ANALYSIS OF PRECIPITATION TREND AND STREAMFLOW SENSITIVITY TO PRECIPITATION IN MADURU OYA RIVER BASIN WITH HEC-HMS MODEL SIMULATIONS

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Water Resources Engineering and Management

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Thesis Submitted in Partial Fulfillment of the Requirements for the

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DECLARATION

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Dr. R.L.H.L. Rajapakse

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Analysis of Precipitation Trend and Streamflow Sensitivity to Precipitation in Maduru Oya River Basin with HEC-HMS Model Simulations

ABSTRACT

Water resources management in a basin needs an intensive analysis of historical data in terms of different climate elements and streamflow. Several researchers have examined the influences of climate change over several main basins during the past years. However, no studies have been performed in the Maduru Oya basin and associated sub-catchments. Hence, the main objective of this study was to identify rainfall trends and then to analyze the streamflow elasticity to the climate in the Maduru Oya basin. Widely used non-parametric trend tests such as Mann-Kendall (MK) test, Modified Mann-Kendall (MMK) test and Sen's slope estimator were adopted to perform the trend analysis in annual, seasonal and monthly scales. The results displayed by all three tests were in very good agreement except for very few cases. On an average, a positive trend of annual rainfall was experienced in Maduru Oya basin with 1.05 and 1.103 trends, respectively from MK and MMK tests with the yearly increment of 12.52 mm/year. During cropping seasons, Maha season predominantly exhibited positive trends where Yala season was witnessed mostly with negative trends. Likewise, during rainfall seasons, except for SWM season, remaining FIM, NEM and SIM seasons displayed positive trends. The monthly analysis found out that November and December experienced strong positive trends whereas the highest negative trends were revealed in September.

Further, for Padiyathalawa sub-basin located in the upstream of Maduru Oya river basin, analysis of streamflow elasticity to precipitation, defined as the proportional change in mean annual streamflow divided by the proportional change in mean annual rainfall, was performed on historical data. This part of the study was carried out using a non-parametric estimator and a method proposed by finding the slope of the graph plotted between the proportional variation of annual streamflow and proportional variation of annual precipitation. Both results indicated that the variations in rainfall are magnified in streamflow. The non-parametric method and the graphical method revealed that a 1% change in mean annual rainfall would respectively result in 1.12% and 1.92% change in mean annual streamflow. Moreover, in an attempt to incorporate the impacts of climate change in streamflow variability due to variation in climate elements, a HEC-HMS hydrological model was developed, calibrated and verified for this sub-basin. The model performance was good in both calibration and verification periods with MRAE and Nash-Sutcliffe Efficiency values of 0.433 and 0.665 and 0.559 and 0.642 respectively. Hypothetical climate change scenarios were predicted as future climate change scenarios by modifying the input rainfall and evapotranspiration data. The results indicated that the relationship between rainfall and streamflow is stronger than that between evapotranspiration and streamflow as an increase of 10% in rainfall without any change in evapotranspiration results in 20.42% increase in streamflow while the same amount of increase in evapotranspiration with no variation in rainfall results 6.30% decrease in streamflow.

In conclusion, the analyses revealed positive trends of rainfall in annual scale for the entire Maduru Oya river basin as well as for Padiyathalawa sub-basin while the streamflow elasticity for the sub-basin using the non-parametric estimator was found out to be 1.12 for the data periods considered.

Keywords: Rainfall trend analysis, Streamflow elasticity to precipitation, Non-parametric estimator, Hydrological modelling

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1.0 INTRODUCTION

1.1 Background of the Study

Water is one of the critical resources which is influenced by many natural and human induced factors. Climate change has been identified to have had a striking effect on different sectors such as agriculture, transportation and various industries by altering the natural resources of the environment. However, when it comes to aquatic resources, much of the impacts of this phenomenon have been found to be felt through variation in available water and rainfall escalating the likelihood of drought and flood.

As stated by the Intergovernmental Panel on Climate Change (IPCC, 2014), both surface and groundwater resources which are claimed to be inexhaustible are predicted to be minimized by the influences of climate change, aggravating the conflict for water predominantly in dry subtropical regions. Moreover, since hydrological system determines most of the major developments and planning activities namely flood control, food security, and plausible aquatic resources management and so on, it is extraordinarily necessary to determine the impacts of climate variability on water resources.

Sri Lankan island is situated between the latitude of 5° 55′ N and 9° 51′ N and the longitude of 79° 42′ E and 81° 53′ E. Monsoonal rainfall has been identified to have contributed an extensive portion of country's total annual precipitation compared to other rainfall sources such as depressional rainfall and convectional rainfall. First Inter Monsoon (FIM), South West Monsoon (SWM), Second Inter Monsoon (SIM) and North East Monsoon (NEM) representing the months of March to April, May to September, October to November and December to February, respectively, have been distinguished as the four principal rainy seasons in Sri Lanka. Considering the rainfall pattern, the island is separated as Dry, Intermediate and Wet zones. The main source of average annual precipitation in Wet zone is North East and South-West monsoons which ranges from 2500 mm to 5000 mm. However, when it comes to the Dry zone, North-East monsoon is the only contributor of mean annual rainfall amounting around 900 to 1750 mm of average yearly rainfall whereas annual average rainfall in the Intermediate zone varies from 1750 mm to 2500 mm. Hence, as a whole, the annual rainfall of the island ranges from below 1000 mm to over 5000 mm at most or all places (Department of Meteorology, 2019).

As the hydrologic cycle is heavily dependent on precipitation, variation in its pattern due to climate change would highly affect the aquatic resources of an area by modifying runoff, soil moisture and groundwater resources (Jain, Kumar, & Sahariad, 2013). Hence, it is also important to compute the elasticity of streamflow to climate variables as it is required to make a definite decision in governing aquatic reserves and environmental systems to deal with hydroclimatic variations and climate change (Chiew, Peel, Mcmahon, & Siriwardena, 2006). Variations in rainfall are likely to be the major factor influencing streamflow (Sharma & Wasko, 2019). The reactivity of streamflow to climate change in various river basins across the world has been interpreted through the computation of streamflow elasticity to rainfall. The elasticity means a fundamental calculation of the responsiveness of streamflow to differences in rainfall over a long period of time. Hence, the streamflow elasticity is particularly handy as an essential evaluation of the impacts of climate variation on land and aquatic resources management projects as it appraises how the equilibrium of a hydrological cycle on river basins varies due to long term climate change and provides valuable data on how water resources and environmental systems should be managed (Kim, Hong, & Lee, 2013).

Sri Lanka, being one of the leading countries in terms of irrigation, tends to face a challenging situation in planning a proper water management system with the increasing changes in water resources of the country due to climate change. As a result of the climate change, both wet zone and dry zone paddy cultivation are affected due to floods and long periods of droughts in both seasons, respectively. By analyzing the variability and trend of the historical rainfall data, certain characteristics of rainfall which influence the effective way of planning and distribution of available water resources can be identified. Moreover, estimating the elasticity of streamflow to rainfall plays a crucial part in enlightening the water resources managers about the influences of climate change on hydrological and environmental systems. In this way, proper mitigation actions can be taken by adopting an efficient method of water management when there is a shortage of water.

This present study was conducted to analyze the precipitation trend using non-parametric tests named Mann Kendall tests and Sen's slope estimator. Furthermore, for the analysis of streamflow elasticity to rainfall, a non-parametric approach, as well as a modelling approach using HEC-HMS hydrological model were utilized.

For the rainfall trend analysis part, the whole Maduru Oya river basin expanding over a region of 1,541 km^2 was considered. Padiyathalawa sub-watershed area located in the upstream of Maduru Oya basin having a drainage area of 170.9 km^2 was selected to carry out the streamflow elasticity part of the study.

1.2 Rainfall Trend Analysis in Watersheds in Sri Lanka

Analyzing the variations in precipitation with the help of past records gives a clear understanding of rainfall characteristics such as the count of rainy days, the extent of the dry season enabling the water resources managers to efficiently take care of the planning and governing of water resources in the future. Moreover, while planning the water resources, it is good for the water scientists and water managers to know how the streamflow changes with the variation of precipitation.

A great deal of studies has been carried out on rainfall trend analysis in Sri Lankan watersheds. Most of the researchers have employed the non-parametric Mann-Kendall test as the tool for trend analysis mainly because it is not mandatory for the data series to be normally distributed and it can cope with the missing data or outliers in the long-term data series which is very common in the region.

In a previous study (Jayawardene, Sonnadara, & Jayewardene, 2005), a rainfall trend analysis was performed in 15 rain-gauging stations using rainfall observations for more than 100 years in Sri Lanka. Accordingly, a statistically significant upward trend was recorded in Colombo while a declining trend was experienced in Nuwara Eliya and Kandy.

Similarly, as per the trend analysis carried out in a study (Ampittiyawatta & Guo, 2009) on Kalu Ganga watershed, a negative trend of annual precipitation was witnessed using the Mann-Kendall test method.

The findings of the trend and variability analysis of precipitation in a study (Muthuwatta, Perera, Eriyagama, Surangika, & Premachandra, 2017) on Malwathu Oya and Kalu river basins revealed that they differ from that of farmer's perceptions of trend changes when compared, as the majority of farmers were unable to comprehend the long-term positive trend in annual precipitation.

In another study (Khaniya, Jayanayaka, Jayasanka, & Rathnayake, 2019) performed in Uma Oya basin, the authors found out that there are no water scarcity issues to the catchment area by analyzing the last 26 years data using the non-parametric Mann-Kendall test.

However, no records of any studies performed in Maduru Oya basin or any other similar basin in the region to evaluate the trend analysis was reported.

1.3 Streamflow Variability Analysis in Watersheds in Sri Lanka

The estimation of streamflow elasticity can be considered as a quantifier of the influences of climate variations on a watershed. As a repercussion of climate variation over a long period, the equilibrium of a hydrological cycle on watersheds gets altered (Kim, Hong, & Lee, 2013). However, as rainfall is the main contributor to the streamflow, it is vital to assess the rainfall elasticity of streamflow. Here, precipitation elasticity is defined by the responsiveness of annual streamflow to the alterations that could possibly occur in annual precipitation.

Plenty of researches have been performed to estimate the sensitivity of streamflow to rainfall in order to understand the impact of climate variation on different water sectors in Sri Lankan river basins.

In a previous study (Dissanayaka & Rajapakse, 2018), where the authors carried out a quantitative analysis to check the effect of variations in temperature and precipitation on surface water in Hanwella watershed of Kelani River basin with the help of HEC-HMS modelling, the findings showed that the variation of streamflow of Hanwella sub-basin, as a whole, decreased in terms of climate forcing criteria. Another past study (Shelton & Lin, 2019) investigated the variation of seasonal streamflow and streamflow extremes for six sub-watersheds located in both upper (UMRB) and lower (LMRB) Mahaweli river basin and thereafter analyzed the relationship between streamflow and seasonal rainfall. Their interpretation of results disclosed that the streamflow pattern in UMRB is strongly in agreement with SWM precipitation whereas streamflow in LMRB is closely correlated with the NEM precipitation.

Another study (Keerthirathne & Wijesekara, 2017) developed design rainfall patterns using the observed rainfall and studied its relationship with Alternating Block, Uniform Intensity and Greater Colombo Flood Design Patterns by evaluating the runoff response with the support of HEC-HMS model developed for a sub-watershed in Greater Colombo region. The study revealed that the highest runoff was given by Enveloped curve developed using historical data. Similarly, in a study (Khandu & Wijesekara, 2015) carried out on Kelani Ganga and Gin Ganga basins using a two-parameter monthly water balance model, the runoff of these catchments were simulated and the impacts of climate change on streamflow were evaluated. The model performance was very much high in both calibration and verification periods and the findings suggested that this model can be effectively incorporated in climate studies. However, no trend analysis or streamflow estimate has been carried out in Maduru Oya basin so far.

1.4 Problem Statement

It has become of great importance to incorporate the impacts of climate change in the planning of future water supplies. One way to evaluate the impact of climate change on aquatic resources is by estimating the streamflow variability. Rainfall is one of the critical hydrological elements that gets influenced by the change of climate. As rainfall is the main contributor to streamflow of a river, streamflow is found to be sensitive to the change in rainfall pattern. Moreover, other climate elements such as evaporation and temperature also influence the streamflow. When it comes to Maduru Oya basin and other similar basins in the region, irrigation has been identified as the main water-using sector. Hence, irrigation is indirectly affected by climate change. However, this water scarcity issue can be effectively overcome with the help of a proper water management plan. Analyzing the historical rainfall data over this particular watershed and thereby estimating the streamflow to understand the impact of the variation in climate for a long term are the initial aspects to be considered while planning a proper water management schedule.

1.5 Objective of the Study

1.5.1 Overall objective

The main objective of this study is to evaluate the effects of climate change by carrying out a precipitation trend analysis and to study the climate change impacts on hydrological elements by computing the sensitivity of streamflow to climate change for effective water management and planning in Maduru Oya river basin.

1.5.2 Specific objectives

1. State of the art literature review to comprehend the present state of research related to rainfall trend analysis and streamflow sensitivity focusing on data scarce situations.
2. Evaluating and identifying a suitable tool to do the rainfall trend analysis.
3. Carrying out the rainfall trend analysis using the available rainfall data in a data-scarce region.
4. Evaluating and identifying a suitable hydrological model for runoff simulation.
5. Developing, calibrating and verifying the model for the selected basin.
6. Estimating the streamflow elasticity to rainfall using non-parametric estimator as well as the modelling approach.
7. Analyzing the rainfall – streamflow relationship (streamflow elasticity to rainfall).
8. Deriving conclusions and providing recommendations.

2.0 LITERATURE REVIEW

2.1 General

It is essential to get a clear understanding of the previous studies performed on similar topics so as to define the methodology of the present study. Hence, an extensive literature survey was carried to decide on the most appropriate approach to be adopted in the analysis of precipitation trend and streamflow elasticity.

2.2 Precipitation Trend Analysis

It is very crucial to study the variations in rainfall because of its contribution to the allocation and management of aquatic resources and flood control. Analysis of rainfall trend is a statistical approach adopted to predict the future behaviour of a series of rainfall data by evaluating the historical data. This is generally performed using either parametric tests or non-parametric tests. By using these tests, it can be detected whether a specific data set follows a distribution or reveals a trend on a particular significance level. However, although parametric trend tests are found to be more substantial and simpler than non-parametric tests, it is necessary for parametric tests to have normally distributed and independent data. Because of this reason, most researchers have used non-parametric tests which have the tolerance to non-normal distribution, outliers, and lost or missing data that are hard to be avoided in a hydrological time series.

While analyzing the trend of climatic variables such as rainfall and temperature in India, the authors found out through an extensive literature survey that two non-parametric trend tests namely Sen's slope estimator and Mann-Kendall test have been the most commonly adopted to detect the magnitude and significance of a trend (Jain & Kumar, 2012). These tests are adopted in the present study as well.

2.2.1 Mann-Kendall test (MK)

The Mann-Kendall test (Mann, 1945; Kendall, 1975) is one of the most widely used methods in trend analysis. This method is mainly utilized in finding the significance of the trend of data series. The Mann-Kendall is a commonly employed non-parametric test for trend analysis of climatic or hydrological data and environmental data. It does not take into account the linearity or nonlinearity of a trend. When a trend exists in a time series, the effect of negative or positive serial correlation on the MK test depends upon many factors such as the size of the sample and magnitude of serial correlation as well as trend (Yue & Wang, 2002).

The Mann-Kendall non-parametric test is tremendously used in analyzing the variability in the time series of various climate elements such as rainfall, temperature, runoff, and water quality in different areas all over the world (Hirsch, Slack, & Smith, 1982).

Furthermore, a past study (Hirsch & Slack, 1984) also highlighted the robustness of this test against censoring and non-normality as it is entirely dependent on ranking.

A trend computation of monthly streamflow of several basins across Turkey was carried out in a study (Kahya & Kalayci, 2003) using four main non-parametric trend tests such as the Mann-Kendall, Seasonal Kendall, Spearman's Rho and the Sen's slope tests. However, they found out that all the tests considered gave the same results regarding the existence of trends in most cases.

Similarly, another study (Yu, Zou, & Whittemore, 1993) adopted three unique non-parametric tests namely Sen's slope test, Seasonal Kendall and Mann-Kendall tests for trend detection in water quality data and found out that the Mann-Kendall is more sturdy compared to the Seasonal Kendall approach.

In another study (Yue & Pilon, 2004) attempting to examine the competence of the Mann-Kendall test by Monte Carlo simulation, it was found out that the robustness of this test depends on many factors such as sample size, amount of variation within a time series and magnitude of the trend. In other words, this test is found to be more powerful with the increase of sample size and magnitude of the trend. Moreover, the power of this test decreases when the amount of variation within a time series increases.

The statistics of the MK test does not depend on the values of variables but rather on the sign of differences. Because of this, it is relevant for data sets with irregularities as well (Adarsh & Reddy, 2014).

The test is based on the statistics S defined below in Eq. (1),

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} sgn(x_i - x_j) \tag{1}$$

where the data set record length is given by n and the data values at time j and i (j>i) are respectively indicated by x_i and x_j. Here, $sgn(x_i - x_j)$ is defined in Eq.(2),

$$sgn(x_i - x_j) = \begin{cases} 1 & if(x_i - x_j) > 0 \\ 0 & f(x_i - x_j) = 0 \\ -1 & f(x_i - x_j) < 0 \end{cases} \tag{2}$$

For n > 10, the statistic S is taken to be normally distributed with mean and variance as given below in Eq. (3),

$$Var(S) = \frac{n(n-1)(2n+5) - \sum_{p=1}^{q} t_p(t_p - 1)(2t_p + 5)}{18} \tag{3}$$

where q is the number of tied groups, t_p is the number of data points in the p^{th} group and n is the number of data points.

The normal Z-statistics is computed as given in Eq.(4),

$$Z = \begin{cases} \frac{S-1}{\sqrt{Var(S)}}, & if\ S > 0 \\ 0\,, & if\ S = 0 \\ \frac{S+1}{\sqrt{Var(S)}}, & if\ S < 0 \end{cases} \tag{4}$$

Here, the positive and negative value of Z indicates an upward and downward trend, respectively. The existence of a statistically significant trend is analyzed using the Z value. The trend is considered to be significant when computed Z-value is greater than the standard normal variate Z corresponding to the significance level considered.

2.2.2 Modified Mann-Kendall test (MMK)

The influence of autocorrelation coefficients in a time series is eliminated when using MMK test (Hamed & Rao, 1997). Hence, in case of an autocorrelated data, the variance in the Mann-Kendall test can be modified as given below in Eq. (5),

$$Var(S) = V(S)\frac{n}{n^*} \tag{5}$$

where n^* is the new sample size defined. After calculating $Var(S)^*$, it is replaced in the normal Z-statistics equation used in normal Mann-Kendall test.

Here, the ratio $\frac{n}{n^*}$ was estimated as shown below adopting the equation (6) proposed by Hamed and Rao (1997).

$$\frac{n}{n^*} = 1 + \frac{2}{n(n-1)(n-2)}\sum_{i=1}^{n-1}(n-1)(n-i-1)(n-i-2)r_i \tag{6}$$

where n is actual number of observed data, and r_i is lag-i significant autocorrelation coefficient of rank i of the time series.

2.2.3 Sen's slope estimator

Although Simple Linear Regression method is the commonly adopted approach in estimating the slope of the linear trend, it is only valid when there is no serial correlation and this approach is sensitive to the outliers. Thus, a more robust method was established to calculate the slope of a linear trend (Sen, 1968).

This method has been extensively employed to find out the magnitude of trend in hydro-meteorological time series (Lettenmaier, Wood, & Wallis, 1994; Yue & Hashino, 2003; Partal & Kahya, 2005; Jain & Kumar, 2012; Jain, Kumar, & Sahariad, 2013).

Equation (7) is used to determine the slope between two rainfall data values.

$$m_{jk} = \frac{(x_j - x_k)}{j-k} \text{ for all combinations of } k>j \qquad (7)$$

where x_j and x_k are data records at time *j* and *k* respectively. The value m_{jk} is the slope between data records x_j and x_k. A time series having data for *n* long years will have a total slope estimates, *N = n (n-1)/2*. The Sen's slope is given by the median slope of these *N* values of slopes. The Sen's slope is given by Eq. (8).

$$m = \begin{cases} m_{\frac{N+1}{2}}, & n \text{ odd} \\ \frac{1}{2}\left(m_{\frac{N}{2}} + m_{\frac{N+2}{2}}\right), & n \text{ even} \end{cases} \qquad (8)$$

Positive Sen's slope specifies a rising trend while negative Sen's slope indicates a declining trend.

2.3 Analysis of Streamflow Sensitivity to Precipitation

When taking into consideration of escalating water shortage issues due to climate change, it is mandatory to assess its impacts to strengthen the water resources planning policy. Streamflow elasticity is one simple tool utilized in assessing the sensitivity of variations in streamflow. Several studies have been conducted to calculate the influence of variations in precipitation on water resources across the world. Both hydrological models (Theoretical study) and nonparametric estimators (Empirical study) have been adopted for the estimation of the influence of climate variation on streamflow.

The concept of rainfall elasticity was first introduced in an attempt to assess the effects of climate change on streamflow (Schaake, 1990). However, this method was found out to be having a shortcoming of producing various output based on the models applied and model parameters selected for estimating the streamflow.

Later, a new index was proposed by taking into account of a median and a mean value (Sankarasubramanian, Vogel, & Limbrunner, 2001). The study compared a non-parametric estimator of rainfall elasticity of streamflow with a number of watershed model-based approaches. The authors found out that the non-parametric estimator is less biased and is as or more powerful than model-based approaches because unlike a model-based approach, it does not require a calibration strategy or possible model assumptions.

A study (Chiew, Peel, Mcmahon, & Siriwardena, 2006) conducted to estimate the sensitivity of streamflow to the climate in around 500 catchments all over the world used the non-parametric estimator of streamflow elasticity proposed by Sankarasubramanian, Vogel, and Limbrunner (2001). The results specified that variations in rainfall are magnified in streamflow as the streamflow elasticity estimated ranges from 1 to 3 which mean that a variation of 1% in mean annual rainfall results in 1-3% variation in mean annual streamflow. The study also pointed out the usefulness of this non-parametric estimator while conducting a global study as it does not require the calibration criteria of all the catchments which is a major requirement while using a hydrological model.

A study (Kim, Hong, & Lee, 2013) performed on 5 river basins in Korea to estimate the streamflow elasticity in an attempt to quantify the effects of climate change, used a semi-distributed hydrological model to simulate the variation of streamflow and potential evapotranspiration. A non-parametric approach was also adopted to calculate the rainfall elasticity of those river basins. Then, using the stochastic downscaling technique and A2 climate change scenario, they created a high-resolution weather change scenario and analyzed the effect of climate variation on precipitation elasticity of each basin considered. The result showed that the analyzed rainfall elasticity on the basins considered ranges from 0.68 to 2.03. Further, they found out that the value of both streamflow and elasticity rose when precipitation or evapotranspiration got higher.

Another study (Zhou, Zhang, & Yang, 2015) compared the Budyko Framework Method and non-parametric method in estimating streamflow elasticity to precipitation in 18 large river basins in China. Both approaches gave high elasticity for dry basins compared to wet basins. Their study suggested that while Budyko-framework approach illustrated only the effect of natural elements on streamflow elasticity to precipitation, the non-parametric method illustrated the influences of both human activity and climate on precipitation elasticity of streamflow.

A previous study (Chiew F. H., 2006) carried out in Australia found out that the streamflow elasticity to precipitation in Australia ranges from 2.0 to 3.5. The researcher used both a non-parametric method and hydrological modelling method to estimate the rainfall elasticity of streamflow and found out that there is a clear relationship between the outputs obtained using both approaches.

2.3.1 Empirical elasticity assessment (Non-parametric estimator)

In this method, observed data are considered to evaluate the streamflow elasticity to rainfall (Andreassian, Coron, Lerat, & Moine, 2016). Equation (9) gives the non-parametric estimator ε_p to calculate the streamflow elasticity to precipitation by incorporating the ideas of a mean and a median (Sankarasubramanian, Vogel, & Limbrunner, 2001).

$$\varepsilon_p = median\left(\frac{Q_t - \overline{Q}}{P_t - \overline{P}}\frac{\overline{P}}{\overline{Q}}\right) \tag{9}$$

where $\overline{P}$ and $\overline{Q}$ indicate the mean annual precipitation and streamflow, respectively. The value of $\left(\frac{Q_t - \overline{Q}}{P_t - \overline{P}}\frac{\overline{P}}{\overline{Q}}\right)$ is estimated for each pair of P_t and Q_t in the annual time series and the median of these values is defined as the non-parametric estimate. The researchers performed Monte Carlo experiments and compared the non-parametric estimator with ε_p, and found through hydrological models and deduced that non-parametric estimator is less biased when compared to the ε_p obtained from modelling approaches (Sankarasubramanian, Vogel, & Limbrunner, 2001). However, there are some constraints in this non-parametric approach (Chiew F. H., 2006). As this method uses yearly records, it can correctly provide an estimation of elasticity of long-term streamflow data related to the variations of long-term rainfall data and fails to interpret the elasticity of streamflow properties except for the long-term mean, to variation in rainfall properties. In order to avoid the numerical issue when $\overline{P}$ is equal to P_t, it was suggested to use the median value as the elastic estimator.

Moreover, as this value has been described at the mean value of the climate elements, for small sample size, the median fails to represent the statistical properties of all samples (Sankarasubramanian, Vogel, & Limbrunner, 2001). In order to overcome this issue, a study suggested to rearrange the equation proposed for non-parametric estimator as given below in Eq. (10) and get the gradient of the graph plotted between $\frac{\Delta Q}{\overline{Q}}$ and $\frac{\Delta P}{\overline{P}}$ (Zheng, et al., 2009).

$$\frac{\Delta Q}{\overline{Q}} = \varepsilon_P \frac{\Delta P}{\overline{P}} \tag{10}$$

This can also be modified using the least squares estimator incorporating correlation coefficients and coefficient of variations of climate variable and streamflow.

$$\varepsilon_p = \rho_{P,Q}\, C_Q / C_P \tag{11}$$

where the correlation coefficient of rainfall and streamflow is denoted by $\rho_{P,Q}$, and C_Q and C_P are the coefficients of variations of streamflow and rainfall.

2.3.2 Theoretical elasticity assessment (Modelling approach)

The modelling approach is convenient when there is a need to calculate the streamflow elasticity to climate by comparing estimates of the simulated streamflow for the current climate with the simulated streamflow for a predicted climate (Schaake, 1990; Xu C. Y., 1999; Chiew & McMahon, 2002). One of the main advantages of adopting model-based assessment of streamflow elasticity is that it is easy to incorporate the impact of different climatic variables independently by keeping one variable fixed while modifying the other variable. However, because all hydrological models are a representation of reality, it is necessary to have some type of initial validation on the observed data before utilizing the models to predict changes (Andreassian, Coron, Lerat, & Moine, 2016).

A study estimated streamflow elasticity to climate for 219 basins all over Australia. The researcher used two rainfall-runoff models; SIMHYD and AWBM and by changing the input to the calibrated models, the climate elasticity of streamflow was found out. However, the writer pointed out that it is essential to have sufficient reliable data to satisfactorily develop and calibrate the model in order to achieve the accountability of the assessment (Chiew F. H., 2006).

2.3.2.1 Hydrological models

Water resource planners increasingly seek to incorporate the support of hydrological modelling to simulate the hydrological responses in a watershed due to rainfall when intending to manage the basin water.

A hydrological model is a simplified version of an actual condition (Sorooshian, et al., 2008). Different kinds of hydrological models have been developed starting with black box models which are handy when there is a minimum amount of data available to use to complicated models that require a large amount of data. But an ideal model is the one which is less complicated and whose results closely represent the actual conditions with less number of parameters.

A model is catchment specific and a model developed for a particular watershed cannot be utilized as it is in the analysis of other basins. The right choice of a model is mainly dependent on the type of basin and the intention of the hydrological study to be performed and this model should be developed by calibration and validation considering model performance criteria. Mathematical models can be categorized into two principal groups: Deterministic models and Stochastic models (Chow, Maidment, & Mays, 1988).

2.3.2.1.1 Deterministic models

A model is considered to be deterministic if all input, processes and parameters are untied from random variations and known with reliability (Scharffenberg, Bartles, Brauer, Fleming, & Greg, 2018). Deterministic hydrologic models are identified as process-based models which constitute the actual processes encountered in the physical environment. A deterministic model can be further categorized as distributed model, semi-distributed model and lumped model. In a lumped model, the system is spatially averaged or the spatial variability is ignored due to which it can be treated as a single unit (Chow, Maidment, & Mays, 1988). In a distributed model, a catchment is separated into a number of sub-catchments and each sub-catchment will be assigned average variables and parameters separately. Although the distributed model requires more data and costly compared to a lumped model, the distributed model is highly reliable (Gosain, Mani, & Dwivedi, 2009). Semi-distributed model, which is often cited as "pseudo-distributed" model, is in the middle of a distributed model and a lumped model. In this method, a catchment is separated into simpler sub-catchments to represent the most important catchment characteristics.

2.3.2.1.2 Stochastic models

Stochastic models possess outputs that are at least partially random. The same set of parameter values and initial conditions will lead to a group of different outputs. For a large random variation, a stochastic model is considered more appropriate as the actual result could differ from the single value that is produced by a deterministic model. The results of these models can rather be considered as predictions and not proper forecasting (Chow, Maidment, & Mays, 1988).

2.3.2.2 Runoff simulation models used

Researchers have utilized different kinds of rainfall-runoff models in their studies to simulate the runoff. For example, 'abcd' model (Sankarasubramanian, Vogel, & Limbrunner, 2001), Sacramento model (Nemec & Schaake, 1982), SIMHYD and AWBM models (Chiew F. H., 2006), two-parameter monthly water balance model (Khandu & Wijesekara, 2015) and HEC-HMS (Halwatura & Najim, 2013; Sampath, Weerakon, & Herath, 2015; De Silva, Weerakon, & Herath, 2014) are some of the very commonly incorporated models in estimating the runoff. However, when it comes to Sri Lankan watersheds, HEC-HMS, two-parameter model, and 'abcd' model are the most extensively used ones. In most of these studies, catchment was considered as either lumped model or semi-distributed model which is less complicated. Distributed modelling is very rarely adopted as it requires detailed data sets, causes model complexity and high computational cost.

2.3.2.2.1 HEC-HMS background

Hydrologic Engineering Center of U.S. Army Corps of Engineers developed the HEC–HMS hydrological model that favours both lumped and distributed parameter-based modelling. The HEC-HMS model comes with a number of mathematical sub-models or modules used in the simulation processes of rainfall-runoff of a dendritic catchment system. A large set of geographical and time series data are essential in hydrological modelling and the corresponding calibration and verification processes of a catchment. In hydrological modelling, the accuracy of the results is more remarkably impacted by the quality of data than the quality of the model itself (Todini, 1996). Hence, one can say that the challenges exist in modelling rainfall-runoff when there is only limited observed data available.

The HEC-HMS model has not been calibrated or validated much in Sri Lankan watersheds and it is essential to have a genuine data set to examine the appropriateness of the model for the study area and purposes (Halwatura & Najim, 2013). By calibrating the models using the measured data, the reliability and the predictability of these models can be improved. When modelled streamflow results match with the measured values of streamflow, users can confidently rely on the application of the model (Muthukrishnan, Harbor, Lim, & Engel, 2006).

According to the HEC-HMS manual, there are six model components or commands available from the components menu as given below.

1. Basin model manager

2. Meteorological model manager

3. Control specification manager

4. Time series data manager

5. Paired data manager

6. Grid data manager

Basin model represents the physical characteristics of the hydrological components such as sub-basin, reach, junction, diversion reservoir, source and sink of a watershed. Meteorological model is used to model the meteorological boundary conditions to sub-basin. It models precipitation, evapotranspiration, snowmelt, shortwave and longwave radiation. The HEC-HMS mainly supports eight precipitation methods, seven evapotranspiration methods, four short- and long-wave methods each and two snowmelt methods. Control specification controls the time span of a simulation by setting the start and end date and time. Observed data such as precipitation, evapotranspiration, discharge, temperature, snowmelt and so on are inputted using time series data manger.

2.3.2.2.2 Precipitation loss model

When estimating the streamflow, it is important to consider the losses that could take place as evaporation, interception from vegetation from above the ground and surface depression as water accumulates in hollows over the surface. In a nutshell, the abstractions or losses are defined as the deviation between total rainfall hyetograph and the excess rainfall hyetograph (Chow, Maidment, & Mays, 1988). The role of the precipitation loss method is to model the actual surface runoff by reducing the infiltration. There are eleven different methods obtainable from HEC-HMS to model loss. The choices include Soil Moisture Accounting Method, SCS Curve Number Method, Initial and Constant Method, Deficit and Constant Method and Green and Ampt Method. Some of the approaches given are designed mainly for simulating events whereas the others are very apt in attending to continuous simulation. However, the total of infiltration and the precipitation left on the surface adds up to total incoming precipitation in all the cases. In HEC-HMS, it is possible to assign different loss methods for each sub-basin or a particular method for several sub-basins. In the case of the ‘None’ method is chosen, all precipitation will be assumed to be excess and subject surface storage and runoff.

Among the different types of models considered earlier, only soil moisture accounting approach and the deficit and constant approach are appropriate for continuous hydrological modelling. When it comes to the deficit and constant method, it uses a single soil layer to account for continuous variations in moisture content. But the soil moisture accounting loss method represents the dynamics of water movement using three layers.

Loss due to plant and surface storage are modelled using canopy and surface methods, respectively. For a lumped hydrological model, simple canopy and simple surface methods can be adopted.

2.3.2.2.3 Transform model

The actual surface runoff estimations in HEC-HMS are executed by a transform method. There are seven (7) different types of transform methods: Clark unit hydrograph, SCS unit hydrograph, Snyder unit hydrograph, Kinematic wave method, User specified unit hydrograph, User specified *S*-graph and ModClark method. If the method selected is 'None', all excess precipitation will be transformed as runoff at the end of each time step.

Among these methods, User specified graphs require proper experimental studies. The ModClark method is appropriate only for distributed modelling while the Kinematic wave method is a data-intensive conceptual method based on shallow water equations (Cunderlik & Simonovic, 2004). Kinematic wave curve method is principally designed for urban areas. In Clark Method, a translation hydrograph is developed using the time of concentration and a time-area curve. However, in ModClark method, instead of a time-area curve, separate travel time index is used for each cell.

2.3.2.2.4 Baseflow method

Baseflow is a component of streamflow which returns from groundwater aquifers into the stream. A total of five (5) baseflow methods are present in HEC-HMS modelling. Among these methods, the recession baseflow method can be applied for both continuous simulations and event-based simulations as this method has been found out to have produced best fit against observations (De Silva, Weerakon, & Herath, 2014). Constant monthly baseflow does not save mass within the sub-basin and it is primarily designed for continuous simulation. The bounded recession method is very much like the recession method, however, this method can specify monthly baseflow limits. The linear reservoir method uses a reservoir to model the recession of baseflow.

2.4 Objective Function

Calibration of hydrologic models is carried out by comparing the measured data with simulated data. This calibration is processed through parameter optimization using an indicator called the objective function. The objective function is in charge of deciphering the goodness-of-fit between modelled result and reality. The selection of objective functions and the requirement of its efficiency mainly depend on the type of data, resolution of data and purpose of modelling such as flood control, water utilization or managing environment with the dry weather flow. The method of evaluating a model is said to be dependent on the purpose (Green & Stephenson, 2009). For example, a study which is mainly focused on peak flows, need not necessarily have to investigate low flows or even the shape of the hydrograph. The researchers have devised various types of objective functions in their studies and it has varied from one to another although the objective of the studies is the same. Following objective functions are most commonly used in stream flow modelling.

2.4.1 Nash-Sutcliffe coefficient (NSE)

The Nash–Sutcliffe efficiency (NSE) (Nash & Sutcliffe, 1970) is an extensively adopted objective function to investigate the reliability of hydrological modelling. The NSE is given by Eq. (12),

$$E = 1 - \frac{\sum_{i=1}^{n}(Q_{model,i} - Q_{obs,i})^2}{\sum_{i=1}^{n}(Q_{obs,i} - \overline{Q_{obs}})^2} \tag{12}$$

where $Q_{model,i}$ and $Q_{obs,i}$ respectively indicate the modelled and measured streamflow values on the i^{th} day. The total number of days is denoted by n and the mean value of all the measured streamflow records is given by $\overline{Q_{obs}}$.

The value of NSE can vary from -∞ to 1. An NSE value of 1 indicates that the model and reality are best correlated while a value of 0 means that the predictions made using the model are as precise as the mean of the measured records. An NSE value below zero reveals that the measured mean is a preferable predictor when compared to the model. For model predictions to be scientifically sound and reliable, an ideal value of the NSE coefficient is recorded to be 0.65 (Lin, Cheng, & Yao, 2017).

2.4.2 Pearson correlation coefficient (R)

Pearson correlation (Pearson, 1895) coefficient is known as a measure of linearity. It is devised to estimate the statistical relationship or association between model predictions and observed data. It is given by Eq. (13),

$$R = \frac{\sum_{i=1}^{n}(Q_{model,i} - \overline{Q}_{model,i})(Q_{obs,i} - \overline{Q}_{obs,i})}{\sigma_{model}\sigma_{obs}} \tag{13}$$

where the modelled and measured streamflow values on the i^{th} day are respectively denoted by $Q_{model,i}$ and $Q_{obs,i}$ and the mean value of all the measured streamflow records is given by $\overline{Q_{obs}}$. σ_{model} and σ_{obs} are the standard deviations of modelled and measured streamflow values.

The range of Pearson Correlation varies from 0 to 1. Here, when R equals 1, it specifies the best correlation between the measured and the modelled data and when R is equal to 0, that indicates that there is no correlation at all.

2.4.3 Root mean square error (RMSE)

The Root Mean Square Error (RMSE) also known as Root Mean Square Deviation (RMSD) is a commonly adopted indicator of the differences between modelled and actual values. This has been employed as a typical statistical measure in gauging the performance of a model in many climates, air quality and meteorological research studies (Chai & Draxler, 2014). The RMSE is given by Eq. (14) as below.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(X_{obs,i} - X_{model,i})^2}{n}} \tag{14}$$

where X_{obs} and X_{model} are termed as measured and calculated values at i^{th} time. An RMSD or RMSE value of zero indicates a perfect match. It is also notable that this value is always positive.

2.4.4 Mean absolute error (MAE)

The mean absolute error is a common indicator of forecast error in model evaluation studies of time series. The MAE is given by Eq. (15) as below. Here, the modelled and measured streamflow values on the i^{th} day are respectively denoted by $Q_{model,i}$ and $Q_{obs,i}$

$$.MAE = \frac{1}{n}\sum_{1}^{n}\left|Q_{obs,i} - Q_{mod\,el,i}\right| \tag{15}$$

2.4.5 Mean relative error (MRE)

This objective function is used to estimate the amount of error in relation to the total observed flow. Mean Relative Error (MRE) is expressed by Eq. (16) as given below.

$$MRE = \frac{\sum_{1}^{n} Q_{mod\,el,i} - Q_{obs,i}}{\sum_{1}^{n} Q_{obs,i}} \tag{16}$$

2.4.6 Ratio of absolute error to mean (RAEM)

One of the many objective functions, as suggested by the World Meteorological Organization (WMO), is the ratio of absolute error to mean (WMO, 1975). The RAEM is defined as the proportion between measured and modelled discharge with regard to the average of measured discharges. The RAEM is given by Eq. (17),

$$RAEM = \frac{\sum_{1}^{n}\left|Q_{obs,i} - Q_{mod\,el,i}\right|}{n\overline{Q_{obs,i}}} \tag{17}$$

where n is the number of observations utilized in the study and $Q_{obs,i}$ and $Q_{model,i}$ are defined as the measured and calculated streamflow records, respectively.

2.4.7 Mean ratio of absolute error (MRAE)

The MRAE is used to evaluate the performance of each and every point of flow. This objective function has been reported to be more effective in modelling where consideration of low flow is also important. This objective function has also been found out to be giving a better representation of error even when there are contrasting data records present in the measured data as this compares the error in relating to each measured data record. The MRAE is given by Eq. (18) as shown below.

$$MRAE = \frac{1}{n}\left[\frac{\sum_{1}^{n}\left|Q_{obs,i} - Q_{model,i}\right|}{Q_{obs,i}}\right] \quad (18)$$

where n is the number of observations utilized in the study and $Q_{obs,i}$ and $Q_{model,i}$ are defined as the measured and calculated streamflow records, respectively.

2.5 Model Calibration and Verification

It is essential to calibrate a hydrological model carefully in order to make certain that predictions made using that particular model are scientifically sound and reliable. Model calibration is considered to be an influential process in making a hydrological model successful. When a hydrological model is developed, better representativeness of that model depends on its parameters. Good representativeness of a model can be achieved through optimizing these parameters so that it gives a good match with reality. In the process of calibration, one part of a time series is used to identify the most appropriate values of the undetermined model parameters through the optimization process. Parameters for which definitive information are not accessible can be improved or determined by testing the model with measured input and output data (Xiong & Guo, 1999).

The model calibration is usually performed either through manual calibration or computer based automatic calibration procedure. Although manual calibration is all about fine-tuning the parameter values through trial and error method, it tests both the skill and the patience of the modeler. Manual calibration alone involves the skills and experience of a hydrologist which is otherwise challenging and time consuming. In the case of manual calibration, the model performance of the calibrated model is primarily determined from a visual judgment by analyzing the match between the modelled and measured hydrographs (Madsen, 2000).

On the contrary, automatic calibration relies heavily on mathematical and statistical methods that use an optimization algorithm so as to lessen the difference between the model and reality. The advantage of automatic calibration is that it maintains the consistent performance of a model by excluding the human judgment involved in the manual approach. However, a blend of both manual and automatic procedures is recommended to be taken into consideration while calibrating a model (Gan, 1987).

Model verification can be stated as an extension of the calibration process. This is commonly carried out by using a different part of the same data set used in the calibration process. The main reason to carry out this process is to check whether the model performance is consistent enough in providing good results even for a different data set using the same parameters derived during the calibration process. The model can be confidently used in practice if only the model performs excellently during both calibration and verification processes (Xiong & Guo, 1999).

3.0 MATERIALS AND METHODOLOGY

3.1 Study Methodology

The present study has been divided into two parts; one is rainfall trend analysis and the second one is streamflow elasticity to climate analysis. This thesis includes six (6) main chapters consisting of the introduction, literature survey, materials and methodology, analysis and results, discussion and conclusion and recommendation. The methodology adopted to carry out the present study is given in Figure 3-1. Chapter one provides the related general information, identification of the problem and main objectives of this research. A comprehensive investigation of past studies was performed and reviewed to discern a suitable non-parametric model to perform the rainfall trend analysis and to identify an empirical formula for streamflow elasticity estimator and adopt a suitable hydrological modelling approach for further analysis incorporating climate change predictions.

The analysis of precipitation was performed for the whole Maduru Oya basin using Sen's Slope Estimator, Mann-Kendall and Modified Mann-Kendall Tests in R version 3.6.1 software (R Core Team, 2013). It is a freely downloadable/public domain statistical software widely used among statisticians for data analysis.

Padiyathalawa sub-watershed, located in the upstream part of Maduru Oya basin, was selected for the analysis of streamflow elasticity. A non-parametric test was performed for the observed data and a hydrological modelling approach was adopted to see the performance of the developed model when incorporating climate change concept. After a thorough review of past studies on various rainfall-runoff models utilized in many river basins under different circumstances, the HEC-HMS model (Hydrologic Modeling System of Hydrologic Engineering Center) was selected in the analyzing process of the present study as it is the only software freely available.

The hydrological model was developed as a lumped model by taking into account three main components; Control specification, Basin model and Precipitation model. Model development, selection of objective functions and estimation of initial parameters are elaborated in details under the Results and Analysis section. Out of eight years of data considered for this study, four years of data since October 1992 to

September 1996 were considered in model calibration process while the remaining four years of data since October 1997 to September 2001 were utilized in the process of the verification of the model.

Mean Ratio of Absolute Error (MRAE) and Nash-Sutcliffe Efficiency were adopted as the objective function in order to evaluate how well the model performs. It was made sure that the error should be minimum to consider the model as an acceptable one. The values of objective functions obtained during both model calibration and verification processes and the graphical representations of the model outputs are also given in the Results and Analysis section.

Subsequently, the calibrated model was used to check the streamflow elasticity to climate variables. For this purpose, the model was operated with the altered input rainfall and evapotranspiration data and the modelled streamflow was analyzed. Generally, the historical time series are scaled by a constant factor to modify the input data (Chiew F. H., 2006). Then, the streamflow elasticity to climate variables was deduced by comparing the simulated streamflow using the original input data with the simulated streamflow with the altered input data.

