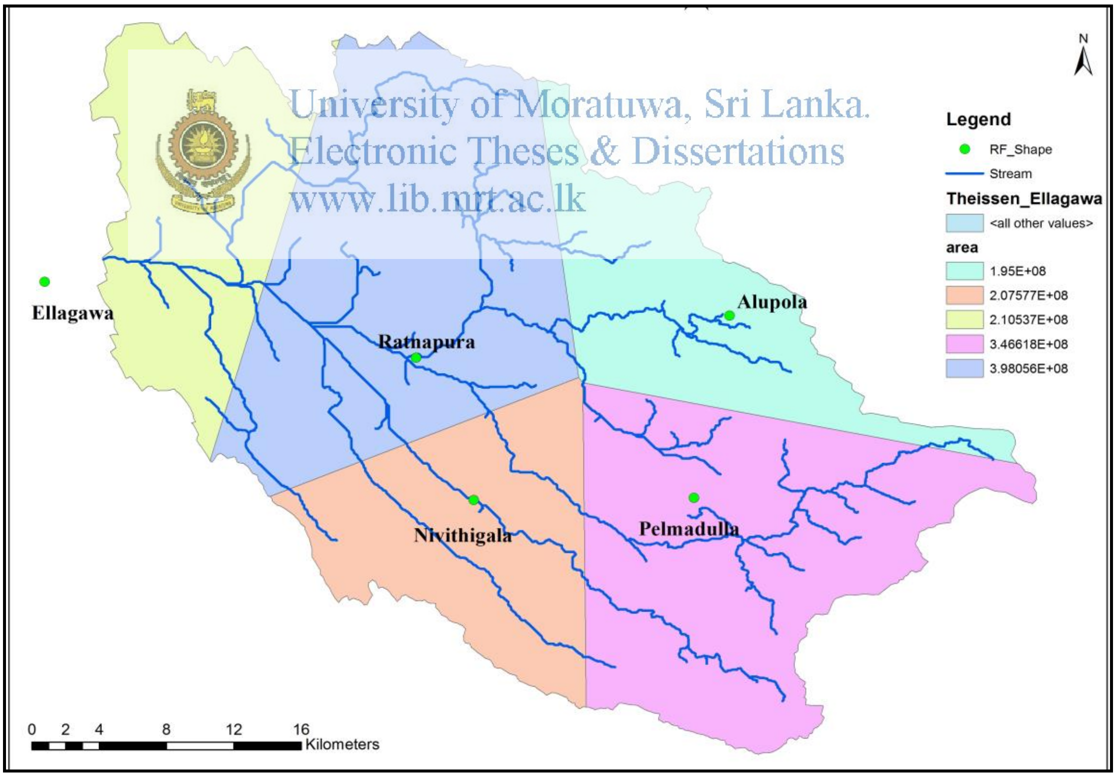

Figure 4-8 Theissen polygons of Ellagawa catchment

Table 4-6 Thiessen weights of rain gauging stations – Ellagawa catchment

Rainfall station	Area (km^2)	Thiessen weight
Ratnapura	237.3	0.39
Alupola	4.5	0.01
Pelmadulla	89.3	0.15
Nivithigala	135.9	0.22
Halwathura	144.4	0.24

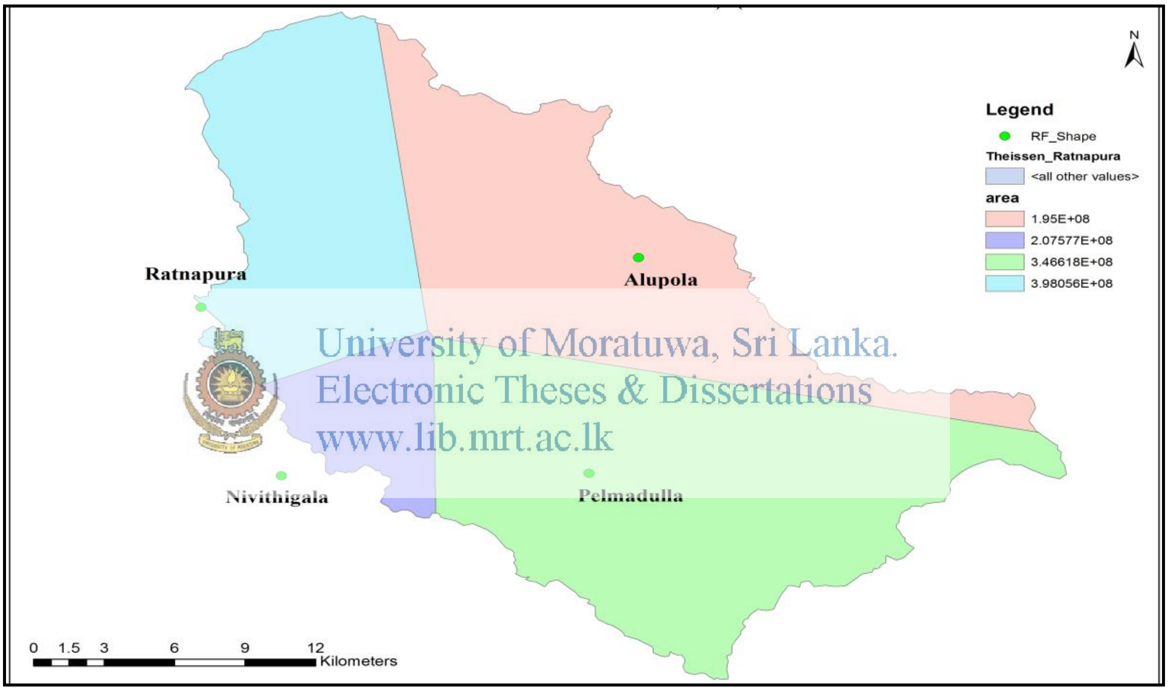

Figure 4-9 Theissen polygons of Ratnapura catchment

Table 4-7 Thiessen weights of rain gauging stations – Ratnapura catchment

Rainfall station	Area (km^2)	Thiessen weight
Ratnapura	156.1	0.25
Alupola	184.5	0.29
Pelmadulla	249.6	0.39
Nivithigala	44.9	0.07

Thiessen average rainfall and streamflow are plotted in the same plot for each year and for each river gauging station. Theissen average rainfall with Ratnapura streamflow are given in Figure 4-10 to Figure 4-11. It can be observed that in each year, most of the high streamflow peaks responded well with rainfall. In year 2006/2007, streamflow does not respond to rainfall in December 2006, May and August 2007 period. It can be observed small peaks on 16th April 2007 and 4th February 2007 without significant increase in rainfall. These peaks can be identified as erroneous streamflow data entry. In 2007/2008 year also, it can be observed some non responsive streamflow peaks such as 22nd January 2008, 2nd February 2008. In 30th March 2008, an erroneous peak can be noted. Figure 4-12 shows a non responsive streamflow peak on 9th December 2008 and an erroneous streamflow peak on 17th February 2009. It was noted that in all years, streamflow response in wet season is good whereas all non responsiveness or erroneous streamflows can be observed in dry season. This indicates that in low flow periods, it can be seen some abnormalities in streamflow either due to streamflow issues or due to spatial variability of rainfall.

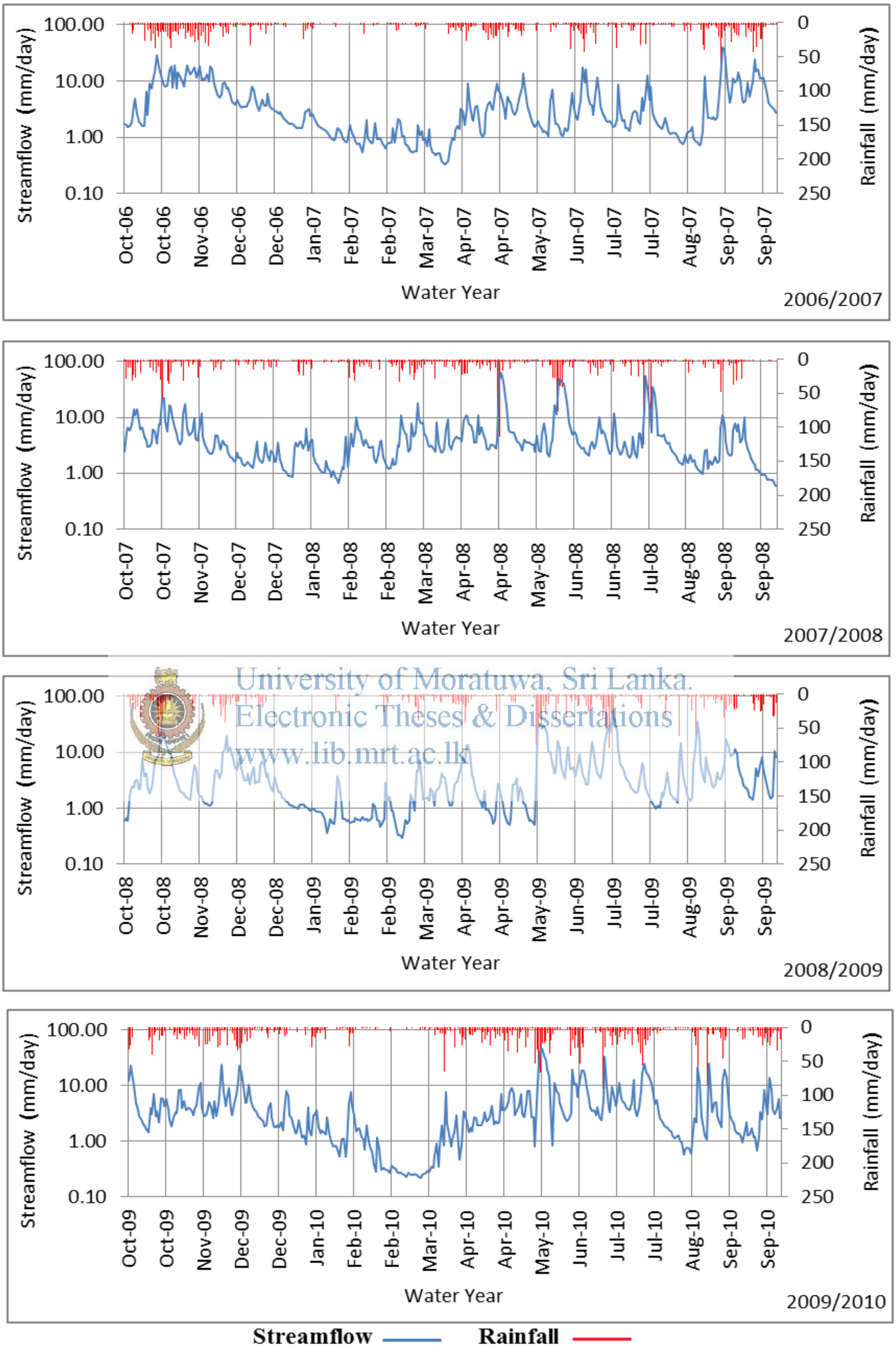

Figure 4-10 Ratnapura streamflow with Theissen average rainfall during calibration period

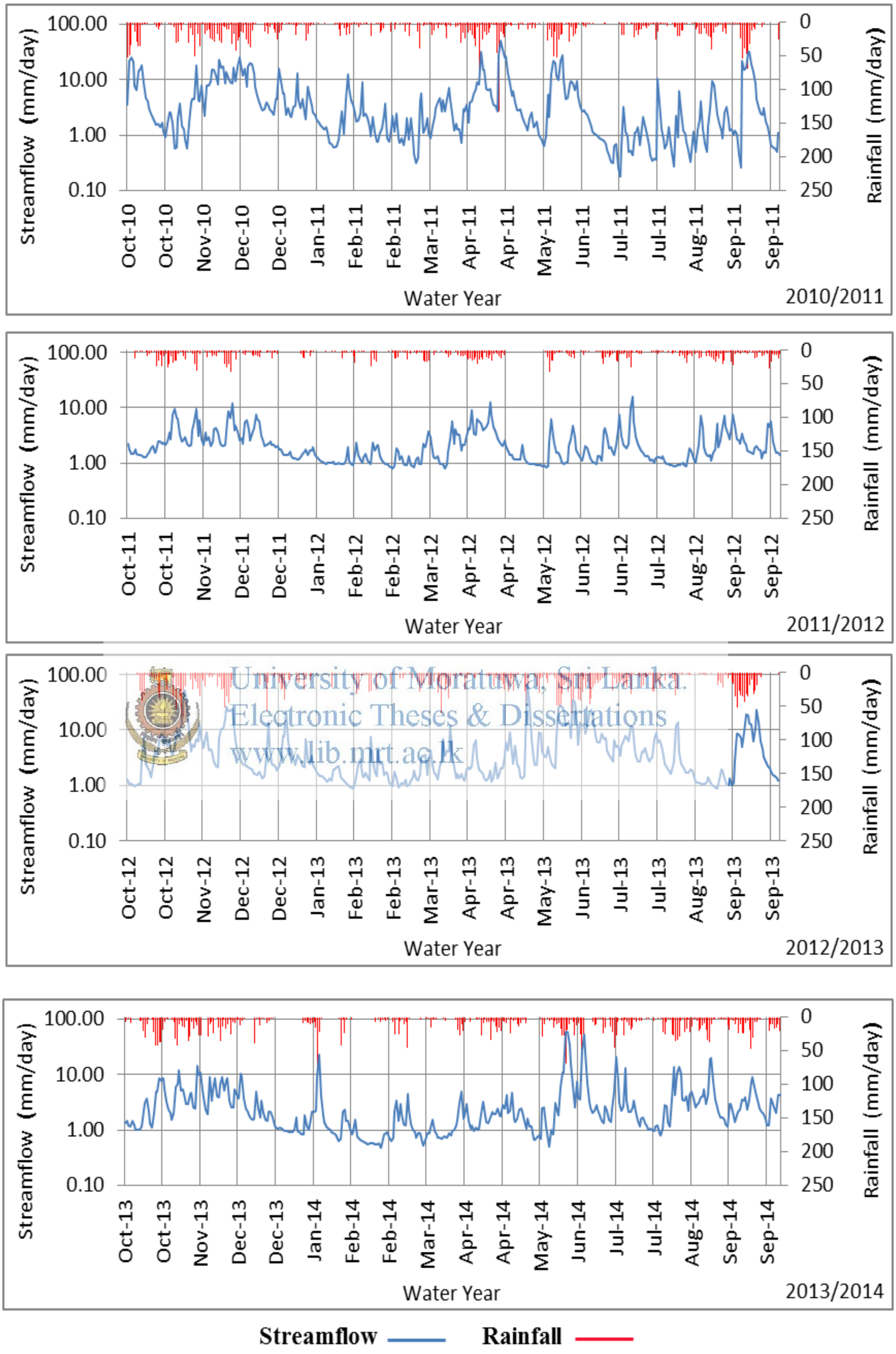

Figure 4-11 Ratnapura streamflow with Theissen average rainfall during verification period

Theissen average rainfall with Ellagawa streamflow are also plotted and shown in Figure 4-12 and Figure 4-13 for model calibration and verification period.

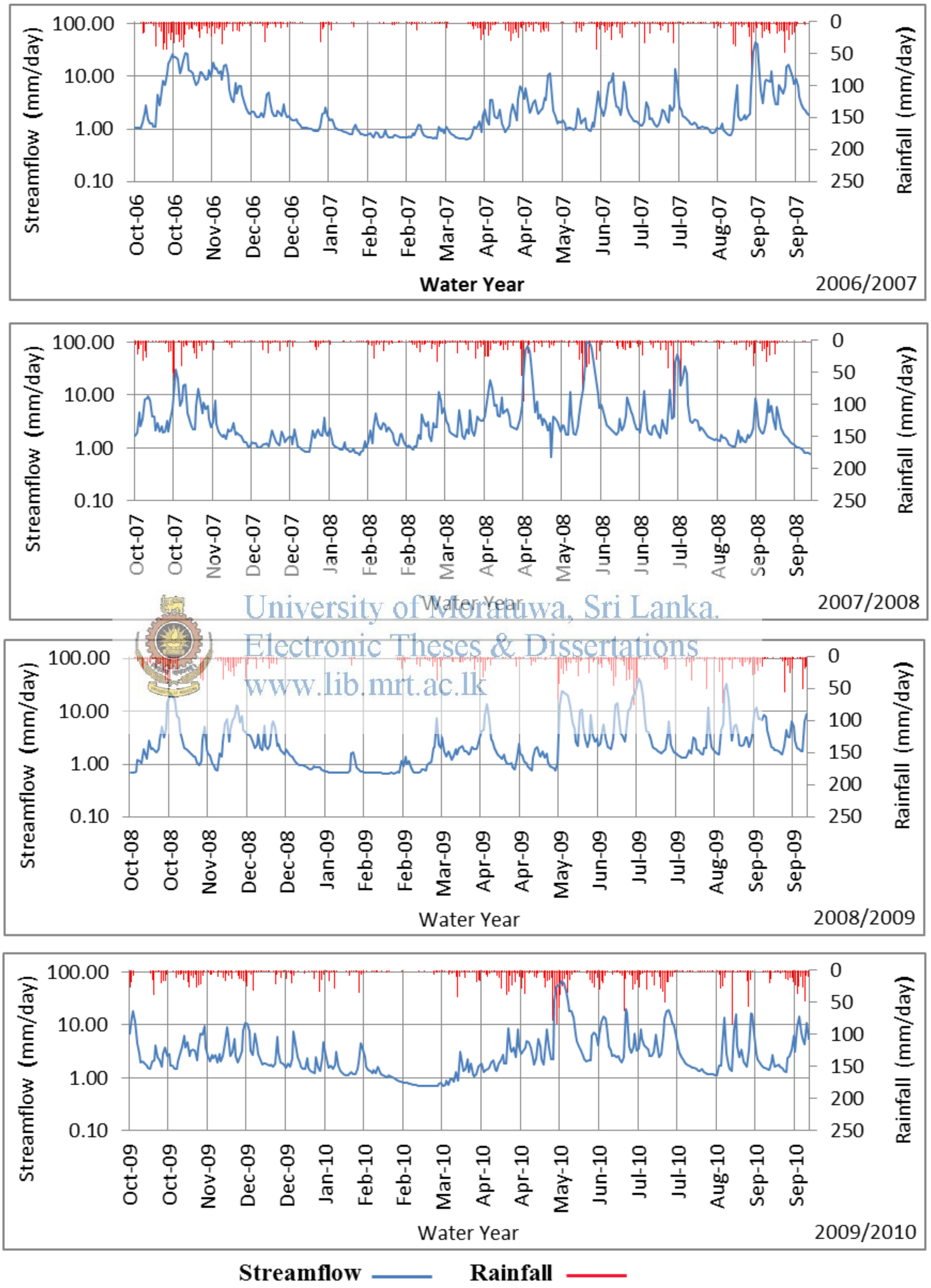

Figure 4-12 Ellagawa streamflow with Theissen average rainfall during calibration period

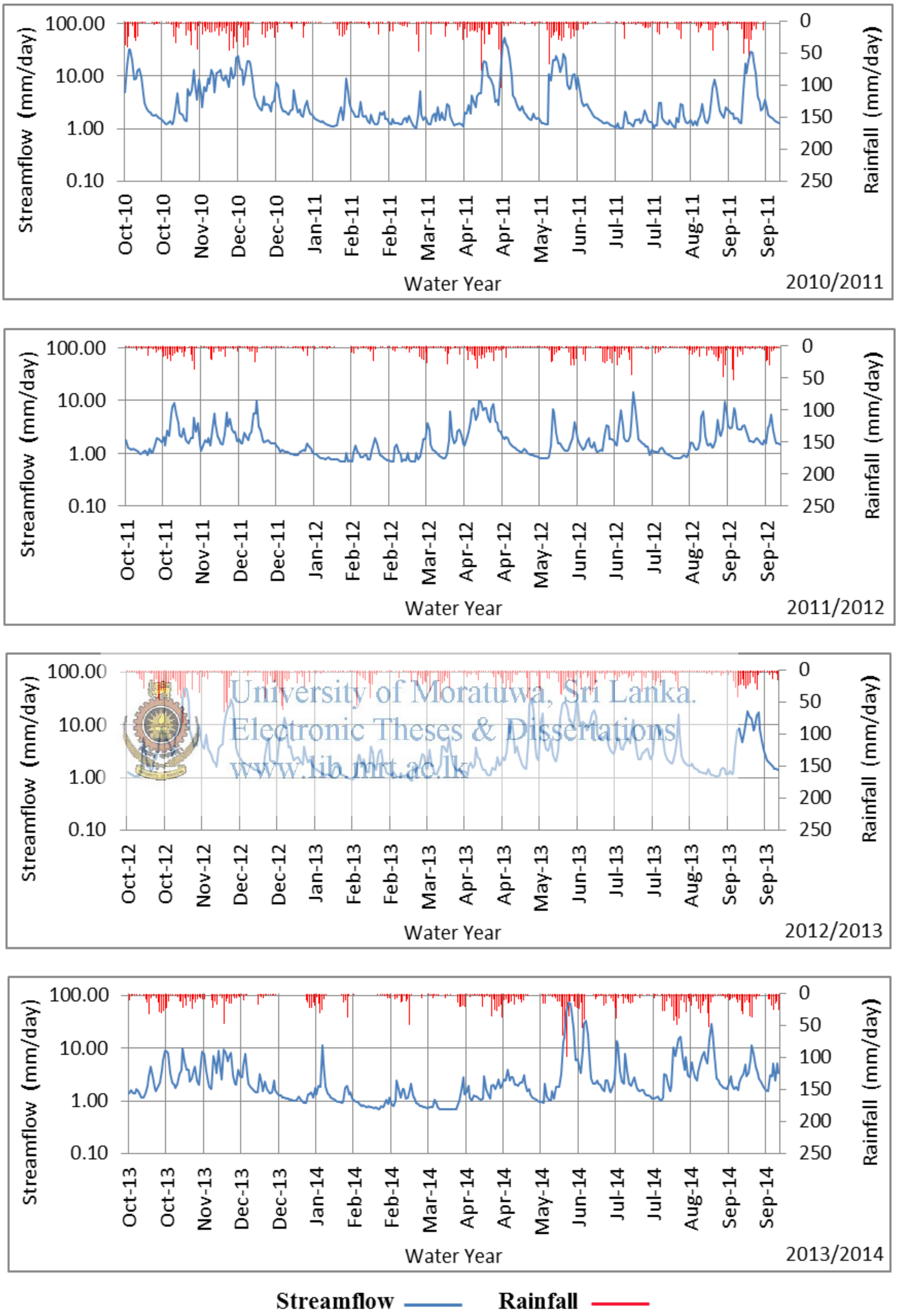

Figure 4-13 Ellagawa streamflow with Theissen average rainfall during verification period

There are some more abnormalities in theissen average rainfall and Ratnapura streamflow too. Although it can be observed in Figure 4-10, that there is a high peak in May 2007, there is no significant increase in rainfall. In 2007/2008, 2010/2011 and 2012/2013, streamflow responses with rainfall is good and there are no identified abnormalities. Here also, it is noticed that there are several non responsive streamflow when compared with rainfall in dry period.

4.2.4 Monthly and annual rainfall

Table 4-8 Comparison of monthly average rainfall

Month	Monthly average rainfall (mm)				
	Halwathura	Ratnapura	Alupola	Pelmadulla	Nivithigala
October	492	381	593	279	203
November	455	338	491	226	202
December	283	178	332	100	86
January	114	116	193	95	85
February	98	99	151	104	69
March	170	174	241	232	138
April	357	476	294	229	164
May	345	351	418	233	184
June	443	451	483	267	204
July	261	277	324	205	153
August	305	304	331	195	168
September	435	342	434	229	159
Annual Total	**3759**	**3487**	**4283**	**2392**	**1815**

Monthly average rainfall of Ratnapura, Alupola, Pelmadulla, Nivithigala and Halwathura rain gauging stations are given in Table 4-8 and it is graphically presented in Figure 4-14. This follows two seasonal rainfall patterns corresponding to North East Monsoon

(October to March) and South West Monsoon (April to September). Monthly average rainfall of Pelmadulla and Nivithigala are lesser than rainfall of other three stations.

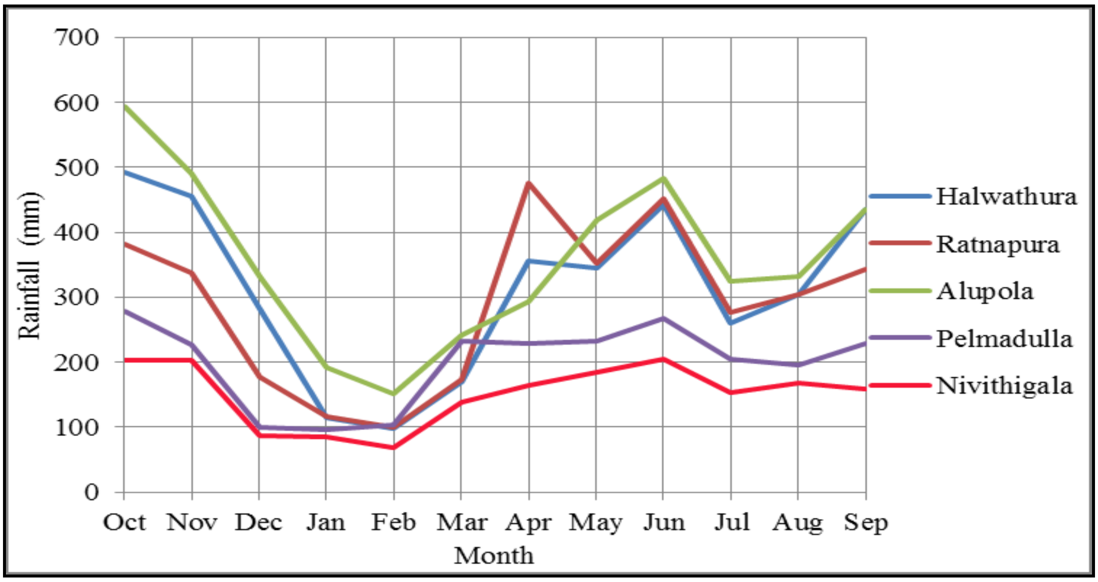

Figure 4-14 Variation of monthly average rainfall in Ellagawa catchment

Table 4-9. Comparison of annual rainfall

Water Year	Annual rainfall (mm)				
	Halwathura	Ratnapura	Alupola	Pelmadulla	Nivithigala
2006/2007	3277	4595	4099	1415	1838
2007/2008	2041	3856	4520	1610	2094
2008/2009	3292	3409	3773	2169	1722
2009/2010	4001	3941	4482	2688	1654
2010/2011	3206	4226	4235	2693	1460
2011/2012	4351	1946	3080	2789	1273
2012/2013	5727	4236	5900	2247	2133
2013/2014	4223	3758	4128	2831	2149

Annual rainfall from October 2006 to September 2014 for each rain gauging station are given in Table 4-9 and it is plotted in Figure 4-15. There is a considerable drop in annual rainfall in Ratnapura and Alupola stations in year 2011/2012 (Figure 4-15). Annual Rainfall of Halwathura station shows an irregular pattern in 2007/2008 and 2010/2011 years. It can be observed that there is a rainfall increase in year 2012/2013 corresponding to all stations.

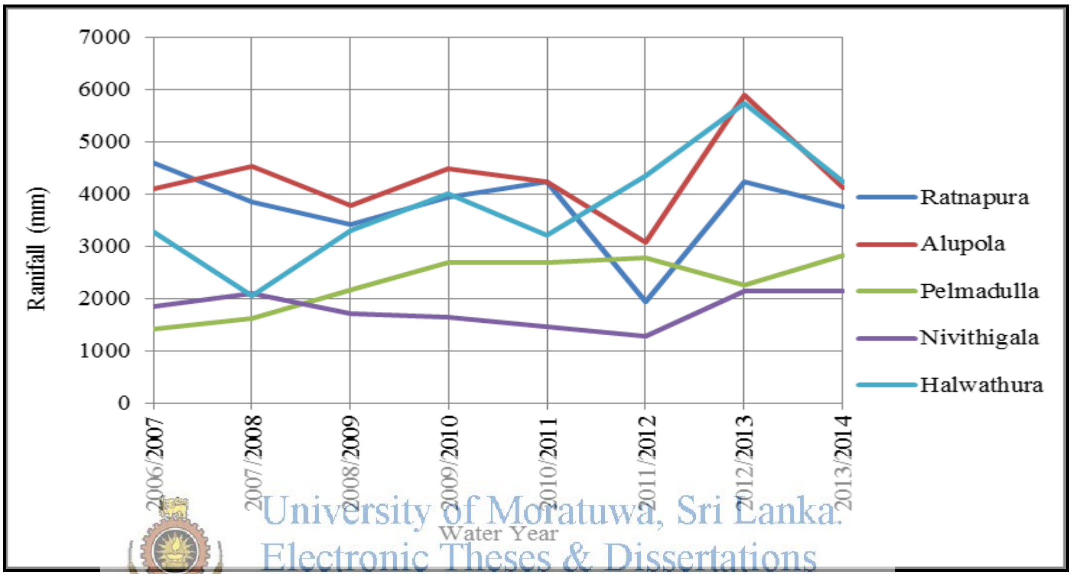

Figure 4-15 Annual rainfall variation in Ellagawa catchment

4.2.5 Moving average rainfall

The moving average rainfall was calculated and plotted for all stations in order to check whether there are significant variations of annual rainfall. Figure 4-16 shows almost a similar pattern. But, there are higher values in 2- year moving average rainfall when compared to others. After 2012/2013, 2 year moving average rainfall increases considerably. This is due to a considerable rainfall increase observed in 2012/2013 and 2013/2014.

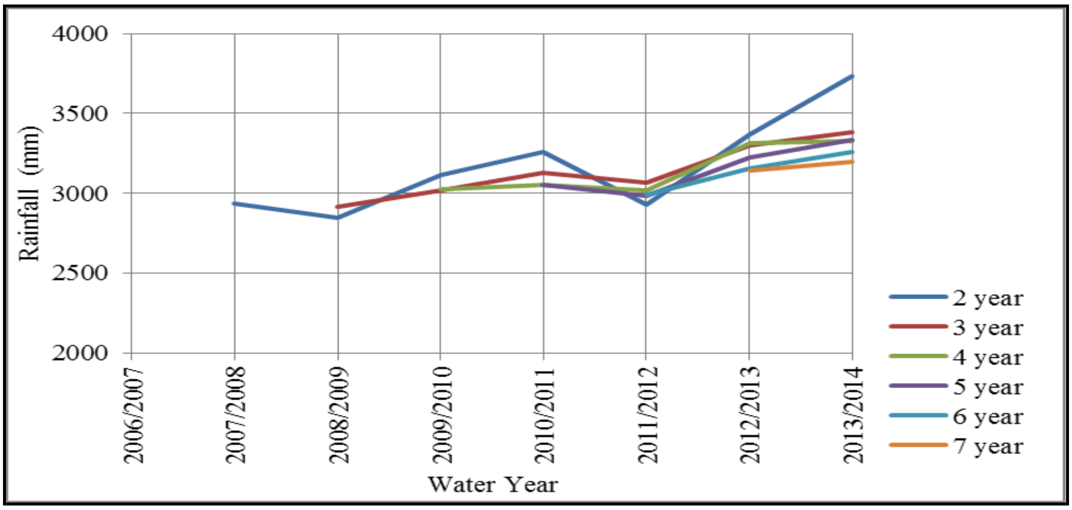

Figure 4-16 Moving average rainfall in Ellagawa catchment

4.2.6 Double mass curve

Double mass curve is used to check the consistency of many hydrologic data by comparing data for a single station with that of a pattern composed of the data from several other stations in the area. Double mass curves of cumulative rainfall data of one rainfall station with cumulative average of four nearby stations in the catchment were plotted to check the consistency of rainfall data. This graph is a straight line so that the relation between rainfall is a fixed ratio. Breaks in the graph are caused by changes in data collection or changes in the rainfall station etc. Cumulative rainfall and cumulative average rainfall are given in Table B-1 and Table B-2 of Appendix B and double mass curve plots are in Figure B-1 in Appendix B. It was observed that there is no significant inconsistency in rainfall data.

5 ANALYSIS AND RESULTS

5.1 Selection of Two Catchments

Two catchments were selected for the purpose of comparison of catchment parameters and model performances. Daily streamflow data are available for both Ratnapura and Ellagawa catchments. Hence, Ratnapura and Ellagawa catchments were selected for model development.

5.2 Model Selection

After reviewing common types of models in literature (Chapter 2.1), HEC HMS model was selected for developing a hydrological model for Ellagawa watershed as it is one of the freely available softwares.

5.3 HEC HMS Model Development

5.3.1 Review of modeling practices in HEC HMS

5.3.1.1 Review of rainfall objective

A sample data set from 01st October 2008 to 06th November 2008 was selected and used with the HEC HMS model for Ratnapura catchment in order to compare the theissen average rainfall output of the model with manual calculation. It was found that same rainfall values were obtained from both methods. Comparison of Theissen average rainfall variation by the model and manual calculation are shown in Figure C-1 of Appendix C.

5.3.1.2 Review of optimization criteria

There are several objective functions commonly used in literature (Chapter 2.4). In order to capture which objective function would serve the objectives of the present study, a qualitative evaluation was carried out considering the following criterion. (1) Reliability when using event or continuous simulation (2) Matching of shape and peak of hydrograph (3) Normalized functionality without relying on magnitude. After reviewing the advantages and disadvantages of each objective function based on the above criterion, Ratio of Absolute Error to Mean (RAEM), Mean Ratio of Absolute Error (MRAE) and Nash- Sutcliff objective functions were selected to evaluate the model performance.

A sample dataset from 01st October 2008 to 05th November 2008 was selected. Several trial computations were carried out by making comparison of several model estimations using trial parameters which was named as the base-set of parameters. This is assumed as a perfect model and named as “perfect”. Description of trials are in Table D-1 in Appendix D.

The outputs corresponding to base-set of parameters of HEC HMS model was considered as inputs (observed flow) when comparing with outputs of other parameter sets. Comparisons were carried out with another five sets of parameters which resulted in various catchment response characteristics. These outputs for the same input and output corresponding to base set of parameter for hydrograph and flow duration curve are shown in Figure D-1 and Figure D-2 in Appendix D. Behavior of the objective functions during each trial was considered. The order of magnitude and the rate of change of order of magnitude of the objective functions during each flow type (high, medium and low) were also computed.

For each trial, the model estimated streamflow time series were compared. Flow duration curves were divided as high, medium and low flow segments and then each segment was compared with the each objective function. Figure D-3 in Appendix D shows objective function variations for both hydrograph and flow duration curves. The values are in Table D-4 to Table D-9 in Appendix D.

5.3.1.3 Evaluation of objective functions

The behavior of objective functions during each trial was considered. The order of magnitude and the rate of change of order of magnitude of objective functions during each flow type (high flow, medium flow and low flow) was also computed and given in Table D-8 in Appendix D. In Table D-8, it was observed that when hydrograph matching, order of magnitude of trials of Nash-Sutcliff function is higher (4.4) than MRAE or RAEM functions. In flow duration curve matching too, order of magnitude of Nash-Sutcliff function is very much higher in high (25.6), medium (25.7) and low flow regions (14.0) than MRAE or RAEM functions. Convergence of objective function during parameter optimization is given in Table D-9 in Appendix D. High convergence can be observed in Nash-Sutcliff function than others. Similarly, the same procedure was followed for another five trials (Trial 6, Trial 7, Trial 8, Trial 9 and Trial 10) for matching time of occurrence and peak. The behavior of objective functions were studied by considering order of magnitude and convergence of objective functions. It was found that Nash-Sutcliff function is more sensitive in achieving time of occurrence with peak flow magnitude while both MRAE and RAEM functions are better for overall matching of hydrographs. In order to select the most suitable objective function for continuous simulation, MRAE and RAEM were compared. Two datasets (two flow series 1 and 2) were selected.(1) one dataset with very high peaks and very small low flows and the majority of the time low and intermediate flows (peak flows and average flow differ) and (2) similar flows all throughout the period. The model was calibrated using MRAE and RAEM separately as the objective function. Model performances were evaluated with respect to MRAE and RAEM for different range of flow series such as peaks, low flows etc. Matching of hydrographs for each range is given in Figure D-4 and Figure D-5 for series 1 and series 2 in Appendix D. The summary table of calculations is in Table D-2 and Table D-3 for each series.

5.3.1.3.1 Recommendation of objective function

Nash-Sutcliff function is more sensitive in peak matching while sensitivity of RAEM and MRAE in peak matching is not so significant. Also, in flow duration curve matching, Nash-Sutcliff function is more sensitive in high and medium flow regions than in low flow regions. Figure D-3 in Appendix D indicates that Nash-Sutcliff is more sensitive in capturing the peak flow while MRAE and RAEM show little sensitivity in peak flow matching. Therefore, when the objective of modeling is only flood prediction where event based modeling and model calibration using Nash-Sutcliff as the objective function would give better prediction of streamflow peaks.

For overall matching of flow duration curve, MRAE and RAEM function can be recommended. As the present study is a continuous simulation, these two functions are important in evaluation of model performance. In Table D-2, MRAE and RAEM values and rate of change of MRAE and RAEM with each cases showed that the cases very well reflected the characters of each streamflow series in MRAE. But, in RAEM, a marked difference cannot be seen in all cases.

Therefore, MRAE was selected for the study as the objective function.

5.3.1.4 Review of simulation time interval

When selecting simulation time interval in HEC HMS model, USACE (2000) states that the simulation time interval should be less than 0.29 times lag time for a subbasin. As there are small subbasins having lag time less than 24 hours, it is necessary to reduce the simulation time interval although the temporal resolution of the data available is 24 hours. Therefore, the model performance was evaluated with the change of simulation time interval from 24 hours to 6 hours.

A sample data set of year 2006/2007 was selected. The model performance for both 24 hour and 6 hour simulation time interval is in Figure D-5 in Appendix D. It was observed that with the change of the simulation time interval from 24 hours to 6 hours, there is a 6% change in annual mass balance and a one day shift of hydrographs.

5.3.2 Development of the basin model

In this study, it was necessary to model the river flow at Ratnapura and Ellagawa river gauging stations where daily streamflow data are available. The basin model for the entire Ellagawa watershed was developed considering subbasins. In addition, Ellagawa lumped model and Ratnapura lumped model were developed for comparison purposes.

5.3.2.1 Delineation of subbasins for Ellagawa watershed

Before delineating subbasins, Triangulated Irregular Network (TIN), Digital Elevation Model (DEM) were developed and stream network for Ellagawa watershed were generated. Figure 5-1, Figure 5-2 and Figure 5-3 show the TIN, DEM and stream network for Ellagawa watershed. Cell size used in making the TIN was 25 m and a threshold value of 20000 was taken when generating the stream network.

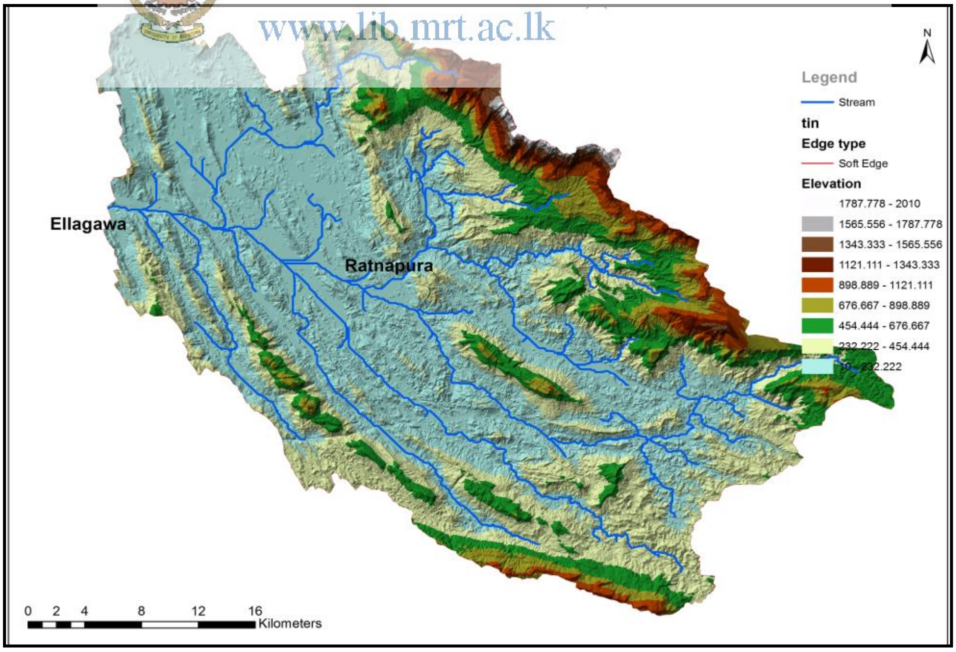

Figure 5-1 Triangulated Irregular Network (TIN) of Ellagawa catchment

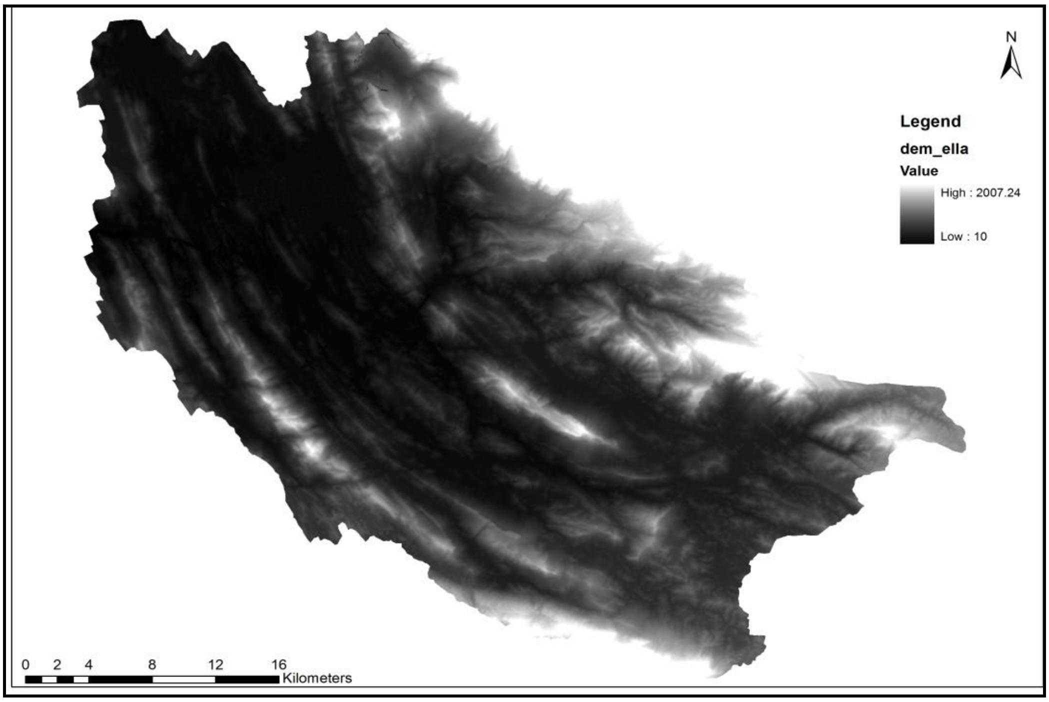

Figure 5-2 Digital Elevation Model (DEM) of Ellagawa catchment

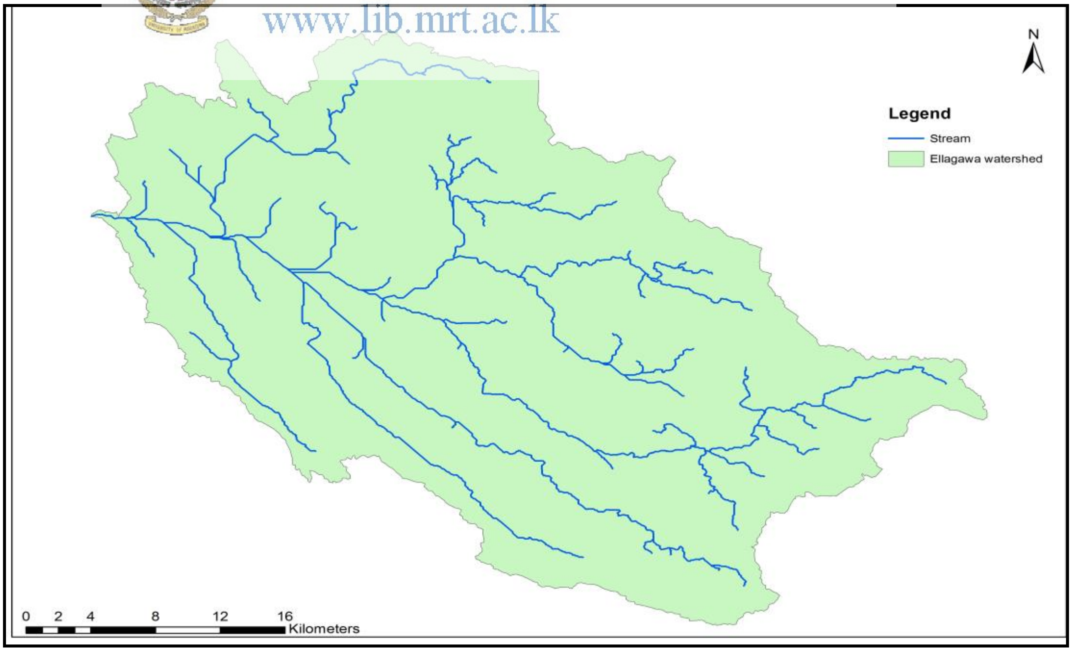

Figure 5-3 Generated stream network of Ellagawa catchment

In strahler method of stream ordering, the stream order is increased slowly and in shreve method, it increases rapidly. When using shreve method for delineating subbasins, it is very unlikely to have similar numbers as the numbers are increasing rapidly when moving from upstream to downstream. In strahler method, the numbers are increasing slowly and there are possibilities of having same numbers at main branches as the river network is a dendritic one. Hence, strahler method was selected and subbasins were delineated at stream order number 4. In addition to that, points at which observed streamflow data is available and the stream network pattern were also considered when delineating subbasins. Delineated subbasins are shown in Figure 5-4.

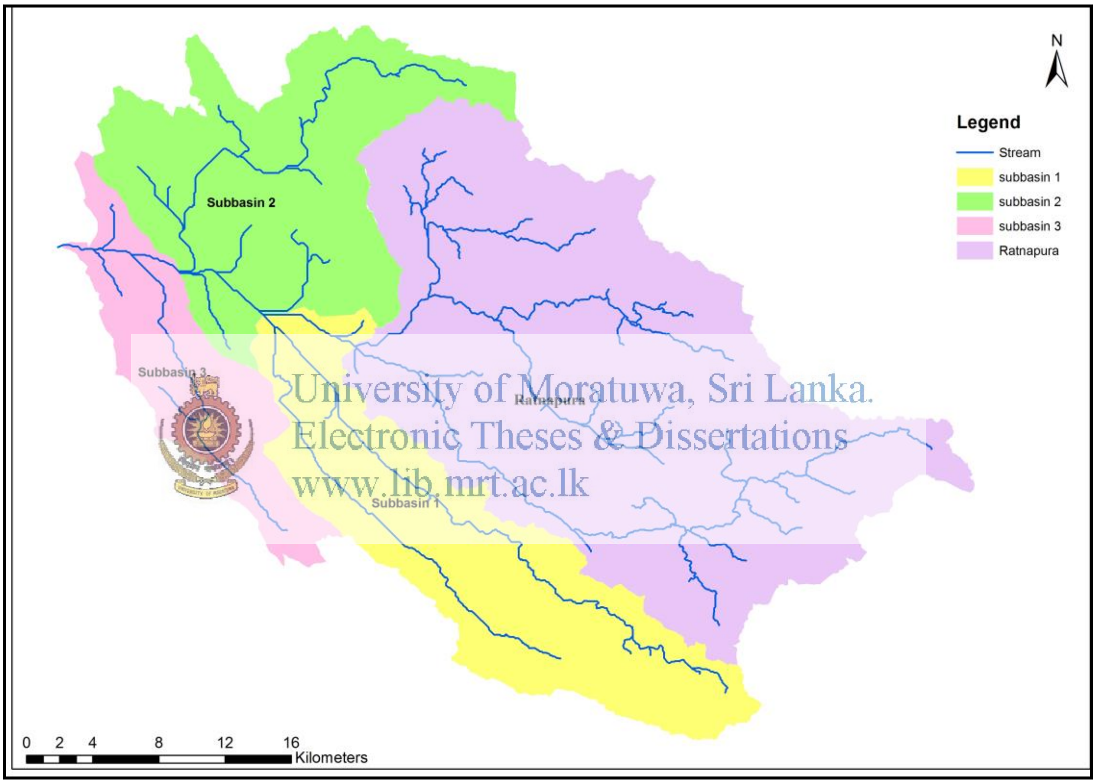

Figure 5-4 Delineated subbasins of Ellagawa watershed

5.3.2.2 Development of the precipitation loss model

Out of five methods available for estimation of precipitation loss given in HEC HMS model, one method was selected for this study based on the following criterion. The present study is to develop a continuous model for Ellagawa watershed using HEC HMS model. These are (1) Number of parameters (2) consideration of soil moisture content (3) applicability for event and continuous modeling

This was only a qualitative evaluation and based on the above criterion the methods were prioritized and finally deficit constant loss method was selected for the study. The parameters such as initial deficit, maximum storage and constant loss were estimated by optimization. But, initial values were required in order to start the model. Maximum potential retention which is similar to maximum storage can be calculated by using SCS equation (Chow et al., 2010). Weighted CN value for Ellagawa watershed was calculated by considering land use, antecedent moisture condition and hydrological soil group of Ellagawa watershed. Land use map of Ellagawa catchment is given in Figure 5-5.