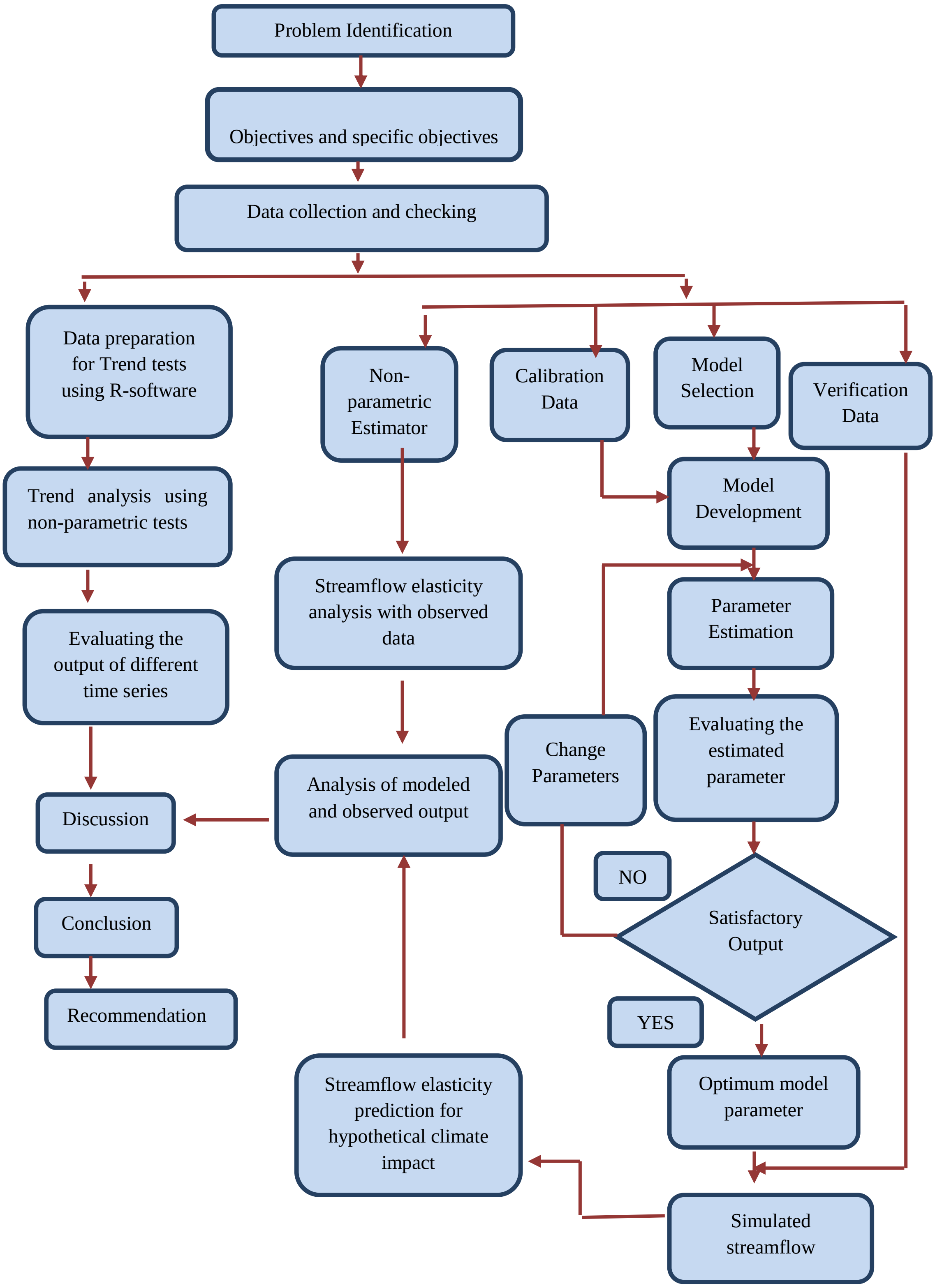

Figure 3-1: Methodology flow chart

3.2 Study Site

The selected study site, Upper Maduru Oya Basin, with the details of its pertinent hydro-meteorological characteristics, sub-basins and stream network is presented.

3.2.1 Maduru Oya watershed

The Maduru Oya originates from Mahiyangana in the Badulla district. A significant portion of this river basin lies in the dry zone, within the administrative districts of Polonnaruwa and Batticaloa and then as shown in Figure 3-2, extends into intermediate zone having a total catchment area of 1,541 km^2. Table 3-1 summarizes the basin details and administrative areas covered under this river basin. It is located with Mahaweli Ganga basin in the West, Gal Oya basin in the South, and Mundeni Aru and Miyangoda Ela basins in the East. Being influenced by the South-West (May to September) and the North-East (December to February) monsoons, Maduru Oya basin encounters a tropical climate. From these two monsoons, most of the yearly precipitation is brought by the North-East monsoon (Maha) and thereby contributing to a major part of the runoff within the catchment.

Table 3-1: Basin details and Administrative areas covered by Maduru Oya basin

Characteristic	Description
Area extent of Maduru Oya River basin	1,541 km^2
Districts covered	Ampara, Badulla, Polonnaruwa, Batticaloa and Moneragala
Provinces covered	East, Uva and North Central

3.2.2 Maduru Oya watershed at Padiyatalawa

The Padiyatala catchment is a sub-catchment of Maduru Oya basin. This sub-basin was selected in the estimation of streamflow elasticity to climate analysis of the present study. A major part of this sub-basin lies within Badulla district and the whole sub-basin area is located in the intermediate zone. A stream-gauging station located in Padiyathalawa is the only station situated in the whole Maduru Oya basin. Padiyathalwa sub-catchment expands to an area 170.9 km^2.

Figure 3-4 below shows the Padiyathalawa sub-basin delineated in Arc GIS 10.3 (ESRI, USA) using 30 m DEM obtained from Survey Department, Sri Lanka with the selected rain-gauge stations and streamflow station at Padiyathalawa.

3.2.3 Distribution and density of rain gauging stations in the study area

The accuracy of a hydrological study is highly affected by the accuracy of the input data. It is necessary to decide on a reasonable number of density and distribution of rain gauging stations to increase the exactness and completeness of the input data. Although it may seem that the accuracy of the estimation of precipitation in a catchment to be increasing with the density of rain gauge stations considered, it is not the case in reality.

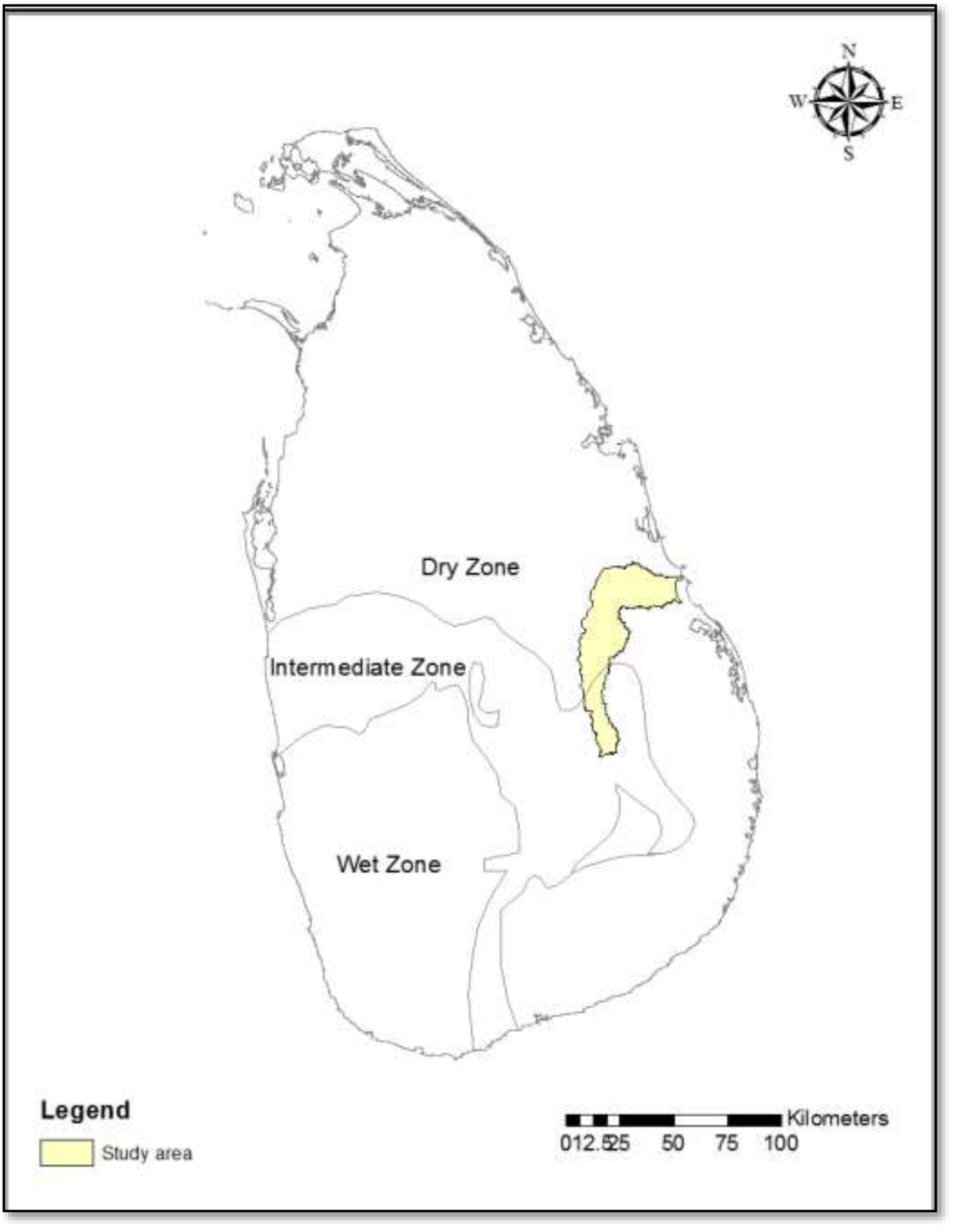

Figure 3-2: Location of Maduru Oya river basin

A past study (Xu, Xu, Chen, Zhang, & Li, 2013) found out that the error range of a model showed no considerable improvement after reaching a threshold value for the number of rainfall gauging stations. Selecting the rain gauge density to be considered for data collection is a crucial task as it is dependent on many factors.

Further, it is said that the rain gauging stations density mainly depends on the purpose of the data collection, the local spatial variability of the rainfall and the geographical variability of the watershed considered (Jones, 1997). In order to set a standard norm regarding the selection of rain gauge stations, WMO has established minimum rain gauge density guidelines for different physiography (WMO, 2008). Accordingly, as given in Table 3-2, for a catchment type of inter plains such as Maduru Oya basin, one rain gauge station can cover an area of 575 km^2. Likewise, when it comes to streamflow-gauges, one station can cover a basin area extent up to 1875 km^2.

There are nearly thirty numbers of rain gauging stations within the proximity of the selected watershed. However, nine stations were selected both from inside and outside of the basin taking the close proximity and the availability of rainfall data into consideration. Moreover, the availability of data length or period is one major factor in determining which rain-gauging stations should be selected for this study.

Table 3-2: Distribution of gauging stations

Gauging station	**Number of stations**	**Station Density (km^2/station)**	**WMO Standards (km^2/station)**
Rainfall	9	171.2	575
Streamflow	1	170.9	1875
Evaporation	1	170.9	5000

Among the nine selected rain-gauge stations, only two stations are located inside the watershed. Further, five stations are established in the upstream of the basin while the remaining four are stationed towards the downstream. Figure 3-3 shows the location map of the considered gauging stations and the details of each station are indicated in Table 3-3.

Three rain-gauge stations given in Figure 3-4 such as Welipitiya Coconut Estate, Padiyathalawa MOH and Ekiriyankumbura out of already selected nine stations which are in close proximity to this sub-watershed can be utilized in the streamflow elasticity part of the study. There is no rain-gauge station located inside this sub-basin.

The nearest Evaporation station, Girandurukotte was selected for collecting the required evaporation data.

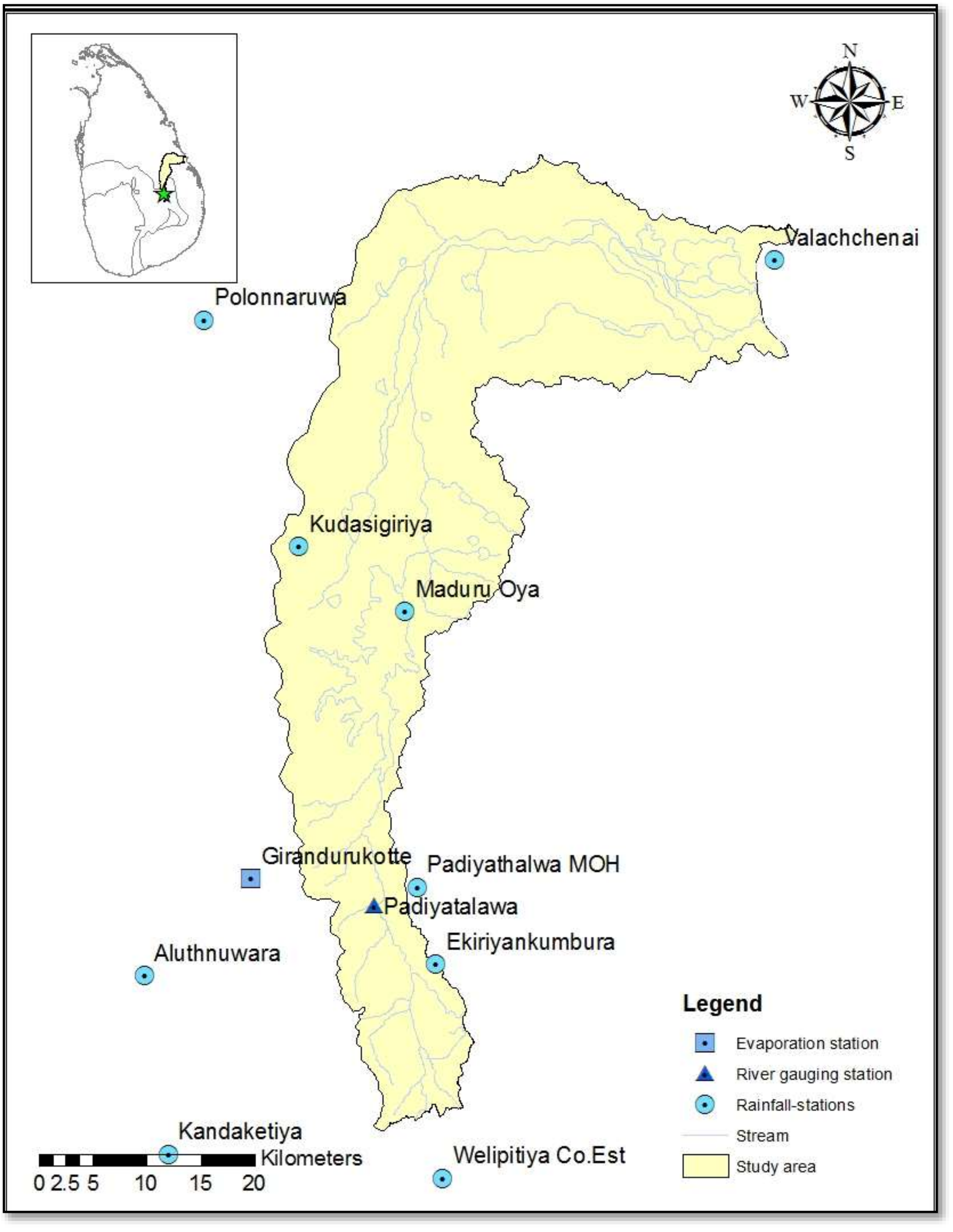

Figure 3-3: Location of selected rainfall stations

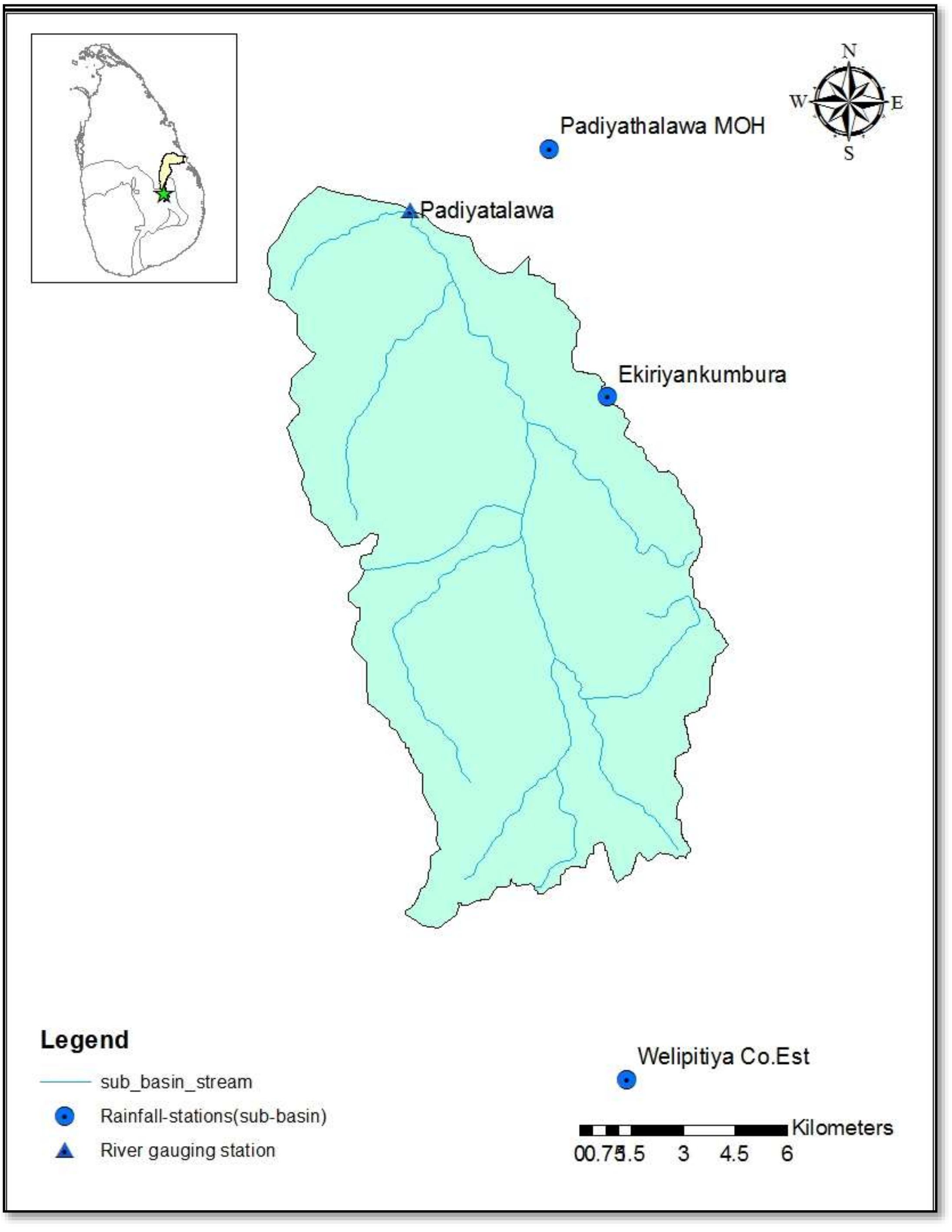

Figure 3-4: Padiyathalawa sub-basin and relevant rainfall stations

Table 3-3: Location of gauging stations

Gauging-Stations	Location		
	Latitude (Deg.)	Longitude (Deg.)	Elevation (m MSL)
Rain-gauge stations			
Kandaketiya	7.04 N	81.02 E	16
Maduru Oya	7.55 N	81.17 E	18
Kudasigiriya	7.68 N	81.13 E	6
Polonnaruwa	7.87 N	81.05 E	43
Aluthnuwara	7.28 N	81.00 E	92
Valachchenai	7.92 N	81.53 E	5
Ekiriyankumbura	7.30 N	81.23 E	16
Padiyathalawa MOH	7.34 N	81.19 E	152
Welipitiya Co. Est.	6.95 N	81.28 E	16
Streamflow stations			
Padiyathalawa	7.34 N	81.14 E	82
Evaporation stations			
Girandurukotte	7.4 N	81.08 E	292

3.3 Data Collection

3.3.1 Data and data source

The Department of Meteorology is accountable for the operation of the rainfall and evaporation gauging stations. Most of the streamflow gauging stations are maintained by the Water Management Unit of Irrigation Department. The rain gauging station located on Maduru Oya reservoir is maintained by Mahaweli Authority of Sri Lanka (MASL). The GIS shapefiles required for the preparation of the maps were gathered from the Survey Department, Sri Lanka. The sources and resolutions of data are given in Table 3-4.

Table 3-4: Data sources and resolution

No.	Data Layer	Method of collection and Temporal / Spatial Resolution
1	Shapefiles for GIS map preparation • Contours • DEM	• From the available shapefile of 1:50,000 from the Survey Department. • 30 m, Survey Department
2	Rainfall data	Daily data from the Department of Meteorology and Hydrology Division of Irrigation Department
3	Streamflow data	Daily data from the Hydrology Division of Irrigation Department
4	Evaporation data	Daily data from Agromet Division of Department of Meteorology

There are several factors related to the collection of data in order to be used in climate study. It is vital to investigate the availability of the rainfall data for the selected stations. According to WMO guidelines on the calculation of climate normal (WMO, 2017), the minimum data period requirement for climatological studies is 30 years. It also defines the climatological reference normal for consecutive periods of 30 years such as 1^{st} January 1981 to 31^{st} December 2010, 1^{st} January 1991 to 31^{st} December 2020 and so forth. Accordingly, in this particular study, a maximum of 34 years of data covering the period of 1981 to 2015 have been collected. For those stations with less data, the available data sets were considered in this study.

Daily streamflow data of 23 years covering year 1992 to 2015 were collected from the Hydrology Division of Irrigation Department and the available evaporation data for 10 years from 1992 to 2002 were collected from Agro-met division of the Department of Meteorology, Colombo. Table 3-5 summarizes the data length available in each station.

Table 3-5: Data length available in each station

Stations	Data availability periods	Data Length (years)
Rain-gauge stations		
Kandaketiya	1981-2015	34
Aluthnuwara	1981-2015	34
Polonnaruwa	1981-2015	34
Maduru Oya	1985-2015	29
Kudasigiriya	1993-2015	22
Valachchenai	1981-2000	19
Welipitiya Co. Est.	1992-2015	23
Ekiriyankumbura	1992-2015	23
Padiyathalawa MOH	1992-2015	23
Stream-gauge station		
Padiyathalawa	1992-2015	23
Evaporation Station		
Girandurukotte	1992-2002	10

3.3.2 Dealing with data-scarce regions

Although Maduru Oya basin has a reasonable number of rain-gauge stations both inside and outside the basin, as the number of rain-gauge stations with required data period conforming to the WMO guidelines is less, this basin ends up being considered as a data-scarce region. Especially, as there is a large gap in meteorological station network to the East of central hills (Warnasooriya, 2016), almost all the stations considered under this study are either located left of or inside the basin.

In a study (Ngongondo, Xu, Gottschalk, & Alemaw, 2011) carried out by evaluating the temporal and spatial properties of rainfall in an area with data scarcity issue in Malawi, the researchers used rainfall records from 42 stations which included some stations with poor data availability to analyze annual, seasonal and monthly time scales. Among the 42 stations considered, 04 stations were having the data periods of less than 15 years.

Moreover, the same concept of selecting the rain-gauge stations with a minimum of 20 years of long records was adopted in another study (Kidemu & Rao, 2016) as the other stations did not have enough data.

In the present study, as given in Table 3-5, only three (3) stations fulfill the requirement of 30 years of data. The minimum data period recorded is from Valachchenai station located in the downstream of the basin with a data period of 19 years. Moreover, streamflow data were collected for 23 years and only 10 years of complete daily evaporation data were available for the selected station.

3.3.3 Spatial averaging with Thiessen Polygons

Padiyathalawa sub-basin was the selected location for the streamflow elasticity analysis. Three rain-gauging stations located near this sub-basin shown in Figure 3-4 were used for this part of the study. The rainfall recorded over a basin area varies in severity and duration from one location to another. Hence, it is vital to weigh the rainfall recorded in each station according to the area covered by the relevant station in order to get the spatial or area average rainfall. The Thiessen Polygon (TP) method is an extensively utilized approach to compute area average rainfall in meteorology and hydrology (Schumann, 1998). Therefore, Thiessen Polygon given in Figure 3-5 for Padiyathalawa sub-basin using three rain gauging stations was adopted to quantify the Thiessen average rainfall. Table 3-6 gives the estimated Thiessen area and weights.

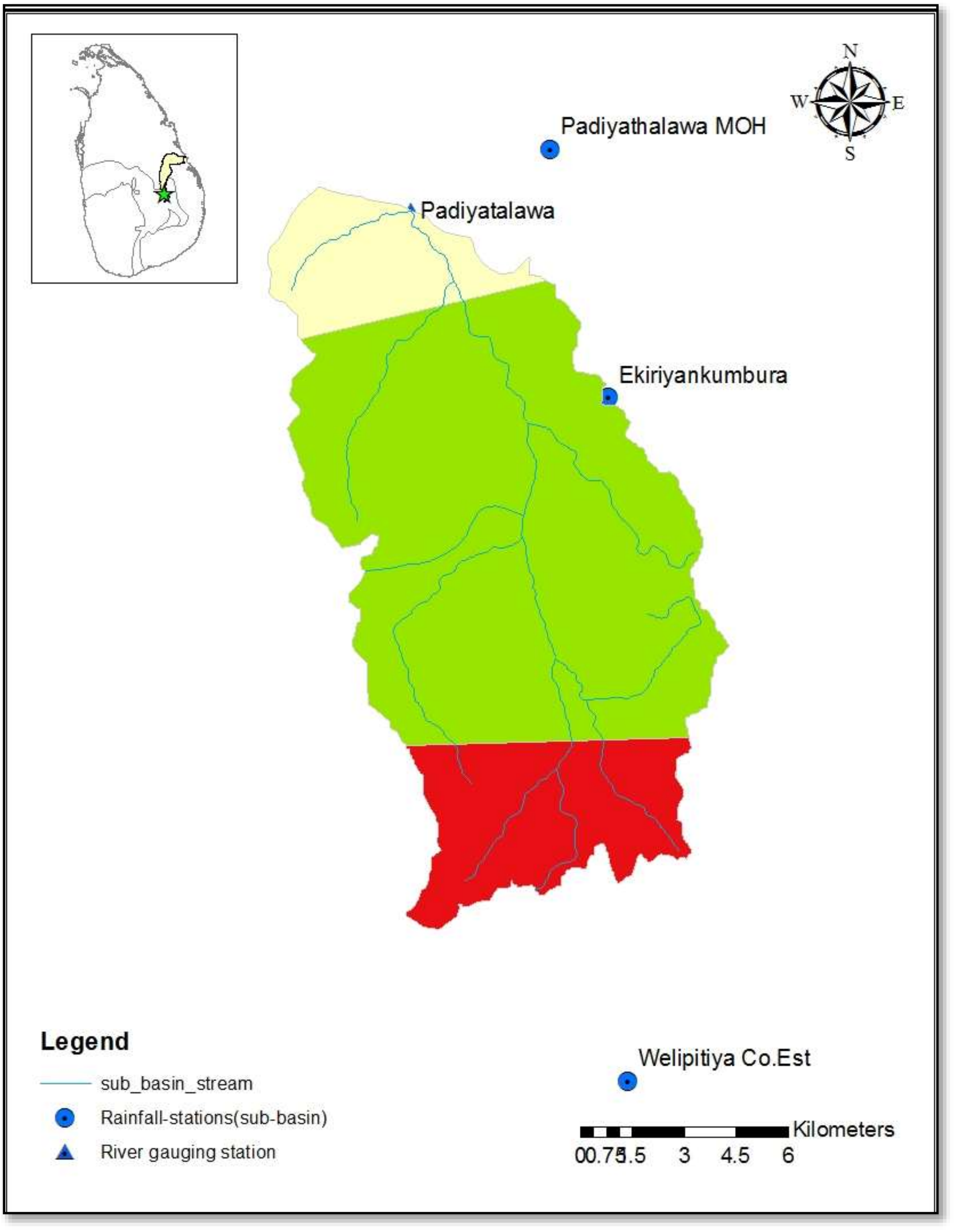

Figure 3-5: Thiessen Polygon of Padiyathalawa Sub-basin

Table 3-6: Thiessen area and weight

Station Name	Area(km^2)	Weightage
Welipitiya Co. Est.	30.7	0.18
Ekiriyankumbura	120.7	0.71
Padiyathalawa MOH	19.5	0.11

3.3.4 Data checking

Data checking can be carried out both visually using graphs and statistically. Usage of a continuous data set for the analysis plays a vital role in producing a reliable result. It is recommended that a data set should have less than only 10% of missing data to avoid biased statistical analysis (Bennet, 2001). For the current study, the percentage of missing data of all nine (9) rain-gauging stations were checked and found out to be well within the maximum limit of 10%. Table 3-7 shows the percentage of missing daily data during the period considered.

Table 3-7: Percentage of missing daily data in each station

Station	Missing data (%)
Rainfall	
Ekiriyankumbura	0
Padiyathalawa MOH	0
Maduru Oya	0
Kandaketiya	1
Valachchenai	2
Kudasigiriya	4
Aluthnuwara	4
Polonnaruwa	5
Welipitiya Co. Est.	9
Streamflow	
Padiyathalawa	0
Evaporation	
Girandurukotte	5

3.3.5 Estimating missing daily rainfall data

The reliability of a hydrological study is mainly determined by the reliability of the data used. Complete and long-term rainfall records are crucial to perform a meaningful hydrological analysis. However, collected data sets may have missing data due to various reasons. Hence, it is important to find out a proper method for filling in the missing records before proceeding with the analysis.

In a previous study (Nandalal, Caldera, & Piyathisse, 2016), seven different approaches were used for gap filling of data series in order to investigate the appropriateness of each method in hilly regions. The researchers found out that an appropriate method can be selected for each station depending on the presence of neighbouring station(s) and the correlation of the neighbouring stations between the particular stations considered for filling the data.

Single mass curves for all nine (9) stations considered were drawn as given in Figure 3-6 so as to identify the stations with similar rainfall pattern with that of the station with missing data. Rain gauging stations located in Maduru Oya, Ekiriyankumbura and Padiyathalwa have been recorded with complete data sets. In addition to these nine stations to be considered in this study, rainfall data from another 4 stations namely Bibile Agriculture Training Centre, Galoola Estate, Angamedilla and Minneriya Tank were also collected just for the purpose of filling in the missing data of the target stations.

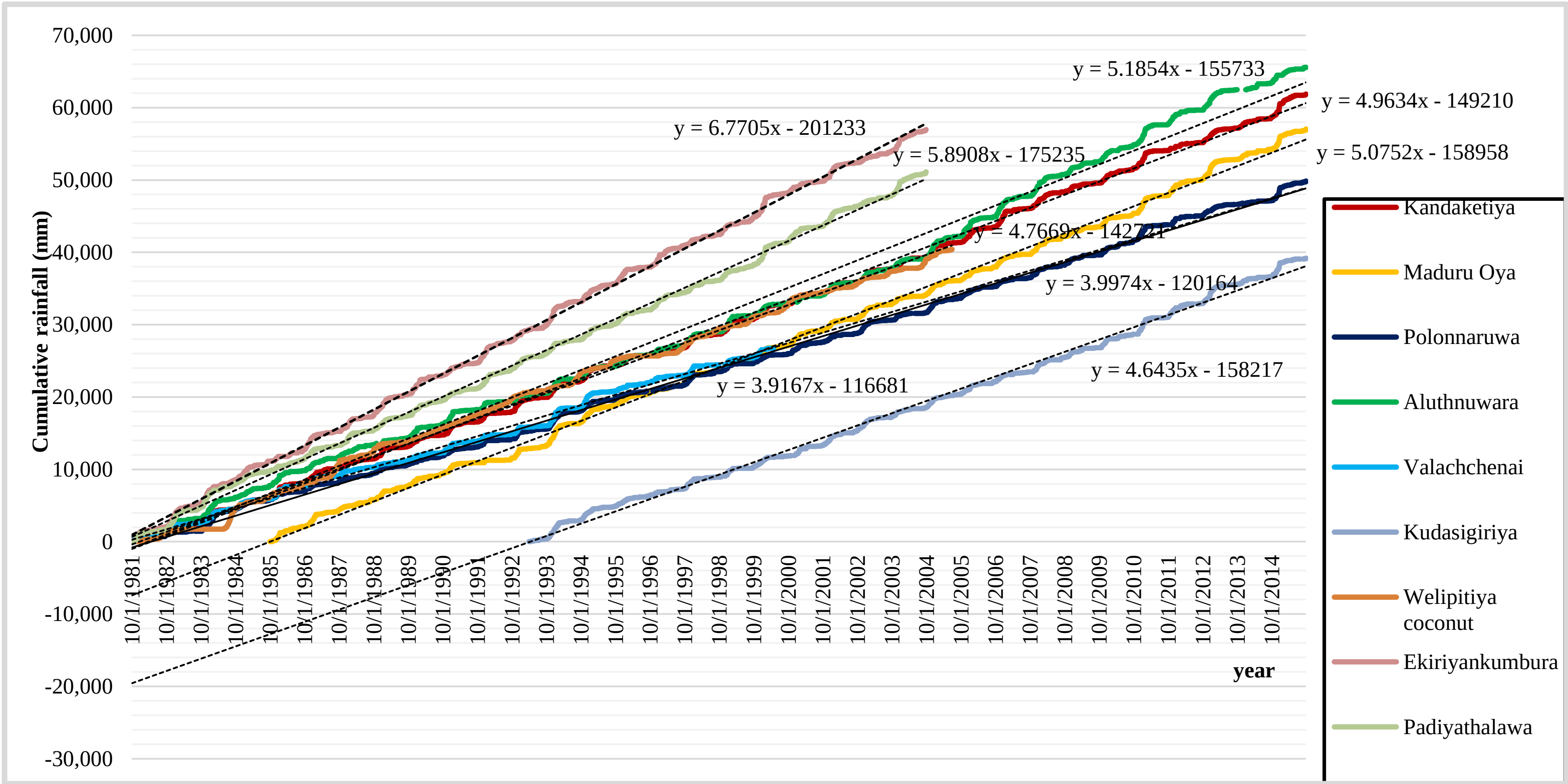

Figure 3-6: Single Mass Curves of stations excluding missing data period

Table 3-8 summarizes the matching stations for each target station based on the above single mass curve and the correlation coefficient between the stations.

Table 3-8: Stations with the relevant matching station

Target Station	**Matching stations**
Kandaketiya	Maduru Oya, Aluthnuwara, Bibile Agri. Training Centre and Galoola Estate
Polonnaruwa	Maduru oya, Kudasigiriya. Angamedilla and Minneriya Tank
Aluthnuwara	Kandaketiya, Maduru Oya, Bibile Agriculture Training Centre and Galoola Estate
Valachchena	Maduru Oya, Polonnaruwa and Kadasigiriya
Kudasigiriya	Maduru Oya
Welipitiya Co. Est.	Kandaketiya, Bibile Agri. Training center and Galoola Estate

In this study, missing data of the above six (6) stations were filled adopting one of the methods proposed by Nandalal, Caldera, & Piyathisse (2016). Their comparison concluded that both the Probabilistic Method and Linear Regression Method give satisfactory results if there is only one closest station that has a good correlation coefficient with the target station. Accordingly, Kudasigiriya gaps were filled using Linear Regression (LR) method as it has Maduru Oya station as the only one close-by station with a high correlation coefficient of 0.73. The formula used for missing value estimation is given below in Eq.(19),

$$p_x = c_i p_i \tag{19}$$

where p_x and p_i are the values of target and matching stations respectively and c_i is the regression coefficient.

The remaining missing records were filled using Normal Ratio Method (NRM) because normal annual precipitation at any close-by matching stations was found to be more than 10% of the normal annual precipitation at the target station. The formula used is given below in Eq. (20),

$$p_x = \frac{1}{m}\sum_{i=1}^{m}\left(\frac{N_x}{N_i}\right)p_i \tag{20}$$

where p_x and p_i are the values of target and matching stations, respectively. Likewise, N_x and Ni respectively indicate the normal annual precipitation of surrounding station and the target station. The number of surrounding stations is given by m.

3.3.6 Double mass curve

The consistency of different types of hydrologic data such as precipitation and streamflow are tested with the help of double mass curve. The double mass curves were plotted for each station separately. As the considered stations do not have data for the same period, out of nine (9) rainfall stations, eight (8) rainfall stations with the same data windows of 1993 to 2015 were selected and their consistencies were checked. Figure 3-7 shows double mass curves for Kandaketiya rainfall station. The double mass curves of the remaining stations are shown in Appendix A. As the correlation coefficient of each double mass curve is nearly one, a linear and consistent relationship between the rainfall station under consideration and the cumulative average rainfall of all the other stations could be assumed. It can also be noted that the variation in the trend line of each curve is insignificant from which it is clear that the location of rainfall station does not differ throughout the considered time period.

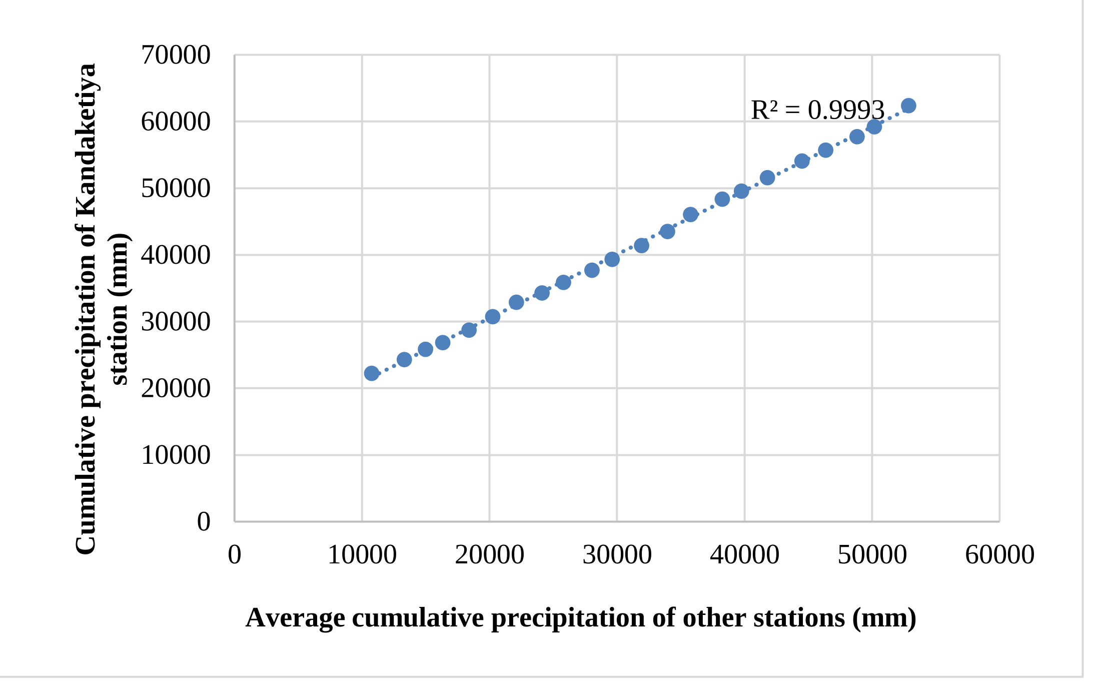

Figure 3-7: Double Mass Curve of Kandaketiya station

3.3.7 Estimation of missing evaporation data

Evaporation data of the selected station was plotted for each year for the purpose of complete visualization and it was observed that the evaporation data was having somewhat similar patterns in each year (Appendix B). When filling the gaps of evaporation records, a factor is computed by considering the slope of the single mass curves for two matching periods. If one year has been recorded with a missing value on a particular day, when drawing single mass curves, that particular day was eliminated from all the other years as well. Both water year 1992/1993 and 1993/1994 have been found to be having the almost the same slopes and the single mass curves for these matching years are shown in Figure 3-8. Single mass curves for other years are shown in Appendix C.

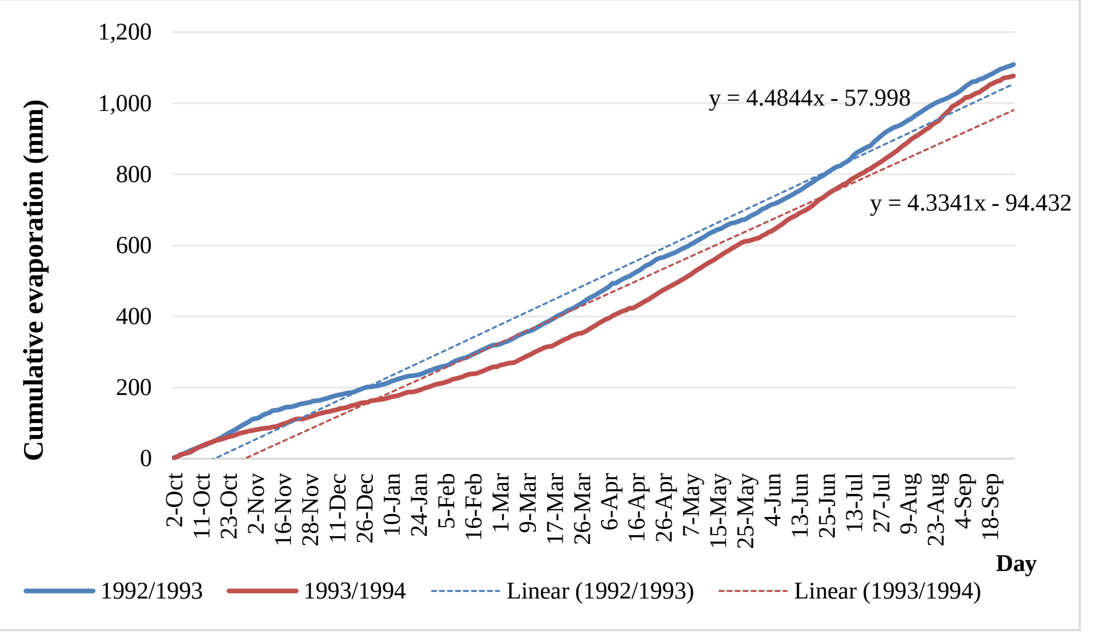

Figure 3-8: Single Mass curve of year 1992/1993 and 1993/1994

After plotting the single mass curves, the gap-filling was carried out by multiplying the value in the year which has the closest slope like the target year by the calculated slope factor. Following formula is considered for restoring the missing values.

$$Evaporation\ of\ Year\ B = \left(\frac{Slope\ of\ Year\ B}{Slope\ of\ Year\ A}\right) x\ Evaporation\ of\ Year\ A \qquad (21)$$

3.3.8 Visual data checking based on streamflow response to rainfall

As the collected streamflow data of 23 years from water year 1992/1993 to 2014/2015 for Padiythalawa river gauging station was complete, no gap filling was required. However, visual checks were performed to find out any discrepancies in the time series. Figure 3-9 and Figure 3-10 show how the streamflow of Padiyathalawa gauging-station responses to precipitation of each considered rain-gauge station for the year 1993/1994 both in normal and semi-log scales, respectively.

It can be observed from Figure 3-9 that all three (3) stations have the almost same pattern of rainfall throughout the year. However, Welipitiya Coconut Estate seems to have low rainfall when compared to the other two stations. Streamflow adequately responds to the rainfall at Ekiriyankumbura station from October 1993 to February

1994. But, the streamflow response between March 1994 to September 1994 is disagreeable. Similarly, when it comes to Padiyathalwa MOH station, streamflow response from October 1993 to April 1994 seems to be acceptable. However, in some cases, streamflow does not proportionately respond to rainfall. For instance, in March 1994, for a rainfall event of 52.3 mm/day, recorded streamflow is 4.3 mm /day whereas for a similar amount of rainfall in July 1994, streamflow has been recorded very low with a value of 0.13 mm/day. Likewise, although there has been a high rainfall event recorded in September 1994 in all three stations, the streamflow value recorded is very much low. These abnormalities can be identified as mismatching periods which may affect the accuracy of results of the study. Streamflow responses of Padiyathalawa to precipitation in other years for all stations are given in Appendix D.

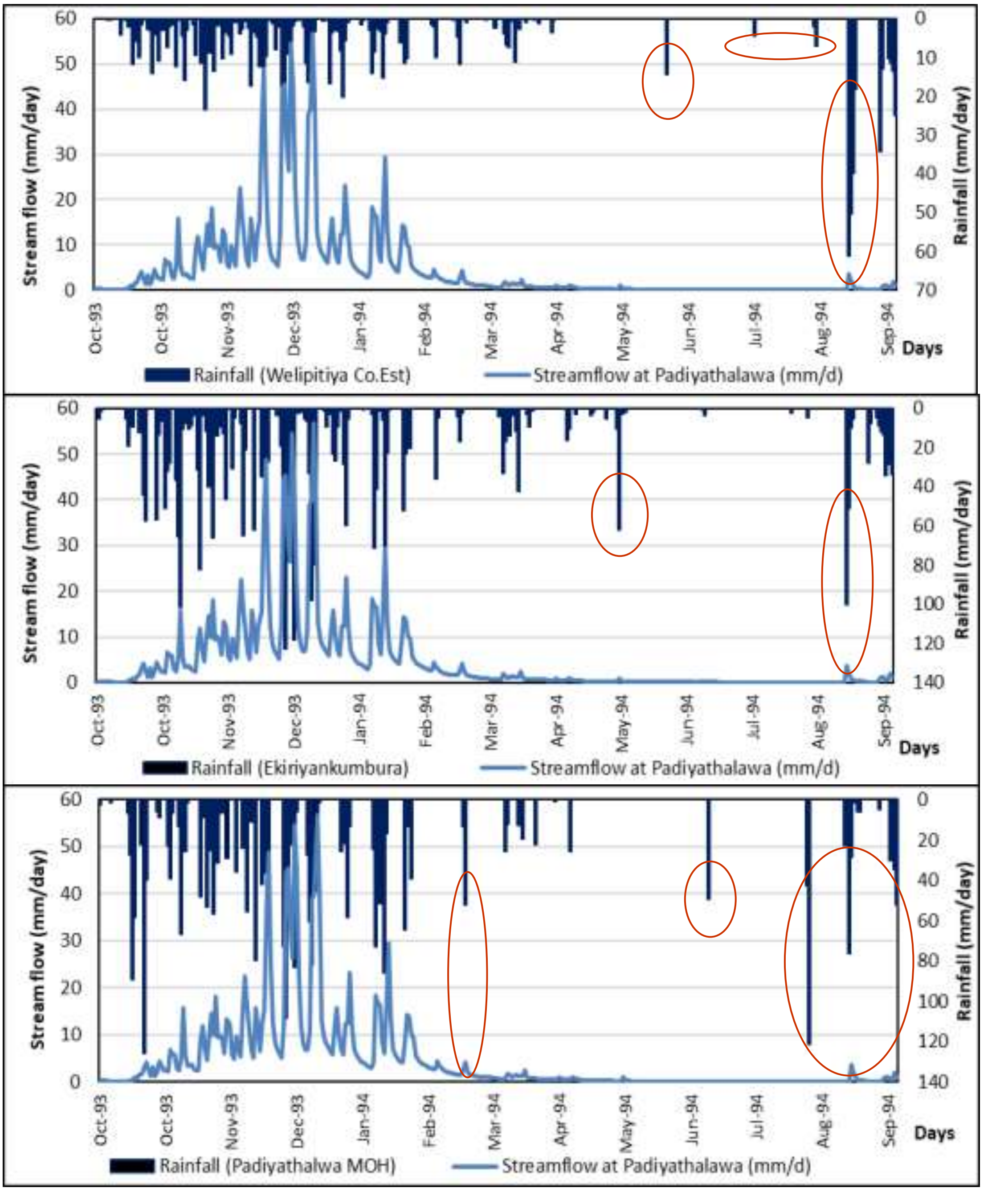

Figure 3-9: Streamflow response to rainfall at different rainfall stations for the period 1993/1994 (normal scale)

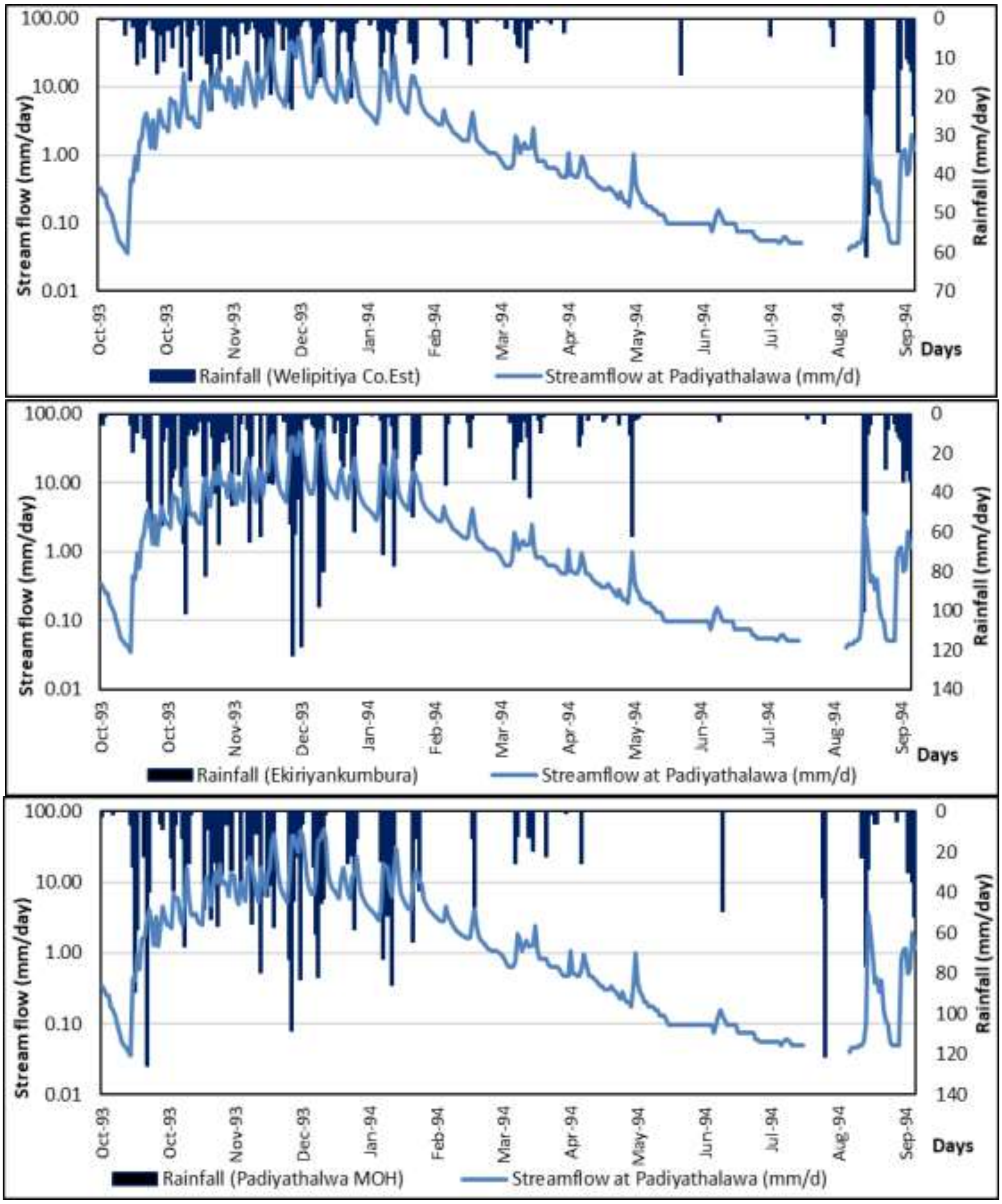

Figure 3-10: Streamflow responses to rainfall at different stations for the period 1993/1994 (semi-log scale)

3.3.9 Data checking in calibration and verification periods

The hydrological model is calibrated using 4 years of data from water year 1992/1993 to 1995/1996 and verified with another 4 years of data from 1997/1998 to 2000/2001. Year 1996/1997 had to be eliminated in order to remove irregularities in that data year. Thiessen average rainfall and streamflow are drawn for each year during both calibration and verification phases. Padiyathalawa streamflow responses to Thiessen average rainfall for all 4 years in calibration duration are given in both normal and semi-log scales in Figure 3-11 and Figure 3-12, respectively.