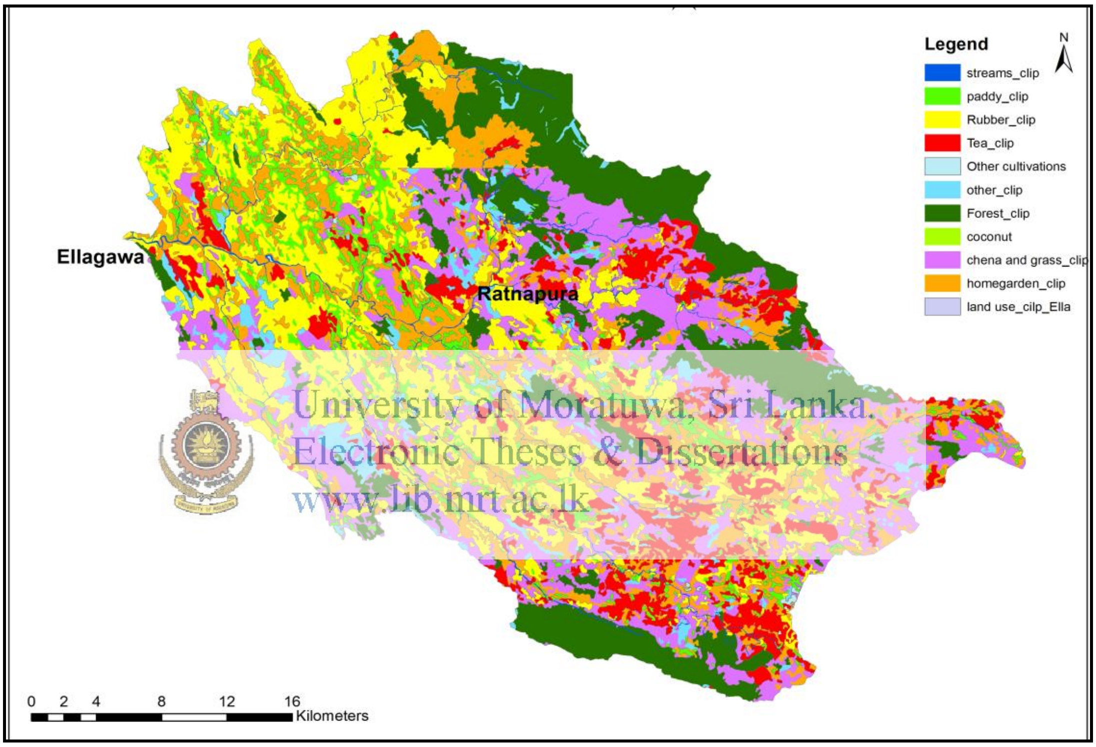

Figure 5-5 Land use map of Ellagawa catchment

CN value for Ellagawa watershed was initially derived from the standard tables (SCS, 1987) where antecedent moisture condition II and hydrological soil group C. As per the computation in Table 5-1, weighted CN value was 80.7, when the CN values for land uses from Chow (2010) were used.

Table 5-1 Weighted Curve Number calculation for Ellagawa watershed

Land Use Type	Area %	Soil Group C	
		CN	Weighted CN
Cultivation	49.8	88	43.4
Forest	13.1	77	10.7
Garden	13.8	74	10.2
Grass and Chena	23.4	71	16.6
Total	**100**		**80.7**

Maximum potential retention, S was calculated using the equation given in Chow et al. (2010) and it was 55.76 mm. By considering Initial abstraction, $I_a = 0.2 * S$ (SCS, 1972), initial abstraction is 11.2 mm.

5.3.2.3 Development of transform model

Transform (Direct runoff) model was selected for the present study by considering the following criterion. (1) Number of parameters (2) use of empirical equations (3) appropriateness of assumptions

A qualitative evaluation was done based on the above criterion and SCS model was selected for the present study. Lag time (t_p) is the only parameter which was calculated using the relationship of t_p with T_c. T_c was calculated using Kirpich formula. Length of the longest water course (L), time of concentration (T_c) and lag time (t_p) for four subbasins were calculated and tabulated in Table 5-2 below.

Table 5-2 Calculation of lag time for subbasins

Sub basin	L(feet)	T_c(hours)	t_p (hours)	t_p(minutes)
Ratnapura	151247	64.9	38.9	2338
Sub basin 1	109696	50.7	30.4	1826
Sub basin 2	107509	49.9	29.9	1798
Sub basin 3	74882	37.8	22.7	1361

5.3.2.4 Development of baseflow model

Out of four models given in HEC HMS, recession baseflow model was selected by order of magnitude evaluation based on the following criterion. (1) Number of parameters and (2) consideration of soil moisture. Initial flow which is the flow at the beginning of simulation was specified. The limits given in the HEC HMS model for recession constant and threshold flow is between 0 and 1 and were considered when optimizing these two parameters.

5.3.2.5 Development of routing model

There are six routing models in HEC HMS and Muskingam model was selected after evaluating each model considering the following criterion. (1) Number of parameters (2) channel slope (3) flood plain storage (4) channel geometry. As a rule of thumb, water in a stream can travel 2 miles/hour (HEC, 2003). Hence, Muskingam k was calculated by dividing the reach length by velocity of stream. Number of sub reaches were calculated by taking the simulation time step as 6 hours. Muskingam k and X values calculated for each reach are given in Table 5-3.

Table 5-3 Calculation of Muskingam k for reaches

Reach	Length (miles)	Muskingam K(hours)	Number of sub reaches
Reach 1	2.91	3.64	0.6
Reach 2	4.13	5.16	0.9
Reach 3	4.32	5.40	0.9

In Table 5-3, number of sub reaches are less than 1 for all reaches. As the lower limit of number of sub reaches given in the HEC HMS is 1, number of sub reaches were taken as 1 for all reaches.

The basin models developed for Ratnapura watershed, Ellagawa watershed and Ellagawa watershed with subbasins are shown in Figure 5-6, Figure 5-7 and Figure 5-8.

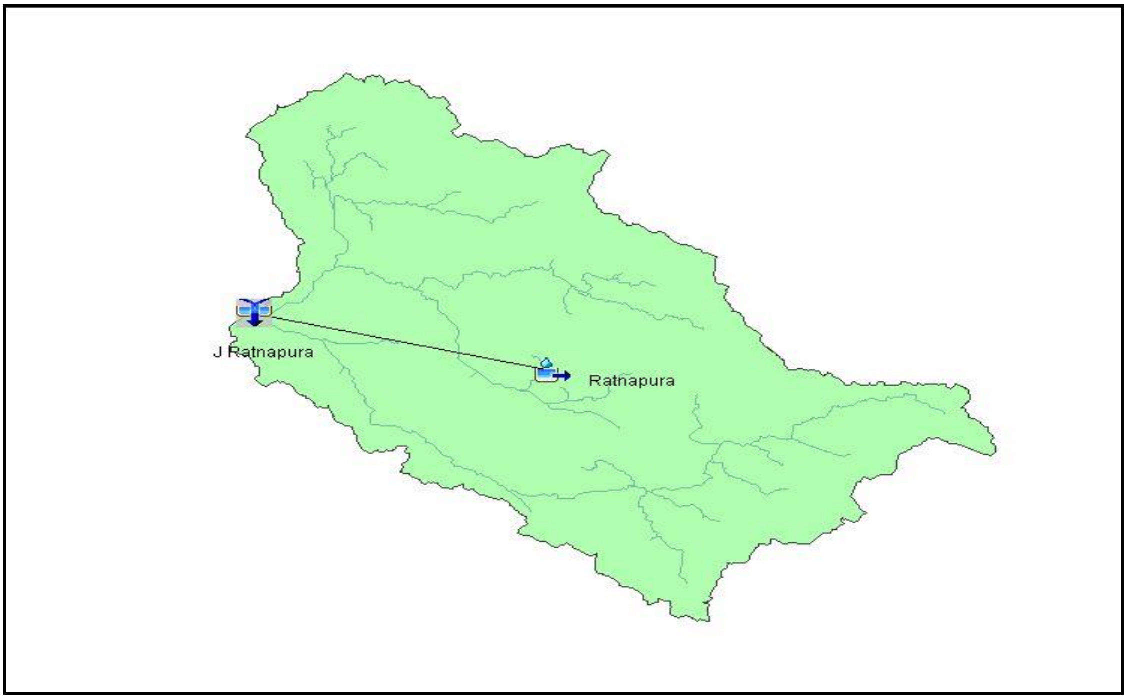

Figure 5-6 Basin model of Ratnapura watershed

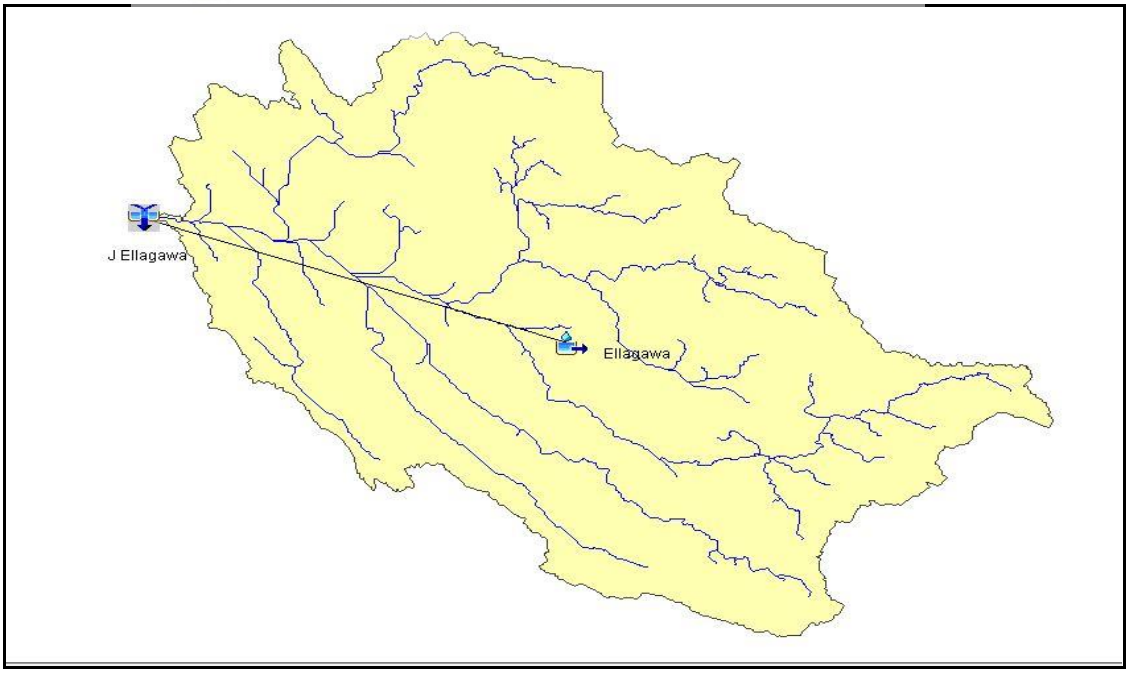

Figure 5-7 Basin model of Ellagawa watershed

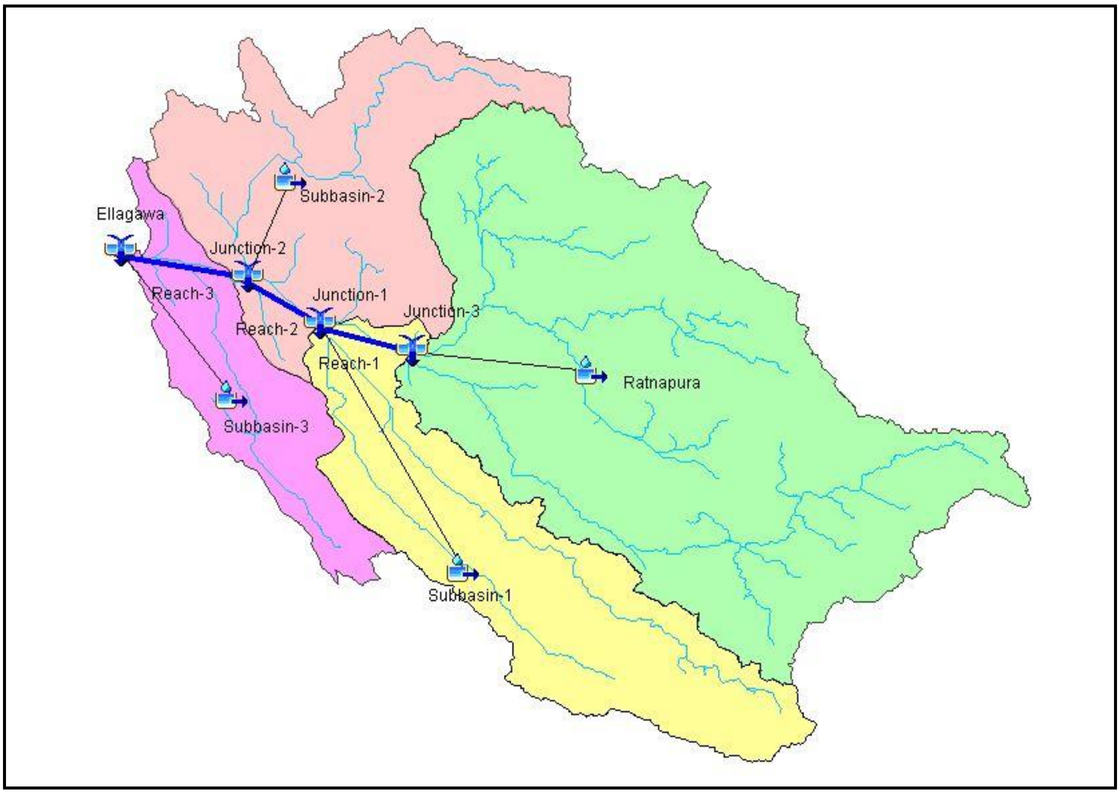

Figure 5-8 Basin model of Ellagawa watershed with subbasins

5.3.3 Development of precipitation model

Theissen average (gauge weight) method for precipitation and monthly average evaporation were used in the precipitation model. Theissen polygons for Ellagawa watershed were created using GIS (Figure 4-8) and Theissen weights for each subbasin were calculated and given in Table 5-4.

Table 5-4 Theissen weights of subbasins

Name of subbasin	Theissen weights				
	Halwathura	Ratnapura	Alupola	Pelmadulla	Nivithigala
Ratnapura		0.25	0.29	0.39	0.07
Subbasin 1			0.25	0.36	0.48
Subbasin 2	0.36	0.62	0.16		
Subbasin 3	0.53	0.35			0.12

Daily rainfall data were used as input to the model for each rain gauging station. Time series discharge data of Ellagawa and Ratnapura river gauging station and monthly evaporation data of Ratnapura station also were the other inputs for model calibration.

5.3.4 Control specification

Starting date and end date for model calibration was taken as 01st October 2006 to 30th September 2010. As determined previously in Chapter 5.3.1.4, simulation time interval was set to 6 hours.

5.3.5 Model simulation

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

5.4 Model Calibration

Once the model is selected and developed, efficiency of the model depends on its parameters. Matching was done by optimizing these parameters. For model calibration, four year data from 2006/2007 to 2009/2010 was used.

Mean Ratio of Absolute Error (MRAE) (equation 7), Nash-Sutcliff (equation 5) and percent error in volume (equation 2) (monthly mass balance error) were used as statistical measures for model calibration. Each optimization output was assessed using the above criteria. The optimum parameters were obtained by changing the initial values of the parameters until the objective function change was negligible. This calibration method was adopted for Ratnapura lumped model, Ellagawa lumped model, Ellagawa distributed model and then the catchment parameters were found. After optimization using automatic calibration, fine adjustments of parameters were done by manual calibration.

Three models were calibrated. First, Ratnapura lumped model and Ellagawa lumped models were calibrated to compare the catchment parameters and model performance of both catchments. Then Ellagawa distributed model with subbasins was calibrated.

5.4.1 Automatic parameter optimization

In automatic parameter optimization, one search algorithm and one objective function were selected.

5.4.1.1 Selection of a search algorithm

In order to select a search algorithm, 28 optimization trials were done. Before selecting an objective function, Peak Weighted Root Mean Square Error objective function was selected randomly for this purpose and model was run for both Univariate Gradient and Nelder and Mead search methods. Comparison of objective function value with different search methods is shown in Figure E-1 in Appendix E.

In Figure E-1, it was observed that the minimum error is same for both Univariate gradient and Nelder and Mead methods, but with different sets of parameters. In Univariate method, Trial 4, Trial 12 and Trial 25 give the minimum error with best fits of model where as in Nelder and Mead method, Trial 5, Trial 14 and Trial 25 give the minimum error. There is a little variation in objective function in case of all best fit trials. Variation of parameters with best fit trials for each search method are given in Figure E-2 and Figure E-3. Table E-1 shows that trial 4 and trial 12 of Univariate gradient method gives almost the same objective function value.

In Figure E-2 and Figure E-3 of Appendix E, both recession constant and constant loss change slightly in all trials. But, there are big variations in initial deficit, recovery factor and threshold flow ratio in trial 4 and trial 12. This shows that the same error can be obtained with different combination of parameter demonstrating inter dependance. Parameters variation in each search method is given in Table E-1 of Appendix E.

In Table E-1, it is seen that out of six parameters, parameter variation of four parameters (initial deficit, recession constant, recovery factor and lag) in univariate gradient method is greater than that of Nelder and Mead method. Also, univariate gradient method is the default of the model. Therefore, considering insignificant change in the minimum objective function, Univariate method was used for parameter optimization.

5.4.1.2 Selection of objective function in HEC HMS

In order to select an objective function for parameter optimization, Ratnapura lumped model was run for the entire calibration period from 2006/2007 to 2009/2010 using four objective functions given in HEC HMS model. These are Peak Weighted Root Mean Square Error (PWRMSE), Sum of Absolute Residuals (SAR), Sum of Squared Residuals(SSR) and Percent Error in Volume (PEV) which are discussed in Chapter 2.4 (equation 9, 10, 11 and 13). The different objective functions were compared based on the following criterion. (1) percent annual mass balance error for both outflow hydrograph and flow duration curve (2) Ratio of calculated flow to observed flow in annual and seasonal basis (3) Nash-Sutcliff error for both outflow hydrograph and flow duration curve and (4) MRAE for both outflow hydrograph and flow duration curve. Comparison of different objective functions are given in Table E-3 in Appendix E. Univariate gradient search method was applied and Parameters corresponding to trial 25 were input to the model.

It was identified that there were no significant changes in the error values for all objective functions (Table E-3). Figure E-4 in Appendix E shows the variation of error values for each objective function.

Model performances for objective functions in year 2006/2007 are shown in Figure E-5 in Appendix E and Figure E-6 shows the flow duration curves for different objective functions.

Comparison of observed and calculated flows are shown in Table E-4 and graphically presented from Figure E-7 to Figure E-10 in Appendix E.

It could be seen that there is no significant change in the calculated flow with the change of objective function. The selection criteria and ranking of four objective functions are in Table E-5 and Table E-6 of Appendix E. Sum of absolute residuals objective function which had the highest score was selected as the objective function in automatic parameter optimization.

5.4.2 Calibration results

5.4.2.1 Ratnapura lumped model calibration

5.4.2.1.1 Statistical goodness of fit measures

Ratnapura lumped model was calibrated by matching with the observed flow at Ratnapura river gauging station. Table 5-5 shows the Nash-sutcliff, Mean Ratio of Absolute Error (MRAE) and percent monthly mass balance error for hydrograph matching of Ratnapura lumped model. The error values at each region of flow duration curve are also given in the same table. Results show satisfactory model performance in hydrograph matching. Nash-sutcliff value is 0.783 and MRAE is 0.5226. Nash-sutcliff and MRAE of high flow region of flow duration curve are 0.642 and 0.273. In medium flow region, Nash-sutcliff value was very low and MRAE was 0.488. Model estimation in the low flow region was comparatively poor.

Table 5-5 Calibration results of Ratnapura catchment

Gauging station	Nash-Sutcliff	MRAE	monthly mass balance error %	Flow duration curve						Model error (Sum of Absolute Residual)
				High		Medium		Low		
				Nash-Sutcliff	MRAE	Nash-Sutcliff	MRAE	Nash-Sutcliff	MRAE	
Ratnapura	0.783	0.5226	14.3	0.642	0.273	-0.35	0.488	-18.87	0.772	19082

5.4.2.1.2 Parameters of Ratnapura catchment

Parameters of Ratnapura catchment are given in Table 5-6.

Table 5-6 Optimized parameters of Ratnapura catchment

Name of Parameter	Unit	Value
Constant loss	mm/hour	0.435
Initial deficit	mm	4.489
Recession constant		0.896
Threshold flow ratio		0.149
Lag time	minutes	2127

5.4.2.1.3 Matching observed and calculated hydrograph

Observed and calculated hydrographs in normal and semi-log scales for Ratnapura catchment are presented in Figure 5-9 and Figure 5-10 respectively. Flow duration curves in normal and semi-log scale are shown in Figure 5-11 and Figure 5-12 respectively. By considering the change of the gradient of flow duration curve, it was divided into three regions. These are high (less than 10% probability of exceedence), medium (between 10% and 80%) and low flows (greater than 80%). Figure 5-10 and Figure 5-12 clearly show that the model does not respond well to rainfall in low flow periods. But most of the peaks are captured by the model. Model response for high and medium flows are good.

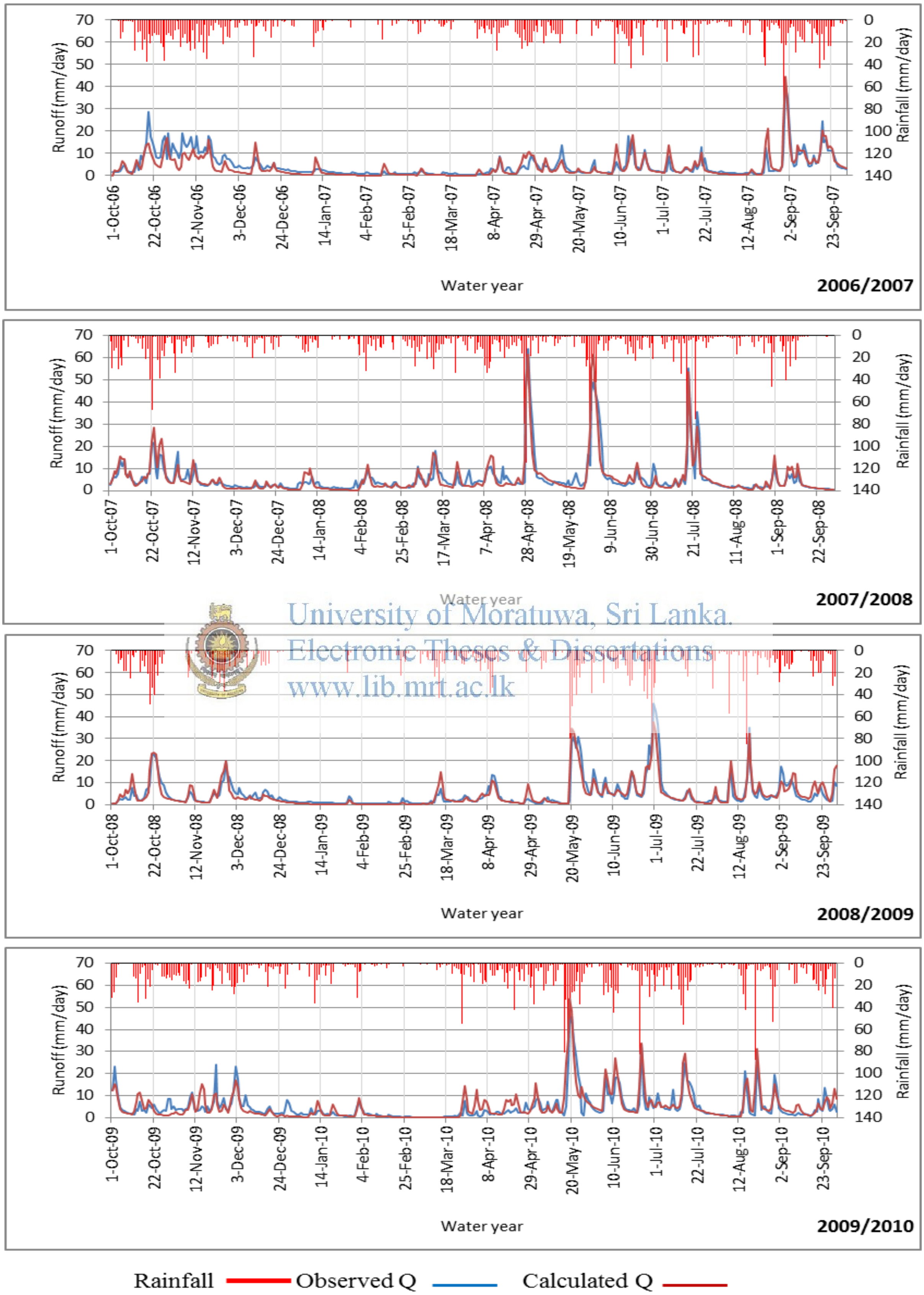

Figure 5-9 Performance of Ratnapura lumped model calibration

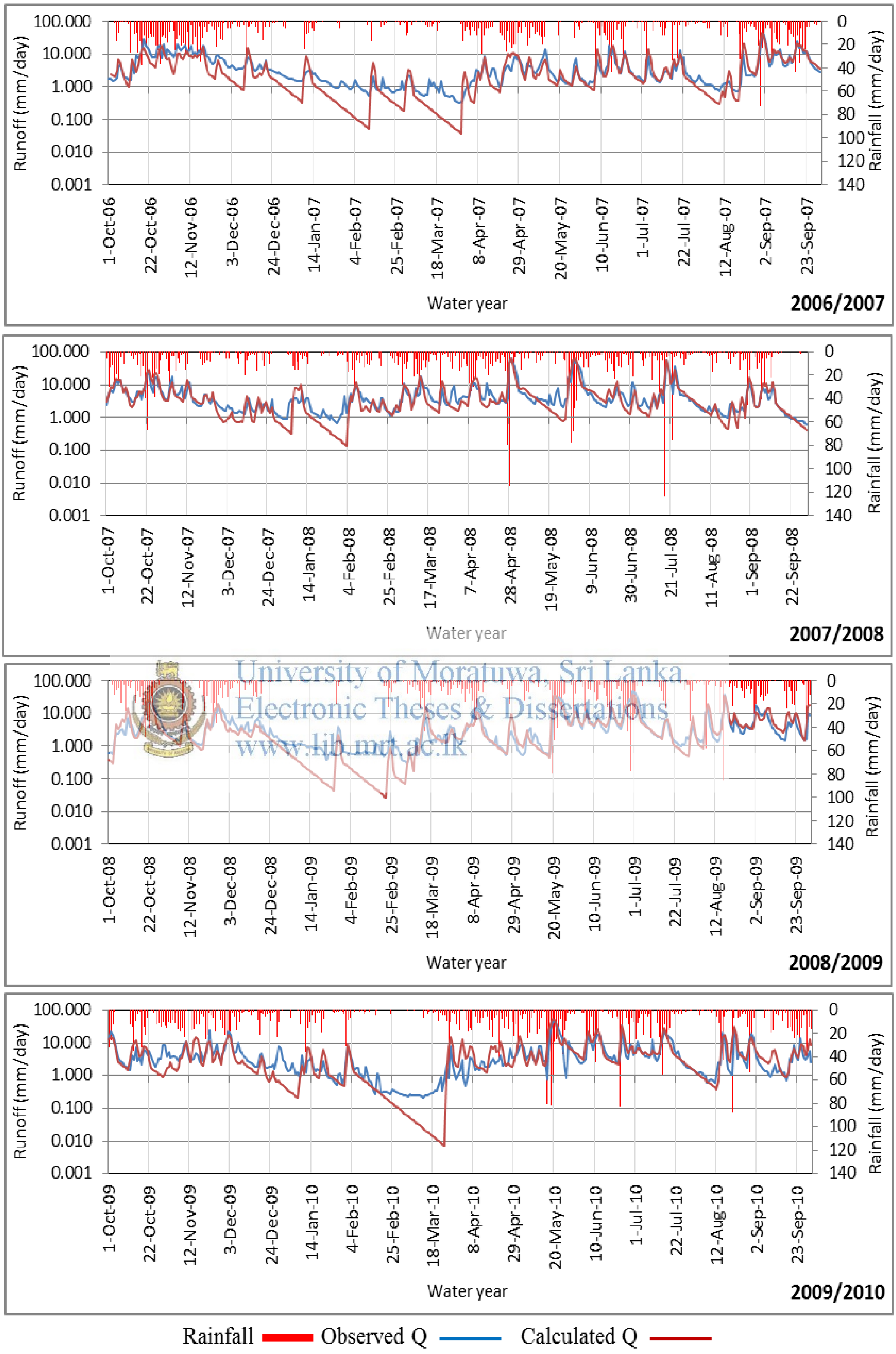

Figure 5-10 Performance of Ratnapura lumped model calibration

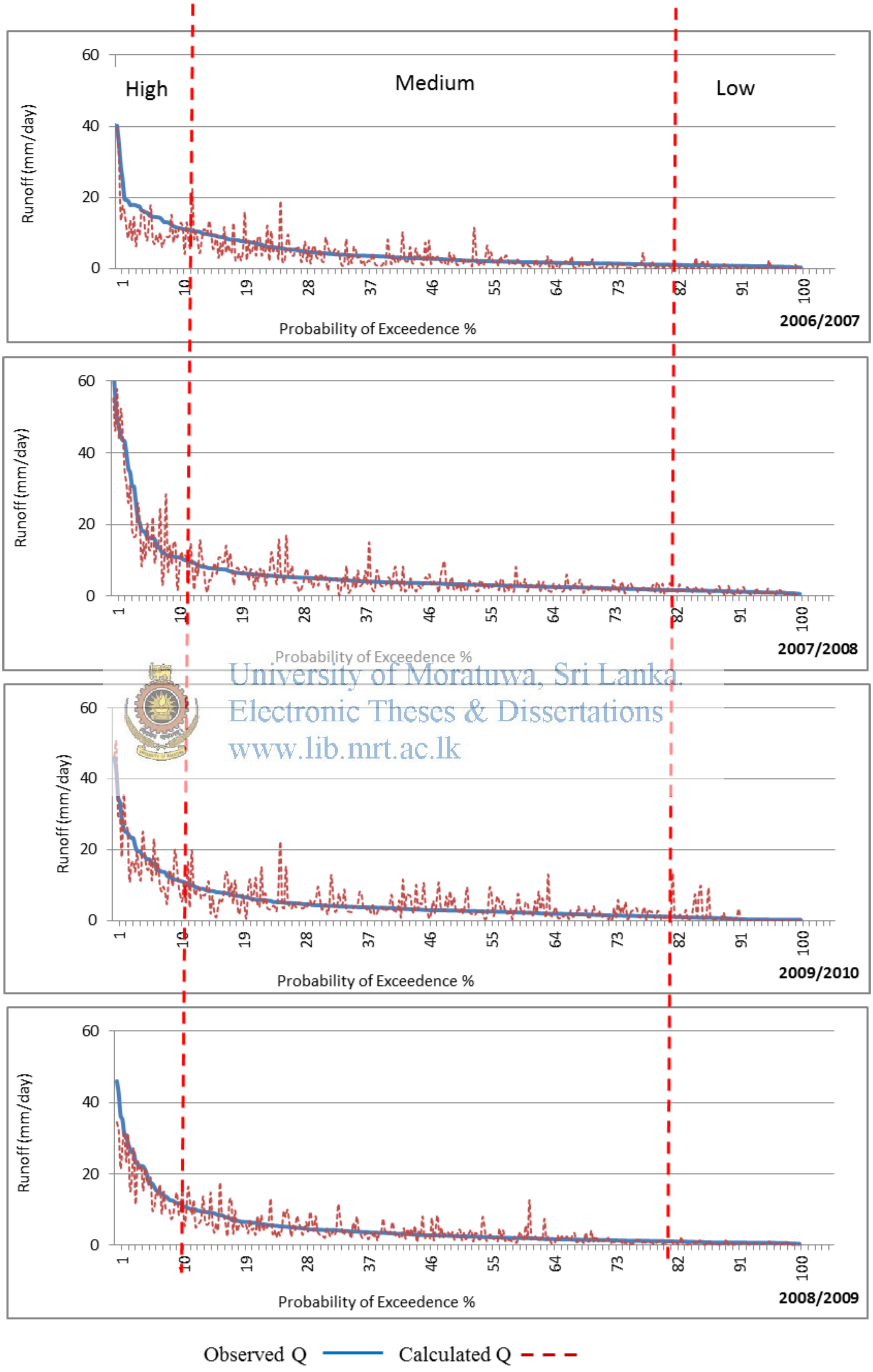

Figure 5-11 Flow duration curves of Ratnapura lumped model calibration

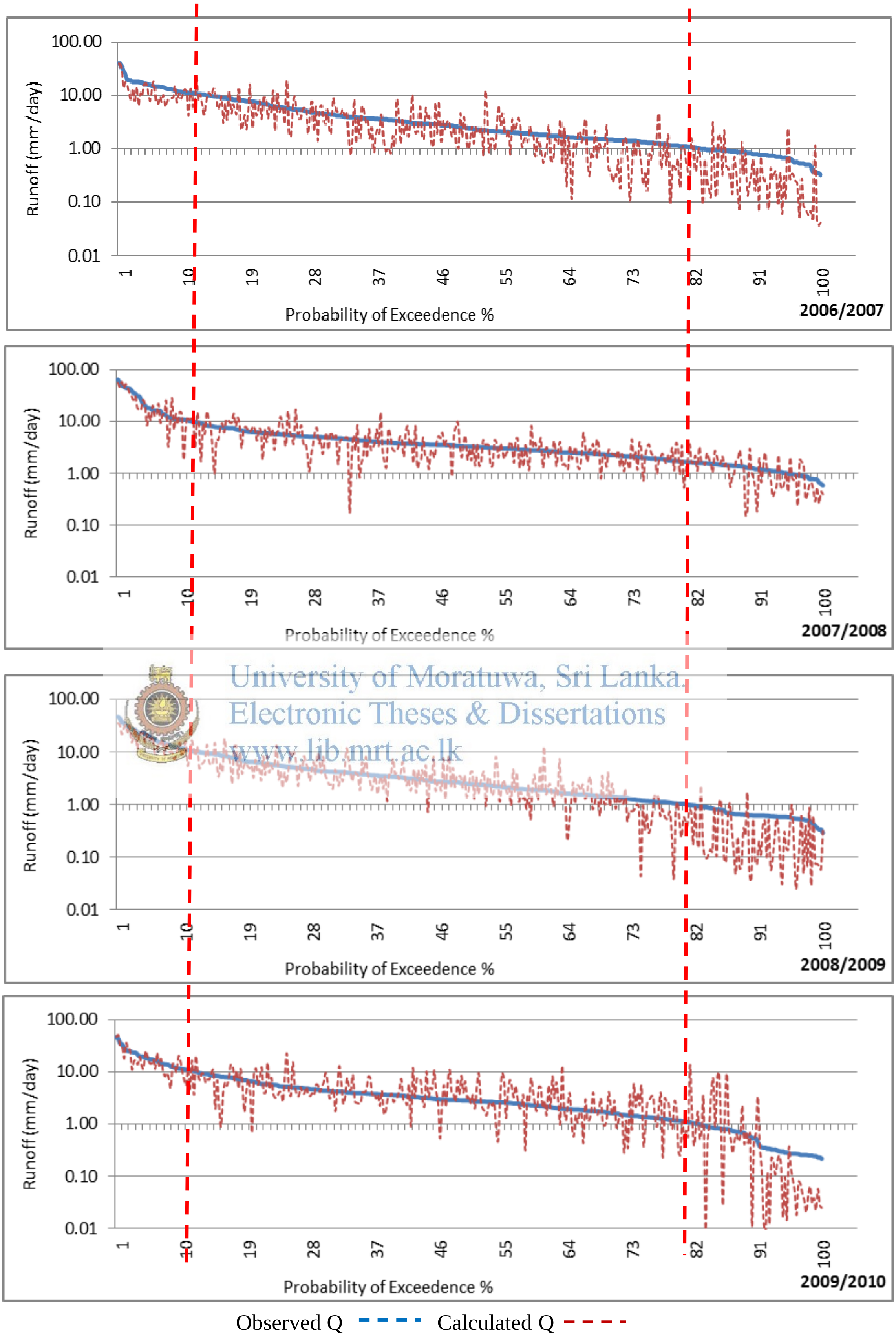

Figure 5-12 Flow duration curves of Ratnapura lumped model calibration

Table 5-7 shows that monthly average observed and calculated flows and monthly mass balance errors. This is graphically presented in Figure 5-13. It shows that in April, June, August and September, model overestimates the monthly average streamflow while in other months, model underestimates the streamflow. Modeled streamflow varies from 31.5 mm in February to 247.5 mm in June. Monthly mass balance error varies from 2% in March to 33.6% in December.

Table 5-7 Monthly average observed and calculated flows

Month	Monthly average observed flow (mm)	Monthly average calculated flow (mm)	Monthly mass balance error (%)
January	48.4	38.4	20.7
February	44.3	31.5	28.9
March	68.1	69.5	2.0
April	141.5	157.5	11.3
May	225.5	220.5	2.2
June	235.0	247.3	5.2
July	195.7	179.8	8.1
August	127.0	152.1	19.8
September	160.4	190.2	18.6
October	216.5	210.2	2.9
November	192.5	157.9	18.0
December	111.9	74.3	33.6

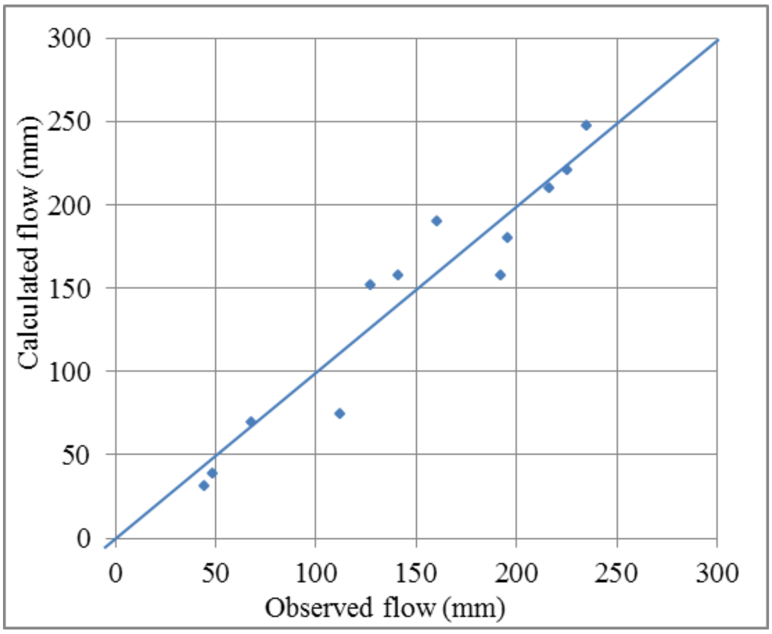

Figure 5-13 Co-relation of monthly observed and calculated flows of Ratnapura lumped model

5.4.2.2 Ellagawa lumped model calibration

5.4.2.2.1 Statistical goodness of fit measures

Ellagawa lumped model was calibrated by matching with the observed flow at Ellagawa river gauging station. Table 5-8 shows statistical measures of Ellagawa lumped model. Nash-sutcliff and MRAE did not show any improvement in Ellagawa model when compared with Ratnapura model. However, monthly mass balance error showed a little improvement. Good model performance could be observed in high and medium flows with MRAE values of 0.35 and 0.56 respectively.

Table 5-8 Calibration results of Ellagawa lumped model

Gauging station	Nash-Sutcliff	MRAE	monthly mass balance error %	Flow duration curve						Model error (Sum of Absolute Residual)
				High		Medium		Low		
				Nash-Sutcliff	MRAE	Nash-Sutcliff	MRAE	Nash-Sutcliff	MRAE	
Ellagawa	0.701	0.5802	11.9	0.314	0.352	-0.64	0.559	-26.1	0.796	181042

5.4.2.2.2 Parameters of Ellagawa catchment

Optimized parameters of Ellagawa catchment are shown in Table 5-9. It can be observed that there are slight changes in recession constant and threshold flow ratio when compared with Ratnapura catchment.

Table 5-9 Optimized parameters of Ellagawa catchment

Name of Parameter	Unit	Value
Constant loss	mm/hr	0.487
Initial deficit	mm	3.384
Recession constant		0.907
Threshold flow ratio		0.151
Lag time	minutes	2677

5.4.2.2.3 Matching observed and calculated hydrographs

Observed and calculated hydrographs and flow duration curves for Ellagawa lumped model are presented in Figure 5-14 and Figure 5-15, respectively. Semi-log plots are shown in Figure 5-16 and Figure 5-17. Ellagawa lumped model also did not respond very well to rainfall during low flow period (Figure 5-16 and Figure 5-17).

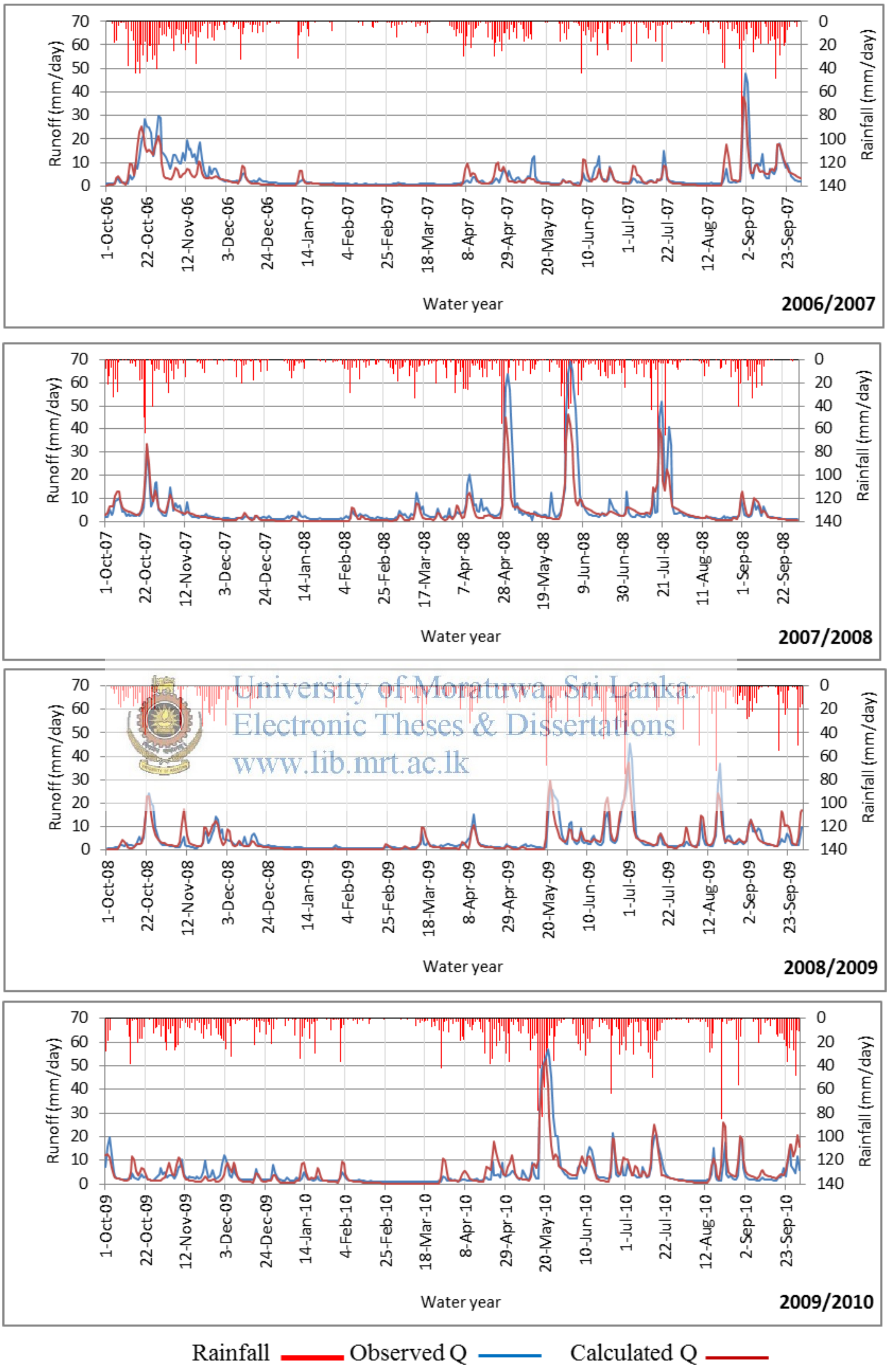

Figure 5-14 Performance of Ellagawa lumped model calibration

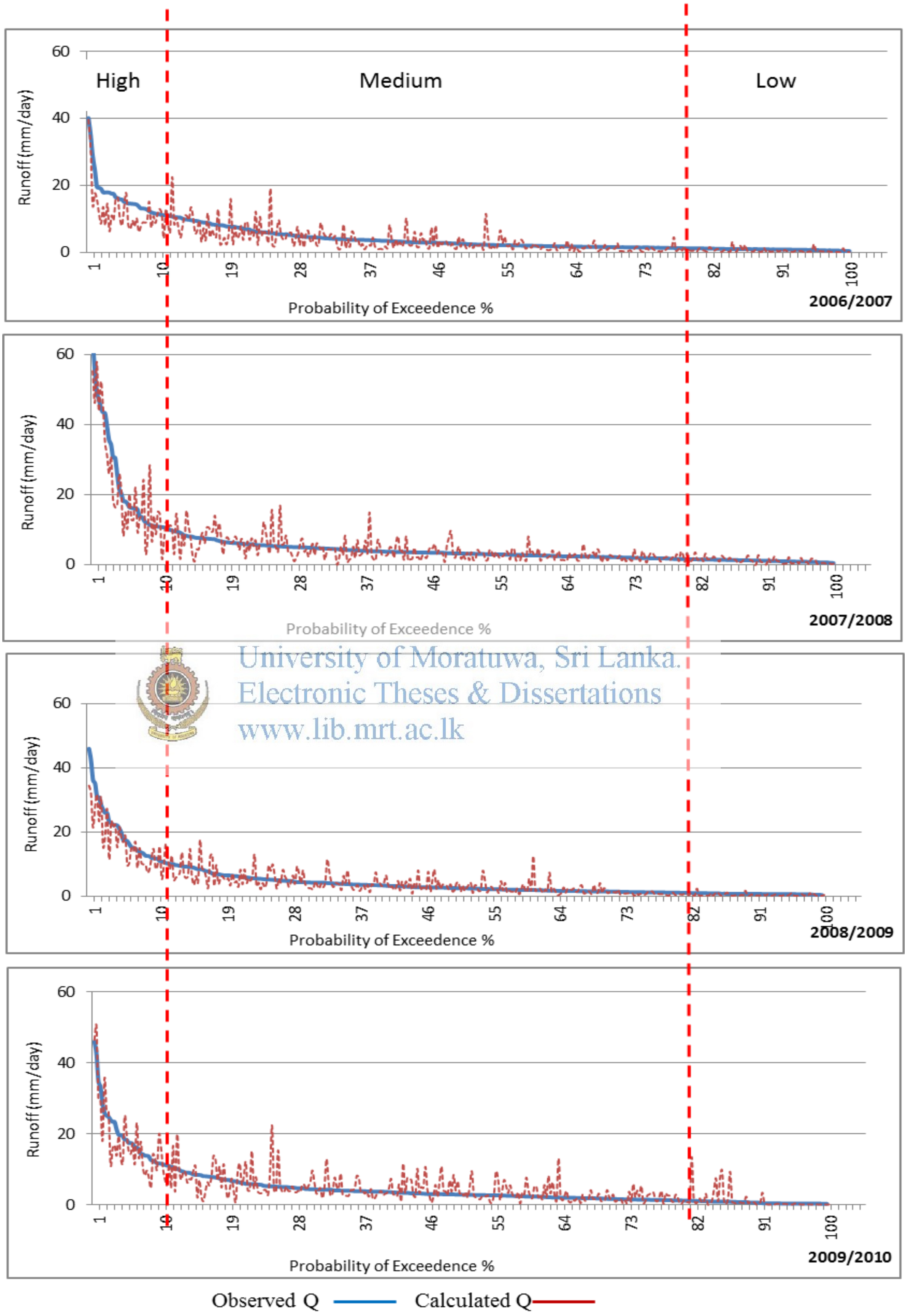

Figure 5-15 Flow duration curves for Ellagawa lumped model calibration

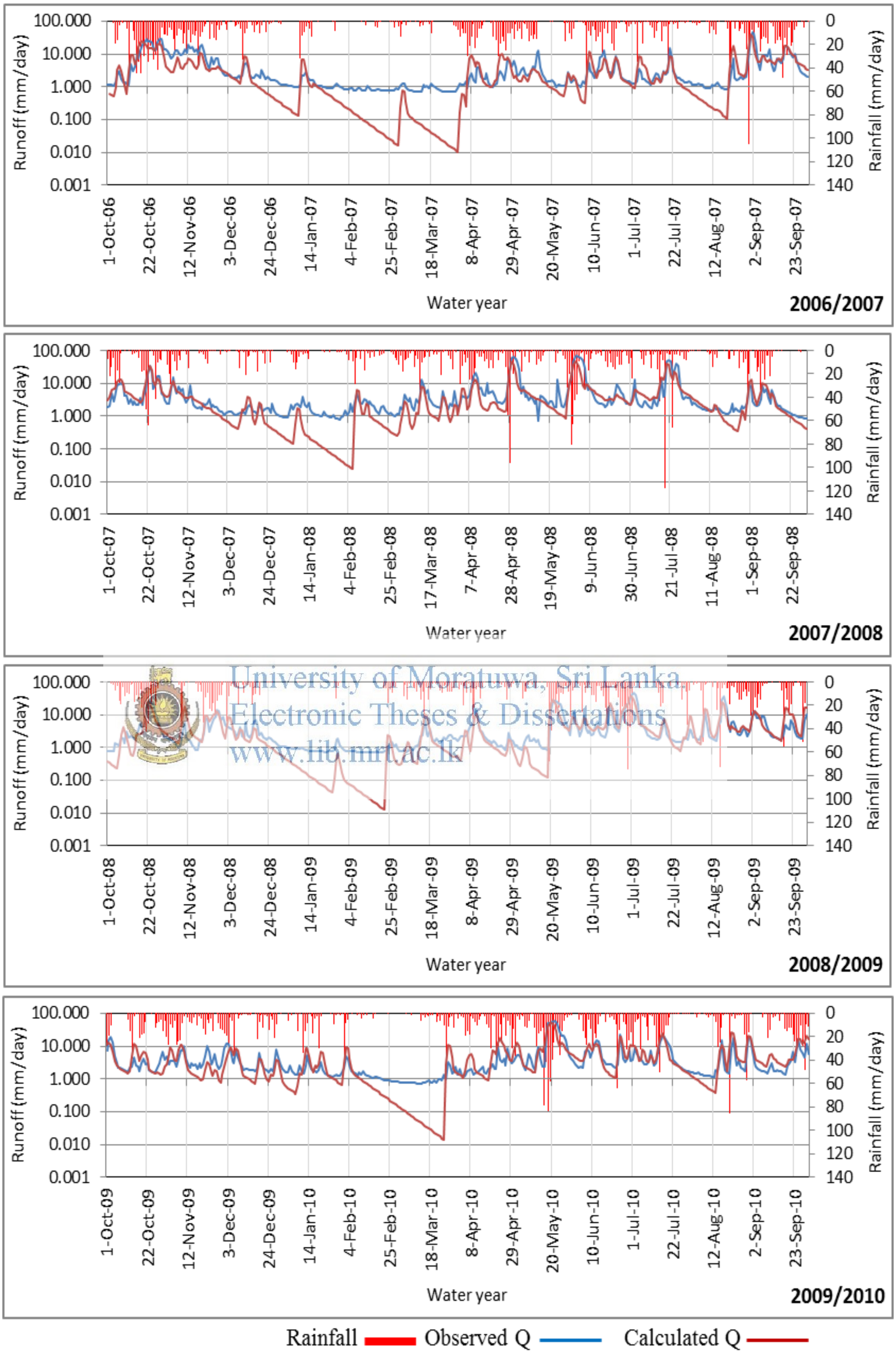

Figure 5-16 Performance of Ellagawa lumped model calibration

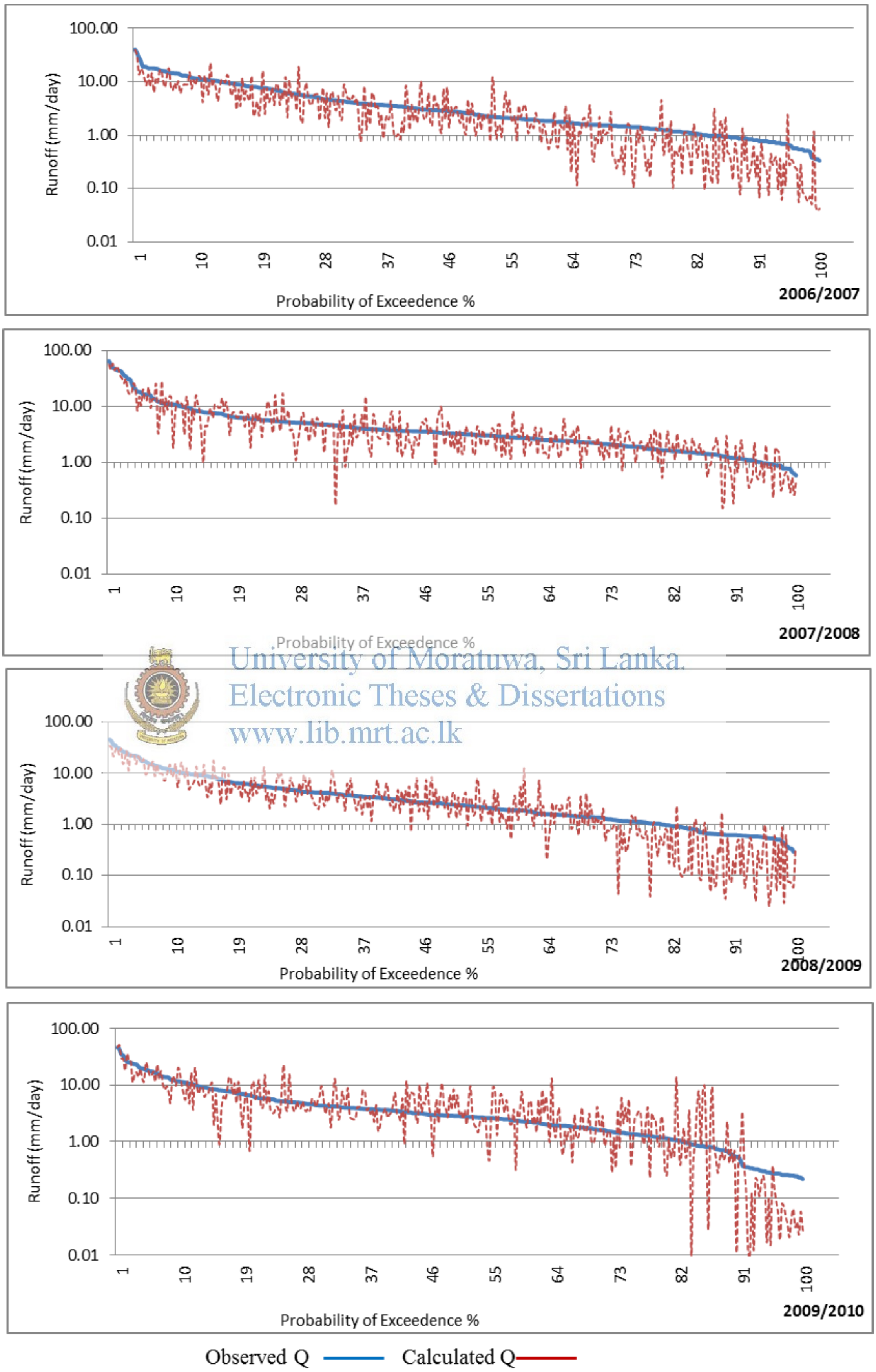

Figure 5-17 Flow duration curves for Ellagawa lumped model calibration

Monthly average observed and calculated flows are given in Table 5-10 and it is graphically presented in Figure 5-18. It can be seen in Table 5-10 that the model over estimates the streamflow only in August and September while under estimates the streamflow in other months. Monthly average streamflow varied from 20.25 mm in February to 211.47 mm in October. Monthly mass balance error varied from 2.1% in October to 42.7% in February.

Table 5-10 Monthly observed and calculated streamflow of Ellagawa lumped model

Month	Monthly average observed flow (mm)	Monthly average calculated flow (mm)	Monthly mass balance error (%)
January	42.25	29.27	30.7
February	35.34	20.25	42.7
March	54.70	36.98	32.4
April	135.95	130.19	4.2
May	270.95	195.79	27.7
June	235.71	206.75	12.3
July	208.18	190.84	8.3
August	113.68	135.69	19.4
September	163.34	191.24	17.1
October	216.07	211.47	2.1
November	164.67	129.77	21.2
December	80.61	62.15	22.9

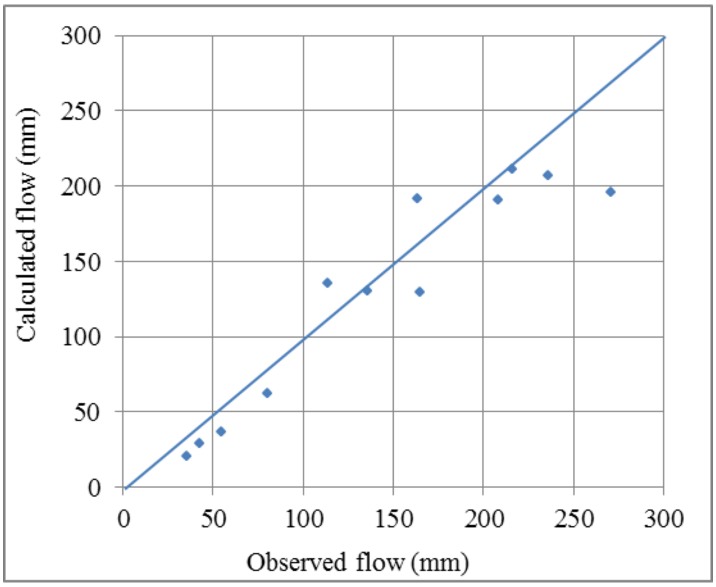

Figure 5-18 Co-relation of monthly observed and calculated flow of Ellagawa lumped model

5.4.2.3 Ellagawa distributed model calibration

5.4.2.3.1 Selection of modeling scenarios

Ellagawa distributed model was calibrated finally for the purpose of comparisons with Ellagawa lumped model. There are two observed river gauging locations (Ratnapura and Ellagawa) within this catchment. Therefore, two scenarios were considered. In the first scenario, both Ellagawa and Ratnapura observed flows were input into the model so that the model was allowed to optimize Ratnapura subbasin parameters by matching with Ratnapura observed flow. In the second scenario, only Ellagawa observed flow was input to the model and the model optimized by considering Ellagawa as a single catchment.

5.4.2.3.2 Statistical goodness of fit measures

Model performances of both Ellagawa and Ratnapura river gauging stations were evaluated by using the same statistical measures as in Chapter 5.4.2.1 and 5.4.2.2. It is observed in Table 5-11 that the results obtained for both scenarios are almost same. At Ellagawa gauging station, MRAE, monthly mass balance error and the model error (sum of absolute residual) show a little improvement when compared with Ellagawa lumped model. Results at Ratnapura gauging station are worse than that of Ratnapua lumped model.

Table 5-11 Calibration results of Ellagawa distributed model

Gauging station	Nash-Sutcliff	MRAE	monthly mass balance error %	Flow duration curve						Model error (Sum of Absolute Residual)
				High		Medium		Low		
				Nash-Sutcliff	MRAE	Nash-Sutcliff	MRAE	Nash-Sutcliff	MRAE	
Ellagawa Scenario 1	0.692	0.5407	11.2	0.264	0.324	-0.46	0.523	-29.65	0.712	167347
Ellagawa Scenario 2	0.692	0.5407	11.3	0.264	0.324	-0.46	0.523	-29.7	0.713	167349
Ratnapura	0.765	0.5852	19.9	0.593	0.2913	-0.43	0.5403	-16.5	0.888	

5.4.2.3.3 Parameters of Ellagawa distributed model

Optimized parameters of all subbasins are given in Table 5-12.

Table 5-12 Optimized Ellagawa subbasin parameters

Name of Parameter	Unit	Ratnapura	Subbasin 1	Subbasin 2	Subbasin 3	Reach 1	Reach 2	Reach 3
Constant loss	mm/hour	0.454	0.454	0.443	0.452			
Initial deficit	mm	3.03	4.522	3.03	4.522			
Recession constant		0.856	0.387	0.936	0.909			
Threshold flow ratio		0.144	0.145	0.149	0.1			
Lag time	minutes	2740	1176	2561	1274			
Muskingam k	hours					2.667	3.334	3.334
X						0.134	0.134	0.134

Observed and calculated flows and flow duration curves at Ellagawa gauging station are plotted and presented in Figure 5-19 and Figure 5-20 respectively. These figures also show non responsiveness of model in low flows. The same plots in semi-log scale are presented in Figure 5-21 and Figure 5-22.

Figure 5-23 and Figure 5-24 present the observed and calculated streamflow and flow duration curves corresponding to Ratnapura river gauging station in calibration of Ellagawa distributed model.

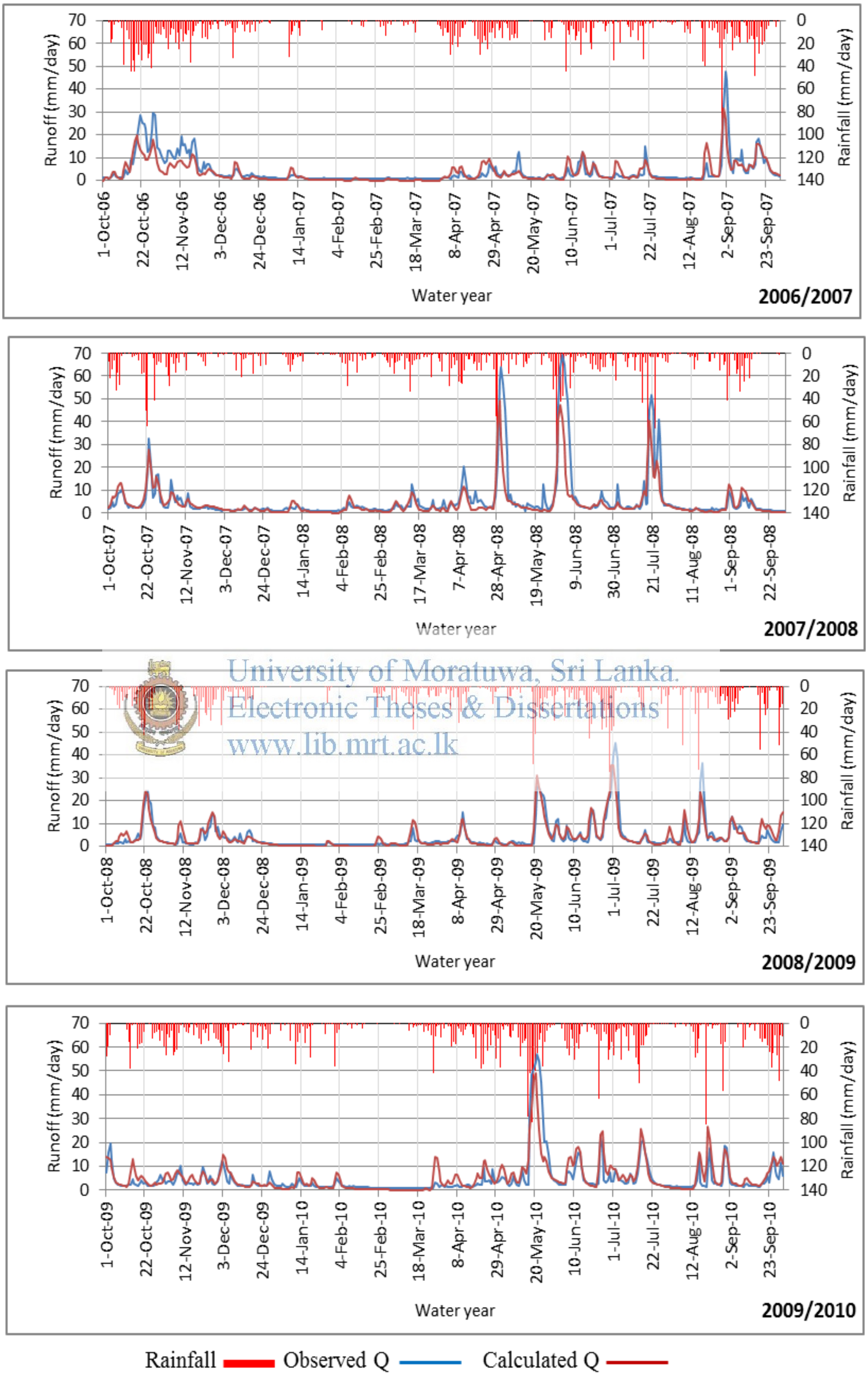

Figure 5-19 Performance of Ellagawa distributed model calibration (normal scale)

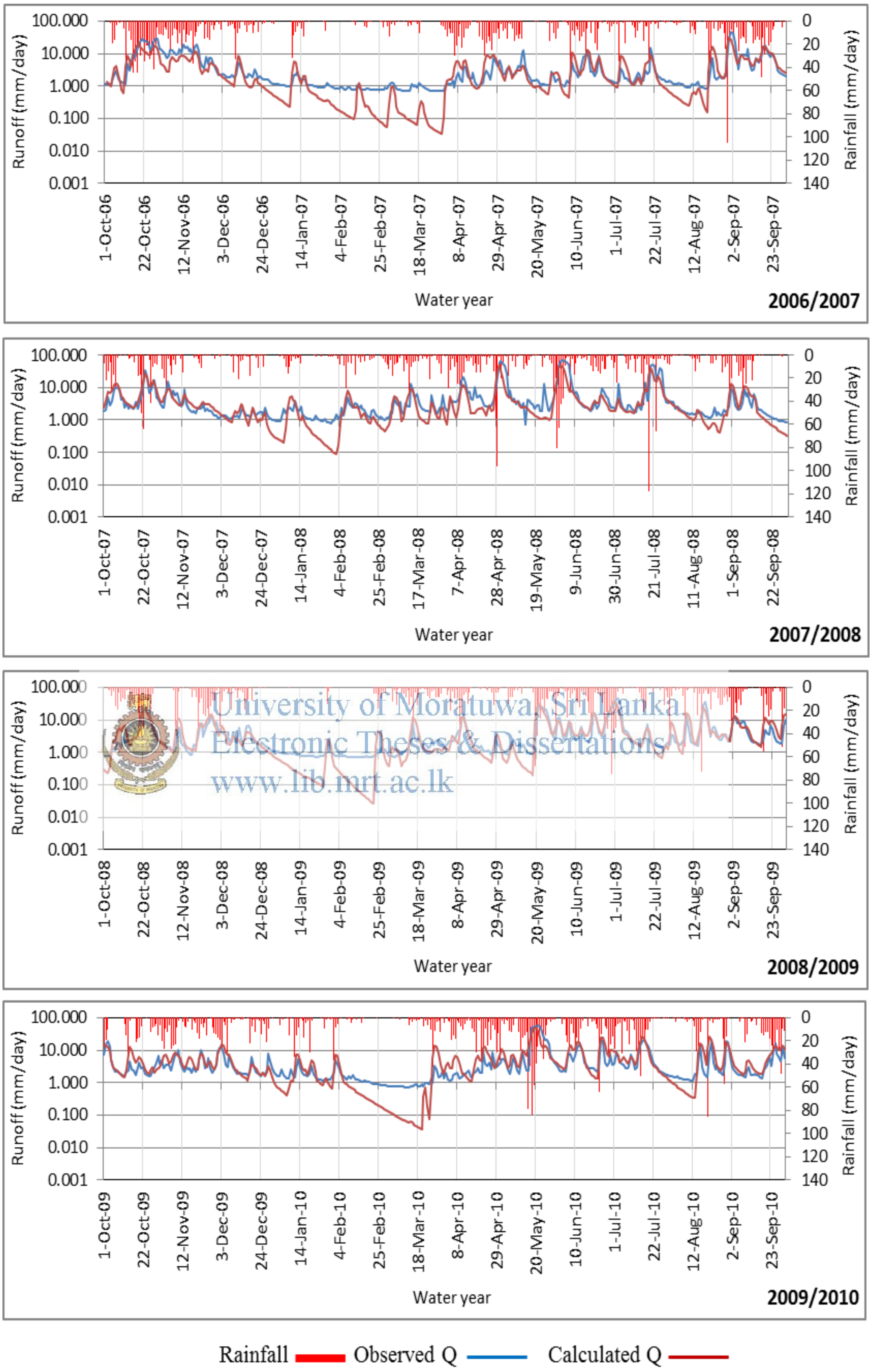

Figure 5-20 Performance of Ellagawa distributed model calibrated (semi log)

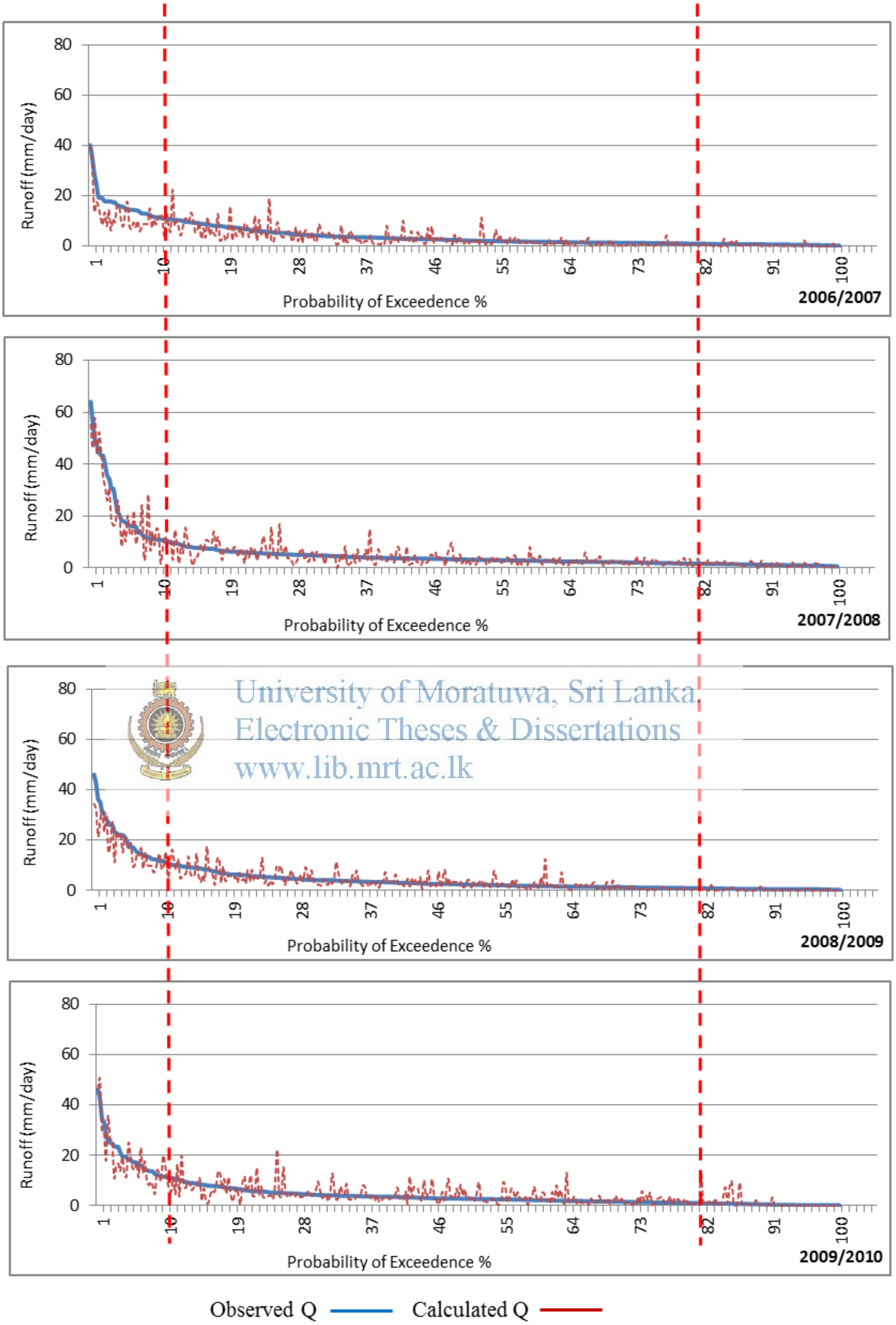

Figure 5-21 Flow duration curve of Ellagawa distributed model

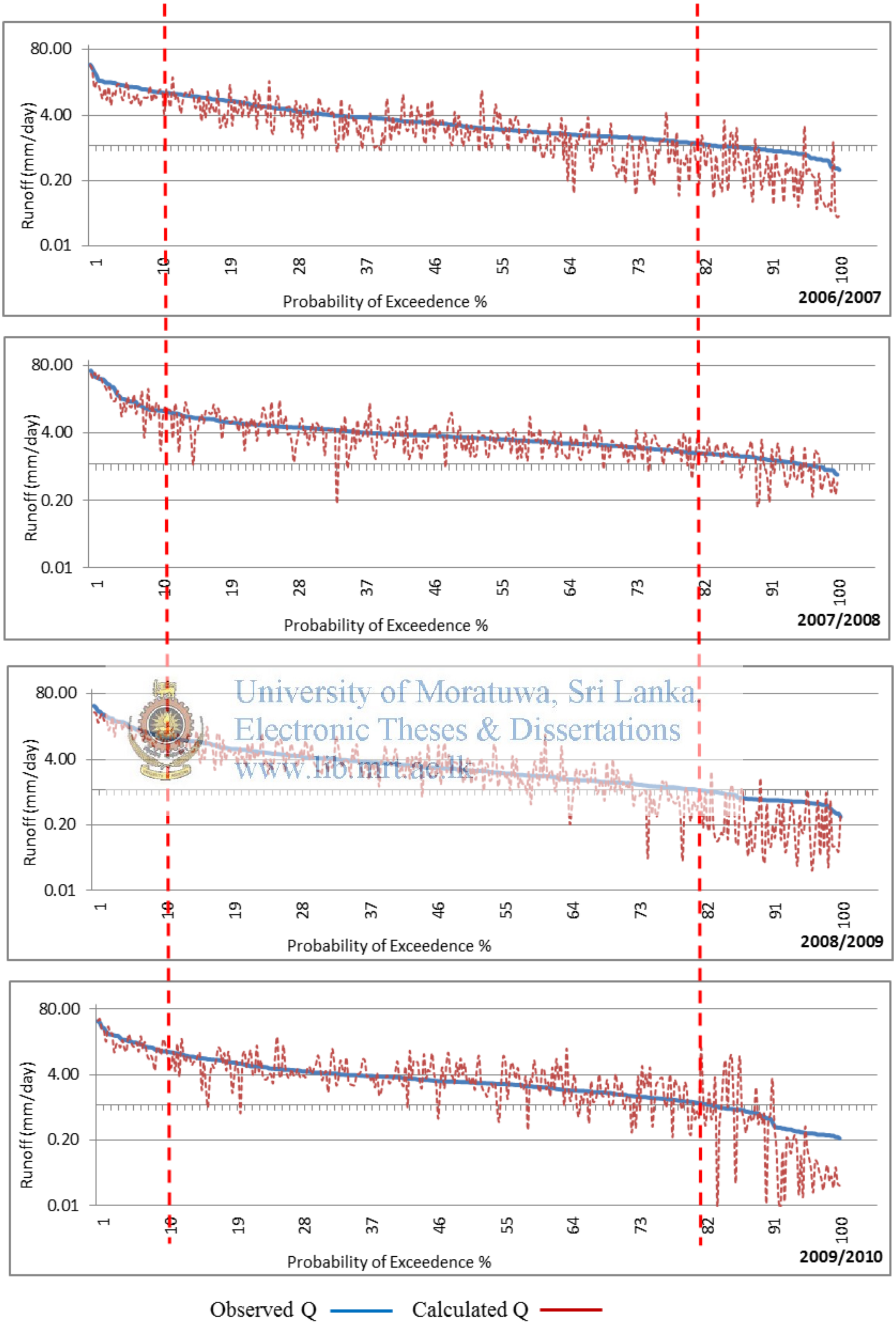

Figure 5-22 Flow duration curve of Ellagawa distributed model calibration (semi log)

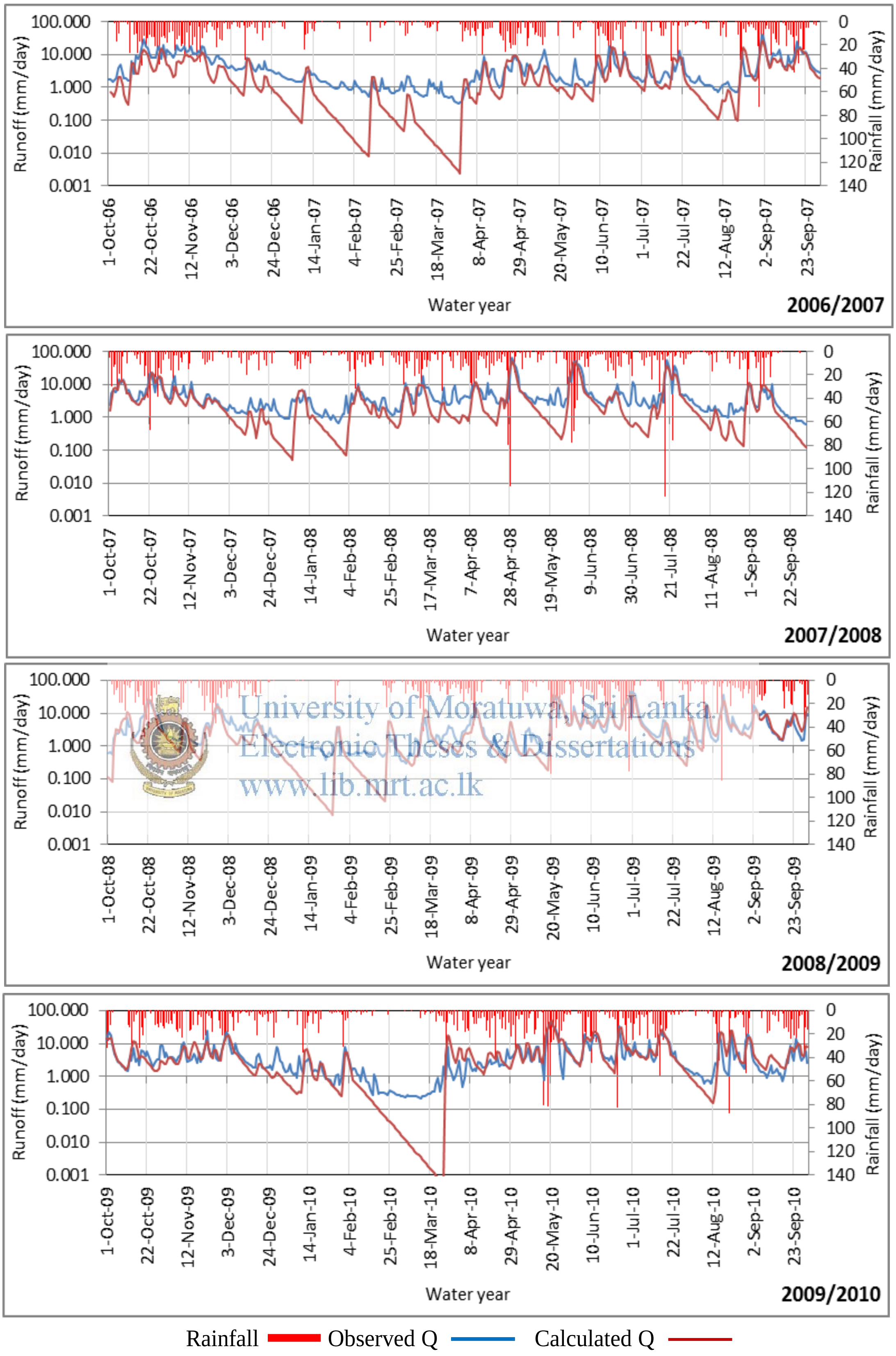

Figure 5-23 Performance at Ratnapura in Ellagawa distributed model calibration (semi-log scale)

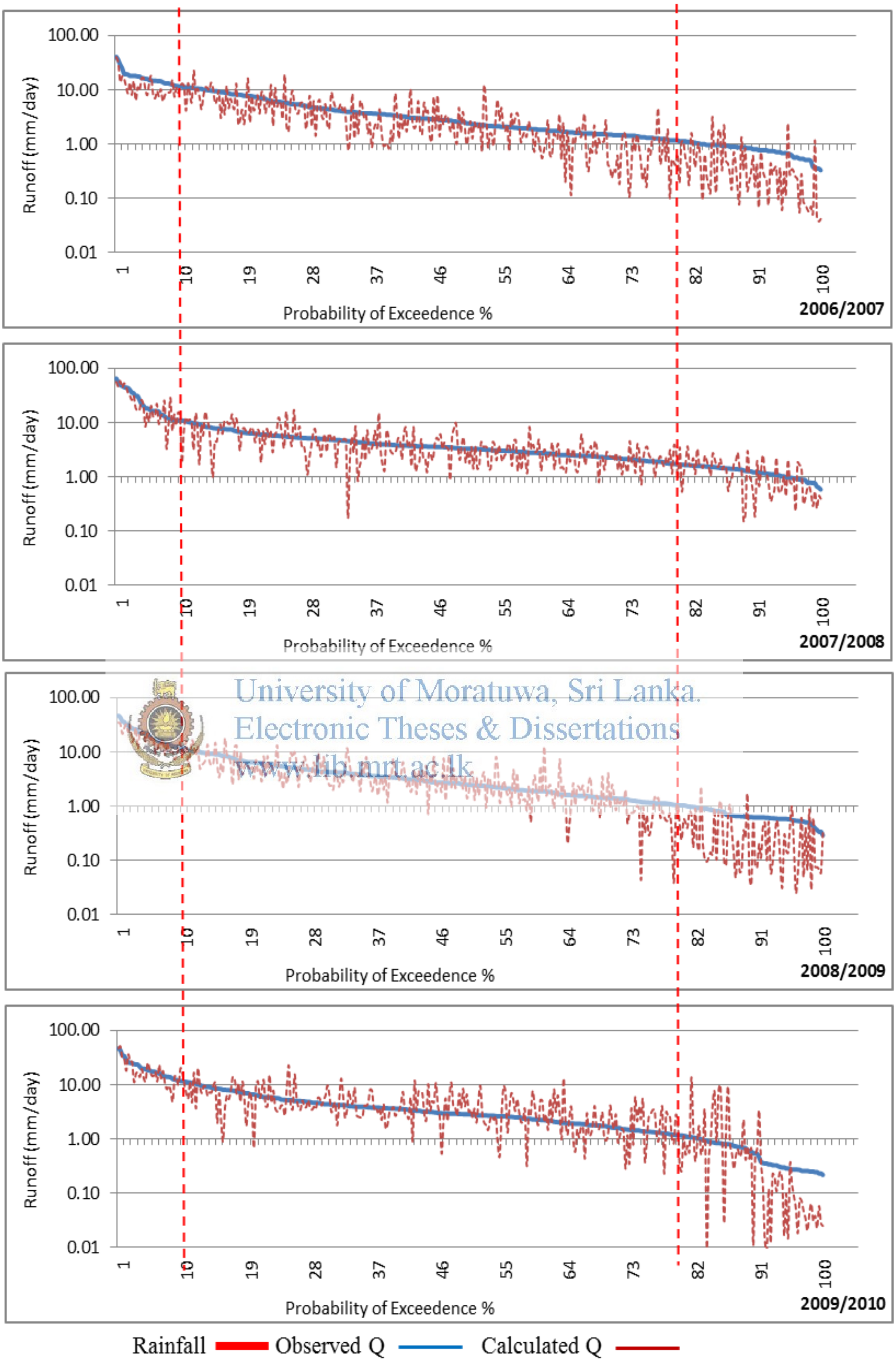

Figure 5-24 Flow duration curves at Ratnapura of Ellagawa distributed model calibration (semi-log scale)

Table 5-13 gives the monthly average observed and calculated flows and mass balance errors at Ellagawa river gauging station. Mass balance errors varied from 1.9% in April to 25.9% in February. Scatter plot of monthly observed and calculated flows are presented in Figure 5-25. Model over estimates the flow in August and September and it under estimates the flow in other months.

Table 5-14 presents the seasonal average observed and calculated flows and seasonal mass balance errors at Ellagawa during calibration period. Scatter plots of observed and calculated flows in maha and yala seasons are shown in Figure 5-26.

Table 5-13 Monthly average observed and calculated flows of Ellagawa distributed model

Month	Monthly average observed flow (mm)	Monthly average calculated flow (mm)	Monthly mass balance error (%)
January	42.25	29.27	15.2
February	35.34	20.25	25.9
March	54.70	36.98	5.5
April	135.95	130.19	1.9
May	270.95	195.79	23.7
June	235.71	206.75	6.7
July	208.18	190.84	14.3
August	113.68	135.69	16.7
September	163.34	191.24	7.6
October	216.07	211.47	3.0
November	164.67	129.77	11.0
December	80.61	62.15	6.8

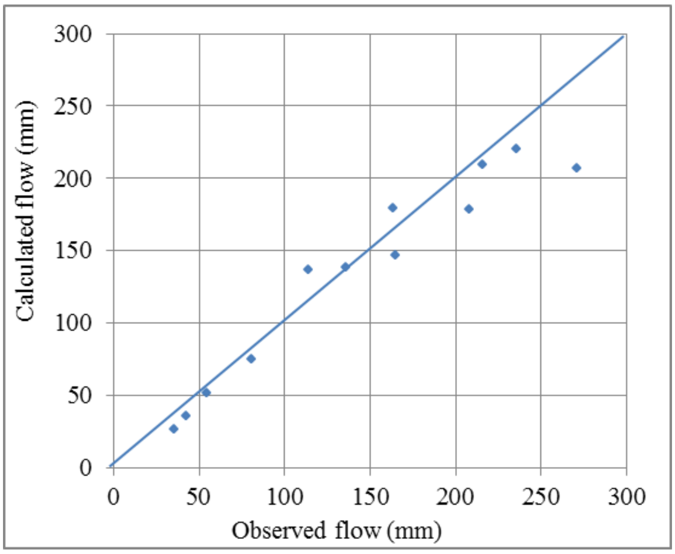

Figure 5-25 Co –relation of monthly observed and calculated flow of Ellagawa distributed model

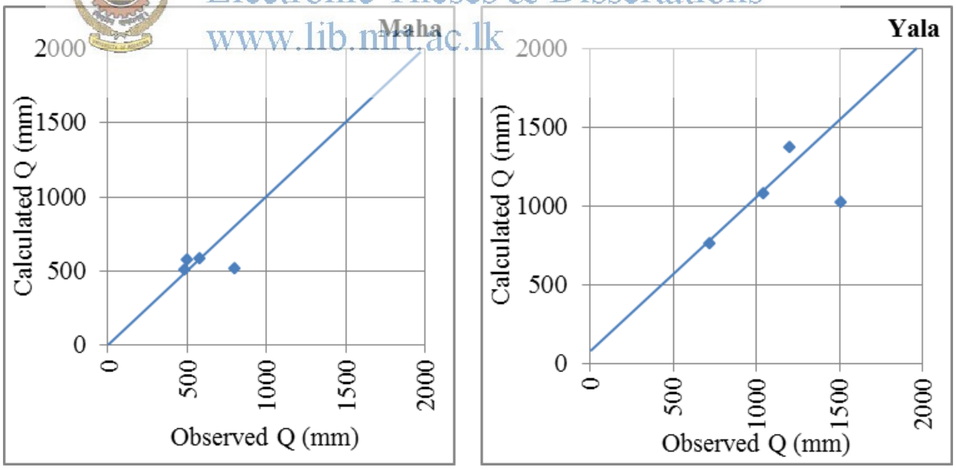

Figure 5-26 Seasonal variation of observed and calculated streamflow in Ellagawa distributed model

Table 5-14 Comparison of seasonal mass balance errors of Ellagawa distributed model calibration

Season	Observed Q (mm)	Calculated Q (mm)	Seasonal mass balance error %
2006/2007 Maha	799.68	515.10	35.59
2007/2008 Maha	581.91	579.18	0.47
2008/2009 Maha	488.21	510.13	4.49
2009/2010 Maha	503.44	574.28	14.07
Average Maha			**13.65**
2006/2007 Yala	730.84	762.00	4.26
2007/2008 yala	1518.91	1025.60	32.48
2008/2009 Yala	1051.96	1077.24	2.40
2009/2010 yala	1209.49	1371.55	13.40
Average Yala			**13.14**

Table 5-14 shows that there are big mass balance errors in 2006/2007 Maha and 2007/2008 Yala. But, seasonal average mass balance errors are almost the same in both Maha and Yala.

5.5 Model Verification

Observed daily streamflow data and daily rainfall data from 2010/2011 to 2013/2014 were used for model verification. Optimized catchment parameters found from model calibration were kept constant during verification. The model performance was assessed with the same statistical measures used in calibration.

5.5.1 Verification results of Ratnapura lumped model

Table 5-15 presents the statistical goodness of fit measures of model verification in Ratnapura lumped model. The performance is similar when compared with calibration results of Ratnapura lumped model. Observed and calculated streamflow and flow duration curves during verification are shown in Figure 5-27 and Figure 5-28. Figures show that the model performance during low flow periods is poor during verification. Non responsiveness of streamflow with rainfall can be clearly observed in Figure 5-29 and Figure 5-30 in semi-log scale plots.