It is obvious that there are some disproportionate streamflow responses to rainfall. In all four years, streamflow responds reasonably well to rainfall peaks from October to February and the responsiveness from March to September is very low. This may be due to the dry periods experienced during March, June and July.

For year 1992/1993, there is a reasonable match from October 1992 to January 1993 whereas streamflow does not respond proportionately from March 1993 to September 1993. Likewise, in 1993/1994, except for some disproportionate streamflow and rainfall correlation from April 1994 to September 1994, streamflow responds pretty well with the rainfall. For year 1994/1995, there is a reasonable match between streamflow and rainfall from October 1994 to February 1995.

Padiyathalawa streamflow responses to Thiessen average rainfall for all 4 years in verification period are given in both normal and semi-log scale in Figure 3-13 and Figure 3-14, respectively. In the verification period also, there are so many occurrences of non-responsiveness of streamflow identified. Streamflow adequately matches with rainfall from October to February in all 4 years, however, it has been noted that there are so many disproportionate peaks in streamflow compared to rainfall from March to September. For example, streamflow does not show significant peaks for a high rainfall of 46 mm and 41.2 mm on 7/2/1998 and 3/4/1998, respectively. Further, although there is no significant rainfall on 19/6/1998, an erroneous peak can be noted. Likewise, in the year 1999, 2000 and 2001, although there are numerous significant rainfall events from May to September, streamflow recorded were not comparative.

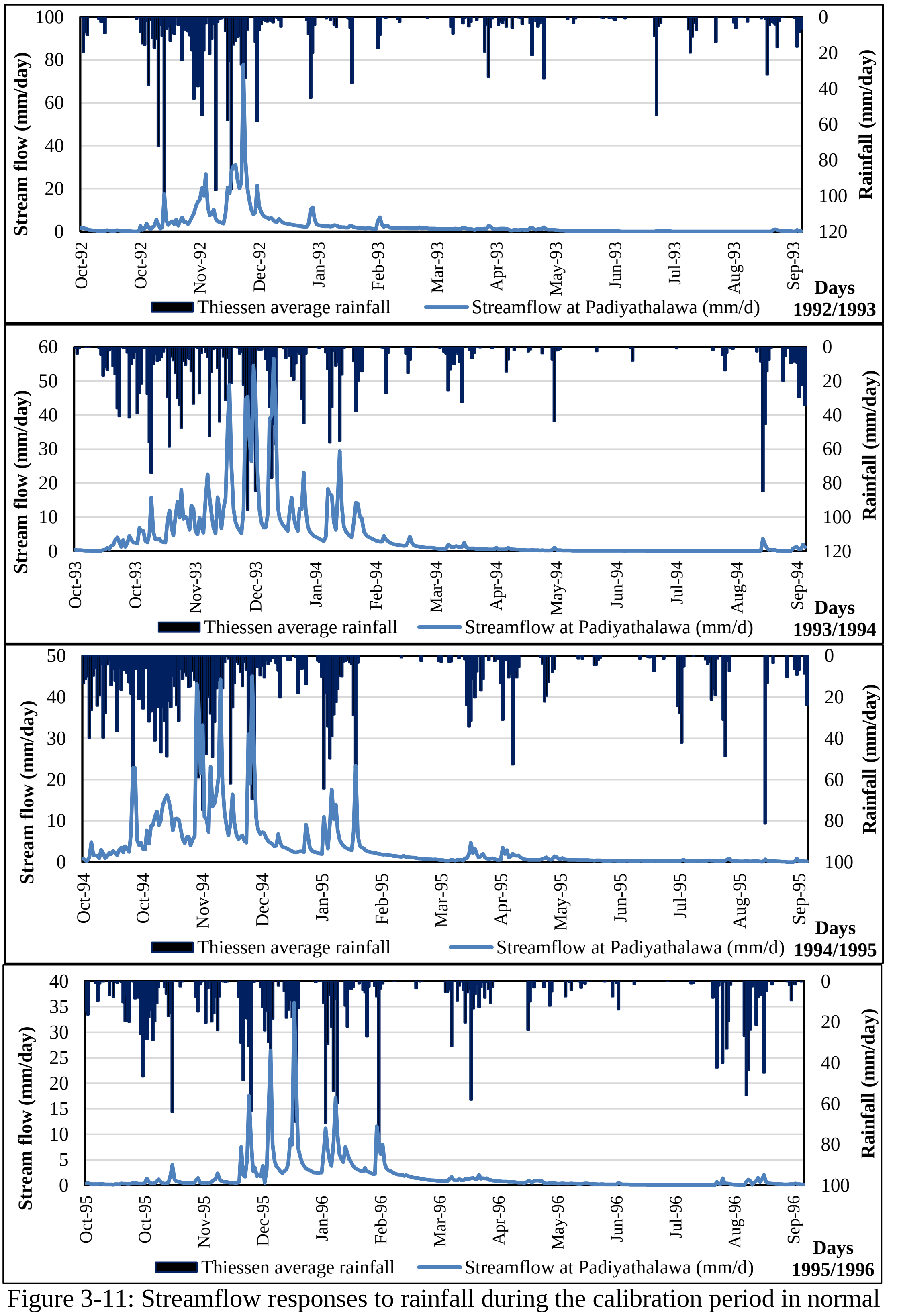

Figure 3-11: Streamflow responses to rainfall during the calibration period in normal scale

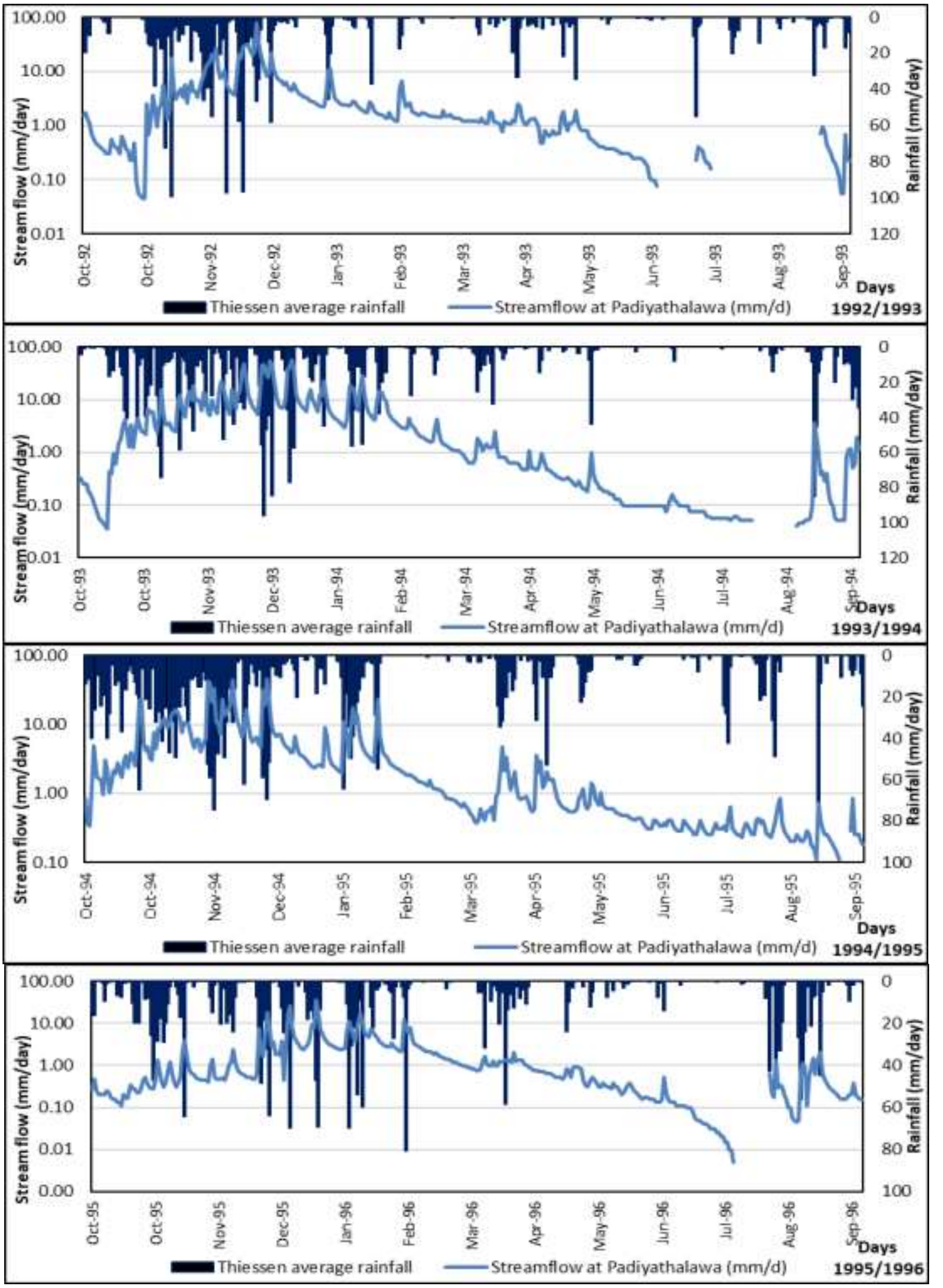

Figure 3-12: Streamflow responses to rainfall during the calibration period in semi-log scale

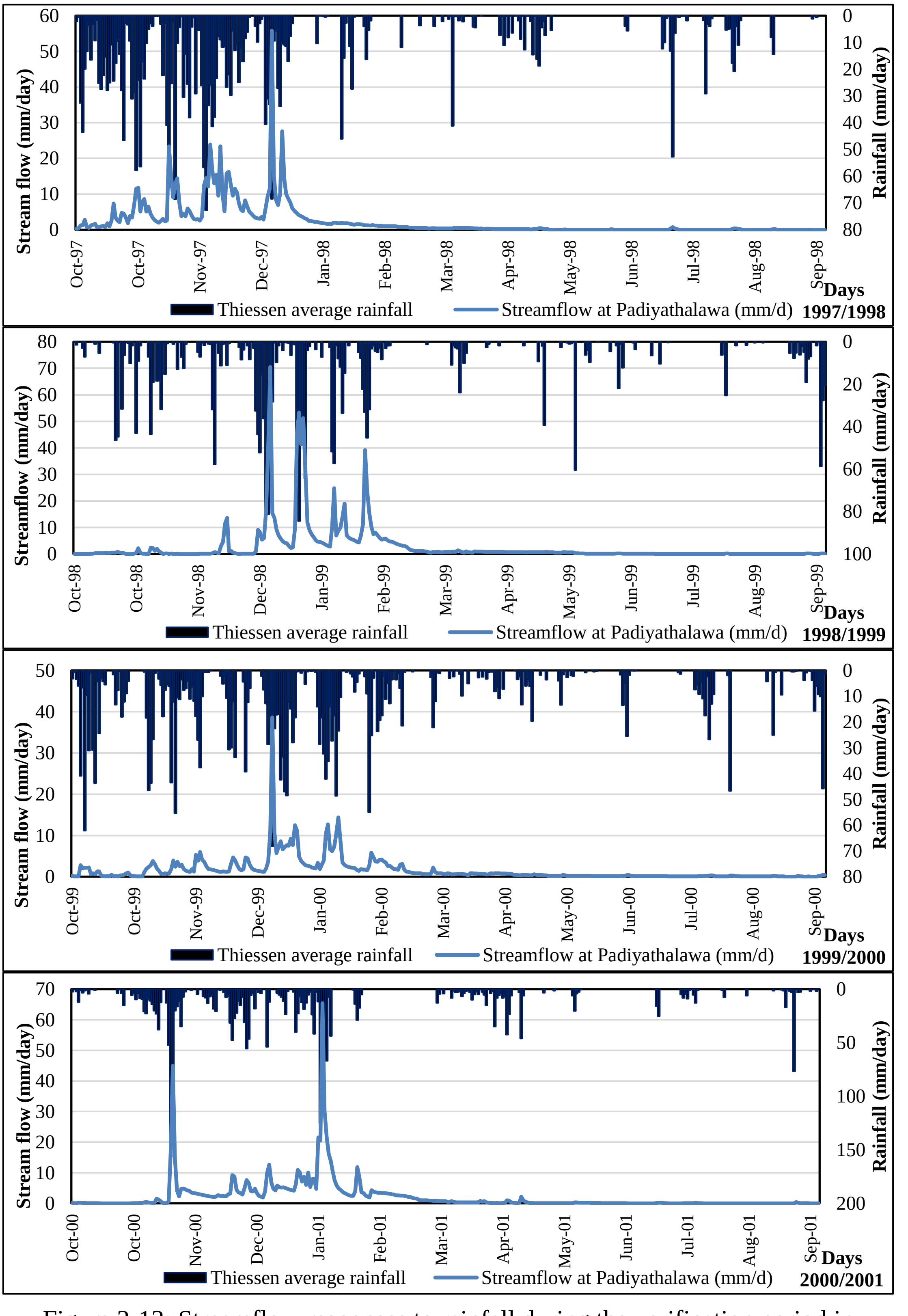

Figure 3-13: Streamflow responses to rainfall during the verification period in normal scale

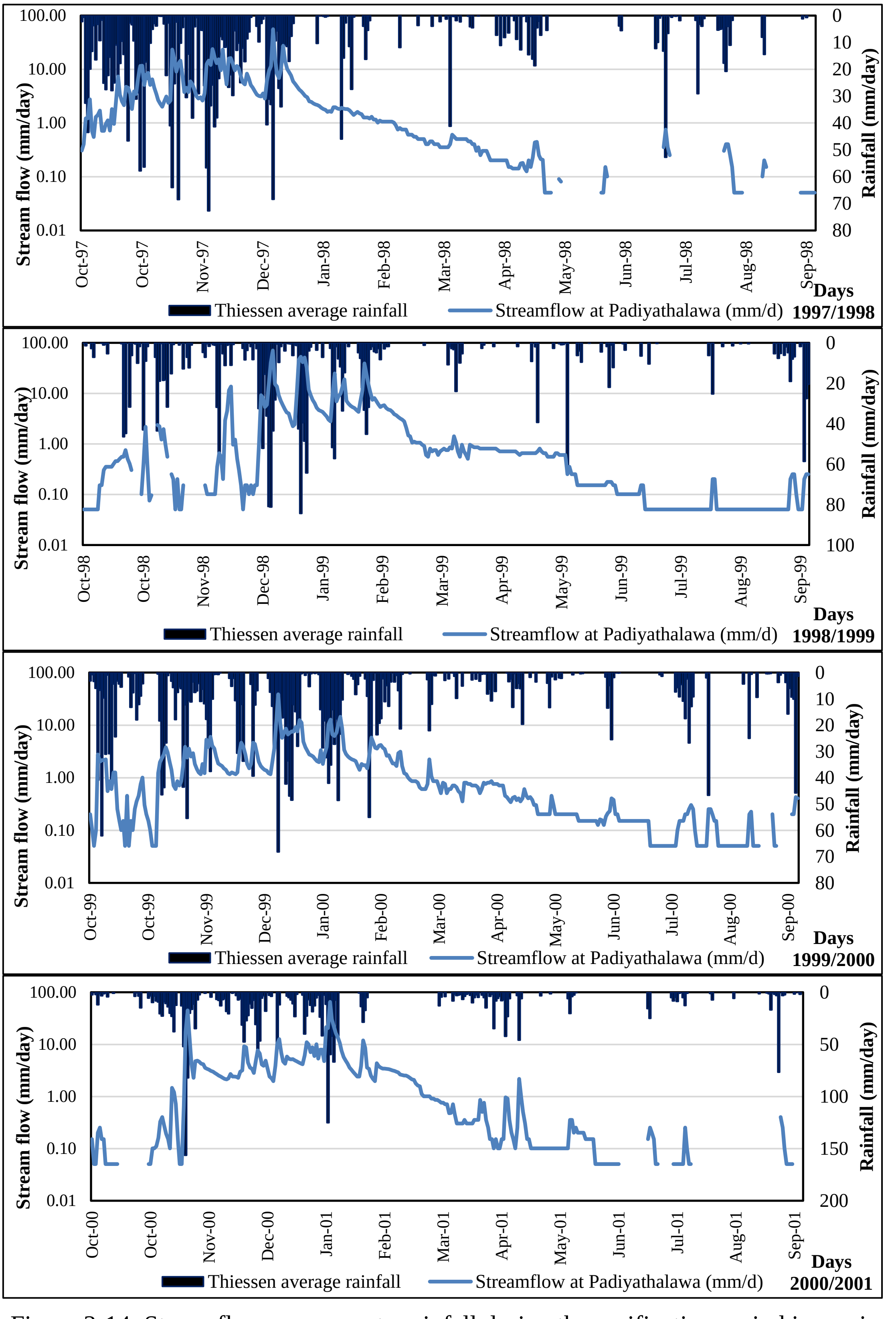

Figure 3-14: Streamflow responses to rainfall during the verification period in semi-log scale

3.3.10 Annual water balance and annual variation of runoff coefficient of Padiyathalawa sub-basin

Water balance of annual data was performed for Maduru Oya basin at Padiyathalawa so as to check the relationship between the annual precipitation and annual streamflow. Yearly water balance of Padiyathalwa sub-basin is tabulated in Table 3-9.

Table 3-9 :Yearly water balance of Padiyathalawa sub-basin

Year	Rainfall (mm)	Stream flow (mm)	Difference (mm)
1992/1993	1932	1053	879
1993/1994	2792	1651	1141
1994/1995	3338	1354	1985
1995/1996	2348	609	1738
1997/1998	2570	869	1701
1998/1999	2140	955	1185
1999/2000	2537	568	1968
2000/2001	2374	646	1728
Average	**2504**	**963**	**1541**
Standard dev.	**429**	**383**	**415**

Accordingly, in year 1999/2000, the recorded streamflow volume is 568 mm although there was a reasonably high rainfall of 2,537 mm. It can be due to the non-responsiveness of streamflow to rainfall due to discrepancies in the recording. Figure 3-15 shows the graphical representation of annual water balance.

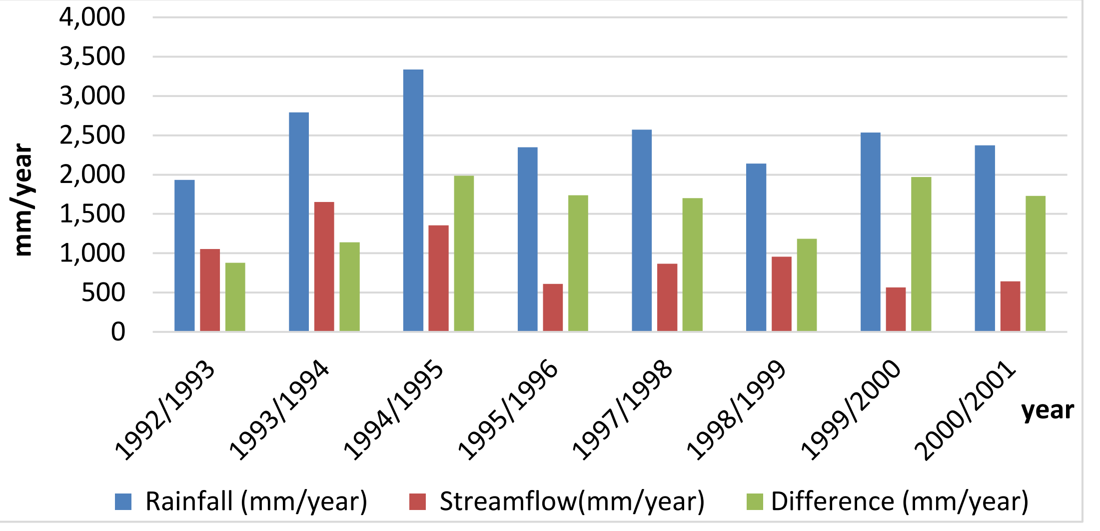

Figure 3-15: Yearly water balance for Padiyathalawa sub-basin

Annual runoff coefficient in the basin varies from 0.22 to 0.59 as given in Table 3-10. Runoff-coefficient gives the highest value of 0.59 in year 1993/1994 whereas it is the lowest in 1999/2000 with a value of 0.22. Evaporation of the basin is almost in the same range in each year varying from 1061 mm in 1997/1998 to 1306 mm in 1992/1993.

Table 3-10: Yearly water balance of Padiyathalawa sub-basin

Year	**Rainfall (mm)**	**Stream flow (mm)**	**Pan Evap. (mm)**	**Pan Coefficient**	**Actual Evap. (mm)**	**Runoff coefficient**
1992/1993	1932	1053	1633	0.8	1306	0.55
1993/1994	2792	1651	1585	0.8	1268	0.59
1994/1995	3338	1354	1516	0.8	1213	0.41
1995/1996	2348	609	1460	0.8	1168	0.26
1997/1998	2570	869	1326	0.8	1061	0.34
1998/1999	2140	955	1555	0.8	1244	0.45
1999/2000	2537	568	1344	0.8	1075	0.22
2000/2001	2374	646	1437	0.8	1150	0.27
Average	**2504**	**963**	**1482**	**0.8**	**1186**	**0.39**
Standard dev.	**429**	**383**	**88**	**0.0**	**111**	**0.14**

3.3.11 Relationship between annual streamflow and rainfall at Padiyathalawa

Figure 3-15 portrays the annual response of streamflow to rainfall in the modeling period. Annual precipitation record escalates from 1992/1993 to 1994/1995, 1995/1996 to 1997/1998 and 1998/1999 to 1999/2000 while it decreases from 1994/1995 to 1995/1996, 1997/1998 to 1998/1999 and1999/2000 to 2000/2001. Although rainfall records show a gradual increase of rainfall between the first three years from 1992/1993 to 1994/1995, streamflow value increases between the first two years and then decreases later which is unexpected. Similarly, from 1998/1999 to 1999/2000, with a rise of rainfall of 395 mm, streamflow value declines by 387 mm showing the non-reactivity of streamflow to precipitation in these years. Year 1999/2000 records the lowest streamflow of the period with a value of 568 mm which is lower than the streamflow value of even the driest year 1992/1993.

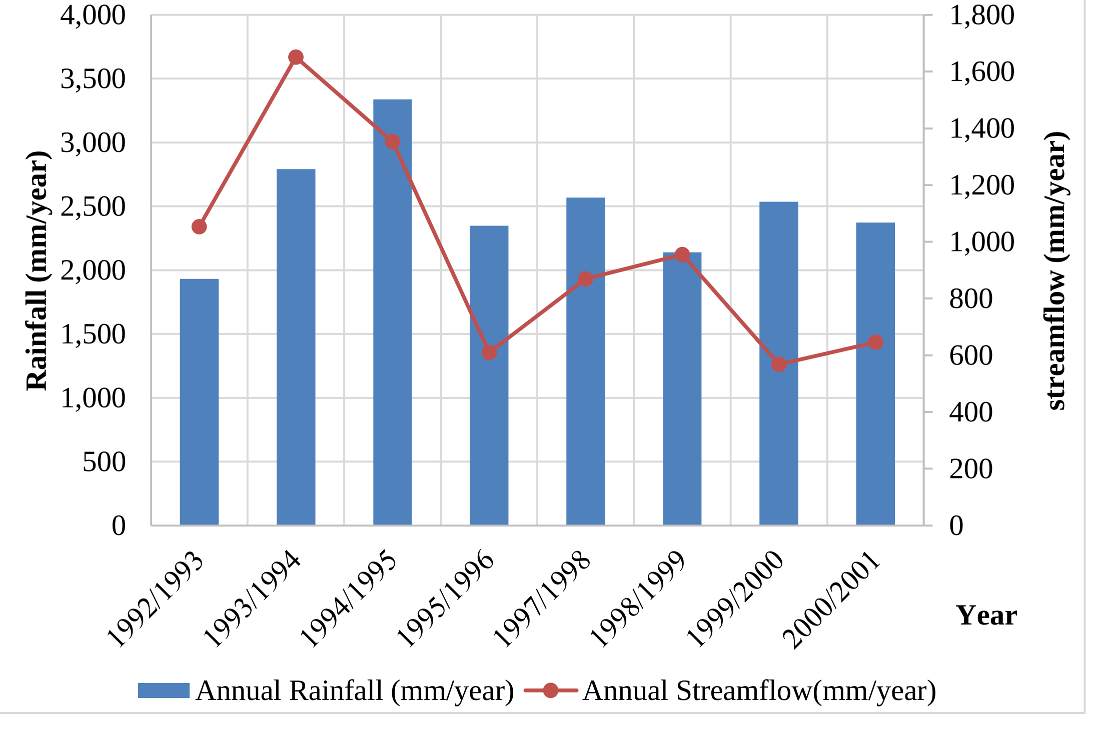

Figure 3-16: Variation of streamflow and rainfall in annual scale at Padiyathalawa

4.0 ANALYSIS AND RESULTS

4.1 Trends in Rainfall Element

As there was a scarcity for data in the selected basin, the analysis could not be performed using the same data window for all the stations. However, all the available rainfall records were collected between 1981 and 2015 at nine spatially representative stations as detailed under Chapter 3. Analyses were performed for annual, seasonal (both rainfall and cropping seasons) and monthly time series for the selected nine stations.

Monthly precipitation time series of each of the twelve months was derived by adding up the daily rainfall values over the selected month (Karunathilaka, Dabare, & Nandalal, 2017; Partal & Kahya, 2005; Barua, Muttil, Ng, & Perera, 2013). Likewise, annual rainfall time series and other seasonal time series were obtained by accumulating the daily rainfall data over the relevant time periods. In this way, altogether 171 rainfall time series were utilized to carry out the trend analyses.

Significance level (α) of 1%, 5%, and 10% were considered in the study. At these significance levels, Mann-Kendall statistic values are 2.330, 1.960 and 1.645, respectively (Gajbhiye, Meshram, Mirabbasi, & Sharma, 2015).

The conventional Mann-Kendall Test (MK) and Modified Mann-Kendall Test (MMK) and Sen’s slope estimator were adopted for studying the annual, monthly and seasonal trends of Maduru Oya basin.

The “modifiedmk” and “trend” packages were installed in R v3.6.1 and later loaded to perform Kendall tests and Sen's slope estimator using mmkh() and sens.slope() functions, respectively.

4.1.1 Mann-Kendall test and Modified Mann-Kendall test

4.1.1.1 Annual and monthly trends

For the period between 1981 and 2015, Table 4-1 and Table 4-2 respectively show the results obtained from Mann-Kendall and Modified Mann-Kendall tests for the annual and monthly precipitation records of all nine rainfall stations considered.

Table 4-1: Values of *Z*-statistic and *P*-value for annual rainfall using both MK and MMK Tests for Maduru Oya basin

Annual Time Series				
Station	**MK**	***P*-value**	**MMK**	***P*-value**
Welipitiya Co. Est.	-0.106	0.916	-0.106	0.916
Kandaketiya	**1.749**	0.080	**1.749**	0.080
Ekiriyankumbura	-0.528	0.597	-0.528	0.597
Aluthnuwara	**2.313** [a]	0.021	**2.313** [a]	0.021
Padiyathalawa MOH	1.321	0.187	1.321	0.187
Maduru Oya	1.320	0.187	1.320	0.187
Kudasigiriya	1.585	0.113	1.585	0.113
Polonnaruwa	**1.809**	0.071	**2.277** [a]	0.023
Valachchena	0.000	1.000	0.000	1.000

Note: Numbers in bold indicate significant values at the 10 % level
[a] Significant at the 5% level

In annual time series data, both tests (MK and MMK) showed similar results for eight out of nine stations. Polonnaruwa showed a significant *(p=0.02)* increasing trend in MMK test at 5% significance level and a significant *(p=0.07)* upward trend at a significance level of 10% in MK test. Two stations namely Welipitiya Coconut Estate and Ekiriyankumbura showed insignificant negative trend at both 5% and 10% significance level. Only Aluthnuwara has been found to be showing positive significant trends at 5% significance level in both MK and MMK tests.

Table 4-2: Values of *Z*-statistic and *P*-value for monthly rainfall using both MK and MMK Tests for Maduru Oya basin

Stations	Jan		Feb		Mar		Apr	
	MK	**MMK**	**MK**	**MMK**	**MK**	**MMK**	**MK**	**MMK**
Welipitiya Co.Est.	-0.338	-0.338	-0.677	-0.677	**1.834**	1.517	0.282	0.282
Kandaketiya	0.821	0.821	1.643	1.643	-0.031	-0.035	1.007	1.007
Ekiriyankumbura	0.620	0.620	-0.790	-0.790	**2.793[b]**	**2.793[b]**	-0.564	-0.564
Aluthnuwara	0.542	0.542	1.612	1.612	0.155	0.106	**1.782**	**1.782**
Padiyathalawa MOH	0.564	0.702	-1.015	-1.015	1.439	**4.244[b]**	0.564	0.564
Maduru Oya	-0.957	-1.199	1.108	1.596	0.377	0.422	1.088	1.088
Kudasigiriya	-0.996	-0.996	-0.997	-0.997	**2.092[a]**	**2.092[a]**	0.876	1.188
Polonnaruwa	0.310	0.257	1.586	1.586	-0.264	-0.264	0.542	0.542
Valchchena	1.364	**2.761[b]**	0.613	0.613	-1.199	-1.199	0.417	0.417

Stations	May		Jun		Jul		Aug	
	MK	**MMK**	**MK**	**MMK**	**MK**	**MMK**	**MK**	**MMK**
Welipitiya Co.Est.	1.024	1.241	-0.593	-0.593	-0.113	-0.113	-0.592	-0.592
Kandaketiya	0.078	0.078	0.619	0.619	-0.445	-0.371	**1.770**	**2.049[a]**
Ekiriyankumbura	-0.902	-0.902	-0.397	-0.397	-0.453	-0.453	0.480	0.480
Aluthnuwara	0.682	0.682	-0.017	-0.017	-1.442	-1.614	0.776	0.776
Padiyathalawa MOH	-0.169	-0.169	-0.593	-0.593	-0.931	-0.931	-0.056	-0.068
Maduru Oya	-1.051	-1.057	-1.318	-1.318	-1.545	-1.545	-1.164	-1.164
Kudasigiriya	-1.552	-1.552	**-1.917**	**-1.917**	0.734	0.734	0.906	**1.959**
Polonnaruwa	-0.420	-0.562	-1.076	-1.076	-0.265	-0.338	0.466	1.157
Valchchena	0.494	0.494	0.569	0.569	-0.967	-0.967	0.967	0.967

Stations	Sep		Oct		Nov		Dec	
	MK	**MMK**	**MK**	**MMK**	**MK**	**MMK**	**MK**	**MMK**
Welipitiya Co.Est.	-1.241	**-3.009[b]**	-0.790	-0.790	0.169	0.169	0.338	0.338
Kandaketiya	-0.325	-0.325	-0.325	-0.325	**2.123[a]**	**2.123[a]**	-0.232	-0.232
Ekiriyankumbura	-1.410	-1.410	-0.733	-0.733	**-1.748**	**-1.748**	-0.282	-0.555
Aluthnuwara	-1.224	-1.163	0.589	0.589	**3.021[b]**	**3.021[b]**	-0.108	-0.133
Padiyathalawa MOH	-0.451	-0.451	0.113	0.113	-0.169	-0.169	0.282	0.282
Maduru Oya	-1.332	**-2.295[a]**	1.219	1.219	1.201	**1.892**	0.994	0.994
Kudasigiriya	-0.785	**-1.973[a]**	-0.211	-0.211	1.359	1.359	**1.963[a]**	**1.963[a]**
Polonnaruwa	**-2.758[b]**	**-7.345[b]**	0.976	0.976	1.596	1.596	1.317	1.317
Valchchena	0.000	0.000	0.833	0.833	0.455	0.455	-0.076	-0.076

Note: Numbers in bold indicate significant values at the 10 % level

[a] Significant at the 5% level

[b] Significant at the 1% level

Almost half of the cases showed negative trends with the other half showing positive trends when the monthly trend was analyzed in MK and MMK tests. However, the majority of the time series showed insignificant trends.

Results obtained in the analysis of monthly time series revealed that from the 108 cases analyzed, eight (8) cases in MK test and eleven (11) cases in MMK test showed statistically significant positive trends at 10% significance level. However, only three (3) cases in MK test and six (6) cases in MMK test indicated statistically significant negative trends. Similarly, when it comes to the significance level of 1%, two (2) cases showed statistically significant increasing trend while only one (1) case showed statistically significant decreasing trend by using MK test. Further, for the same significance level, MMK test produced four (4) statistically significant upward trends and two (2) statistically significant downward trends. For the significance level of 5%, five (5) cases in MK test and eight cases (8) in MMK test exhibited a statistically significant increasing trend. Likewise, while four (4) cases revealed a statistically significant negative trend in MMK test, only one significant decreasing trend was revealed at this significance level for MK test. Moreover, there were no significant trends witnessed in February, May, July and October at any station considered using any of the two tests adopted.

It is notable that the majority number of the stations considered revealed an upward trend in April, while most of the stations witnessed decreasing trends in June, July and September when using MK and MMK tests.

4.1.1.2 Seasonal trends

Trend analysis for the seasonal time series was carried out under two categories; cropping seasons and rainfall seasons. Results obtained from Mann-Kendall and Modified Mann-Kendall tests for seasonal precipitation records of all nine rainfall stations considered are given in Table 4-3 and Table 4-4. Table 4-3 shows the results of cropping seasonal analysis while Table 4-4 shows rainfall seasonal analysis.

Table 4-3: Values of *Z*-statistic and *P*-value for seasonal rainfall using both MK and MMK Tests for Maduru Oya basin (Cropping season)

Station	Maha Season				Yala Season			
	MK	***P*-value**	**MMK**	***P*-value**	**MK**	***P*-value**	**MMK**	***P*-value**
Welipitiya Co. Es.	0.26	0.79	0.76	0.45	0.00	1.00	0.00	1.00
Kandaketiya	1.60	0.11	1.60	0.11	**1.75**	0.08	**1.75**	0.08
Ekiriyankumbura	-0.53	0.60	-1.40	0.16	-0.69	0.49	-1.17	0.24
Aluthnuwara	**1.96** [a]	0.05	**1.96** [a]	0.05	0.39	0.70	0.39	0.70
Padiyathalawa MOH	0.58	0.56	0.58	0.56	0.48	0.63	0.48	0.63
Maduru Oya	1.50	0.13	1.50	0.13	-1.25	0.21	-1.25	0.21
Kudasigiriya	0.85	0.40	0.85	0.40	-0.40	0.69	-0.40	0.69
Polonnaruwa	**2.46** [b]	0.01	**2.46** [b]	0.01	-1.04	0.30	-1.04	0.30
Valachchena	0.00	1.00	0.00	1.00	-0.35	0.73	-0.58	0.56

Note: Numbers in bold indicate significant values at the 10 % level
[a] Significant at the 5% level
[b] Significant at the 1% level

Seven out of nine stations revealed increasing trends in rainfall in Maha season using MK and MMK tests where Polonnaruwa witnessed a significant increasing trend at a significance level of 1% while Aluthunuwara revealed a significant increasing trend at a significance level of 5%. In Maha season, Ekiriyankumbura is the only station which revealed an insignificant negative trend in both MK and MMK tests.

At the seasonal time scale of Yala, five stations among nine stations considered revealed an insignificant decreasing trend. Out of three rainfall stations witnessing an increasing trend, only Kandaketiya station revealed a significant trend at a significance level of 10%. Notably, Ekiriyankumbura showed a decreasing trend in both Maha and Yala seasons.

Table 4-4 : Values of *Z*-statistic and *P*-value for seasonal rainfall using both MK and MMK Tests for Maduru Oya basin (Rainfall season)

Stations	FIM		SIM		NEM		SWM	
	MK	**MMK**	**MK**	**MMK**	**MK**	**MMK**	**MK**	**MMK**
Welipitiya Co.Es.	1.53	1.36	-0.16	-0.16	-0.26	-0.26	-0.69	-0.69
Kandaketiya	0.28	0.22	1.41	**1.65**	1.10	1.10	0.90	0.90
Ekiriyankumbura	1.06	1.06	-1.11	-1.11	-0.32	-0.34	-0.74	-0.74
Aluthnuwara	1.33	1.33	**2.76** [b]	**2.76** [b]	0.98	0.99	-0.83	-0.83
Padiyathalawa MOH	**1.95**	**1.95**	-0.05	-0.05	0.00	0.00	-0.26	-0.26
Maduru Oya	0.71	0.71	1.64	1.64	0.50	0.64	**-2.03** [a]	**-2.03** [a]
Kudasigiriya	**1.95**	1.47	0.06	0.06	0.39	0.39	-0.69	-0.69
Polonnaruwa	0.45	0.45	**2.31** [a]	**2.31** [a]	**1.72**	**1.72**	**-1.81**	**-1.81**
Valachchena	-1.12	-1.12	0.35	0.35	0.84	0.84	-0.15	-0.42

Note: Numbers in bold indicate significant values at the 10 % level
[a] Significant at the 5% level
[b] Significant at the 1% level

In First Inter Monsoon (FIM) season, all stations except Valachchena showed an increasing trend in MK and MMK tests where Padiyathalawa MOH exhibited a positive trend which is significant at a significance level of 10% in both tests and Kudasigiriya revealed significant upward trend at a significance level of 10% only in MK test. Contrastingly, strong negative trends in rainfall dominated in the South-West Monsoon (SWM) season with only Kandaketiya station showing a positive trend. In SWM, all stations showed insignificant trends except Maduru Oya which has a significantly decreasing trend at a significance level of 5% and Polonnaruwa, a significant negative trend at 10% significance level.

For Second Inter Monsoon (SIM) season, Welipitiya Coconut Estate, Ekriryankumbura and Padiyathalwa showed insignificant decreasing trends in both Kendall tests. Out of six stations with positive trends, Aluthnuwara witnessed a significant trend at a significance level of 1% and Polonnaruwa revealed a significant trend at 5% significance level in both MK and MMK tests. Further, Kandaketiya exhibited a significant trend at a significance level of 10% only in Modified Mann Kendall test.

In North-East Monsoon (NEM), two stations witnessed downward trends and six stations revealed upward trends. However, only Polonnaruwa station has been identified to be witnessing an increasing trend which is significant at a 10% significance level.

4.1.2 Sen's slope estimator

The magnitudes of the trends of rainfall series under different time scale were estimated using Sen's slope estimator and the results obtained for annual and seasonal data are given in Table 4-5.

Table 4-5: Magnitudes of slope obtained for annual and seasonal time scale using Sen's Slope Estimator

Station	Annual	Maha	Yala	FIM	SWM	SIM	NEM
Welipitiya Co. Est.	-3.66	3.05	-0.10	6.06	-2.18	-1.27	-2.20
Kandaketiya	16.82	13.18	3.30	0.53	1.25	4.14	7.95
Ekiriyankumbura	-6.54	-14.19	-4.60	5.13	-5.37	-11.68	-7.28
Aluthnuwara	19.77	19.97	1.35	4.55	-1.69	11.60	6.86
Padiyathalawa MOH	15.56	11.92	3.53	6.43	-1.78	-0.60	-0.92
Maduru Oya	15.72	18.46	-4.57	1.43	-7.54	9.04	3.70
Kudasigiriya	36.64	14.95	-1.76	5.37	-2.55	2.91	5.53
Polonnaruwa	18.67	18.09	-2.66	0.81	-3.92	8.09	10.51
Valachchena	-0.33	0.73	-1.80	-4.71	-0.93	3.68	11.74

When considering annual rainfall series, the magnitude of the positive trend varies from 15.56 mm/year at Padiyathalawa MOH to 36.64 mm/year at Kudasigiriya station. Ekiriyankumbura has the maximum reduction of rainfall value of 6.54 mm/year in annual time scale.

In the seasonal analysis, all stations except Ekiriyankumbura have positive trend which falls in the range of 0.73 mm/season at Valachchena to 19.97 mm/season at Aluthnuwara station in Maha season. The seasonal reduction in Maha season for Ekiriyankumbura is 14.19 mm/season.

Contrastingly, a major number of stations have negative trends ranging from 0.1 mm/season to 4.6 mm/season in Yala season. Kandaketiya, Aluthnuwara and Padiyathalawa MOH stations have a seasonal increment of rainfall which is also the same in Maha season as well.

In First Inter Monsoon season (FIM), Valachchena is the only station which has a negative trend of 4.71 mm/season. All the remaining stations give a positive value of the Sen's slope estimator ranging from 0.53 mm/season to 6.43 mm/season. Both North East Monsoon (NEM) and Second Inter Monsoon (SIM) have three negative trends in Welipitiya Coconut Estate, Ekiriyankumbura and Padiyathalawa MOH stations. Positive trends in SIM lie between 2.91 mm/season at Kudasigiriya and 11.60 mm/season at Aluthnuwara whereas for NEM, it ranges from 3.7 mm/season at Maduru Oya to 11.74 mm/season at Valachchena station. When it comes to South West Monsoon (SWM), only Kandaketiya station has a positive trend with a magnitude of 1.25 mm/season. All the other eight stations have negative trends of magnitude varying between 0.93 mm/ year at Valachchena and 7.54 mm/season at Maduru Oya station.

Table 4-6: Magnitudes of slope obtained for monthly data using Sen's Slope Estimator

Stations	**Sen's Slope**											
	Jan	**Feb**	**Mar**	**Apr**	**May**	**Jun**	**Jul**	**Aug**	**Sep**	**Oct**	**Nov**	**Dec**
Welipitiya Co.Est.	-1.66	-2.62	3.99	1.63	2.10	-0.53	0.00	-0.70	-2.63	-5.09	1.93	0.71
Kandaketiya	2.09	2.95	0.00	1.06	0.00	0.00	0.00	9.66	-0.13	-0.75	4.84	-0.82
Ekiriyankumbura	7.88	-5.78	4.35	-1.34	-2.07	-0.11	-0.57	1.40	-6.99	-4.20	-7.20	-3.31
Aluthnuwara	2.58	3.03	0.00	2.90	0.51	0.00	-0.61	0.29	-1.59	1.57	9.19	-0.63
Padiyathalawa MOH	6.82	-3.80	3.09	1.40	-0.45	-0.61	-1.21	-0.16	-1.55	0.98	-0.72	3.06
Maduru Oya	-5.13	2.35	0.22	1.95	-0.88	0.00	-0.98	-1.41	-2.92	4.03	3.39	5.81
Kudasigiriya	-8.98	-4.58	5.10	1.45	-2.55	0.00	0.48	1.64	-1.61	-1.01	7.54	22.34
Polonnaruwa	0.80	2.08	-0.09	0.69	-0.14	0.00	0.00	0.24	-4.60	2.63	4.46	4.91
Valachchena	14.40	2.13	-3.23	0.66	0.70	0.00	-1.48	0.50	0.03	2.29	4.46	-0.16

From Table 4-6 summarizing Sen's slope results of monthly rainfall records, it can be said that the entire set of the stations used in the study have both negative and positive values of the Sen's slope estimator throughout the year. Most of the stations have positive trends in April, August and November. Rainfall during September shows a negative trend ranging from 0.13 mm/month at Kandaketiya to 6.99 mm/month at Ekiriyankumbura except for Valachchena which has a positive trend of 0.03 mm/month. On the contrary, rainfall during April has a positive trend varying from 0.66 mm/month at Valachchena to 2.90 mm/month at Aluthnuwara except for Ekiriyankumbura with a negative trend of 1.34 mm/month. The highest positive trend of the considered time period is detected at Kudasigiriya station during December. Likewise, the highest negative slope is detected as 8.98 mm/month in the month of January at Kudasigiriya station. In June, six out of nine stations considered show no trend value and the remaining three stations have negative values of the Sen's estimator.

4.2 Streamflow Elasticity Analysis

Streamflow elasticity analysis was performed only on Padiyathalawa sub-basin located in the upstream part of Maduru Oya river basin. This analysis was carried out both by using a non-parametric estimator initially established by Sankarasubramanian, Vogel, & Limbrunner (2001) and then using the hydrological modelling approach as well. In the present study, due to the limited data accessibility, only the streamflow elasticity to rainfall is considered.

In the present study, the time period from October to September (water year) was used to add up to get the annual values and find out the annual average values of the required data. Figure 4-1 shows the variation of annual streamflow with annual precipitation over the 23 years considered. Accordingly, with a correlation coefficient of 0.56, it can be said that streamflow-rainfall relationship has a reasonably strong relationship.

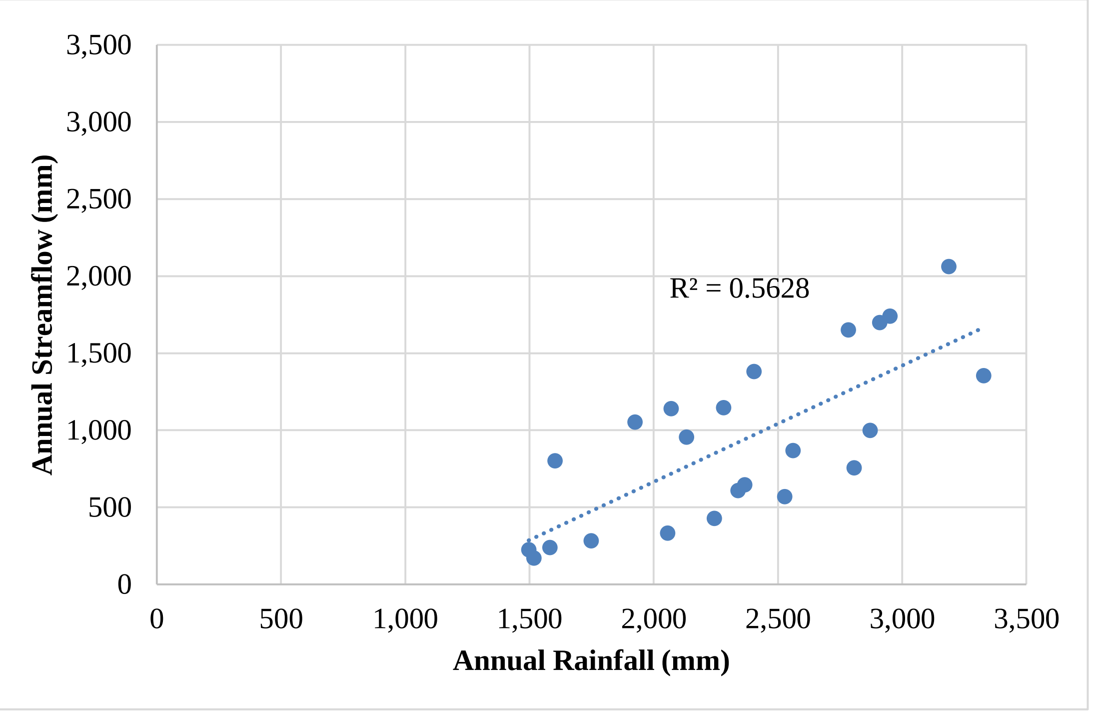

Figure 4-1: Annual variation of streamflow with rainfall from 1992 to 2015

Figure 4-2 shows the variation between average monthly rainfall and average monthly streamflow in Padiyathalawa sub-basin of Maduru Oya river basin for the period of 1992-2015. Both patterns are the same from October to March. The highest rainfall has been reported in December with rather lower rainfall has been measured in June and July. The lowest records of precipitation and streamflow for Padiyathalawa catchment have been observed to be occurring from March to September. However, when it comes to precipitation data, a small peak can be identified in April which later decreases up to June and then gradually increases up to September. Contrastingly, when streamflow data is considered, it gradually decreases up to September starting from March. This plot further depicts that during North-East Monsoon (December to February) and Second Inter Monsoon (October to November) periods, streamflow records of the catchment responds significantly well with the rainfall records.

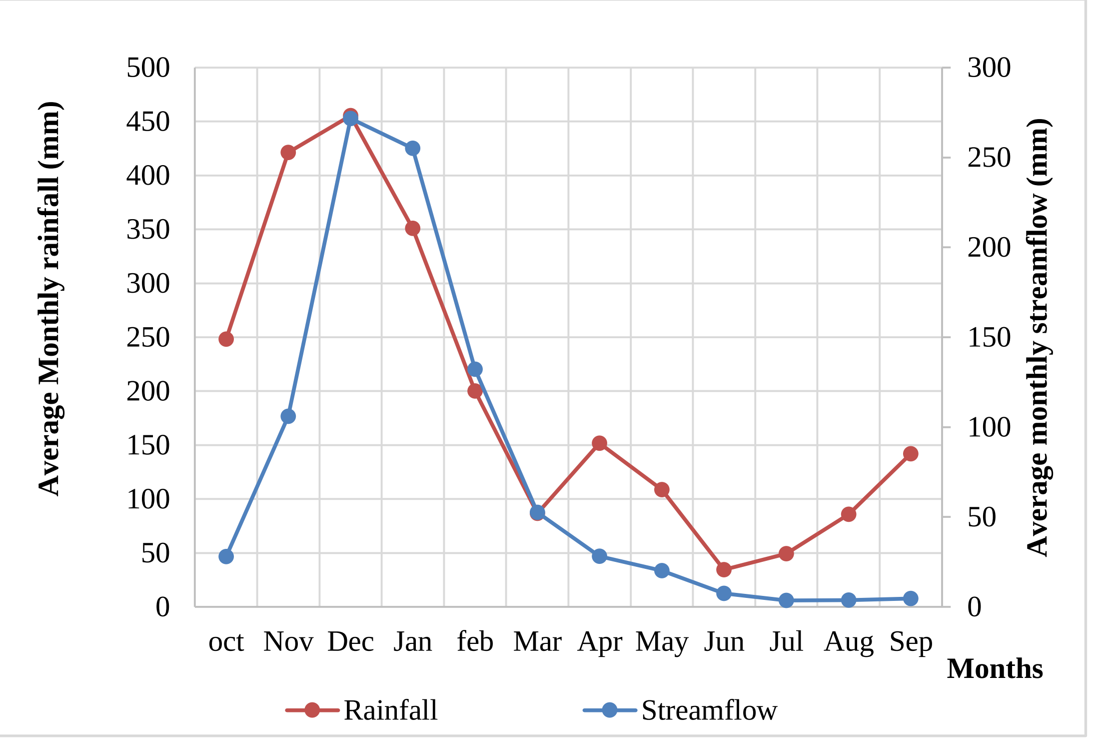

Figure 4-2: Variation of average monthly streamflow and average monthly rainfall

4.2.1 Non-parametric estimator

Daily rainfall data of three stations from which Thiessen average rainfall was calculated and daily streamflow data of Padiyathalawa river gauge from October 1992 to September 2015 (23 years) were considered in the streamflow elasticity analysis using observed records. In the present study, precipitation is the only climate variable that was used to calculate the streamflow elasticity using non-parametric approach.

Considering water year (October to September), the 23-years mean annual rainfall in Padiyathalawa sub-basin of Maduru Oya river basin is 2343 mm. On average, about 39.3% of precipitation, or 918 mm, becomes streamflow resulting in an average runoff coefficient of 0.39. Table 4-7 shows rainfall and streamflow statistics of the considered basin.

Table 4-7: Streamflow and Rainfall statistics of the basin

Hydroclimatic Statistics	**Padiyathalawa sub-basin**
Mean annual Q (mm)	917.6
Mean annual P (mm)	2342.9
Coefficient of variation of Q	0.59
Coefficient of variation of P	0.23
Correlation coefficient of P and Q	0.75
Standard deviation of Q (mm)	543.0
Standard deviation of P (mm)	542.5
Runoff coefficient	0.39

As per the non-parametric estimator used by Sankarasubramanian, Vogel, & Limbrunner (2001), for each pair of annual time series (*Pi, Qi)*, mean values of long term precipitation and streamflow values are deduced from the annual precipitation and annual streamflow to find out the change in precipitation and change in streamflow for each year. The output data are calculated for each year as given in Table 4-8. Further, the median of these outputs is found out which is defined to be the non-parametric estimate of ε_p .

Table 4-8: Non-parametric estimator calculation for 23 years in Padiyathalawa sub-basin

Year	Annual Streamflow (mm)	Annual Thiessen R/F (mm)	Change in streamflow (mm) $Q - \overline{Q}$	Change in precipitation (mm) $P_t \quad \overline{P}$	$\left(\frac{Q_t - \overline{Q}}{P_t - \overline{P}} \frac{\overline{P}}{\overline{Q}}\right)$
1992/1993	1052.7	1931.6	135.1	-411.3	-0.33
1993/1994	1651.0	2791.6	733.4	448.7	1.63
1994/1995	1353.7	3338.2	436.2	995.3	0.44
1995/1996	609.4	2347.6	-308.2	4.7	-65.52
1996/1997	238.0	1590.6	-679.5	-752.3	0.90
1997/1998	868.8	2569.8	-48.8	226.9	-0.21
1998/1999	955.1	2140.0	37.5	-202.9	-0.18
1999/2000	568.3	2536.6	-349.3	193.7	-1.80
2000/2001	645.7	2373.8	-271.9	30.9	-8.80
2001/2002	283.5	1755.9	-634.1	-587.0	1.08
2002/2003	755.3	2815.5	-162.3	472.6	-0.34
2003/2004	332.7	2064.5	-584.9	-278.4	2.10
2004/2005	1698.2	2918.7	780.6	575.8	1.36
2005/2006	1146.6	2290.8	229.0	-52.1	-4.40
2006/2007	1139.9	2078.3	222.3	-264.6	-0.84
2007/2008	999.1	2880.8	81.5	537.9	0.15
2008/2009	224.0	1504.4	-693.6	-838.5	0.83
2009/2010	426.9	2253.5	-490.7	-89.4	5.49
2010/2011	2062.3	3196.7	1144.8	853.8	1.34
2011/2012	802.0	1610.9	-115.5	-732.0	0.16
2012/2013	1380.1	2412.8	462.5	69.9	6.62
2013/2014	170.5	1524.5	-747.1	-818.4	0.91
2014/2015	1740.5	2959.5	822.9	616.6	1.33

Accordingly, the non-parametric estimator ε_p is estimated by finding the median value of $\left(\frac{Q_t - \overline{Q}}{P_t - \overline{P}} \frac{\overline{P}}{\overline{Q}}\right)$.

This gives a value of 1.12 to ε_p . This implies that the streamflow would change, on average, 11.2% for every 10% change in precipitation when considering the 23 years of historical data.

When adopting the approach suggested by Zheng, et al. (2009) to solve the issues related to small sample size, considering the gradient of the scatter plot between proportional changes of precipitation and streamflow as given in Figure 4-3, ε_p has been calculated to be 1.92 illustrating that a variation of 10% in precipitation would induce 19.2% change in streamflow in Maduru Oya river basin which is larger than that of the value obtained from the equation of Sankarasubramanian, Vogel, & Limbrunner (2001).

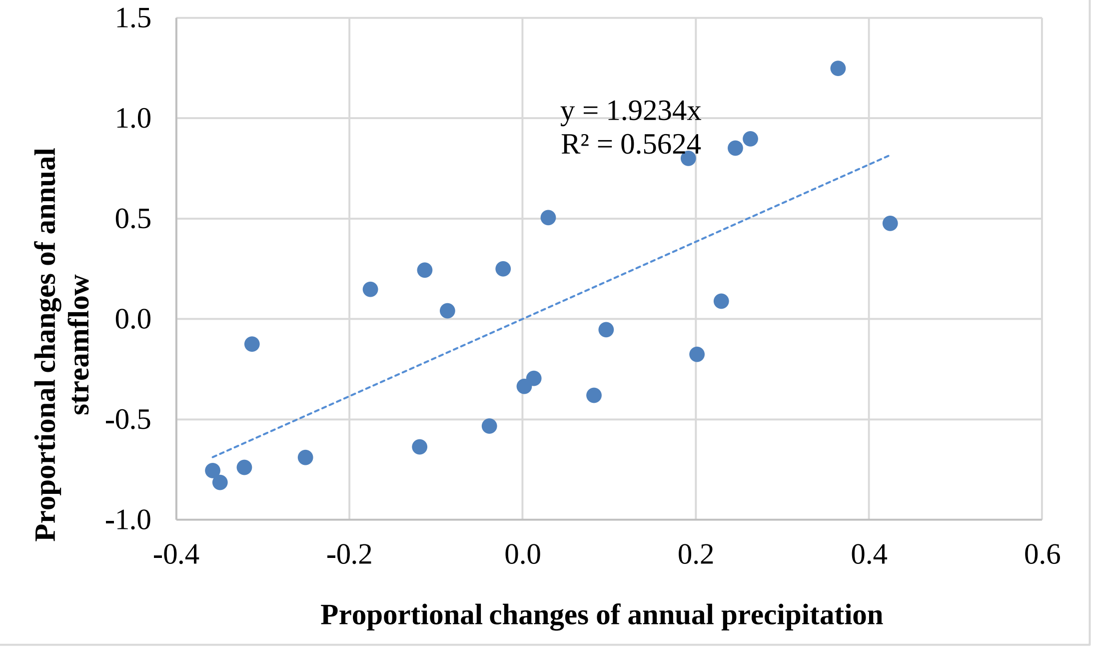

Figure 4-3: Relationship between proportional changes of annual streamflow and Proportional change of annual precipitation

4.2.2 Modeling approach

Streamflow elasticity to precipitation was estimated using a hydrological model based on HEC-HMS model platform as well.

4.2.2.1 Developing the basin model

The lumped model of Padiyathalawa sub-basin was developed to carry out the rainfall-runoff simulation in the present study.

4.2.2.2 Developing the loss model

Soil Moisture Accounting method has been identified to be the most commonly used appropriate method when continuous modelling of complex evapotranspiration and infiltration processes are involved (De Silva, Weerakon, & Herath, 2014; Sampath, Weerakon, & Herath, 2015; Kamran & Rajapakse, 2018). Much attention is not paid to the loss component in event-based modelling, however, it should be modelled carefully in continuous modelling. Because this method does not incorporate evaporation loss, observed evaporation data had to be fed into the model. Losses that could take place through surface and plant storage were represented with simple surface and simple canopy methods. The soil storage which is further split into tension and gravity storage and lower and upper groundwater percolation are computed in the soil moisture accounting loss method (Wicher, 2016). The soil storage is subdivided into tension storage and gravity storage. Canopy and surface components may also be added if interception and capture processes are needed to be represented (Scharffenberg, Bartles, Brauer, Fleming, & Greg, 2018).

The parameters required for this method are percolation or infiltration rate from one layer to other layer and maximum and initial storage of each layer and these were determined by optimization. However, the initial values of these parameters were necessary in order to start the model.

4.2.2.3 Developing the transform model

Here, excess rainfall is transformed into the direct runoff. Selection of a direct runoff model differs from one user to another depending on his preference and data available for estimating parameters and model calibration (Cunderlik & Simonovic, 2004). One frequently adopted approach in rainfall-runoff modelling is Clark Unit Hydrograph (De Silva, Weerakon, & Herath, 2014; Sampath, Weerakon, & Herath, 2015; Kamran & Rajapakse, 2018). Translation and attenuation are the two key processes that are represented in this method. Here, attenuation process is represented by a linear reservoir that constitutes the influences of all basin storage while the translation process is dependent on a synthetic time-area histogram and time of concentration (Cunderlik & Simonovic, 2004).

The parameter, Time of concentration (Tc) was calculated using different equations proposed by different researchers as given in Table 4-9 (Kamran & Rajapakse, 2018).

The length of the longest channel path of Padiyathalawa sub-basin is 32.2 km. The channel slope is found out to be 0.0016 km/km.

Table 4-9: Calculation of time of concentration using different empirical equations

Methods	**Time of Concentration (hours)**
Kirpich Equation	10.4
Bransby-William formula	17.2
Ven Te Chow equation	11.8

4.2.2.4 Developing the baseflow model

The contribution of baseflow to sub-basin outflow is represented by five various approaches in HEC-HMS. Out of these, recession baseflow model was selected based on past studies and the number of parameters (De Silva, Weerakon, & Herath, 2014; Sampath, Weerakon, & Herath, 2015; Kamran & Rajapakse, 2018). Here, the flow at the starting of the simulation was considered as the initial flow (Kamran & Rajapakse, 2018). An exponentially reducing baseflow established from the usual baseflow separation methods is adopted in recession baseflow method (Cunderlik & Simonovic, 2004).

4.2.2.5 Development of time series data manager

Thiessen average rainfall based on the gauge weight and daily evaporation data for a nearby evaporation station were used in the time series data manager. Thiessen polygon for Padiyathalawa watershed was created with the help of Arc GIS and Table 4-10 summarizes the Thiessen weight calculated for each sub-basin.

Table 4-10: Thiessen area and weight in Padiyathalawa sub-basin

Station Name	**Area(km^2)**	**Weightage**
Welipitiya Co. Est.	30.7	0.18
Ekiriyankumbura	120.7	0.71
Padiyathalawa MOH	19.5	0.11

Daily Thiessen average rainfall using the above selected rain-gauge stations, daily streamflow data of Padiyathalawa gauging station and daily evaporation data of Girandurukotte evaporation station were used as inputs to the model.

4.2.2.6 Control specification

In the model calibration process, 01 October 1992 and 30 September 1996 were fixed as the starting and ending dates based on four water years while the simulation time interval was set to 1 day.

4.2.2.7 Model calibration

This process includes systematic approaches of fine-tuning the values of parameters until the output hydrograph obtained from the model and that obtained using observed data match with each other (Cunderlik & Simonovic, 2004). In the present study, the model was calibrated using four years of data during October 1992 to September 1996. Calibration can be performed either manually or automatically with the help of the optimization manager that allows automated model calibration.

Initial parameters were selected based on the past study carried out by Kamran & Rajapakse, (2018) on a Sri Lankan river basin. First, manual calibration was performed after which automatic calibration was carried out for the purpose of optimization of the parameters with the help of optimization trial manger available in

HEC-HMS. The parameters are considered to be optimum when the changes in the selected objective functions are no more significant.

4.2.2.8 Selection of objective functions

Depending on the past studies carried out in Sri Lankan river basins, Nash-Sutcliff Efficiency and Mean Ratio of Absolute Error (MRAE) (De Silva, Weerakon, & Herath, 2014; Kamran & Rajapakse, 2018; Sampath, Weerakon, & Herath, 2015) were adopted to check the error in model calibration. The initial values of the parameters were changed in a way that it gives a negligible change in objective functions. The parameters that give almost zero change in the objective function are the optimum parameters. Here, MRAE measures the error with respect to each measured value and thereby it calculates the error between the shape of the hydrograph of observed data and modelled data. Nash-Sutcliff Efficiency coefficient was used to calculate the error by matching the peaks of observed and modelled hydrographs. The percentage of annual mass balance error of Padiyathalawa lumped model was also checked to evaluate the deviation between observed and simulated flow. Out of two search algorithms given, Univariate Gradient method was selected in the present study.

4.2.2.9 Model verification

Model verification was performed using a different set of observed data. Optimized parameters found out during calibration are used during this process.

4.2.2.10 Model output

4.2.2.10.1 Model performance using initial parameters

The initial parameter values considered in the model are summarized in Table 4-11. The model performance was checked using Nash-Sutcliff Efficiency, Mean Ratio of Absolute Error (MRAE) and the percentage of annual mass balance error.

Table 4-11- Initial parameters used in the initial trial

Parameters	Unit	Initial values
Loss Parameters		
Soil Moisture Accounting - GW1 Percolation	mm/hr	0.3
Soil Moisture Accounting - GW1 Storage	mm	40
Soil Moisture Accounting - GW1 Storage Coefficient	hr	10.2
Soil Moisture Accounting - GW2 Percolation	mm/hr	0.25
Soil Moisture Accounting - GW2 Storage	mm	10
Soil Moisture Accounting - GW2 Storage Coefficient	hr	30
Soil Moisture Accounting - Initial GW1 Content	%	80
Soil Moisture Accounting - Initial GW2 Content	%	90
Soil Moisture Accounting - Initial Soil Content	%	90
Soil Moisture Accounting - Max Infiltration	mm/hr	4.5
Soil Moisture Accounting - Soil Percolation	mm/hr	0.8
Soil Moisture Accounting - Soil Storage	mm	500
Soil Moisture Accounting - Tension Storage	mm	23
Transform Parameters		
Clark Unit Hydrograph - Storage Coefficient	hr	15
Clark Unit Hydrograph - Time of Concentration	hr	20
Baseflow Parameters		
Recession - Initial Discharge	m^3/s	3.04
Recession - Ratio to Peak		0.164
Recession - Recession Constant		0.923
Canopy Parameters		
Initial storage	%	3
Maximum storage	mm	4
Surface Parameters		
Initial storage	%	3
Maximum storage	mm	4

Figure 4-4 and Figure 4-5 present the comparison between measured flow and modelled flow for year 1996/1997 in both normal and log scales respectively. The shapes of measured and modelled hydrographs show a reasonably good match. The comparison of observed and modelled hydrographs for the remaining years are presented in Appendix E.

The output hydrographs show a reasonably adequate model performance when using Nash-Sutcliff as the objective function with a value of 0.502. However, the model did not seem to produce a good result when the performance was checked using MRAE as the objective function as it gave an overall value of 0.765. Annual average mass balance error during the calibration period using initial parameters is 30.5%.

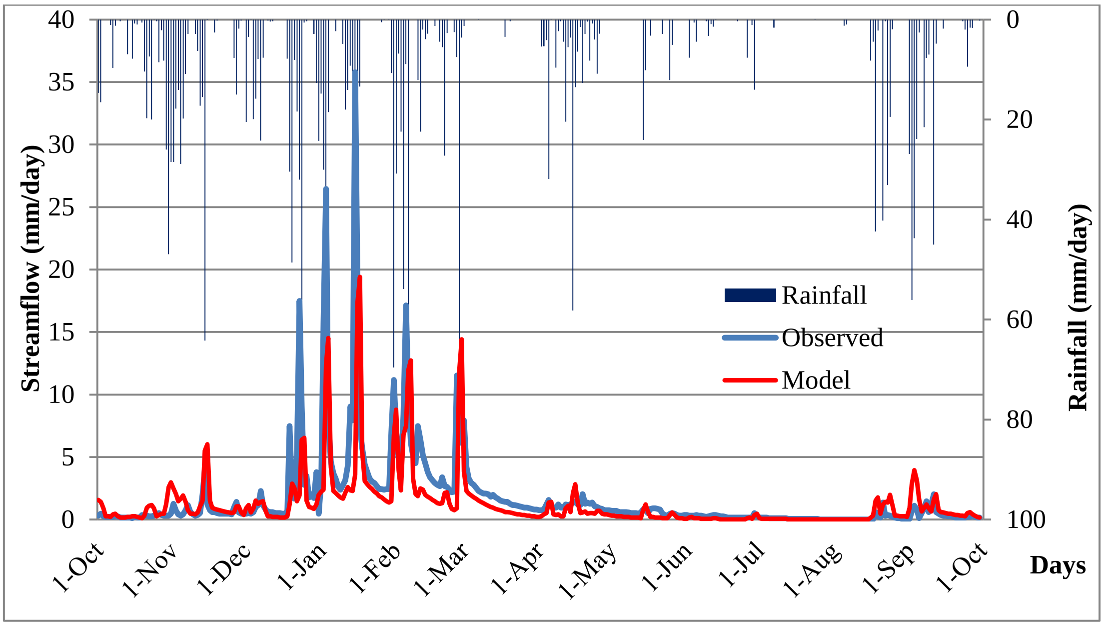

Figure 4-4:Outflow hydrograph with initial parameters for 1996/1997 at the calibration period (normal-scale)

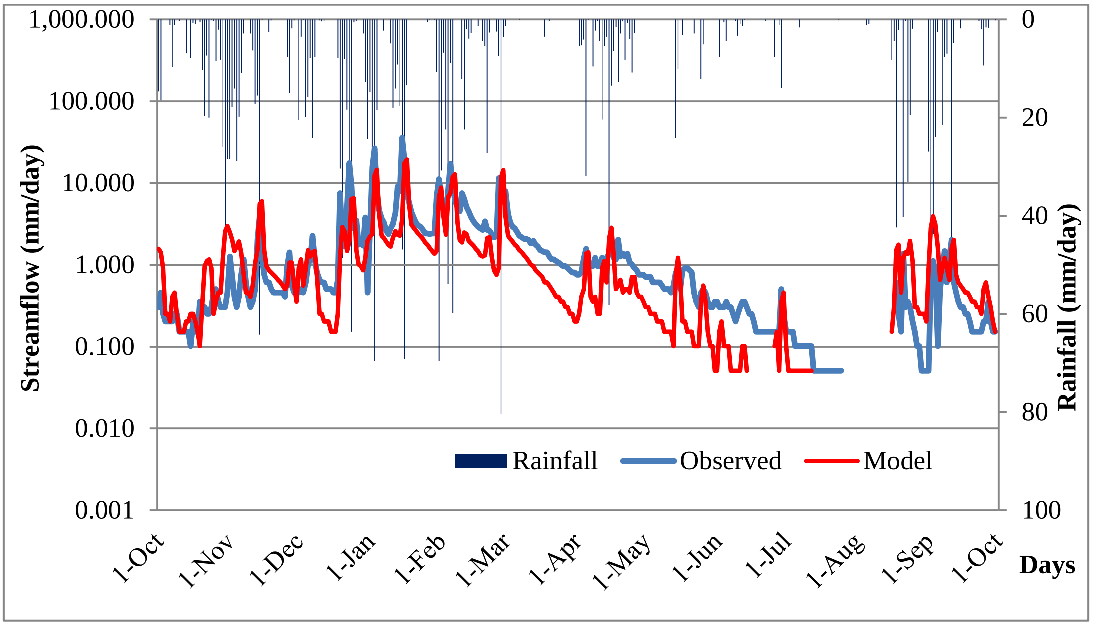

Figure 4-5:Outflow hydrograph with initial parameters for 1996/1997 at the calibration period (log-scale)

Figure 4-6 and Figure 4-7 show the flow duration curves in normal and semi-log scale, respectively. The flow duration curve was separated into three regions depending on the variation in its gradient. Probability Exceedance of less than 15% was considered as high flows while flows between 15% and 80% and that are above 80% were considered as medium flows and low flows, respectively.

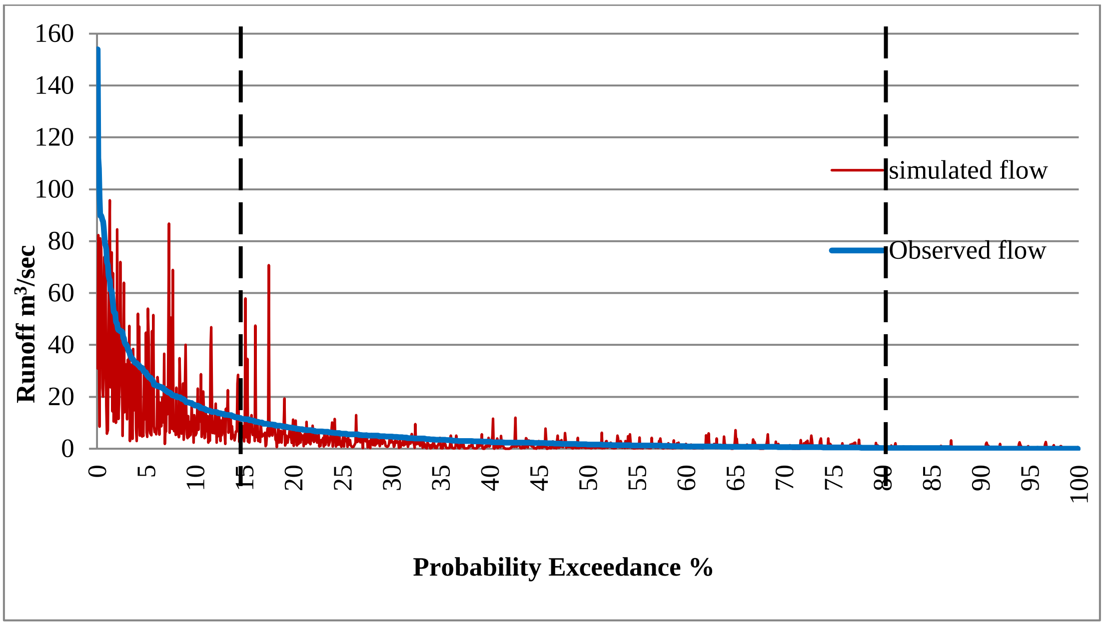

Figure 4-6:Flow Duration Curve (normal scale) with initial parameters in the calibration period (1992/1993 to 1995/1996)

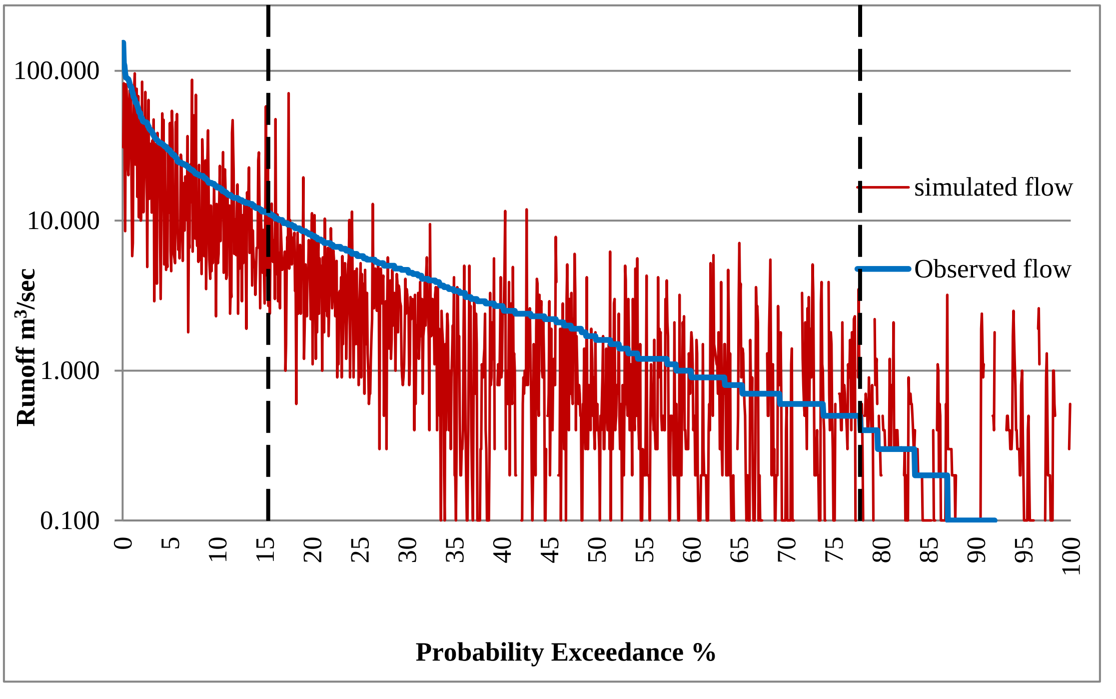

Figure 4-7:Flow Duration Curve (log-scale) with initial parameters in the calibration period (1992/1993 to 1995/1996)

Summary obtained for objective functions and mass balance error during the initial trial are respectively given in Table 4-12 and Table 4-13. Table 4-12 gives the values of objective functions in the above three flow regions considered. Accordingly, the model doesn't seem to respond well to rainfall in low and medium flow periods. Model responds in high flow period with an MRAE value of 0.559.

Table 4-12: Results obtained for objective functions in the initial trial

Objective function	Overall	High flow	Medium flow	Low flow
Nash-Sutcliffe Efficiency	0.502	-0.066	-0.579	-19.411
MRAE	0.765	0.559	0.778	0.884

Table 4-13: Annual Mass balance in Initial trial

Year	Annual Mass Balance Error (%)
1992/1993	35.3
1993/1994	46.1
1994/1995	14.6
1995/1996	26.0

4.2.2.10.2 Model performance in calibration period

The optimized parameters were obtained through manual and automatic calibration processes. Table 4-14 summarizes the optimized parameters of the model that gives low error values.

The outflow hydrographs of both observed and simulated streamflow corresponding to daily Thiessen rainfall obtained considering the selected rainfall stations for year 1996/1997 during calibration period are given in Figure 4-8 and Figure 4-9 respectively in normal and log scale. The output hydrographs for remaining calibration period are presented in Appendix E.

Table 4-14:Optimized parameters obtained in the calibration

Parameters	**Unit**	**Optimized Parameters**
Loss Parameters		
Soil Moisture Accounting - GW1 Percolation	mm/hr	0.20099
Soil Moisture Accounting - GW1 Storage	mm	26.629
Soil Moisture Accounting - GW1 Storage Coefficient	hr	9.8441
Soil Moisture Accounting - GW2 Percolation	mm/hr	0.16915
Soil Moisture Accounting - GW2 Storage	mm	6.7647
Soil Moisture Accounting - GW2 Storage Coefficient	hr	12.059
Soil Moisture Accounting - Initial GW1 Content	%	34.148
Soil Moisture Accounting - Initial GW2 Content	%	52.822
Soil Moisture Accounting - Initial Soil Content	%	48.02
Soil Moisture Accounting - Max Infiltration	mm/hr	4.3218
Soil Moisture Accounting - Soil Percolation	mm/hr	0.78094
Soil Moisture Accounting - Soil Storage	mm	480.2
Soil Moisture Accounting - Tension Storage	mm	34.36
Transform Parameters		
Clark Unit Hydrograph - Storage Coefficient	hr	16.093
Clark Unit Hydrograph - Time of Concentration	hr	22.029
Baseflow Parameters		
Recession - Initial Discharge	m^3/s	0.75
Recession - Ratio to Peak		0.175
Recession - Recession Constant		0.972
Canopy Parameters		
Initial storage	%	1.8824
Maximum storage	mm	2.6957
Surface Parameters		
Initial storage	%	2.7671
Maximum storage	mm	2.5098

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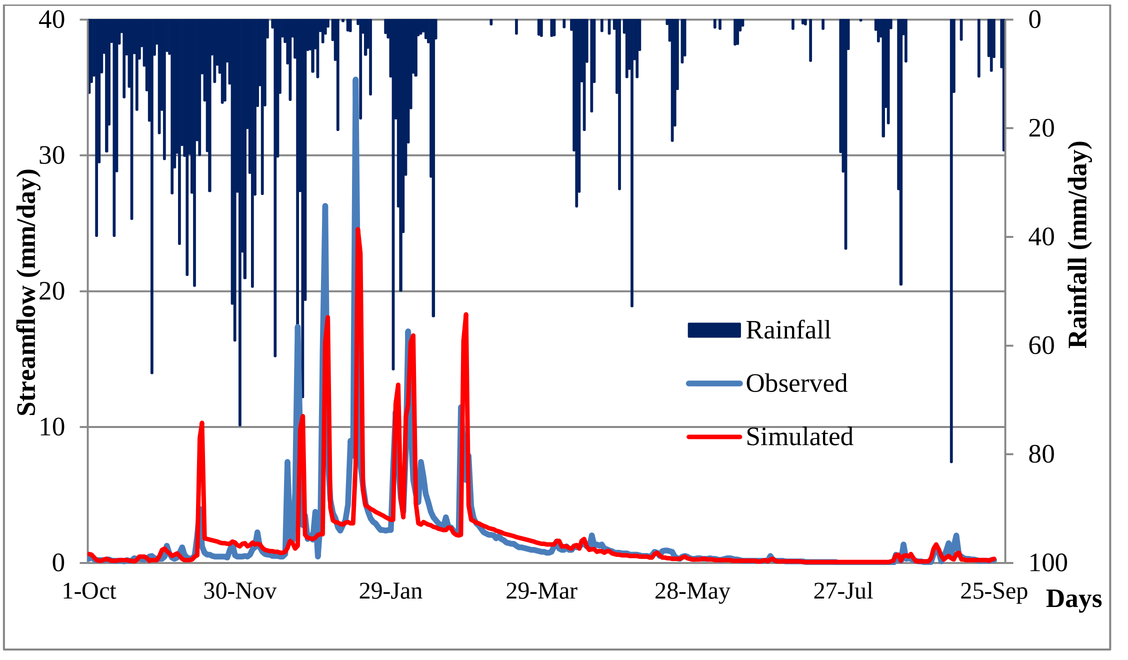

Figure 4-8:Outflow hydrograph with optimum parameters for 1996/1997 at the calibration period (normal-scale)

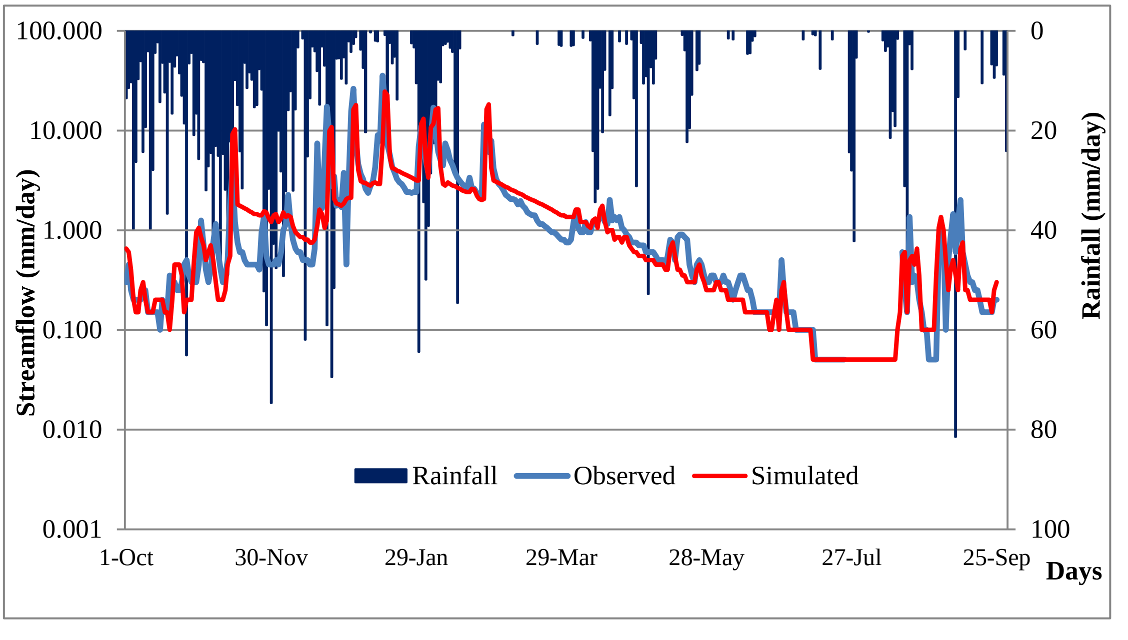

Figure 4-9:Outflow hydrograph with optimum parameters for 1996/1997 at the calibration period (log-scale)

Flow duration curve categorized into three different zones both in normal and semi-log scales are presented in Figure 4-10 and Figure 4-11 for sorted observed flow and unsorted simulated flow.

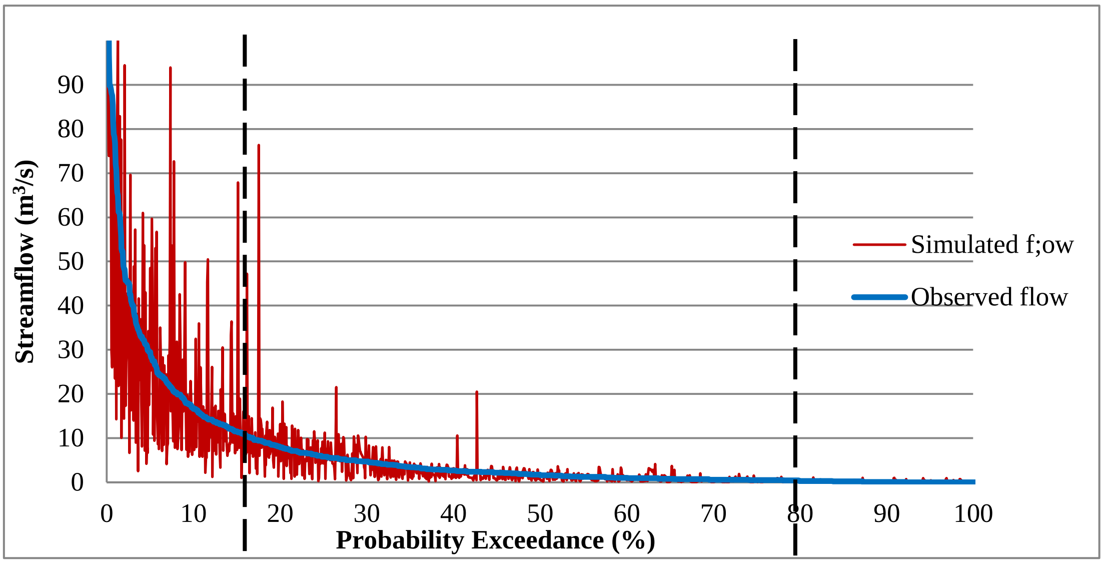

Figure 4-10: Flow Duration Curve (normal-scale) for optimum parameters in the calibration period (1992/1993 to 1995/1996) when observed flow is sorted

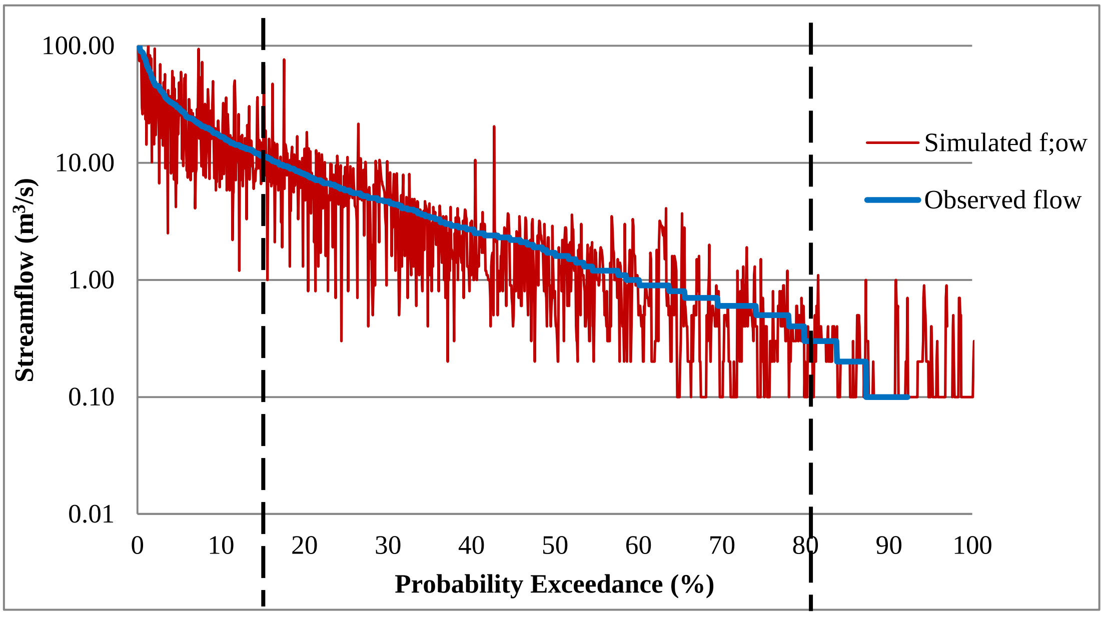

Figure 4-11: Flow Duration Curve (log-scale) for optimum parameters in the calibration period when observed flow is sorted

Figure 4-12 and Figure 4-13 present the flow duration curves when both observed and simulated flows are sorted.