Table 5-15 Verification results of Ratnapura lumped model

Gauging station	Nash-Sutcliff	MRAE	monthly mass balance error %	Flow duration curve						Model error (Sum of Absolute Residual)
				High		Medium		Low		
				Nash-Sutcliff	MRAE	Nash-Sutcliff	MRAE	Nash-Sutcliff	MRAE	
Ratnapura	0.585	0.773	21.5	0.455	0.367	-2.7	0.803	-21.7	0.875	93456

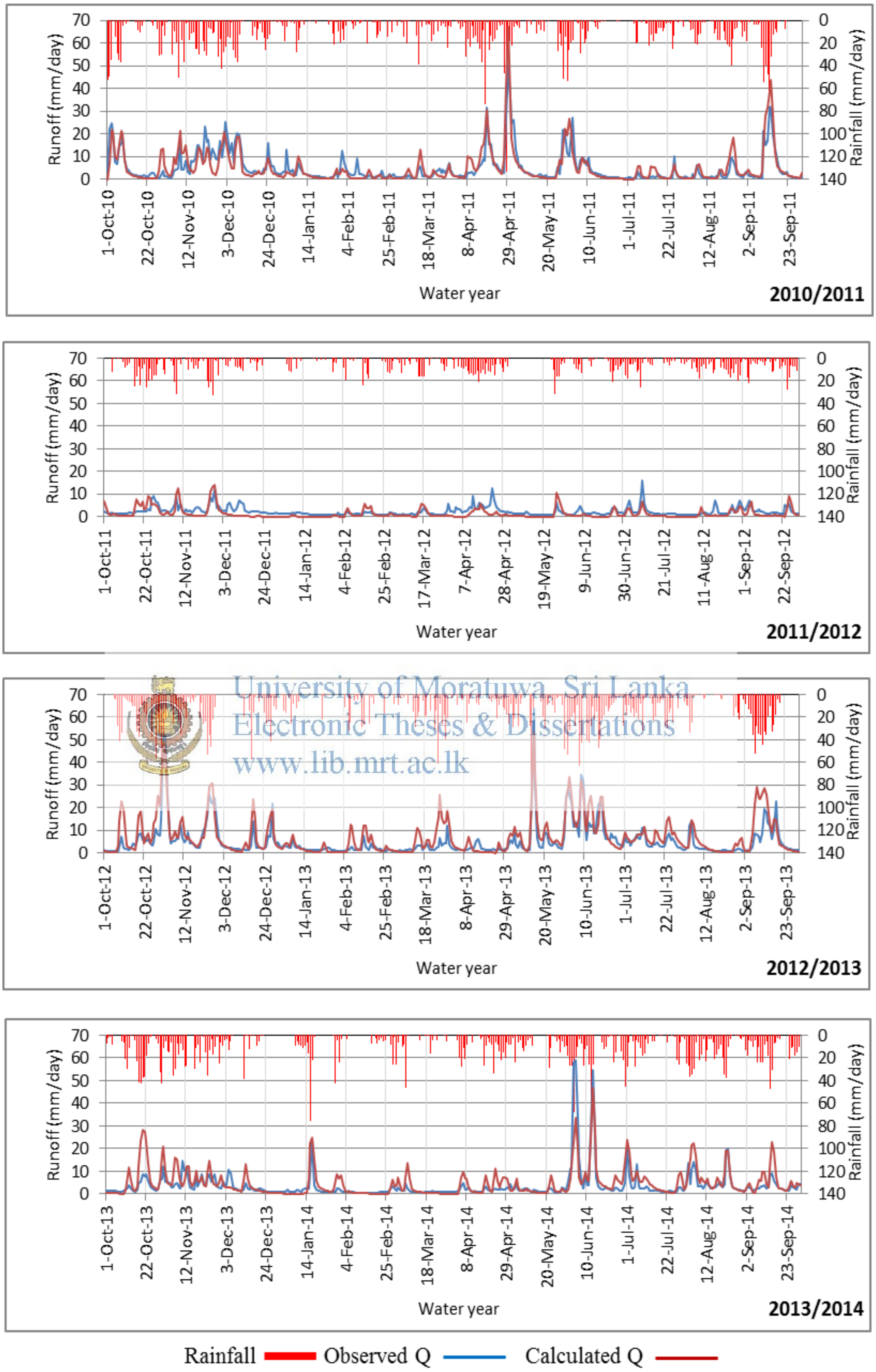

Figure 5-27 performance of Ratnapura lumped model verification (normal scale)

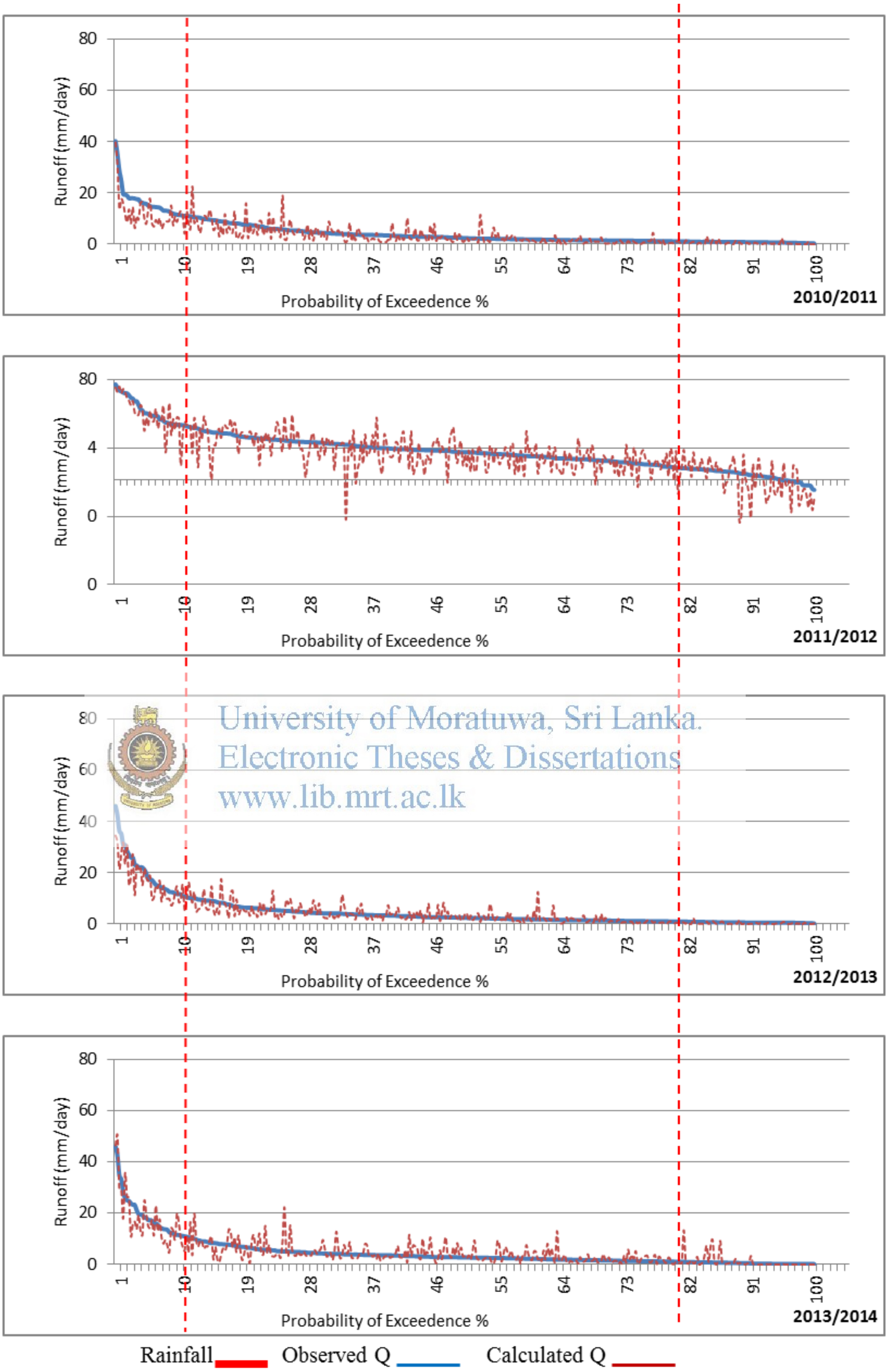

Figure 5-28 Flow duration curves of Ratnapura lumped model verification (normal scale)

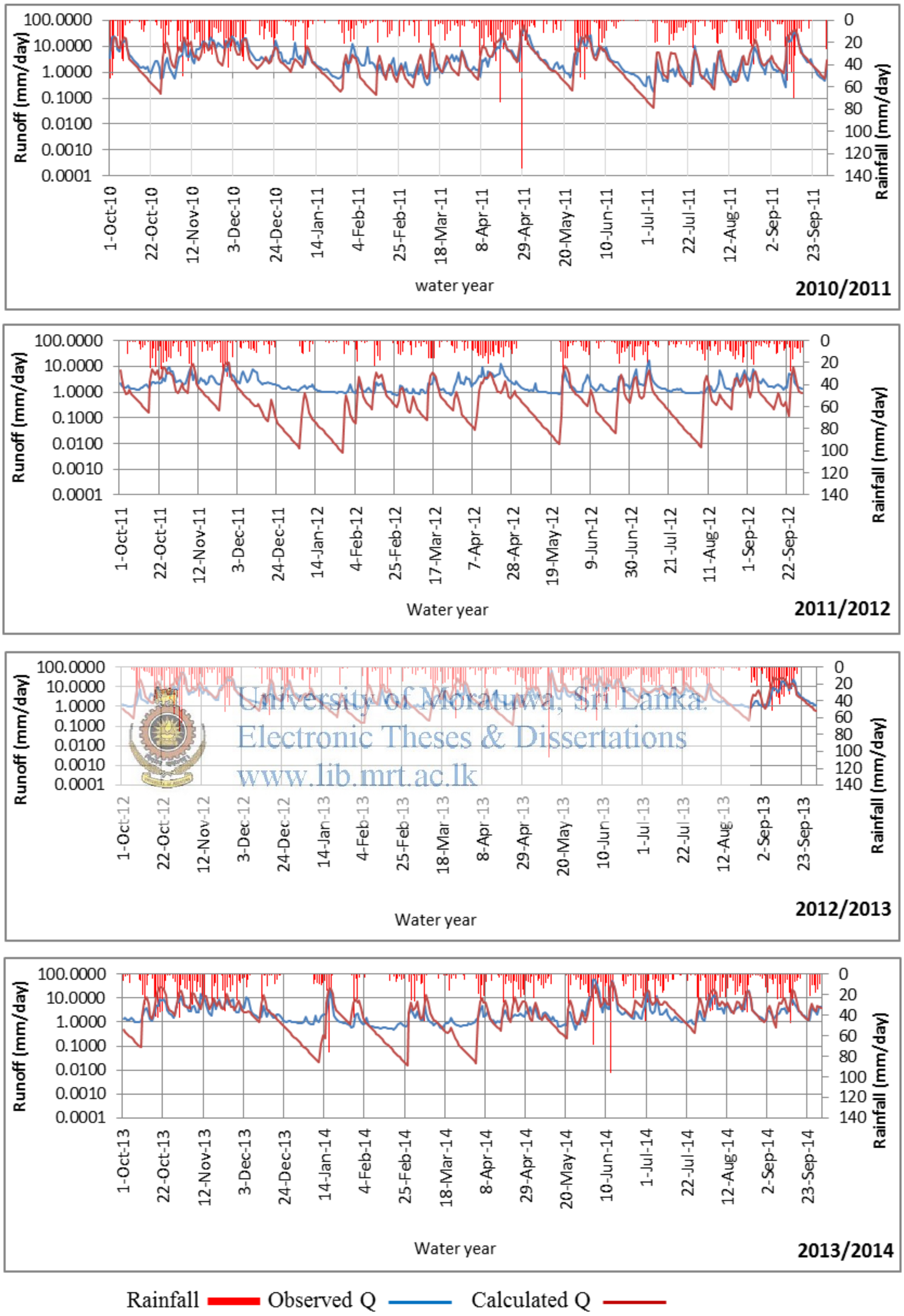

Figure 5-29 Performance of Ratnapura lumped model verification (semi-log scale)

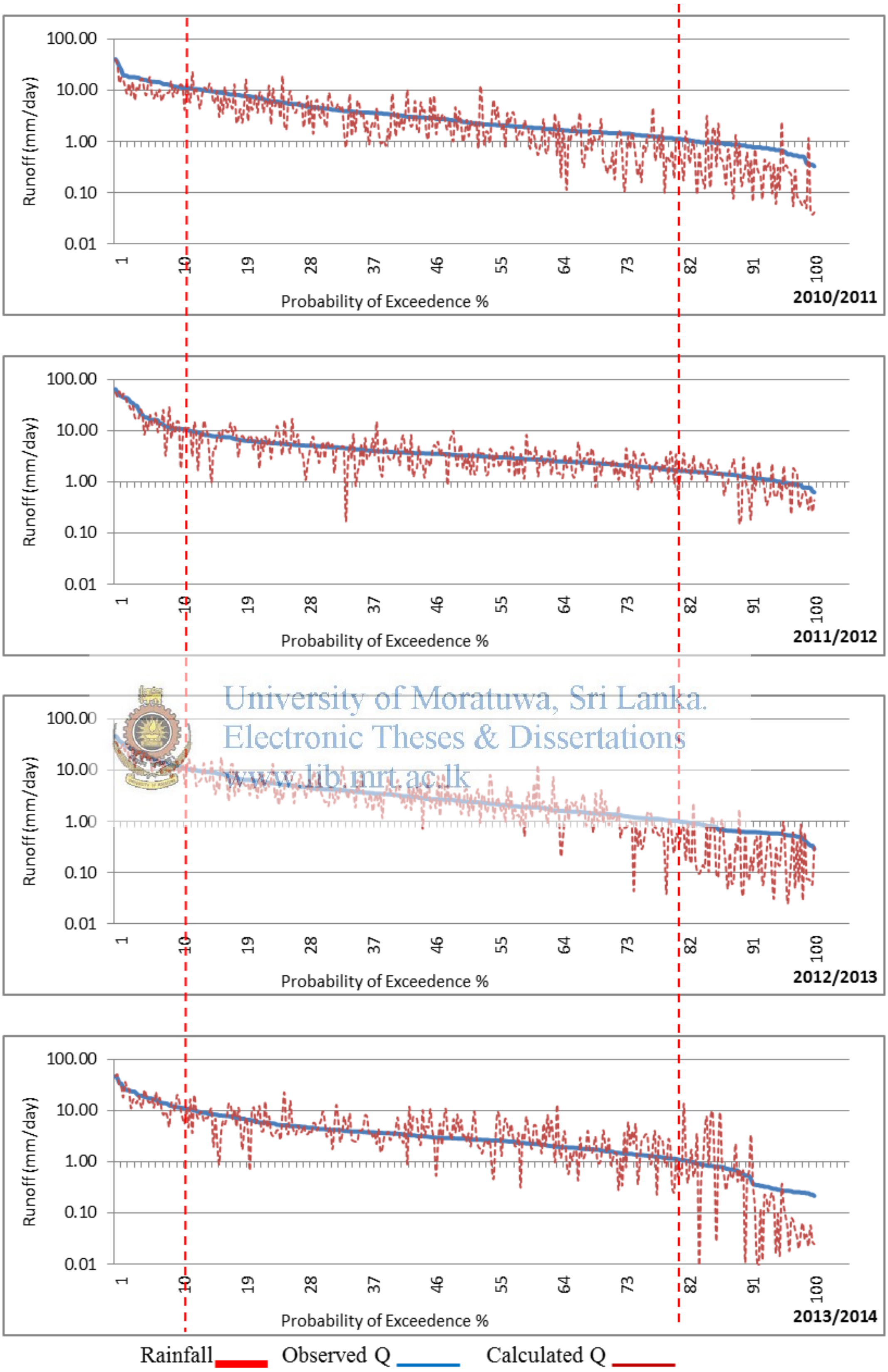

Figure 5-30 Flow duration curve of Ratnapura lumped model verification (semi-log scale)

Table 5-16 gives the monthly average observed and calculated flows and monthly mass balance errors at Ratnapura during verification. This is graphically presented in Figure 5-31. It shows that the model under estimates the flow in January, June and December while in other months, streamflow is overestimated.

Table 5-16 Monthly observed and calculated streamflow at Ratnapura verified model

Month	Monthly average observed flow (mm)	Monthly average calculated flow (mm)	Monthly mass balance error (%)
January	64.19	61.62	4.0
February	47.88	52.31	9.3
March	59.54	90.64	52.2
April	126.48	139.44	10.2
May	138.30	148.03	7.0
June	237.74	217.59	8.5
July	92.58	120.25	29.9
August	93.90	118.94	26.7
September	139.28	188.63	35.4
October	127.31	193.15	51.7
November	233.54	242.85	4.0
December	138.87	111.69	19.6

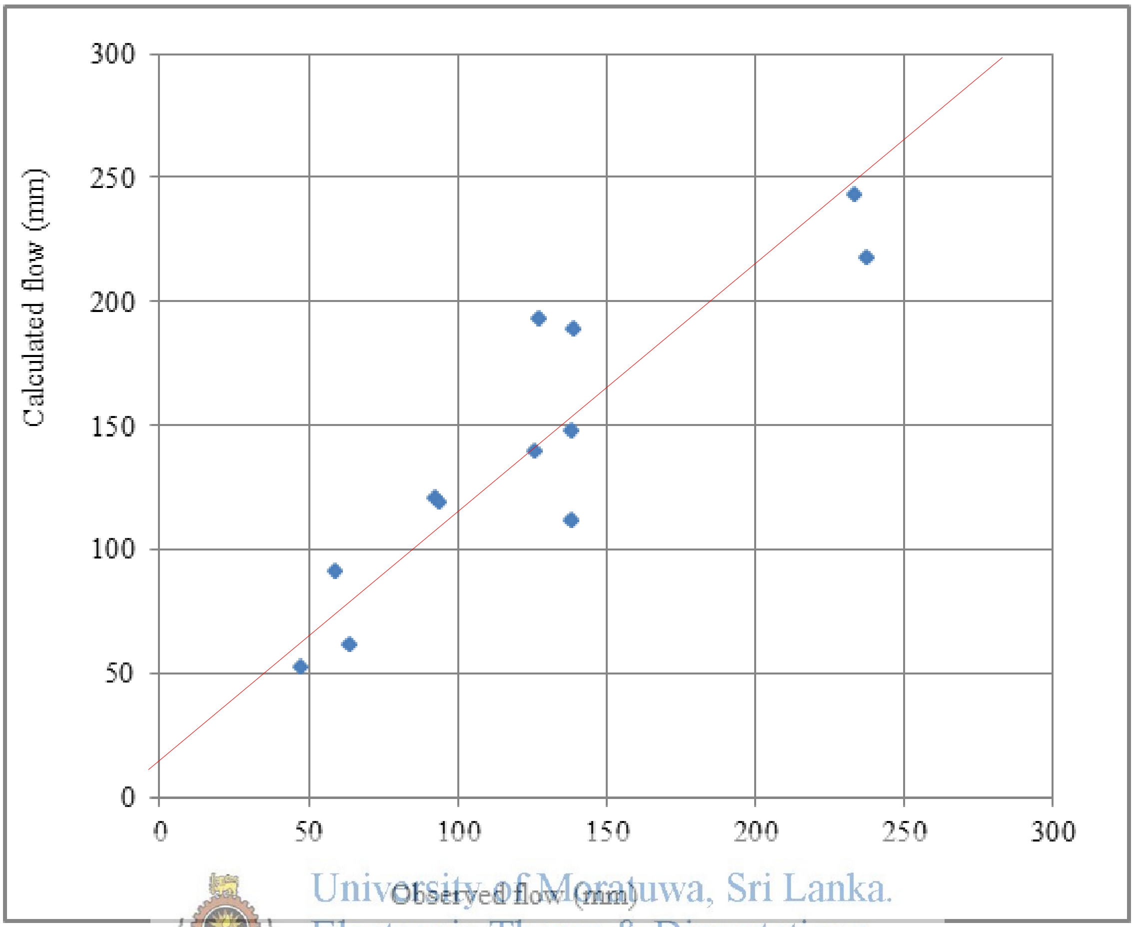

Figure 5-31 Monthly observed and calculated streamflows at Ratnapura of Ratnapura lumped model verification

5.5.2 Verification results of Ellagawa lumped model

Table 5-17 Verification results of Ellagawa lumped model

Gauging station	Nash-Sutcliff	MRAE	monthly mass balance error %	Flow duration curve						Model error (Sum of Absolute Residual)
				High		Medium		Low		
				Nash-Sutcliff	MRAE	Nash-Sutcliff	MRAE	Nash-Sutcliff	MRAE	
Ellagawa	0.64	0.616	10.97	0.29	0.4222	-1.47	0.6412	-20	0.728	194619

Statistical performance measures of Ellagwa lumped model during verification are shown in Table 5-17. Observed and calculated hydrographs and flow duration curves are presented in Figure 5-32 and Figure 5-33.

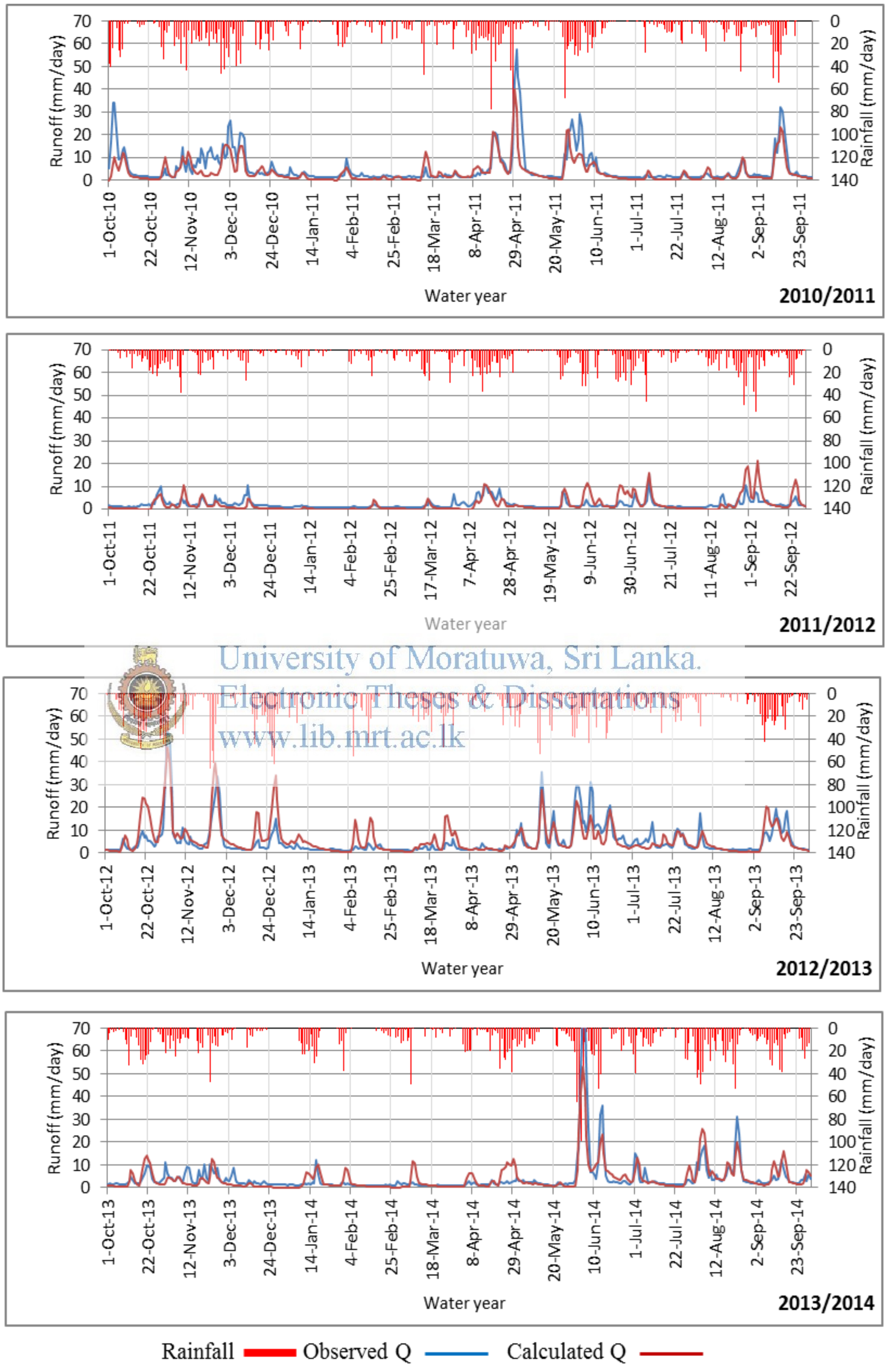

Figure 5-32 Performance of Ellagawa lumped model verification (normal scale)

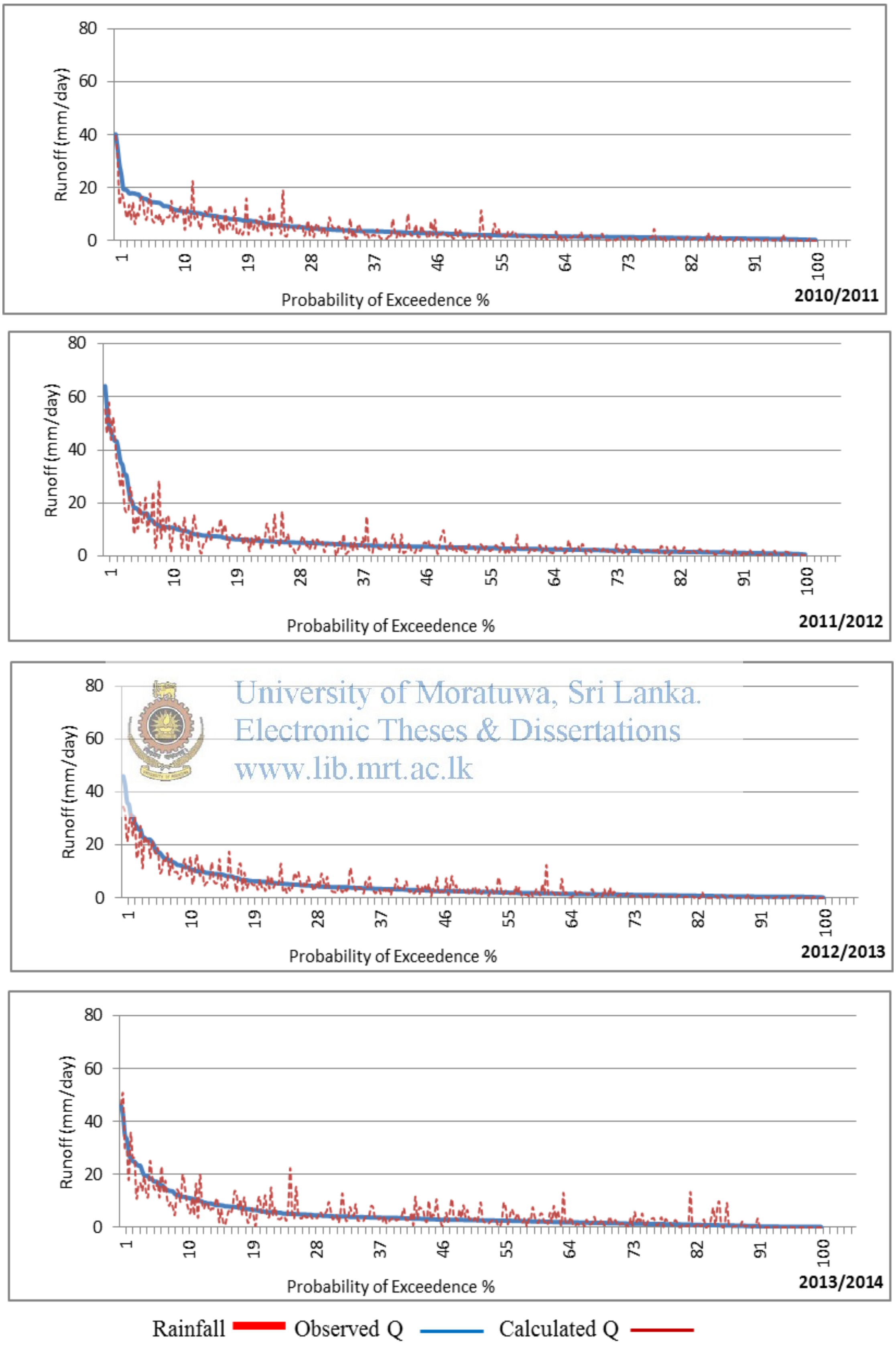

Figure 5-33 Flow duration curves of Ellagawa lumped model verification (normal scale)

Model performances of Ellagawa lumped model in semi-log scale during verification are in Appendix F.

5.5.3 Verification results of Ellagawa distributed model

Table 5-18 shows the statistical performance measures at Ellagawa and Ratnapura of Ellagawa distributed model verification.

Table 5-18 Verification results of Ellagawa distributed model

Gauging station	Nash-Sutcliff	MRAE	monthly mass balance error %	Flow duration curve					
				high		medium		low	
				Nash-Sutcliff	MRAE	Nash-Sutcliff	MRAE	Nash-Sutcliff	MRAE
Ellagawa	0.651	0.607	18.66	0.337	0.335	-1.3	0.655	-18.76	0.574
Ratnapura	0.572	0.754	18.8	0.341	0.382	-2.38	0.783	-19.45	0.812

Observed and calculated hydrographs and flow duration curves at Ellagawa distributed model are shown in Figure 5-34 and Figure 5-35 respectively.

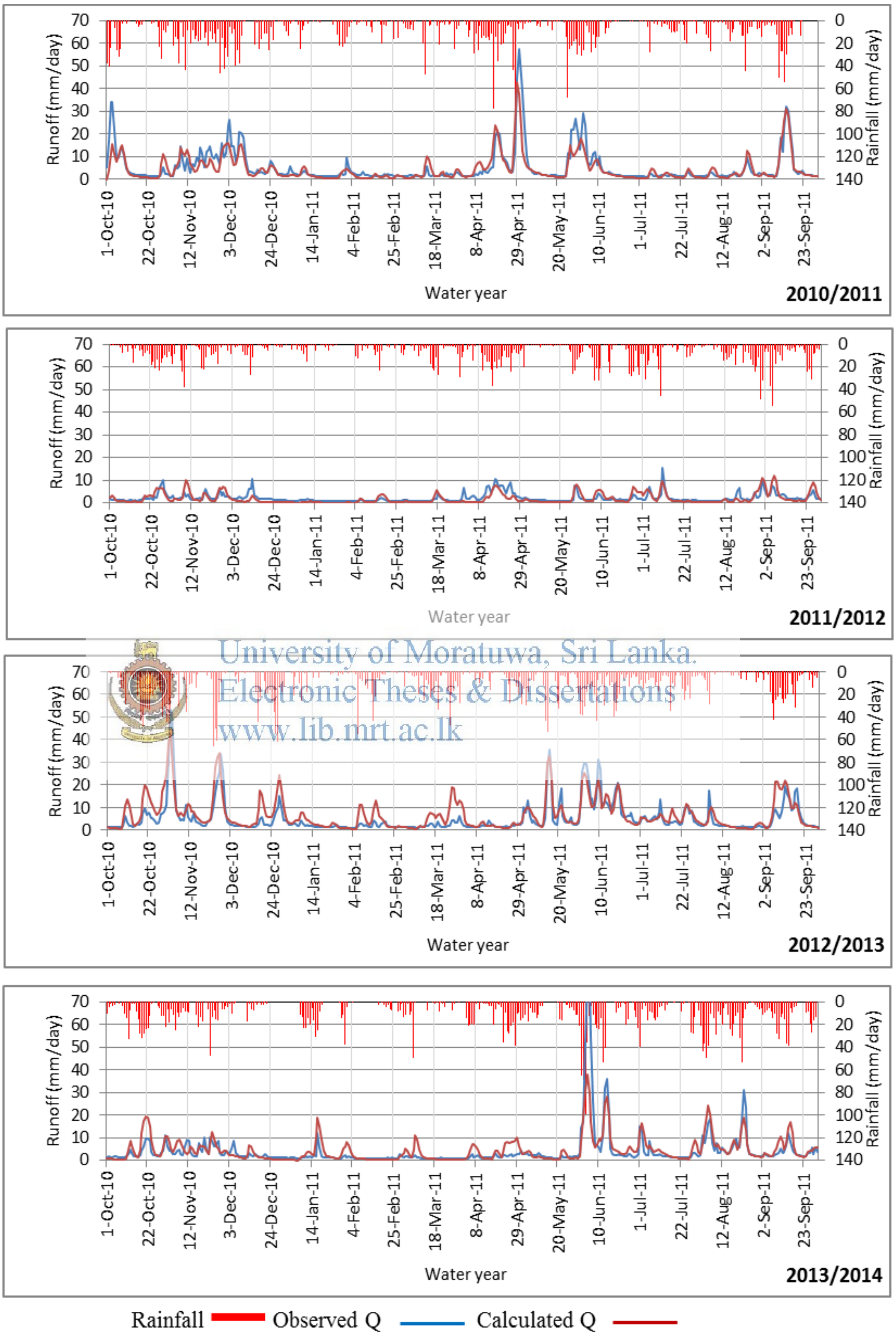

Figure 5-34 Performance of Ellagawa distributed model verification (normal scale)

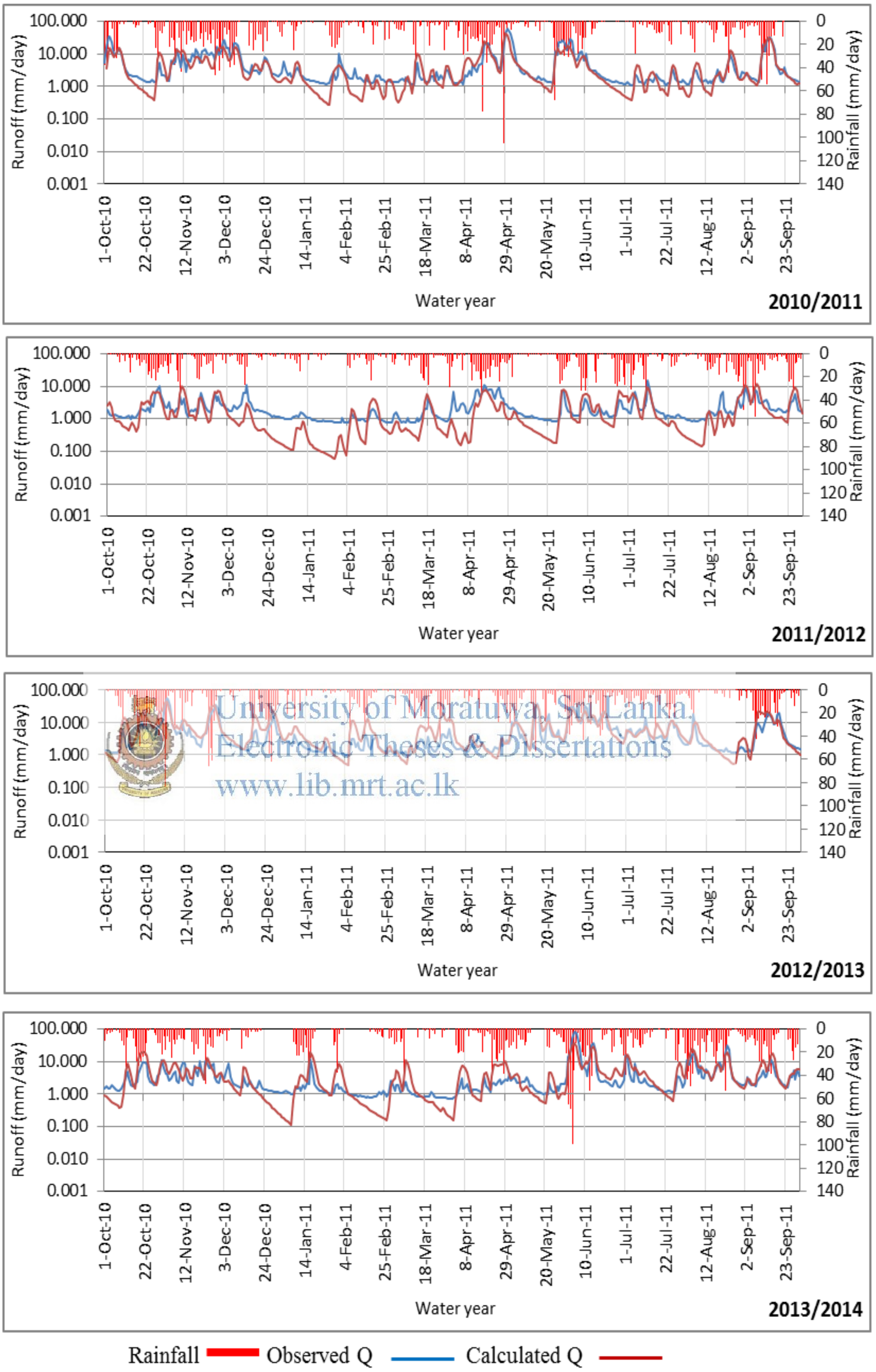

Figure 5-35 Performance of Ellagawa distributed model verification (semi-log scale)

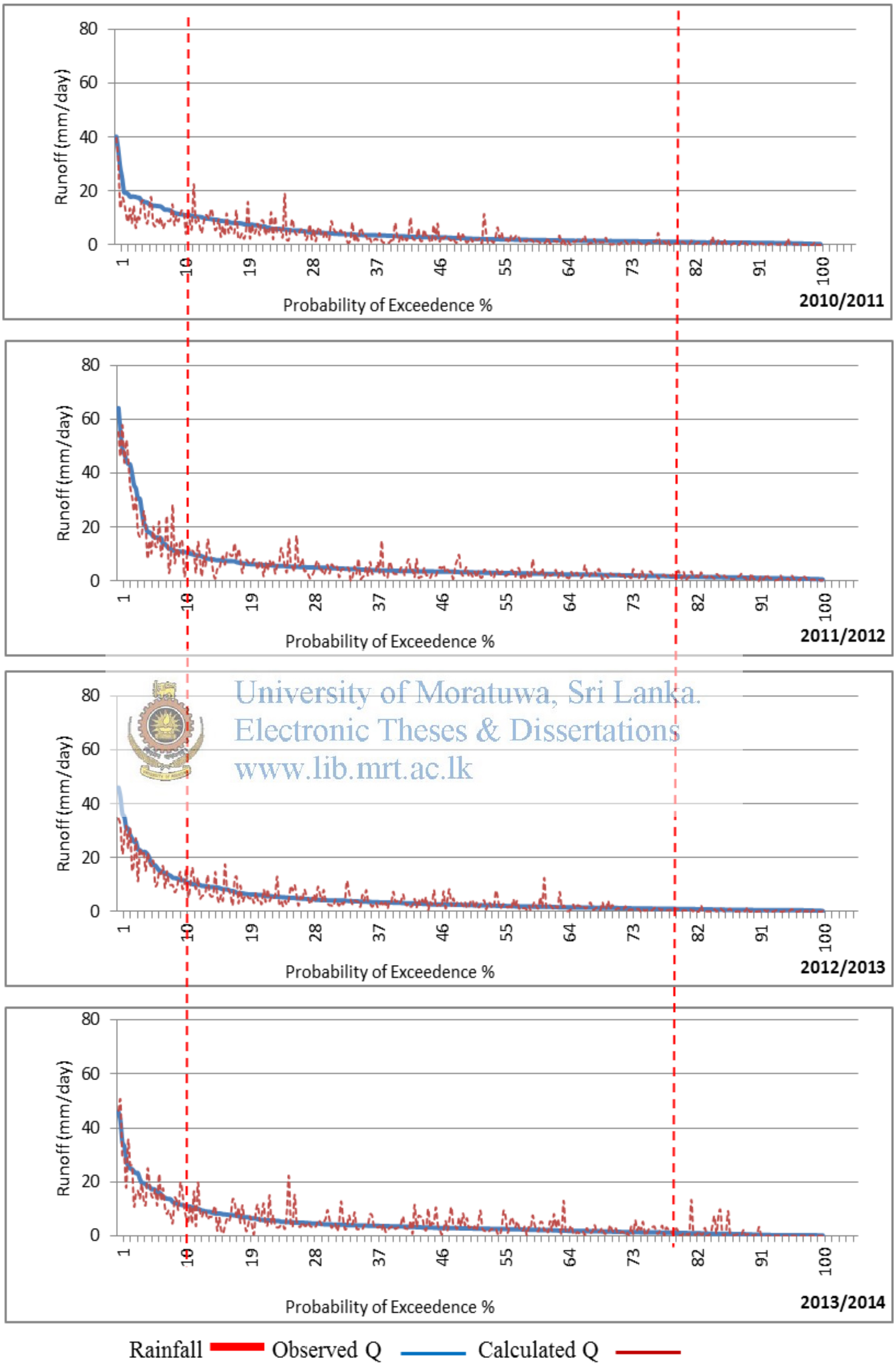

Figure 5-36 Flow duration curves of Ellagawa distributed model verification (normal scale)

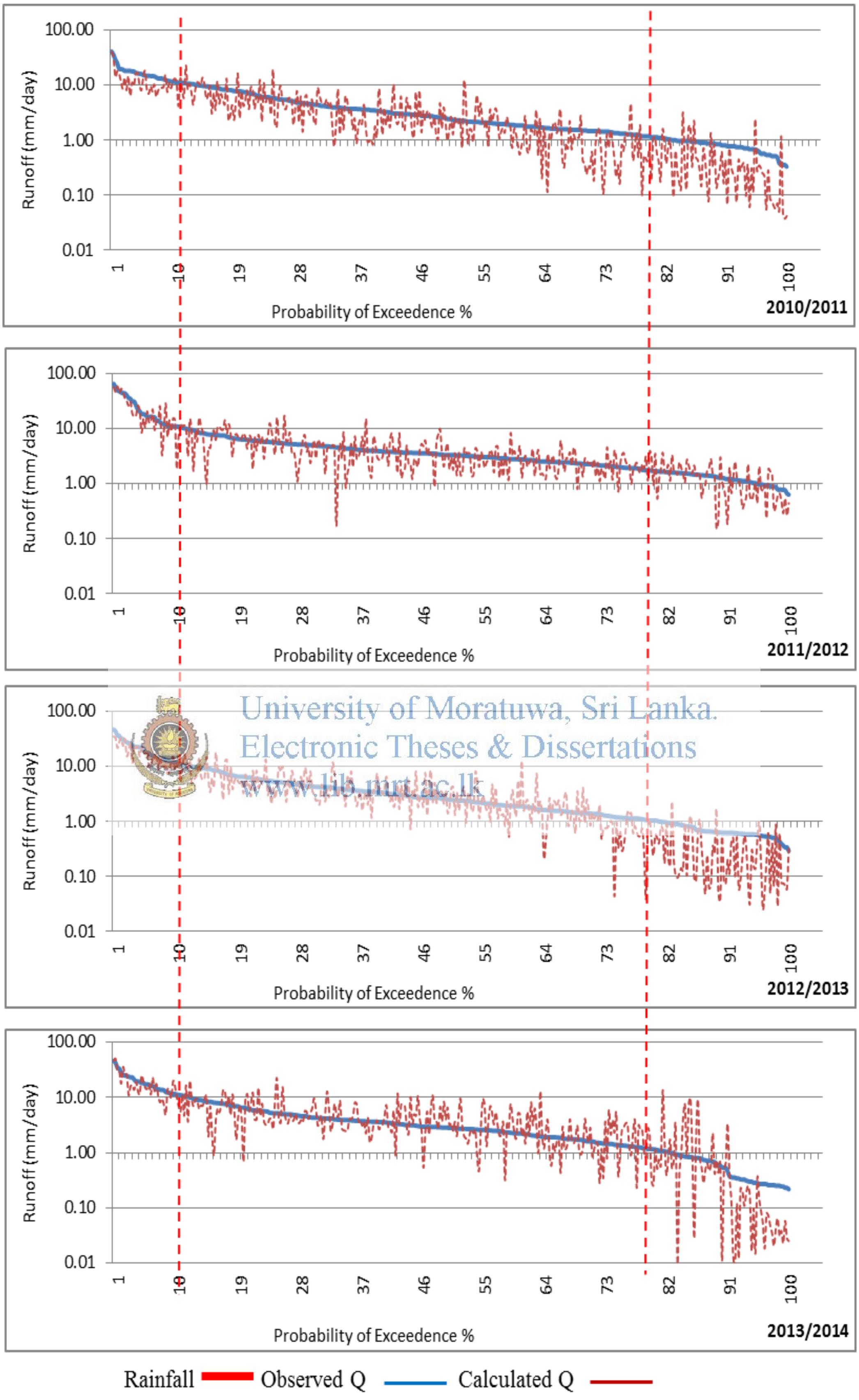

Figure 5-37 Flow duration curves of Ellagawa distributed model verification (semi-log scale)

5.6 Comparison of Error Values in Flow Duration Curves during Calibration

Two types of flow duration curves were drawn, (1) by sorting only observed streamflow and (2) by sorting both observed and calculated streamflow assuming there is no time shift in estimation. Error values for all high, medium and low flow regions were calculated for both flow duration curves. Flow duration curves of type 2 for Ratnapura lumped, Ellagawa lumped and Ellagawa distributed models are in Figure 5-38, Figure 5-39 and Figure 5-40 respectively.

Table 5-19 Comparison of errors in flow duration curve 1

	Ellagawa catchment			Ratnapura catchment		
	High	Medium	Low	High	Medium	Low
Observed Q (MCM)	1012	1307	79	467	605	36
Calculated Q (MCM)	864	1369	80	398	633	36
Error (MCM)	149	112	30	69	52	14
% error w.r.t. Average annual flow	6.2	4.7	1.2	6.2	4.7	1.3

Calculation of error values in all regions of flow duration curve 1 and 2 for both Ellagawa and Ratnapura catchments are given in Table 5-19 and Table 5-20. Average annual flow in Ellagawa and Ratnapura catchments are 2399 MCM and 1108 MCM, respectively.

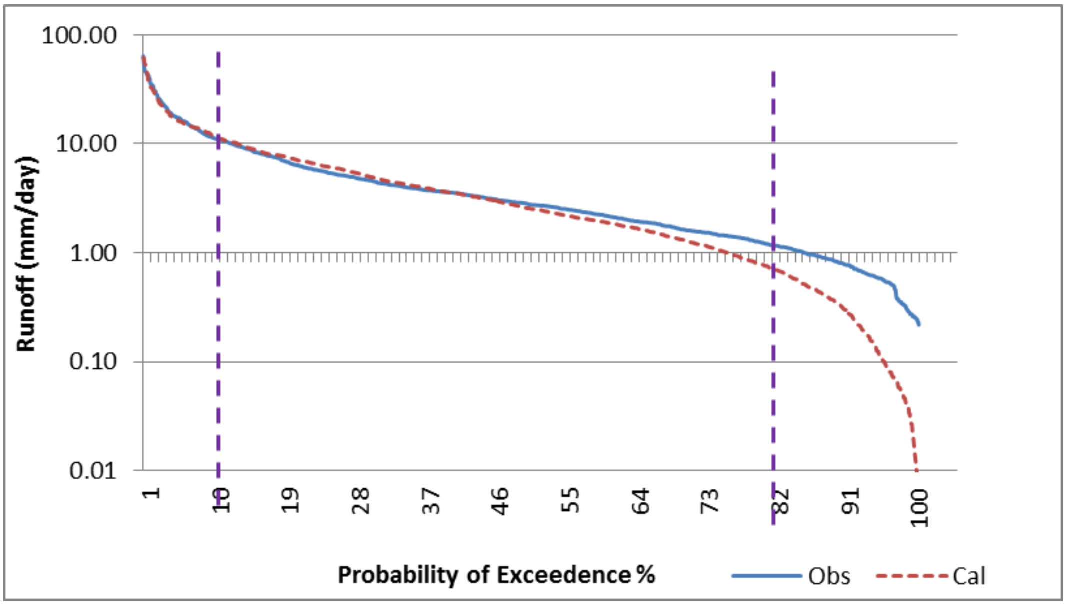

Figure 5-38 Flow duration curve type 2 for Ratnapura

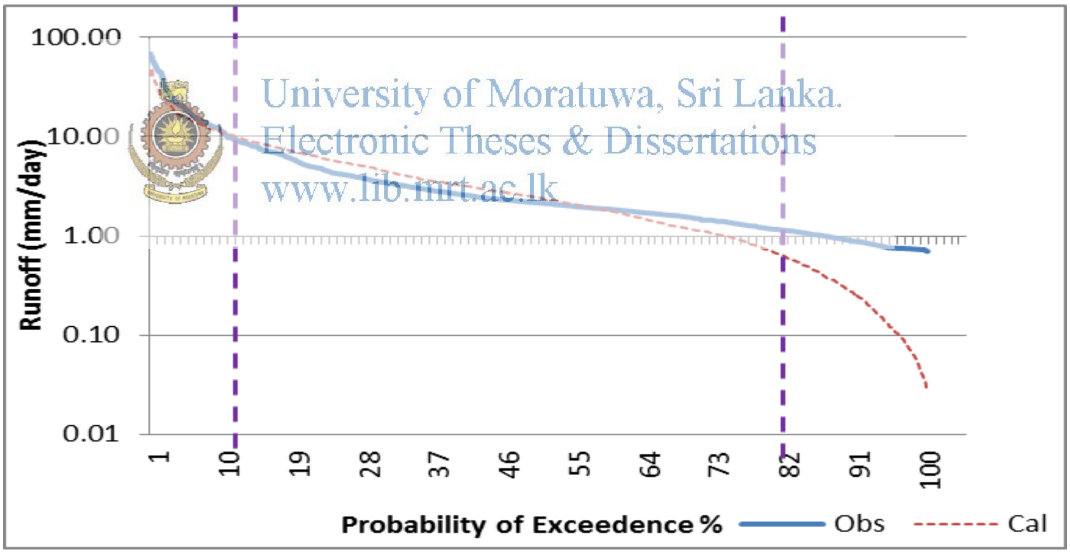

Figure 5-39 Flow duration curve type 2 for Ellagawa

In Figure 5-38 and Figure 5-39, it can be seen a very good matching in high and medium flow regions.

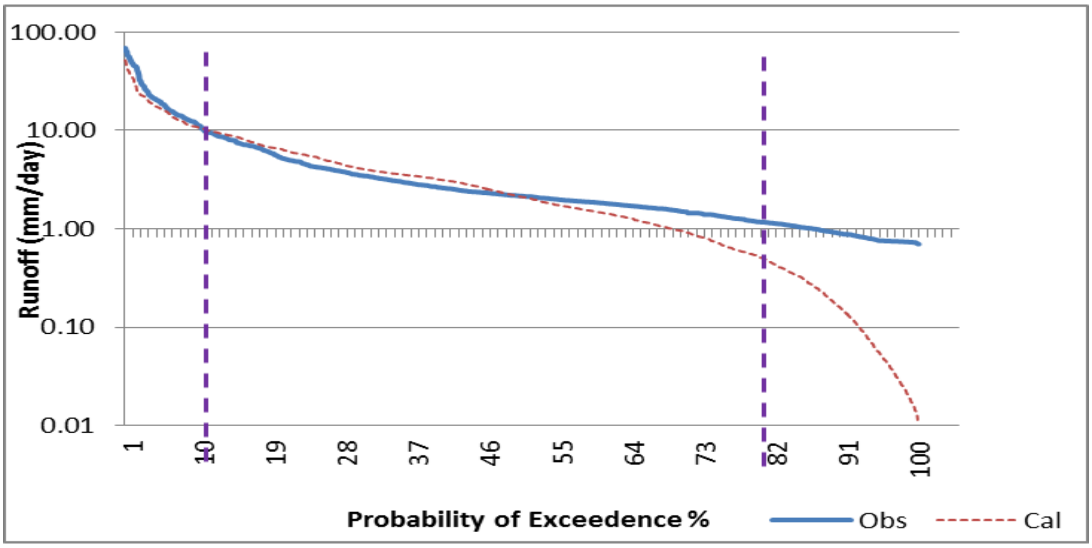

Figure 5-40 Flow duration curve type 2 for Ellagawa lumped model

Table 5-20 Comparison of errors in flow duration curve 2

	Ellagawa catchment			Ratnapura catchment		
	High	Medium	Low	High	Medium	Low
Observed Q (MCM)	1012	1307	79	467	605	36
Calculated Q (MCM)	915	1234	30	459	611	15
Error (MCM)	97	73	49	8	6	21
% error w.r.t. Average annual flow	4	3	2	0.7	0.5	1.9

Table 5-19 and Table 5-20 showed that the magnitude of errors in low flow period is small compared to errors in other regions (high and medium) for both Ellagawa and Ratnapura catchments. Even in flow duration curve 2 where time shift was not considered, the error is 49 MCM. It is a 2% of the average annual flow of Ellagawa catchment which amounts to 2399 MCM.

5.7 Modeling approach in HEC HMS Model

5.7.1 Data collection and checking

At least 4-5 year data for calibration and verification need to be used to ensure that extreme conditions are included in the dataset. Spatial distribution of the rainfall stations over the catchment is very much important.

The following data checking have to be carried out.

1. Annual water balance
2. Visual checking
3. Aggregated rainfall
4. Monthly and annual rainfall
5. Moving average rainfall
6. Double mass curve

5.7.2 Selection of model

Type of model whether event based or continuous has to be selected depending on the modeling objective, whether flood modeling or water resource modeling etc.

5.7.3 Selection of precipitation loss model / direct runoff model / baseflow model and channel routing model

Out of nine different precipitation loss models in HEC HMS, deficit constant model and Soil Moisture Accounting (SMA) model can be recommended for continuous simulation in combination with monthly evaporation data. But, in event based modeling, any loss model can be used. An order of magnitude evaluation can be adopted based on the following criteria when selecting the model. (1) Number of parameters and (2) Soil moisture content.