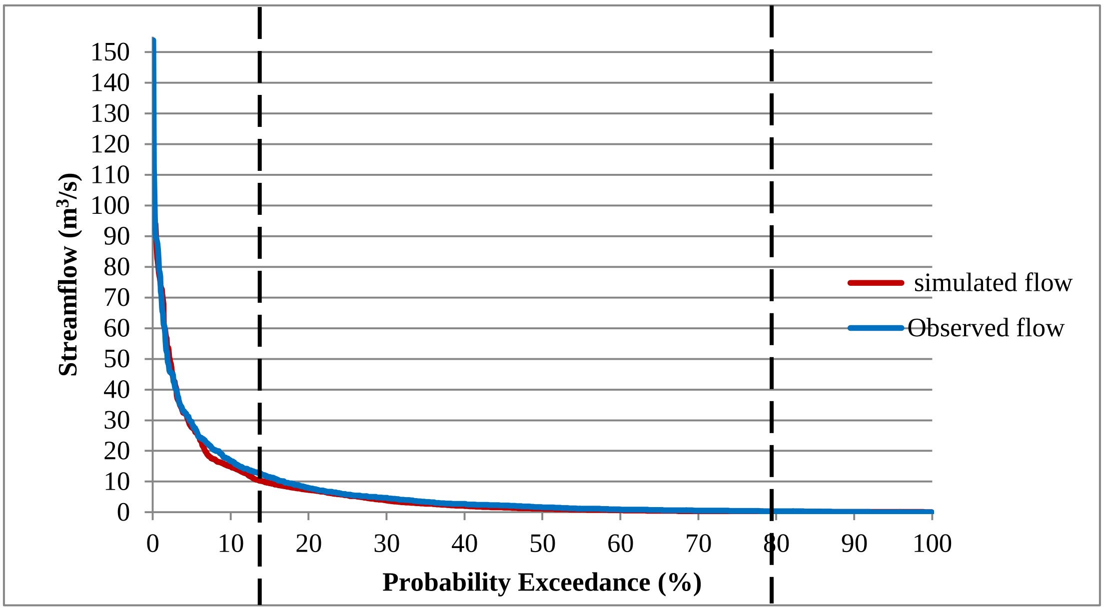

Figure 4-12: Flow Duration Curve (normal-scale) for optimum parameters in the calibration period (1992/1993 to 1995/1996) when observed and simulated flows are sorted

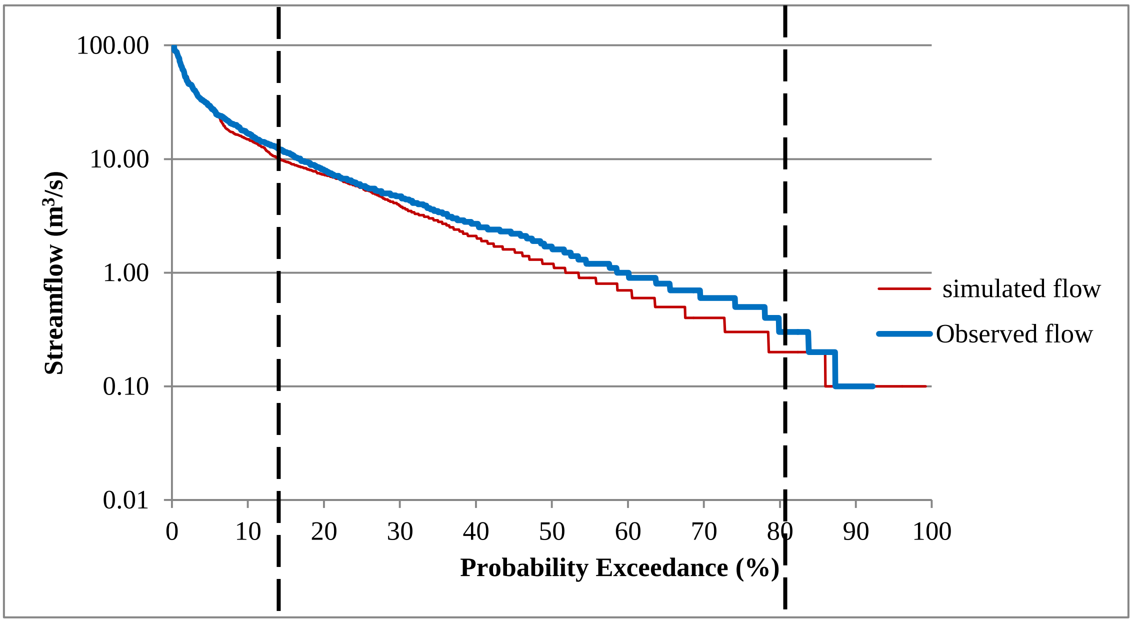

Figure 4-13: Flow Duration Curve (log-scale) for optimum parameters in the calibration period (1992/1993 to 1995/1996) when observed and simulated flows are sorted

Table 4-15 presents statistical measures of the model. The overall values of the objective functions Nash-Sutcliffe Efficiency and MRAE are 0.665 and 0.433 for the maximum calibrated model. Accordingly, it can be stated that the model performs well with the two objective functions selected. Good model performance can be noted in high, medium and low flow zones with MRAE values of 0.482, 0.459 and 0.304. The model response is good with Nash-Sutcliffe value of 0.310 in high flow zone and worse in low and medium flow zones with very low values as given in Table 4-15. Annual mass balance error obtained during calibration period is summarized in Table 4-16. Accordingly, the annual mass balance error is the highest in 1993/1994 and the lowest in 1995/1996.

Table 4-15: Results obtained for objective functions in the calibration period

Objective function	**Overall**	**High flow**	**Medium flow**	**Low flow**
Nash-Sutcliffe Efficiency	0.665	0.31	0.12	-2.48
MRAE	0.433	0.482	0.459	0.304

Table 4-16: Annual mass balance error in calibration

Year	**Annual Mass Balance Error (%)**
1992/1993	12.34
1993/1994	23.01
1994/1995	-8.01
1995/1996	0.51

4.2.2.10.3 Model performance in the verification period

The calibrated model was verified with a data set of a different period. The same optimized parameters obtained in calibration period were used and the model was run again. Figure 4-14 and Figure 4-15 present measured and modelled streamflow for 1998/1999 during the verification period in both normal scale and semi-log scale respectively. The output hydrographs for the remaining verification period are presented in Appendix E.

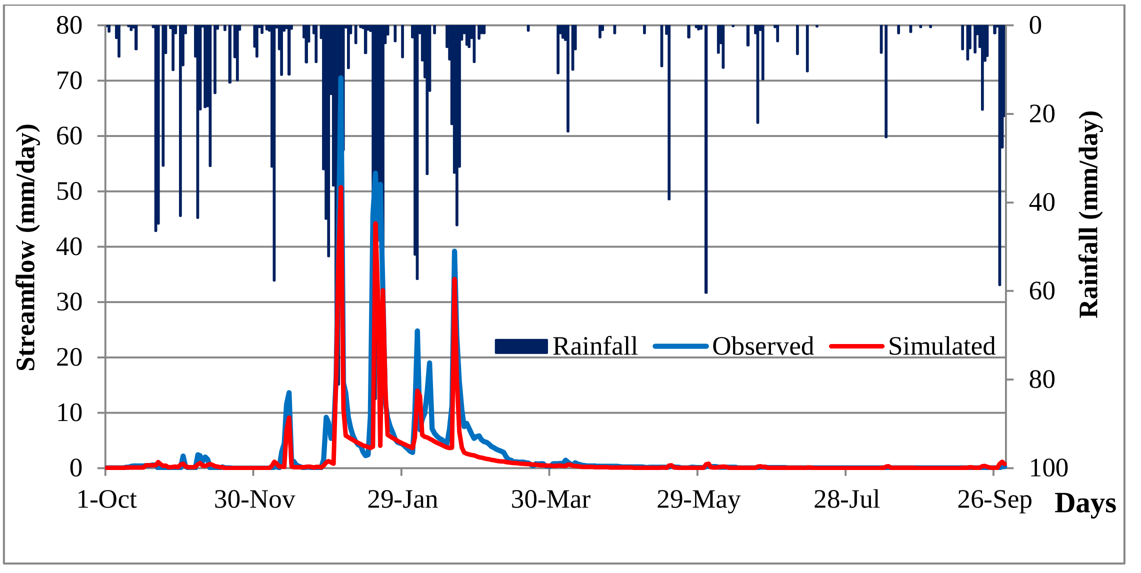

Figure 4-14: Outflow hydrograph for 1998/1999 at the verification period (normal-scale)

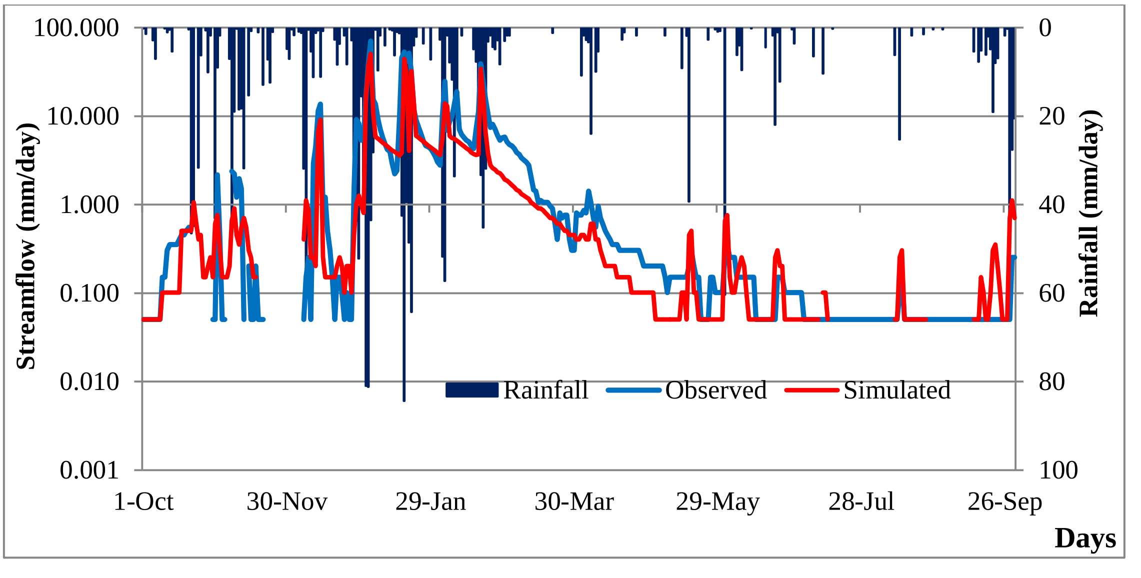

Figure 4-15:Outflow hydrograph for 1998/1999 at the verification period (log-scale)

Figure 4-16 and Figure 4-17 give the flow duration curves respectively in both scales when only the observed flow is sorted.

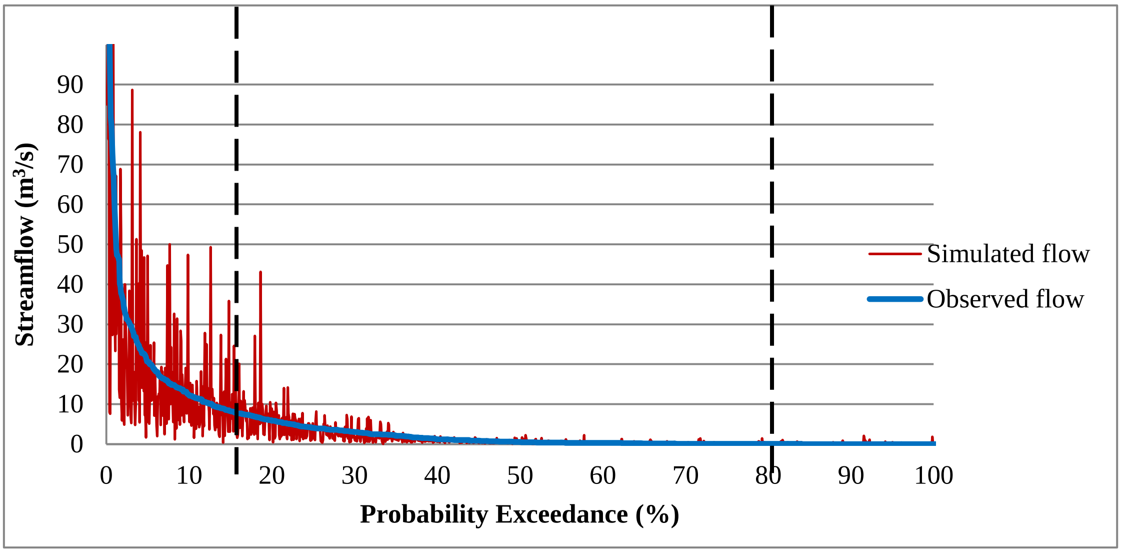

Figure 4-16:Flow Duration curve (normal scale) during the verification period (1997/1998 to 2000/2001) when observed flow is sorted

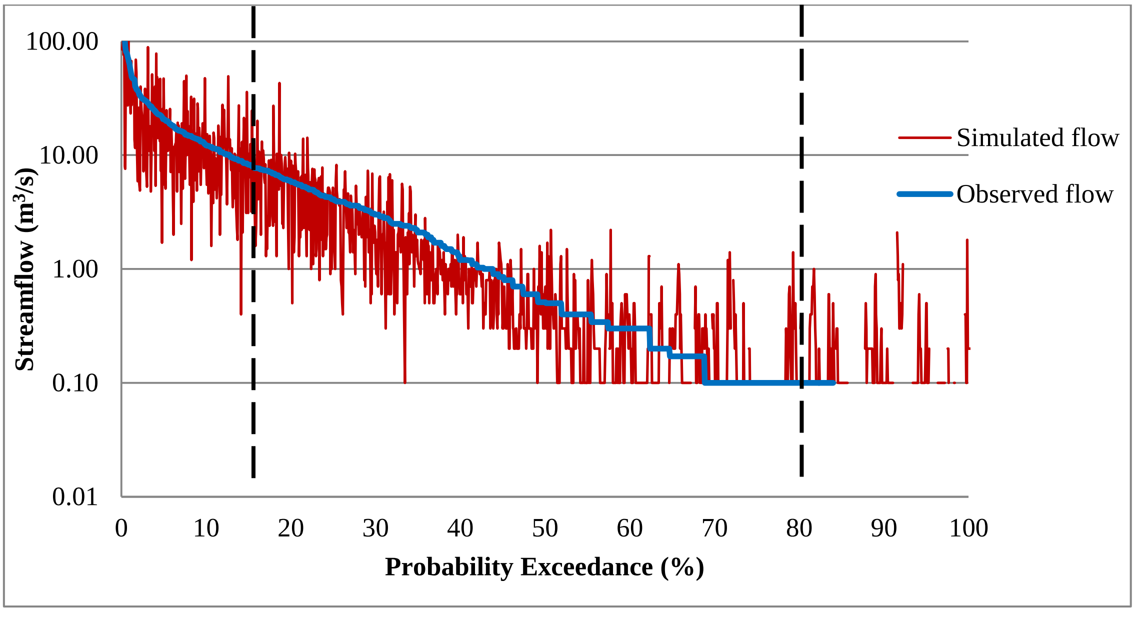

Figure 4-17:Flow Duration curve (log scale) during the verification period (1997/1998 to 2000/2001) when observed flow is sorted

Figure 4-18 and Figure 4-19 give the flow duration curves respectively in both scales when both the observed and simulated flows are sorted.

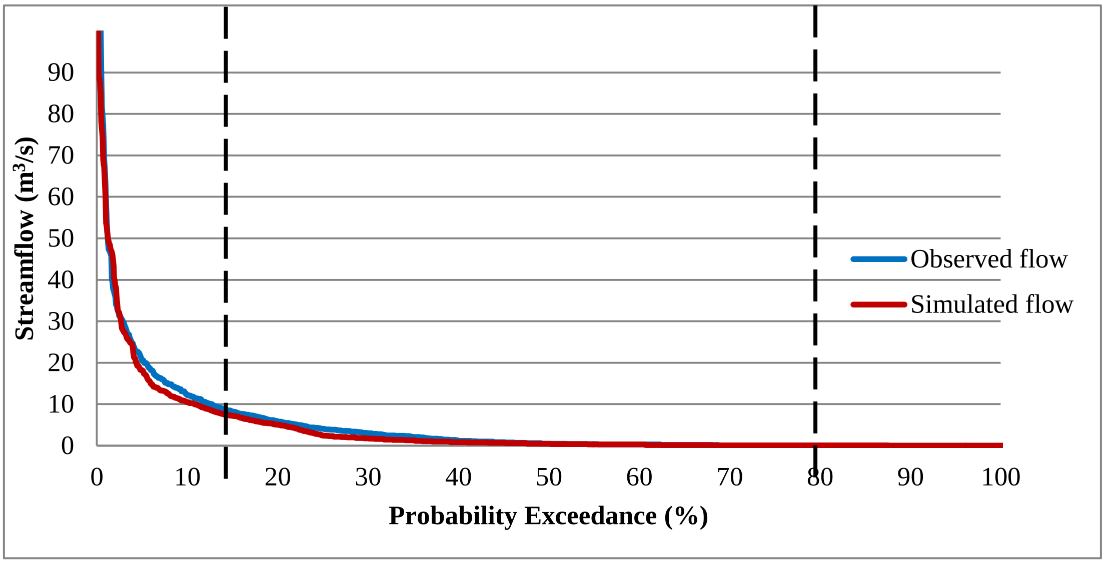

Figure 4-18:Flow Duration Curve (normal-scale) for optimum parameters in the verification period (1997/1998 to 2000/2001) when observed and simulated flows are sorted

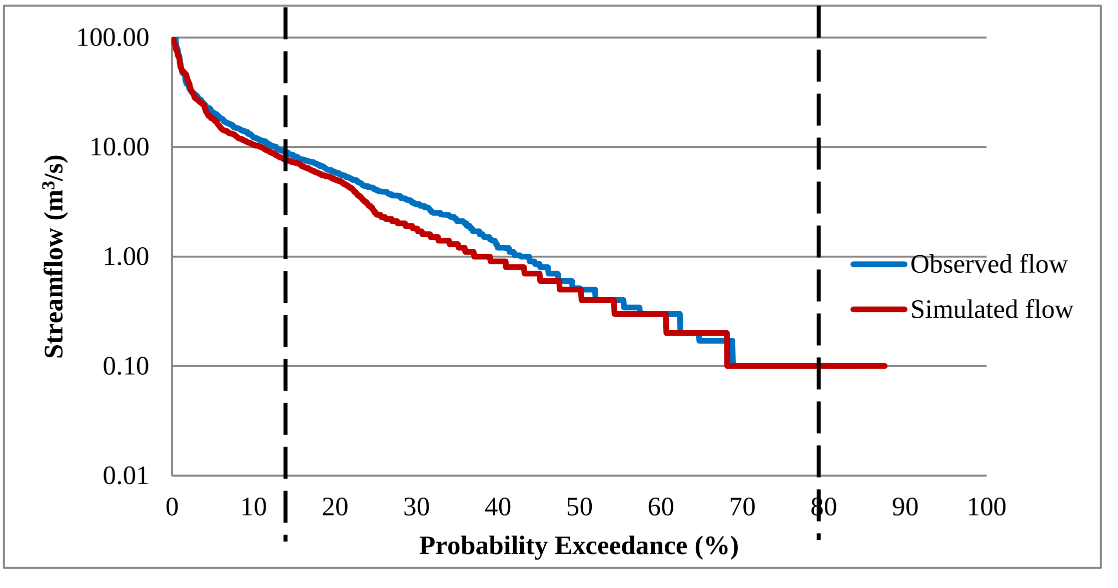

Figure 4-19:Flow Duration Curve (log-scale) for optimum parameters in the verification period (1997/1998 to 2000/2001) when observed and simulated flows are sorted

Table 4-17 presents statistical measures of the model during verification period. The overall values of the objective functions NSE and MRAE are 0.642 and 0.559 for the verification period.

Table 4-17: Results obtained for objective functions in the verification period

Objective function	Overall	High flow	Medium flow	Low flow
Nash-Sutcliffe Efficiency	0.642	0.394	0.078	-19.31
MRAE	0.559	0.515	0.662	0.253

Table 4-18 shows the water balance error of each year during the verification period. The error is the highest in year 1998/1999 and the lowest in 1997/1998.

Table 4-18: Annual mass balance error in the verification period

Year	Annual Mass Balance Error (%)
1997/1998	-17.87
1998/1999	36.49
1999/2000	-23.54
2000/2001	18.74

4.2.2.10.4 Streamflow elasticity estimation using the model

The data set in calibration period was considered to carry out this part of the study. According to the non-parametric estimator proposed by Sankarasubramanian, Vogel, & Limbrunner (2001), ε_p was found out to be 2.72 for the calibration period with observed data. However, the ε_p found out from the model was 2.01. According to the present study, ε_p from the observed flow is higher than that of the simulated flow.

After that, the potential influences of climate variability were investigated for the same period by finding out the streamflow elasticity to climate elements. In the modelling approach, both the input, rainfall and evapotranspiration were modified to incorporate the climate change impact and the variation in streamflow was monitored using the calibrated model.

For the calibrated model, the precipitation and evapotranspiration input data were scaled by a constant factor and combination of climate change scenarios were created to be used as the model input to get an idea of the influences made by the changes in climate on streamflow.

In this study, purely hypothetical scenarios were used for the analysis (Nash & Gleick, 1991). Rainfall was scaled by -20%, -10%, 0%, 10% and 20% while evapotranspiration was scaled by 0%, 5% and 10% and for different climatic conditions, streamflow variability was found by calculating the difference in the mean annual streamflow from that of the base scenario. The modelled mean annual streamflow with the original data without any modification was considered as the base scenario.

Table 4-19 shows the comparison of streamflow variation between the base scenario and modified scenarios which represent a hypothetical variation of climate elements such as rainfall and evapotranspiration in the catchment.

Table 4-19: Variation in streamflow due to variation in climate elements

Climate change scenarios	**Annual mean streamflow (m^3/s)**	**Variability in streamflow (%)**
Modelled streamflow with original data (Base)	5.77	0.00
ET +0% & RF -20%	2.72	-52.82
ET +0% & RF -10%	4.01	-30.41
ET +0% & RF +10%	6.95	20.42
ET +0% & RF +20%	8.54	48.10
ET +5% & RF -20%	2.72	-52.90
ET +5% & RF -10%	4.01	-30.50
ET +5% & RF +0%	5.41	-6.21
ET +5% & RF +10%	6.94	20.30
ET +5% & RF +20%	8.53	47.90
ET +10% & RF -20%	2.72	-52.91
ET +10% & RF -10%	4.00	-30.54
ET +10% & RF +0%	5.40	-6.30
ET +10% & RF +10%	6.93	20.09
ET +10% & RF +20%	8.53	47.8

For the Padiyathalwa sub-basin, the percentage of change in annual mean streamflow for the analyzed hypothetically adopted climate change conditions lies within the range of 52.91% decrease to 48.10% increase. The highest decrease of 52.91% in streamflow is obtained for 10% increase in evapotranspiration together with 20% decrease in rainfall. Likewise, the highest increase of 48.10% in streamflow is obtained when there is an increase of 20% in rainfall without any change in evapotranspiration. When the evapotranspiration is increased by 10% while keeping the rainfall input unchanged, the decrease in streamflow is 6.3%. On the other hand, when the rainfall is increased by 10% without changing the evapotranspiration to study the impact on the change in streamflow only because of the change in rainfall, the increase in streamflow is 20.42%. This ensures that the streamflow-precipitation relationship is very much stronger compared to the relationship between evapotranspiration and streamflow.

5.0 DISCUSSION

5.1 Data Collection and Data Errors

Data scarcity is one of the main issues identified in this study area. Although there are nearly 30 rainfall stations in the proximity of the region, based on the data availability and spatial locations of the rainfall stations, only nine stations were selected with a maximum of 34 years and a minimum of 19 years data between 1981 and 2015. Valachchena rain-gauging station had stopped operating in the year 2000. However, as there are no other stations located in the downstream of the basin, Valachchena was considered with the available data from 1981 to 2000.

Padiyathalawa is the only available river-gauging station located in Maduru Oya river basin. This is situated in the upstream part of the basin and expands to a drainage area of 170.9 km^2 which was used to conduct the streamflow elasticity analysis. Thiessen average rainfall of three selected stations located in the proximity of Padiyathalawa sub-watershed which has a complete 23 years of data was considered for this study.

The nearest evaporation station located in Girandurukotte was used for evaporation data. As there were so many incomplete months in recent years, 10 years of data from 1992 to 2002 were collected and used in the study.

Among the nine rainfall stations, three stations namely, Maduru Oya, Ekiriyankumbura and Padiyathalawa MOH and Padiyathalwa river-gauging stations have a complete data set. All the other stations were having missing data and were filled with a suitable method explained in Chapter 3.

5.2 Rainfall Trend Analysis

Rainfall trends have been detected in the Maduru Oya river basin from 1981 to 2015. Trends were identified for different time series and this systematic analysis for the 19 to 34 years of records give a general picture of how the rainfall varied for different time series during the past decades.

In terms of annual rainfall trend analysis, out of nine stations considered, only two stations showed negative trends. Positive trend detected in Polonnaruwa station was significant at a confidence level of 90% for the standard Mann-Kendall test and at a confidence level of 95% for Modified Mann-Kendall test. Other than this, Aluthnuwara showed significant positive trends at a significance level of 5% and Kandaketiya at a significance level of 10% for both MK tests. In brief, when annual rainfall trend is considered, Maduru Oya river basin whose main area located in the dry zone of the country witnessed an increasing trend with *Z*-statistic values of 1.05 and 1.103 both in MK and MMK tests.

A study carried out for Malwathu Oya River basin, which is located in the dry zone of Sri Lanka reported relatively similar results as the authors observed increasing trend for annual time series using Mann-Kendall test (Muthuwatta, Perera, Eriyagama, Surangika, & Premachandra, 2017). Another study performed to analyze the recent rainfall trend over Sri Lanka from 1987 to 2017 also reported an increasing trend in annual rainfall in dry zone of the country (Nisansala, Abeysingha, Islam, & Bandara, 2020). Further, a study analyzing the changes in rainfall in Sri Lanka during 1966 to 2015 also reported that most parts of dry zone have had an increasing annual rainfall trend (Karunathilaka, Dabare, & Nandalal, 2017).

Like wise, according to Sen's slope estimator, three stations exhibited a decreasing trend as given in Figure 5-1. Kudasigiriya reveals a positive trend with the highest magnitude and Ekiriyankumbura has the highest magnitude of the negative trend.

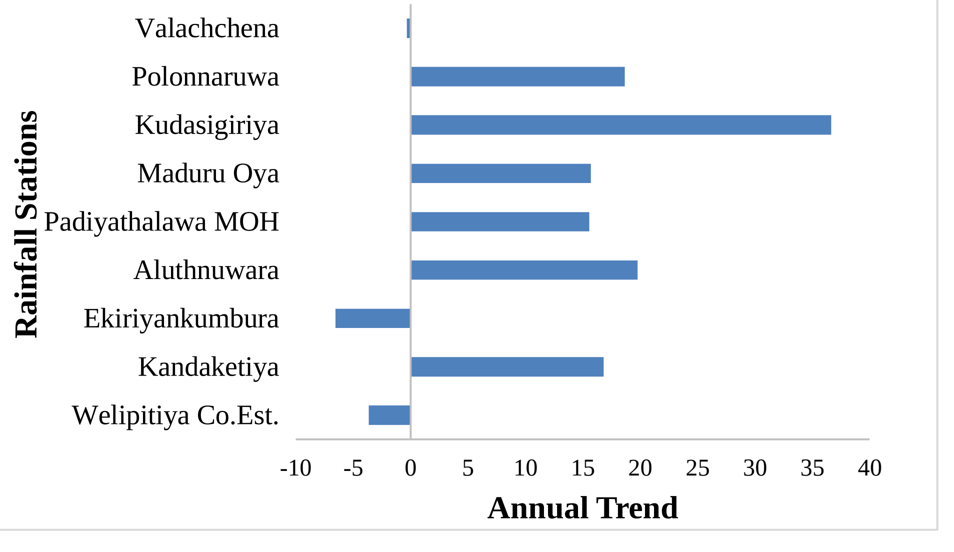

Figure 5-1: Magnitude of the annual trend using Sen's slope estimator

In terms of seasonal analysis, seven stations out of nine stations showed positive trends in Maha season while the majority of stations exhibited negative trends in Yala season. Aluthnuwara, Padiyathalawa MOH and Kandaketiya showed positive trends in both seasons whereas Ekiriyankumbura showed negative trends.

While all the stations except Valachchena showed positive trends in FIM season, all the stations excluding Kandaketiya showed negative trends in SWM season. Stations showed the same pattern of trends in both SIM and NEM seasons. Figure 5-2 portrays the variation in magnitude of the slope at each station for different seasons.

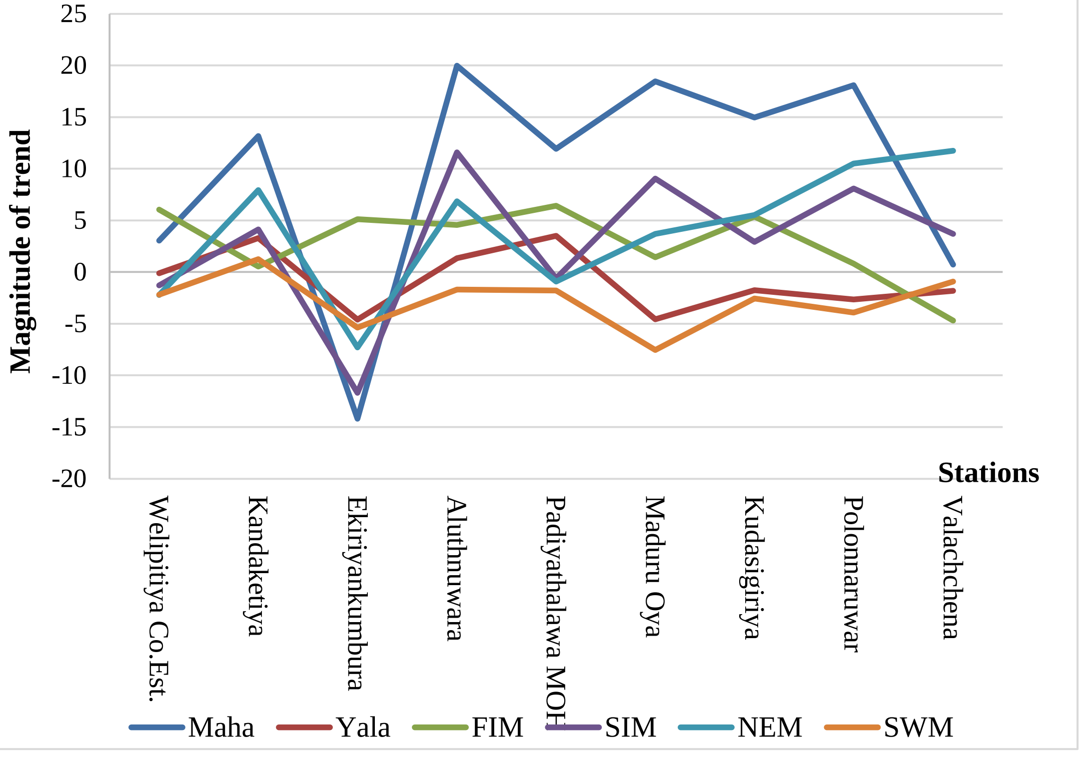

Figure 5-2: Variation of magnitudes in seasonal trend at each station

It can also be noted that both Yala and SWM show similar trends in each station which is expected as these two seasons fall almost on the same periods of the year.

In brief, for cropping season, Maha season was majorly witnessed with positive trend while Yala sesason revealed negative trend. And when it comes to rainfall seasons, except SWM season, all the other seasons were primarily detected with positive trend. This result was found to be in good agreement when compared with the results obtained for seasonal time series analysis in a study performed to analyse the recent rainfall trend over Sri Lanka from 1987 to 2017 which also reported that majority of the stations were detected with increasing trends in FIM, SIM and NEM seasons whereas SWM was mainly witnessed with decreasing trend (Nisansala, Abeysingha, Islam, & Bandara, 2020).

In terms of annual and seasonal analyses, both Kendall tests showed a very good agreement in most of the cases. Sen's slope estimation seemed to have been effective in detecting trends even when the other two tests failed to identify a trend.

Trend analysis for monthly series was carried out for all tweleve months in each station under consideration and Figure 5-3 shows the trends for the month of January illustrated over the study area in a bubble chart. Here, red colour bubbles indicate decreasing trend while increasing trends are indicated by green colour bubbles. The magnitude of the trends are represented by the size of the bubbles.

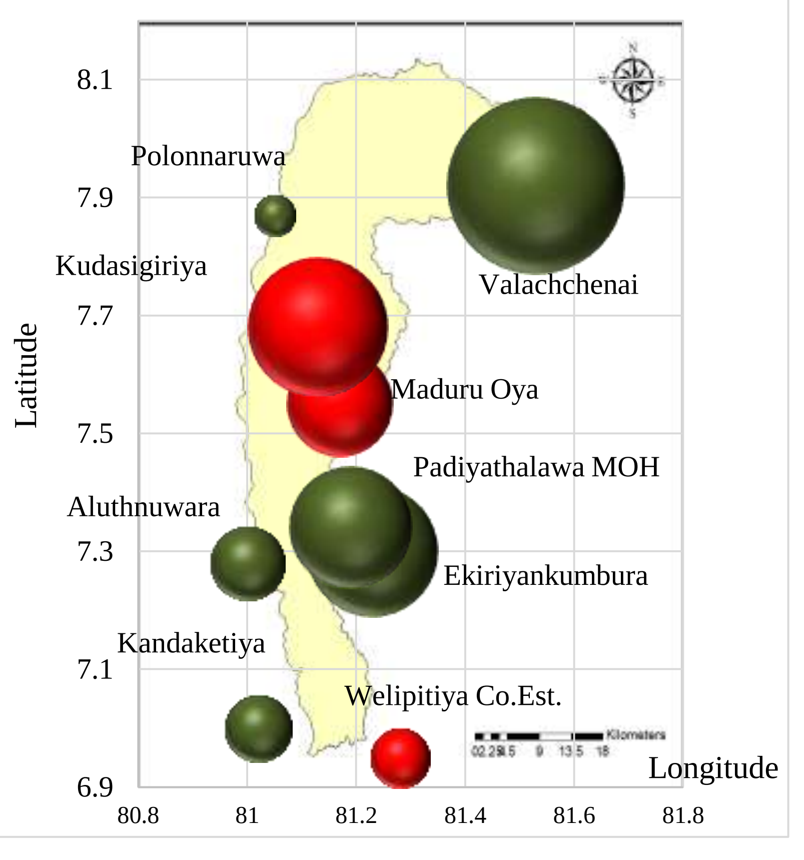

Figure 5-3: Magnitude of trends in January

Accordingly, Table 5-1 shows the average magnitude of trends in each month over the basin over the years considered using Sen's slope estimator and the plot of these average trends is given in Figure 5-4. It can be observed from the trend analysis of long term monthly rainfall, that a large number of months showed an upward trend.

Table 5-1: Average monthly trend variation

Months	Positive Trend	Negative Trend	Average Trend
January	14.40	-8.98	2.09
February	3.03	-5.78	-0.47
March	5.10	-3.23	1.49
April	2.90	-1.34	1.15
May	2.10	-2.55	-0.31
June	0.00	-0.61	-0.14
July	0.48	-1.48	-0.49
August	9.66	-1.41	1.27
September	0.03	-6.99	-2.44
October	4.03	-5.09	0.05
November	9.19	-7.20	3.10
December	22.34	-3.31	3.55

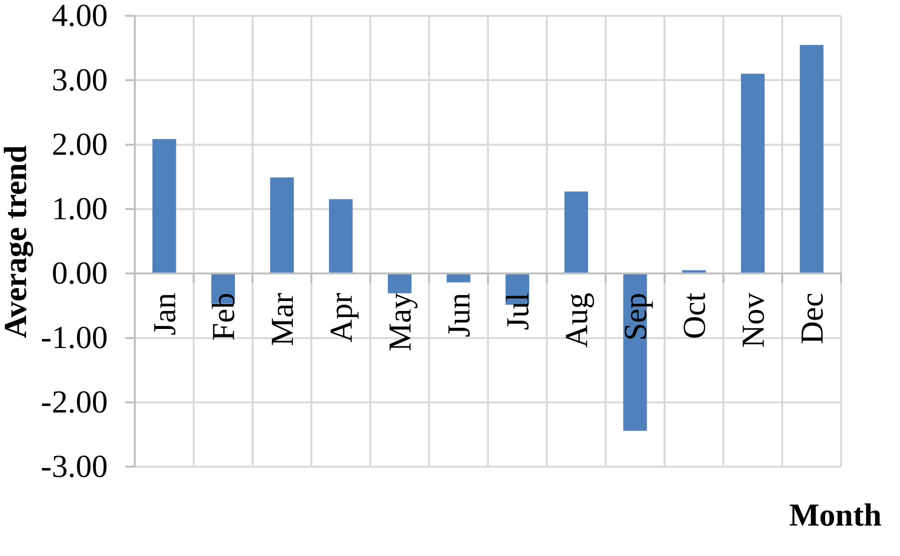

Figure 5-4: Average trend over the years

Accordingly, higher positive trends are principally detected during November and December. On the contrary, September has the highest negative trend. When compared to the results obtained in a study (Ampittiyawatta & Guo, 2009) performed in Kalu Ganga watershed, located in the wet zone of the country, unlike the present study, majority of the months reported decreasing trends with only January, July and November showing positive trends. Further, November has been identified to have witnessed with the highest positive trend in both the cases.

When findings on the annual scale are briefed out, Ekiriyankumbura, Welipitiya and Valachchenai showed decreasing rainfall trend where there is a possibility for water scarcity. This may lead to problems like droughts and soil moisture reduction. On the other hand, stations which have an increasing rainfall trend may have favourable weather conditions for agricultural activities, however, these areas have the risk of getting impacted by flooding as a consequence of high precipitation intensity. Thus, it is essential to take a note of these changing scenarios of aquatic resources while planning and managing them.

It is also necessary to keep in mind the limitations encountered in the current work. One major limitation is the length of data records. As this is a data-scarce region, it was not possible to collect data for 30 years for all the stations which is the minimum requirement for climate study. One station even had data as short as 19 years period. Another limitation is incomplete data sets of most of the rain-gauge stations. As these missing data had to be filled with data derived from other stations, uniqueness of that station or the series is affected which in turn affect the reliability of the result. Moreover, there were very few stations located in the downstream of the basin and among the nine stations considered in the study, only two stations are from the downstream. Hence, generalizing the results of trend analysis over the entire basin can be sometimes misleading.

5.3 Effects on Water Resources within the Maduru Oya River basin

The study found out that most of the stations located within the Maduru Oya river basin, revealed positive trends in different time scales analyzed. However, it is important to convert the available water in to exploitable resource by coming up with a solution to store more water in order to overcome water scarcity issues. In terms of negative trends, there was at least one station identified with negative trend in all the time scales. Moreover, seasonal analysis revealed that Yala season as well as South West Monsoonal seasons were witnessed with severe negative trends. In case of the monthly analysis, most of the stations considered were identified with remarkable statistically significant decreasing trends. These findings imply that there was a reduction in water resources in some areas located within the basin in the past years. Hence, it is advisable to take note of these varying conditions of water availability while planning long-term water management for the basin.

5.4 Streamflow Elasticity Analysis using Non-Parametric Estimator

Streamflow elasticity analysis was carried out for Padiyathalwa sub-basin. Three rain-gauging stations situated in the close proximity of the area of concern and a river-gauging station located in Padiyathalwa were selected to obtain the observed rainfall and streamflow data, respectively. The area average rainfall was estimated with the Thiessen Polygon method.

Although there are various climate elements identified such as evaporation, temperature and precipitation, variation in rainfall has been identified to be the largest causative climate variable affecting streamflow (Sharma & Wasko, 2019). Furthermore, another study (Yang & Liu, 2011) analyzed the reactivity of streamflow to climate variations through the variation in rainfall and evapotranspiration and found out that the streamflow and precipitation showed a much powerful relationship compared to the streamflow - evapotranspiration relationship. Accordingly, in the present study, when the non-parametric estimator was used, the climate elasticity of streamflow was analyzed only using the sensitivity of streamflow to precipitation as it was the only variable that was accessible for a reasonable long period.

The strength of the precipitation – streamflow relationship has a strong impact on the calculation of streamflow-elasticity analysis. Hence, it is essential to investigate the strength of streamflow-precipitation relationship by accumulating the annual values of streamflow and precipitation for the entire twelve months period of the year and considering the period with the strongest precipitation-streamflow relationship to produce an appropriate elasticity value (Fu, Chiew, Charles, & Mpelasoka, 2011).

However, in the present study, water year was considered to accumulate the streamflow and precipitation values. The correlation coefficient of streamflow-precipitation relationship for the water year is 0.56 which can be considered as a fairly good correlation.

Streamflow elasticity to precipitation was carried out with 23 years of historical data adopting the non-parametric estimator established by Sankarasubramanian, Vogel, & Limbrunner (2001). Although this data length does not satisfy the requirement of minimum 30 years of data length for climate study, it was proceeded based on the literature as there are some researches carried out for data series in the range of 20 years (Chiew, Peel, Mcmahon, & Siriwardena, 2006).

When it comes to the graphical method suggested by Zheng, et al. (2009), considering that this 23 years period is a small sample size, the streamflow elasticity obtained is 1.92 which is greater than the value obtained from the equation proposed by Sankarasubramanian, Vogel, & Limbrunner (2001), which is 1.12.

In brief, according to the findings from non-parametric estimator, where the percentage change in streamflow is found out with regards to the percentage change in rainfall, the change in streamflow variability is positive when the rainall is increasing. However, when the annual rainfall and streamflow are plotted as given in Figure 5-5 in order to have an idea of the linear trend over the years considered in the present study, it can be noted that the streamflow is increasing even when the rainall decreases.

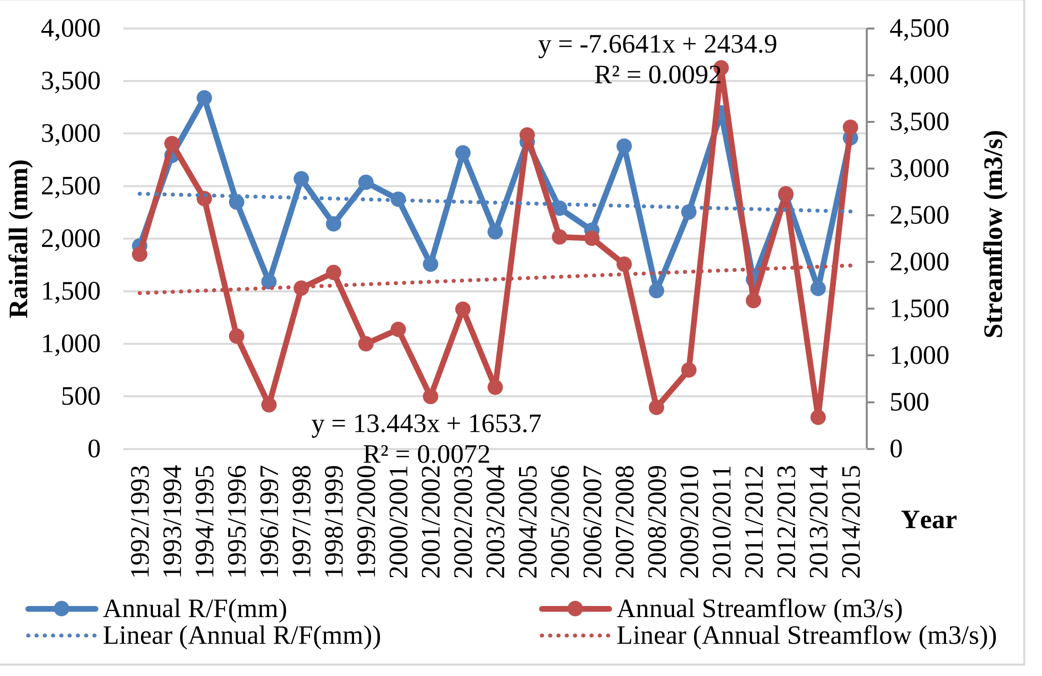

Figure 5-5: Annual variation of streamflow with rainfall

This contradiction between the results obtained from non-parametric test and linear trend test could be mainly because the non-parametric test considered only the effect of rainfall on streamflow whereas the linear trend test should have considered the combination of both the impacts of climate elements as well as the land use and land cover changes and other human induced activities.

5.5 Hydrological Modelling

Selection of data period for modelling purpose was mainly based on the accessibility of rainfall, evaporation and streamflow data. Rainfall data were obtained from 1981 to 2016, and the Theissen average rainfall was estimated form three rain-gauging stations, namely Ekiriyankumbura, Padiyathalawa MOH and Welipitiya Coconut Estate from the year 1992 to 2015. Two evaporation stations namely Ulhitiya and Girandurukotte were identified in the proximity of the region in concern. Ulhitiya station had no data during the period considered and therefore Girandurukotte station was selected instead. However, Girandurukotte had completely missing data in the year 2005, 2012 and 2013. Hence, as periods before 2005 had to be selected,10 years data from 1992 to 2002 were selected. As both dry and wet periods are representatively covered in the data set considered, it can be assumed that the resultant runoff was independent of the data period considered. There were so many data discrepancies observed and it is explained in detail under the Data Checking section of Chapter 3.

Initial model parameters and objective functions were selected based on the literature available on HEC-HMS models developed for Sri Lankan watersheds. The MRAE and Nash-Sutcliffe Efficiency coefficient were selected as the objective functions so as to monitor the interpretation of the model.

Automatic calibration was carried out using optimization manager to get the soft limits of the parameters selected and then the error between the measured and modelled data was minimized as much as possible by carefully adjusting the parameters manually.

The results obtained for initial parameters, calibration period after optimizing the parameters and verification period are given in Results and Analysis section of Chapter 4. For the calibration period, when using MRAE as the objective function, overall model interpretation is satisfactory with an error indicator of 0.433. However, the MRAE value for validation is 0.559 which is not satisfactory.

When using the Nash-Sutcliffe Efficiency coefficient as the objective function for calibration purpose, it gave an overall model efficiency value of 0.665 which is good. A past study concluded that Nash-Sutcliffe Efficiency of 0.5 and above can be considered satisfactory which confirms the reliability of the model in the present study (Moriasi, et al., 2007).

Coefficient of determination (R^2) was also checked to see the correlation between the observed and calculated records and the variation is represented in Figure 5-6. According to the plot, the correlation between these two data sets is 0.69. Generally, if R^2 value is greater than 0.5, then the correlation between two data sets can be regarded as acceptable or satisfactory (Santhi, et al., 2001; Liew, Arnold, Garbrecht, & J, 2003).

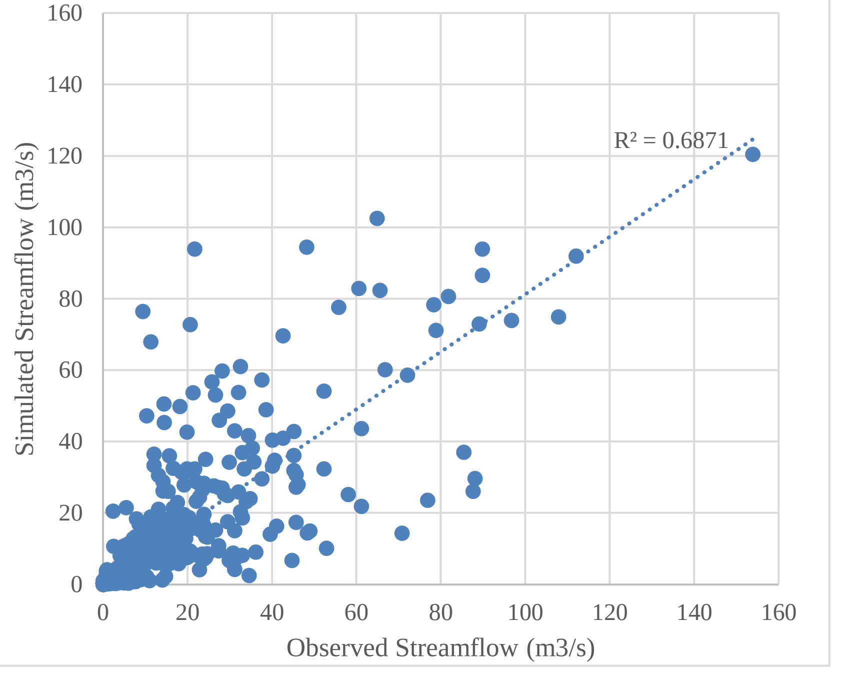

Figure 5-6: Relationship between observed and simulated flow in calibration period

When it comes to the verification period, as given in Figure 5-7, Coefficient of determination (R^2) is 0.65 which is also satisfactory.