Out of seven different direct runoff methods, evaluation was carried out considering number of parameters and whether empirical equations can be used etc. Whether it is event or continuous modeling, any direct runoff model can be used for runoff estimation.

A total of four different baseflow methods, some of the methods are very basic methods for event simulation where as the others are used for continuous simulation. Recession baseflow method is the widely used primary method. Baseflow models are evaluated by considering number of parameters and whether it is complex or simple for application etc. HEC, (2000) recommends that baseflow recession method is best suited for event modeling, but in continuous modeling too it can be applied as it automatically model the baseflow between storm events. Linear reservoir method is much suitable for continuous simulation as it model the recession of baseflow after a storm event.

Six methods are available for channel routing in HEC HMS. Order of magnitude evaluation is done considering the number of parameters and whether it depends on the channel geometry. Nandalal and Ratnayake (2010) concluded that lag model is suitable for steeper slopes in upper reaches of rivers in which case the flows are not attenuated. Muskingam model is used for lower reaches of gradual slopes near coast.

5.7.4 Selection of meteorological model

Any meteorological model can be used. In continuous modeling, monthly evaporation data has to be used.

5.7.5 Model calibration

5.7.5.1 Selection of objective function

The calibration process include following objectives

1. Matching simulated and observed runoff volume (overall mass balance)
2. Matching shape of the hydrograph
3. Matching peak flows with respect to timing, rate and volume
4. Matching low flows

For the purpose of flood forecast, the first three objectives are to be considered.

The following numerical performance measures are recommended to achieve the above calibration objectives.

1. Percent Error in Volume (PEV) – overall mass balance
2. Mean Ratio of Absolute Error (MRAE) / Ratio of Absolute Error to Mean (RAEM) – matching shape of the hydrograph
3. Nash-Sutcliff / Coefficient of determination – Matching peaks
4. Sum of Absolute Residuals / Root Mean Square Error (RMSE) – matching shape

There is no big difference in RAEM whether peaks or low flow match better. Therefore, a marked difference could not be seen. In MRAE, the cases very well reflect the characters of streamflow series. Therefore, when there are high peaks and low flows, MRAE is good especially for low flow matching. If the flow series has the same order of magnitude of flows, RAEM or MRAE could be used.

In RMSE method, error values in high peaks and low peaks vary drastically. Hence, this method is suitable for single peak events and not recommended for continuous simulation.

5.7.5.2 Automatic parameter optimization in HEC HMS

For continuous modeling sum of absolute residual or sum of squared residual method can be recommended to use as the objective function. Out of two search algorithms, Univariate Gradient or Nelder and Mead, whichever the method used, there are no significant change in objective function values.

Automatic parameter optimization is used to get the soft limits of parameters and the manual calibration can be done with the use of that range of parameter values.

5.7.6 Model verification

Different data set is to be used for model verification. Optimized parameters obtained after calibration are used during model verification.

5.7.7 Evaluation of model performance

For continuous modeling, evaluation of flow duration curve is important as it gives the overall flow regime of the river for the entire period. By considering the gradient of curve, flow duration curve may be divided into three main regions such as high, medium and low. The above described statistical measures are calculated for each region from which best fit region and poor matching regions can be identified.

6 SUMMARY OF RESULTS

6.1 Comparison of Model Calibration Results

Comparison of statistical performance measures of Ratnapura and Ellagawa lumped model and Ellagawa distributed model calibration results are given in Table 6-1.

Table 6-1 Comparison of model calibration results

Model	Nash-Sutcliff	MRAE	monthly mass balance error %	Flow duration curve					
				high		medium		low	
				Nash-Sutcliff	MRAE	Nash-Sutcliff	MRAE	Nash-Sutcliff	MRAE
Ratnapura lumped	0.7834	0.5226	14.3	0.641	0.2722	-0.35	0.4877	-18.87	0.7717
Ellagawa lumped	0.7001	0.5802	11.9	0.31	0.3519	-0.64	0.5591	-26.1	0.7693
Ellagawa distributed	0.6918	0.5407	11.2	0.26	0.3244	-0.46	0.5228	-29.65	0.7123
Difference %	1.3	6.7	5.9	15.9	8	26.6	6.4	13.6	10.6

When looking at the statistical performance measures for calibration in Table 6-1, Ratnapura lumped model gives the best performance in terms of Nash-Sutcliff and MRAE values which are 0.7834 and 0.5226 respectively. Nash-Sutcliff and MRAE in high flow regions of flow duration curve are 0.641 and 0.2722 which are fairly good figures. Medium and low flow matching is poor in terms of Nash-Sutcliff value where as MRAE gives 0.4877. When comparing the model performances of Ellagawa lumped and distributed models, there is a considerable improvement in terms of monthly mass balance error in the distributed model. This varies from 11.95% to 11.2% in lumped to distributed models which indicates a 5.9% improvement of model performance. MRAE value also show an improvement in model performance. It varies from 0.5802 lumped to 0.5407 in distributed model. This has a 6.7% model improvement. There is an improvement of MRAE in all regions of the flow duration curve. However, in terms of Nash-Sutcliff, the model performance has become poor when moving from lumped to distributed. Variation of error values with respect to each model is shown in Figure 6-1 and Figure 6-2.

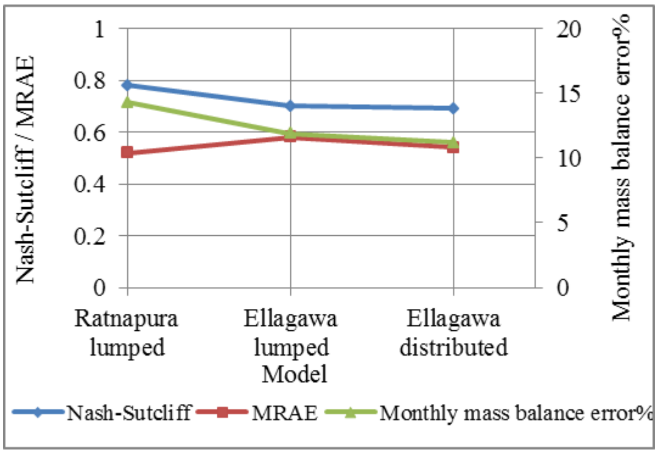

Figure 6-1 Variation of error values during calibration of Ellagawa distributed model with change of model

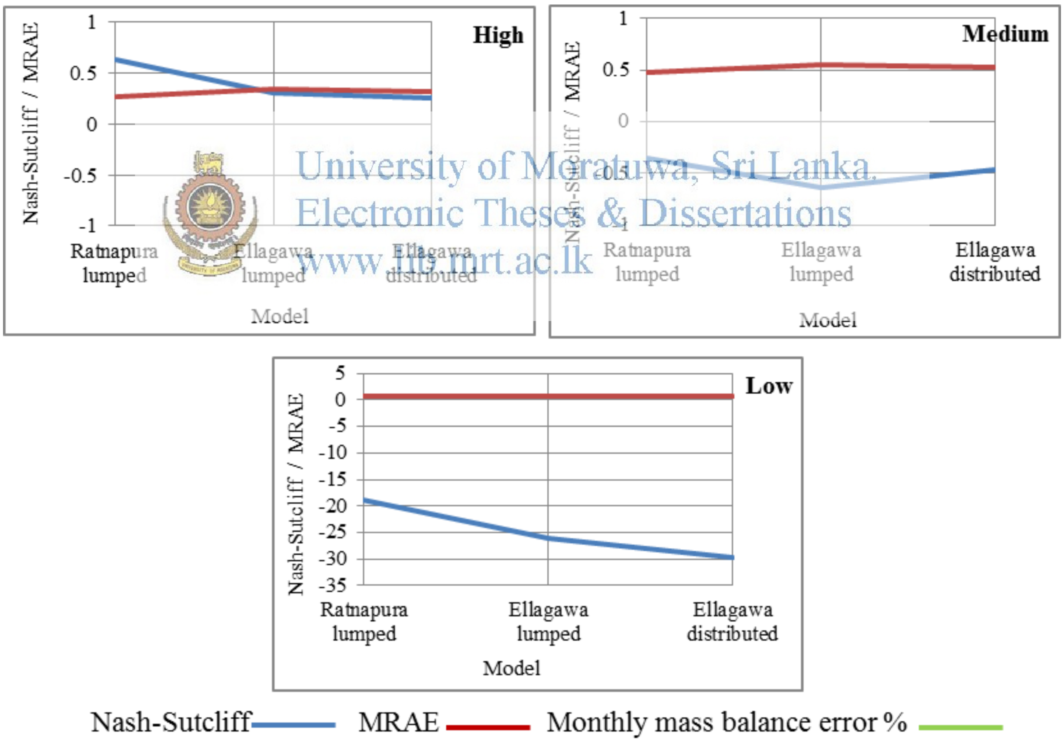

Figure 6-2 Variation of error values during calibration of Ellagawa distributed model in flow duration curve with change of model

6.2 Comparison of Annual Mass Balance Errors

6.2.1 Comparison of annual mass balance errors in calibration

Annual mass balance errors are compared in Table 6-2, Table 6-3 and Table 6-4 for Ratnapura lumped model, Ellagawa lumped model and Ellagawa distributed model during calibration. Variation of annual mass balance errors are shown in Figure 6-3, Figure 6-4 and Figure 6-5 respectively.

Table 6-2 Comparison of annual mass balance errors in Ratnapura lumped model calibration

Year	**Observed Q (mm)**	**Calculated Q (mm)**	**Annual mass balance error %**
2006/2007	1630.21	1426.61	12.49
2007/2008	2019.56	1994.93	1.22
2008/2009	1707.31	1662.54	2.62
2009/2010	1716.15	1842.28	7.35
Average			**5.92**

Table 6-3 Comparison of annual mass balance errors in Ellagawa lumped model calibration

Year	**Observed Q (mm)**	**Calculated Q (mm)**	**Annual mass balance error %**
2006/2007	1530.53	1270.10	17.02
2007/2008	2104.03	1592.84	24.30
2008/2009	1540.18	1513.05	1.76
2009/2010	1712.94	1792.05	4.62
Average			**11.92**

Table 6-4 Comparison of annual mass balance errors in Ellagawa distributed model calibration

Year	**Observed Q (mm)**	**Calculated Q (mm)**	**Annual mass balance error %**
2006/2007	1530.5	1277.1	16.5
2007/2008	2107.9	1610.1	23.6
2008/2009	1540.1	1591.7	3.3
2009/2010	1712.9	1945.8	13.6
Average			**14.2**

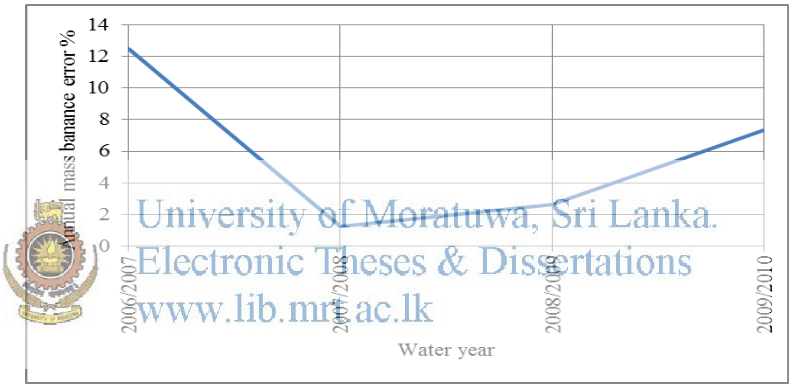

Figure 6-3 Variation of annual mass balance error in Ratnapura lumped model calibration

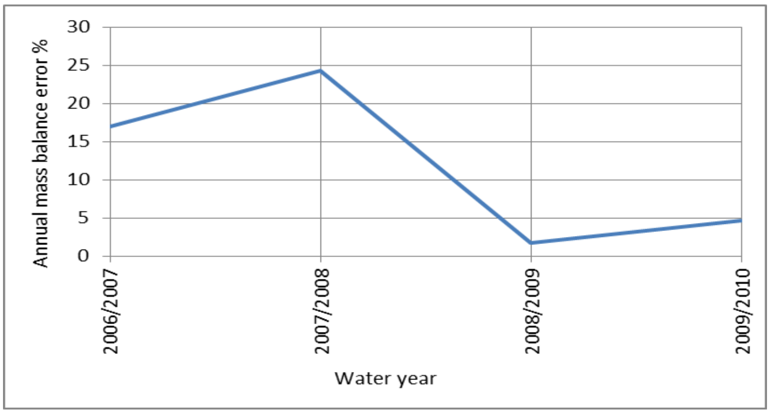

Figure 6-4 Variation of annual mass balance error in Ellagawa lumped model calibration

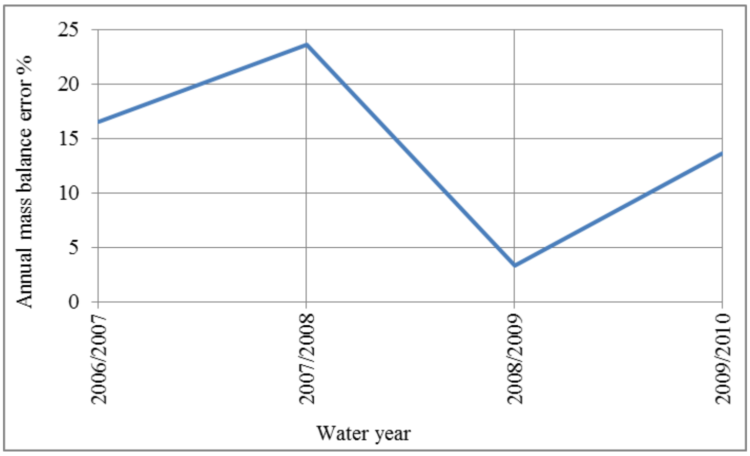

Figure 6-5 Variation of annual mass balance error in Ellagawa

A considerable increase in annual mass balance error can be observed in Table 6-3 and Table 6-4, and Figure 6-4 and Figure 6-5 in year 2007/2008 for Ellagawa watershed. But in Ratnapura watershed, annual mass balance error is highest in year 2006/2007.

6.2.2 Comparison of annual mass balance errors during verification

Annual mass balance errors during verification are compared in Table 6-5, Table 6-6 and Table 6-7 for Ratnapura lumped model, Ellagawa lumped model and Ellagawa distributed model respectively. These are graphically presented in Figure 6-6, Figure 6-7 and Figure 6-8.

Table 6-5 Comparison of annual mass balance errors in Ratnapura lumped model verification

Year	Observed Q (mm)	Calculated Q (mm)	Annual mass balance error %
2010/2011	1854.06	1864.67	0.57
2011/2012	870.79	504.43	42.07
2012/2013	1963.78	2633.23	34.09
2013/2014	1311.38	1741.22	32.78
2010/2011	1854.06	1864.67	0.57
Average			**27.38**

Table 6-6 Comparison of annual mass balance errors in Ellagawa lumped model verification

Year	**Observed Q (mm)**	**Calculated Q (mm)**	**Annual mass balance error %**
2010/2011	1943.31	1339.97	0.57
2011/2012	822.12	800.71	42.07
2012/2013	1933.58	2214.14	34.09
2013/2014	1484.80	1423.56	32.78
2010/2011	1943.31	1339.97	0.57
Average			**13.07**

Table 6-7 Comparison of annual mass balance errors in Ellagawa lumped model verification

Year	**Observed Q (mm)**	**Calculated Q (mm)**	**Annual mass balance error %**
2010/2011	1943.31	1339.97	0.57
2011/2012	822.12	800.71	42.07
2012/2013	1933.58	2214.14	34.09
2013/2014	1484.80	1423.56	32.78
2010/2011	1943.31	1339.97	0.57
Average			**16.55**

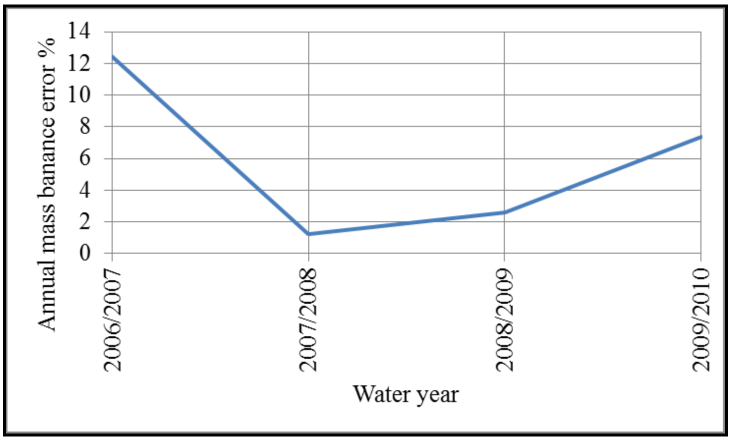

Figure 6-6 Variation of annual mass balance error for Ratnapura lumped model

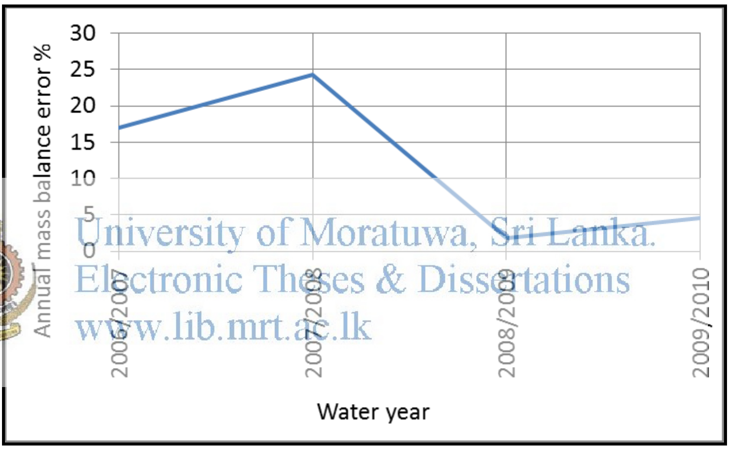

Figure 6-7 Variation of annual mass balance error for Ellagawa lumped model

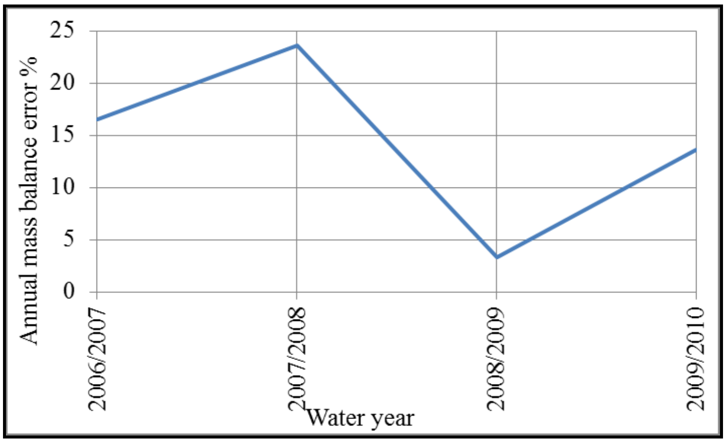

Figure 6-8 Variation of annual mass balance error for Ellagawa distributed model

6.3 Comparison of Model Verification Results

Comparison of statistical performance measures of Ratnapura and Ellagawa lumped model and Ellagawa distributed model verification results are given in Table 6-8.

Table 6-8 Comparison of model verification results

Model	Nash-Sutcliff	MRAE	monthly mass balance error %	Flow duration curve					
				High		Medium		Low	
				Nash-Sutcliff	MRAE	Nash-Sutcliff	MRAE	Nash-Sutcliff	MRAE
Ratnapura lumped	0.5852	0.7732	21.5	0.4514	0.3669	-2.7169	0.8026	-21.6704	0.8752
Ellagawa lumped	0.6157	0.6399	10.9	0.2922	0.4160	-1.5487	0.6700	-20.7868	0.6354
Ellagawa distributed	0.6515	0.6070	18.6	0.3567	0.3359	-1.3045	0.6551	-18.7658	0.5750

Ellagawa lumped and Ellagawa distributed models show better performances than Ratnapura lumped model in model verification. The lowest monthly mass balance error is observed in Ellagawa lumped model which is 10.97% whereas that for Ratnapura lumped model is 21.5%. It shows very poor performance in Ratnapura model in terms of Nash-Sutcliff, MRAE and monthly mass balance error. Nash-Sutcliff of Ellagawa lumped and distributed remains same at 0.65 and MRAE shows slight changes. But, in high flow regions of flow duration curve, Nash-Sutcliff varies from 0.29 to 0.35.

6.4 Comparison of Calibration and Verification Results

6.4.1 Comparison of calibration and verification results at Ellagawa

Calibration and verification results of two models are compared and tabulated in Table 6-9.

Table 6-9 Comparison of model calibration and verification results

Model	Nash-Sutcliff	MRAE	monthly mass balance error %	Flow duration curve						Model Error (sum of absolute residual)
				High		Medium		Low		
				Nash-Sutcliff	MRAE	Nash-Sutcliff	MRAE	Nash-Sutcliff	MRAE	
Ratnapura calibrated	0.7834	0.5226	14.3	0.64	0.2722	-0.3	0.4877	-18.87	0.7717	82299
Ratnapura verified	0.5852	0.7732	21.5	0.45	0.3669	-2.7	0.8026	-21.64	0.8752	93456
Difference %	25	48	50	29	34	-64	65	-1	13	13
Ellagawa lumped calibrated	0.7001	0.5802	11.9	0.31	0.3519	-0.6	0.5591	-26.1	0.7693	181042
Ellagawa lumped verified	0.6157	0.6399	10.9	0.29	0.4160	-1.5	0.6700	-20.78	0.6354	194619
Difference %	9	6	8	7	1	-13	14	-23	8	7
Ellagawa distributed calibrated	0.6918	0.5407	11.2	0.26	0.3244	-0.4	0.5228	-29.65	0.7123	167347
Ellagawa distributed verified	0.6515	0.6070	18.6	0.35	0.3359	-1.3	0.6551	-18.78	0.5750	189581
Difference %	6	12	66	35	3	214	25	-36	19	13

Table 6-9 shows that calibrated Ratnapura model performs 25% better than verified model in terms of Nash-Sutcliff error. Model performance during calibration is 50% better than during verification in terms of MRAE and monthly mass balance error. But, in Ellagawa lumped is concerned, there are no much difference with calibration and verification results. Model performance has been improved only by 9%, 6% and 8% in terms of Nash-Sutcliff, MRAE and monthly mass balance error respectively in calibration when compared to verification. In Ellagawa distributed model, model performance is improved by 66% in calibration in terms of monthly mass balance error.

6.4.2 Comparison of calibration and verification at Ratnapura

Calibration and verification results of Ratnapura lumped is compared with distributed model and given in Table 6-10.

Table 6-10 Comparison of model performance at Ratnapura

Model	Nash-Sutcliff	MRAE	monthly mass balance error %	Flow duration curve					
				High		Medium		Low	
				Nash-Sutcliff	MRAE	Nash-Sutcliff	MRAE	Nash-Sutcliff	MRAE
lumped calibration	0.78	0.52	14.3	0.64	0.27	-0.3	0.48	-18.7	0.77
Distributed calibration	0.76	0.58	20	0.59	0.28	-0.44	0.54	-16.5	0.89
Difference %	2.6	11.5	39.9	7.8	3.7	-46.7	12.5	-11.8	15.6
Lumped verification	0.58	0.77	21.5	0.45	0.36	-2.7	0.80	-21.7	0.87
Distributed verification	0.57	0.75	18.8	0.345	0.38	-2.38	0.78	-19.45	0.81
Difference %	1.7	2.6	12.6	23.3	5.6	-11.9	2.5	-10.4	6.9

6.5 Comparison of Catchment Parameters

6.5.1 Comparison of catchment parameters of Ratnapura and Ellagawa

Parameters optimized for Ratnapura and Ellagawa lumped model calibration, are compared and given in Table 6-11

Table 6-11 Comparison of parameters of Ratnapura and Ellagawa catchments

Name of Parameter	Unit	Ratnapura	Ellagawa	% Difference with respect to Ratnapura
Constant loss	mm/hour	0.435	0.487	11.95
Initial deficit	mm	4.489	3.384	24.62
Recession constant		0.896	0.907	1.23
Threshold flow ratio		0.149	0.151	1.13

Table 6-11 shows that there is a 24.62% difference in initial deficit in two catchments. But, recession constant and threshold flow ratio have almost 1% difference.

6.5.2 Comparison of subbasin parameters with Ellagawa catchment parameters

Parameters optimized for subbasins are compared with the Ellagawa total catchment parameters and it is shown in Table 6-12.

Table 6-12 Comparison of subbasin parameters with Ellagawa lumped model parameters

Parameter	Ratnapura lumped model	Ellagawa lumped model	Ellagawa distributed model						
			Ratnapura	Subbasin 1	Subbasin 2	Subbasin 3	Reach 1	Reach 2	Reach 3
Constant loss (mm/hour)	0.435	0.487	0.454	0.454	0.443	0.452			
Initial deficit(mm)	4.489	3.384	3.03	4.522	3.03	4.522			
Recession constant	0.896	0.907	0.856	0.387	0.936	0.909			
Threshold flow ratio	0.149	0.151	0.144	0.145	0.149	0.1			
Lag(minutes)	2127	2678	2740	1176	2561	1274			
Muskingam k (hours)							2.667	3.334	3.334
X							0.134	0.134	0.134

In Table 6-12, it can be observed that there is not a significant difference of constant loss values among the subbasins. But all are less than the constant loss of Ellagawa whole catchment. Recession constant of subbasin 1 is very low with compared to other subbasins.

Change in parameters of subbasins with respect to Ellagawa catchment is compared and given in Table 6-13.

Table 6-13 Change in subbasin parameters with respect to Ellagawa catchment

Parameter	% change in parameters with respect to Ellagawa parameters				Ellagawa parameters
	Ratnapura	Subbasin 1	Subbasin 2	Subbasin 3	
Constant loss	6.8	6.7	9.1	7.1	0.487
Initial deficit	10.4	33.6	10.4	33.7	3.384
Recession constant	5.5	57.3	3.3	0.3	0.907
Threshold flow ratio	4.3	3.8	1.2	33.6	0.151

7 DISCUSSION

7.1 Data and Data Period

7.1.1 Selection of data period

In selecting the data period, first, data availability of 8 -10 years both at Ratnapura and Ellagawa river gauging stations were considered. Ratnapura gauging station had not been functioned for 8 years from1998 to 2006. Hence, either data period before 1998 or after 2006 had to be selected. The data reliability of recent data is good when compared to old data. Therefore, 8 years of data period from 2006 to 2014 was considered and the existence of extreme conditions within the data period was checked. In Figure 4-3 and Figure 4-5, it was observed a dry year, 2011/2012 and wet years, 2012/2013 and 2013/2014 were covered within the data period. Therefore it is assumed that the results are independent of the data period.

7.1.2 Existence of data errors

It can be observed in Table 4-4 that although rainfall in 2006/2007 and 2007/2008 are almost the same, streamflow had increased from 2006/2007 to 2007/2008 by 756 mm which is unexpected. Streamflow in years 2011/2012 does not respond with rainfall. Year 2011/2012 is a dry year and the streamflow is very much small leading to a high evaporation and a very low runoff coefficient. This reveals that there may be inconsistencies in streamflow data. It was difficult to find complete continuous dataset spanning at least 8 years in both Ratnapura and Ellagawa river gauging stations.

7.2 Evaluation Criteria of Model Performance

7.2.1 Model performance in calibration

7.2.1.1 Validity of calibration results

Table 6-1 gives satisfactory objective function values with respect to MRAE for Ratnapura lumped model, Ellagawa lumped model and Ellagawa distributed model in hydrograph matching. MRAE values of 0.5226, 0.5802 and 0.5407 for Ratnapura lumped, Ellagawa lumped and Ellagawa distributed models show satisfactory model performance. MRAE values of high and medium flows also show good matching.

MRAE had improved by 6.7% from lumped to distributed models (Table 6-1). The objective function also had improved by 8%, 6% and 10% in high, medium and low flow regions respectively. This indicates that the 4 subbasin model performs slightly better than the lumped basin model but still not a significant improvement. Nandalal and Ratnayake (2010) also concluded that there is no scale effect (number of subbasins) in modeling using HEC HMS for flood prediction.

Comparison of annual MRAE values are in Table 7-1.

Table 7-1 Comparison of annual MRAE of Ellagawa distributed model during calibration

Water year	MRAE
2006/2007	0.57
2007/2008	0.43
2008/2009	0.51
2009/2010	0.64

Table 7-1 indicates that objective function values during year 2009/2010 and 2006/2007 were high when compared to other years. The MRAE values were high during the entire 4 year calibration period.

7.2.1.2 Behavior of simulated hydrographs

There is no significant difference in the behavior of simulated hydrographs in Ratnapura lumped model, Ellagawa lumped model and Ellagawa distributed model (Figure 5-9, Figure 5-14 and Figure 5-25). Most of the high peaks were captured by the model but there are shifts in time of peak flow occurrence in small peaks. In semi log scale, minor deviations could be observed. Flow duration curves are given in Figure 5-11, Figure 5-15 and Figure 5-20. It is observed that the model doesn’t respond well during low flow periods. Table 7-2 gives the behavior of hydrograph peaks of Ellagawa distributed calibration.

Table 7-2 Peak flow evaluation of Ellagawa distributed model calibration

Region	Probability of Exceedence %	Peak Flows			Time of Peak flow Occurrence
		Number of Peaks	Peak flow error %	% under estimate/over estimate	
High Flow	<10%	45	25	75% of peaks are under estimated by 30%	60% No time shift
				25% of peaks are over estimated by 30%	30% one day earlier
Medium Flow	between 10% & 80%	162	53	60% of peaks are under estimated by 40%	70% No time shift
				40% of peaks are over estimated by 70%	25% one day after

curve, average peak flow error is 25%. It can be seen that 75% of peaks are under estimated and the balance 25% of peaks are over estimated by the model without any bias for Maha or Yala season peaks. Out of 45 peaks in high flow region , there are no shift in time of peak flow occurrence in 60% of peaks. 30% of high peaks are having one day time shift. This shift leads to a high error values in high flow region (Table 6-1). Otherwise, objective function value in high flows would have been improved further. In intermediate flows between 10% and 80% of the time, average peak flow error is 53% , but in 70% of peaks, there are no shift in time of peak flow occurrence. Although the peak flow errors are high, because of the time of peak occurrence is matching in most of the peaks, overall matching can be seen in this region. Therefore, this model is expected to predict reasonable results in flood management.

7.2.1.3 Matching flow duration curve

Five - point moving average Flow Duration Curve was drawn for calculated flows of Ellagawa distributed model and is presented in Figure 7-1.

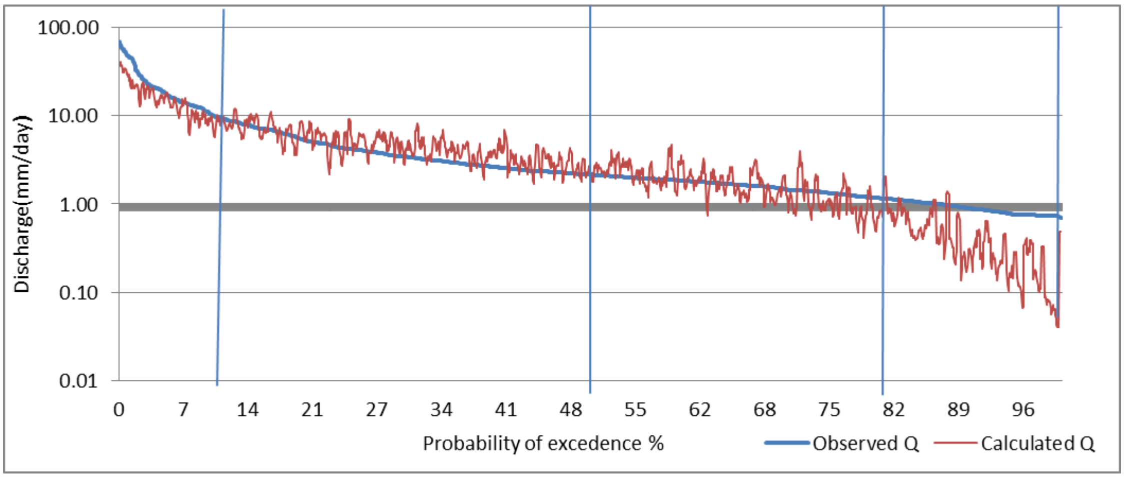

Figure 7-1 Flow duration curve of Ellagawa distributed model

When the flow duration curve is divided into four regions at probability of exceedence of 10%, 50%, 80% the values were 143 m^3/s, 31 m^3/s and 17 m^3/s respectively. The MRAE for each range of flow duration curve are tabulated in Table 7-3.

Table 7-3 Comparison of error values

% Probability of Excedence	Corresponding streamflow value (m^3/s)	MRAE	Mass balance error %
<10%	Greater than 143	0.3244	28.5
10% - 50%	Between 143 and 31	0.5279	17.9
50% - 80%	Between 31 and 17	0.326	7.7
80% - 100%	Less than 17	0.7096	50.5

The model performance in low and intermediate regions are very important to analyze as this study is focused on continuous simulation and it is necessary to predict streamflow in intermediate and low regions rather than predicting flood peaks. It can be seen in Table 7-3 that in high flows less than 10% probability of exceedence, the model underestimates the flows by 28.5%. In this region, 60% of peaks have no shift in time of peak occurrence

(Table 7-2). Therefore, although mass balance error is 28.5% and flow duration curve is shifted downward, MRAE value becomes 0.32 and the model tries to match with the observed hydrograph. A reasonably good MRAE value in high flow period has got as there is a 60% probability of matching time of peak flow occurrence in this region. In low flows greater than 80% probability, it under estimates the flows by 50% and MRAE value is very high (0.7) which indicates that the model cannot match low flows. The flow corresponding to 80% probability of exceedence is 17m^3/sec. and that for 10% probability of excedence is 143 m^3/sec. In the range from 10% to 50%, the model over estimates the flow by 17.9% and try to match with the observed hydrograph having a MRAE value of 0.5. In the range from 50% to 80%, model shows a good approach in fitting hydrographs. Under estimation of flows is still there in this range too, but only 7.7%. MRAE is 0.32 which is a good value. Hence, the model performance from 0% to 80% of probability of exceedence (greater than 17 m^3/sec) can be accepted and the best fit range is from 50% to 80% (31 m^3/sec to 17 m^3/sec). There are some unrealistic over predictions in the range from 10% to 80% and if those points are avoided, a better fitting could be expected and the results would be improved accordingly. Hence, this model is expected to predict reasonable results in modeling flows greater than 17 m^3/sec.

Flow duration curves were drawn by sorting both observed and calculated streamflow for all Ratnapura lumped model, Ellagawa lumped model and Ellagawa distributed model. This was done to evaluate the computed and observed flows without considering the shifts in time. The corresponding objective function values (MRAE) for model calibration are in Table 7-4 and flow duration curves are in Figure 5-41 to Figure 5-43 in Chapter 5. These results showed very good matching of high and intermediate flows.

Table 7-4 Comparison of MRAE values during calibration in flow duration curve type 2

Flow duration curve Range	Model calibration		
	Ellagawa lumped	Ellagawa distributed	Ratnapura lumped
High	0.1514	0.1603	0.0500
Medium	0.2148	0.2054	0.1198
Low	0.8083	0.6919	0.6315

As per Table 7-2, it can be observed time shifts in peak flow occurrence in high and medium flow regions. While looking at Figure 5-41 to Figure 5-43, it is clearly seen that the best fit region is high and medium flow regions. The time shift in peak flow estimation in these regions is causing high error values in best fit regions. Hence, this model is very good in fitting flow duration curve.

7.2.1.4 Comparison of flow residuals

Variation of flow residuals throughout the calibration period is shown in Figure 7-2 for Ellagawa distributed model. Highest flow residuals are marked with circles in Figure 7-2. It can be observed that there are higher residuals in year 2006/2007, 2007/2008 and in year 2009/2010. Flow residuals calculated in model calibration of Ellagawa are tabulated in Table G-1 and Table G-2 of Appendix G.

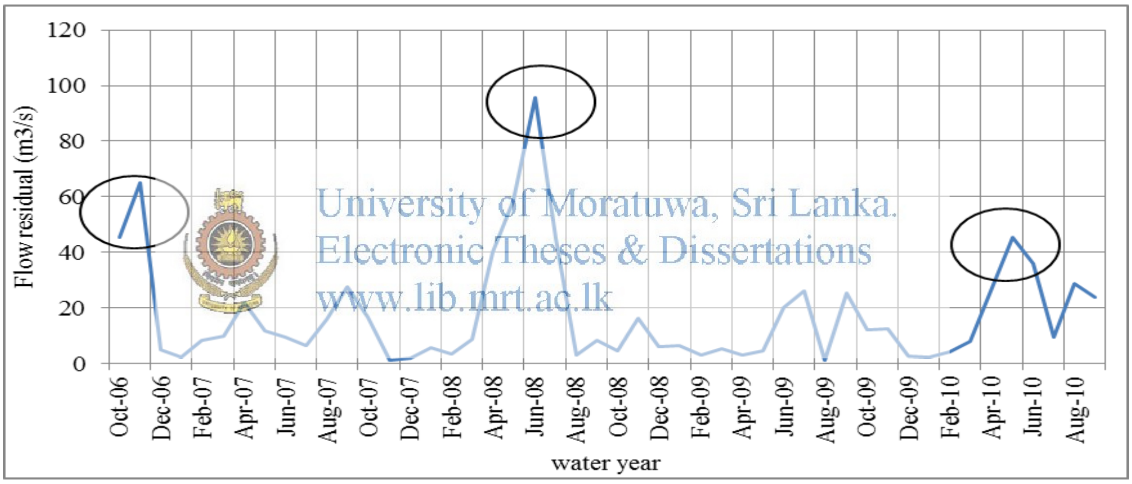

Figure 7-2 Variation of flow residuals during calibration in Ellagawa distributed model

7.2.1.5 Comparison of magnitude of errors in flow duration curves during calibration

Table 5-19 and Table 5-20 showed the magnitude of errors in high, medium and low flow regions in flow duration curve for both Ellagawa and Ratnapura catchments. It was noticed that the magnitude of errors in low flow regions are very small compared to other regions. In flow duration curve type 1, model estimation in low flow region of Ellagawa catchment is 80 MCM with an error of 30 MCM. This is only 1.2% of the average annual streamflow of Ellagawa catchment. In parameter optimizing using MRAE as the objective function, MRAE value in high and medium flows are low compared to low flows indicating that a good matching only in high and medium flows. As mentioned in

Table 7-2, the time shift occurred in high and medium flows leads to a high errors in Table 5-19 and Table 5-20. Although the MRAE value is unexpected in low flows, when comparing in magnitude, it is very small in quantity. Hence, this may not be cause a significant change on streamflow estimation for water resource management.

7.2.2 Model performance in verification

7.2.2.1 Validity of verification results

As given in Table 6-8, the objective function value, MRAE considerably increases during model verification in all three models, Ratnapura lumped, Ellagawa lumped and Ellagawa distributed models. But, in high flow regions, MRAE shows good matching. But, in medium and low flows, it is worse than that the case of high flows. In Figure 7-2, high flow residuals can be observed in November 2006, May, June and July in 2008, May and June 2010. In Figure 7-2, these points are marked with circles. There are spatial variabilities of rainfall over the catchment and may be some data errors in some years. These reasons may lead to a high objective function value during verification.

Statistical performance measures at Ratnapura and Ellagawa of Ellagawa distributed model verification in Table 6-8 (Comparison of model verification results) shows that MRAE varies from 0.7732 at Ratnapura to 0.6070 at Ellagawa. Nash-sutcliff value at Ratnapura is 0.5852 and at Ellagawa it is 0.6515 whereas monthly mass balance error remains same. Hydrograph plots reveals that although the error indicators reflect acceptable values, matching of hydrograph shapes is not satisfactory especially in low flows. Hence, hydrograph matching in low flows needs more improvement.

7.2.2.2 Comparison of Mean Ratio of Absolute Error (MRAE) values during verification

Comparison of annual MRAE values at Ellagawa verified distributed model is given in Table 7-5.

Table 7-5 Comparison of MRAE values during model calibration

Year	MRAE
2010/2011	0.4353
2011/2012	0.5970
2012/2013	0.6842
2013/2014	0.7115
Average	**0.6070**

Flow duration curves drawn by sorting both observed and calculated streamflow for all three models are shown in Figure 7-3 to Figure 7-5. MRAE values corresponding to each model is tabulated in Table 7-6.

Table 7-6 Comparison of MRAE values during model verification

FDC Range	Model verification		
	Ellagawa lumped	Ellagawa distributed	Ratnapura lumped
High	0.0921	0.1214	0.2333
Medium	0.2289	0.2930	0.3160
Low	0.7931	0.6183	0.8316

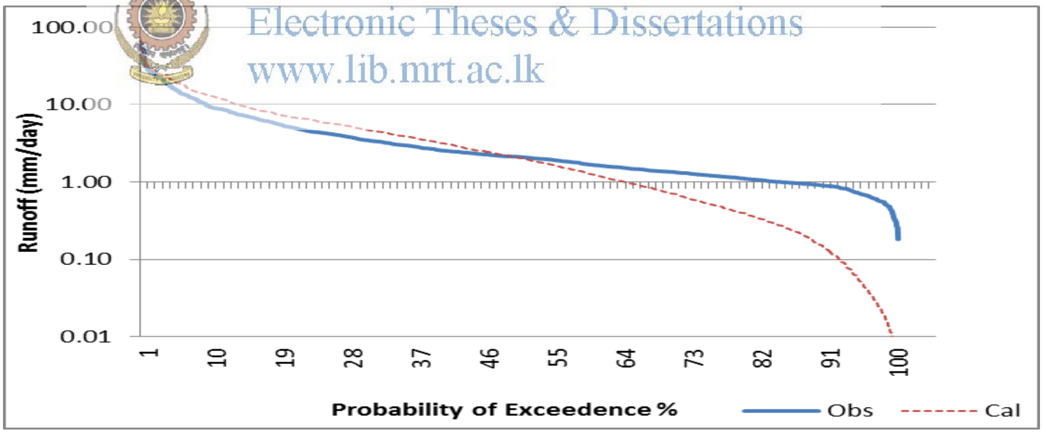

Figure 7-3 Flow duration curve for Ratnapura lumped model verification

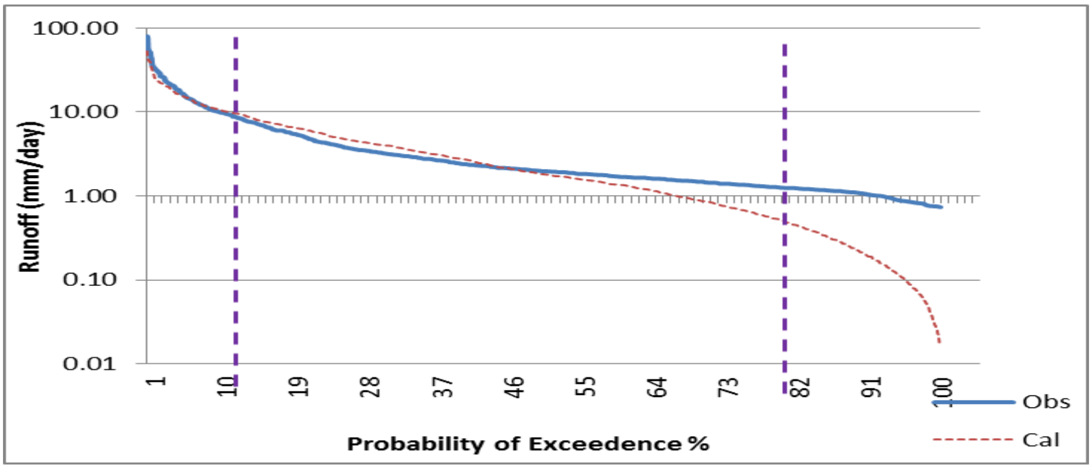

Figure 7-4 Flow duration curve for Ellagawa lumped model verification

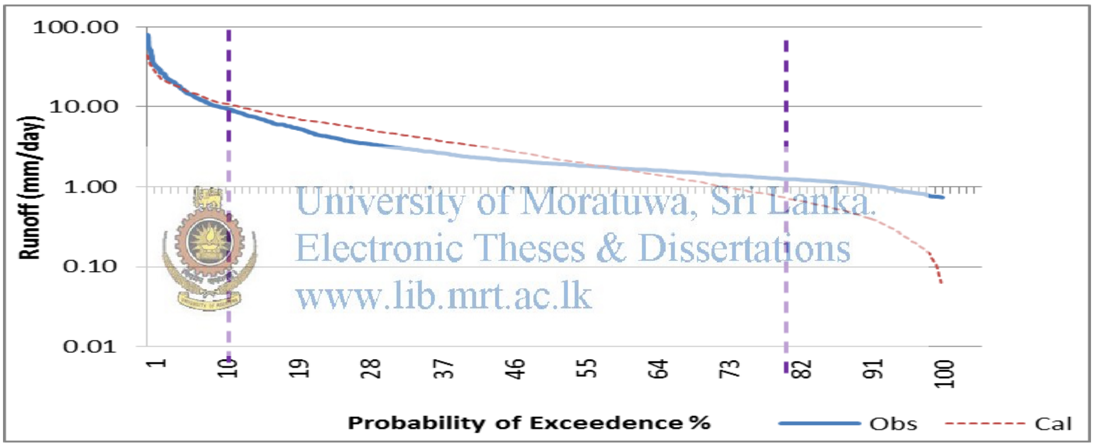

Figure 7-5 Flow duration curve for Ellagawa distributed model verification

Table 7-5 shows that MRAE varies from 0.4353 in year 2010/2011 to 0.7115 in year 2013/2014. This was also discussed in Chapter 4.2.1 under data checking that runoff coefficients of 2011/2012, 2012/2013 and 2013/2014 are much smaller compared with the values given in literature. Table 7-5 shows that MRAE also are much higher in these three years. Hence, there may be some disparity of rainfall and streamflow data. Figure 7-3, Figure 7-4 and Figure 7-5 show that there is best fitting of flow duration curve in high and medium flow regions. As given in Table 7-2, the time shift in peak flow estimation in these regions leads to high MRAE values. However, the model fitting in flow duration curve during verification is good. This time shift in peak flow estimation leads to higher errors in exact matching regions of the flow duration curve. Therefore, the model shows very good fitting in flow duration curve and hence can be used satisfactorily for flood and water resource management except during low flow situations.

7.3 Reliability of Model Results

7.3.1 Uncertainty in meteorological data

Uncertainty of data has direct impact on the reliability of model results. Rainfall spatial and temporal variability are the basic reasons for uncertainty in precipitation data. Other model inputs such as evapotranspiration and catchment morphology data also affect uncertainty in model results. This is a common difficulty faced during model development which could not be avoided.

7.3.2 Uncertainty in catchment parameters

The use of limited data and uncertain data in calibration will result to uncertainty in parameter estimation. In estimation CN value, there were many assumptions made for the catchment such as soil group, hydrological condition, land use classification etc. and final output will depend on these assumptions. There were many difficulties obtaining realistic parameter values by model calibration. The optimized initial deficit value varies from 3.03 mm to 4.523 mm over the entire Ellagawa catchment. It was very difficult to optimize the recession constant. The optimized values seemed to be unrealistic in subbasin 1 which corresponds to 0.387. This value is very much smaller than the values of other subbasins.

7.4 Selection of Parameter Range for Optimization

In automatic parameter optimization, in order to skip the local minimum points in the objective function space, initial values of parameters were in a way that it capture the global minimum error by skipping the local minimum. Parameters were gradually varied and then parameters and the combinations were changed to the extreme values to excite the model and get the global minimum error. Minimum objective function value was found by 50 iterations as given by the HEC HMS model default. Range of parameters used in optimization are given in Table 7-7. Variation of objective function with iterations is given in Figure 7-6.