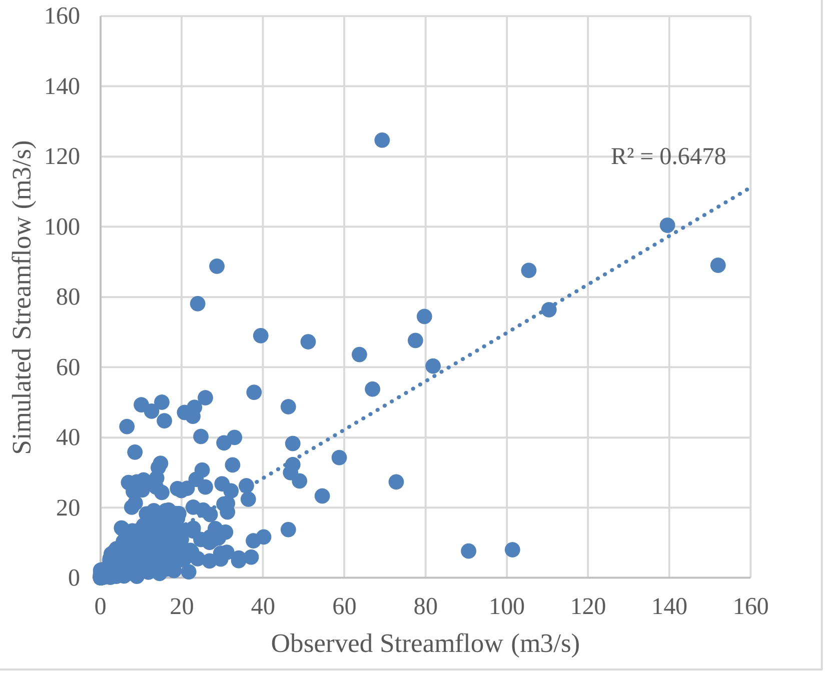

Figure 5-7: Relationship between observed and simulated flow in verification period

5.6 Adaptation of the Model for Streamflow Elasticity Analysis

As long as the error between the modelled and measured data series is within an acceptable range, the elasticity values calculated for measured and modelled data series will find themselves in a very good agreement. In the present study, as the model is satisfactoriliy calibrated, the streamflow elasticity analysis using the model is expected to be reliable.

One of the major assumptions made in this work is that the model is capable of simulating the streamflow of the catchment under the other climate change scenarios that deviate from the original climatic conditions with which the model was calibrated. In the case of a major deviation in climatic conditions, the usage of the model is not reliable and not recommended.

The present study was carried out purely based on hypothetical climate change scenarios and that is sufficient to get an idea of how far a particular climate element influence the streamflow variability. For the hypothetical climate change scenarios, the analysis shows an exceptional sensitivity of annual runoff to rainfall when compared to evapotranspiration.

Further, it should also be noted that this present study considered the effect of only climate change on streamflow and other factors such as land use and land cover changes were not in the scope of the present study.

6.0 CONCLUSIONS AND RECOMMENDATIONS

The findings of the study are summarised with the conclusions and recommendations derived based on the present study.

6.1 Conclusions

1. The current work tends to examine the trends and variability of rainfall data under various time series such as annual, seasonal and monthly scales. Non-parametric trend analysis methods namely Sen's slope estimator, Modified Mann-Kendall Test and Mann-Kendall test were utilized in the study.
2. When annual rainfall trend is considered, Maduru Oya river basin, on average, witnessed an increasing trend with *Z*-statistic values of 1.05 and 1.103 both in MK and MMK tests and the annual precipitation increment is 12.52 mm/year. Similarly, Padiyathalawa sub-basin revealed an increasing trend with the same Z-statistic value of 0.229 from both MK and MMK tests and an annual increment of 1.787 mm/year from Sen's slope estimator. As a consequence of this increasing trend in the recent years, it can be expected that the possible water scarcity issues in Maduru Oya river basin in the areas with decreasing rainfall trends can be effectivle overcome if a proper solution is found out to convert all the available water into utilizeable resources.
3. During the trend analysis of cropping seasonal data series, all the stations except for one station exhibited positive trend in Maha season and Yala season witnessed a contrasting rainfall pattern where the majority of the stations revealed negative trends. Likewise, while analyzing the rainfall seasonal data series, the results indicated that First Inter Monsoon (FIM), North East Monsoon (NEM) and Second Inter Monsoon (SIM) seasons exhibited positive trends and South-West Monsoon (SWM) season showed negative trends.
4. When it comes to monthly data series, when using Sen's slope estimator, higher upward trends are primarily detected in November and December with an average monthly increment of 3.1 mm/month and 3.55 mm/month respectively. On the contrary, September has the highest negative average trend of 2.44 mm/month where majority of the stations considered within the basin revealed negative trend.

5. Although majority of the stations analyzed in different time scales revealed positive trends, dcreasing trends identified in September, and Yala and South-West Monsoon seasonal analysis in most of the stations within the study area imply that there was a reduction in the availability of water resources in the past years considered. Hence, based on the significant decreasing or increasing trends, it is important to take account of the varying conditions of water availability while planning long-term water management schedule for the basin.

6. Streamflow elasticity to rainfall analysis using 23 years of observed data with the non-parametric estimator proposed by Sankarasubramanian et al. (2001) reveals that 10% of change in precipitation would result in 11.2% percentage increase in streamflow. Likewise, the graphical method suggested by Zheng et al. (2009) shows that 10% of the change in precipitation would result in 19.2% increase in streamflow. However, the linear trend method shows that the streamflow decreases with increasing rainfall. This concludes that other than rainfall, factors such as land use and land cover changes and other human activities have had a significant influence on streamflow variability in the basin over the past years.

7. Hypothetical climate scenario in modelling approach concludes that the relationship between streamflow and precipitation is robust than that of streamflow and evapotranspiration. A 10% increase in rainfall when there is no change in evapotranspiration results in 20.42% increase in streamflow whereas the same amount of increase in evapotranspiration with no variation in rainfall results 6.3% decrease in streamflow.

6.2 Recommendations

1. The information extracted from the trend analysis using the historical data can be utilized to predict the future trends which thereafter can be incorporated in water resources planning and management in the study area.
2. The findings of rainfall trend analysis might have resulted due to several causes such as climate change and/ or other man-made activities. However, this study did not analyse the degree of impacts of each factor and further analysis needs to be carried out to analyse the influence level of each factor.

3. The present study includes the estimation of streamflow elasticity to climate elements purely based on hypothetical climate change scenarios. Further analysis can be carried out for actual climate change scenarios predicted for the study area.

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APPENDIX A: Double Mass Curves

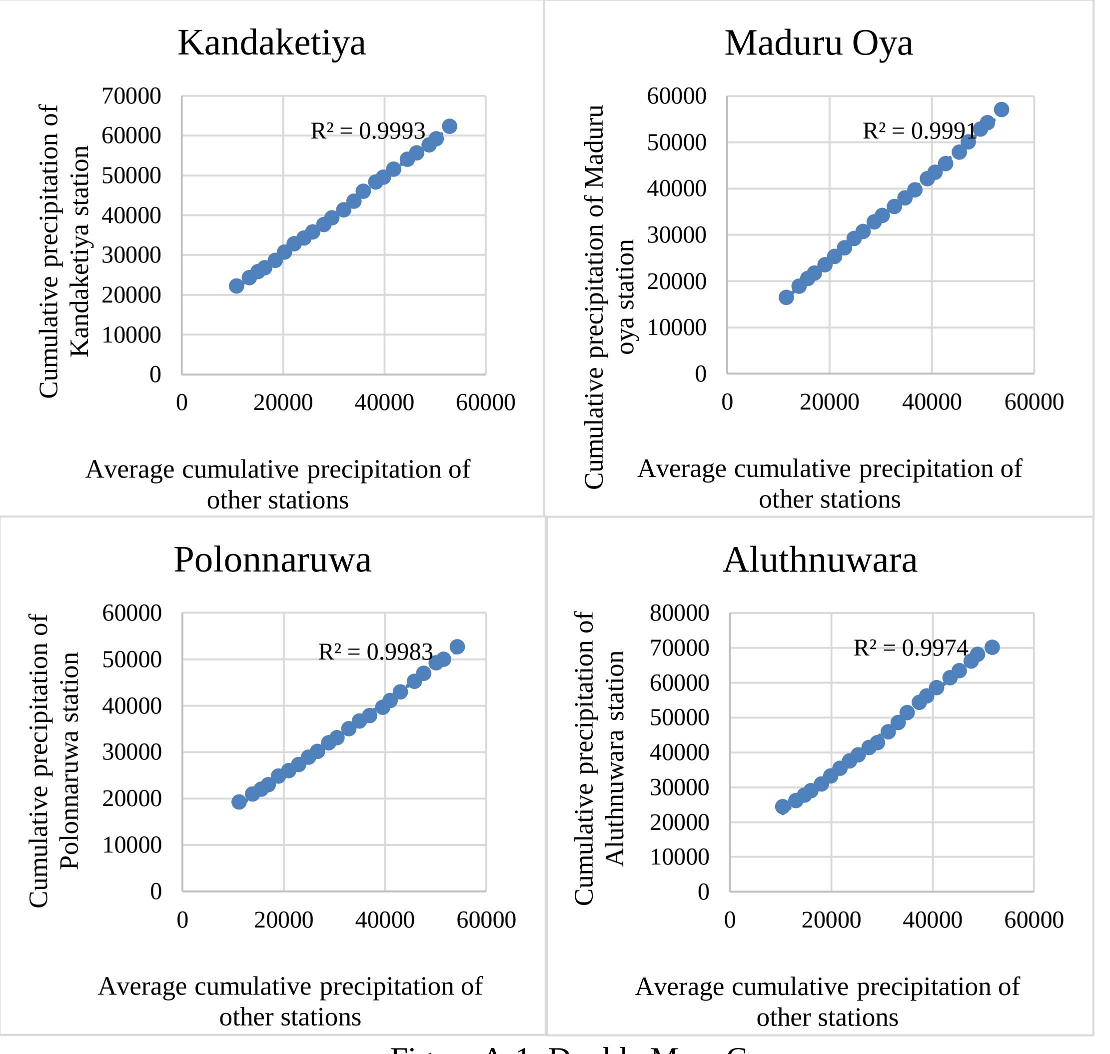

Figure A-1: Double Mass Curves

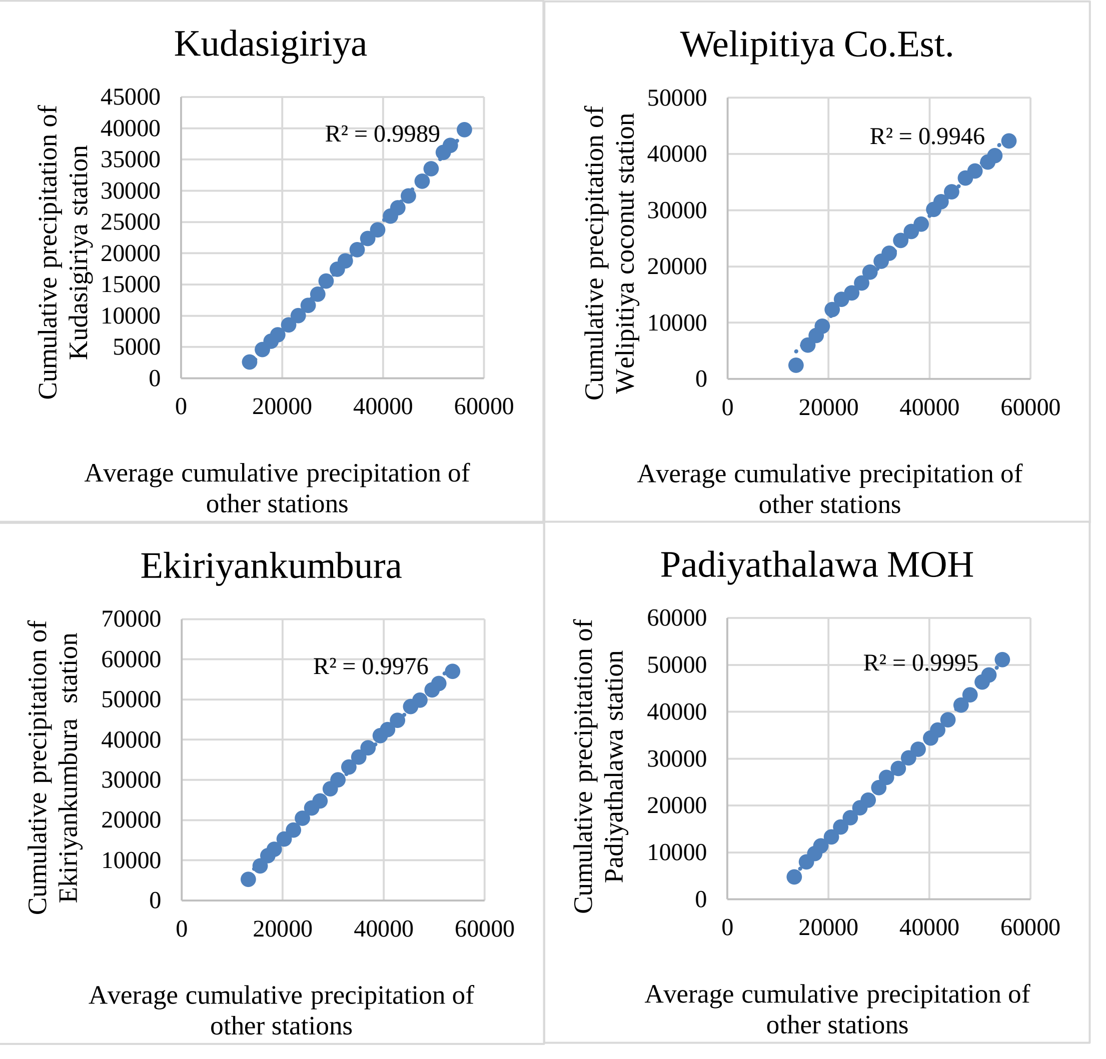

Figure A-2: Double Mass Curves

APPENDIX B: Variation Of Annual Evaporation Data

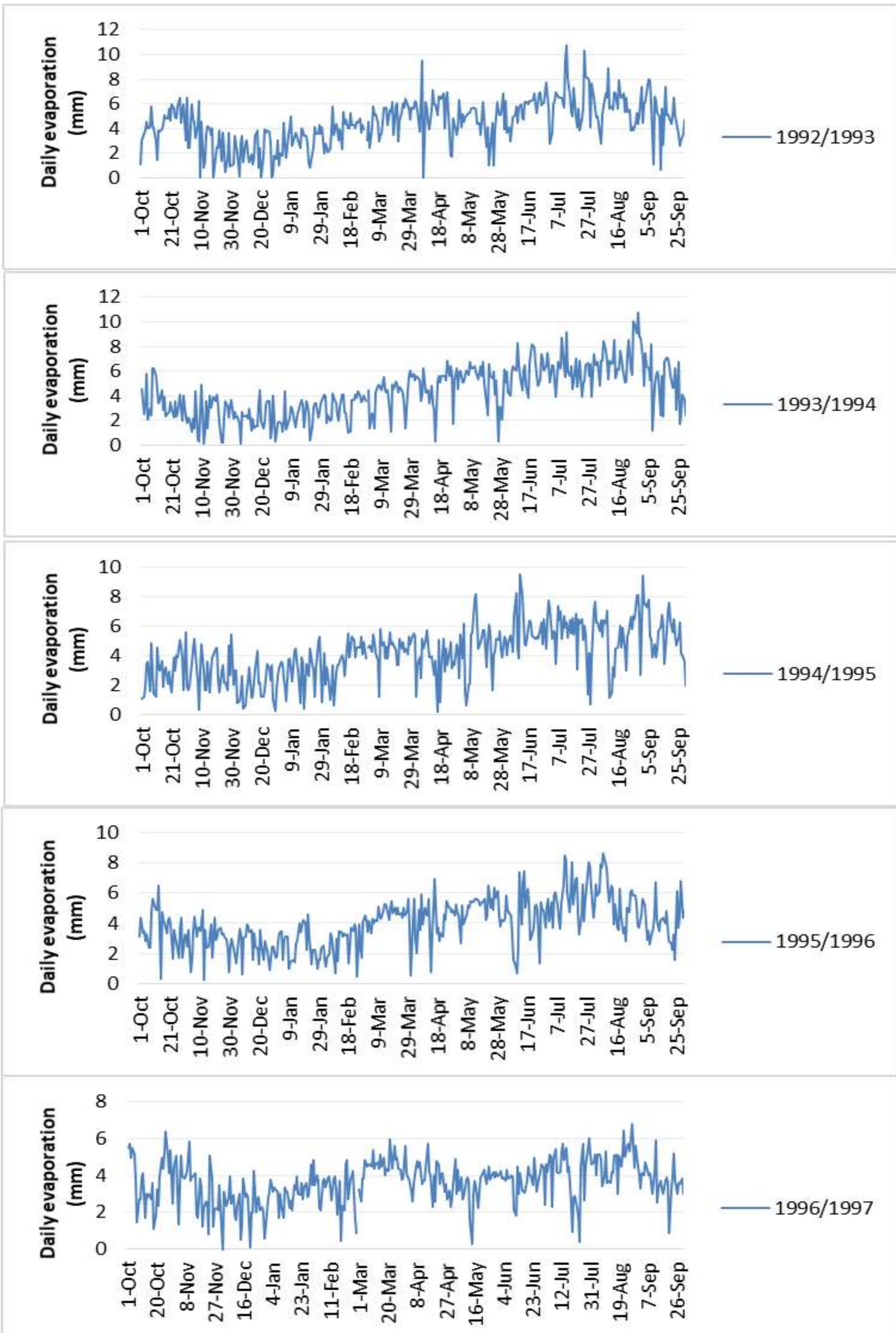

Figure B-1: Variation of annual evaporation data from 1992/1993 to 1996/1997

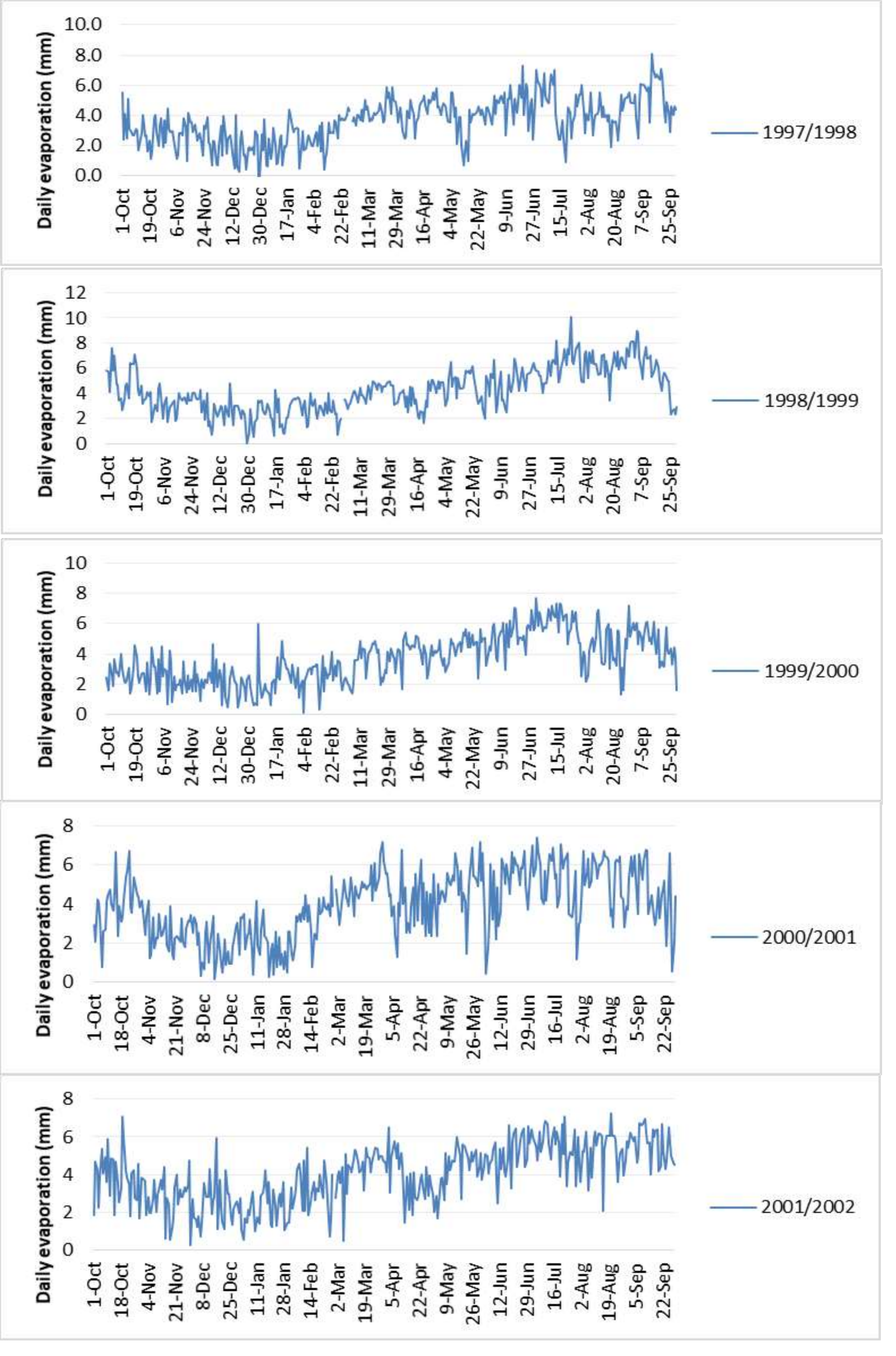

Figure B-2: Variation of annual evaporation data from 1998/1999 to 2001/2002

APPENDIX C: Single Mass Curves of Evaporation Data

Table C-1: Years having similar evaporation pattern

Year	Slope of year	Matching Years
1992/1993	4.4844	1992/1993 and 1993/1994
1993/1994	4.3341	1993/1994 and 1992/1993
1994/1995	4.2202	1994/1995 and 1993/1994
1995/1996	4.0264	1995/1996 and 2000/2001
1996/1997	3.6227	1996/1997 and 1997/1998
1997/1998	3.6282	1997/1998 and 1996/1997
1998/1999	3.9538	1998/1999 and 2001/2002
1999/2000	3.7447	1999/2000 and 1997/1998
2000/2001	4.0481	2000/2001 and 1995/1996
2001/2002	3.9369	2001/2002 and 1998/1999

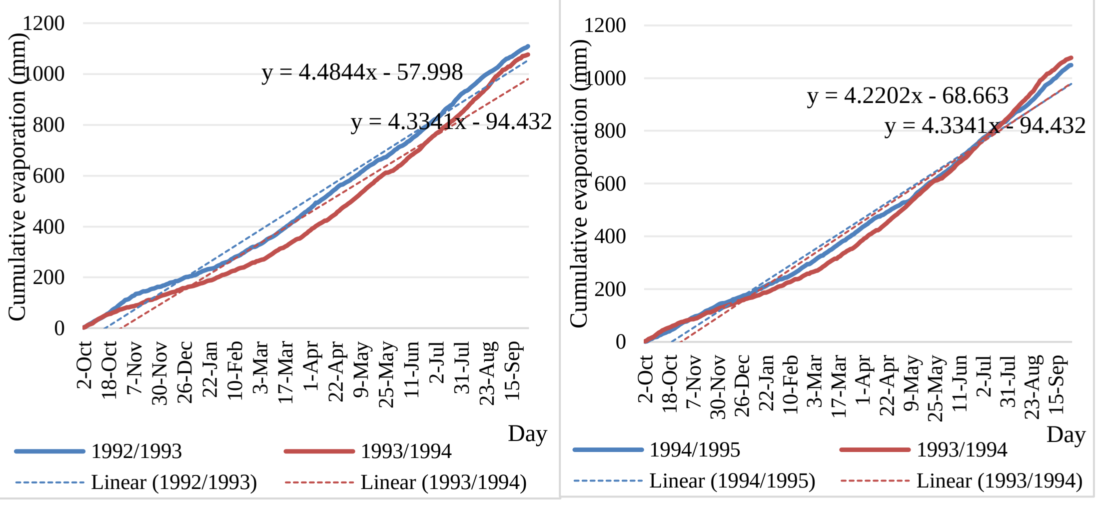

Figure C-1: Single mass curve for evaporation

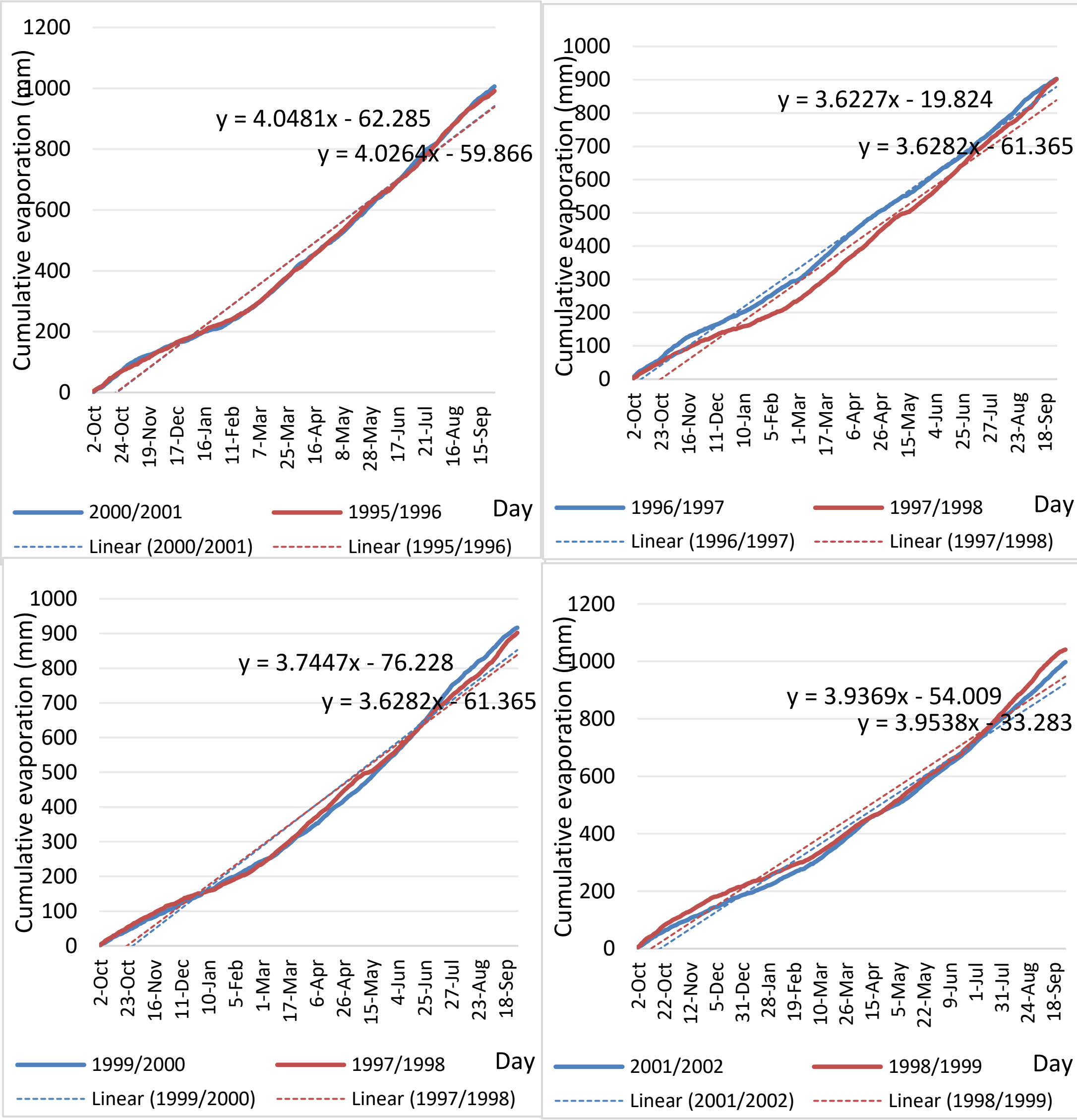

Figure C-2: Single mass curve for evaporation

APPENDIX D: Visual Checking of Streamflow Responses to Rainfall

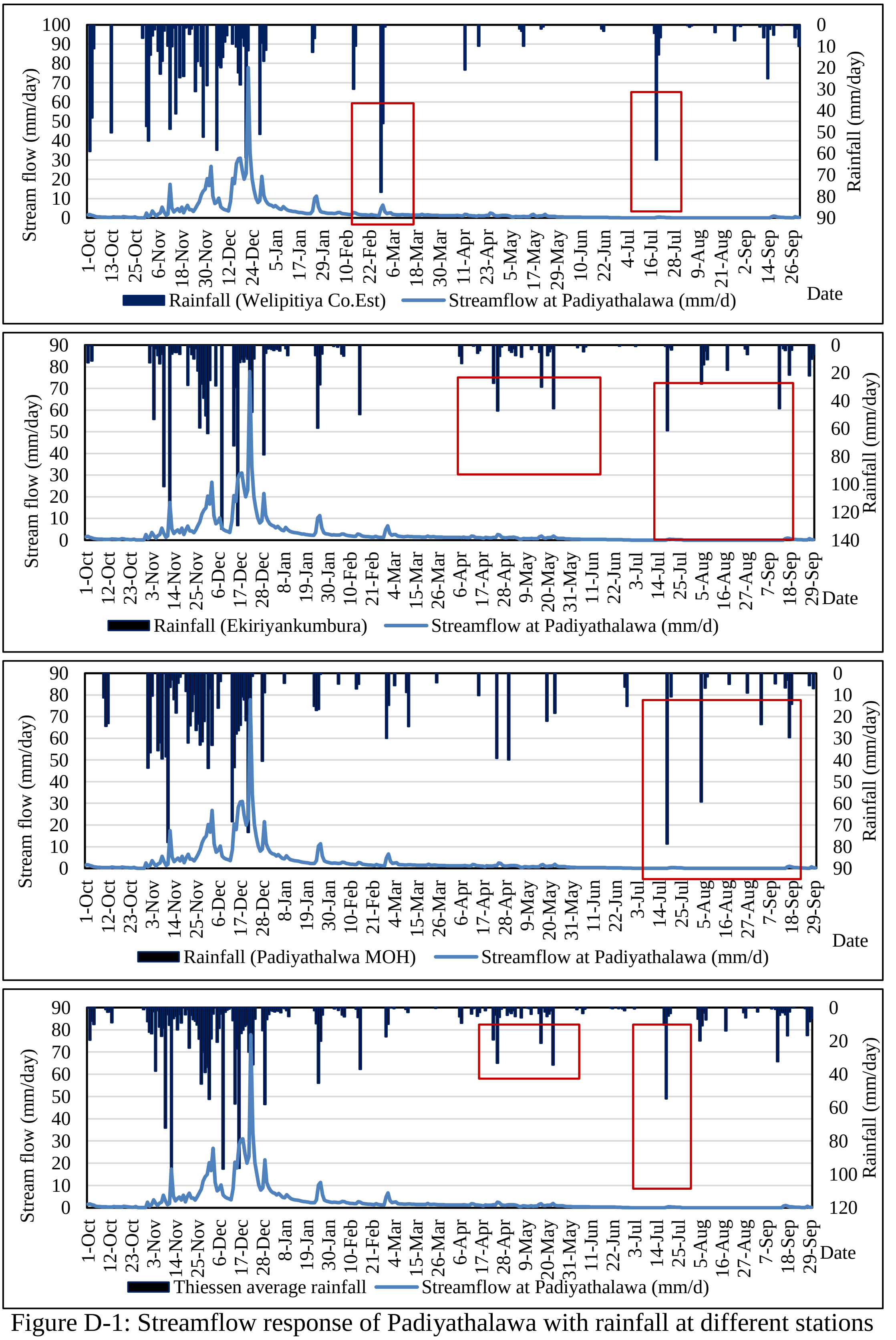

Figure D-1: Streamflow response of Padiyathalawa with rainfall at different stations for 1992/1993

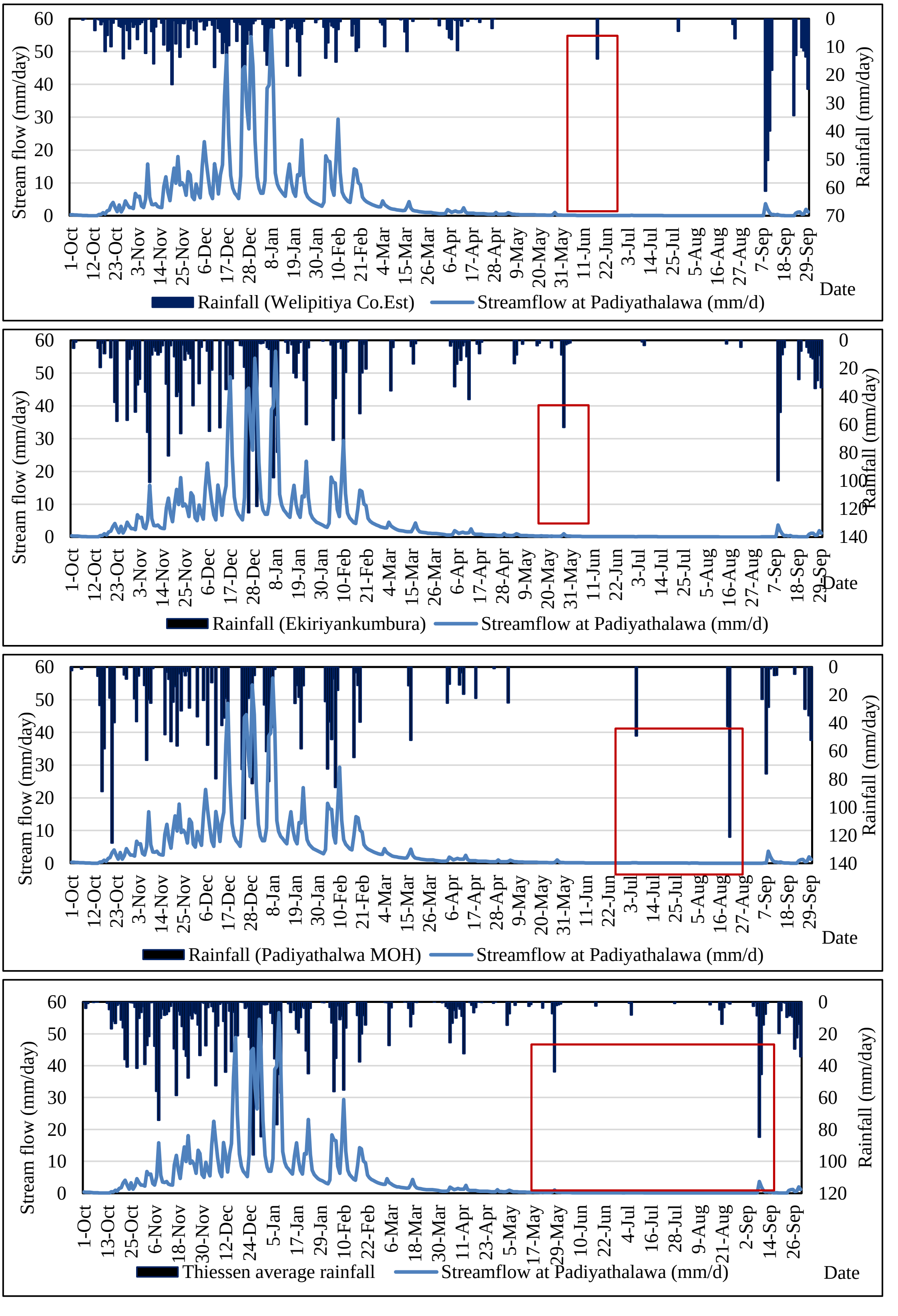

Figure D-2: Streamflow response of Padiyathalawa with rainfall at different stations for 1993/1994

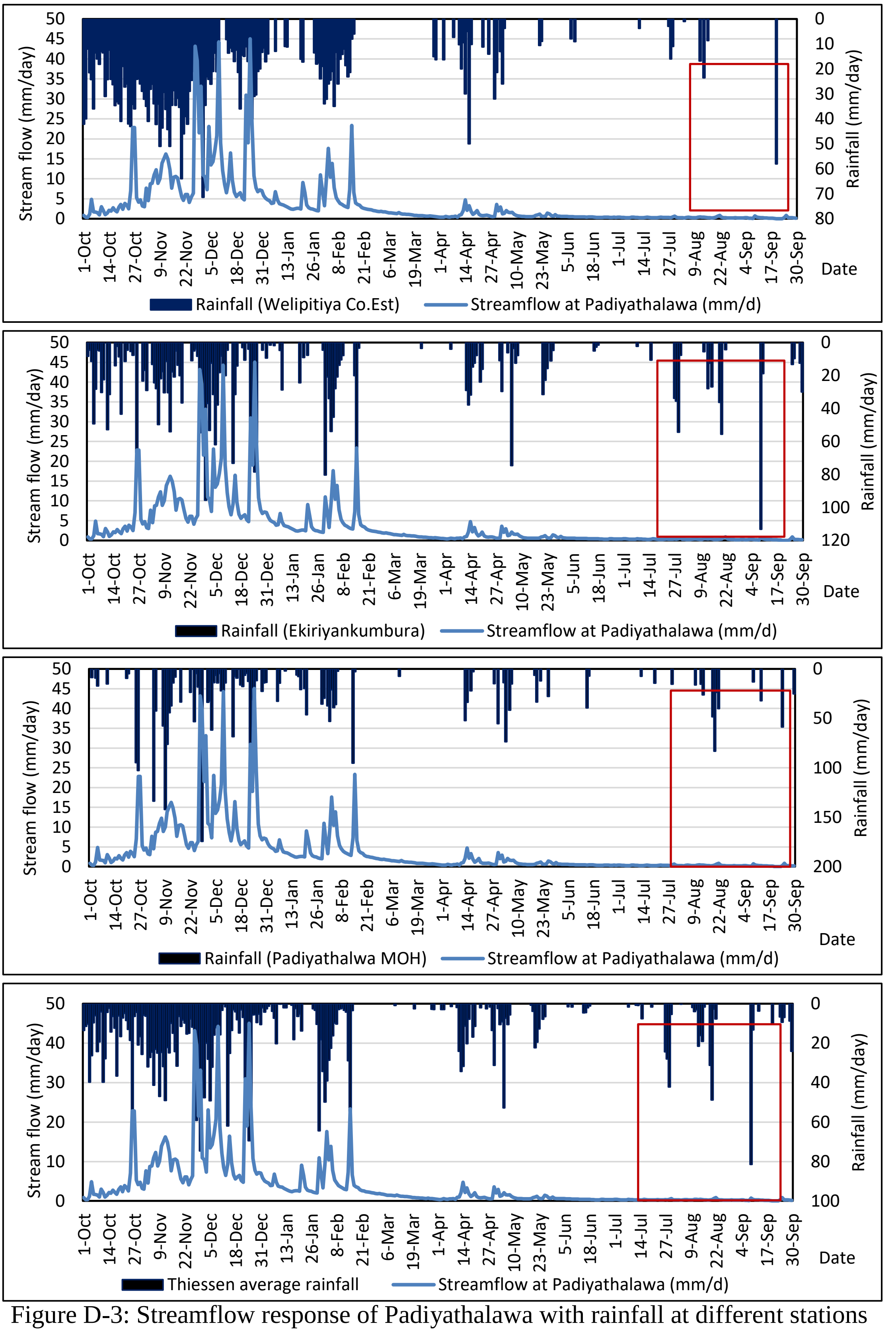

Figure D-3: Streamflow response of Padiyathalawa with rainfall at different stations for 1994/1995

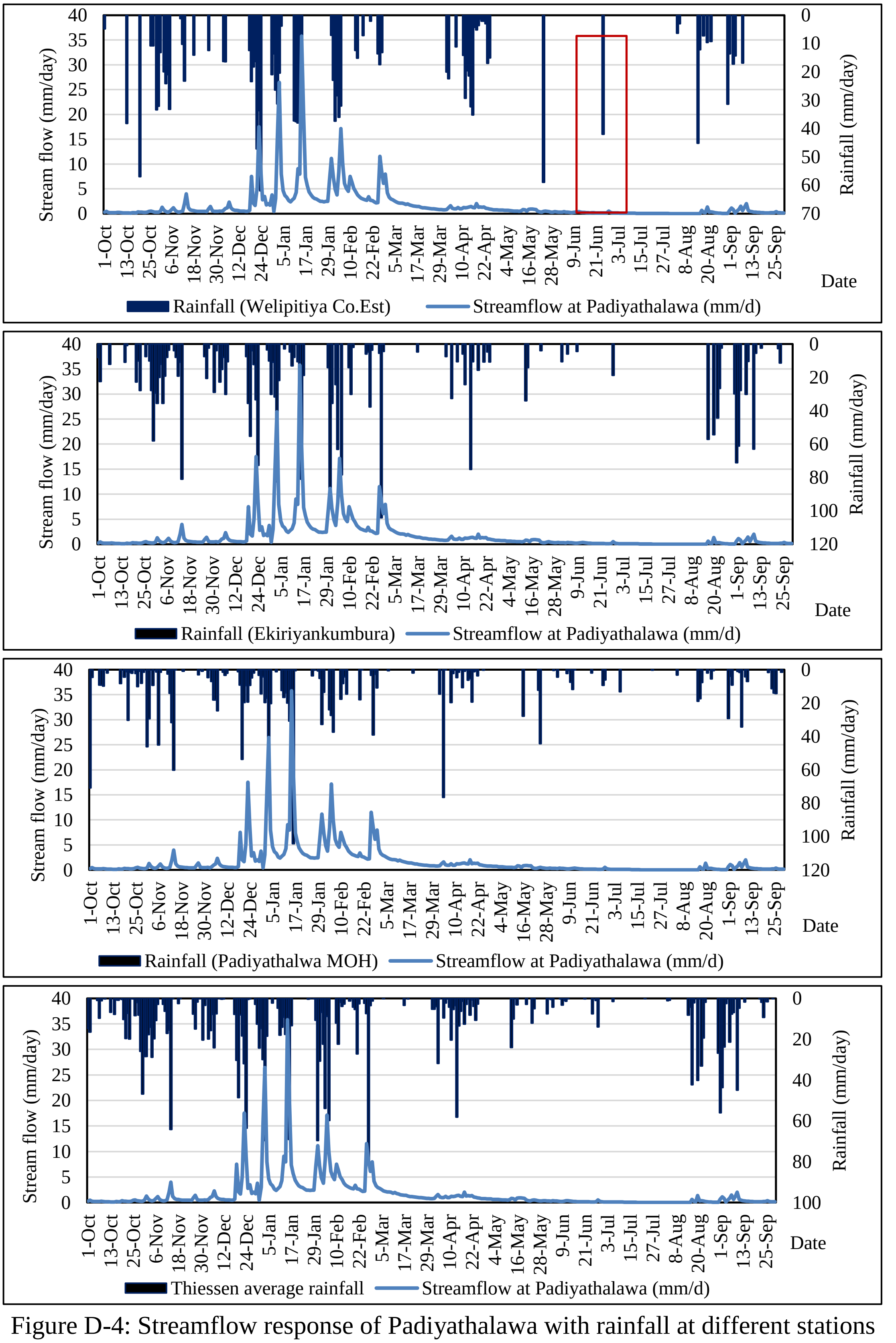

Figure D-4: Streamflow response of Padiyathalawa with rainfall at different stations for 1995/1996

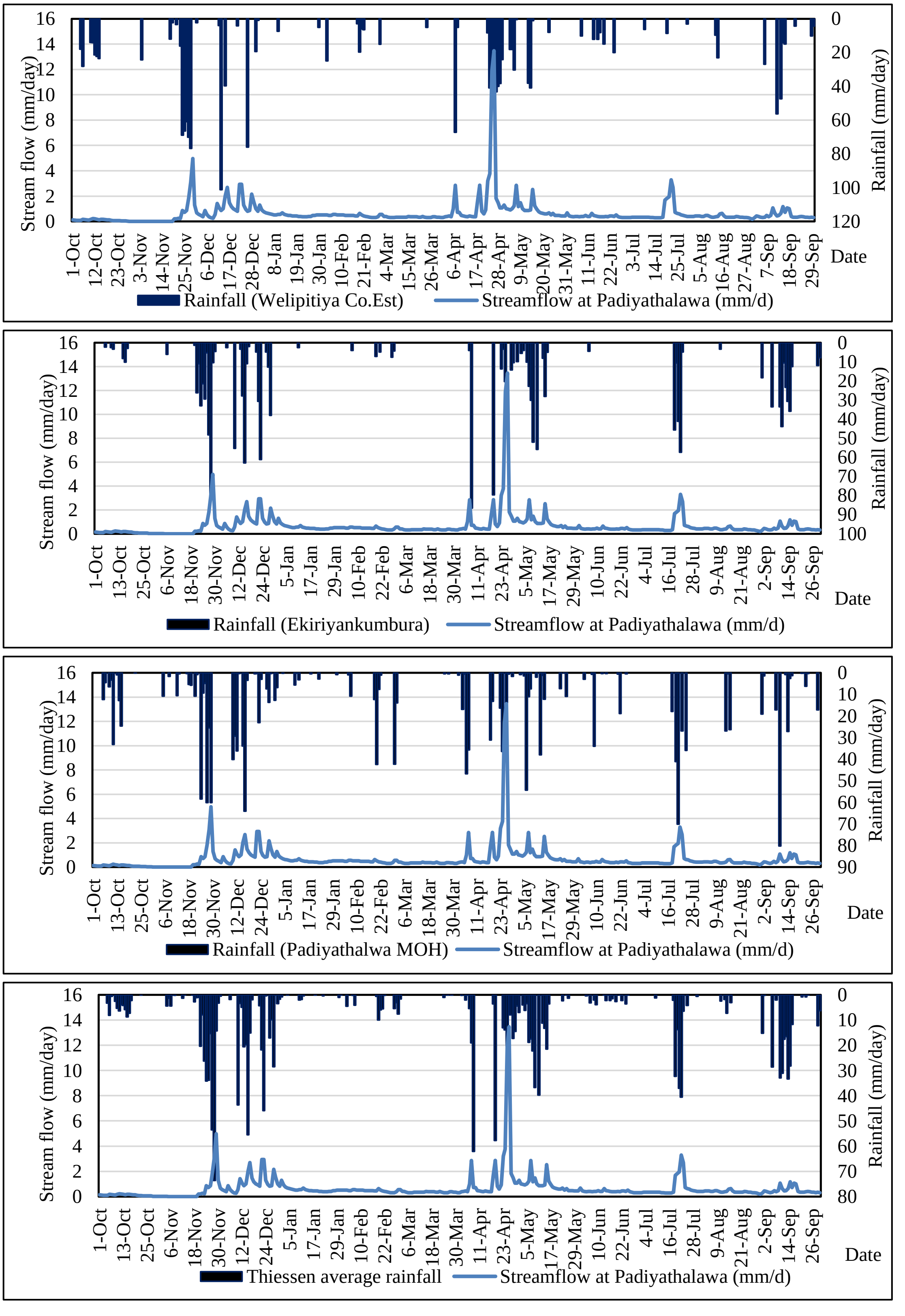

Figure D-5: Streamflow response of Padiyathalawa with rainfall at different stations for 1996/1997