Table 7-7 Range of parameter values used during optimization

Parameter	Value Range
Constant loss (mm/hr)	0.1- 15
Initial Deficit (mm)	1 - 400
Recession constant	0.1 - 1.0
Threshold flow Ratio	0.1 - 1.0
Lag (minutes)	1000 - 8000

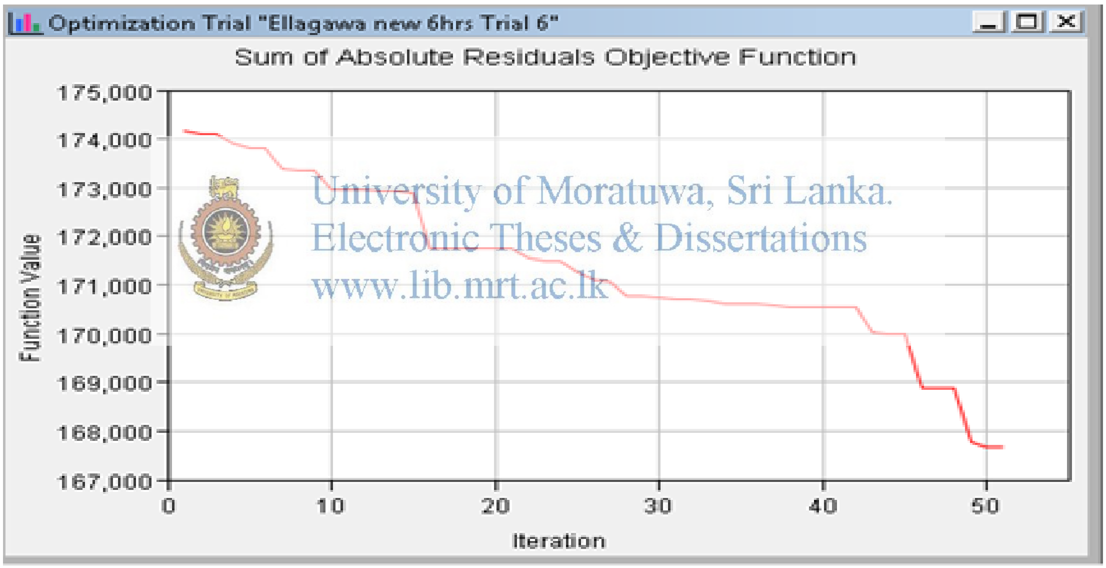

Figure 7-6 Variation of objective function with iterations

The decreasing values of objective function in Figure 7-6 indicates that a minimum had been found during optimization. Variation of each parameter with values of objective function during parameter optimization is shown in Figure 7-7.

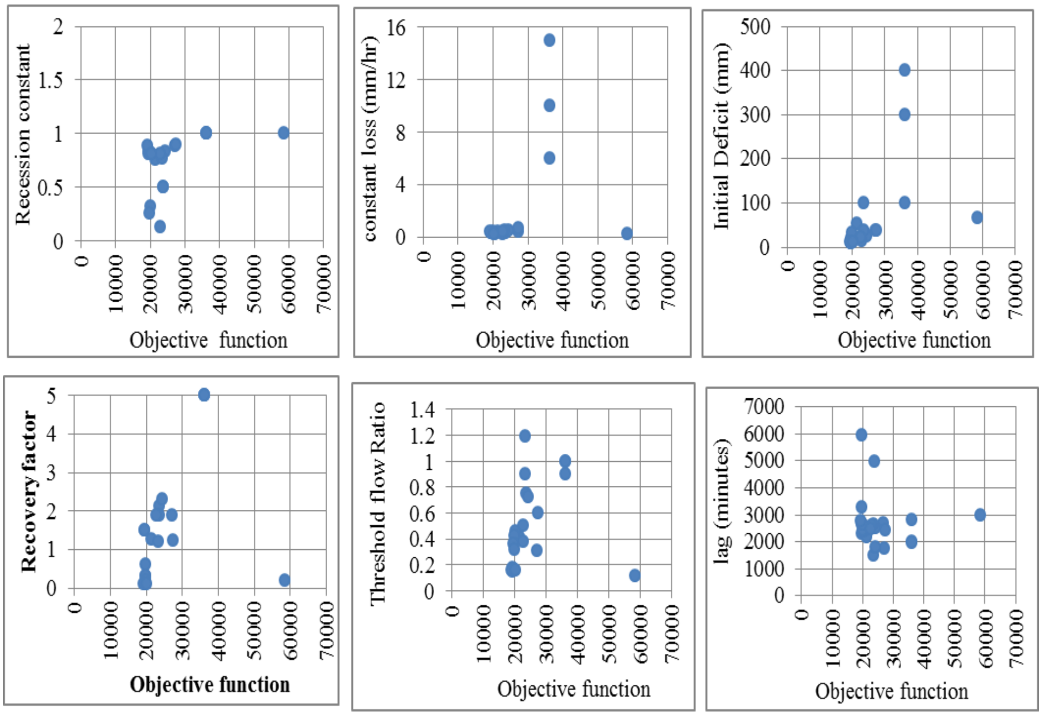

Figure 7-7 Variation of parameters with value of objective function

7.5 Results of Lumped and Semi Distributed Models

7.5.1 Comparison of Ratnapura and Ellagawa lumped models

7.5.1.1 Comparison of model performances

Table 6-1 and Figure 6-1 and Figure 6-2 present the comparison of the value of objective function (MRAE), Nash-Sutcliff and monthly mass balance error for Ratnapura lumped and Ellagawa lumped models. It showed that MRAE had increased from 0.5226 to 0.5802 from Ratnapura to Ellagawa respectively. Also, average annual mass balance error had increased from 5.9% to 11.9%. In flow duration curve also, MRAE had increased when moving from Ratnapura to Ellagawa. But, the objective function value can be accepted in both catchments and the two models had better fitting in high and medium flow regions while in low flow region, the models didn’t respond very well.

7.5.1.2 Comparison of catchment parameters

It was indicated in Table 6-11 that constant loss of Ellagawa had increased by 12% with respect to Ratnapura. Initial deficit of Ellagawa had decreased by 25%. This shows that the soil moisture condition of two catchments are different (Table 6-11). Recession constant and threshold flow ratio had increased only by 1% indicating that the baseflow recession is similar in both catchments.

7.5.2 Comparison of Ellagawa lumped and distributed models

7.5.2.1 Comparison of model performances

Model performance of Ellagawa distributed model had improved when compared with the Ellagawa lumped model. The objective function, MRAE, had decreased from 0.5802 to 0.5407 when moving from lumped to distributed model. High and medium flow regions of flow duration curve also, MRAE had improved in distributed model. But, this may not be a significant model improvement.

7.5.2.2 Comparison of catchment parameters

Table 6-12 and Table 6-13 indicated the parameter values of each subbasin and percent change with respect to Ellagawa lumped model parameters. Tables showed that the constant loss of all subbasins had decreased by 6.8%, 6.7%, 9.1% and 7.1% with respect to lumped model parameters in Ratnapura subbasin, subbasin 1, subbasin 2 and subbasin 3 respectively. But, in initial deficit, it could be observed a considerable increase in subbasin 1 and subbasin 3 by 33% while other two subbasins have 10% change. Recession constant had changed slightly except in subbasin 1 where there is a great decrease by 57% (Table 6-12). This indicates that streamflow decay response in subbasin 1 is faster. Threshold flow ratio of subbasin 3 had decreased by 33.6% while others have a marginal change (Table 6-13). Subbasin 2 and Ratnapura subbasin have almost similar response characteristics. Subbasin 1 and subbasin 3 also have similar response characteristics in initial deficit and constant loss which implied that the soil moisture condition of two subbasins are similar.

7.6 Selection of Most Appropriate Objective Function

The results of two flow series given in Table D-2 and Table D-3 and Figure D-4 and Figure D-5 clearly showed the variation of MRAE and RAEM values with all cases. The four cases considered are (1) Generally match the hydrograph (base) (2) Peak flows match better (3) Peak magnitudes match better and (4) low flows match better. It showed that there is no overall improvement in MRAE, but there is an overall improvement in RAEM in the second decimal. MRAE is not sensitive to few points matching and with time shifts.

In MRAE, it shows that the magnitude of matching is reflected but only limited because good matching is only for a few points. Few points and a large number of points matching is well reflected in MRAE. The majority flow matching is also influences the value with a low MRAE when low and intermediate points are matching.

Just a few points matching can give a significant change in RAEM. This may not reflect the objective of long term matching. In case 1, there is no big difference in RAEM whether peaks or low flow match better. Therefore, a marked difference could not be seen. In MRAE, the cases very well reflect the characters of streamflow series.

8 CONCLUSIONS

1. A HEC HMS model was systematically developed for Kalu Ganga basin at Ellagawa and Ratnapura with an acceptable levels of accuracy corresponding to a Mean Ratio of Absolute Error (MRAE) of 0.5406 and 0.5226 respectively during calibration. MRAE values during verification were 0.6070 and 0.7732 for Ellagawa and Ratnapura respectively.
2. Model estimated intermediate flows between 17 m^3/s and 31 m^3/s, with a very high accuracy of MRAE 0.326 and flows between 31 m^3/s and 143 m^3/s, estimations was acceptable at a MRAE of 0.5279. Model estimated high flows greater than 143 m3/s with a very high accuracy of MRAE 0.3244, while the low flows which was less than 17 m^3/s, could not be estimated adequately.
3. Although the values of objective function (MRAE) showed that the model did not estimate low flows accurately, when compared with the magnitude of errors of observed and calculated streamflow quantities in low flows, the magnitude of the error corresponds to Ellagawa and Ratnapura catchments were 30 MCM and 14 MCM which was only 1% of the average annual streamflow of Ellagawa and Ratnapura. This indicated that the magnitude of low flow errors were not very significant and therefore this model can be used satisfactorily for water resources management.
4. The model matching of time of peak flow occurrence was at an accuracy of 60% while the peak flow magnitude accuracy was 75%. Therefore, this model is acceptable to use in flood management.
5. A HEC HMS model for Kalu Ganga Basin was developed demonstrating a rational selection of HEC HMS Model options such as rainfall loss model, direct runoff model, baseflow model, routing model, selection of objective functions enabling the demonstration of scientific mathematical modeling of Rainfall and Streamflow using HEC HMS.
6. The two flow series showed that when the flow is seasonal or when there is distinct dry season and a wet season, the MRAE objective function reflects the behavior in an easily identifiable manner.

9 RECOMMENDATIONS

1. This model can be recommended to use for water resource management in a catchment.
2. It is necessary to explore and make improvements for model performance in low flows less than 17 m^3/s.
3. Automated parameter optimization option in HEC HMS has to be used with caution. Wide range of parameters and parameter combinations should be used in order to get the minimum error. It is recommended to explore and incorporate an appropriate search algorithm other than Univariate gradient and Nelder and Mead methods in order to find the global minimum error.
4. It is necessary to explore and make further improvements in matching time of peak flow occurrence.

REFERENCES

Ajami, N.K., Guptha, H., Wagener, T. & Sorooshian, S. (2004). Calibration of a semi-distributed hydrologic model for streamflow estimation along a river system. *Journal of Hydrology*. 298, pp.112-135.

Alaghamand, S., Abdullah, R. B. & Abustan, I. (2010). Selecting the best set value in Calibration process for validation of hydrological modeling : A case study on Kayu Ara River Basin, Malaysia.

Arumugam, S. (1969). *Water Resources of Ceylon its utilization and Development*. Water Resource Board, Sri Lanka.

Bakir, M. & Xingnan, Z. (2008). GIS Based Hydrological modeling : A comparative study of HEC HMS and the Xinanjiang model. *Proceedings of the Twelfth International Water Technology Conference, IWTC12 2008*, Alexandria, Egypt.

Bronstert,V. K.A. & Wohlfeil, D.I.M. ((1999). Modeling river discharge for large drainage basins : From lumped to distributed approach. *Journal of Hydrological Science*,44(2).

Central Environmental Authority, Sri Lanka. *Environmental Atlas* (2005).

Chow, V.T., Maidment, D.R., & Mays, L.W. (1988). *Applied Hydrology*. McGraw- Hill, New York.

Chow, V.T., Maidment, D.R. & Mays, L.W. (2010). *Applied Hydrology*. Tata MacGraw Hill, New Delhi, India.

Costa, S.D. (1995). Response characteristics of the Kalu ganga catchment and lumped system model for flood forecasting. *Journal of Engineer, Institution of Engineers*, Sri Lanka, December, 1995.

CropWat, (1998). User's Guide. University of Southampton, United Kingdom.

Cunderlik, J. & Simonovic, S.P. (2004). Calibration, Verification and Sensitivity analysis of the HEC HMS Hydrological model: Assessment of water resources risk and vulnerability to changing climatic condition. CFCAS, *Water Resources Research Project* Report 048, August 2004.

Department of Irrigation, Sri Lanka. Retrieved from www.irrigation.gov.lk.

Department of Irrigation, Sri Lanka (2006, October). *Feasibility Report on Proposed Heda Oya Reservoir Project* (Main Report Volume I).

Department of Irrigation, Sri Lanka (2014, February). *Pre-Feasibility Study on Mundeni Aru basin*.

Department of Irrigation, Sri Lanka (2013, August). *Feasibility Study on proposed Kumbukkan Oya Reservoir Project.*

Department of Meteorology, Sri Lanka. Retrieved from www.meteo.gov.lk.

Dharmasena G.T. (1997). Application of Mathematical models for flood forecasting in Sri Lanka, Destructive water : Water caused natural disasters, their abatement and control. *Proceedings of the conference held at Anaheim, California, June 1996.* IAHS publ.No.239:225.

Disaster Management Centre, Sri Lanka. Retrieved from www.dmc.gov.lk.

Disaster and Risk profile, Sri Lanka (2015). Retrieved from

h*ttp://www.preventionweb.net/countries/lka/data/*

El-Kafagee, M. & Rahman, A. (2011). 19th International Congress on Modeling and simulation, Perth, Australia, 12-16 December 2011.

Giang, N.T., & Phuong, T.A . (2010). Calibration and verification of a hydrological model using event data. *VNU Journal of Science, Earth Sciences, (26), 64-74.*

Green, I.R.A. & Stephenson, D. (2009). Criteria for comparison of single event models. *Journal of Hydrological Sciences*, 31(3), pp. 395-411.

Hafezparast, M., Araghinejad, S., Fateml, S. E. & Bressers, H. (2013). A conceptual Rainfall-Runoff model using the auto calibrated NAM models I the Sarisoo River. *Hydrology Current Research,* 4,pp.148.

Halwatura, D. & Najim, M.M.M. (2013). Application of the HEC HMS model for runoff simulation in a tropical catchment. *Environmental Modelling & Software,* 46(2013), pp.155-162.

Khakbaz, B., Imam, B., Hsu, K. & Sorooshian, S. 92012). From Lumped to Distributed via Semi-Distributed : Calibration strategies for semi-distributed hydrologic models. *Journal of Hydrology,* 418-419, pp. 61-77.

Krysanova, V. & Bronstert, A. (1999). Modelling river discharge for larger drainage basins : from lumped to distributed approach. *Hydrological Sciences,* 44(2), pp. 313-331.

Liechti, T.C., Matos, J.P., Boillat, J. L., Portela, M.M. & Schleiss, A. J. (2014). Hydraulic-Hydrologic model for water resources management of the Zambezi basin. *Journal of Applied Water Engineering and Research,* 2(2), pp. 105-117.

Loucks et al., (2005). Water Resources Planning and Management. An Introduction to methods, models and applications. *Studies and Reports in Hydrology.*

Madsen, H. (2000). Automatic calibration of a conceptual rainfall-runoff model using multiple objectives. *Journal of Hydrology*,235, pp. 276-288.

Madsen, H.,Wilson, G. & Ammentorp. H.C. (2002). Comparison of different automated strategies for calibration of rainfall – runoff models. *Journal of Hydrology*. 261(1-4), pp.48-59.

Majidi, A. & Vagharfard, H. (2013). Surface Runoff simulation with two methods using HEC HMS model. *Current Advances in Environmental Scienc*, 1(1), pp.7-11.

Manchanayake, P., Sumanaweera, S., & Jayaratne, J. A. (1985). Some Preliminary Studies on Loss Rates of Few Sri Lankan Catchments. *Engineers*, vol (XIII), No.02, 7-12.

McEnroe, B.M. (2010). Guidelines for continuous simulation of streamflow in Johnson County, Kansas with HEC-HMS. *Johnson County Public works and Infrastructure stormwater Management Programme.*

McColl, C & Aggett, G. (2006). Land use forecasting and hydrologic model integration for improved land use decision support. *Journal of Environmental Managemen*, 84(2007), pp. 494-512.

MIKE BASIN, (2012). User's Guide. Danish Hydraulic Institute.

Mohommad,A., Khan, S.J., Aslam, I. & Khan, Z. (2011). Simulation of the impacts of land use change on surface runoff of Lai Nullah basin in Islamabad, Pakistan. *Landscape and Urban Planning*, 102(2011), pp. 271-279.

Nandalal, H.K. & Ratnayake, U.R. (2010). Event based Modeling of a Watershed using HEC HMS. *Engineer*,43(2), pp. 28-37.

Orellana, B., Pechlivanidis, I.D., McIntyre, N., Weater, S.H. & Wagener, T. (2008). A toolbox for the identification of parsimonious semi-distributed rainfall-runoff models : Application to the upper Lee catchment. *International Congress on Environmental Modeling and Software*, 1, 670-677, 7-10 July, Barcelona, Spain.

Pechlivanidis I.G., Jackson, B.M., Mcintyre, N.R. & wheater,H.S. (2001). Catchment scale hydrological modeling : A review of model types, calibration approaches and uncertainty analysis methods in the context of recent developments in technology and applications. *Journal of Global NEST*, 13(3), pp. 193-214.

Ren, L., Huang, Q., Yuan, F., Wang, J., Xu, J., Yu, Z. & Liu, X. (2006). Evaluation of the Xinanjiang model structure by observed discharge and gauged soil moisture data in the HUBEX/GAME Project : Predictions in ungauged basins, *Proceedings of Symposium S7 held during the seventh IASH Scientific Assembly* at Foz do Iguacu, Brasil, 2005. IASH publ. 303,2006.

Roy, D., Begam, S., Ghosh, S. & Jana, S. (2013).Calibration and Validation of HEC HMS Model for a river basin in eastern India. *Journal of Engineering and Applied Science,* 891.

Samarasinghe, S.M.J.S., Nandalal, H.K., Weliwitiya, D. P., Fowze, J.S.M., Hazarika, M.K. & Samarakoon, L. (2010). Application of remote sensing and GIS for flood risk analaysis : A case study at Kalu ganga river, Sri Lanka. *International Archives for the Photogrammetry, Remote Sensing and Spatial Information Science*, 38(8), Kyrato, Japan, 2010.

SCS. (1987). *Hydrology National Engineering Handbook,* Supplement A, Section 4. Soil Conservation Service. US Department of Agriculture: Washington DC; Chapter 10.

Skahill, B. E. (2006). Potential Improvements for HEC HMS automated parameter estimation. *Coastal and Hydraulics Laboratory, Engineering Research and Development Centre,* U.S. Army Corps of Engineers.

Sudheer, K.P., Chaubey, I., Garg, V. & Migliaccio, K.W. (2006). Impact of time scale of the calibration objective function on the performance of watershed models. *Journal of Hydrological Processes,* DOI:10.1002/hyp. 6555.

Theresa, M.C, and Konstantine, P.G. (2006). Inter comparison of lumped versus distributed hydrologic model ensemble simulations on operational forecast scales. *Journal of Hydrology*, 329(1-2), pp.174-185.

United States Army Corps of Engineers, Hydrologic Engineering Centre (USACE 2000), *Technical Reference Manual*, Davis, California.

United States Army Corps of Engineers, Hydrologic Engineering Centre (USACE 1998), *User's Manual*, Davis, California.

Vanderkimpen, P., Melger, E. & Peeters, P. (2009). Flood modeling for risk evaluation – A MIKE FLOOD vs. SOBEK 1D2D benchmark study. Flood Risk Management: *Research and Practice,* Taylor & Francis group, London.

Wijesekera, N.T.S.(2010). Surface Water Resources and Climate Change. *Proceedings of the National Forum on Water Research "Identification of Gaps and Priorities". National Science Foundation,* Sri Lanka.

Wijesekera, N.T.S. & Musiake, (1990a). Streamflow Modeling of Sri Lankan catchments (1)- Mahaweli River catchment at Peradeniya, Seisan-Kenkyu, *Journal of the Institute of Industrial Science,* University of Tokyo,Japan, 42(11), November 1990.

Wijesekera, N.T.S. & Musiake, (1990b). Streamflow Modeling of Sri Lankan catchments(2)- Kalu River catchment at Putupaula, Seisan-Kenkyu, *Journal of the Institute of Industrial Science,* University of Tokyo,Japan, 42(11), November 1999.

Wijesekera, N. T. S. (2010). Climate Change Impacts On Water Resources in Sri Lanka and Recommendations for Adaptation Measures. *Regional Workshop on "Climate Change and Water Resources", Bangladesh Centre for Advanced Studies,* Dhaka, Bangladesh.

Wijesekera N.T.S. & Abeynayake J.C. (2003). Watershed similarity conditions for peak flow transition. A study of river basins in the wet zone of Sri Lanka, Engineer *Journal of the Institution of Engineers*, Sri Lanka, 2003.

World Meteorological Organization. (1975). *Intercomparison of conceptual models used in operational hydrological forecasting.* (Operational hydrology report no.7/WMO-No 429). Geneva, Switzerland.

Wu, C.L., Chau, K. W. & Fan, C. (2010). Prediction of Rainfall time series using Modular Artificial Neural Networks coupled with Data-Preprocessing techniques. *Journal of Hydrology,* 389(1-2), pp. 146-167.

Xuefeng Chu, A.M.ASCE and Steinman, A. (2009). Event and Continous Hydrologic modeling with HEC HMS. *Journal of Irrigation and Drainage Engineering,* ASCE.