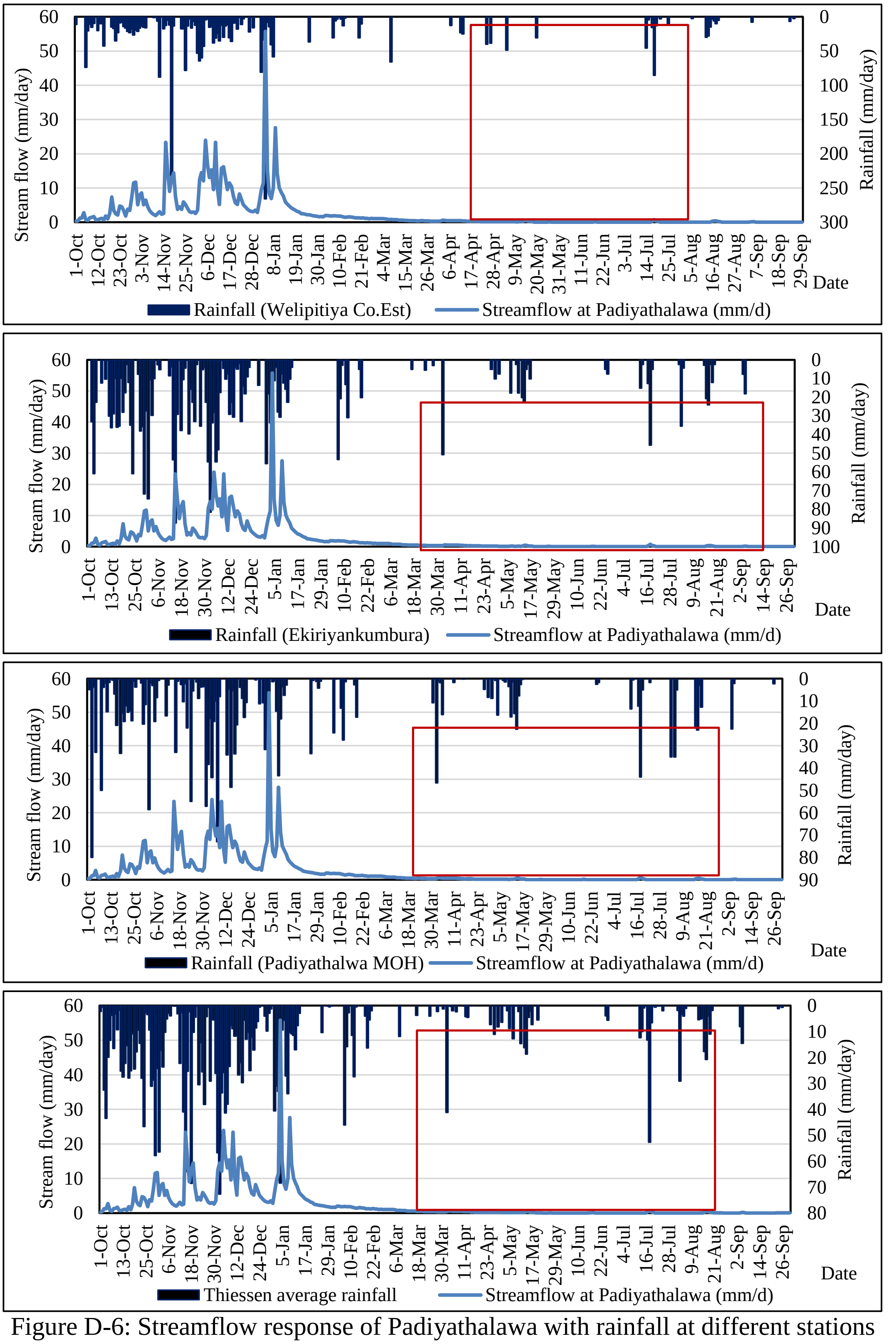

Figure D-6: Streamflow response of Padiyathalawa with rainfall at different stations for 1997/1998

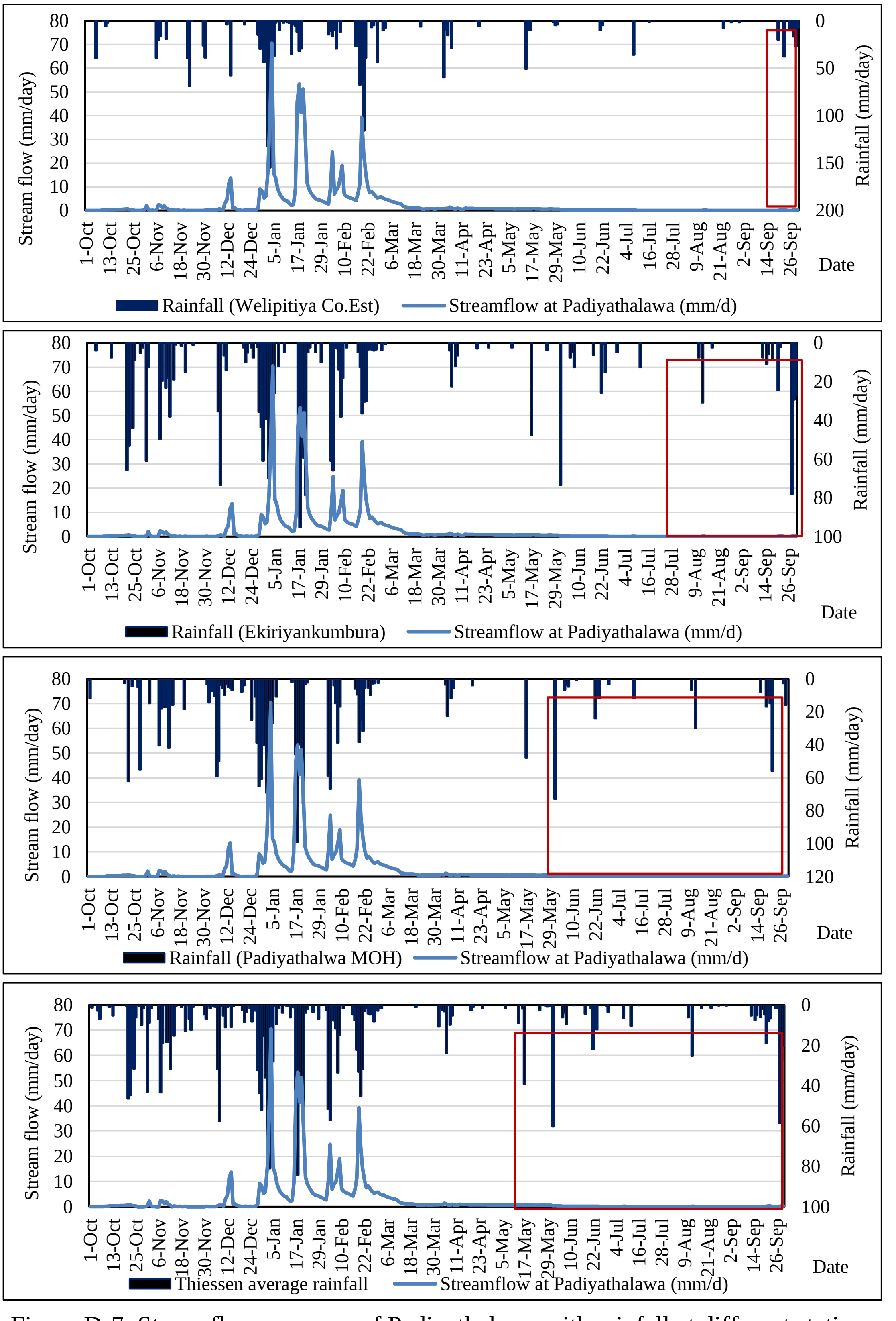

Figure D-7: Streamflow response of Padiyathalawa with rainfall at different stations for 1998/1999

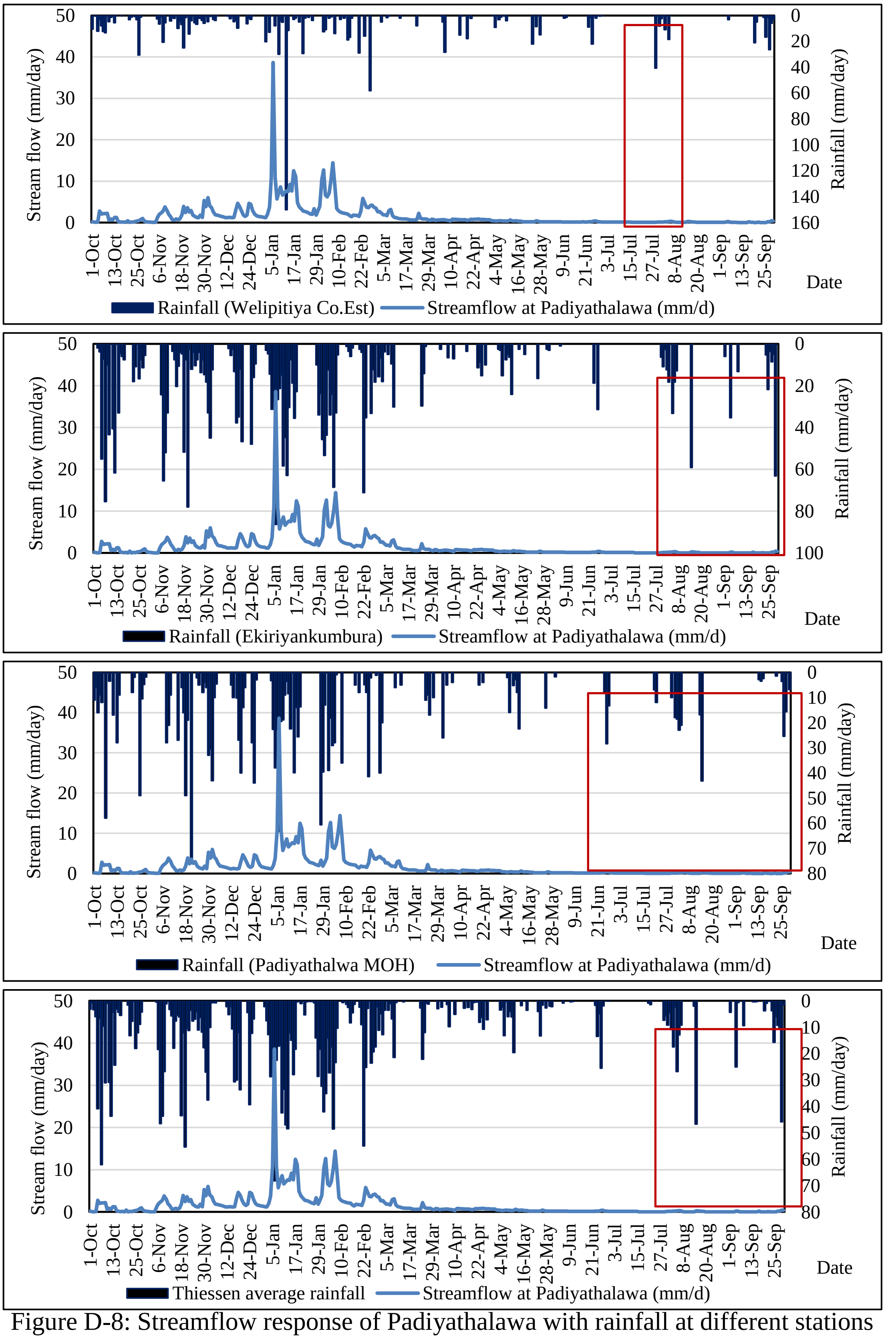

Figure D-8: Streamflow response of Padiyathalawa with rainfall at different stations for 1999/2000

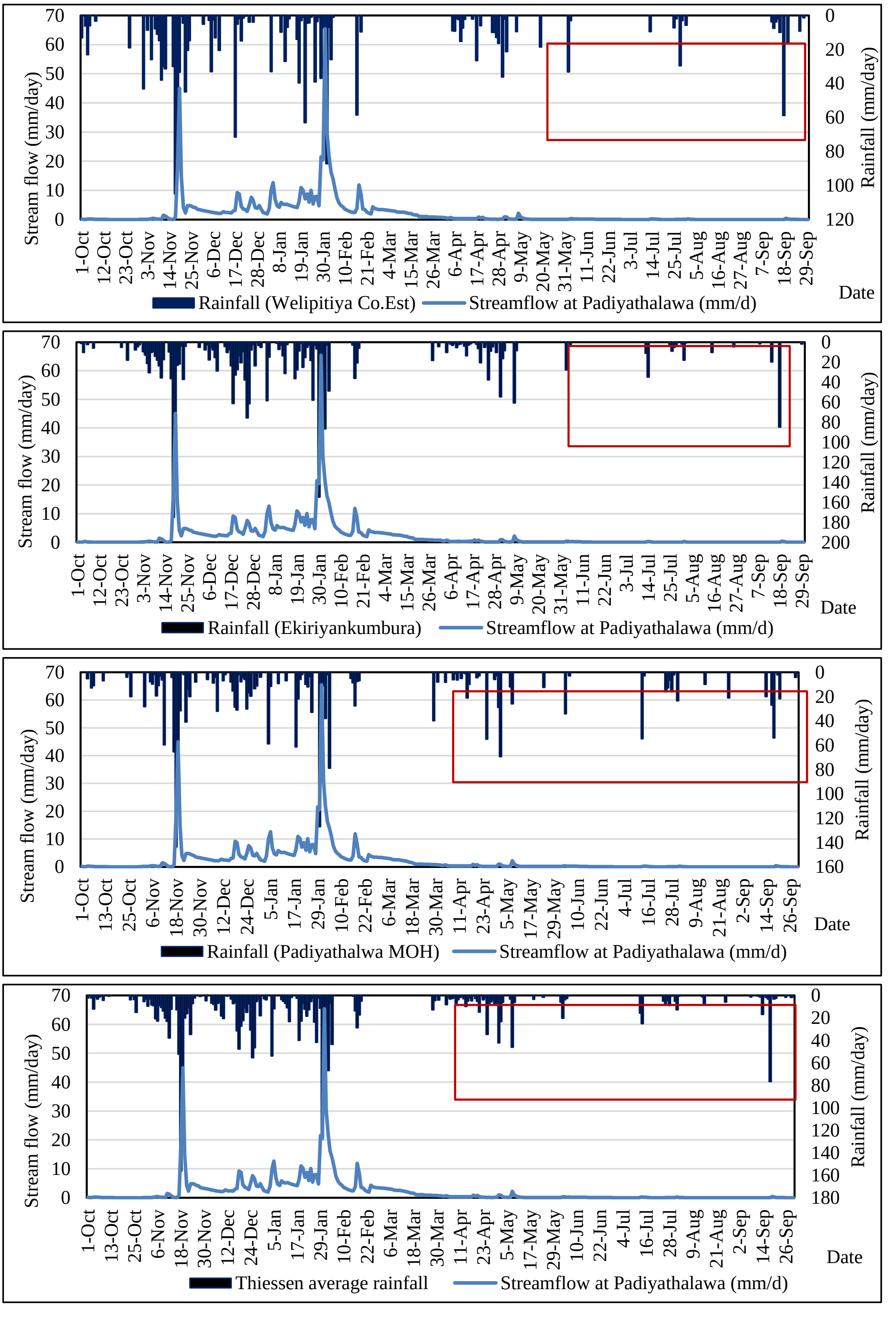

Figure D-9: Streamflow response of Padiyathalawa with rainfall at different stations for 2000/2001

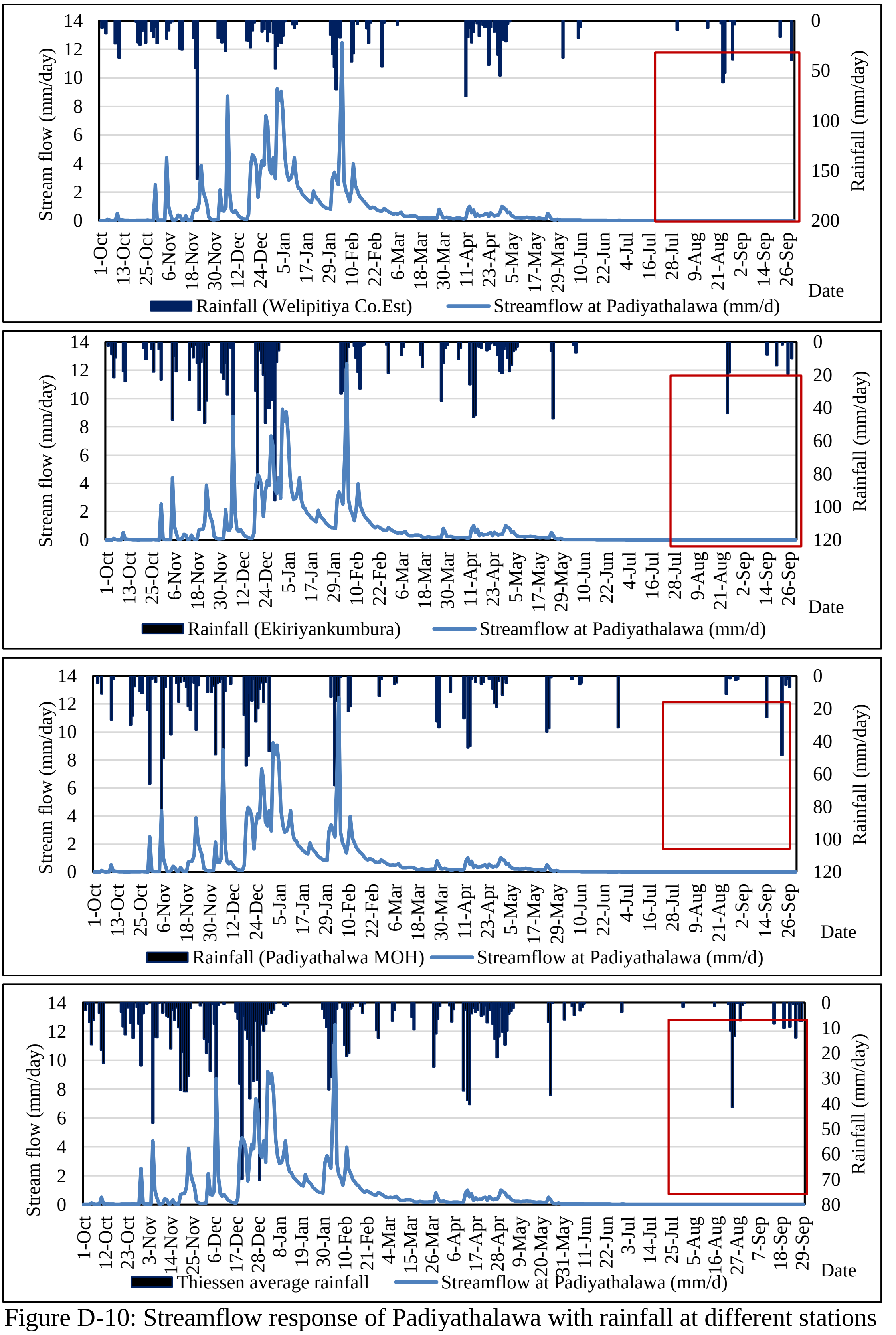

Figure D-10: Streamflow response of Padiyathalawa with rainfall at different stations for 2001/2002

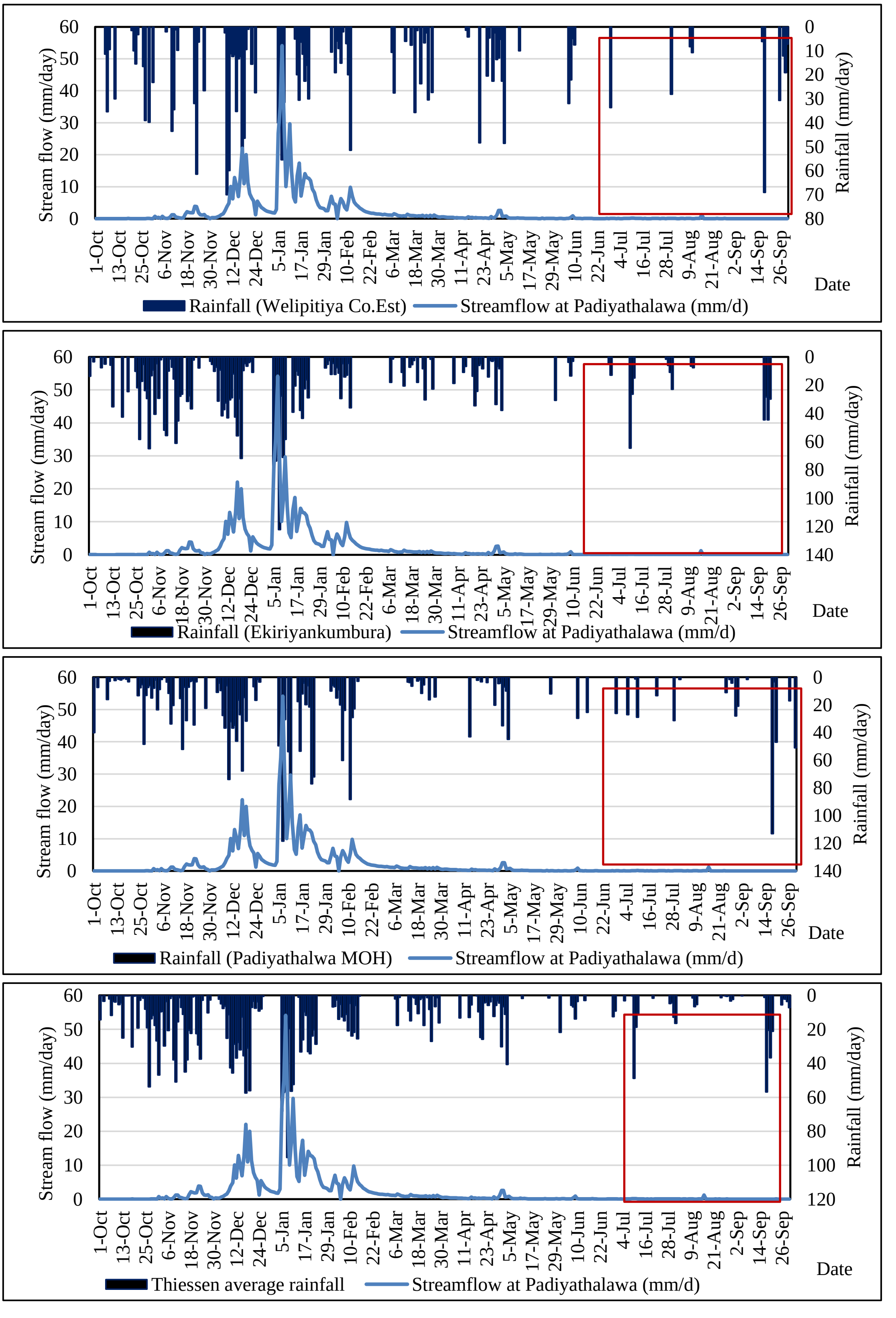

Figure D-11: Streamflow response of Padiyathalawa with rainfall at different stations for 2002/2003

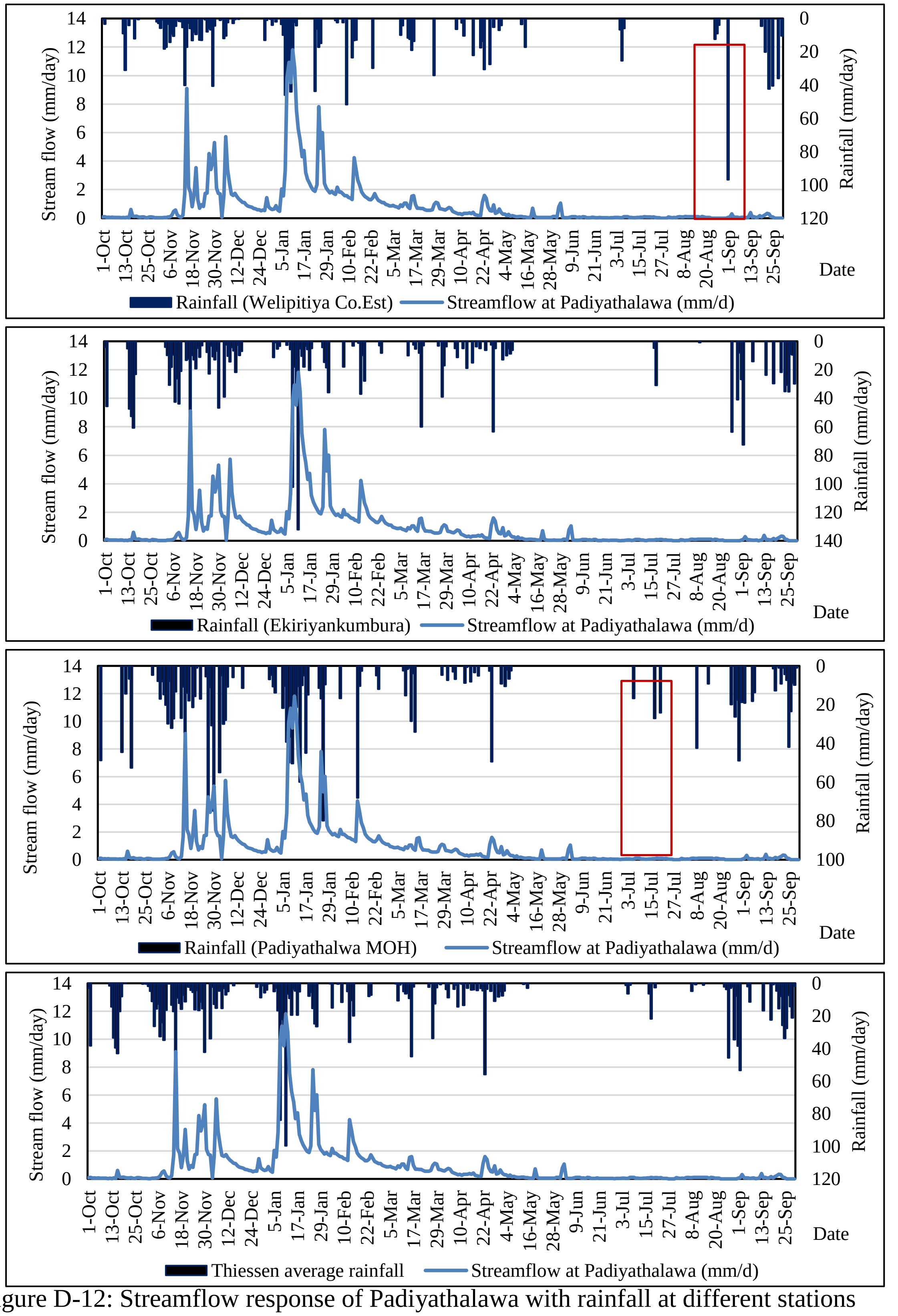

Figure D-12: Streamflow response of Padiyathalawa with rainfall at different stations for 2003/2004

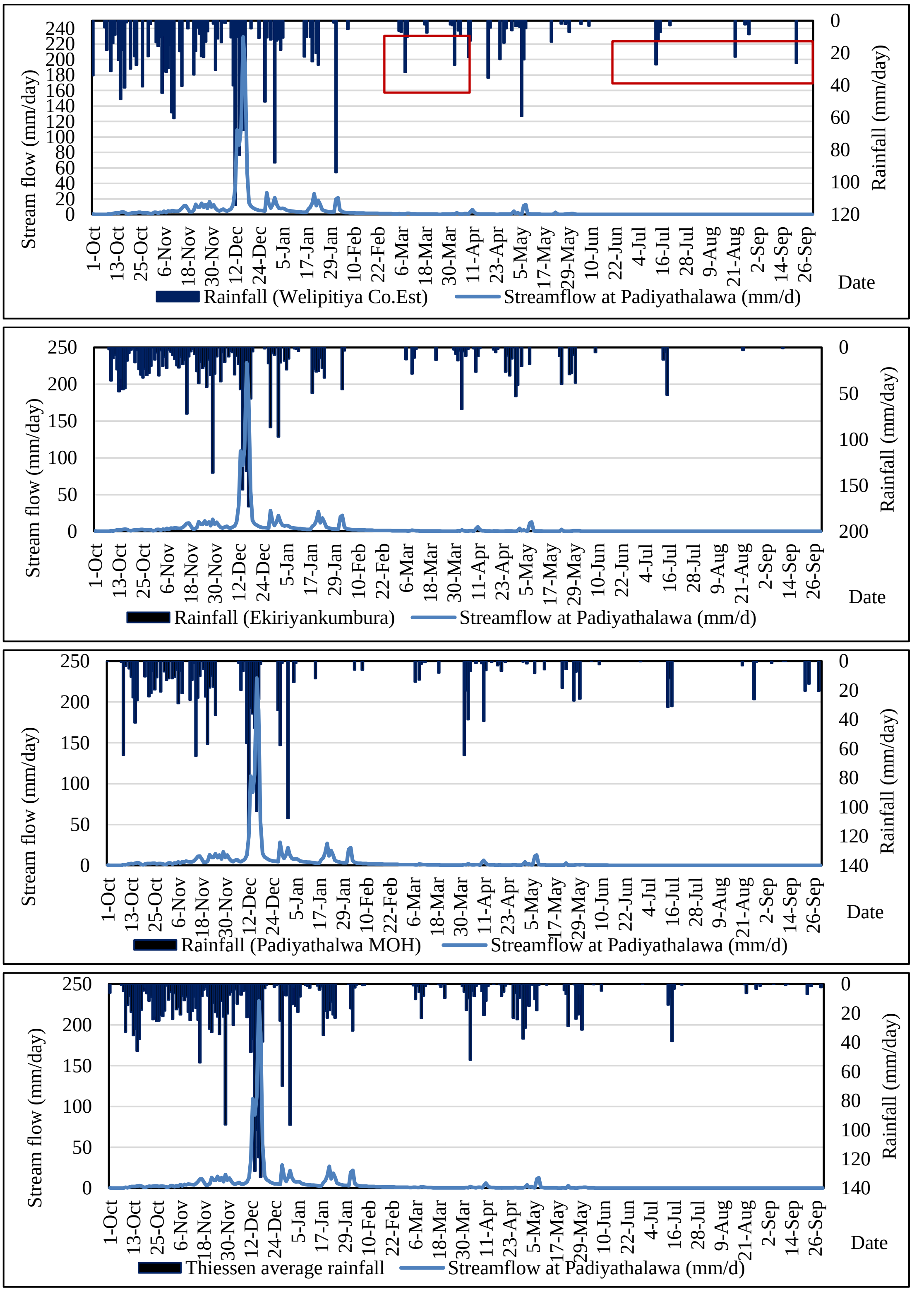

Figure D-13: Streamflow response of Padiyathalawa with rainfall at different stations for 2004/2005

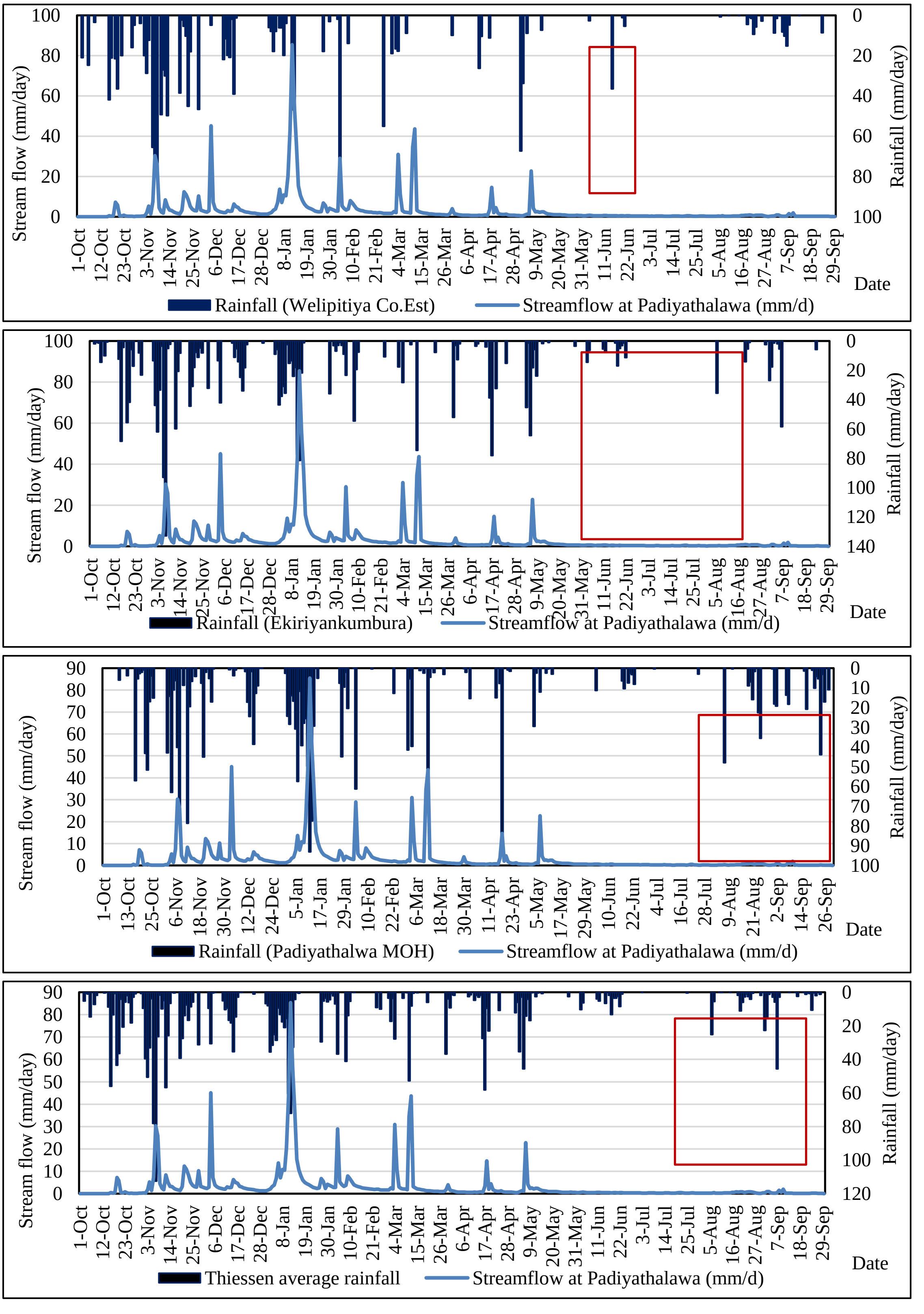

Figure D-14: Streamflow response of Padiyathalawa with rainfall at different stations for 2005/2006

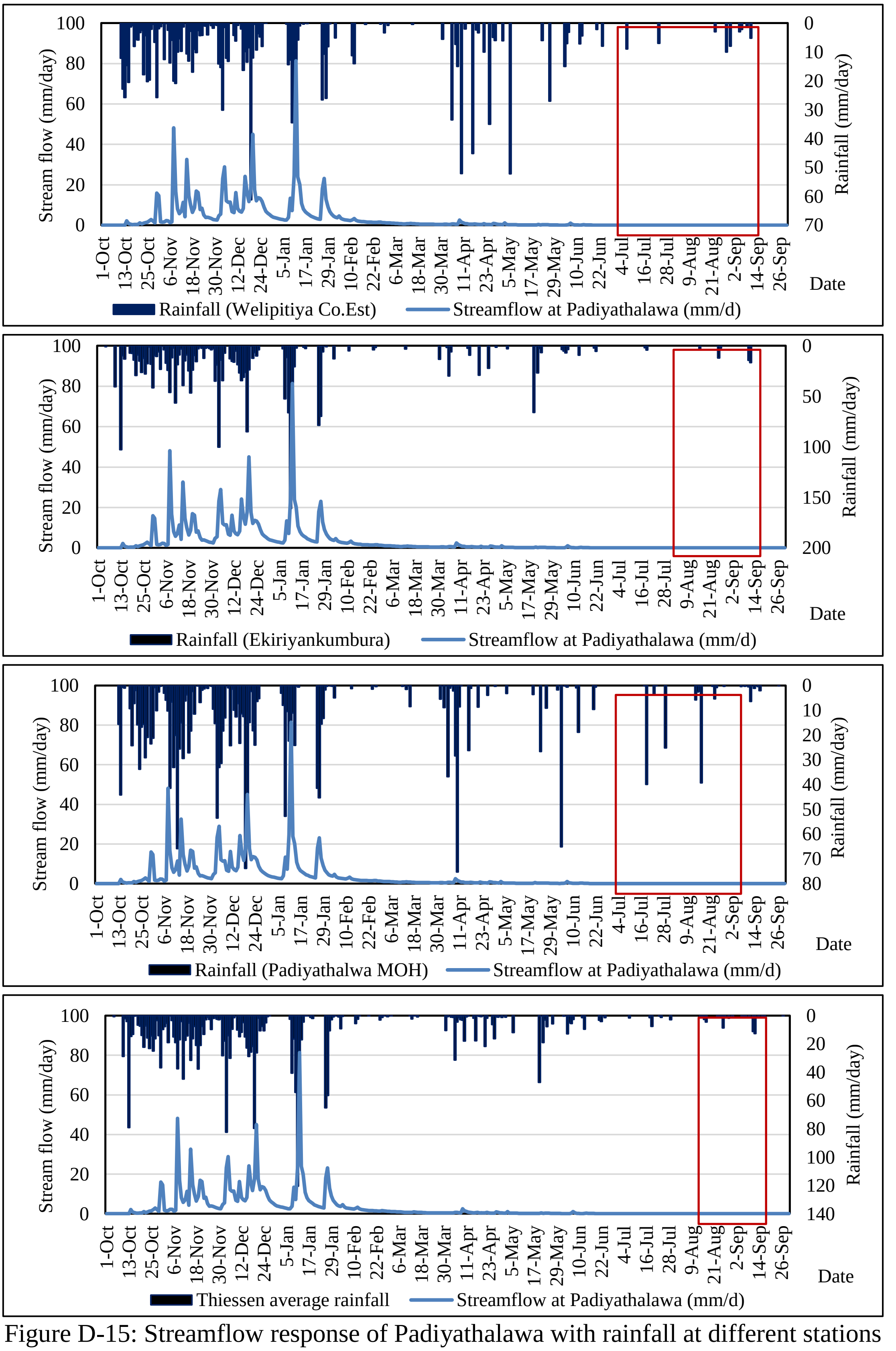

Figure D-15: Streamflow response of Padiyathalawa with rainfall at different stations for 2006/2007

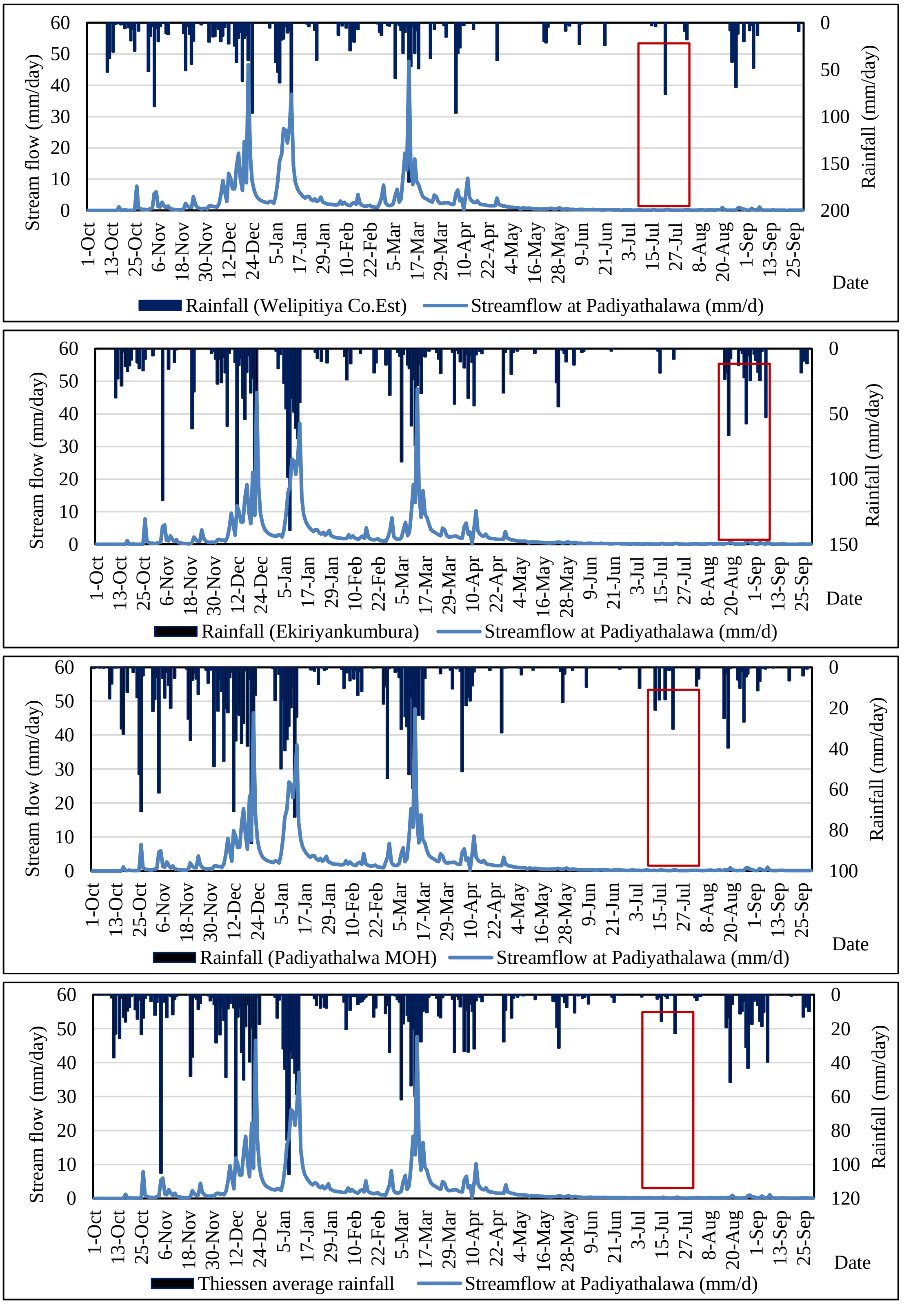

Figure D-16: Streamflow response of Padiyathalawa with rainfall at different stations for 2007/2008

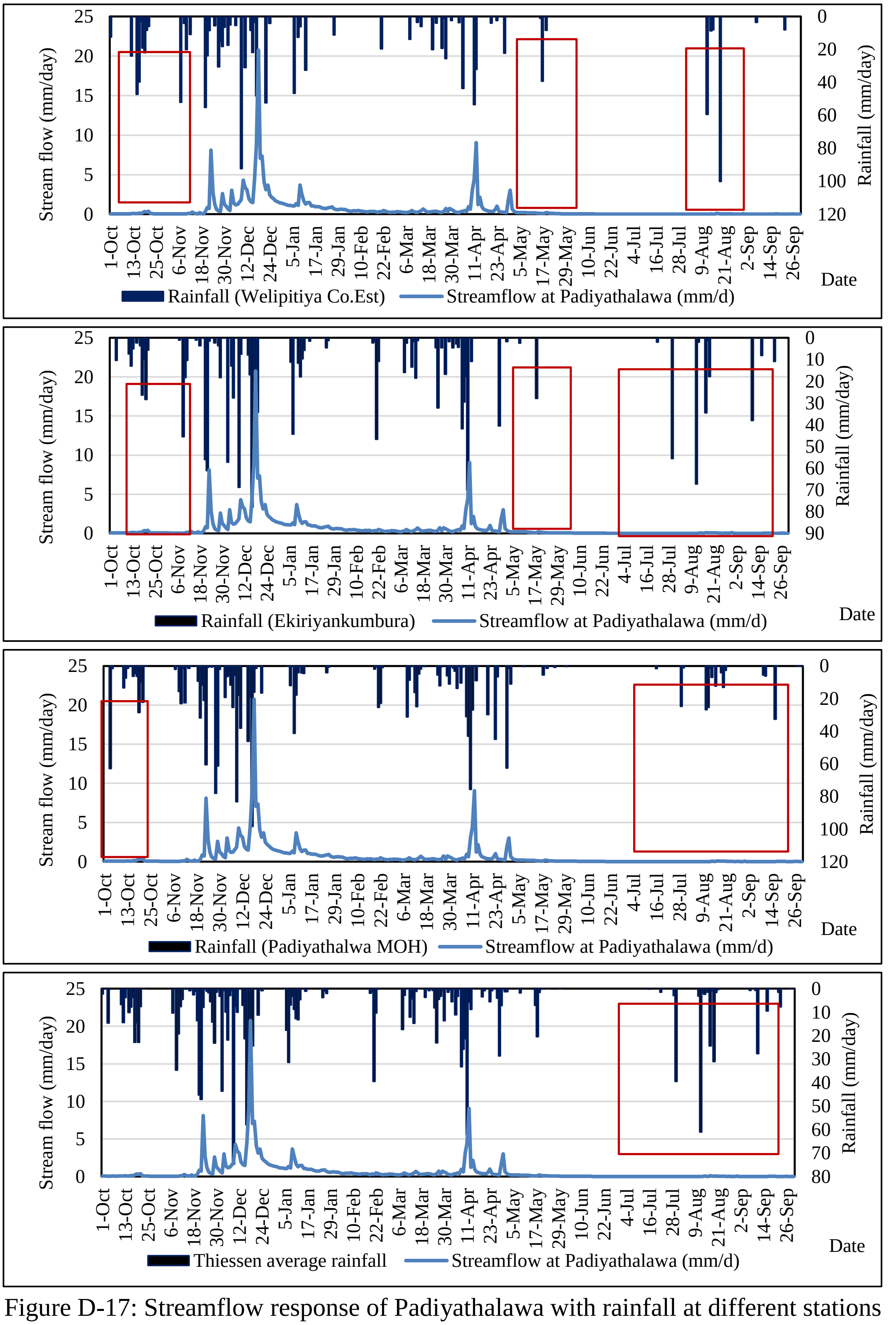

Figure D-17: Streamflow response of Padiyathalawa with rainfall at different stations for 2008/2009