APPENDIX A : STREAMFLOW RESPONSE WITH RAINFALL

\

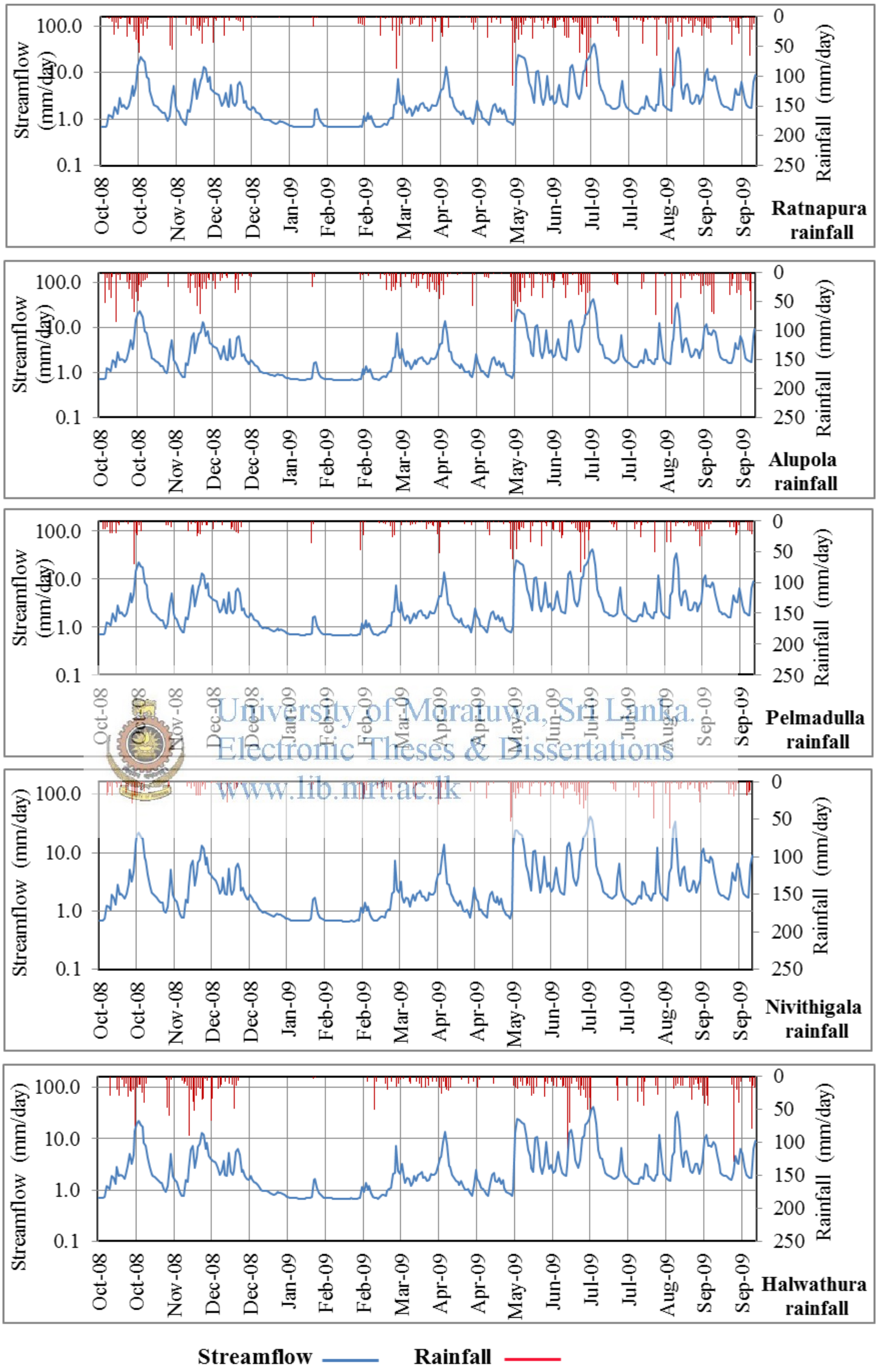

Figure A-1 Streamflow response of Ellagawa with rainfall in 2008/2009

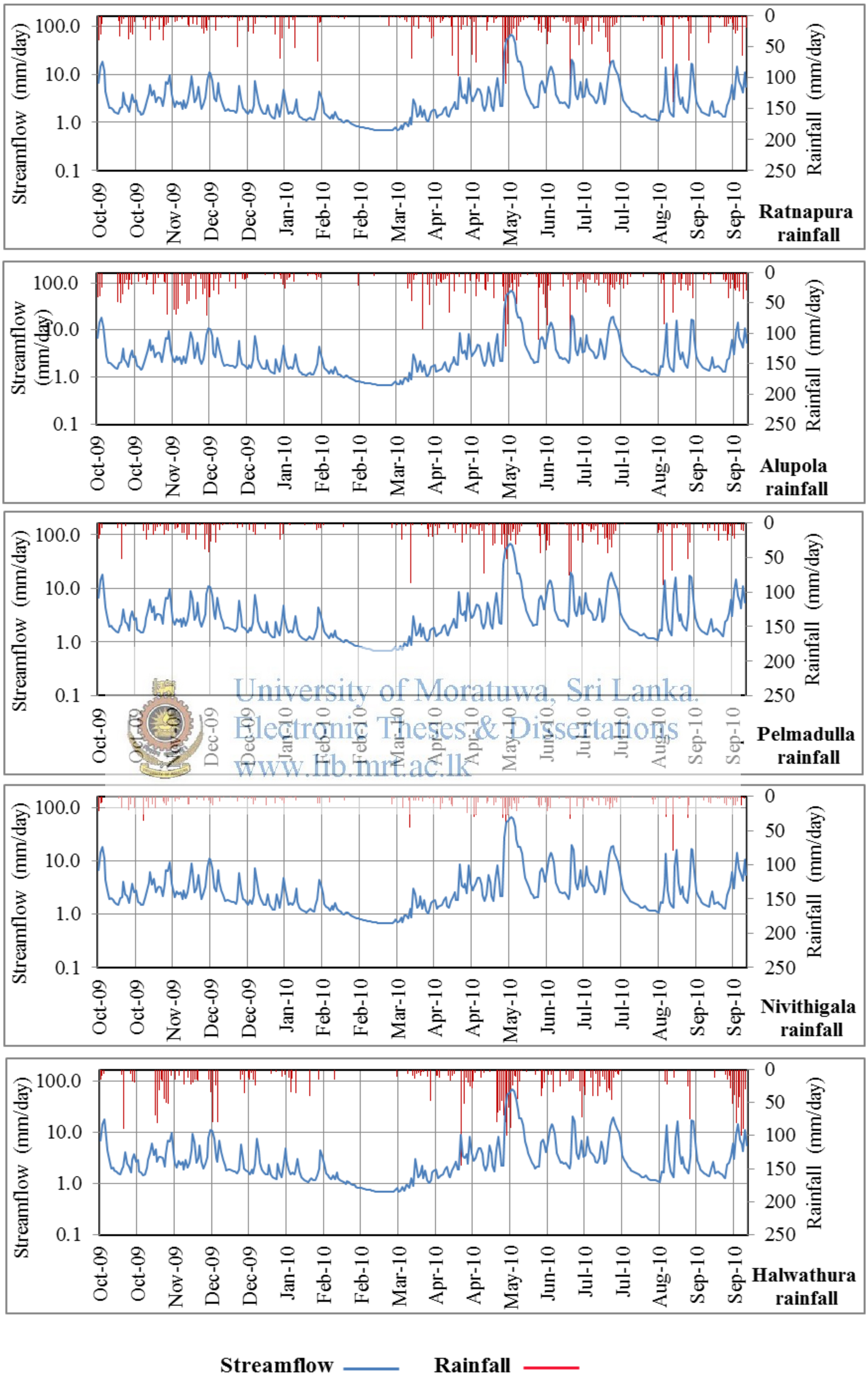

Figure A-2 Streamflow response of Ellagawa with rainfall in 2009/2010

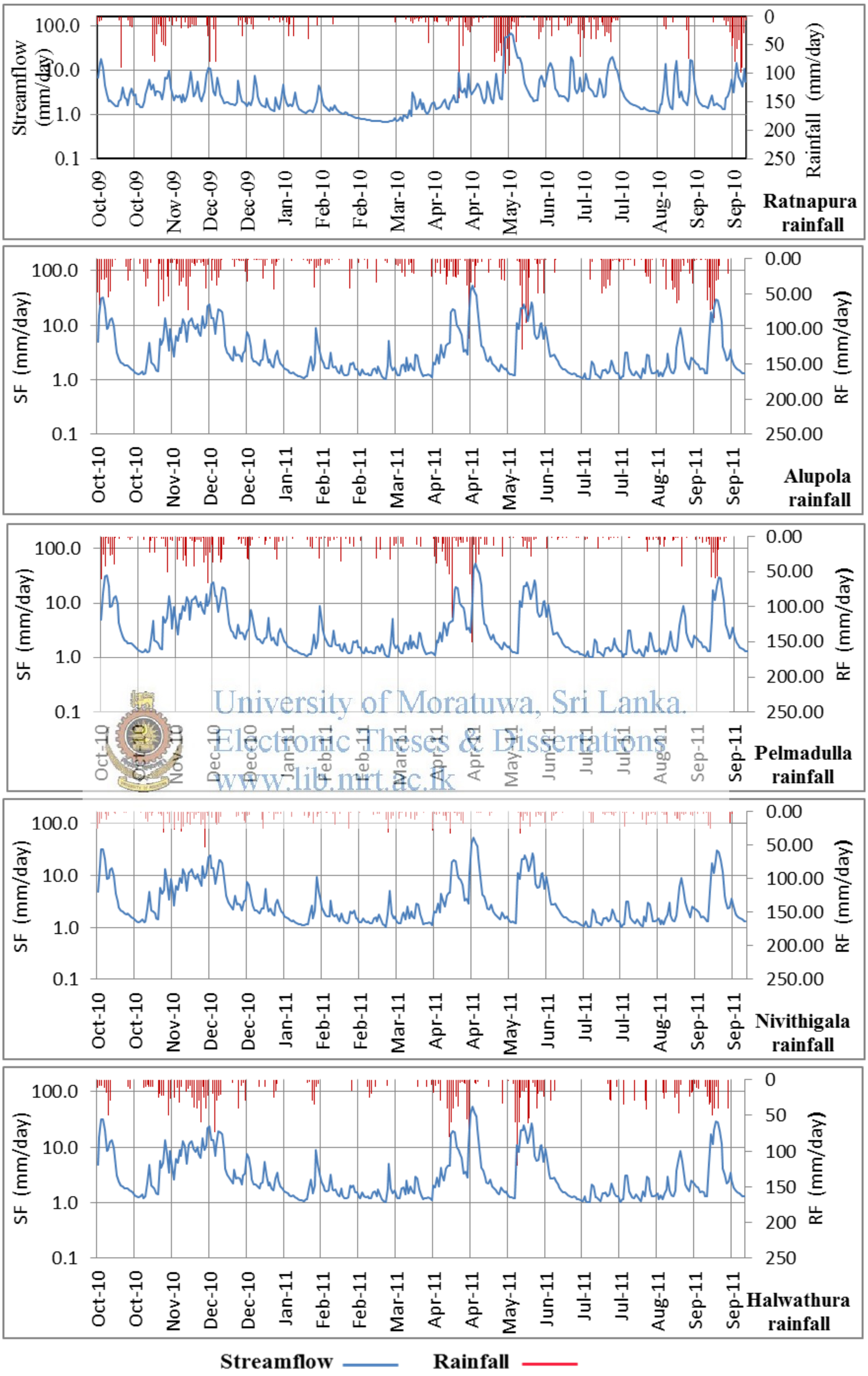

Figure A-3 Streamflow response of Ellagawa with rainfall in 2010/2011

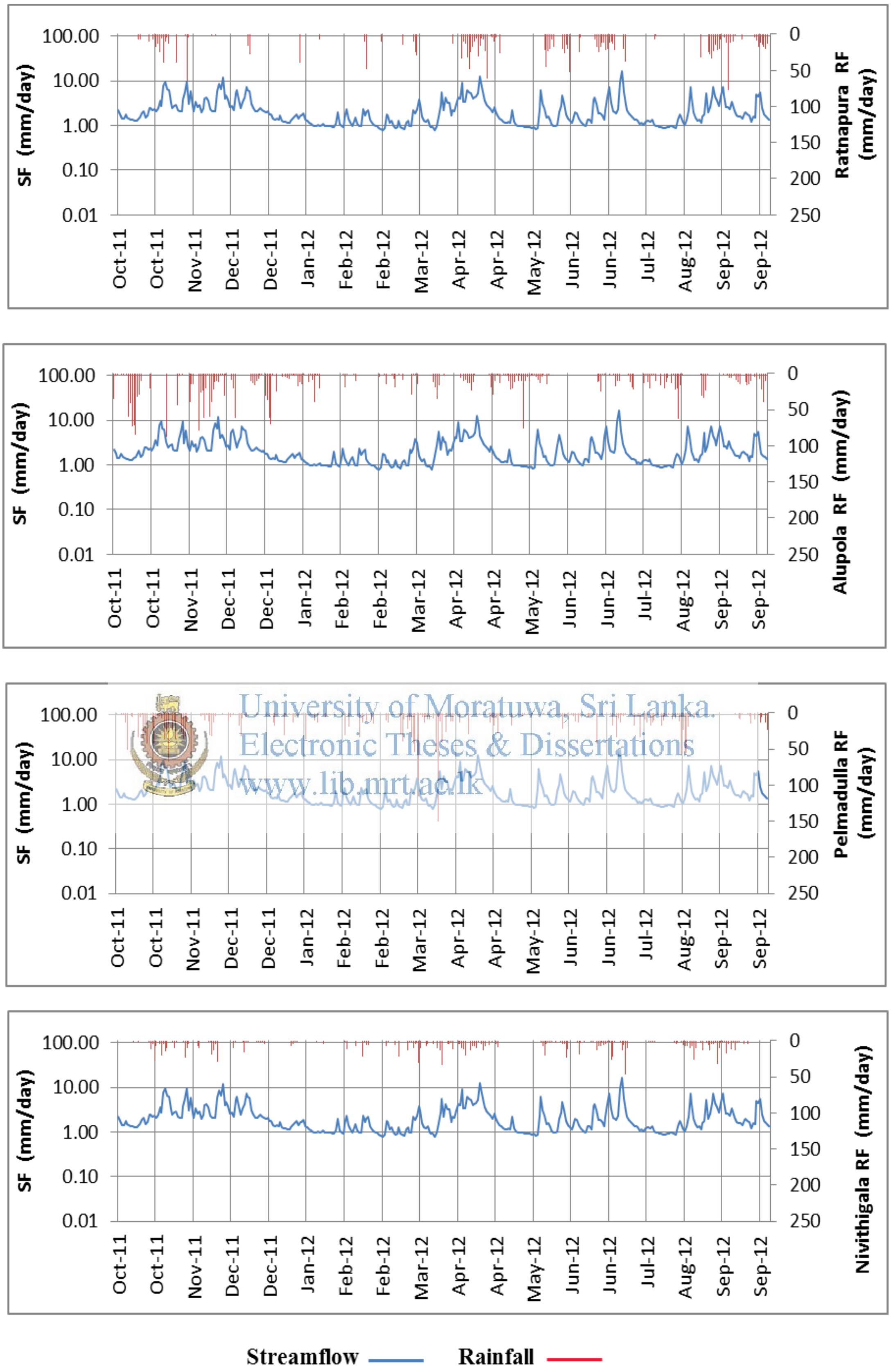

Figure A-4 Streamflow response of Ellagawa with rainfall in 2011/2012

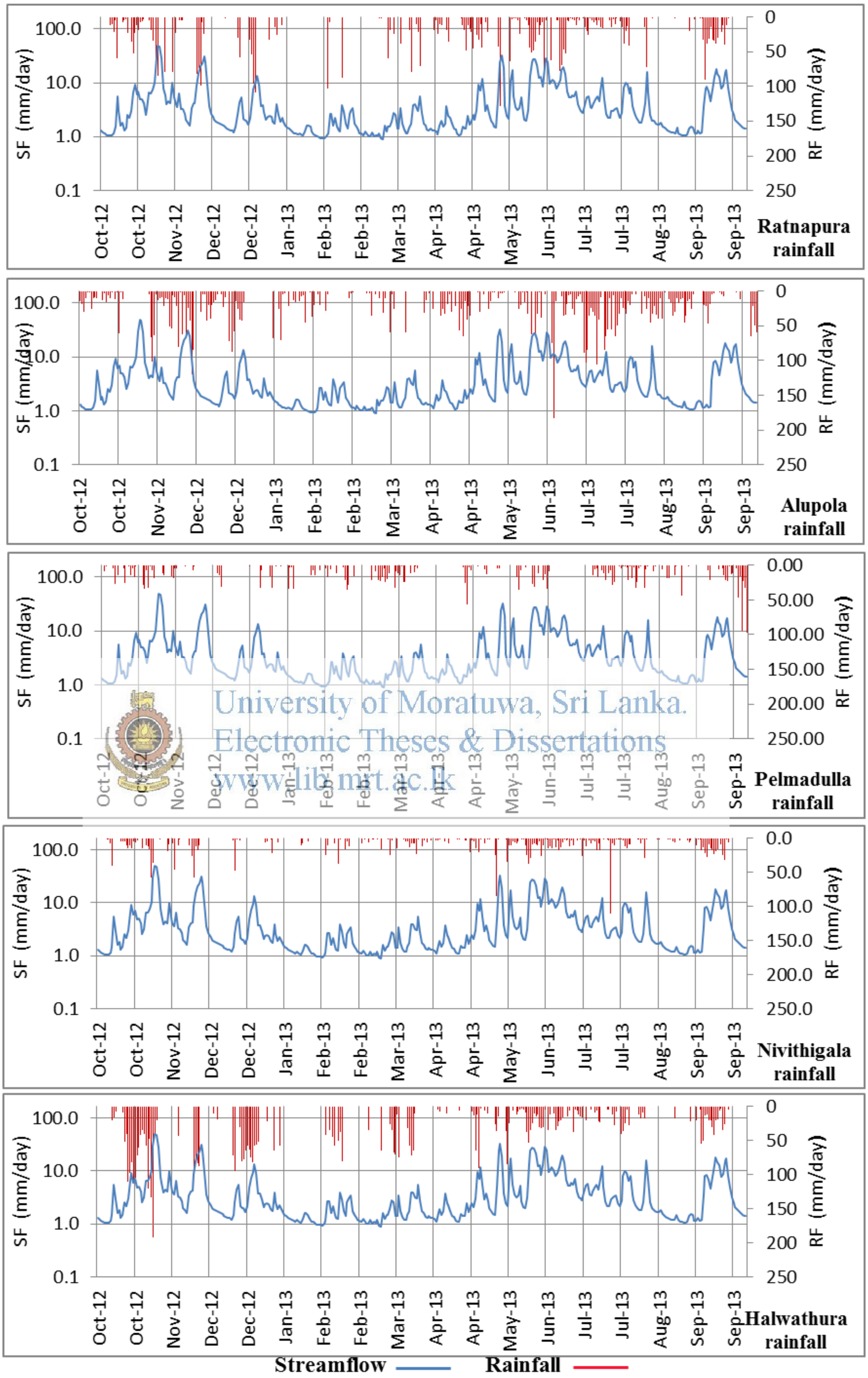

Figure A-5 Streamflow responses of Ellagawa with rainfall in 2012/2013

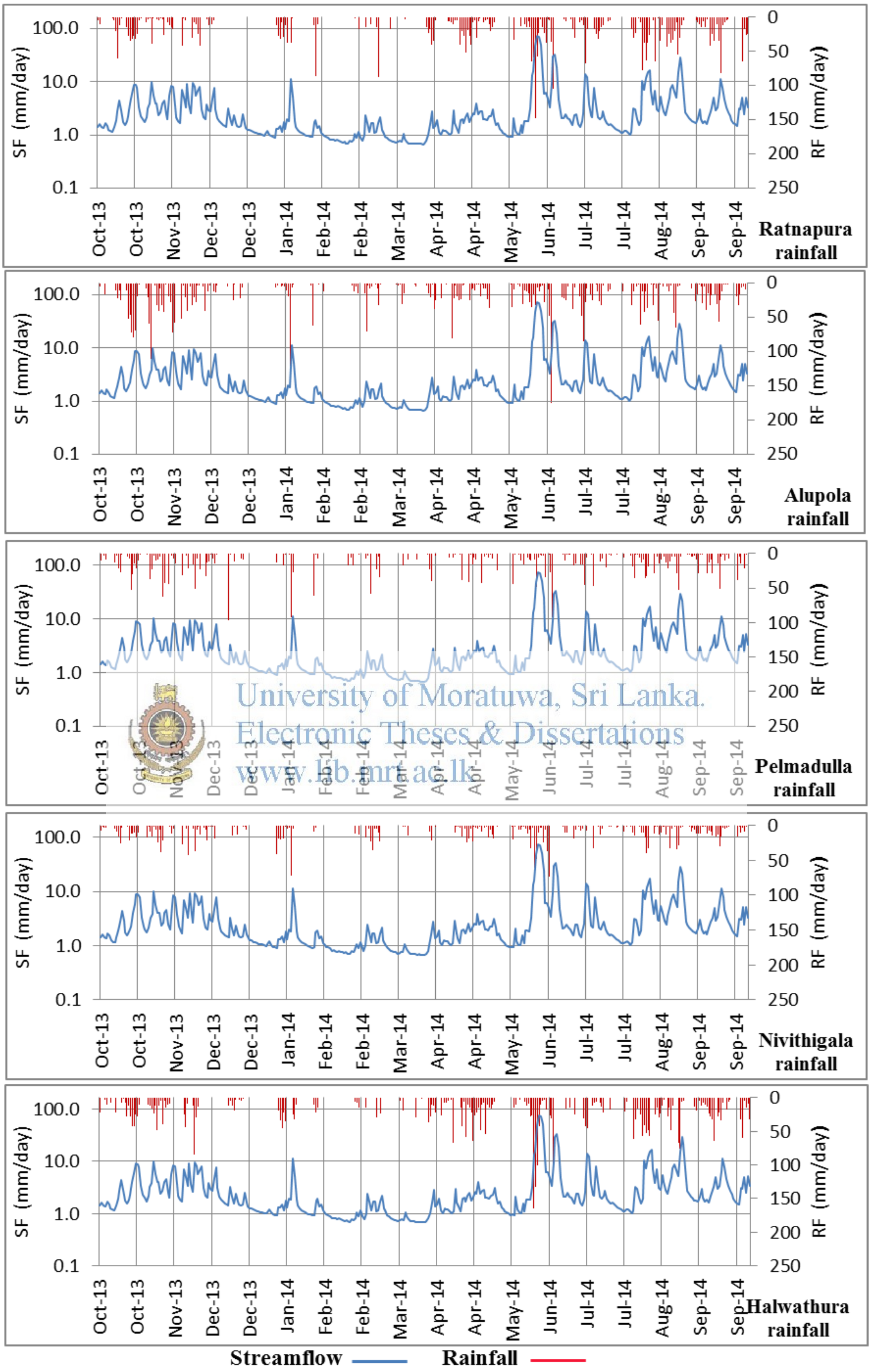

Figure A-6 Streamflow responses of Ellagawa with rainfall in 2013/2014

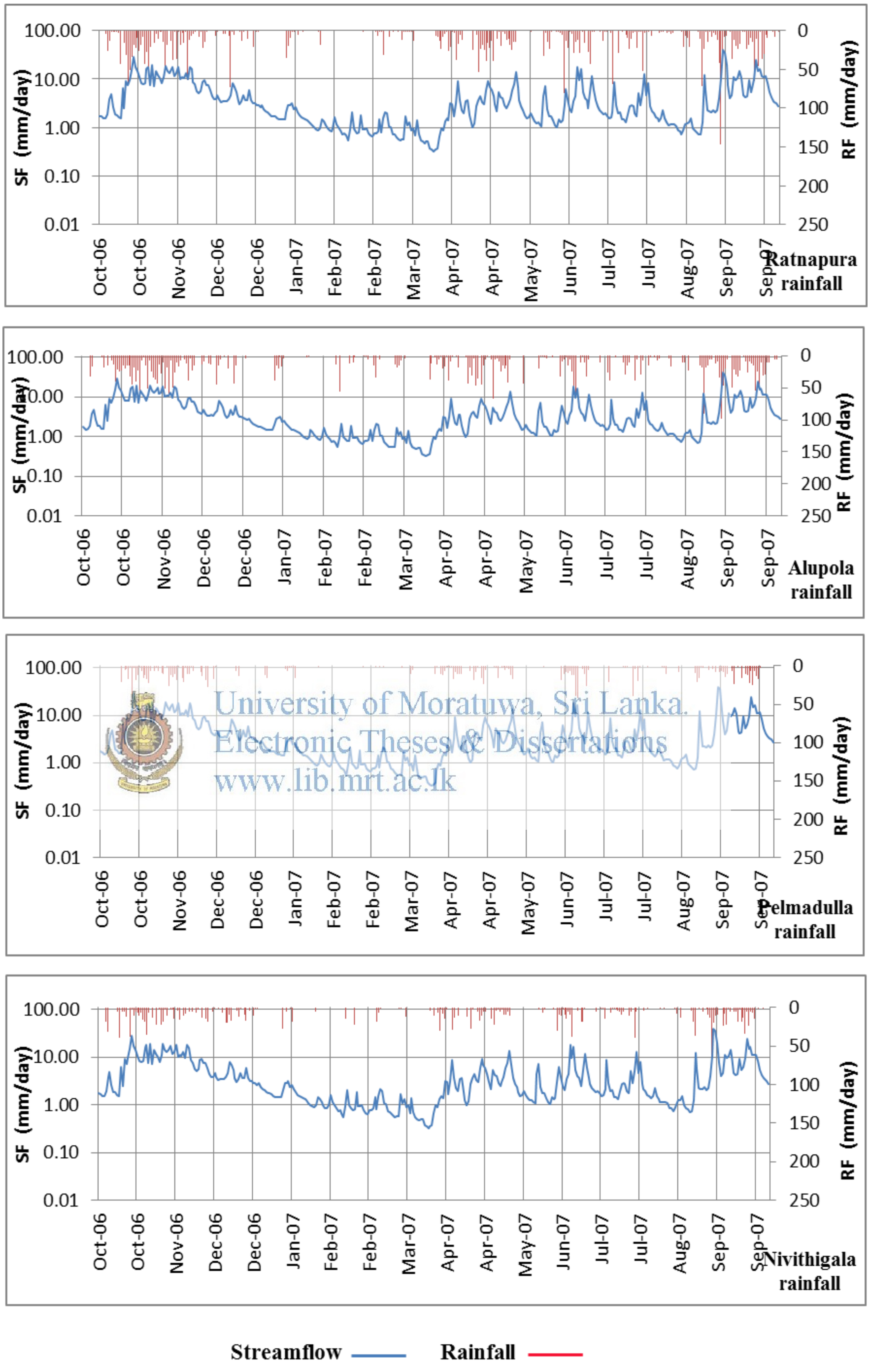

Figure A-7 Streamflow response of Ratnapura with rainfall in 2006/2007

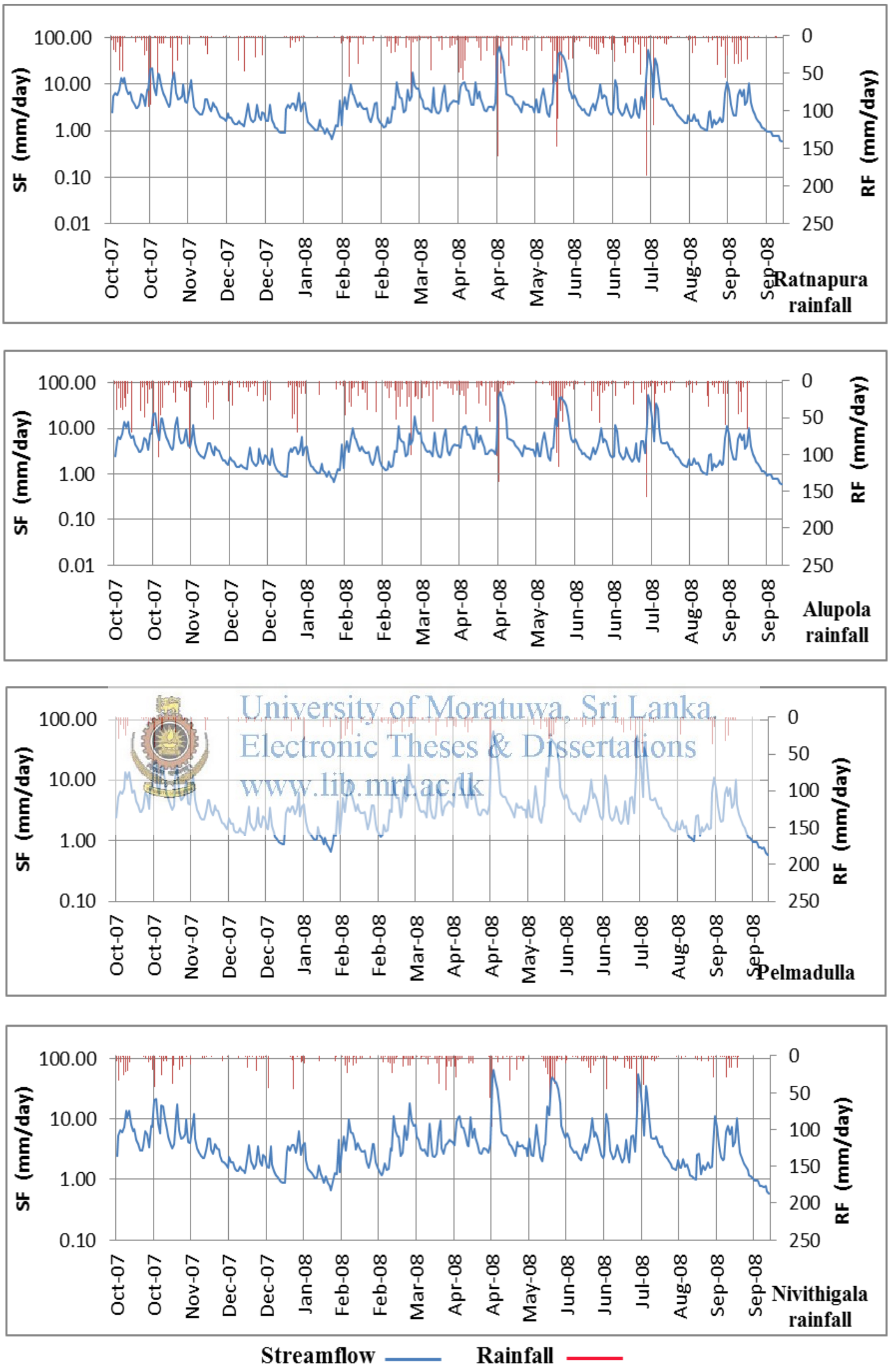

Figure A-8 Streamflow response of Ratnapura with rainfall in 2007/2008

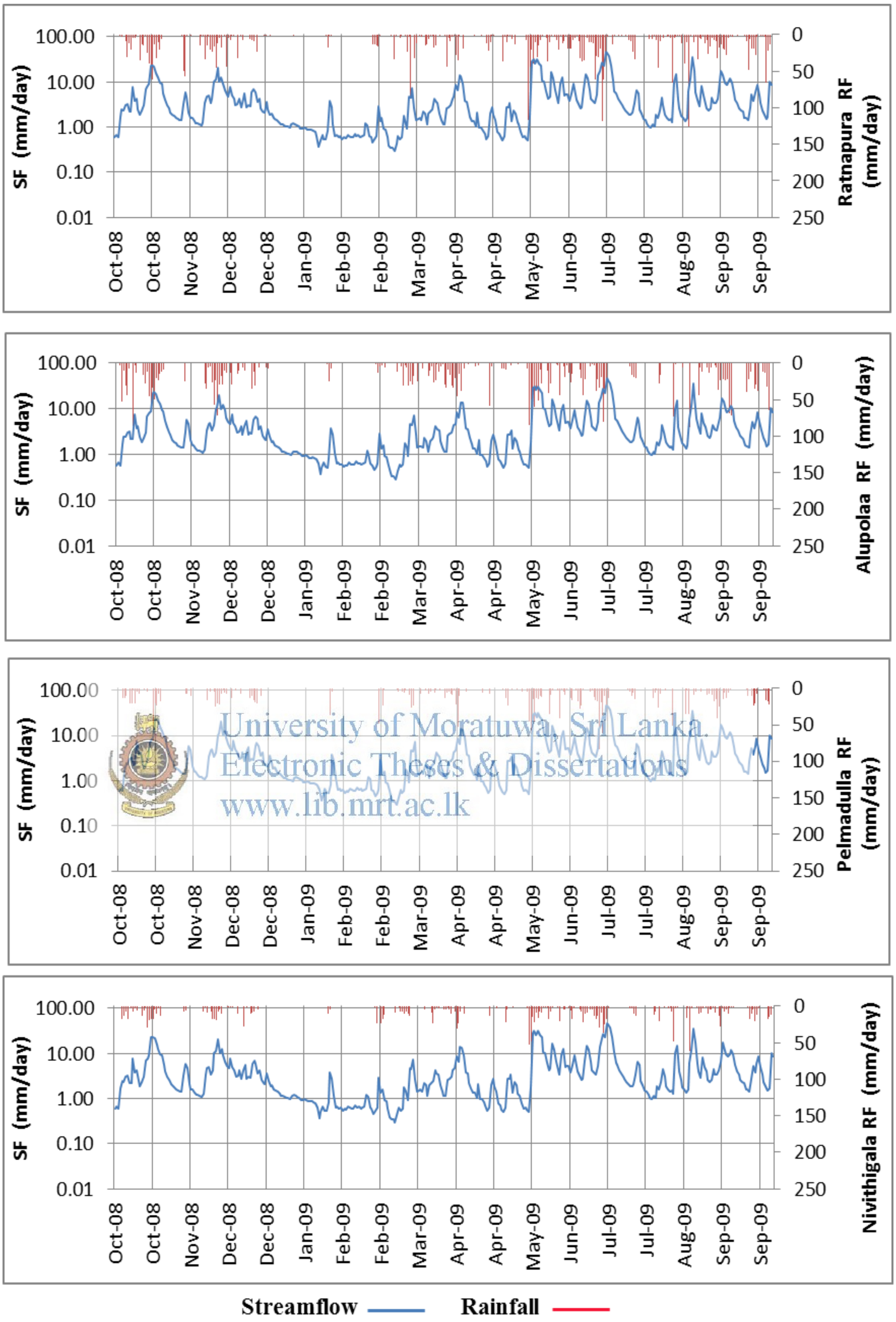

Figure A-9 Streamflow response of Ratnapura with rainfall in 2008/2009

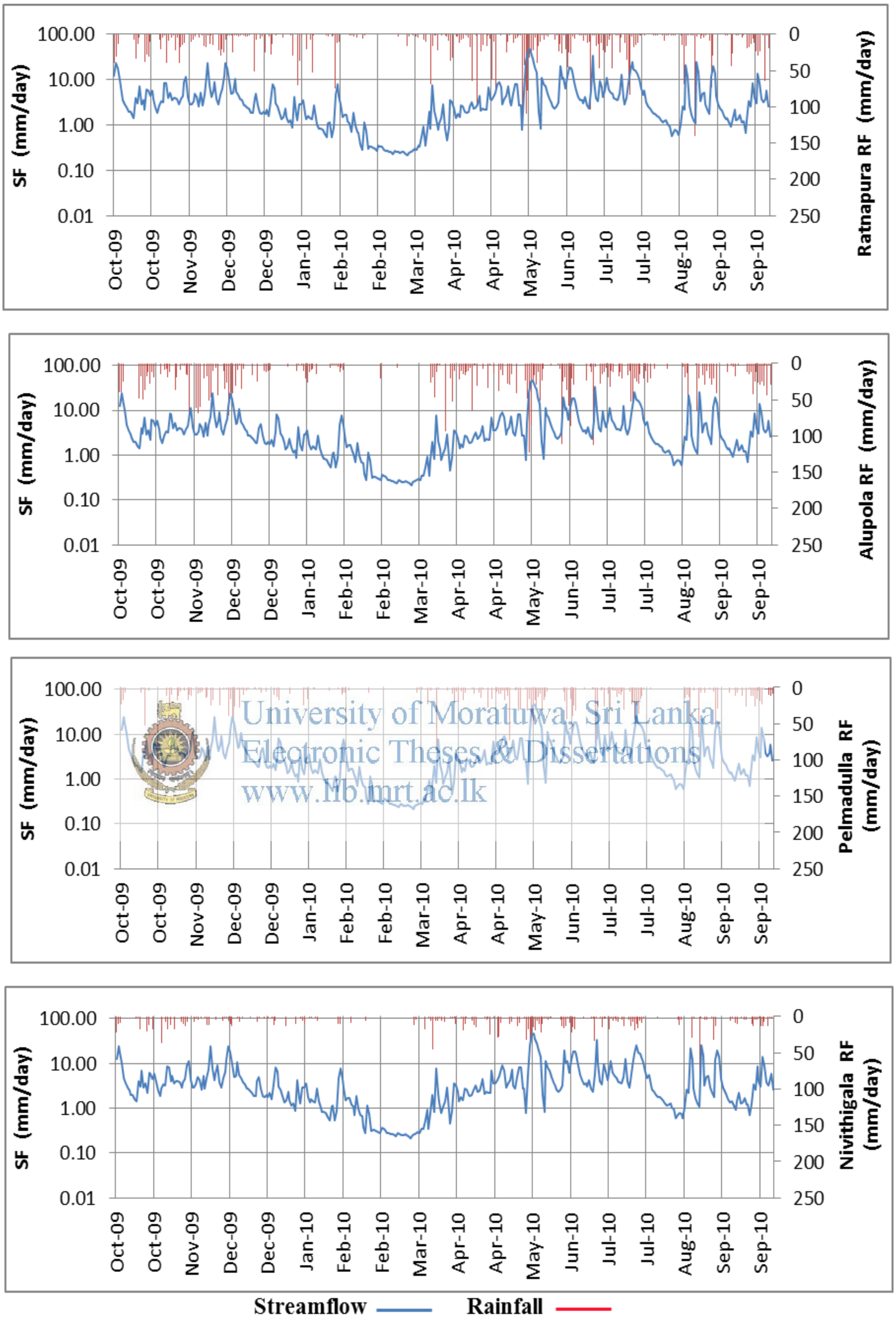

Figure A-10 Streamflow response of Ratnapura with rainfall in 2009/2010

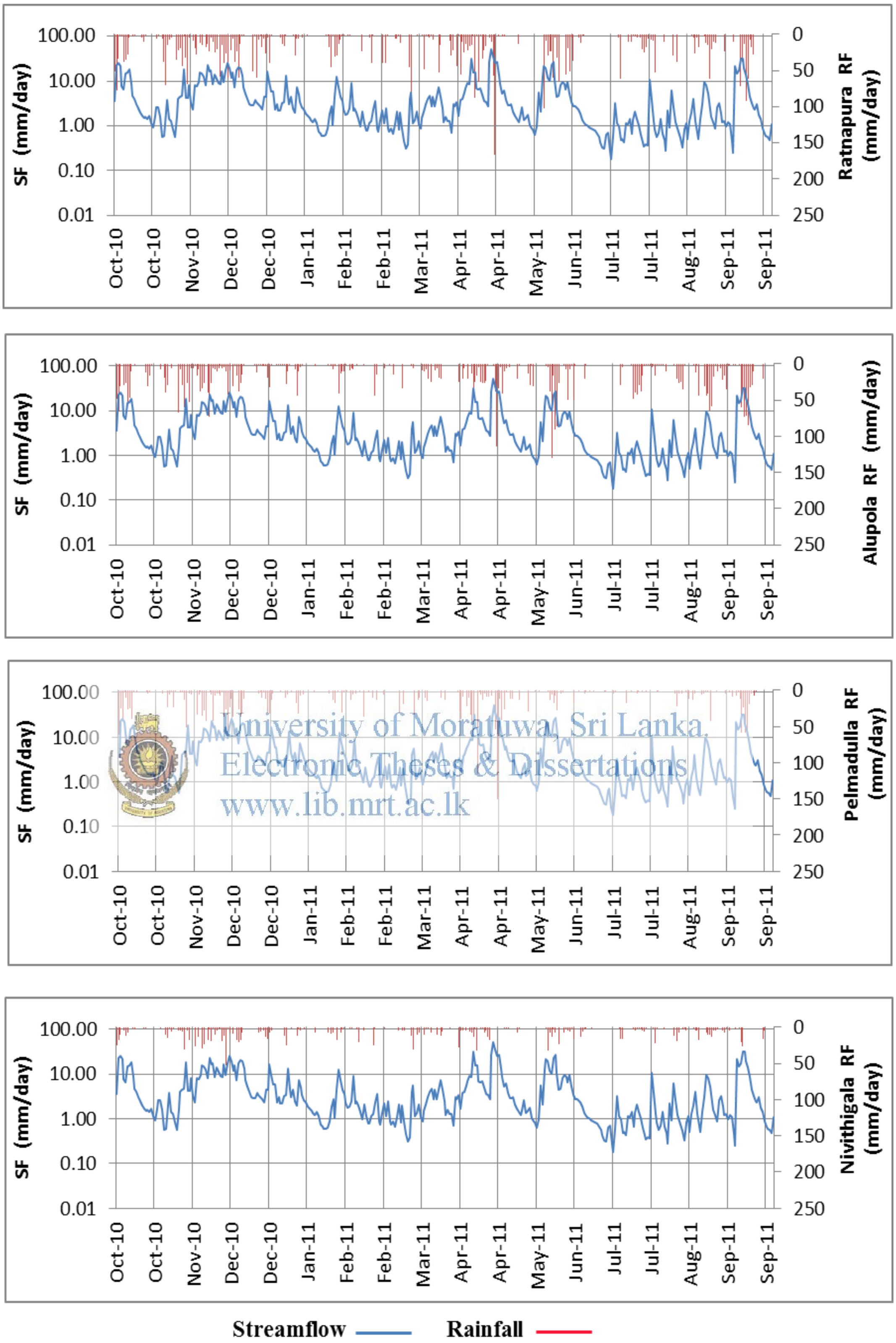

Figure A-11 Streamflow response of Ratnapura with rainfall in 2010/2011

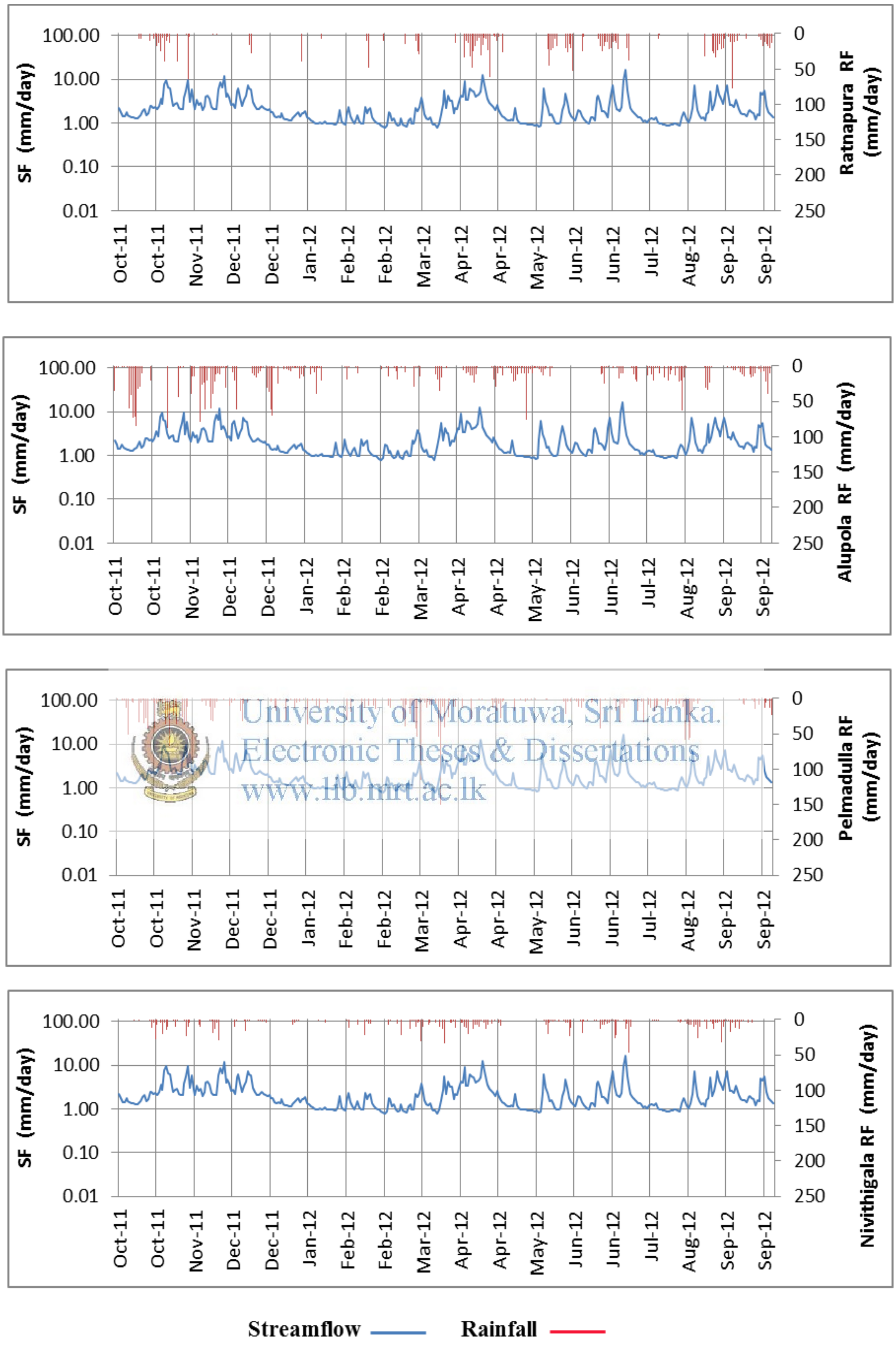

Figure A-12 Streamflow response of Ratnapura with rainfall in 2011/2012

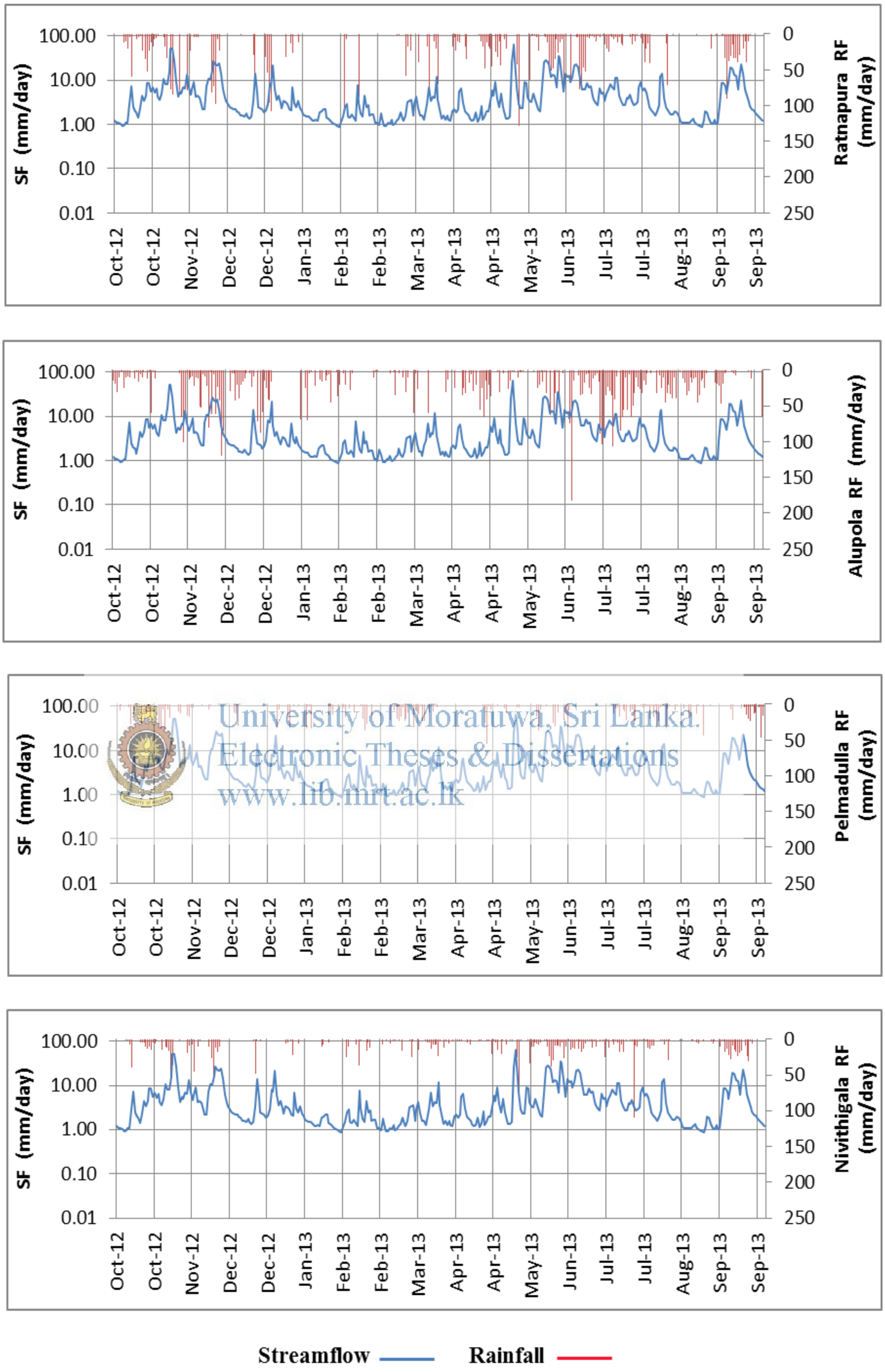

Figure A-13 Streamflow response of Ratnapura with rainfall in 2012/2013

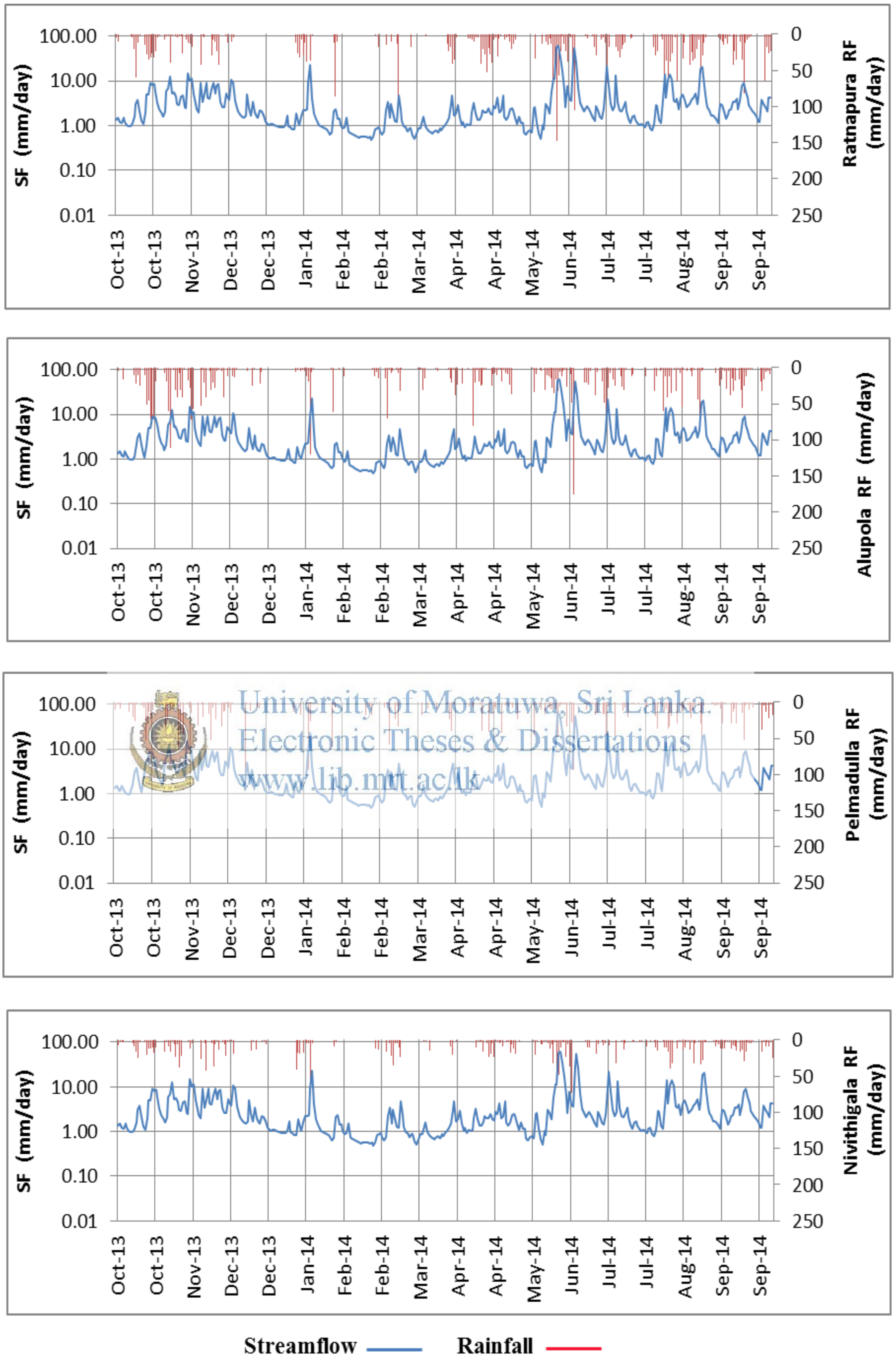

Figure A-14 Streamflow response of Ratnapura with rainfall in 2013/2014

APPENDIX B : DOUBLE MASS CURVES

Table B-1 Variation of cumulative rainfall

Water year	Cumulative rainfall				
	Halwathura	Ratnapura	Alupola	Pelmadulla	Nivithigala
2006/2007	3277	4595	4099	1415	1838
2007/2008	5318	8450	8619	3026	3932
2008/2009	8609	11859	12392	5195	5654
2009/2010	12610	15800	16874	7882	7307
2010/2011	15815	20026	21109	10575	8767
2011/2012	20166	21972	24189	13364	10040
2012/2013	25893	26208	30089	15610	12173
2013/2014	30116	29966	34217	18441	14321

Table B-2 Variation of cumulative average rainfall

Water year	Cumulative average rainfall				
	Halwathura	Ratnapura	Alupola	Pelmadulla	Nivithigala
2006/2007	2987	2657	2781	3452	3347
2007/2008	6007	5224	5181	8330	6353
2008/2009	8775	7962	7829	12004	9514
2009/2010	11966	11168	10900	15297	13292
2010/2011	15119	14067	13796	18536	16882
2011/2012	17391	16940	16386	21332	19923
2012/2013	21020	20941	19971	24762	24450
2013/2014	24236	24274	23211	24762	28185

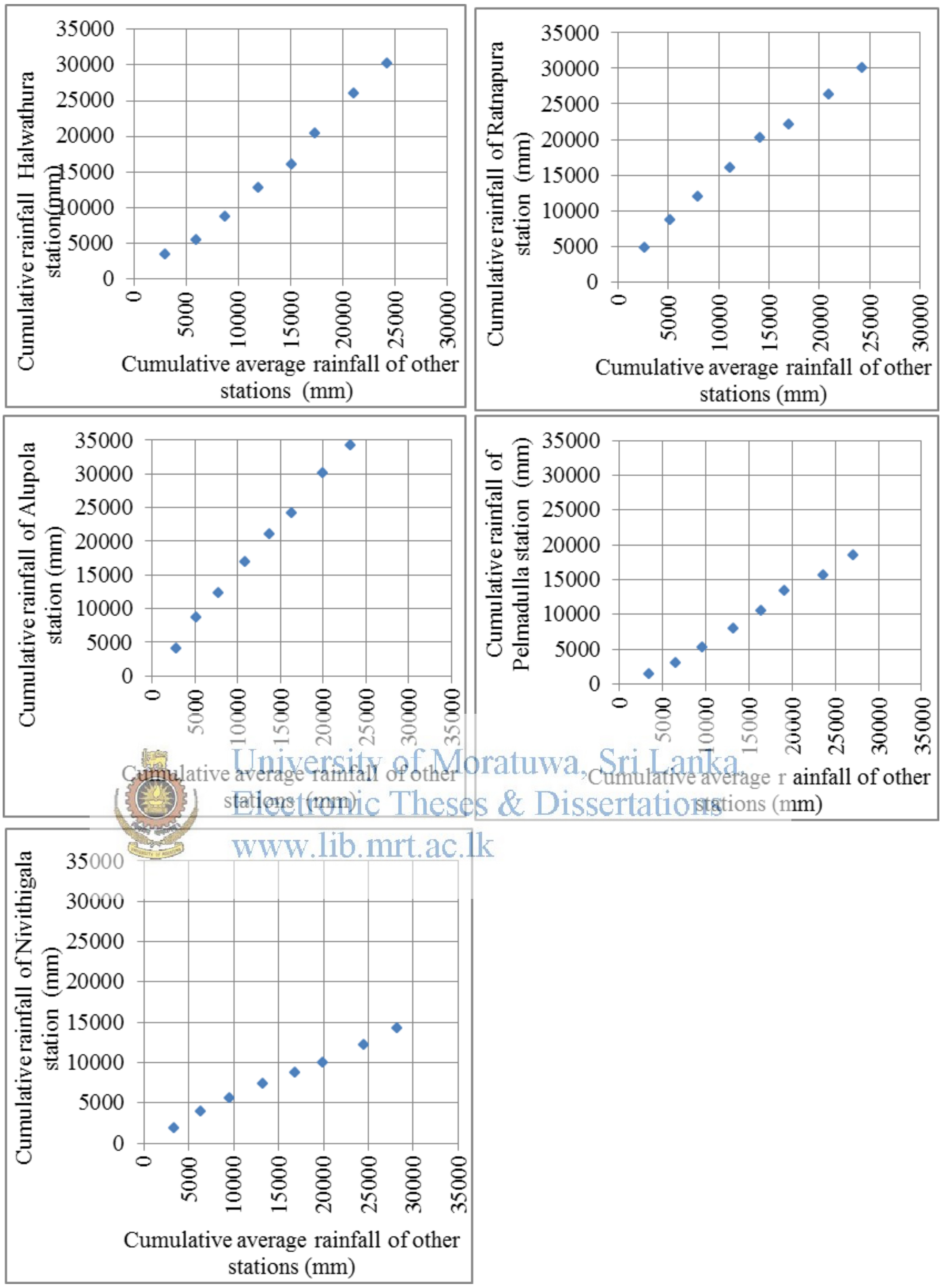

Figure B-1 Double Mass Curves

APPENDIX C : COMPARISON OF RAINFALL CALCULATIONS

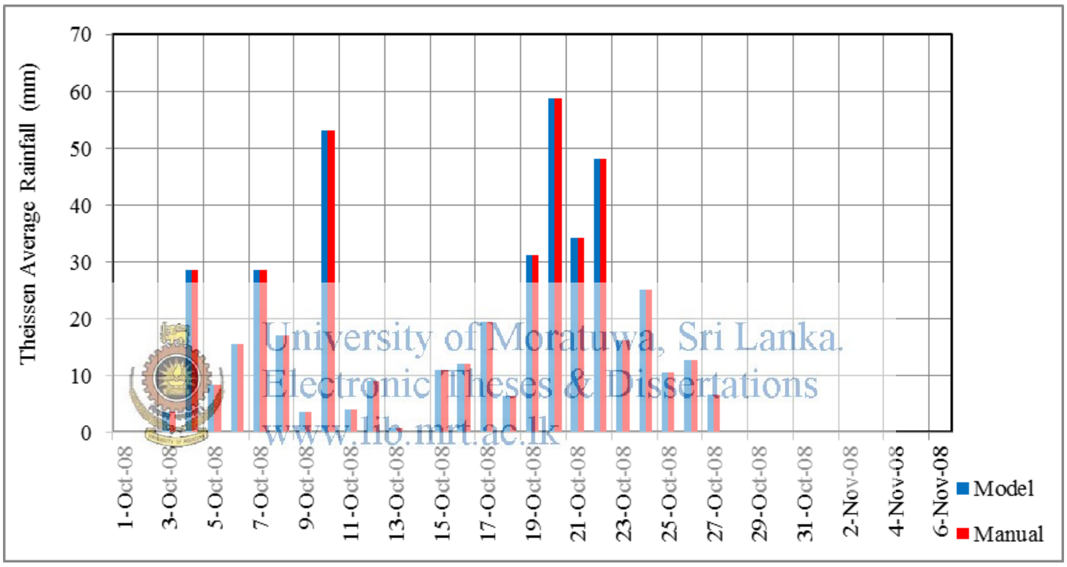

Figure C-1 Comparison of model and manual calculation of rainfall

APPENDIX D : REVIEW OF OPTIMIZATION CRITERIA & SIMULATION TIME INTERVAL

Table D-1 Description of Trials

Trial	Description of Model Output
1	Peak magnitude is matching but the time of occurrence is poor
2	
3	
4	
5	
6	Time of occurrence and peak are matching
7	
8	
9	
10	

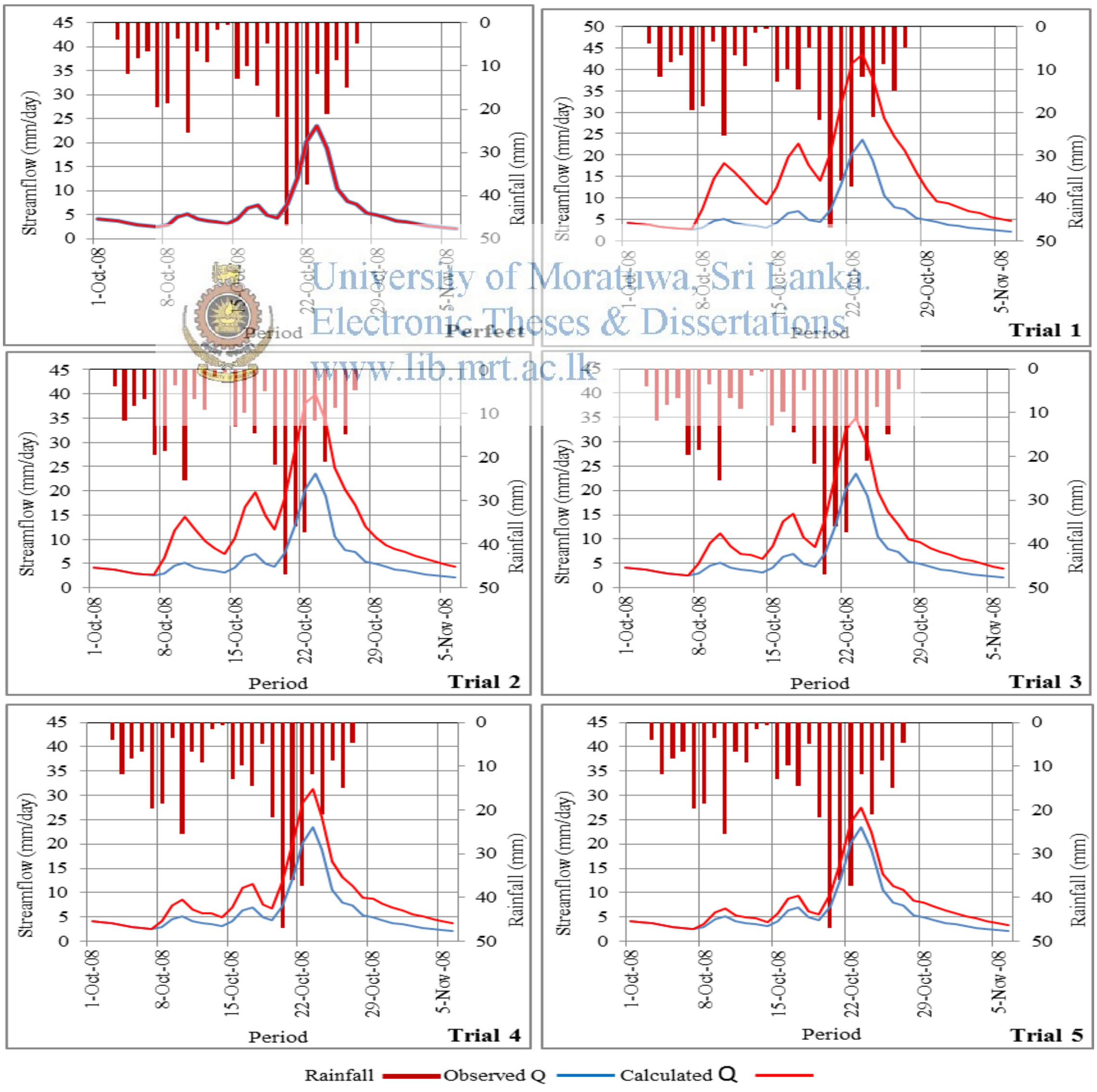

Figure D-1 Model outputs for different trials

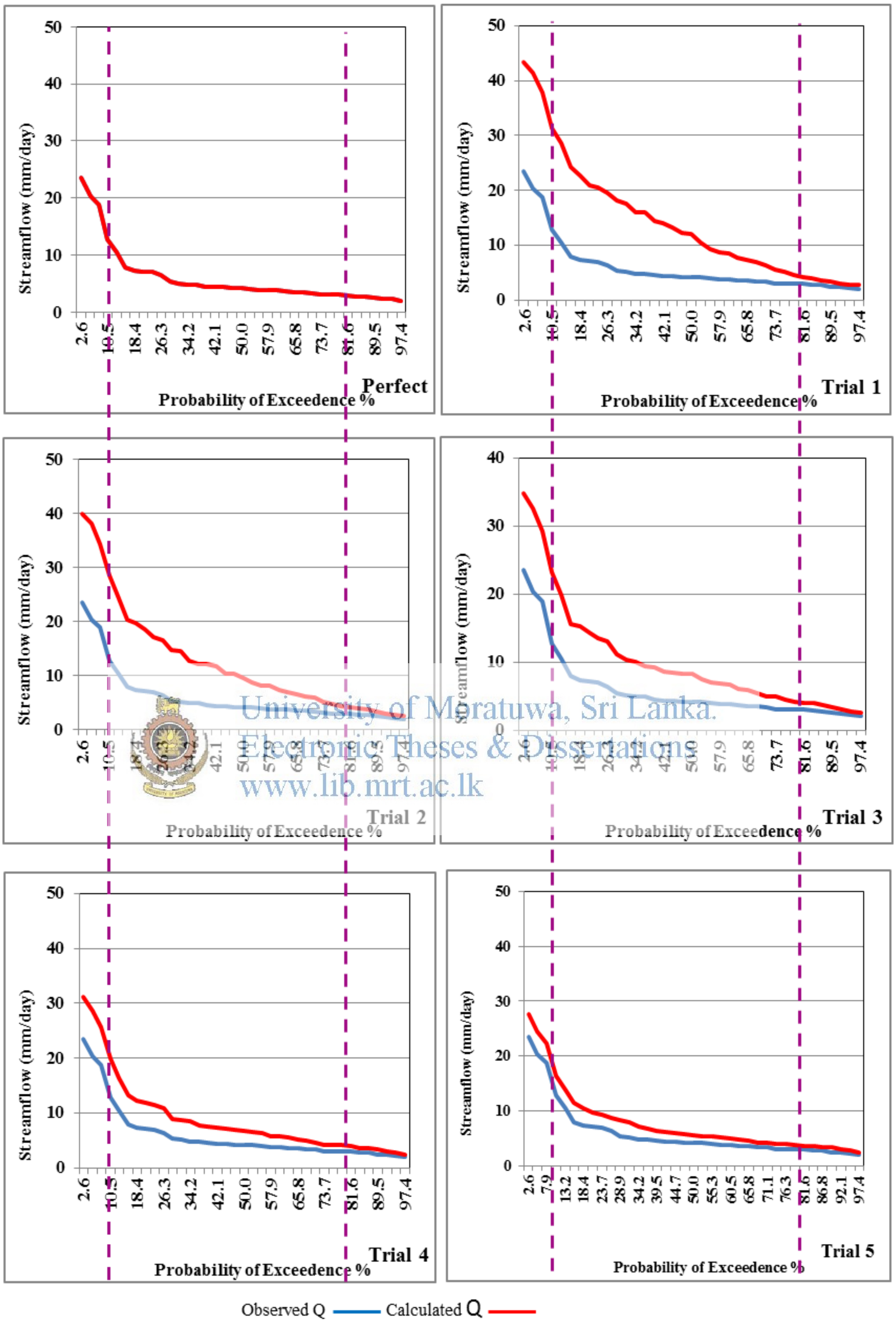

Figure D-2 Flow duration curves for different trials

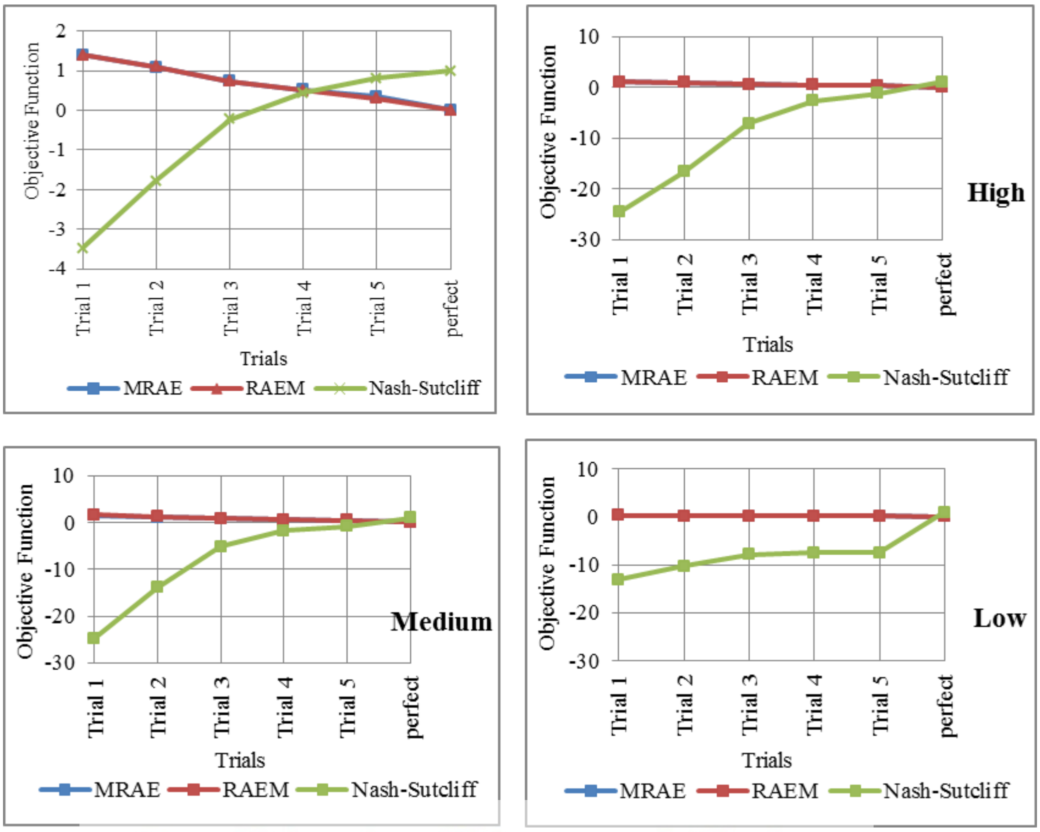

Figure D-3 Variation of objective function with trials

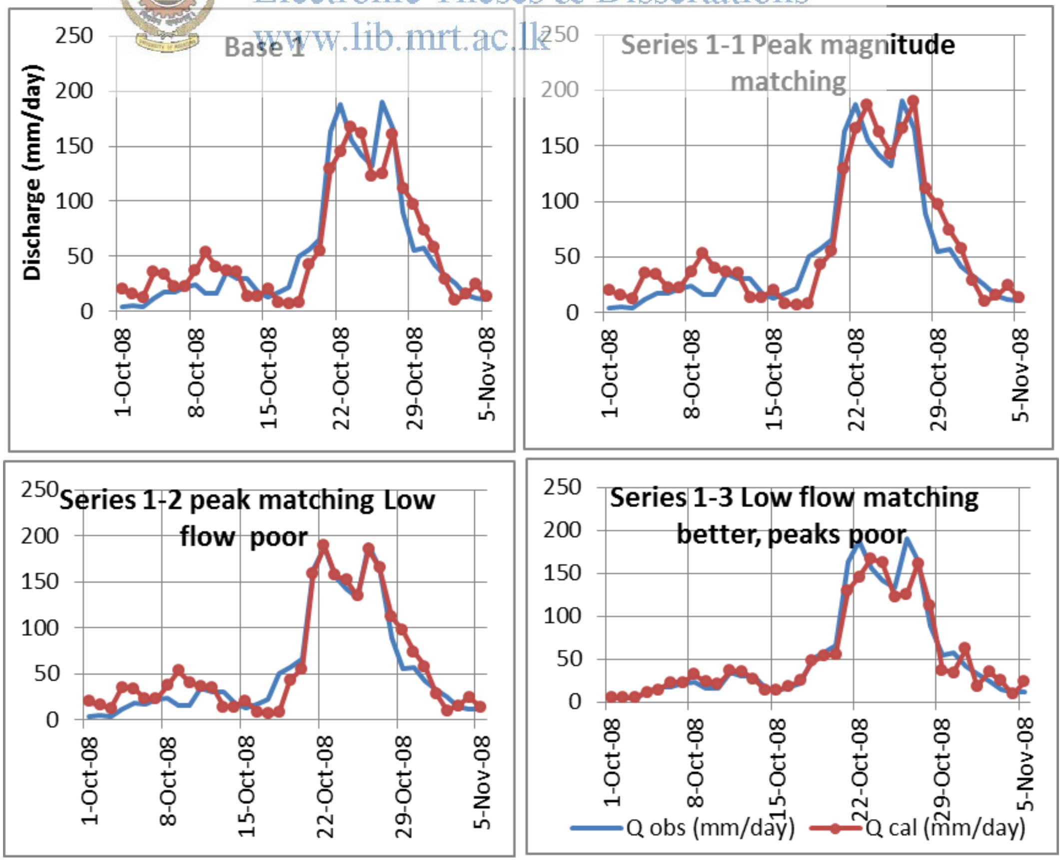

Figure D-4 Model performance for flow series 1

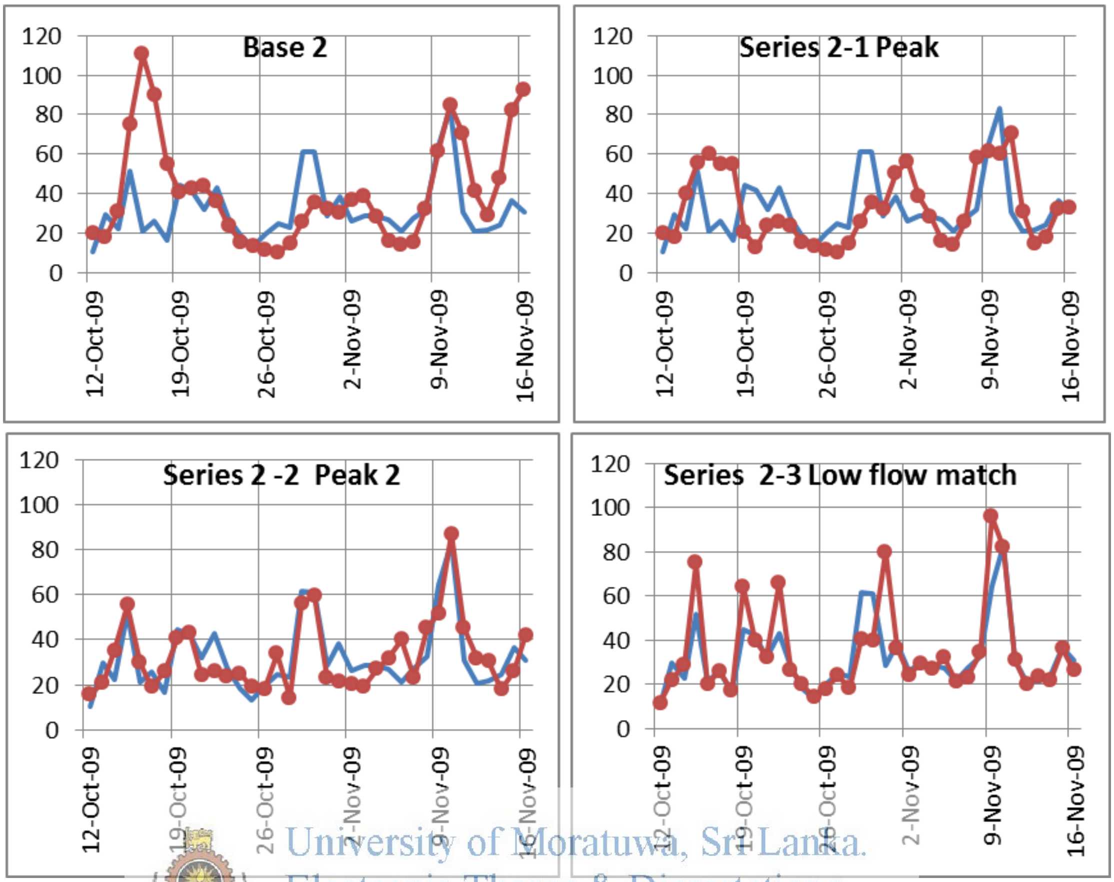

Figure D-5 Model performance for flow series 2

Table D-2 Summary of calculations for RAEM and MRAE for series 1

	Series 1 - Case of Peak flows and Average flows differ - Seasonal Rains				
		Base Series 1	Series 1-1 Peak	Series 1-1	Series 1-2
Observed flow	Peak Flow	190.49	190.49	190.49	190.49
	Average Flow	54.40	54.40	54.40	54.40
	Lowest Flow	4.27	4.27	4.27	4.27
		Generally match	Peak flows Match better	Peaks Match better	Low flow match better
Calculated flow	Peak Flow	167.31	189.98	189.30	167.31
	Average Flow	55.20	58.79	58.82	51.72
	Lowest Flow	6.98	6.98	6.98	4.70
MRAE		0.6678	0.6662	0.6419	0.2368
RAEM		0.3058	0.2963	0.2229	0.1974
Rate of Change MRAE			0.00	0.04	0.65
Rate of Change RAEM			0.03	0.27	0.35