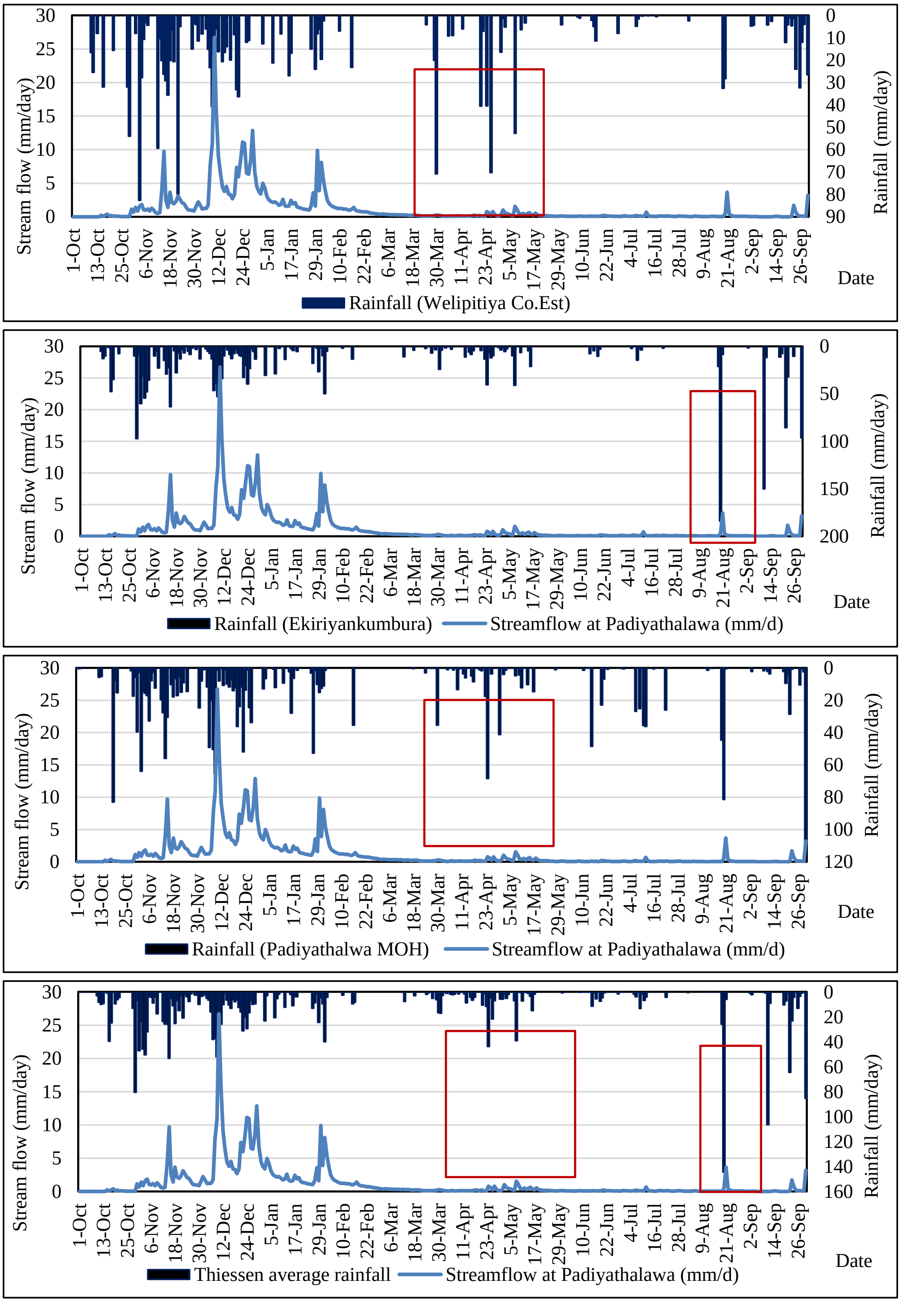

Figure D-18: Streamflow response of Padiyathalawa with rainfall at different stations for 2009/2010

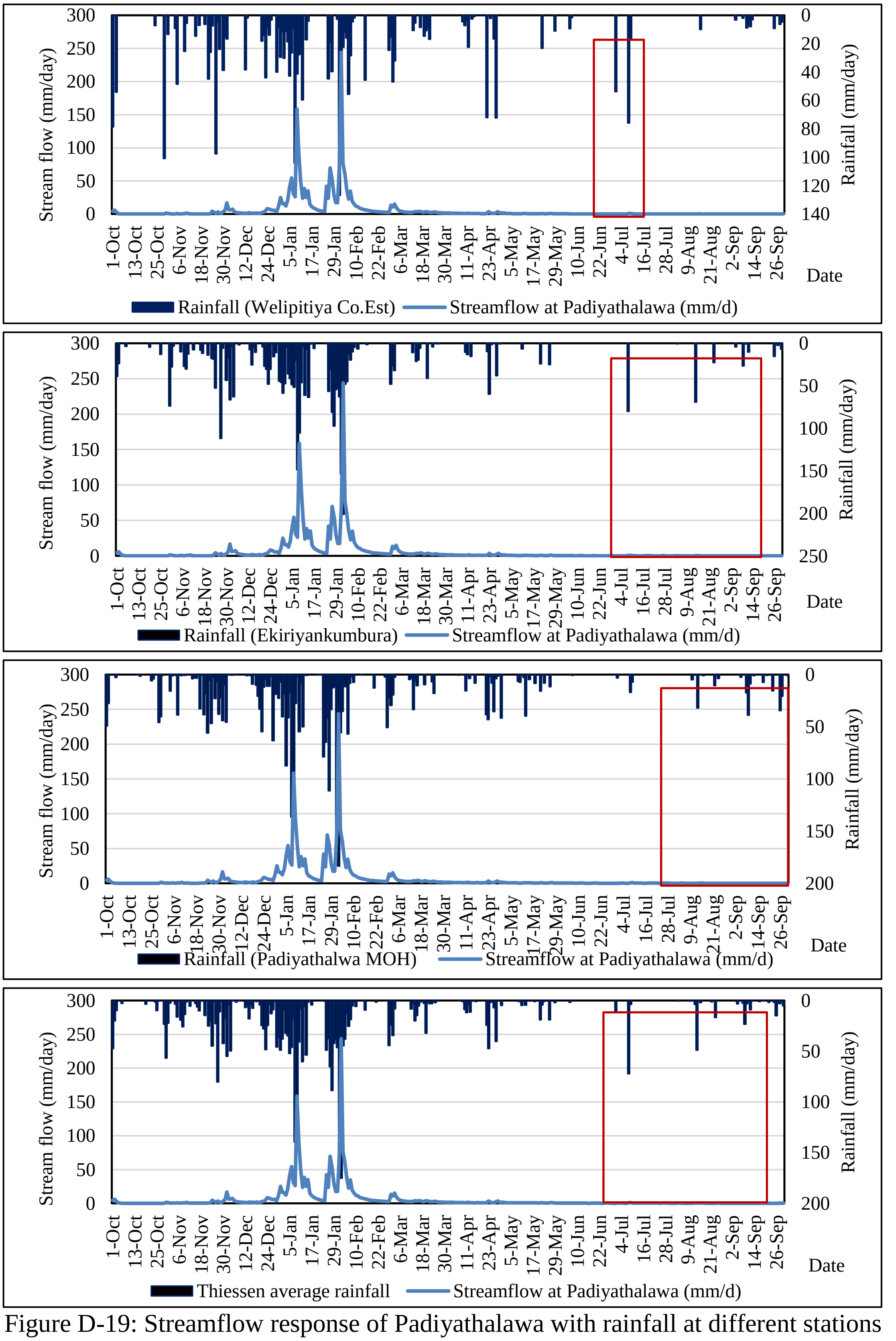

Figure D-19: Streamflow response of Padiyathalawa with rainfall at different stations for 2010/2011

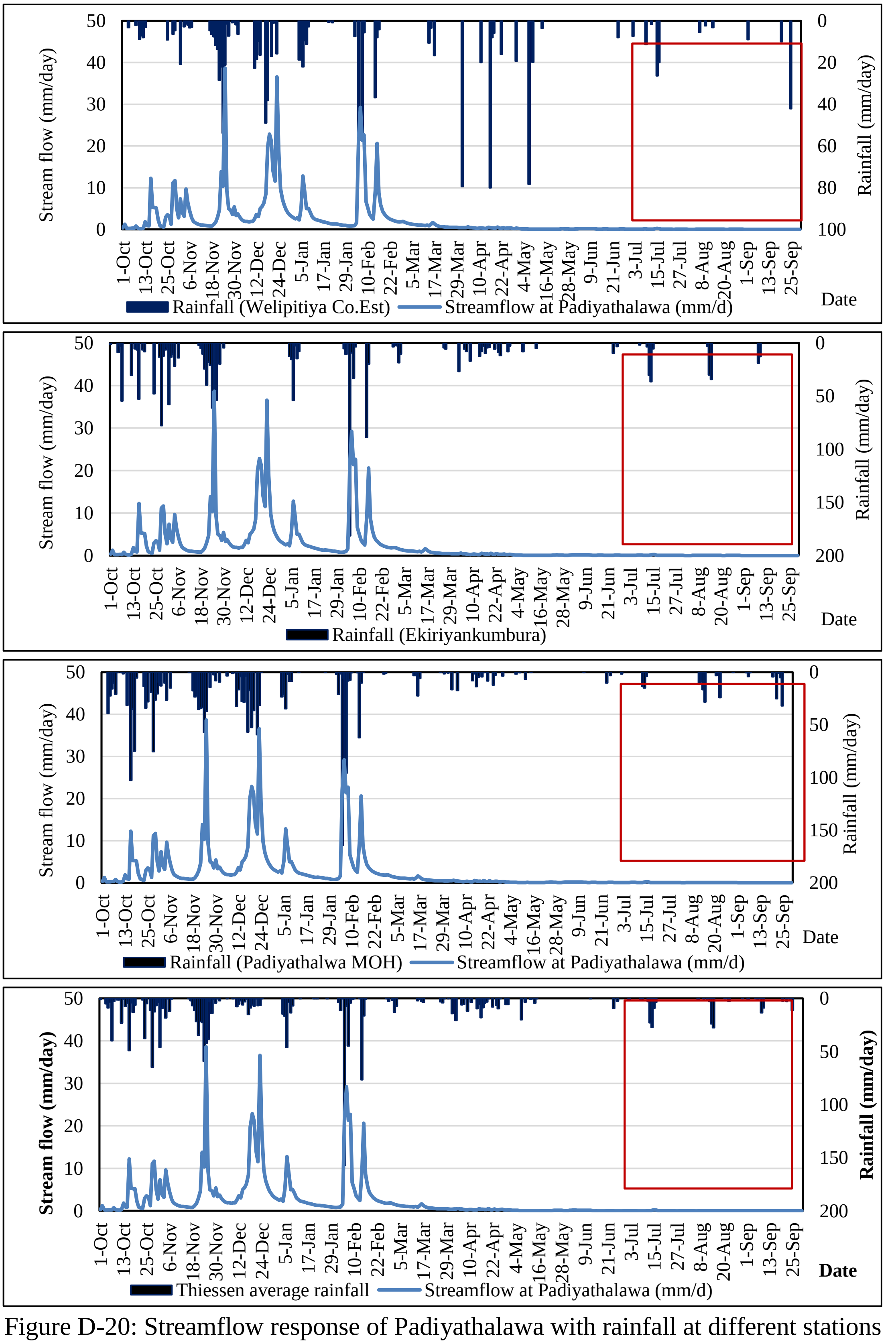

Figure D-20: Streamflow response of Padiyathalawa with rainfall at different stations for 2011/2012

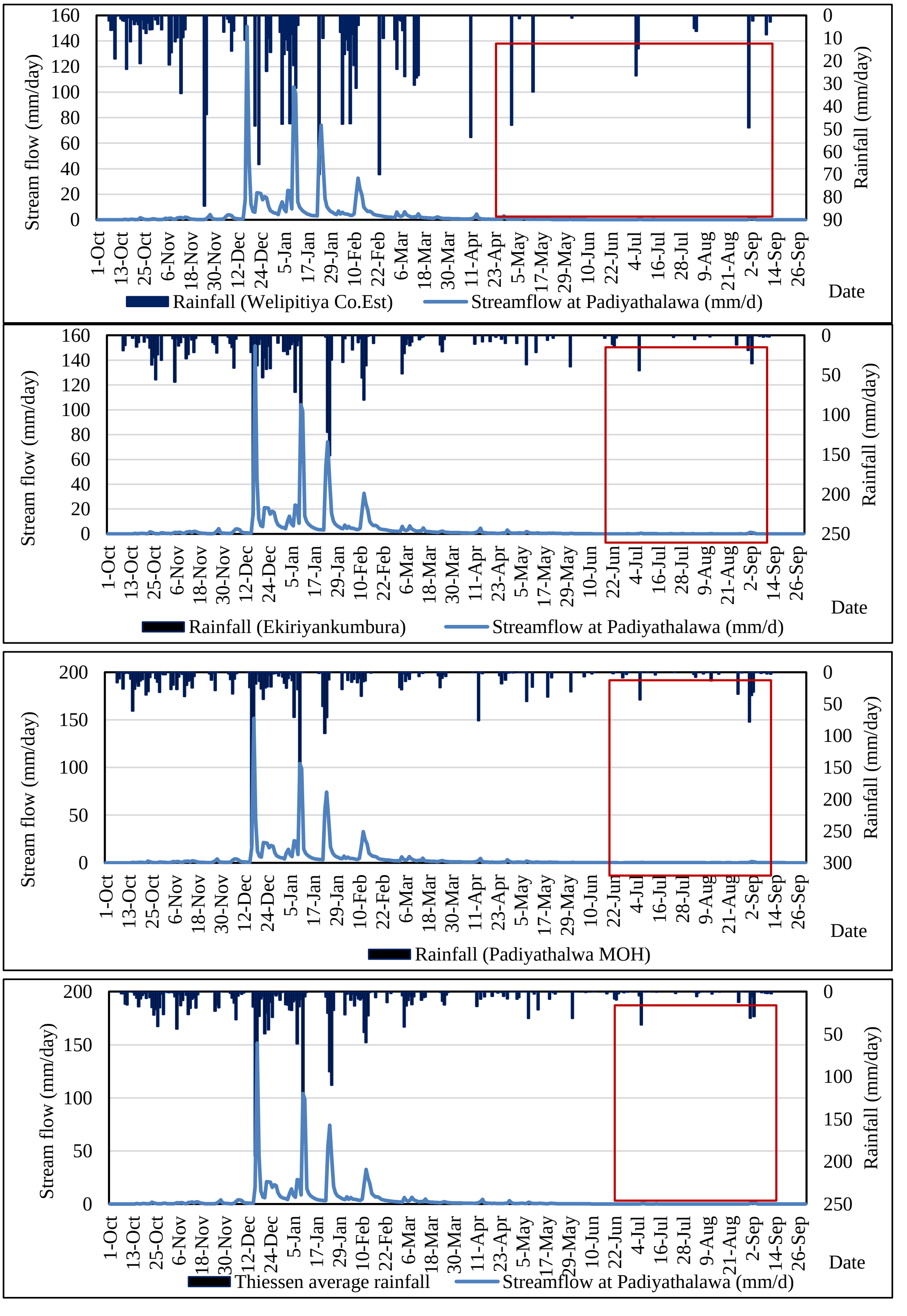

Figure D-21: Streamflow response of Padiyathalawa with rainfall at different stations for 2012/2013

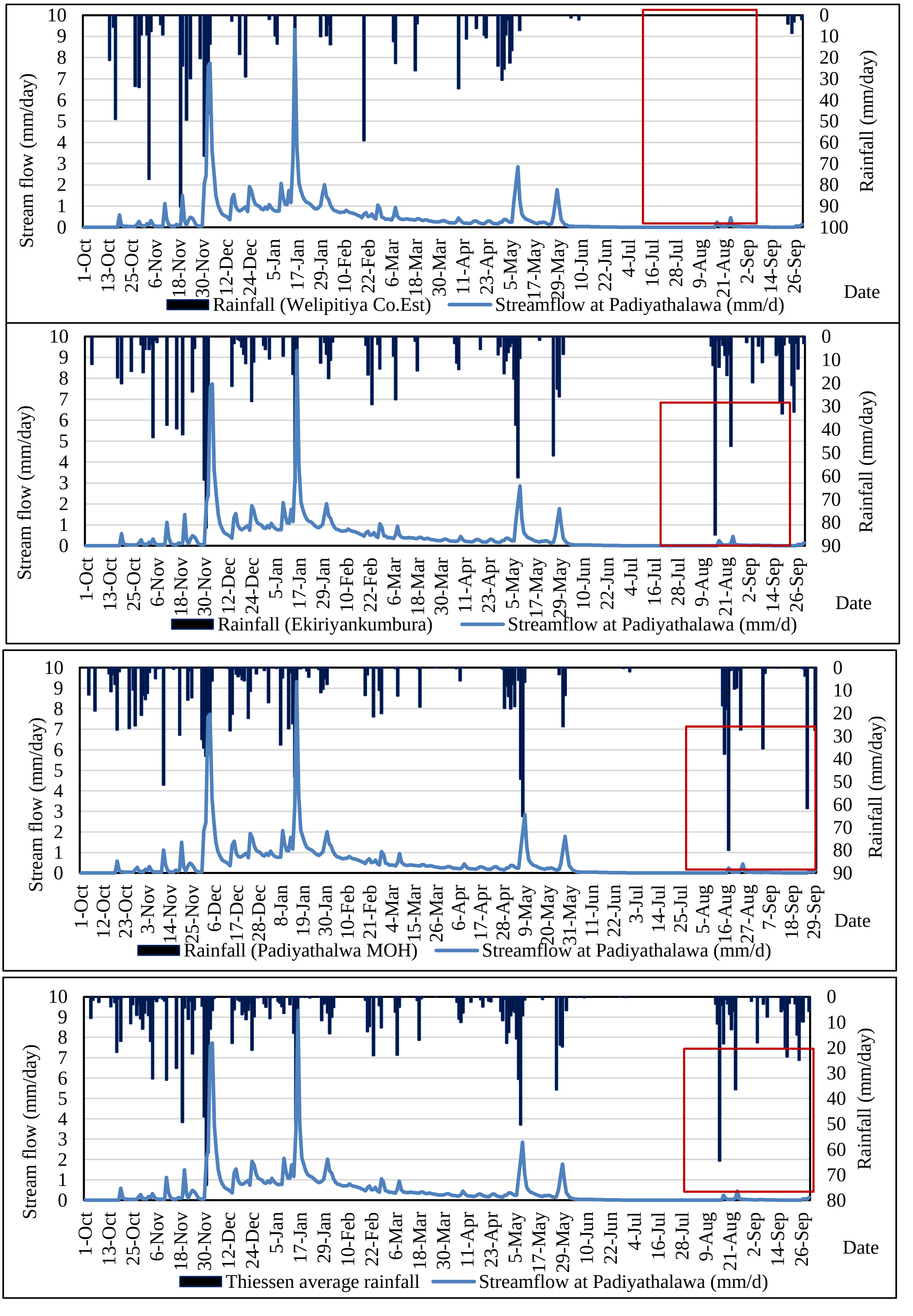

Figure D-22: Streamflow response of Padiyathalawa with rainfall at different stations for 2013/2014

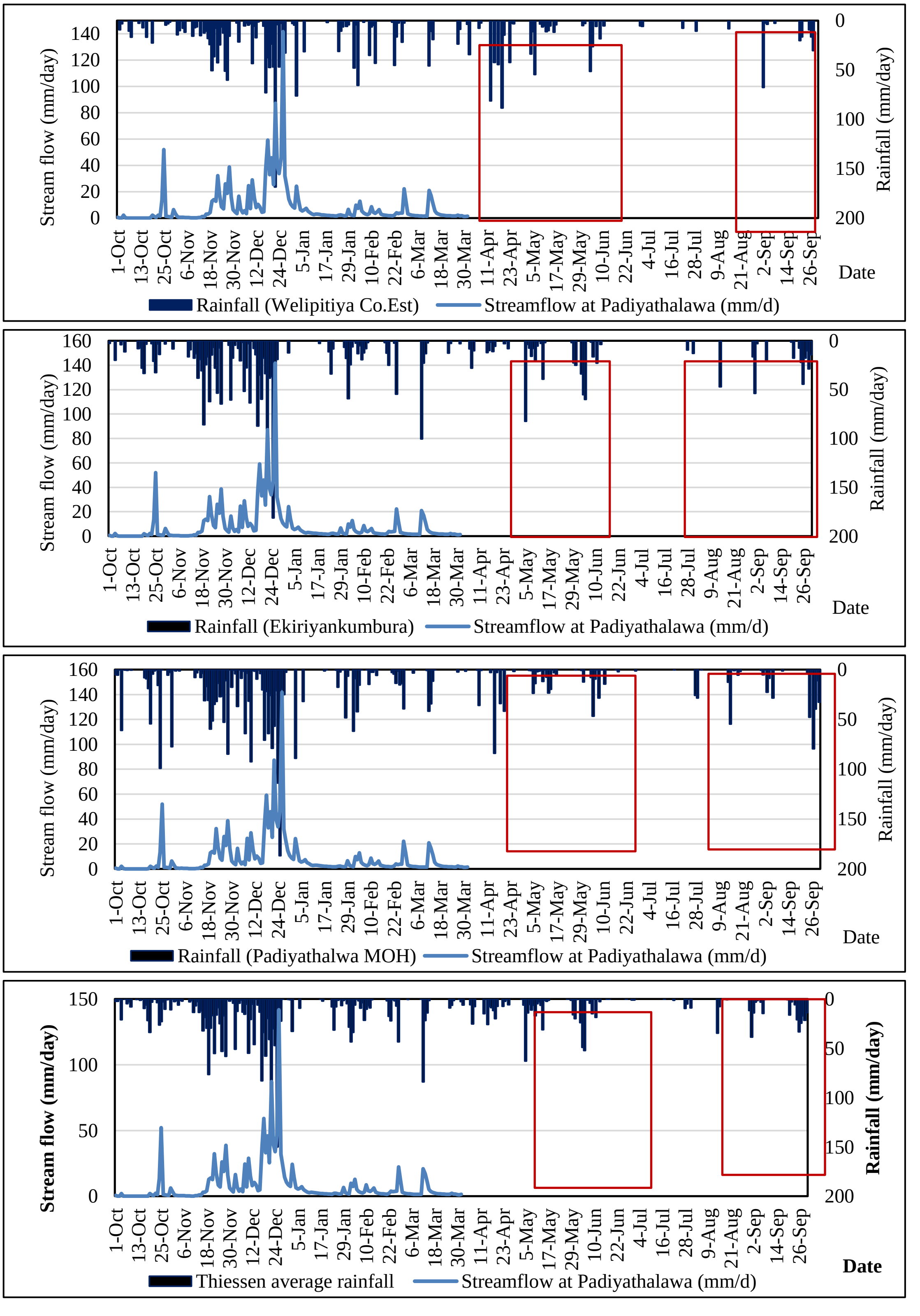

Figure D-23: Streamflow response of Padiyathalawa with rainfall at different stations for 2014/2015

APPENDIX E: The output hydrographs of observed and simulated flows for both calibration and verification periods

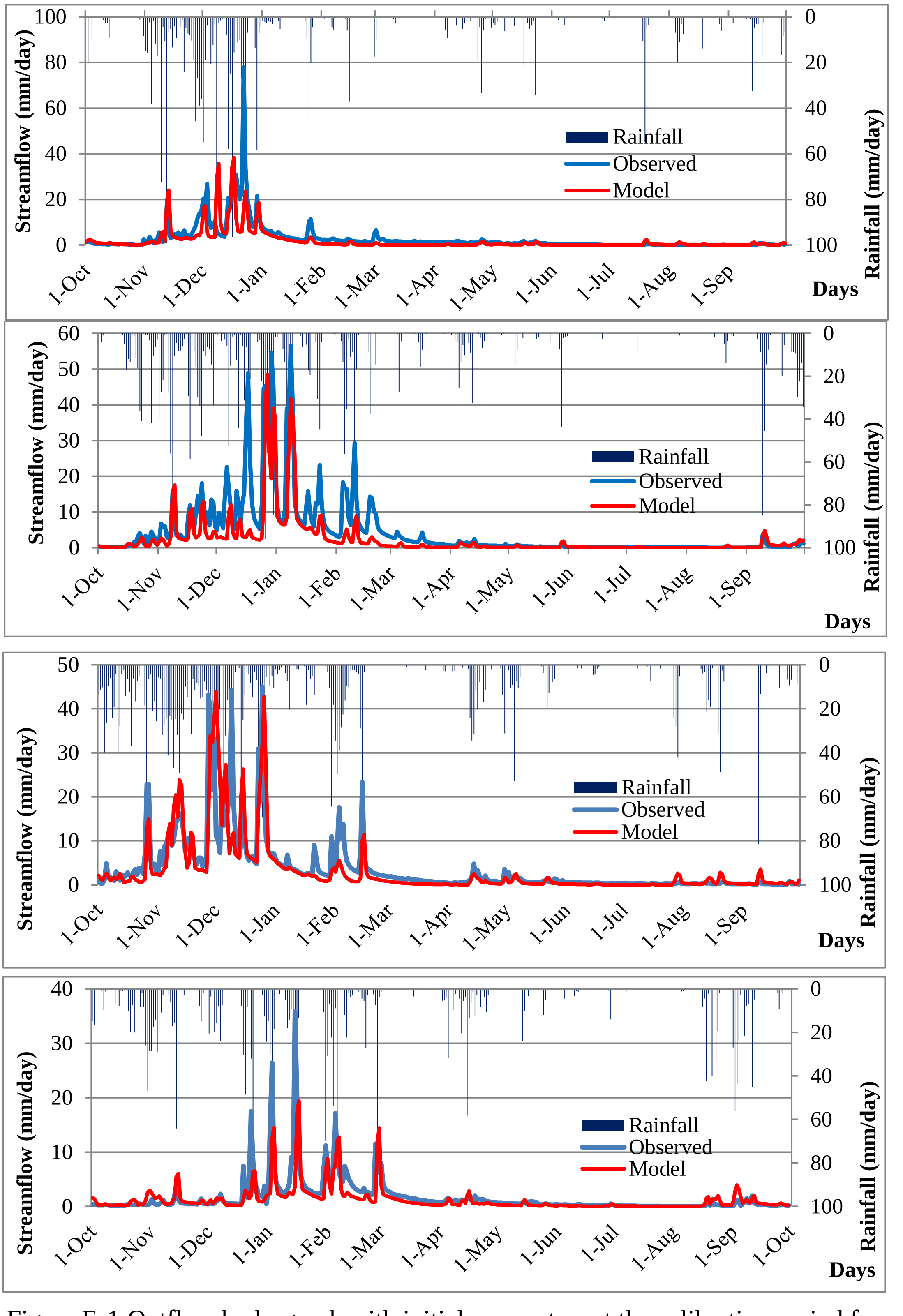

Figure E-1:Outflow hydrograph with initial parameters at the calibration period from 1992/1993 to 1996/1997 (normal-scale)

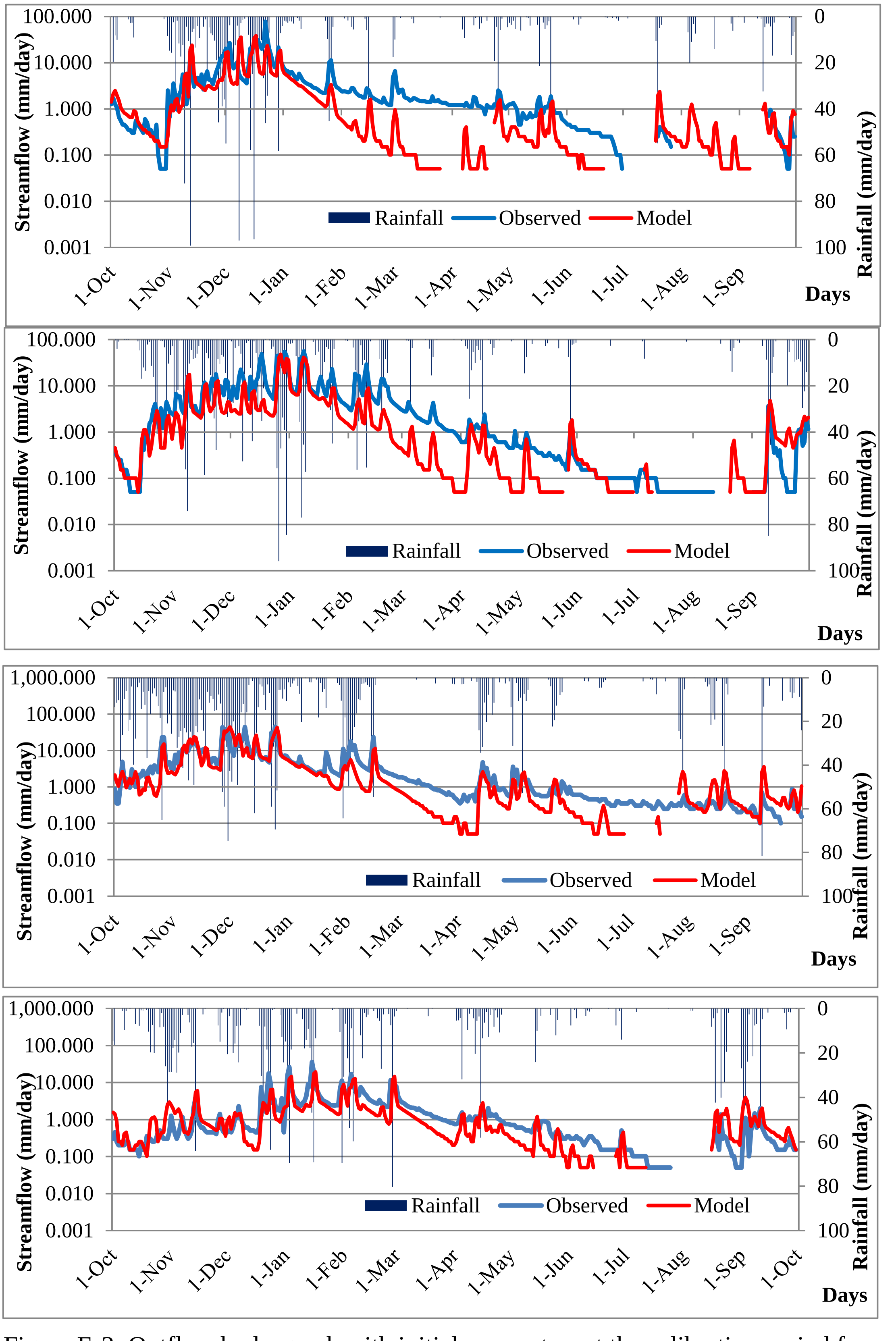

Figure E-2: Outflow hydrograph with initial parameters at the calibration period from 1992/1993 to 1996/1997 (log-scale)

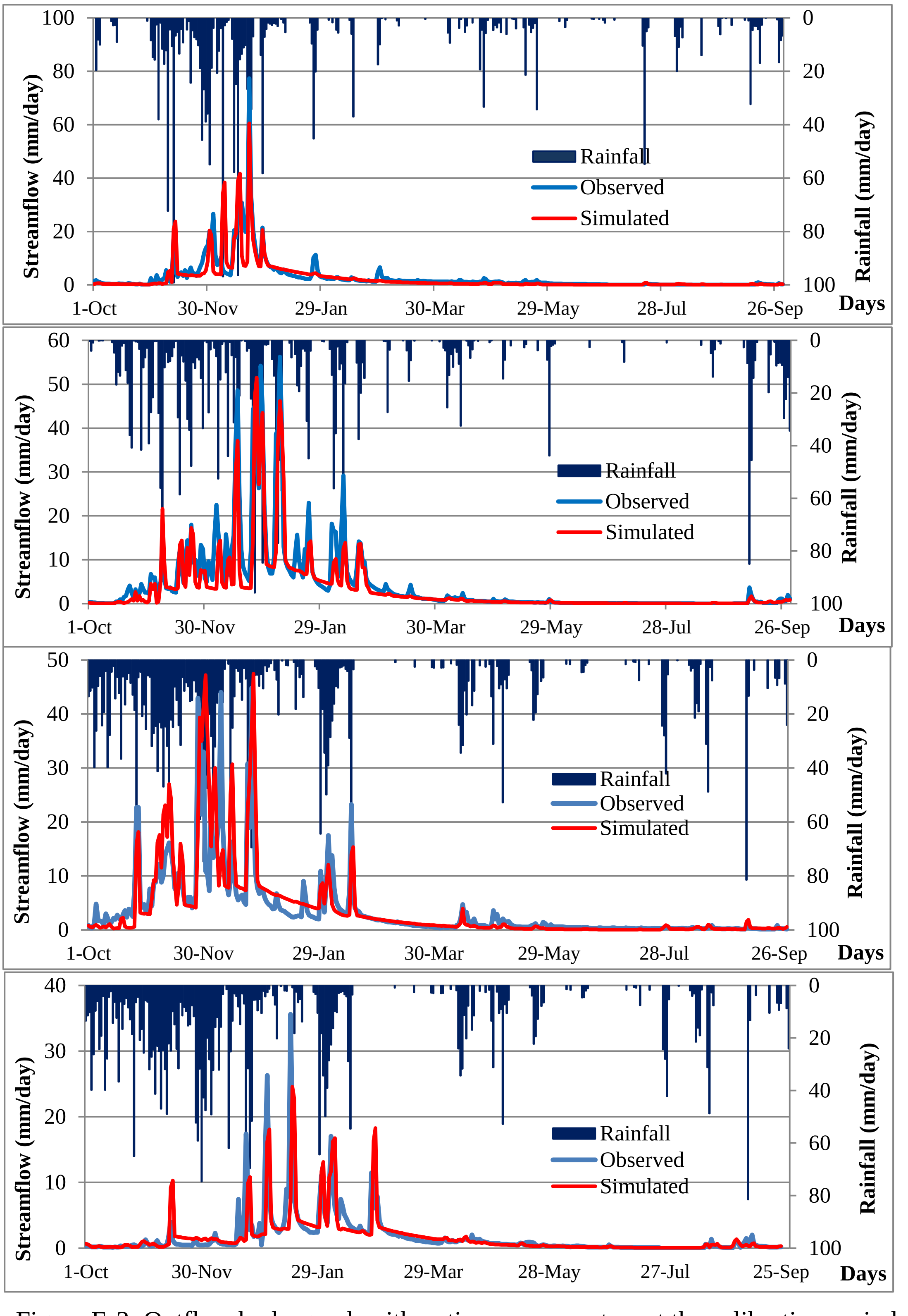

Figure E-3: Outflow hydrograph with optimum parameters at the calibration period from 1992/1993 to 1996/1997 (normal-scale)

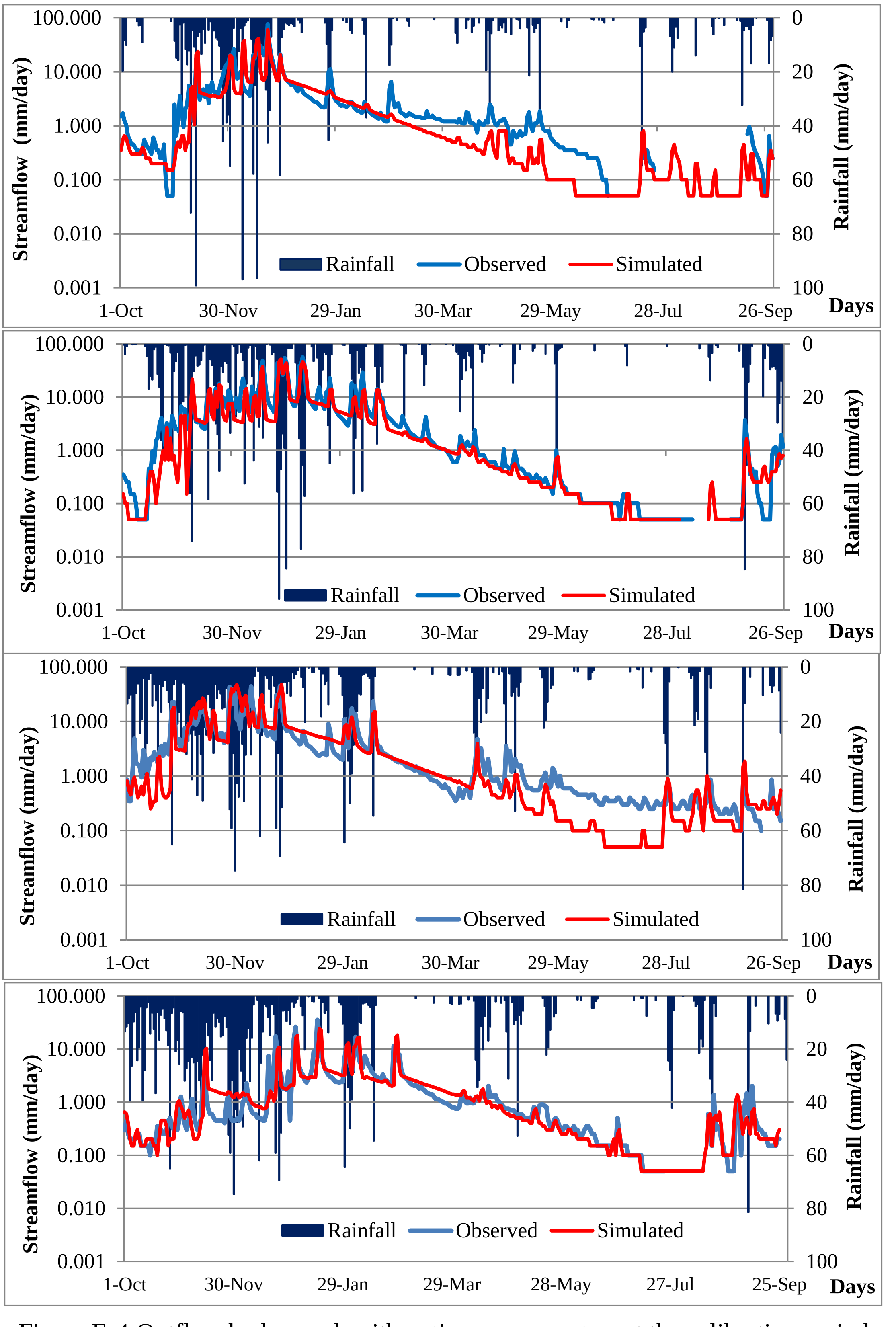

Figure E-4:Outflow hydrograph with optimum parameters at the calibration period from 1992/1993 to 1996/1997 (log-scale)

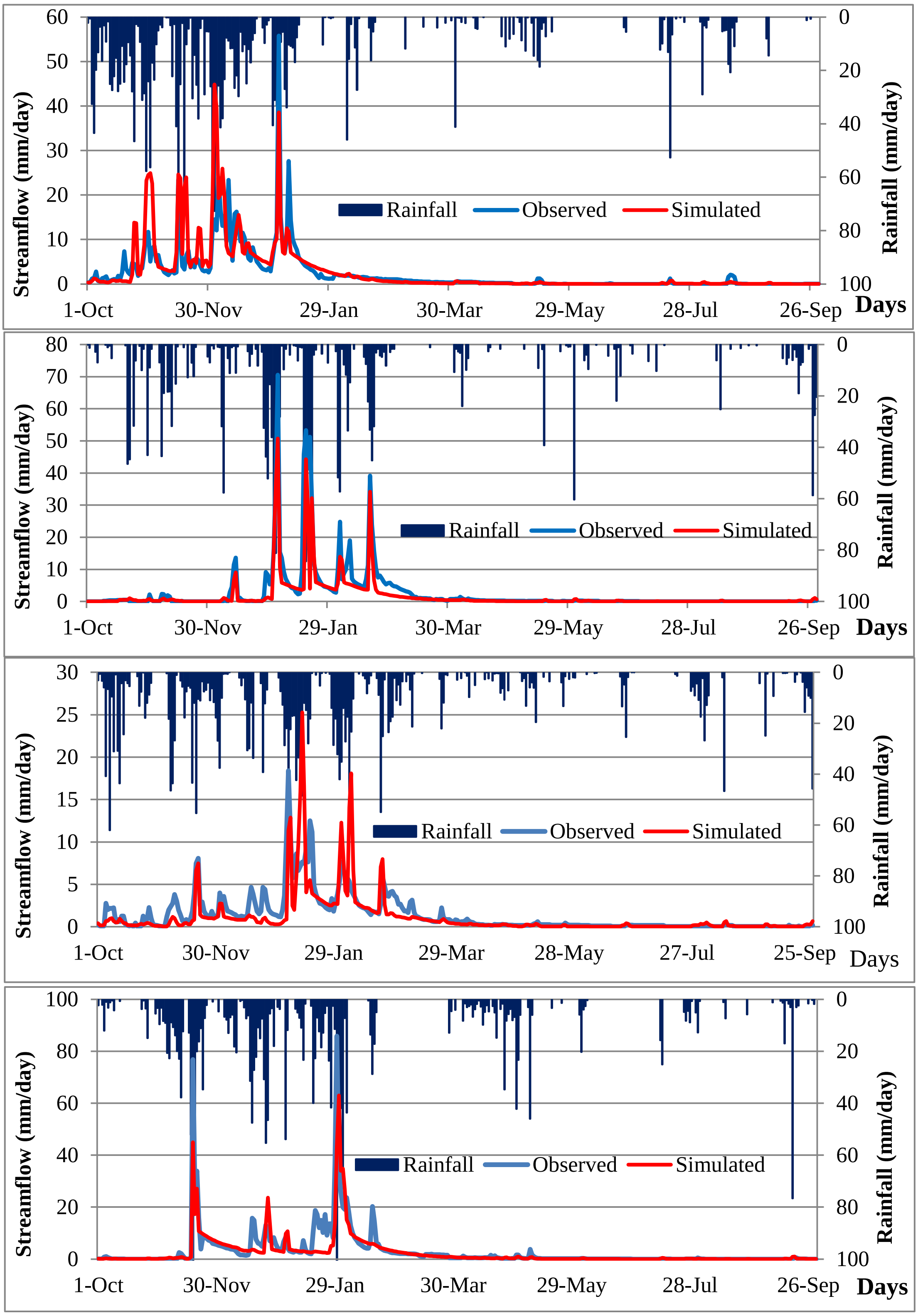

Figure E-5:Outflow hydrograph with optimum parameters at the verification period from 1997/1998 to 2000/2001 (normal-scale)

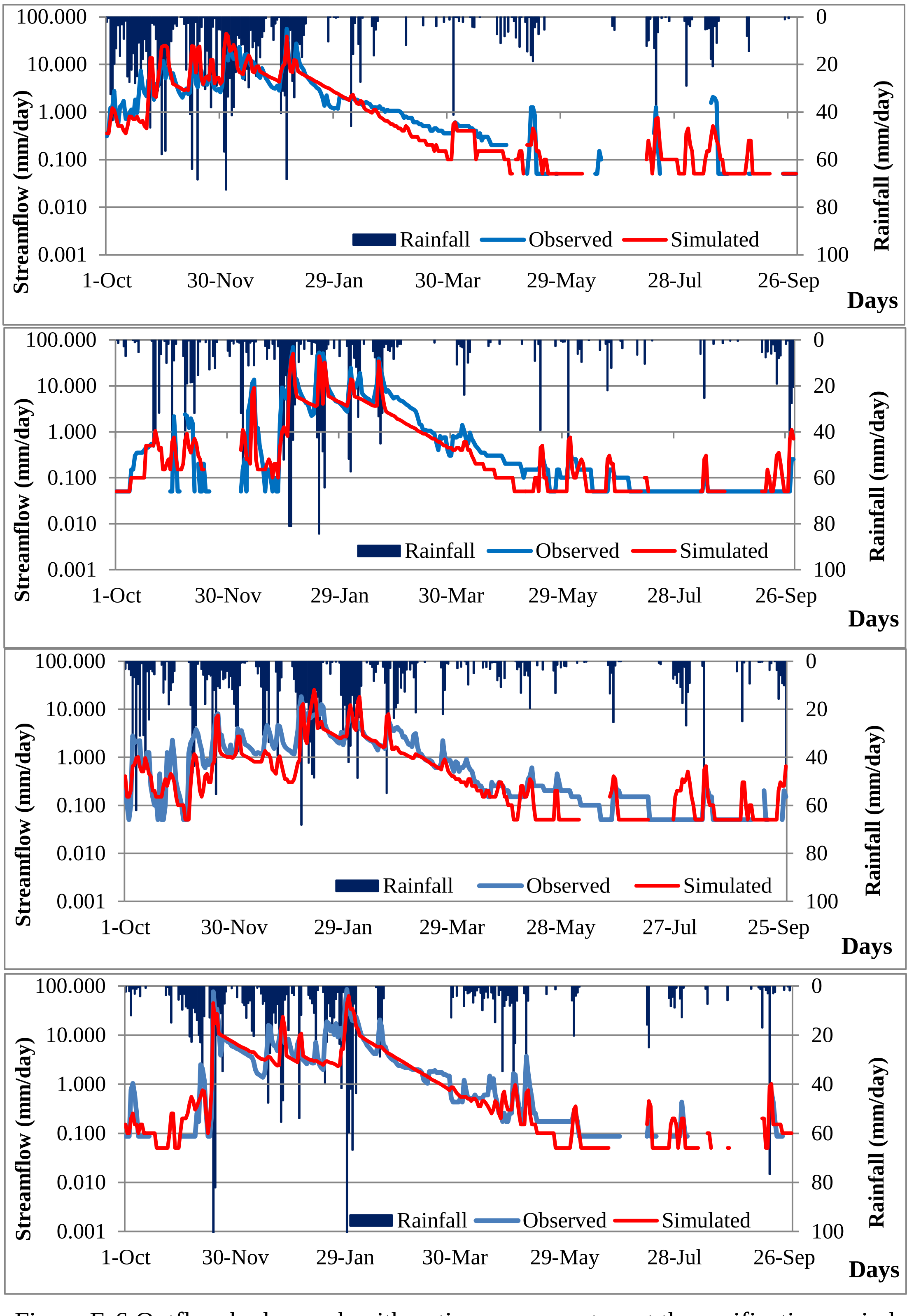

Figure E-6:Outflow hydrograph with optimum parameters at the verification period from 1997/1998 to 2000/2001 (log-scale)