Table D-3 Summary of calculations for RAEM and MRAE for series 2

	Series 2 - Case of Similar flows all through out				
		Base Series 1	Series 1-1 Peak	Series 1-1	Series 1-2
Observed flow	Peak Flow	83.22	83.22	83.22	83.22
	Average Flow	32.24	32.24	32.24	32.24
	Lowest Flow	10.53	10.53	10.53	10.53
Calculated flow	Peak Flow	110.40	70.28	87.03	96.00
	Average Flow	40.91	32.88	32.50	34.68
	Lowest Flow	10.58	10.58	14.30	11.60
MRAE		0.6678			
RAEM		0.3058	0.6553	0.5093	0.2997
Rate of Change MRAE			0.5440	0.4489	0.2483
Rate of Change RAEM				0.22	0.54

Table D-4 Comparison of objective function with trials

Name of Objective function	Value of objective function in hydrograph					
	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5	Perfect
MRAE	1.396	1.079	0.737	0.522	0.340	0
RAEM	1.401	1.095	0.733	0.503	0.304	0
Nash-Sutcliff	-3.487	-1.791	-0.228	0.441	0.805	1

Table D-5 Comparison of objective function in high flow region

Name of Objective function	Value of objective function in flow duration curve - High					
	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5	perfect
MRAE	1.089	0.905	0.616	0.415	0.322	0
RAEM	1.044	0.866	0.591	0.397	0.308	0
Nash-Sutcliff	-24.627	-16.646	-7.216	-2.717	-1.237	1

Table D-6 Comparison of objective function in medium flow region

Name of Objective function	Value of objective function in flow duration curve - Medium					
	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5	perfect
MRAE	1.480	1.135	0.770	0.541	0.451	0
RAEM	1.651	1.261	0.837	0.575	0.476	0
Nash-Sutcliff	-24.759	-13.923	-5.205	-1.783	-0.882	1

Table D-7 Comparison of objective function in low flow region

Name of Objective function	Value of objective function in flow duration curve - Low					
	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5	perfect
MRAE	0.277	0.246	0.216	0.210	0.210	0
RAEM	0.274	0.244	0.217	0.211	0.211	0
Nash-Sutcliff	-13.021	-10.274	-7.852	-7.442	-7.442	1

Table D-8 Values and order of magnitude of objective functions

Trial	Hydrograph matching			Flow duration curve matching								
				High			Medium			Low		
	RAEM	MRAE	Nash-Sutcliff	RAEM	MRAE	Nash-Sutcliff	RAEM	MRAE	Nash-Sutcliff	RAEM	MRAE	Nash-Sutcliff
Trial 1	1.401	1.396	-3.47	1.044	1.089	-24.6	1.480	1.651	-24.7	0.277	0.274	-13.0
Trial 2	1.095	1.079	-1.79	0.866	0.905	-16.6	1.135	1.261	-13.9	0.246	0.244	-10.2
Trial 3	0.733	0.737	-0.22	0.591	0.616	-7.21	0.770	0.837	-5.20	0.216	0.217	-7.85
Trial 4	0.503	0.522	0.441	0.397	0.415	-2.71	0.541	0.575	-1.78	0.210	0.211	-7.44
Trial 5	0.304	0.340	0.805	0.308	0.322	-1.23	0.451	0.476	-0.88	0.210	0.211	-7.44
Base date set	0	0	1	0	0	1	0	0	1	0	0	1
Order of magnitude of trials	1.401	1.396	4.486	1.044	1.089	25.62	1.45	1.651	25.75	0.277	0.274	14.05

Table D-9 Convergence of objective functions

Trial	Hydrograph matching			Flow duration curve matching								
				High			Medium			Low		
	RAEM	MRAE	Nash-Sutcliff	RAEM	MRAE	Nash-Sutcliff	RAEM	MRAE	Nash-Sutcliff	RAEM	MRAE	Nash-Sutcliff
Trial 1												
Trial 2	0.219	0.227	0.486	0.170	0.169	0.324	0.236	0.233	0.438	0.110	0.110	0.211
Trial 3	0.330	0.317	0.873	0.318	0.320	0.566	0.336	0.321	0.626	0.112	0.123	0.236
Trial 4	0.315	0.292	2.934	0.328	0.327	0.623	0.313	0.298	0.657	0.027	0.030	0.052
Trial 5	0.395	1	0.826	0.224	0.223	0.545	0.172	0.166	0.505	0.000	0.000	0.000
Base date set	1	1	0.24	1.000	1.000	1.808	1.000	1.000	2.133	1.000	1.000	1.134
Order of magnitude of trials	0.287	0.213	0.48	0.17	0.165	0.345	0.254	0.287	0.445	0.134	0.154	0.254

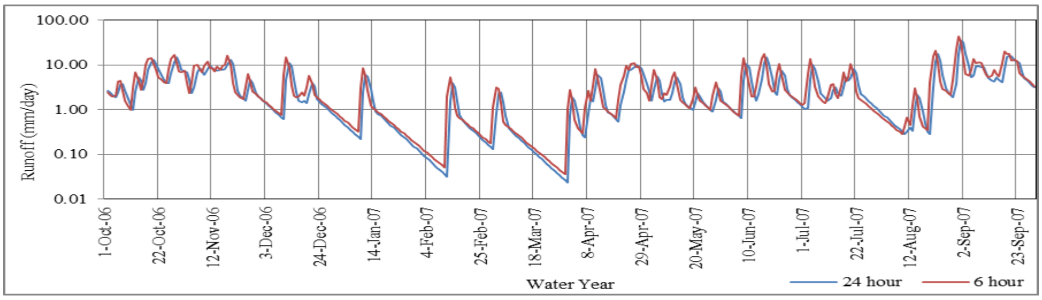

Figure D-5 Comparison of simulation time interval

APPENDIX E : AUTOMATIC PARAMETR OPTIMIZATION

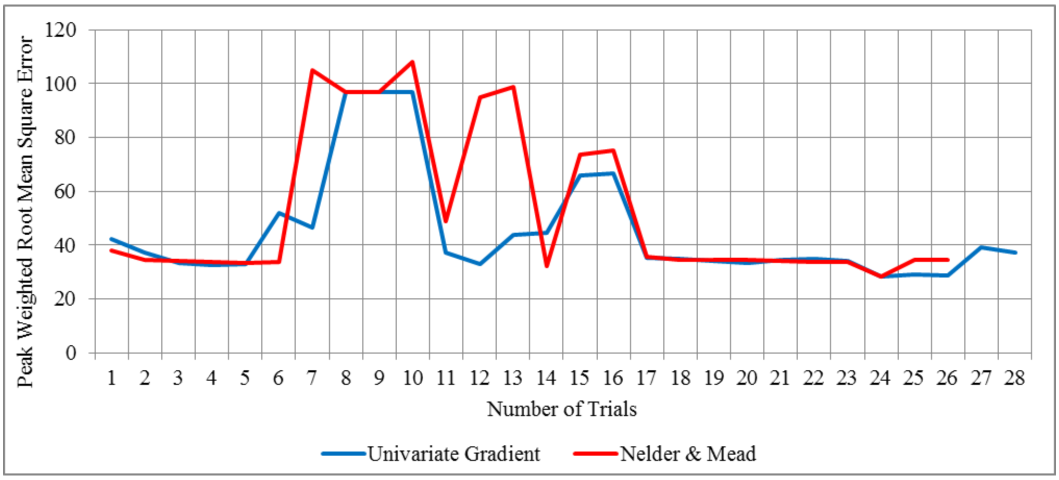

Figure E-1 Comparison of objective function value for different search methods

Table E-1 Comparison of parameters in best fit trials

Parameter	Univariate Graident			Nelder and Mead		
	Trial 4	Trial 12	Trial 25	Trial 5	Trial 14	Trial 25
Constant Loss	0.24	0.33	0.3	0.29	0.3	0.25
Initial Deficit	18	77	11	20	85	13
Recession Constant	0.74	0.78	0.82	0.8	0.75	0.91
Threshold Flow Ratio	0.17	1	0.23	0.29	0.81	0.08
Recovery Factor	0.21	1.84	1.02	0.1	2.49	0.15
Lag	2898	2541	2344	2600	2800	3247
Objective function	32.6	32.8	28.2	33.2	32.2	34.6

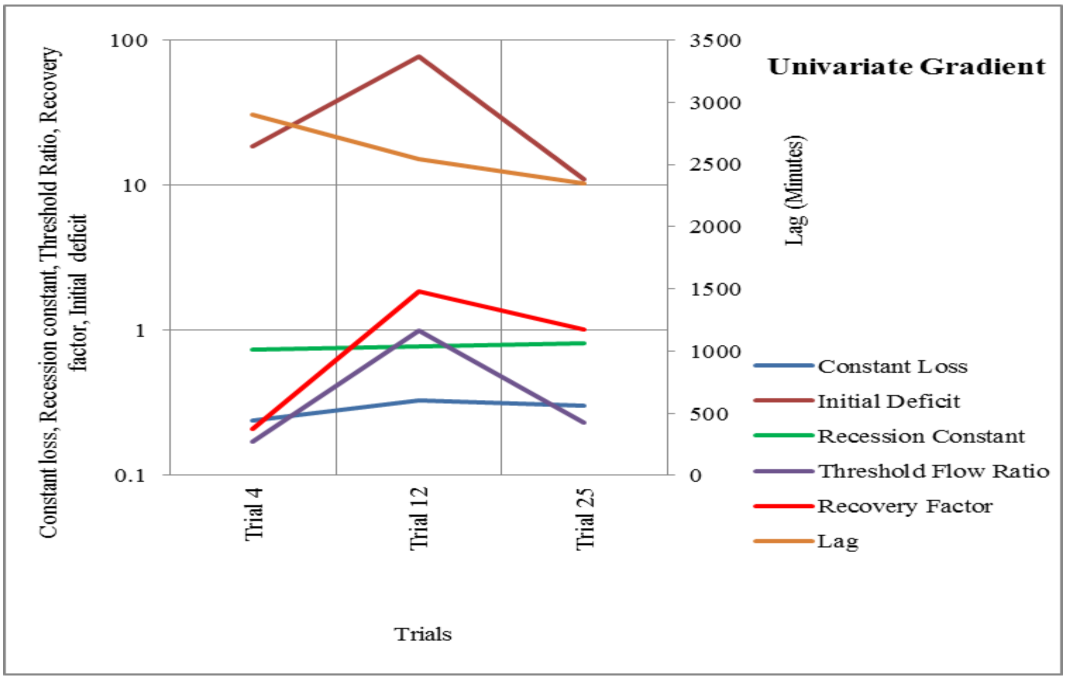

Figure E-2 Variation of parameters with best fit trials in Univariate Gradient method

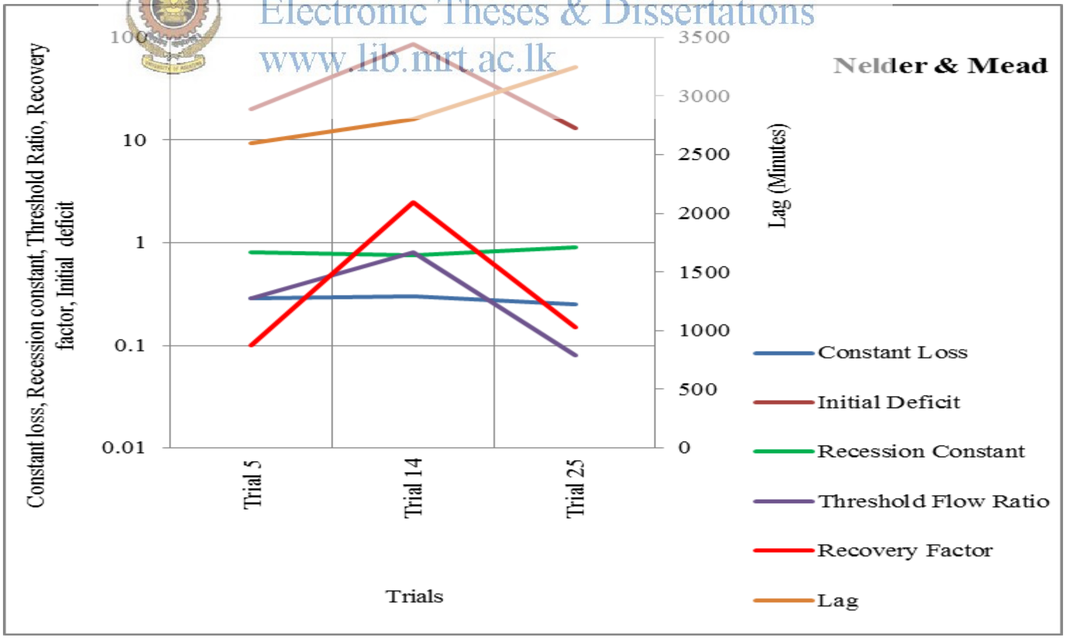

Figure E-3 Variation of parameters with best fit trials in Nelder and Mead method

Table E-2 Variation of parameters with respect to search methods

Parameter	Parameter variation	
	Univariate	Nelder and Mead
Constant Loss	0.09	0.05
Initial Deficit	66	72
Recession Constant	0.08	0.16
Threshold Flow Ratio	0.83	0.73
Recovery Factor	1.63	2.39
Lag	555	647

Table E-3 Variation of error values corresponding to different minimum objective function values

Evaluation criteria	Model Objective Function			
	Peak Weighted Root Mean Square Error (PWRMSE)	Sum of Absolute Residual (SAR)	Sum of Squared Residual (SSR)	Percent Error in Peak (PEV)
Constant Loss	0.39	0.44	0.42	0.43
Initial Deficit	11	15	12	12
Recession constant	0.87	0.90	0.89	0.87
Threshold Flow Ratio	0.15	0.14	0.15	0.14
Recovery factor	0.10	0.1	0.1	0.1
Lag	2418	2146	2157	2500
Model Error	29.2	19546	691720	10.4
Mass balance Error% (H/G)	10.13	8.27	8.14	10.27
Mass balance error % - High	10.00	14.18	13.23	17.70
Mass balance error % - Medium	18.14	4.79	5.05	0.45
Mass balance error % - Low	1.41	8.76	10.23	22.27
Annual Mass balance Error %				
2006/2007	9.64	16.26	15.77	21.23
2007/2008	13.42	1.86	1.92	3.04
2008/2009	0.27	5.99	5.77	12.70
2009/2010	17.18	8.94	9.08	4.07
calculated Q /observed Q				
2006/2007	0.90	0.84	0.65	0.79
2007/2008	1.13	0.98	1.04	0.97
2008/2009	1.00	0.94	0.93	0.87
2009/2010	1.17	1.09	0.97	1.04
Maha season	1.01	0.9	0.9	0.86
Yala season	1.13	1.03	1.03	1.01
Nash-Sutcliff (H/G)	0.72	0.70	0.71	0.69
Nash-Sutcliff -High	0.69	0.65	0.66	0.66
Nash-Sutcliff -Medium	-0.46	-0.27	-0.27	-0.13
Nash-Sutcliff -Low	-23.25	-20.94	-21.07	-16.17
MRAE (H/G)	0.58	0.52	0.53	0.52
MRAE - High	0.25	0.27	0.27	0.27
MRAE - Medium	0.55	0.49	0.49	0.48
MRAE -Low	0.84	0.81	0.82	0.83

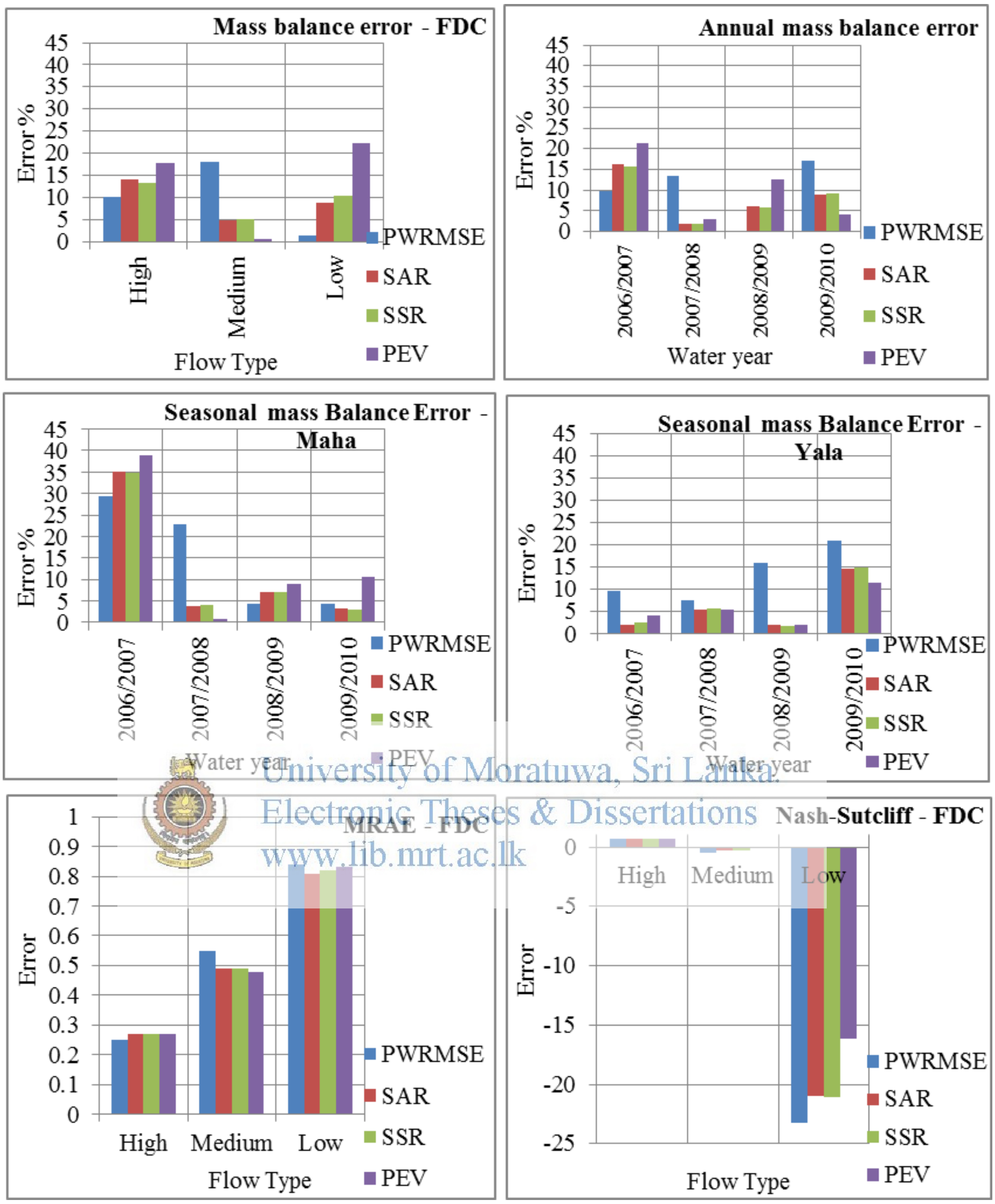

Figure E-4 Comparison of error values corresponding to different minimum objective function values

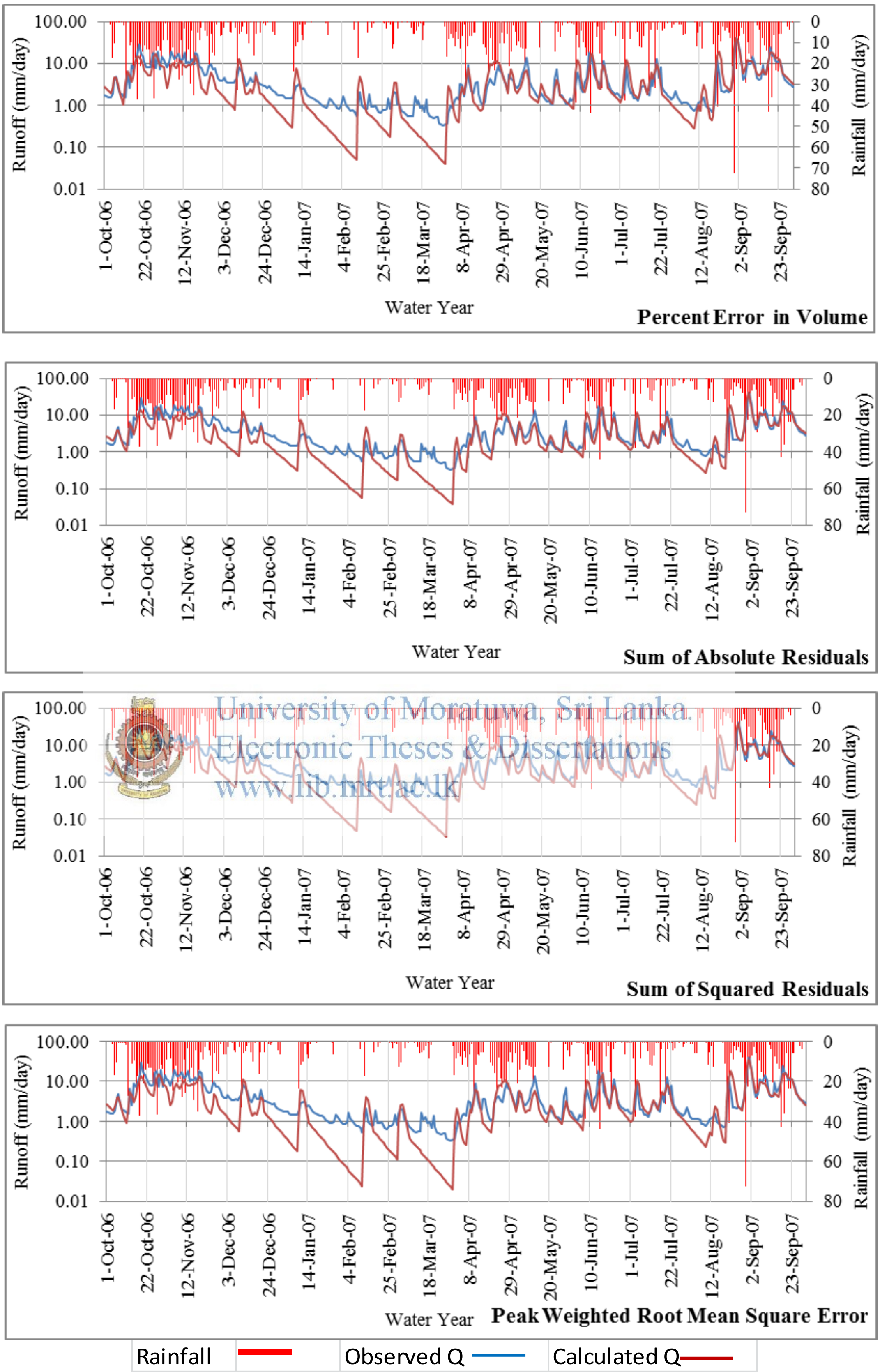

Figure E-5 Model performance with respect to different objective functions in Ratnapura lumped model

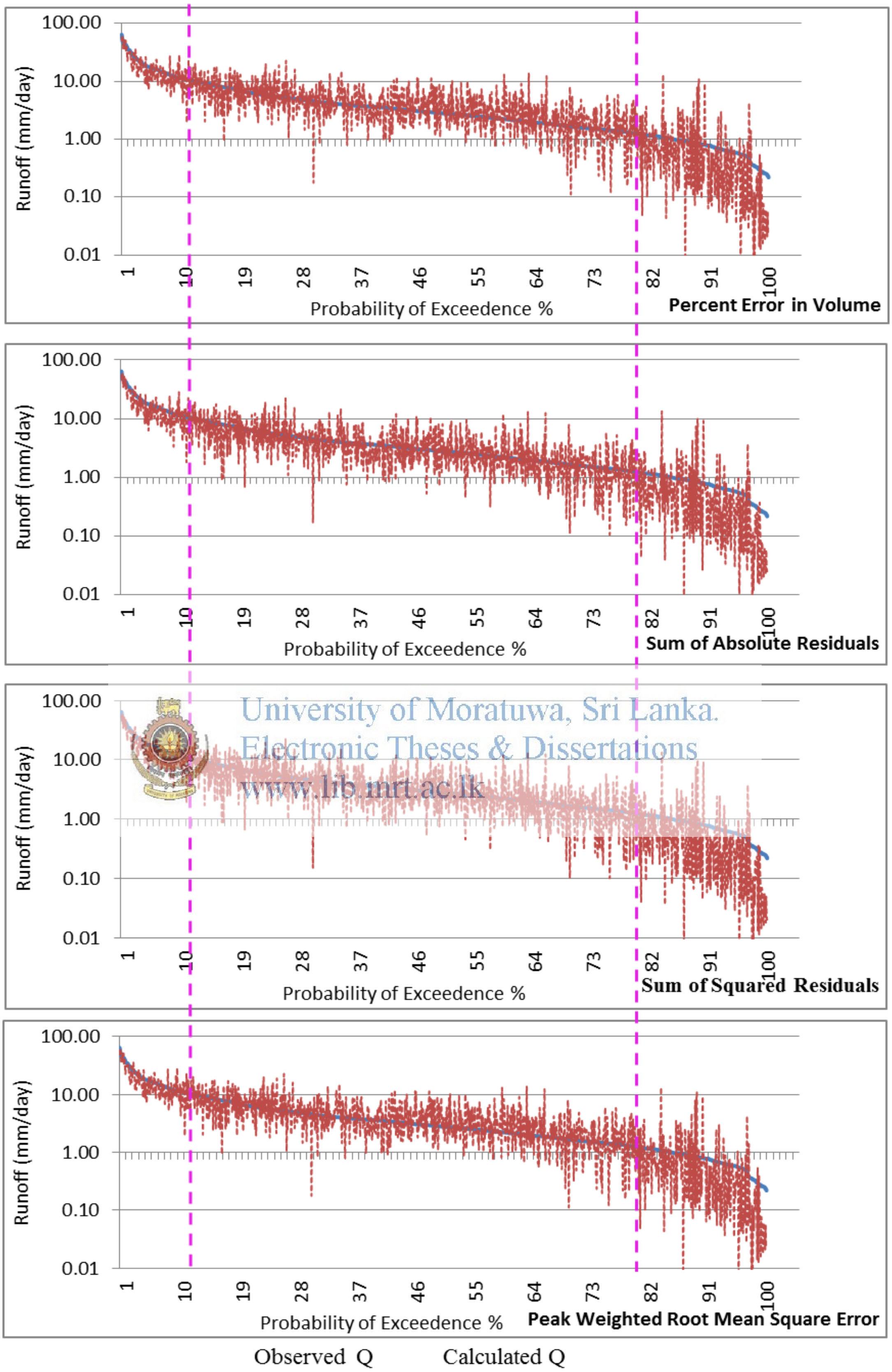

Figure E-6 Flow duration curve with respect to different objective functions in Ratnapura lumped model

Table E-4 Comparison of observed and calculated flows in Ratnapura lumped model

Month	Observed Q	PWRMSE	PEV	SAR	SSR
		Calculated Q	Calculated Q	Calculated Q	Calculated Q
January	48.44	47.32	36.64	40.35	39.98
February	44.27	32.61	26.95	29.70	29.79
March	68.11	74.69	63.27	67.36	67.93
April	141.45	164.09	140.99	151.74	152.54
May	225.52	221.39	198.91	211.73	211.99
Jun	234.96	255.17	233.59	236.54	236.69
July	195.65	199.30	182.97	170.76	170.73
August	127.02	150.94	132.37	143.32	143.08
September	160.38	199.32	171.45	187.61	188.04
October	216.53	237.13	208.73	215.15	216.08
November	192.55	182.95	153.94	162.72	163.46
December	111.86	104.08	77.48	86.05	85.92
Maha					
2006/2007	802.45	565.87	489.75	520.65	523.84
2007/2008	768.75	944.52	774.98	798.13	799.52
2008/2009	554.11	538.69	459.52	493.77	495.75
2009/2010	600.70	663.50	541.80	590.78	591.57
Yala					
2006/2007	827.76	907.10	794.35	844.37	849.18
2007/2008	1243.49	1337.52	1175.68	1176.77	1174.09
2008/2009	1153.20	1168.64	1026.73	1106.72	1108.53
2009/2010	1115.5	1347.5	1244.4	1278.9	1280.5

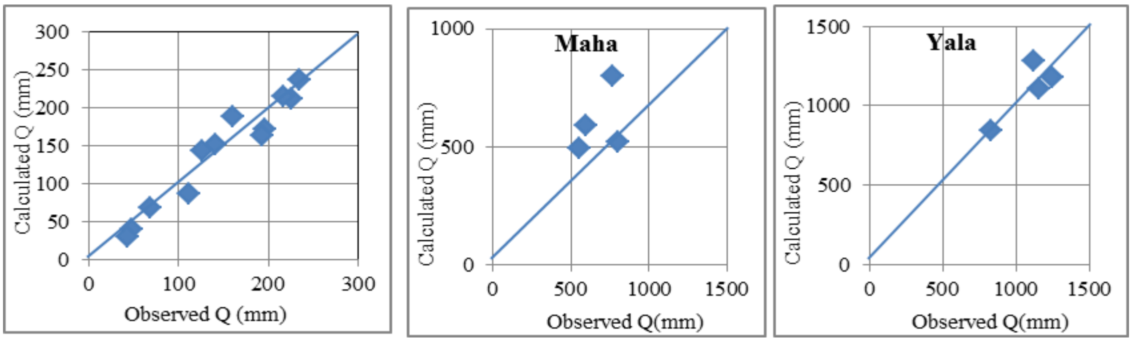

Figure E-7 Co-relation of observed and calculated flows - SAR

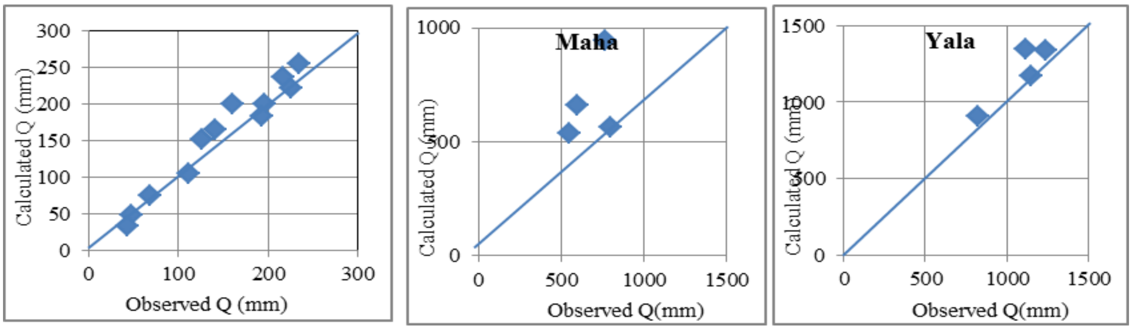

Figure E-8 Co-relation of observed and calculated flows – PWRMSE

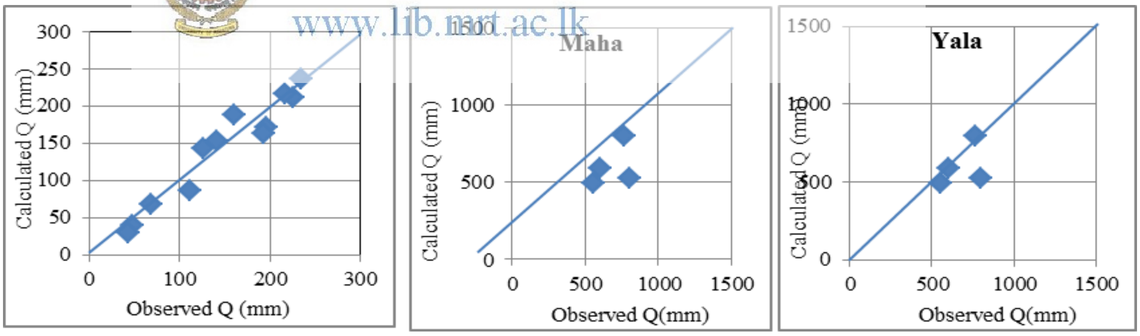

Figure E-9 Co-relation of observed and calculated flows – SSR

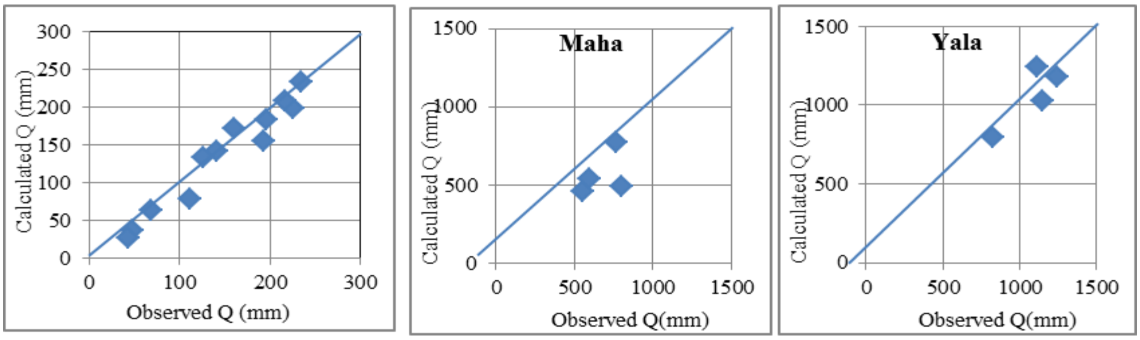

Figure E-0-10 Co-relation of observed and calculated flows – PEV

Table E-5 Selection criteria of objective functions

Criteria	Range of error values	Marks
Mass Balance error (Hydrograph)	< 9%	3
	9< E<15	2
	>15%	1
Mass Balance error (Flow duration curve)	0< E<1	4
	1< E<5	3
	5< E<20	2
	➢ 20	1
Calculated Q / observed Q Ratio	0.98< E<1.02	10
	0.96<E<1.04	9
	0.94<E<1.06	8
	0.92<E<1.08	7
	0.9<E<1.1	6
	0.85<E<1.15	5
	0.8<E<1.2	4
	0.7<E<1.3	3
	0.6<E<1.4	2
	0.5<E<1.5	1
Nash -Sutcliff	0.71<E<1	3
	0.6<E<0.71	2
	0.5< 0.6	1
	0<E0.3	3
	0.3<E<0.6	2
	0.6<E	1

Table E-6 Marks allocated for objective functions

	PWEMSE	SAR	SSR	PEV
Mass balance error				
Entire period	2	3	3	2
FDC - High	2	2	2	2
Medium	1	3	2	4
Low	3	2	2	1
Annual -	2	1	1	1
2007/2008	2	3	3	3
2008/2009	3	3	3	2
2009/2010	1	2	2	3
Nash – H/G	3	2	2	1
Nash – FDC	3	3	3	2
Medium	0	0	0	0
Low	0	0	0	0
MRAE – H/G	2	2	2	2
MRAE - FDC				
High	3	3	3	3
Medium	2	2	2	2
Low	1	1	1	1
Qcal / Q obs				
Annual				
2006/2007	6	4	2	3
2007/2008	5	10	9	9
2008/2009	6	8	7	5
2009/2010	4	6	9	9
Seasonal				
Maha	10	6	6	5
Yala	5	9	9	10
Total Marks	**62**	**75**	**73**	**70**

APPENDIX F : PERFORMANCE OF ELLAGAWA LUMPED MODEL DURING VERIFICATION

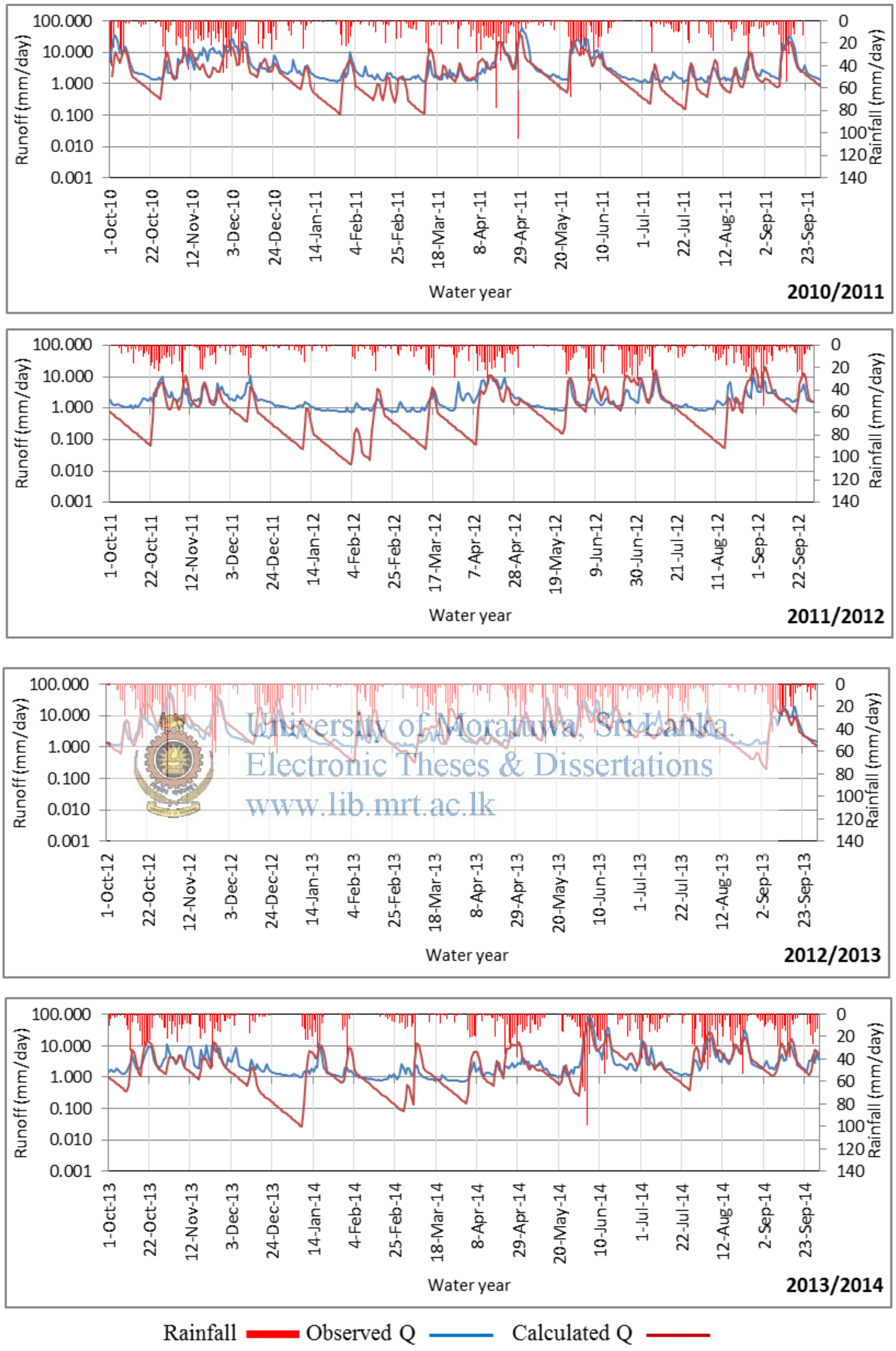

Figure F-1 Performance of Ellagawa lumped model verification

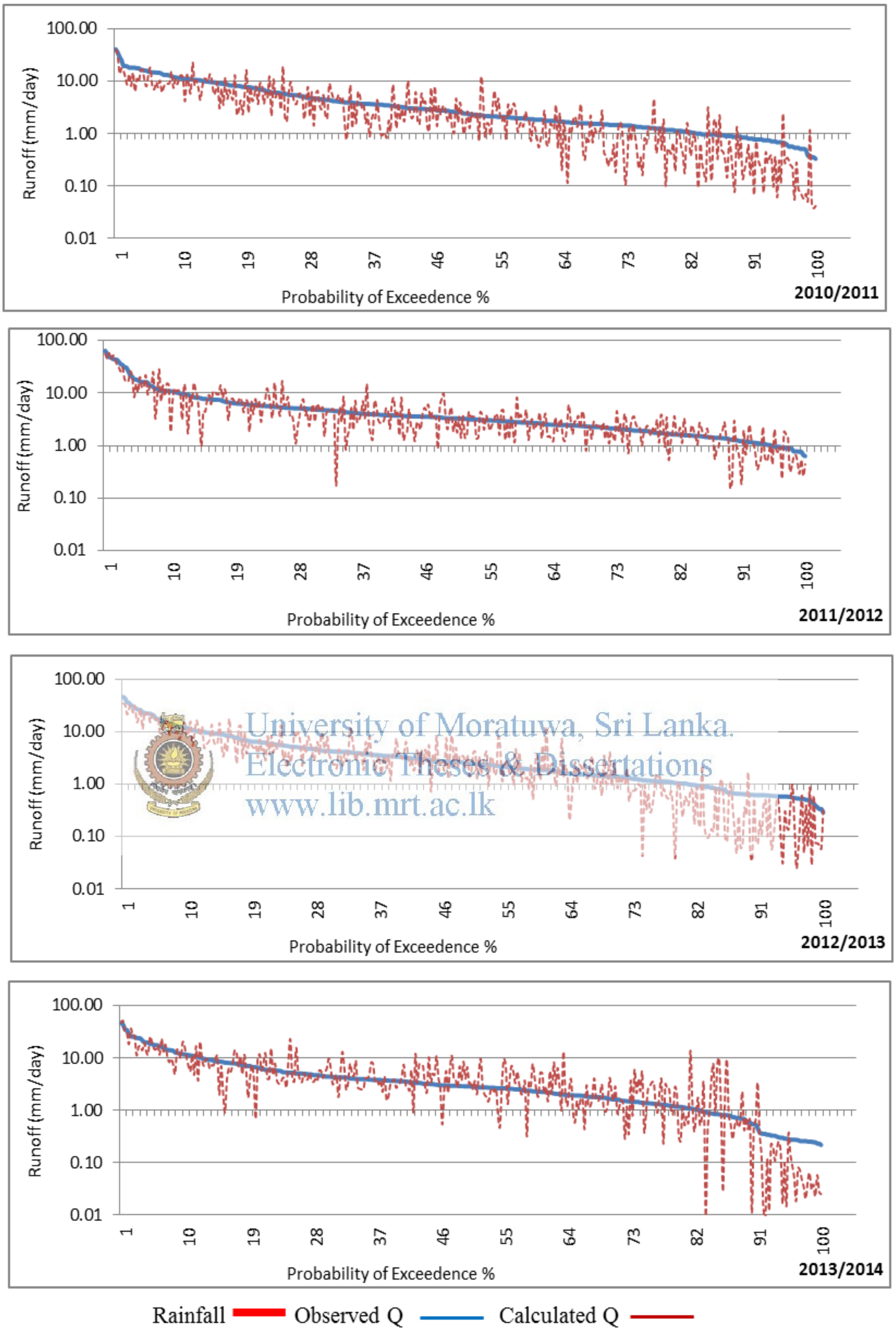

Figure F-2 Flow duration curve of Ellagawa lumped model verification

APPENDIX G : COMPARISON OF FLOW RESIDUALS OF ELLAGAWA DISTRIBUTED MODEL DURING CALIBRATION

Table G-1 Comparison of flow residuals during calibration in 2006/2007 to 2007/2008

Water Year	Observed streamflow (m3/s)	Calculated streamflow (m3/s)	Flow residuals (m3/s)
Oct-06	157.40	111.90	45.50
Nov-06	147.61	82.73	64.87
Dec-06	31.76	26.85	4.91
Jan-07	18.00	15.87	2.13
Feb-07	11.77	3.42	8.34
Mar-07	12.58	2.61	9.97
Apr-07	34.77	56.74	21.97
May-07	40.77	29.22	11.56
Jun-07	48.94	58.21	9.28
Jul-07	36.44	42.92	6.48
Aug-07	38.91	54.84	15.93
Sep-07	148.75	121.31	27.43
Oct-07	104.87	121.61	16.74
Nov-07	54.52	55.67	1.16
Dec-07	20.54	18.85	1.69
Jan-08	20.90	15.36	5.54
Feb-08	27.70	24.30	3.39
Mar-08	48.09	39.35	8.74
Apr-08	146.37	106.37	39.99
May-08	135.00	76.32	58.68
Jun-08	209.46	113.63	95.83
Jul-08	163.92	118.87	45.05
Aug-08	28.41	25.36	3.05
Sep-08	38.44	46.70	8.25

9 1 1 1 1 1

Table G-2 Comparison of flow residuals during calibration in 2008/2009 to 2009/2010

Water Year	Observed flow	Calculated flow	Flow residuals
Oct-08	80.42	85.00	4.58
Nov-08	56.60	72.84	16.25
Dec-08	42.38	36.33	6.05
Jan-09	13.31	6.75	6.56
Feb-09	12.07	9.21	2.86
Mar-09	26.06	31.19	5.13
Apr-09	42.35	39.38	2.97
May-09	93.28	88.81	4.47
Jun-09	106.80	127.02	20.22
Jul-09	100.96	74.76	26.19
Aug-09	84.56	85.81	1.25
Sep-09	70.07	95.41	25.34
Oct-09	60.67	72.72	12.05
Nov-09	58.93	71.51	12.59
Dec-09	55.81	58.30	2.49
Jan-10	26.65	28.92	2.27
Feb-10	21.50	17.18	4.33
Mar-10	15.38	23.35	7.97
Apr-10	38.75	64.80	26.05
May-10	236.75	191.44	45.31
Jun-10	89.48	125.34	35.86
Jul-10	87.31	96.61	9.30
Aug-10	60.34	88.95	28.61
Sep-10	57.83	81.72	23.89